MACHINE VISION TECHNOLOGIES FOR EVALUATING KEY PRODUCTION AND WELFARE INDICATORS OF CAGE-FREE LAYERS

by

XIAO YANG

(Under the Direction of Lilong Chai)

ABSTRACT

With rising consumer concerns about animal welfare, the United States (USA) egg industry is shifting towards cage-free farming practices. This shift introduces challenges in poultry management, sustainable egg production, and automation in poultry farming. In response, this study investigates updated computer vision techniques, thermal cameras, and robotics to monitor poultry floor distribution, predict bird body weight, manage floor eggs, and detect behaviors and welfare conditions. The objective of this dissertation was to evaluate the performance of traditional convolutional neural network (CNN) models (e.g., YOLO series, EfficientNetV2, SegFormer, and SETR) and large vision models (LVM) (e.g., Segment Anything Model and Track Anything Model) in assessing key production and welfare indicators of cage-free layers. Furthermore, the research explored advanced robotic systems for detecting floor eggs and dead chickens. For this study, 800 hens were raised in four cage-free research rooms under different experimental designs based on specific research objectives. The results demonstrated that CNN models can effectively track chickens' spatial distribution (90.0% precision), detect floor eggs (94.8% accuracy), and classify six behaviors (i.e., feeding, drinking, walking, perching, dust bathing, and nesting) with 95.3% accuracy. LVMs, combined with thermal cameras, predicted chicken body weight ($R^2 = 0.90$) and tracked individual hens (RMSE = 0.02 m/s). Moreover, integrating CNN models with intelligent bionic quadruped robots allowed for the detection of floor eggs in dimly lit areas, such as beneath feeders and in corner spaces, as well as the identification of dead chickens within the flock. In conclusion, this dissertation highlights the cutting-edge techniques of precision farming technologies in advancing automated poultry management in cage-free systems. By integrating CNN, LVM, and robotic technologies, this research offers an interdisciplinary approach to addressing the challenges of modern cage-free farming, advancing the poultry industry with more ethical, efficient, automated, and sustainable production practices.

INDEX WORDS: Cage-free farming, Precision poultry management, Computer vision, Large vision models, Robotics

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DEDICATION

I would like to dedicate this dissertation to my beloved father, Zurong Yang, and my mother, Xianmei Tang. Without their unwavering support, unconditional love, and constant encouragement, I would not have been able to complete this journey. Their guidance, sacrifices, and belief in me have been my driving force, especially during the most challenging moments. From the earliest days of my education, they have been my strongest pillars, fostering a sense of perseverance and determination that has carried me through to the completion of this dissertation. This achievement is as much theirs as it is mine, and I am deeply grateful to them from the bottom of my heart.

我要将我的论文献给我亲爱的父亲杨祖荣和母亲汤先美。没有他们坚定不移的支持、无条件的爱和持续不断的鼓励，我不可能完成这段旅程。他们的指导、奉献以及对我的信任，一直是我前进的动力，尤其是在最艰难的时刻。从我求学的早期，他们就是我最坚实的后盾，培养了我面对挑战时的毅力和决心，最终帮助我完成了这篇论文。这项成就不仅属于我，也属于他们，我从心底里深深感激他们。

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最后，我要向我的父母和所有亲戚表达我最诚挚的感谢，感谢你们让我能够专注于博士学位的学习，而不必担心祖父母的健康问题。父母教导我的谦逊与自信，让我能够在博士旅程中面对任何挑战。你们的坚定信任和支持是我学术生涯的基石，正因为你们的无私帮助，我才能走到今天。

TABLE OF CONTENTS

APPENDICES

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

COMPUTER VISION-BASED CYBERNETICS SYSTEMS FOR PROMOTING MODERN POULTRY FARMING: A CRITICAL REVIEW[1]

[1]Yang, X., Bist, R. B., Paneru, B., Liu, T., Applegate, T., Ritz, C., ... & Chai, L. (2024). Computer Vision-Based cybernetics systems for promoting modern poultry Farming: A critical review. Computers and Electronics in Agriculture, 225, 109339.https://www.sciencedirect.com/science/article/pii/S0168169924007300. Reprinted here with permission of the publisher.

ABSTRACT

As global demands on the poultry production and welfare both intensify, the precision poultry farming technologies such as computer vision-based cybernetics system is becoming important in addressing the current issues related to animal welfare and production efficiencies. The integration of computer vision technology has become a catalyst for transformative change in precision farming, particularly concerning productivity and welfare. This review paper delineates the central role of computer vision in precision poultry farming, focusing on its applications in non-contact monitoring methods that employ advanced sensors and cameras to enhance farm biosecurity and bird observation without disturbance. We delved into the multifaceted advancements such as the utilization of convolutional neural networks (CNNs) for behavior analysis and health monitoring, evidenced by the high accuracy sorting of eggs and identification of health concerns within target-dense farm environments. The review paper underscores advancements in precision agriculture, including accurate egg weight estimation and egg classification within cage-free systems, paralleling the poultry sector's evolution towards more ethical farming practices. Moreover, it addresses the progress in poultry growth monitoring and examines case studies of commercial farms, showcasing how these innovations are being practically applied to enhance productivity and animal welfare. Challenges remain, particularly in terms of environmental variability and data annotation for deep learning models. Nevertheless, the review emphasizes the scope for future innovations like voice-controlled robotics and virtual reality applications, which have the potential to enhance poultry farming to new levels of efficiency, humanity, and sustainability. The insights assert that the continued exploration and development in computer vision technologies are not only instrumental for the poultry sector but also offer a blueprint for agricultural enhancement at large.

