申报	系列：教师系列教学科研并重型
	专业：计算机科学与技术
	职称：副教授

业绩成果材料

（申报人的业绩成果材料包括论文、科研项目、获奖以及其他成果等）

单　位（二级单位）：数学与信息学院

姓　名　杨秋妹

材料核对人：　　单位盖章：

核对时间：

华南农业大学制

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3	教学改革项目	善境伦理学与风景园林专业实践教学深度融合的探索与实践	重点	林学与风景园林学院	翁殊斐
4	教学改革项目	面向智慧国土空间规划的《区域规划》 数智化教学改革	重点	公共管理学院	李玮
5	教学改革项目	基于批判性思维培养的公共管理类专业课“GenAI+”教学模式探索——以投资学课程为例	重点	公共管理学院	李韵婷
6	教学改革项目	“AI赋能-人机协同”课堂互动重构研究—以C语言课程为例	重点	数学与信息学院 软件学	彭利民
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人工智能时代《数据结构》课程的教学探讨

杨秋妹
(华南农业大学 数学与信息学院,广东 广州 510642)

摘 要:教育应与时代接轨,人工智能时代给高等教育带来了智慧教学新工具,也给学生的专业知识培养带来了新要求。文章针对人工智能时代下《数据结构》课程的教学改革问题,分析了课程理论教学及实验教学需要改进的地方,阐述了《数据结构》课程应充分利用人工智能时代的新工具,调整授课方式,改善教学效果。同时也应根据人工智能时代的新要求,将课程的教授内容与时代研究热点相结合,激发学生的学习兴趣,培养人工智能时代所需要的特色人才。

关键词:数据结构;人工智能;计算思维;教学改革
中图分类号:G434;TP311.12 **文献标志码**:B **文章编号**:1673-8454(2020)24-0048-04

一、引言

人工智能已渗透到人们日常生活的各个环节,个性化的购物体验、新闻定制、医疗保健、智能家居、城市安保等无一不是人工智能的应用范畴。互联网、大数据、人工智能技术的发展引领社会的未来发展方向,带动社会岗位技能需求变革,也给高校的教育体系带来了挑战[1]。为迎接人工智能时代的到来,高校需要在教学思想以及专业设置等多方面进行调整[2]。人工智能研究主要集中学习、推理、问题解决、感知和使用语言这几方面的研究,分为两种类型:一种是数据驱动的人工智能,以机器学习为研究方法;另一种是基于知识的人工智能,以领域知识的推理为解决方案。当前人工智能的成功主要是以数据驱动的人工智能技术的进步。

《数据结构》作为大学计算机相关专业的基础课程,教学目标为提高学生以计算机为工具的问题求解能力,是一门研究数据建模的学科。其不仅仅是大学程序设计能力训练的核心课程,也是人工智能技术的基础课程。《数据结构》课程于1968年由Knuth教授提出,其在《计

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算机程序设计艺术》一书中系统地讲述了数据的逻辑结构、物理结构以及在数据集合上常用的操作。20 世纪 70 年代初,《数据结构》开始进入大学课堂,是一门历史悠久的经典课程。计算机科学与技术是一个持续发展、快速更新的学科,对应的学科知识讲授也应与时俱进。在《数据结构》课程的教学过程中,应结合当前人工智能时代的发展需求以及研究热点,调整相应的教学内容以及教学方法[3]。本文将结合《数据结构》教学环节中的理论教学以及实践教学,探讨如何在现有的基础上利用新技术,结合新需求,进一步改革该课程的教学。

二、《数据结构》课堂理论教学探讨

《数据结构》知识点多且抽象程度高,学习难度大。而授课的对象多为大一下学期或大二上学期的学生,大部分学生仅进行了《计算机导论》及《程序设计语言》的专业基础课程学习,程序设计能力较为薄弱,对计算机专业知识接触面窄,理解不够深刻。在此背景下,任课教师应结合学生的知识体系,适当地引入人工智能时代涉及的新技术、新概念,引导学生更好地完成课程的学习。

1.注重授课内容与人工智能时代核心技术的关联

图灵奖得主、计算机科学家 N.Wirth 提出程序等于数据结构加算法的观点。《程序设计语言》《数据结构》及《算法设计与分析》这三门课程组成大学计算机相关专业进行程序设计能力培养的一个课程体系,在课程安排上按照“《程序设计语言》—《数据结构》—《算法设计与分析》”的授课次序开展。《数据结构》教学内容起到承上启下的作用。《程序设计语言》以语法学习为主,学习变量、运算符、表达式、顺序、循环、分支、函数及递归、结构体、指针等程序设计的基本概念,培养学生程序阅读、代码编写及调试能力。《数据结构》在此基础上,主要讲授在程序设计过程中对于数据的建模。《数据结构》课程研究的是非数值计算问题处理过程中,数据元素之间的逻辑关系、数据在计算机上的存储结构以及在各种结构上相关的运算。《数据结构》学科讲授的内容包括基本的数据结构,如线性表、栈和队列、串、数组和广义表、树和二叉树、图以及常用的计算机操作,如查找、排序的介绍及实现。《算法设计与分析》则旨在进一步提高学生问题求解能力,学习内容主要包括通用的算法设计技术及算法复杂度分析理论。课程包括分治及递归、动态规划、贪心、回溯与分支限界等常用算法的学习。这三门课程的教学相辅相成,互相促进。在如今的人工智能时代下,该课程体系也应适应技术变更需求,进行相应的改革。

更快的计算机处理器、大数据的可用性和计算方法的进步引发了人工智能时代的到来。机器学习、深度学习、大数据处理等都是人工智能时代的核心技术。结合当前人工智能的发展,可在《数据结构》讲授的过程中作为扩展内容,给学生介绍当今的研究热点。从数据结构的基础学习内容出发,探讨课程知识点在人工智能热点技术中的应用,激发学生学习的兴趣[4]。可在查找算法的学习中引出大数据中对应的搜索策略等,结合深度学习中广泛采用的人工神经网络结构,如图 1 所示,其实现时可用《数据结构》中的带权图结构进行表示,图中顶点表示神经元,边表示神经元之间的连接线,每条连接线拥有一个不同的权值,该权值经由训练得到。

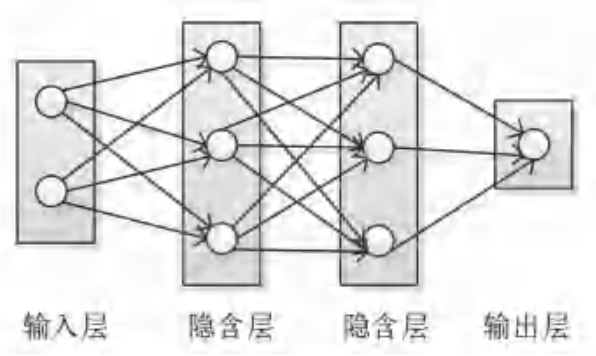


图 1 人工神经网络结构

2.利用智慧教学工具加强课堂互动及推广个性化教学

人工智能技术改变了传统的教学模式。传统的课堂教学由于人数众多,教师无法与学生有效互动,较难快速获取课堂教学效果的直接反馈。同时,由于智慧手机应用花样层出,成为分散学习者上课注意力的主要原因。为了充分借助现代化信息手段改善课堂讲学效果,雨课堂、超星学习通等平台应时而生,将信息技术与教学需求相融合,更好地让学生利用手中资源,革新传统的教学模式,产生教学“线下”和“线上”相结合的模式[5]。虚拟化技术在《数据结构》课堂中得到应用[6],各类新型教学平台在《数据结构》的教学上也得到了应用及推广[7][8]。

《数据结构》课程教学内容抽象,如果只是由授课教师做理论讲述,学生较难掌握。结合“线上”平台,可通过设计与课程内容密切关联的线上互动,提高学生的上课积极性,同时任课教师可实时了解学生对知识点的掌握程度,及时调整上课进度。以雨课堂的使用为例,其通过 PowerPoint 插件的方式使用,将丰富的教学

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资源插入到讲义中，学生通过手机端实时地与任课教师进行互动,系统提供完善的数据分析反馈。任课教师可在课前备课时设计与知识点相关的习题。如在讲授栈这一种数据结构时,可设计与栈的进栈、出栈相关的练习;在讲授串的模式匹配问题时,由于 KMP 模式匹配算法较难理解,可设计失效函数计算的习题。另外,由于《数据结构》课程还涉及到代码实现问题,但是在课堂教学中由于时间及硬件条件的限制，任课教师往往无法对代码实现进行详尽的讲解，由此导致学生在代码实现这一环节出现困难。利用雨课堂可以帮助教师把较难编写的关键代码抽出来，通过互动的形式教导学生进行代码编写。

智慧教学的主要特色是自适应性、突出用户个性化。通过收集和分析大量的教学相关智能数据,形成人工智能技术驱动的教学效果评价系统。教师可充分利用智能评价系统的反馈，更好地对学生进行个性化的教学,根据各个学生在知识点上掌握的差异进行不同的学习资料推送,因材施教,达到更好的教学效果。

3.人工智能时代下计算思维的培养

计算思维与阅读、写作、算术并列,被认为是当今人类应掌握的四大基本技能。计算思维利用可计算的理论去解决问题、设计系统及理解人类行为。计算思维的本质是抽象与自动化[9]。计算思维关注的核心为:什么是可计算的，并探索什么问题人类比机器擅长以及什么问题机器比人类更擅长。在问题的可计算考量上,如何选择符合实际需求的数据结构及算法很重要。选取的数据结构不同,相应设计的算法也会有差异。

人工智能未来的发展依然存在着各种可能性,因此从人类的基本技能培养出发更能顺应多变的未来需求。《数据结构》的教学目标之一是教会学生分析问题、解决问题。计算机问题求解的过程为从问题出发,抽象出问题求解的数学模型,设计相应的数据结构及算法,最终在计算机上编写程序并运行得到结果。

在《数据结构》课程的学习过程中,研究如何抽象出问题的求解模型是很重要的一个环节。问题的求解模型一般以抽象数据类型表示。抽象数据类型指的是从求解问题的数学模型中抽象出来的数据逻辑结构和抽象运算,不考虑计算机的具体实现,独立于程序设计语言,研究的是数据元素之间的逻辑关联。如何正确定义抽象数据类型非常重要，在抽象的过程中提取需关注的细节及忽略无关的部分是计算思维的体现。通过学习常用的抽象数据类型，掌握在问题求解中抽象方法的运用。

此外,在《数据结构》课程中,还应教导学生进行算法的时间复杂度及空间复杂度分析。在问题求解中,一般将多项式时间复杂度的算法称为好算法。通过图表等形式向学生直观展示多项式时间复杂度及指数时间复杂度的算法差异,引导学生进行算法评价。教师在课堂教学中与学生探讨改进算法复杂度的可用方案,如在讲授线性表的归并时，引入空间换取时间提高算法时间效率的策略介绍。在学习查找、排序等计算机常用算法时,可探讨人类与计算机求解问题的区别等等。

三、《数据结构》实验教学探讨

人工智能也通常被称作为高级的计算机程序。由此看出程序设计是人工智能的基础,优良的编程能力依旧是一个必不可缺的基本技能。《数据结构》课程也是一门训练学生动手编写代码能力的课程。学习数据结构的理论知识与编程实现数据结构及其操作是两个不同的挑战。《数据结构》的实验教学主要包括三个部分,分别是配套的实验课程、综合性实验以及课程设计。结合人工智能时代的技术热点,合理设计好这三个部分的实验内容,有助于学生在巩固课程知识点的同时更好地与现实接轨,学以致用。

1.与程序设计比赛相联合的编程实验练习

在实验内容的设计上,传统的《数据结构》实验课主要以实现教材介绍的各种数据结构及其基本操作为主,为验证性的实验,大部分代码在教材中已经给出,需要学生自主编写的部分不多。人工智能时代,对该领域专业人员解决问题、算法设计能力的要求进一步提高。程序设计竞赛通过结合当前研究热点,设计题目激励当代大学生运用计算机编程技术和技能解决实际问题。可在《数据结构》实验课程中利用程序设计竞赛内容设计合适的扩展编程训练[10]。

ACM-ICPC 国际大学生程序设计竞赛为全球最有影响力的大学生程序设计竞赛。该竞赛要求 3 人组队,各队在限定时间内使用一台计算机编写程序，解决给定的问题并通过在线评判,考核了大学生的团队精神及创新能力。要提高学生的编程能力,可借鉴该竞赛的评判模式,引入在线评判系统。实验的正确性评判一般依赖有限的具有代表性的测试数据来完成。初学者编写程序在测试时往往主观性强,导致无法全面地评估程序的正确性。利用程序设计竞赛的“黑盒子”测试模式则能较客观地进行程序正确性评判。另外,在实验题目的设计上,可结合《数据结构》课程知识点选取相关的竞赛题目作为训练。常用的程序设计竞赛题库网站有北京大学在线评判系统、浙江大学在线评判系统等。

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2.串联多个学习知识点的综合性实验设计

《数据结构》综合性实验在学生已经完成课程的大部分学习内容后开展。综合性实验是对课程学习到的多个知识点进行应用以及巩固,题目的选取要区分于实验课的基本练习。《数据结构》课程中经常布置的综合性实验题目有“平衡二叉排序树的实现及应用”“利用哈夫曼编码实现文件压缩”等。“平衡二叉排序树的实现及应用”要求实现平衡二叉排序树这一种数据结构,并且实现其插入、删除、查找、递归及非递归遍历(先序、中序、后序、层次)、求最值、交换子树等基本操作,综合队列、堆栈、树、递归等多个知识点来解决问题。“利用哈夫曼编码实现文件压缩”要求根据输入的字符创建哈夫曼树,并生成每个字符对应的哈夫曼编码,综合运用了二叉树、顺序存储、查找、文件压缩等知识点。

综合性实验的考核方式应从代码测试以及文档编写两方面进行。除了按传统的程序设计要求检查程序的正确性外,还要求学生编写综合性实验报告,锻炼其文档编写能力。综合性实验报告的内容应包括题目分析、解题思路、测试、算法分析及总结等。

3.与当前新技术相结合的课程设计

《数据结构》课程设计是在课程所有知识点学习完毕后,为了深化对课程内容理解,拓宽学生知识面而开设的。《数据结构》课程设计的形式一般采用教师布置任务,学生自主查阅资料完成对应任务的形式。鼓励学生以多人组队的形式完成比课堂配套实验难度更高、综合性更强的题目。教师在课程的开展期间为学生提供资源,负责解答学生遇到的疑问。

在《数据结构》课程设计中,可结合当前研究的热点来布置题目。可以设计与大数据分析、人工智能、图像处理、机器学习等研究方向相关的题目。由于大多数学生的程序设计水平还不高,在题目的设定上不宜选用大而难的题目,应围绕着《数据结构》课程的教学内容作适度简单的扩展为佳。可结合当前大数据的应用需求,让学生运用《数据结构》课程知识解决问题,例如,给定100亿个整数,设计算法找到里面出现次数最多的整数,则可以用到哈希查找算法思想。人工智能领域可设计人机对弈程序如五子棋等。结合图像处理需求,让学生了解图像的存储机制,并进行简单的灰度图像的平滑、锐化等基本操作的实现。在机器学习方面,可通过构建决策树的创建及使用,让学生了解预测模型的建立原理。

在提供扩展题目让学生拓宽视野之外,《数据结构》课程设计的题目也应考虑到知识掌握程度处于不同层次的学生,提供一系列难度不同的题目供学生选择。基础的题目可包括数据结构在各种信息系统中的应用,实现教学内容以外的其他数据结构等,也应鼓励学生根据自己的兴趣爱好结合课程学习内容自由选题。在代码实现上,放宽程序设计语言的限制,除了基于C语言的程序实现外,鼓励学生采用当前在人工智能领域广泛使用的Python语言进行代码编写。

四、结语

人工智能技术给计算机相关专业人员带来了大量的工作机遇,与此同时也给专业学习带来了巨大的挑战。《数据结构》科目的学习,能够培养学生数据处理及问题解决能力。在《数据结构》的理论教学环节中,将该科目与《程序设计语言》《算法设计与分析》等多门课程的学习内容进行关联,形成完整的知识体系。借助新时代的智慧教学工具加强师生互动,在学习过程中深化计算思维的培养。在实践教学环节,充分利用课程配套实验课、综合性实验以及课程设计多种形式的实践锻炼,结合人工智能时代研究热点,合理设计实验内容。通过课程的教学调整,让相关专业的学生更好地顺应人工智能时代的人才需求。

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地理信息科学专业“数据结构”实验教学改革探讨

杨秋妹，郑　婵

（华南农业大学 数学与信息学院，广东 广州 510642）

[摘　要]“数据结构”实验课程是提高学生代码编写能力、强化课程知识点学习的关键。从地理信息科学专业的专业培养方案设定出发，根据学生的程序设计能力基础，设计合理的“数据结构”实验题目及丰富多样的做题形式，充分利用综合性实验的开展作为实验学时的补充。在教学手段上，通过动态的代码演示帮助学生更好地理解算法的设计原理及运行过程，引入在线评判手段更好地评估学生的实验情况，加强学生程序能力的培养。为地理信息科学专业建立有特色的“数据结构”实验教学方案，以更好地提升学生的计算机问题求解能力。

[关键词] 数据结构；地理信息科学；实验教学改革

[基金项目] 2020年度华南农业大学校级教改项目“将思政之盐融入计算机算法类课程之汤的隐性教育探索和实践”

[作者简介] 杨秋妹(1983—)，女，广东茂名人，博士，华南农业大学数学与信息学院讲师，主要从事计算机应用技术、农业图像处理、农业人工智能研究；郑　婵(1978—)，女，福建邵武人，博士，华南农业大学数学与信息学院讲师，主要从事计算机视觉研究。

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地理信息科学(GIS)专业是一门交叉学科，研究的内容涉及地理科学、测绘学、计算机科学、数学与统计学等[1]多个学科。GIS研究如何应用计算机技术对地理信息进行处理、存储、提取及管理和分析。GIS专业的学生需具备利用计算机进行数据分析与处理及应用系统开发能力[2]。因此，“C语言程序设计”“数据结构”等计算机专业基础课程是GIS专业的必修课程。“数据结构”研究的是非数值计算问题中数据的建模问题，其配套的实验课作为理论学习的补充，通过程序设计将抽象的数据结构在计算机上具体实现。实验的开展可深化学生对知识点的理解，是提高学生计算机求解问题能力提升的关键[3]，为后继课程如“GIS算法基础”“网络GIS”“GIS开发新技术”等学习做好准备[4]，也为其以后进行地理信息系统的设计及开发打下基础。作为GIS专业“数据结构”课程的任课教师，应充分利用实验教学环节，促进学生对于数据结构相关知识的学习，形成有GIS专业特色的“数据结构”课程教学方法。

一、GIS专业“数据结构”课程实验教学中存在的问题分析

(一)课程知识点多，实验学时不足

当前，高校GIS专业开设的“数据结构”课程，学时普遍比计算机专业的要少，配套的实验学时普遍不足，无法将各个知识点进行一一验证。以华南农业大学GIS专业的教学安排为例，其理论学时为32学时，实验学时为16学时，而计算机相关专业“数据结构”课程的理论学时为56学时，实验学时为32学时，GIS专业的学时明显压缩，这导致GIS专业“数据结构”的教学大纲不能直接照搬计算机相关专业，由于理论学时的减少，相关内容的学习则会有明显的侧重点不同，而实验环节的教学也应该做相应的调整。

(二)学生程序设计基础相对薄弱

“C语言程序设计”课程作为“数据结构”课程的先导课，学习的知识是“数据结构”课程顺利开展的前提保证，但是很多高校GIS专业的“C语言程序设计”课程是作为通识教育课程而非专业教育课程开设，这导致学生程序设计水平不高，并且由于学时的不足，“数据结构”中要用到的重要知识点如链表、结构体等内容都没有进行深入的学习。由于在“C语言程序设计”课程中编写代码的能力没有得到充足的训练，导致学生产生畏难情绪，在刚开始接触“数据结构”课程时听到需要上机编程都感到紧张害怕，没有信心学好“数据结构”这门课程。

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（三）学生重视程度不够

GIS专业的部分学生存在错误认知，认为“数据结构”课程是计算机专业的核心课程，但是对于GIS专业来说并不重要，只需要作为一门通识教育课程去学习就可以了。但实际上GIS技术与数据结构密切关联，数据结构探讨现实世界中的一对一、一对多及多对多的数据关系，这些都与GIS中的矢量、栅格等数据结构相关。GIS多以现实的地图作为基础数据，主要涉及两大应用类型的地图，一种是地形图，用于展示地球表面特征的基本地图；一种是专用地图，用于表达事物变化模式的地图。而真实世界的地图在计算机上实现则需要用到“图”数据结构的相关知识点，如邻接矩阵存储法、最小生成树算法、最短路径算法等。GIS的问题求解需要大量“数据结构”课程中的知识点作为支撑。

二、GIS专业“数据结构”实验教学内容改革

（一）设计合理的实验题目

“数据结构”是一门强调动手实践的课程，因此几乎每个章节都需要配备相应的实验题目以深化学生对知识点的理解。但是GIS专业不能照搬计算机专业的实验内容，应该根据实验学时及学生编码水平进行调整。以笔者授课的2020级GIS专业的学生为例，多数学生在第一次实验课无法顺利完成一道实验题目，如果布置的实验题目过多，容易打击学生的学习积极性，使其产生厌学情绪。

GIS专业的“数据结构”实验题目设计应在紧扣教学内容的同时从学生的实际情况出发考虑。通过观察学生的实际做题情况，在计算机专业的“数据结构”实验题目的基础上进行调整，形成GIS专业实验题目集。实验题目集分为线性表、栈和队列、串数组和广义表、树和二叉树、图、查找、排序七个模块。线性表的实验包括顺序线性表的实现、合并顺序表、顺序表逆置、链式线性表的实现、合并链表、线性链表逆置；栈和队列的实验包括顺序栈的实现、循环队列的实现、栈的应用—进制转换、括号匹配检验；串数组和广义表的实验为串的模式匹配—蛮力法；树和二叉树的实验包括二叉树的构建、二叉树的遍历运算；图的实验为实现图的存储结构；查找的实验包括顺序查找、二分查找；排序的实验包括直接插入排序、冒泡排序、快速排序、简单选择排序；经过调整，将部分较难的实验题目去除，但保留了线性表、树、图核心数据结构的实现及基本操作，保证学生对重要知识点的验证实验，确保学习质量。

（二）丰富实验做题的形式

笔者授课的GIS专业采用的教材为人民邮件出版社出版、严蔚敏主编的《数据结构(C语言版)》。书中的各类数据结构以结构体的形式实现，在实现时涉及结构体变量的定义、函数的调用等知识点，对于程序设计能力普遍有限的学生来说入手比较难。根据笔者授课的班级情况统计，在课程学习初期存在着部分学生无法完整编写一个程序的现象。因此，实验题目的设置形式应多样化，不能单纯地只给出题干，直接要求学生从无到有编写出一个完整程序。实验题目可包括程序填空题、程序阅读题及算法设计题。在实验初期，可多以程序填空题及程序阅读题为主，这样可保证学生既能快速进入学习状态，也能通过代码的阅读加深对代码的理解，规范代码的编写。到实验中后期，则可多以算法设计题为主，进一步锻炼学生的编码能力。

以“顺序线性表的实现”为例，如果只给出题干要求学生给出实验—顺序线性表，即便是书本上已经给出了大部分的代码，大部分同学还是不清楚该如何下手编写程序，而以程序填空的方式则可让学生快速上手，同时也起到了验证课程学习内容的功效。程序填空题不是简单地填一个空，而是给出程序的总框架，如函数定义等，让学生往里面补充代码，所补充的代码可以是单条或多条语句。

（三）重视综合性实验的开展

综合性实验是布置给学生课后完成的实验，可弥补实验学时不够的缺陷。因此，应充分利用综合性实验的开展来加强学生对知识点的掌握。树、图部分的内容对于GIS专业的学生来说非常重要，综合性实验可从这两方面来设计题目，可用“实现二叉排序树的各种算法”及“实现图的各种算法”作为基本题目出发点，学生可从两个题目中任选一个来进行扩展实验。通过综合性实验的开展，可进一步训练学生函数的调用、递归、栈、队列、树、图等知识点的编码能力。

综合性实验的题目与课堂内完成的实验相比，难度大，工作量多，允许学生以2人组队的形式完成，通过团队合作锻炼程序模块的划分、组合。

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综合性实验开展过程中，鼓励学生积极灵活地运用所学的课程知识，并通过查阅参考资料将其与自己所学专业结合。如二叉排序树可扩展到地理信息系统中的空间索引问题，创建四叉树解决二维空间数据的高效查询。而图算法则可应用在地理信息系统中的网络分析问题上，包括旅游路线规划问题、电子导航问题、通信规划问题、城市基础设施搭建问题等[5]。

三、GIS专业“数据结构”实验教学方法改革

对于计算机相关专业，由于其大部分学生已具备了一定的程序设计能力，所以“数据结构”实验的开展主要以学生动手编码为主，教师讲解为辅。而GIS专业的学生则需要教师更多地参与到其实验的开展过程中。

（一）加强代码演示讲解环节

根据学生给的教学反馈，学生反映无法将算法思想与代码编写进行关联。在实验环节增加代码演示环节很有必要。尽管学时不多，仍需对较难理解的算法通过代码演示的形式给学生进行讲解。教师运行程序，输入有代表性的数据，在关键步骤结合中间输出结果讲解程序语句的执行过程，解释算法思想。如链表的插入，其代码演示页面如图1所示。上课讲解时结合代码给学生介绍在链表的第i个位置插入新元素，首先找到第i个元素所在的位置(代码2～5行)，接着生成新结点并对其赋值(代码6～8行)，加深学生对代码的理解掌握。

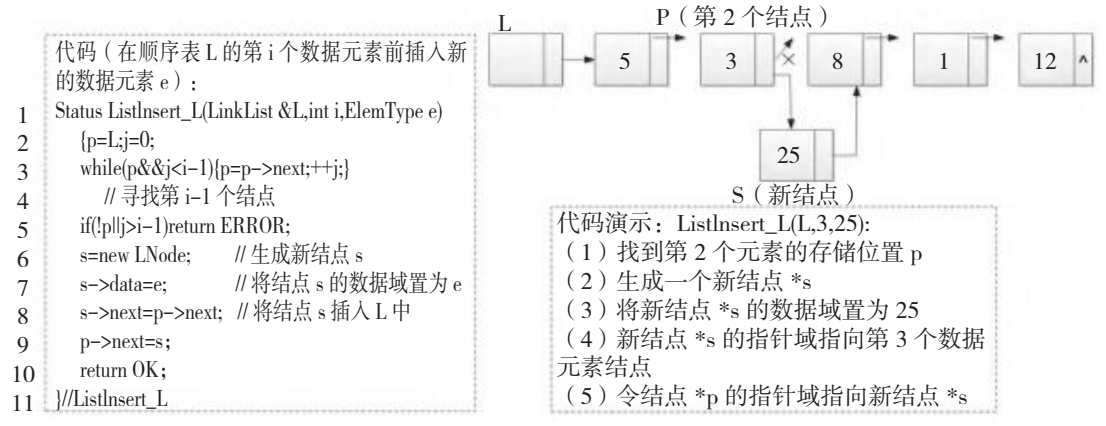


图1　程序代码演示页面

除了教师直接给学生进行代码演示外，在教材《数据结构(C语言版)》中已经对大部分的数据结构操作都录制了代码演示，可通过书本提供的二维码扫码观看。学生在学习完每个知识点后，可结合书本的代码实现及算法的动态演示，了解算法的一步步运行过程，加深对算法的理解。

（二）引入在线评判的考核方式

“数据结构”实验每次课都需要学生完成一定量的实验题目，对学生实验的完成情况进行检查能端正学生的做题态度，督促学生按时完成作业，促进学生做题的积极性。但由于现在的课程多采用大班教学，人数众多，任课教师无法每次课一一对学生的代码进行检查。国际大学生程序设计竞赛(ACM-ICPC)为全球最有影响力的大学生程序设计竞赛，比赛采用在线评判的方式检查参赛者的代码是否正确[6]。在GIS专业的“数据结构”实验课程中，也可引入在线评判系统，教师对每道题目设计合理的测试样例，学生通过在线评判系统提交实验代码，由在线评判系统自动进行评判，及时反馈实验结果，学生根据反馈结果进行代码的修改，由此提高实验效率。教师也可通过在线评判系统及时获取学生的实验情况，了解学生的掌握程度，并由此做出相应的实验教学辅导。采用在线评判的另一个好处是可引导学生自己设计样例测试数据。通常系统只给出1～2个测试样例，但是实际评判时会有多组数据，做题时学生经常会出现测试样例通过但提交到评判系统则无法通过的情况，但是设置成多次提交会扣除部分分数，鼓励学生多考虑程序的边界条件、异常情况等因素，加强程序的健壮性。

除了在线评判系统外，对于部分迟迟未在系统上提交实验或多次提交都无法通过的学生，应由教师及助教对其进行一对一的作业检查及辅导。由于在线评判系统是黑箱子评判模式，只有通过全部测试数据才标记为已通过，有部分学生因为程序设计知识掌握不扎实，被某组测试数据

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卡住后无法独立找出错误原因。教师可通过与其分析代码，帮助其较快地解决问题，赶上实验的做题进度。

在实验评分上，除了依据在线评判系统的做题情况外，教师也应根据学生在实验上投入的精力及努力程度对其进行分数的嘉奖。

（三）加强学生程序调试能力的培养

通过多年观察学生在“数据结构”实验课堂的表现情况，发现当程序对于给定输入得不到预期输出结果时，很多学生不清楚如何进行代码错误定位，从而浪费大量实验时间。因此，在“数据结构”实验教学中，应加强学生程序调试能力的培养。程序调试指的是根据错误提示信息及算法逻辑的推理，找到有可能会导致错误发生的位置。

程序的调试手段之一，通过在程序源代码中设置多个输出点，通过中间输出结果来定位错误位置。在线评判系统要求输出结果严格按照给定的要求，否则出错，在此要求下学生编写的程序一般只输出目标结果。一旦出错，很难确定出错位置。此时，则需要增加中间结果输出作为程序调试的依据。

程序的调试手段之二，利用程序集成开发环境（IDE）提供的debug调试模式，在程序可能出错的代码行设置断点，通过debug中提供的单步运行、进入函数内部或跳出函数等方法，监控程序中各个相关变量的情况，尽快定位出错的地方。

教学应因材施教，GIS专业“数据结构”实验课程的开展应根据学生的专业背景，结合学生对先导课程的掌握程度，设计合理的课程教案。在教学内容上，可通过调整实验题目、增加实验题型，以综合性实验的方式拓展实验深度。在教学方法上，重视实验代码演示，采用在线评判系统结合人工评判的考核方式，加强学生的程序调试能力训练。借由GIS专业“数据结构”实验课程教学的改革，为GIS专业的学生在后续的专业学习提供保障，也为其在未来从事GIS二次开发、底层开发的工作打下坚实的基础。

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Exploration on the Reform of Experimental Teaching of Data Structure in Geographic Information Science Specialty

YANG Qiu-mei, ZHENG Chan

(College of Mathematics and Informatics, South China Agricultural University, Guangzhou, Guangdong 510642, China)

Abstract: The experimental course of is very important to improve students' ability of code writing and strengthen their knowledge learning. Starting from the training program of Geographic Information Science, according to the students' programming ability, we design reasonable experimental topics of Data Structure, and make full use of comprehensive experiments as a supplement to the experimental hours. In terms of teaching means, we help students better understand the design principle and operation process of the algorithm through dynamic code demonstration, introduce online evaluation means to better evaluate students' experimental situation and strengthen the cultivation of students' program ability. This experimental teaching scheme can better improve students' computer problem-solving ability.

Key words: Data Structure; Geographic Information Science; reform in experimental teaching

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广东省重点领域研发计划项目
课题任务书

课题名称：	生猪立体工厂化养殖模式下的生猪生理生长及健康移动巡检技术研究
所属项目：	生猪立体工厂化健康养殖技术研究与示范
项目承担单位（甲方）：	温氏食品集团股份有限公司
项目负责人：	黎少松
课题承担单位（乙方）：	华南农业大学
课题负责人：	杨秋妹
起止年限：	2023 年 01 月 - 2025 年 12 月

广东省科学技术厅制

2023 年 06 月

一、项目验收指标

（一）成果指标（请认真对照申报指南和项目申报书的内容进行填写，不得降低或删减相关目标要求；结题验收时可用项目内同类型同水平指标替换。）

1. 核心考核指标（必填）

序号	成果名称	成果类型	验收指标	评测方式/方法
1	突破封闭及高密度养殖模式猪只表型识别、个体异常行为感知、疾病预警等算法技术	新技术	2～3项	发表论文； 专利受理或授权书
2	创制生猪立体健康多层封闭式散养生物安全智能预警平台	软件	1套	软件著作权证书
3	创制生猪立体健康多层封闭式环境下的猪场健康巡检机器人、母猪诱情机器人	新技术；新产品	各1套	第三方专业机构检测报告； 专利受理或授权书
4	研发自主移动式猪只健康行为监测系统	软件	1套	软件著作权证书；
5	生猪生理生长及健康移动巡检技术相关专利	专利	2～3项	专利受理或授权书
6	生猪生理生长及健康移动巡检技术相关论文	论文	2～3篇	发表论文

2. 高水平知识产权指标（必填）

序号	内容	类型	结题时状态	拟解决关键问题
1	立体工厂化养殖模式下的生猪健康识别算法	PCT专利	受理	形成技术首创
2	生猪立体工厂化养殖巡检机器人	国内发明专利	授权	突破行业制约

3. 科技报告考核指标（必填）

注意事项：

1）报告类型。包括验收前撰写的最终科技报告；研究期限超过 2 年（含2 年）的项目，每年撰写的年度技术进展报告；根据研究内容、期限和经费强度，撰写的数量不等的专题科技

报告。科技报告应按国家标准规定的格式撰写。

2）公开类别及时限。公开项目科技报告分为公开或延期公开，内容需要发表论文、申请专利、出版专著或涉及技术诀窍的，可标注为“延期公开”。需要发表论文的，延期公开时限原则上在2年（含2年）以内；需要申请专利、出版专著的，延期公开时限原则上在3年（含3年）以内；涉及技术诀窍的，延期公开时限原则上在5年（含5年）以内。涉密项目科技报告按照有关规定管理。

序号	报告类型	提交时间	公开类别及时限
1	2023年度进展报告	2023-12	延期2年公开
2	2024年度进展报告	2024-12	延期2年公开
3	2025年度进展报告	2025-12	延期2年公开
4	项目实施总结报告	2025-12	延期2年公开

（请认真对照合作协议的内容，以上各指标尚未详尽的，可在此补充填写，包括发表的论文/专著数量、发布标准数量、引进人才情况、获得国家/省部级奖项情况）

对于发表的论文、标准、专利、软件著作权等指标，已在上述表格中详细列出。此外，联合合作单位培养研究生数量10人以上。

课题负责人（签章）：　　2023年 9 月 11 日

（三）阶段性成果评价：（请对照以上内容自行填报，作为中期评估及结题验收的重要参考依据）

序号	指标名称	立项时已有指标值/状态	中期指标值/状态	完成时指标值/状态	评估方式（方法）及评价手段
1	突破封闭及高密度养殖模式猪只表型识别、个体异常行为感知、疾病预警等算法技术	已有针对生猪耳部的体温非接触式测量算法；已有针对限位栏定点的生猪体尺体重智能估测算法；已有养殖密度较低场景的生猪跟踪及行为识别算法；已有基于体温、运动量及行为的生猪健	突破封闭式及高密度养殖模式下猪只表型识别、个体异常行为感知、疾病预警等算法模型技术2项；实现生猪不同部位体温的智能测定；实现移动	突破封闭式及高密度养殖模式猪只表型识别、个体异常行为感知、疾病预警等算法模型技术2-3项	发表论文； 专利受理或授权书

		康识别	场景下的生猪体尺体重估测		
2	创制生猪立体健康多层封闭式散养生物安全智能预警平台		创制生猪立体健康多层封闭式散养生物安全智能预警平台1套	创制生猪立体健康多层封闭式散养生物安全智能预警平台1套	软件著作权证书
3	创制生猪立体健康多层封闭式环境下的猪场健康巡检机器人、母猪诱情机器人	已有平养环境下的第一代滑轨式巡检机器人、地面行走型机器人	创制第二代生猪立体健康多层封闭式环境下的猪场健康巡检机器人1套	创制第二代生猪立体健康多层封闭式环境下的猪场健康巡检机器人、母猪诱情机器人各1 套	第三方专业机构检测报告； 专利受理或授权书
4	研发自主移动式猪只健康行为监测系统			研发自主移动式猪只健康行为监测系统1套	软件著作权证书；
5	生猪生理生长及健康移动巡检技术相关专利			2～3项	专利受理或授权书
6	生猪生理生长及健康移动巡检技术相关论文			2～3篇	发表论文

二、课题研究内容、研究方法及技术路线、主要创新点

（一） 课题拟解决的关键问题（限 2000 字以内）

研究热带气候下不同楼层不同阶段的生猪应激程度差异性，突破封闭式高饲养密度猪场复杂环境下生猪生长与生理多维参数的精准采集技术，研究基于生理、生长及行为规律的生猪健康识别模型、发情期预测算法，在立体工厂化养殖模式和大数据育种的背景下，构建智能化生猪养殖体系。

（二） 课题的主要研究内容（限 2000 字以内）

生猪立体工厂化养殖模式下的生理生长及健康智能巡检技术研究：针对热带气候工厂化养殖下的生猪应激性，研究多楼层、楼层间封闭及高密度养殖模式的猪只行为、生理生长规律及疾病特征，构建生猪生长模型、重大疾病远程诊断与健康预警模型；研究工厂化、封闭空间模式下的生物安全精细管控及预警等关键技术；研究适用于立体工厂化养殖的健康智能巡检技术，创制猪场健康巡检机器人、查情机器人等智能养猪装备；研发立体健康多层封闭式散养自主移动式猪只健康行为监测系统。

（三） 课题采取的研究方法及技术路线（限 2000 字以内）

针对生猪立体工厂化养殖模式下建筑结构和应用场景需求，设计轨道式和地面巡检小车型两种类型巡检机器人以适应不同工厂化养殖舍的需要。对于轨道式机器人采用栏位定点技术。对于地面巡检小车型机器人拟通过激光雷达、MEMS惯性传感器、视觉传感器等多传感器信息融合的SLAM技术，结合路况、任务和速度的智能路径规划算法，解决猪舍巡检环境下机器人无缝定位和巡行问题，获得较强的环境适应能力、鲁棒性和实时性。

巡检机器人集成环境传感器、彩色摄像头、热红外摄像头、3D摄像头及声音采集器等多个传感器。通过巡检机器人可采集环控数据、生猪活动视频图像数据、生猪热红外图像、三维点阵图及声音频率数据。利用图像处理、深度学习等相关算法，以实现机器人自动巡行、生猪目标识别定位与自动跟踪、生猪生理生长数据提取、生猪异常信息检测、健康预警等功能。

生物安全精细管控包括对人员进行自动识别，检测其消毒是否规范，是否出现串层等异常行为；移动式采集多栏舍的各种健康数据，从群体中去寻找生理特征异常的个体，一旦确认后“定位移除”；通过生猪行为在更早的阶段预警疫病的发生，完成感染猪只的及时发现与尽早处理，有效避免群体传染；对猪只进行自动化识别，检测是否出现越栏等异常情况，对场内出现的携带严重病原体的种猪坚决淘汰，以有效确保种猪群的健康状态。

（四） 主要创新点

针对立体工厂化养殖模式下生物安全隐患突出的问题，突破高密度养殖模式下生猪个体健康异常感知的制约问题，通过热红外成像仪、2D/3D 数字成像等非接触式生理生长指标采集方式，研制适用楼房猪场的自动化智能化巡检机器人，在更早的阶段预警疫病的发生，完成感染猪只的及时发现与尽早处理，有效避免群体传染，创制生猪立体健康多层封闭式散养生物安全智能预警平台。同时建立生物安全信息管理系统构建一道坚固高效的生物安全防线。实现“全流程确认、全过程监督、全线路监控”，自动采集防疫现场各种参数，智能监控车辆、人员、物资洗消流程的执行情况，为猪瘟等疫情防控提供坚实的保障手段。

三、课题进度和阶段目标

（一）课题起止时间：2023年1月1日——2025年12月31日

（二）课题实施进度及阶段主要目标（建议以 1 年或 6 个月为一阶段）

开始日期-结束日期	主要工作内容（每条限 500 字）	预期目标	成果形式
2023.01.01-2023.12.31	研究多楼层、楼层间封闭及高密度养殖模式的猪只行为、生理生长规律及疾病特征，构建生猪生长模型、重大疾病远程诊断与健康预警模型	突破猪只表型识别、个体异常行为感知、疾病预警等算法、模型技术 2～3 项	发表论文； 专利受理或授权书
2024.01.01-2024.12.31	研究工厂化、封闭空间模式下生物安全精细管控及预警等关键技术	创制生猪立体健康多层封闭式散养生物安全智能预警平台 1 套	软件著作权证书；
2025.01.01-2025.12.31	创制猪场健康巡检机器人、查情机器人等智能养猪养殖装备以及健康行为监测系统	创制生猪立体健康多层封闭式环境下的猪场健康巡检机器人、查情机器人、各 1 套； 研发自主移动式猪只健康行为监测系统 1 套；	第三方专业机构检测报告； 发表论文； 专利受理或授权书

四、课题研究人员

课题负责人：						
姓　名	性别	年龄	技术职称	学位	身份证号码	在课题中承担的任务
杨秋妹	女	40	讲师	博士	44092119831230162X	全面负责课题的开展
课题团队成员：						
姓　名	性别	年龄	技术职称	学位	身份证号码	在课题中承担的任务
肖德琴	女	53	教授	博士	510212197005140829	课题总规划、设计
王春桃	男	44	教授	博士	441425197904033096	项目规划与指标构建
殷建军	男	42	副教授	博士	421003198101080551	智能巡检装备设研发
王燕	女	42	教授	博士	352230198004160026	生猪养殖生物安全精细管控及预警技术研究
冯健昭	男	42	讲师	博士	440602198110310637	机器人研发
周敏	女	50	副教授	博士	510225197307183666	生猪生理生长规律分析
黄一桂	男	27		博士生	440981199604111415	生猪健康预警模型构建
刘俊彬	男	25		博士生	445202199801170319	生猪健康预警模型构建
谭祖杰	男	26		硕士生	440111199711263016	生猪健康预警模型构建
陈淼彬	男	27		硕士生	441481199610101719	生猪行为分析
刘克坚	男	27		硕士生	430481199603020037	生物安全精细管控及预警
黄森鹏	男	23		硕士生	445224200007020376	生猪行为分析
惠向阳	男	23		硕士生	411302200011074519	生猪行为分析
吴耿潜	男	24		硕士生	445221199912045376	机器人研发
张彬	男	24		硕士生	440825199908080578	生物安全精细管控及预警
陈泽中	男	21		硕士生	360728200201081613	生猪行为分析
吴纪沿	男	22		硕士生	441521200108040812	生猪行为分析
吴曼婷	女	23		硕士生	445121200003253143	生猪行为分析

五、课题经费预算：（单位：万元）

	项目总经费		省财政科技资金	
支出经费	经费额	用途说明	经费额	用途说明
1. 直接费用	85.00		85.00	
(1) 设备费	15.00	精准饲喂系统相关设备	15.00	精准饲喂系统相关设备
(2) 业务费	45.00	生猪智能健康感知传感器、配件等；生猪智能感知测试；调研、试验、学术会议等；论文和专利费用	45.00	生猪智能健康感知传感器、配件等；生猪智能感知测试；调研、试验、学术会议等；论文和专利费用
(3) 直接人力资源成本	25.00	聘用人员/学生；聘请专家指导费	25.00	聘用人员/学生；聘请专家指导费
2. 间接费用	15.00		15.00	
(1) 绩效支出	7.50	项目人员绩效	7.50	项目人员绩效
(2) 管理费用	6.00	项目管理费	6.00	项目管理费
(3) 其他间接费用	1.50	审计费、网费等	1.50	审计费、网费等
合计	100.00		100.00	
其它需说明的情况：				

六、合约条款

甲方（项目承担单位及负责人）：温氏食品集团股份有限公司 黎少松

乙方（课题承担单位及负责人）： 华南农业大学 杨秋妹

根据广东省科技厅与甲方签订的项目任务书要求，甲方与乙方签订本合约。

（一）权利与义务

甲方全面负责项目的各个课题，督促课题负责人按照课题任务书要求实施研究工作，合理使用课题经费，如期完成课题任务；甲方有权对乙方的年度计划执行情况进行监督、检查，并提供有关支持与保障条件；乙方具体负责课题的各项任务，应严格按照合约保证及时完成研究任务，并接受甲方的监督检查。乙方有权参与甲方组织的课题方案制定等相关活动。

（二）团队管理

课题团队是为完成某一具体课题，由课题负责人牵头，联合相关研究成员组成的研发群体。团队成员组成应根据研究任务的需要，在尊重自愿的基础上，由甲方与乙方共同协商确定。

在签订本合约之前，课题团队负责人应与课题团队其他成员之间协商确定团队任务安排、参与时间、收益分配等。

（三）经费管理

由甲方负责财务管理，具体管理办法参照广东省科技厅与甲方签订的任务书中的“任务书条款”。甲方在收到财政专项拨款后，应在十个工作日内告知乙方，并根据“任务书条款”的第六条向乙方提供相应的经费。

具体而言，若广东省科技厅将立项经费统一拨付给甲方，则在甲乙双方签订任务书后，由甲方拨付给乙方合作协议书中约定的课题资金的 30%；经中期评估，项目进展顺利并取得阶段性进展的，拨付合作协议中约定的资金的 50%；项目任务完成 90%或达到验收条件的，可提出后续资金申请，经评估，拨付剩余 20%资金。评估或验收结题不通过的，甲方有权终止课题，停止拨付后续资金；发现课题存在重大异常或违规使用财政资金的，甲方有权追回已经拨付的资金。若由广东省科技厅根据合作协议书的约定直接向各合作方拨付课题资金，则甲乙双方遵循广东省科技厅的经费拨付方式。

乙方使用经费应严格按照经费预算和约定的支出范围执行，保证专款专用，不得弄虚作假、挪用、挤占课题经费或违反相关法律法规。甲方根据国家有关法规和科技计划经费开支的规定，监督乙方经费的使用情况。广东省科技厅和项目官员有权对甲乙双方经费使用进行监督管理。

（四）成果管理

双方在研发过程中应加强研究成果管理，严格执行《中华人民共和国科学技术进步法》、《关于加强国家科技计划知识产权管理工作的规定》、《中华人民共和国专利法》和《中华人民共和国著作权法》等有关规定。研究成果在申报国家及有关部门、地方的科技成果奖励时，需由甲乙双方共同协商成果署名等相关事宜。

甲乙双方应根据有关法律法规，及广东省科技厅与甲方签订的任务书规定，协商确定课题研究成果的收益分配等事宜并签订知识产权合作协议。

（五）资产管理

按照科技计划专项经费管理办法执行，专项经费形成的大型仪器设备固定资产归甲方管理，乙方在执行课题任务时，与甲方享有同等使用权。甲乙双方可以自行协商确定设备使用共享的相关办法。

（六）信用管理

广东省科技厅和项目官员有权对甲乙双方进行信用监管。甲乙双方均需建立信用管理档案，对参加人员进行信用记录。记录内容包括科研活动情况、任务完成情况、按时提交材料情况、经费使用情况等。双方均需遵守有关科研诚信建设的相关规定，积极配合有关单位或部门组织的信用评估工作。

（七）保密管理

按《中华人民共和国保守国家秘密法》和科学技术部《科技保密规定》及相关国家科技计划管理办法等有关规定执行。

（八） 任务与经费调整

乙方须及时向甲方报告研究进展。乙方未能按规定进度和考核指标完成任务的，甲方可对乙方及其团队的任务和经费在本合约范围内进行调整。由甲方提出调整意见，报广东省科技厅审定后执行。

（九）争议处理和合约变更

1. 广东省科技厅是双方争议的调解机构。项目官员具有对纠纷处理的监督权和问责权。

2. 合约在履行过程中发生争议的，双方应首先通过协商的方式解决。协商不成时，双方向广东省科技厅申请调解。

3. 任何一方因不可抗力不能履行合约义务时，可以免除违约责任，但应及时通知另一方，并在 30 天内出具因不可抗力导致合约不能履行的证明。

4．合约一方要求变更或解除合约，应在 30 日前书面通知另一方，并同时向广东省科技厅提交书面申请，经批准后执行。

（十）补充条款

1．如有特别需要，经甲乙双方协商，同意 华南农业大学作为乙方的依托单位，按相关的科技计划和经费管理办法，对甲方拨付乙方的经费进行管理并同意承担相关责任和义务。

2．甲乙双方均须遵守科技部关于国家科技计划项目（课题）实施法人管理责任制的意见的相关规定。

（十一） 附 则

1．本合约由甲乙双方单位盖章及相关负责人签字后生效。

2．本合约正本一式 4 份（甲方 2 份、乙方 2 份）。

七、签约各方签章

项目承担单位（甲方）：温氏食品集团股份有限公司（公章）

甲方账 户 名：温氏食品集团股份有限公司

甲方账 号：670457744671

甲方开户银行：中国银行新兴支行

单位负责人（签字）：

项目负责人（签字）：

2023 年 9 月 12 日

课题负责人（乙方）（签字）：

乙方所在单位（公章）：华南农业大学

乙方账 户 名：华南农业大学

乙方账 号：3602002609000310520

乙方开户银行：广东广州工行五山支行

2023 年 9 月 11 日

受理编号：c232022032111800007　　项目编号：2023B0202140001

项目下达文号：

广东省重点领域研发计划项目

任务书

项目名称：生猪立体工厂化健康养殖技术研究与示范

专项名称：精准农业及生态绿色技术（智慧农业）

项目起止时间：2023年 01月 01日　至　2025年 12月 31日

管理单位(甲方)：广东省科学技术厅

牵头承担单位一（乙方）：温氏食品集团股份有限公司

项目推荐（主管）单位（丙方）：新兴县科技局

通讯地址：广东省云浮市新兴县广东省新兴县新城镇东堤北路9号

邮政编码：527400　　单位电话：0766-2986008

项目负责人：黎少松　　联系电话：0766-2986008

项目联系人：陈丽　　联系电话：13411714197

广东省科学技术厅
二〇一九年制

（广东科技微信公众号）　　（受理纸质材料二维码）

项目基本信息表

项目名称	生猪立体工厂化健康养殖技术研究与示范			
项目编号	2023B0202140001			
专项名称	精准农业及生态绿色技术（智慧农业）			
专题名称	20220214--生猪立体工厂化健康养殖技术研究与示范		单位总数	6
经费预算	总投入 1700.00 万元，其中财政科技资金投入 500.00 万元			
项目周期节点	起始时间	2023年 01月 01日	结束时间	2025年 12月 31日
	实施周期	共 35 个月	预计中期时间点	2024-06-30
项目牵头承担单位一	单位名称	温氏食品集团股份有限公司	单位性质	股份有限公司
	单位所在地	广东省-云浮市-新兴县	统一社会信用代码	91445300707813507B
	通信地址	广东省-云浮市-新兴县广东省新兴县新城镇东堤北路9号	邮政编码	527400
	银行账号	670457744671	法定代表人姓名	温志芬
	单位开户名称	温氏食品集团股份有限公司		
	开户银行（全称）	中国银行新兴支行		

2023B0202140001

项目负责人一	姓名	黎少松	性别	男	出生日期	1979-10-01
	证件类型	身份证	证件号码	441228197910010315		
	所在单位	温氏食品集团股份有限公司				
	最高学位	硕士				
	职称	高级工程师		职务	常务副总裁	
	电子邮箱	710930556@qq.com		移动电话	18807663232	
项目联系人	姓名	陈丽		电子邮箱	chenlili0826@163.com	
	固定电话	13411714197		移动电话	13411714197	
	证件类型	身份证		证件号码	430725198209261941	
项目财务负责人	姓名	关雪峰		电子邮箱	wskygl@163.com	
	固定电话	0766-2291903		移动电话	13826861392	
	证件类型	身份证		证件号码	441228197710141628	

其他参与单位

序号	单位名称	单位性质	统一社会信用代码
1	华南农业大学	高等院校	12440000455416563 4
2	中国农业科学院北京畜牧兽医研究所	科研机构	12100000400882305E
3	佛山鲲鹏现代农业研究院	科研机构	12440600MB2D80149R
4	广州华农大智慧农业科技有限公司	有限责任公司	91440101MA5AT65P6R
5	高州温氏畜牧有限公司	有限责任公司	91440981MA544HT88J

项目参加人数 15 人。其中	高级职称 7 人，中级职称 4 人，初级职称 0 人，其他 4 人； 博士学位 9 人，硕士学位 3 人，学士学位 2 人，其他 1 人。

六、参与人员信息

项目负责人：

姓名	性别	年龄	职务	职称	学位	在项目中承担的任务	所在单位	签名
黎少松	男	44	常务副总裁	高级工程师	硕士	项目总负责	温氏食品集团股份有限公司	

主要研究开发人员：

姓名	性别	年龄	职务	职称	学位	在项目中承担的任务	所在单位	签名
顾如海	男	50	总经理	工程师	其他	统筹管理工作	温氏食品集团股份有限公司	
杨秋妹	女	39	重点实验室秘书	讲师	博士	负责“生猪立体工厂化养殖模式下的生猪生理生长及健康移动巡检技术研究”课题	华南农业大学	
陈丽	女	40	执行总经理	高级畜牧师	博士	项目管理及协调	温氏食品集团股份有限公司	
杨亮	男	42	无	研究员	博士	负责“生猪立体工厂化养殖模式下的精准饲喂技术与装备研究”课题	中国农业科学院北京畜牧兽医研究所	
唐中林	男	48	佛山鲲鹏现代农业研究院执行院长	研究员	博士	负责“生猪立体工厂化养殖模式下的种猪生产性能测定技术研究”课题	佛山鲲鹏现代农业研究院	
吴彻	男	28	副总经理	未取得	硕士	负责“生猪立体工厂化养殖全过程数字化技术及智能管控平台”课题	广州华农大智慧农业科技有限公司	

李冰	男	39	总经理	未取得	硕士	负责“生猪养殖全过程数字化及智能管控平台集成与应用示范”课题	高州温氏畜牧有限公司	
曾西泉	男	39	副总经理	未取得	学士	统筹管理工作	温氏食品集团股份有限公司	
王春桃	男	43	工程中心副主任	副教授	博士	项目规划与指标构建	华南农业大学	
殷建军	男	41	教研室主任	讲师	博士	智能巡检装备设研发	华南农业大学	
王燕	女	42	系副主任	教授	博士	生猪养殖生物安全精细管控及预警技术研究	华南农业大学	
熊本海	男	59	国家重点研发专项首席科学家	研究员	博士	生猪采食量模型	中国农业科学院北京畜牧兽医研究所	
胡伟	男	32	无	助理研究员	博士	智能性能测定体系建立	佛山鲲鹏现代农业研究院	
欧周才	男	29	研发总监	未取得	学士	生猪立体工厂化健康养殖全过程智能管控平台开发	广州华农大智慧农业科技有限公司	

七、承担、参与单位工作分工及经费分配情况

承担/参与单位名称（盖章）	工作分工	总经费分摊（万元）	省级财政科技资金分配（万元）
温氏食品集团股份有限公司	生猪立体工厂化养殖环境精准调控技术及应用示范	100.00	100.00
华南农业大学	生猪立体工厂化养殖模式下的生猪生理生长及健康移动巡检技术研究	100.00	100.00
中国农业科学院北京畜牧兽医研究所	生猪立体工厂化养殖模式下的精准饲喂技术与装备研究	100.00	100.00
佛山鲲鹏现代农业研究院	生猪立体工厂化养殖模式下的种猪生产性能测定技术研究	25.00	25.00
广州华农大智慧农业科技有限公司	生猪立体工厂化养殖全过程数字化技术及智能管控平台	75.00	75.00
高州温氏畜牧有限公司	生猪养殖全过程数字化及智能管控平台集成与应用示范	1300.00	100.00
合计		1700.00	500.00

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八、项目总经费及财政科技经费预算

（一）省财政科技资金拟投入总额：（大写）伍佰万圆整；（小写）500.00万元；

（二）省财政科技资金分期下达计划：

分期	经费（万元）
第1期	300.00
余款	200.00

（三）总经费及财政科技资金投入情况 （单位：万元）

项目总经费投入	财政科技资金			自筹经费			合计
	省级	中央	地方	自有经费	贷款	地方政府投入及其他	
	500.00			1200.00			1700.00

自筹资金投入情况说明：

参与单位“高州温氏畜牧有限公司”自筹经费1200万，主要用于开展本项目的基建费、设备费和材料费。基建费预算400万，主要用于楼房猪舍建设的桩基础、混凝土浇筑；构造柱、板浇筑混凝土，地基基础设计等级为丙级。设备费预算400万，主要用于购置楼房猪舍的饲喂系统、除臭系统、环控系统。材料费预算400万，主要用于楼房猪舍建设所需的栏架钢材、料线管材、塞链、刮粪机板材和钢丝绳等。

项目经费预算 （单位：万元）

是否为数学等纯理论基础研究项目： 否

	项目总经费		省级财政科技资金	
支出经费	经费额	用途说明	经费额	用途说明
1、直接费用	1630.00		430.00	
（1）设备费	480.00	养殖场饲喂系统、除臭系统、环控系统、监控设备、红外热像仪等	80.00	轮式机器人、轨道机器人、算法开发电脑等
（2）业务费	1046.32	材料费、测试化验加工外协费、燃料动力费、差旅、会议费、出版知识产权、桩基础混凝土浇筑	246.32	材料费、测试化验加工外协费、燃料动力费、差旅/会议/国际合作与交流费、出版/文献/信息传播/知识产权
（3）直接人力资源成本	103.68	用于课题执行过程中支付给研究生和临聘工人的费用、项目参与人员补助、专家咨询费	103.68	用于课题执行过程中支付给研究生和临聘工人的费用、项目参与人员补助、专家咨询费
2、间接费用	70.00		70.00	
（1）绩效支出	40.00	项目人员绩效	40.00	项目人员绩效
（2）管理费用	26.00	项目管理费	26.00	项目管理费
（3）其他间接费用	4.00	用与支付与项目有关的审计费、办公费、邮寄费、网费等	4.00	用与支付与项目有关的审计费、办公费、邮寄费、网费等
合计	1700.00		500.00	

其他需说明的情况

无。

单价50万元以上购置/试制设备预算明细表

序号	设备名称	设备分类	功能和技术指标	单价（万元）	数量	金额（万元）	购置或试制单位	安置单位	购置设备类型	主要生产厂家及国别	规格型号	拟开放共享范围
单价50万元以上购置设备合计							/	/	/	/	/	/
单价50万元以上试制设备合计							/	/	/	/	/	/

2023B0202140001

九、签约各方

管理单位（甲方）： 广东省科学技术厅（盖章）

单位地址： 广东省广州市越秀区连新路171号

法定代表人（或授权代表）： 王月琴 （签章）

联系人（经办人）姓名： 叶毓峰 （签章）

Email： yeyf@gdstc.gov.cn QQ：

电话： 微信：

2023年6月13日

牵头承担单位一（乙方）： 温氏食品集团股份有限公司 （盖章，单位法人章或单位法人授权章）

单位地址： 广东省云浮市新兴县广东省新兴县新城镇东堤北路9号

法定代表人（或法人代理）： 温志芬 （签章）

联系人（项目主管）姓名： 王凯 （签章）

Email： wskygl@163.com QQ：

电话： 0766-2986008 微信：

2023年8月7日

项目推荐（主管）单位（丙方）： 新兴县科技局 （盖章，单位法人章或单位法人授权章）

单位地址： 广东省云浮市新兴县广东省云浮市新兴县新城镇茅园新街茅园路46号四楼

法定代表人（或法人代理）： 彭炳南 （签章）

联系人（项目主管）姓名： 彭炳南 （签章）

Email： 2546486260@qq.com QQ：

电话： 0766-2889903 微信：

2023年8月7日

任务编号： 2021YFD2000802-4 密　级：公开

国家重点研发计划
团队任务书

任务名称/编号：生猪健康识别算法及预警模型研究
/2021YFD2000802-4

所属课题/编号：生猪生长及健康状态感知技术与装备研究
/2021YFD2000802

所属项目/编号：绿色高效智能养猪工厂创制与应用
/2021YFD2000800

课题承担单位（甲方）：华南农业大学

研究任务团队负责人（乙方）：杨秋妹

起止年限：2021 年 12 月 —— 2024 年 11 月

中华人民共和国科学技术部　制

二〇二一 年 十二 月

一、研究任务分解	
任务一	非直接感知指标元数据的提取算法
任务二	生猪生长监测模型构建
任务三	生猪重大疾病远程诊断及大数据健康预警模型研究

二、任务指标及考核要求

1、 约束性指标

突破养猪信息与生产过程等数字化采集技术 4 项，构建生猪重大疾病远程诊断及健康预警模型，模型精度达 90%以上。

2、考核指标

获第 3 方检测报告 1 份，申报专利 3 件，发表高水平论文 4 篇，获得计算机软件登记 2 项。

三、年度安排

年度	年度工作内容、考核指标及考核方法
2021.12-2022.11	工作内容： 非直接感知指标元数据的提取算法：针对 2D 彩色图像、3D 图像、热图像及音频元数据，利用计算机视觉、声频处理、人工智能等技术，设计猪只运动量提取、行为检测、体温关键部位提取、体重体尺估测与背膘测定以及猪只声纹特征提取等智能算法。 考核指标： 突破养猪信息与生产过程等数字化采集技术 2 项，申报专利 2 件，发表高水平论文 1 篇，获得计算机软件登记 1 项。 考核方法： 专利受理证明、期刊论文、软著授权证明。
2022.12-2023.11	工作内容： 生猪生长监测模型构建：针对不同类型、不同阶段的猪只生长特点与生产需求，研究猪只体尺、体重及背膘的生长变迁规律，构建不同类型、不同阶段的猪只生长（体尺、体重及背膘）曲线模型。并研究用该模型进行猪只生长发育性能监测与评估的方法，为进一步精准调控养殖方案提供依据。 考核指标： 突破养猪信息与生产过程等数字化采集技术 2 项，申报专利 1 件，发表高水平论文 2 篇，获得计算机软件登记 1 项 考核方法： 专利受理证明、期刊论文、软著授权证明。
2023.12-2024.11	工作内容： 生猪重大疾病远程诊断及大数据健康预警模型研究：针对非洲猪瘟、猪流感及猪蓝耳病等重大疾病和亚健康状态，依据生猪发病前后体温变化、采食量变化、体征变化，躺卧时长、神态异常、排泄异常、呼吸异常、声音异常等多源大数据的疾病特征，探索不同体重、不同类型、不同生长生理阶段生猪的体型体征、行为特性、生产性能等与疾病、健康的量化关联关系，进而构建生猪重大疾病远程诊断与健康预警系列模型。 考核指标： 构建生猪重大疾病远程诊断及健康预警模型，模型精度达 90%以上，获第 3 方检测报告 1 份，发表高水平论文 1 篇。 考核方法： 第 3 方检测报告、期刊论文。

四、团队研究人员

研究任务团队负责人

姓　名	性别	年龄	技术职称	身份证号码	所在单位	用于本任务的工作时间占本人总工作时间的百分比(%)
杨秋妹	女	38	讲师	44092119831230162X	华南农业大学数学与信息学院	50%

团队成员

郭艾侠	女	47	副教授	342223197407092523	华南农业大学数学与信息学院	30%
黄一桂	男	25	博士生	440981199604111415	华南农业大学数学与信息学院	30%
陈淼彬	男	25	硕士生	441481199610101719	华南农业大学数学与信息学院	60%
刘俊彬	男	23	硕士生	445202199801170319	华南农业大学数学与信息学院	60%
曾瑞麟	男	25	硕士生	440111199602183017	华南农业大学数学与信息学院	30%
周家鑫	男	22	硕士生	420583199902201037	华南农业大学数学与信息学院	30%

五、经费来源与支出预算

单位：万元（保留两位小数）

预算科目名称	合计	专项经费	其中下拨经费	其它经费来源
一、经费来源	100	100	100	0
1. 国家专项经费	100	100	100	0
2. 其它经费	0	0	0	0
二、经费支出	100	100	100	0
（一）直接费用	82.5	82.5	82.5	0
1. 设备费	13.5	13.5	13.5	0
（1）购置设备费	0	0	0	0
（2）试制设备费	13.5	13.5	13.5	0
（3）设备改造与租赁费	0	0	0	0
2. 业务费	46.5	46.5	46.5	0
3. 劳务费	20	20	20	0
（二）间接费用	20	20	20	0
（三）合计	100	100	100	0

六、合约条款

甲方（课题承担单位）： 华南农业大学

乙方（研究任务团队负责人）： 杨秋妹

根据项目组织（牵头）单位与甲方签订的课题任务书要求，项目组织（牵头）单位授权甲方与乙方签订本合约。

（一）权利与义务

甲方全面负责课题各项任务，督促课题负责人按照课题任务书要求实施研究工作，合理使用课题经费，如期完成课题任务；甲方有权对乙方的年度计划执行情况进行监督、检查，并提供有关支持与保障条件；乙方具体负责研究任务团队的各项任务，应严格按照合约保证及时完成研究任务，并接受甲方的监督检查。乙方有权参与甲方组织的课题方案制定等相关活动。

（二）团队管理

研究任务团队是为完成某一具体研究任务，由负责人牵头，联合相关研究成员组成的研发群体。团队成员组成应根据研究任务的需要，在尊重自愿的基础上，由甲方与乙方共同协商确定。

团队成员及其任务确定后，由项目组织（牵头）单位报请科技部，向团队及其所在单位正式发文通告。项目正式验收后，由甲方提出团队成员及其绩效报告，报项目组织（牵头）单位和科技部审核，由科技部正式发文认定。

在签订本合约之前，团队负责人应与研究团队其他成员之间协商确定团队任务安排、参与时间、收益分配等。

（三）经费管理

由甲方负责财务管理。根据有关经费管理办法和财务规定，甲方提供给乙方相应经费。甲方在收到财政专项拨款后，应在十个工作日内告知乙方，并按双方共同约定的办法给乙方提供相应的经费。

乙方使用经费应严格按照经费预算和约定的支出范围执行，保证专款专用，不得弄虚作假、挪用、挤占课题经费或违反相关法律法规。甲方根据国家有关法规和科技计划经费开支的规定，监督乙方经费的使用情况。项目组织（牵头）单位和项目官员有权对甲乙双方经费使用进行监督管理。

（四）成果管理

双方在研发过程中应加强研究成果管理，严格执行《中华人民共和国科学技术进步法》、《关于加强国家科技计划知识产权管理工作的规定》、《中华人民共和国专利法》和《中华人民共和国著作权法》等有关规定。研究成果在申报国家及有关部门、地方的科技成果奖励时，需由甲乙双方共同协商成果署名等相关事宜。

甲乙双方应根据有关法律法规，及甲方与项目组织（牵头）单位签订的任务书规定，协商确定课题研究成果的收益分配等事宜并签订知识产权合作协议。

（五）资产管理

按照科技计划专项经费管理办法执行，专项经费形成的大型仪器设备固定资产归甲方管理，乙方在执行课题任务时，与甲方享有同等使用权。甲乙双方可以自行协商确定设备使用共享的相关办法。

（六）信用管理

项目组织（牵头）单位和项目官员有权对甲乙双方进行信用监管。甲乙双方均需建立信用管理档案，对参加人员进行信用记录。记录内容包括科研活动情况、任务完成情况、按时提交材料情况、经费使用情况等。双方均需遵守有关科研诚信建设的相关规定，积极配合有关单位或部门组织的信用评估工作。

（七）保密管理

按《中华人民共和国保守国家秘密法》和科学技术部《科技保密规定》及相关国家科技计划管理办法等有关规定执行。

（八） 任务与经费调整

乙方须及时向甲方报告研究进展。乙方未能按规定进度和考核指标完成任务的，甲方可对乙方及其团队的任务和经费在本合约范围内进行调整。由甲方提出调整意见，报项目组织（牵头）单位审定后执行，并报科技部备案。

（九）争议处理和合约变更

1、项目组织（牵头）单位是双方争议的调解机构。项目官员具有对纠纷处理的监督权和问责权。

2、合约在履行过程中发生争议的，双方应首先通过协商的方式解决。协商不成时，双方向项目组织（牵头）单位申请调解。

3、任何一方因不可抗力不能履行合约义务时，可以免除违约责任，但应及时通知另一方，并在30天内出具因不可抗力导致合约不能履行的证明。

4、合约一方要求变更或解除合约，应在30日前书面通知另一方，并同时向项目组织（牵头）单位提交书面申请，经批准后执行。

（十）补充条款

1、甲乙双方均须遵守科技部关于国家科技计划项目（课题）实施法人管理责任制的意见的相关规定。

（十一） 附　则

1、本合约由甲方盖章乙方签字，经项目组织（牵头）单位审核通过后生效，并报科技部备案。

2、本合约正本一式6份（甲、乙双方各2份、项目组织（牵头）单位1份、科技部1份）。

七、签约各方签章

课题承担单位（甲方）：华南农业大学　　（公章）

单位负责人（签字）：

课题负责人（签字）：

2022 年 1 月 4 日

任务承担单位（乙方）：华南农业大学　　（公章）

研究任务团队负责人（签字）：

2022 年 1 月 4 日

项目编号：2021YFD2000800　　密　级：公开

国家重点研发计划
项目任务书

项目名称：	绿色高效智能养猪工厂创制与应用
所属专项：	工厂化农业关键技术与智能农机装备
指南方向(榜单任务)：	2. 绿色高效智能养猪工厂创制与应用
创新分类：	技术开发
项目管理专业机构：	中国农村技术开发中心
推荐单位：	农业农村部
项目牵头承担单位：	中国农业科学院北京畜牧兽医研究所　（公章）
项目负责人：	熊本海
执行期限：	2021 年 12 月 至 2024 年 11 月

中华人民共和国科学技术部制

0002YF 2021YFD2000800 2022-04-01 11:08:31

项目基本信息表

<table>
<tr><td colspan="2">项目名称</td><td colspan="6">绿色高效智能养猪工厂创制与应用</td></tr>
<tr><td colspan="2">项目编号</td><td colspan="6">2021YFD2000800</td></tr>
<tr><td colspan="2">所属专项</td><td colspan="6">工厂化农业关键技术与智能农机装备</td></tr>
<tr><td colspan="2">指南方向
（榜单任务）</td><td colspan="6">2. 绿色高效智能养猪工厂创制与应用</td></tr>
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<tr><td colspan="2">项目实施模式</td><td colspan="6">揭榜挂帅</td></tr>
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<tr><td colspan="2">经费预算</td><td colspan="6">总预算 8000.00 万元，其中中央财政专项资金 4000.00 万元，地方财政资金 0.00 万元，单位自筹资金 4000.00 万元，其他渠道获得资金 0.00 万元</td></tr>
<tr><td colspan="2" rowspan="2">项目周期节点</td><td>起始时间</td><td>2021 年 12 月</td><td>结束时间</td><td colspan="2">2024 年 11 月</td></tr>
<tr><td>实施周期</td><td>共 36 个月</td><td>预计中期时间点</td><td colspan="2">2023 年 05 月</td></tr>
<tr><td rowspan="8">项目牵头承担单位</td><td>单位名称</td><td colspan="2">中国农业科学院北京畜牧兽医研究所</td><td>单位法定代表人姓名</td><td colspan="2">秦玉昌</td></tr>
<tr><td>单位性质</td><td colspan="2">事业型研究单位</td><td>组织机构代码</td><td colspan="2">12100000400882305E</td></tr>
<tr><td>单位主管部门</td><td colspan="2">中国农业科学院</td><td>隶属关系</td><td colspan="2">中央</td></tr>
<tr><td>单位所属地区</td><td colspan="2">北京市</td><td>地市（市、自治州、盟）</td><td colspan="2">北京市　海淀区</td></tr>
<tr><td>通信地址</td><td colspan="2">北京市海淀区圆明园西路 2 号</td><td>邮政编码</td><td colspan="2">100193</td></tr>
<tr><td>单位开户名称</td><td colspan="4">中国农业科学院北京畜牧兽医研究所</td></tr>
<tr><td>开户银行（全称）</td><td colspan="2">中国农业银行股份有限公司北京海淀支行营业部</td><td>汇入地点</td><td colspan="2">北京市　北京市</td></tr>
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<tr><td rowspan="2">推荐单位</td><td>单位名称</td><td colspan="2">农业农村部</td><td>推荐单位性质</td><td colspan="2">■部门□地方□行业协会□产业技术创新战略联盟□其他</td></tr>
<tr><td>项目</td><td>姓 名</td><td>熊本海</td><td>性 别</td><td>■男 □女</td><td>出生日期</td><td>1963-06-20</td></tr>
</table>

负责人	证件类型	身份证	证件号码	110108196306202350	
	所在单位	中国农业科学院北京畜牧兽医研究所			
	最高学位	■博士□硕士□学士□其他			
	职 称	■正高级□副高级□中级□初级□其他		职 务	研究室主任
	电子邮箱	xiongbenhai@caas.cn	移动电话	13801090939	
项目联系人	姓 名	郑姗姗	电子邮箱	zhengshanshan@caas.cn	
	固定电话	010-62815988	移动电话	13661029298	
	证件类型	身份证	证件号码	110103197710050929	
项目财务负责人	姓 名	王爱辰	电子邮箱	wangaichen@caas.cn	
	固定电话	010-62815886	移动电话	13520780804	
	证件类型	身份证	证件号码	371482198109076023	

	序号	课题名称	承担单位	负责人	总经费(万元)	其中中央财政专项资金(万元)
课题分解	01	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	浙江大学	汪开英	740.00	740.00
	02	生猪生长及健康状态感知技术与装备研究	华南农业大学	肖德琴	740.00	740.00
	03	猪舍环境精准控制与智能环控器创制	重庆市畜牧科学院	徐顺来	740.00	740.00
	04	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	中国农业科学院北京畜牧兽医研究所	杨亮	1100.00	1100.00
	05	生猪养殖智能化管控平台及智能猪厂建设与运行	北京大北农科技集团股份有限公司	高华杰	4680.00	680.00

	序号	单位名称	单位性质	组织机构代码
其他参与单位	1	浙江大学	大专院校	12100000470095016Q

	2	华南农业大学	大专院校	124400004554165634
	3	重庆市畜牧科学院	事业型研究单位	12500000450402779M
	4	北京大北农科技集团股份有限公司	私营企业	91110000102006956C
	5	中国科学院亚热带农业生态研究所	事业型研究单位	12100000717807303X
	6	南京农业大学	大专院校	12100000466007562R
	7	温氏食品集团股份有限公司	私营企业	91445300707813507B
	8	北京佳沃天河智能科技有限公司	私营企业	91110108MA01C7X37R
	9	成都肇元科技有限公司	私营企业	054900178

项目参加人数	57 人。其中：	高级职称 19 人，中级职称 18 人，初级职称 0 人，其他 20 人；
		博士学位 23 人，硕士学位 21 人，学士学位 12 人，其他 1 人。

项目简介（限1500字以内）	近年来，随着饲料资源、养殖环境、劳动力结构尤其非洲猪瘟将常态化等压力的增加，猪业结构不断调整，工厂化养猪模式比例逐年提高，规模化标准化饲养成为主流。但与养猪业发达国家相比，我国猪业仍存在母猪生产力低、健康问题突出、死淘率高、智能装备低，饲喂相对粗放等问题，导致养殖综合成本高、养猪业的“猪周期”问题日益凸显。为有效破解上述问题，本项目将突破养猪饲养工艺、健康感知、智能饲喂关键技术、大数据管控平台构建等“卡脖子”技术，研发创绿色高效智能养猪工厂，助力我国现代生猪养殖技术体系的构建。 项目主要研究内容：1）开展不同生理阶段猪群的福利化健康养殖工艺方案研究，确定不同养殖工艺的建筑结构主要参数、养殖设备设施技术参数，以及不同功能猪舍环境空气质量控制参数，创制猪舍环境精准调控、环境空气净化关键技术与设备及物联网环境控制系统。2）研究不同生理生长阶段猪的体征、健康状态等养殖过程信息的数字化表征方法和获取技术，建立猪只主要体征感知及健康识别的预估模型，研制智能感知巡检机器人，实现对主要疫病远程监测与辅助诊断。3）创制适合不同猪只类别及养殖模式的精准饲喂控制设备甚至饲喂机器人；创制消毒、清粪、排污消毒等生猪养殖机器人。4）集成项目研究所形成的养殖工艺、关键技术与装备，开发养殖过程大数据生猪管控分析平台，建成出栏 50 万头以上智能养猪工厂 2 个。 项目拟解决的关键科学及技术问题：1）揭示不同性质猪群实现福利健康养殖对饲养工艺、建筑结构、养殖设施设备的差异性需求特征，探明工厂化猪舍内环境质量与建筑结构、通风、饲喂、清粪、消毒等相互关联与制约规律，为不同生理阶段猪群环境精准调控、高效环境净化关键技术及智能设备开发提供理论基础；2）突破不同猪只体征与健康行为等信息数字化表征和获取的复杂性，建立生猪体征感知及健康识别的预估模型；3）突破环境多元动态控制的瓶颈，提出环境智能动态控制的模型化技术；4）突破生猪养分需求的动态性及差异性，创制精准饲喂理

	论与智能设备；突破猪舍地面与环境的不规则性挑战，提出养猪机器人开发基础理论与技术路线。 该项目申报单位是我国最早开展数字畜牧业及智能装备等关键技术研究的单位之一，尤其在“十三五”期间，重点开展了生猪的精准饲喂理论、智能饲喂设备的创制研究，先后建立了家畜电子标识、智能感知及智能饲喂设备的生产基地。此外团队拥有“动物营养学国家重点实验室”、“国家生猪技术创新中心”、“畜禽养殖污染控制与资源化技术国家工程实验室”、“国家生猪大数据中心”等 20 多个国家或省部级平台，平台基础优势明显。 项目执行将采用“反弹琵琶倒逼机制”思路，确定每个研究团队的“里程碑”目标，形成技术、装备的完善提升与创制的技术路线，尤其确定每个课题的示范猪场任务，优化绿色智能养猪工厂的创制和数字化、智能化改造方案，确保目标完成。 项目预期研究目标，形成生猪养殖生产过程等数字化采集技术 9 项，实现养殖过程数字化率 90%以上；创制智能感知设备 3~5 种，产品自主率 95%以上；构建养殖数据库 15 个，构建重大疾病诊断及预警模型 3-5 套，模型精度达 90%以上；研发福利健康养殖工艺 7 套，智能环控器 5 种，创制母猪分娩及转运、精准饲喂及加药设备共 9 套；创制高效环境净化等关键装备 6 套，创制消毒、清粪、巡检、饲喂机器人 4 类 6 种，开发环控、饲养营养、健康感知及母体一体化 4 个智能管控平台，产品自主率 95%以上；建立技术装备示范验证基地 45 个以上，其中，年出栏 50 万头以上的智能养猪工厂 2 个。 通过本项目的实施，将从整体上提升我国工厂化养猪智能化水平、节省劳动力、减少环境污染、加快传统生猪产业的转型升级，增强养猪业的国际竞争力。

填表说明：1.组织机构代码指企事业单位国家标准代码，单位若已三证合一请填写单位统一社会信用代码，无组织机构代码的单位填写“000000000”；

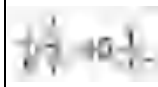
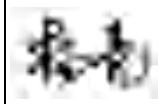
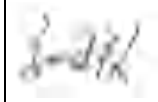
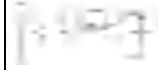
2.单位公章名称必须与单位名称一致；

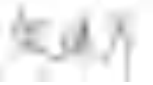
3.单位开户名称应与单位名称一致，如有开户名称不一致等特殊情况，必须提供证明文件。

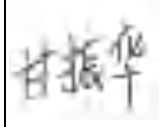
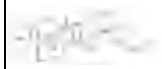
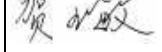
十、项目参加人员基本情况表

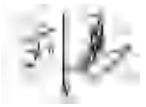
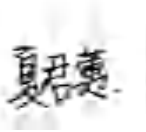
填表说明： 1.专业技术职称：A、正高级　B、副高级　C、中级　D、初级　E、其他；
2.投入本项目的全时工作时间（人月）是指在项目实施期间该人总共为项目工作的满月度工作量；累计是指项目组所有人员投入人月之和；
3.项目固定研究人员需填写人员明细；
4.是否有工资性收入：Y、是　N、否；
5.人员分类代码：A、项目负责人　B、课题负责人　C、项目/课题骨干　D、其他研究人员；
6.工作单位：填写单位全称，其中高校要具体填写到所在院系。

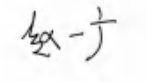
序号	姓名	性别	出生日期	证件类型	证件号码	专业技术职称	职务	最高学位	专业	投入本项目的全时工作时间（人月）	人员分类代码	所属课题	是否有工资性收入	工作单位	参加人员签字
1	熊本海	男	1963-06-20	身份证	110108196306202350	正高级	研究室主任	博士	动物营养	18	项目负责人		是	中国农业科学院北京畜牧兽医研究所	
2	汪开英	女	1968-05-06	身份证	330104196805061623	副高级	无	博士	农业（畜牧）工程	24	任务(课题)负责人	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	浙江大学生物系统工程与食品科学学院农业生物环境工程研究所	
3	肖德琴	女	1970-05-14	身份证	510212197005140829	正高级	工程中心主任	博士	农业电气化与自动化	36	任务(课题)负责人	生猪生长及健康状态感知技术与装备研究	是	华南农业大学数学与信息学院计算机科学与工程系	
4	徐顺来	男	1971-12-30	身份证	510229197112302253	正高级	所长	硕士	畜牧	24	任务(课	猪舍环境精	是	重庆市畜牧	

											题)负责人	准控制与智能环控器创制		科学院	
5	杨亮	男	1980-08-16	身份证	220303198008162411	正高级	骨干专家	博士	智能装备与畜牧信息	18	任务(课题)负责人	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	中国农业科学院北京畜牧兽医研究所	
6	高华杰	女	1983-09-06	身份证	372929198309064226	副高级	创新平台总监	硕士	畜牧信息	18	任务(课题)负责人	生猪养殖智能化管控平台及智能猪厂建设与运行	是	北京大北农科技集团股份有限公司	
7	张玺铭	男	1978-02-23	身份证	210502197802232718	正高级	副所长	博士	农业工程	15	项目/课题骨干	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	浙江大学生物系统工程与食品科学学院	
8	汪海峰	男	1977-09-27	身份证	342425197709277914	正高级	副所长	博士	动物养殖	12	项目/课题骨干	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	浙江大学动物科学学院	
9	赵庆江	男	1976-05-02	身份证	232125197605021410	副高级	无	硕士	机械设计与制造	12	项目/课题骨干	猪群福利化健康养殖工艺研究与猪舍环境净化	是	北京佳沃天河智能科技有限公司	

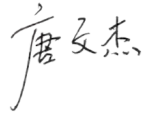
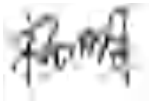
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10	王浩	男	1990-08-22	身份证	142702199008223319	中级	无	硕士	农业生物环境与能源工程	12	项目/课题骨干	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	重庆市畜牧科学院	
11	杨秋妹	女	1983-12-30	身份证	44092119831230162X	中级	无	博士	农业电气化与自动化	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	华南农业大学数学与信息学院	
12	蓝天	男	1973-10-01	身份证	440106197310011870	副高级	无	硕士	预防兽医学	24	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	华南农业大学动物科学学院	
13	殷建军	男	1981-01-08	身份证	421003198101080551	中级	无	博士	农业电气化与自动化	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	华南农业大学数学与信息学院	
14	刘又夫	男	1995-02-27	身份证	440105199502270917	其他	无	硕士	农业电气化与自动化	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	否	华南农业大学数学与信息学院	
15	宋爽	男	1986-09-24	身份证	420106198609240417	其他	技术总监	博士	预防兽医学	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	温氏食品集团股份有限公司	
16	龚琪	男	1988-09-01	身份证	429004198809011758	其他	技术创新专员	硕士	预防兽医学	36	项目/课题骨干	生猪生长及健康状态感	是	温氏食品集团股份有限	

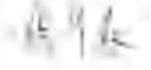
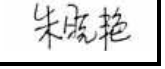
												知技术与装备研究		公司	
17	白霖	男	1992-05-02	身份证	520203199205022418	其他	技术创新专员	硕士	临床兽医学	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	温氏食品集团股份有限公司	
18	甘振华	男	1994-10-10	身份证	445321199410102532	其他	现代化装备专员	硕士	机械工程	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	温氏食品集团股份有限公司	
19	冯泽猛	男	1985-08-23	身份证	371522198508236011	副高级	无	博士	动物营养与饲料科学	18	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	中国科学院亚热带农业生态研究所	
20	龙次民	男	1988-02-18	身份证	430524198802182438	中级	无	硕士	动物营养与饲料科学	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	是	中国科学院亚热带农业生态研究所	
21	贺玉敏	男	1992-07-24	身份证	430424199207242714	其他	无	硕士	生理学	36	项目/课题骨干	生猪生长及健康状态感知技术与装备研究	否	中国科学院亚热带农业生态研究所	
22	蒲施桦	女	1986-08-05	身份证	500383198608050586	副高级	无	硕士	环境工程	16	项目/课题骨干	猪舍环境精准控制与智能环控器创制	是	重庆市畜牧科学院	
23	朱佳明	男	1993-04-11	身份证	61042419930411083X	中级	无	硕士	环境工程	12	项目/课题骨干	猪舍环境精准控制与智	是	重庆市畜牧科学院	

												能环控器创制			
24	刘勇	男	1979-11-18	身份证	510231197911180012	副高级	无	学士	信息技术	12	项目/课题骨干	猪舍环境精准控制与智能环控器创制	是	重庆市畜牧科学院	
25	王校帅	男	1988-11-26	身份证	330825198811260177	副高级	无	博士	农业工程	15	项目/课题骨干	猪舍环境精准控制与智能环控器创制	是	浙江大学生物系统工程与食品科学学院	
26	曹孟冰	男	1989-12-24	身份证	362232198912240018	中级	无	博士	环境与能源工程	12	项目/课题骨干	猪舍环境精准控制与智能环控器创制	是	浙江大学生物系统工程与食品科学学院	
27	廖建兵	男	1985-07-27	身份证	511529198507277015	中级	无	学士	应用电子	16	项目/课题骨干	猪舍环境精准控制与智能环控器创制	是	成都肇元科技有限公司	
28	夏君蕙	女	1995-11-09	身份证	510106199511090023	其他	无	学士	数字媒体	12	项目/课题骨干	猪舍环境精准控制与智能环控器创制	是	成都肇元科技有限公司	
29	陈睿鹏	男	1992-07-12	身份证	410423199207129551	中级	无	博士	生物医学工程	18	项目/课题骨干	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	中国农业科学院北京畜牧兽医研究所	

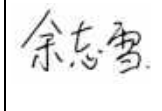
30	赵一广	男	1986-02-23	身份证	370285198602230415	中级	无	博士	反刍动物营养	18	项目/课题骨干	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	中国农业科学院北京畜牧兽医研究所	
31	夏天	男	1964-06-08	身份证	510111196406080779	其他	总经理	学士	机械制造与自动化	24	项目/课题骨干	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	成都肇元科技有限公司	
32	路遥	男	1988-05-17	身份证	230103198805175515	中级	无	学士	机械设计制造及其自动化	24	项目/课题骨干	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	北京佳沃天河智能科技有限公司	
33	宋洋	男	1986-02-16	身份证	232101198602164030	中级	无	学士	电子信息与通信工程	24	项目/课题骨干	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	北京佳沃天河智能科技有限公司	
34	沈明霞	女	1964-09-25	身份证	320111196409251224	正高级	无	博士	农业电气化与自动化	24	项目/课题骨干	生猪养殖智能化管控平台及智能猪厂建设与运	是	南京农业大学人工智能学院	

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35	陆明洲	男	1981-02-27	身份证	320106198102270437	正高级	无	博士	计算机应用技术	36	项目/课题骨干	生猪养殖智能化管控平台及智能猪厂建设与运行	是	南京农业大学人工智能学院	
36	刘龙申	男	1983-09-09	身份证	412726198309092035	副高级	无	博士	农业电气化与自动化	24	项目/课题骨干	生猪养殖智能化管控平台及智能猪厂建设与运行	是	南京农业大学人工智能学院	
37	郑卫江	男	1985-11-19	身份证	362529198511192519	副高级	无	博士	动物营养与饲料科学	24	项目/课题骨干	生猪养殖智能化管控平台及智能猪厂建设与运行	是	南京农业大学动物科技学院	
38	王辉	男	1988-09-24	身份证	612701198809240612	中级	无	博士	农业电气化与自动化	12	项目/课题骨干	生猪养殖智能化管控平台及智能猪厂建设与运行	是	中国农业科学院北京畜牧兽医研究所	
39	聂鹏程	男	1982-07-25	身份证	422324198207255232	副高级	无	博士	农业工程	9	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	浙江大学生物系统工程与食品科学学院	
40	瞿芳芳	女	1990-10-12	身份证	420983199010125245	中级	无	博士	农业工程	15	其他研究人员	猪群福利化健康养殖工	是	浙江大学生物系统工程	

											艺研究与猪舍环境净化设备创制		与食品科学学院	
41	唐文杰	男	1995-03-01	身份证	511023199503016212	其他	无	硕士	畜牧学	18	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学动物科学学院	
42	刘蒋龙	男	1992-02-02	身份证	141082199202020091	其他	无	硕士	农业生物环境与能源工程	15	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学生物系统工程与食品科学学院	
43	杨明	女	1994-07-24	身份证	211122199407241725	其他	无	硕士	农业生物环境与能源工程	15	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学生物系统工程与食品科学学院	
44	鄂爽	女	1993-02-24	身份证	21011319930224114X	其他	无	硕士	农业生物环境与能源工程	18	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学生物系统工程与食品科学学院	
45	曾雅琼	女	1991-12-01	身份证	622322199112012827	中级	无	硕士	农业生物环境与能源工程	12	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	重庆市畜牧科学院	