Key words: Poultry production, Animal welfare, Computer vision, Deep learning

1.1 INTRODUCTION

Facing the dual pressures of a growing population and the need for sustainable farming, the poultry sector has embraced non-contact monitoring as a crucial innovation (Li et al., 2020). As the global population expands, the sector is compelled to evolve, necessitating more efficient and sustainable farming practices. Precision farming in poultry production is one such evolutionary step, referring to the use of advanced technologies to increase the efficiency of production processes, improve animal welfare status, and reduce environmental impacts. Precision farming is characterized by the precise management of food, water, and living conditions, and is particularly attentive to the health and well-being of the poultry. Animal welfare is a central component of this approach, acknowledging that healthier and less stressed animals yield greater productivity. Machine vision technologies are at the forefront of these innovations. They offer non-intrusive methods to monitor poultry, thereby supporting farm biosecurity and animal welfare. This technique, powered by advanced sensors and cameras, allows for subtle observations of poultry behavior and physiology, enhancing early detection capabilities while remaining non-invasive and maintaining biosecurity. The widespread implementation of computer vision for animal monitoring signifies a dramatic shift from conventional practices, utilizing a blend of learning algorithms to interpret behavior from visual data - a task that hinges on the precise extraction of features (Okinda et al., 2020a).

Challenges on poultry farms, such as dust, low light conditions, and varying flock density, complicate the capture of clear visual data, which is essential for detailed behavior analysis. The advent of deep learning, particularly the use of Convolutional Neural Networks

(CNNs), represents a considerable leap forward in overcoming these issues (Bist et al., 2023b; Guo et al., 2023). These models have equipped farmers with the tools to delve into the nuances of animal behavior and health, evidenced by high-accuracy applications ranging from sorting eggs to identifying sick birds in crowded environments using algorithms like You Only Look Once (YOLO) (Jocher, 2020; Ma et al., 2020). Additionally, the field of poultry farming has seen technological advancements in the evaluation of egg weight - a key quality and value determinant - through automated measurement systems that employ a range of techniques from Artificial Neural Networks (ANN) to Support Vector Machine (SVM) (Amraei et al., 2017; Pacure Angelia et al., 2022). This innovation offers a substantial upgrade over manual weighing methods, streamlining the process with improved efficiency and precision (Yang et al., 2023c). The integration of deep learning with machine learning regression techniques has been particularly significant for the comprehensive classification and weighing of eggs, including those from cage-free systems, a change aligned with the sector's move from traditional caging to more ethical farming practices. The shift toward cage-free egg production has necessitated adaptable computer vision systems capable of handling a wide array of egg types, from floor eggs to those destined for commercial distribution (Bist et al., 2022, 2023a). Such advancements underscore the necessity for computer vision systems that can accurately classify and weigh eggs, ensuring uniform quality for both producers and consumers (Mertens et al., 2005).

Significant progress has been made in other aspects of poultry farming as well, like monitoring growth and detecting health disorders and body weight prediction (Bist et al., 2023a, Yang et al., 2024). Neethirajan (2022) proposed a novel methodology, centering on the locomotive behaviors of poultry. By integrating sophisticated tracking algorithms, notably the Kalman Filter, their system was capable of projecting growth trajectories from the birds' activity levels (Neethirajan, 2022). Angelia et al. (2021) explored egg classification techniques. Employing a region-convolutional neural network, they succeeded in classifying eggs with a remarkable 93.3% accuracy, demonstrating the efficacy of image processing technologies in determining egg grades such as Grade A, B, C, and Inedible (Pacure Angelia et al., 2022). Lamping et al. (2022) developed ChickenNet, an innovative framework designed to evaluate the plumage condition of laying hens. This system, an extension of the Mask Region-Based Convolutional Neural Network (R-CNN) model, underwent testing at various image resolutions, resulting in a mean average precision (mAP) of 98.02% in identifying hens and a 91.83% accuracy rate in predicting the status of their plumage(Lamping et al., 2022). Advanced computer vision techniques have shown promising results in improving precision, reducing labor-intensive processes, and enhancing overall farm efficiency. The use of sophisticated algorithms and multimodal systems, incorporating different sensors and data types, further amplifies the potential of these technologies (Astill et al., 2020; Li et al., 2023a). However, the journey is not without its hurdles. Real farm applications still face challenges such as environmental variability and the need for vast, labeled datasets for deep learning models (Andriyanov et al., 2021; Joffe et al., 2017). Future directions in this field appear promising, with potential advancements like voice-controlled robotics and virtual reality integration (Zang et al., 2011; Kanash et al., 2021). The amalgamation of computer vision with these cutting-edge technologies could further revolutionize poultry farming, making it more efficient, welfare-friendly, and sustainable by offering a more intelligent system to manage poultry production. The ongoing research and development in this domain are not only crucial for the poultry sector but also serve as a blueprint for other sectors in agriculture, demonstrating the vast potential of computer vision and artificial intelligence (AI) in enhancing productivity and welfare (Franzo et al., 2023; Zhang et al., 2023e).

An extensive review of literature spanning from January 2013 to October 2023 reveals a significant body of research - 246 papers, by searching the core keywords - *Computer Vision* and *Poultry*, dedicated to computer vision's transformative impact on poultry management. Using the "AND" function in the search bar of scientific databases helps refine results to papers that utilize poultry as experimental animals and employ image vision as a method. This research collectively emphasizes the potential of computer vision to enhance and streamline poultry management, historically dependent on manual processes. The dedication to precision and efficiency is evident throughout these works, showcasing the dynamic capabilities of computer vision technologies. These research works foretell the emergence of a new era in farming focused on sustainability, efficiency, and improved welfare, led by the advances in computer vision.

1.2 COMPUTER VISION IN POULTRY FARMING: A DECADE OF PUBLICATION TRENDS

Within the poultry sector, advancements in technology have ushered in a new era of research possibilities. Computer vision, powered by deep learning and neural networks, is fast becoming a game-changer. To gauge the depth of this integration, established databases like PubHub and Web of Science (aligned with search results from Scopus and PubMed) were scoured focusing on terms synonymous with both computer vision (“deep learning”, “neural networks”, “image processing”, “image recognition”) and poultry studies (“chickens”, “avian”, “layers”, “broilers”).