46	彭云	男	1988-01-07	身份证	230921198801072910	中级	无	学士	电子信息工程	12	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	是	北京佳沃天河智能科技有限公司	
47	胡斐悦	女	1998-03-05	身份证	431202199803050016	其他	无	学士	农业工程	18	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学生物系统工程与食品科学学院	
48	李鑫	女	1997-10-18	身份证	130921199710184846	其他	无	学士	农业工程	18	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学生物系统工程与食品科学学院	
49	魏宇森	男	1998-06-23	身份证	350427199806238513	其他	无	学士	动物养殖	15	其他研究人员	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	否	浙江大学动物科学学院	
50	邹永继	男	1990-06-29	身份证	51322119900629131X	其他	无	其他	水电	24	其他研究人员	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	是	成都肇元科技有限公司	
51	朱晓艳	女	1996-05-02	身份证	130481199605021366	其他	无	学士	畜牧	24	其他研究人员	猪精准饲喂、加药、	否	中国农业科学院北京畜	

											清粪、消毒机器人等智能作业装备创制		牧兽医研究所	
52	吕硕	女	1986-05-28	身份证	130634198605280028	中级	无	博士	农学	36	其他研究人员	生猪养殖智能化管控平台及智能猪厂建设与运行	是	北京大北农科技集团股份有限公司	
53	李泽林	男	1984-09-09	身份证	510824198409096134	中级	无	硕士	地图制图学与地理信息系统	36	其他研究人员	生猪养殖智能化管控平台及智能猪厂建设与运行	是	北京大北农科技集团股份有限公司	
54	段政均	男	1983-12-22	身份证	140107198312224511	中级	无	硕士	工业工程	36	其他研究人员	生猪养殖智能化管控平台及智能猪厂建设与运行	是	北京大北农科技集团股份有限公司	
55	朱玉霞	女	1984-03-14	身份证	412322198403148229	其他	生物安全经理	博士	临床兽医	36	其他研究人员	生猪养殖智能化管控平台及智能猪厂建设与运行	是	北京大北农科技集团股份有限公司	
56	李华	男	1982-04-26	身份证	370323198204262135	其他	育种经理	硕士	动物遗传育种与繁殖	36	其他研究人员	生猪养殖智能化管控平台及智能猪厂建设与运	是	北京大北农科技集团股份有限公司	

												行			
57	余志雪	女	1997-02-08	身份证	130727199702080526	其他	无	学士	畜牧	24	其他研究人员	生猪养殖智能化管控平台及智能猪厂建设与运行	否	中国农业科学院北京畜牧兽医研究所	
固定研究人员合计										1295	/	/	/	/	/
流动人员或临时聘用人员合计										0	/	/	/	/	/
累计										1295	/	/	/	/	/

项目预算表

表A1 项目编号： 2021YFD2000800 项目名称： 绿色高效智能养猪工厂创制与应用 金额单位：万元

序号	课题编号	课题名称	课题承担单位	课题负责人	课题预算							
					资金来源			资金支出				
					中央财政专项资金	其他来源资金	合计	中央财政专项资金			其他来源资金	合计
								直接费用	间接费用	小计		
	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）	（9）	（10）	（11）	（12）
1	2021YFD2000801	猪群福利化健康养殖工艺研究与猪舍环境净化设备创制	浙江大学	汪开英	740.00		740.00	610.50	129.50	740.00		740.00
2	2021YFD2000802	生猪生长及健康状态感知技术与装备研究	华南农业大学	肖德琴	740.00		740.00	610.50	129.50	740.00		740.00
3	2021YFD2000803	猪舍环境精准控制与智能环控器创制	重庆市畜牧科学院	徐顺来	740.00		740.00	610.50	129.50	740.00		740.00
4	2021YFD2000804	猪精准饲喂、加药、清粪、消毒机器人等智能作业装备创制	中国农业科学院北京畜牧兽医研究所	杨亮	1100.00		1100.00	907.50	192.50	1100.00		1100.00
5	2021YFD2000805	生猪养殖智能化管控平台及智能猪厂建设与运行	北京大北农科技集团股份有限公司	高华杰	680.00	4000.00	4680.00	561.00	119.00	680.00	4000.00	4680.00
累计					4000.00	4000.00	8000.00	3300.00	700.00	4000.00	4000.00	8000.00

任务书签署

甲乙双方根据《国务院印发关于深化中央财政科技计划（专项、基金）管理改革方案的通知》（国发〔2014〕64号）、《国务院关于优化科研管理提升科研绩效若干措施的通知》（国发〔2018〕25号）、《国务院办公厅关于改革完善中央财政科研经费管理的若干意见》（国办发〔2021〕32号）、《科技部 财政部关于印发<国家重点研发计划管理暂行办法>的通知》（国科发资〔2017〕152号）、《财政部 科技部关于印发<国家重点研发计划资金管理办法>的通知》（财教〔2021〕178号）、《科学技术活动违规行为处理暂行规定》（科学技术部令第19号）、《科技部财政部关于印发<中央财政科技计划（专项、基金等）监督工作暂行规定>的通知》（国科发政〔2015〕471号）、《科技部 自然科学基金委关于进一步压实国家科技计划（专项、基金等）任务承担单位科研作风学风和科研诚信主体责任的通知》（国科发监〔2020〕203号）等有关文件规定，以及有关法律、政策和管理要求，依据项目立项通知，签署本任务书。

同时，本单位和项目负责人**郑重承诺**：对本项目所有成果产出（包括但不限于新产品、新技术、标准、论文、专利等）的真实性、与项目的关联性等负责，将按要求落实科研作风学风和科研诚信主体责任；项目经费全部用于与本项目研究工作相关的支出，不截留、挪用、侵占，不用于与科学研究无关的支出；接受并积极配合相关部门的监督检查。如有违反，本单位和项目负责人以及相关成果产出者愿接受项目管理专业机构和相关部门做出的各项处理决定，包括但不限于终止项目执行、追回项目（课题）经费，取消一定期限国家科技计划项目申报资格，记入科研诚信严重失信行为数据库以及主要负责人接受相应党纪政纪处理等。

项目管理机构（甲方）：

法定代表人签字（签章）：

（公章）

2021年12月1日

项目牵头承担单位（乙方）：

法定代表人签字（签章）：

（公章）

2021年11月18日

项目负责人签字（签章）：

2021年11月28日

推荐单位（盖章）

2021年11月29日

广东省科学技术厅

粤科函社农字〔2018〕2136号

广东省科学技术厅关于核准2018年省级农村科技特派员千村大对接人员名单和任务清单（第一批）的通知

省农科院、华南农业大学、省科学院、仲恺农业工程学院:

按照《广东省科学技术厅关于开展2018年省级农业科技特派员千村大对接行动的通知》（粤科函社农字〔2018〕664号）要求，各单位按照“大专项+任务清单”的方式，组织本单位科技特派员与贫困村进行了对接，并报送了实施方案、科技特派员名单和任务清单。本次共选派科技特派员206个（组），其中省农科院79个（组），华南农业大学66个（组），省科学院30个（组），仲恺农业工程学院31个（组），共对接618个贫困村。覆盖了肇庆、云浮、梅州、汕头、韶关、河源、清远、阳江、汕尾、揭阳、潮州、茂名、惠州等14个地级以上市。

现将2018年省级农村特派员千村大对接选派对接人员名单和任务清单（第一批）印发给你们，请按照要求认真组织实施，并做好科技特派员后续管理，包括签订合同书、资金使用、日常

监管和验收结题等相关工作，确保科技特派员真正下乡进村，推动乡村振兴战略实施。

附件：广东省农村科技特派员千村大对接选派对接人员名单和任务清单（第一批）

省科技厅

2018年10月12日

公开方式：依申请公开

附件

广东省农村科技特派员千村大对接选派对接名单和任务清单（第一批）

省农科院							
序号	姓名	性别	派出单位（院、所系）	职务/职称	对接工作内容	对接贫困村名称	所在地市
1	涂从勇	男	广东省农业科学院水稻研究所	主任/副研究员	优质稻及特用稻品种的推广种植	梅州市大埔县枫朗镇大埔角村、枫朗镇四联村、百侯镇南山村	梅州
	陈志远	男	广东省农业科学院水稻研究所	副主任/研究员			
	陆秀明	女	广东省农业科学院水稻研究所	副研究员			
	许立超	男	广东省农业科学院水稻研究所	助理研究员			
2	潘俊峰	男	广东省农业科学院水稻研究所	副主任/副研究员	罗定市优质稻低碳高产栽培技术的示范应用	罗定市围底镇渡头村、华石镇寨脚村、华石镇三屋村	云浮
	黄农荣	男	广东省农业科学院水稻研究所	研究员			
	胡香玉	女	广东省农业科学院水稻研究所	助理研究员			
	陈志远	男	广东省农业科学院水稻研究所	研究员			
	刘彦卓	男	广东省农业科学院水稻研究所	研究员			
	彭碧琳	女	广东省农业科学院水稻研究所	研究实习员			
3	刘迪林	男	广东省农业科学院水稻研究所	副主任/副研究员	发展优质稻生产促进农户增收	肇庆市怀集县冷坑镇楼边村、岗脚村、团结村	肇庆
	李金华	男	广东省农业科学院水稻研究所	助理研究员			

30	徐永坚	女		城乡规划高级工程师	梅州市大埔县枫朗镇古驿道沿线贫困村乡村振兴发展战略研究	大埔县角村、隔背村、下木村	梅州
华南农业大学							
序号	姓名	性别	派出单位（院、所系）	职务/职称	对接工作内容	对接贫困村名称	所在地市
1	吴伟斌	男	工程学院	教授	丘陵山区林果茶园运输机械化技术示范和推广	平安村、绿水村、竹坑村	梅州市
2	闫国琦	男	工程学院	副教授	精准对接扶贫脱贫农渔业机械化科技成果推广与示范	孔美村、巴东村、五里村	揭阳、湛江
3	罗明珠	女	农学院	副教授	稻田养鱼防控病虫害技术集成在紫金县的示范和推广应用	洋头村、礼坑村、璜光村	河源市
4	邹记兴	男	海洋学院	教授	稻田养鱼之适宜鱼种的筛选与应用	水口村、鱼水村、五爱村	清远

39	杨秋妹	女	数信学院	讲师	家畜养殖健康状况自动化监测	南星村、罗东村、石崇村	清远市
40	彭红星	男	数信学院	副教授	互联网+农业绿色生态产品可追溯电商平台构建与应用	马催村、上洋村、彭村村	阳江市
41	徐民俊	男	海洋学院	副教授	鱼鳖混养生态养殖技术	礼堂村、米贝村、新渡村	河源市
42	兰雅淇	女	食品学院	教授	基于低温连续相变设备的米糠高直化利用技术援助与示范	敬里村、塘社村、溪上村	梅州市
43	赵会宏	男	海洋学院	副教授	河源市东源县贫困村水产养殖通识技术推广服务与特色养殖品种推介	小水村、群星村、鹊田村	河源市
44	连腾祥	男	农学院	首聘副教授	高产优质黑大豆品种华春 17 号及膜侧施肥技术示范推广	联一村、白石村、由坪村	清远市、韶关市
45	种云霄	女	资环学院	教授	粤东西北欠发达村镇水环境治理的低成本生态技术推广应用	轮源村、孔美村、天井岗村	阳江市、揭阳市、湛江市

广东省农业科技特派员项目

合 同 书

*项目名称：家畜养殖健康状况自动化监测

*起止时间：2018 年 6 月 1 日至 2020 年 6 月 1 日

*二级单位：数学与信息学院

*项目负责人：杨秋妹 *联系电话：13560377262 *手机：13560377262

*电子邮箱：yqmbegonia@163.com

华南农业大学

二零一八年制

一、主要实施内容和项目目标

本项目的目标是研究规模化养殖模式下家畜（猪、牛）的健康识别以及自动化监测。重点开展家畜的体温、运动量等生理生态指标在亚健康状态下的表征及监测技术研究，包括感知方法、传感器件及系统研究，以及在现实养殖环境下的应用部署。采用物联网技术，研究基于家畜在不同的生理及生长阶段的环境控制的阈值参数，实现家畜健康感知信息的智能分析。集成家畜的健康识别数据的采集、环境数据的采集，并与家畜生产性能数据进行多属性数据的融合，为实现设施家畜健康养殖多维空间的大数据分析提供了必要的平台。项目的技术路线如下图：



项目的实施主要分为 3 个阶段：

第一个阶段为养殖场的监控设施搭建及监控数据的获取。监控设施包括无线传感器网络、智能协调器等网络节点的部署，养殖场环境监控传感器的部署，监控摄像头、红外测温仪的安装，以及运动传感器在家畜身上的佩戴。监控设施搭建完毕后，则可长期持续采集养殖场及家畜的相关数据，包括养殖场环境温湿度、有毒气体浓度等环境数据，监控家畜的体温，每天的运动量数据，以及由养殖户记录的饲喂、用药等生产数据，生成监控数据库。此阶段可先从 2-3 个示范点开始，每个示范点监控 8-10 头家畜（猪或牛）。

第二阶段为家畜健康监测预警系统的建立。基于现场监测到的各种类型数据，提取出家畜健康状态良好时的常规数据表征以及家畜健康出现问题时的异常数据表征，建立各类数据与家畜健康状况之间的关联模型，找出影响家畜健康状况的关键因子，并设定关键因子出现异常的预警阈值。本阶段的顺利实施依赖于养殖场数据获取的规模与质量，除了关联本项目示范点的监控数据外，也接入已有的其他养殖场监控数据作为模型建立的依据。

第三阶段为家畜监控监测预警模型的验证与进一步的应用示范。根据第二阶段建立的预警模型，将其应用到更多的示范点进行效果验证，不断修正完善模型参数设置，直到满足养殖场实际养殖需求。本阶段需要养殖户参与进行模型的评估。在项目开展期间，项目负责人及其团队成员负责保证各阶段任务的顺利开展，为对接单位提供各种智能化设备，并将装备在对接单位提供的养殖场进行部署使用，在项目开展过程中，保护各种实验对象和实验设施。

项目实施的关键在于家畜的健康识别，重点关注家畜体表温度、运动量及环境监测，以对家畜最易出现的亚健康问题进行早期识别与预警。项目拟在自动化设备获取的大数据基础上，融合对接单位养殖户的生产经验，实现适合对接单位的监控模型。

项目目标：项目专家拟进村指导 3 次，开展 2 次培训，培训和指导农业科技服务 80 人次，提供技术咨询/技术服务等 80 人次，分别为清新县龙颈镇南星村、禾云镇罗东村、龙颈镇石崇村农民提供技术帮扶服务。

（项目实施内容及目标以合同书为准，原则上不予调整。）

二、项目实施绩效

（选填，所填报内容作为项目中期检查和结题验收依据）

	一级指标	二级指标	三级指标	指标值
绩效指标	产出指标	数量指标	培训从事技术创新服务人员（人次）	
			培训和指导农业科技服务（人次）	80
			提供技术咨询/技术服务等（人次）	80
			开展创业辅导活动（场）	
		质量指标	科研仪器设备利用率（%）	
			技术帮扶贫困人数（人）	
			支持地方小微企业/机构/创新团队数	
	效益指标	经济效益指标	技术合同成交额（万元）	
			新增在孵企业（家）	
			培育高新技术企业（家）	
			促进科技投融资金额（万元）	
		社会效益指标	开放共享仪器设备数	
			科技成果转化数	
	满意度指标	服务对象满意度	被服务企业满意度（%）	90%
			被服务农民满意度（%）	90%
其他说明（限300字）				

三、项目进度和阶段目标

*起止时间	*主要工作内容
2018 年 06 月 - 2018 年 12 月	（1）与对接单位进行调研，选取合适的示范养殖场作为实验开展场所； （2）制定智能化设备安装方案； （3）进村指导 1 次。
2019 年 01 月 - 2019 年 06 月	（1）养殖场传感器网络拓扑结构确定、各节点间距离、节点与网关距离的确定； （2）养殖场多传感器监测网络部署； （3）养殖场环境、监控、测温设备的安装与调试； （4）养殖场相关数据的采集及存储； （5）进村指导 1 次，开展技术培训 1 次，提供农业科技服务和技术指导。
2019 年 07 月 - 2019 年 12 月	（1）建立家畜健康大数据库； （2）建立家畜健康识别模型； （3）计算生成家畜健康预警阈值。 （4）开展技术培训 1 次，提供农业科技服务和技术指导。
2020 年 01 月 - 2020 年 06 月	（1）家畜健康识别模型的进一步完善； （2）家畜健康识别模型的应用推广。 （3）进村指导 1 次。

四、经费情况表

经费预算：（单位：万元）		
支出经费	经费额	用途说明
（一）直接费用	10	
1、设备费	2	购置专业图像数据分析处理机器
2、材料费	1	购置养殖场环境传感器、视频监控摄像头、测温耳标等
3、测试化验加工费	1	外协各类监控设备的防水防尘加工
4、差旅费/会议费	3.5	参加学术会议、开展扶贫往返清远、广州的差旅费
5、出版/文献/信息传播/知识产权事务费	1	发表论文、申请专利/软著等费用
6、劳务费	1.5	学生及临聘人员费用
7、专家咨询费		
合计	10	

注：如需购买设备，须详细说明设备名称及金额，原则上不超过总经费的40%；劳务费不超过总经费的40%。本项目不扣管理费。经费不外拨，如有合作单位，采取报账制。

五、项目组人员情况

项目负责人

序号	*姓名	*职称	*职务	*最高学位	*现从事专业	*所在单位	*身份证件号码	*在本项目中承担的工作任务	签名
1	杨秋妹	讲师	无	硕士	农业信息化	华南农业大学数学与信息学院	44092119831230162X	项目总体规划及实施	

主要参与人员

序号	*姓名	职称	职务	学位	现从事专业	*所在单位	*身份证件号码	在本项目中承担的工作任务	签名
1	沈小旺	中级	队长	学士	扶贫工作	清远市清新区	440106197303293611	扶贫工作规划与平台搭建	
2	张连宽	副教授	无	博士	农业信息化	华南农业大学数学与信息学院	320721197608124 21X	系统建模	
3	潘春华	讲师	无	硕士	农业信息化	华南农业大学数学与信息学院	362525197401150932	养殖场网络搭建及数据传输、存储	
4	刘勤	无	无	硕士	农业信息化	华南农业大学数学与信息学院	362204199408287633	家畜体温测量及数据分析	
5	林思聪	无	无	学士	农业信息化	华南农业大学数学与信息学院	440509199601134416	家畜运动量分析、健康模型创建	

六、本合同签约各方

管理单位（甲方）：　　华南农业大学（盖章）

法定代表人（或法人代理）：　　陈晓阳　　（签章）

2018 年　8月　31 日

依托单位（乙方）：　　华南农业大学数学与信息学院（盖章）

单位负责人：　　（签章）

2018 年　8 月　31 日

联系人（项目负责人）姓名：杨秋妹　　（签名）

Email：yqmbegonia@163.com

电话：　13560377262

2018 年　8　月　31 日

项目收支明细账（预算）

起始日期：2018年01月01日　截止日期：2025年07月21日

是否包含往来款：是　收支方式：全部

金额：大于等于0

单位：元

部门	项目	凭证日期	凭证编号	摘要	科目编号	科目名称	项目收入	项目支出	项目借款	项目还款	项目余额
				年初余额			0.00	0.00	0.00	0.00	0.00
				期初余额			0.00	0.00	0.00	0.00	0.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2018-08-28	(Z)02285	下达转/零A365-2018精准扶持贫困村特色产业发展乡村振兴项目	4001020135	其他科技条件与服务支出（206-05-99）	100,000.00	0.00	0.00	0.00	100,000.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2018-11-02	(Z)00987	杨秋妹报肖德琴等5人重庆荣昌差费	50020102-3021103	财政补助项目支出-科研差旅费	0.00	12,809.00	0.00	0.00	87,191.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-01-25	(Z)03039	杨秋妹报杨秋妹北京调研差旅费用	7201020201-3021103	科研财政拨款项目支出-科研差旅费	0.00	4,513.00	0.00	0.00	82,678.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-02-28	(Z)03094	数学与信息学院杨秋妹发放蔡家豪2人19.01研究生三助金	7201020201-3030802	科研财政拨款项目支出-硕士生助学金	0.00	6,000.00	0.00	0.00	76,678.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-04-28	(Z)07605	数信学院杨秋妹发放张远琴2人19.04研究生三助金	7201020201-3030803	科研财政拨款项目支出-博士生助学金	0.00	2,800.00	0.00	0.00	73,878.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-04-28	(Z)07605	数信学院杨秋妹发放陈焕坤4人19.04研究生三助金	7201020201-3030802	科研财政拨款项目支出-硕士生助学金	0.00	6,200.00	0.00	0.00	67,678.00

5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-05-13	(Z)01957	杨秋妹购置笔记本电脑	7201020201-3100201	科研财政拨款项目支出-教学设备	0.00	19,000.00	0.00	0.00	48,678.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-06-14	(Z)04478	杨秋妹报杨秋妹等6人清远技术扶贫差旅费用	7201020201-3021103	科研财政拨款项目支出-科研差旅费	0.00	1,143.00	0.00	0.00	47,535.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-06-18	(Z)05758	数学与信息学院杨秋妹报资料信息费-图书	7201020201-3029912	科研财政拨款项目支出-资料信息费	0.00	110.00	0.00	0.00	47,425.00
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-06-18	(Z)05758	数学与信息学院杨秋妹报科研实验材料-内存、U盘、激光笔、鼠标	7201020201-3021802	科研财政拨款项目支出-科研实验材料	0.00	508.70	0.00	0.00	46,916.30
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-08-28	(Z)02727	杨秋妹报杨秋妹等12人清远扶贫差旅费用	7201020201-3021103	科研财政拨款项目支出-科研差旅费	0.00	6,239.00	0.00	0.00	40,677.30
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-11-27	(Z)10238	数学与信息学院杨秋妹报科研实验材料-鼠标	7201020201-3021802	科研财政拨款项目支出-科研实验材料	0.00	149.80	0.00	0.00	40,527.50
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-11-27	(Z)10238	数学与信息学院杨秋妹报专利及知识产权-计算机学会会员费	7201020201-3029907	科研财政拨款项目支出-专利及知识产权	0.00	50.00	0.00	0.00	40,477.50
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-11-27	(Z)10238	数学与信息学院杨秋妹报资料信息费-深度学习图书	7201020201-3029912	科研财政拨款项目支出-资料信息费	0.00	209.40	0.00	0.00	40,268.10
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-12-16	(Z)08830	杨秋妹报资料信息费-办公软件WPS会员费	7201020201-3029912	科研财政拨款项目支出-资料信息费	0.00	122.00	0.00	0.00	40,146.10

5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2019-12-16	(Z)08847	杨秋妹报杨秋妹、钟丽芳惠州调研差旅费用	7201020201-3021103	科研财政拨款项目支出-科研差旅费	0.00	1,579.01	0.00	0.00	38,567.09
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2021-02-25	(Z)01846	数学与信息学院杨秋妹报资料信息费-版面费	7201020201-3029912	科研财政拨款项目支出-资料信息费	0.00	2,500.00	0.00	0.00	36,067.09
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2021-06-21	(Z)08362	数学与信息学院杨秋妹报物联网控制电路板加工费	7201020201-3022702	科研财政拨款项目支出-加工试制费	0.00	10,000.00	0.00	0.00	26,067.09
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2021-06-23	(Z)09222	数学与信息学院杨秋妹报科研实验材料-RFID、电子测温仪等	7201020201-3021802	科研财政拨款项目支出-科研实验材料	0.00	19,900.00	0.00	0.00	6,167.09
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2022-08-26	(Z)03263	杨秋妹报专利及知识产权	7201020201-3029907	科研财政拨款项目支出-专利及知识产权	0.00	3,560.00	0.00	0.00	2,607.09
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2022-11-08	(Z)03139	杨秋妹报资料信息费	7201020201-3020203	科研财政拨款项目支出-资料信息费	0.00	773.50	0.00	0.00	1,833.59
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2022-11-08	(Z)03139	杨秋妹报科研实验材料-硬盘	7201020201-3021802	科研财政拨款项目支出-科研实验材料	0.00	335.00	0.00	0.00	1,498.59
5600/数学与信息学院、软件学院	E18141/转/零A365家畜养殖健康状况自动化监测	2023-10-23	(Z)07982	杨秋妹报科研实验材料费	7201020201-3021802	科研财政拨款项目支出-科研实验材料	0.00	840.50	0.00	0.00	658.09
负责人:杨秋妹	E18141/转/零A365家畜养殖健康状况自动化监测			合计			100,000.00	99,341.91	0.00	0.00	658.09
总计							100,000.00	99,341.91	0.00	0.00	658.09

任务编号： 2017YFD0701601-2　　密　级：公开

国家重点研发计划
团队任务书

任务名称：生猪体温测量及发情监测技术研究

所属课题：生猪健康识别、养殖环境控制设备技术研发与规模化示范

所属项目：设施畜禽养殖智能化精细生产管理技术装备研发

课题承担单位（甲方）：广东温氏食品集团股份有限公司

研究任务负责人（乙方）：肖德琴

起止年限：2017 年 07 月 至 2020 年 12 月

中华人民共和国科学技术部制

2017 年 09 月



二、任务指标及考核要求

1、 约束性指标

（1）基于机器视觉的猪运动量及行为识别技术研究

通过视频录像和机器学习的方法，掌握生猪正常生长情况下的运动信息，建立猪只运动信息基本模型，统计每头猪每天的运动量和运动轨迹，在此基础上，对猪只的坐卧走跳等基本行为进行识别和统计，同时，从监控视频中提取出猪爬跨、打斗等异常行为。同期监测统计生猪的运动信息、生长性能和健康状况，构建猪只运动信息与生产性能、健康状况的关联模型。

（2）生猪耳温非接触式测量技术研究

研究非接触式生猪测量方法，拟借助热红外图像采集器采集生猪图像，结合计算机图像处理技术在采集到的图像上对猪只耳部位置进行定位，将猪耳根部区域特征用于检测生猪体温；另外，开展攻毒实验，采集猪只发病过程中的体温变化，验证测量精度并研究对发病体温阈值的设定。进一步的，设计滑动式导轨承载热红外图像采集器，安装于集约化猪舍中，实现对猪舍中的猪只体温数据进行批量采集。借助无线传输和云存储等技术，实现体温的远程传输和存储，在此基础上，利用数据统计分析技术实现猪体温异常预警模型。

（3）母猪发情监测系统

根据实际调研，提出采用母猪运动量异常、爬跨行为发生及对公猪诱情的反应三个方面来进行母猪发情监测。母猪运动量由监控视频中通过图像处理算法获取并计算，通过长期的监控及与实际记录数据对照，获取其发情期与非发情期的运动量差异，以此捕捉发情期的到来；设计相应的图像处理算法，识别出猪只爬跨行为的发生，用于作为发情监测的另一指标；除此之外，在公猪诱情过程中，拍摄母猪反应视频，研究发情的相关特征用于发情检测。

2、考核指标

研制生猪耳温、运动量等新型健康指标传感器件 1-2 种，创制猪只健康智能识别装备和新一代母猪发情监测系统各 1 套。申请专利 1-2 项，发表论文 2-3 篇，软件登记 1-2 项。

三、年度安排

年度	年度工作内容、考核指标及考核方法
2017 年	工作内容：在温氏实验猪场开展种猪环境、喂食、体温、视频等基础数据采集实验。 考核指标：发表论文 1 篇。 考核方法：由课题组负责人组织考核。
2018 年	工作内容：生猪体温预警技术研究与设计；母猪发情监测技术研究与设计。 考核指标：发表论文 1 篇，申报专利 1 项，研制 1 种生猪体温测量传感器件。 考核方法：由课题组负责人组织考核。
2019 年	工作内容：实现母猪发情监测系统，实现生猪体温预警系统。 考核指标：获得新装备 1 套，母猪发情监测系统 1 套，申报软件著作权 1 项，发表论文 1 篇。 考核方法：由课题组负责人组织考核。
2020 年	工作内容：集成生猪健康养殖精准控制系统，母猪发情监测系统应用示范。 考核指标：申报软件著作权 1 项，申报专利 1 项。 考核方法：由课题组负责人组织考核。

四、团队研究人员

研究任务负责人

姓　名	性别	年龄	技术职称	身份证号码	所在单位	用于本任务的工作时间占本人总工作时间的百分比(%)
肖德琴	女	47	正高	510212197005140829	华南农业大学	60

团队成员

杨秋妹	女	34	中级	44092119831230162X	华南农业大学	60
殷建军	男	36	中级	421003198101080551	华南农业大学	60
刘德武	男	51	正高	42010619660711563X	华南农业大学	50
张连宽	男	41	副高	32072119760812421X	华南农业大学	50
潘春华	男	43	中级	362525197401150932	华南农业大学	50
冯健昭	男	36	中级	440602198110310637	华南农业大学	50
叶耀文	男	24	硕士生	441900199301194316	华南农业大学	50
刘勤	男	23	硕士生	362204199408287633	华南农业大学	60
李泽森	男	24	硕士生	441302199301295416	华南农业大学	60
张昌桢	男	23	博士生	522630199410090471	华南农业大学	50
蔡家豪	男	22	硕士生	441900199504023218	华南农业大学	50
刘小平	男	23	硕士生	511324199402231071	华南农业大学	50
王诗吟	女	23	硕士生	520201199403090021	华南农业大学	50

五、经费来源与支出预算

单位：万元（保留两位小数）

预算科目名称	合计	中央财政资金	其他来源资金
一、经费支出	112.00	112.00	
（一）直接费用	98.92	98.92	
1. 设备费	3.00	3.00	
（1）购置设备费	3.00	3.00	
（2）试制设备费			
（3）设备改造与租赁费			
2. 材料费	42.00	42.00	
3. 测试化验加工费	12.76	12.76	
4. 燃料动力费			
5. 差旅/会议/国际合作与交流费	14.00	14.00	
6. 出版/文献/信息传播/知识产权事务费	5.00	5.00	
7. 劳务费	20.00	20.00	
8. 专家咨询费	2.16	2.16	
9. 其他支出			
（二）间接费用	13.08	13.08	
二、经费来源			
（一）中央财政资金	112.00	112.00	
（二）其他来源资金			
1.地方财政拨款			
2.单位自有货币资金			
3.其他资金			

六、合约条款

甲方（课题承担单位）：广东温氏食品集团股份有限公司

乙方（研究任务负责人）：肖德琴

根据项目组织（牵头）单位与甲方签订的课题任务书要求，项目组织（牵头）单位授权甲方与乙方签订本合约。

（一）权利与义务

甲方全面负责课题各项任务，督促课题负责人按照课题任务书要求实施研究工作，合理使用课题经费，如期完成课题任务；甲方有权对乙方的年度计划执行情况进行监督、检查，并提供有关支持与保障条件；乙方具体负责研究任务团队的各项任务，应严格按照合约保证及时完成研究任务，并接受甲方的监督检查。乙方有权参与甲方组织的课题方案制定等相关活动。

（二）团队管理

研究任务团队是为完成某一具体研究任务，由负责人牵头，联合相关研究成员组成的研发群体。团队成员组成应根据研究任务的需要，在尊重自愿的基础上，由甲方与乙方共同协商确定。

团队成员及其任务确定后，由项目组织（牵头）单位报请科技部，向团队及其所在单位正式发文通告。项目正式验收后，由甲方提出团队成员及其绩效报告，报项目组织（牵头）单位和科技部审核，由科技部正式发文认定。

在签订本合约之前，团队负责人应与研究团队其他成员之间协商确定团队任务安排、参与时间、收益分配等。

（三）经费管理

由甲方负责财务管理。根据有关经费管理办法和财务规定，甲方提供给乙方相应经费。甲方在收到财政专项拨款后，应在十个工作日内告知乙方，并按双方共同约定的办法给乙方提供相应的经费。

乙方使用经费应严格按照经费预算和约定的支出范围执行，保证专款专用，不得弄虚作假、挪用、挤占课题经费或违反相关法律法规。甲方根据国家有关法规和科技计划经费开支的规定，监督乙方经费的使用情况。项目组织（牵头）单位和项目官员有权对甲乙双方经费使用进行监督管理。

（四）成果管理

双方在研发过程中应加强研究成果管理，严格执行《中华人民共和国科学技术进步法》、《关于加强国家科技计划知识产权管理工作的规定》、《中华人民共和国专利法》和《中华人民共和国著作权法》等有关规定。研究成果在申报国家及有关部门、地方的科技成果奖励时，需由甲乙双方共同协商成果署名等相关事宜。

甲乙双方应根据有关法律法规，及甲方与项目组织（牵头）单位签订的任务书规定，协商确定课题研究成果的收益分配等事宜并签订知识产权合作协议。

（五）资产管理

按照科技计划专项经费管理办法执行，专项经费形成的大型仪器设备固定资产归甲方管理，乙方在执行课题任务时，与甲方享有同等使用权。甲乙双方可以自行协商确定设备使用共享的相关办法。

（六）信用管理

项目组织（牵头）单位和项目官员有权对甲乙双方进行信用监管。甲乙双方均需建立信用管理档案，对参加人员进行信用记录。记录内容包括科研活动情况、任务完成情况、按时提交材料情况、经费使用情况等。双方均需遵守有关科研诚信建设的相关规定，积极配合有关单位或部门组织的信用评估工作。

（七）保密管理

按《中华人民共和国保守国家秘密法》和科学技术部《科技保密规定》及相关国家科技计划管理办法等有关规定执行。

（八） 任务与经费调整

乙方须及时向甲方报告研究进展。乙方未能按规定进度和考核指标完成任务的，甲方可对乙方及其团队的任务和经费在本合约范围内进行调整。由甲方提出调整意见，报项目组织（牵头）单位审定后执行，并报科技部备案。

（九）争议处理和合约变更

1、项目组织（牵头）单位是双方争议的调解机构。项目官员具有对纠纷处理的监督权和问责权。

2、合约在履行过程中发生争议的，双方应首先通过协商的方式解决。协商不成时，双方向项目组织（牵头）单位申请调解。

3、任何一方因不可抗力不能履行合约义务时，可以免除违约责任，但应及时通知另一方，并在30天内出具因不可抗力导致合约不能履行的证明。

4、合约一方要求变更或解除合约，应在30日前书面通知另一方，并同时向项目组织（牵头）单位提交书面申请，经批准后执行。

（十）补充条款

1、如有特别需要，经甲乙双方协商，同意华南农业大学（单位）作为乙方的依托单位，按相关的科技计划和经费管理办法，对甲方拨付乙方的经费进行管理并同意承担相关责任和义务。

2、甲乙双方均须遵守科技部关于国家科技计划项目（课题）实施法人管理责任制的意见的相关规定。

（十一） 附　则

1、本合约由甲方盖章乙方签字，经项目组织（牵头）单位审核通过后生效，并报科技部备案。

2、本合约正本一式8份（甲方2份、乙方4份、项目组织（牵头）单位1份、科技部1份）。

七、签约各方签章

课题承担单位（甲方）：广东温氏食品集团股份有限公司（公章）

甲方账 户 名： 广东温氏食品集团股份有限公司

甲方账 号： 670457744671

甲方开户银行： 中国银行云浮新兴支行

单位负责人（签字）：

课题负责人（签字）：

2017年10月30日

研究任务负责人（乙方）（签字）：

乙方所在单位（公章）：华南农业大学

乙方账 户 名：华南农业大学

乙方账 号：3602002609000310520

乙方开户银行：广州工行五山支行

2017年9月29日

项目组织（牵头）单位审核意见：（公章）

单位负责人（签字）：

项目负责人（首席专家）（签字）：

2017年10月30日

课题编号：2019B020215002-1　　密　级：公开

广东省重点领域研发计划项目
课题任务书

课题名称： 主要畜禽健康养殖专用传感器件研发集成与感知系统研究

所属项目： 畜禽精准健康养殖关键技术研究与示范

项目承担单位（甲方）： 温氏食品集团股份有限公司

项目负责人： 温志芬

课题承担单位（乙方）： 华南农业大学

课题负责人： 王春桃

起止年限： 2019 年 01 月 - 2021 年 12 月

广东省科学技术厅制

2019 年 04 月

一、项目验收指标

（一）成果指标（请认真对照申报指南和项目申报书的内容进行填写，不得降低或删减相关目标要求；结题验收时可用项目内同类型同水平指标替换。）

1. 核心考核指标（必填）

序号	成果名称	成果类型	验收指标	评测方式/方法
1）	畜禽生理生态监测	■新技术	2-3项	畜禽生理生态监测技术2-3项
2）	防尘、防水、防震畜禽行为、健康、环境监测等新型核心传感器件	■新技术 ■实验装置/系统	2-3种（适合环境温度范围-40℃~+85℃，在线检测误差±0.05℃）	①畜禽行为传感器1种 ②畜禽健康传感器1种 ③环境监测传感器1种
3）	核心传感器件专利	■专利	1项	畜禽行为、健康或环境监测专用传感器专利1件

2. 高水平知识产权指标（必填）

序号	内容	类型	结题时状态	拟解决关键问题
1）	畜禽生理生态监测器件	国内发明专利	受理	形成技术首创
2）	畜禽行为、健康、环境方面的监测新型传感器件	国内发明专利	受理	形成技术首创

3. 科技报告考核指标（必填）

注意事项：

1）报告类型。包括验收前撰写的最终科技报告；研究期限超过 2 年（含2 年）的项目，每年撰写的年度技术进展报告；根据研究内容、期限和经费强度，撰写的数量不等的专题科技报告。科技报告应按国家标准规定的格式撰写。

2）公开类别及时限。公开项目科技报告分为公开或延期公开，内容需要发表论文、申请专利、出版专著或涉及技术诀窍的，可标注为“延期公开”。需要发表论文的，延期公开时限原则上在2 年（含2 年）以内；需要申请专利、出版专著的，延期公开时限原则上在 3 年

（含3 年) 以内；涉及技术诀窍的，延期公开时限原则上在 5 年（含5 年) 以内。涉密项目科技报告按照有关规定管理。

序号	报告类型	提交时间	公开类别及时限
1）	课题进展报告	2019-12	延期2年
2）	课题进展报告	2020-12	延期2年
3）	课题进展报告	2021-12	延期2年

（请认真对照合作协议的内容，以上各指标尚未详尽的，可在此补充填写，包括发表的论文/专著数量、发布标准数量、引进人才情况、获得国家/省部级奖项情况）

对于发表的论文、标准、专利、软件著作权等指标，已在上述表格中详细列出。此外，培养研究生数量5人以上。

课题负责人（签章）：　　2019年　　月　　日

（三）阶段性成果评价：(请对照以上内容自行填报，作为中期评估及结题验收的重要参考依据）

序号	指标名称	立项时已有指标值/状态	中期指标值/状态	完成时指标值/状态	评估方式（方法）及评价手段
1）	畜禽生理生态监测技术	对于畜禽生理生态监测技术，已有前期基础，但其功能及性能需要进一步提升	实现畜禽生理生态监测技术1-2项	实现畜禽生理生态监测技术2-3项	①　相应的设备和装置 ②专利申请受理证明
2）	防尘、防水、防震畜禽行为、健康、环境监测等新型核心传感器件	当前已有畜禽行为、健康、环境监测等硬件基础	设计防尘、防水、防震畜禽行为、健康、环境监测等新型核心传感器件1-2种	设计防尘、防水、防震畜禽行为、健康、环境监测等新型核心传感器件2-3种	①　相应的传感器芯片 ②专利申请受理证明
3）	核心传感器件专利	有前期相关的专利	申请相关专利1项，获得受理通知书。	申请专利1项，获得受理通知书，争取获得授权1项	专利受理通知书

二、课题研究内容、研究方法及技术路线、主要创新点

（一） 课题拟解决的关键问题（限 2000 字以内）

我国的畜禽养殖效率、质量等与国际畜禽养殖发达国家相比，仍有较大的差距。利用物联网、大数据等现代信息技术，促进我国畜禽的健康、标准及精准饲喂技术势在必行。

而要实现畜禽健康精准养殖，就必须要准确、有效地捕获畜禽养殖的生理、生长、生态信息。但现有的生态或生命体征传感器不能适应养殖环境的长期应用、或畜禽在特定部位或恶劣环境的可佩带等局限性。为此需要通过项目的专业性开发，解决畜禽养殖专用传感器的技术瓶颈，即实现畜禽健康养殖专用传感器的小型化、稳定性、可佩戴行及低功耗的可续航性。

（二） 课题的主要研究内容（限 2000 字以内）

本课题主要畜禽健康养殖专用传感器件研发集成与感知系统研究。具体而言，基于畜禽生理、生长及生态信息数字化表征体系，研究针对主要畜禽（鸡、猪、牛）的生态、生长及生理等新型传感器件，开发开发防尘、防水、防震畜禽行为、健康、环境监测等新型核心传感器件。研发集成环境多元调控系统。

（三） 课题采取的研究方法及技术路线（限 2000 字以内）

课题拟采取的研究方法及技术路线如下：

针对主要畜禽的生理、生长、生态数字化表征指标，研发集成相应的专用传感器件，以采集对应的畜禽健康养殖的、需要通过传感器感知的信息。主要研究或集成内容：

1） **养殖生态传感器研究**：首先熟化温湿度、光照、噪声等传感器，适合范围－40～＋85℃；其次研究环境中 H_2S、NH_3、CO_2 等有害气体小范围浓度、面源分布和排放通量监测的检测技术，适合范围 0～500ppm；以及 PM10 和 PM2.5 传感器技术。

2) **畜禽生理、生长**体征感知传感器研究：①基于行为机器视觉、声音、热红

外等传感方法，研制母猪/母牛发情监测系统（准确率达 98%以上）、群体动物体表温度传感器、体重传感器；②研制动物智能背心和颈环，实现动物心率、运动量、取食量等生理信息感知；③研究动物生理的侵入式传感技术，研制牛瘤胃发酵酸碱平衡 pH 无线传感器件系统；④研制畜禽特定疫病的荧光免疫快速检测传感器，判断准确率 90%以上。

（四） 主要创新点

突破现有的生态或生命体征传感器不能适应养殖环境的长期应用、或畜禽在特定部位或恶劣环境的可佩带等局限性，通过项目的专业性开发，解决畜禽养殖专用传感器的技术瓶颈，就是实现畜禽健康养殖专用传感器的小型化、稳定性、可佩戴行及低功耗的可续航性。

三、课题进度和阶段目标

（一）课题起止时间：2019年1月1日——2021年12月31日

（二）课题实施进度及阶段主要目标（建议以 1 年或 6 个月为一阶段）

开始日期-结束日期	主要工作内容（每条限 500 字）	预期目标	成果形式
2019年1月1日—2019年12月31日	畜禽养殖专用传感器研发集成	创制生理生态监测技术 1 项	（1）生理生态监测技术 1 项 （2）年度进展报告
2020 年 1 月 1 日--2020 年 12 月 31 日	畜禽养殖专用传感器研发集成	突破生理生态监测技术 1 项，申请专利 1 项	（1）生理生态监测技术 1 项 （2）年度进展报告
2021 年 1 月 1 日 -- 2021 年 12 月 31 日	畜禽养殖专用传感器研发集成	创制生理生态监测技术 1 项，申请专利 1 项	（1）生理生态监测技术 1 项 （2)专利受理证明 1 项 （3）年度进展报告

四、课题研究人员

课题负责人：

姓　名	性别	年龄	技术职称	学位	身份证号码	在课题中承担的任务
王春桃	男	40	副教授	博士	441425197904033096	动物养殖信息感知与分析，负责课题的设计与落实

课题团队成员：

姓　名	性别	年龄	技术职称	学位	身份证号码	在课题中承担的任务
谢青梅	女	46	教授	博士	440106197209061822	家禽健康养殖
杨秋妹	女	35	讲师	博士	44092119831230162X	动物行为识别
郭勇庆	男	37	讲师	博士	13042119810616031X	家禽健康养殖
凌立文	女	35	讲师	硕士	44010619830413182X	动物行为分析
王诗吟	女	24	无	学士	520201199403090021	实验分析
陈焕坤	男	24	无	学士	440582199403040432	实验研究
黄一桂	男	22	无	学士	440981199604111415	动物行为分析

五、课题经费预算：　　**(单位：万元)**

	项目总经费		省财政科技资金	
支出经费	经费额	用途说明	经费额	用途说明
1. 直接费用	121.8		121.8	
(1) 设备费	5	视频图像数据处理工作站	5	视频图像数据处理工作站
(2) 材料费	30	实验动物、视频传感器节点、温湿度传感器、氨气监测仪 RFID 等实验装备材料	30	实验动物、视频传感器节点、温湿度传感器、氨气监测仪 RFID 等实验装备材料
(3) 测试化验加工外协费	9	课题执行期研制的传感器和数据采集终端	9	课题执行期研制的传感器和数据采集终端
(4) 燃料动力费				
(5) 差旅费/会议费/国际合作与交流费	38.05	养殖场试验、参加国内学术会议及交流活动、组织学术会议、国际合作与交流	38.05	养殖场试验、参加国内学术会议及交流活动、组织学术会议、国际合作与交流
(6) 出版/文献/信息播/知识产权事务费	10	论文发表，专利申请	10	论文发表，专利申请

(7)劳务费	24	实验员、研究生的劳务费用	24	实验员、研究生的劳务费用
(8)人员费				
(9)专家咨费	5.76	专家咨询费	5.76	专家咨询费
(10)直接费其他支出				
2.间接费用	28.2		28.2	
(1)间接成本				
(2)管理成本	7.5	项目管理费	7.5	项目管理费
(3)绩效支出	20.7	人员绩效	20.7	人员绩效
3.其他支出费用				
合计	150		150	
其它需说明的情况：无。				

六、合约条款

甲方（项目承担单位及负责人）：温氏食品集团股份有限公司 温志芬

乙方（课题承担单位及负责人）： 华南农业大学 王春桃

根据广东省科技厅与甲方签订的项目任务书要求，甲方与乙方签订本合约。

（一）权利与义务

甲方全面负责项目的各个课题，督促课题负责人按照课题任务书要求实施研究工作，合理使用课题经费，如期完成课题任务；甲方有权对乙方的年度计划执行情况进行监督、检查，并提供有关支持与保障条件；乙方具体负责课题的各项任务，应严格按照合约保证及时完成研究任务，并接受甲方的监督检查。乙方有权参与甲方组织的课题方案制定等相关活动。

（二）团队管理

课题团队是为完成某一具体课题，由课题负责人牵头，联合相关研究成员组成的研发群体。团队成员组成应根据研究任务的需要，在尊重自愿的基础上，由甲方与乙方共同协商确定。

在签订本合约之前，课题团队负责人应与课题团队其他成员之间协商确定团队任务安排、参与时间、收益分配等。

（三）经费管理

由甲方负责财务管理,具体管理办法参照广东省科技厅与甲方签订的任务书中的“任务书条款”。甲方在收到财政专项拨款后，应在十个工作日内告知乙方，并根据“任务书条款”的第六条向乙方提供相应的经费。

具体而言，若广东省科技厅将立项经费统一拨付给甲方，则在甲乙双方签订任务书后，由甲方拨付给乙方合作协议书中约定的课题资金的 30%；经中期评估，项目进展顺利并取得阶段性进展的，拨付合作协议中约定的资金的 50%;项目任务完成 90%或达到验收条件的，可提出后续资金申请，经评估，拨付剩余 20%资金。评估或验收结题不通过的，甲方有权终止课题，停止拨付后续资金；发现课题存在重大异常或违规使用财政资金的，甲方有权追回已经拨付的资金。若由广东省科技厅根据合作协议书的约定直接向各合作方拨付课题资金，则甲乙双方遵循广东省科技厅的经费拨付方式。

乙方使用经费应严格按照经费预算和约定的支出范围执行，保证专款专用，不得弄虚作假、挪用、挤占课题经费或违反相关法律法规。甲方根据国家有关法规和科技计划经费开支的规定，监督乙方经费的使用情况。广东省科技厅和项目官员有权对甲乙双方经费使用进行监督管理。

（四）成果管理

双方在研发过程中应加强研究成果管理，严格执行《中华人民共和国科学技术进步法》、《关于加强国家科技计划知识产权管理工作的规定》、《中华人民共和国专利法》和《中华人民共和国著作权法》等有关规定。研究成果在申报国家及有关部门、地方的科技成果奖励时，需由甲乙双方共同协商成果署名等相关事宜。

甲乙双方应根据有关法律法规，及广东省科技厅与甲方签订的任务书规定，协商确定课题研究成果的收益分配等事宜并签订知识产权合作协议。

（五）资产管理

按照科技计划专项经费管理办法执行，专项经费形成的大型仪器设备固定资产归甲方管理，乙方在执行课题任务时，与甲方享有同等使用权。甲乙双方可以自行协商确定设备使用共享的相关办法。

（六）信用管理

广东省科技厅和项目官员有权对甲乙双方进行信用监管。甲乙双方均需建立信

用管理档案，对参加人员进行信用记录。记录内容包括科研活动情况、任务完成情况、按时提交材料情况、经费使用情况等。双方均需遵守有关科研诚信建设的相关规定，积极配合有关单位或部门组织的信用评估工作。

（七）保密管理

按《中华人民共和国保守国家秘密法》和科学技术部《科技保密规定》及相关国家科技计划管理办法等有关规定执行。

（八） 任务与经费调整

乙方须及时向甲方报告研究进展。乙方未能按规定进度和考核指标完成任务的，甲方可对乙方及其团队的任务和经费在本合约范围内进行调整。由甲方提出调整意见，报广东省科技厅审定后执行。

（九）争议处理和合约变更

1. 广东省科技厅是双方争议的调解机构。项目官员具有对纠纷处理的监督权和问责权。

2. 合约在履行过程中发生争议的，双方应首先通过协商的方式解决。协商不成时，双方向广东省科技厅申请调解。

3. 任何一方因不可抗力不能履行合约义务时，可以免除违约责任，但应及时通知另一方，并在 30 天内出具因不可抗力导致合约不能履行的证明。

4. 合约一方要求变更或解除合约，应在 30 日前书面通知另一方，并同时向广东省科技厅提交书面申请，经批准后执行。

（十）补充条款

1. 如有特别需要，经甲乙双方协商，同意 华南农业大学作为乙方的依托单位，按相关的科技计划和经费管理办法，对甲方拨付乙方的经费进行管理并同意承担相关责任和义务。

2. 甲乙双方均须遵守科技部关于国家科技计划项目（课题）实施法人管理责任制的意见的相关规定。

（十一） 附 则

1. 本合约由甲乙双方单位盖章及相关负责人签字后生效。

2. 本合约正本一式 4 份（甲方 2 份、乙方 2 份）。

七、签约各方签章

项目承担单位（甲方）：温氏食品集团股份有限公司（公章）

甲方账 户 名：温氏食品集团股份有限公司

甲方账　　号：670457744671

甲方开户银行：中国银行新兴支行

单位负责人（签字）：

项目负责人（签字）：

年　月　日

课题负责人（乙方）（签字）：丁春桃

乙方所在单位（公章）：华南农业大学

乙方账 户 名：华南农业大学

乙方账　　号：36020026090000310520

乙方开户银行：广东广州工行五山支行

2019 年 6 月 17 日

SCAULIB202624898

检索证明

根据委托人提供的论文材料，委托人**华南农业大学数学与信息学院 杨秋妹(学科类型:自然科学)** 10 篇论文收录情况如下表。

序号	论文名称	发表刊物及发表的年月卷期/页码等	作者排名	论文等级	作者文中单位	收录情况	影响因子	中科院大类分区	引用
1	Long-term video activity monitoring and anomaly alerting of group-housed pigs	COMPUTERS AND ELECTRONICS IN AGRICULTURE 出版年：2024 出版日期：SEP 卷期：224 页码：- 文献号：109205 文献类型：Article	第一作者	T2 类	华南农业大学数学与信息学院	SCI	IF2-year=8.9 IF5-year=9.3 （2024）	农林科学 1 区 Top 期刊：是 OA 期刊：否 （2025）	SCI 核心合集 总引：10 CNKI 总引：
2	Quantifying behavioural patterns for group-housed pigs based on deep learning and statistical analysis	COMPUTERS AND ELECTRONICS IN AGRICULTURE 出版年：2025 出版日期：OCT 卷期：237 页码：- 文献号：110521 文献类型：Article	通讯作者	T2 类	华南农业大学数学与信息学院	SCI	IF2-year=8.9 IF5-year=9.3 （2024）	农林科学 1 区 Top 期刊：是 OA 期刊：否 （2025）	SCI 核心合集 总引：0 CNKI 总引：

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3	Pig mounting behaviour recognition based on video spatial-temporal features	BIOSYSTEMS ENGINEERING 出版年：2021 出版日期：JUN 卷期：206 页码：55-66 文献类型：Article	第一作者	A类	华南农业大学 数学与信息学院	SCI	IF2-year=5.002 IF5-year=5.321 （2021）	农林科学 2区 Top 期刊：是 OA 期刊：否 （2021）	SCI 核心合集 总引：37 CNKI 总引：
4	A Long-Term Video Tracking Method for Group-Housed Pigs	ANIMALS 出版年：2024 出版日期：MAY 卷期：14 10 页码：- 文献号：1505 文献类型：Article	第一作者	A类	华南农业大学 数学与信息学院	SCI	IF2-year=2.7 IF5-year=3.2 （2024）	农林科学 2区 Top 期刊：否 OA 期刊：是 标注：Mega-Journal （2025）	SCI 核心合集 总引：9 CNKI 总引：
5	A review of video-based pig behavior recognition	APPLIED ANIMAL BEHAVIOUR SCIENCE 出版年：2020 出版日期：DEC 卷期：233 页码：- 文献号：105146 文献类型：Review	第一作者	A类	华南农业大学 数学与信息学院	SCI	IF2-year=2.448 IF5-year=2.843 （2020）	农林科学 2区 Top 期刊：是 OA 期刊：否 （2020）	SCI 核心合集 总引：56 CNKI 总引：
6	Feeding behavior recognition for group-housed pigs with the Faster R-CNN	COMPUTERS AND ELECTRONICS IN AGRICULTURE 出版年：2018 出版日期：DEC	第一作者	B类	华南农业大学 数学与信息学院	SCI	IF2-year=3.171 IF5-year=3.538 （2018）	工程技术 3区 Top 期刊：否 （2018）	SCI 核心合集 总引：141 CNKI 总引：

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		卷期：155 页码：453-460 文献类型：Article							
7	基于关键点和步行特征的猪只跛行检测方法	农业机械学报 出版年：2025 出版日期：2025-05-25 卷期：56 05 页码：466-474 文献号： 文献类型：期刊论文	第一作者	A 类	华南农业大学数学与信息学院	北大核心	无	无	SCI 核心合集总引： CNKI 总引：0
8	基于改进 YOLO v5n 的猪只盘点算法	农业机械学报 出版年：2023 出版日期：2022-12-16 10:26 卷期：54 01 页码：251-262 文献号： 文献类型：期刊论文	第一作者	C 类	华南农业大学数学与信息学院	北大核心	无	无	SCI 核心合集总引： CNKI 总引：32
9	猪只饮水行为机器视觉自动识别	农业机械学报 出版年：2018 出版日期：2018-04-17 09:36 卷期：49 06 页码：232-	第一作者	B 类	华南农业大学数学与信息学院	北大核心	无	无	SCI 核心合集总引： CNKI 总引：121

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		238 文献号： 文献类型：期刊论文							
10	基于 IFSSD 卷积神经网络的柚子采摘目标检测模型	农业机械学报 出版年：2020 出版日期：2020-03-16 16:25 卷期：51 05 页码：28-35+97 文献号： 文献类型：期刊论文	通讯作者	C 类	华南农业大学数学与信息学院	北大核心	无	无	SCI 核心合集总引： CNKI 总引：37

说明：论文等级和中科院大类分区按《华南农业大学学术论文评价方案（试行）》划分。

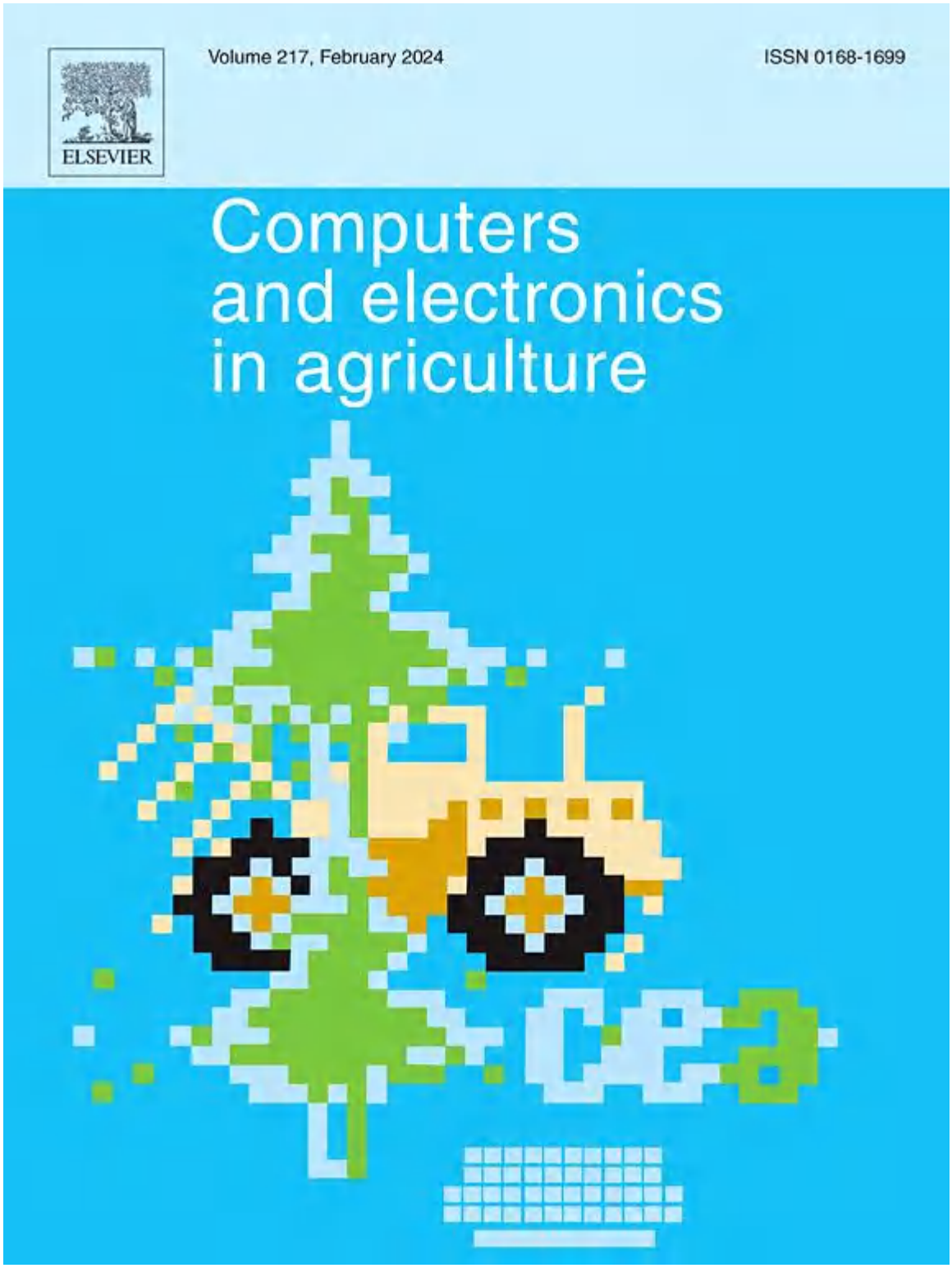
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Original papers

Long-term video activity monitoring and anomaly alerting of group-housed pigs

Qiumei Yang [a,b], Miaobin Chen [a,b], Deqin Xiao [a,b,*], Senpeng Huang [a,b], Xiangyang Hui [a,b]

[a] College of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China
[b] Key Laboratory of Smart Agricultural Technology in Tropical South China Ministry of Agriculture and Rural Affairs, Guangzhou 510642, China

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ABSTRACT

The activity level of group-housed pigs can reflect their daily behavioral patterns and health conditions. Currently, most pig farms mainly rely on manual daily patrols to monitor the activities of group-housed pigs, which is labor-intensive and inaccurate. In this paper, we propose a computer vision-based method for the automatic monitoring and alerting of group-housed pigs activity anomaly. We established a pig segmentation model based on an improved Mask R-CNN incorporating the CBAM attention mechanism and CIoU loss function for segmenting pigs from video frames. The CBAM attention mechanism enables the model to focus more effectively on target regions, while CIoU loss function guides precise learning of object boundaries, outperforming the traditional IoU loss. Grounded on the segmentation results, we invocated a frame difference method to quantify the activity level of group-housed pigs. Subsequently, we adopted the K-means clustering algorithm to explore the daily behaviors of these pigs. Furthermore, we constructed a SARIMA model using historical data to proactively forecast potential shifts in activity levels. The experimental results demonstrated that the accuracy and recall rate of the pig instance segmentation model were 98.7% and 97.9%, respectively. The SARIMA model performed well in predicting activity levels of group-housed pigs with differing health status. For the pig herds under healthy status, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were 6.01 and 7.67 respectively, while for the pig herds under unhealthy status, the MAE and RMSE were 6.41 and 9.30 respectively. We proposed an effectively method to monitor daily behavioral patterns and anomalies of group-housed pigs, providing valuable references for pig farm management.

1. Introduction

The activity level of group-housed pigs is an important basis for analyzing their health status (Ott et al., 2014). First, activity level directly correlate to the physical health and behavioral patterns of pigs (Xiao et al., 2016). Healthy pigs demonstrate regular daily activity fluctuations, while abnormal changes often signal issues like disease or stress from improper nutrition or environment (Tu et al., 2021). Second, monitoring activity levels over time provides a basis for optimizing the breeding environment (Gómez et al., 2021). For instance, when pigs enter a new group, aggression and fighting behaviors may appear due to territorial disputes and rearrangement of social status, resulting in abnormal changes in group activity levels (O'Malley et al., 2022; Peden et al., 2018); Alternatively, when living space is insufficient, activity levels may decrease significantly. By observing such patterns, pen configurations can be adjusted to improve conditions. Third, real-time monitoring enables timely response to anomalies, allowing for corrective actions to maintain health and productivity. In addition, changes in the activity level of group-housed pigs may also be an early sign of disease outbreaks (Matthews et al., 2016). During the incubation period of a disease, due to discomfort in bodily functions, there can be abnormal changes in the daily activity patterns of group-housed pigs, such as a significant decrease in activity level and alterations in behavior patterns (Martínez-Avilés et al., 2017). Once abnormal activity levels are observed among group-housed pigs, it should be taken seriously, as it may indicate the presence of disease within the pig population. At this time, preventive measures such as isolation and disinfection should be taken immediately to effectively curb the spread of diseases within the group-housed pigs. On the contrary, if monitoring is neglected and this early warning window is missed, diseases may rapidly spread within the pig, resulting in significant economic losses for the group-housed pigs. Therefore, continuous monitoring of the activity levels of group-housed

* Corresponding author at: College of Mathematics and Informatics, South China Agricultural University, China.
E-mail address: deqinx@scau.edu.cn (D. Xiao).

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pigs and promptly identifying abnormal fluctuations are crucial for early disease warning.

The main traditional method of monitoring the activity of group-housed pigs relied on manual inspection of pens by farmers. However, this manual method had clear drawbacks, including wasted labor and potential inaccuracies (Ho et al., 2021). Some studies tried using wearable devices attached to pigs to track metrics like movement patterns, step count, and active time (Cornou and Lundbye-Christensen, 2008). But these devices were prone to falling off and irritating the pigs due to their rooting behavior and thin legs (Pandey et al., 2021). Therefore, there is an urgent need for automatic and effective methods that can monitor and quantify the activity levels of group-housed pigs.

Video-based monitoring has the advantage of non-contact, avoiding direct damage or disturbance to pigs, while continuously acquiring rich information about group-housed pigs (Chen et al., 2021). It's an efficient and safe monitoring method. The current research mainly focuses on pig detection, tracking, and behavior recognition (Guo et al., 2023; Larsen et al., 2023; Xu et al., 2022). However, most video analysis methods had limitations in comprehensively evaluating pig activity levels over long durations. They lacked semantic understanding of complex pig behaviors and interactions (Leroy et al., 2006). This could lead to errors in quantifying activity levels from video data. In addition, while some studies had analyzed short video clips (Costa et al., 2013a; Costa et al., 2013b; Kashiha et al., 2013; Lind et al., 2005), there remained a research gap in leveraging long-term, round-the-clock video footage to fully automate activity level assessment. Some initial studies have explored using activity index derived from video to monitor pigs. For instance, infrared cameras were used to monitor fattening pig pens over several days, and activity index was calculated and correlated with behaviors (Costa et al., 2013a; Costa et al., 2013b; Leroy et al., 2008). This demonstrates the potential of activity index for automated assessment.

Although some early studies have enhanced our understanding and monitoring of group-housed pig behaviors to some extent, they still have some obvious limitations, such as heavily reliance on manual feature extraction, making adaptation to complex scenes difficult. While deep learning has brought new potential to video analysis through automated features learning and enhanced visual understanding, its application still faces constraints. For example, Wutke et al.(2020) used a semi-supervised neural network to detect and classify pig activities based on thresholds. However, the thresholds were prone to biases from multiple factors. Xu et al.(2023) conducted a months-long analysis of the activity of group-housed pigs.YOLOv5s was adopted to identify pig postures and quantified movement center values with a mean-shift algorithm. The XGBoost model was applied to classified the movement of grouped pigs. It focused on quantifying and assessing the movement of grouped pigs, instead of anomaly alerting. Ding et al.(2022)detected the regions of the active piglets by combining the frame difference method with the YOLOv5s network model, but it is still limited to specific scenarios. Overall, some common issues remain, including overemphasis on detecting specific behaviors while ignoring overall activity trends of group-housed pigs, a lack of capabilities for anomaly alerting.

To address these challenges, this paper proposes an automatic monitoring and anomaly alerting method for long-term video surveillance of group-housed pigs. Compared to complex behavior recognition approaches, our method used instance segmentation and pixel change computation to efficiently detect and quantify activity levels. It provided wide monitoring scope and real-time capturing of activity changes for health tracking. The method also enabled anomaly alerting through time series prediction modeling. Our method aims to reduce the workload of manual surveillance and improve monitoring efficiency. It represents a scalable automated solution for continuous activity level assessment and health monitoring in group-housed pigs.

2. Material and methods

2.1. Data acquisition

The experimental data was collected from two commercial pig farms, each of which selected a pen for monitoring. One of the pens (Pen 1) raised four healthy pigs and was monitored from July 8, 2016 to July 14, 2016, lasting 7 days. Another pen (Pen 2) raised sick pigs, which were collected from other pens for quarantine purposes. It was monitored from June 27, 2019 to July 11, 2019, lasting 15 days. During our monitoring period, some pigs experienced symptoms such as seizures and bloody diarrhea, resulting in a decrease in the number of pigs from 7 to 2.

Both pig pens used Hikvision infrared network cameras with a lens focal length of 2.8 mm (DS-2CD3345-I, Hikvision, Hangzhou, China). The videos taken were stored locally in the pig pen using Hikvision network video recorders (DS-7804 N-K1/C, Hikvision, Hangzhou, China). Fig. 1 shows the sample images from our monitored pens. Fig. 2.

2.2. Data sampling and annotation

In order to train pig instance segmentation models, images containing pigs were selected from key frame sequences to build a pig instance segmentation dataset. The Labelme annotation software was used to manually annotate each image. A total of 3000 images were annotated and split into training, validation, and test sets with a ratio of 6:2:2 following the MS COCO data format. Details of the pig instance segmentation dataset are shown in Table 1.

2.3. Workflow of pig activity pattern analysis algorithm

This paper aims to automatically extract activity data of group-housed pigs from monitoring videos. The following steps are taken:

(1) Build a monitoring system platform to acquire original surveillance video.

(2) Extract images from surveillance video, annotate pig segmentation samples, and construct training, validation and test sets for pig instance segmentation.

(3) Train a pig segmentation model based on Mask R-CNN.

(4) Use the trained instance segmentation model to segment pig instances every 5 frames of the surveillance video, obtain pig target pixels in video frames, and quantify group-housed pigs activity levels using the frame difference method.

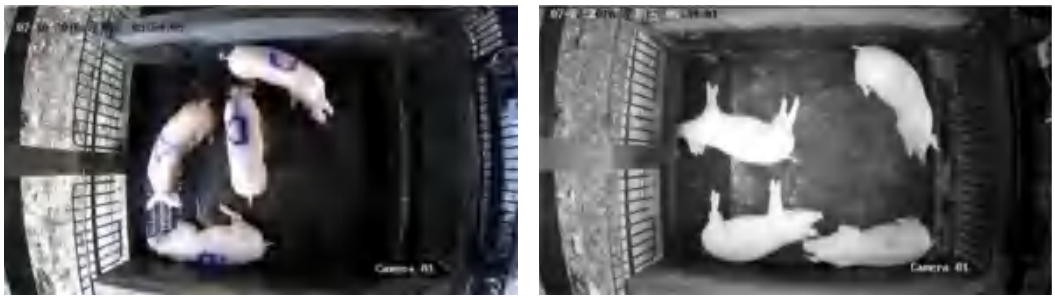
(5) Utilize the K-Means clustering algorithm to analyze the spatial–temporal patterns of group-housed pig activity levels.

(6) Anomaly warning using SARIMA time series prediction algorithm.

3. Implementation of the pig activity pattern analysis algorithm

3.1. Pig instance segmentation algorithm based on Mask R-CNN

Instance segmentation of pigs requires precise recognition of the complex morphology of pigs and the ability to accurately distinguish each pig. Due to the possibility of obstructions or overlaps between pigs, the chosen model must be able to effectively address these challenges. Based on these requirements, Mask R-CNN is selected as the instance segmentation model. As a commonly used algorithm for instance segmentation, Mask R-CNN was proposed by He et al.(2017) in 2017 through the improvement of Faster R-CNN (Ren et al., 2015). It not only can accurately detect each pig instance, achieve target location and classification in the input images, but also capture more precise pig shapes through pixel-level segmentation. Meanwhile, its parallel detection and segmentation structure enables it to perform instance segmentation efficiently. The built-in RoI Align (Regions of interest Align) solves the pixel-level position offset problem, which makes the



(a)



(b)

Fig. 1. Sample images from monitored pens.

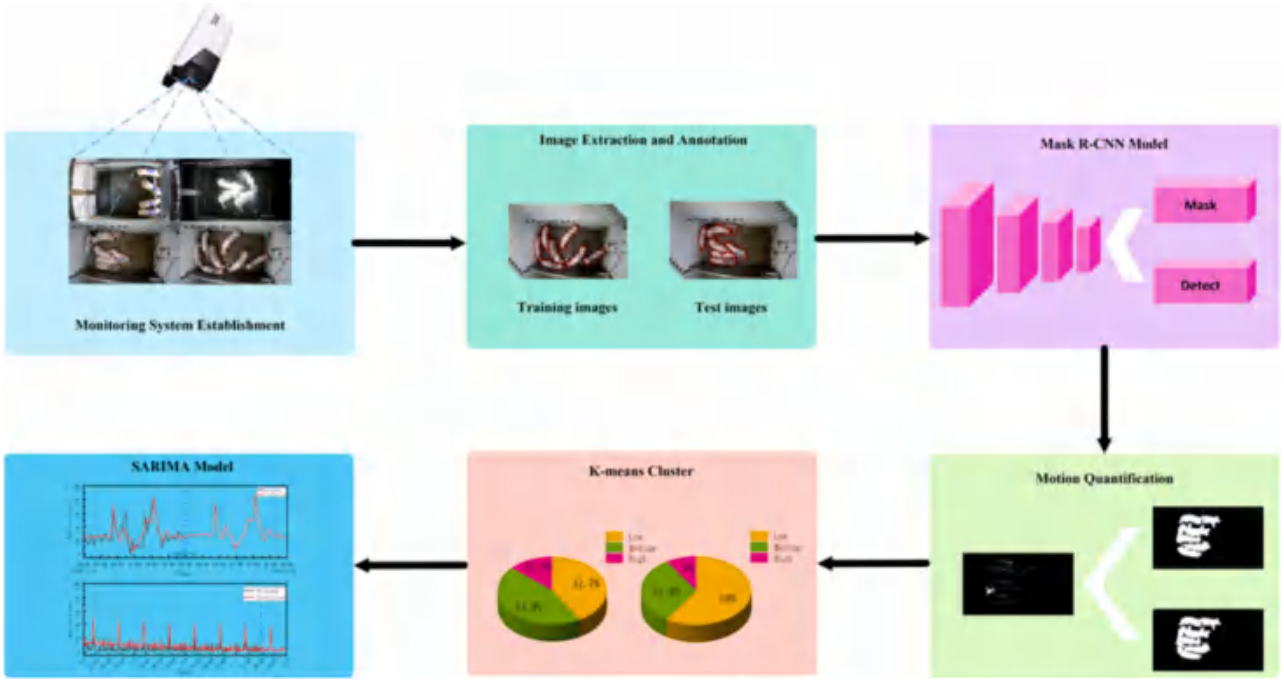


Fig. 2. Pig activity pattern analysis algorithm flowchart.

segmentation results more accurate and more suitable for extracting pig information from videos. Compared with other algorithms, Mask R-CNN is more robust to complex environments and pig distribution variations. Its end-to-end training is easier to optimize as well. Therefore, Mask R-CNN satisfies the requirements for effective pig instance segmentation in this application.

The Mask R-CNN instance segmentation module has two branches: class prediction and instance mask prediction. The class prediction branch generates class labels and bounding box coordinates for the regions of interest. The instance mask prediction branch generates pixel-level masks for the regions of interest in the bounding boxes to extract pig targets. The structure is shown in Fig. 3, mainly composed of the

Table 1
Data set for pig detector.

Data set	Total images
Training set	1800
Verification set	600
Test set	600

feature extraction network, feature fusion network, region proposal network, and others. In this paper, we chose the deep residual network ResNet50 as the feature extraction network, which not only reduces the number of parameters but also simplifies model training. Moreover, in order to better characterize multi-scale objects and achieve better feature integration, the Feature Pyramid Network (FPN) is introduced (Lin et al., 2017).

To enhance the detection accuracy of the original Mask R-CNN model, this paper proposes an improved Mask R-CNN network model. Specifically, we integrate the CBAM attention module into the backbone of the network and employ the CIoU loss function to replace the traditional IoU loss. The CBAM module enhances the model's ability to learn features of occluded or small targets by introducing attention mechanisms in both the channel and spatial dimensions. Additionally, CIoU can further improve the matching accuracy between the predicted and ground truth bounding boxes.

3.1.1. The CBAM attention module

Attention mechanism draws inspiration from the ability of human visual perception. When processing visual information, people tend to focus their attention on the key areas in the current context, while reducing attention to other areas accordingly. This provides more processed and relevant information for higher-level visual perception, logical reasoning, and more complex computer vision tasks (Niu et al., 2021). The traditional Mask R-CNN network has some problems in the feature fusion process of pigs, such as the long path between low-level and high-level features, and the lack of attention to key information, which leads to the inability to effectively utilize low-level information.

To address these issues, CBAM was proposed as a lightweight general module that can be easily integrated into any CNN architecture (Woo et al., 2018). As shown in Fig. 4, CBAM consists of a channel attention module and a spatial attention module. When using CBAM, the output of the convolutional layer is first passed through the channel attention module, then through the spatial attention module, and finally the weighted result is obtained. By introducing the CBAM structure, the model can pay more attention to important features and effectively utilize low-level information, thereby improving the model's performance and generalization ability.

In the experiment of adding CBAM attention mechanism to the ResNet50 backbone network of Mask R-CNN, as shown in Fig. 5, ResNet50 contains five Conv layers. In the first stage, the input passes through a 7×7 convolution layer and then enters a maximum pooling layer to obtain the output features. The subsequent second to fifth stages

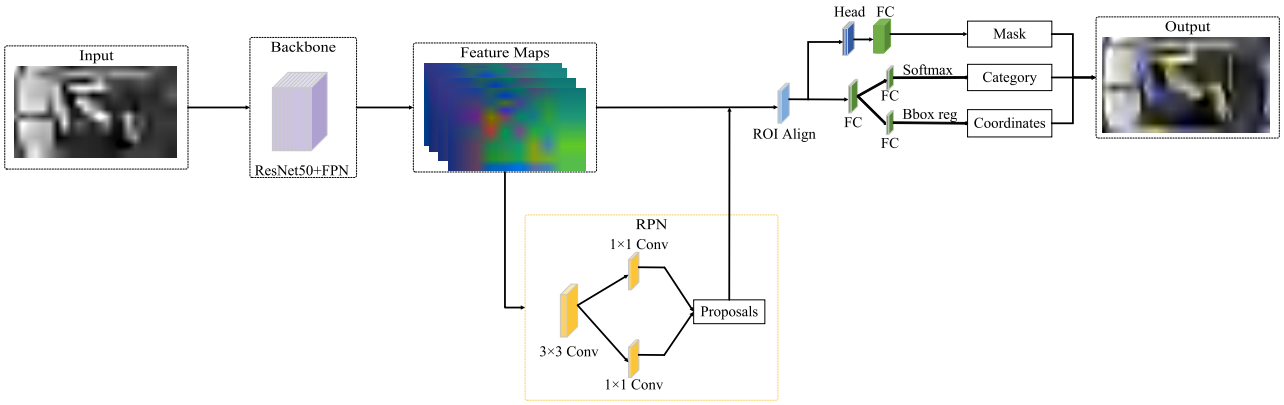


Fig. 3. Mask R-CNN network structure diagram.

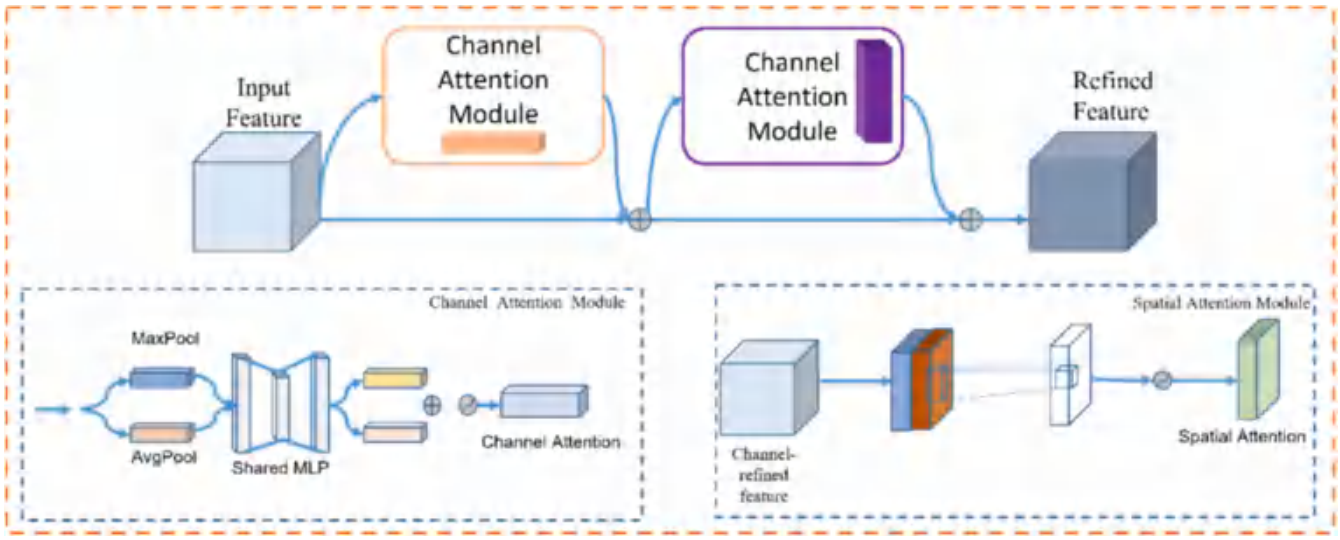


Fig. 4. The structure of the CBAM module.

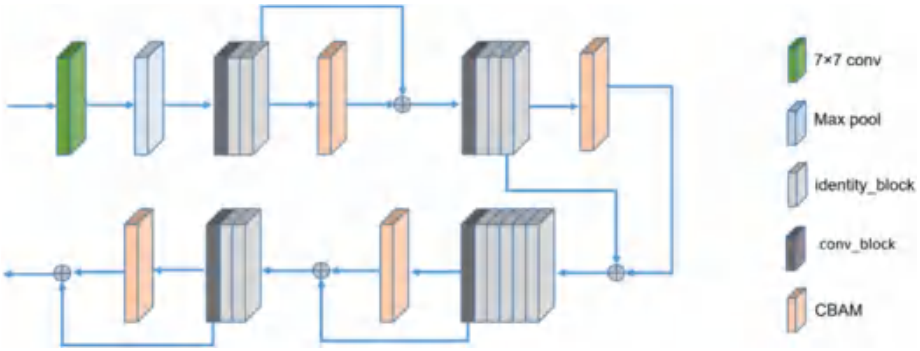


Fig. 5. Integration of CBAM attention module in the ResNet50 backbone of Mask R-CNN.

pass through 3, 4, 6, and 3 Bottleneck modules, respectively, to obtain the output features. We connect the CBAM modules to the second to fifth stages, respectively, to extract the features of the pig image again and focus on the more important feature information in the image. Then, the features output by the CBAM module are added to the original features to obtain the final output features of each stage.

3.1.2. CIoU loss function for boundary box regression optimization

As an instance-level segmentation algorithm, Mask R-CNN model's performance is heavily dependent on accurate bounding box regression. The bounding box regression loss function is used to measure the error between the ground truth and the predicted values, and is used to predict the coordinate positions of the target. In Mask R-CNN network, IoU is used as the bounding box regression loss function to calculate the intersection over union (IoU) between the predicted box and the ground truth box for iterative optimization of the model. However, when the predicted box and the ground truth box do not intersect, IoU is equal to 0, resulting in an inability to perform gradient computation.

Therefore, this paper proposes to use CIoU (Complete IoU)(Zheng et al., 2019) instead of ordinary IoU for loss calculation. As shown in Fig. 6, CIoU considers the aspect ratios of both rectangles, that is, the similarity of their shapes. The calculation formula is as follows:

$$CIOU = IOU - \frac{\rho^2(b, b^{gt})}{c^2}\alpha v \tag{1}$$

$$v = \frac{4(arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w}{h})^2}{\pi^2} \tag{2}$$

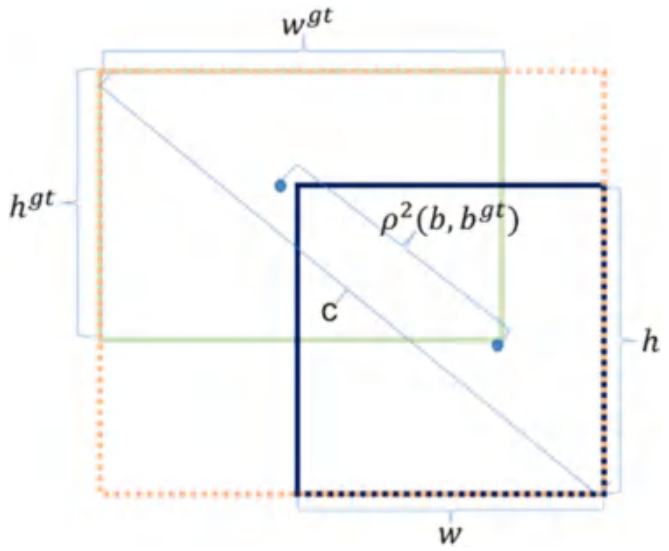


Fig. 6. CIoU calculation diagram.

$$\alpha = \frac{v}{(1 - IOU) + v} \tag{3}$$

In this equation, $p^2(b, b^{gt})$ represents the Euclidean distance between the center points of the predicted and ground-truth bounding boxes; c represents the diagonal distance of the smallest enclosing area that can contain both the predicted and ground-truth bounding boxes. (w^{gt}, h^{gt}) and (w, h) represent the width and height of the target and predicted bounding boxes, respectively.

3.2. Quantification of the activity levels for group-housed pigs

In order to more accurately measure the activity level of group-housed pigs, we introduce the pig activity index, denoted as ***PAIndex (t)***. This index is calculated based on the absolute value between the pixel points labeled as pigs in the segmentation results of the instances at moment *t* and at moment *t-1*. Specifically, in a frame image W, the value of pixel point(x, y) at frame *t* is ***I(x, y, t)***. If ***I(x, y, t)*** = 0, it means this pixel point is a non-interested region, i.e. the background. Otherwise, if ***I (x, y, t)*** = 1, this pixel is an region of interest, i.e. the foreground pig. As shown in Fig. 7, assume that the white area represents the position of the pig in the image, represented by 1, while the black area represents the background, represented by 0. The blue area in the image represents the moving pixels.

To reduce computation time, our model carries out recognition every 5 frames considering that the activity of pigs does not change much in consecutive frames. Therefore, the activity index of the group-housed pigs at time *t*, ***PAIndex(t)***, is defined as Eq.4. The activity levels of the group-housed pigs from time *t1* to *t2*, ***PActivity(t1,t2)***, is defined as Eq.5.

$$PAIndex(t) = \sum_{(x,y)\in W} |I(x, y, t) - I(x, y, t-5)| \tag{4}$$

$$PActivity(t1, t2) = \sum\nolimits_{t1\le t\le t2} PAIndex(t) \tag{5}$$

Fig. 8(a) shows the binarized segmented image of the frame t-5, and Fig. 8(b) shows the binarized segmented image of frame t. Fig. 8(c) is the difference between the above two frame, reflecting the motion of the pigs. When a pig herd is stationary, the changes in image pixels are minimal. On the contrary, a large number of pixel changes indicate that a pig herd is active.

The algorithm for calculating pig activity is shown in Algorithm 1:

Algorithm 1: Activity Index Calculation (ActIndex-cal)

Input: Surveillance video V
Output: Activity Index array of video V
1: n = 1
2: while n < V.frameNums do
3: frame = read(v, n) // Read frame n from video v
4: Execute Pig-seg(frame) to get a binary image // Segment pigs in the frame
5: if n == 1 then

(*continued on next page*)

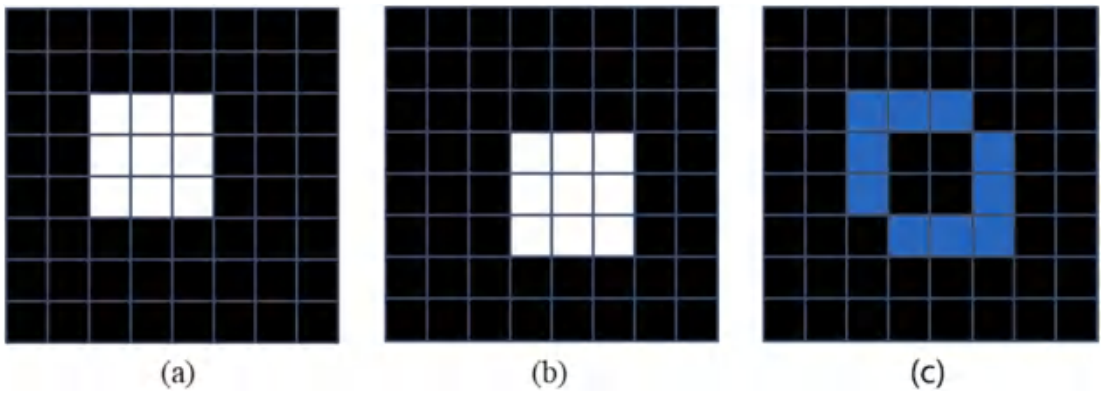


Fig. 7. Pixel Changes Between Adjacent Frames.

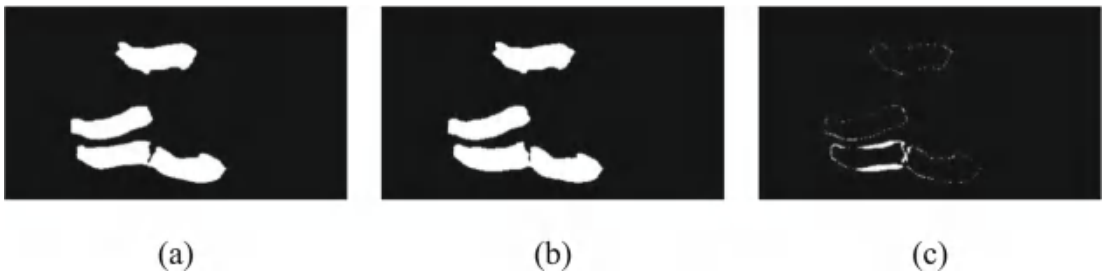


Fig. 8. Pixel changes between frames for quantifying pig activity levels.

(*continued*)

Algorithm 1: Activity Index Calculation (ActIndex-cal)

```
6:        preFrame = frame
7:      currentFrame = frame //Set current frame and previous frame to the first frame
8:    else
9:        preFrame = currentFrame
10:       currentFrame = frame // Update previous frame and current frame
11:   end if // Calculate Activity Index: subtract previous frame from current frame
12:   PAIndex(n) = sub(currentFrame, preFrame)
13:   n = n + 5
14: end while
```

In order to analyze the activity pattern of group-housed pigs, we calculated the total activity level of group-housed pigs in every 30-minute period as the research data measurements. This can effectively reduce the influence of noise and make the activity levels better reflect the actual behaviors of group-housed pigs. Based on these processed data, we can more effectively explore the intrinsic connections between activity levels and behaviors of group-housed pigs.

3.3. Approach to evaluate activity levels for group-housed pigs

3.3.1. K-means clustering to classify pig activity levels

In order to deeply analyze the changing patterns of activity levels of group-housed pigs during different periods of a day, we used the K-means clustering algorithm to classify the activity levels. K-means clustering algorithm can classify the samples into multiple clusters based on the similarity of the data in an unsupervised manner(Hartigan & Wong, 1979), which is a good way to reveal the distribution and patterns of the data. We first normalized the continuous activity levels of group-housed pigs (*PActivity*) by day, and then utilized the K-means clustering algorithm to classify the activity levels into 3 clusters, representing low, medium and high activity states. This helps us to observe the ranges of values and the change pattern of activity levels during various time periods. By clustering the activity levels of different period of a day, we can more accurately assess the activity and health status of the group-housed pigs during these times and detect anomalies in activity levels. If the activity level of group-housed pigs originally categorized as high activity states continues to decline over a period of time, this may be suggestive of an underlying health problem or a change in environmental factors and alert should be issued.

3.3.2. SARIMA time series prediction

Due to factors such as feeding environments and physiological rhythms, the activity levels of group-housed pigs demonstrate distinct cyclical patterns (Maselyne et al., 2014; Villagrá et al., 2007). Within a single breeding cycle, the activity patterns of the pigs remain relatively consistent daily, displaying recurring patterns such as distinct peaks and troughs of activity within each feeding cycle or specific time windows over the course of a day. To effectively predict these cyclical variations, we adopt the SARIMA time series forecasting approach.

The SARIMA model, building on the ARIMA (Autoregressive Integrated Moving Average) framework, incorporates seasonal factors into its time series forecasting. The model parameters include p, d, q, P, D, Q, generally expressed as SARIMA (p, d, q) (P, D, Q). Specifically, p, d, and q represent the orders of autoregression, difference, and moving average, describing the general trend. Conversely, P, D, and Q correspond to the counts of seasonal autoregression, seasonal difference, and seasonal moving average, capturing the seasonal factors. In this study, we observed cyclical patterns in the activity levels of group-housed pigs that often occurred at similar times each day. These intra-day cycles are primarily influenced by factors such as fixed feeding times and physiological rhythms. The seasonal parameters in the SARIMA model are specifically designed to account for these intra-day cyclical patterns. Consequently, the SARIMA model stands as a robust tool for forecasting the activity levels of group-housed pigs with enhanced accuracy.

Specifically, to predict the continuous activity level of the group-housed pigs, we employed the following steps.

(1) **Normalization**: Firstly, we normalized *PActivity* to ensure that the data were compared on a consistent scale.

(2) **Train-Test Split**: The data were divided into training and test sets for model training and evaluation.
(3) **Decomposition of the Training Data for Periodicity**: The training data were decomposed to extract trend, period, and residual components. In this context, the periodic parameter of the SARIMA model was set to 48, corresponding to 48 counts in a day.
(4) **Modeling Trend Data**: The trend component was independently trained using the SARIMA model to anticipate future trend trajectories.
(5) **Combining Trend and Cyclical Data**: The predicted trend data were combined with cyclical data to present the final prediction outcomes.

In summary, we have innovatively revealed the effects of health status on the activity patterns of group-housed pigs by utilizing the SARIMA model to dissect and predict activity time series. This allowed us to delve deeper into and accurately predict their activity modes. Furthermore, the employment of the SARIMA model also allows us to anticipate upcoming activity trends, such as shifts in pig activity levels or potential anomalous behaviors. This holds crucial significance for the health monitoring and disease prevention of pigs.

4. Results

4.1. Training results of pig instance segmentation model

This experiment used Detectron2(Wu et al., 2023), an open-sourced object detection framework from Facebook AI Research. Input images were resized to 1333 × 800 pixels for the training procedure. The experimental environment was Windows 10, Pytorch 1.12, and CUDA 11.3, running on a Nvidia RTX3070 GPU with 8 GB of memory. Details of the training parameters are presented in Table 2.

To facilitate a better understanding of the training process, we plotted the changes in loss during the training process, as shown in Fig. 9. It demonstrates the decreasing trend of the model's loss function throughout the entire training cycle, indicating that the model gradually learned the task of instance segmentation of pigs. The model was fine-tuned on the basis of the unimproved Mask R-CNN model, so the change in the loss function was relatively subtle throughout the training process, which is reasonable and normal.

After confirming the model training had converged well, we further evaluated the instance segmentation performance metrics of the model on the test dataset. Following the COCO dataset standards, we adopted AP (Average Precision) and AR (Average Recall) as our evaluation metrics for this segmentation task. To validate the performance improvements brought by incorporating the CABM attention module and using the CIoU loss instead of the ordinary IoU loss in the Mask R-CNN model, we conducted ablation experiments on a dataset for pig instance segmentation. The experimental results are presented in Table 3.

As the baseline model, Mask R-CNN achieved an average precision (AP) of 88.1 % and an average recall (AR) of 90.0 %. Introducing the CABM module and CIoU loss function significantly improved the model performance, reaching the highest AP of 98.7 % and AR of 97.9 %.

Table 2
Parameters setting for training procedure.

Define	Parameter	Annotation
batch-size	2	batch size
MAX_ITER	9000	maximum number of iterations
lr	0.0001	learning rate
MAX_SIZE_TRAIN	1333	picture size
MIN_SIZE_TRAIN	640	picture size
Adam	True	optimizer
momentum	0.9	momentum
weight decay	0.0001	weight decay

Additionally, YOLOv8n-Seg as a lightweight model demonstrated high performance in instance segmentation tasks, but its performance was lower than the improved Mask R-CNN. Specifically, YOLOv8n-Seg achieved an AP of 93.5 % and an AR of 92.6 %, while the improved Mask R-CNN (incorporating CABM and CIoU) achieved AP and AR as high as 98.7 % and 97.9 %, respectively. This indicates that introducing CABM and CIoU technologies helps to enhance the Mask R-CNN model's ability to localize and classify target objects, thus improving its performance.

To illustrate the performance differences among various models on the instance segmentation task, Fig. 10 provides a visual comparison of the segmentation results from different models. As shown in Fig. 10, compared to the original Mask R-CNN model, the model incorporating the CABM and CIoU improvements achieved more precise edge detection and more accurate segmentation results for pig instance segmentation.

On the other hand, although YOLOv8n-Seg as a lightweight model also demonstrated high performance, it still cannot match the improved Mask R-CNN. In complex environments, the improved Mask R-CNN can generate more accurate instance segmentation results, especially when targets are occluded or have unclear boundaries, the improved Mask R-CNN can still segment complete boundaries and successfully identify different individual instances, while YOLOv8n-Seg shows noticeable missed detections. This validates the robustness of the improved Mask R-CNN in handling complex dense scenes, meeting the requirements for segmentation accuracy in applications such as monitoring group-housed pigs in occluded environments.

In summary, these results further emphasize the practical application value and efficiency of the lightweight improved Mask R-CNN in continuous monitoring of the activity levels of the group-housed pigs. Especially in environments requiring real-time monitoring, the efficient lightweight design and excellent performance of this model make it a more suitable choice.

4.2. Activity quantification and statistics of group-housed pigs

4.2.1. Statistics and quantification of activity levels for healthy group-housed pigs

For Pen 1, we normalized the daily activity data to a 0–100 scale. This normalization revealed the patterns and trends of pig activity levels more clearly. The activity data of the group-housed pigs at different time periods in a day and the corresponding normalized activity levels are listed in Table 4. We can clearly observe that the activity levels of the group-housed pigs were significantly higher at 7.00–7.30 am and 5.00–5.30 pm, reaching 99.842 and 100 respectively, corresponding to the main feeding times of the group-housed pigs. While at other time periods, such as 0:00–0:30, the activity level of the group-housed pigs was only 14.945, corresponding to the resting state of the group-housed pigs at night that we observed.

Fig. 11 displays the activity data of the Pen 1 from July 8 to 14, 2016, with each curve representing the data for one day. We can observe that the activity patterns of healthy group-housed pig exhibit clear periodicity. Moreover, the daily activity curves have a high degree of similarity, with peaks and troughs of activity occurring at relatively consistent times. It clearly reflects the daily routines of pigs, characterized by activity peaks during feeding time and troughs during resting time. Additionally, to present the overall trend of activity changes within a period, we aggregated all the daily activity data across the period and drew an overall activity line chart, as shown in Fig. 12. From the chart, it is evident that despite slight fluctuations, the activity level of the group-housed pigs remains relatively stable throughout the entire period without any significant anomalies. It further confirms that under healthy conditions, the activity patterns of the group-housed pigs exhibit cyclical regularity and stability.

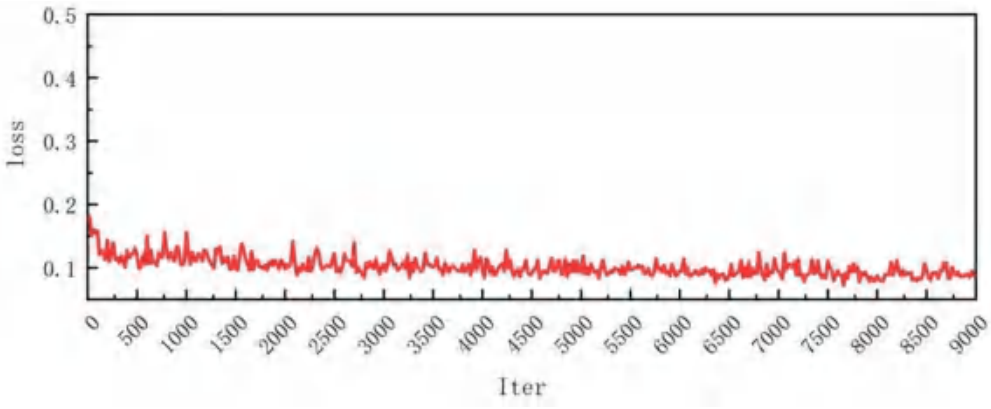


Fig. 9. The graph of loss variation during training.

Table 3
Comparison of performance among different models.

Model	AP	AR
Mask R-CNN	88.1 %	90.0 %
Improved Mask R-CNN	98.7 %	97.9 %
YOLOv8n-Seg	93.5 %	92.6 %

4.2.2. Statistics and quantification of the activity levels for unhealthy group-housed pigs

In order to eliminate the effect of data dimensionality and to better observe and compare the changes in activity levels of group-housed pigs in different time periods and pig numbers, we normalized the activity level data of group-housed pigs in Pen 2 from June 27 to July 11, 2019. We selected 6 days as representative samples, corresponding to different stages of the gradual decline in pig numbers due to disease. By analyzing the activity data from such stages, we can understand the changes in activity patterns among group-housed pigs with decreased numbers caused by disease, as shown in Fig. 13. Initially, the activity level of the group-housed pigs remained at a relatively high level. However, when some pigs developed symptoms such as convulsions and bloody diarrhea, leading to decreased activity ability or even death, the activity level began to gradually decline. When the number of pigs was reduced to only 2, the remaining two pigs had relatively more space to move freely in the pen, the activity level didn't significantly decrease and remained stable at a certain level.

Furthermore, we analyzed the activity level data of the group-housed pigs during the main feeding stage (9.00–10.00 am) over the 15 days in detail, as shown in Table 5 and Fig. 14. The data shows that the activity level was highest on June 27, normalized to 100. Afterwards, the activity level gradually declined, with significant drops on July 2, 5 and 6, decreasing to 45.974 %, 20.775 % and 12.233 % respectively. On July 7–9, the activity levels rebounded slightly but remained relatively low levels (around 10 %). In addition, as shown in Fig. 15, we can see that the overall trend of the activity level for the group-housed pigs is gradually decreasing and then showing a stable fluctuation trend. The changing trends of activity levels reflects the close relationship between the activity levels of group-housed pigs and their health conditions and quantity. It also reflects the ability of group-housed pigs to adapt to the new environments and conditions after number and health declines, resulting in a new stable state of activity levels.

By comparing the changing trends in activity levels of group-housed pigs in healthy and unhealthy status, it could be found that group-housed pigs in a healthy status demonstrated regularity and stability in their activity patterns, reflecting their daily living habits such as main feeding times and nightly rest. These observations help to understand and predict the behavioral patterns of group-housed pigs, to assess their health and to analyze their adaptability in the face of their environment.

4.3. Results of K-means clustering algorithm

4.3.1. Clustering results of the activity levels for healthy group-housed pigs

We calculated the temporal distribution of activity levels throughout the day on July 8th, as shown in Fig. 16(a). The high activity periods were mainly concentrated from 7.00 am to 8.00 am and 4.00 pm to 6.00 pm, which was related to the peak hours of daily feeding times. Moderate activity levels are mostly observed around midday and early evening. Low activity periods predominantly occur during the deep night, early morning, and midday, corresponding to the primary resting times for the group-housed pigs. In addition, we calculated the periods of low, medium, and high active status. And the top 10 time periods for each category were selected, as shown in Fig. 16(b). These results were consistent with our previous observations and further validated the close relationship between activity levels and behavioral activities in healthy pigs. It also revealed the daily behavioral patterns and feeding habits of the group-housed pigs.

In terms of the number of samples clustered in each category, the activity level of pigs was mainly distributed in the low and medium active clusters, as shown in Fig. 16(c) and (d). Specifically, there are 133 samples in the cluster of low activity, 152 samples in the cluster of medium activity, and a smaller number of 51 samples in the cluster of high activity. This distribution pattern reflected the daily behavioral patterns and biorhythms of group-housed pigs, as they were predominantly low or moderately active during most of the day, with relatively few high activity states. This pattern provides us with an important reference benchmark to further identify and understand potential health issues of the group-housed pigs.

4.3.2. Clustering results of the activity levels for unhealthy group-housed pigs

The changes in activity patterns over time for group-housed pigs in Pen 2 are shown in Fig. 17. In the initial monitoring stage, the daily activity levels of the group-housed pigs fluctuated with certain regularity, with the main activity peak occurring during the 9–10 am feeding times. In subsequent stages, the daytime activity pattern of the group-housed pigs became more flattened, out, with no obvious peaks in activity. The activity levels across different time periods became relatively similar, with the previously observed peak in the morning becoming more irregular. This pattern deviated distinctly from the normal circadian rhythm expected for a group-housed pigs. Furthermore, the proportion of high activity states during the pigs' usual feeding time (9:00–10:00 am) decreased. In contrast, high activity states were observed multiple times during the late night (1:00–1:30 am). Based on the daily trends observed in Fig. 17(c) and (d), there were clear fluctuations in the high activity state, with only about 9.4 % of the time showing a high activity state. In contrast, more than half of the time was in a low activity state, which is a distinct deviation from the rhythm of



(a) Mask R-CNN



(b) Improved Mask R-CNN



(c) YOLOv8n-Seg

Fig. 10. Comparison of segmentation effects between different models.

life of normal group-housed pigs. This apparent deviation might indicate that the herd was being affected by some external stress or health-related problem.

To delve deeper into the correlation between the activity levels of group-housed pigs and their health, we meticulously compared equal numbers of pigs across different groups. We focused on a specific case study: the daily activity patterns of seven pigs in Pen 2, spanning from June 27 to July 1, 2019. This analysis aimed to shed light on the health conditions of the group-housed pigs. Fig. 18 reveals a marked decline in activity among the group-housed pigs during a peak period, which could be indicative of an adverse effect on their overall health. This trend is concerning as it suggests that the pigs' well-being may be compromised to some degree.

Moreover, we aggregated the daily activity counts for the days

Table 4
The original data and normalized values of the activity levels of the group-housed pig on July 8, 2016 at the Pen 1.

Time Period(t1-t2)	PAIndex(t)	PActivity(t1,t2)	Norm_activity(t1,t2)
0:00–0:30	1743	19,012,111	14.945
0:30–1:00	282	21,190,533	17.242
1:00–1:30	445	17,962,685	13.838
1:30–2:00	538	23,375,278	19.547
2:00–2:30	588	20,836,694	16.869
2:30–3:00	330	17,166,927	12.998
3:00–3:30	679	21,816,501	17.903
3:30–4:00	421	22,259,359	18.369
4:00–4:30	326	13,678,280	9.319
4:30–5:00	1007	20,850,489	16.884
5:00–5:30	1185	20,975,850	17.016
5:30–6:00	738	22,489,875	18.613
6:00–6:30	2872	23,261,209	19.427
6:30–7:00	1334	18,321,700	14.217
7:00–7:30	204,629	99,505,431	99.842
7:30–8:00	4913	67,396,781	65.977
8:00–8:30	5585	45,347,194	42.721
8:30–9:00	1056	10,569,193	6.039
9:00–9:30	877	12,881,109	8.478
9:30–10:00	4299	41,399,467	38.558
10:00–10:30	5154	38,560,367	35.563
10:30–11:00	4707	31,434,947	28.047
11:00–11:30	20,039	36,675,940	33.575
11:30–12:00	659	4,842,754	0
12:00–12:30	4571	28,946,131	25.422
12:30–13:00	1761	27,349,126	23.737
13:00–13:30	5370	25,766,912	22.069
13:30–14:00	4009	19,394,603	15.348
14:00–14:30	3316	8,367,600	3.717
14:30–15:00	39,211	70,607,184	69.363
15:00–15:30	35,167	33,198,394	29.907
15:30–16:00	12,119	21,973,766	18.068
16:00–16:30	11,971	57,579,846	55.623
16:30–17:00	87,917	70,654,981	69.413
17:00–17:30	29,860	99,654,811	100
17:30–18:00	6487	53,850,736	51.689
18:00–18:30	6723	28,660,860	25.121
18:30–19:00	5894	31,836,865	28.471
19:00–19:30	7769	29,307,431	25.803
19:30–20:00	3549	37,658,287	34.611
20:00–20:30	29,713	39,613,160	36.673
20:30–21:00	20,183	39,783,149	36.852
21:00–21:30	9053	20,101,427	16.093
21:30–22:00	17,064	44,408,280	41.730
22:00–22:30	8016	20,567,798	16.585
22:30–23:00	10,865	27,191,368	23.571
23:00–23:30	9937	26,727,320	23.082
23:30–00:00	5601	22,633,563	18.764

Note: PAIndex(t) represents the activity value at a certain time during the time period t1 to t2.

leading up to this peak period, from June 27 to June 30, which were 1389942902, 1300127393, 1,287,138,571 and 1160991294, respectively. The progressive decrease in activity levels over these four days is a strong indicator of a developing health problem within the group-housed pigs. This pattern underscores the importance of monitoring and interpreting activity data as a potential early warning sign of health issues in group-housed pigs.

In summary, the behavioral patterns of unhealthy group-housed pigs demonstrated significant differences compared to healthy group-housed pigs, such as a decrease in the periodicity of activity levels and a reduction in states of high activity. These differences reveal how declines in pig numbers and health can disrupt the continuity and stability of behavior patterns of group-housed pigs, thus providing important clues for identifying abnormalities. Simultaneously, it also highlights the significant impact of diseases on the fluctuations in activity levels of group-housed pigs, which can help enable more effective anomaly monitoring and early alerting.

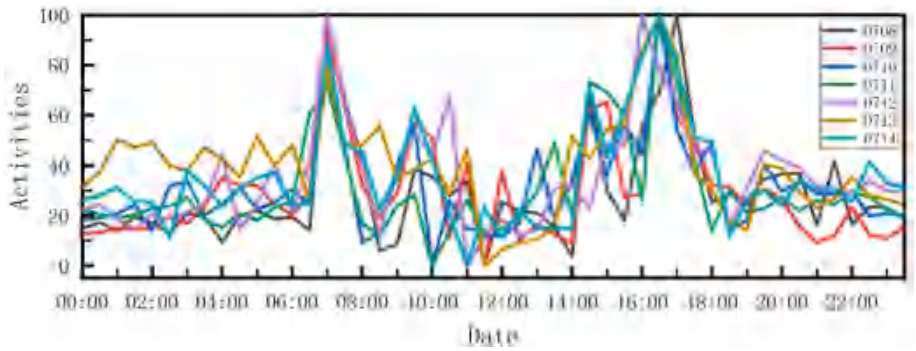


Fig. 11. Daily activity curve of pigs at the Pen 1. (00:00 in the charts in this paper uniformly represents the half-hour time period from 00:00 to 00:30, 00:30 represents the time period from 00:30 to 01:00, and so on.).

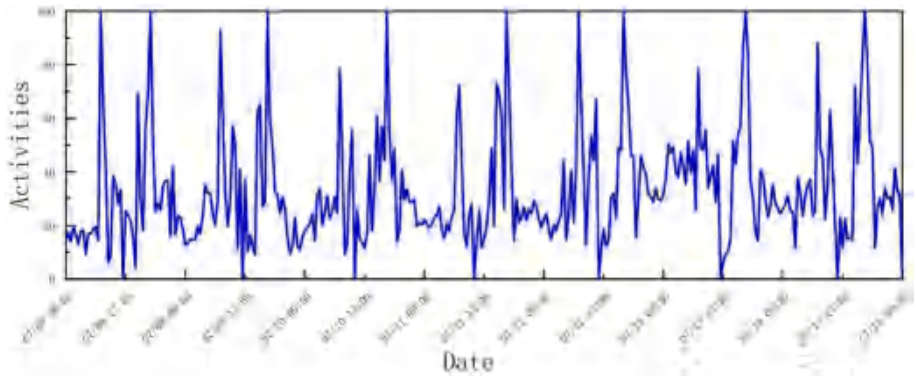


Fig. 12. Curve of activity levels of group-house pigs in the Pen 1.

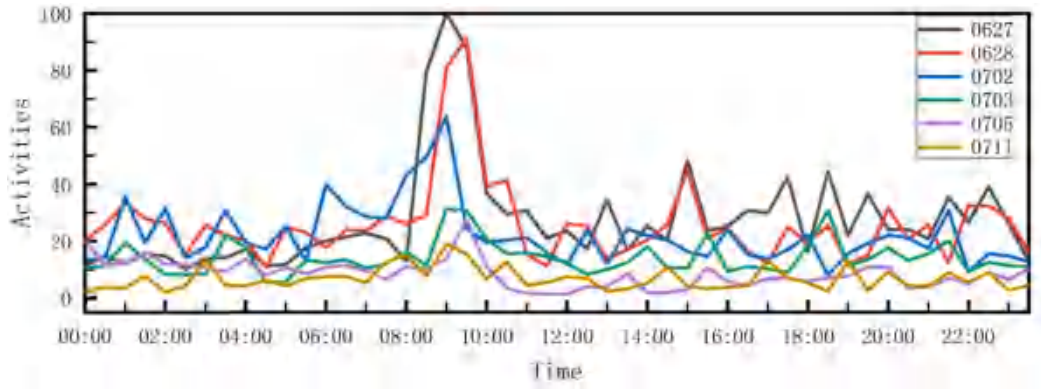


Fig. 13. Statistics of pig number reduction and daily activity levels.

4.4. Time series forecasting of activity levels

We constructed SARIMA time series prediction models to forecast the activity levels of group-housed pigs. By analyzing the prediction results and comparing them to actual observations, we aimed to reveal potential patterns of change and anomalies in the activity levels of group-housed pigs. MAE and RMSE were adopted as model evaluation metrics, with calculation formulas shown in Eq. (6) and (7):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t - y_{tp}\right| \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - y_{tp}\right)^2} \tag{7}$$

where y_t denotes the actual observations in the test set, y_{tp} denotes the predicted values of the model, and n denotes the total amount of data in the test set.

Additionally, we employed four different prediction models, namely XGBoost (Chen and Guestrin, 2016), Random Forest (Louppe, 2015), LSTM (Bandara et al., 2020), and SVM, to further explore the time series forecasting capability of pig activity patterns. These models possess distinct characteristics and application scenarios. We selected them as prediction models to comprehensively evaluate the performance of different approaches in this task.

From Table 7, it is evident that there are significant differences in the performance of different models across different datasets. In both experimental datasets, the SARIMA model consistently exhibited the best predictive performance, with lower MAE and RMSE compared to other models, although its prediction error slightly increased in the

Table 5
The original data and normalized value of the group-housed pig activity in the Pen 2 during 9:00——10:00.

Time Period(t1-t2)	PActivity(t1, t2)	Norm_activity(t1, t2)	Pig Number
6/27 9:00–10:00	176,966,000	100	7
6/28 9:00–10:00	162,670,252	91.438	7
6/29 9:00–10:00	121,403,752	66.724	7
6/30 9:00–10:00	106,626,003	57.874	7
7/1 9:00–10:00	137,815,596	76.553	7
7/2 9:00–10:00	86,755,364	45.974	6
7/3 9:00–10:00	63,228,429	31.884	4
7/4 9:00–10:00	55,268,504	27.117	4
7/5 9:00–10:00	44,678,328	20.775	3
7/6 9:00–10:00	30,415,132	12.233	2
7/7 9:00–10:00	21,891,708	7.128	2
7/8 9:00–10:00	35,049,279	15.008	2
7/9 9:00–10:00	29,346,370	11.593	2
7/10 9:00–10:00	32,120,698	13.254	2
7/11 9:00–10:00	38,324,273	16.969	2

dataset from experimental site 2. Further analysis revealed that the LSTM model produced higher prediction errors when handling normal datasets, possibly due to insufficient sequence length, which failed to effectively capture the long-term dependencies within the data. In contrast, the predictive performance of the SVM model was average, possibly because of its weaker capability in handling nonlinearities in the data. In comparison, the random forest and SVM models showed slightly inferior predictive capabilities compared to the XGBoost and SARIMA models across both datasets.

Overall, the SARIMA model demonstrated superior and more robust performance in predicting the activity levels of group-housed pigs from environmental and production data.

4.4.1. *Activity level forecasting for healthy group-housed pigs*

Table 6 shows that the MAE of the SARIMA time series model's prediction for the activity levels of group-housed pigs in Pen 1 is 6.01, and the RMSE is 7.67. This indicates that our SARIMA model performed well in predicting the activity levels of group-housed pigs, demonstrating high accuracy and reliability. Moreover, as shown in Fig. 19, through fitting historical data and model validation, we observe that the model can effectively capture the trend and periodic changes in activity levels, providing accurate predictions for future periods.

4.4.2. *Activity level forecasting for unhealthy group-housed pigs*

For Pen 2, we used different training proportions and compared the accuracy of the prediction results, as shown in Table 6. The SARIMA (4,1,1)(2,0,0) model, constructed using the training and test sets with a ratio of 1:2, had a large prediction error. The MAE was 7.26 and the RMSE was 11.18, indicating a large deviation between predicted and observed values. Specifically, when the number of pigs decreased or health issues arose among the group-housed pigs, the observed values during the feeding stage were significantly lower than the model's predictions, as shown in Fig. 20(a). This suggested that the model couldn't effectively predict the trend and pattern of such anomalies. When the proportion of training data was increased, the prediction accuracy of the SARIMA (5,1,1)(0,0,1)model improved significantly, with the MAE reduced to 6.41 and RMSE reduced to 9.30. This indicates that the model's performance improved in predicting abnormal conditions for group-housed pigs. The SARIMA (5,1,1)(0,0,1) model not only predicted the activity levels of group-housed pigs under normal conditions more accurately but also performed well in predicting when there was a decrease in pig numbers or health issues, as shown in Fig. 20(b). However, the observed values during the feeding stage were still lower than the model's predictions. This suggested that by comparing the model's forecasted and observed values, early detection and alerting of anomalies could be achieved.

In summary, from the predictive analysis of the activity patterns of group-housed pigs under these two different health conditions, we can

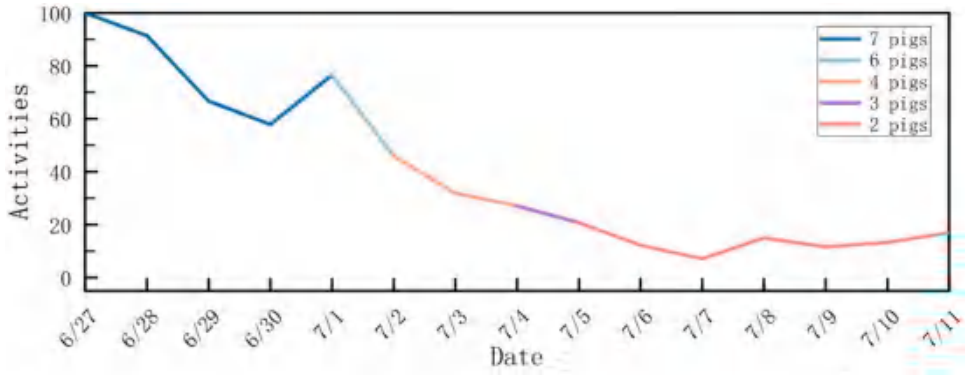


Fig. 14. Activity levels of group-housed pig in the Pen 2.

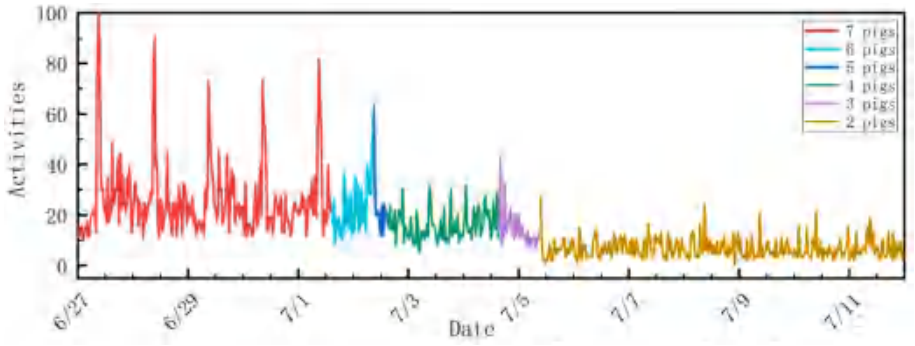
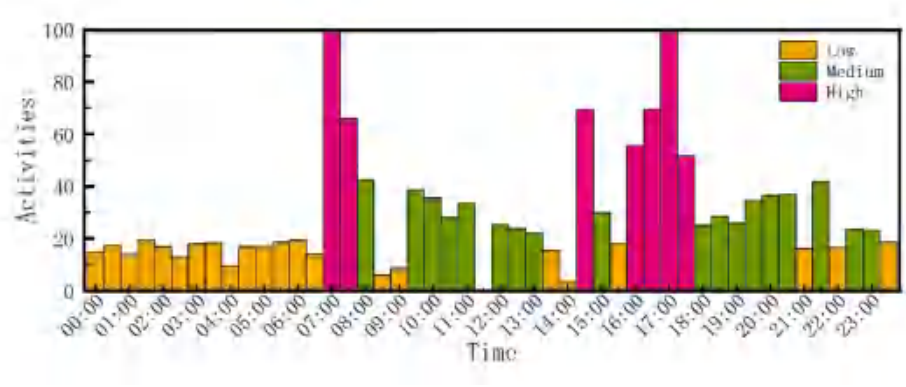
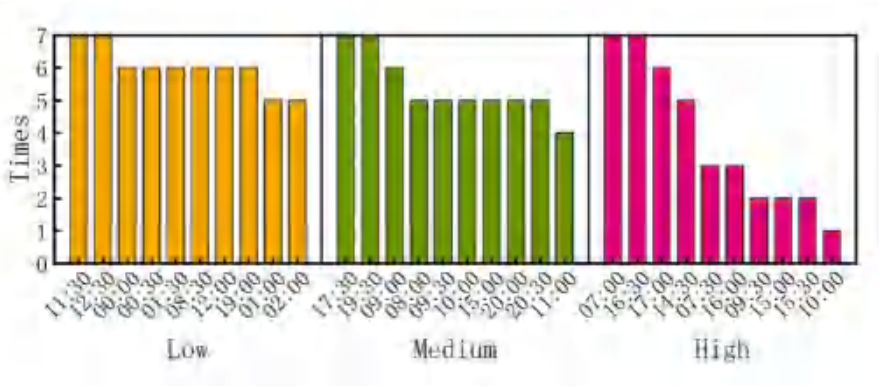


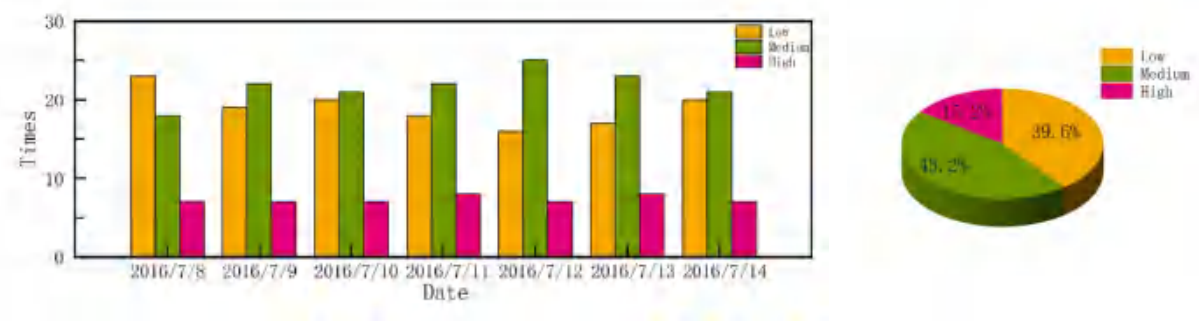
Fig. 15. Curve of activity levels of group-house pigs in the Pen 2. (Different legend colors represent the number of pigs in the pen.).



(a)



(b)



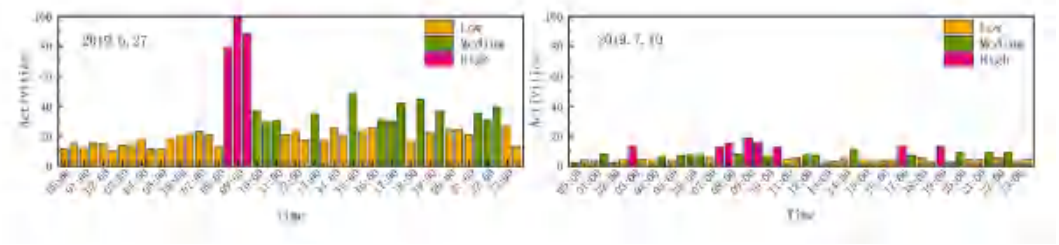
(c) (d)

Fig. 16. (a) Time distribution of pig activity in Pen 1 on July 8, 2016. (b) Total occurrences of low, medium and high activity states during July 8 – July 14, 2016. (c) Daily count of low/medium/high activity levels. (d) Ratio of low/medium/high active movement state level.

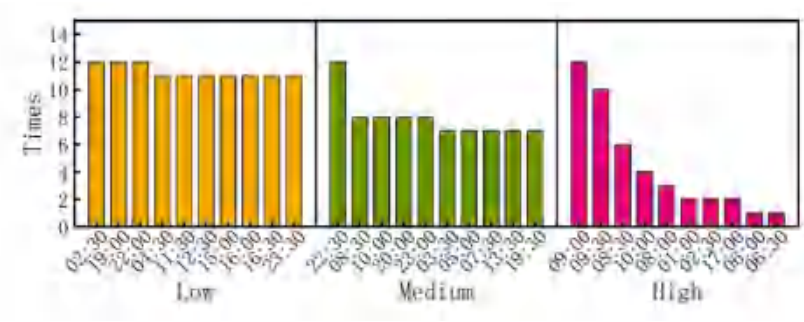
clearly see that when there are changes in the number of pigs or health issues arise, their behavioral patterns change. This change results in an increased error in prediction results. At the same time, the activity patterns of the group-housed pigs become more complex and unpredictable, making it harder for the SARIMA model to accurately capture their behavior. This discrepancy underscores the importance of regularly monitoring the health of group-housed pigs and analyzing their behavioral patterns in order to detect potential health problems early and take appropriate management and treatment measures in a timely manner.

5. Discussion

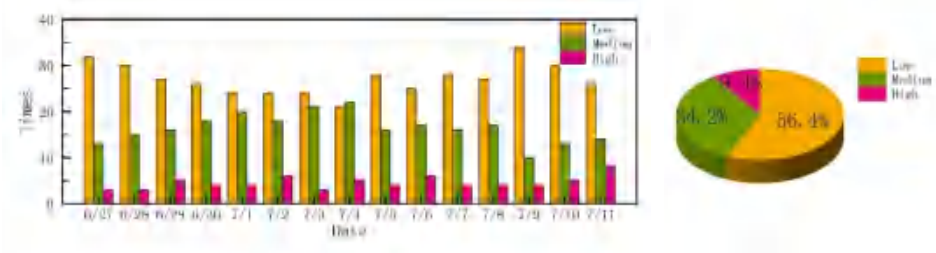
In this paper, we propose a new method for automatic quantifying and analyzing the activity levels of group-housed pigs based on instance segmentation. This method effectively overcomes the difficulties and inaccuracies associated with manual inspection and assessment of the movement of group-housed pigs by integrating deep learning and statistical techniques. In the following, we will delve into some of the key aspects of this method, including the factors that affect the results of the proposed algorithm, the limitations of the methodology, and potential applications of the algorithm and future directions.



(a)



(b)



(c) (d)

Fig. 17. (a)Time distribution of pig activity in Pen 2 on June 27, 2019 and July 11, 2019. (b) Total occurrences of low, medium and high activity states.(c) Daily count of low/medium/high activity levels. (d) Ratio of low/medium/high active movement state level.

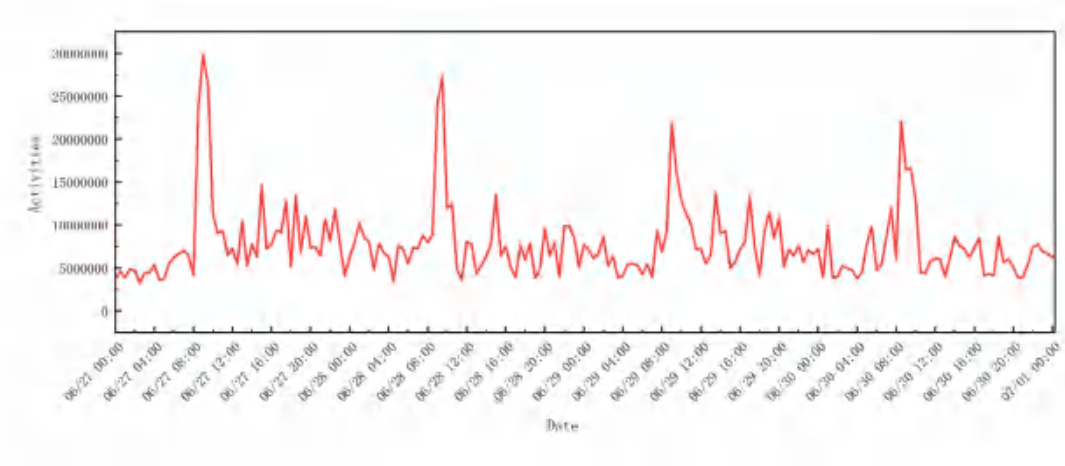


Fig. 18. Trend of activity of 7 pigs in Pen 2 from June 27th to July 1st, 2019.

Table 6
SARIMA time series model parameters and results.

Dataset	(p, d, q) (P, D, Q)	MAE	RMSE
Pen 1	(1,2,1)(3,0,0)	6.01	7.67
Pen 2(1:2)	(4,1,1)(2,0,0)	7.26	11.18
Pen 2(8:7)	(5,1,1)(0,0,1)	6.41	9.30

Table 7
Comparison of time series prediction results among different forecasting models.

Dataset	Model	MAE	RMSE
Normal	SARIMA	6.01	7.67
	XGBoost	6.95	9.16
	Random forests	8.15	11.14
	LSTM	16.45	18.69
	SVM	7.83	10.24
Abnormal	SARIMA	6.41	9.31
	XGBoost	8.56	12.77
	Random forests	8.31	11.92
	LSTM	14.31	16.64
	SVM	7.75	13.07

5.1. Factors affecting the results of this study

In this study, our model performs well in detecting and segmenting pigs. However, when dealing with the adhesion situations between pigs, the segmentation performance of the model still needs further improvement, as shown in Fig. 21. This may be due to noise in the video data (shown in Fig. 22) affects the segmentation effect of the model, subsequently affecting the accuracy of calculating the activity levels of group-housed pigs. To further improve the performance of instance segmentation model, we plan to implement the following strategies in our future research, such as data augmentation, noise reduction, fine-tuning and collect data from group-housed pig in multiple locations for training.

5.2. Multi-dimensional investigation of activity patterns for group-housed pigs

In this study, we deeply delved into the activity patterns of group-housed pigs under different healthy conditions. We found that the activity levels of healthy group-housed pigs exhibit a stable periodic pattern. However, when there were changes in the number or health status of group-housed pigs, their activity level fluctuations became more complex and dynamic.

Firstly, we investigated the activity patterns of group-housed pigs under different healthy conditions from the perspective of overall activity statistical analysis. It was found that under stable environments, changes in group-housed pigs activity levels follow intrinsic stable regularities. However, when influenced by external conditions or altered internal states, these stable patterns can exhibit dynamic shifts. A decrease in the number of pigs or an outbreak of disease within the group might lead to notable anomalies in activity levels (Madsen and Kristensen, 2005), such as a stark reduction in activity during peak feeding times or unexpected heightened activity in the early morning. These pronounced changes in behavior serve as potent early indicators of potential health issues (Clouard et al., 2022; Statham et al., 2009). This is very beneficial for us to understand the activity patterns of pigs and formulate more precise and customized farming strategies.

Secondly, from the perspective of activity level clustering, we analyzed the regularity of activity level changes for group-housed pigs at different times of the day under different healthy conditions. Generally, the daily activity patterns of group-housed pigs are very regular, with three different activity states evenly distributed throughout the day. This is consistent with the main behavioral activities of group-housed pigs. However, when the number of pigs decreases or their health changes, their activity levels may deviate from expectations, resulting in unconventional activity peaks. This may be related to impaired functions of the nervous and endocrine systems in disease states, leading to reduced motivation and abnormal activity patterns (Sutherland et al., 2007). Additionally, as can be seen in Fig. 17, the high activity states increased in the last two days instead. One possible explanation for this is that the relative spatial resources enjoyed by each pig within the pens increased due to a reduction in the number of pigs. This led to a decrease in competitive pressure within the pens, providing more space for each pig to move around and promoting autonomous activity and exploratory behavior. However, due to the limited sample size and narrow time span in this study, there may be certain biases or instabilities in the clustering results. Future research will focus on expanding sample sizes, lengthening observation periods, and creating models of anomaly detection to reveal behavioral nuances in situations such as changes in health status.

Finally, in order to explore more deeply the differences in activity levels of group-housed pigs under different healthy conditions in each time dimension, we used the SARIMA time series prediction model. As shown in Fig. 19, the SARIMA model can predict the periodic patterns and trends of activity levels in healthy group-housed pigs relatively well. However, our study relies on a video surveillance system to obtain activity data, which can be subject to a variety of interferences that can lead to inaccurate information on activity levels, which can adversely affect modeling. Additionally, when disease outbreaks occurred in pig groups, although the SARIMA model demonstrated an overall good fit, it exhibited overestimation issues during active peak periods, as shown in Fig. 20. This might be because the periodic patterns during peak activity times had changed. Disease might cause subtle changes in the cyclic activity patterns of group-housed pigs, while the SARIMA model was still predicting according to normal cyclic patterns, resulting in biased predictions at peak times (Cornou et al., 2008; Matthews et al., 2016). It

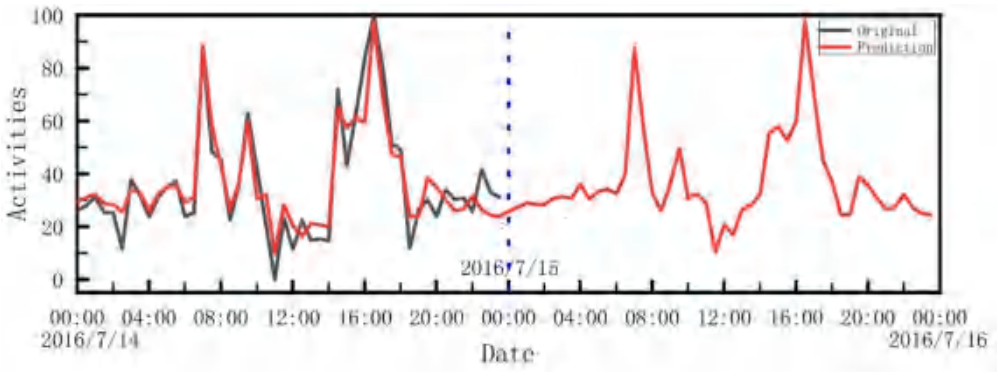
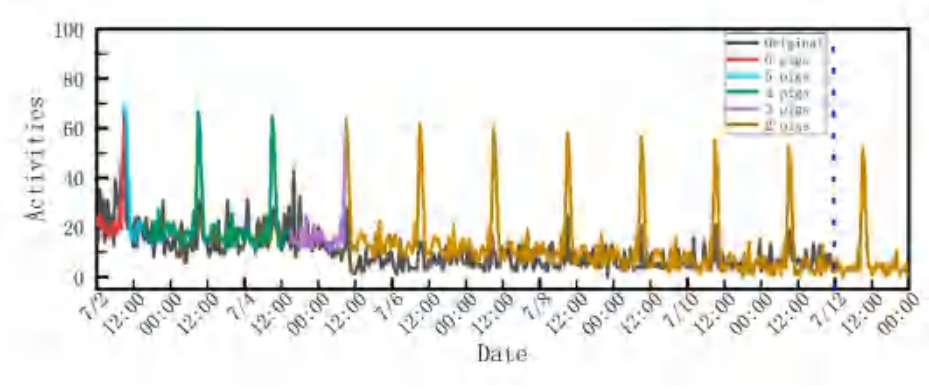
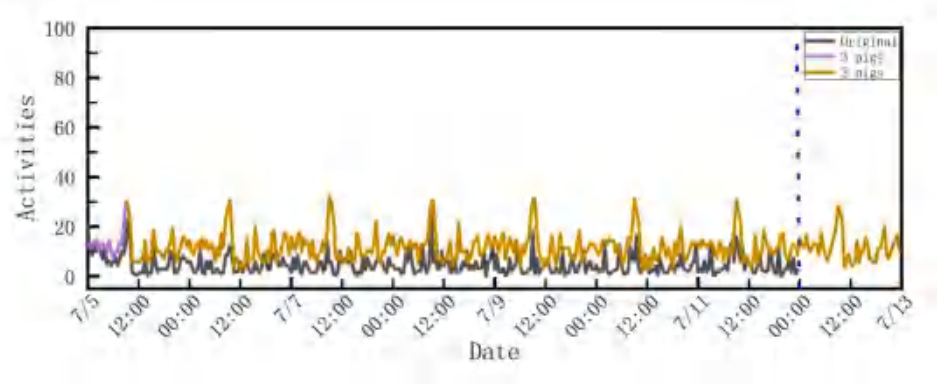


Fig. 19. Fitting and prediction results of the SARIMA (1,2,1)(3,0,0) model for the activity levels of the group-housed pig in Pen 1. (The part after the blue dotted line is the prediction data.).



(a)



(b)

Fig. 20. Fitting and prediction results of SARIMA models for the activity levels of the group-housed pigs in Pen 2. (a) SARIMA (4,1,1)(2,0,0) (X pigs represents predicted values when there were X pigs). (b) SARIMA (5,1,1)(0,0,1).



Fig. 21. Poor segmentation performance of model when pigs are in adhesion.

can be seen that when faced with variations in herd size or health conditions, modeling abnormal pig behavior through time series becomes challenging. Because the activity level of group-housed pigs is usually dynamic, relying on cycle patterns alone is not sufficient. Therefore, when constructing models, we should consider more factors that may affect the activity levels of group-housed pigs and enlarge the sample size while also optimizing video quality in order to improve the adaptability of models to dynamic changes.

5.3. Potential applications and future directions

Through the in-depth analysis in this study, we demonstrated the tremendous potential of using AI technologies for behavior monitoring and activity levels prediction in group-housed pigs. Applying this method to real-world scenarios can enable real-time monitoring of pig health, early detection and prevention of potential health issues. It can also optimize the operation and management of farms and improve the



Fig. 22. Noise in the video data.

overall health and productivity of the group-housed pigs.

Our method sheds light on deeper behavioral insights into group-housed pigs. Based on the available activity data, we can incorporate classification algorithms to identify and categorize different pig behaviors. As shown in Fig. 23, different behaviors such as feeding and resting have significantly different activity levels. In this way, we can gain a deeper understanding of the behavioral patterns and habits of group-housed pigs, and hopefully discover behavioral anomalies that may affect pig health.

However, the proposed methodology has its shortcomings. The segmentation model's accuracy is underwhelming, and the K-means classification might overlook intricate behavioral details. For prediction, the SARIMA model doesn't aptly handle nonlinear fluctuations. To address the issue, we can incorporate deep learning techniques in the prediction phase. Both Gradient Boosting Machine (Cai et al., 2020), Deep Reinforcement Learning (Francois-Lavet et al., 2019) and Temporal Convolutional Networks (TCN) can offer more accurate forecasting, especially when handling large volumes of activity data. Additionally, we might consider introducing other advanced models, such as random forest and Prophet model (Taylor and Letham, 2018), to further enhance prediction accuracy.

Conclusively, melding deep learning with cutting-edge predictive models holds significant promise for enhancing activity pattern analysis and health surveillance in group-housed pigs. Fortifying our existing methodology with these advanced techniques, we aim to offer a more robust and scientifically-grounded method for optimizing pig health management.

6. Conclusion

This paper proposed an automatic monitoring and anomaly alerting method applicable to long-term video monitoring.

(1) A pig segmentation model based on improved Mask R-CNN was built, augmented with the CBAM attention mechanism and CIoU loss function. The model achieved an accuracy of 98.7 % and a recall of 97.9 %, which can effectively identify pigs and enable automated monitoring of group-housed pigs.
(2) A frame difference method to extract motion information was implemented, thereby obtaining time series data of overall activity levels of the group-housed pigs. By applying the K-means clustering algorithm, we classified the activity levels and analyzed the characteristic activity patterns of group-housed pigs in different health conditions. During health changes, overall activity and medium–high activity frequencies reduced. This indicates that there are significant differences in the activity patterns of group-housed pigs in different states.
(3) Finally, the SARIMA model we constructed demonstrated excellent fitting performance. It not only accurately captured and predicted the periodic changes in the activity levels of group-housed pigs, but can also promptly identified anomalies in activity levels when there was decrease in pig numbers or a change in health. Specifically, under two different health conditions, the model's MAE was 6.01 and7.67, and the RMSE was 6.41 and 9.30, respectively. Therefore, by utilizing the SARIMA time series forecasting method, we can detect potential abnormal states earlier, enabling timely intervention and management.

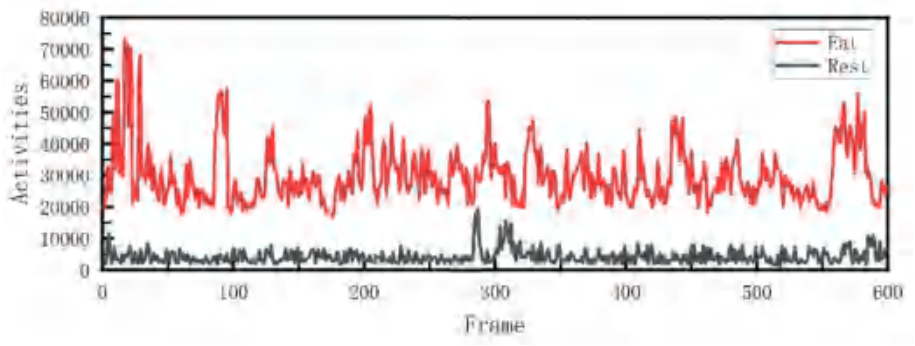


Fig. 23. Example of activity levels of group-housed pigs while feeding and resting (2 min video intercepted).

The results indicate that the method proposed in the paper can continuously, rapidly, and automatically monitor the activity and health status of group-housed pigs, understanding their health conditions. It overcomes the limitations of manual monitoring and offers livestock producers more effective management and decision-making support, enhancing the efficiency and economic benefits of pig breeding.

CRediT authorship contribution statement

Qiumei Yang: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. **Miaobin Chen:** Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Deqin Xiao:** Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Senpeng Huang:** Conceptualization, Project administration, Supervision. **Xiangyang Hui:** Software, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Animal ethical welfare statement

All of the animal experiments in this study were conducted in compliance with a protocol reviewed and approved by the Institutional Animal Care and Use Committee at South China Agricultural University.

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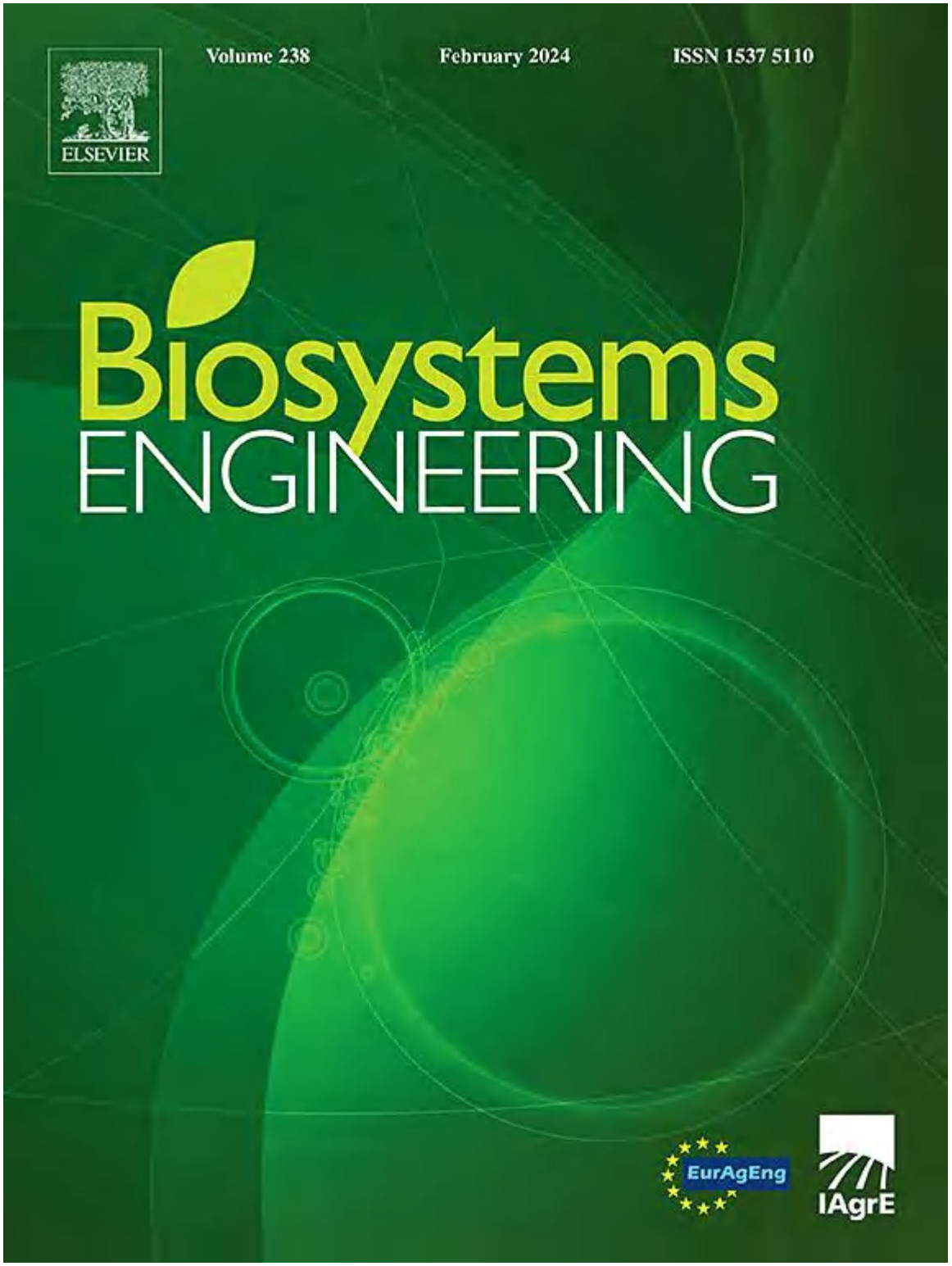
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Research Paper

Pig mounting behaviour recognition based on video spatialetemporal features

Qiumei Yang, Deqin Xiao, Jiahao Cai*

College of Mathematics and Informatics, South China Agricultural University, Guangzhou, Guangdong 510642, China

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The mounting behaviour of pigs is a symptom of oestrus and is also related to their welfare. It can be recorded by surveillance video, which is a kind of streaming data. This paper proposes a pig mounting behaviour recognition algorithm by exploiting video spatial etemporal features. First, a pig detector is constructed based on Faster ReCNN to locate the pig's body, head, and tail from the image frames. Then, the distance, the overlap area and the intersection angle between two pigs in a single frame are selected as the spatial features related to mounting behaviour. The changing rate of these variables in adjacent frames is considered as the temporal feature. Data mining methods are applied to handle these features and a classifier is built based on XGBoost for distinguishing pigs' mounting and non-mounting behaviour. Finally, for the video sequences, measures such as the merging of adjacent frames and noise filtering are taken to achieve a dynamic and continuous mounting behaviour recognition algorithm. The results show that the accuracy of our pig detector is 97% and the average accuracy of the pig mounting behaviour detection in videos is 95.15%, which can be effectively applied to the mounting behaviour recognition in the video sequence.

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1. Introduction

Accurate recognition of pig behaviours is important in smart livestock farming (Han, Zhang, Zhu, Wu, & Kong, 2017). In this way, useful information about pig breeding can be effectively extracted to assist in breeding decision-making. The recognition of pig mounting behaviour is helpful to detect the oestrus period of sows accurately and improve sows' reproductive performance, as studies have shown that there will be a significant increase in the mounting behaviour of sows before oestrus. In addition, when pigs are in a new or overcrowded environment, there can also be an increase in mounting behaviours. Therefore, effective detection of mounting behaviour can also be used as an indicator to help farmers to determine whether the pigs are in a comfortable status (Godyń et al., 2019).

Video surveillance can take the place of the traditional human observation, using image processing technologies to automatically identify the event that is happening on the farm. This has been widely applied in smart pig farming. A variety of image processing algorithms have been utilised to

* Corresponding author.
E-mail address: 18819447241@163.com (J. Cai).
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Nomenclature

Symbols

Dis_{ij}^{t}	the centre distance of the i-th pig and the j-th pig at time t
IoU_{ij}^{t}	the overlapping area of the i-th pig and the j-th pig at time t
q_{ij}^{t}	the intersection angle of the i-th pig and the j-th pig at time t
$DDis_{ij}^{t}$	the change in the centre distance of the i-th pig and the j-th pig from time t-1 to time t
$DIoU_{ij}^{t}$	the change in the overlapping area of the i-th pig and the j-th pig from time t-1 to time t
Dq_{ij}^{t}	the change in the intersection angle of the i-th pig and the j-th pig from time t-1 to time t

Abbreviations

CART	Classification and Regression Trees
CNN	convolutional neural network
Faster ReCNN	an object detection algorithm
NVR	Network Video Recorder
RPN	region proposal network
SMOTE	Synthetic Minority Oversampling Technique
XGBoost	eXtreme Gradient Boosting

automatically identify pigs from images and recognise their behaviours. Otsu algorithm has been used to binarise images to get the outline of pigs and to study their locomotion behaviour (Kashiha et al., 2014; Lu et al., 2016; Xiao, Feng, & Liu, 2019) and was suitable for scenes where the colour of the pig's body was significantly different from the background. Pig locomotion could also be quantified by the image activity index (Costa, Ismayilova, Borgonovo, Viazzi, & Guarino, 2014). The different behaviours of pigs, such as aggressive behaviour and imminent farrowing behaviour, could be recognised through their locomotion (Küster et al., 2020; Oczak et al., 2014). Some classic object tracking algorithms, such as Kalman filter tracking (Yu, Chen, Ou, & Zhou, 2015), correlation filter-based tracking (Sun et al., 2018; Zhang, Gray, Ye, Collins, & Allinson, 2019), deep simple online and real-time tracking (Deep SORT) (Cowton et al., 2019), have been applied to track pigs through video sequences and to analyse the motion of pigs. The postural behaviour of pigs, such as lying and standing, have been detected using image classification algorithms (Kim et al., 2017; Nasirahmadi et al., 2019). Some area-related behaviours, such as drinking and feeding, have been recognised by the relationship between the heads of pigs and the corresponding functional area (Kashiha et al., 2013; Yang, Xiao, & Lin, 2018). Some special behaviour of sows, such as nursing behaviour, have been studied by Faster ReCNN and FCN (Yang et al., 2018; Zheng et al., 2018). There have also been related research on mounting behaviour recognition. Pigs have been detected by background subtraction and the distance between the pigs' bodies was used to recognise mounting behaviour (Nasirahmadi, Hensel, Edwards, & Sturm, 2016). Mask ReCNN has been applied to segment video images, and the kernel-extreme learning machine (KELM) has been used to determine whether mounting behaviour occurred or not (Li, Chen, Zhang, & Li, 2019). For cows, the specific regions have been detected by colour and texture features, and then the geometric and optical flow characteristics of that region were extracted as the input to an SVM classifier, thereby detecting cow mounting behaviour (Guo, Zhang, He, Niu, & Tan, 2019).

The features used for pig behaviour recognition can be classified into hand-crafted features and deep convolutional features. The hand-crafted features are designed based on the object's colour, textures, shape, etc. The deep convolutional features are generated by deep neural network models. The latter approach is less affected by light, posture, etc., and has given better classification results. Therefore, it has gradually become the mainstream method of behaviour recognition. Video is a collection of consecutive frames. In addition to the spatial features from image granularity, video-based behaviour recognition can also utilise temporal features between frames. The SlowFast-based spatial temporal convolutional network has been applied to classify pig behaviours, including feeding, lying, motoring, scratching and mounting behaviour (Li, Zhang, Li, & Chen, 2020). Two-stream convolutional neural networks have also been used to extract spatialetemporal features from pig farm videos (Zhang, Li, Huang, & Chen, 2020). Spatialetemporal features are crucial in pig behaviour recognition. A novel pig mounting behaviour recognition algorithm is proposed based on the fusion of video spatialetemporal features in this paper. The algorithm considers not only the relationship between pigs but also how the feature changes over time.

2. Materials and methods

2.1. Animals and housing

A modern pig production base of Guangzhou Lizhi Agricultural Co., Ltd. was selected to carry out our experiment. The pig farm is located in Luogang District, Guangzhou. The size of the selected pigpen was 4 m × 5 m. In order to record the entire pigpen day and night, a Haikang infrared network camera (DS-2CD3345-I, Hikvision, Hangzhou, China) with a focal length of 2.8 mm was selected. To prevent the situation in which pigs were occluded by others, the camera was placed on the ceiling to get a top-view image of the pigpen. The frame rate of the camera was 25 fps and the resolution is 2560 × 1440. Each frame was expressed in RGB colour space. The video captured was stored locally in the pigpen using a Network Video Recorder (NVR, DS-7804N-K1/C, Hikvision, Hangzhou, China) (Fig. 1).

The breed of the pigs raised in the pigpen during the experiment was Landrace. Since the colour of each pig was the same and there was not much difference in their appearances, it was difficult to distinguish them. To make it easier to identify individual pigs, we manually drew a letter on the back of ech pig. There were a total of 4 pigs, marked as A, B, C and D. When the marks fade, it would be repainted in the original position. The letters on the pig's back would be used as part of

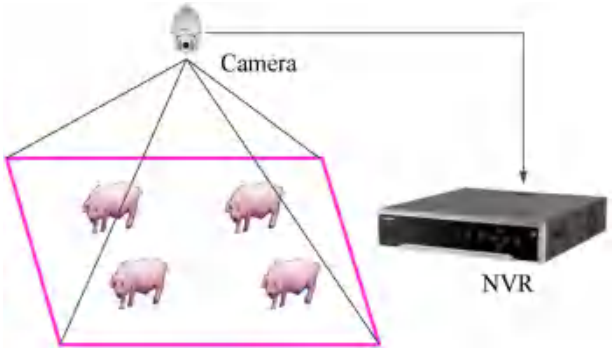


Fig. 1 e The experimental deployment. The camera was set directly above the pig pen and the video data was store in a NVR.

its appearance and used to distinguish different pigs during image detection.

2.2. Video data acquisition

2.2.1. Data collection

The video was recorded 24 h per day from July 8, 2016 to August 6, 2016. A total of 30 days of video data were collected. The pigpen was open around, and curtains could be put down to block the light. It was illuminated by natural light during the day time and generally no light at night. Only the video taken during the daytime under natural light was selected for the data analysis. A sample frame of the collected video is shown in Fig. 2.

Since pigs sleep for most of the night, only the daytime video was selected for pig mounting behaviour recognition. For the purpose of machine learning for pig detection, some images were randomly grabbed from the video to build a pig image data set. Meanwhile, video clips of the pig mounting behaviour were picked out from the massive surveillance video to build a mounting behaviour video data set. For each video clip, the start frame, the end frame, and the pigs associated with the mounting behaviour were marked out manually.



Fig. 2 e A top view image of the entire pig pen was captured. It could reduce occlusion, and could clearly capture the identity mark on the pig's back.

2.2.2. Experimental data set

In order to construct a pig detector, the pig image data set needs to be manually labelled. Six labels, namely A, B, C, D, head and tail, are defined. A, B, C and D are used to represent the 4 pigs in the pen respectively. LabelImg software is used to label images in the data set and generate data in PASCAL VOC format (Everingham et al., 2015). The sample of data labelling is shown in Fig. 3.

A data set with a total of 1000 images and 12,000 labels was constructed for pig and body part detection, as shown in Table 1.

To improve the generalisation ability of the detector, we sampled one frame per second instead of processing all the frames of the video sequence. A data set was constructed from the sampled images. Data augmentation, such as image flip, was applied to enrich the sample set.

A pig mounting behaviour data set was constructed too. We extracted different pig pairs from the image frames, including mounting and non-mounting pig pairs. These pig pairs were be used to distinguish between mounting and non-mounting behaviours. Since the number of mounting samples (positive) is much smaller than the number of non-mounting samples (negative) in practise, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to balance the number of positive and negative samples (Chawla et al., 2002). The basic idea of the SMOTE algorithm is to analyse minority samples and artificially synthesise new samples, based on minority samples, and add them to the data set. The final data set is shown in Table 2.

2.3. Pig mounting behaviour recognition algorithm

2.3.1. Definition of mounting behaviour

A mounting behaviour generally involves two pigs. From the surveillance video, it can be observed that a mounting behaviour usually started by one pig, which can be called the initial pig. It gradually approached another pig, which can be called the mounted pig, and then placing its foreleg span on it. The mounting behaviour lasts for a period. When the mounting pig moves its foreleg away from the mounted pig, the mounting behaviour ends.

We set the frame when one pig's front part was firstly placed on the other pig's body as the start of the mounting and the frame when the two pigs were completely separated was

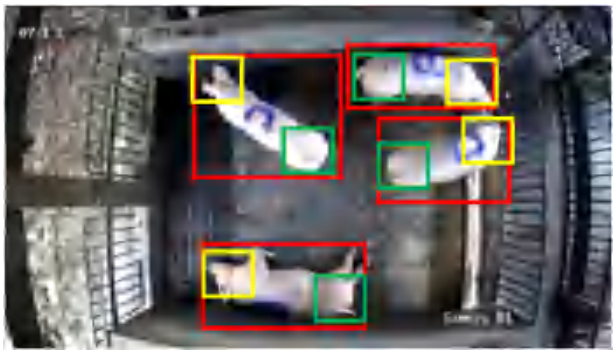


Fig. 3 e Image labelling. Each pig is labelled with its identity, head, and tail.

Table 1 e Data set for pig detection.

	Image	A	B	C	D	Head	Tail
Training	800	800	800	800	800	3200	3200
Testing	200	200	200	200	200	800	800
Total	1000	1000	1000	1000	1000	4000	4000

Table 2 e Data set for pig mounting behaviour classification.

	Original	After SMOTE Training	Testing
Mounting (positive)	674	20848	162
Non-mounting (negative)	27801	20848	6576
Total	28475	41696	6738

considered to be the end of the mounting. According to our observations from the video, the longest mounting behaviour lasted for 63 s, and mounting behaviour that lasted less than 2 s was considered to be general random behaviour among pigs. Therefore, we set the maximum duration of the mounting behaviour to 120s and the minimum duration to 2s. Any mounting behaviour that did not meet this condition was ignored.

The occurrence of mounting behaviour can be described by the changes in the spatialetemporal relationship between the initial pig and the mounted pigs. From the spatial perspective, a pig's body can be divided into different parts, including the head, back, and tail. The distance, the intersection angle, and the overlapping area of different parts between two interacting pigs can be considered. From the temporal perspective, the change of each variable over time is also very important for behaviour recognition.

2.3.2. Pig mounting behaviour recognition based on spatialetemporal features

In a video sequence, a mounting behaviour happens not just in a single frame but a series of consecutive frames. We propose a mounting behaviour recognition algorithm for pigs based on spatialetemporal features. According to the definition of the mounting behaviour between two pigs, to recognise a mounting behaviour, pigs must first be detected in each frame of the surveillance video. A pig detector based on Faster ReCNN is proposed to detect each pig, as well as its head and tail. Then we explore which spatialetemporal features are related to the occurrence of mounting behaviour. The framework of the algorithm is shown in Fig. 4.

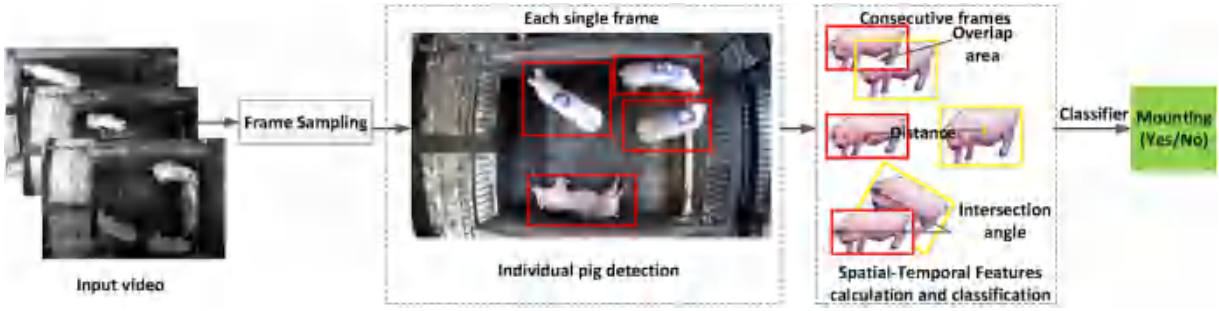


Fig. 4 e The framework of pig mounting behaviour recognition.

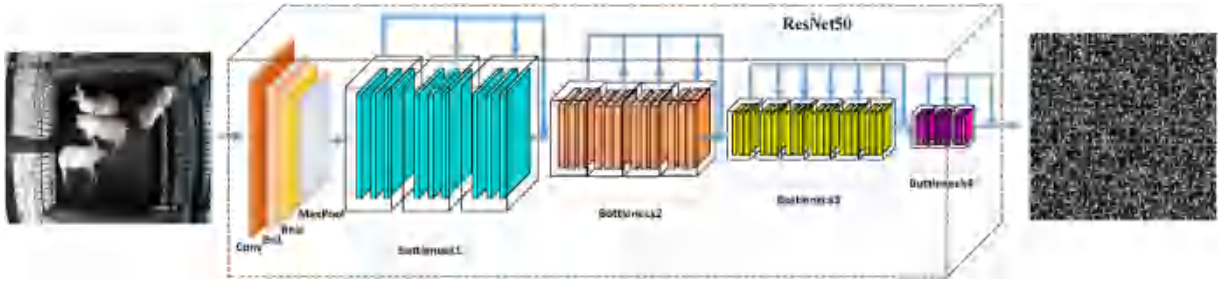


Fig. 5 e Convolutional feature extraction. Images were fed into ResNet50 to generate depth convolutional features, which would be applied to the classification task.

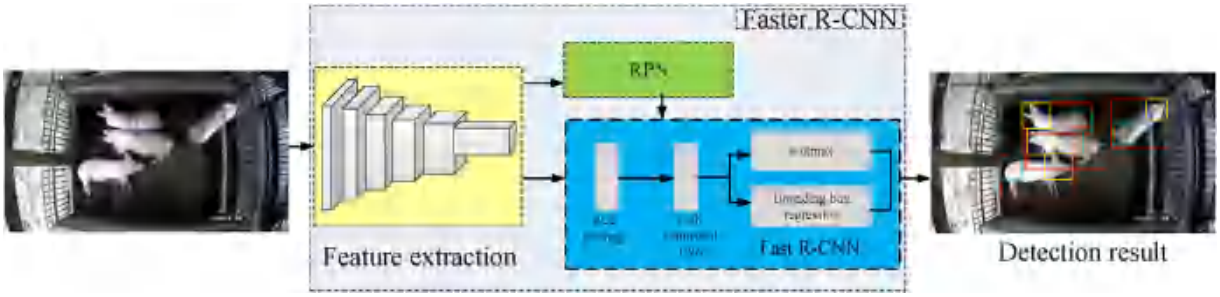


Fig. 6 e The structure of our pig detector. The input image is subjected to feature extraction, region proposal, and classification, then finally the detection result is obtained.

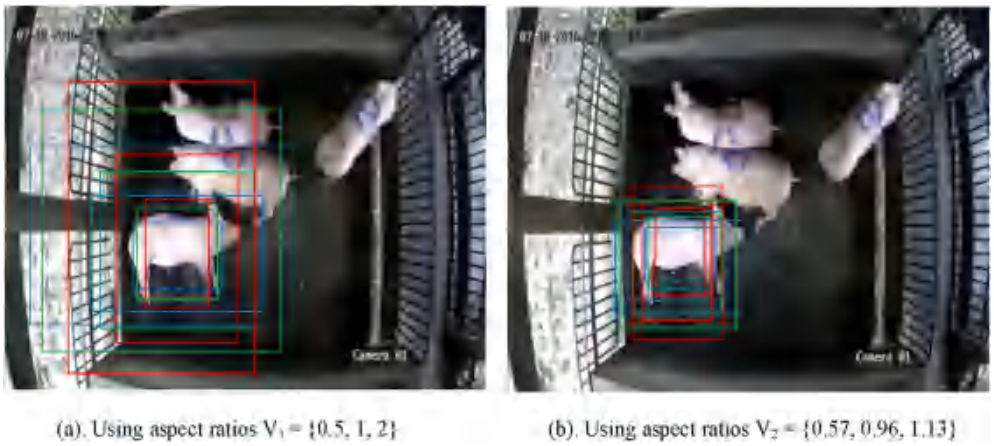


Fig. 7 e The comparison of using different aspect ratios. (a)When using the default aspect ratio, it cannot fit the pigs well. (b) When using the aspect ratios we proposed, it can fit the pigs better.

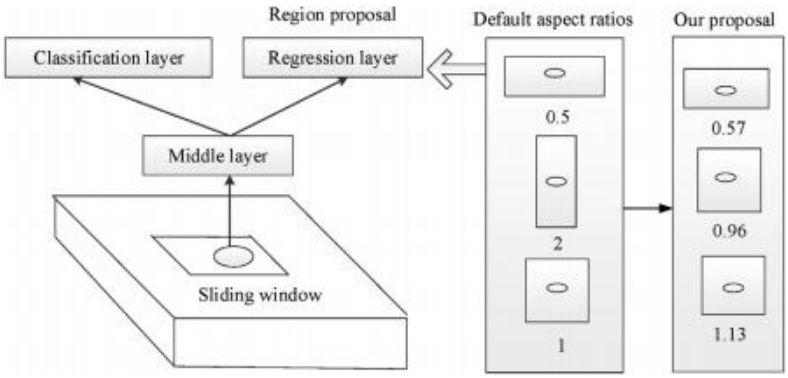


Fig. 8 e The RPN proposed in our pig detector. We have replaced the aspect ratios to better fit the pig detection problem.

Algorithm for associating pig's body with its head and tail

Input: The result of Faster R-CNN, i.e. bounding box for pigs' body, head, and tail

Output: Pig tuple

1. for $body_i$ in bodys:
2. $pig_i \leftarrow body_i,\ IoU_{max} = 0,\ Max = 0$
3. for $head_i$ in heads:
4. $IoU_i \leftarrow (head_i \cap body_i)/(head_i \cup body_i)$
5. $if\ IoU_i > IoU_{max}$
6. $IoU_{max} = IoU_i,\ Max = i$
7. End for
8. $pig_i \leftarrow pig_i + head_i$
9. $IoU_{max} = 0,\ Max = 0$
10. for $tail_i$ in tails:
11. $IoU_i \leftarrow (tail_i \cap body_i)/(tail_i \cup body_i)$
12. $if\ IoU_i > IoU_{max}$
13. $IoU_{max} = IoU_i,\ Max = i$
14. End for
15. $pig_i \leftarrow pig_i + tail_i$
16. End for

3. Implementation of the pig mounting behaviour recognition algorithm

3.1. Pig detection based on Faster ReCNN

3.1.1. Construction of the Faster ReCNN network

Faster ReCNN is a region-based target detection algorithm and has a wide range of applications in various target detection tasks (Ren, He, Girshick, & Sun, 2017). It is suitable for the detection of complex targets. A pig detector based on Faster ReCNN is built in this paper. A pre-trained model ResNet is chosen for convolutional feature extraction (He et al., 2016). In order to solve the problem of decreasing accuracy as the number of network layers increases, identity mapping and residual mapping are proposed in ResNet and great performance can be achieved on object detection and classification. ResNet50 is applied in this paper. The feature extraction process is shown in Fig. 5.

The feature maps obtained by ResNet50 are input into the region proposal network (RPN) and object detection network Fast ReCNN. The RPN is a fully connected neural network for extracting candidate boxes, and Fast ReCNN is used to detect and identify the targets in the candidate boxes extracted by RPN. The structure of the detector is shown in Fig. 6.

3.1.2. Training procedure of the Faster ReCNN based pig detector

In the training period, 80% of the images in the dataset are randomly chosen as a training set and the other 20% are used as a testing set. Parameters of the two networks, RPN and Fast ReCNN, are fine-tuned during the training procedure. The training procedure is divided into 4 steps.

Step 1. The RPN is initialised with the ResNet50 pre-trained model and then trained by the training data. After training, the parameters of the ResNet50 and the RPN will be updated.

Step 2. The Fast ReCNN is initialised with the ResNet50 pre-trained model and then trained using proposals generated by the trained RPN in step 1. After training, the parameters of the ResNet50 and the Fast ReCNN will be updated.

Step 3. The RPN is initialised with the ResNet50 model updated in step 2 and then trained again by the training data. Only the parameters of the RPN will be updated.

Step 4. The Fast ReCNN is initialised with the ResNet50 model updated in step 2 and then trained again using proposals generated by the trained RPN in step 3. Only parameters of the Fast ReCNN will be updated.

When training the RPN, anchor boxes will be generated to predict the region of objects to be detected. There are three default aspect ratios $V_1 = \{0.5, 1, 2\}$. In order to adapt to the detection of pigs, K-means clustering algorithm is applied to the statistics of the aspect ratios of pigs in the image. Three aspect ratios $V_2 = \{0.57, 0.96, 1.13\}$ are selected to replace the default values. The comparison of using different aspect ratios is shown in Fig. 7. It can be seen that our proposed method works better. The improved RPN structure is shown in Fig. 8.

3.2. Pig mounting behaviour recognition

3.2.1. Calculation of the variables related to mounting behaviour

After the detection procedure, the body, head, and tail of each pig can be located by a bounding box (x, y, w, h), where x, y, w, and h denote the two coordinates of the box centre, width, and height. In some cases, some of the targets may not be detected due to object occlusion. An algorithm is designed to associate each pig's body with its head and tail.

After that, we define a triple to represent each pig. Each element in the triple is a bounding box detected by our pig detector, if not detected, it will be represented by a null value.

$$\text{pig} \nearrow (\text{body}; \text{head}; \text{tail})$$

Several variables, such as the distance, overlap ratio, intersection angle of two pigs, and the changing rate of each of them, are defined to represent the spatialetemporal features related to pig mounting behaviour recognition.

Dis_{ij}^t is defined to represent the centre distance of the i-th pig and the j-th pig at time t. $DDis_{ij}^t$ is defined to represent the change in the centre distance of the i-th pig and the j-th pig from time t-1 to time t.

$$Dis_{ij}^t = \sqrt{\left(x_i^t - x_j^t\right)^2 + \left(y_i^t - y_j^t\right)^2}$$

$$DDis_{ij}^t = \left|Dis_{ij}^t - Dis_{ij}^{t-1}\right|$$

IoU_{ij}^t is defined to represent the overlapping area of the i-th pig and the j-th pig at time t. $DIoU_{ij}^t$ is defined to represent the change in the overlapping area of the i-th pig and the j-th pig from time t-1 to time t.

$$IoU_{ij}^t = \frac{Boundingbox_i^t \cap Boundingbox_j^t}{Boundingbox_i^t \cup Boundingbox_j^t}$$

$$DIoU_{ij}^t = \left|IoU_{ij}^t - IoU_{ij}^{t-1}\right|$$

q_{ij}^t is defined to represent the intersection angle of the i-th pig and the j-th pig at time t. Dq_{ij}^t is defined to represent the change in the intersection angle of the i-th pig and the j-th pig from time t-1 to time t. A vector $\overrightarrow{p}$ is used to indicate the direction of a pig. If the head of a pig is detected, $\overrightarrow{p}$ is a vector that points from the centre of the pig's body to the centre of its head. Otherwise, $\overrightarrow{p}$ is a vector that points from the centre of the pig's tail to the centre of its body.

Algorithm for pig mounting behaviour recognition

Input: The detection result of the video frames by our pig detector

Output: The time period during which the mounting behaviour occurred

1. Calculate the value of each variables, Dis_{ij}^{t}, ΔDis_{ij}^{t}, IoU_{ij}^{t}, ΔIoU_{ij}^{t}, θ_{ij}^{t}, $\Delta\theta_{ij}^{t}$

2. Multiply all the variables in pairs to get the cross features

3. Calculate the Pearson Correlation Coefficient between each feature and the mounting behaviour, then select the features with the top correlation

4. Construct an XGBoost classifier with the selected features as input and train

5. Use the trained XGBoost classifier to determine whether there is a mounting behaviour between any two pigs in the sample frames of the video

6. Merge the adjacent frames with mounting behaviour detected in each video and form the union of frames (f_1,f_2...,f_m) that represent a same mounting behaviour, where f_1 denotes the begin frame and denotes f_m the end frame

7. For each union that represents a mounting behaviour, if the time interval between the end time of the previous one and the start time of the next is less than 20s, it is considered to be the same mounting behaviour, so merge the two unions into one

8. Filter: Delete all the detected mounting behaviours that last less than 2s

$$q_{ij}^{t} = \vec{p}_i^{\,t} \times \vec{p}_j^{\,t} \Big/ \left(\left| \vec{p}_i^{\,t} \times \vec{p}_j^{\,t} \right| \right)$$

$$Dq_{ij}^{t} = \left| q_{ij}^{t} - q_{ij}^{t-1} \right|$$

3.2.2. Implementation of pig mounting behaviour algorithm

We sample at a rate of 1 frame per second from the video sequences. For each sampled frame, the pig detector obtains the location of each pig, which is used to calculate the features related to mounting behaviour recognition.

Intuitively, a mounting behaviour is related to the variables we define, but it is difficult to determine which features play a decisive role. Hence we apply a feature selection method based on Pearson's correlation coefficient. Feature Selection is a method to remove redundant and useless features from the existing feature set, and select a decisive feature subset. In such a way we can improve the classification performance. The Pearson correlation coefficient is used to determine the degree of correlation between features and results. Its value range is

Table 3 e Evaluation of our pig detector.

	IoU ≥ 0.7	IoU ≥ 0.8	IoU ≥ 0.9
A	1.00	0.99	0.90
B	1.00	0.99	0.91
C	0.99	0.97	0.90
D	1.00	0.98	0.89
head	0.94	0.87	0.78
tail	0.95	0.89	0.77
Average	0.97	0.92	0.82

Table 4 e Person correlation coefficient between each feature and mounting behaviour.

	Dis_{ij}^{t} [a]	$DDis_{ij}^{t}$ [b]	IoU_{ij}^{t} [c]	$DIoU_{ij}^{t}$ [d]	q_{ij}^{t} [e]	Dq_{ij}^{t} [f]
Dis_{ij}^{t}	−0.21	−0.03	0.32	0.09	−0.12	−0.04
$DDis_{ij}^{t}$	−0.03	0.03	0.23	0.05	0.04	0.01
IoU_{ij}^{t}	0.32	0.23	0.43	0.21	0.50	0.24
$DIoU_{ij}^{t}$	0.09	0.05	0.21	0.15	0.16	0.08
q_{ij}^{t}	−0.12	0.04	0.50	0.15	0.05	0.03
Dq_{ij}^{t}	−0.04	0.01	0.24	0.08	0.03	0.03

[a] The centre distance of the i-th pig and the j-th pig at time t.
[b] The change in the centre distance of the i-th pig and the j-th pig from time t-1 to time t.
[c] The overlapping area of the i-th pig and the j-th pig at time t.
[d] The change in the overlapping area of the i-th pig and the j-th pig from time t-1 to time t.
[e] The intersection angle of the i-th pig and the j-th pig at time t.
[f] The change in the intersection angle of the i-th pig and the j-th pig from time t-1 to time t.

[−1,1], where a positive value indicates a positive correlation, a negative value indicates a negative correlation, and a larger absolute value indicates a higher degree of correlation.

After the features have been selected, an XGBoost classifier is constructed to distinguish between mounting frames and non-mounting frames. XGBoost is a boosting algorithm based on regression tree (Chen et al., 2016). The idea of the boosting algorithm is to integrate many classifiers to form a stronger classifier. Since XGBoost is a boosted tree model, it integrates many tree models. The tree model used here is the CART regression tree model.

The procedure of the pig mounting behaviour recognition algorithm is as follows.

4. Results and discussion

4.1. Results

4.1.1. Evaluation of the Faster ReCNN based pig detector

The pig detector needs to precisely locate the target, which is critical for the calculation of the spatialetemporal feature value. IoU is used to evaluate the accuracy of the detection results. It defines the overlap degree of the bounding box between the detection result and the ground truth value. Generally, when the IoU exceeds 70%, it can be considered as a correct detection. However, because the precision of the bounding box is related to mounting behaviour recognition, we have specifically studied the cases when the IoU is up to 80% and 90%. The result is shown in Table 3.

Table 5 e The confusion matrix of the XGBoost mounting behaviour classifier.

		Predictive value	
		non-mounting	mounting
Ground Truth	non-mounting	6576	0
	mounting	31	131

Table 6 e Detection results of mounting behaviour in videos.

Video number	Original detection result	After merge	After filter	Truth value	Accuracy
1	[[402, 419], [670, 717]]	[[402, 419], [670, 717]]	[[402, 419], [670, 717]]	[[402, 419], [670, 717]]	1.0
2	[[896, 912]]	[[896, 912]]	[[896, 912]]	[[895, 914]]	0.84
3	[[725, 743], [745, 746]]	[[725, 746]]	[[725, 746]]	[[725, 746]]	1.0
4	[[0, 8], [13, 14], [27, 31], [33, 50], [53, 58], [59, 60]]	[[0, 60]]	[[0, 60]]	[[0, 62]]	0.97
5	[[468, 473], [475, 478]]	[[468, 478]]	[[468, 478]]	[[468, 480]]	0.83
6	[[603, 605], [606, 613], [615, 616], [621, 626], [627, 628], [629, 631], [634, 637], [642, 649]]	[[603, 649]]	[[603, 649]]	[[603, 650]]	0.98
7	[[180, 210], [211, 220]]	[[180, 220]]	[[180, 220]]	[[179, 222]]	0.93
8	[[1115, 1129]]	[[1115, 1129]]	[[1115, 1129]]	[[1115, 1129]]	1.0
9	[[0, 9], [11, 13], [15, 17], [19, 67]]	[[0, 67]]	[[0, 67]]	[[0, 67]]	1.0
10	[[468, 474]]	[[468, 474]]	[[468, 474]]	[[468, 475]]	0.85
11	[[615, 624], [625, 628], [629, 641], [642, 645], [646, 647], [649, 652], [653, 654], [655, 656], [657, 662]]	[[615, 662]]	[[615, 662]]	[[615, 662]]	1.0
12	[[180, 195]]	[[180, 195]]	[[180, 195]]	[[179, 195]]	0.94
13	[[447, 466]]	[[447, 466]]	[[447, 466]]	[[445, 467]]	0.86
14	[[920, 938]]	[[920, 938]]	[[920, 938]]	[[920, 938]]	1.0
15	[[486, 500]]	[[486, 500]]	[[486, 500]]	[[486, 500]]	1.0
16	[[96, 97], [100, 101]]	[[96, 101]]	[[96, 101]]	[[95, 101]]	0.83
17	[[400, 417]]	[[400, 417]]	[[400, 417]]	[[400, 417]]	1.0
18	[[530, 559]]	[[530, 559]]	[[530, 559]]	[[530, 559]]	1.0
19	[[224, 225], [226, 227]]	[[224, 227]]	[[224, 227]]	[[224, 227]]	1.0
20	[[615, 627]]	[[615, 627]]	[[615, 627]]	[[615, 627]]	1.0

Table 7 e Detection results of mounting behaviour on a day.

Pig pairs	The number of mounting events (Truth)	The number of mounting events (Detected)	The average duration of each mounting events (Truth)	The average duration of each mounting events (Detected)	The total duration of mounting on a day (Truth)	The total duration of mounting on a day (Detected)
A&B	7	8	17.28	15.37	121	123
A&C	5	5	4.8	4.8	24	24
A&D	11	14	15.27	12.42	168	174
B&C	6	8	9.83	8	59	64
B&D	6	6	9.33	9.33	56	56
C&D	7	10	15.14	10.9	106	109



Fig. 9 e A missed detection of pigs. Pig D was not detected because the letter on its back was blocked by Pig C. Therefore, the mounting behaviour between pig C and D cannot be detected.