1.2.1 Yearly Publication Analysis

When searching with the “core keywords” *Computer Vision* and *Poultry*, there were 246 papers published from January 2013 to October 2023, averaging 23 papers annually. As shown in Figure 1.1, 2022 had the peak annual publication rate with 64 papers, and 2019 had the fastest growth rate at 127.27%. This suggests that research in this field is undergoing rapid development and is in a swift ascending phase. The surge in publications indicates a growing interest and significant advancements in merging computational technologies such as machine learning within avian studies. This upward trajectory may be attributed to the realization of the potential impacts of applying AI techniques to poultry research, such as improved poultry health monitoring, better disease detection, and enhanced production efficiency. The trend also highlights a collaborative effort between the tech sector and poultry science, bringing forth interdisciplinary solutions. For researchers and stakeholders, this trend underscores the importance of investing in this intersection of technologies, as it promises to redefine the future of poultry management and production.

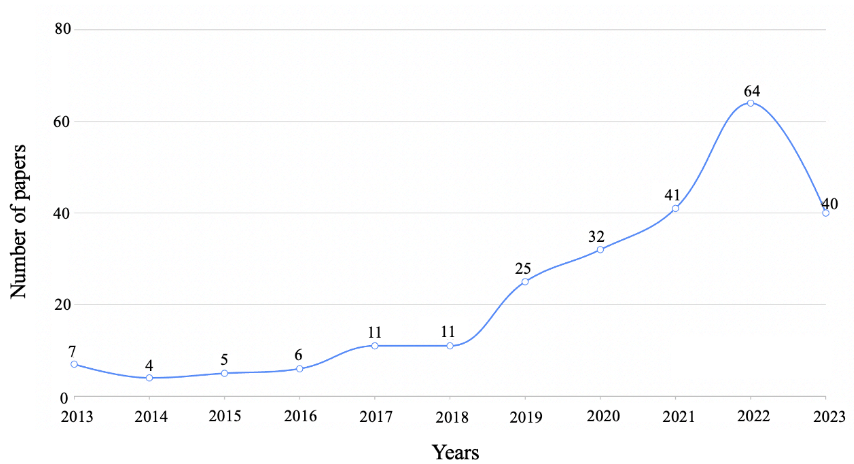

Figure 1.1. Annual publication trend of literature related to computer vision and poultry from January 2013 to October 2023.

1.2.2 Journals at the Forefront

The top 30 journals by publication volume are shown in Figure 1.2. The journal with the most publications on this topic is “Animals” with 20 articles; “Poultry Science” ranks second with 14 articles, and “Sensors” is third with 10 articles. Navigating the evolving landscape of computer vision as it intersects with poultry research can be significantly enhanced by closely analyzing leading journals in the field. By pinpointing and routinely checking into authoritative journals such as “Animals”, “Poultry Science”, and “Sensors”, researchers can stay abreast of the most recent and impactful findings. These publications often serve as reservoirs of quality information, given their rigorous peer-review processes. Beyond the immediate academic content, these journals can spotlight emerging technological trends, novel methodologies, and innovative applications specific to the realm of poultry. This is particularly vital for those who aim to integrate advanced computer vision techniques into poultry research and management.

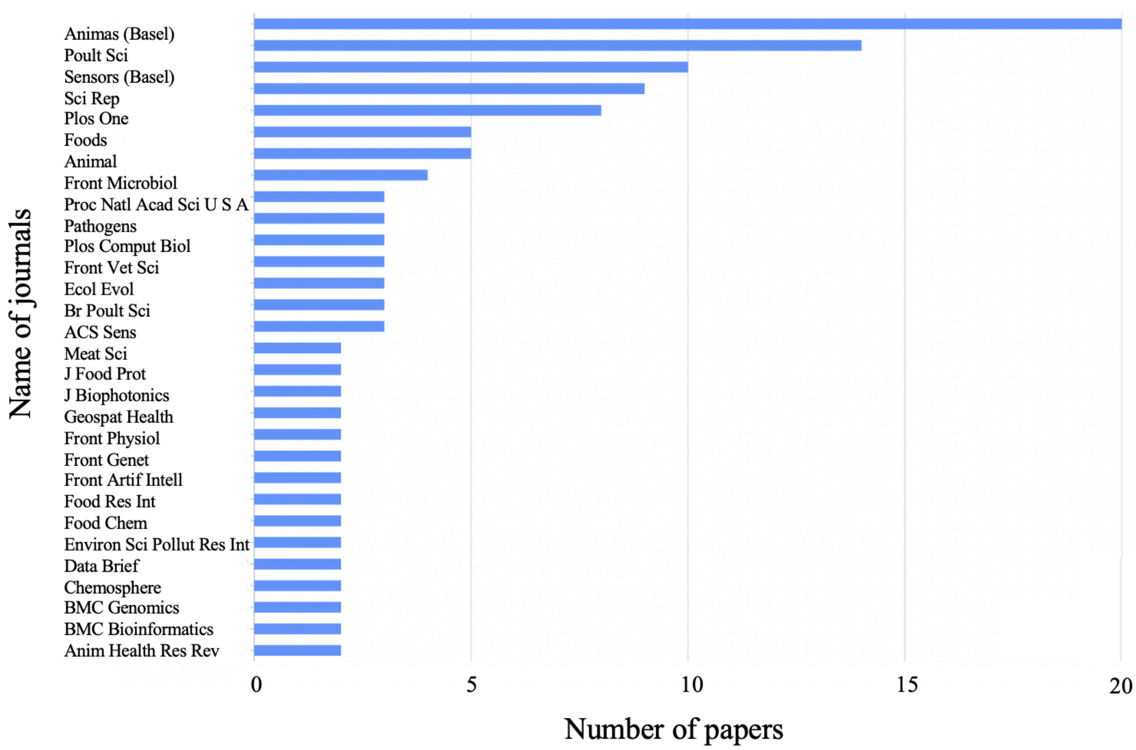

Figure 1.2. Journal publication analysis from January 2013 to October 2023 on computer vision and poultry.