4.1.2. Evaluation of the pig mounting behaviour recognition algorithm

The Person correlation coefficient between each feature and mounting behaviour is shown in Table 4. The value of the (i, j) element in the table represents the Person value of the cross feature obtained by multiplying the i-th feature and the j-th feature.

Features with a Pearson absolute value greater than 0.2 are selected for the training of the XGBoost mounting behaviour classifier, which solves a binary class problem with mounting being the positive class and non-mounting as the negative class. The parameters for training XGBoost classifier is set as {'booster':'gbtree', 'objective':'binary:logistic', 'verbosity':3, 'eval_metric':'auc', 'max_depth':6, 'lambda':10, 'subsample':0.75, 'colsample_bytree':0.75, 'min_child_weight':0.5, 'eta':0.025, 'seed':0, 'nthread':8, 'silent':1}.

The confusion matrix of our XGBoost mounting behaviour classifier is shown in Table 5. The classifier achieves an accuracy of 99.5% and a recall rate of 80.9%。

After the XGBoost mounting behaviour classifier has been trained, it is used to recognise the mounting behaviour of videos. A total of 20 video clips of mounting behaviour are tested and the result is shown in Table 6. The average accuracy for pig mounting behaviour recognition in the videos is 95.15%.

Table 8 e Comparison of our algorithm and the result before optimisation. The detection accuracy of the 20 video clips in Table 6 without optimisation.

Video number	Accuracy (Our algorithm)	Accuracy (Without the Pearson correlation coefficient filter)	Accuracy (Without SMOTE optimisation)
1	1.0	0.75	0.60
2	0.84	0.85	0.60
3	1.0	0.90	0.61
4	0.97	0.85	0.76
5	0.83	0.74	0.41
6	0.98	0.7	0.82
7	0.93	0.89	0.61
8	1.0	0.88	0.71
9	1.0	0.94	0.72
10	0.85	1.0	0.23
11	1.0	0.76	0.89
12	0.94	0.89	0.64
13	0.86	0.85	0.69
14	1.0	0.78	0.64
15	1.0	0.82	0.65
16	0.83	0.75	0.24
17	1.0	0.89	0.53
18	1.0	0.87	0.57
19	1.0	0.9	0.43
20	1.0	0.83	0.67

In order to further evaluate our algorithm, we use it to detect the mounting behaviour of long-term video data. A consecutive video that lasted for 12 h, from 6:30am to 6:30pm, representing a whole daytime, is selected. The number of mounting events and the total mounting duration on that day are calculated. The result is shown in Table 7.

4.2. Discussion

In contrast to the existing algorithms for detecting pig mounting behaviour based on pig contour, an object detection method is used in this paper. Contour is a pixel-level description of an image, which gives meaning to each pixel. Object detection only needs to provide the category and location of the target, which is usually denoted by a bounding box. Object detection is simpler and more time-saving than contour segmentation. More importantly, individual pig identification is achieved through object detection in this paper, which makes it possible to find out exactly which pig performs the mounting behaviour. Whether the bounding box

can precisely represent the boundary of the pig directly affects the consequent pig mounting behaviour recognition effect. In this paper, an improved RPN structure is proposed in the pig detector to obtain a more precise bounding box result for pigs. It can be seen from the experimental results (Table 3) that 97% of the detection results have an IoU that exceeds 70%. But there is still room for improvement since only 82% of the detection results have an IoU that exceeds 90%. When there are adhesion and occlusion between pigs, the model is likely to make mistakes about the identity of the pigs. As shown in Fig. 9, the missed detection of pig D will lead to the missed detection of the mounting behaviour between pig C and pig D.

The distance, the overlap area and the intersection angle between two pigs are selected as the spatial features related to the mounting behaviour. The changing rates of these three features between adjacent frames are used as temporal features related to the mounting behaviour. From the Pearson correlation coefficient, it can be seen that the cross feature obtained by multiplying the overlap area and the intersection angle is most related to the mounting behaviour, which is consistent with what we have observed from the appearance of the mounting behaviour. The SMOTE algorithm and the Pearson correlation coefficient have significantly improved the overall effect of mounting behaviour classification. The main function of SMOTE is to balance the positive and negative samples. The Pearson correlation coefficient can help to filter out the more representative features. Without such optimisation, the accuracy of our algorithm will decrease, as shown in Table 8.

From our final detection results of streaming videos (Table 6), we can see that our algorithm can recognise most of the mounting behaviours. Some videos are not well detected mainly due to occlusion between pigs, which leads to the failure of individual pig detection. Thereafter, it leads to the missed detection of some frames in the subsequent mounting behaviour recognition algorithm. Some of the true frames are regarded as noise and filtered out.

When pigs are in oestrus, their behaviour will change. Mounting behaviour is one of the most commonly features to represent oestrus behaviour. Pedersen (2007) found that sows' mounting behaviour gradually increased 2e3 days before oestrus, and some sows were observed to perform mounting behaviour more than 40 times a day before oestrus. Therefore, if the number of mounting behaviours can be automatically recorded every day, it could play an important role in accurate oestrus detection.

5. Conclusion

A novel pig mounting behaviour recognition algorithm based on video spatialetemporal features is proposed and implemented in this paper. The algorithm explores the features that related to the recognition of mounting behaviour in video sequences, including the distance between pigs, their overlap area and intersection angle, and the change value of these features in video time series. A pig detector based on Faster ReCNN and a classifier of mounting behaviour recognition based on XGBoost have been built. The accuracy of the pig detector is 97% and the average accuracy of pig mounting behaviour recognition in videos is 95.15%. The algorithm achieves the automatic extraction of useful information for pig farming from streaming video data. It can provide a basis for decision-making in pig farming.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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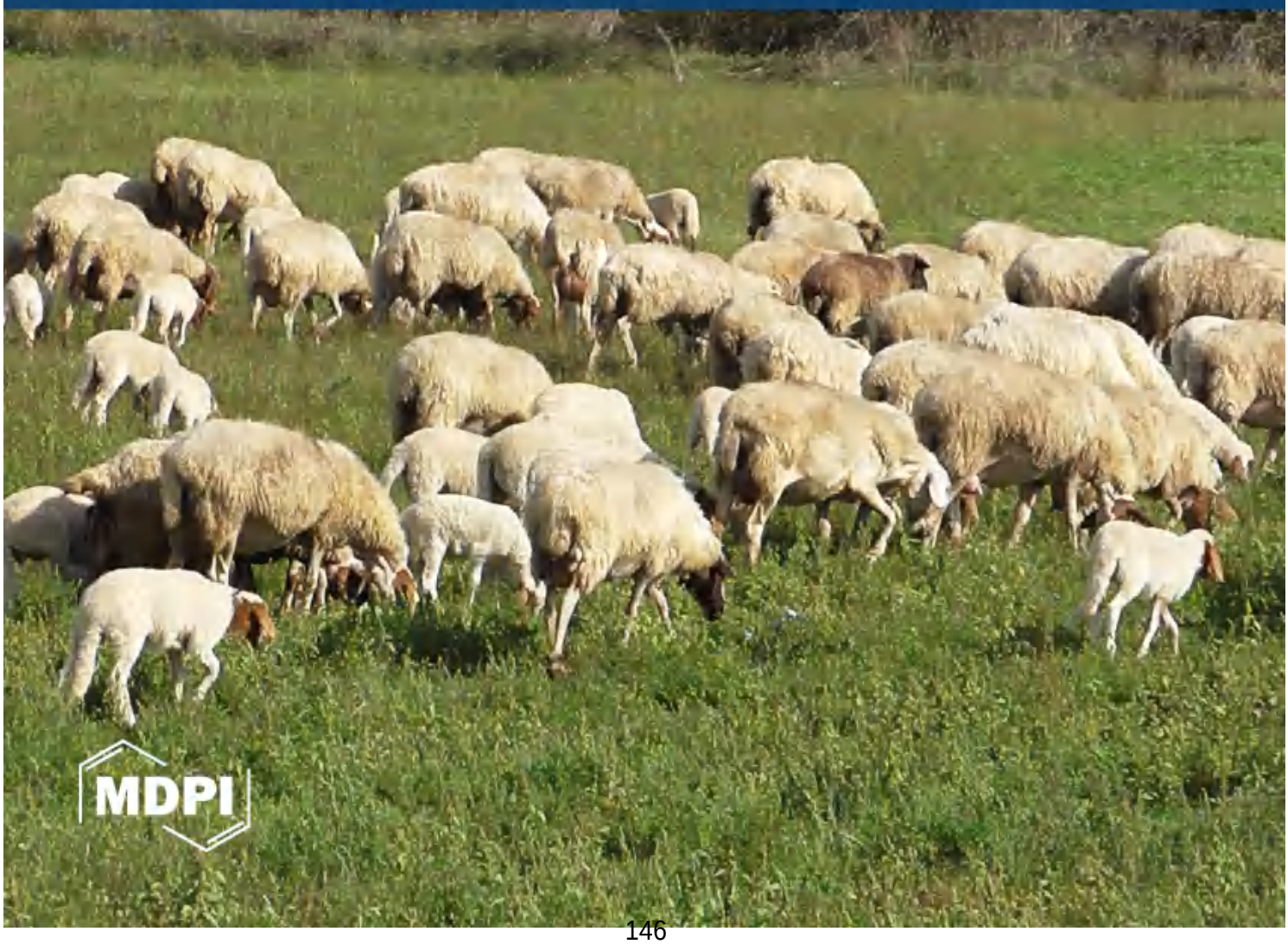
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A Long-Term Video Tracking Method for Group-Housed Pigs

Qiumei Yang [1,2], Xiangyang Hui [1,2], Yigui Huang [1,2], Miaobin Chen [1,2], Senpeng Huang [1,2] and Deqin Xiao [1,2,*]

[1] College of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China; yqmbegonia@scau.edu.cn (Q.Y.); scau_hxy@stu.scau.edu.cn (X.H.); hyg2021scau@stu.scau.edu.cn (Y.H.); 20213162019@stu.scau.edu.cn (M.C.); hsp2454@stu.scau.edu.cn (S.H.)

[2] Key Laboratory of Smart Agricultural Technology in Tropical South China, Ministry of Agriculture and Rural Affairs, Guangzhou 510642, China

* Correspondence: deqinx@scau.edu.cn; Tel.: +86-13794412658; Fax: +86-020-85285393

Simple Summary: Simple Summary: Pig tracking provides strong support for refined management in pig farms and can assist in realizing customized, automated, and intellectualized management. However, there are many complex factors in actual production that result in pigs not being tracked consistently over time. To address this issue, we proposed a long-term video tracking method for group-housed pigs based on improved StrongSORT. The experimental results proved that our study demonstrates high practicality, catering to the needs of practical production. It improved the efficiency of farming personnel and lays the foundation for the automated monitoring of pigs. Additionally, it is worth mentioning that we have also released a dataset specifically designed for long-term pig tracking in this paper.

Abstract: Pig tracking provides strong support for refined management in pig farms. However, long and continuous multi-pig tracking is still extremely challenging due to occlusion, distortion, and motion blurring in real farming scenarios. This study proposes a long-term video tracking method for group-housed pigs based on improved StrongSORT, which can significantly improve the performance of pig tracking in production scenarios. In addition, this research constructs a 24 h pig tracking video dataset, providing a basis for exploring the effectiveness of long-term tracking algorithms. For object detection, a lightweight pig detection network, YOLO v7-tiny_Pig, improved based on YOLO v7-tiny, is proposed to reduce model parameters and improve detection speed. To address the target association problem, the trajectory management method of StrongSORT is optimized according to the characteristics of the pig tracking task to reduce the tracking identity (ID) switching and improve the stability of the algorithm. The experimental results show that YOLO v7-tiny_Pig ensures detection applicability while reducing parameters by 36.7% compared to YOLO v7-tiny and achieving an average video detection speed of 435 frames per second. In terms of pig tracking, Higher-Order Tracking Accuracy (HOTA), Multi-Object Tracking Accuracy (MOTP), and Identification F1 (IDF1) scores reach 83.16%, 97.6%, and 91.42%, respectively. Compared with the original StrongSORT algorithm, HOTA and IDF1 are improved by 6.19% and 10.89%, respectively, and Identity Switch (IDSW) is reduced by 69%. Our algorithm can achieve the continuous tracking of pigs in real scenarios for up to 24 h. This method provides technical support for non-contact pig automatic monitoring.

Keywords: pig; object detection; deep learning; multi-object tracking

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1. Introduction

Pig tracking is of significant importance in pig farm management. Through the individual localization and tracking of pigs, it is possible to collect data on pig movements, analyze pig behavior, and monitor various pig-related information, to find the abnormal pigs in a timely manner [1,2]. At the same time, the automatic tracking and monitoring of

pigs can avoid labor-intensive and error-prone manual management, thereby improving management efficiency [3–5].

Current research for pig tracking mainly includes contact methods and non-contact methods. The contact methods realize tracking using sensor devices such as ear tags worn by pigs. Eisermann et al. [6] used an UHF-RFID system to individually identify pigs and combined a single point load cell (SPLC) to assess the individual manipulative behaviour of group-housed pigs. Knoll et al. [7] mounted UWB tags on pig ear tags and worked with UWB tags in each pen to achieve the accurate positioning of individual pigs. Lee et al. [8] developed a monitoring system to estimate the location and movement of each pig using Bluetooth low-energy (BLE) tags and wireless broadband leaky coaxial cable (WBLCX) antennas. However, the sensors used in these methods are costly, easily damaged, and detached. In addition, the pigs tend to have stress reactions during sensor installation, which in turn affects their welfare.

In contrast, using non-contact tracking methods based on video imagery can help avoid these issues. The current research on image-based pig tracking algorithms is mainly divided into manual feature-based tracking methods and deep learning-based tracking methods. For manual feature-based tracking methods, Xiao et al. [9] identified pigs based on color information, removed the noise through the connected region of the binary image, and proposed a set of association rules with constraints (DT-ACR) for pig tracking. Sun and Li [10] designed a multi-pig tracking algorithm based on joint probability data association and particle filtering. Although such methods can track pigs, they need to define features manually, which have poor generalization, and the tracking performance is easily degraded in real-world scenarios due to challenges such as insufficient light and pigs sticking to and obscuring each other [11]. These limitations make it difficult to meet the needs of the actual scene.

Deep learning-based methods have the advantage of automatically extracting and learning features, which allows models to exhibit strong robustness even under various challenging conditions such as varying lighting and occlusion [12]. Li et al. [13] proposed a correlation matrix combining the embedding cosine distance and GIoU distance to address tracking failures caused by occlusion or temporary target loss. Tu et al. [14] presented a multi-object tracking method that simultaneously outputs classification, bounding box, and appearance information to complete the behavioral tracking of group-housed pigs. The above methods are based on the Joint Detection and Embedding (JDE) paradigm. Although they have good real-time tracking performance, their tracking accuracy is generally not as good as the Tracking-by-Detection (TBD) method.

The principle of the TBD method is to treat object detection and object tracking as two separate steps, and employ a correlation matching algorithm to associate the detected object candidates with existing tracked targets [15]. Van der Zande et al. [16] used Yolo v3 to detect pigs and then tracked them by the SORT algorithm. Zhang et al. [17] combined the CenterNet detection algorithm with an improved DeepSORT algorithm to track weaned piglets. Gong et al. [18] proposed an improved IOU-tracker combined with YOLOv5s for real-time pig tracking. Shirke et al. [19] introduced a multi-camera pig tracking system that initially employed YOLOv4 for pig detection, followed by using homography estimation to locate the same pig in different camera regions, and finally tracked pigs using the DeepSORT algorithm. These methods are prone to switching pig identities due to prolonged occlusions, making it challenging to achieve long-term continuous tracking.

To address the above issues, we propose a multi-pig long-term tracking algorithm based on improved StrongSORT, which aims to achieve the long-term and continuous tracking of individual pigs in real-world scenarios. Furthermore, this study explored the significance of pig tracking in the field of pig farming to satisfy actual production demands.

2. Materials and Methods

2.1. Video Acquisition

Both self-collected videos and the public videos [20] were used for our research. The self-collected videos were captured from two pig farms in Luogang and Xinxing, Guangdong, China.

The pen selected from Luogang Pig Farm has 4 pigs, and the pen size is 4 m × 5 m. Landrace gilts were selected as experimental subjects, and they were continuously monitored 24 h a day. The video was taken from July 2016 to August 2016. The pen selected from Xinxing Pig Farm has 7 pigs, and the pen size is 2 m × 4 m. The experimental videos were captured between July 2020 and August 2020. The public videos include pens with 7 to 16 pigs each, including a total of 15 video clips during the daytime and nighttime, each with a length of 30 min. The information of each video set is shown in Table 1.

Table 1. Information on each video collection.

Video Collection	Experimental Pig Farm	Number of Pigs	Light Conditions	Pig Pen Size
Self-collected videos	Luogang Pig Farm	4	Daytime and nighttime	4 m × 5 m
Self-collected videos	Xinxing Pig Farm	7	Daytime	2 m × 4 m
Public videos	Not mentioned	7–16	Daytime and nighttime	Not mentioned

The video data were captured from the top view and covered the entire pen, as shown in Figure 1. There were no pigs disappearing within the camera's field of view. In order to facilitate the manual identification of different pigs in subsequent experiments, the pigs in Luogang Pig Farm were marked on their backs with "A", "B", "C", and "D", as shown in Figure 1a. Similarly, the pigs in Xinxing Pig Farm were marked on their backs with labels "1", "2", "3", "4", "5", "6", and "7", as shown in Figure 1b.



Figure 1. View of each pig farm: (**a**) Luogang Pig Farm, (**b**) Xinxing Pig Farm, (**c**) the public videos.

2.2. Data Preprocessing and Dataset Construction

This study constructed datasets for pig detection and multi-pig tracking. The former was used to train the pig detection model, while the latter was employed to evaluate multi-pig tracking algorithms.

2.2.1. Data Preprocessing

Due to the camera's angle of view, the acquired videos contained corridors or other pens where unrelated pigs may be detected during the pig detection process. It can seriously affect the experimental results. To overcome this, a mask operation was performed on videos with these issues (Luogang Pig Farm videos and public videos). The specific operation is illustrated in Figure 2, where the green box area is the main monitoring area and the red box area signifies areas that can potentially affect the experimental results. After preprocessing, the red box area is covered by a black mask while the green area is retained. Figure 2a shows the mask for Luogang Pig Farm, which mainly covers pigs moving in the corridor and pigs in other pens. And Figure 2b shows the mask for the public videos, primarily covering pigs in neighboring pens.

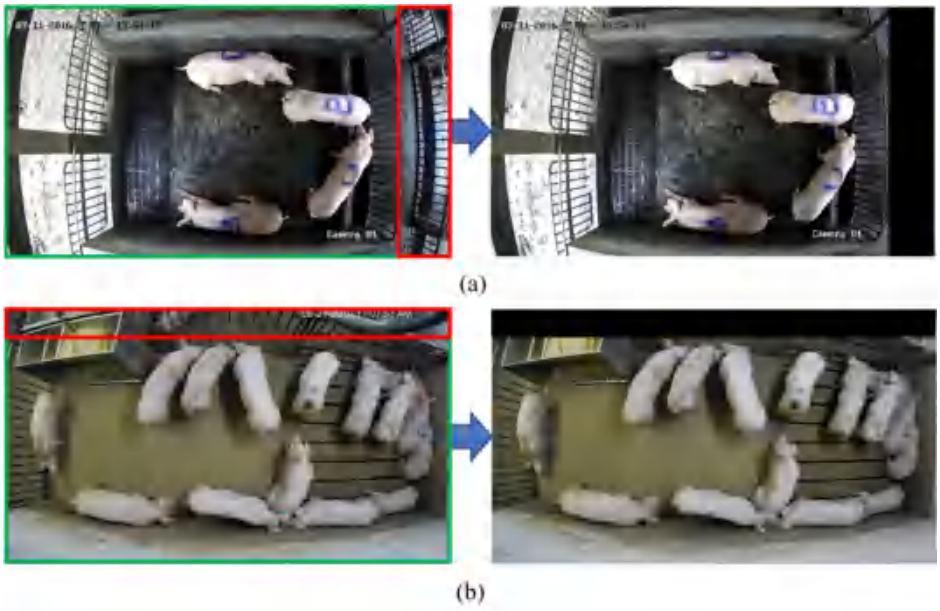


Figure 2. Comparison of the effect before and after preprocessing: (**a**) Luogang Pig Farm, (**b**) public videos.

2.2.2. Pig Detection Datasets

Our public video dataset was taken from reference [20], which can be downloaded at http://psrg.unl.edu/Projects/Details/12-Animal-Tracking (accessed on 10 December 2022). To create the pig detection dataset, we extracted image frames from the captured videos. For each pig farm, we selected 1800 images with high clarity and low similarity and included four different environments: daytime crowded, daytime sparse, nighttime crowded, and nighttime sparse. These images were manually annotated using LabelImg software(v1.8.6). Finally, the annotated images were randomly divided into a training set and testing set following a ratio of 8:2, as detailed in Table 2.

Table 2. The pig detection datasets.

Dataset	Experimental Pig Farm	Number of Pictures	Total
Training	Luogang Pig Farm	1440	
Training	Xinxing Pig Farm	1440	4320
Training	The public videos	1440	
Testing	Luogang Pig Farm	360	
Testing	Xinxing Pig Farm	360	1080
Testing	The public videos	360	

2.2.3. Pig Tracking Datasets

For pig tracking, we selected 10 video clips of group-housed pigs, as detailed in Table 3. The selected videos included different lighting conditions during the day and night, covering three different pig farm scenarios, with low and high frame rates. The density of pigs within the pens varied as well. These videos ranged in length from 2 min to 24 h, and notably, the 24 h pig tracking video was the longest in the literature currently available in the field. The selected videos were annotated frame by frame using DarkLabel software(v 2.4), creating a bounding box for each pig and ensuring the same identification number (ID) was assigned to the same pig across adjacent frames.

Table 3. The pig tracking datasets.

Video No.	Duration	Frame Rate	Light Conditions	Density Level	Experimental Pig Farm
1	2 min	5	daytime	dense	The public videos
2	10 min	5	nighttime	dense	The public videos
3	30 min	5	daytime	dense	The public videos
4	2 min	10	daytime	dense	Xinxing Pig Farm
5	10 min	10	daytime	dense	Xinxing Pig Farm
6	1 h	10	daytime	dense	Xinxing Pig Farm
7	2 min	25	daytime	sparse	Luogang Pig Farm
8	10 min	25	nighttime	sparse	Luogang Pig Farm
9	1 h	25	nighttime	sparse	Luogang Pig Farm
10	1 day (24 h)	25	daytime and nighttime	sparse	Luogang Pig Farm

2.3. Multi-Pig Long-Term Tracking Methods

2.3.1. Framework of Multi-Pig Long-Term Tracking Method

In practical pig farm management, there is a need for highly accurate and stable pig tracking algorithms. The TBD paradigm can meet this demand as it is capable of providing highly accurate tracking results. Our study used the TBD paradigm.

The multi-pig tracking algorithm proposed in this paper was divided into two modules: pig detection and multi-pig tracking. Its framework is shown in Figure 3. Firstly, the video sequence was input into the pig detector YOLO v7-tiny_Pig to detect and obtain pig location. Then, the detection result was fed into the optimized StrongSORT [21] multi-object tracker for feature extraction to obtain the pig appearance feature. Simultaneously, NSA Adaptive Kalman filtering was employed to predict and update pig trajectories. Finally, the Hungarian algorithm was utilized to globally match the pig appearance feature, pig location, and pig trajectories, thus accomplishing multi-pig tracking.

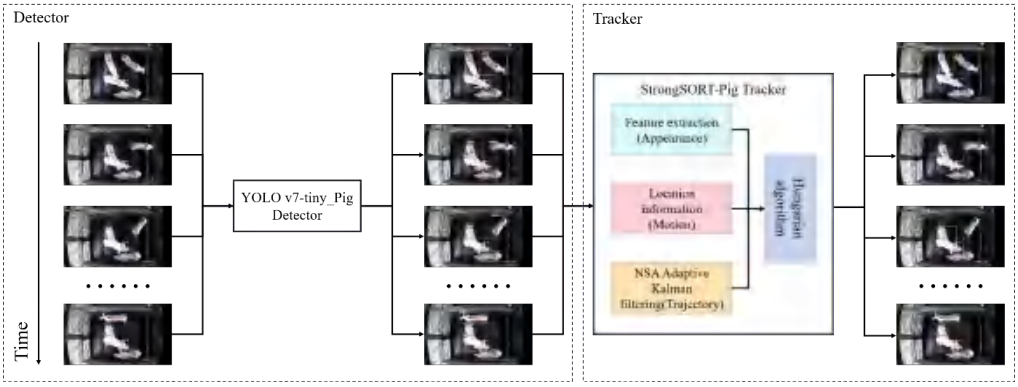


Figure 3. The framework of multi-pig tracking algorithm.

2.3.2. Lightweight Pig Detector YOLO v7-Tiny_Pig

Since our tracking algorithm was based on the TBD paradigm, the performance of the pig detector directly impacts the effectiveness of tracking. Currently, the YOLO series detectors have shown excellent performance. Therefore, we used the most popular YOLO v7 [22] series network for pig detection. It is a one-stage object detection algorithm and offers three basic models designed for different scenarios: YOLO v7-tiny is suitable for edge GPUs, YOLO v7 is designed for regular GPUs, and YOLO v7-W6 is intended for cloud GPUs. The accuracy of these three basic models increases successively, while the number of parameters increases.

On the one hand, due to the fact that the object detection in this study only involves one category, which is simple, there was no need for complex network models. On the other hand, for further analysis of the pig tracking results, a faster processing speed was required. Therefore, the YOLO v7-W6 model was excluded. To further select an appropriate pig

detection model, we used the aforementioned pig detection dataset to train and test the other two models YOLO v7 and YOLO v7-tiny, respectively. After experimental comparison, the lighter YOLO v7-tiny model was chosen as the base model, with the network structure shown in Figure 4a.

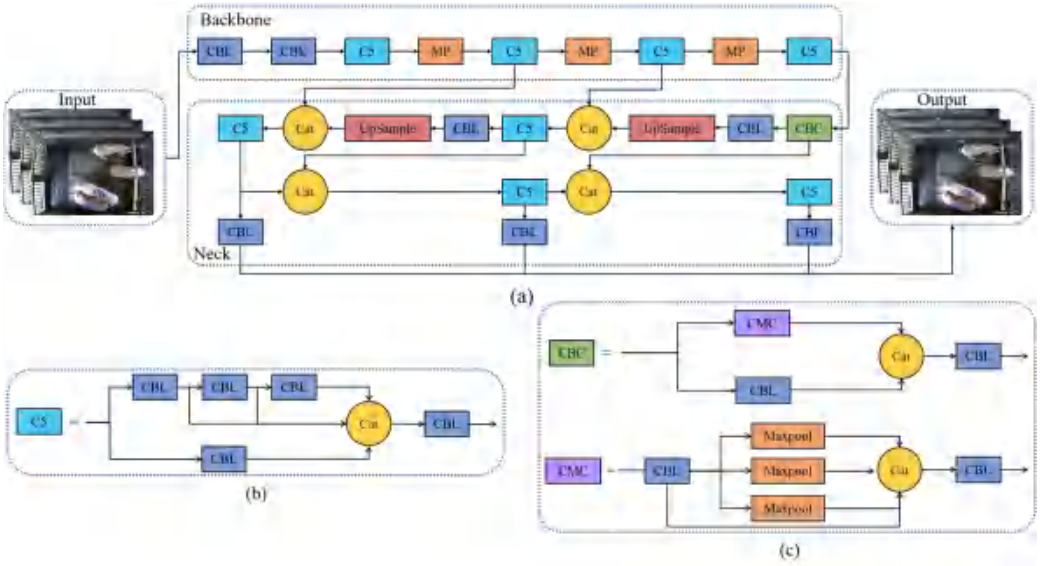


Figure 4. YOLO v7-tiny network architecture. (**a**) YOLO v7-tiny model structure, (**b**) C5 Network structure, (**c**) CBC Network structure.

The YOLO v7-tiny network consists of four parts, including the Input, Backbone, Neck, and Output. The purpose of the Input stage is to feed the data into the Backbone after performing data augmentation. The Backbone consists of convolutional layers and the C5 structure, which feeds the extracted features into the Neck for feature fusion. The network structure of C5 is illustrated in Figure 4b. The Neck consists of the CBC structure (Figure 4c), C5, and convolutional layers, and it performs downsampling to reduce feature dimensionality. The Output includes three feature maps of different scales predicting targets of different sizes, and finally feature fusion is performed to output the detection results.

Since the cameras in our experiment were installed directly above the center of the pig pens, and the proportion of pigs in any location within the pen relative to the entire image did not vary significantly, a single scale YOLOHead can complete the task of detecting pigs [23]. Therefore, we made modifications to YOLO v7-tiny by removing the shallow and deep feature maps, retaining only the mid-level feature maps to obtain the pig detection network YOLO v7-tiny_Pig. The improved network structure reduced the number of parameters and accelerated the detection speed. The network structure is illustrated in Figure 5.

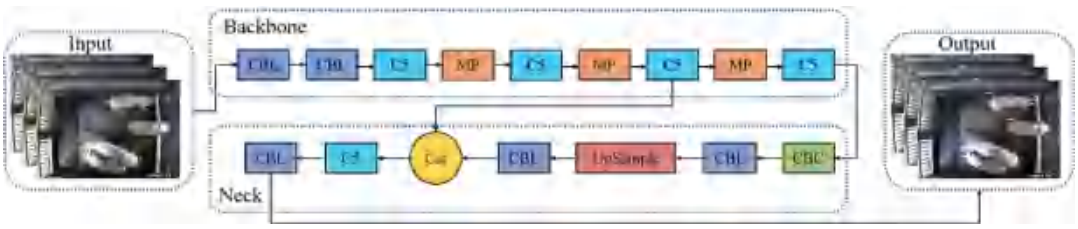


Figure 5. The network structure of YOLO v7-tiny_Pig.

2.3.3. Multi-Pig Tracker StrongSORT-Pig

The multi-pig tracker StrongSORT-Pig proposed in this study is an improved version of the StrongSORT algorithm, tailored to the specific characteristics of the real scenario.

The StrongSORT algorithm is an improvement on the DeepSORT [24] algorithm, which is further developed based on the SORT [25] algorithm. The SORT algorithm uses only motion information for multi-object tracking, which can lead to ID switches when targets are occluded. The DeepSORT algorithm introduces a re-identification model, combines motion and appearance information, and employs a cascade matching strategy, thereby improving matching accuracy. The StrongSORT algorithm optimizes the motion branch and the appearance branch of the DeepSORT algorithm separately, and introduces advanced methods and strategies.

Since the pig pens in our experiment were enclosed spaces with restricted access and the number of pigs did not change over time, this study improved the StrongSORT algorithm and optimized the trajectory management strategy. These improvements aimed to reduce the number of ID switches, allowing pigs to be retracked even after prolonged occlusion, thus extending the tracking time. Figure 6 shows the algorithmic process of StrongSORT-Pig.

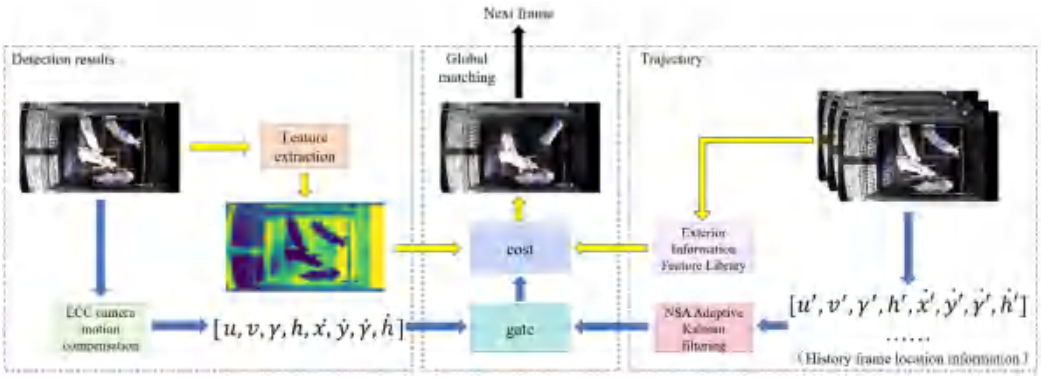


Figure 6. Flow chart of multi-pig tracking process.

The StrongSORT-Pig ensures that the same pig maintains the same ID throughout the time sequence by globally matching the pig detection results with predicted trajectories. The matching result is jointly determined by both the motion branch and the appearance branch, represented by the blue and yellow arrows in Figure 6, respectively.

1. The motion branch

Due to the random and irregular movement behaviors of pigs, it can easily lead to image blurring and thus affect the detection and tracking performance. To address this issue, the motion branch in this study was divided into two stages. In the first stage, we adopted the Enhanced Correlation Coefficient (ECC) model to compensate the blurred images caused by pig movements. In the second stage, the NSA Kalman filtering algorithm was applied to predict and smooth the motion trajectories of each pig through dynamically adjusting the noise covariance based on detection confidence scores. It consisted of two phases: the prediction phase and the update phase. In the prediction phase, the current pig trajectory state was predicted based on the pig trajectory state in the previous frame and the noise matrix in the current frame. In the update phase, the trajectory state was updated using the results from the prediction stage, along with the noise of the pig detection and the pig detection results in the current frame. The confidence of pig detection results affected the accuracy of state updates. It is worth noting that Kalman filtering was only used to predict the pig's trajectory before the matching operation. The entire process made full use of the pig motion state from the previous frame and the current pig detection results. By dynamically and adaptively adjusting the weights of the detection results, the impact of various noises on the tracking results was effectively reduced, thereby making the pig tracking results more accurate.

2. The appearance branch

The appearance features of pigs, such as body color and body shape, are relatively stable. However, in a video stream, the appearance of the same pig in different frames may change slightly due to factors like lighting changes. Additionally, due to the small differences between individual pigs, it is necessary to establish a sensitive pig appearance feature extractor to capture highly discriminate features, thereby improving the performance of the tracker. On the other hand, the Exponential Moving Average (EMA) feature update strategy can update the trajectory appearance of the corresponding pigs based on the detailed features obtained by the feature extractor, which helps to smoothly adapt the appearance changes and improve the accuracy and robustness of tracking. Therefore, the appearance branch contained the pig appearance feature extractor and the feature update strategy based on the EMA. Equation (1) represents the appearance state e_i^t of the i-th trajectory updated based on the EMA strategy in the t-th frame:

$$e_i^t = \alpha e_i^{t-1} + (1-\alpha) f_i^t \tag{1}$$

where e_i^{t-1} is the appearance state of the ith trajectory in the $(t-1)$th frame, f_i^t is the appearance feature matched to the ith trajectory (i.e., the current trajectory) in the tth frame (i.e., the current frame), and α is the weight parameter.

The feature update strategy was able to efficiently update the appearance state of the trajectory by combining the appearance features detected in the current frame while preserving the appearance information of the previous video frames. It can reduce the impact of detection noise and rapid changes in the tracked targets on appearance information and capture changes in appearance features between video frames, thereby improving the performance of the tracking system.

3. The global matching process

During the global matching stage, different weights were assigned to appearance and motion information to calculate the pairwise association costs between all pigs and trajectories, thereby solving the assignment problem between targets and trajectories.

For the appearance information, the minimum cosine distance d_α was used as the matching cost, and it was computed between the current detection r_j and the appearance of all trajectories, following the rule defined in Equation (2).

$$d_\alpha = min\left\{1 - r_j^T e_i^{t-1} \middle| i \in R\right\} \tag{2}$$

where r_j is the appearance state of the jth detection, e_i^{t-1} is the appearance state of the ith trajectory in the $(t-1)$th frame, and R is the number of all trajectories.

For the motion information, the Mahalanobis distance d_m^M between the center point of the pig detection bounding box and the center point of the pig track bounding box was used as a gate to filter out unlikely matches. Then, the cosine distance d_m of motion information was used as the matching cost for further matching. The final cost matrix was the weighted sum of appearance and motion costs, which was calculated as shown in Equation (3).

$$C = \lambda A_\alpha + (1-\lambda) A_m \tag{3}$$

where A_α represents the appearance cost matrix, which is the set of d_α. Similarly, A_m represents the motion cost matrix, which is the set of d_m, and λ is the weight factor.

When pigs are obstructed by other objects or other pigs, the original trajectories and the detection results cannot be matched. This leads to the generation of more trajectories, causing a continuous increase in pig identity IDs. The actual maximum ID value is far greater than the actual number of pigs in the pigpen, resulting in tracking failures. To address this issue, this study optimizes the trajectory deletion and generation process, taking into account the particular scenario of pigsties.

Since the number of pigs in the pen does not suddenly decrease, the maximum matching lifetime is not set for unmatched tracks in our research. Unmatched trajectories will never be deleted to reduce ID switching caused by long-term occlusion. Similarly, as the number of pigs in the pigpen does not suddenly increase, we introduce additional constraints on the generation of new trajectories. The total number of pigs in the pigpen is set as a threshold for the maximum value of ID increase. New trajectories can be generated only when the number of trajectories is less than the threshold, which can limit the endless increase in ID.

By combining the above two optimizations, on the one hand, trajectory deletion is prohibited, and on the other hand, ID growth is restricted. This approach is applied to multi-pig tracking. The specific matching process is shown in Figure 7.

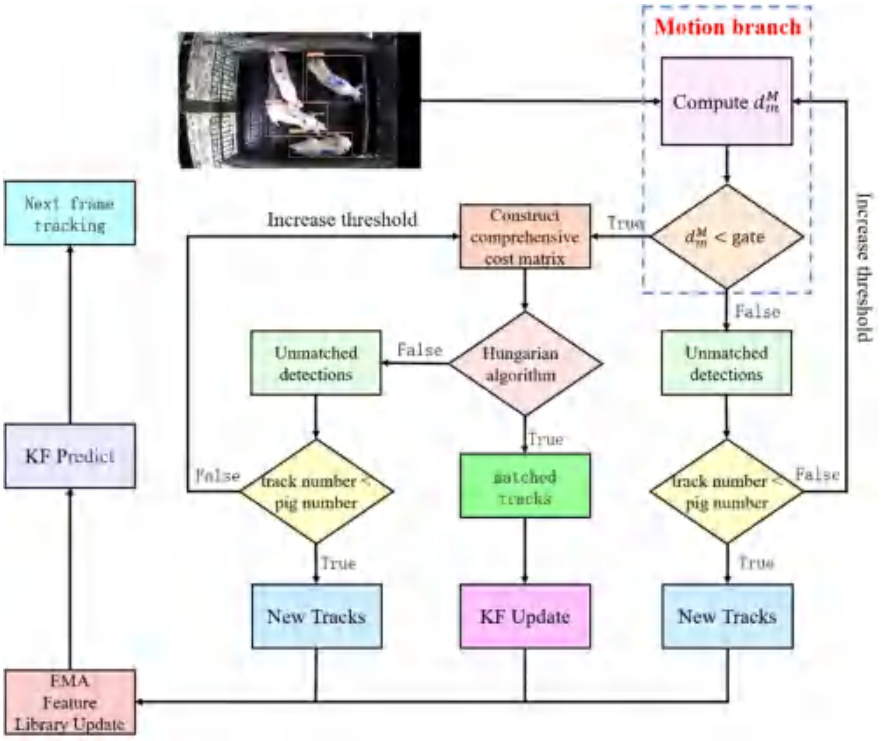


Figure 7. Global matching flowchart.

(a) The matching of the motion branch is performed by calculating the Mahalanobis distance between the center point of the pig detection bounding box and the center points of all pig trajectory bounding boxes. If the distance is less than the threshold, the combined matching of motion information and appearance information is performed. If the distance between the pig detection box and all the trajectories is greater than the threshold, the detection box is in the unmatched state, and it is further judged whether it meets the conditions for generating new trajectories. The number of available tracks is less than the total number of pigs.

(b) An integrated matching of motion and appearance information is performed, a combined cost matrix is constructed for both, and then the Hungarian algorithm is used for global matching. If the match is successful, the process continues to the next step. If there is no suitable match, the detection box is in the unmatched state, and further judgment is made to determine whether it meets the conditions for new trajectory generation. If it meets the conditions, a new track is generated; otherwise, the threshold is increased, and the matching process is repeated.

(c) For successfully matched detection boxes and trajectories, the motion and appearance models of the corresponding trajectories are updated. For unmatched detection boxes, new trajectories are initialized.

(d) The next frame of the image is proceeded to and the above process is repeated.

4. Correction algorithm of multi-pig tracking performance

Due to adhesion and occlusion between pigs, some pigs may not be detected at certain times. It can cause pig trajectories to be lost and their location to not be recorded during the missing period. However, when such pigs are detected again, their trajectories reappear. Associating the trajectories before and after missing and filling in the missing detections are crucial for the tracking results. Therefore, two correction algorithms, the appearance-free link model (AFLink) and Gaussian-smoothed interpolation (GSI), which are based on motion information and are independent of appearance information, are incorporated in the tracking procedure.

AFLink utilizes spatiotemporal information to predict the correlation between two trajectories as a way to solve the problem of correlating the trajectories before and after missing. As shown in Figure 8, it takes two trajectories T_i and T_j as inputs and is calculated by Equation (4).

$$T_* = \{f_k, x_k, y_k\}_{k=1}^{N} \quad (4)$$

where x_k and y_k represent the position coordinates of the nearest $N = 30$ frames of f_k, and if N is less than 30, it is padded with zeros. The temporal module extracts feature information along the temporal dimension. Then, the fusion module integrates feature information from different dimensions and compresses the information of two trajectories into feature vectors, respectively. Finally, these feature vectors are concatenated to predict the confidence score of the association by a Multilayer Perceptron (MLP), to determine whether the two trajectories belong to the same track. In the association process, spatiotemporal constraints are used to filter out unreasonable trajectory pairs. Then, the global association is decomposed into a linear assignment task using the predicted confidence scores for associations.

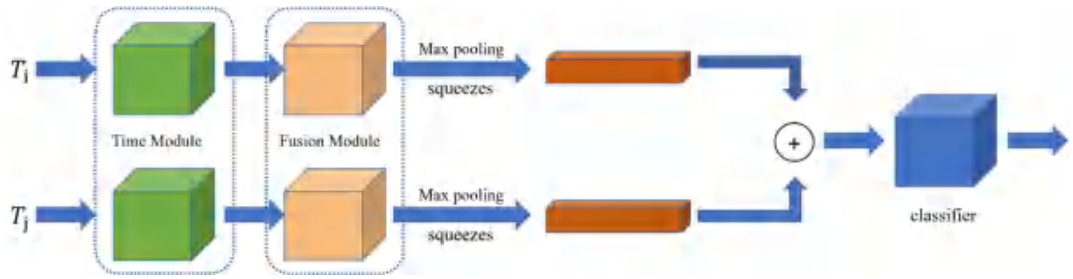


Figure 8. AFLink module.

GSI employs Gaussian process regression to simulate nonlinear motion and fits undetected trajectory updates using Gaussian-smoothed interpolation, given the tracking trajectories before and after the lack of detection, assuming that the actual motion follows a Gaussian process, based on the properties of Gaussian processes, fitting its Gaussian process distribution based on the given observed trajectories, and using this information to predict and fill in the missing trajectories at the time of detection loss.

The application of AFLink and GSI can significantly improve the robustness of pig tracking algorithms in complex environments. It substantially reduces the loss of pig tracking targets caused by occlusions and unstable detections, resulting in higher tracking accuracy. The stability and continuity of the pig tracking algorithm have also been enhanced.

3. Results and Analysis

3.1. Experimental Platform and Parameter Settings

The experiments were conducted on the Windows 10 platform, equipped with a 2.50 GHz 12th-Gen Intel(R) Core (TM) i5-12400F processor, 16 GB of memory, and a 1 TB hard drive. The GPU used was an NVIDIA GeForce RTX 3060. The programming language used was Python 3.8, and the deep learning framework used was PyTorch 1.11.0.

3.2. Evaluation and Analysis of Pig Detection

3.2.1. Pig Detection Evaluation Metrics

In the pig detection stage, the performance of the pig detection model was evaluated using five metrics: Precision (P), Recall (R), $F1$ Score, FPS, and mAP. The mathematical expression of these metrics is given by Equations (5)–(9).

$$P = \frac{TP}{TP + FP} \times 100\% \tag{5}$$

$$R = \frac{TP}{TP + FN} \times 100\% \tag{6}$$

$$F1 = \frac{2PR}{P + R} \times 100\% \tag{7}$$

$$\text{FPS} = \frac{frameNum}{elapsedTime} \tag{8}$$

$$mAP = \int_0^1 P(R)dR \tag{9}$$

where TP (True Positives) refers to the number of pigs correctly detected; FN (False Negatives) represents the number of pigs that were not detected; FP (False Positives) is the number of pigs incorrectly detected; $frameNum$ is the total number of frames; and $elapsedTime$ represents the total processing time. This study used single target detection, so calculating mAP means calculating the area under the P-R curve.

3.2.2. Comparison Experiments of Different Models

During the training procedure, we employed the pre-trained YOLO v7-tiny model. The input image size was set to 1280 pixels × 1280 pixels, with a batch size of 8, a learning rate of 0.01, momentum of 0.937, and 150 epochs. Adam optimizer was used to iteratively optimize network parameters.

In order to select a more suitable pig detection model, this study used the same pig detection dataset to conduct experiments in YOLO v7, YOLO v7-tiny, and the YOLO v7-tiny_Pig network, respectively. The experimental results are shown in Table 4.

Table 4. Performance comparison of different pig detection models. P: Precision; R: Recall; F1: F1 Score; FPS: frames per second; mAP: Mean Average Precision.

Models	P (%)	R (%)	F1 (%)	FPS ($f \cdot s^{-1}$)	mAP (%)	Parameter
YOLO v7	99.7	97.9	98.8	127	99.0	3.7×10^7
YOLO v7-tiny	99.5	98.4	98.9	370	98.6	6×10^6
YOLO v7-tiny_Pig	99.3	98.3	98.8	435	98.4	3.8×10^6

From Table 4, it can be observed that although the accuracy of YOLO v7-tiny_Pig is slightly lower than those of YOLO v7 and YOLO v7-tiny, it still exceeds 99%, which can meet the requirements of pig tracking. Meanwhile, it has a higher FPS, which processes images 3.4 times faster than YOLO v7, and the number of model parameters is about 10% of YOLO v7. Compared to YOLO v7-tiny, YOLO v7-tiny_Pig processes 65 more frames per second and reduces the number of model parameters by 36.7%. To meet the requirements of real-world production, the pig tracking algorithm needs to have a shorter processing time and can be deployed on edge devices, which requires higher detection speed and smaller model size. Therefore, YOLO v7-tiny_Pig is more suitable for pig detection in this study.

3.2.3. Analysis of Pig Detection Using YOLO v7-Tiny_Pig

In this section, the performance of the proposed pig detection method is further validated through manual observation.

The detection results of pigs in four different environments using YOLO v7-tiny_Pig are shown in Figure 9. Figure 9a,c show the detection results for the sparse pig scenarios during the day and night. The model is able to accurately detect the pig positions, even in Figure 9c where the pigs have a similar appearance to the floor color at night. Figure 9b shows the detection results for the dense pig scenario during the daytime, where pigs are heavily occluded, making it difficult for human observers to distinguish them. However, the model is still able to accurately and quickly detect the pigs. In Figure 9d, it displays the detection results for the dense pig scenario at night. Not only can the pigs in the light part be detected accurately, but the pigs in dark areas are also not missed by the model. Overall, YOLO v7-tiny_Pig demonstrates the ability to accurately detect pigs in different environments, laying a foundation for subsequent multi-pig tracking in natural scenarios.

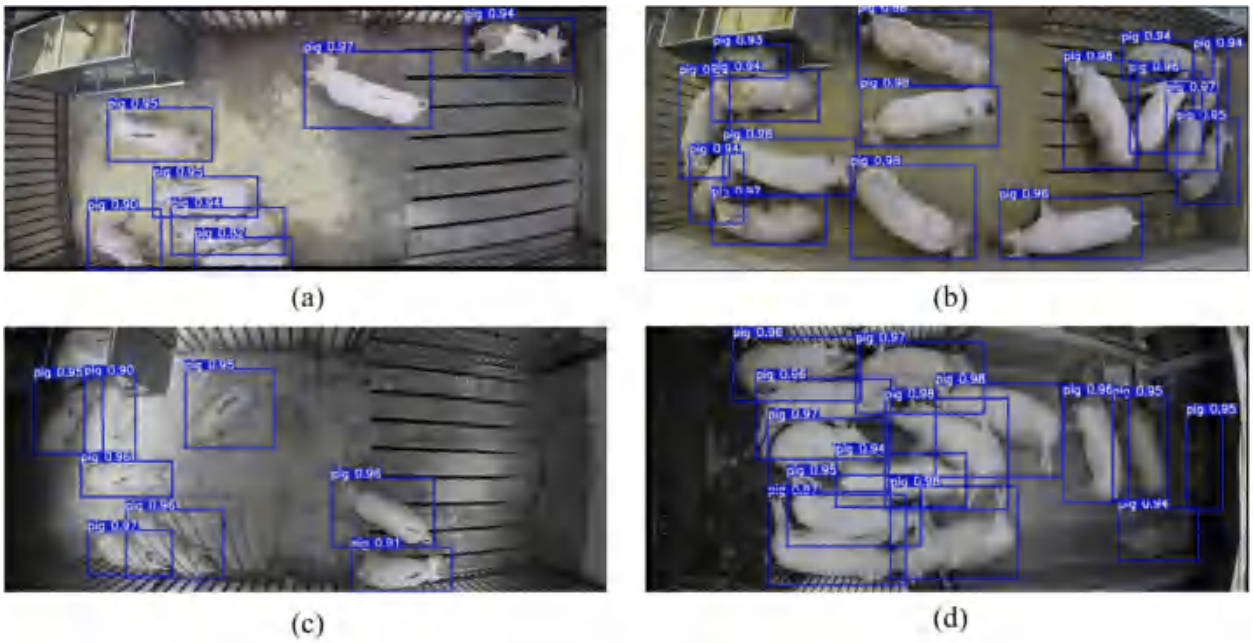


Figure 9. Example of pig detection results based on YOLO v7-tiny_Pig. (**a**) Sparse during the day, (**b**) dense during the day, (**c**) sparse at night, (**d**) dense at night.

3.3. Evaluation and Analysis of Multi-Pig Tracking Results

3.3.1. Multi-Pig Tracking Evaluation Metrics

HOTA [26], MOTA [27], IDF1 [28], MOTP, and IDSW were chosen to evaluate the multi-pig tracking model.

HOTA considers the accuracy of target matching, tracking, and localization simultaneously, which can evaluate the performance of the tracker more comprehensively and accurately. Particularly in cases of target overlap and occlusion, it is more consistent with the human visual assessment of tracking performance. Its mathematical expression is given by Equation (10).

$$\text{HOTA} = \sqrt{\frac{\sum_{\rfloor \in \{TP\}} \text{A}_{(\rfloor)}}{|TP| + |FN| + |FP|}} \tag{10}$$

$$\mathrm{A}_{(\mathrm{J})} = \frac{\left|TP\mathrm{A}_{(\mathrm{J})}\right|}{\left|TP\mathrm{A}_{(\mathrm{J})}\right| + \left|FN\mathrm{A}_{(\mathrm{J})}\right| + \left|FP\mathrm{A}_{(\mathrm{J})}\right|} \tag{11}$$

where $\mathrm{A}_{(\mathrm{J})}$ is the association accuracy, defined by Equation (11). $TP\mathrm{A}_{(\mathrm{J})}$ is the accuracy of correct correlation, $FN\mathrm{A}_{(\mathrm{J})}$ represents the accuracy of targets that are related but not successfully matched, and $FP\mathrm{A}_{(\mathrm{J})}$ represents the accuracy of completely unrelated false detections.

The mathematical expression of *MOTA* is given by Equation (12), where $IDSW$ represents the number of times the target label ID switched during tracking in frame t; gt represents the number of targets observed in frame t.

$$MOTA = 1 - \frac{\sum_t (FN + FP + IDSW)}{\sum_t g_t} \tag{12}$$

where IDF1 represents the proportion of detected targets that acquire the correct IDs. It is used to measure the overall performance of target identification and tracking, and its mathematical expression is given by Equation (13).

$$\mathrm{IDF1} = \frac{2IDTP}{2IDTP + IDFP + IDFN} \tag{13}$$

where $IDTP$ represents the total number of pigs tracked correctly with unchanged IDs, $IDFP$ represents the total number of pigs tracked incorrectly with unchanged IDs, and $IDFN$ represents the total number of pigs tracked missing with unchanged IDs.

MOTP is used to measure the accuracy of the tracker in terms of target position estimation and its mathematical expression is given by Equation (14), where $\mathrm{d}_{i,t}$ represents the distance between the pig detection box and the hypothetical pig bounding box in frame t; c_t represents the total number of matches between pig and hypothesis positions in frame t, and i represents the current detection target.

$$\mathrm{MOTP} = \frac{\sum_{t,i} \mathrm{d}_{i,t}}{\sum_t \mathrm{c}_t} \tag{14}$$

3.3.2. Comparison of Effects before and after Improvement in the Algorithm

To better demonstrate the performance of the improved tracking algorithm in this study, nine videos (Video1–Video9) from the pig tracking dataset were used to compare the performance of the original StrongSORT, the optimized StrongSORT-Pig tailored for pig farming characteristics, and StrongSORT-Pig_Plus with the inclusion of correction algorithms. The model performance test results are shown in Table 5.

Table 5. Performance comparison of different multi-pig tracking models. HOTA: Higher-Order Tracking Accuracy; MOTA: Multiple Object Tracking Accuracy; IDF1: Identification F1; MOTP: Multiple Object Tracking Precision; IDSW: Identity Switch.

Algorithms	Video No.	HOTA (%)	MOTA (%)	IDF1 (%)	MOTP (%)	IDSW (Times)	FPS ($\mathbf{f \cdot s^{-1}}$)
StrongSORT	1	72.2	91.7	79.0	88.6	25	26.3
	2	68.4	96.2	72.2	86.0	41	24.6
	3	49.2	98.9	42.6	93.7	47	22.5
	4	89.7	98.9	97.9	91.3	3	25.8
	5	85.8	98.0	92.8	90.4	14	25.2
	6	67.5	98.7	62.7	92.8	23	23.6
	7	89.4	99.6	87.6	94.3	1	29.6
	8	90.8	99.1	99.5	91.2	0	28.7
	9	79.7	99.1	90.5	89.4	17	27.8
	Average/Total	76.97	97.8	80.53	90.86	171	26.01

Table 5. *Cont.*

Algorithms	Video No.	HOTA (%)	MOTA (%)	IDF1 (%)	MOTP (%)	IDSW (Times)	FPS ($f \cdot s^{-1}$)
StrongSORT-Pig	1	77.8	90.5	89.7	88.7	14	28.6
	2	73.3	95.3	84.5	86.0	43	27.3
	3	62.9	98.7	64.2	93.8	22	26.8
	4	90.8	98.9	99.4	91.3	2	27.2
	5	89.1	98.0	99.0	90.4	8	26.9
	6	83.2	98.7	91.2	92.8	12	26.5
	7	95.1	99.6	99.8	94.3	0	32.6
	8	91.0	99.6	99.8	91.2	0	32.4
	9	80.9	99.2	92.3	89.4	2	30.9
	Average/Total	82.68	97.6	91.1	90.88	103	28.8
StrongSORT-Pig_Plus	1	78.9	91.7	90.2	88.6	8	23.2
	2	73.9	96.5	85.2	85.8	18	20.8
	3	62.8	98.9	64.3	93.4	20	18.9
	4	90.8	99.2	99.6	91.0	0	22.7
	5	89.9	98.2	99.1	90.4	0	21.8
	6	83.1	99.0	91.4	92.4	7	19.2
	7	95.2	100.0	100.0	94.1	0	25.2
	8	91.5	99.9	99.9	91.3	0	24.9
	9	82.3	99.3	93.1	89.3	0	22.5
	Average/Total	83.16	98.1	91.42	90.7	53	22.13

Compared with the original StrongSORT, the StrongSORT-Pig algorithm had shown varying degrees of improvement in most metrics, especially its average value of IDF1 that reached 91.1%, which was improved by 10.57%. The IDSW had reduced by 68 times, which was a 39.78% reduction compared with the original algorithm. In addition, HOTA was improved by an average of 5.71%, indicating the overall superior performance of our method. By incorporating the correction module, the performance of our method was further improved. HOTA was improved by 6.19% compared with the original algorithm. IDF1 was improved by 10.89%, and IDSW was reduced by 118 times, which is a decrease of 69%. This indicated that the correction module significantly enhanced the stability of pig tracking through the predictive interpolation of missing frames.

There was no significant improvement in the MOTA and MOTP metrics, and in some cases, there was a slight decrease, but they still reached 97.6% (MOTA) and 90.88% (MOTP), respectively. This ensured that the algorithm can correctly detect and track the majority of targets with relatively few false positives and false negatives. It can also estimate the position of the target accurately.

In addition, among the three algorithms, StrongSORT-pig had the highest FPS, while StrongSORT-Pig_Plus had the lowest FPS, which does not meet the speed needs of realistic scenarios. This is because the correction algorithm used in the StrongSORT-Pig_Plus model is more time-consuming, resulting in a lower FPS. Therefore, taking both accuracy and FPS into account, we used the StrongSORT-Pig algorithm in the subsequent experiments.

The tracking results of StrongSORT-pig are shown in Figure 10. The 77th, 110th, and 190th frames from Video1 were selected for comparison before and after optimization. In Figure 10a, both pig 7 and pig 15 can be detected in the 77th frame, but they cannot be detected in the 110th frame. They reappeared in the 190th frame, but their IDs had changed. Pig 7 was now identified as pig 18, and pig 15 was identified as pig 17, exceeding the total number of pigs, which was 16. In Figure 10b, both pig 7 and pig15 can also be detected in the 77th frame, and they cannot be detected in the 110th frame. However, when they reappeared in the 190th frame, their IDs remained unchanged. The results show that the proposed method had good tracking performance compared to the original model.

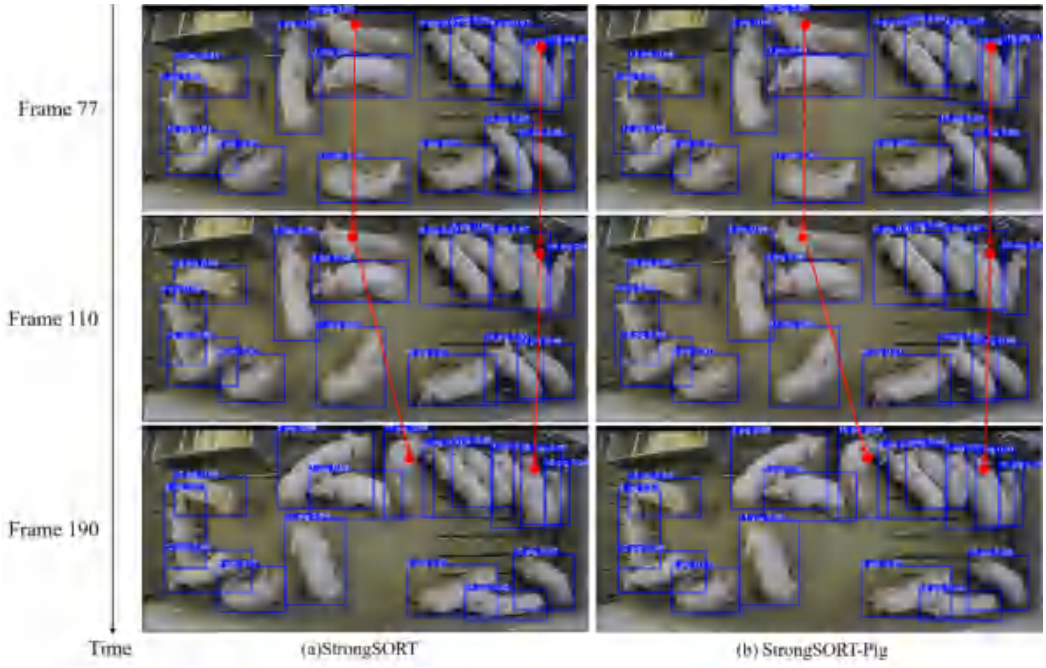


Figure 10. The tracking results of the proposed model compared to the original model.

3.3.3. Evaluation on Pig Tracking Duration

In order to validate the tracker's ability for continuous long-term tracking, this study conducted tracking tests on Video10 using both the StrongSORT and StrongSORT-Pig algorithms. The results are shown in Table 6.

Table 6. Performance comparison of long-term tracking results of different algorithms. HOTA: Higher-Order Tracking Accuracy; MOTA: Multiple Object Tracking Accuracy; IDF1: Identification F1; MOTP: Multiple Object Tracking Precision; IDSW: Identity Switch.

Algorithms	HOTA (%)	MOTA (%)	IDF1 (%)	MOTP (%)	IDSW (Times)	FPS ($f \cdot s^{-1}$)
StrongSORT	56.3	97.4	47.6	98.9	33	25.6
StrongSORT-Pig	97.5	97.6	98.9	99	0	28.1

For the 24 h long video tracking, it can be seen from Table 6 that the improved algorithm increases the HOTA by 41.2% and the IDF1 by 51.3%, and the MOTA and the MOTP are slightly improved. The IDSW is 0, indicating that there are no ID switches throughout the tracking process. Since no ID switching occurred during the whole process, it can be promised that the tracking result of the algorithm can serve as the basis for further analysis of the individual pigs.

3.3.4. Comparison of Different Multi-Object Tracking Algorithms

To evaluate the performance of the proposed method in multi-pig tracking, we conducted tests on the multi-pig tracking dataset and compared with four state-of-the-art models in the field of multi-object tracking. The results are shown in Table 7.

According to Table 7, our proposed model StrongSORT-Pig demonstrates the best performance in terms of HOTA, IDF1, and IDSW metrics. Our proposed method increases the likelihood of successful matching. It achieves this by imposing restrictions on new trajectory generation and unmatched trajectory deletion. This ensures that the model does not endlessly add new trajectories and can only match among existing trajectories. Although our method does not achieve the best performance in terms of MOTA and MOTP metrics, it is only slightly lower than the highest scores. It is worth noting that C_BIOU also

demonstrates good performance across various metrics, thanks to its utilization of buffer technology during the matching process. We can also consider incorporating this technique into the StrongSORT algorithm to further improve the effectiveness of multi-pig tracking.

Table 7. Tracking results of different algorithms for multi-pig tracking. HOTA: Higher-Order Tracking Accuracy; MOTA: Multiple Object Tracking Accuracy; IDF1: Identification F1; MOTP: Multiple Object Tracking Precision; IDSW: Identity Switch.

Algorithms	HOTA (%)	MOTA (%)	IDF1 (%)	MOTP (%)	IDSW (Times)	FPS ($f \cdot s^{-1}$)
BotSORT	75.83	94.8	82.94	91.3	155	23.73
DeepSORT	71.68	88.63	78.63	90.62	252	28.68
ByteTrack	73.3	91.82	84.82	89.2	128	32.21
C_BIOU	75.26	95.38	85.6	92.12	138	33.85
StrongSORT	76.97	97.8	80.53	90.86	171	26.01
StrongSORT-Pig	82.68	97.6	91.1	90.88	103	28.8

To further validate the effectiveness of the proposed method in this study, we selected Video6 for visualization of the tracking results using BotSORT, DeepSORT, ByteTrack, C_BIOU, StrongSORT, and StrongSORT-Pig. The tracking results are shown in Figure 11.

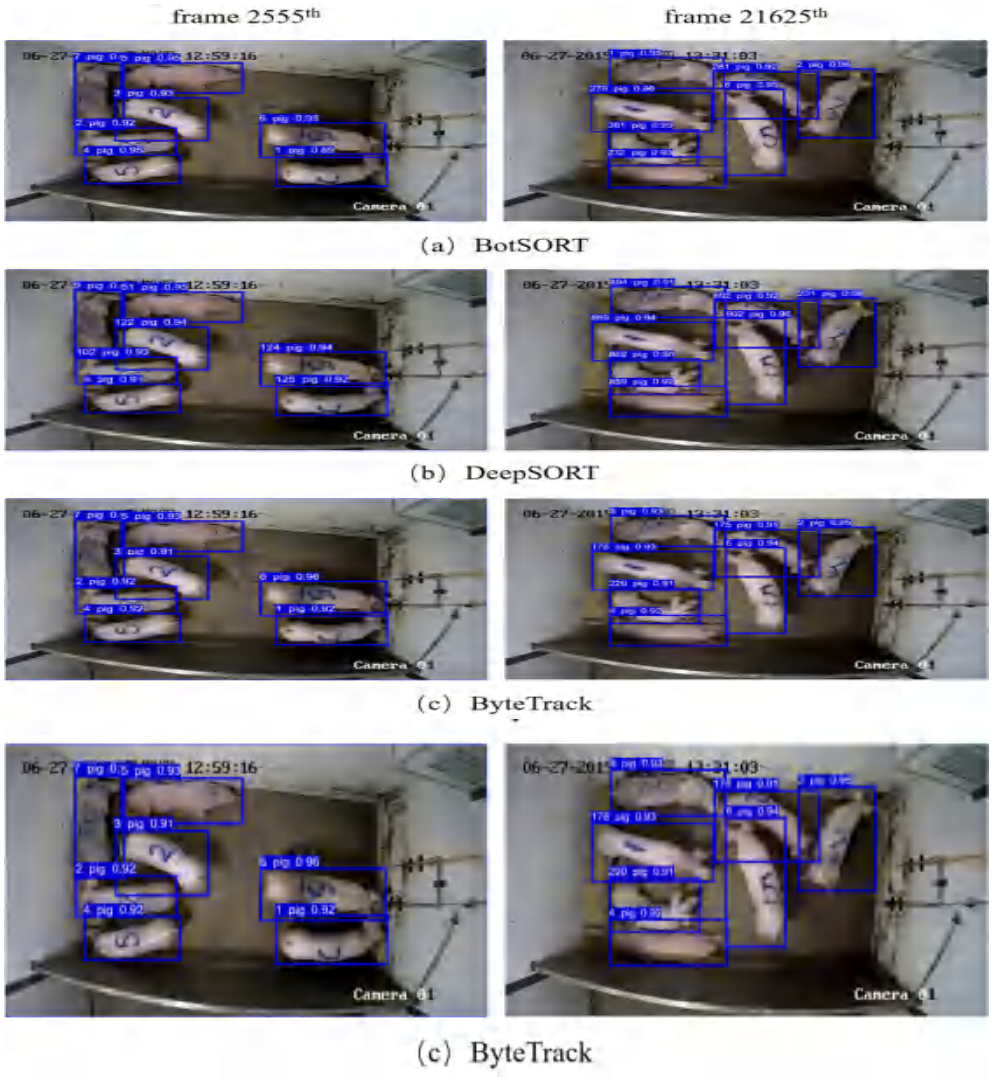


Figure 11. *Cont.*

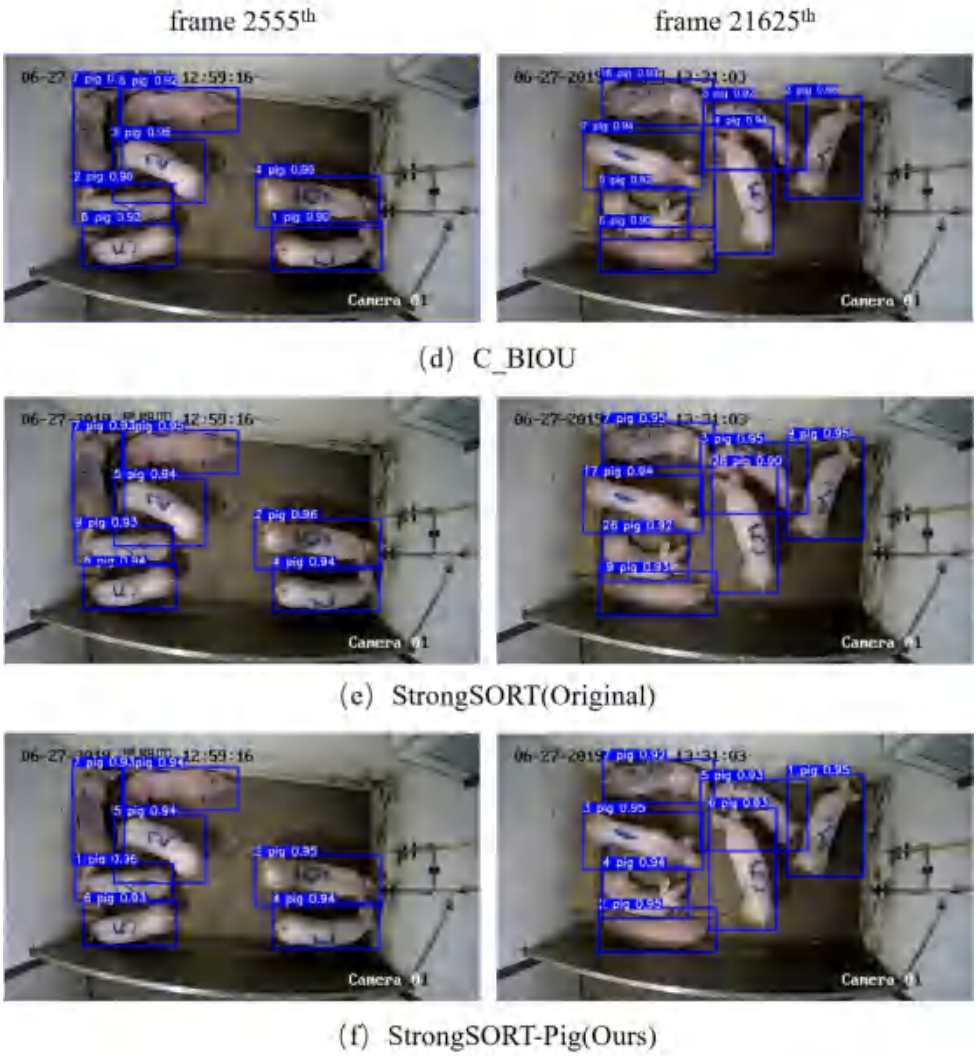


Figure 11. Comparative example of tracking results for different tracking algorithms.

We selected the tracking results in the 2555th frame and the 21,625th frame. From Figure 11, it can be observed that none of the six algorithms exhibited any instances of missed tracking. However, only our proposed algorithm achieved successful tracking, correctly matching all pigs. When tracking using the DeepSORT algorithm, all pigs failed to be tracked. With BotSORT and ByteTrack, only one pig was tracked successfully, and using the C_BIOU and StrongSORT algorithms, two pigs could be tracked successfully. In addition, as shown in Figure 11c, d, pigs numbered "5" and "6" exchanged IDs between the 2555th and 21,625th frames. This occurred because during a certain period of time, these two pigs were in close proximity, and both C_IOU and ByteTrack algorithms relied solely on motion models for matching without considering re-identification features to compute appearance similarity. In summary, compared to other multi-object tracking methods, our algorithm shows superior tracking performance in complex scenarios for pig tracking tasks, enabling the stable tracking of pigs.

3.4. Generalization

To validate the generalization of our research model, we conducted testing using unseen data from the training set. The test video had a duration of 30 min and was recorded in May 2022. The recording took place indoors with lighting provided by artificial sources. The occlusion in the video was not severe, and the camera was positioned at a 45-degree angle. It is important to note that the camera's field of view did not cover the

entire pig pen, which resulted in instances where pigs would momentarily disappear and then reappear in the frame.

3.4.1. Generalization for Pig Detection

To validate the generalization ability of the pig detection model, we utilized ffmpeg to extract keyframes from the test videos. In order to maintain consistency with the original test set, a total of 360 images were selected for this testing. The model achieved Recall and mAP scores of 95.3% and 96.6%, respectively. The actual test results are shown in Figure 12.



Figure 12. Generalization experiment results for pig detection. (**a**) Dense pig scene, (**b**) Sparse pig scene.

From the provided figures, it can be observed that in Figure 12a, the occlusion is more severe compared to Figure 12b, and the detected confidence is lower. However, both images do not exhibit any cases of missed detections. Additionally, in comparison to the results in Section 3.2.2, Recall and mAP decreased by 3% and 1.8%, respectively. This could be attributed to the differences in the shooting angles between the training set and the test data used in this particular experiment.

In conclusion, based on the above analysis, the pig detection algorithm in this research demonstrates good generalization ability, as it successfully detects pigs even in the presence of occlusion and varying shooting angles between the training and test datasets.

3.4.2. Generalization for Multi-Pig Tracking

We conducted testing on unseen videos from the training set using the StrongSORT-pig algorithm, and the results are shown in Figure 13. In the 34,625th frame, all pigs were successfully tracked. However, in the 35,775th frame, the pig with ID 3 disappeared. In the 36,925th frame, the previously disappeared pig reappeared but was not detected by the algorithm. Finally, in the 37,025th frame, the pig with ID 3 reappeared completely and was successfully detected, maintaining its original ID, resulting in successful tracking.

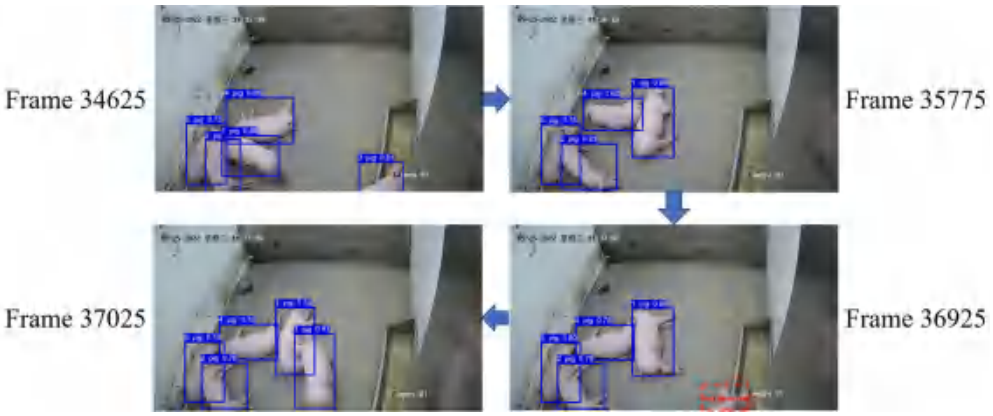


Figure 13. Generalization experiment results for multi-pig tracking.

Compared to the results in Table 5, all performance metrics had decreased. HOTA, MOTA, IDF1, and MOTP had decreased by 2.8%, 3.9%, 2.9%, and 4.2%, respectively, reaching 79.8%, 93.7%, 88.2%, and 86.6%. The decrease in MOTP, which reflected the accuracy of the detection's spatial position, is related to the pig detection model. The decrease in MOTA and IDF1 was due to the presence of a blind spot in the test video, where pigs disappear and cannot be detected, leading to changes in their IDs. The combined effect of these three metrics resulted in a decrease in HOTA.

Although the results obtained from testing in unseen scenarios were not as good as those from the seen scenarios, the StrongSORT-pig algorithm demonstrated its ability to effectively track pigs, even when they temporarily disappear and reappear in the video sequence.

4. Discussion

4.1. Discussion on Factors Affecting Pig Tracking Performance

In the multi-pig tracking task, there are many factors affecting the tracking effect, such as pig density, pig movement intensity, and the video frame rate.

It is worth noting that the nine videos, Video1–Video3, Video4–Video6, and Video7–Video9, were from three different scenes. In the scenes from Video 1 to Video 3, there are a large number of pigs present, with frequent occlusions, crowded environments, and active pig movements. In Video 7 to Video 9, the number of pigs is relatively small, and the scenes are relatively spacious. As for Video 4 to Video 6, these scenes have a moderate number of pigs, with a less crowded environment, and the level of pig movement is moderate. The results in Table 5 also indicate that the performance of the algorithm is influenced by the complexity of the scenes.

Particularly in the case of Video3, both HOTA and IDF1 are lower compared to the other videos. This is attributed not only to the pigs in this video exhibiting notably intense activity but also to its low frame rate of only 5 frames per second. The significant variations between adjacent frames make it challenging to accurately predict tracking trajectories, resulting in poorer algorithm performance.

In order to reduce the influence of these factors on the tracking performance, we can combine the detection model with dense optical flow, enhance the optical flow results by adding a mask to the detection frame, compute the motion of each detected object, and realize the prediction and matching of the target's position between the front and back frames [29]. The introduction of optical flow can effectively alleviate the issue of large displacements of tracked objects in low-frame-rate videos.

4.2. Discussion on the Application of Long-Term Pig Tracking Algorithm

Although it has been difficult for existing research to achieve the long-term regular analysis of individual pigs [30], it is valuable for behavioral studies and is beneficial for a deeper understanding of the health status of pigs [31]. In this study, we realized the all-day tracking of pigs. Based on this, we can use the results for analyzing the behavioral rhythms of individual pigs throughout the day, as a basis for detecting pig abnormalities, and early health warnings.

The pen was divided into four sections based on the positions of different areas in the video frames, as shown in Figure 14. The area of (490,200)~(720,975) was classified as the defecation area, (720,200)~(1480,975) was classified as the resting area, (1480,200)~(1580,975) was classified as the eating area, and the remaining parts of the video frames that were unrelated to this experiment were considered irrelevant zones. To further validate the practicality of the tracking algorithm, this study counted the time spent by each pig in different areas (resting area, eating area, and defecating area) based on the 24 h tracking of the pigs. The results were compared with the observed results, which manually recorded the time spent by each pig in each area, and the duration of each area was added up to calculate the total time spent.

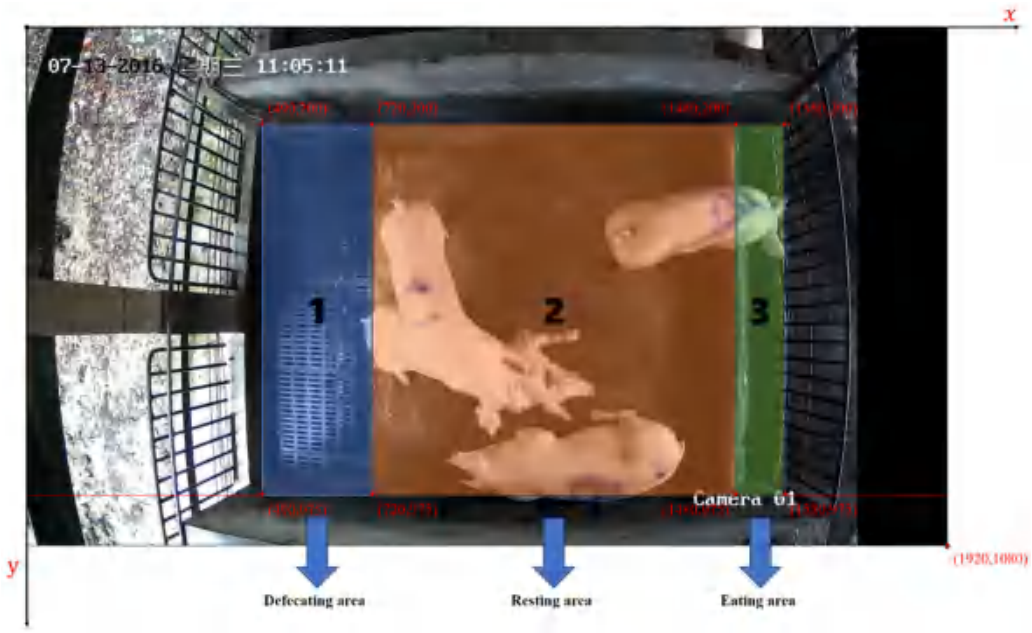


Figure 14. Area division of pig pens.

The data were preprocessed according to the following procedure: (a) Grouping the tracking results by pig ID (1, 2, 3, 4). (b) Calculating the center-point positions of the bounding boxes for each pig. (c) Filling in missing data. The pig detector is not fully able to detect pigs in all scenarios, and there are very few frames in which a particular pig cannot be detected during the tracking process, so filling in the missing frames ensures that there are detection data for every frame of every pig to facilitate subsequent grouping based on time. (d) Aggregating the data for each pig every 1 s.

After preprocessing the tracking results, the area where the pig is located every second can be determined by the position of the center point of the pig bounding box. The specific steps were as follows: (a) Determine frame by frame the area where the center point of the pig detection frame is located. (b) Identify the area with the highest proportion within that second (25 frames) to determine the pig's location for that second. (c) Summarize the time each pig stays in each area.

It should be noted that due to the distance between the center point of the detection box and the pig's head, it may not accurately reflect the pig's actual position when the pig is eating. Therefore, adjustments to the eating area will be needed. In the case of pigs eating, the length of the pig's body was measured, and the average distance from the center point of the detection box to the head was 230 pixels. So, the left boundary of the eating area was extended outward to a position of 1350 pixels as the criterion for determining that the pig is in the feeding area.

From Table 8, it can be seen that all pigs spent the most time in the resting area throughout the entire day, which is consistent with their natural behavior. In addition, there are differences in the amount of time each pig spent in different areas, which might be related to individual differences. The more intuitive comparison of the statistical results of the two methods is shown in Figure 15. The four bar charts represent the comparison of the time each of the four pigs spent in different areas. It is evident from the charts that our statistical results differ very little from the manually observed results.

Table 8. Duration of stay statistics in each area.

Methods	Pig Identity	Defecating Area Time (s)	Resting Area Time (s)	Eating Area Time (s)
Manual observation method	1	9039	67,530	9791
	2	32	73,850	12,478
	3	14,407	55,649	16,304
	4	4150	75,939	6271
Video tracking method	1	9138	67,213	10,009
	2	32	74,190	12,138
	3	14,665	55,136	16,559
	4	4033	75,787	6540

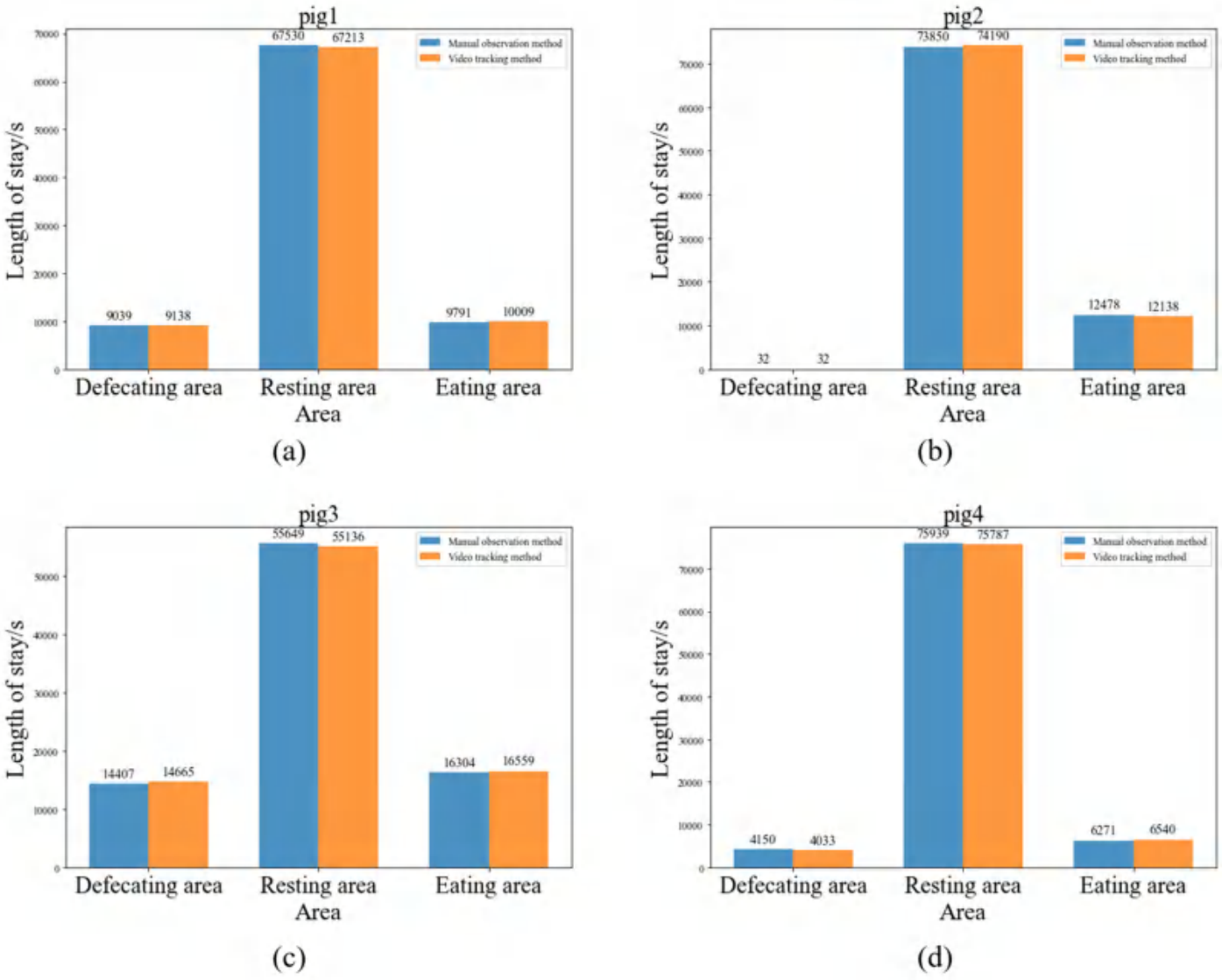


Figure 15. Comparison of length of stay. (**a**) pig1, (**b**) pig2, (**c**)pig3, (**d**) pig4.

Table 9 shows the error between the video tracking method and the manual observation method for each pig in each area. The table indicates that there are slight differences between the two methods, with an overall error of 1.55%, which falls within an acceptable range. For all pigs, pig 4 has the largest statistical error, but it is only 2.44%. For each area, the statistical error is highest in the eating area, at 2.70%, while the other two areas are within 2%, demonstrating good consistency. Overall, this set of data show that both

methods have very small errors, validating the accuracy and reliability of the results. This also indicates that pig tracking has certain application value in the field of pig farming.

Table 9. Error analysis of the multi-pig tracking method.

Pig Identity	Error in Defecating Area (%)	Error in Resting Area Time (%)	Error in Eating Area Time (%)	Average Error (%)
1	1.10	0.47	2.22	1.26
2	0	0.46	2.72	1.06
3	1.79	0.92	1.56	1.42
4	2.82	0.20	4.29	2.44
Average	1.43	0.51	2.70	1.55

In terms of pig tracking algorithm applications, Huang et al. [32] combined YOLO v5 with DeepSORT to achieve efficient pig counting through tracking, but they have not incorporated behavior analysis of the pigs. Additionally, Tu et al. [33] combined behavior recognition with pig tracking, using a pig detection model to extract pig behaviors and a pig tracking algorithm to determine pig identities, enabling static behavior tracking of the pigs. Zhang et al. [34] combined pig tracking with the Slowfast action recognition network, achieving the tracking of complex pig behaviors. However, due to overlapping and occlusion among the pigs, it is challenging to achieve long-term tracking. By improving the StrongSORT algorithm, our study enables accurate tracking for 24 h, laying the foundation for long-term pig tracking applications.

5. Conclusions

This paper proposed a multi-pig tracking algorithm StrongSORT-Pig and explored its application in pig farming. The core technical contributions are as follows:

1. We proposed a lightweight pig detection model, YOLO v7-tiny_Pig, which reduced the number of parameters by 36.7% and improved the recognition speed by 17.6% while ensuring detection accuracy.
2. The StrongSORT multi-object tracking algorithm was optimized to suit the characteristics of pig tracking tasks. After testing on datasets from different scenarios, the optimized pig tracking algorithm achieved HOTA and IDF1 scores of 83.16% and 91.42%, respectively, which improved by 6.19% and 10.89%. The IDSW was reduced by 69%, significantly enhancing the algorithm's stability and enabling the long-term tracking of pigs.
3. This study enabled the continuous video tracking of pigs throughout the day. Our automated tracking method calculated pigs' stay times in different areas of the pigsty and achieved an overall error rate of 1.55% compared to manual counting, demonstrating a high degree of correlation. The conclusions drawn from the automated tracking results also aligned with pig behavior patterns.

In summary, the multi-pig tracking method proposed in this study demonstrates high practicality, catering to the needs of practical production. It improves the efficiency of farming personnel and lays the foundation for the automated monitoring of pigs.

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Institutional Review Board Statement: Only video data were used to perform the study; no experiments were performed on animals directly.

Informed Consent Statement: Written informed consent has been obtained from the owner of the animals involved in this study.

Data Availability Statement: Data are contained within the article.

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A review of video-based pig behavior recognition

Qiumei Yang, Deqin Xiao *

College of Mathematics and Informatics, South China Agricultural University, Guangzhou, Guangdong, 510642, China

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ABSTRACT

Video surveillance technology has been applied in many farms and a large amount of video data has been generated. Extracting valuable information about the pig industry from video data is a challenging problem. Pig behavior recognition is one of the research hotspots. In order to facilitate scholars to systematically understand the research status and development trends of this field, the paper summarizes the research on pig segmentation, pig detection and pig behavior recognition. The applications of traditional image processing methods and deep learning methods are introduced. The recognition strategies for different kinds of behavior, such as postural behavior, locomotion behavior, area-related behavior and interactive behavior, are summarized. Finally, some of the existing challenges in the current research are highlighted and future research work envisioned to address these is proposed.

1. Introduction

Pig health diagnosis depends on many factors, and behavior observation is one of the most important factors. In the past, the preliminary judgment on the health of pigs was determined by the stockperson's personal judgment, which was subjective and laborious. More objective and intelligent pig management tools are needed. Nowadays, the pig industry has gradually shifted from household production to intensive large-scale farming. With the development of sensor technology, video surveillance technology, information communication technology, big data and artificial intelligence technology, the pig industry has stepped into the era of intelligent pig farming. Intelligent pig farming provides precise management for pigs. It has continuous monitoring of pigs in a fully automatic way to ensure that they are provided with a better quality of life and welfare(Berckmans, 2014).

Pigs behave different behaviors in different conditions. Under normal environmental conditions, pigs perform daily behaviors such as eating, drinking and excreting. Sows may perform maternal behaviors such as nesting and nursing. Boars may perform sexual behaviors such as mounting. When the living environment changes or pigs feel uncomfortable, pigs may perform abnormal behaviors such as lethargy, attacking and tail biting. It is proved that pig behavior will change due to sickness(Matthews et al., 2016). Therefore, the supervision of pig behavior is essential in precision pig farming. Technologies such as sensors, radio frequency identification (RFID) and video surveillance have been applied to automatically monitor pig behavior. Sensors apply physical, chemical and biological technologies to convert physical quantities, chemical quantities, and biomass into electricity quantities. Motion parameters, including speed, acceleration and direction, can be measured by sensors. They have been applied to detect walking, running, jumping and stationary behaviors of pigs (Cornou et al., 2011). The RFID system consists of three parts, including electronic tags, readers and antennas. RFID technology can identify specific targets through non-contact data communication between the reader and the tag. The electronic tag can be punched into the pig's ears, and the reader can be installed in a fixed position on the pig farm. It is applied to the identification of individual pigs. It can be used to monitor behaviors in specific areas, such as drinking and eating (Maselyne et al., 2016). Some abnormal behaviors such as eating too little or excretes too much can also be monitored using RFID to identify suspicious sick pigs (Zhu et al., 2010). When applying sensors or RFID technology, pigs must wear some corresponding equipment, which are invasive methods. In addition, replacing the battery of the equipment is also a troublesome problem when using sensors or RFID technology. Video surveillance technology is an emerging method that has been widely accepted by the animal husbandry industry. It provides a non-invasive and visible method for animal behavior detection. Through video surveillance, it is possible to locate each pig, identify its posture and quantify its movement. It provides an effective way for pig behavior recognition. The video-based pig behavior recognition process is shown in Fig. 1. With pig farm surveillance video as input, pigs are first detected in the frames, and then behavior recognition is performed. Research related to video-based pig

* Corresponding author.
E-mail address: deqinx@163.com (D. Xiao).

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behavior recognition will be introduced in this paper.

2. Pig segmentation and detection

The primary task of video-based pig behavior recognition is to identify pigs from video frames. In previous research, there are two main methods for detecting pigs. One method is to distinguish the outline of pigs as foreground from background objects by pixels, which is called pig segmentation. Another method is to locate pigs by rectangles according to their features, which is called pig detection.

2.1. Image features of pigs

Feature description is essential for object detection. Image features of the object include color, texture, and shape, etc. Color histogram (Sergyan, 2008), color moment invariant(Duanmu, 2010), etc., are used to describe color features. Gray level co-occurrence matrices(Roberti De Siqueira et al., 2013), tamura texture feature(Qi, 2009), etc., are used to describe texture features. Fourier descriptors (Persoon and Fu, 1986), moment-based shape descriptors(Celebi and Aslandogan, 2005), etc., are used to describe shape features. Based on these basic features of images, some feature descriptors, such as scale-invariant feature transform(SIFT)(Lowe, 2004), Histogram of oriented gradients(HOG) (Dalal and Triggs, 2005), and Haar-like features (Lienhart and Maydt, 2002), have been proposed. With the development of deep learning, the convolutional neural network (CNN) has been widely used for image feature extraction. Deep CNN has an ability for feature representation of large-scale images and has promoted the progress of object detection (Krizhevsky et al., 2012). GoogLeNet, VggNet, ResNet, etc., are popular CNN models. They have achieved outstanding performance in the ImageNet large-scale visual recognition challenge. Color feature(Sun et al., 2020), texture feature (Li et al., 2019a, 2019b), shape feature (Fernandes et al., 2019), and CNN (Yang et al., 2018a)have all been applied to the feature description of pigs.

2.2. Research on pig segmentation

Pig segmentation can obtain a complete outline of the monitored object. It is the basis for analyzing the body size, weight and posture of pigs. Pig segmentation can be done by feature classification of a single frame, which is called static image segmentation. Static image segmentation algorithms include threshold segmentation(Otsu, 1979), edge detection segmentation(Kang et al., 2009), watershed segmentation (Nguyen et al., 2003), graph theory-based segmentation (Parihar and Thakur, 2014), and morphological segmentation(Meyer, 2001). Pig segmentation can also be done through correlation features between multiple frames, which is called dynamic image segmentation. Dynamic image segmentation algorithms include optical flow method(Narayana et al., 2013), frame difference method(Zhao et al., 2012), and background subtraction method(Spagnolo et al., 2006).

Given a frame, the most commonly used static image segmentation algorithm is color threshold segmentation. In the early days, black and white cameras were used for pig pen monitoring. Using the color difference between the body of pigs and the pen, the Otsu algorithm(Otsu, 1979)was proposed to binarize images of pigs. After a series of morphological operations, the noise of the binarized image was removed and the outline of the pigs was obtained. The back of pigs is the most stable part of the image captured by the top-view camera. Some man-made markings were added on the back of pigs to distinguish them individually (Kashiha et al., 2013a). This method was also applicable to images captured by color cameras. An adaptive threshold segmentation method was proposed to segment pigs captured by RGB cameras under natural conditions (Xiao et al., 2019). Pigs may stick to each other, so it is difficult to obtain the outline of each pig separately. To solve this problem, by fitting each segmented outline with an ellipse, individual pigs could be separated according to their body size. Such an algorithm was useful for separating adhesive pigs (Lu et al., 2016). When the color of the body area of pigs is uneven, it is difficult to obtain its complete outline by a color threshold segmentation method. A full convolution neural network (FCN) was used to segment MeiHua sows. It solved the problem of uneven illumination and random noise. The model was suitable for the segmentation of different breeds of pigs (Yang et al., 2018a). For the images taken by the depth cameras, the Otsu method was applied to get the outline of pigs for weight estimation (Jun et al., 2018). A CNN-based detector called YOLO was used to solve the problem of touching pigs segmentation in the images captured by a kinect camera (Ju et al., 2018) and images acquired from an Intel RealSense camera (Seo et al., 2019). For thermal infrared images, the Otsu method was also applicable to pig segmentation (Lu et al., 2018).

Dynamic image segmentation relies on the difference between frames to detect foreground objects, which is appropriate for moving object detection. Mixed Gaussian model (GMM) for foreground extraction combined with maximum entropy threshold segmentation was applied to obtain the outline of the pigs (Guo et al., 2014). On this basis, a multi-level threshold segmentation method was proposed to get a more accurate outline of pigs(Guo et al., 2015). By changing the sampling frequency and learning rate, the GMM based pig segmentation was improved(Li et al., 2017b). Using Gabor wavelet transform and local binary pattern(LBP) to extract texture features from segmented pigs, a support vector machine(SVM) classifier was established to identify individual pigs in groups(Huang et al., 2018). In order to solve the problem of separating touching pigs, the concave points and edge information were used to detect the boundary of each pig(Baek et al., 2017).

It can be seen from the existing research that the segmentation of pigs depends on the distinction between the background and the pigs. Since pigsty environments are varied, it is difficult to have a general segmentation algorithm. Factors such as illumination and pig adhesion also affect the segmentation results. When pigs are not moving, dynamic segmentation is not effective. A summary of studies on pig segmentation is listed in Table 1.

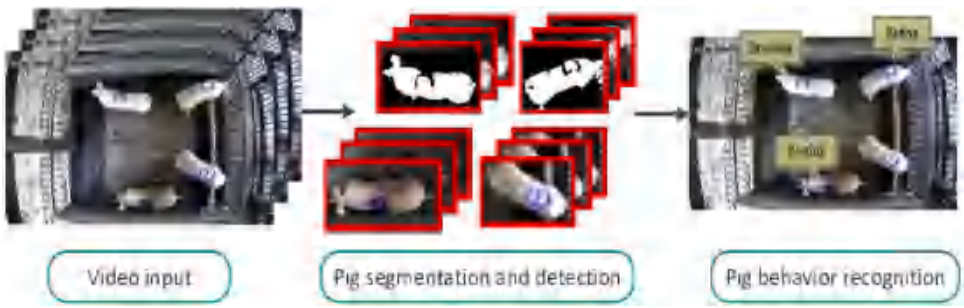


Fig. 1. The process of video-based pig behavior recognition.

Table 1
The summary of pig segmentation methodologies.

Data Type	Technique	Handling of touching pigs	Results (Accuracy)	Reference
Black and white or color image	Otsu	No	88.7 %	Kashiha et al., 2013a
			87.32 %	Xiao et al., 2019
	Otsu and ellipse fitting	Yes	86 %	Lu et al., 2016
	FCN	No	Accuracy: 96.4 % Sensitivity: 92.0 % Specifificity:98.5 %	Yang et al., 2018a
	GMM	No	92 %	Guo et al., 2014
			92.5 %	Guo et al., 2015
			91.86 %	Huang et al., 2018
	GMM and concave points and edge information	Yes	93.67 %	Baek et al., 2017
Depth image	Otsu	No	Not specified	Jun et al., 2018
	YOLO	Yes	91.96 %	Ju et al., 2018
			85%	Seo et al., 2019
Thermal image	Otsu	No	97 %	Lu et al., 2018

2.3. Research on pig detection

Object detection is to learn target features and then mark them out in the image (Zhao et al., 2015). It is a matching problem to study the possible location of a specific object in the image and then identify it. Template matching is a primitive and basic pattern recognition method. By learning pig templates from training images, pigs with similar attributes to the templates could be detected (Li et al., 2019a, 2019b). The principal component analysis convolution kernel was selected to extract image features, and an SVM was trained to determine whether a sliding window area was a pig (Sun et al., 2019). CNN-based detectors have been the mainstream methodologies in recent years, and there have been relevant studies on pig detection. For example, Faster R-CNN detector was applied for pig detection (Cowton et al., 2019; Sun et al., 2018). In order to identify each individual pig, the back of each of them was marked with a character. The body and head of pigs were labeled out in the images for training. Through a procedure of feature extraction, region proposal and object classification, a detector for individual pigs identification was built (Yang et al., 2018b). Although the Faster R-CNN detector had high accuracy in pig detection, the single shot multi-box detector (SSD) did better in terms of time performance. Through a hierarchical data association algorithm, the coupling SSD detector and a correlation filter-based tracker could track individual pigs effectively (Zhang et al., 2019). The FCN was also applied to detect various parts of pigs, such as ears, shoulders, tails, etc., and then combined the various parts together to form a complete detection result (Psota et al., 2019).

Individual pig identification is very important for precision pig farming, and it is also very useful in situations such as pig insurance that requires pig identity. Some attempts have been made to solve the automatic visual identification of pigs. For human identification, facial and gait features were commonly used and a good identification result was achieved. Similar work to identify pigs based on their faces has been done. The eigenspace method was used for the facial identification of pigs. It came to the conclusion that eyes of pigs were crucial features for pig identification(Wada et al., 2013). Learned from the human face identification models, such as Fisher's face and the VGG pre-trained face model, a pig face specified CNN model was built(Hansen et al., 2018). It is a great way to collect pig face images at resource points such as drinkers. However, if the behaviors of individual pigs need to be monitored throughout the day, it is not feasible because pigs will leave the specific area and lie down or lower their heads. All in all, pig identification is a tough task since pigs in the same pen often have high similarities.

The detection methodologies used for pig monitoring are summarized in Table 2. Since pigs are non-rigid objects, their body shapes will bend, curl and vary with changes in behavior. They will display different postures and appear differently on the images over time. More consideration should be given to improve detection accuracy and enhance model generalization capabilities.

3. Pig behavior recognition

Video-based pig behavior recognition is mainly accomplished through image processing techniques and machine learning methodologies. Research can be divided into postural behavior recognition, locomotion behavior recognition, area-related behavior recognition and interactive behavior recognition.

3.1. Research on postural behavior recognition

Postural behavior recognition is a static way of studying pig behavior. The body of a pig can be divided into head, back, belly, tail, fore legs and hind legs. Different placement of the body parts can form different postures. In a video surveillance scene, different shooting angles have different imaging effects on the body parts of pigs. For side viewed images, the belly of pigs is the main visible part, while for top viewed images the back of pigs is the main focus. There are three main modes of pig posture, i.e. standing, sitting and lying (Lou and Hurnik, 1998), as shown in Table 3.

It is considered that postural behavior is related to environmental comfort. A three-layer neural network (NN) was trained to divide the postural behavior of the pigs into three thermal comfort states, namely cold, comfortable and warm(Xin, 1999). Various features were further explored to classify the lying behavior of pigs for environmental

Table 2
The summary of pig detection methodologies.

Target detected	Technique	Handling of individual pig identification	Results (Accuracy)	Reference
Whole pig	Template matching	No	86.8 %	Li et al., 2019a, 2019b
Whole pig	Sliding windows and SVM	No	95.21 %	Sun et al., 2019
Whole pig and pig head	Faster R-CNN	Yes	Precision:96.58 % Recall: 87.04 %	Yang et al., 2018b
Whole pig		No	83.781 %	Sun et al., 2018
Whole pig		No	Precision:90.1 %	Cowton et al., 2019
Whole pig	SSD	Yes	Precision:94.72 %	Zhang et al., 2019
Ear, shoulder, tail	FCN	No	Precision: 99 % Recall: 96 %	Psota et al., 2019
Pig face	Eigenspace	Yes	97.9 %	Wada et al., 2013
	CNN	Yes	96.7 %	Hansen et al., 2018

Table 3
The definition of pig posture.

Posture	Description	
Lying	Side lying (Lateral recumbency)	One side of the body is touching the floor, exposing the belly and legs.
	Belly lying (Ventral recumbency)	The belly is touching the floor, and the front legs are folded under the body.
Siting	The front legs stand up, with the hind legs folded and tail touching the floor.	
Standing	Both the front and hind legs touching the floor, and the body stands upright with a distance from the ground.	

assessment (Shao and Xin, 2008). The Delaunay triangulation method was used to detect changes in the lying behavior of pigs in a commercial farm environment and to assess the correlation between lying behavior and changes in ambient temperature (Nasirahmadi et al., 2015). Monitoring the proportion of pigs lying down during different periods was one way to assess pig welfare(Nasirahmadi et al., 2017). There are different kinds of lying postures, which are essential for pig behavior analysis. Pigs prefer to sternal lying when the temperature is lower and lateral lying when the temperature is higher. Using the background subtraction result of the 2-dimensional(2D) images, the two lying postures were distinguished by an SVM classifier (Nasirahmadi et al., 2019a). The postures of sows, including standing, sitting, sternal recumbency, ventral recumbency and lateral recumbency, were detected by the Faster R-CNN detector to study the behavior of lactating sows (Zheng et al., 2018).

The most obvious difference between lying, sitting, and standing is that pigs have different body heights in different postures. When recognizing postures of different heights, depth images have more advantages than 2D images. Lying pigs were detected in 3-dimensional (3D) Kinect images (Kim et al., 2017a). Compared with the lying posture, the height value of the standing posture is significantly different, hence the standing posture can be detected by setting different height thresholds (Kim et al., 2017b). Since the height threshold plays an important role in distinguishing the postures of pigs, different deep learning methods have been proposed to discuss the height difference between the standing and lying postures (Nasirahmadi et al., 2019b).

3.2. Research on locomotion behavior recognition

Locomotion behavior is used to study the movement of pigs in the pigpen, including where they stay, how long they stay, and how many steps they take. The activity level of pigs or pig herds can be measured. When a pig is sick, its activity will decrease. It is a direct indicator of pig health.

The locomotion behavior can be recognized by monitoring pixel variations of video frames. By finding out the moving pixels through image subtraction, the movement of pigs was calculated(Lind et al., 2005). Another way for quantifying the movement of a pig was to calculate the moving distance of its centroid. The segmentation method was used to obtain the outline of each pig, which was then fitted with an ellipse. The distance between the centroids of the ellipse of adjacent frames was regarded as the moving distance of the pig(Kashiha et al., 2014). The optical flow method combined with a modified angle histogram was proposed to analyze the movement of pig herds to prevent undesirable tripping and stepping(Gronskyte et al., 2016). Optical flow has also been used to try and predict behavioral problems from increases in group activity(Larsen et al., 2020 ; Li et al., 2020). The background subtraction and optical flow method were used to calculate the activity level of pre-farrowing sows. Three activity patterns were defined, i.e. normal activity, increased activity and decreased activity. It could predict the time of parturition correctly(Küster et al., 2020).

Pig tracking is to locate each individual pig on every frame of the video. It can monitor the movement of pigs over time. After segmenting the video frame to locate each pig, the Kalman filter tracking algorithm was further proposed to study the trajectory of pigs (Yu et al., 2015). The deep simple online and real-time tracking (Deep SORT) algorithm were applied to the detection result of the Faster R-CNN detector (Cowton et al., 2019). In order to improve the tracking accuracy, a tracking target correction algorithm was proposed to revise position offset based on the result of the Faster R-CNN detector (Sun et al., 2018). To speed up the tracking process, a tracking method based on discriminative correlation filters (DCF) was applied to multiple pigs tracking (Zhang et al., 2019).

The activity index between two consecutive image frames, which is the ratio of the amount of moving pixels to the amount of pixels occupied by the pigs, is defined to measure the locomotion behavior of a pig herd. After the outline of pigs was obtained by segmentation, the pixels representing pigs were extracted. The movement of a pig herd was obtained by subtracting pixels from two adjacent frames. The video sequences were processed in seconds to calculate the activity index. Five different activity levels were manually marked. 0 meant no activity, 1 meant fighting or struggling, 2 meant biting each other, 3 meant abnormal behavior and 4 meant eating. Research was conducted to discover the relationship between the activity index and different kinds of pig behavior, providing an effective and non-invasive way to study the pig herd behavior(Costa et al., 2013 ; Leroy et al., 2009). According to the activity index, the pig herd behavior was divided into generally active and inactive (Ott et al., 2014). The activity index level could also be used to determine whether there was aggressive behavior in a pig herd. An artificial neural network (ANN) architecture was trained to distinguish the activity index of highly aggressive and moderately aggressive pig herds (Oczak et al., 2014). Using CNN and long short-term memory network(LSTM) to extract spatial and temporal features respectively, the aggressive behavior of pigs were recognized through a softmax classifier(Chen et al., 2020).

3.3. Research on area-related behavior recognition

Smart farming suggests that it is necessary to provide animals with the most comfortable environment to improve animal welfare. A pigpen is divided into different functional areas. There are places for pigs to drink, to eat, to rest, and to excrete, as shown in Fig. 2.

In Fig. 2, the area marked with 1 is the place for pigs to drink water, the area marked with 2 is the place to excrete, the area marked with 3 is the place to eat, and the middle area of the pen is the place to rest. Most of the time, pigs perform different activities in different areas. The key to recognizing the behavior of pigs in relation to the area is to detect whether the pigs have entered a corresponding functional area or not.

The definition of pig drinking behavior means that a pig is sucking a drinking nipple and there are water flowing into its mouth. The video-based automatic detection function of pig drinking behavior is to detect that the head of the pig is in the drinking area and stays for a certain period of time. It was suggested that the distance between certain key points of a segmented outline of a pig could be used to detect its ears, and then consequently deduced the position of its head. The relationship between the head of a pig and the drinking nipple was then used to



Fig. 2. Different functional areas in a pigpen.

determine whether a drinking behavior occurred (Kashiha et al., 2013b). The recognition of pig feeding behavior is similar to that of pig drinking behavior. The image occupation index was used to determine whether the feeding area was occupied by pigs or not, so as to determine the occurrence of pig feeding behavior (Yang et al., 2018b). When a pig doesn't excrete in the designed area, it is considered to be showing pen fouling behavior. With the position of pigs as input, random forests and ANN were trained to see if a fouling behavior happened or not (Jensen et al., 2020).

3.4. Research on interactive behavior recognition

The interactive behavior of pigs involves two or more pigs communicating with each other. The spatial relationship between multiple pigs, such as the distance and intersection angle between heads, tails, bodies, is essential to behavior recognition. The temporal relationship changing over time is another key factor. In the current research, video-based multi-pigs behavior recognition mainly includes mounting, nursing and tail biting, etc.

The mounting behavior usually involves two pigs. In a video sequence, it is characterized by a pig gradually approaching another pig and then placing its fore legs on the other pig. The mounting process will last for a period of time. The mounting behavior ends when the mounting pig removes its fore legs from the mounted pig. This behavior can be reflected by changes in the distance between pigs. The distance between the body of pigs was used to recognize the mounting behavior (Nasirahmadi et al., 2016). Mask R-CNN was used to segment the images to get the outline of pigs and the kernel-extreme learning machine (KELM) was applied to determine whether a mounting behavior occurred or not (Li et al., 2019a, 2019b). Recognition of mounting behavior is helpful for accurate detection of estrus in pigs, as studies show that there will be a significant increase in mounting behavior before the estrus of sows. In addition, when pigs are in a new pigpen or overcrowded breeding environment, they will also be accompanied by a lot of mounting behavior. If the mounting behavior can be detected in time, manual intervention can be performed to reduce injuries between pigs and improve pig welfare.

The nursing behavior of pigs refers to the interaction between the sow and the piglets. The sow was first detected by an FCN in the images, and then its udder zone was located. If piglets were detected in this area, nursing behavior may occur. The optical flow features were used to train an SVM to build a model for nursing behavior recognition (Yang et al., 2018a).

The interactive pig behavior, such as face-to-face communication, head-to-head attack, head-to-body attack, side-by-side squeezing, neck biting, body biting, ear chewing, and jumping on others, were studied through automatically recorded videos and manual annotation (Oczak et al., 2013). An SVM classifier was trained to detect the occurrence of head knocking and chasing behavior between pigs (Lee et al., 2016). There was also research on tail posture scoring to predict tail biting behavior (D'Eath et al., 2018).

The pig behavior recognition methodologies are summarized in Table 4.

Table 4
The summary of pig behavior recognition methodologies.

	Detail	Technique	Object studied	Results (Accuracy)	References
Postural behavior	Lying	Segmentation and NNclassification	Group-housed pigs	90 % 90 %	Xin, 1999 Shao and Xin (2008)
		Delaunay triangulation	Finishing pigs	95.8(±2)%	Nasirahmadi et al., 2015
		Segmentation and Ellipse fitting	Finishing pigs	93–95 %	Nasirahmadi et al., 2017
		Background subtraction and SVM	Weaning and fattening pigs	94.4 %	Nasirahmadi et al., 2019a
		Faster R-CNN	Sow	93.58 %	Zheng et al., 2018
	Standing	Depth values	Weaning pigs	80.0 %	Kim et al., 2017a
		Depth values	Weaning pigs	94.47 %	Kim et al., 2017b
		Deep learning in depth boundary	Weaning and fattening pigs	mAP: 93 %	Nasirahmadi et al., 2019b
	Movement	Image subtraction	Mini pigs	Not specified	Lind et al., 2005
		Centroid distance	Group-housed pigs	89.8 %	Kashiha et al., 2014
		Optical flow	Pigs to be slaughtered	Not specified	Gronskyte et al., 2016
			Finisher pigs	Not specified	Larsen et al., 2020
			Gilts and barrows	Not specified	Li et al., 2020
			Sows	53.4, 78.6, 100 %	Küster et al., 2020
Locomotion behavior	Tracking	Kalman filter tracking	Group-housed pigs	92.3 %	Yu et al., 2015
		Deep SORT		92 %	Cowton et al., 2019
		Tracking target correction algorithm		83.78 %	Sun et al., 2018
		DCF		94.72 %	Zhang et al., 2019
	Aggression	Activity index	Group-housed pigs	Not specified	Costa et al., 2013
				Not specified	Leroy et al., 2009
				Not specified	Ott et al., 2014
				94.2 %, 99.2 %	Oczak et al., 2014
Area-based behavior	Drinking	CNN and LSTM	Group-housed pigs	97.2 %	Chen et al., 2020
		Image segmentation	Group-housed pigs	92 %	Kashiha et al., 2013b
	Feeding	Faster R-CNN		99.6 %	Yang et al., 2018b
	Fouling	Random forests and ANN	Fattening pigs	71 %, 76 %	Jensen et al., 2020
Interactive behavior	Mounting	Background subtraction	Group-housed pigs	Accuracy: 92.7 % Sensitivity: 94.5 % Specifiificity: 88.6 %	Nasirahmadi et al., 2016
		Mask R-CNN and KELM	Male pigs in oestrus	Accuracy: 91.47 % Sensitivity: 95.2 % Specifiificity: 88.34 %	Li et al., 2019a, 2019b
	Nursing	Optical flow and SVM	Sows and piglets	Accuracy: 97.6 % Sensitivity: 90.9 % Specifiificity: 99.2 %	Yang et al., 2018a
	Tail biting	Tail posture	Intact-tailed pigs	Accuracy: 73.9 % Sensitivity: 88.4 % Specifiificity: 66.8 %	D'Eath et al. (2018)
	Attack	Manual annotation	Fattening pigs	Not specified	Oczak et al., 2013
		SVM	Group-housed pigs	90.2 %	Lee et al., 2016

4. Discussion and outlook for future work

4.1. Discussion

The behavior of different types of pigs, including group housed pigs, sows, boars, piglets and fattening pigs, have been studied through video sequences. For group housed pigs and fattening pigs, their daily routine behavior such as locomotion, drinking, feeding and excretion have been the focus of research. For sows and piglets, their nursing behavior requires special attention. For boars, their sexual behavior such as mounting has been studied.

The equipment deployed in the pigpens includes 2D cameras, 3D depth cameras and thermal infrared cameras. Most of the cameras are installed on the top of the ceiling. The 2D cameras are inexpensive and have been widely deployed. It can meet most surveillance needs, but the processing effect is poor in the case of overlapping pigs. The 3D depth cameras can better solve the problem of overlapping pigs and the result of behavior recognition is more accurate, but they cost more than the 2D cameras. Hence they are not the first choice for the pig farm video surveillance systems. In addition to capturing the appearance of the monitored animal, the application of thermal infrared cameras can also obtain animal temperature data, thereby providing more supporting data for animal health supervision. Now, they are also deployed in some special occasions, such as monitoring the estrus behavior of sows.

The research of video-based pig behavior analysis focuses on pig segmentation and detection, behavior recognition. The techniques used in pig segmentation include color threshold segmentation, background subtraction, GMM, and CNN-based segmentation. Template matching, sliding windows, and various CNN-based detectors such as Faster R-CNN, SSD, YOLO, have been applied to detect pigs. Pig behavior recognition is divided into recognition based on a single-frame and recognition based on multi-frames. Behavior recognition based on a single-frame is to study the postural behavior of pigs. The lying and standing postural behavior have been studied. The multi-frames behavior recognition explored spatial and temporal information in the video to study time-continuous behavior, such as walking, drinking, eating, etc. Pig behavior recognition algorithms can be divided into traditional methods and deep learning methods. The traditional methods mainly rely on manually extracting features to build models for some specific behavior, and then trained the models to classify pig behavior. Compared with the traditional methods, the deep learning methods do not need to manually extract features but take advantage of CNN to replace the traditional image processing. Most of the time, the deep learning methods can achieve higher accuracy.

Although video-based pig behavior recognition has made some progress, there are still some problems. The existing research is aimed at individual self-built datasets, and there is no benchmark dataset for researchers to compare the results of their algorithms. For pig segmentation, the problem of pig adhesion is still not solved well. Identifying individual pigs in large-scaled pig farms is still tricky. Most of the experiments performed are based on edited video clips. Real-time behavior recognition in unedited continuous long videos is still a challenge.

The study of animal behavior includes animal communication behavior, emotional expression, social behavior, learning behavior, reproductive behavior, etc. It requires a large amount of raw behavioral data such as feeding, walking, resting, etc. as support. To establish animal behavior patterns, animal data from different populations, population sizes and housing conditions are required as support. Animal personality is also essential in the management and welfare of animals (O'Malley et al., 2019). Video-based automatic behavior recognition technology can continuously record the raw behavior of pigs all day long, and form a pig behavior database, providing the basis for animal behavior research. The establishment of the pig behavior database requires collaboration between animal behavior researchers and automation technology researchers. It should be determined which behavior needs to be collected and at what time interval the collected behavior should be quantified. Only by converting the stream video data into discrete quantitative values can it help behavioral researchers conduct further analysis.

4.2. Outlook for future work

Benchmark datasets for pig farming should be established in the future. Data on different types of pigs from different farms will be collected. Generative adversarial networks can be used to generate more generalized samples (Sankaranarayanan et al., 2018).

In the field of image processing, there is lots of advanced and mature research on video-based human behavior detection, which can provide a reference for pig behavior recognition. At present, the main scheme of pig behavior recognition is to detect the target pig from each frame and then determine its ongoing behavior according to its posture and position in the image. This approach only uses the spatial features of the image, but does not make full use of the temporal features that distinguish video data from image data. In human behavior recognition, algorithms based on spatio-temporal features have become mainstream. The behavior recognition schema based on spatial-temporal features is shown in Fig. 3.

In order to better handle the 3D features of video data, some special ideas have been proposed. By applying CNN to extract 2D spatial features and LSTM to extract temporal features, human activities could be recognized through their score fusion(Li et al., 2017a). By adding a time dimension, 3D CNN was derived from 2D CNN. It can simultaneously learn spatial and temporal information from the input video. Some 3D CNN based models, such as C3D(Tran et al., 2015)and R-C3D(Xu et al., 2019) were proposed for feature extraction and human behavior recognition. The two-stream network extracted spatial and temporal features separately at the beginning and merged them at the end. The temporal segment network (TSN) proposed a sparse temporal sampling strategy and a video-based learning strategy. TSN could not only reduce model complexity but also integrate multiple fragments, so as to obtain more context information (Wang et al., 2016). The decisive factors of the recognition result are the network structure and the features fusion method.

Since it is time-consuming to produce a large amount of labeled training data, unsupervised learning and semi-supervised methods have been advocated (Zhu et al., 2019). Only a small amount or even no labeled training data is needed, such methods have a broad application prospect and will be a very promising research hotspot in the future. A comparison of human behavior recognition based on supervised learning and unsupervised learning has been carried out. The results showed that the performance of unsupervised learning was not as good as supervised learning. Some supervised classifiers could solve the problem with 99 % accuracy, while unsupervised classifiers could only achieve accuracy below 90 %(Verma et al., 2019). Therefore, the application of unsupervised learning and semi-supervised methods in pig behavior recognition still needs to be considered.

5. Conclusion

The paper systematically summarizes the current research on video-based automatic pig behavior recognition algorithms. Pig behavior recognition has become a research hotspot in the field of smart livestock farming. The techniques used for pig segmentation, pig detection and behavior recognition are summarized. There are traditional image processing algorithms and deep learning methods. So far, some great work has been done, but there is still a lot of work to do to improve the accuracy and time efficiency of pig behavior recognition. Deep learning has gradually become the mainstream technology for animal behavior recognition and has evolved from simple models to complex models. In the future, weakly supervised and unsupervised methods will be more widely used. Due to the application of various intelligent technologies, the pig industry will become more labor-saving and sustainable.

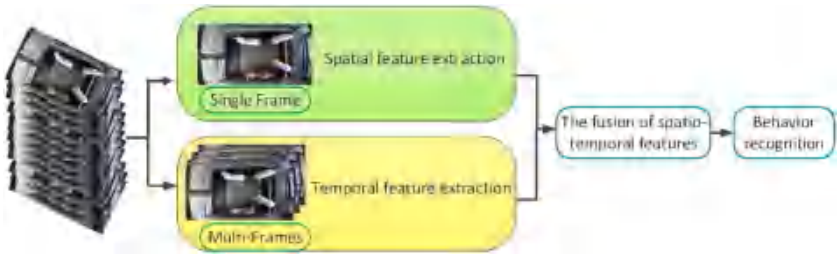


Fig. 3. The behavior recognition schema based on spatial-temporal features.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

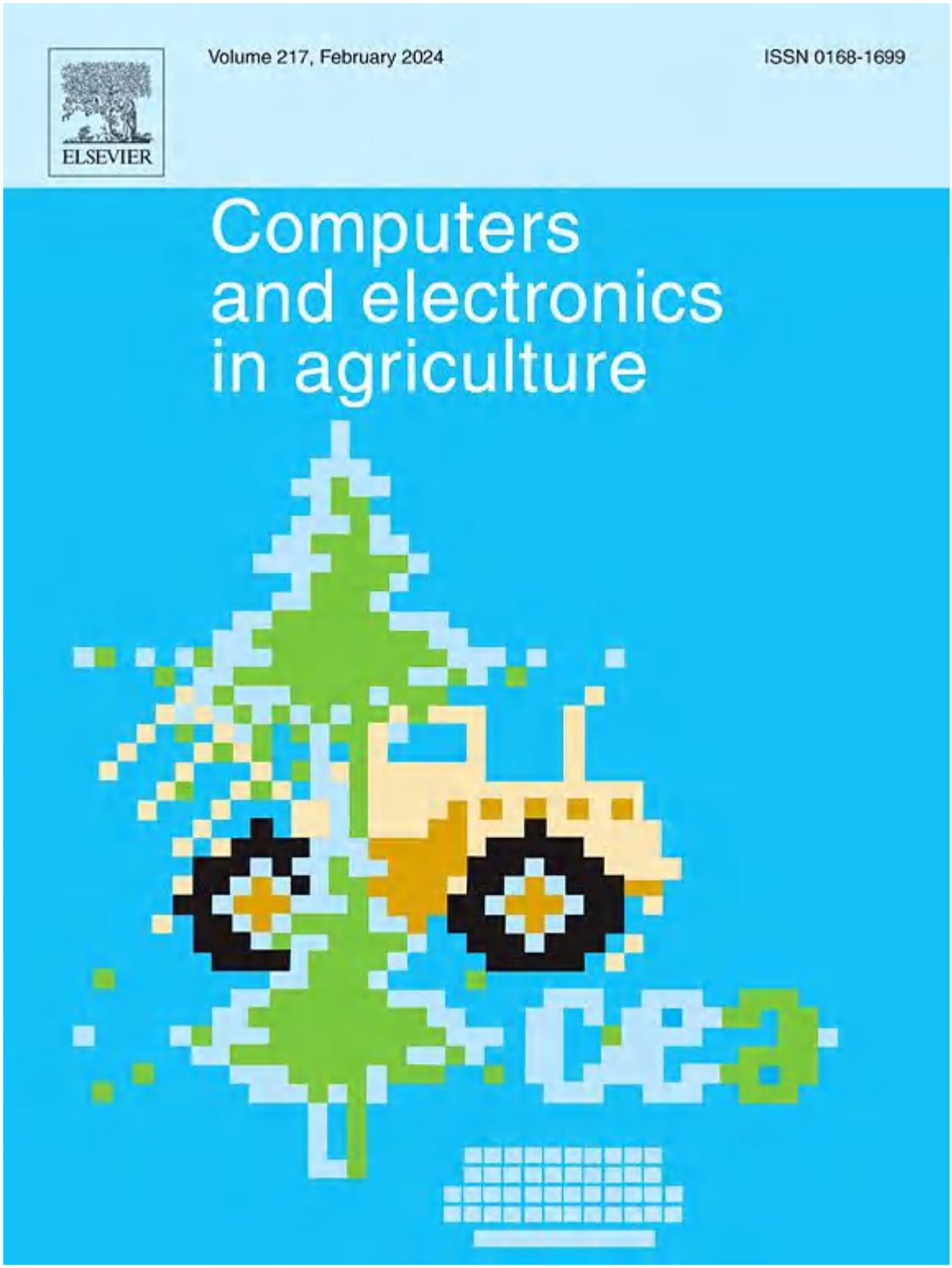
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Original papers

Feeding behavior recognition for group-housed pigs with the Faster R-CNN

Qiumei Yang, Deqin Xiao*, Sicong Lin

College of Mathematics and Informatics, South China Agricultural University, Guangzhou, Guangdong 510642, China

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ABSTRACT

The feeding behavior of each individual pig is an important indicator to determine whether it is healthy or not. Therefore, automatic behavior recognition for individual pig is one of the core problem in precision pig farming. Video surveillance is a common tool for monitoring animal behaviors. To accurately identify each pig from the video sequences is a prerequisite for individual pig behavior recognition. This paper proposed to use Faster R-CNN to locate and identify individual pigs from a group-housed pen. The head of each pig was also located. An algorithm for associating the head of each pig with its body was designed. On this basis, a behavior recognition algorithm based on feeding area occupation rate was implemented to measure the feeding behavior of pigs. Experiment showed that our algorithm can recognize the feeding behavior of pigs with a precision rate of 99.6% and recall rate of 86.93%.

1. Introduction

Pigs' feeding behavior plays a very important role in the breeding process. A deviation from a set of diurnal pattern in food intake is often associated with food or environmental changes or an early symptom of disease (Matthews et al., 2016). At present, the majority of farms in China still rely on breeders' own long-term feeding experience to raise pigs. Pig breeders estimate the total food consumption of pigs roughly. The feeding data is subjective and not accurate. Precision pig farming proposes using modern equipment to accurately acquire the breeding data of each individual pigs (Berckmans, 2014). Therefore, it is necessary to introduce new techniques to extract pigs' feeding behavior, which will be helpful in alerting abnormal health status of pigs and improving breeding efficiency.

Feeding behaviour can be described by 'chewing or biting food' or 'putting the head in the trough' (Maselyne et al., 2015). Since detecting whether a pig is chewing or biting food is hard to accomplish, it is a common practice to decide a feeding visit by checking whether the pig's head is in the trough or not. For individually housed pigs, a specific feeder was used to record its food intake (Montgomery et al., 1978) and sensors were installed to measure feeding duration (Liang and Wood-Gush, 1984). For group-housed pigs, the individual pig must be identified before measuring its feeding behavior. Radio Frequency Identification (RFID) provides a good solution for individual identification. Several RFID systems were designed to check the pig feeding behavior. Electronic feeding station is used to monitor feeding behavior of sows. Pigs have to wear electronic ear tags. When entering the protective feeder area, pigs will be identified by RFID antenna. Data is transmitted to the computer system, which calculates the amount of food the pig needs (Cornou et al., 2008; Marcon et al., 2015). The electronic feeding station can accurately feed each pig. However, due to its high cost and special restriction on the feeding space, it is mostly used for sows. It is more naturally to incorporate RFID technology with a common feeder. The main problem with this approach is how to identify multiple pigs at the same time as they enter the trough area. Low-frequency(LF), high-frequency(HF) and ultra-high frequency(UHF) RFID systems were applied to detect the feeding behavior of pigs. LF RFID was used to monitor feeding behavior of group-housed swine (Brown-Brandl and Eigenberg, 2011; Brown-Brandl et al., 2013). The radio-frequency signal was distributed to a series of antennas using a multiplexer. Maselyne et al. (2014) applied HF RFID system to detect growing finishing pigs at a round trough, with only one antenna. Anti-collision algorithms were designed to detect several transponders quasi-simultaneously. A UHF RFID system made use of a reader, antennas and passive transponder ear tags to monitor the visits of growing-finishing pigs at a short trough for liquid feeding(Adrion et al., 2018). On the whole, RFID systems are effective in monitoring the feeding behavior of pigs. However, the RFID method restricts pigs from wearing RFID ear tags and identifying multiple pigs at a time is still a tricky problem.

Video surveillance is an alternative way to detect feeding behavior. It is a low-cost and easy-to-implement method. How to extract effective breeding information from surveillance videos is an essential problem. There have been some relevant studies. For each frame, pig detection is the first thing to do. Otsu segmentation was proposed to binaries the image and distinguish pigs from the background (Kashiha et al.,

* Corresponding author.
E-mail address: deqinx@scau.edu.cn (D. Xiao).

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2013b). The mixed Gaussian model was combined with the maximum entropy segmentation method to detect pigs (Guo et al., 2014). A multi-level threshold segmentation was proposed to accurately obtain pig's profile (Guo et al., 2015). The performance of these methods is depended on the distinction between pigs and backgrounds. It is affected by illumination. In addition, when pigs are adhesive, it is difficult to distinguish them separately. For individual pig identification from video sequence, some researchers stamped special marks on the back of each pig and used pattern recognition techniques to identify each pig (Kashiha et al., 2013b). A combination of Gabor and Local Binary Pattern features was used to the classification of group-housed pigs (Huang et al., 2018). The location of pigs' heads was used to determine the occurrence of drinking behavior (Kashiha et al., 2013a). The frequency and duration of drinking behavior were obtained. Machine vision and Delaunay triangulation were proposed to detect changes in the lying behavior of pigs in a commercial farm environment (Nasirahmadi et al., 2015). Optical flow method and modified angle histogram were used to analyze the movement of pig herds (Gronskyte et al., 2016). Locomotion was also calculated using image analysis (Kashiha et al., 2014). Aggressive behavior of pigs was studied through video recordings (Oczak et al., 2013). From these related studies, we can see that the automatic identification of individual pigs from video surveillance is still a tricky problem in precision pig farming. How to select the right feature as an identity is a key issue.

The convolution neural network (CNN), which can automatically extract features without manual selection of features, was used for object detection from images. Region Proposal method called R-CNN was used to solve the object detection problem. Selective Search algorithm was used to obtain thousands of local candidate regions, and then enter these regions into the CNN respectively. After extracting regional characteristics and finally using classifiers to distinguish different regions as backgrounds or targets, R-CNN achieved breakthrough results on the VOC2007 data set (Girshick et al., 2014). In order to solve the problem of large numbers of duplicate calculations in R-CNN, the Fast R-CNN was proposed to map the candidate regions to the feature map of the last layer of the CNN. An image only needed to be extracted once, which greatly improved the performance of the target detection (Girshick, 2015). The Faster R-CNN, which consisted of a Regional Proposal Network (RPN) and Fast R-CNN, was proposed (Ren et al., 2015) later. The speed of target detection and the mAP on VOC2007 were further improved. Zheng et al. (2018) applied Faster R-CNN to recognize lactating sow postures. Five postures, including standing, sitting, sternal recumbency, ventral recumbency and lateral recumbency, were identified. It shows that Faster R-CNN can be effectively used for animal behavior detection.

The objective of this study is to explore a method for recognizing feeding behavior of group housed pigs from video sequences. Since Faster R-CNN can not only detect but also classify the objects and has a better performance, we intend to introduce the Faster R-CNN model to identify individual pigs. The Faster R-CNN is also used for the detection of pigs' heads. According to the present research, the feeding behavior of pigs can be described by bout size, bout frequency, total food intake, etc. Feeder occupation time, which can be obtained from surveillance video, is also an important parameter. Hence, this study takes feeder occupation time to describe feeding behavior.

2. Materials and methods

The experimental data came from a pig farm in Luogang District, Guangzhou. A pen with 4 pigs was selected as a monitoring scene since the number of pigs in it is suitable for our research. The pen size was 4 m * 5 m. There were 2 drinking nipples and a 1 feeding trough in it. Pigs were fed twice a day, once in the morning and once in the afternoon. Pigs were free to walk around and can drink at any time. A camera was arranged on the horizontal bar about 5 m high in the middle of the pen and photographed from a top view angle. In order to cover the pen completely, an infrared network camera with a focal length of 2.8 mm (DS-2CD3345-I, Hikvision, Hangzhou, China) was used. Videos were recorded with a frame rate of 25 frames per second, frame width of 2560 pixels, frame height of 1440 pixels. The videos were stored using a Haikang network hard disk recorder (DS-7804 N-K1/C, Hikvision, Hangzhou, China). The experiment lasted from July 8, 2016 to August 6, 2016 for a total of 30 days. Sample frames from the video sequence are shown in Fig. 1.



Fig. 1. Some sample frames of the video sequence.



Fig. 2. Pig feeding behavior recognition procedure.

The pigs in our experiment belonged to the same species, Landrace. They were all white and with a similar body size. It was difficult to distinguish them directly. To make the identification of each pig possible, we drew letters on the back of each pig. Those letters were used as pig's ID and will be helpful in automatic identification of pigs. Since the number of pigs raised in the piggery was limited, this was a feasible solution to distinguish them.

In this study, we define the feeding behavior of pig as putting its head in the area of a feeder. The feeder occupation time is calculated. The procedure of pig feeding behavior recognition is shown in Fig. 2.

For each frame, it is necessary to extract visual features and classify them to identify individual pig. The same works for the detection of pig's head, whose position is closely related to feeding behavior recognition.

3. Algorithm for individual pig identification and feeding behavior recognition

Instead of defining two detectors to identify pigs and their heads separately, we train a detector based on the Faster R-CNN, called FRPD (Faster R-CNN Pig Detector), to identify pigs and their heads simultaneously.

3.1. Data set construction

Sample frames are selected from our monitoring video sequences to construct a data set for the FRPD training and testing. To make the data set more diverse and more representative, frames with different pig postures, such as standing, lying down, half licking, looking up, bowing, are selected. Frames that pigs are adhesive and with different illumination are also considered. We take 500 images to label manually. There are totally four pigs in the experimental pen. Each pig body is circled with a rectangle box and labeled respectively as A, B, C, and D, representing 4 pigs' ID. In addition, the head of a pig is a mostly critical part for judging the occurrence of pig's daily behaviors, such as drinking and feeding. Therefore, the head of each pig is also circled and labeled. The constitution of our data set are listed in Table 1.

The labeled images adopt the format of PASCAL VOC2007(Everingham et al., 2015), which is supported by the Faster R-CNN. Image flipping is used to expand the data set.

3.2. Training procedure of the FRPD

The FRPD mainly accomplishes two tasks. Firstly, it locates each pigs in the image, and secondly identifies each pigs' ID. The first task is completed by the regional proposal network (RPN), and the second task is completed by the Fast R-CNN object detection network. These two tasks share the convolution feature map. The principle of FRPD pig detection model is shown in Fig. 3.

During the training process, in order to solve the problem of insufficient sample, this paper adopts transfer learning and introduces a pre-trained model on Image-net dataset. ImageNet has more than 10,000,000 images and exceeds 1,000 categories. Pre-trained model

Table 1
The constitution of our data set.

Object	Pig with ID A	Pig with ID B	Pig with ID C	Pig with ID D	Head of a pig
Label	A	B	C	D	Head
Amount	500	500	500	500	2000

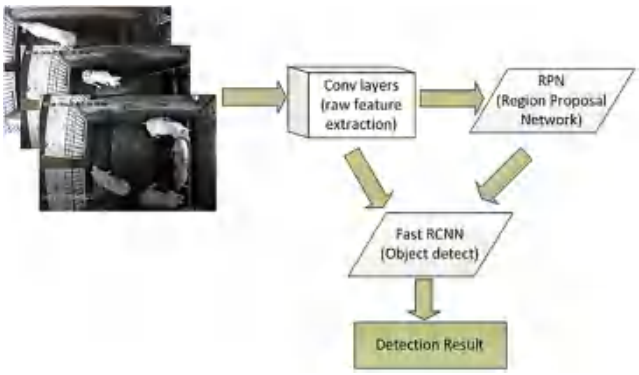


Fig. 3. Overview of the FRPD.

based on it has a certain ability to extract general characteristics of image. When the size of data set is small, the parameters can be adjusted based on the pre-trained model to obtain better recognition results. Faster R-CNN provides pre-trained models such as ZF-net, VGG_CNN_M_1024 and VGG16. In this paper, ZF-net (Zeiler and Fergus, 2014) with fewer layers is selected to extract image features. ZF-net contains five convolution layers. The regional proposal network and detection network are obtained by adding a specific layer after the output of ZF-net.

The detection network Fast R-CNN shares the convolution layer with the RPN. During the training, four-step alternate training method is used to learn the shared features by alternate optimization. In the first stage of RPN training, end-to-end fine-tuning is done through the initialization of ZF-net. Regional proposal is generated at the end of this phase. In the first stage of Fast R-CNN training, output of the previous RPN is taken as input. A detector network is trained during this phase. In the second stage of RPN training, Fast R-CNN detector network is used to initialize RPN. Only the layers unique to RPN are trained in this phase. In the second stage of Fast R-CNN training, only non-public layers are fine-tuned. A sliding window is constructed on the convolution feature map to train the RPN. K anchors are predicted for each sliding window. The anchors go through a regression layer (reg) and a classification layer (cls). The reg layer has 4 k outputs, which are the coordinates of k boxes. The cls layer outputs 2 k scores, which are the estimated probability of each boxes being a target or non-target. The training procedure is shown in Fig. 4.

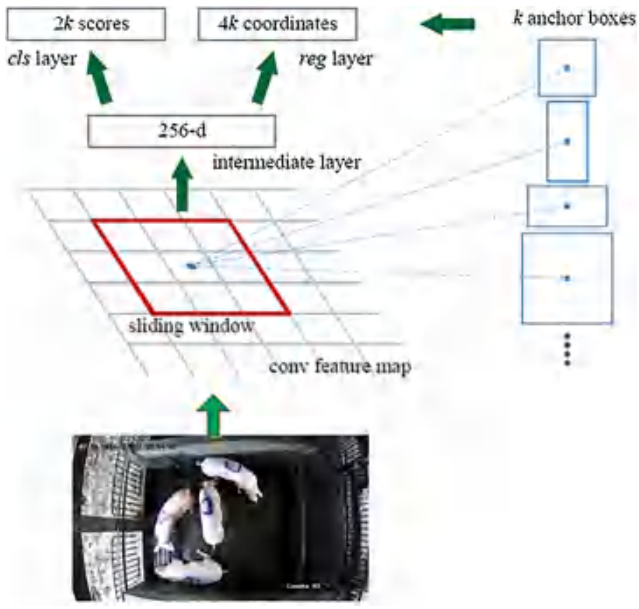


Fig. 4. The training procedure of FRPD.



Fig. 5. The testing procedure of FRPD.



Fig. 6. Association of each head with its body.

3.3. Testing procedure of the FRPD

When the FRPD training is done, image can be input to the model to detect all the pigs and their heads. The input image is firstly performed convolution operation and its feature maps are generated. RPN takes the feature maps as input and marks out those regions regarded as objects with bounding boxes. Only 300 bounding boxes with highest score are kept for the sake of efficiency. Every boxes kept is checked by the trained detection network to see if it matches our detection target. The matching bounding boxes are preserved while others are discarded. The process is shown in Fig. 5.

3.4. Algorithm for association of a pig head with its body

The FRPD can detect two kinds of object, pig body with individual ID and pig head. Each head must belong to a certain individual pig body. The intersection ratio (IoU) between each detected head and each pig body, as shown in equation (1), is calculated to decide the relationship between pig head and its body.

$$IoU = \frac{Area\ of\ Head \cap Area\ of\ Pig}{Area\ of\ Head \cup Area\ of\ Pig} \quad (1)$$

For each detected head, the algorithm deciding which pig body it belongs to is defined as follow.

Algorithm 1Input: a bounding box labeled with headmaxIoU = 0For the i-th individual pig in the same frameCalculate the IoU based on formula(1) If IoU > maxIoU then maxIoU = IoU, label = the label of the i-th individual pigEnd ForOutput: the pig ID of the processing pig head

As shown in Fig. 6, each head is related to a corresponding pig body.



Fig. 7. Feeding zone in the monitoring piggery.

3.5. Feeding behavior recognition for group-housed pigs

The feeding behavior of pigs is correlated with certain functional area. It will only occur when a pig's head is in the trough. In order to monitor the feeding behavior of pigs, we define feeding zone in our monitoring scene. As shown in Fig. 7, the [1]blue rectangle represents the feeding zone.

Using FRPD, pig's head can be detected and marked with a bounding box. When a bounding box labeled as head is intersect with feeding zone, it is possible that feeding behavior happens. Combined with feeding time, a feeding behavior will be recognized.

Occupation index is used to determine whether a place is covered by a certain object or not (Costa et al., 2013). The occupation index of drinking zone and feeding zone are listed respectively in equation (2).

$$OcpIndex_{feed} = \frac{Area\ of\ Head \cap Area\ of\ Feedingzone}{Area\ of\ Feedingzone} \quad (2)$$

When $OcpIndex_{feed}$ is greater than 0, it is considered the pig is eating. The algorithm for feeding behavior recognition is listed below.

Algorithm 2Input: a frame from the monitoring video sequenceUsing FRPD to detect each pig and headUsing algorithm 1 to associate each pig head with its bodyFor the i-th pig head bounding boxCalculate $OcpIndex_{feed}$ If it is at feeding time && $OcpIndex_{feed}$ > 0 then record the i-th pig is feedingEnd ForOutput: the drinking and feeding behavior happened or not in the input frame

4. Results and Discussion

4.1. Experiment and Evaluation of individual pig identification

The experiment is done under a Caffe deep learning framework (Jia et al., 2014), with NVIDIA Tesla K80 (NVIDIA, Santa Clara, California,

[1] For interpretation of color in Fig. 7, the reader is referred to the web version of this article.

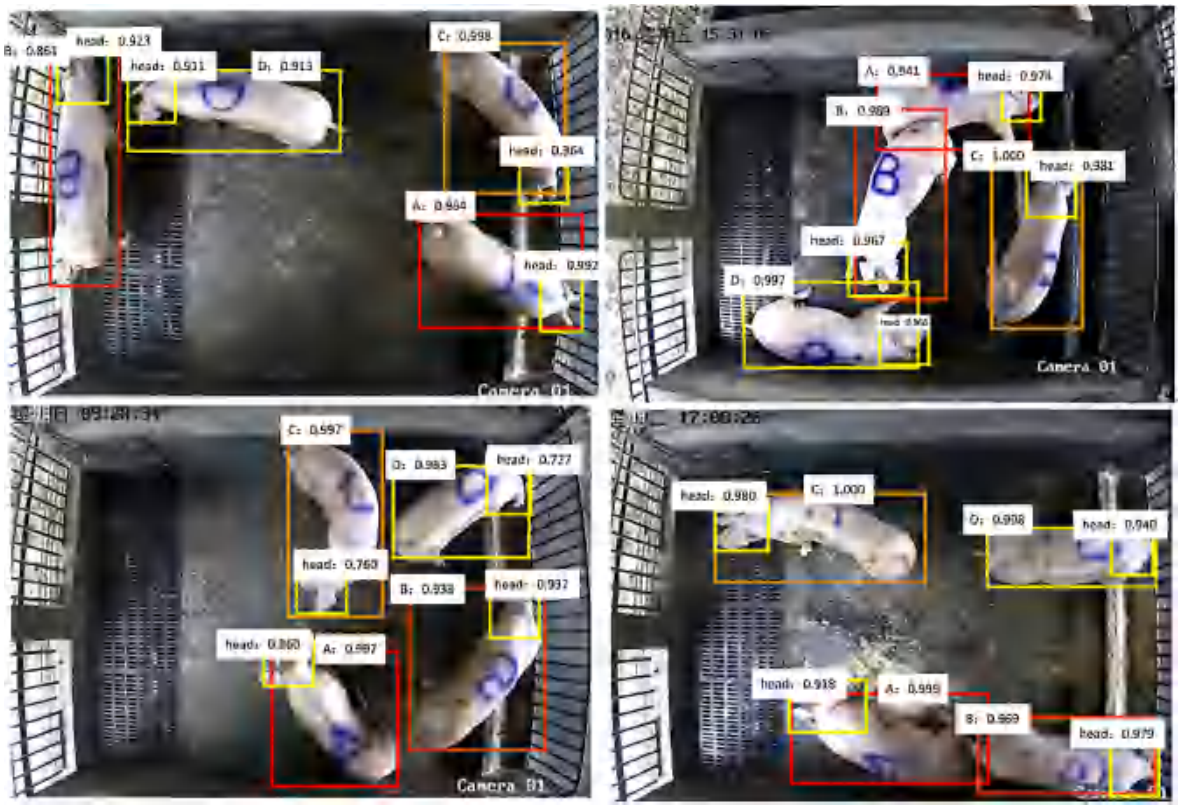


Fig. 8. Samples of our detection result.

Table 2
Confusion matrix of the FRPD detection results.

		Predicted Class					
		A	B	C	D	head	null
Ground Truth	A	100					
	B	1	95	7	2		
	C			99			1
	D	1		9	95		
	head					316	84
	null			2		4	

Table 3
Precision Rate and Recall Rate of the FRPD.

	A	B	C	D	head
Precision Rate	0.9804	1	0.8462	0.9896	0.9875
Recall Rate	1	0.9048	0.99	0.9048	0.79

USA) for GPU acceleration. Faster R-CNN in Matlab is used. During the experiment, 80% of the images in the data set are randomly selected for training, and the other 20% are used for testing. The learning rate is set to 0.001.

After training, the FRPD can detect each pig and their heads when given an image. Every detection result will be marked out with a bounding box, which has a label and a number indicating its probability belonged to this label. Samples of the detection result are shown in Fig. 8.

A data set including 100 images from our surveillance video sequence are used for testing. The confusion matrix of the test results is shown in Table 2. A null class is added to represent objects that are not in our detection range.

Precision (P) and recall (R) rate, which follows equation (3), are used to evaluate the result of the FRPD model.

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN} \tag{3}$$

TP is the number of cases that are positive and detected positive. FP is the number of cases that are negative but detected positive. FN is the number of cases that are positive but detected negative. The precision and recall rate for each detection class of the FRPD is shown in Table 3. The precision rate for all the categories is 0.9658 and recall rate is 0.8704.

4.2. Evaluation of pig feeding behavior recognition

For each frame of the surveillance video, our algorithm can determine if the feeding behavior occurs or not, as shown in Fig. 9.

In order to evaluate our algorithm, 100 images with pig-related behavior were selected from the surveillance video sequence to constitute a pig behavior test set. The feeding behavior recognition result is shown in Table 4.



Fig. 9. Display of the feeding judgment.

Table 4
Feeding behavior recognition result.

		Predicted Feeding Behavior				
		A	B	C	D	null
Ground Truth	A	35				2
	B		49	1		6
	C			70		19
	D			1	90	8
	null	1				



Fig. 10. Feeder occupation time.

Table 5
Precision Rate and Recall Rate of the feeding behavior recognition.

	A	B	C	D
Precision Rate	0.9722	1	0.9722	1
Recall Rate	0.9459	0.8771	0.7865	0.91

The precision and recall rate for the feeding behavior recognition of each pig is shown in Table 5. The overall precision rate is 0.996 and recall rate is 0.8693.

Our algorithm can work continuously to judge the occurrence of the feeding behavior in each frames. We chose 3 days of video sequences for verification purpose. During these three days, the breeder fed twice a day. A half-hour surveillance video of each meal, which started from food was offered, was extracted and considered to be a valid feeding period. By applying the algorithm of this paper in each frame of the video, we could get the number of frames consumed as feeding for each pigs. Finally, the feeder occupation time per pig per meal was obtained, as shown in Fig. 10. Some pigs sometimes spent a particularly short time in food intake, such as pig B in the morning of July 14, 2016. We reviewed the video and found that it fell asleep at that time. But on the afternoon of that day it spent more time eating. The daily food intake time was maintained at a normal level.

5. Discussion

Comparing with the segmentation method used for pig detection (Kashiha et al., 2013a), FRPD can do better in dealing with situations that pigs are adhesive and when there are noises.

It can be seen from Fig. 11a. that pig A and pig D are closed to each other. The traditional segmentation method treats them as a single continuous object (Fig. 11b), which is difficult to separate them individually. In Fig. 11d., the floor is dirty and the segmentation method mistake the spot as a pig (Fig. 11e). It can be seen that our method can handle such situations well (Fig. 11c and f).

For the over-fitting problem, we have designed several experiments on different sets of pigs. Firstly we applied our model to the same batch of pigs as training set but in different time periods. Secondly we applied our model to detect different batches of pigs with the same breed and in the same monitoring piggery as training set. The detection result of these two experiments were quite good. Thirdly we tried to construct a different data set using images from other piggeries or from the internet, and without images from our own monitoring scene, as shown in Fig. 12. A new model was trained to detect pigs and their heads. Then the new model was used to test images from our monitoring video sequences. The detection result was not satisfactory. It can be inferred that pig breeds and piggery environment will affect the detection result. But the size of pigs doesn't matter much. As only a small amount of labeled images is needed to train a new model from the pre-trained model, it is suggested to fine-tune the model by actual scene.

In this paper, letters were drawn on the back of the pig as its auxiliary identity since we can't easily distinct pigs from their appearance. Kashiha et al. (2013b) also tried to identify individual pigs by recognizing special paint patterns. Compared with this, our method not only rely on the letters but also other characteristics of the pig itself as its identity. As shown in Fig. 13, pig A is lying down and the letter on the back can't be seen. But our method still can identify it correctly.

The feeding behavior is described by feeder occupation time in this paper. When the head of a specific pig is in the feeder, it will be considered to be occupied. The most important thing is to locate heads of pigs. Experiments show that when pig head is obscured or when pig is in specific postures such as lying down with ears not visible, the

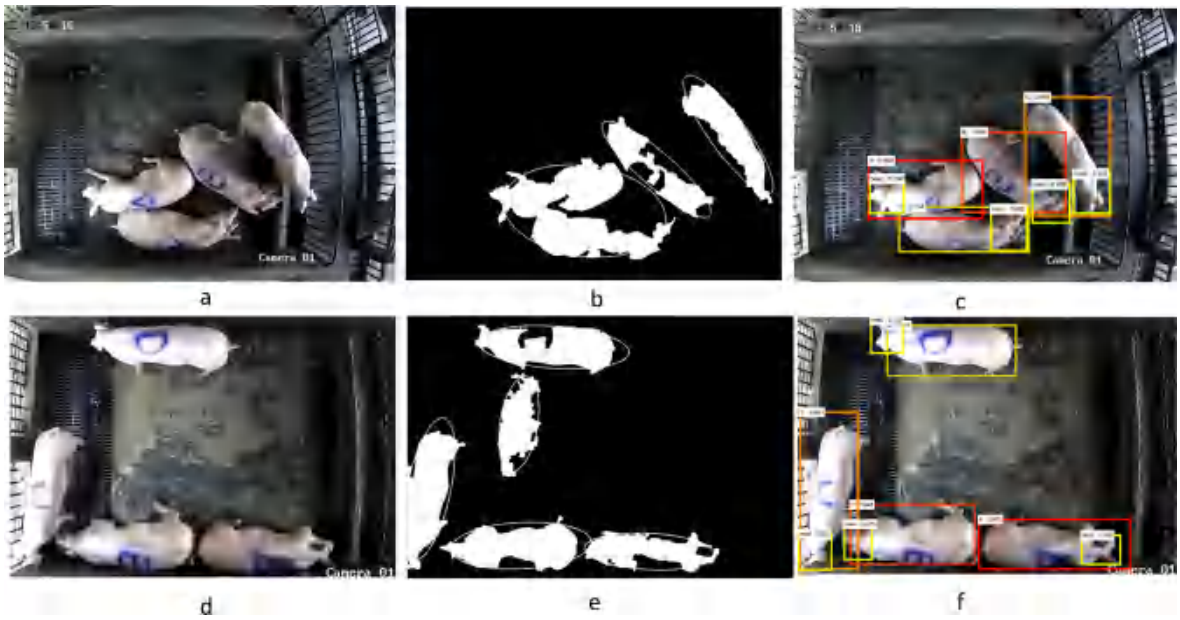


Fig. 11. Comparison between our method and traditional segmentation method (a. An original image with two pigs adhesive b. Detection result of image a using segmentation method c. Detection result of image a using FRPD d. An original image with dirty floors e. Detection result of image d using segmentation method f. Detection result of image d using FRPD).



Fig. 12. Sample images from other sources for training.

detection of heads is not ideal. However, since pigs are standing while eating, most of the head contours are easier to detect. Considering the possibility that the trough may have no food, the feeding behavior recognition will only applied at a fixed feeding time when food is supplied. Our method can be used to an ad-libitum setting if there are foods in the trough all the time.

6. Conclusions

During the pig breeding process, it is crucial to figure out the daily food intake of each pig. The paper proposed a corresponding solution to this problem. Taking advantage of the video surveillance, an algorithm for automatically extracting the individual feeding behavior of pigs was designed. Firstly a model to identify individual pigs based on Faster R-CNN was trained. The precision rate for detecting pigs and their heads was 0.9658 and the recall rate was 0.8704. Then we associated the detected heads with the bodies of the pigs by their location. Pigs are fed in the trough at a set time. According to this characteristics, we proposed to set a feeding zone in the frames. For each frame, if the feeding zone was occupied by the head of pig, it would be considered that feeding behavior was happened. The precision rate for pig feeding behavior recognition is 0.996 and the recall rate is 0.8693. The paper provides a practical implementation for the precision breeding of pigs. It only depends on the pig farm video surveillance. There is no extra requirement to the piggery. It provides helpful information for pig breeding.

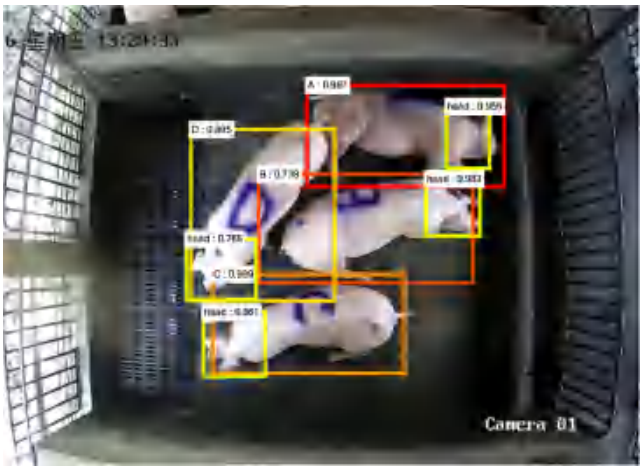


Fig. 13. Pig identification when letters on the back not visible.

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专栏主编: 张若宇 教授



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基于关键点和步行特征的猪只跛行检测方法

杨秋妹[1,2]　黄森鹏[1,2]　肖德琴[1,2]　惠向阳[1,2]　黄一桂[1,2]　李文刚[1,2]
(1.华南农业大学数学与信息学院,广州 510642;2.农业农村部华南热带智慧农业技术重点实验室,广州 510642)

摘要:猪只跛行问题为猪场的生产和管理带来了挑战,因此准确检测猪只跛行情况至关重要。目前猪场主要依赖人工观察和记录,效率低耗时长,且可能存在主观误差。鉴于此,提出一种基于关键点和步行特征的猪只跛行检测方法。首先,定义并确定了猪只的关键点信息,关键点包括猪只的腿、膝盖、背部等重要部位。基于关键点,采用改进 YOLO v8n-pose 模型进行检测。该模型在 YOLO v8n-pose 的基础上,在颈部引入 BiFPN 双向特征金字塔网络进行多尺度特征融合,同时在骨干网络中引入 RepGhost 网络,以降低特征提取网络的参数量和浮点运算量。然后利用检测出的关键点坐标计算猪只的步长、膝盖弯曲程度和背部曲率等步行特征,并将这些特征输入到 K 最近邻算法进行跛行与非跛行的分类。实验结果表明,改进 YOLO v8n-pose 模型平均精度均值(mAP)达到 92.4%,比原始 YOLO v8n-pose 模型提高 4.2 个百分点。与其他关键点检测模型(HRNet-w32、Lite-HRNet、ResNet50、ViPNAS 和 Hourglass)相比,mAP 分别提高 10.2、11.6、14.2、11.8、12.5 个百分点。K 近邻算法在猪只跛行测试集上的检测精度为 81.7%,比 BP 算法、Decision Tree 算法和 SVM 算法分别提高 1.5、11.3、6.5 个百分点。以上结果表明,本文提出的猪只跛行检测方法可行,能够为猪场检测提供技术支持。

关键词:猪只;跛行;关键点检测;YOLO v8n-pose;步行特征
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Pig Lameness Detecting Method Based on Key Points and Walking Features

YANG Qiumei[1,2]　HUANG Senpeng[1,2]　XIAO Deqin[1,2]　HUI Xiangyang[1,2]　HUANG Yigui[1,2]　LI Wen'gang[1,2]
(1. *College of Mathematics and Informatics, South China Agricultural University, Guangzhou* 510642, *China*
2. *Key Laboratory of Smart Agricultural Technology in Tropical South China, Ministry of Agriculture and Rural Affairs, Guangzhou* 510642, *China*)

Abstract: The problem of lameness in pigs presents significant challenges to the production and management of pig farms, making accurate detection of pig lameness crucial. Currently, pig farms primarily rely on manual observation and recording, which is inefficient, time-consuming, and prone to subjective judgment errors. In light of this, a method for detecting pig lameness based on key points and walking characteristics was proposed. Firstly, key point information for pigs was defined and determined, including critical parts such as the legs, knees, and back. Based on these key points, an improved YOLO v8n-pose model was employed for detection. This model built upon the original YOLO v8n-pose by introducing a bidirectional feature pyramid network (BiFPN) at the neck for multi-scale feature fusion and incorporating a RepGhost network into the backbone to reduce the parameter count and computational complexity of the feature extraction network. Then using the coordinates of the detected key points, walking characteristics such as stride length, knee bending degree, and back curvature were calculated. These features were inputed into a K-nearest neighbors (KNN) algorithm to classify pigs as lame or non-lame. Experimental results showed that the improved YOLO v8n-pose model achieved a mean average precision (mAP) of 92.4%, which was 4.2 percentage points higher than the detection accuracy of the original YOLO v8n-pose model. Compared with other key point detection models (HRNet-w32, Lite-HRNet, ResNet50, ViPNAS, and Hourglass), the mAP was improved by 10.2, 11.6, 14.2, 11.8 and 12.5 percentage points, respectively. The KNN algorithm achieved a detection accuracy of 81.7% on the

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作者简介:杨秋妹(1983—),女,讲师,博士,主要从事农业图像视频处理研究,E-mail:yqmbegonia@163.com
通信作者:肖德琴(1970—),女,教授,博士生导师,主要从事物联网和农业图像视频处理研究,E-mail:deqinx@scau.edu.cn

pig lameness test set, which was 1.5, 11.3 and 6.5 percentage points higher than that of the BP algorithm, Decision Tree algorithm, and SVM algorithm, respectively. These results demonstrated that the proposed method for detecting pig lameness was feasible and can provide technical support for pig farm detection.

Key words: pig; lameness; keypoint detection; YOLO v8n - pose; gait features

0　引言

跛行是影响猪只健康和发育的常见问题，严重影响猪只福利和养殖经济效益。及早发现并治疗猪只蹄部和腿部异常，可以减少损失[1-2]。当猪只跛行时，可能表现为不愿站立、腿部摆动不协调或幅度减小、膝盖弯曲角度偏小，以及背部轻微拱起等现象[3-4]。因此，通过观察这些表现可以判断猪只是否跛行。传统的动物跛行检测主要依赖人工，存在成本高和主观误差等问题，急需自动化检测方法。目前，非人工检测方法分为接触式和非接触式。接触式方法通过传感器穿戴设备检测运动数据识别跛行[5-8]。尽管接触式方法有效，但易受环境影响，且可能导致动物应激。

随着深度学习的发展，越来越多的研究转向利用计算机视觉技术进行非接触式动物跛行检测[9-10]。例如，通过摄像头记录奶牛的行走视频，提取背部轮廓、步态特征，并使用 SVM 或 LSTM 等算法进行分类[11-13]。LI 等[14]通过改进的 SOLO v2 网络和匈牙利算法对视频中的多头奶牛进行分割和跟踪，使用 Canny 算法提取奶牛颈部和背部特征进行跛行检测。康熙等[15]利用可见光图像和红外图像记录奶牛运动视频，计算奶牛弓背曲率以检测跛行。杜粤猛等[16]通过 Faster RCNN 和 ResNet101 网络模型构建奶牛姿态估计模型，使用 1 - D 卷积分类模型根据奶牛行走时膝关节的角度特征识别跛行。基于关键点的研究方法也被用于检测动物跛行，王祥等[17]通过猪只的关键轮廓点模型采集步态信息，并利用这些信息判断猪是否跛行。

综上所述，基于计算机视觉技术对动物进行跛行检测是可行的，并且相较于传统的人工观察和传感器方法具有显著优势。尽管计算机视觉在动物行为分析中已取得一定进展，但目前针对猪只跛行检测的研究仍较为有限，许多先进的计算机视觉方法尚未充分应用于此领域[18-20]。传统的目标检测和实例分割方法通常优先捕获猪只的边界和轮廓信息，难以准确识别猪只的身体姿态和四肢变化。相比之下，关键点检测技术更擅长捕捉猪只身体姿态的细微变化，特别是在跛行过程中，猪只通常表现出背部弯曲、膝关节异常及步长不一致等特征。因此，本文提出一种基于关键点和步行特征的猪只跛行检测方法。在 YOLO v8n - pose 的基础上，结合 BiFPN 双向特征金字塔和 RepGhost 网络来检测猪只的关键点，并利用这些关键点的检测结果计算猪只的步行特征，以期实现对跛行和非跛行猪只的分类识别。

1　数据来源与数据集构建

1.1　数据来源

实验数据于 2023 年 8 月在广东省云浮市温氏集团旗下农户猪场拍摄。为捕捉猪只行走特征，从猪只侧面进行拍摄。如图 1 所示，采用人工驱赶方式，让猪只通过通道，摄像头位置垂直于猪只行走方向，离地高度约为 0.8 m。帧率为 25 f/s，分辨率为 3 840 像素 ×2 160 像素。

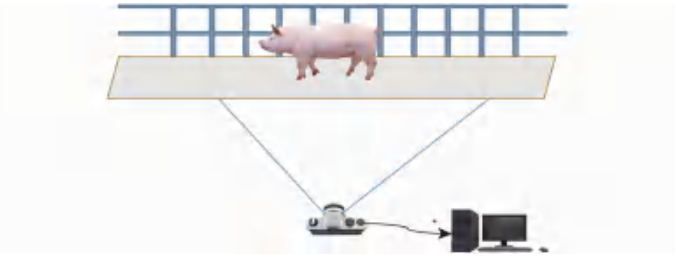


图 1　猪只数据拍摄示意图

Fig. 1　Example diagram of pig data capture

1.2　数据集构建

1.2.1　关键点数据集构建

从收集的视频数据中隔 25 帧截取 1 幅图像，去除相似的图像后共获得 1 623 幅，其中 600 幅作为测试集。对剩余的 1 023 幅图像通过随机添加高斯噪声、调整亮度、平移等方式进行数据增强，形成训练集，图像包含跛行和非跛行的情况。使用 Labelme 软件标注，通过 group_id 来区分关键点的可见性，0 表示不在图中，1 表示被遮挡，2 表示可见。由于所选图像中猪只均完整出现，因此排除 group_id 为 0 的情况。随后，将标注数据转换为 YOLO 格式。为研究猪只跛行，标注了猪只的四肢和上半身的 17 个关键点，如图 2 所示。具体关键点信息和标注位置详见表 1。

1.2.2　跛行检测数据集构建

将采集到的数据切分成若干片段，每个片段包含 50 帧图像，确保每个片段中猪完成了一个完整的行走动作，其中包含 101 个跛行片段和 114 个非跛

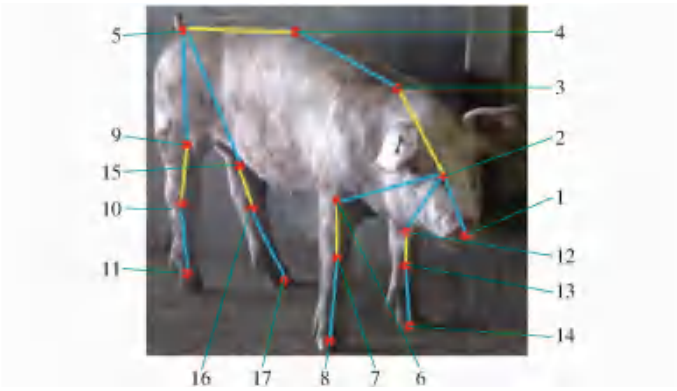


图 2 猪只关键点标注示意图

Fig. 2 Example diagram of pig keypoint annotation

表 1 关键点信息

Tab. 1 Keypoint information

坐标	部位	标注位置
(x_1, y_1)	鼻子	鼻尖最前端(通常为头部最突出的位置)
(x_2, y_2)	头部	眼睛偏下一点的位置(从侧面)
(x_3, y_3)	颈部	脖子中间区域(连接头部与身体的部分)
(x_4, y_4)	背部	脊椎中间、微微拱起的位置
(x_5, y_5)	臀部	尾巴根部
(x_6, y_6)	右肩部	右前肢与躯干连接中点处
(x_7, y_7)	右前膝	腿关节处(右前腿弯曲处)
(x_8, y_8)	右前蹄	右前脚蹄尖(最接近地面的位置)
(x_9, y_9)	右后臀	右后肢与躯干连接处(靠近臀部右侧边缘)
(x_{10}, y_{10})	右后膝	右后腿膝盖外侧中央(腿关节弯曲处)
(x_{11}, y_{11})	右后蹄	右后脚蹄尖(最接近地面的位置)
(x_{12}, y_{12})	左前肩	左前肢与躯干连接中点处
(x_{13}, y_{13})	左前膝	腿关节处(左前腿弯曲处)
(x_{14}, y_{14})	左前蹄	左前脚蹄尖(最接近地面的位置)
(x_{15}, y_{15})	左后臀	左后肢与躯干连接处(靠近臀部左侧边缘)
(x_{16}, y_{16})	左后膝	左后腿膝盖外侧中央(腿关节弯曲处)
(x_{17}, y_{17})	左后蹄	左后脚蹄尖(最接近地面的位置)

行片段。将跛行片段和非跛行片段分别按比例 7∶3 划分,得到数据集情况如表 2 所示。

表 2 跛行检测数据集样本数

Tab. 2 Lameness detection dataset

数据集	训练集	测试集
跛行	70	31
非跛行	79	35
总计	149	66

2 猪只跛行检测方法

2.1 研究方法

猪只跛行检测方法是基于跛行特征实现的,猪只跛行表现为步态不稳、步幅缩短、行动困难、背部微弓和头部低垂等特征[21]。如图 3 所示,本文设计了一种基于关键点和步行特征的跛行检测方法。首先,通过 YOLO v8n-pose 模型检测出猪只步行的关键点,同时引入 BiFPN 特征融合网络和 RepGhost 轻量化网络,以提升关键点特征提取和模型精度。然后利用所获取的关键点信息计算猪只行走过程中的步长、背部弯曲程度和膝盖弯曲程度。最后,利用机器学习方法对计算得到的步行特征进行分类检测。

2.2 基于 YOLO v8n-pose 的猪只关键点检测网络

YOLO v8-pose 相较于 YOLO v5 和 YOLO v7 等算法在速度和精度上均有显著提升,可用于目标检测、实例分割和关键点检测等领域[22]。YOLO v8-pose共有 n、s、m、l、x 5 个版本,其中 YOLO v8n-pose 在保持参数量和速度较优的情况下,仍能准确检测。因此,本文选择 YOLO v8n-pose 作为猪只的关键点检测模型。

如图 4 所示,YOLO v8n-pose 主要由输入层、主干网络(Backbone)、颈部网络(Neck)和输出层组成。主干网络负责特征提取,Conv 模块对输入图像进行卷积操作以提取特征,C2f 模块对数据进行特征转换和分支处理,从而提高网络对复杂数据的建模能力,丰富特征表达。最后,SPPF 模块通过将特征池化到固定大小的特征图,加速计算[23-24]。而 Neck 网络主要是将来自不同层级的特征进行融合,以捕捉不同尺度下的目标信息。

2.3 YOLO v8n-pose 模型改进

2.3.1 BiFPN 双向特征金字塔

BiFPN 可以实现快速的多尺度特征融合,是一

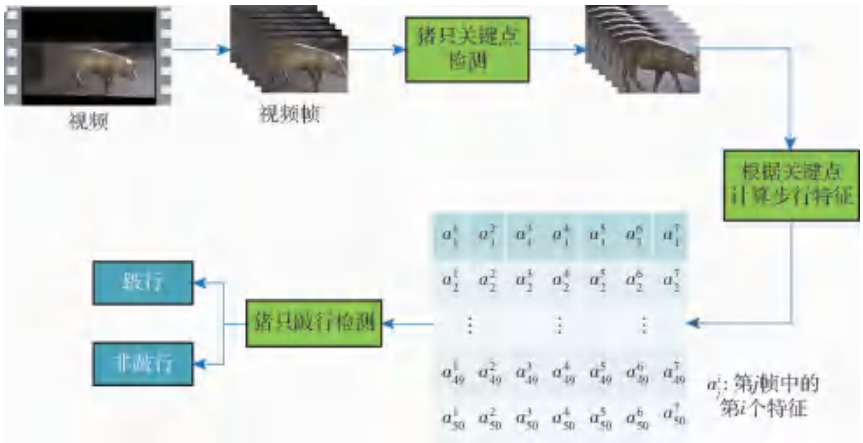


图 3 技术路线图

Fig. 3 Technical roadmap

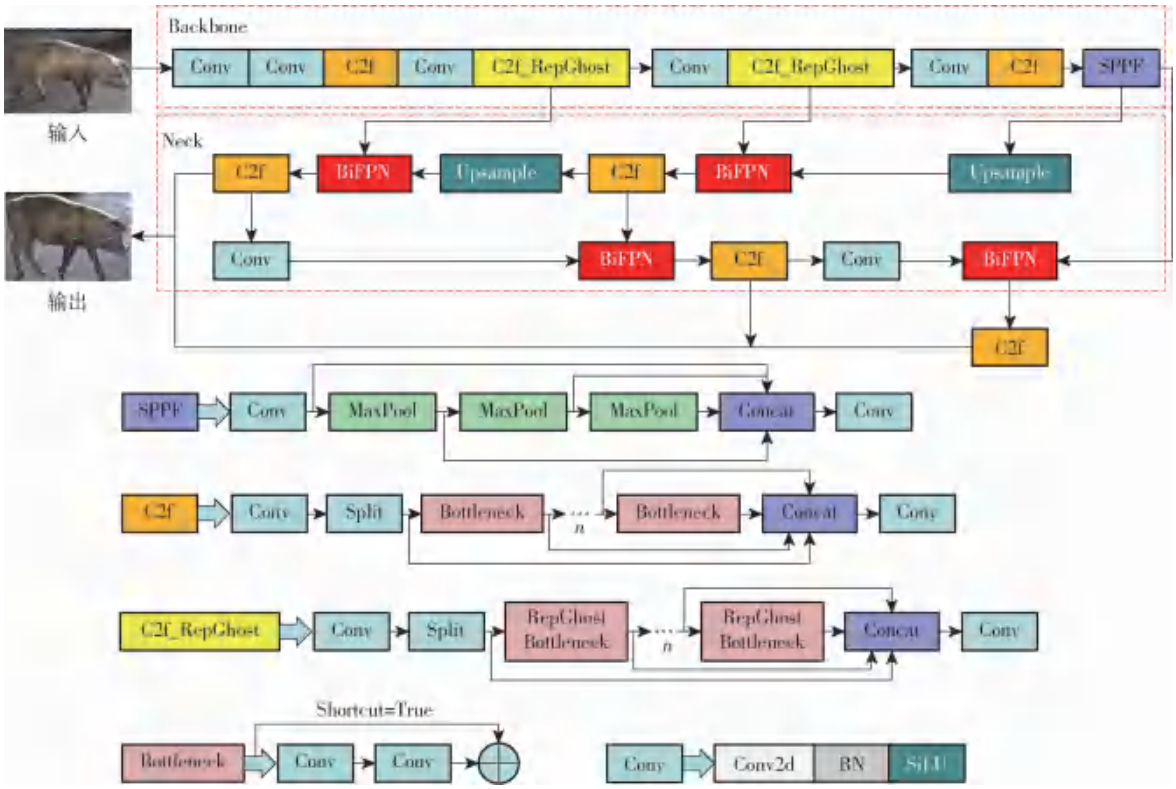


图 4　改进的 YOLO v8n－pose 网络结构图

Fig. 4　Diagram of improved YOLO v8n－pose network structure

种高效的加权双向特征金字塔网络[25]。如图 5a、5b 所示，原始 YOLO v8－pose 采用的是 PAN－FPN 的双向融合金字塔结构，其中 FPN 引入自顶向下的路径来融合多尺度特征，PAN 对 FPN 进行补充，引入自底向上的路径，融合不同层次的特征图。然而，为了进一步提升特征融合效率和检测性能，本文将 PAN－FPN 替换为 BiFPN。如图 5c 所示，BiFPN 允许特征信息在自顶向下和自底向上两个方向流动和融合，使网络能够更有效地利用不同尺度的信息，从而提高检测的性能[26]。BiFPN 通过双向融合机制，更全面地整合不同层级的特征信息，确保特征图的高效表达和利用。同时，BiFPN 引入了加权融合并简化了融合路径，能够根据训练过程中的优化需求，动态调整各特征图的贡献，减少计算复杂度，从而提升融合效果和模型性能。

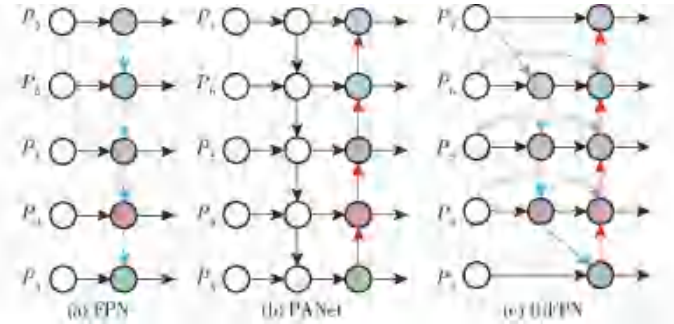


图 5　特征结构图

Fig. 5　Feature structure diagram

在猪只行走过程中，身体不同部位的关键点特征尺度可能存在着差异，准确捕捉这些不同尺度的特征对于提高检测精度至关重要。与 Concat 操作相比，BiFPN 能够在处理不同尺度的特征时表现更优，能够更好地捕捉和利用大小不同的目标信息，进一步提升检测精度，因此本文使用 BiFPN 替换掉颈部中的 Concat 操作，如图 4 所示。

2.3.2　RepGhost 网络

注意力机制是一种智能过滤机制，可以有选择地从大量数据中挑选出关键信息，将注意力集中在这些关键信息上，同时忽略大部分不相关或不太重要的数据，从而提高模型的精度或减少计算量[27]。RepGhost 模块在 Ghost 模块[28]的基础上引入了重参数化技术，有效降低了模型的计算复杂度。如图 6 所示，基于原始的 Ghost 模块，首先将 Ghost 中的 Concat 操作替换成 add 操作，以得到更高的效率。然后再将 add 操作移动到 ReLU 操作后面，同时将归一化操作 BN 添加到重参数化的结构分支中。最后为了能够更加快速推断，将图 6d 中的模块融合成图 6e 中的结构，最终仅包含常规卷积和 ReLU[29]。

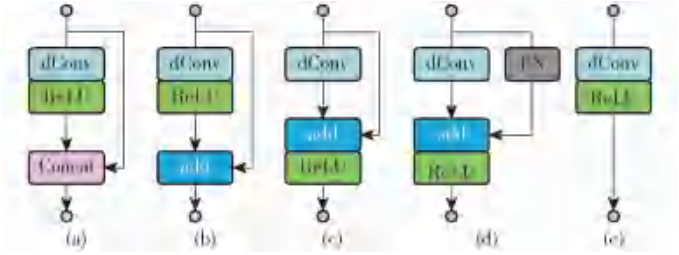


图 6　RepGhost 模块

Fig. 6　RepGhost module

如图 7 所示,通过替换 Ghost 模块为 RepGhost 模块构建 RepGhost 网络。图 7b、7c 分别为 RepGhost 网络在训练和推理时的结构。在训练阶段,输入特征通过一个 1×1 的 Conv 层和 ReLU 激活函数,然后经过带有批量归一化(BN)操作的 RepGhost 模块。接着,通过下采样和 SE 模块增强通道特征。最后,经过另一个带有 BN 操作的 RepGhost 模块,与通过 SBlock 模块处理后的原始输入特征融合,输出最终特征。在推理阶段,RepGhost 模块通过参数融合将深度卷积(dConv)和 BN 转换为等效的深度可分离卷积。利用结构重参数化,RepGhost 能够合并不同的特征图,从而减少特征信息的丢失,提高推理精度。

如图 4 所示,使用 RepGhost 网络替换 YOLO v8-pose 中 C2f 模块的 Bottleneck 网络,构成了 C2f_RepGhost 模块。并用 C2f_RepGhost 模块替换了 Backbone 网络中第 4 层和第 6 层的 C2f 模块。

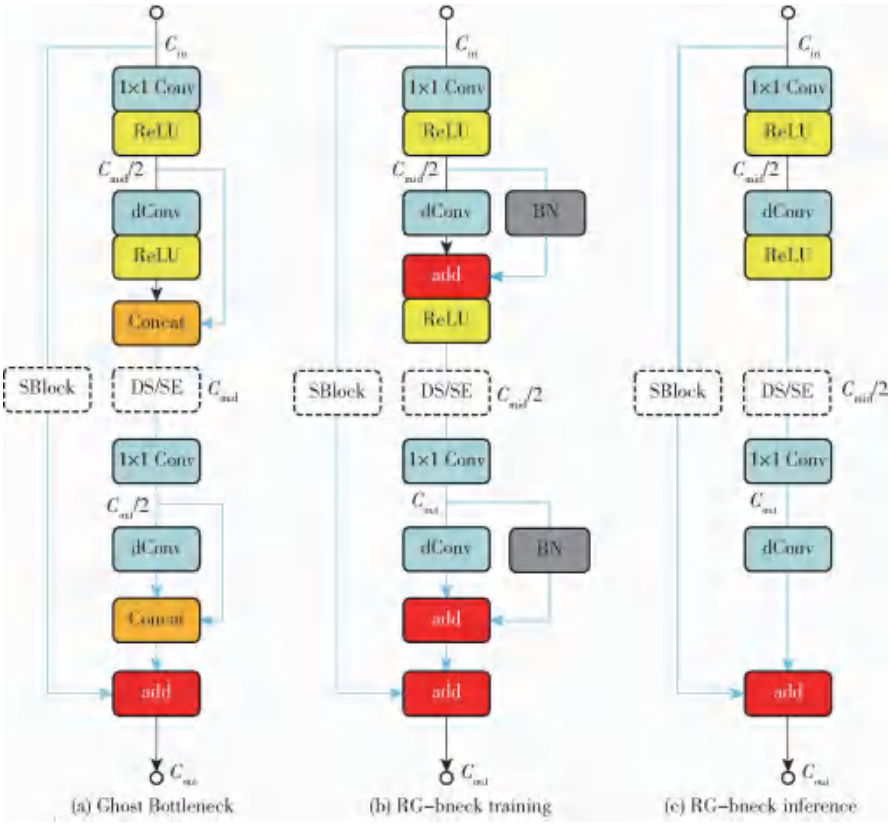


图 7 RepGhost 网络图

Fig. 7 RepGhost network diagram

2.4 步行特征计算

对于跛脚猪只,由于蹄部或腿部疼痛,行走时可能会表现为步长变长或变短。此外,受影响的腿部对应的膝盖也可能出现异常弯曲。跛行的猪只还会通过拱起背部来减轻疼痛。本文利用步长、膝盖弯曲程度和背部弯曲程度 3 个变量变化规律来探讨猪只跛行的检测方法,计算特征所用的(x_i,y_i)对应表 1 中的关键点信息,7 个特征如表 3 所示。