1.2.3 Global Contributions: Country-wise Analysis

The top 54 countries in terms of publication volume in the research fields of computer vision and poultry are shown in Figure 1.3. The country with the highest publication volume in this area is the United States of America with 75 papers (30.49%), followed by China with 58 papers (23.58%), and the United Kingdom ranking third with 22 papers (8.94%). This distribution provides a roadmap for researchers and institutions. Engaging with the leading countries can open doors for international collaborations, knowledge exchange, and access to more extensive datasets and resources. It is crucial for individuals and institutions to understand these global research dynamics to effectively position themselves in this evolving landscape, seek partnerships, and stay updated with the latest methodologies and findings from these leading nations.

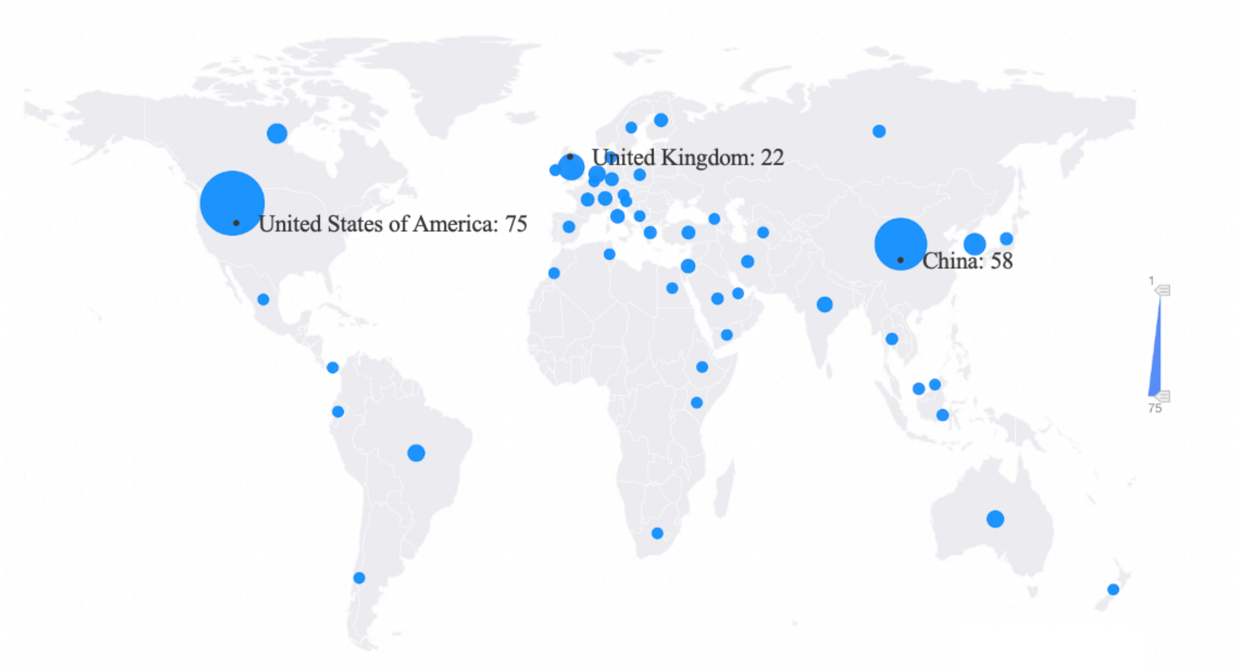

Figure 1.3. Analysis of research countries from January 2013 to October 2023 on computer vision and poultry.

1.2.4 Keyword Trends: Evolution of Focus Topics

Keywords in a paper are a concise summary and encapsulation of the research objectives, subjects, and methods. Analysis based on keywords can reflect the evolution of themes and research hotspots in a specific field over a certain period. Using computer vision and poultry as search keywords for the timeframe from January 2013 to October 2023, as shown in Figure 1.4, the top five keywords in terms of frequency are: machine learning, poultry, avian influenza, random forest, and salmonella. Dividing the time frame from January 2013 to October 2023 into four periods, as shown in Figure 1.5, represents the popularity ranking and ranking changes of keyword frequency related to computer vision and poultry. Over the span of a decade, from 2013 to 2023, the persistent prominence of machine learning stands out, as it emerges as a pivotal topic across all four distinct time periods. This underscores its enduring relevance and crucial role in various domains. Delving into the evolution of computer vision topics, the early phase from 2013 to 2015 was marked by the presence of concepts such as "hyperspectral imaging" and "information gain". Progressing to 2016-2018, there was a notable introduction of terms like "random forest" and "2D, 3-dimensional". As we transitioned into the 2019-2021 period, the field exhibited a pronounced tilt towards advanced methodologies, prominently featuring "convolutional neural networks". This momentum carried forward into 2022-2023, where "convolutional neural networks" remained at the forefront, complemented by the emergence of "big data". In poultry science, the evolution of these keywords reflects the sector's intricate response to emerging challenges and opportunities. The prominence of terms like "avian influenza" underscores the ongoing efforts in disease management and prevention, while the emergence of "animal welfare" indicates a growing emphasis on ethological research and ensuring optimal living conditions for poultry. Moreover, the keyword 'Salmonella' brings to the forefront issues of food safety, highlighting the critical need to monitor and control bacterial pathogens that can affect both animal and human health. This progression mirrors the sector's dedication to leveraging technology for holistic advancements in poultry health, production, and welfare.