表 3 步行特征描述

Tab. 3 Description of walking features

编号	特征	描述
F_1	前步长	两个前蹄间距离
F_2	后步长	两个后蹄间距离
F_3	右前膝盖角度	右肩部、右前膝和右前蹄 3 个部位间角度
F_4	右后膝盖角度	右后臀、右后膝和右后蹄 3 个部位间角度
F_5	左前膝盖角度	左肩部、左前膝和左前蹄 3 个部位间角度
F_6	左后膝盖角度	左后臀、左后膝和左后蹄 3 个部位间角度
F_7	背部弯曲程度	颈部、背部和臀部形成的弧的弯曲程度

步长特征可分为两个前蹄的步长 F_1 和两个后蹄的步长 F_2,对应的步长公式为

$$F_1 = \sqrt{(x_8 - x_{14})^2 + (y_8 - y_{14})^2} \tag{1}$$

$$F_2 = \sqrt{(x_{11} - x_{17})^2 + (y_{11} - y_{17})^2} \tag{2}$$

膝盖角度用来量化行走过程中猪只的腿部弯曲程度,即

$$F_3 = \arccos \frac{(x_7 - x_6, y_7 - y_6)(x_7 - x_8, y_7 - y_8)}{|(x_7 - x_6, y_7 - y_6)||(x_7 - x_8, y_7 - y_8)|} \frac{180}{\pi} \tag{3}$$

$$F_4 = \arccos \frac{(x_{10} - x_9, y_{10} - y_9)(x_{10} - x_{11}, y_{10} - y_{11})}{|(x_{10} - x_9, y_{10} - y_9)||(x_{10} - x_{11}, y_{10} - y_{11})|} \frac{180}{\pi} \tag{4}$$

$$F_5 = \arccos \frac{(x_{13} - x_{12}, y_{13} - y_{12})(x_{13} - x_{14}, y_{13} - y_{14})}{|(x_{13} - x_{12}, y_{13} - y_{12})||(x_{13} - x_{14}, y_{13} - y_{14})|} \frac{180}{\pi} \tag{5}$$

$$F_6 = \arccos \frac{(x_{16} - x_{15}, y_{16} - y_{15})(x_{16} - x_{17}, y_{16} - y_{17})}{|(x_{16} - x_{15}, y_{16} - y_{15})||(x_{16} - x_{17}, y_{16} - y_{17})|} \frac{180}{\pi} \tag{6}$$

通过三点法计算离散曲率，计算颈部、背部和臀部 3 个点之间距离，并使用反余弦函数计算对应的角度，最终利用曲率计算公式求出背部所在部位的曲率 F_7，即

$$F_7 = \frac{2\sin\theta}{L_3} \tag{7}$$

其中

$$\theta = \arccos\frac{L_1^2 + L_2^2 - L_3^2}{2L_1L_2} \tag{8}$$

$$L_1 = \sqrt{(x_4 - x_3)^2 + (y_4 - y_3)^2} \tag{9}$$

$$L_2 = \sqrt{(x_4 - x_5)^2 + (y_4 - y_5)^2} \tag{10}$$

$$L_3 = \sqrt{(x_3 - x_5)^2 + (y_3 - y_5)^2} \tag{11}$$

式中　L_1——颈部和背部间距离

L_2——臀部和背部间距离

L_3——颈部和臀部间距离

θ——颈部、背部和臀部在背部处的夹角

2.5　跛行检测方法

通过上述方法构建步行特征，对于每一帧数据，提取出 2 个前蹄的步长、2 个后蹄的步长、4 条腿的膝盖弯曲角度以及背部曲率，共 7 个特征，构成特征 F_i（$i = 1, 2, \cdots, 7$）。K 最近邻算法（K-nearest neighbors，KNN）是一种基本的分类和回归算法。对于给定的有标签样本集 D，当输入一个待分类的无标签样本时，该算法将该样本的每一个特征与样本集 D 中的数据进行比较，计算它与样本集中其他样本距离，并选择距离最近的 k 个样本。然后根据这 k 个样本中出现次数最多的标签，决定待分类样本的类别标签。本文使用的距离度量是欧氏距离，公式为

$$D(m_a, m_b) = \sqrt{\sum_{i=1}^{n}(F_i^a - F_i^b)^2} \tag{12}$$

式中　m_a、m_b——样本 a、b

F_i^a、F_i^b——样本 m_a、m_b 的第 i 个特征

n——特征维度

3　实验

3.1　实验环境及参数设置

实验基于 Pytorch 和 Python 3.9，操作平台为 64 位Windows 10，显卡为 RTX3060，内存为 12 GB，处理器为 Intel（R） Core（TM） i7 - 10700 CPU@ 2.90 GHz。YOLO v8 - pose 模型超参数如表 4 所示。

3.2　评价指标

为评估 YOLO v8 - pose 模型的性能，利用关键点相似度（OKS）来衡量预测关键点和真实关键点间的差距。设置阈值为 0.5，当 OKS 大于阈值时判定为检测正确，通过平均精度均值（mean Average Precision，mAP）和召回率（Recall，R）对关键点检测模型进行评估。对于 KNN 分类模型，使用准确率（Accuracy）进行评估。

表 4　YOLO v8 - pose 训练参数

Tab.4　YOLO v8 - pose training parameters

参数	数值
批次大小（batch_size）	16
训练轮次（epoch）	300
学习率（lr）	0.01
权重衰减（weight_decay）	0.000 5
动量（momentum）	0.937

3.3　YOLO v8 - pose 性能评估

3.3.1　消融实验

为提高猪只关键点检测模型的精度并减少计算量，对模型进行改进，引入 RepGhost 网络和 BiFPN 双向特征金字塔。为说明本文改进的有效性，进行消融实验，实验结果如表 5 所示。原 YOLO v8n - pose 在测试集上的 mAP 和召回率分别为 88.2% 和 86.9%。当模型引入 RepGhost 模块后，召回率下降 1.5 个百分点，而 mAP 提升 0.7 个百分点，同时参数量和浮点运算量分别下降 2×10^5、6×10^8。在模型中引入 BiFPN 模块时，模型的 mAP 相比原模型提高 1 个百分点，参数量和浮点运算量保持不变。将 RepGhost 和 BiFPN 模块一起添加到 YOLO v8n - pose 后，相较于原模型，mAP 提高 4.2 个百分点，而召回率提升 0.9 个百分点，同时参数量和浮点运算量分别下降 2×10^5、6×10^8。综合而言，在 YOLO v8n - pose 中添加 RepGhost 和 BiFPN 模块，不仅显著提升了模型 mAP 和召回率，还有效减少了参数量和浮点运算量，实现了性能和效率的双重优化。

表 5　消融实验结果

Tab.5　Results of ablation experiments

模型	mAP/%	R/%	参数量	浮点运算量
YOLO v8n - pose	88.2	86.9	3.3×10^6	9.2×10^9
+ RepGhost	88.9	85.4	3.1×10^6	8.6×10^9
+ BiFPN	89.2	85.3	3.3×10^6	9.2×10^9
+ RepGhost + BiFPN	92.4	87.8	3.1×10^6	8.6×10^9

3.3.2　不同模型对比实验

为更好地验证本文算法的性能，将改进模型与其他关键点检测模型（HRNet - w32[30]、Lite - HRNet[31]、ResNet50[32]、ViPNAS[33]、Hourglass[34]），在同一数据集下进行对比，结果如表 6 所示。

由表 6 可知，模型 HRNet - w32、Lite - HRNet、ResNet50、ViPNAS 和 Hourglass 的 mAP 分别为 82.2%、80.8%、78.2%、80.6% 和 79.9%。改进

表 6 不同模型对比结果

Tab. 6 Comparison results of different models %

模型	mAP	*R*
HRNet - w32	82.2	83.0
Lite - HRNet	80.8	82.3
ResNet50	78.2	80.3
ViPNAS	80.6	81.7
Hourglass	79.9	81.2
改进 YOLO v8 - pose	92.4	87.8

YOLO v8 - pose 模型 mAP 和召回率均优于上述对比模型,mAP 和召回率分别达到 92.4% 和 87.8%。相比 HRNet - w32 模型,mAP、召回率分别高出 10.2、4.8 个百分点。与 ResNet50 模型相比,改进模型 mAP、召回率分别高出 14.2、7.5 个百分点。综上所述,YOLO v8 - pose 模型及其改进版本在猪只关键点检测方面均优于其他关键点检测模型。

3.4 猪只跛行检测模型评估

选用 KNN 算法对猪只步行特征进行分类检测。在 KNN 算法中,*K* 值的选择至关重要,取值范围为 1 ~ 17[35]。为选取最佳 *K* 值,对该范围内每个 *K* 值逐一验证,结果如图 8 所示。当 *K* 取 1 时,KNN 算法对猪只跛行的准确率达到最高,为 81.7%。

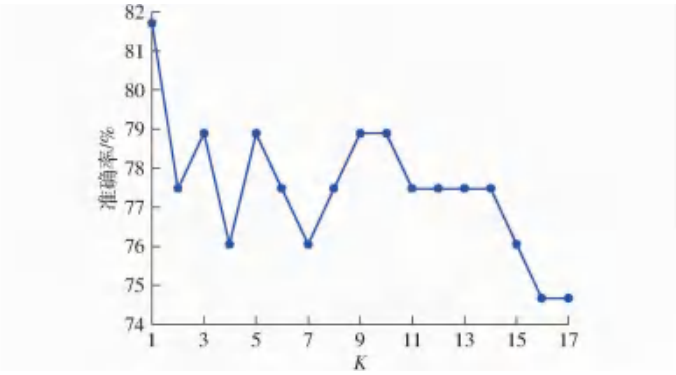


图 8 不同 *K* 值的 KNN 精度曲线

Fig. 8 Accuracy graph for different values of *K* in K-nearest neighbors

为验证分类算法的有效性,将 KNN 算法与 BP 算法、Decision Tree、SVM 进行对比。BP 算法的准确率为 80.2%,比 KNN 算法低 1.5 个百分点。Decision Tree 算法和 SVM 算法的准确率分别为 70.4% 和 75.2%,分别比 KNN 算法低 11.3、6.5 个百分点。

3.5 不同步行特征对跛行检测的影响

将猪只的步长、背部曲率和膝盖弯曲程度作为关键特征,用以检测猪只是否跛行。为探究这 3 个特征对跛行检测的有效性,采用 KNN 算法对每个特征单独进行训练和检测。单独使用膝盖弯曲程度、背部曲率和步长作为特征时,准确率分别达到 57.7%、77.5% 和 69.0%。这表明,每个特征都在一定程度上对猪只跛行检测起到了作用。将所有特征结合起来进行跛行检测时,准确率达到 81.7%。这表明,结合多个特征进行跛行检测比单独使用任一特征更为有效。这可能是因为不同特征之间存在相关性,结合起来可以提供更全面、更准确的信息,从而提高了跛行检测的准确性。因此,综合利用猪只的步长、背部曲率和膝盖弯曲程度等多特征进行跛行检测,相较于单一特征,能够显著提升检测的准确性。

4 结论

(1)提出了一种基于关键点检测和步行特征的猪只跛行检测方法,使用 YOLO v8n - pose 对猪只关键点进行检测,通过引入 RepGhost 网络和 BiFPN 双向特征金字塔结构,关键点检测的平均精度和召回率分别达到 92.4% 和 87.8%。相比 YOLO v8n - pose,mAP 和召回率分别提高 4.2、0.9 个百分点。将改进 YOLO v8n - pose 模型与其他经典关键点检测模型(HRNet - w32、Lite - HRNet、ResNet50、ViPNAS 和 Hourglass)进行对比,改进模型 mAP 分别高出 10.2、11.6、14.2、11.8、12.5 个百分点。

(2)通过分析猪只关键点坐标和跛行特征,计算出猪只步行时的步长、膝盖角度和背部曲率 3 大特征,作为检测猪只是否跛行的依据。

(3)使用 K 最近邻(KNN)算法对猪只步行特征进行跛行检测,通过对 1 ~ 17 的 *K* 值逐一检验,最终确定 *K* 为 1 时准确率最高,为 81.7%。与其他算法(BP 算法、Decision Tree 算法和 SVM 算法)对比,KNN 算法的准确率分别高出 1.5、11.3、6.5 个百分点。

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特约专稿

果实目标深度学习识别技术研究进展

宋怀波　尚钰莹　何东健

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基于改进 YOLO v5n 的猪只盘点算法

杨秋妹[1,2]　陈淼彬[1,2]　黄一桂[1,2]　肖德琴[1,2]　刘又夫[1,2]　周家鑫[1,2]
(1. 华南农业大学数学与信息学院，广州 510642；2. 农业农村部华南热带智慧农业技术重点实验室，广州 510642)

摘要： 猪只盘点是规模化养殖中的重要环节，为生猪精准饲喂和资产管理提供了依据。人工盘点不仅耗时低效，而且容易出错。当前已有基于深度学习的生猪智能盘点算法，但在遮挡重叠、光照等复杂场景下盘点精度较低。为提高复杂场景下生猪盘点的精度，提出了一种基于改进 YOLO v5n 的猪只盘点算法。该算法从提升猪只目标检测性能出发，构建了一个多场景的生猪数据集；其次，在主干网络中引入 SE-Net 通道注意力模块，引导模型更加关注遮挡条件下猪只目标信息的通道特征。同时，增加了检测层进行多尺度特征融合处理，使模型更容易学习收敛并预测不同尺度的猪只对象，提升模型遮挡场景的检测性能；最后，对边界框损失函数以及非极大值抑制处理进行了改进，使模型对遮挡的目标有更好的识别效果。实验结果表明，与原 YOLO v5n 算法相比，改进算法的平均绝对误差(MAE)、均方根误差(RMSE)以及漏检率分别降低 0.509、0.708 以及 3.02 个百分点，平均精度(AP)提高 1.62 个百分点，达到 99.39%，在复杂遮挡重叠场景下具有较优的精确度和鲁棒性。算法的 MAE 为 0.173，与猪只盘点算法 CClusnet、CCNN 和 PCN 相比，分别降低 0.257、1.497 和 1.567。在时间性能上，单幅图像的平均识别时间仅为 0.056 s，符合实际猪场生产的实时性要求。

关键词： 猪只计数；目标检测；注意力机制；多尺度感知
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Pig Counting Algorithm Based on Improved YOLO v5n

YANG Qiumei[1,2]　CHEN Miaobin[1,2]　HUANG Yigui[1,2]　XIAO Deqin[1,2]　LIU Youfu[1,2]　ZHOU Jiaxin[1,2]
(1. *College of Mathematics and Informatics, South China Agricultural University, Guangzhou* 510642, *China*
2. *Key Laboratory of Smart Agricultural Technology in Tropical South China, Ministry of Agriculture and Rural Affairs, Guangzhou* 510642, *China*)

Abstract: Pig counting is an important part in large-scale farming, which provides the basis for precise pig feeding and asset management. Manual counting is both time-consuming and inefficient, more than error-prone. In recent years, as the performance of deep learning systems far outperforms traditional machine learning systems, deep learning-based methods have demonstrated state-of-the-art performance in tasks such as image classification, segmentation, and object detection. Although there are currently existing intelligent pig counting algorithms based on deep learning, the counting accuracy is low in complex scenes such as occlusion and different illumination. So as to increase the accuracy of pig counting in complex scenarios, a pig counting algorithm was proposed based on improved YOLO v5n. Starting from improving the performance of pig target detection, the algorithm constructed a multi-scene pig dataset. In the field of target detection, each target was surrounded by the surrounding background, and the environment around the target object had rich contextual information. However, in the deep convolutional neural network, although the convolutional layer can capture the features of the image from the global receptive field to describe the image, it essentially only modeled the spatial information of the image without modeling the information between channels. By introducing the SE-Net channel attention module into the Backbone network, the model was guided to place greater emphasis on the channel features of the pig target information under occlusion conditions, so that it can better locate the features to be detected and enhance the network performance. At the same time, there may be pig targets of various

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作者简介： 杨秋妹(1983—)，女，讲师，博士，主要从事农业图像视频处理研究，E-mail: yqmbegonia@163.com
通信作者： 肖德琴(1970—)，女，教授，博士生导师，主要从事物联网和农业图像视频处理研究，E-mail: deqinx@scau.edu.cn

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scales in an actual picture of a dense scene of a pig farm. In order to deal with the complex and densely occluded actual production pig farm scene and obtain more abundant and comprehensive feature information, a detection layer was added based on the original three detection layers of different scales for multi-scale feature detection, so as to better learn the multi-level features of the occlusion target and improve the detection performance of model complex occlusion scenes. Finally, the loss function of the boundary box and the non-maximum suppression processing were improved to make the model have better recognition effect on the occluded targets. According to experimental results, in contrast with the original YOLO v5n algorithm, the mean absolute error (MAE), root mean square error (RMSE) and missed detection rate of the improved algorithm were reduced by 0.509, 0.708 and 3.02 percentage points, respectively, and the average precision (AP) was improved by 1.62 percentage points to 99.39%. The improved algorithm had high accuracy and good robustness in complex occlusion overlapping scenarios. Compared with other pig inventory algorithms: CClusnet, CCNN and PCN, the MAE of this algorithm was 0.173, which was 0.257, 1.497 and 1.567 lower than that of the other three algorithms. In terms of time performance, it only took 0.056 s to recognize a single image on average, satisfying the real-time requirements of actual pig farm production.

Key words: pig counting; object detection; attention mechanism; multi-scale perception

0 引言

猪只盘点是猪场集约化资产管理中的一项重要任务。依据准确的猪只数量可以制定更加合理的养殖计划,帮助养殖户降低成本,减少不必要的损失,提高养殖场收益。传统的人工盘点方法需要高劳动力成本,且容易受到猪群重叠、相互遮挡、摄像头视角或者光照等影响,容易出错。另外,人工盘点会引起猪只的应激反应,出现猪只受惊或乱跑,增加盘点的难度,无法保证盘点的准确性。

随着规模化、信息化智慧养猪建设的快速推进,计算机视觉算法因其具有无侵扰、不间断、成本低等优势,成为智能猪只盘点方法的主要发展趋势[1]。早期的视觉猪只盘点方法利用形态学算法和区域生长法相结合的方法将背景与前景分割,从而实现猪只数量的统计[2-3]。深度学习方法在处理复杂遮挡计数问题上有很大的优势[4-8]。目前,有不少的研究人员已经将深度学习应用于猪只盘点。基于神经网络的密度图回归的计数方法受到不少研究人员的重视[9-11]。此类方法利用像素将图像转换为密度图回归,并对密度图进行积分得到计数。文献[12]提出了一个自底向上的猪只身体关键点检测方法,然后再基于 STRF(空间敏感时序响应)方法进行猪只计数。文献[13]用改进的 Mask R-CNN 网络减少了因光照和生猪遮挡致使猪只目标漏检的问题,其网络在 12~22 头猪只的单栏的计数准确率达到 98%。

综上,基于深度学习的猪只盘点算法虽然优于人工计数方法,但由于猪是一种群居的动物,通常挨靠在一起致使猪只互相遮挡重叠。而且同一猪舍的猪只颜色相近,当猪只体型发生变化的时候,更容易导致猪只个体难以区分,使得识别难度增大。因此,针对猪只相互遮挡、体型变化或者光线暗的情况下导致漏检或者多检的问题,本文结合注意力机制和多尺度特征检测,在 YOLO v5n 网络的基础上进行改进,拟实现一种改进 YOLO v5n 猪只计数算法。

1 数据集构建与计数原理

1.1 数据来源

本文的实验数据来源于 5 种不同的猪场数据集,分别是 3 个自建实验猪场数据集:广州萝岗实验猪场、云浮范金树实验猪场、隔离舍实验猪场,以及两个公开数据集:文献[14-15]公开的数据集。广州萝岗实验猪场选取长白后备母猪为实验对象,猪栏尺寸为 4 m×5 m,单栏内饲养 4 头猪,猪只数量较少;云浮范金树实验猪场选取育肥期的长白母猪为实验对象,群养猪栏尺寸为 5 m×8 m,单栏内平均饲养 40 头猪,猪只数量较多,但局限于摄像头拍照角度肉眼可见的猪只数量平均为 26 头;隔离舍实验猪场选取育肥期的长白母猪为实验对象,猪栏尺寸为 2 m×4 m,单栏内饲养 6 头猪;文献[14]的数据集描述了 17 个不同的猪圈位置,包括 1.5~5.5 月龄猪只,单栏内饲养的猪只数量有 7、8、10、11、14、15 头,既包括日间拍摄的图像也包括晚上拍摄的图像;文献[15]实验猪场的单个猪圈尺寸为5.8 m×1.9 m,有 8 头猪,体质量约为 30 kg。各实验猪场信息如表 1 所示。

广州萝岗猪场、云浮范金树猪场、隔离舍猪场均采用海康威视 DS-2CD3345-I 型红外网络摄像头。广州萝岗猪场每天 24 h 共持续 32 d 对猪栏进行监控,但只选取 08:00—18:00 猪只比较活跃的时段。云浮范金树猪场与隔离舍猪场每天 24 h 不间

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断拍摄监控,同时选取白天活跃时段和夜晚睡眠阶段拍摄。

表 1　各猪场信息

Tab. 1　Information of pig farms

猪场	生长阶段	猪舍尺寸/(m×m)	单栏饲养数量/只	选取时间
广州萝岗猪场	育肥期	4×5	4	08:00—18:00
云浮范金树猪场	育肥期	5×8	40	08:00—18:00
隔离舍猪场	育肥期	2×4	6	23:00—03:00
文献[14]	保育期、育肥期		7~15	白天、夜晚
文献[15]	育肥期	5.8×1.9	8	07:00—19:00

1.2　数据预处理与数据集构建

对采集到的视频每隔 35 帧截取一幅图像,并去除相似度过高、清晰度较差的图像。为更准确地计算单栏内猪只数量,排除其他相邻栏位猪只对实验计数结果的影响,本文对包含多个猪栏的图像进行了掩膜处理,在原始图像上以盘点猪栏为界限,添加一掩膜层,遮住其他栏位的猪只,掩膜的处理效果如图 1 所示。



图 1　掩膜处理图像

Fig. 1　Mask processing pictures

最终数据集共有 3 000 幅图像,并用 LabelImg 标注软件进行标注。整个猪只盘点数据集按 6∶2∶2 的比例划分训练集、验证集和测试集。为保证数据集的多样性,利用 Python 脚本程序分别从各猪场随机选取 600 幅图像,其中训练集 360 幅图像,验证集和测试集均为 120 幅图像。依据上述方法本文构建的猪只盘点数据集如表 2 所示。

表 2　猪只盘点数据集

Tab. 2　Pig counting dataset

数据集	图像数量/幅	猪总数/头
训练集	1 800	19 205
验证集	600	6 481
测试集	600	6 316
合计	3 000	32 002

1.3　研究方法

本文提出了一种改进 YOLO v5n 猪只计数方法。首先,构建多场景的猪只盘点数据集(包括不同猪舍尺寸、不同群养猪只数量、不同遮挡程度、不同拍摄角度、不同光线强度等)。该方法在处理猪只遮挡重叠的问题,通过利用通道注意力机制在筛选特征时,能够提高感兴趣的区域信息权重,弱化与当前任务无关的特征信息以提升模型效果[16],同时增加多尺度物体检测层,获得更丰富全面的特征信息,增强模型在复杂场景下多尺度学习的能力;并对边界框的损失函数以及加权的非极大值抑制(Non-maximum suppression,NMS)进行改进,提高模型在遮挡场景下的检测精度和速度,降低漏检率。最后经过非极大值抑制(DIoU-NMS)处理输出最终预测结果,并计算得到最终的猪只数量。本文方法流程如图 2 所示。

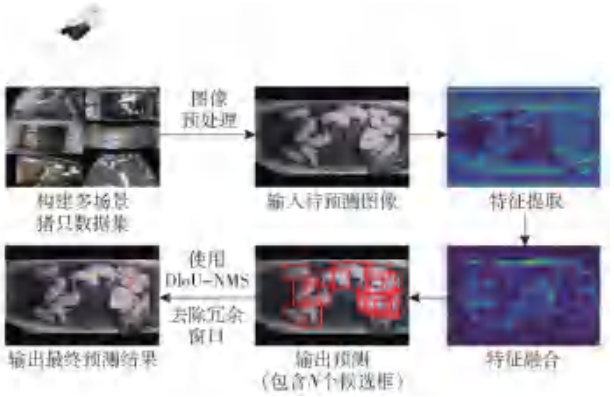


图 2　本文方法流程图

Fig. 2　Flow chart of proposed method

2　猪只计数网络实现

2.1　YOLO v5n 网络

YOLO v5[17] 是基于 YOLO v4 算法基础上进行改进,同属于单阶段目标检测算法,其速度与精度较之前版本都得到了大幅提升。YOLO v5 支持 5 个不同规模的模型,根据网络的深度和宽度可分为 YOLO v5n、YOLO v5s、YOLO v5m、YOLO v5l、YOLO v5x 版本,其相对应模型的检测精度和模型参数量依次提高。为了从上述 5 个不同规模的模型中选择更适合猪只盘点的模型,使用本文的猪只盘点数据集重新训练上述 5 个模型,并分别用训练好的模型对测试数据集中的图像进行测试。其实验结果如表 3 所示,平衡模型的精度、参数量以及在猪只盘点实际应用

表 3　YOLO v5 不同规模模型的准确度比较

Tab. 3　Accuracy comparison of different scale models of YOLO v5

模型	准确率/%	召回率/%	AP/%	参数量	单幅图像平均识别时间/s
YOLO v5n	97.71	95.94	97.77	1.90×10^6	0.017 4
YOLO v5s	98.12	96.41	98.05	7.20×10^6	0.018 9
YOLO v5m	98.90	97.17	98.53	2.12×10^7	0.027 9
YOLO v5l	98.87	98.21	99.09	4.65×10^7	0.038 9
YOLO v5x	98.83	98.78	99.26	8.67×10^7	0.065 8

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中实时 5 性要求 3 个指标，在精度相近的情况下，YOLO v5n 模型的参数量只有 1.9×10^6，其单幅图像平均识别时间仅为 0.017 4 s，相比较于参数量最多的 YOLO v5x，平均精确度(Average precision，AP)相差 1.49 个百分点，但单幅图像平均识别时间快了 48.4 ms。其次，与 YOLO v5s 模型相比，虽然识别速度相近，但两者的参数量相差近 4 倍。由于在猪场的盘点应用中，常采用边缘设备进行猪只盘点，此类设备对算法的处理速度要求较高。因此，本文最终选用参数量最少、识别速度最快的 YOLO v5n 作为本次实验的基础模型以便能够实时获取猪场猪只总数。

如图 3 所示，YOLO v5n 网络结构分为输入端、主干特征提取网络 Backbone、颈部 Neck 网络和输出端共 4 部分。

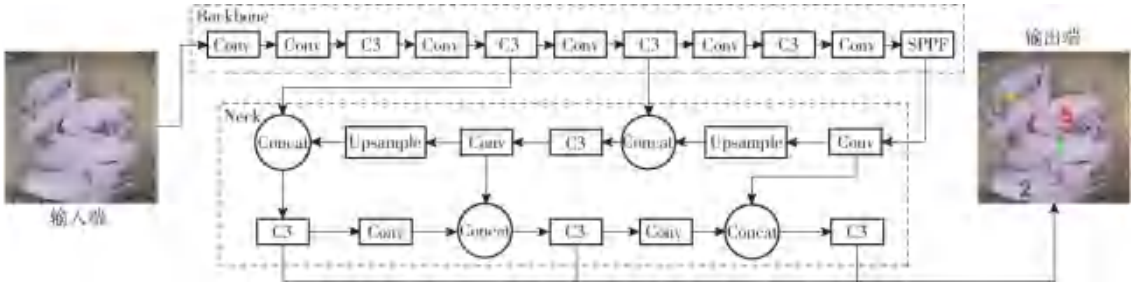


图 3 YOLO v5n 网络结构图

Fig. 3 YOLO v5n network structure diagram

YOLO v5n 的输入端对输入图像预处理，即将任意尺寸的输入图像缩放为网络的输入尺寸，并进行 Mosaic 数据增强丰富图像检测目标的背景，而且能够提高小目标的检测效果，并且在归一化计算时一次性处理多幅图像。其次，YOLO 系列检测算法中，针对不同的数据集往往需要设定特定长宽的锚框。在网络训练阶段，模型在初始锚框的基础上输出边界框，从而跟真实框对比，计算两者间的差距，再反向更新，迭代网络参数。在 YOLO v3 和 YOLO v4 检测算法中，在网络训练前单独采用 K－Means 聚类方法以获取不同数据集的最佳锚框值。但在 YOLO v5 检测算法中通过内嵌自适应锚框计算方法，每次训练前对数据集标注信息进行计算，得到该数据集标准信息针对默认锚框的最佳召回率，当最佳召回率大于或等于 98% 时，则不需要更新锚框；否则，重新计算符合该数据集的锚框，从而能够自适应地计算出不同训练集中最佳锚框值。

主干特征提取网络 Backbone 使用 CSPDarknet53 结构，且加入 Conv 卷积，CSP 及 SPPF[18] 结构。通过使用一个卷积核尺寸为 6×6，步长为 2 的卷积结构代替 Focus 结构，既能达到 2 倍下采样特征图的效果，又可避免多次采用切片操作，提高计算和推理速度[19]。其次，不同于 YOLO v4，YOLO v5n 设计了两种 CSP 结构，CSP1_X 结构应用于主干特征提取网络 Backbone 中，CSP2_X 结构应用于 Neck 网络中，其结构图如图 4 所示。SPPF 结构(图 5)与 SPP 结构一样，均采用 1×1、5×5、9×9 和 13×13 的最大池化方式，进行多尺度特征融合，但 SPPF 结构可以降低每秒浮点运算次数，运行的更快。

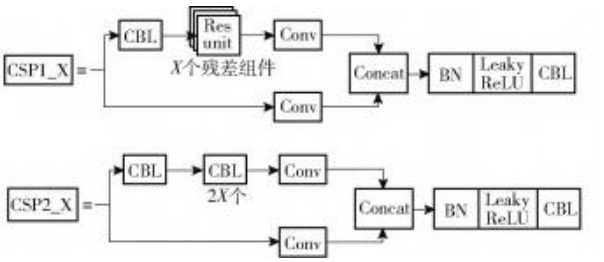


图 4 两种 CSP 结构

Fig. 4 Two CSP structures

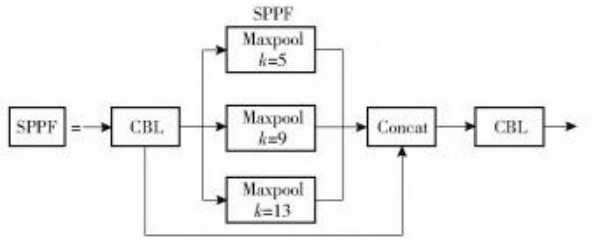


图 5 SPPF 结构

Fig. 5 SPPF structure

Neck 部分将特征金字塔的不同层级的图像组合在一起来完成多尺度混合，并将图像特征传递给预测层[20]。该部分仍采用 FPN 和 PANet 结合的双金字塔结构。特征金字塔网络(Feature pyramid networks，FPN)自顶向下，将高层的语义特征往下传递，得到预测的特征图[21]。路径聚合网络(Path aggregation network，PANet)是针对 FPN 只增强了语义信息，但并没有对定位信息进行传递的缺点[22]。通过在特征金字塔 FPN 的后面增加一个自底向上的路径，用底层精确的定位信息来增强整个特征层次结构，从而缩短底层特征与高层特征之间的信息路径。

输出端采用 GIoU Loss 作为边界框损失函数，其解决了当边界框与真实框没有交集时，交并比

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(Intersection over union,IoU) 等于 0,其损失函数导数也为 0,从而无法优化两框重叠的问题。在目标检测的最后处理过程中,YOLO v5n 使用加权的 NMS 方式筛选 N 个目标框。

2.2　SE－Net 注意力模块

注意力机制是通过参考人的视觉感知能力,即人在处理视觉信息初期会集中专注于当前情景下重点区域,而其他区域将相应降低,这为更高层级的视觉感知和逻辑推理以及更加复杂的计算机视觉处理任务提供更易于处理且更相关的信息[23]。

在深度卷积神经网络中,通过构建一系列的卷积层、非线性层和下采样层使得网络能够从全局感受野上提取图像特征来描述图像,但归根结底只是建模了图像的空间特征信息而没有建模通道之间的特征信息,整个特征图的各区域均被平等对待。然而,在猪只遮挡重叠、光线不足、皮毛颜色相似等实际猪场生产场景下,原始 YOLO v5n 算法难以检测到被遮挡的猪只,或者容易漏检一些边缘区域的猪只。在目标检测领域中每一个目标都被周围背景所包围,目标物体周围的环境有着丰富的上下文信息,这可以作为网络判断目标类别和定位的重要辅助信息[24]。通常在实际猪场生产图中,通过对目标区域的特征进行加权能使其更有效地定位到待检测猪只,提高网络性能[25]。SE－Net 通道注意力模块基于特征图上通道间的相关关系,网络通过损失函数去学习权重,强化有效特征,弱化低效或无效特征,提高了特征图的表现能力,从而提高了模型识别精度,能够在光线不足、密集遮挡的情况下有效检测出目标物体[26-27]。

针对 YOLO v5n 目标检测算法存在边界框定位不够准确导致难以区分重叠物体、鲁棒性差等问题,本文在主干特征提取网络中加入 SE－Net(Squeeze-and-Excitation networks) 通道注意力模块来改进算法,在特征图的通道间建立特征映射,使网络自动学习全局特征信息并突出重要的特征信息,同时弱化对当前任务无关的特征信息,使模型更专注于训练遮挡对象的目的。

SE－Net 结构单元图如图 6 所示,SE－Net 模块具体含括 3 个操作: 压缩(Squeeze)、激励(Excitation) 和缩放(Scale)。首先对原始输入进行全局平均池化操作(即压缩过程) 将原始特征层维度 $H \times W \times C$ 压缩为 $1 \times 1 \times C$,使得感受野更大,得到每个通道的全局特征。然后用两个全连接层(第一个全连接层用于降低维度,另一个还原为原始的维度) 融合各特征通道的特征图信息。再使用 Sigmoid 函数对权值进行归一化。最后是缩放操作,将激励操作后输出的权重映射为一组特征通道的权重,然后与原始特征图的特征相乘加权,实现对原始特征在通道维度上的特征重标定。网络通过加强训练 SE－Net 模块学习后的特征,提高了猪只遮挡的通道权重,指导模型更侧重学习猪只间遮挡的特征信息,进而提升模型在猪只遮挡场景下的检测性能[28]。

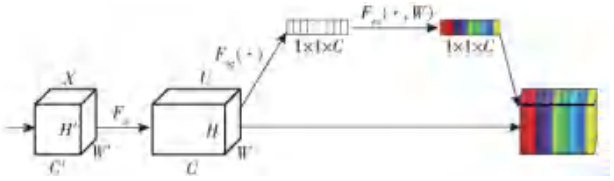


图 6　SE－Net 结构单元图

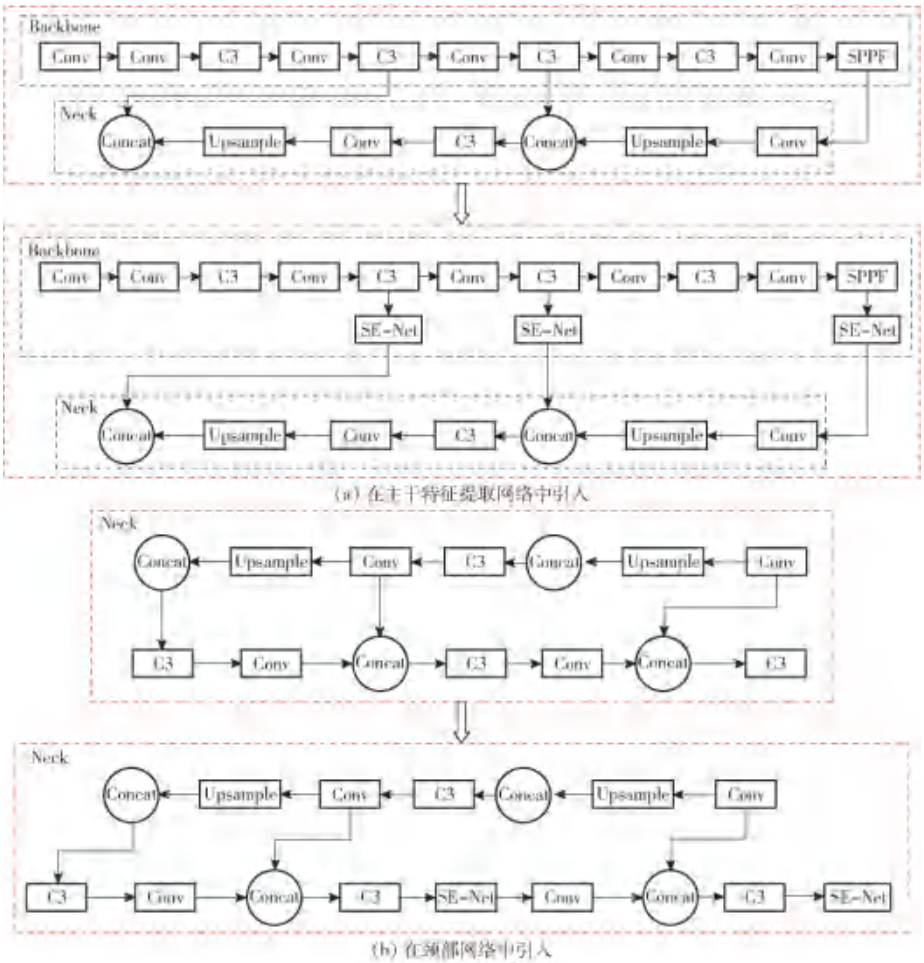
Fig. 6　SE－Net block

如图 7 所示,本文将 SE－Net 通道注意力模块分别加入到原始 YOLO v5n 主干特征提取网络 Backbone 的 C3 卷积模块后(图 7a) 和颈部网络 Neck 的 C3 卷积模块后(图 7b)。两种添加方法的检测结果对比如图 8 所示: 图 8a 为原始 YOLO v5n 检测效果图,漏检的情况比较严重; 图 8b 为在主干特征提取网络中加入 SE－Net 模块,图 8c 为在颈部网络中加入 SE－Net 模块,加入 SE－Net 注意力模块后漏检猪只数量相对较小,但在主干特征提取网络中引入相比于在颈部网络中能够更好地检测到遮挡猪只。因此本文采用在 YOLO v5n 主干特征提取网络引入 SE－Net 通道注意力模块。

2.3　多尺度特征检测

原始 YOLO v5n 网络使用 3 种类型的输出特征图来检测不同尺寸的物体,当输入图像尺寸为 1 280 像素×1 280 像素时,其对应的 3 种检测尺度分别为 40 像素×40 像素、80 像素×80 像素、160 像素×160 像素,用来检测大、中、小目标,其感受野大小依次递减。在现有的 3 个尺度特征图上进行猪只检测,对于某些尺度超大的猪只,感受野最大的特征图可能仍然提取不到有效的高级语义信息,相反,对于某些尺度超小的猪只,感受野最小的特征图也会丢失其轮廓和位置信息[29]。在实际猪场应用场景中,猪只姿态各式各样,猪只间相互拥挤遮挡,而且,由于摄像头安装位置不同,其拍摄的猪只体积、体形也有较大的差异。例如,受限于猪场的高度,范金树实验猪场的摄像头拍摄出猪只形状既存在超大尺度的猪只,也存在超小尺度的猪只,所以映射到图像中的猪只也有多种不同尺度。为了应对复杂密集遮挡的实际生产猪场场景,得到更加丰富全面的特征信息,本文在原有 3 个不同尺度的检测层的基础上,增加一个超小尺度的检测层[30]。选择此

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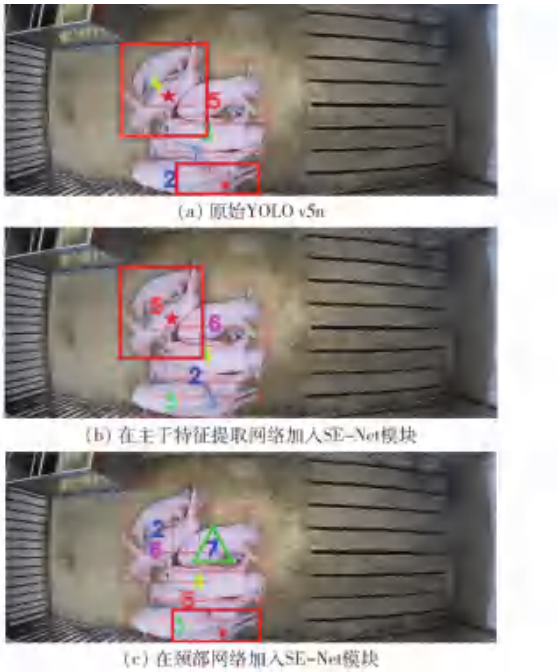


(a) 在主干特征提取网络中引入

(b) 在颈部网络中引入

图 7 引入 SE－Net 通道注意力模块

Fig. 7 Introducing SE－Net channel attention module



(a) 原始YOLO v5n

(b) 在主干特征提取网络加入SE-Net模块

(c) 在颈部网络加入SE-Net模块

图 8 增加 SE－Net 模块前后检测效果对比

Fig. 8 Comparison of results before and after adding SE－Net module

尺度的检测层对于超小的猪只来说，能够保留下有效语义信息的可能性更大；另外，对尺寸超大的猪只来说，能够提取到更高层次的语义信息，同时也包含了更多的轮廓信息和位置信息，将此类特征图融合之后会使得融合之后的特征信息更加丰富全面，从而有利于提高猪只定位的准确率[29]。

本文在原始 YOLO v5n 的主干网络中加入 SE－Net 模块的基础上，在 32 倍下采样后继续增加一次下采样得到 20×20 的特征图，同时颈部 Neck 网络相应增加一次上采样，与主干网络的第 8 层拼接（原始颈部网络只经过两次上采样，分别与主干网络的第 6 层和第 4 层拼接）。改进后的 YOLO v5n 颈部网络经过 3 次上采样后再进行下采样操作。即主干网络在 32 倍下采样后继续一次 2 倍下采样得到 20×20 的特征尺寸图。同时，在颈部网络增加一次 2 倍上采样，然后经过 8、16、32 倍下采样分别得到 160×160、80×80、40×40 尺度的检测层特征图。再进行 64 倍的下采样得到 20×20 尺度的检测层特征图。

经过改进后的 YOLO v5n 网络（图 9）存在 4 个检测层，加深了网络的深度，进一步提高模型的表达能力，使得模型能够提取到更高层次更丰富的语义信息，帮助模型在复杂猪舍场景下提取多尺

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度特征信息，将复杂的目标区分开来，提升模型的检测性能[31]。在猪只遮挡密集场景下 YOLO v5n 网络改进前后的检测效果如图 10 所示，左边为原始 YOLO v5n 检测结果，右边为增加一个检测层后的检测结果。由图 10 可以看出，改进后的模型在猪只挤靠相互遮挡的场景下，仍能更好地检测识别出被大面积遮挡的猪只，且也可检测出图 10d 中边缘的猪只，而原始 YOLO v5n 模型并没有检测到被大面积遮挡的猪只。由此可见添加一个检测层后的模型在复杂遮挡场景下的检测效果更佳。

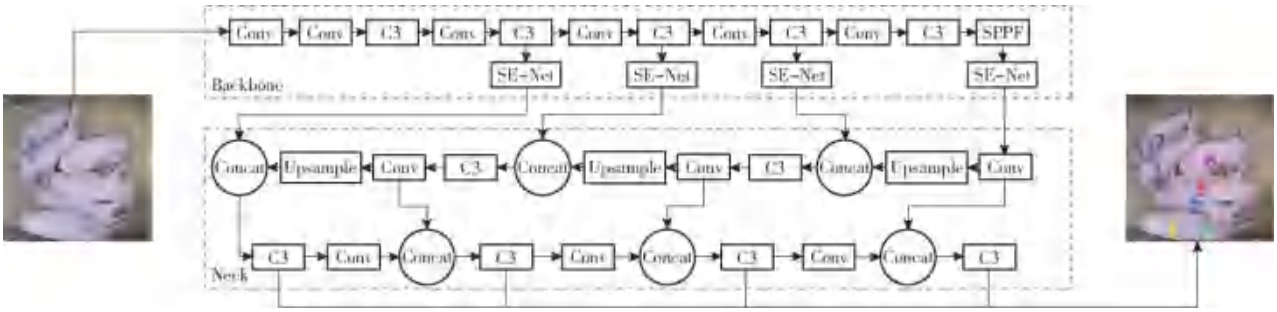


图 9　添加一个检测层后的 YOLO v5n 网络结构

Fig. 9　YOLO v5n network structure after adding a detection layer

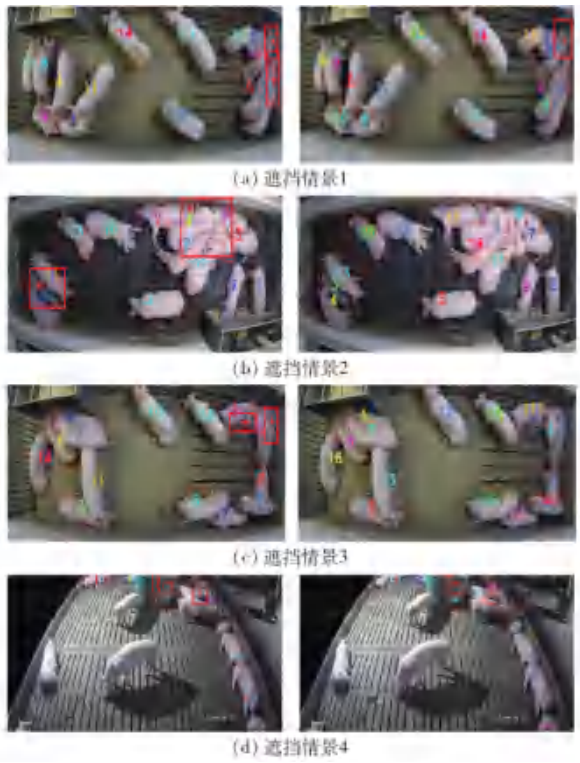


图 10　增加检测层前后效果对比

Fig. 10　Comparison of effects before and after adding a detection layer

2.4　改进边界框损失函数

根据 2.1 节，YOLO v5n 的边界框(Bounding box)采用 GIoU Loss 作为损失函数，在 IoU 的基础上，解决了边界框不重合的问题，但当边界框与真实框有包含情况时(如图 11 所示，绿色和红色分别表示目标框和预测框)，GIoU 退变为 IoU，导致难以分辨两框的相对位置关系，此时 GIoU 的优势消失[32]。因此，GIoU 不能准确反映两个边界框之间的重叠关系，也不能给出一个边界框被另一个边界框包围时的优化方向[33]。文献[34]提出的 CIoU 是在 DIoU



图 11　边界框包含检测目标的示例

Fig. 11　Schematic of a bounding box containing the detection target

的基础上，不仅考虑边界框的重叠区域和中心点的距离，还权衡了边界框的纵横比，弥补了 GIoU 损失函数的不足。因此，本文采用更优的 CIoU Loss 测量方法，包括重合面积、中心距离和宽高比 3 个测量维度，具有更快的收敛速度和更佳的性能。CIoU Loss 函数定义为

$$L_{CIoU}=1-I_{oU}+\frac{\rho^2(b,b^{(gt)})}{c^2}+\alpha\nu \tag{1}$$

其中

$$\alpha=\frac{\nu}{1-I_{oU}+\nu} \tag{2}$$

$$\nu=\frac{4}{\pi^2}\left(\arctan\frac{w^{(gt)}}{h^{(gt)}}-\arctan\frac{w}{h}\right)^2 \tag{3}$$

式中　b——边界框中心点坐标

$b^{(gt)}$——真实框中心点坐标

ρ——两个中心点间的欧氏距离

I_{oU}——交并比

c——边界框和真实框最小外接矩形的对角线距离

w、h——边界框的宽、高

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$w^{(gt)}$、$h^{(gt)}$——真实框的宽、高

α——权重系数

ν——宽高比度量函数

2.5 DIoU - NMS 代替加权 NMS

在经典的 NMS 中，对同一类别中所有边界框的得分排序，选择分数最高的边界框，然后计算出其与剩余的边界框的 IoU 值，并将大于阈值的边界框全部过滤掉[35]。但是在实际猪场中，猪群的重叠相互遮挡，当几头猪相互靠近时，IoU 值变大，若采用加权 NMS，那么其筛选结果可能只留下一个边界框，从而可能致使多头猪只漏检。采用 DIoU - NMS 算法[36]代替原始的加权 NMS，同时考虑了重叠区域和两个边界框的中心点距离，即如果出现两框间的 IoU 值较大，且中心距离也较大时，DIoU - NMS 将此类情况视为是两个目标的边界框，不会被筛选，从而有效提高检测精度，降低漏检率[32]，DIoU - NMS 的更新公式为

$$s_i=\begin{cases}s_i & (I_{oU}-R_{DIoU}(M,B_i)<\varepsilon)\\ 0 & (I_{oU}-R_{DIoU}(M,B_i)\geqslant\varepsilon)\end{cases} \tag{4}$$

其中

$$R_{DIoU}=\frac{\rho^2(b,b^{(gt)})}{c^2} \tag{5}$$

式中 s_i——分类得分　　ε——NMS 的阈值

M——最高分类得分的检测框

B_i——其余初始检测框

如图 12 所示，当两头猪只互相粘连时，对应的两个边界框重叠区域较大，但它们的中心点距离较远，若采用 DIoU - NMS，因为其不仅考虑到两框的重合部分，还综合权衡了两框中心点的欧氏距离，将两个中心点距离较远的框可以看成是不同猪只目标产生的，所以，在筛选边界框时保留这类边界框，不会将其删除，从而降低了猪只漏检率。因此，本文算法选用 DIoU - NMS 替换加权的 NMS 是切实有效的。

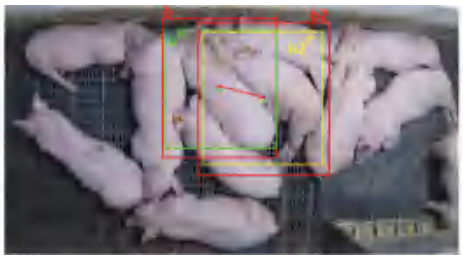


图 12 DIoU - NMS 示意图

Fig. 12 Schematic of DIoU - NMS

3 实验结果与分析

3.1 实验设置

本次实验用 Pytorch 框架搭建，操作平台为 64 位 Windows 10，GPU 模式（GPU 型号为 Nvidia RTX3070），显存 8GB。本文模型训练的超参数设置如表 4 所示。

表 4 训练参数设置

Tab. 4 Parameters setting for training procedure

参数	数值	含意
batch - size	16	每批处理的图像数量
epoch	200	训练迭代次数
img - size	1 280 × 1 280	输入图像尺寸
lr	0.001	学习率
adam	N/Y	是否使用 adam 优化器
momentum	0.843	动量
weight_decay	0.000 36	权重衰减项

3.2 评估指标

采用准确率、召回率、平均精度（AP）作为衡量目标检测算法性能的指标。

针对深度学习的计数研究常使用平均绝对误差（Mean absolute error，MAE）和均方根误差（Root mean square error，RMSE）。一般情况下，MAE 越小，预测的准确率就越高，RMSE 越小，鲁棒性也越好。本文选取上述两个指标作为猪只盘点模型的评估指标。

另外，加入漏检率作为模型性能偏差和变化的辅助指标。

3.3 消融实验

为了更直观地评估改进技术对模型性能的影响，本文进行了消融实验。如表 5 所示，以未做任何改进的原始 YOLO v5n 为基准，+ 表示模块混合改进，分别训练划分好的 6 组实验。如表 5 所示，在本文的测试集中原始 YOLO v5n 的 MAE、RMSE、AP 和漏检率分别为 0.682、1.21 和 97.71% 和 4.06%。以此为基线，每一处改进后各评估指标都有所提升。由表 5 可知，在主干特征提取网络中引入 SE - Net 模块，其 MAE、RMSE 以及漏检率均比添加在颈部网络中低，分别低 0.095、0.38 以及 1.34 个百分点，AP 也提高 0.67 个百分点。无论是原始 YOLO v5n，还是增加一个检测层后，在主干特征提取网络加入注意力机制模块比在颈部网络加入注意力机制模块，MAE、RMSE、AP 和漏检率均比未增加相应模块有所提升。而增加检测层和在主干特征提取网络中引入 SE - Net 模块，MAE、RMSE 以及漏检率也比基线分别降低 0.509、0.708 以及 3.02 个百分点，AP 达到 99.39%，较基线提高 1.62 个百分点。其次，结合表 3 可知，改进后的模型的参数量是 YOLO v5x 模型的 1/46，而且两者的 AP 很相近。综合而言，增加一个检测层与在主干特征提取网络加入注意力机

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表 5　不同模型的消融实验

Tab. 5　Ablation experiment of different modules

模型	MAE	RMSE	准确率/%	召回率/%	AP/%	漏检率/%	参数量
YOLO v5n	0. 682	1. 210	97. 71	95. 94	97. 77	4. 06	1.900×10^6
+ SE - Net(Backbone)	0. 488	1. 020	98. 98	97. 85	98. 91	2. 15	1.940×10^6
+ SE - Net(Neck)	0. 583	1. 400	98. 84	96. 51	98. 24	3. 49	1.910×10^6
+ Adding Detect Layer	0. 327	0. 742	99. 06	98. 69	99. 12	1. 31	3.087×10^6
+ Adding Detect Layer + SE - Net(Backbone)	0. 173	0. 502	99. 14	98. 96	99. 39	1. 04	3.115×10^6
+ Adding Detect Layer + SE - Net(Neck)	0. 340	0. 753	98. 92	98. 43	98. 95	1. 57	3.102×10^6

制模块的组合改进效果最佳,虽然模型参数量相对比较大,但其在复杂遮挡场景下的检测效果比其他组合更好。

3.4　不同盘点算法对比

为更好地分析验证本文算法的性能,将本文改进后 YOLO v5n 与 YOLO v4[37]、YOLO X[38]、Faster R - CNN[39]、专门修改用于猪计数的 CCNN[9]、基于多尺度感知的猪计数网络 PCN[10]、基于关键点检测和 STRF 的猪计数网络[12]和中心集群计数网络 CClusnet[40]的猪只计数网络进行比较。其中,YOLO v4、YOLO X 和 Faster R - CNN 网络均采用本文的猪只盘点数据集进行训练和测试; 而基于多尺度感知的猪计数网络 PCN、专门修改用于猪计数的 CCNN、中心集群计数网络 CClusnet 以及基于关键点检测和 STRF 的猪计数网络则引用文献中的相关实验结果。实验结果如表 6 所示。

表 6　不同猪只盘点算法性能比较

Tab. 6　Performance comparison of different pig counting algorithms

网络	MAE	RMSE	单幅图像平均识别时间/s
CCNN[9]	1. 67	2. 13	0. 042
PCN[10]	1. 74	2. 28	0. 108
Keypoint Tracking + STRF[12]	3. 32		
YOLO v4[37]	0. 193	0. 574	0. 045
YOLO X[38]	0. 242	0. 647	0. 066
Faster R - CNN[39]	0. 88	1. 65	0. 071
CClusnet[40]	0. 43		
改进后的 YOLO v5n(本文)	0. 173	0. 502	0. 056

由表 6 可知,CCNN、CClusnet、YOLO v4、YOLO X 和 Faster R - CNN 的 MAE 分别为 1. 67、0. 43、0. 193、0. 242 和 0. 88,说明这 5 种计数方法在一定程度上能够处理遮挡问题。虽然 CCNN 计数方法的单幅图像平均识别时间最低(0. 042 s) ,本文改进后的 YOLO v5n 网络模型与其只差 0. 014 s,但本文的计数网络准确性和鲁棒性均优于其他计数网络。这是因为本文的计数网络在处理不同场景时,如光照变化、遮挡和重叠,通过增加注意力机制和多尺度特征检测,减少了猪只漏检多检情况,且不需要控制特定的环境,速度和精度均能达到实际猪场的猪只计数要求。

3.5　实验结果分析

猪只遮挡是造成猪只盘点精度低的主要原因之一。当猪只严重拥挤相互遮挡时,猪只目标轮廓信息缺失。图 13 为 YOLO v5n 改进前后的检测结果,左侧为原始 YOLO v5n 检测图,右侧为改进后的 YOLO v5n 检测效果图。图 13a 可知,改进后的 YOLO v5n 对于边缘小目标的检测效果有一定的提升,图 13a 中改进后的模型能够检测出原始模型漏检的目标; 图 13b、13c 为不同场景下遮挡重叠的图像。通过观察可知,原始模型对于猪只相互遮挡密集或者边缘小目标模糊的图像漏检相对严重,而

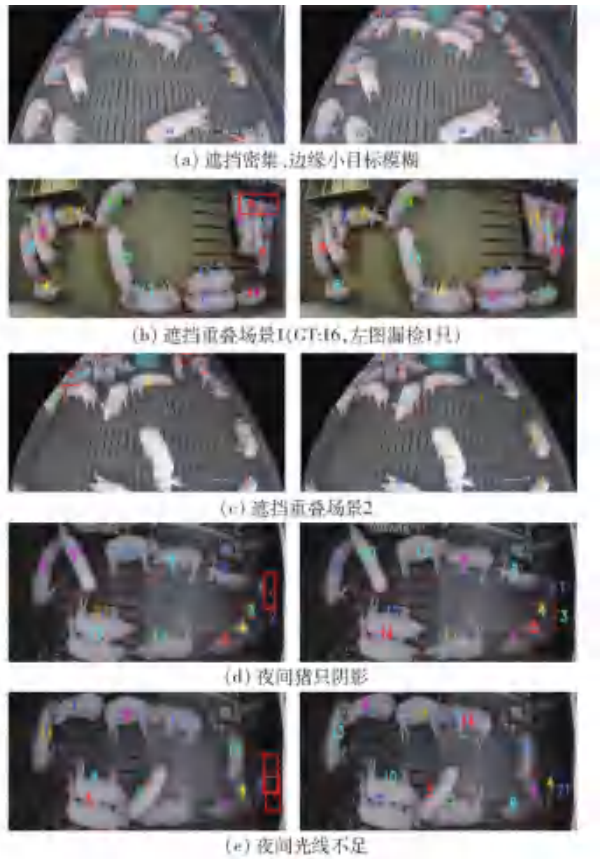


图 13　检测结果对比

Fig. 13　Comparison of test results

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改进后的模型依旧可以准确检测到上述复杂情景下的猪只目标。

另外,光照也是影响猪只盘点精度的原因之一。在实际生产应用中,猪场可能会突然遇到短暂光照骤变等噪声致使出现猪只阴影[41],或者夜间光线不足导致猪只目标轮廓特别不清晰。尽管 YOLO v5n 算法能在一定程度上尽量减少光照影响,但是猪只阴影、目标轮廓不清晰还是会造成算法的误检或者漏检。如图 13d 所示,右侧围栏处的两头猪只间形成了阴影,加之光线暗等原因导致原始 YOLO v5n 算法将中间的猪只阴影识别为一头猪只,而改进后的算法能够准确检测出阴影处的所有猪只。如图 13e 所示,图中绿框的猪只因光线不足,且被其他猪只夹在中间,猪只目标轮廓不清晰致使原始 YOLO v5n 算法漏检该猪只,但改进后的模型能够检测出原始模型因阴影漏检的猪只。

综上所述,改进的 YOLO v5n 算法对复杂场景中的猪只图像盘点鲁棒性更强,这表明改进后的网络在不同遮挡重叠目标场景下泛化能力有所提升。但目前本文算法在应对特别严重遮挡目标导致目标轮廓的特征信息不明显的情况时会存在一定程度的漏检。

4 结束语

为了改进现有的猪只盘点算法在遮挡、体型变化或者光线较暗等场景下的不足,提出并实现了一种改进的 YOLO v5n 猪只盘点算法。该算法针对复杂场景下的猪只盘点问题提出了在主干特征提取网络中加入 SE - Net 注意力模块,从而提升了模型对于复杂密集遮挡、光照不足等场景下的鲁棒性;增加了一个尺度的检测层,加深网络的深度,进一步提取多尺度特征信息将复杂的目标区分开来,提升模型的检测性能;改进边界框损失函数和 NMS,以此提高模型在复杂遮挡场景下的泛化能力。消融实验结果表明,改进的 YOLO v5n 模型在本文测试集中的检测精度较原 YOLO v5n 模型得到改善,其 MAE、RMSE 以及漏检率分别比原 YOLO v5n 降低 0.509、0.708 以及 3.02 个百分点,平均精度提高 1.62 个百分点,其 AP 为 99.39%。对比实验结果表明,与 Faster R - CNN、CCNN 和 PCN 猪只盘点算法相比,本文算法的 MAE 和 RMSE 分别为 0.173 和 0.502,MAE 比其他 3 种算法分别减少 0.707、1.497 和 1.567,RMSE 比其他 3 种算法分别降低 1.148、1.628 和 1.778。在遮挡拥挤、光照不良等复杂场景下,本文提出的 YOLO v5n 算法减少了猪只漏检的情况,能得到理想的计数结果,具备较好的准确性和鲁棒性;模型的单幅图像识别时间仅为 0.056 s,比大多数猪只盘点算法快,能够满足实际应用场景的实时性要求,为后续应用到边缘设备(如猪只盘点仪等)提供了算法支撑。

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猪只饮水行为机器视觉自动识别

杨秋妹　肖德琴　张根兴
(华南农业大学数学与信息学院，广州 510642)

摘要： 猪只饮水行为往往与猪舍环境的舒适度以及猪只的健康水平密切相关，实时地监控猪栏中猪只饮水状况对猪舍管理和提高养殖福利具有重要意义。目前，主要采用 RFID 和机器视觉两种技术自动识别饮水行为，RFID 方式需要给猪只佩戴耳标，存在对猪身有侵入和不便操作的缺点，机器视觉方法能非接触式监测和提取猪只饮水行为，具有低成本易实施的优点。本文实现了基于机器视觉的猪只饮水行为自动识别，首先通过传统的阈值分割方法得到二值化图像来实现猪只从背景中的提取，接着引入图像占领指数对猪只饮水行为进行预判，最后利用深度学习方法构造猪只头部检测器，更精准地判定饮水行为的发生。试验表明，该方法在本文构建的饮水视频数据集中识别正确率为 92.11%，且能识别饮水猪只的身份，可应用到实际的猪只生产过程中辅助管理决策。

关键词： 猪只；饮水行为；图像分割；图像占领指数；深度学习
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Automatic Pig Drinking Behavior Recognition with Machine Vision

YANG Qiumei　XIAO Deqin　ZHANG Genxing
(*College of Mathematics and Informatics, South China Agricultural University, Guangzhou* 510642, *China*)

Abstract: Pig drinking behavior is closely related to pig's physical condition and piggery environment. Recording such data continuously is beneficial to the pig industry. However, it is difficult to get the detailed drinking data of each pig manually. An automated method is expected. RFID is used to detect pig drinking behavior recently. But this approach invades pigs and the piggery needs to be equipped with auxiliary facilities. There is no such concern by using video monitoring. Therefore, using machine vision to recognize pig drinking behavior was proposed. Firstly, to distinguish pigs from the background, threshold segmentation was used to get a binary image, in which pixels belonged to pigs were assigned to 1 and others were assigned to 0. From the binary image, each pig's centroid and angle were computed and used to decide whether a pig was static or not. Drinking behavior is likely to happen when a pig stays in the drinking zone. Secondly, occupation index was computed to determine if a static pig was closed to the drinking nipple. Drinking behavior could be preliminarily judged through this way. Thirdly, a pig head detector was implemented by using deep learning algorithm to accurately confirm the occurrence of pig drinking behavior. At last, to confirm which pig was performing the drinking behavior, a pig identification detector was implemented. Through the multi-step judgment, pig drinking behavior can be recognized precisely. Experiment showed that the precision rate of the proposed algorithm in the video data set was 92.11%, which was suitable to aid managerial decision making in pig production.

Key words: pig; drinking behavior; image segmentation; image occupation index; deep learning

0　引言

正常情况下，猪的饮水行为呈稳定持续的模式，当疾病出现、喂食质量或环境发生变化时则会导致其饮水行为改变。人工对猪的饮水行为进行监控需要投入大量的人力并且难以实现长期持续的观察。因此，需要自动化实时地监控猪只的饮水行为，提取其饮水行为节律，这对猪只的健康异常预警，改善其

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作者简介： 杨秋妹(1983—)，女，讲师，博士生，主要从事农业图像视频处理研究，E-mail：yqmbegonia@163.com
通信作者： 肖德琴(1970—)，女，教授，博士生导师，主要从事物联网和农业图像视频处理研究，E-mail：deqinx@scau.edu.cn

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生长福利有很重要的作用[1-3]。

目前,自动监控猪饮水行为已有相关的研究成果,主要采用两种方式: 无线射频技术 RFID 和机器视觉技术。采用 RFID 技术识别猪只饮水主要是通过给猪只佩戴电子耳标,另外在饮水器旁边安装 RFID 接收器,当猪只靠近饮水器时接收器则读取相应的信息,从而记录饮水行为的发生,有学者对高频 RFID 的有效使用范围作了相应的研究,开展了基于 RFID 的猪只个体饮水行为和猪场产量与健康问题的相关分析[4-7]; 陆明洲等[8]则用此方法来检测母猪个体的饮水频率。但是,基于 RFID 的监控方式需要给猪只打入耳标,为入侵式的实验方式,并且耳标容易丢失,给管理带来不便。机器视觉作为一种无入侵的方式可以实时地监控动物的日常行为,由于其价格低廉、容易安装,已经在猪场生产管理中得到广泛的应用,很多猪场都已经获得了大量的监控录像数据,但是利用动物视频监控数据进行信息提取,获得对生产管理有用信息的研究还不多,在猪只上的应用主要有关于移动、爬跨、攻击及饮食等行为的探讨[9-11]。在饮水识别上,KASHIHA 等[12-13]提出二值化图像后,借助猪只轮廓关键点与质心的距离来识别猪只头部,从而确定饮水行为的发生,得到饮水次数与持续时间,建立猪只饮水量与其饮水时间的关联模型,但该方法对猪只头部的识别过度依赖于图像分割结果,如分割出来的图像不能较好地还原猪只轮廓则无法准确识别猪只头部。精准检测猪只头部与饮水器发生接触是采用机器视觉自动识别猪只饮水行为的关键,本文拟在已有的饮水识别方法基础上,加入图像占领指数、深度学习等机器视觉算法,提出一种新的基于机器视觉的猪只饮水行为识别方法(Pig drink recognition,PDR) 。

1　材料与方法

1.1　试验数据来源

试验数据来源于广州力智农业有限公司位于广州市萝岗区的现代化生猪生产基地。选取种猪栏作为监控场景,监控猪栏面积为 4 m × 5 m,摄像机布置于猪栏正中高约 5 m 的横柱上,以俯视的角度进行拍摄,为了将整个猪栏完全覆盖在摄像机成像范围内,采用镜头焦距为 2.8 mm 的海康 DS-2CD3345-I 型红外网络摄像机,视频利用海康 DS-7804N-K1/C 型网络硬盘录像机存储。

试验期间监控猪栏共饲养 4 头种猪,试验周期为 2016 年 7 月 8 日至 2016 年 8 月 8 日共 32 d,每天 24 h 对猪栏进行监控,但是由于晚间时段猪只多处于睡眠状态,因此每日只选取白天猪只比较活跃时段的视频作为研究素材,具体为每日的 08:00 至 18:00。为了便于区分猪栏里的各头猪,在猪只背部采用油性笔标上 A、B、C、D 作为猪只编号,试验猪栏有一高一低 2 个直式饮水器供栏中的所有猪只饮水。猪只在栏中活动画面如图 1 所示,饮水器安装在图 1 中的黄色框内。



图 1　猪栏监控画面

Fig. 1　Scene of piggery monitoring

1.2　猪只饮水行为识别体系结构

本文旨在通过猪栏的监控视频,自动提取出猪栏中各头猪只的饮水情况,具体的体系结构如图 2 所示。

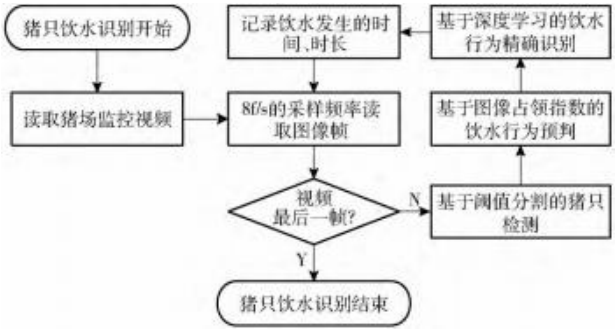


图 2　猪只饮水行为体系识别结构

Fig. 2　Framework for pig drinking behavior recognition

从图 2 可以看到,猪只饮水行为自动化识别主要有 3 部分。第 1 部分为基于阈值分割的猪只检测,本文通过大津法对图像进行二值化,将猪只作为前景与背景区分开来,得到每头猪只的轮廓,并用其轮廓的外接矩形将其提取出来。第 2 部分为基于图像占领指数的饮水行为预判,本文将通过识别猪栏的饮水区域是否有监控对象进入,如果有,并且监控对象在此区域停留一定的时间长度,则认为有可能发生饮水行为,没有则无饮水行为发生。第 3 部分为基于深度学习的饮水行为精准识别,为了进一步确认饮水行为是否发生,本文将提取猪只头部、身体的图像进行训练,构建猪只头部身体区分的分类器模型,截取饮水区域的图像判别是否有猪只头部进入,如果是则可确认饮水行为发生。

1.3　猪只饮水行为识别算法设计原理

1.3.1　基于阈值分割的猪只检测算法

在监控视频中,猪只作为研究对象,在每帧图像

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中,要将前景与背景区分开来,现有的研究主要是采用图像分割方法来完成[14-16]。在猪场监控场景下,摄像头的位置固定,拍摄成像的猪场区域固定,猪只在限定的猪栏范围内活动,不会出现越出猪栏的情景,因此,猪栏以外的图像区域不属于有效的猪只活动区域,可以在图像处理前,设定一个有效监控区域将其排除在外,得到矩形框内的有效监控区域。如图 3 所示,红色矩形框为有效猪只活动范围。猪只饮水自动化识别的整个流程都在该有效监控区域内进行。



图 3 设定的猪只有效活动区域

Fig. 3 Setting up valid region for pigs

从图 3 可以看到,猪栏地板为偏黑色的水泥地,围栏颜色也偏黑,而猪身体为白色,与背景有明显的颜色差异,所以本文采用基于颜色的图像分割方法来检测猪只。将原始的 RGB 图像转换为灰度图像后,利用大津法确定图像分割阈值[17-18],将图像中的像素点分成前景和背景。具体做法是假设任意值 T 为前景与背景的分割阈值,小于阈值 T 的像素点为背景,大于等于该阈值的则为前景,背景、前景像素点个数占图像总像素点个数的比例分别为 w_0、w_1,背景、前景所有像素点的灰度平均值分别为 u_0、u_1,则有

$$u = w_0u_0 + w_1u_1 \tag{1}$$

$$g = w_0(u_0 - u)^2 + w_1(u_1 - u)^2 \tag{2}$$

式中 u——整帧图像的平均灰度

g——背景和前景图像的类间方差

计算 T 取不同值时 g 的值,直到 g 取得最大值,此时 T 为最终分割阈值。

灰度图像经过阈值分割得到二值图像后,该二值图像因为光线等原因存在一些噪声,采用 Canny 边缘检测获取猪只轮廓,对其利用形态学腐蚀、膨胀等方法进行噪声去除,并根据实际的猪只大小情况将一些较小的不可能为猪的连通区域去除,最终得到只含猪只轮廓的二值图像。经过处理得到猪只轮廓二值图像后,对于图中每头猪的轮廓用其最小外接矩形将其框出,得到每头猪的感兴趣区域,第 i 头猪的感兴趣区域记为 $PROI(i)$。每头猪保存其质心、角度等信息作为饮水行为的判断依据,第 i 头猪的质心记为 $P(i)$,第 i 头猪的角度记为 $\theta(i)$。针对猪只监控视频数据,本文以 8 f/s 的采样方式抽取视频帧,定义猪只检测算法 A,每一帧图像 I 采用该算法进行猪只检测,(x,y) 为图像中像素点坐标,A 算法过程如下:

while (x,y) in I

if (x,y) 没有超出有效监控区域保留像素点(x,y);

else 舍弃像素点(x,y);

rgb2gray(I) 转为灰度图像;

im2bw(I, graythresh(I)) 转为灰度图像;

imerode(I,se) 腐蚀膨胀解决粘连;

imdilate(I,se) 膨胀填充孔洞;

bwareaopen(I,P,conn) 删除小面积连通区域;

for each 连通区域生成其外接矩形和椭圆拟合;

output: 每块连通区域为一头猪,第 i 头猪输出其感兴趣区域 $PROI(i)$,质心 $P(i)$,角度 $\theta(i)$。

1.3.2 基于图像占领指数的饮水行为预判

在实际的猪栏中,猪只通过饮水器饮水,每次饮水必须进入饮水器的邻近区域,并且通过观察发现猪只饮水时处于接近静止状态,本文通过监控猪只饮水区域,当猪只处于静止状态并且此饮水区域有足够多的面积被猪只身体占领时则有可能发生饮水行为。

猪只是否静止可以通过猪的质心及角度的变化来判断,当相邻两帧中同一头猪的质心变化不超过给定范围,并且其角度变化不超出给定值,则认为其处于静止状态,超出此范围则认为是处于运动状态。

记第 i 头猪在第 t 帧的质心为 $P(i,t)$,静止时猪的质心变化满足

$$P(i,t+1) - P(i,t) < \alpha \tag{3}$$

式中 α——质心变化阈值

记第 i 头猪在第 t 帧的角度为 $\theta(i,t)$,静止时猪的角度变化满足

$$\theta(i,t+1) - \theta(i,t) < \beta \tag{4}$$

式中 β——角度变化阈值

当猪处于静止状态时,则判断其是否处于饮水区域。图像占领指数可用于识别在某个区域范围有无出现特定的监控对象[19],本文引入饮水区域的图像占领指数这一概念来判断猪只是否发生了饮水行为。

在任意时刻,饮水区域的占领指数通过二值图像来描述,一帧图像中饮水区域记为 W,(x,y) 表示 W 中的像素点坐标,像素点取值记为 $B_I(x,y)$,$B_I(x,y)=0$ 表示此像素点未被猪只覆盖,$B_I(x,y)=1$ 表示此像素点已被猪只覆盖。其中,w 表示区域 W

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的像素点总数,饮水区域 W 被猪只占领的指数定义为

$$W_{\text{OccupiedIndex}} = \sum_{(x,y)\in W} B_I(x,y) \Big/ w \qquad (5)$$

经过猪只检测算法 A 处理后得到的二值图像如图 4 所示。猪只作为前景对象每个像素点的值记为 1,背景对象每个像素点值记为零,图 4a 中黄色矩形无猪只进入,该区域中所有像素点取值均为零,此时饮水区域的占领指数为零; 图 4b 中有猪只进入黄色矩形区域,此时该区域占领指数值为猪只进入饮水区域的像素点数与饮水区域总像素点数的比值。

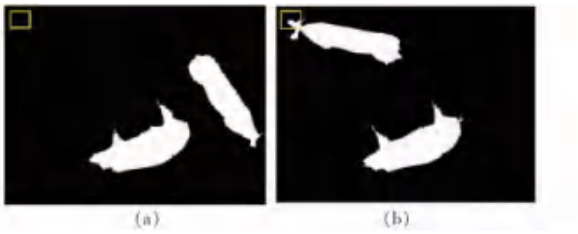


图 4　猪只占领区域示意图

Fig. 4　Schematics of pig occupation area

定义猪只饮水预判定算法 B,对于上一步得到的二值化图像做出是否可能发生猪只饮水行为的判别,B 算法步骤如下:

(1) 计算相邻两帧图像中每头猪的质心和角度变化。

(2) 如果变化小于给定阈值,则对于猪斑点区域的每个点判断其是否位于饮水区域,累计饮水区域内的像素点数。

(3) 判断饮水区域内的像素点数是否大于给定阈值,若大于给定阈值则可初步判定饮水行为发生。

1.3.3　基于深度学习的饮水行为精准识别

仅是通过饮水区域是否有猪只存在来判断饮水行为是否发生并不够准确,实际的猪场中,经常会设置一高一低 2 个饮水器,高位饮水器需要猪只抬起头才够得着,低位饮水器则需要低头饮水。低位饮水器往往会出现由于猪只身体占领了饮水区域,但实际并没有饮水行为发生的情况,如图 5 所示,猪只尾部占领了图像中低饮水器的位置,但是实际没有发生饮水行为。

为了避免将此种情况误判为饮水行为的发生,本文加入了猪只头部、背部、尾部的识别判断。当出现饮水区域被占领的情况后,则在饮水器周围截取部分图像,截取出来的图像有可能是头部,也有可能是尾部或地板,或者不属于上面的几种情况(如猪身中部等)。因此,本文采用物体分类的方法来区分这几个类别。在物体分类上,深度学习模型



图 5　猪只进入饮水区域但无饮水图

Fig. 5　Picture of pig in drinking zone but no drinking

GoogLenet 在 2014 年刷新了图像分类的性能记录[20],本文引入该方法构建猪只头部识别模型 C。

GoogLenet 增加了网络的宽度和深度,共 22 层,利用如图 6 所示的 Inception 结构,实现有效降维。

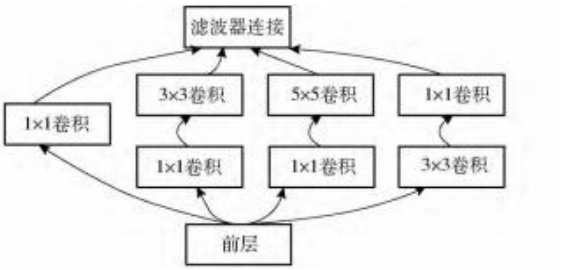


图 6　Inception 模型

Fig. 6　Inception model

为了解决训练样本不足的问题,本文采用迁移学习的思想,利用预训练好的模型,结合有标签数据进行 fine-tuning,得到猪只头部识别模型。猪只头部识别模型 C 的训练步骤如下:

(1) 构造带标签类别(头部、尾部、地板)的训练样本数据集与测试集。

(2) 计算数据集的图像均值。

(3) 选定预训练好的模型,修改分类层的参数。

(4) 调整训练过程的配置参数。

(5) 启动训练,对预训练模型进行参数微调。

训练结束后得到的猪只头部识别模型 C 具有识别输入图像是否为猪只头部、猪只尾部以及地板的功能。采用 1.3.2 节的方法初步检测到猪只饮水行为的发生后,在饮水器周围截取部分图像,用上述训练得到的模型 C 判断该图像是否为猪只头部,如果是则可记录为饮水行为的发生,并且计算其饮水时长。

当猪只的饮水行为得到确认后,从精准养殖的角度出发,需更进一步确认发生饮水行为的猪只身份,本文再次利用深度学习模型 GoogLenet,构建猪只个体身份分类器,当猪只饮水行为发生后,能准确识别出饮水个体。采集每头猪的个体图像作为训练样本,由于猪背已经人为标记蓝色的 A、B、C、D 作为区分,以此人工添加标签,再次利用预训练好的 GoogLenet 进行 fine-tuning 得到猪只个体身份分类

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器,训练过程与猪只头部识别模型 C 相同。

2 试验与结果分析

2.1 猪只检测算法试验

利用本文提出的猪只检测算法 A 对猪只图像进行处理,得到图 7 所示的识别结果。

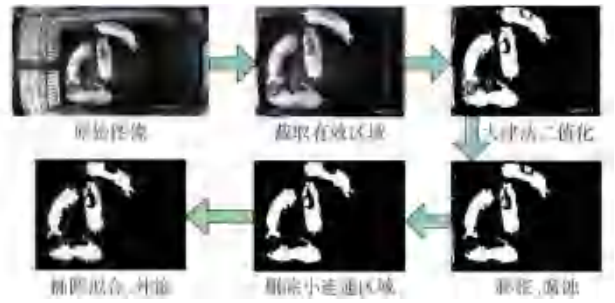


图 7 检测算法 A 识别结果

Fig. 7 Recognition result of A

对于每一帧图像,从原始图像截取边界后得到有效监控区域,在此基础上对图像采用大津法阈值分割后得到二值图像,接着采用形态学去噪进行膨胀腐蚀,之后删除小面积连通区域,最终每块有效的连通区域则分别代表一头猪,每头猪用其外接矩形框圈出。

为了验证猪只检测算法 A 的有效性,在猪场监控视频中采样 100 帧监控图像,每帧图像有 4 头猪,共 400 头猪,考虑到该算法运行结果可能会受光照、猪只粘连等情况影响,在采样时特别考虑了不同时间段光照不一样的图像,也对猪只出现粘连的情况进行了采样。采用 A 算法进行猪只检测,在这 100 帧图像中共检测出 370 头猪,其中完全正确检测的猪只有 356 头,将粘连在一起的 2 头猪检测为 1 头的有 11 次共涉及 22 头猪,错误将光斑检测为猪只的有 3 次,有 22 头猪漏检。

定义猪只检测正确率为:算法正确识别出的猪只数目与所有被算法认为是猪只的连通区域数目之比。猪只检测召回率为:算法正确识别出的猪只数目与图像中实际存在的猪只数目之比,由此计算得到猪只检测正确率为 96.22%,召回率为 89%。召回率偏低的原因是将粘连猪只作为一头猪只识别,此种情况不属于正确识别出猪只,但并不影响本文的饮水行为识别。

2.2 猪只头部识别算法试验

在本次猪只头部识别试验中,采用 caffe 深度学习平台,GPU 模式(Nvidia GTX 1060),在预训练好的 BVLC GoogLeNet 模型上进行 fine-tuning。

用于猪只头部识别模型 C 训练的图像总数为 1 204 幅,用于测试的图像总数为 1 396 幅,其中地板的训练图像为 200 幅,测试图像为 401 幅,地板样例图像如图 8 所示。



图 8 地板样例图像

Fig. 8 Sample pictures of floor

猪只头部的训练图像为 475 幅,测试图像为 422 幅,样例图像如图 9 所示。

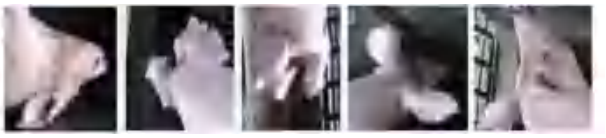


图 9 猪只头部样例图像

Fig. 9 Sample pictures of pig head

猪只尾部的训练图像为 529 幅,测试图像为 573 幅,样例图像如图 10 所示。

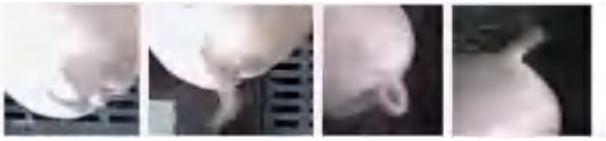


图 10 猪只尾部样例图像

Fig. 10 Sample pictures of pig tail

训练前,利用 caffe 中的 convert_imageset 将图像转换为特定的数据库,使用 compute_image_mean 生成图像数据的均值文件,数据库文件和均值文件是 caffe 进行训练的必要文件,本次训练有 3 个类别,分别为地板、头部、尾部。在 train_val.prototxt、solver.prototxt 以及 deploy.prototxt 中设置相关的训练参数,具体设置如表 1 所示。

表 1 训练参数设置

Tab. 1 Parameter setting for training procedure

参数	数值	用途
batch_size	24	每批处理的图像数量
max_iter	10 000	训练迭代次数
test_iter	59	测试的迭代次数
test_interval	100	测试前的训练次数
base_lr	0.01	基础学习率

训练的迭代次数为 10 000 次,此时训练结果已收敛,正确率为 97.64%。在错误识别的图像中,有一部分是由于图像光线不足而导致识别出错,有一部分是由于外界干扰(如浇水冲洗猪舍)及猪只运动导致的图像模糊。由此可见,本次试验的结果可用于实际的猪只头部判别。

2.3 猪只个体分类器试验

猪只个体分类器训练参数 test_iter 设为 12,训

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练有 4 个类别,分别为 A、B、C、D,其他的参数与猪只头部识别试验相同。从监控视频中,采样 A、B、C、D 4 头猪的图像用于训练学习,为了减少由于截取范围过大而造成的识别误差,利用本文提出的猪只检测算法 A 定位得到每头猪只的外接矩形,在原图中将该区域图像截取出来作为训练样本,用于训练的图像共 949 幅,其中猪 A 227 幅,猪 B 217 幅,猪 C 270 幅,猪 D 235 幅; 另外每头猪分别利用 100 幅图像进行测试,构建了一个大小为 400 幅图像的测试样本集。A、B、C、D 4 头猪的样例图像如图 11 所示。

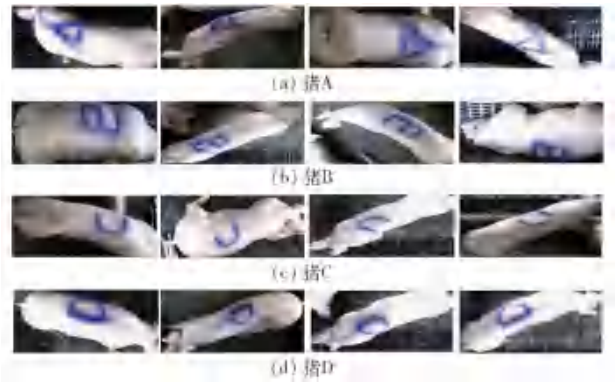


图 11　猪只个体训练样本示例图

Fig. 11　Sample pictures of individual pig

训练迭代次数为 10 000 次,此时训练结果已收敛,正确率为 95%。在测试中发现,得到的分类器对处于侧卧状态看不到背部标记的猪只无法正确识别其身份,但由于猪只饮水时多为站立且背部朝上字母没遮挡,所以该分类器可以用于饮水猪只的身份识别。

由于猪背上所打标记会随着时间褪色,也会因为猪只长大会出现变形,在试验期间,当所打标签显示模糊时,则在原来的痕迹上重新上色。用原模型对 32 d 后采集的数据进行测试,共测试 146 幅图像,正确识别 135 幅,错误 11 幅,识别正确率为 92.47%,仍保持较高的识别正确率。

2.4　猪只个体饮水行为识别试验

为了验证本文提出的基于机器视觉的猪只饮水行为识别算法的可行性,本文构建了一个猪只饮水视频数据集。在 32 d 试验周期内,抽取 30 个长度不等的视频序列,选取的视频序列中包含仅高位饮水器有猪只饮水、仅低位饮水器有猪只饮水、高低位饮水器均有猪只饮水、无猪只饮水 4 种情况。

由于猪只饮水为时间持续行为,有一定的时长规律,本文加入了额外的判断条件,对于在饮水区域逗留时间小于 2 s 或者大于 3 min 的都认为不属于饮水行为,小于 2 s 的有可能是猪只从饮水器经过,大于 3 min 的很有可能是猪躺卧在饮水器旁边休息,低的饮水器往往会出现此种情形。

在抽取的 30 个视频中,人工观看视频并记录饮水行为的发生次数及时长,与本文算法检测结果做对照。试验结果如表 2 所示。

表 2　猪只饮水次数试验结果

Tab. 2　Result of experiment for pig's drinking frequency

视频编号	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
本文算法	1	1	2	1	2	1	2	1	1	2	0	1	0	2	1
人工记录	1	1	2	1	2	1	2	0	1	2	1	1	1	2	1
视频编号	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
本文算法	1	1	2	2	1	3	0	2	1	2	2	0	1	1	1
人工记录	2	2	2	2	1	2	1	2	1	2	1	0	1	2	1

据统计,人工观察视频记录得到的实际饮水次数为 41 次,而采用本文算法共检测出 38 次饮水,通过人工验证,正确识别饮水的次数为 35 次,将非饮水行为识别为饮水行为的次数为 3 次,实际发生了饮水却没检测到的次数为 6 次。出现误判的情况主要是由于猪只有时会在饮水区域玩耍,头部靠近了饮水器,但是却没有实际饮水; 漏判的出现则主要因为光线问题导致猪只轮廓获取不完整,没有识别出猪只到达饮水区域。

定义猪只饮水识别正确率为本文算法正确识别出的猪只饮水次数与所有被算法认为是饮水的视频片段数目之比,饮水识别召回率为算法正确识别出的猪只饮水次数与视频中实际出现的猪只饮水次数之比,由此计算得到猪只饮水识别正确率为 92.11%,召回率为 85.37%。从试验结果可以看到,本文提出的算法能识别大部分的猪只饮水行为。

在正确识别的 35 次饮水中,利用本文提出的猪只身份分类器统计可得各头猪只的饮水情况,其中猪 A 实际饮水 9 次,正确识别 6 次,猪 B 实际饮水 9 次,正确识别 9 次,猪 C 实际饮水 13 次,正确识别 11 次,猪 D 实际饮水 4 次,正确识别 3 次,正确识别饮水的猪只共 29 次,能较好地在饮水行为中确定猪只身份。

3　结束语

提出了基于图像处理技术的猪只饮水行为识别算法,该算法可以应用在背景相对固定的圈养猪栏

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中。本文算法采用图像分割的方式实现了猪只检测,该方法对背景相对固定的养猪场有很高的正确率,能有效帮助在自动化猪只视频监控过程中对猪只进行检测,本文提出的算法 A 正确率达 96.22%。通过计算图像占领指数来确定猪只是否位于饮水区域,该方法可以用于识别猪只的其他与区域相关的行为,如饮水、排泄等。结合深度学习模型 GoogLenet 来确认是否为猪只头部接触饮水器,该方法可以精准识别猪身体的各个部位,为其他与猪身体部位相关的行为判断提供辅助。在本文构建的视频数据集上测试得到文中提出的猪只饮水行为识别算法 PDR 的正确率为 92.11%,并能识别出饮水的猪只个体身份,因此 PDR 方法能准确识别猪只饮水行为,且整个算法实现过程只依赖于猪场监控视频,对猪舍改造投入少,对猪身无损伤,不影响猪只的正常生活秩序,更容易被养殖场所接受,可方便在我国传统养猪场中进行部署实施,从大量的监控视频数据中获取有用信息辅助养猪管理决策。

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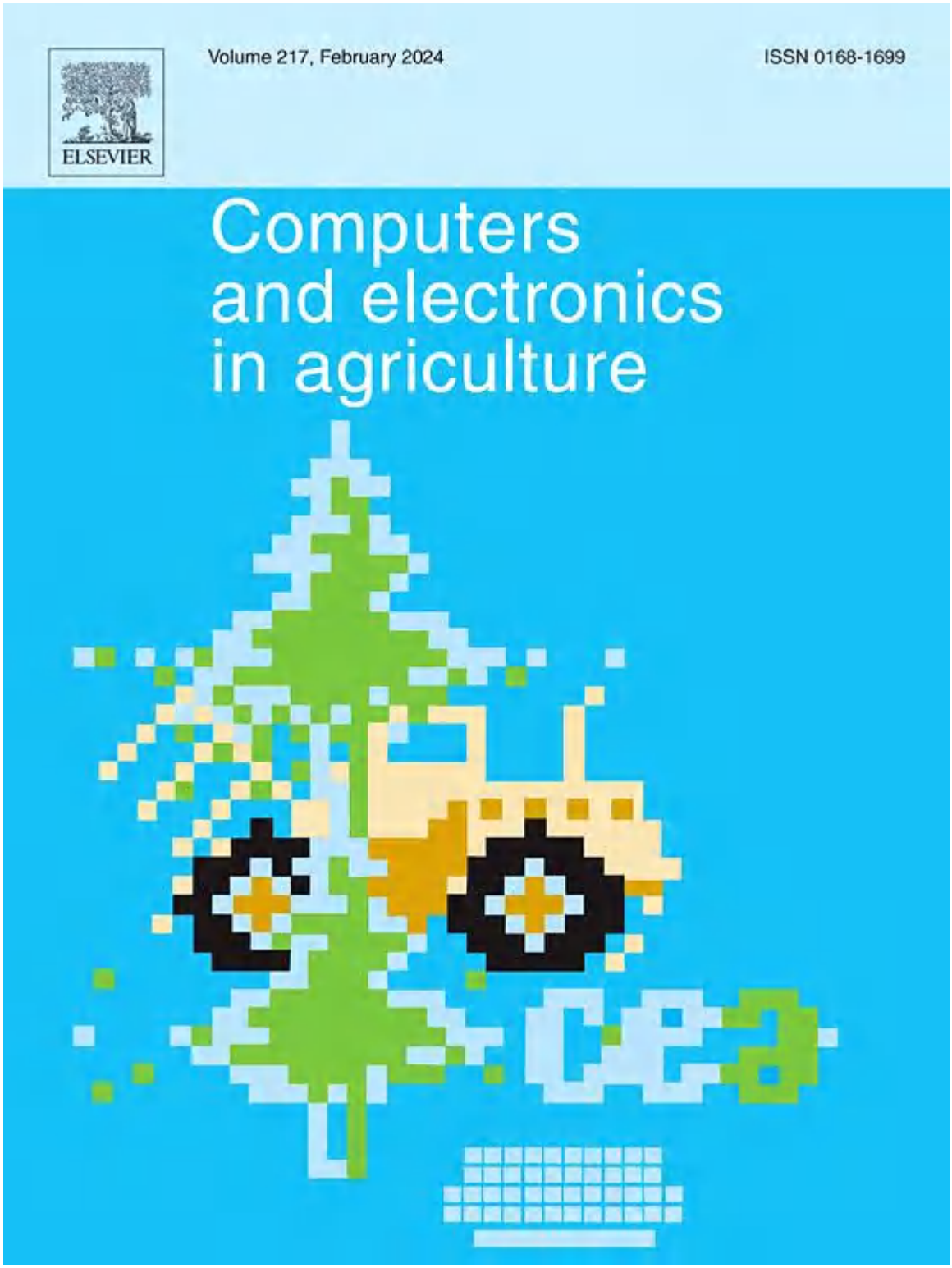
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Original papers

Quantifying behavioural patterns for group-housed pigs based on deep learning and statistical analysis

Jiyan Wu [a,b], Qiumei Yang [a,b,*], Deqin Xiao [a,b], Manting Wu [a,b], Zezhong Chen [a,b], Qiwei Hong [a,b]

[a] College of Mathematics and Informatics, South China Agricultural University, Guangdong, China
[b] Key Laboratory of Smart Agricultural Technology in Tropical South China Ministry of Agriculture and Rural Affairs, Guangdong, China

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ABSTRACT

The behavior patterns of group-housed pigs provide valuable information about animal health and overall welfare. Accurate and efficient identification and monitoring the behaviour patterns of group-housed pigs play a crucial role in pig farm management. This study proposes a method based on deep learning and statistical analysis to quantify the behaviour patterns of group-housed pigs, offering technical support for behaviour management and monitoring. Firstly, an improved SlowFast model called ViTAM-SlowFast is introduced to recognize eating, exploring, lying, moving, and standing behaviours of group-housed pigs. The ViTAM-SlowFast model integrates a Video Transformer Encoder and a Temporal Adaptive Module to improve the extraction of spatiotemporal features, enabling superior performance in pig behaviour recognition tasks. Experimental results demonstrate that the ViTAM-SlowFast model exhibits strong recognition capabilities for pig behaviours, achieving a mAP value of 92.68 % for the five behaviours, representing a 2.68 % improvement over the SlowFast. The AP values for eating, exploring, lying, moving, and standing behaviours are 96.34 %, 92.42 %, 99.56 %, 88.52 %, and 86.57 %, respectively. Furthermore, based on the behaviour recognition results obtained from the ViTAM-SlowFast, a statistical analysis method is developed to analyse and quantify the group-housed pig behaviour patterns. The results showed that, overall, the daily duration of various behaviours in healthy group-housed pigs remains consistent. The daily behaviour performance of pigs is influenced by the eating process. The patterns of various behaviours of pigs may vary slightly across different eating stages but exhibit stable and similar regularities within the same eating stage, which can provide important evidence for the early detection of health abnormalities in pigs. The quantification method for group-housed pig behaviour patterns proposed in this study helps farmers intuitively monitor and manage the daily behaviour of pigs, providing valuable references for assessing pig health through behaviour patterns.