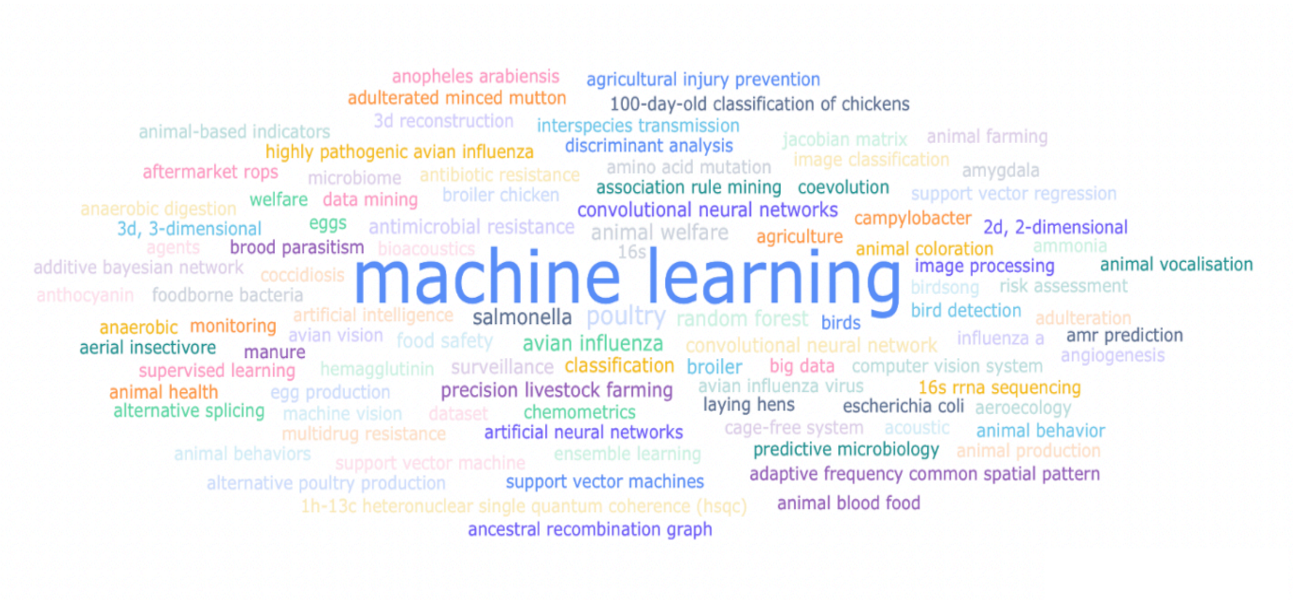

Figure 1.4. Keyword frequency analysis of computer vision and poultry from January 2013 to October 2023 (This word cloud was generated through bibliometric analysis to count the frequency of each word in the dataset. Words that appear more frequently are displayed in larger fonts).

Figure 1.5. Analysis of popularity rankings and ranking changes for computer vision and poultry across different time periods from January 2013 to October 2023.

1.3 DELVING INTO THE CORE APPLICATIONS AND IMPLICATIONS OF COMPUTER VISION IN POULTRY FARMING

1.3.1 Fundamentals of Computer Vision in Poultry Management

Computer vision, rooted in interpreting visual data similarly to human vision, has seen a surge in applications, notably in animal farming. With the growing demand for poultry products due to a rising global population, the sector is pushed to maintain quality care for increasing numbers of animals (Li et al., 2021a). Traditional methods sometimes fail to detect early signs of abnormalities in animals, which may affect their health and productivity. To address this, computer vision technologies, particularly CNNs, provide objective and real-time monitoring tools (Fernandes et al., 2020). Emerging digital image acquisition technologies have enabled areas like digital image processing and image analysis, which play crucial roles in interpreting visual data. Modern sensors, such as infrared cameras and hyperspectral imaging tools, enable diverse applications in poultry farming, including behavior monitoring and body weight measurement (Li et al., 2020; Olejnik et al., 2022). Cameras and sensors, the foundational components of computer vision, offer a holistic view of an environment when their data is fused. Red, green, and blue wavelengths (RGB) cameras, known for high-resolution images, capture the visual spectrum (Brenner et al., 2023). Thermal infrared cameras provide insights into heat patterns, and depth sensors offer spatial information by combining with RGB data (Feng et al., 2021). However, challenges like the photogrammetric co-processing of thermal infrared and RGB images, make calibrated systems and advanced algorithms indispensable for accurate data interpretation (Dlesk et al., 2022). In poultry farming, obtaining clear visual data poses a challenge. Factors like dust, varying light conditions, and bird movement introduce noise and imperfections into raw images (Zhang and Zhou, 2023; Zhang et al., 2023e). Adaptive image noise removal tools, equipped with classification capabilities, ensure data remains free from visual degradation (Chen et al., 2020a). Deep learning techniques further address challenges such as blur, shadows, and poor lighting (Anvari and Athitsos, 2022). Therefore, specialized image processing techniques that cater to the unique challenges in poultry environments, like bird movement and dust, are essential for preparing data for further analysis. Feature extraction in poultry imaging involves extracting relevant features, like bird size or health indicators. Techniques like the vision transformers and segment anything model have facilitated bird detection (Dosovitskiy et al., 2021; Jamil et al., 2022; Yang et al., 2023c). Moreover, similarity search concepts have been valuable in high-resolution imaging, making multi-modal imaging frameworks crucial for efficient feature extraction (Somnath et al., 2018). Computer vision's integration with broader management systems has been paramount in sectors like livestock and transportation. These systems enable real-time and accurate data acquisition, leading to predictive modeling for precise decisions. In poultry management, computer vision offers myriad benefits. It improves efficiency in monitoring livestock, facilitating real-time egg quality monitoring, disease detection, and growth pattern evaluations (Dorea et al., 2020; Kumar et al., 2023). Applications even extend to monitoring chicken behavior, showcasing the potential in recognizing and classifying behaviors for livestock well-being. Moreover, decision-making is enhanced; mobile health apps equipped with computer vision offer non-invasive assessments of superficial wounds (e.g., inflammation or tissue damage can be used to determine the severity of feather damage), improving poultry health care (Zhang et al., 2023d). In sum, computer vision's integration in poultry management promotes better health monitoring, minimizes manual labor, and encourages data-driven decisions, thus enhancing overall poultry farming efficiency (Zheng et al., 2021; Abraham et al., 2021). Figure 1.6 below provides a succinct flowchart that illustrates the end-to-end integration of computer vision into poultry management, capturing each pivotal step from image acquisition to data-driven decision making.

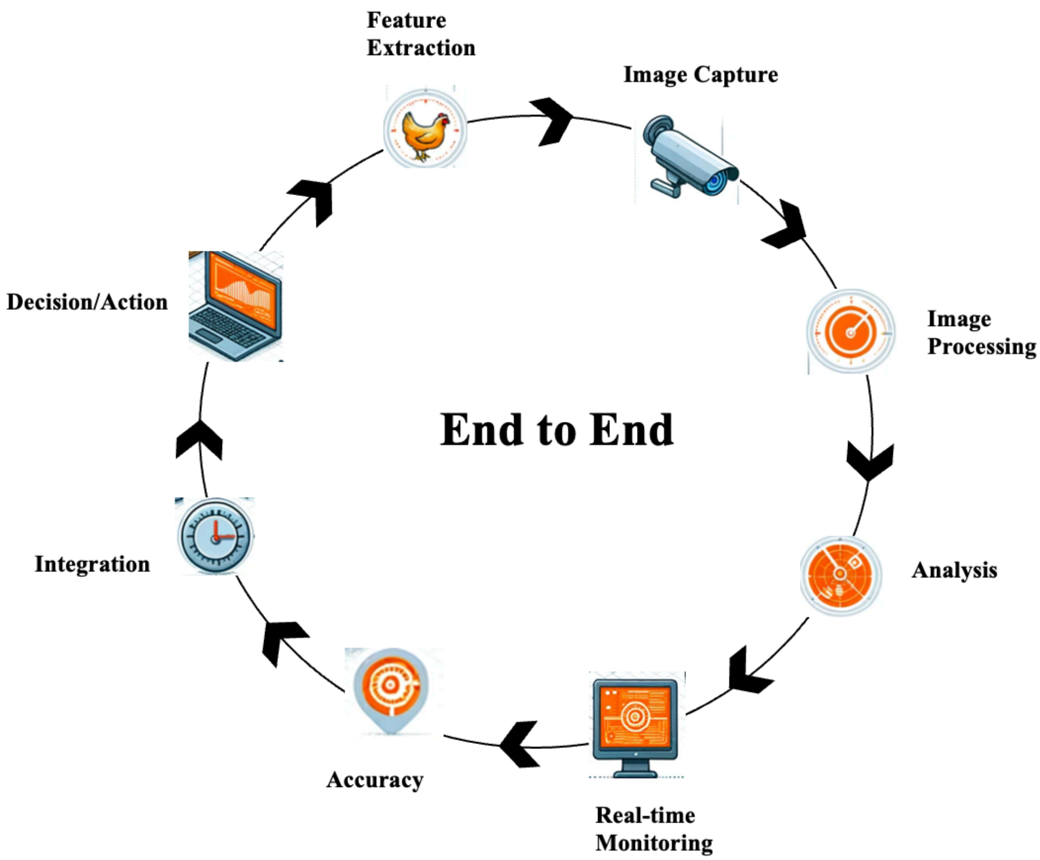

Figure 1.6. A flowchart that illustrates the end-to-end process of computer vision-based cybernetics system in poultry management.