1. Introduction

In the field of livestock farming, the behaviour patterns of group-housed pigs serve as a crucial indicator for assessing their health, production, and overall welfare. It is not only necessary to continuously monitor the behaviour of group-housed pigs but also to analyse and extract the behavioural patterns from the collected behavioural data. This approach aids farmers in evaluating the health status of group-housed pigs to promptly detecting abnormal behaviour and significantly improving the management efficiency of pig farming (Riaboff et al., 2022). In large-scale pig pens, monitoring and analysing the activity patterns of group-housed pigs through manual observation are labor-intensive, costly, inefficient, and prone to errors. Therefore, it is highly necessary to provide a technology capable of automatically monitoring pig behaviour and quantifying their behavioural patterns.

With the maturation of sensor technology and artificial intelligence, extensive research has been conducted in the field of automatic detection of livestock behaviour. These researches have focused on contact-

Abbreviations: ViT, Video Transformer; AP, Average Precision; EM, Expectation-Maximization; KS, Kolmogorov-Smirnov; JS, Jensen-Shannon; KL, Kullback-Leibler; TAM, Temporal Attention Module; mAP, mean Average Precision; YOLO, You only look once; MHSA, Multi-head Self-attention Mechanism; LN, Layer Normalization; RoI, Regions of Interest.

* Corresponding author at: College of Mathematics and Informatics, South China Agricultural University, China.
E-mail address: yqmbegonia@scau.edu.cn (Q. Yang).

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based and non-contact-based technologies (Huang et al., 2024; Wu et al., 2021). Contact-based technologies involve attaching sensors to the animals, these sensors collect data related to behavior, which is then used to develop models for behaviour classification. Alghamdi et al.(2022) collected data on pig behaviour using sensors that captured acceleration, angular velocity and posture angles. And then the behaviour recognition and classification were accomplished by applying machine learning techniques, achieving F1 scores exceeding 90 % for each behaviour. Achour et al.(2019) obtained behavior-related data by installing inertial measurement units on cows, then analysed and processed this data using decision trees to classify lying, standing, lying down, standing up, walking and stationary behaviours of dairy cows, achieving an accuracy rate exceeding 95 %. Although these methods exhibit acceptable recognition performance, contact-based sensor approaches can easily induce stress responses in animals and the detection results are significantly influenced by the sensitivity of the sensors (Sadeghi et al., 2023).

To overcome the limitations of contact-based technologies for behaviour recognition, computer vision has emerged as a prominent trend in livestock behaviour recognition with its non-contact, high-efficient, and low-cost nature. Alameer et al.(2020) utilized grayscale images and an improved GoogLeNet network to recognize eating behaviour in pigs, achieving a recognition accuracy of up to 99.4 %. Tu et al.(2022) employed YOLOv5 to classify standing, lying, and eating behaviours of pigs. Although these image-based approaches perform adequately in detecting certain behaviours, they do not fully leverage the spatial–temporal features of videos. Relying solely on image information fails to establish temporal connections between consecutive video frames, making it difficult to recognize behaviours with temporal features, such as walking. To address this issue, Ma et al.(2022) extended the ResNet 3D network by incorporating a temporal dimension, enabling effective classification of cow behaviours such as lying down, standing, and walking. Wu et al.(2021) used a CNN network to extract features from video frames and then fed these features into a Bi-LSTM to capture the semantic information of the temporal sequence data, thereby enabling the classification of basic behaviours in cattle. Peng et al.(2020) proposed an accurate cow behaviour recognition method based on Long Short-Term Memory Recurrent Neural Network (LSTM-RNN). Gao et al.(2023) proposed a method for recognizing aggressive behaviours in group-housed pigs using a hybrid CNN-GRU model to extract spatiotemporal features. While the aforementioned behaviour recognition methods can leverage spatial–temporal features in videos to identify behaviours with temporal characteristics and enhance behaviour recognition performance, they typically classify behaviours in videos containing only a single behaviour and featuring individual livestock or isolated scenes, limiting their applicability in detecting behaviours in group-housed pig environments.

The advancement of behaviour recognition technologies has provided robust support for capturing behaviours of pig. Further, the quantification and surveillance of behaviour patterns in group-housed pigs using the result of behaviour recognition can significantly assist farmers in assessing the health status of the group-housed pigs. Tran & Thanh(2023) employed YOLOv7 to identify pig behaviours and subsequently established behaviour patterns under healthy conditions. By comparing the current behaviour patterns with these healthy benchmarks, they were able to detect potential health anomalies in pigs. Similarly, Yang et al.(2024) used the frame difference method to quantify pig activity and the K-means clustering algorithm to explore daily behavioural patterns, thus enabling early health anomaly warnings. Although these methods have proven effective in health monitoring, they lack a clear methodology for behaviour patterns quantification and management, making it challenging for farmers to gain a clear and in-depth understanding of the specific behaviours exhibited by the group-housed pigs. In contrast, Mluba et al.(2024) proposed a pattern mining-based pig behaviour analysis system aimed at automating the monitoring and assessment of pig health and welfare using video data. This system not only detects individual pig behaviours but also employs a behaviour analysis module to conduct an in-depth examination of behaviours such as movement and aggression. This approach demonstrates notable strengths in behaviour pattern extraction and visualization. However, the study has yet to comprehensively address other critical pig behaviours, leaving room for further investigation into multidimensional behaviour recognition and the comprehensive quantification of behaviour patterns in group-housed pigs.

In response to the aforementioned challenges, the overall objective of this study is to enhance the recognition accuracy of multiple behaviours in group-housed pigs by developing an improved spatiotemporal feature extraction method for video data. Simultaneously, an exploratory quantification of pig behaviour patterns is conducted using statistical analysis approaches. This approach is intended to facilitate the informatized management of behavioural data in group-housed pigs in a more intuitive and effective manner, thereby providing valuable references for farmers to assess the health status of pigs based on the monitoring of their behaviour patterns. To achieve accurate behaviour recognition, the study proposes a behaviour recognition strategy that integrates temporal and spatial information. The proposed approach not only overcomes the shortcomings of image-based recognition methods in identifying temporal behaviours but also enables the recognition of multiple behaviours in group-housed pigs within a single scene. The proposed behaviour recognition method aims to locate pigs in group housing environments and identify five specific behaviours: eating, exploring, lying, moving, and standing. Additionally, this study proposes a data-driven approach to quantify the recognized pig behaviour data and perform exploratory analysis of their patterns. This is designed to help farmers efficiently monitor and manage the behavioral patterns of group-housed pigs.

2. Materials and methods

2.1. Data acquisition

The videos used in this study were collected from May to August 2022 at a pig farm in Yunfu City, Guangdong Province, China. The videos captured various activities of the pigs. The subjects of this experiment were six pigs, housed in a pigpen with a tiled floor. The average weight of the pigs is about 40 kg. The pigpen measured 3.0 m in length and 2.6 m in width. The pen is equipped with a single feeding trough. The feeding protocol involved manual feeding by farm staff once daily between 8:30 AM and 10:30 AM, during which an adequate amount of food was provided based on the pigs' nutritional requirements. During our experiments, a Hikvision TB-1217A-3/PA camera was used to record the video continuously throughout the day. The camera was installed in the corner of the pen at a height of 2.2 m from the ground and the captured video resolution and frame rate were 1912×1080 pixels and 25 fps, respectively. To minimize the impact of lighting variations, incandescent lights were used to illuminate the pen both during the day and at night. After observation and comparison with relevant studies (Xu et al., 2022; Nasirahmadi et al., 2015), it was found that continuous lighting does not have a significant impact on the behaviour of the pig group once they have adapted to the specific lighting conditions.

2.2. Dataset construction

The dataset used for behavior recognition of pigs in this study consists of two parts: a pig object detection dataset in COCO format and a pig behavior recognition dataset in AVA format. The specific method for constructing the dataset is as follows: firstly, the pig object detection dataset was built by randomly sampling 1,500 images from raw surveillance videos. These images were split into a training set and a test set in a 7:3 ratio, resulting in 1,050 images for the training set and 450 images for the test set.

Next, the pig behavior recognition dataset was constructed by

randomly clipping several 10-second video segments from the original surveillance videos, each of which recorded multiple behaviors of several pigs. A total of 525 video segments were extracted for behavior recognition and were divided into a training set and a test set in an 8:2 ratio, with 420 video segments in the training set and 105 in the test set. Subsequently, key frames were extracted from the training and test video segments at a rate of 1 frame per second for model training, yielding 4,200 key frames for the training set and 1,050 key frames for the test set. The results of training-test set partitioning are shown in Table 1.

Additionally, the pigs and their behaviors in the keyframe images were annotated using the Anylabeling software and stored in COCO format for object detection and AVA format for behavior recognition. The behaviors annotated included five types: eating, exploring, moving, standing, and lying, as described in Fig. 1.

2.3. Data augmentation for pig behavior recognition

Compared to human behavior recognition, the activities of pigs are typically confined within pig pens, resulting in a relatively fixed background for their movements. In order to increase the diversity of data and thus improve the generalization ability of the model, this study extends the classic Mosaic data augmentation method in the field of image object detection to video Mosaic augmentation and incorporates it into the network training for pig behavior recognition.

Mosaic data augmentation is an advanced technique originally introduced in YOLOv4 (Bochkovskiy et al., 2020), designed to improve the robustness and generalization of object detection models. Similar to image-based Mosaic, the proposed video mosaic augmentation method randomly combines four different video frame sequences into a new sequence during the network training phase. This allows the model to process multiple scenes and objects simultaneously. The process of video Mosaic data augmentation is illustrated in Fig. 2. Firstly, the video frame sequences are proportionally scaled to ensure that the longer side meets the input size requirements of the network. Gray pixels are then padded along the shorter side of the video frames to obtain sequences with equal width and height. The four video frame sequences are then randomly flipped horizontally and subsequently stitched together using a video random mosaic.

The specific method of video random mosaic stitching involves creating a new video frame sequence with double the original width and height (corresponding to the black box in Fig. 2). A center point (depicted by the green dot in Fig. 2) is randomly generated at the centre 1/4 area within this new sequence (corresponding to the green box in Fig. 2). Using this center point as a reference, four video frame sequences are stitched together. The excess portions outside the new video frame sequence are then cropped, and any missing areas are filled with gray pixels. Next, object boxes whose areas become smaller than half of their original size after stitching (depicted by the orange areas in Fig. 2) are discarded to avoid losing too many important features of the pigs, which may interfere with the model. Finally, the newly created video frame sequence is resized to half of its original size to meet the input requirements of the model. This processing method not only preserves the integrity of the original video but also introduces contextual relationships between different video sequences, enriching the background features. As a result, it enhances the behavior recognition capability of the model, which will be validated in the ablation experiments.

Table 1
Dataset splitting results.

Dataset	Dataset splitting	Number of keyframe images	Total
object detection	Training	1050	1500
	Test	450	
behavior recognition	Training	4200	5250
	Test	1050	

2.4. Process for pig behavior patterns quantification

The study proposes an intelligent method for quantifying behavior patterns of group-housed pigs using surveillance video, providing technical support for intelligent farming management. The quantification process is illustrated in Fig. 3. Specifically, a monitoring platform is first set up in the pig house to obtain real-time surveillance video data of group-housed pigs. The surveillance videos are then used to construct the dataset required for model training. Next, a behavior recognition model is developed to identify various behaviors of group-housed pigs. Finally, a statistical analysis method is applied to the behavior recognition results to quantify the behavior patterns of group-housed pigs.

3. Multi-behavior recognition of pigs based on ViTAM-SlowFast

In this study, the ViTAM-SlowFast is improved based on the SlowFast network (Feichtenhofer et al., 2019). SlowFast is a two-stage behavior recognition model that first detects the target with an object detector and then classifies behavior of the target. SlowFast employs a dual-pathway network architecture for behavior classification: a slow pathway and a fast pathway. In the slow pathway, the number of video frames input into the network is reduced by a factor of $1/\alpha$ compared to the fast pathway, thereby focusing on extracting spatial feature information. The fast pathway is designed to capture motion information more effectively and thus has fewer convolutional filters and a weaker ability to process spatial information. However, it does not require temporal pooling to reduce temporal resolution, so the number of channels is set to β times that of the slow pathway. Both pathways utilize 3D ResNet convolutional neural networks (Hara et al., 2017) as backbone networks for spatial–temporal feature extraction and fuse the information from the two pathways through lateral connections.

Similar to SlowFast, ViTAM-SlowFast consists of an object detection module and a behavior recognition module, as illustrated in Fig. 4. The object detection module employs YOLOv7 (Wang et al., 2023), and the behavior recognition module also adopts a dual-pathway network structure. The difference is that, in the slow pathway, the 3D ResNet convolutional network of the original model is replaced by a video Transformer (ViT) encoder (Arnab et al., 2021). In the fast pathway, we incorporate a residual structure with a 3D Temporal Attention Module (TAM) (Liu et al., 2021). We believe that this improvement enables the slow pathway to better extract spatial features and enhance the capability of the fast pathway to process motion information of the pigs. Moreover, this design integrates the strengths of both Vision Transformers (ViTs) and convolutional networks, enabling the model to effectively learn global contextual features and local detailed features simultaneously, thereby enhancing the overall performance of the model.

Once the data flow in both the slow and fast pathways is completed, the spatial–temporal feature maps obtained from each pathway are fused together. The fused spatial–temporal features, along with the pig boxes output by YOLOv7, are then input into the 3D RoIAlign layer (He et al., 2017). The 3D RoIAlign layer extracts the features from regions of interest (RoI) in the spatial–temporal feature maps output by ViTAM-SlowFast, and the RoI features are subsequently fed into the classification layer to classify the behaviors of group-housed pigs. To enable information exchange between the fast and slow pathways, a lateral connection is added between the two pathways at each “stage”, which will be detailed in subsequent sections.

3.1. YOLOv7 object detection for group-housed pigs

In this study, YOLOv7 is selected as the object detection module for group-housed pigs. YOLOv7 is a single-stage object detection algorithm widely applied for its outstanding real-time performance (Wang et al., 2023). YOLOv7 is primarily composed of three modules: Backbone, Neck, and Head, as illustrated in Fig. 5. The main task of the Backbone

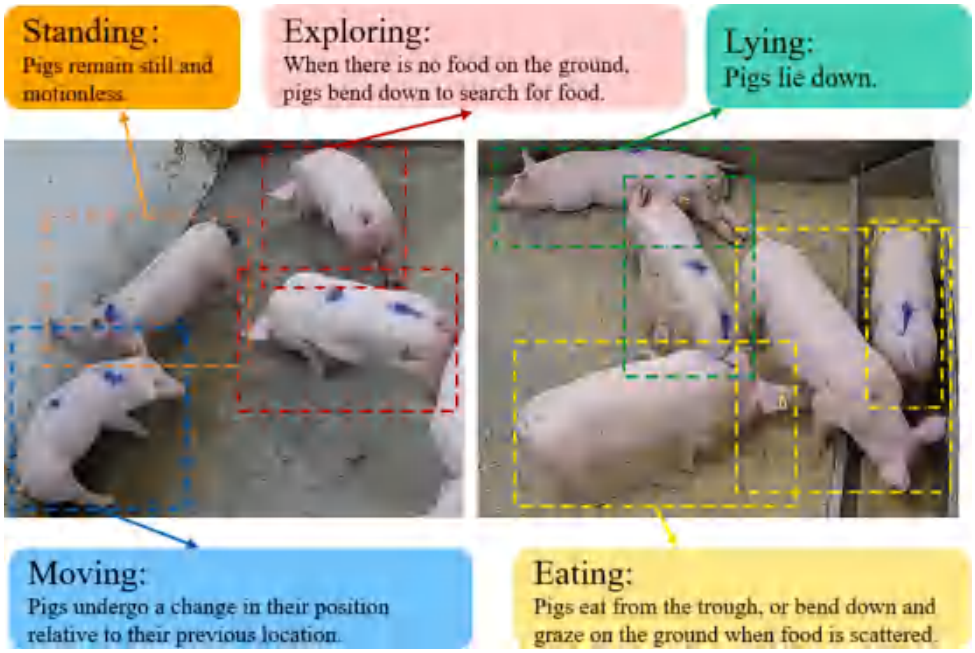


Fig. 1. Multiple behavior descriptions of pigs.

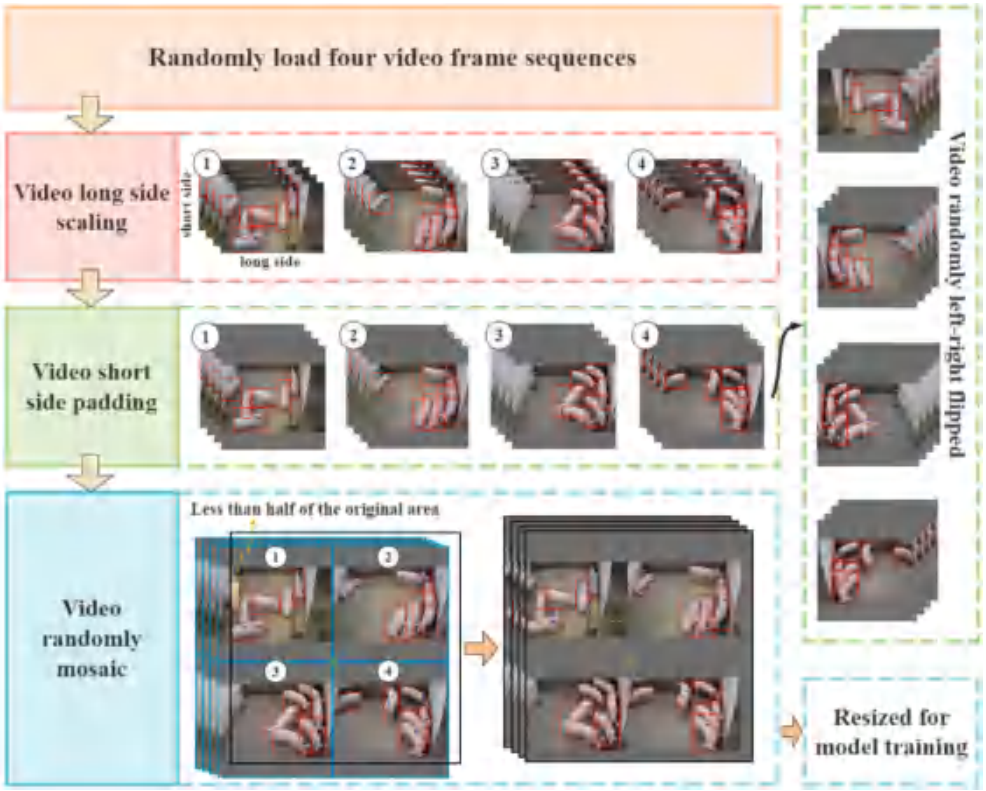


Fig. 2. Video mosaic data augmentation procession.

module is to extract features of pigs from the input image using a convolutional network. The Neck module aims to capture multi-scale information of pigs by performing multi-scale feature fusion on the feature maps extracted by the Backbone module. The Head module uses the outputs from the Neck module to perform regression predictions, yielding the final detection results. In this study, the YOLOv7 achieves a detection accuracy of 98.86 %.

3.2. Slow pathway of ViTAM-SlowFast

The ViT encoder backbone used in the slow pathway of the ViTAM-SlowFast, shown in Fig. 6, is based on vanilla video Transformers (ViT) (Arnab et al., 2021) with joint space–time attention (Bertasius et al., 2021). Compared to traditional 3D CNN that process video information through local sliding windows, ViT processes video information in the form of tokens. By leveraging multi-head attention layers (Dosovitskiy

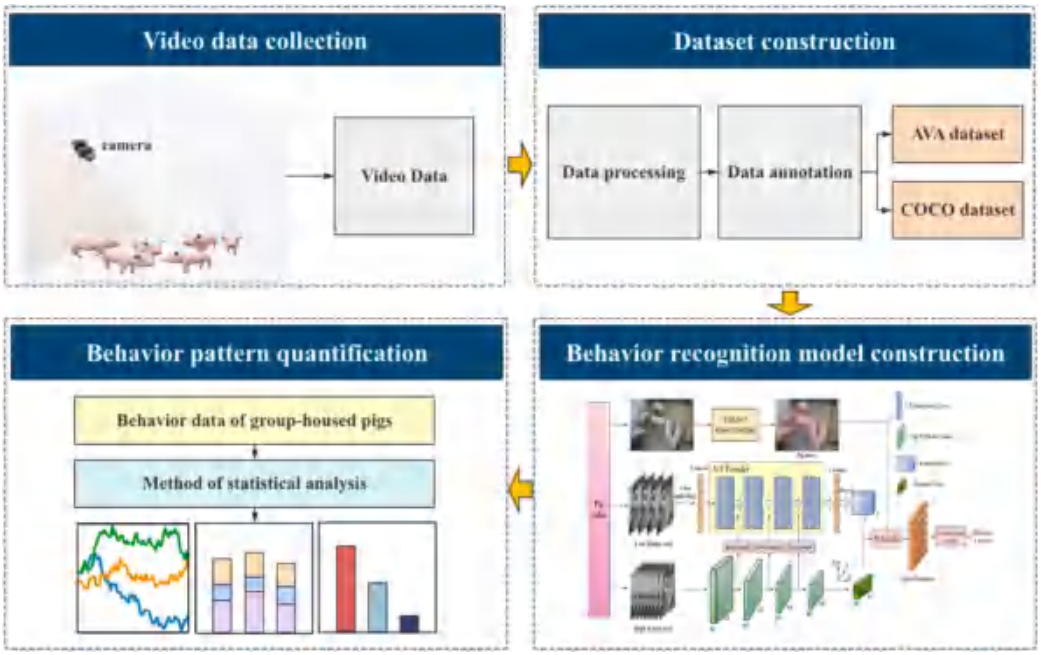


Fig. 3. Quantification process of behavior patterns of group-housed pigs.

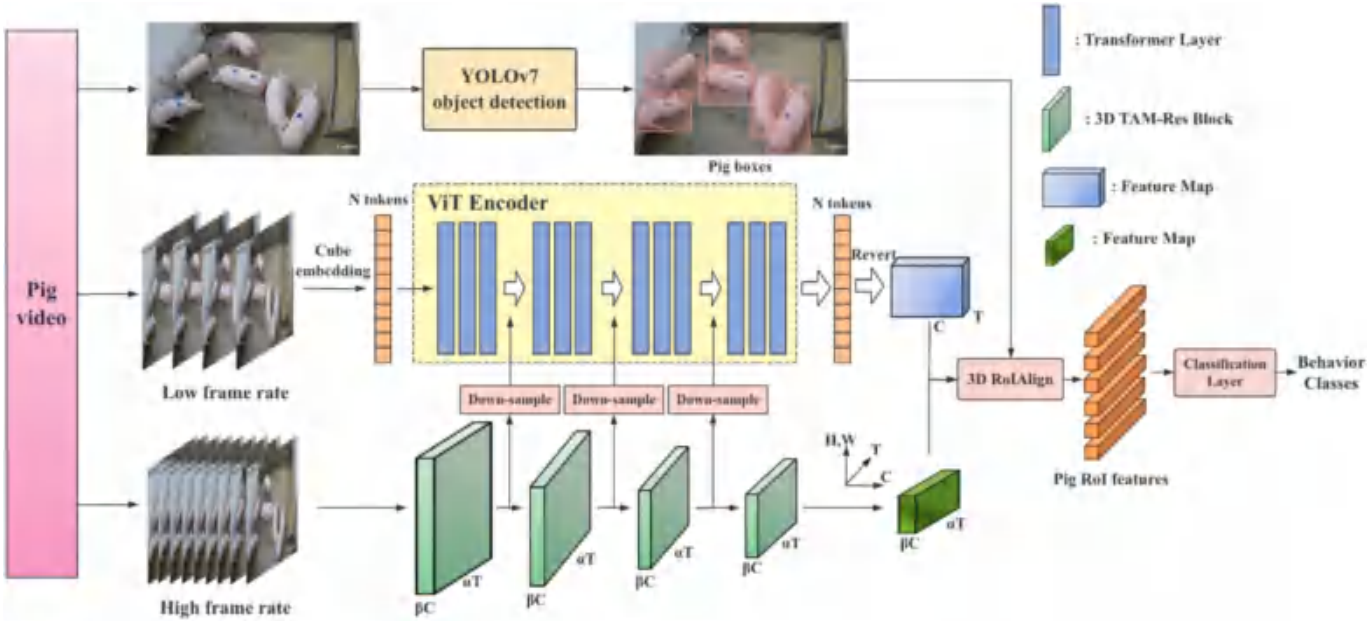


Fig. 4. The structure of ViTAM-SlowFast.

et al., 2021), ViT enables more effective interaction between temporal and spatial information, allowing it to capture higher level global contextual information from videos. Incorporating global contextual information aids the slow pathway in understanding the overall changes and continuity in pig behavior, rather than being restricted to localized motion recognition. Additionally, the incorporation of video mosaic data augmentation introduces richer background features to the video data, thereby maximizing the global advantages of the ViT and enhancing the ability of the slow pathway to extract spatial features related to pig behavior.

Specifically, the raw video clips are first processed into N tokens using Tubelet embedding (Arnab et al., 2021). All tokens are then added with positional encodings and fed into the ViT encoder backbone for feature extraction. The ViT encoder backbone used in this study consists of 12 transformer layers. Each transformer layer is composed of multi-head self-attention mechanism (MHSA), layer normalization (LN), and MLP layers, following the formula below. Where, $z \in R^{N \times d}$, represents the tokens at each layer. The MHSA employs joint space–time attention (Bertasius et al., 2021), and the MLP block consists of two fully connected layers separated by a GELU activation function.

$$\boldsymbol{y}^{\ell} = MHSA(LN(\boldsymbol{z}^{\ell})) + \boldsymbol{z}^{\ell} \tag{1}$$

$$\boldsymbol{z}^{\ell+1} = MLP(LN(\boldsymbol{y}^{\ell})) + \boldsymbol{y}^{\ell} \tag{2}$$

Finally, the tokens output by the ViT encoder are remapped into a structured spatial–temporal feature map, which is then used for subsequent fusion with the spatial–temporal feature map output by the fast

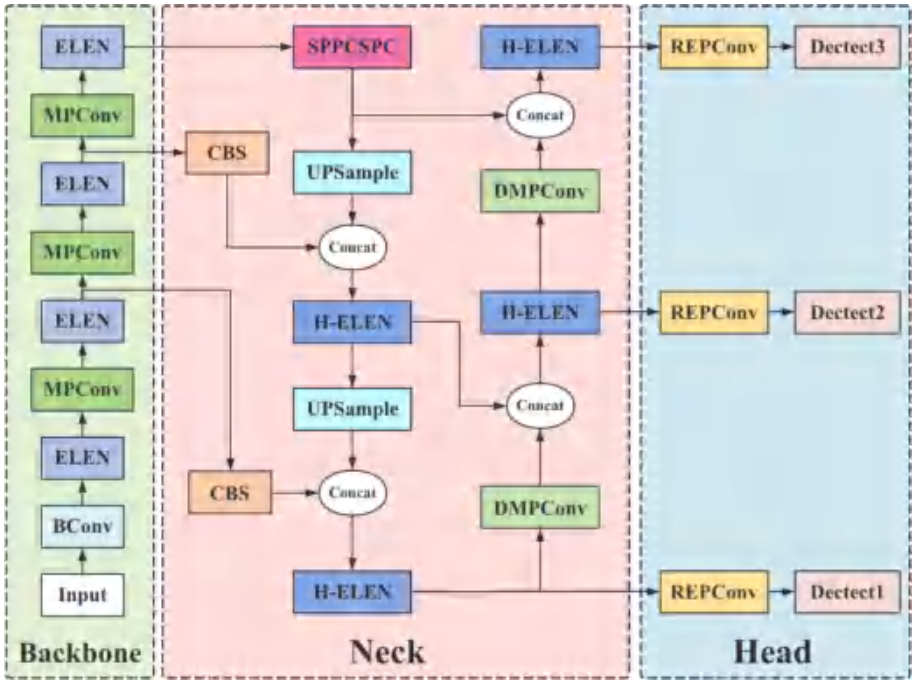


Fig. 5. The structure of YOLOv7.

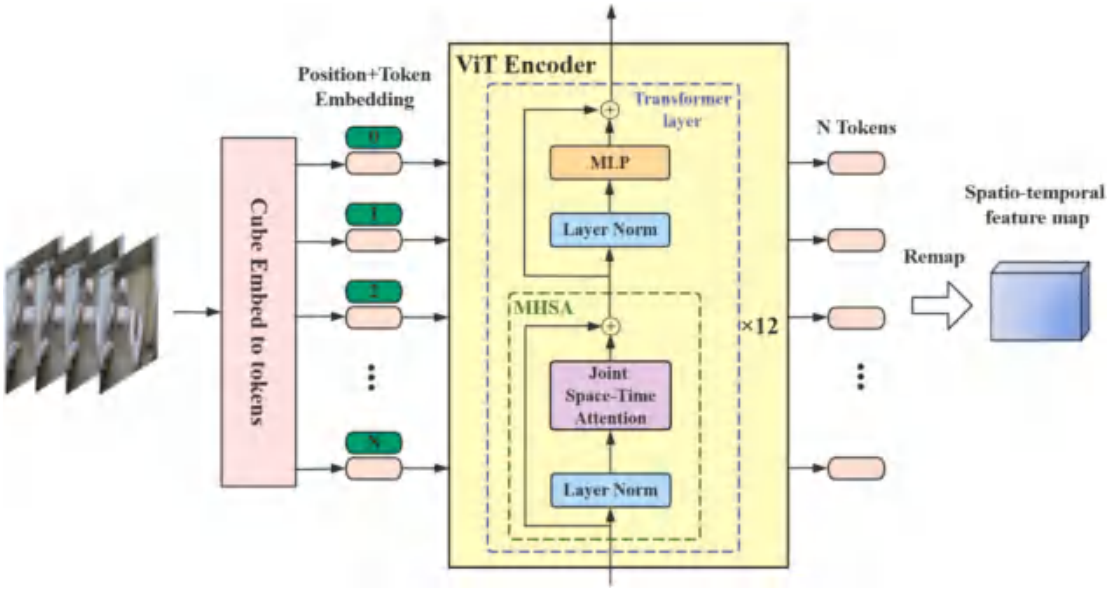


Fig. 6. The structure of the ViT encoder backbone of the slow pathway.

pathway.

3.3. Fast pathway of ViTAM-SlowFast

Given the critical role of local feature representation in behavior recognition, the convolutional network architecture is retained in the fast pathway. Additionally, it is optimized to better suit the specific requirements of pig behavior recognition scenarios. In behavior recognition of pigs, where pigs are prone to stress and can exhibit sudden and intense movements, traditional 3D convolutional networks may struggle to capture the onset and cessation of these rapid movements effectively. To enhance the ability of the fast pathway to capture fine-grained details of quick behavioral changes in pigs, the ViTAM-SlowFast integrates the Temporal Adaptive Module (TAM) (Liu et al., 2021) into the 3D ResNet50 (Hara et al., 2017) of the fast pathway. The TAM employs an attention mechanism along the temporal dimension to dynamically enhance input features based on the significance of motion information, thereby improving the capability of the model to process rapid motion details.

Specifically, the TAM module is embedded after the first Conv3D layer in each residual block of the 3D ResNet50, converting the original 3D ResNet block into a 3D TA-block, as shown in Fig. 7. The TAM module consists of a local branch ($\mathscr{L}$) and a global branch ($\mathscr{G}$). The local branch ($\mathscr{L}$) is constructed with temporal convolution layers with ReLU non-linearity. It is designed to generate corresponding importance weights based on the sensitivities of different locations of the input features. The calculation formula is as follows, where V represents the learned location sensitive importance map, Conv1D denotes the

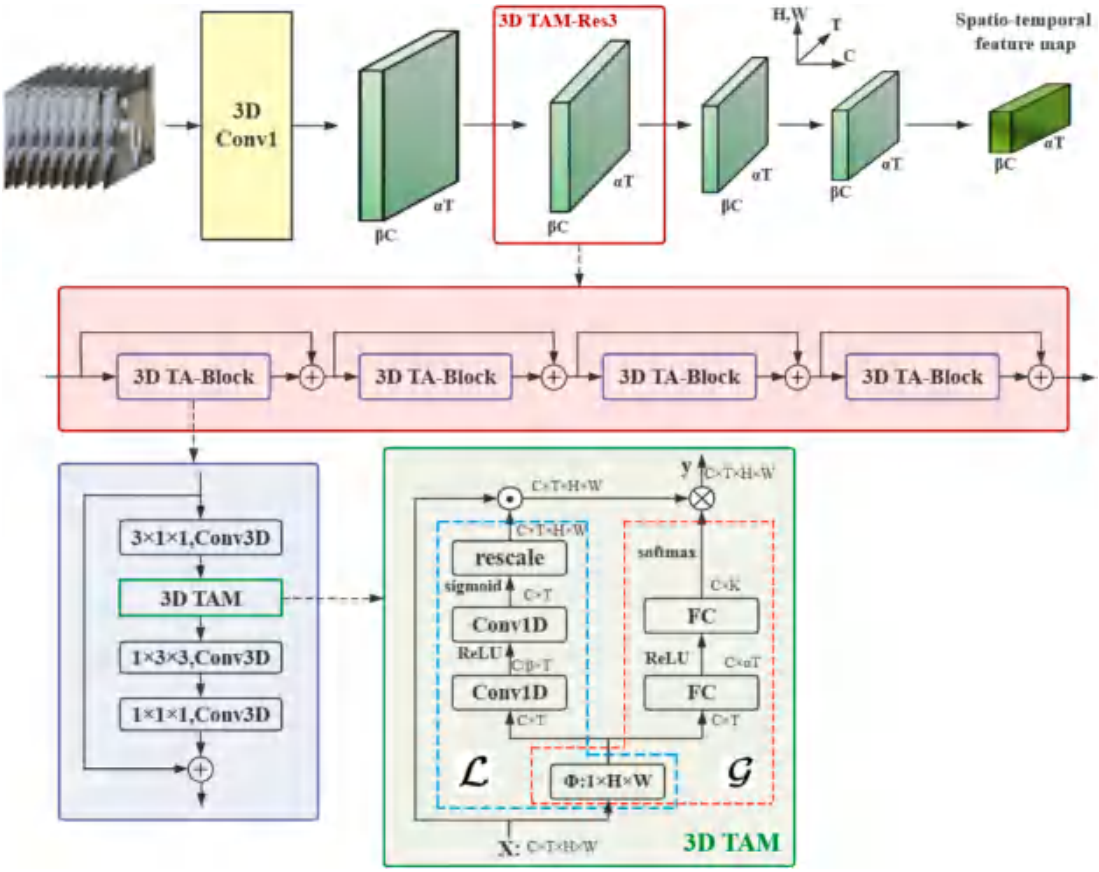


Fig. 7. The structure of the 3D TA-Block of the fast pathway.

temporal convolution operation, K represents the kernel size, C/β represents output channel size of the temporal convolution, δ represents the ReLU activation function, X denotes the input features, and F_r represents replication in the spatial dimension, rescaling V to $V \in \mathbb{R}^{C\times T\times H\times W}$.

$$U = \delta\left(Conv1D\left(X, K, \frac{C}{\beta}\right)\right) \tag{3}$$

$$V = sigmoid(Conv1D(U, 1, C)) \tag{4}$$

$$\mathscr{L}(X) = F_r(V) \tag{5}$$

The global branch ($\mathscr{G}$) consists of two fully connected layers and a softmax layer, which are used to incorporate global contextual information from the input features and generate dynamic convolutional kernels. The calculation formula is as follows, where FC represents the fully connected layer, W_1 and W_2 are the weights of the two fully connected layers, and δ denotes the ReLU activation function.

$$U = \delta(FC(W_1, X)) \tag{6}$$

$$\mathscr{G}(X) = softmax(FC(W_2, U)) \tag{7}$$

When performing the TAM operation, the first step is to squeeze the feature map by employing global spatial average pooling. Then, the input features are enhanced in the temporal domain using the importance map generated by the local branch. Finally, the temporally enhanced feature map is convolved with the dynamically generated convolutional kernels from the global branch to obtain the aggregated temporal information. The calculation formula is as follows, where ϕ represents the global spatial average pooling, $\otimes$ represents the convolution operation, and $\odot$ denotes element-wise multiplication.

$$\widehat{X} = \phi(X) \tag{8}$$

$$Y = \mathscr{G}(\widehat{X}) \otimes (\mathscr{L}(\widehat{X}) \odot X) \tag{9}$$

3.4. Lateral connections

To ensure that the slow pathway perceives the movement representations of pigs learned by the fast pathway throughout the entire training process and achieves the synergistic modeling of global context and local details, we follow the original SlowFast network and achieve this by employing lateral connections. We utilize unidirectional connections that fuse features of the fast pathway into the slow one, the fusion is illustrated in Fig. 4. Due to the different data dimensions between the two pathways, it is necessary to transform the data from the fast pathway before performing the lateral connection to ensure compatibility between the two pathways. Specifically, the following procedure is performed after each 3D TAM-Res block in the fast pathway. Firstly, a 3D convolution is applied to the data from the 3D TAM-Res block to down-sample it in both the temporal and spatial dimensions. After down-sampling, the shape of the features of 3D TAM-Res block is defined as $\{C, T, H, W\}$, we then reshape it into $\{C, T \times H \times W\}$ so that it can match the dimensions of the features in the slow pathway. Finally, the reshaped features of the fast pathway are concatenated to those of the slow pathway along the channel dimension, enabling lateral connections.

3.5. Experiment and results for pig behavior recognition

3.5.1. Experiment setup

The environment used in this study includes Ubuntu 18.04.6 LTS operating system, Intel Core i7-9700 CPU with a clock speed of 3.0 GHz, NVIDIA A30 GPU with 24 GB of memory, PyTorch 1.11.0 and CUDA 12.3. During training, the batch size was set to 4, and the initial learning

rate was set to 0.01. The frame rate ratio (α) between the fast pathway and the slow pathway was set to 4, and the channel ratio (β) was set to 1/8. The Adam optimizer was used for training the data. The original video frames were transformed into a size of 512 × 512 pixels as the input to the model through random cropping and random scaling.

3.5.2. Performance evaluation

The performance metrics of the proposed model were Average Precision (AP) for each behavior and mean Average Precision (mAP) for 5 behaviors, using a frame-level IoU threshold of 0.5. The calculation of AP and mAP are as follows:

$$P = \frac{TP}{TP + FP} \tag{10}$$

$$R = \frac{TP}{TP + FN} \tag{11}$$

$$AP = \int_0^1 P(R)\mathrm{d}R \tag{12}$$

$$mAP = \frac{1}{N}\sum_1^N AP_i \tag{13}$$

where, TP, FN, FP are the number of correctly predicted positive samples, incorrectly predicted negative samples, and incorrectly predicted positive samples, respectively. N represents number of behaviour categories and i represents specific behaviour category being evaluated.

The efficiency of the model is evaluated by measuring the inference time in milliseconds for each individual video clip, with each clip consisting of 25 frames.

To validate the effectiveness of the proposed method in behavior recognition of group-housed pigs, I3D (Carreira & Zisserman, 2017), X3D (Feichtenhofer, 2020), Slow-only (Feichtenhofer et al., 2019), and SlowFast were selected for comparison with the proposed method. The performance of the ViTAM-SlowFast on the test set is shown in Table 2. The AP values for eating, exploring, lying, moving, and standing were 96.34 %, 92.42 %, 99.56 %, 88.52 %, and 86.57 %, respectively. The mAP value for the five behaviors was 92.68 %, indicating superior performance compared to other methods. Specifically, the proposed model achieved higher accuracy compared to the SlowFast model, with an improvement of 2.68 %. It was noteworthy that the proposed model improved the recognition accuracy of the standing and lying behaviors, indicating that the ViT encoder in the slow pathway of ViTAM-SlowFast enhanced the ability of the model to extract spatial information from the features. Meanwhile, the recognition performance of the model on behaviors with temporal features, such as eating and exploring, was significantly better than that of other models. However, the recognition effect of moving behavior had a slight decrease compared with SlowFast. Observing the video, we founded that when the pig moved from moving to the last moment of stopping, the ViTAM-SlowFast model easily misclassified it as moving behavior. We speculate that this may be attributed to the improved fast pathway being more sensitive to the details of the movement of pigs, which leads to a small decrease but does not affect the overall model performance. This suggests that the 3D TAM module used to improve the residual backbone of the fast pathway effectively enhanced the sensitivity to motion information, thereby improving its ability to handle temporal information. Additionally, the proposed model achieved an average inference time of 61 ms per clip while maintaining high accuracy, outperforming other comparative models. This further demonstrates the advantages of the proposed method in both accuracy and execution efficiency.

Furthermore, Fig. 8 illustrates partial detection results of the original SlowFast and ViTAM-SlowFast models. In Fig. 8(a), the original model was prone to misclassify the pig as eating behavior because of the position of the pig at the trough. However, the head of pig was raised and not eating, the improved model promptly classified it as standing behavior. In Fig. 8(b), when the leg information of the pig was partially occluded during eating, the original model was prone to misclassify it as lying behavior. However, the improved model could more easily differentiate eating behavior based on subtle motion cues during the eating process. In Fig. 8(c), when the pig slightly lowered its body while standing, the original model exhibited significantly lower confidence in determining it as standing behavior compared to the improved model. In Fig. 8(d), when the movement amplitude of the pig was not pronounced during the exploring process, the original model tended to misclassify it as standing behavior, whereas the improved model accurately distinguished it as exploring behavior. The observations in (a) and (c) demonstrate that the improved model has stronger extraction capabilities for static features. The observations in (b) and (d) show that the improved model is more sensitive to motion information, making it more adept at recognizing behaviors with temporal features. These results further validate the effectiveness of the improved model.

3.5.3. Ablation experiments

The performance impact of different improvement strategies on behavior recognition for group-housed pigs was evaluated in this experiment. The results are presented in Table 3, where SlowFast-V represents the SlowFast with the addition of ViT, SlowFast-T represents the SlowFast with the addition of the TAM module. It was observed that incorporating the ViT backbone into the model, the mAP increased by 1.6 % compared to the original model. After introducing the TAM-block into the Fast pathway, the mAP of the model improved by 0.98 % compared to the original model. ViTAM-SlowFast, which integrated the advantages of the ViT encoder backbone and the 3D TAMRes-block, not only strengthened the spatial information extraction capability but also enhanced the temporal information processing capability, enabling the best mAP performance to be achieved. Furthermore, the addition of the ViT backbone eliminated the convolution operation in the slow pathway, enhancing the inference speed of the model. This experiment further validates the effectiveness of the proposed improvements to the model.

Table 4 demonstrates the impact of lateral connection on the performance of the model. The ViTAM-SlowFast model without lateral connection, which only connected the final outputs of the two pathways, the mAP was only 90.94 %. However, when lateral connections were introduced in ViTAM-SlowFast, there was an improvement in AP for each behavior, leading to an overall mAP increase of 1.74 %. This indicates that it is necessary for the two pathways to interact with each other, as this can effectively improve the accuracy of the model.

Table 5 illustrates the impact of video mosaic data augmentation on

Table 2
Comparison on the performance of ViTAM-SlowFast with other models.

Model	mAP	AP					Time
		eating	exploring	lying	moving	standing	
I3D	84.28 %	89.33 %	83.01 %	98.59 %	83.61 %	66.84 %	184 ms
X3D	85.68 %	91.38 %	88.46 %	97.83 %	72.42 %	78.33 %	92 ms
Slow-only	88.29 %	89.83 %	86.66 %	98.71 %	86.23 %	80.01 %	169 ms
SlowFast	90 %	91.62 %	88.79 %	98.52 %	89.03 %	82.06 %	106 ms
ViTAM-SlowFast	92.68 %	96.34 %	92.42 %	99.56 %	88.52 %	86.57 %	61 ms

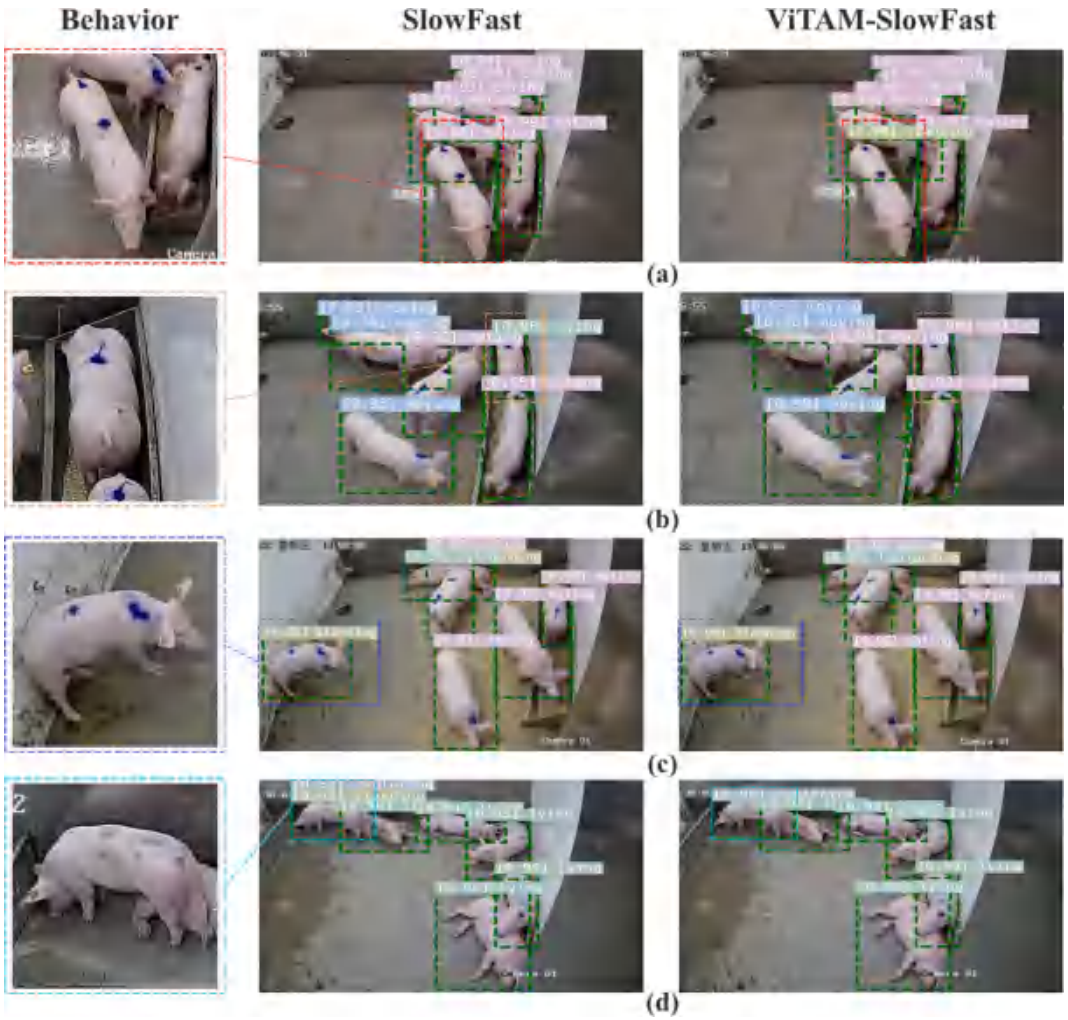


Fig. 8. Detection results comparing SlowFast and ViTAM-SlowFast models. **(a)** and **(b)** represent the detection results from morning, while **(c)** and **(d)** represent the detection results from afternoon and nighttime.

Table 3
Comparison on the performance of ViTAM-SlowFast different improvement strategies.

Model	Slow pathway backbone	Fast pathway backbone	mAP	Time
SlowFast	3D ResNet50	3D ResNet50	90 %	106 ms
SlowFast-V	ViT encoder	3D ResNet50	91.60 %	55 ms
SlowFast-T	3D ResNet50	3D TAM-ResNet50	90.98 %	136 ms
ViTAM-SlowFast	ViT encoder	3D TAM-ResNet50	92.68 %	61 ms

the performance of the model. It was evident that after applying video mosaic, the mAP improved by 1.01 %. This enhancement contributes to greater robustness in the model, leading to improved behaviour recognition performance.

3.5.4. Error analysis

Fig. 9 shows some examples of ViTAM-SlowFast misclassifications. In Fig. 9(a), a pig is nudging another pig with its snout, which standing behavior resembles the characteristics of exploring behavior. This situation leads to the standing behavior being easily misclassified as exploring. In Fig. 9(b), the lying behavior of pig is mistakenly detected as standing behavior since the pig transitions from lying to standing. Such misclassification occurs due to there is no clear boundary between the two behaviors during the transitional period, making it prone to misclassification. In Fig. 9(c), the mouth-to-ground contact of the pig during exploring is obscured, and the pig does not exhibit significant head-lowering, leading to exploring being misclassified as standing. In Fig. 9(d), when multiple pigs gather together, standing is more likely to be misclassified as eating because the body parts of the pig are significantly obscured by other pigs. This situation makes it difficult to observe the movement information, leg position, and back curvature of the pig, leading to difficulties for the model in distinguishing the standing state of the pig.

Table 4
The impact of lateral connections on the performance of the model.

ViTAM-SlowFast	mAP	Eating(AP)	Exploring(AP)	Lying(AP)	Moving(AP)	Standing(AP)
non-lateral	90.94 %	93.78 %	90.35 %	98.12 %	87.63 %	84.81 %
lateral	92.68 %	96.34 %	92.42 %	99.56 %	88.52 %	86.57 %

Table 5
The impact of video mosaic data augmentation on the performance of the model.

ViTAM-SlowFast	mAP	Eating(AP)	Exploring(AP)	Lying(AP)	Moving(AP)	Standing(AP)
no video mosaic	91.67 %	95.08 %	91.05 %	98.32 %	88.41 %	85.49 %
our video mosaic	92.68 %	96.34 %	92.42 %	99.56 %	88.52 %	86.57 %

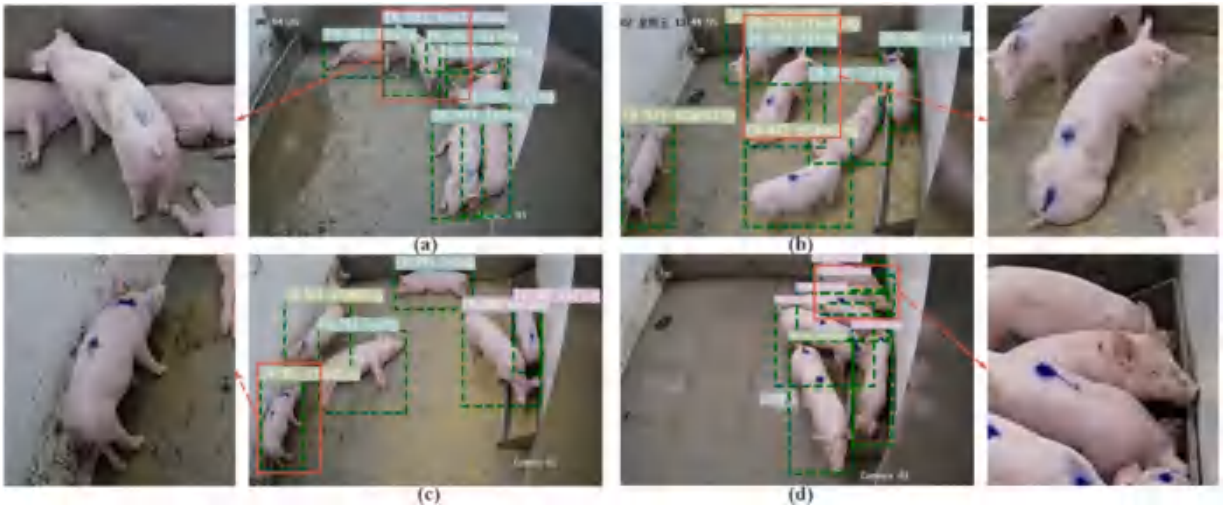


Fig. 9. Examples of error detection. **(a)** Standing behavior misclassified as exploring behavior; **(b)** Lying behavior misclassified as standing behavior; **(c)** Exploring behavior misclassified as standing behavior; **(d)** Standing behavior misclassified as eating behavior.

4. Behavior patterns quantification of pigs based on statistical analysis

The behavior of pigs is often an external manifestation of their internal states. Under healthy conditions, pigs exhibit stable periodicity and consistent patterns in key behaviors such as eating, activity, and resting (Maselyne, 2014; Matthews et al. 2017). When pigs are ill or exhibit abnormal behaviors, significant deviations from their normal behavior patterns are often observed (Tran & Thanh, 2023; Yang et al., 2024). Therefore, it is of great significance to quantify and monitor the behavioral patterns of pigs. It not only aids farmers in intuitively observing the daily behavioral performance of the pigs but also provides an important reference for the early detection of the health status of pigs by the farmers. When the observed behaviors significantly deviate from the expected healthy patterns, it may indicate potential health abnormalities in the pigs.

4.1. Quantitative assessment of pig behavior

The period from May 18, 2022, to May 31, 2022, was selected for the quantification and monitoring of the behavioral patterns of group-housed pigs in the experiment. Before quantifying behavior patterns, the behavior data of group-housed pigs needed to be collected. Firstly, the videos of the group-housed pigs were input into the ViTAM-SlowFast model for behavior recognition, resulting in daily data for five behaviors: eating, exploring, lying, moving, and standing. Due to the similar low movement amplitude and energy consumption exhibited by pigs in both lying and standing states, akin to resting, thus these two behaviors were combined for processing and defined as resting behavior. Finally, based on the behavior recognition results, the average duration of each behavior per 30-minute interval was calculated.

4.2. Analysis of approaches to establishing pig behavior patterns

In pig farming practice, farmers typically rely on observing appetite and activity level of pigs to assess their health status (Garrido-Izard et al., 2019; Ott et al., 2014). This indicates that investigating behavior of group-housed pigs during their eating time periods is of significant importance and value. Therefore, it provides us with a new approach to establish behavioral patterns in group-housed pigs by quantifying their behavior durations during the eating time periods. This method of extracting behavior data helps us monitor both the eating conditions and the activity levels of pigs during eating times, thus facilitating timely attention to their health status. For example, when the duration of eating behavior is low while resting behavior is high during eating time periods, this may indicate potential health issues.

4.2.1. Preliminary exploration of eating behavior

Given the importance of investigating behavior of group-housed pigs during their eating periods, a preliminary exploratory analysis of the eating patterns of group-housed pigs was conducted to gain deeper insights. Studies have revealed that under healthy conditions, the daily eating behavior patterns of group-housed pigs exhibited a certain regularity and periodicity. The activity curve of the pig group showed stable cyclical fluctuations, with the temporal distribution of activity peaks and troughs displaying consistent similarity (Huang et al., 2024; Xiao et al., 2016). These patterns were confirmed within the experimental pig housing in our study. The daily eating duration of group-housed pigs in this study also demonstrated multiple stable fluctuations over time, as illustrated by the bar chart in Fig. 10. Observation of the bar chart in Fig. 10 and incorporation of the video clip revealed that after the feeding started, the group of pigs concentrated on eating for a period, during which the eating duration rapidly rose to the first peak. After a while, the pigs would start resting, causing a sharp decline in eating activity. Following this rest period, the eating duration gradually increased again, reaching the second eating peak. The subsequent increase in eating duration was due to a few pigs in the group waking up and beginning to eat, gradually rousing the others, leading to more pigs joining the eating activity. Subsequently, the pigs returned to rest, causing the eating duration to decrease once more. This cyclical pattern continued until the food on the ground was almost consumed.

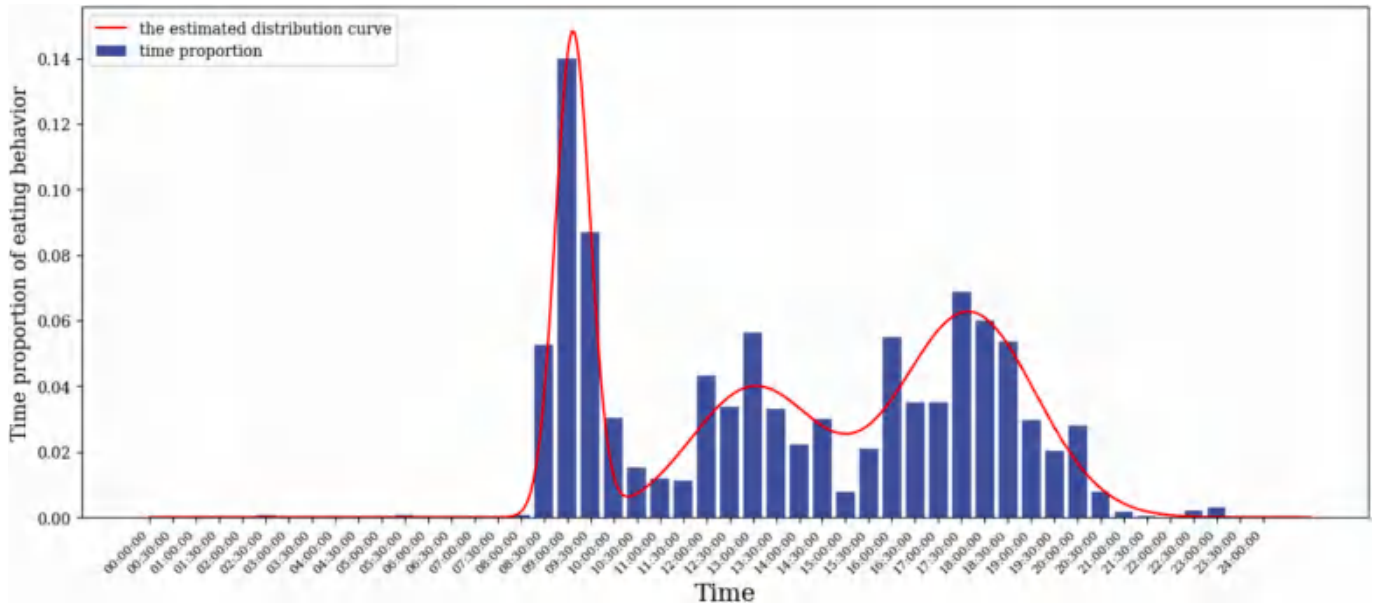


Fig. 10. The result of learning Gaussian mixture distribution using the EM algorithm, with the x-axis representing moments in time with a time interval of 30 min and the y-axis representing the time proportion of eating behavior for each 30-minute time period.

4.2.2. The analysis of the distribution of eating time

To further investigate the distribution characteristics of eating behavior of pigs and then identify the peak time period of pig eating, a density estimation approach is applied to model the daily eating behavior distribution of the group-housed pigs. Compared to the discrete eating behavior data (the bar in Fig. 10), the estimated eating distribution (the curve in Fig. 10) is smoother and more continuous, providing a more accurate reflection of eating behavior patterns. This helps the system capture the trends in eating frequency of pigs by identifying peaks and valleys of the continuous estimated eating distribution. Specifically, for estimating the daily eating behavior distribution, the duration of the eating behavior for each day is first normalized. This is achieved by dividing the original eating duration by the total eating time of the day, converting it into a proportion of eating behavior ranging from 0 to 1. The bar shown in Fig. 10 displays the normalized proportion of eating behavior. The normalized eating data facilitates the subsequent modeling of the eating behavior distribution. Subsequently, given that the eating behavior pattern distribution of group-housed pigs showing multiple periodic fluctuations, it is assumed to follow a Gaussian mixture distribution (Zhuang et al., 1996). The parameters of the distribution are estimated using the Expectation-Maximization (EM) algorithm (Moon, 1996), resulting in the eating distribution function for the day.

The EM algorithm is an effective method for learning Gaussian mixture models. Its fundamental idea is to iteratively calculate the expectation of the log-likelihood using the current parameter estimates (Expectation step, E-step), and find the parameter values that maximize the expected likelihood (Maximization step, M−step). The newly obtained parameter values are then applied to the next iteration of E-step and M−step. This process continues until the algorithm converges. According to the above method, the estimated eating time distribution curve using EM algorithm is shown in Fig. 10. Visually, the fitting effect of the estimated Gaussian mixture distribution curve appears to be good, as the distribution curve can effectively cover the distribution characteristics of the original data without obvious bias.

To further validate the effectiveness of the estimated Gaussian mixture distribution, the Kolmogorov-Smirnov (KS) test (Massey, 1951) is performed to examine the differences between the estimated Gaussian mixture distribution and the actual eating data for each day. The KS test is a non-parametric statistical method used to determine whether there are significant differences between two sample sets. The p-value from the KS test indicates the degree of statistical difference between the original data and the fitted distribution. If the p-value is greater than the significance level (0.05), the null hypothesis cannot be rejected, suggesting no significant difference between the actual eating behavior data of the pigs and the estimated Gaussian mixture distribution. The results of KS test are shown in Fig. 11. As observed, the p-values for each day are significantly greater than the significance level. This suggests that the distribution obtained by the estimation is not significantly different from the original data, and it can adequately represent the actual eating behavior of the grouped-housed pigs. Therefore, the estimated eating distribution is utilized to further analyze the eating patterns of the pigs.

To investigate eating peaks in pigs, a statistical method based on the estimated distribution of eating behaviors of pigs is employed to segment eating times into multiple peak intervals according to their eating frequency. Specifically, we first extract the 95 % confidence interval from the eating distribution, which represents the time period encompassing 95 % of the total daily eating duration of group-housed pigs. Then, using this confidence interval and the extrema points of the Gaussian mixture distribution, the daily eating duration is segmented into distinct intervals. Each segmented interval corresponds to a peak eating period during which pigs exhibit frequent eating behavior. The specific procedure is as follows: the time segment formed by the interval between the starting point of the confidence level and the position of the first extremum is defined as the first eating period, representing the first eating peak of the group. From the second eating period onward, the time segments between consecutive extremum points are used to define the eating peak periods. This process is repeated until the final segment, which is formed by the last extremum point and the end of the confidence level interval, is designated as the last peak eating period. During the remaining time period, we observe from the video that the pigs are almost entirely sleeping. Therefore, it is regarded as a low eating activity period and also represents the resting period of the pigs.

In the experimental pig pen, using this method, we divide the eating periods into three peak eating periods, as shown in Fig. 12. The red, green and blue regions in the Fig. 12 correspond to the first, second and third eating peak respectively, and the white regions correspond to the low eating activity period.

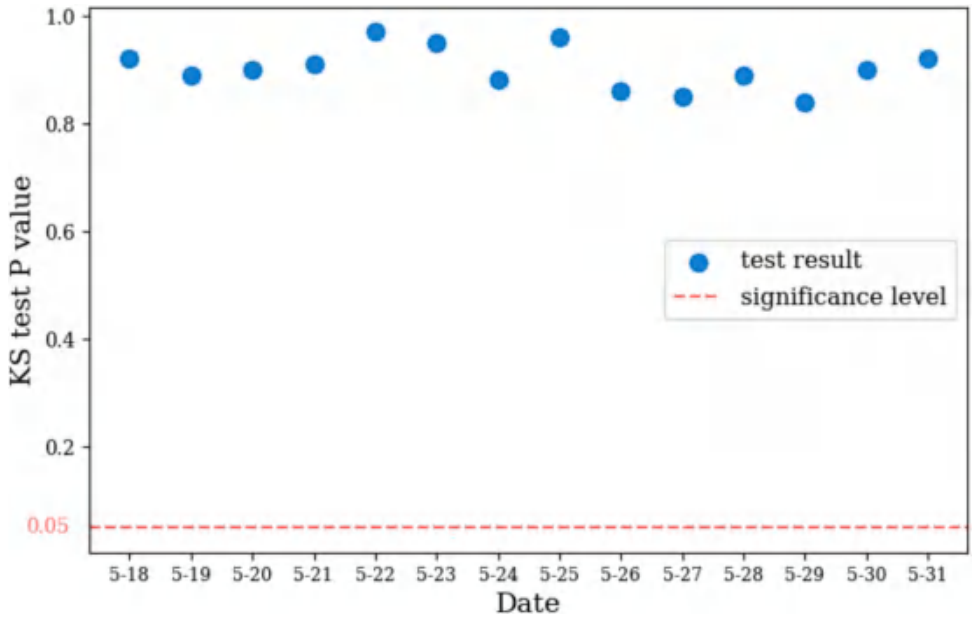


Fig. 11. The significance test results for the difference between daily estimated distribution and original data.

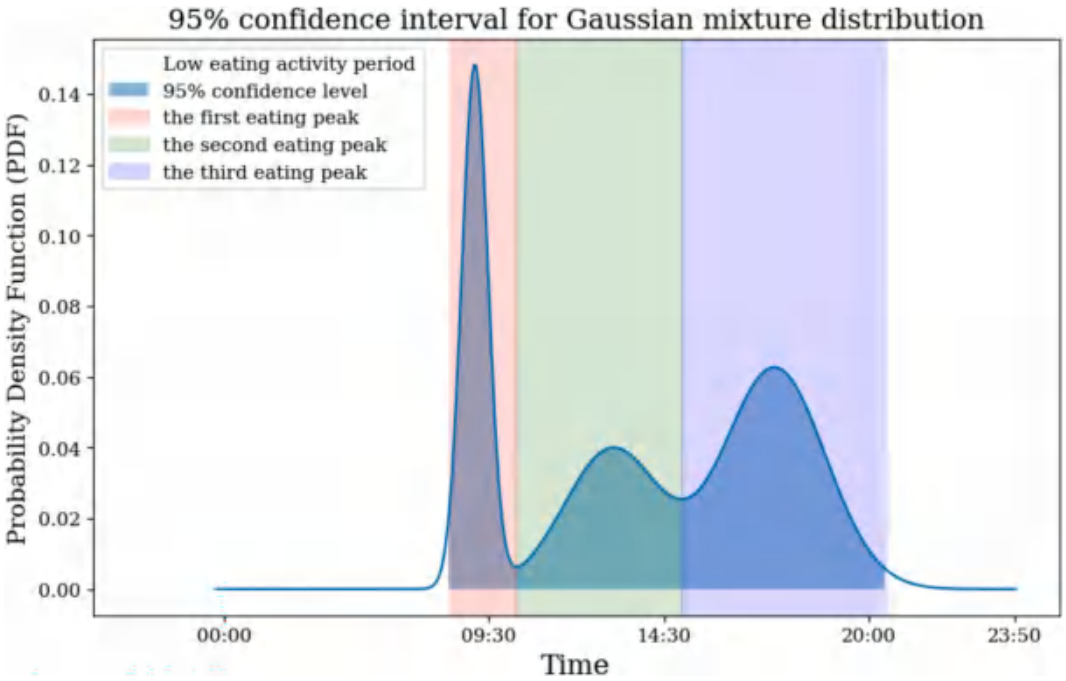


Fig. 12. Result of eating period segmentation.

4.2.3. Analysis of daily eating patterns similarity

Further, to investigate whether the daily eating distributions exhibit similar patterns, the Jensen-Shannon (JS) divergence (Menéndez et al., 1997) is utilized to measure the similarity between the daily eating behavior distributions. JS divergence is a statistical measure used to quantify the similarity between two distributions. It is a symmetric version of the Kullback-Leibler (KL) divergence (Sankaran et al., 2016), possessing non-negativity and symmetry. Given two distributions P and Q, the JS divergence approaches 0 as their similarity increases. When P and Q are identical, the JS divergence is 0, and when P and Q are entirely different, the JS divergence approaches 1. The JS divergence is defined as follows:

$$JS(P\|Q) = \frac{1}{2}KL(P\|M) + \frac{1}{2}KL(Q\|M) \tag{14}$$

$$M = \frac{1}{2}(P+Q) \tag{15}$$

where, $KL(P\|Q) = \sum p(x) log\frac{p(x)}{q(x)}$, represents the KL divergence of P relative to Q.

In our experiment, food is not provided to the pigs at a fixed time of the day, but with a deviation of 1 to 2 h. Therefore, the daily eating data of the pigs are first aligned according to their eating start times before calculating the JS divergence. The partially aligned data are shown in Fig. 13(a). To validate the similarity of daily eating distributions, the JS

divergence is calculated pairwise for distribution of each day, the calculation results shown in Fig. 13(b). It can be observed that the JS divergence ranges between 0 and 0.1, indicating that the daily eating patterns of the pigs in our experiment are similar. Therefore, in a healthy state, the peak eating periods of pigs can be distinctly delineated based on the frequency of their eating behavior. It also implies that in the event of any abnormal eating patterns, JS divergence can be employed to quickly distinguish them from the normal ones.

4.3. Quantification of behavioral patterns of pigs

Based on the analyses in the previous sections, behavioral data during eating time periods can help farmers to focus on both eating and activity levels of pigs and thus monitor their health more effectively. Therefore, the duration of each behavior within the peak eating periods is used to quantify the behavioral patterns of the pigs. The proposed behavior patterns quantification algorithm is as follow. Firstly, the eating behavior distribution for each day is first learned using the EM algorithm. Subsequently, based on the learned distribution, each day is divided into the first eating peak ($Peak_1$), the second eating peak ($Peak_2$), the third eating peak ($Peak_3$), and low eating activity period ($T_{low-eat}$) using the confidence interval and extremum points of the distribution. Finally, the duration of each behavior within these defined eating periods is extracted as the quantified result of the behavioral patterns. The behaviors to be extracted include eating, resting, exploring, and moving. Here, resting is the sum of lying and standing behaviors. In total, four behavior patterns are obtained for each day:

$$(pEat_c, pRes_c, pExp_c, pMov_c) = \sum_{i \in c} (eat_i, res_i, exp_i, mov_i) \tag{16}$$

where, $(pEat_c, pRes_c, pExp_c, pMov_c)$ represents behavior patterns during the c-th eating period, $c \in \{Peak_1, Peak_2, Peak_3, T_{low-eat}\}$, $\sum_{i \in c}(eat_i, res_i, exp_i, mov_i)$ represents the durations of the four behaviors during the time periods corresponding to the c-th eating period.

The visualization results of the four behavior patterns are shown in Fig. 14 to Fig. 16. From these figures, it can be observed that the behavioral patterns of the four behaviors of the pigs every day showed stability and similarity, which will be able to provide an important basis for the early detection of behavioral abnormalities in pigs. The behavior patterns of pigs will be analyzed in detail next.

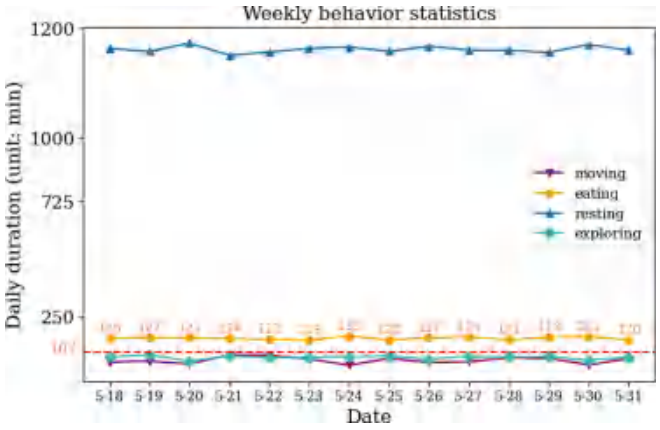


Fig. 14. Comparison of the daily duration of different behaviors.

The behavioral patterns of pigs from the daily duration of the four behaviors are analyzed in Fig. 14. It can be seen that the fluctuation of the duration of the four behaviors per day is relatively stable. Among them, resting behavior is the most dominant behavior by group-housed of pigs, with daily duration fluctuating between 1000 and 1200 min. Secondly, pigs maintain their daily activities through intermittent eating, with eating behavior being the second longest in duration, fluctuating between 120 and 140 min. Lastly, since exploring and moving behaviors typically occur under specific conditions, such as limited food availability or stress, their duration is relatively short, generally remaining below 107 min.

The behavioral patterns of pigs based on the activity of the same behaviors during different peak eating periods are analyzed in Fig. 15. It is noteworthy that the eating duration of pigs during the third eating peak is longer. Video analysis reveals that this phenomenon primarily occurs during the early eating stage when the pigs experience the strongest hunger, leading to a more concentrated eating behavior and a relatively shorter eating cycle. As time progresses, the hunger of pigs gradually diminishes. Their eating behavior shifts to an intermittent pattern, with more frequent alternation between eating and resting. This continues until the food is completely consumed, resulting in an extended eating cycle during the subsequent eating peaks. Therefore, as eating time progresses, the eating behavior of pigs gradually becomes discontinuous and the intervals between eating events progressively

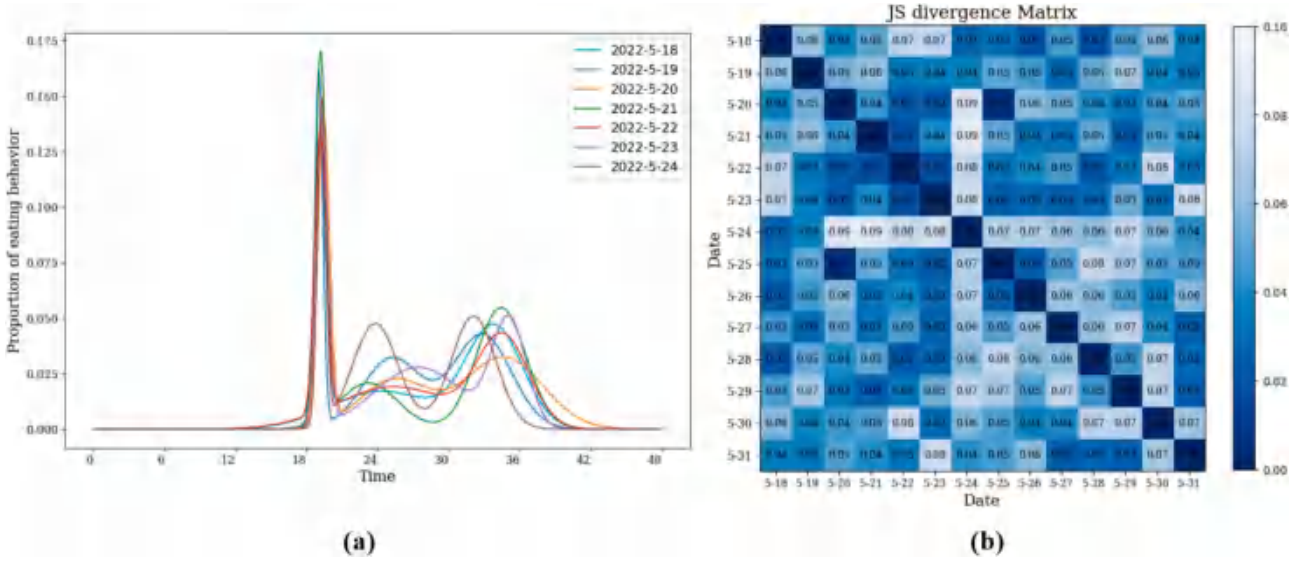


Fig. 13. Results of the similarity analysis of daily eating patterns. **(a)** displays the aligned distribution curves of daily eating patterns; **(b)** shows the solution result of JS divergence.

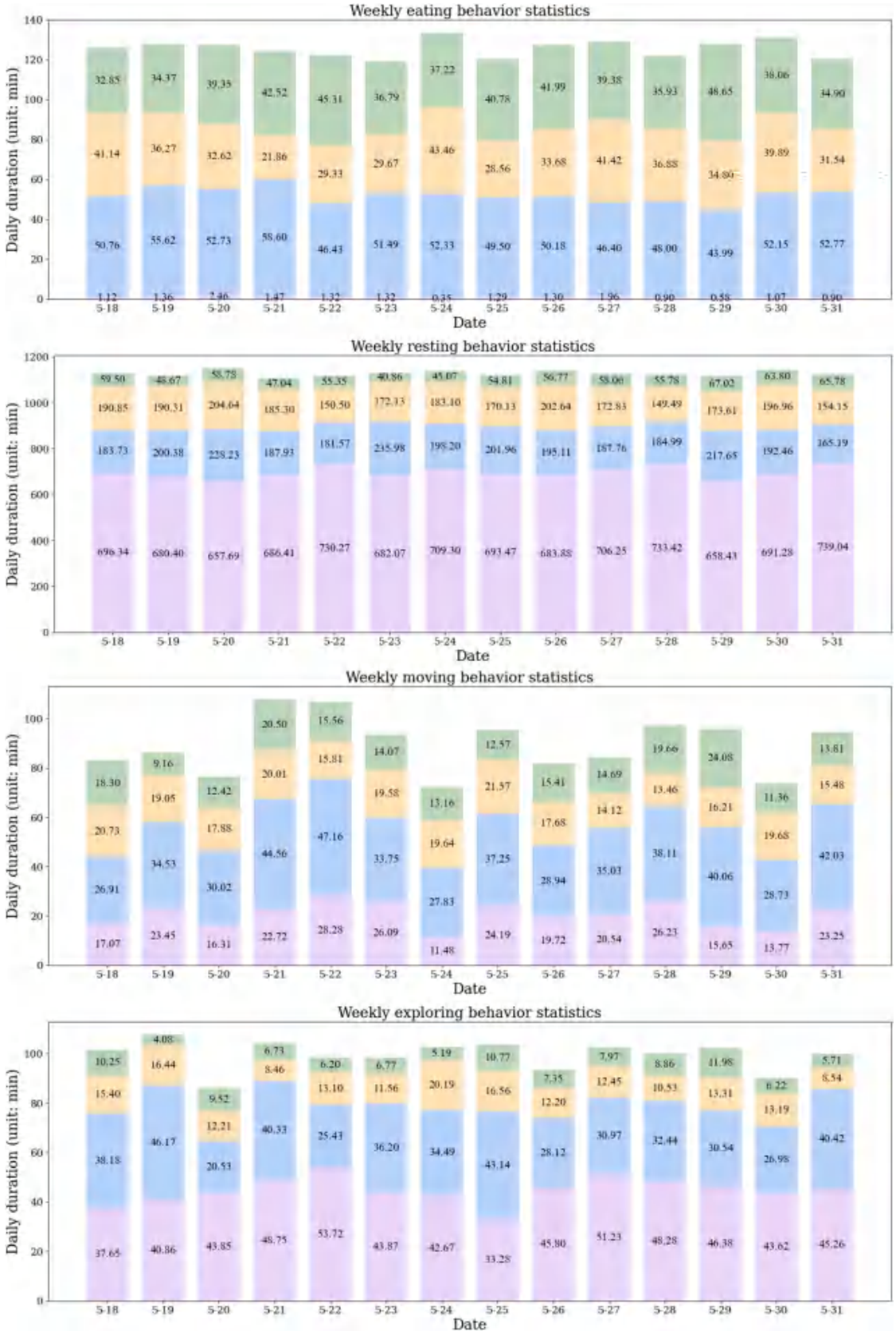


Fig. 15. Comparison of the activity of the same behavior across different eating periods.

lengthen. Additionally, the resting patterns of pigs exhibit remarkable stability and consistency. Pigs are most active during the first eating peak after the caretaker enters the pig pen to start feeding, while the longest resting duration occurs during the low eating activity period. These patterns align with the natural daily rhythm of pigs. Finally, the behaviors of exploring and moving typically occur under specific conditions of limited food or stress. Therefore, we can find that compared to eating and resting, these two behaviors exhibit relatively lower stability in their patterns, but they still follow similar regularities. Notably, the duration of exploring and moving behaviors increases over time, especially during the third eating peak. Video analysis suggests that this increase is associated with food scattered on the ground, which requires the pigs to move frequently to locate and consume it. Additionally, as food becomes scarcer, pigs are more likely to exhibit stress-induced moving behaviors due to competition for food. During the low eating activity period, a high frequency of exploring behavior is observed due to the lack of food, as pigs continuously search for food.

The pig behavioral patterns based on the duration proportions of different behaviors within the same eating period are analyzed in Fig. 16. It is observed that the proportion of each behavior remains highly stable across the eating period. Specifically, during the first eating peak, the pigs are most active because the caretaker begins feeding, with the smallest difference between the proportions of eating and resting behaviors. Additionally, the proportion of moving behavior is relatively high during this period, which may be related to stress responses triggered by the entry of external personnel. In the second eating peak, the proportion of eating duration decreases significantly, likely due to a reduced motivation to eat after the pigs have consumed a certain amount of food. During the third eating peak, as food gradually decreases, pigs increase their moving and exploring behaviors to search for food, resulting in a rise in activity. In the last stage, the pigs almost entirely transition to resting, with over 90 % of their time spent resting. This process is consistent with the habituation of pigs and aligns with our expectations, making it a reasonable and predictable pattern.

Further, the visualization of the aforementioned behavior patterns allows livestock managers to intuitively comprehend the daily eating duration and activity status of group-housed pigs, enabling more effective monitoring of their behavioral patterns. Additionally, previous

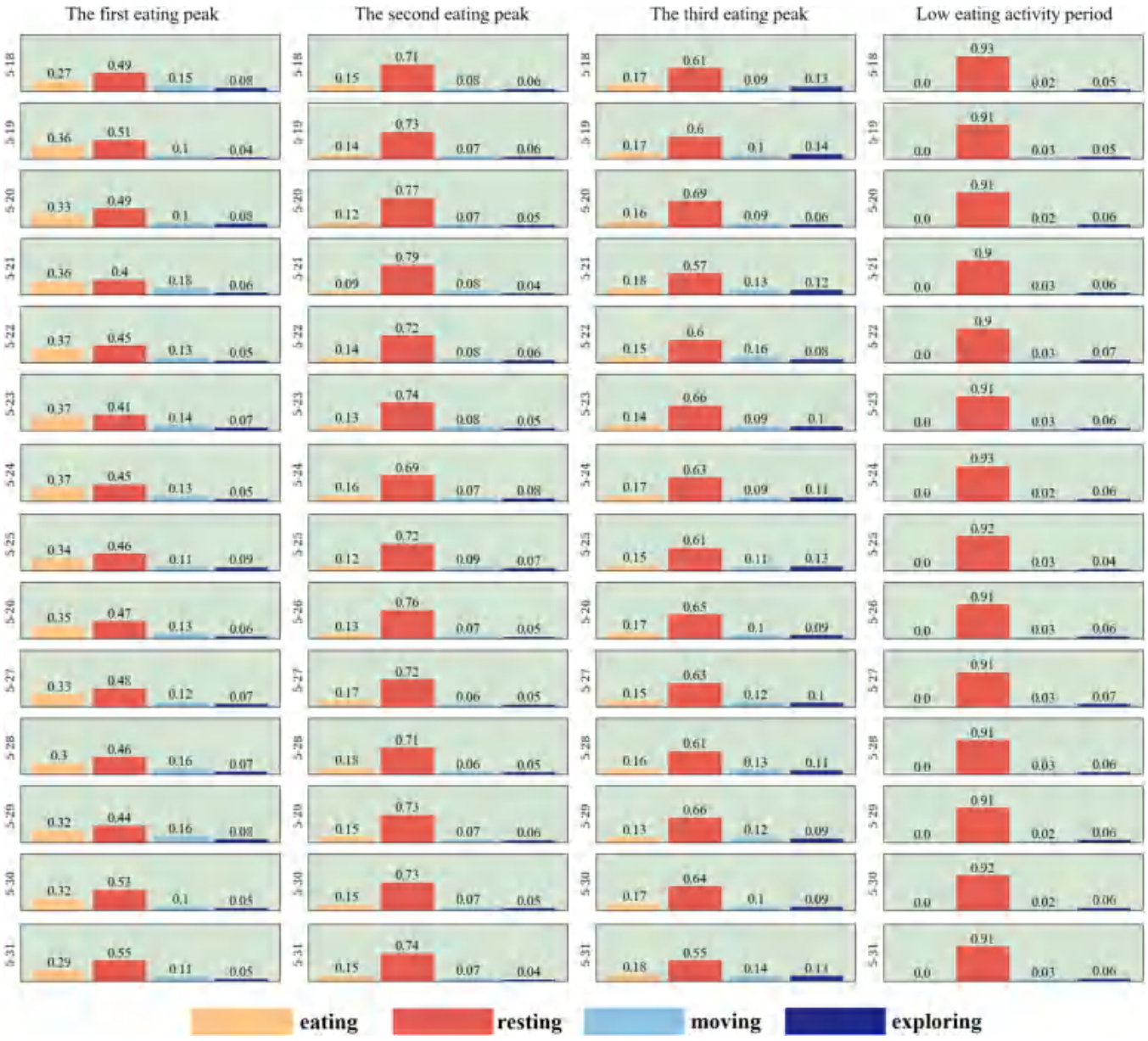


Fig. 16. Proportional comparison of different behaviors within the same eating period.

studies (Bus et al., 2021; Larsen et al., 2016; Matthews et al., 2016; Fernández-Carrión et al., 2017) have shown that changes in behavior patterns can be used for the early detection of health and welfare issues in pigs. Therefore, significant fluctuations in the visualized behavior results may indicate potential health issues within the group-housed pigs, necessitating timely intervention. Based on the guidance and recommendations provided by the pig behavior experts overseeing the experimental pig pen in this study, we offer the following criteria as a reference for identifying abnormal behavior in this specific environment. The similar methods may be applicable in other pigsties. (1) Eating Reduction: If the number of eating peaks decreases to two or even one, with eating duration significantly below the normal range, or if resting duration far exceeds 1200 min, this may suggest a decline in appetite or activity due to health issues of pigs. Such observations warrant increased vigilance about the health of pigs from livestock managers. (2) Increased Movement: A substantial increase in moving behavior may indicate that the pigs have experienced intense physical activity, which may be a response to severe stress or serious fighting. In such cases, it is crucial to inspect for any injuries among the pigs to prevent further harm. (3) Elevated Exploring: A significant rise in exploring duration may suggest insufficient feed supply. In response, the amount of food provided should be adjusted to reduce the occurrence of exploring behavior among the pigs. These criteria help in providing early detection of potential health or management issues within the pig pen, facilitating timely interventions and improving overall animal welfare.

The main contributions of this study are as follows:

(1) A model named ViTAM-SlowFast is proposed for multi-behavior recognition in group-housed pigs, which is an improved version of the SlowFast model, enhancing its ability to extract temporal and spatial features for better behavior recognition performance.
(2) The effectiveness of the proposed model in detecting the behaviors is validated through comparative experiments on group-housed pigs.
(3) A statistical analysis-based method is introduced for the automatic quantification of behavior patterns in group-housed pigs, which can extract the behavioral information of pigs at appropriate time periods based on their daily activity. This approach aims to provide valuable insights for farmers, enabling them to assess the health status of pigs through the monitoring of their behavior patterns.

5. Discussion

The study proposes a method for quantifying behavior patterns of group-housed pigs based on deep learning and statistical analysis. The method helps farmers efficiently and intuitively monitor daily eating duration and activity level during eating and resting periods. It facilitates the monitoring of behavior patterns in healthy group-housed pigs, providing a strong basis for assessing their health status through behavior patterns monitoring. In this section, we primarily discuss the prospects for practical applications of the study, the current limitations and further research.

5.1. Discussion on the application of the proposed method in the pig farming

5.1.1. Application prospects

The study utilizes statistical analysis to deeply explore the behavior patterns of group-housed pigs in healthy states, revealing that their daily behaviors exhibit similar regularities. This finding can assist us in leveraging these consistent patterns to monitor the health status of the pigs. The study holds promising practical application potential. Firstly, the method proposed in this study has the potential to be applied to the early warning of the health status of pig herds. Since eating behavior directly reflects the health condition of pigs, any health anomalies typically lead to a decrease in eating frequency (Kavlak, Pastell, and Uimari 2023), resulting in altered eating behavior distributions. Current methods for estimating eating distributions demonstrate good fitting performance on existing data, providing a solid foundation for constructing long-term eating behavior distributions. This will enable rapid detection of abnormal distributions based on the method of quantifying daily eating behavior distribution similarities, offering a reference for health warning systems for pig herds. Moreover, the method can be extended to monitor other abnormal behaviors in group-housed pigs. By analyzing behavior patterns, farmers can more efficiently observe and identify unusual activities, enabling quicker intervention. For example, a significant increase in the duration of moving behavior during resting period might indicate severe stress or serious fighting, requiring prompt intervention from the farmers.

5.1.2. Applicability in larger-scale pig farming

To validate the applicability of the proposed method in larger-scale commercial pig pens, the behavior recognition method was tested on an existing publicly available dataset containing data from 13 pigs (Wutke et al., 2021). This dataset includes 47 video clips, each lasting 25 s. Using the method in Section 2.2, training and testing datasets were constructed, and video frames were annotated. The ViTAM-SlowFast and YOLOv7 models were retrained and tested, with the test results shown in the Table 6.

As observed, the model achieves good performance with a small training dataset, with the AP values for the eating and lying behaviors reaching 92.85 % and 91.94 %, respectively. However, the AP values for other behaviors is less satisfactory. Upon reviewing the videos, it was found that as the number of pigs increases, the frequency of occlusion among pigs also rises, leading to a decrease in the overall mAP of the object detection and behavior recognition models. This experiment has provided a preliminary validation of the model's potential in larger-scale environments. However, further optimization of the model is needed to ensure reliable performance in such settings, particularly in addressing occlusion and object overlap, which directly impact the model's accuracy. Several advanced methods have been proposed and applied to address occlusion problems (Deng et al., 2015; S. Li et al., 2021; Y. Li et al., 2023; Wang et al., 2018; Zhang et al., 2018). These methods have demonstrated promising performance in behavior recognition tasks involving dense crowds and in object detection tasks under occlusion conditions, providing technical support and development directions for future applications in large-scale pig farms. With the expansion of data resources and further optimization of algorithms, our model holds significant potential for application in larger commercial farms. In the future, we plan to integrate more advanced occlusion handling techniques and conduct experiments on larger-scale datasets to further enhance the model's adaptability and robustness.

5.2. Current limitation and future outlook

Although the method proposed in this study can accurately identify multiple behaviors of group-housed pigs and effectively quantify their behavioral patterns, providing valuable references for pig behavior monitoring and management, there are still some limitations. Firstly, the current study focuses on quantifying group-housed pig behavior patterns and does not yet monitor individual behaviors. However, individual behavior tracking helps improve the sensitivity of abnormal behavior detection, enabling earlier disease warnings and health interventions. Therefore, in the future, we plan to integrate technologies such as object tracking, RFID, and thermal imaging to monitor individual behaviors and enhance the detection of abnormal behaviors. Secondly, this study has only explored the behavior patterns of healthy group-housed pigs and has not examined the behavioral characteristics of pigs with health anomalies. Therefore, in future research, we will further investigate the behavioral patterns under abnormal health

Table 6
Validation results of the model in larger-scale pig pen.

Model	mAP	AP					
		Eating	Exploring	Lying	Moving	Standing	Pig
ViTAM-SlowFast	78.64 %	92.85 %	71.53 %	91.94 %	72.24 %	64.65 %	—
YOLOv7	96.20 %	—	—	—	—	—	96.20 %

conditions. Additionally, we plan to extend the time span of data collection to cover different seasons and farming stages throughout the year, to deeply analyze the similarities and differences in pig behavior at different times. This will help develop a universal behavior quantification method applicable to various health and environmental conditions, improving the accuracy and practicality of health monitoring in precision livestock systems.

6. Conclusions

In summary, the study proposes a novel approach and reference based on deep learning and statistical analysis to quantify the behavior patterns of group-housed pigs, providing technical support for the intelligent monitoring and management of their behavior. The ViTAM-SlowFast network is proposed to recognize the behaviors of group-housed pigs and the experimental results demonstrate the effectiveness of the proposed model in pig behavior recognition. The proposed model achieves a mAP value of 92.68 %. The AP values for eating, exploring, lying, moving, and standing behavior are 96.34 %, 92.42 %, 99.56 %, 88.52 %, and 86.57 %, respectively, outperforming existing behavior detection methods. Nevertheless, the model remains prone to misclassification when occlusion occurs among pigs. In the future, advanced occlusion-robust techniques will be integrated to enhance the robustness of the proposed method. Furthermore, based on the behavior recognition results, this study introduces a statistical analysis-based approach to quantify the behavior patterns of group-housed pigs and visualizes these patterns to explore the regularities in their behavior. The visualization of pig behavior patterns not only enables farmers monitor daily eating duration and the activity level during eating and resting periods more efficiently and intuitively, but also provides valuable insights into the behavior patterns of healthy pigs. This serves as an important reference for detecting abnormal health conditions by monitoring changes in the behavior patterns of group-housed pigs. Further exploration will be conducted to investigate the similarities and differences in behavior patterns across different growth stages of pigs, as well as the characteristics of abnormal behaviors. This will provide a deeper understanding of pig behavior across various physiological states and expand the practical applicability of this study in real farming environments.

7. Animal ethical welfare statement

All of the animal experiments in this study were conducted in compliance with a protocol reviewed and approved by the Institutional Animal Care and Use Committee at South China Agricultural University.

CRediT authorship contribution statement

Jiyan Wu: Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Qiumei Yang:** Writing – original draft, Validation, Supervision, Investigation, Data curation, Conceptualization. **Deqin Xiao:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Manting Wu:** Writing – review & editing, Methodology, Conceptualization. **Zezhong Chen:** Project administration, Conceptualization. **Qiwei Hong:** Validation, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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基于 IFSSD 卷积神经网络的柚子采摘目标检测模型

肖德琴[1]　蔡家豪[1]　林思聪[1]　杨秋妹[1]　谢晓君[2]　郭婉怡[1]
(1. 华南农业大学数学与信息学院，广州 510642；2. 广州中医药大学医学信息工程学院，广州 510006)

摘要： 为了解决柚子采摘时传统水果检测模型对于小目标柚子漏检和将叶子误检为膨大期柚子的问题，设计了一种改进的特征融合单镜头检测器(InceptionV3-feature fusion single shot-multibox detector，IFSSD)。该检测器以特征融合单发多盒探测器(Feature fusion single shot-multibox detector，FSSD)为基础检测器，以改进的 InceptionV3 网络作为骨干网络代替超深度卷积神经网络(Very deep convolutional networks 16，VGG16)，从而提高了计算效率，同时使用 Focal Loss 损失函数代替 Multibox Loss 损失函数，进而改善了由于正负样本不平衡导致的检测器误检情况。对测试数据集进行检测，结果表明，该模型的检测准确率为 93.7%(IoU 大于 0.5)，在单个 NVIDIA RTX 2060 GPU 上每幅图像检测时间为 29 s。本文模型可以实现树上柚子的自动检测。

关键词： 柚子；采摘；实时检测；深度学习；特征融合；改进的特征融合单镜头检测器
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Grapefruit Detection Model Based on IFSSD Convolution Network

XIAO Deqin[1]　CAI Jiahao[1]　LIN Sicong[1]　YANG Qiumei[1]　XIE Xiaojun[2]　GUO Wanyi[1]
(1. *College of Mathematics and Informatics*, *South China Agricultural University*, *Guangzhou* 510642, *China*
2. *School of Medical Information Engineering*, *Guangzhou University of Chinese Medicine*, *Guangzhou* 510006, *China*)

Abstract: The detection, identification and precise positioning of fruit under natural conditions based on machine vision is very important for the development of intelligent picking robots. In order to solve the problem that the traditional fruit detection model for the small target grapefruit missed detection and the leaf was falsely detected as the expansion period grapefruit, an improved feature fusion single multibox detector (InceptionV3-feature fusion single shot-multibox detector, IFSSD) was designed. The feature fusion single multibox detector (feature fusion single shot-multibox detector, FSSD) was used as a base detector and optimized in two ways. On the one hand, the improved InceptionV3 network was used instead of very deep convolutional networks 16 (VGG16) as the backbone network to improve computational efficiency. On the other hand, the Focal Loss function was used instead of the Multibox Loss function, which improved the mischeck ingresss of the detector due to the imbalance of positive and negative samples. Finally, the test data set was verified, and the results showed that the model achieved an average accuracy of 93.7% (mAP) (IoU was greater than 0.5). The time of one image was 29 s. The model proposed can automatically detect the grapefruit in the grapefruit tree and locate it accurately in real time, which effectively promoted the development of intelligent picking robot.

Key words: grapefruit; picking; real-time detection; deep learning; feature fusion; IFSSD

0　引言

我国是柚子种植面积最大的国家，柚子产量仅次于美国，位于世界第二位[1]。自 2000 年以来，我国柚类产品得到国际市场的认可，柚类出口量急剧增长，具有巨大的发展前景。在柚子的生产过程中，

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作者简介： 肖德琴(1970—)，女，教授，博士生导师，主要从事物联网和农业图像视频处理研究，E-mail：deqinx@scau.edu.cn
通信作者： 杨秋妹(1983—)，女，讲师，博士，主要从事农业图像视频处理研究，E-mail：yqmbegonia@163.com

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采摘是最耗时费力的过程,后续的存储和加工过程直接取决于采摘效果,所以保证柚子采摘质量成为关键环节。目前,国内的水果采摘主要是由人工完成,工作强度大,且效率低下[2]。有研究表明,用于采摘过程的费用占生产总费用的 50% ~70%。随着水果的大面积种植,传统的人工采摘方式已经不能满足生产需求,研究水果采摘机械化意义重大[3]。

在自然环境下,快速、准确识别与定位柚子是实现柚子自动化采摘的重点研究方向之一,因此,研究者提出一系列水果检测识别方法[4-6]。深度学习在农业领域取得了显著的进展[7-9]。在传统方法中,柚子的颜色、形状以及纹理特征因受自然环境的影响而产生变化,所以很难对柚子进行有效的描述,从而对算法的泛化性产生了极大影响。基于深度学习的方法可以通过学习训练数据的特征来提供准确的结果。深度学习方法已被用于农业研究的各个领域,如 FERENTINOS[10] 使用卷积神经网络对健康和患病植物的简单叶片图像进行植物疾病检测和诊断。彭红星等[11] 使用 Res101 结合 SSD 构建了深度水果检测模型,对自然条件下的多种水果进行检测识别。然而小目标柚子在图像视野中占比较少,边缘特征不明显,甚至缺失,由于分辨率和信息有限,使得传统基于深度学习的柚子检测算法效果并不理想[12]。同时,常见的目标检测算法是根据重叠度(Intersection over Union,IoU)阈值,从先验框中挑选 IoU 小于 0.7 和 IoU 大于等于 0.7 的先验框分别作为正负样本,进行分类网络的训练。然而包含叶子背景的柚子负样本远远大于正样本,导致样本不平衡,使柚子检测模型存在很严重的偏向性。

为此,本文提出一种基于 IFSSD 卷积网络的柚子检测模型,对膨大期、成熟期两个阶段的柚子进行检测试验。

1　材料与方法

1.1　试验数据的获取

试验中的柚子图像于 2018 年 4 月 1 日—10 月 10 日在广东省梅州市的顺兴果园获得。果园中共种植柚子树 1 500 余棵,柚子树随机分布。选用海康威视 DS-2CD3T56WD-I3 型摄像头进行拍摄,将 4 个摄像头固定在离地面 3 m 的支架上,摄像头分别向正北、正东、正西、正南 4 个方向。支架之间的距离为 60 m,共 9 个支架。试验设备和现场图如图 1 所示。拍摄图像的尺寸为 1 920 像素 ×1 080 像素,JPG 格式。于每天 09:00—17:00 每隔 1 h 拍摄一次图像,其中包含了晴天正午、晴天傍晚以及阴天正午等特殊光照条件,共获得了 5 000 幅图像。其中图像中存在枝叶遮挡和果实互相遮挡的图像数量分别为3 563 幅和 2 469 幅。



图 1　试验设备和现场图

Fig. 1　Photos of experimental equipment and site

1.2　柚子检测数据集的构建

在 5 000 幅柚子树图像中利用随机抽取的方式选择 4 000 幅图像,使用 Labelme 软件进行标记作为训练集,其他图像作为测试集。

图 2 为训练集的样本预处理过程,通过对图像分别进行翻转、平移和裁剪来扩充数据集。



图 2　图像预处理

Fig. 2　Image preprocessing

在柚子训练集中,柚子分为膨大期果实和成熟期果实,如图 3 所示,膨大期果实和成熟期果实在颜



图 3　膨大期和成熟期柚子果实

Fig. 3　Grapefruit fruit during expansion and maturity

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色上有明显的区分。

1.3 基于深度学习的柚子检测算法

1.3.1 InceptionV3 网络

InceptionV3 是 Google Inception 系列网络中的一种，该网络在 InceptionV2 的基础上提出了一种新的结构，网中网(Network in network，NIN)结构[13]。InceptionV3 是 Inception 模块按照 NIN 结构构建的一种新型网络。InceptionV3 的 Inception 模块如图 4 所示。

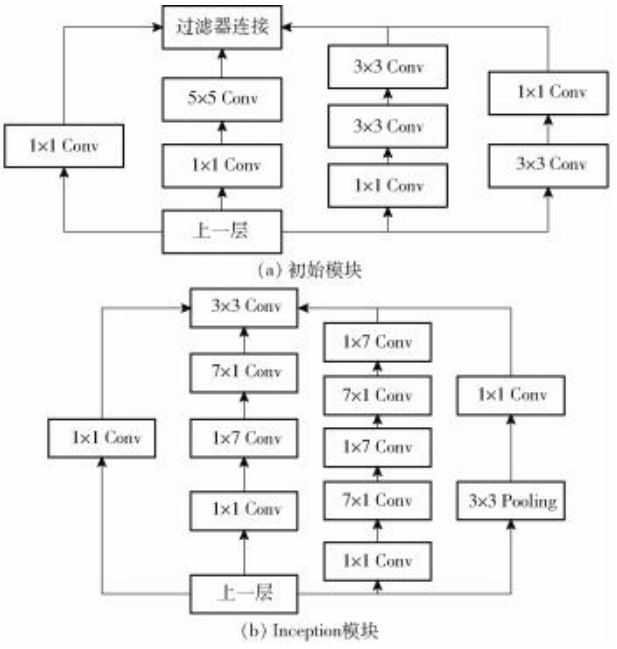


图 4 InceptionV3 的 Inception 模块结构

Fig. 4 Structure of InceptionV3 Inception module

如图 4 所示，InceptionV3 模块通过提取不同尺度的特征来减少模型的参数数量[14]，同时多尺度特征可以提高模型的识别能力。研究证明，卷积核为 1×1 的卷积层可以通过少量的计算实现特征的转换、提高网络的识别能力以及改变卷积模块输出的通道数[15]。InceptionV3 的第 5～9 Inception 模块使用更大的卷积核来获取更加抽象的特征。针对于卷积核为 7×7 且容易产生大量参数的卷积层，InceptionV3 使用 1×7 卷积层和 7×1 卷积层，从而提高算法的效率并降低过拟合的风险。试验证明，这种不对称卷积结构可以处理越来越丰富的空间特征并增加特征多样性。

1.3.2 SSD 与 FSSD

InceptionV3 网络模型主要是对柚子的成熟情况进行分类，存在一个局限条件就是每幅图像中只能有一个柚子，柚子占据图像的面积要尽量大。为了解决这个问题，许多目标检测方法被提出，例如使用颜色和纹理特征来检测水果。由于柚子等水果是簇状结果，因此在柚子检测过程当中容易发生重叠和误检的情况，使得检测精度大大降低。

目前有许多用于目标检测的深度学习方法被广泛应用于农业领域，如借助区域提议网络实时目标检测算法(Towards real-time object detection with region proposal networks，Faster-RCNN)[16]、通过基于区域的全卷积网络目标检测算法(Object detection via region-based fully convolutional networks，R-FCN)[17]、单镜头多盒探测器算法(Single shot multibox detector，SSD)[18]、YOLO 算法(You only look once，YOLO)[19]以及 RetinaNet[20]等。此外，柚子检测对于算法的实时性能和小物体检测有着更高的要求，所以需要在保证精度符合要求的情况下尽量选择效率更高并且对小物体检测更有效的算法。

SSD 是一种在图像中使用同一个深度神经网络进行检测和识别检测目标的算法。SSD 生成一系列尺寸不同的候选框，通过计算标注框与候选框的偏置值来匹配两者，一般每个标注框都会匹配多个候选框。SSD 将 IoU 大于 0.5 的候选框认为是正样本，其他设置为负样本[21]。

SSD 使用 VGG16 作为骨干网络[22]，通过在 Conv4_3、FC7、Conv7_2、Conv6_2、Conv8_2 和 pool6 中提取不同尺寸的特征图来形成多尺度检测，SSD 的网络结构图如图 5a 所示。其中特征图尺寸为 5 像素×5 像素、3 像素×3 像素和 1 像素×1 像素，低级特征图有利于小目标的检测，特征图尺寸为 38 像素×38 像素、19 像素×19 像素和 10 像素×10 像素的高级特征图则有利于大目标检测。SSD 使用通道数为 1 024 的 3×3 卷积层和 1×1 卷积层代替全连接层和丢失层，从而达到减少模型参数、提高计算效率以及有效防止过度拟合的目的。SSD 的损失函数为

$$L(x,c,l,g)=\frac{1}{N}(L_{conf}(x,c)+\alpha L_{loc}(x,l,g)) \quad (1)$$

式中 $L(x,c,l,g)$——总体损失值

x——卷积特征值　　c——真实类别

l——预测框的位置坐标值

g——真实框的位置坐标值

L_{loc}——预测框和真实框间的平滑损失值

N——候选框的数量

L_{conf}——多类置信度下的 softmax 损失值

α——L_{loc}的权重

Multibox Loss 由两部分组成，前者使用了 softmax 进行分类损失计算，后者通过局部损失来预测位置。

SSD 为柚子检测任务提供了坚实的基础，其主要优点是检测速度快。然而，试验表明，SSD 存在以

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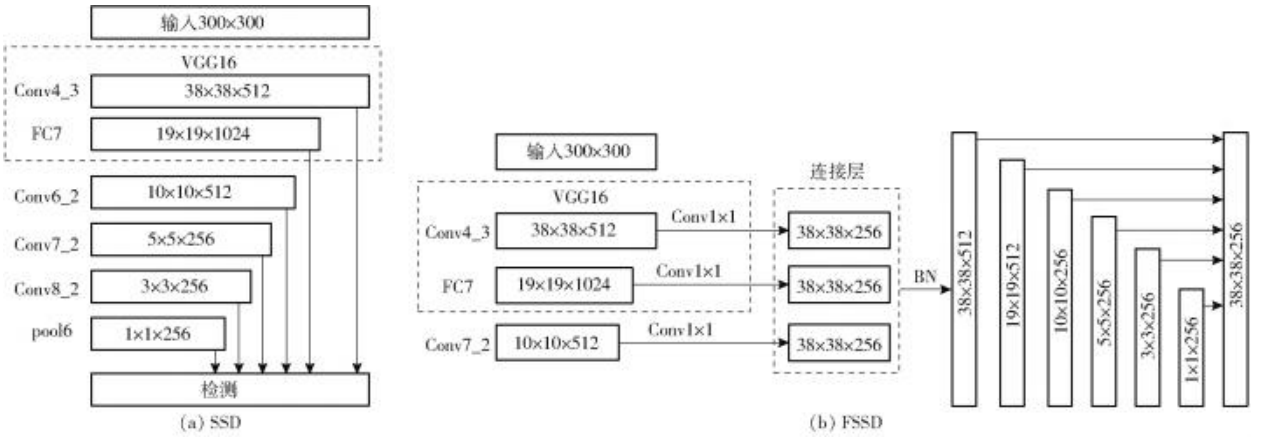


图 5　SSD 和 FSSD 模型的结构

Fig. 5　Model structure of SSD and FSSD

下问题: 较小的目标难以识别; 一些背景区域被识别为目标对象; 重复识别目标。为了解决这些问题, SSD 模型被修改为 FSSD 模型且不增加模型参数的数量,并降低检测速度。

FSSD 模型的提出者认为 SSD 模型中用于预测的每个层之间的关系是相互独立的[23]。FSSD 模型是将这些层与不同比例的特征图进行融合[24],以便它们相互通信并提高准确性。但是,这种方法不适合在 FSSD 模型中融合小于 10 × 10 的特征映射,因为几乎没有要合并的信息。合并 3 个较大层的特征图以生成 38 像素 × 38 像素的特征图,并生成特征金字塔网络(Feature pyramid networks,FPN)[25]。最后,FSSD 模型从 FPN 中提取特征。

FSSD 模型的结构如图 5b 所示。FSSD 模型以 VGG16 作为主要骨干网络。Conv7_2 的特征映射变为 10 × 10。FC7 和 Conv7_2 使用双线性插值将特征图尺寸调整为 38 像素 × 38 像素,然后将它们与 Conv4_3 连接,在该步骤中,合并层的通道数为 768 (256 + 256 + 256) 。然后 BN 作用于合并层,该层的通道数减小到 512。另外使用 5 个卷积层来减小特征图的尺寸。最后,获得 6 种不同尺寸特征图(38 像素 × 38 像素、19 像素 × 19 像素、10 像素 × 10 像素、5 像素 × 5 像素、3 像素 × 3 像素和 1 像素 × 1 像素) ,并将它们用于多尺度预测。这种方法可以将浅层细节特征与高级语义特征相结合,可以比 SSD 模型更好地识别小物体[26],并降低误检率。但 FSSD 模型的速度比 SSD 模型的速度略有下降。

1.3.3　IFSSD 模型建立

在本文中,只需要判断检测目标是否是柚子,并不需要进行多类别分类。柚子的特征相对简单,可以简化模型,所以本文选择 InceptionV3 作为 IFSSD 的骨干网络。IFSSD 模型结构如图 6 所示。

(1) InceptionV3 深度网络优化

为了减少参数数量和提高对小目标的检测效果,本文对 InceptionV3 进行了调整,以实现检测器基于不同感受野的多尺度检测。本文对 mixed7 层进行了删除。IFSSD 模型在 mixed6 层之后添加 1 × 1 卷积,步长为 2,通道数为 768,然后进行批量归一化。新添加的图层 mixed6_s 的特征图尺寸为 18 像素 × 18 像素。mixed7 层的特征图尺寸从原来的 35 像素 × 35 像素变成 18 像素 × 18 像素。在 mixed7 之后加入卷积核为 1 × 1、步长为 2、通道数为 768 的卷积层。mixed7 _s 的特征图尺寸为 9 像素 × 9 像素。图 6 中改进后的网络结构用黄色方框表示。

IFSSD 模型与 FSSD 模型类似,都对较大的特征图进行合并。在 IFSSD 模型的 InceptionV3 中,分别

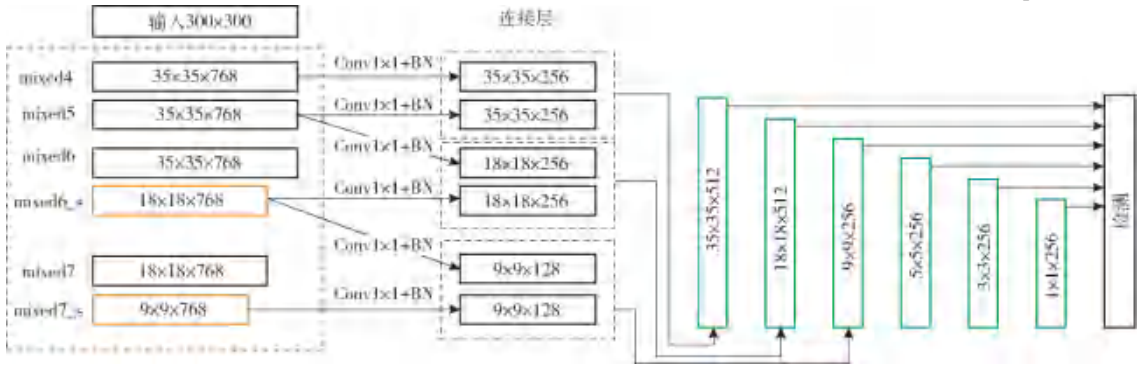


图 6　基于 IFSSD 的柚子检测模型结构

Fig. 6　IFFSD-based grapefruit detection model structure

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选择特征图尺寸各不相同的 4 层模块，分别是 mixed4、mixed5、mixed6_s、mixed7_s。在第 1 个连接层中，卷积核为 1 × 1、步长 1、通道数为 256 的卷积层被应用于 mixed4 和 mixed5。这样做的目的是在不改变特征图尺寸的前提下减小模型参数，从而减少模型中的参数数量并增加增强模型的非线性识别能力。卷积后生成的特征图尺寸为 35 像素 × 35 像素，然后将 mixed4 和 mixed5 卷积生成的特征图合并到一起。在第 2 个连接层中，在 mixed5 模块之后添加一层卷积核为 1 × 1、步长为 2、通道数为 256 的卷积层，其生成的特征图尺寸为 18 像素 × 18 像素。在 mixed6_s 之后添加一个卷积核为 1 × 1、步长为 1、通道数为 256 的卷积层。其生成的特征图尺寸为 18 像素 × 18 像素。然后，对两个特征图进行合并。在第 3 个连接层中，一个卷积核为 1 × 1、步长为 2、通道数为 128 的卷积层被添加到 mixed6_s 之后，生成了 9 × 9 × 128 的特征图。最后卷积核为 1 × 1、步长为 1、通道数为 128 的卷积层被添加到 mixed7_s 之后，其生成了 9 × 9 × 128 的特征图，并将两个特征图进行合并。

在 IFSSD 模型中，35 × 35 × 512、18 × 18 × 512 和 9 × 9 × 256 的连接层用于生成 FPN。在 9 × 9 × 256 的连接层之后添加一个卷积核为 3 × 3、步长为 2、通道数为 256 的 SAME 卷积层，生成特征图尺寸为 5 像素 × 5 像素。其后，添加一个卷积核为 3 × 3、步长为 1 × 1、通道数为 256 以及使用 VALID 的卷积层，生成特征图尺寸为 3 像素 × 3 像素。最后，在 3 × 3 × 256 层之后，添加一个卷积核为 3 × 3、步长为 1、通道数为 256 的 VALID 卷积层，生成的特征图尺寸为 1 像素 × 1 像素。图中绿色方框所示的 6 层不同尺度的预测框用于获得柚子的位置和置信度。

可以看出，FSSD 模型使用双线性插值从 VGG16 中 3 个不同层获得相同的尺寸，并将它们融合在一起以获得输出层并生成 FPN。IFSSD 模型使用 1 × 1 卷积来修改 InceptionV3 中的 mixed4、mixed5、mixed6_s、mixed7_s 层的通道数和图像尺寸，并且成对地融合上述修改后的卷积层以获得 3 个不同层，然后基于这 3 个层生成 FPN。

(2) 损失函数优化

一阶段算法(one-stage)和二阶段算法(two-stage)的表现不同主要是由大量前景背景类别不平衡导致[27]。二阶段算法中，在候选框阶段，通过得分和非极大值抑制(Non-maximum suppression，NMS)筛选过滤掉了大量的负样本，然后在分类回归阶段又固定了正负样本比例，或者通过难例挖掘(OHEM)在线挖掘困难样本使得前景和背景相对平衡。而一阶段算法需要产生约 100 kB 的候选位置。虽然有重复采样，但是训练仍然被大量负样本所主导。本文使用的 IFSSD 模型属于 one-stage 模型，使用 Focal Loss 代替原有的损失函数。

Focal Loss 主要是为了解决 one-stage 目标检测中正负样本比例严重失衡的问题[28]。该损失函数降低了大量简单负样本在训练中所占的权重，也可理解为一种困难样本挖掘。Focal Loss 是在交叉熵损失函数基础上进行的修改。二分类交叉熵损失值计算式为

$$L=\begin{cases}-\lg y' & (y=1)\\ -\lg(1-y') & (y=0)\end{cases} \tag{2}$$

式中 L——二分类交叉熵的损失值

y——真实分类 y'——预测分类

y'是激活函数的输出，取值在 0 ~ 1 之间。可见普通的交叉熵对于正样本而言，输出概率越大损失越小；对于负样本而言，输出概率越小则损失越小。此时的损失函数在大量简单样本的迭代过程中比较缓慢且可能无法优化至最优。

Focal Loss 在原有基础上加了一个常数因子 γ，以减少易分类样本的损失，从而更关注于困难的、错分的样本。此外，加入平衡因子 a_t，用来平衡正负样本本身的比例不均，具体公式如下

$$F_L(p_i)=-a_t(1-p_i)^{\gamma}\lg p_i \tag{3}$$

式中 p_i——不同类别的概率

a_t——正样本和负样本的比例，前景类别使用 a_t 时，对应的背景类别使用 $1-a_t$

2 试验与结果分析

2.1 试验方法与参数设置

柚子数据集中包含一定量果实膨大期和成熟期的图像。训练集和验证集以 4∶1 的比例进行随机划分。其中训练集包含 4 000 幅图像，使用 Labelme 标注软件对每幅图像中成熟期和果实膨大期的柚子进行标注，最后按照 PASCAL VOC 数据格式[29]构建训练集，另外 1 000 幅未被标注图像作为测试集，用来评价模型在未知柚子图像数据集上的泛化性能。

为了评估 IFSSD 模型对柚子的检测识别性能，首先通过预处理的 4 000 幅 RGB 图像创建 IFSSD 模型。剩余的 1 000 幅测试图像用于 IFSSD 模型的测试。测试环境为 IntelXeon E3 - 1245 v3 CPU、主频 3.40 GHz、内存 32 GB，GPU 为 GeForce RTX 2060、操作系统为 Ubuntu 16.04，Cuda 版本为 9.0，Keras 深度学习框架，OpenCV 4.0、Python3.7 编程语言。

IFSSD 模型使用自适应矩估计(Adaptive moment estimation)作为优化算法，同时以 TensorFlow 作为张量操作库的 Keras 深度学习框架

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在 GeForce RTX2060 显卡上进行加速运算。

本文模型设置不同参数,通过交叉验证选取最优参数设置,初始学习率设置为 0.001,经过多次迭代后微调为 10^{-4},偏差 1 设置为 0.9,偏差 2 设置为 0.999,归一化的最小值边界设置为 0.000 1,权重衰变为 5×10^{-4},图像批量为 16。

本文模型对 300 像素 ×300 像素图像的检测速率为 29 f/s,训练过程中损失值变化曲线如图 7 所示,随着迭代次数增加,IFFSD 模型的损失值不断下降,经过 100 次迭代后,下降趋势趋向于平缓,并在 200 次迭代后趋于稳定。

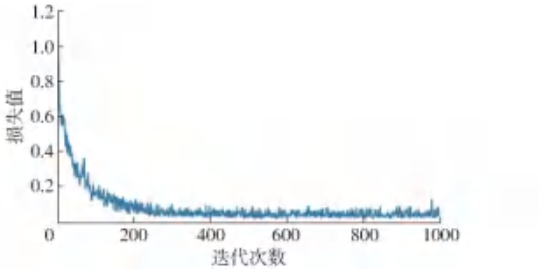


图 7　IFSSD 模型训练过程中损失值的变化曲线

Fig. 7　Change of loss value during IFSSD training

2.2　检测结果分析

本文使用 IFSSD、SSD、FSSD 模型分别对数据集进行检测。表 1 为检测结果,其中检测出来的目标定为正样本,未检测出来的目标定为负样本。IoU 阈值为 0.5,试验结果有 4 种,分别为 IoU 值小于等于 0.5(FP)、IoU 值大于 0.5(TP)、未检测出真实目标 FN、TN。本文不统计 TN 类样本。准确率计算公式为

$$P=\frac{T_P}{T_P+F_P}\times100\% \tag{4}$$

式中　T_P——检测出的正样本数量

F_P——检测出的负样本数量

表 1　不同检测模型的检测结果

Tab. 1　Detection results of different detection models

模型	准确率/%	模型规模/MB	每幅图像检测时间/s
SSD	84.3	28.2	38
FSSD	91.5	28.2	41
IFSSD	93.7	19.7	29

在检测精度方面,IFSSD 模型的准确率为 93.7%,分别比 SSD 模型和 FSSD 模型提高了 9.4 个百分点和 2.2 个百分点。在图像检测速率方面,IFSSD 模型每幅图像检测时间为 29 s,低于 SSD 模型的 38 s 和 FSSD 模型的 41 s。

如表 2 所示,IFSSD 模型的准确率比梯度直方图(Histogram of oriented gradient, HOG) + 支持向量机(Support vector machine, SVM) 和变形零件模型(Deformable parts model, DPM) + SVM 提高了 14.1 个百分点和 16.4 个百分点,这是由于传统目标检测算法只适用于特征明显、背景简单的图像,而在实际应用中,背景复杂多变,且待检测的目标复杂多变,很难通过一般的抽象特征完成对目标的检测,而深度学习可以提取同一目标的丰富特征,完成目标的检测。然而在模型规模上 IFSSD 模型要大于 HOG + SVM 和 DPM + SVM,这是由于 IFSSD 模型的参数较多。从效率方面看,IFSSD 模型的效率与传统方法较接近。

表 2　IFSSD 与传统检测模型性能的比较

Tab. 2　Comparison of IFSSD and traditional grapefruit detection models

模型	准确率/%	模型规模/MB	每幅图像检测时间/s
IFSSD	93.7	19.7	29
HOG + SVM	79.6	3.0	27
DPM + SVM	77.3	2.5	31
Faster R-CNN	85.9	52.0	30
YOLOv2 - DarkNet - 19	84.3	23.5	21

相对于 Faster R-CNN 和 YOLOv2 - DarkNet - 19,由于 IFSSD 模型加入了 FPN 结构和 Inception 骨干网络,使得准确率分别提高了 7.8 个百分点和 9.4 个百分点;从检测时间看,IFSSD 模型与 Faster R-CNN 模型较接近。

本文分别从目标大小、物候期、重叠情况、光照情况以及有无枝叶遮挡等方面分别对 SSD、FSSD、IFSSD 模型进行比较。从表 3 可以看出,IFSSD 模型的总体性能优于 FSSD、SSD 模型。从目标大小方面看,加入了 FPN 模块的 FSSD、IFSSD 模型在小目标检测方面有了一定的提升,这是由于 FPN 能够从更

表 3　不同图像类型下不同模型的检测准确率

Tab. 3　Detection accuvaey of different models under different image types　%

图像类型	SSD	FSSD	IFSSD
小目标	79.63	85.15	86.68
中目标	85.64	86.24	89.53
大目标	92.12	92.14	94.16
膨胀期	85.42	86.12	90.63
成熟期	89.63	91.18	92.78
相互重叠	77.14	79.36	83.14
无重叠	90.88	91.24	93.26
强光	86.11	86.26	88.66
弱光	85.31	87.22	89.67
正常光	92.11	92.65	94.68
有枝叶遮挡	88.12	88.21	89.74
无枝叶遮挡	90.41	93.12	96.88

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小的特征跨度进行特征融合，来进行多尺度预测。从不同物候期方面进行分析，IFSSD 模型对膨胀期的识别提升较为明显，相对于 SSD、FSSD 模型分别提高了 5.21 个百分点和 4.51 个百分点，这是由于膨胀期的柚子颜色为绿色，容易因正负样本不平衡而导致错检和漏检，Focal Loss 的引入缓解了这个问题。但是在重叠、光照和有枝叶遮挡的情况下，IFSSD 模型检测效果没有明显的提高，仍然需要进一步优化。由于摄像机型号不同，不同的焦距和距离导致柚子图像的尺寸不同，本文采用将摄像头固定并通过调整焦距来获得小目标、中目标和大目标 3 种类型的图像。图 8 是使用以上 3 种模型对部分图像处理的效果。从图中可以看出，对于中型和大型目标，3 种模型都能检测到大部分的目标。对于大型目标，3 种模型的准确率均达到 92% 以上。但是对于极小的目标，SSD 模型效果要比 IFSSD 模型和 FSSD 模型差，SSD 模型容易漏检大部分小目标柚子。这是由于 SSD 模型虽然从不同层次的特征进行预测，ConvNets 提取的特征随着层次的增加语义越来越强，但是 SSD 模型却把它们当成一样的层次去预测，不能充分地利用局部细节特征和全局语义特征。FSSD 模型采用 FPN 方法把细节特征(定位)和全局语义(识别)结合起来，即把浅层的细节特征和高层的语义特征结合起来，因此 IFSSD、FSSD 模型在小目标检测方面得到了进一步的提升。



图 8 3 种模型对图像的处理效果

Fig. 8 Processing effect of three models on images

进一步通过试验来分析 IFSSD 模型在数据不平衡下对柚子检测效果的改进。

如图 9 所示，对于成熟期的柚子而言，IFSSD、FSSD、SSD 模型都具有较精确的检测效果。这是由于成熟期的柚子是黄色的，相对于背景和果实膨大期的柚子有着明显的颜色区别。但是 SSD 模型和 FSSD 模型会将某些叶片检测为果实膨大期的柚子，这是因为叶子与果实膨大期的柚子的颜色相似，同时在数据不平衡的情况下，以叶子为主的背景样本明显要多于果实膨大期的柚子样本，这会造成模型对于果实膨大期柚子的识别效果较差，同时在光线等自然条件的影响下，容易将成簇的叶子错认为是处于膨大期的果实。



图 9 柚子识别检测结果示例

Fig. 9 Examples of grapefruit identification results

图 10 为 SSD、FSSD 模型将绿色叶子错误检测为膨大期柚子的情况，而 IFSSD 模型能够极大地避免此类情况的发生，这表明 Focal Loss 损失函数的引入能够改善数据不平衡带来的影响，从而提高柚子的检测精度。



图 10 膨大期柚子漏检示例

Fig. 10 Examples of expanded leaves misidentified as grapefruit

3 结束语

本文设计了一种改进的特征融合单镜头检测器

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(IFSSD),提出了基于 IFSSD 卷积神经网络的柚子检测模型,并对所提模型进行检测试验。结果表明,本文模型对柚子检测的准确率达到 93.7%,每幅图像的检测时间为 29 s。

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广东省农业技术推广奖

获奖证书

为表彰在农业技术推广工作中做出贡献的单位和个人，特颁发此证书，以资鼓励。

获奖项目：生猪生理生长信息感知装备研究与推广

奖励等级：一等奖

奖励个人：杨秋妹

奖励日期：2023年12月21日

证 书 号：2022-1-N02-R02

广东省农业技术推广奖
评审委员会

广东省农业技术推广奖

获奖证书

为表彰在农业技术推广工作中做出贡献的单位和个人，特颁发此证书，以资鼓励。

获奖项目：实蝇害虫快速监测系统应用及推广

奖励等级：二等奖

奖励单位：杨秋妹

奖励日期：2017 年 10 月 31 日

证 书 号：2016-2-Z16-R07

广东省农业技术推广奖

评审委员会

证书号第7779213号

专利公告信息

发明专利证书

发 明 名 称：一种母猪发情监控方法及系统

专 利 权 人：华南农业大学

地　　址：510640 广东省广州市天河区五山

发　明　人：杨秋妹;吴曼婷;肖德琴;陈泽中;吴纪沿;惠向阳;黄森鹏

专　利　号：ZL 2024 1 0408276.7　　授权公告号：CN 118097560 B

专利申请日：2024年04月07日　　授权公告日：2025年03月07日

申请日时申请人：华南农业大学

申请日时发明人：杨秋妹;吴曼婷;肖德琴;陈泽中;吴纪沿;惠向阳;黄森鹏

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局长

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国家知识产权局

2025年03月07日

证书号第7806379号

专利公告信息

发明专利证书

发 明 名 称：基于环境特征和猪只行为特征的养殖环境调控方法及系统

专 利 权 人：华南农业大学

地　　址：510640 广东省广州市天河区五山

发　明　人：杨秋妹;吴纪沿;肖德琴;吴曼婷;陈泽中;惠向阳;黄森鹏

专　利　号：ZL 2024 1 0387002.4　　授权公告号：CN 118192717 B

专利申请日：2024年04月01日　　授权公告日：2025年03月18日

申请日时申请人：华南农业大学

申请日时发明人：杨秋妹;吴纪沿;肖德琴;吴曼婷;陈泽中;惠向阳;黄森鹏

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国家知识产权局
2025年03月18日

证书号第8453175号

专利公告信息

发明专利证书

发 明 名 称：一种基于关键点骨架和运动轨迹的猪只跛脚分级方法及系统

专 利 权 人：华南农业大学

地　　址：510642 广东省广州市天河区五山路483号

发　明　人：杨秋妹;黄森鹏;肖德琴;陈淼彬;黄一桂;惠向阳;张彬

专　利　号：ZL 2023 1 0754818.1　　授权公告号：CN 116824448 B

专利申请日：2023年06月25日　　授权公告日：2025年11月07日

申请日时申请人：华南农业大学

申请日时发明人：杨秋妹;黄森鹏;肖德琴;陈淼彬;黄一桂;惠向阳;张彬

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国家知识产权局

2025年11月07日

证书号第7974195号

专利公告信息

发明专利证书

发明名称：一种猪只异常行为检测方法

专利权人：华南农业大学

地　　址：510642 广东省广州市天河区五山路483号

发 明 人：杨秋妹;陈淼彬;肖德琴;刘啸虎;康俊琪;黄一桂;周家鑫
刘克坚

专　利　号：ZL 2022 1 0934696.X　　授权公告号：CN 115359511 B

专利申请日：2022年08月04日　　授权公告日：2025年05月30日

申请日时申请人：华南农业大学

申请日时发明人：杨秋妹;陈淼彬;肖德琴;刘啸虎;康俊琪;黄一桂;周家鑫
刘克坚

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国家知识产权局
2025年05月30日

农业农村部办公厅文件

农办科〔2022〕1号

农业农村部办公厅关于加强农业农村部学科群重点实验室建设的通知

各有关单位：

农业农村部学科群重点实验室作为国家农业科技创新体系的重要组成部分，经过多年的建设发展，已经成为支撑农业高质量发展、乡村全面振兴的重要战略科技力量。2021年，我部在高效育种、耕地保育、智能装备、绿色生产等领域遴选新增一批重点实验室，学科群体系进一步优化，重点实验室力量进一步增强。根据新形势新要求，为进一步加强农业农村部学科群重点实验室体系建设，有关事项通知如下。

一、加强学科群管理

一是优化提升学科群。按照改造改组、优化提升的总体思路，

在“十三五”建设基础上，新增1个学科群、更名4个学科群、合并4个学科群，形成34个学科群的农业农村部学科群重点实验室体系（具体名单见附件1）。综合性重点实验室要发挥好群主单位作用，组织好学科群年会，积极开展学术交流，做好各重点实验室的年度考核。

二是调整科学观测实验站。科学观测实验站不再列入学科群体系，将符合条件的科学观测实验站逐步纳入国家农业科学观测实验站体系。

三是制定建设任务书。综合性重点实验室牵头各重点实验室，强调聚焦重点，坚持服务产业，紧紧围绕支撑乡村全面振兴和农业高质量发展，梳理出2—3项重点突破的攻关任务，研究制定本学科群“十四五”建设任务书（格式见附件2）。

二、加强实验室管理

一是明确实验室主任。因年龄、人事调整等原因，部分重点实验室主任发生变化，2021年又遴选新增了一批重点实验室。请各重点实验室按照《农业农村部重点实验室管理办法》要求上报实验室主任，优先推荐45周岁以下的中青年优秀人才担任实验室主任（具体要求见附件3）。

二是强化任务牵引。每个重点实验室围绕服务产业发展，聚焦2—3个基础理论或前沿技术问题，基础理论研究要着力抢占科技制高点，前沿技术攻关要强化支撑引领产业发展，制定本实验室“十四五”任务书（格式见附件4）。联合共建实验室的牵头单位要强化主体作用，组织共建单位确定研究方向、研究任务，牵头制定

实验室“十四五”任务书，确保围绕主责主业开展创新，集中发力、重点突破。

三是加强规范化建设。各重点实验室根据《农业农村部重点实验室管理办法》，制定实验室章程，制作规范标牌（样式见附件5），及时通过管理系统报送信息，提高规范化建设水平。

三、加强运行管理

一是加强开放共享。加快推动重点实验室间科研设施、仪器设备、科学数据等开放共享，并将开放共享情况列入年度考核任务。

二是加强考核管理。探索实行目标考核和绩效考核新方式，对重点实验室依托单位实施末位淘汰。

三是加强联合攻关。强化学科群和重点实验室协同创新，鼓励实验室设立开放课题，共同开展重大科研攻关，形成开放合作的良好氛围。

四是加强成果转化。各学科群和重点实验室要进一步明确成果转化落地的目标任务，把实验室放大到农业农村主战场。可在县域建立技术示范基地或推动技术成果在企业熟化转化，尽快落地应用。

四、其他要求

一是请新增重点实验室及时与主管单位联系，争取重点实验室建设和运行的必要支持。

二是请各重点实验室于2022年2月20日前将重点实验室主任信息表（一式2份）报送至农业农村部科技发展中心。

三是请各学科群、重点实验室于2022年3月31日前将任务书纸质版(一式3份)报送至农业农村部科技发展中心,电子版发送至 kjsgx@ agri. gov. cn。

五、联系方式

(一)农业农村部科技教育司

联 系 人:杨国辉

联系电话:010-59192916

(二)农业农村部科技发展中心

联 系 人:肖茂华

联系电话:010-59199379

地　　址:北京市朝阳区东三环南路96号农丰大厦

邮　　编:100122

附件:1.“十四五”农业农村部学科群重点实验室名单

2.“十四五”农业农村部学科群建设任务书

3.农业农村部学科群重点实验室主任信息表

4.“十四五”农业农村部学科群重点实验室任务书

5.标牌工艺图

中华人民共和国农业农村部办公厅

2022年1月24日

“十四五”农业农村部学科群重点实验室名单

03 农业信息技术学科群			
类别	**序号**	**重点实验室名称**	**依托单位**
综合性重点实验室	1	农业农村部农业信息技术重点实验室	北京市农林科学院
专业性重点实验室	1	农业农村部农业信息获取技术重点实验室	中国农业大学
	2	**农业农村部农业监测预警技术重点实验室（原：农业农村部农业信息服务技术重点实验室）**	中国农业科学院农业信息研究所
	3	农业农村部农业信息软硬件产品质量检测重点实验室	北京市智能装备技术研究中心
	4	农业农村部光谱检测重点实验室	浙江大学
	5	农业农村部农作物系统分析与决策重点实验室	南京农业大学
	6	农业农村部农产品信息溯源重点实验室	浙江省农业科学院
	7	农业农村部渔业信息重点实验室	上海海洋大学
	8	农业农村部农业物联网重点实验室	西北农林科技大学
	9	农业农村部农业大数据重点实验室	中国农业科学院农业信息研究所
	10	农业农村部农业信息化标准化重点实验室	中国农业大学
	11	**农业农村部区块链农业应用重点实验室（试运行）**	中国农业科学院农业信息研究所
	12	**农业农村部智慧养殖技术重点实验室（试运行）**	中国农业大学 华中农业大学
	13	**农业农村部农业传感器重点实验室（试运行）**	安徽农业大学 北京市农林科学院智能装备技术研究中心
	14	**农业农村部数字乡村技术重点实验室（试运行）**	北京市农林科学院信息技术研究中心
	15	**农业农村部黄淮海智慧农业技术重点实验室（试运行）**	山东农业大学 河南省农业科学院农业经济与信息研究所
	16	**农业农村部东北智慧农业技术重点实验室（试运行）**	东北农业大学

类别	序号	重点实验室名称	依托单位
专业性重点实验室	17	**农业农村部华南热带智慧农业技术重点实验室（试运行）**	华南农业大学
	18	**农业农村部长三角智慧农业技术重点实验室（试运行）**	江苏省农业科学院 上海市农业科学院 上海交通大学 江苏大学
企业重点实验室	1	农业农村部农业物联网系统集成重点实验室	北京派得伟业科技发展有限公司
	2	农业农村部农业物联网技术集成与应用重点实验室	安徽朗坤物联网有限公司
	3	农业农村部农业电子商务重点实验室	中邮（安徽）网络技术有限公司

注：加粗为遴选新增的重点实验室和更名的重点实验室

附件4

“十四五”农业农村部学科群重点实验室
任务书

农业农村部科技教育司　制

2022 年 3 月 23 日

一、基本信息

重点实验室名称	农业农村部华南热带智慧农业技术重点实验室				
所属学科群	农业信息技术学科群				
依托单位	华南农业大学				
重点实验室主任	姓名	出生年月	学历	职务/职称	联系电话
	肖德琴	1970年5月	博士	教授	13794412658
实验室联系人	姓名	出生年月	学历	职务/职称	联系电话
	王春桃	1979年4月	博士	副教授	13760732070
通讯地址	广东省广州市天河区五山路483号华南农业大学数学与信息学院				
	姓名	出生年月	学历	职务/职称	单位
	肖德琴	1970年5月	博士	主任/教授	华南农业大学
	兰玉彬	1961年7月	博士	院长/教授	华南农业大学
	黄琼	1982年9月	博士	院长/教授	华南农业大学
	李震	1981年8月	博士	教授	华南农业大学
	王春桃	1979年4月	博士	副教授	华南农业大学
	韩宇星	1983年8月	博士	教授	华南农业大学
	梁云	1981年6月	博士	教授	华南农业大学
	张哲	1984年3月	博士	教授	华南农业大学
	岳学军	1971年11月	博士	教授	华南农业大学
	龙拥兵	1979年7月	博士	教授	华南农业大学

固定人员名单
（根据实际情况填写）

高立志	1968年6月	博士	教授	华南农业大学
张群洁	1981年3月	博士	副研究员	华南农业大学
张连宽	1976年8月	博士	副教授	华南农业大学
王文策	1982年10月	博士	副教授	华南农业大学
张新珩	1989年3月	博士	副教授	华南农业大学
蔺文成	1987年1月	博士	副教授	华南农业大学
肖克辉	1981年8月	博士	高级实验师	华南农业大学
尹令	1977年12月	博士	副教授	华南农业大学
黄栋	1987年11月	博士	副教授	华南农业大学
熊俊涛	1981年2月	博士	副教授	华南农业大学
杜治国	1980年12月	博士	副教授	华南农业大学
周敏	1973年6月	博士	副教授	华南农业大学
黄沛杰	1980年8月	博士	副教授	华南农业大学
王金凤	1978年10月	博士	副教授	华南农业大学
李西明	1974年12月	博士	副教授	华南农业大学
彭红星	1976年3月	博士	副教授	华南农业大学
高月芳	1979年7月	博士	副教授	华南农业大学
李泽华	1977年7月	博士	副教授	华南农业大学
邓小玲	1978年7月	博士	副教授	华南农业大学
徐兴	1978年2月	博士	副教授	华南农业大学
张建桃	1978年12月	博士	副教授	华南农业大学
边山	1986年2月	博士	副教授	华南农业大学

孙道宗	1979年12月	博士	副教授	华南农业大学
薛秀云	1981年1月	博士	高级实验师	华南农业大学
陈湘骥	1978年1月	博士	副教授	华南农业大学
杨秋妹	1983年12月	博士	讲师	华南农业大学
殷建军	1981年1月	博士	讲师	华南农业大学
冯健昭	1981年10月	博士	讲师	华南农业大学
蓝连涛	1985年9月	博士	讲师	华南农业大学
汪沛	1983年6月	博士	讲师	华南农业大学
陈盛德	1989年10月	博士	讲师	华南农业大学
郑婵	1978年12月	博士	讲师	华南农业大学
王国华	1988年4月	博士	讲师	华南农业大学
李双娟	1983年10月	博士	讲师	华南农业大学
古万荣	1982年1月	博士	讲师	华南农业大学
陈丽（兼）	1982年6月	博士	副院长	温氏食品集团有限公司研究院
赖建诚（兼）	1982年9月	学士	数字化中心部长	广东省供销集团有限公司
盛耀辉（兼）	1982年6月	博士	总经理	华为政企事业部
吴彻（兼）	1994年1月	硕士	副总经理	广州华农大智慧农业科技有限公司
蓝天（兼）	1973年10月	博士	副教授	华南农业大学
郭玉彬（兼）	1976年1月	博士	副教授	华南农业大学
陈欣（兼）	1990年5月	博士	副教授	华南农业大学
吕石磊（兼）	1984年1月	博士	副教授	华南农业大学
毛宜军(兼)	1979年12月	博士	讲师	华南农业大学

3	华南热带智慧农业共享平台关键技术突破	围绕华南热带特色动作物标准化生产管控共享服务、高速移动农情信息采集分析和农业农村信息综合服务三大共享平台，主要包括如下三大关键技术： （1）重点研究丝苗米、荔枝、龙眼、金柚、柑橘、猪、鸡、番鸭、狮头鹅及水产等华南特色动作物生产管控的数字化标准、种养标准及其标准化管理模式； （2）创制一套集动作物生产环境、生理生长状态、农产品品质等农情信息的快速移动、高可靠、高集成、高通量的高速采集与分析工具，核心是采集分析指标体系构建与设备集成； （3）重点构建农村综合服务平台的农机设备共享调度、农产品产销调度、农技服务精准推送、农村灾害预警等应用模型与软件架构设计； （4）平台共享机制研究，以供实验室外部访问和便捷共享。	针对我国“农业农村信息采集、传输、处理、应用的标准缺失、挖掘困难和共享不足”等“卡脖子”应用问题，以水稻、荔枝、龙眼、金柚、柑橘、猪、鸡、番鸭、狮头鹅及水产等华南特色产业生产精准服务为对象，通过对物联网、大数据、移动互联、云计算、空间信息技术、人工智能等技术手段的集成应用和产学研协同攻关，重点从突破标准、模型、装备集成和系统架构设计等关键技术问题着手，研发具有自主知识产权的华南特色动植物标准化生产服务平台、农情信息移动采集分析平台和农业农村精准服务共享平台，为建立高质高效的华南热带数字农业生产体系提供有力的科学理论和技术支撑。	（1）2022年度：制定共享平台的采集、分析、入库标准规范，基于所制定的标准，进行各平台需求分析与架构设计，移动农情信息高速采集分析平台底座设计； （2）2023年度：构建华南热带农业物联网公共平台，丝苗米、生猪和狮头鹅等标准化生产管控平台，集成动植物生产环境、生理生长状态、农产品品质等农情信息的移动实时采集与分析平台；华南特色动植物生产农事模型、农机设备共享调度、农产品产销调度、农技服务精准推送、农村灾害危害预警等模型研究。共享服务平台及移动农业大数据采集分析平台，为科研院校研究人员和企业提供检测与数据分析服务10万条以上； （3）2024年度：构建其他几类华南特色动植物标准生产管控平台；构建集成农机设备共享调度、农产品产销调度、农技服务精准推送等模型的农业农村信息精准服务平台；共享服务平台及移动农业大数据采集分析平台，为科研院校研究人员和企业提供检测与数据分析服务20万条以上； （4）2025年度，利用平台进行社会服务。共享服务平台及移动农业大数据采集分析平台，为20家以上科研院校研究人员和企业提供检测与数据分析服务20万条以上。

四、依托单位意见

同意。

负责人签章

华南农业大学

（单位公章）

年 月 日

3	华南热带智慧农业共享平台关键技术突破	围绕华南热带特色动作物标准化生产管控共享服务、高速移动农情信息采集分析和农业农村信息综合服务三大共享平台，主要包括如下三大关键技术： （1）重点研究丝苗米、荔枝、龙眼、金柚、柑橘、猪、鸡、番鸭、狮头鹅及水产等华南特色动作物生产管控的数字化标准、种养标准及其标准化管理模式； （2）创制一套集动作物生产环境、生理生长状态、农产品品质等农情信息的快速移动、高可靠、高集成、高通量的高速采集与分析工具，核心是采集分析指标体系构建与设备集成； （3）重点构建农村综合服务平台的农机设备共享调度、农产品产销调度、农技服务精准推送、农村灾害预警等应用模型与软件架构设计； （4）平台共享机制研究，以供实验室外部访问和便捷共享。	针对我国“农业农村信息采集、传输、处理、应用的标准缺失、挖掘困难和共享不足”等“卡脖子”应用问题，以水稻、荔枝、龙眼、金柚、柑橘、猪、鸡、番鸭、狮头鹅及水产等华南特色产业生产精准服务为对象，通过对物联网、大数据、移动互联、云计算、空间信息技术、人工智能等技术手段的集成应用和产学研协同攻关，重点从突破标准、模型、装备集成和系统架构设计等关键技术问题着手，研发具有自主知识产权的华南特色动植物标准化生产服务平台、农情信息移动采集分析平台和农业农村精准服务共享平台，为建立高质高效的华南热带数字农业生产体系提供有力的科学理论和技术支撑。	（1）2022年度：制定共享平台的采集、分析、入库标准规范，基于所制定的标准，进行各平台需求分析与架构设计，移动农情信息高速采集分析平台底座设计； （2）2023年度：构建华南热带农业物联网公共平台，丝苗米、生猪和狮头鹅等标准化生产管控平台，集成动植物生产环境、生理生长状态、农产品品质等农情信息的移动实时采集与分析平台；华南特色动植物生产农事模型、农机设备共享调度、农产品产销调度、农技服务精准推送、农村灾害危害预警等模型研究。共享服务平台及移动农业大数据采集分析平台，为科研院校研究人员和企业提供检测与数据分析服务10万条以上； （3）2024年度：构建其他几类华南特色动植物标准生产管控平台；构建集成农机设备共享调度、农产品产销调度、农技服务精准推送等模型的农业农村信息精准服务平台；共享服务平台及移动农业大数据采集分析平台，为科研院校研究人员和企业提供检测与数据分析服务20万条以上； （4）2025年度，利用平台进行社会服务。共享服务平台及移动农业大数据采集分析平台，为20家以上科研院校研究人员和企业提供检测与数据分析服务20万条以上。

四、依托单位意见

同意。

负责人签章

华南农业大学

（单位公章）

年 月 日

2017年度广东省工程技术研究中心认定名单

广州(288家)

序号	工程中心名称	依托单位	工程中心主任
1	广东省虚拟资产与区块链工程技术研究中心	广州广电运通金融电子股份有限公司	梁添才
2	广东省特种通信（汇智）大数据应用工程技术研究中心	广州汇智通信技术有限公司	黄晓雄
3	广东省面向软件定义架构的云计算大数据工程技术研究中心	广州市品高软件股份有限公司	刘忻
4	广东省移动互联网电子商务大数据工程技术研究中心	广州品唯软件有限公司	李锦恒
5	广东省健康危害因素监测信息工程技术研究中心	广东智源信息技术有限公司	白振国
6	广东省程序化广告平台工程技术研究中心	广州太平洋电脑信息咨询有限公司	麦文军
7	广东省SaaS工作平台工程技术研究中心	广东道一信息技术股份有限公司	袁立颖
8	广东省犯罪地理学与应用工程技术研究中心	广东精一规划信息科技股份有限公司	张宏利
9	广东省智慧工地工程技术研究中心	广东赛百威信息科技有限公司	刘勇勤
10	广东省智能数据工程技术研究中心	广州市申迪计算机系统有限公司	游永明
11	广东省教育云PaaS平台工程技术研究中心	广东恒电信息科技股份有限公司	高静
12	广东省广州天源信息科技有限公司工程技术研究中心	广州天源信息科技有限公司	吴晓鹏
13	广东省广州华资软件技术有限公司工程技术研究中心	广州华资软件技术有限公司	翁庄明
14	广东省财税大数据（中标）工程技术研究中心	广东中标数据科技股份有限公司	郭朝
15	广东省有线数字电视运营支撑及大数据应用工程技术研究中心	广州市诚毅科技软件开发有限公司	唐昊
16	广东省互联网营销云服务工程技术研究中心	广州凡科互联网科技股份有限公司	刘晓聪
17	广东省智慧房产工程技术研究中心	广州佳禾科技有限公司	何告生
18	广东省中小学智慧数字教育工程技术研究中心	广东格灵教育信息技术有限公司	柯禄队
19	广东省智慧旅游工程技术研究中心	广州广之旅国际旅行社股份有限公司	杨鸿声
20	广东省燃气安全工程技术研究中心	广东未来信息技术有限公司	徐业清
21	广东省能源互联网网络安全工程技术研究中心	南方电网科学研究院有限责任公司	许爱东
22	广东省行业智能数据模型工程技术研究中心	广东精点数据科技股份有限公司	许飞月
23	广东省商用密码应用工程技术研究中心	广州江南科友科技股份有限公司	叶盛元
24	广东省汽车后市场大数据工程技术研究中心	中经汇通电子商务有限公司	郝波
25	广东省视频图像智能分析与合成指挥工程技术研究中心	广州嘉崎智能科技有限公司	谢佳亮
26	广东省医疗大数据应用工程技术研究中心	东软集团（广州）有限公司	王敏
27	广东省智慧机场工程技术研究中心	广东机场白云信息科技有限公司	石嵘
28	广东省物联网防灾监测工程技术研究中心	广州市吉华勘测股份有限公司	彭炎华
29	广东省现代信息化物流工程技术研究中心	侨益物流股份有限公司	黄一笃
30	广东省智慧城市安全管理工程技术研究中心	广州烽火众智数字技术有限公司	杨军

14	广东省功能性复合材料工程技术研究中心	清远市齐力合成革有限公司	郑重
15	广东省废旧覆铜板综合利用工程技术研究中心	清远市进田企业有限公司	赖建明
16	广东省高性能PVB树脂工程技术研究中心	建滔（佛冈）特种树脂有限公司	叶俊生
17	广东省建滔积层板工程技术研究中心	建滔（佛冈）积层板有限公司	黄吉军
18	广东省高性能水性环保涂料工程技术研究中心	英德市雅家涂料有限公司	刘文革
19	广东省高性能环保生物质纤维复合材料工程技术研究中心	广东金发科技有限公司	李影
20	广东省高性能夹层玻璃PVB中间膜工程技术研究中心	忠信（清远）光伏材料科技有限公司	黄佳慰
21	广东省光电子功能材料工程技术研究中心	清远先导材料有限公司	朱刘
22	广东省高性能电解铜箔制备及应用工程技术研究中心	佛冈建滔实业有限公司	陈红侠
23	广东省高精细电解铜箔工程技术研究中心	建滔（连州）铜箔有限公司	黄文荣
24	广东省高精度铜板带工程技术研究中心	清远楚江铜业有限公司	徐家祥
25	广东省高性能大型铸件制造及模拟工程技术研究中心	广东中天创展球铁有限公司	陈永成
26	广东省铝基合金材料工程技术研究中心	广东隆达铝业有限公司	叶艳平
27	广东省高性能铸造铝合金工程技术研究中心	清远市顺博铝合金有限公司	王启
28	广东省智能门窗铝型材工程技术研究中心	广东兴裕铝业有限公司	林龙鑫
29	广东省取向硅钢工程技术研究中心	广东盈泉高新材料有限公司	彭志华
30	广东省高性能铝硅酸盐玻璃（南玻）工程技术研究中心	清远南玻节能新材料有限公司	龚锋杰
31	广东省建筑陶瓷（博华）工程技术研究中心	广东博华陶瓷有限公司	王志强
32	广东省环保高品质陶瓷及高效节能3D喷墨技术工程技术研究中心	广东昊晟陶瓷有限公司	余昭啟
33	广东省高性能保温环保玻璃棉工程技术研究中心	清远瀚江玻璃棉科技有限公司	王卫健
34	广东省功能性纳米碳酸钙工程技术研究中心	连州市凯恩斯纳米材料有限公司	晏华中
35	广东省环氧覆铜板基材工程技术研究中心	建滔(连州)玻璃纤维有限公司	姚森
36	广东省造纸助剂工程技术研究中心	英德市良仕工业材料有限公司	周明星
37	广东省功能性纺织印染助剂工程技术研究中心	清远市宏图助剂有限公司	方伟洪
38	广东省兽用原料药工程技术研究中心	丽珠集团新北江制药股份有限公司	李敬辉
39	广东省绿色环保气雾剂工程技术研究中心	清远市立道精细化工有限公司	莫诒杰
40	广东省UV抗菌涂料(翔鹰)工程技术研究中心	广东翔鹰化工有限公司	黄荣昌
41	广东省微生物制药工程技术研究中心	广东蓝宝制药有限公司	徐会根

高校(219家)

序号	工程中心名称	依托单位	工程中心主任
1	广东省智能光信息处理与应用工程技术研究中心	中山大学	李朝晖
2	广东省公共安全与灾害工程技术研究中心	中山大学	柳林
3	广东省地下空间开发工程技术研究中心	中山大学	王复明

4	广东省海洋生物质化工原料及其功能化转化工程技术研究中心	中山大学	万一千
5	广东省环境与健康风险评价工程技术研究中心	中山大学	董光辉
6	广东省废弃物3R工程技术研究中心	中山大学	熊亚
7	广东省室内空气污染控制工程技术研究中心	中山大学	黄海保
8	广东省海岸与岛礁工程技术研究中心	中山大学	杨清书
9	广东省重要经济鱼类健康养殖工程技术研究中心	中山大学	李文笙
10	广东省中药超临界流体萃取工程技术研究中心	中山大学	葛发欢
11	广东省仿制药一致性评价工程技术研究中心	中山大学	钟国平
12	广东省干细胞与创新药物工程技术研究中心	中山大学	邓文斌
13	广东省健康医疗大数据工程技术研究中心	中山大学	周毅
14	广东省热带海洋动态防腐材料工程技术研究中心	中山大学	罗莊竹
15	广东省营养转化工程技术研究中心	中山大学	凌文华
16	广东省炎症性肠病精准诊疗工程技术研究中心	中山大学附属第六医院	吴小剑
17	广东省烧伤与伤口精准诊治关键技术与系列产品研发工程技术研究中心	中山大学附属第一医院	吴军
18	广东省微创脊柱外科工程技术研究中心	中山大学附属第三医院	戎利民
19	广东省慢阻肺康复工程技术研究中心	中山大学附属第三医院	周宇麒
20	广东省口腔颌面头颈数字化精准修复重建工程技术研究中心	中山大学孙逸仙纪念医院	李劲松
21	广东省临床数据仓库工程技术研究中心	南方医科大学珠江医院	张巍
22	广东省医学内镜工程技术研究中心	南方医科大学南方医院	刘思德
23	广东省脊柱外科虚拟现实与器械工程技术研究中心	南方医科大学南方医院	陈建庭
24	广东省口腔医学临床转化工程技术研究中心	南方医科大学口腔医院（广东省口腔医院）	周磊
25	广东省软件开发与服务工程技术研究中心	华南理工大学	李东
26	广东省大数据与计算广告工程技术研究中心	华南理工大学	段淳林
27	广东省智能网络通信与计算工程技术研究中心	华南理工大学	傅予力
28	广东省多媒体智能营销工程技术研究中心	华南理工大学	宋恒杰
29	广东省智能传感器与专用集成电路工程技术研究中心	华南理工大学	李斌
30	广东省智能焊接制造装备及机器人工程技术研究中心	华南理工大学	王振民
31	广东省智能与康复装备工程技术研究中心	华南理工大学	谢龙汉
32	广东省智能无人船与系统工程技术研究中心	华南理工大学	洪晓斌
33	广东省金属增材制造工程技术研究中心	华南理工大学	杨永强
34	广东省生态透析环境治理工程技术研究中心	华南理工大学	黄少斌
35	广东省水利工程安全与绿色水利工程技术研究中心	华南理工大学	周小文
36	广东省植物纤维高值化清洁利用工程技术研究中心	华南理工大学	万金泉
37	广东省风景园林工程技术研究中心	华南理工大学	林广思

38	广东省香蕉精深加工与综合利用工程技术研究中心	华南理工大学	王娟
39	广东省生物制药工程技术研究中心	华南理工大学	张雷
40	广东省人工智能中医工程技术研究中心	华南理工大学	文贵华
41	广东省柔性OLED显示工程技术研究中心	华南理工大学	彭俊彪
42	广东省智慧城市规划工程技术研究中心	华南理工大学	王世福
43	广东省金属材料表面功能化工程技术研究中心	华南理工大学	匡同春
44	广东省特种纸与纸基功能材料工程技术研究中心	华南理工大学	陈港
45	广东省特种酶工程技术研究中心	华南理工大学	崔春
46	广东省电化学能源工程技术研究中心	华南理工大学	梁振兴
47	广东省能源材料表面化学工程技术研究中心	华南理工大学	杨成浩
48	广东省智能科学工程技术研究中心	华南师范大学	蒋运承
49	广东省城市排水管理与污水处理工程技术研究中心	华南师范大学	江峰
50	广东省新型超声成像设备工程技术研究中心	华南师范大学	杨思华
51	广东省心脑血管个体化医疗大数据工程技术研究中心	华南师范大学	张涵
52	广东省生态与健康工程技术研究中心	华南师范大学	李续娥
53	广东省光子中医信息治疗仪器工程技术研究中心	华南师范大学	郭周义
54	广东省透明导电薄膜材料工程技术研究中心	华南师范大学	高进伟
55	广东省基因大数据处理与分析工程技术研究中心	暨南大学	汪超男
56	广东省大数据协同育人与应用创新工程技术研究中心	暨南大学	全渝娟
57	广东省教育大数据服务与应用工程技术研究中心	暨南大学	张焕明
58	广东省舆情大数据工程技术研究中心	暨南大学	林如鹏
59	广东省数量金融大数据工程技术研究中心	暨南大学	张传林
60	广东省电气与智能控制工程技术研究中心	暨南大学	刘新东
61	广东省3D打印与增材制造工程技术研究中心	暨南大学	王小健
62	广东省疾病易感性及中医药研发工程技术研究中心	暨南大学	何蓉蓉
63	广东省抗体药物与免疫检测工程技术研究中心	暨南大学	邓宁
64	广东省药物载体开发工程技术研究中心	暨南大学	薛巍
65	广东省耐蚀材料与抗磨蚀工程技术研究中心	暨南大学	涂小慧
66	广东省晶体材料和晶体激光技术与应用工程技术研究中心	暨南大学	陈振强
67	广东省石墨烯类功能及高性能材料与制品（器件）工程技术研究中心	暨南大学	谭绍早
68	广东省食品安全分子快速检测工程技术研究中心	暨南大学	白卫滨
69	广东省真空薄膜技术与新能源材料工程技术研究中心	暨南大学	麦文杰
70	广东省薄膜光伏关键工艺与设备工程技术研究中心	暨南大学	麦耀华
71	广东省农业大数据工程技术研究中心	华南农业大学	肖德琴

省级工程中心认定申请报告

中心名称：广东省农业大数据工程技术研究中心

负 责 人：肖德琴

依托单位：华南农业大学

合作单位：新华三技术有限公司

联系邮箱：deqinx@scau.edu.cn

起始时间：2017-2020

			理系统	
9	软件著作	2013SR003522	农业视频/图像采集网络管理系统	肖德琴
10	软件著作	2013SR069492	农情现场信息综合管理平台	肖德琴
11	软件著作	2016SR030043	南方蔬菜重大害虫监测平台	肖德琴
12	软件著作	2016SR203472	基于视频追踪猪只运动行为分析系统	肖德琴
13	软件著作	2015SR005556	基于视觉传感器的果蝇远程计数系统	肖德琴
14	软件著作	2015SR037234	基于 ARM 平台的多光谱图像采集系统	肖德琴
15	软件著作	2015SR.030043	华南农业大学动物科学学院猪场远程监控教学管理系统	肖德琴
16	软件著作	2016SR203472	基于视频追踪猪只运动行为分析系统	肖德琴
17	软件著作	2016SR188621	多光谱图像处理系统	肖德琴
18	软件著作	2013SR069492	基于现场信息综合管理平台	肖德琴
19	软件著作	2015SR063926	连平县陂头镇大米信息服务平台	肖德琴
20	软件著作	2015SR034063	惠东县梁化镇蔬菜信息网络服务平台	肖德琴
21	发明专利	ZL201620246973.8	一种屋式昆虫诱捕器	陆永跃
22	实用新型专利	ZL201220643379.4	一种昆虫诱捕器	陆永跃
23	软件注册权	2017SR167088	畜禽产品 RFID 质量安全溯源系统 V1.0	杜治国
24	发明专利	ZL 2013 1 0714873.4	基于叶片骨架模型的植物叶片图像自动识别方法	张连宽
25	软件著作	2016SR061610	作物叶面图像自动分割	张连宽
26	软件著作	2014SR045853	基于 Android 移动平台的作物图像采集系统	张连宽
27	软件著作	2013SR082289	无线传感器数据监测信息平台	张连宽
28	软件著作	2015SR148641	作物叶片图像自动识别软件	张连宽
29	软件著作	2015SR181187	基于全基因组高密度 SNP 标记的亲子鉴定软件 V1.0	张哲
30	软件著作	2013SR070948	全基因组多性状遗传数据模拟软件 V1.0	张哲

（四）中心工程技术开发队伍

本中心拥有一支技术水平高、工程化开发能力强的工程技术队伍，其中专职研发人员 21 人，拥有高级职称人员 12 人，14 人拥有博士学位，核心人员情况如 3 所示。团队人员覆盖了计算机科学与技术、统计学、农学、动物学、农业电气化与自动化等多个相关学科，人缘和学缘结构合理，并兼有产品设计推广的企业高管加盟，学术水平高，工程化能力强。

表 3 中心主要成员信息表

序号	姓名	工作单位	职称/职务	从事专业
1	肖德琴	数学与信息学院	教授/博导	大数据采集应用
2	吕建秋	新农村发展研究院	研究员/副院长	大数据服务

3	张大斌	数学与信息学院	教授/博导	大数据分析
4	刘金山	数学与信息学院	教授	大数据处理
5	陆永跃	农学院	教授/博导	病虫害监测预警
6	张连宽	数学与信息学院	副教授	大数据分析
7	杜治国	数学与信息学院	副教授	农业物联网
8	王春桃	数学与信息学院	副教授/硕导	大数据安全
9	张哲	动物科学学院	青年教授/硕导	动物大数据
10	李泽华	数学与信息学院	副教授	农业统计
11	夏强	数学与信息学院	副教授	大数据统计分析
12	项灿	数学与信息学院	讲师	大数据安全
13	殷建军	数学与信息学院	讲师	网络服务
14	杨秋妹	数学与信息学院	讲师	智能学习
15	田兴国	新农村发展研究院	助理研究员	农业大数据服务
16	郭艾侠	数学与信息学院	副教授/硕导	大数据处理
17	凌立文	数学与信息学院	讲师	大数据处理
18	骆威	数学与信息学院	讲师	大数据分析
19	岳鹏	新华三技术有限公司	大数据产品部总监	大数据平台
20	黄文龙	新华三技术有限公司	工程师	大数据分析平台
21	张庭伟	新华三技术有限公司	工程师	大数据采集平台

中心主任：肖德琴，生于 1970 年 5 月，华南农业大学数学与信息学院三级教授，博士生导师，华南农业大学农业大数据工程中心主任，华南农业大学计算机系统结构二级学科带头人，网络工程本科专业主任。主要从事农业物联网、农业大数据、农业害虫监测、猪场监测与调控等科学研究与应用推广工作。主持国家十三五重点研发专项子课题 1 项、国家星火计划重点项目 1 项、国家十二五农村领域重大项目子课题 1 项、广东省自然科学基金 3 项，省科技计划 2 项，参加国家自然科学基金、863 等课题 20 余项，主持获得软件著作登记 15 项，已获得发明专利 3 项，正在公开发明专利 4 项，获得实用新型专利 3 项，获得省部级以上奖励 3 项，已经发表论文 100 余篇，主编著作 5 部，参加编著 3 部，SCI/EI 收录 40 余篇。中国物联网专委会委员，广东省高等院校计算机课程教学指导委员会副主任委员，广东省大数据专家委员会委员，计算机学会高级会员、农业工程学会高级会员。

机械化工程专业。主要从事统计推断和农业工程数据分析等方面的研究。已公开发表论文 30 余篇，主持完成全国统计科学研究计划项目和华南农业大学校长基金各 1 项，主持广东省科技计划项目 1 项，主要参与国家高科技研究发展计划（863 计划）项目、国家自然科学基金、中国工程院重大咨询项目等国家级项目多项，主编出版教材 2 部，获湖南省第七届统计科研优秀成果奖 1 项。

科研骨干：夏强，男，华南农业大学，数学与信息(软件)学院，副教授。主要研究方向：时间序列分析、贝叶斯计算、高维数据分析，发表相关论文 12 篇。主持项目有广东省自然科学基金面上项目“高维数据中因子模型的统计推断及应用”、全国统计科学研究重点项目“高维时间序列因子模型的统计推断方法的改进及应用研究”、国家社会科学基金青年项目“两类门限型计量经济学模型的贝叶斯检验及应用研究”、“教育部人文社科基金青年项目”。

（五）产学研合作情况（产学研合作、人员培训与开放服务等）

（1）产学研合作

本中心强调产学研合作，一直与政府、企业有深度合作，与惠东县梁化镇、连平县陂头镇、广东省农推总站、广东东升农场有限公司、温氏集团、广州云宏、新华三技术有限公司等政府或企业具有多年的产学研合作基础，已有一批科技成果在企业中进行了实际应用，为企业生产提供了成熟配套的先进技术、工艺、产品和装备，推动了企业的科技进步，产生了较好的经济效益。近年团队开展的部分合作项目内容如表 4 所示。

表 4 中心近年产学研合作项目清单

序号	合作项目名称	合作单位	时间	负责人	效果
1	惠东县梁化镇蔬菜专业镇信息网络服务平台	惠东县梁化镇	2013-01-01 至 2015-10-31	肖德琴 刘远军	良好
2	建设用地市场分析系统	广东友元国土信息工程有限公司	2010-01-01 至 2012-12-31	肖德琴 叶云	良好
3	华南农业大学动物科学学院猪场远程监控教学管理系统	中山食品集团有限公司	2014-01-01-至今	张哲 邓振强	良好
4	连平县陂头镇信息网络服务平台	连平县陂头镇	2013-01-01 至 2015-10-31	冯健昭 肖德琴	良好
5	实蝇害虫快速监测系统应用及推广	广东省农推总站、广东东升农场	2014-01-01 至 2016-12-31	肖德琴 许志峰	良好

获奖证书

Certificate of Achievement

编号/No. CCPCSS2023SZT058AU030S2

颁给/Awarded to

华南农业大学 / South China Agricultural University

赖伟鑫 / Lai Weixin,陈国豪 / Chen Guohao,李相廷 / Li Xiangting

杨秋妹 (教练) / Yang Qiumei

银奖 / Silver Medal

2023 年中国大学生程序设计竞赛-广东省大学生程序设计竞赛

2023 China Collegiate Programming Contest - Guangdong Provincial Collegiate Programming Contest

深圳技术大学，2023年5月

Shenzhen Technology University, May 2023

广东省计算机学会

Computer Academy of Guangdong

获 奖 证 书

Certificate of Achievement

编号/No. CCPCSS2023SZT125AU049B1

颁给/Awarded to

华南农业大学 / South China Agricultural University

冯雨泽 / Feng Yuze,杨天浩 / Yang Tianhao,谢昊峻 / Xie Haojun

杨秋妹 (教练) / Yang Qiumei

铜奖 / Bronze Medal

2023 年中国大学生程序设计竞赛-广东省大学生程序设计竞赛

2023 China Collegiate Programming Contest - Guangdong Provincial Collegiate Programming Contest

深圳技术大学，2023年5月

Shenzhen Technology University, May 2023

广东省计算机学会

Computer Academy of Guangdong

证书编号：201901166

获奖证书

第七届 “泰迪杯”数据挖掘挑战赛

全国

三等奖

作品名称： 运输车辆安全驾驶行为的分析

作品单位： 华南农业大学

作品成员： 林思聪 蔡家豪 陈焕坤

指导老师： 杨秋妹

中国高校大数据教育创新联盟

泰迪杯数据挖掘挑战赛组织委员会

证书编号：201901166

获奖证书

第七届 “泰迪杯”数据挖掘挑战赛

广东省

二等奖

作品名称： 运输车辆安全驾驶行为的分析

作品单位： 华南农业大学

作品成员： 林思聪 蔡家豪 陈焕坤

指导老师： 杨秋妹

广东省工业与应用数学学会 广东泰迪智能科技股份有限公司

2019 年 7 月 10 日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导梁思炤荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021549610

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导赵云龙荣获第十五届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：021549505

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2024年4月29日

获奖证书

Certificate of Achievement

THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY (GUANGZHOU)

编号/No. CCPCYQS2024GDT102AU041B2

颁给/Awarded to

华南农业大学 / South China Agricultural University

陈国豪 / Chen Guohao,郑昊驰 / Zheng Haochi,梁嘉俊 / Liang Jiajun

杨秋妹 (教练) / Yang Qiumei

铜奖 / Bronze Medal

2024年中国大学生程序设计竞赛-全国邀请赛（广东）

2024 China Collegiate Programming Contest - National Invitational Contest (Guangdong)

香港科技大学（广州），2024年5月26日

The Hong Kong University of Science and Technology (Guangzhou), May 26, 2024

俞勇

中国大学生程序设计竞赛组委会，主席

Committee for CCPC, Chairman

获奖证书

Certificate of Achievement

编号/No. CCPCYQS2024GDT161AU065B3

THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY (GUANGZHOU)

颁给/Awarded to

华南农业大学 / South China Agricultural University

吴智铉 / Wu Zhixuan,卢豪禧 / Lu Haoxi,肖超 / Xiao Chao

杨秋妹 (教练) / Yang Qiumei

铜奖 / Bronze Medal

2024年中国大学生程序设计竞赛-全国邀请赛（广东）

2024 China Collegiate Programming Contest - National Invitational Contest (Guangdong)

香港科技大学（广州），2024年5月26日

The Hong Kong University of Science and Technology (Guangzhou), May 26, 2024

俞勇

中国大学生程序设计竞赛组委会，主席

Committee for CCPC, Chairman

获 奖 证 书

Certificate of Achievement

编号/No. CCPCSS2025GDT038AU018S2

颁给/Awarded to

华南农业大学 / South China Agricultural University

陈钢 / Chen Gang,颜乾彪 / Yan Qianbiao,谭伟杰 / Tan Weijie

杨秋妹 (教练) / Yang Qiumei

银奖 / Silver Medal

2025 年中国大学生程序设计竞赛-广东省大学生程序设计竞赛

2025 China Collegiate Programming Contest - Guangdong Provincial Collegiate Programming Contest

广东省计算机学会，2025年6月2日

Guangdong Computer Academy, June 2, 2025

广东省计算机学会

Computer Academy of Guangdong

获 奖 证 书

Certificate of Achievement

编号/No. CCPCSS2025GDT053AU021S1

颁给/Awarded to

华南农业大学 / South China Agricultural University

江煊杰 / Jiang Xuanjie,钟启航 / Zhong Qihang,袁菱 / Yuan Ling

杨秋妹 (教练) / Yang Qiumei

银奖 / Silver Medal

2025 年中国大学生程序设计竞赛-广东省大学生程序设计竞赛

2025 China Collegiate Programming Contest - Guangdong Provincial Collegiate Programming Contest

广东省计算机学会，2025年6月2日

Guangdong Computer Academy, June 2, 2025

广东省计算机学会

Computer Academy of Guangdong

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导欧启成荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组二等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602057396

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导黄浩圳荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602057817

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导李锐嘉荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602058181

证件号码：440921198312301 62X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导李雨倩荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602057360

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导麦智轩荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602058255

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导莫卓玥荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602057821

证件号码：440921198312301 62X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导韦楚炬荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602057395

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

蓝桥杯大赛

获奖证书

华南农业大学杨秋妹：

指导余佳荣获第十六届蓝桥杯全国软件和信息技术专业人才大赛广东赛区C/C++程序设计大学B组三等奖，被评为优秀指导教师。

特发此证，以资鼓励。

证书编号：1602056352

证件号码：44092119831230162X

工业和信息化部
人才交流中心

蓝桥杯大赛组委会

2025年5月26日

荣誉证书

杨秋妹同志：

被评为华南农业大学“教书育人、管理育人、服务育人”先进个人，特发此证，以资鼓励。

中共华南农业大学委员会
华南农业大学
二〇一〇年九月十日

奖 状

杨秋妹 同志：

在二〇〇九年度学院班主任工作中，表现突出，被评为“优秀班主任”。在特发此状，以资鼓励。

信息学院党委 软件学院党委

二〇一〇年三月二十日

荣誉证书

杨秋妹 同志：

在二〇〇九年度学院学生科技创新工作中，表现突出，获“学生科技创新训练优秀指导教师”称号。特发此状，以资鼓励。

信息学院　　软件学院

二〇〇九年十二月二十九日

服务号：181129SN0001 学校审核通过

服务类型：教工个人参加的校外各类社会服务工作

服务时间：2018-11-29~2018-11-29

申请人：杨秋妹

服务号：FW20230612134705646 学校审核通过

服务对象：温氏食品集团股份有限公司

服务类型：教工个人参加的校外各类社会服务工作

服务地区：广东省-云浮市-新兴县

服务时间：2023-06-12~2023-06-12

申请人：杨秋妹