1.3.2 Egg Quality Assessment

In the modern poultry and egg sector, ensuring the quality of eggs is not just a matter of meeting consumer expectations but also a testament to the advancements in technology and research. As the global demand for eggs continues to rise, the sector faces the challenge of maintaining quality while scaling up production. Traditional methods of quality assurance, often manual and time-consuming, are increasingly being replaced by automated systems. Among these, computer vision, when synergized with machine learning, has emerged as a frontrunner in revolutionizing egg quality assurance. Okinda et al. (2020) delved into the realm of volume estimation, introducing a depth image-based system specifically for chicken eggs. Their approach ingeniously tackled challenges like varying ambient light conditions and the potential occlusion of eggs, achieving remarkable accuracy (R^2 of 0.984) in volume estimation (Okinda et al., 2020b). Another study took on the task of recognizing cracks on eggshells, a task made challenging due to natural dark spots on the egg surface. Their method used negative laplacian of gaussian (LOG) operator to enhance crack visibility, achieving an impressive 92.5% recognition rate, which could significantly reduce the risk of selling damaged eggs (Guanjun et al., 2019). The weight of an egg can be a direct indicator of its quality (Schwagele 2011). Recognizing this, Cen et al. (2006) embarked on developing a machine vision system specifically for this purpose. Their system, which employed image segmentation based on RGB intensity, showed a strong correlation between predicted and actual weights, indicating its reliability (Cen et al., 2006). Angelia et al. (2021) ventured into the domain of egg classification. Using the region-convolutional neural network, they achieved a 93.3% accuracy rate, showcasing the potential of image processing in egg grade (Grade A, B, C, Inedible) determination (Pacure Angelia et al., 2022). Sex determination in breeder eggs has always been a topic of interest. A comprehensive review in this area highlighted the potential of non-invasive methods, discussing cutting-edge techniques like Raman spectroscopy and computer colorimetric setups, which could revolutionize hatchery practices (Aleynikov, 2022). Another noteworthy development was an automated system for egg grading. This system, capable of identifying, counting, and classifying eggs, achieved a staggering 98% accuracy for individual classifications based on a two-stage model (real-time multitask detection (RTMDet) and random forest networks) (Yang et al., 2023a). Other pioneering studies in egg quality field focused on diverse areas such as eggshell quality assessment (Pan et al., 2011), determining egg freshness (Qi et al., 2020), yolk color analysis (Ma et al., 2017), contamination detection, size and shape analysis (Nasir et al., 2018), surface defect detection (Mota-Grajales et al., 2019), and a deep dive into internal quality assessment (like blood spots) (Arivazhagan et al., 2013). While the aforementioned studies have made significant strides in egg quality assurance using computer vision, there's still room for growth. One avenue for exploration is the integration of real-time monitoring systems. These systems, capable of instantly processing and providing feedback on the data they receive, could revolutionize poultry farms by allowing instantaneous quality checks. As eggs are produced, any issues such as cracks and stains could be immediately identified and addressed, ensuring optimal quality. However, the challenges of poultry environments, characterized by varying levels of light, temperature, and humidity, necessitate the development of systems robust enough to operate under these varying environmental conditions (Bist et al., 2022, 2023a, 2023c). Lighting is pivotal for computer vision; different lighting conditions can affect image quality and analysis accuracy. As we advance, reducing false positives-instances where a system mistakenly flags a good quality egg as subpar-becomes paramount. This ensures that quality eggs aren't wrongfully discarded, preventing unnecessary wastage. The future also beckons the exploration of multi-modal systems, which amalgamate traditional computer vision techniques with other types of data input. For instance, combining computer vision with other sensors like infrared (Zhang et al., 2023c), which can detect temperature variations indicating egg freshness, or ultrasonic sensors (Mocanu et al., 2016), adept at identifying minuscule, otherwise invisible eggshell cracks, can offer a more comprehensive egg quality assessment. Such holistic evaluations ensure that only the best eggs make their way to consumers (Figure 1.7).

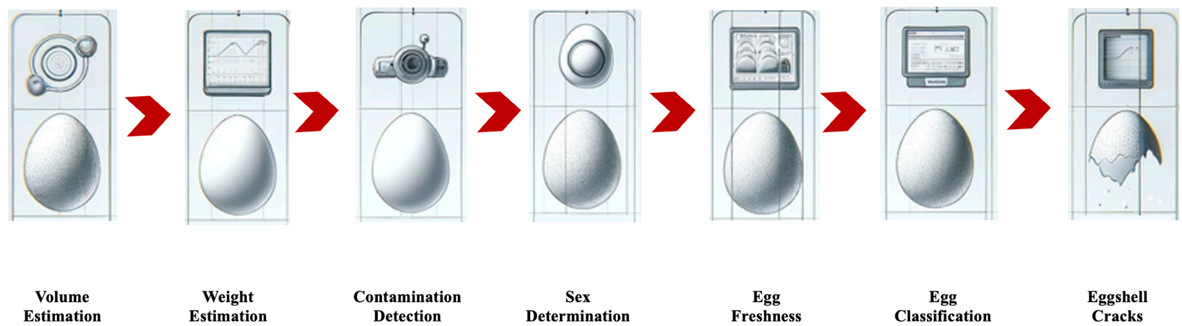

Figure 1.7. Revolutionizing egg quality assurance with computer vision.

1.3.3 Broiler Growth Monitoring through Computer Vision

In the rapidly evolving poultry sector, monitoring the growth of meat chickens (broilers) has become paramount. As the global poultry market expands, optimizing growth rate becomes imperative while ensuring the health and well-being of the broilers. Traditional methods, which often rely on manual measurements and visual checks, are gradually being overshadowed by the precision and efficiency of computer vision, especially when augmented by machine learning techniques. A groundbreaking study by delving deep into the potential of computer vision for monitoring poultry growth. By addressing challenges like bird movement, they introduced a depth image-based system. Their method, which adeptly navigated these challenges, achieved real-time weight estimation, ensuring consistent growth rates and early detection of growth anomalies (Mortensen et al., 2016). Furthering the discourse, Aydin et al. (2010) concentrated on poultry posture and activity levels as indicators of health and growth. Using sophisticated image processing techniques like the CNN, they discerned between postures of healthy and potentially ailing birds. Their system, which melded edge detection with pattern recognition, demonstrating the promise of computer vision in early detection of gait abnormalities and its association with body weight and growth rate (Aydin et al., 2010).

Nakarmi et al. (2014)'s research, on the other hand, was centered on poultry feeding patterns. Recognizing the direct correlation between feeding patterns and poultry health and growth, they devised a computer vision system to monitor individual bird feeding activity. By employing image segmentation techniques combined with deep learning algorithms, their system demonstrated a robust correlation between feeding behaviors and growth trajectories, with an efficacy rate of 95% (Nakarmi et al., 2014). Neethirajan (2022) took a different approach, focusing on the movement patterns of poultry. Their system, which employed advanced tracking algorithms like the Kalman Filter, could predict growth rates based on the activity levels of the birds. This not only ensured optimal the tracking of the chicken's temporal and spatial changes but also provided insights into the overall movement the flock (Neethirajan, 2022).

Jung et al. (2021) investigated the keel bone development in poultry using computer vision techniques and 3D imaging. They were able to monitor the keel bone damage of laying hens providing crucial insights into their overall physical development and health with a precision rate of 86% (Jung et al., 2021). You et al. (2021) provided a deep dive into the nutritional aspect. Their system, which utilized the random forest classifier, could monitor the food intake of individual birds, correlating it with their growth rates, and ensuring that the birds received optimal nutrition for healthy growth (You et al., 2021). Lin et al. (2020) introduced a system using time-lapse imaging and Faster region-based convolutional neural network (R-CNN) deep learning algorithms to monitor chicken movement, drinking habits, and growth patterns. With a detection accuracy of 98.16% and tracking accuracy of 98.94%, this method offers a comprehensive insight into chicken behavior and growth, especially in addressing heat stress in tropical regions (Lin et al., 2020). Thompson et al. (2023) and Nakrosis et al. (2023) all focused on different aspects of poultry growth, from dropping classification to feather growth patterns.

Their computer vision systems, which employed techniques like the YOLOv5 and K-means algorithm, provided comprehensive insights into each aspect, ensuring that the birds grew healthily and uniformly with an average accuracy rate of 89% (Thompson et al., 2023; Nakrosis et al., 2023). While these studies have significantly advanced the field of poultry growth monitoring using computer vision, there's still a vast expanse to explore. Future research could delve into real-time system integration in poultry farms for continuous monitoring (Raj and Jayanthi, 2018). Adaptable systems, such as those with depth camera for different poultry sizes or those that can recalibrate based on varying light conditions, will be pivotal (Lee, 2012; Lin et al., 2019). As machine learning models evolve, integrating them with computer vision can further refine system accuracy. The exploration of multi-modal systems, merging computer vision with other sensory data like acoustic or thermal sensors, can offer a comprehensive solution, revolutionizing poultry growth monitoring. Table 1.1 lists Primary methods in computer vision technology for overseeing and tracking poultry growth in monitoring systems.

Table 1.1. Main computer vision techniques in poultry growth monitoring systems.

Technique	Target	Sensor	Bird type	Reference
Bayesian artificial neural network	Body weight	3d camera	Broiler	(Mortensen et al., 2016)
Linear real-time model	Distribution	Top view camera	Broiler	(Kashiha et al., 2013)
Yolov3	Gender	Digital camera	Hens and roosters	(Yao et al., 2020)
Commercial software	Growth rate	Upper view camera	Broiler	(De Wet et al., 2003)

K-nearest neighbors' algorithm	Bone	Digital camera	Broiler	)(Castro Júnior et al., 2022)
Faster R-CNN	Heat stress	Web camera	Broiler	(Lin et al., 2018)
Matlab	Inactive birds	3d camera	Broiler	(Aydin, 2017)
Matlab	Thermal comfort	Top view camera	Laying hens	(Del Valle et al., 2021)
Bot-SORT	Tracking	Top view camera	Cage-free chickens	(Siriani et al., 2023)
Segment anything model	Body weight	Thermal camera	Cage-free chickens	(Yang et al., 2023c)
Faster region-based convolutional neural network	Drinking time	Digital camera	Broiler	(Lin et al., 2020)
Software carne 2.2	Fat content	Digital camera	Boiler and turkey	(Chmiel et al., 2011)
Generative adversarial network-masked autoencoders	Chicken face	Digital camera	Chicken	(Ma et al., 2022)
Faster R-CNN	Droppings	Top view camera	Broiler	(Zhou et al., 2023)
Mobilenetv2	Health assessment	Digital camera	Broiler	(Li et al., 2023)

YOLOv5	Floor eggs	Top view camera	Cage-free chickens	(Subedi et al., 2023b)
YOLOv5	Pecking	Top view camera	Cage-free chickens	(Subedi et al., 2023a)
YOLOv5	Mislaying	Vertical view camera	Cage-free chickens	(Bist et al., 2023d)
YOLOv4	Preference behavior	Top view camera	Laying hens	(Kodaira et al., 2023)
YOLOX	Counting	Top view camera	Broiler	(Li et al., 2022)

1.3.4 Poultry Health, Welfare and Disease Detection

The field of poultry health management stands on the cusp of transformation with the potential adoption of computer vision technologies. The precision in monitoring sick birds, a key welfare indicator, has markedly improved by leveraging image analysis to estimate growth and detect health anomalies. Zhuang et al. (2018) developed a real-time health monitoring algorithm for broilers using image processing and Support Vector Machine (SVM), achieving 99.469% accuracy in detecting H5N2 bird flu (Zhuang et al., 2018). This is particularly evident in the processing sector, where machine vision systems have been adeptly employed to correlate carcass characteristics with viscera, thereby ensuring quality control during evisceration (Chen et al., 2023). The adaptability of broilers to their rearing environment has been quantified using computer-vision-based indices, Massari et al. (2022) tested cluster and unrest CV-based indexes on twenty broilers to monitor movement, validating their effectiveness in controlled settings, and suggesting applicability in precision livestock farming (Massari et al., 2022). Additionally, the task of pose estimation has been addressed through multi-part detection models (Zheng et al. (2022). In addition, exploring automatic poultry pose recognition using deep neural networks (DNNs), outperforming algorithms like YOLOV3 with higher precision and recall, indicating potential for monitoring poultry health on large-scale farms (Fang et al., 2022).

In the realm of disease detection, thermographic and AI methodologies have been synergized to facilitate the early identification of diseases, such as Newcastle Disease and Avian Influenza, showcasing the utility of thermal imaging in preemptive health measures (Sadeghi et al., 2023). This advancement is complemented by the prowess of deep learning in disease diagnostics through the deployment of convolutional neural networks, with models like MobileNetV2 and extreme inception (Xception) achieving high diagnostic accuracies (98%) in fecal image classification, thus equipping farmers with powerful tools for disease management. Furthermore, the behavioral patterns of laying hens have been decoded using computer vision, enabling continuous and individual behavior (standing, walking, and scratching) monitoring, a significant advancement over traditional human observation. The potential of computer vision systems in agriculture is substantial, inviting the development of sophisticated algorithms capable of adapting to the ever-changing farm conditions, such as variable ambient light and the multiple behaviors of poultry (Khairunissa et al., 2021; Ifuchenwuwa et al., 2023). The ongoing refinement and validation of these technologies across different poultry breeds and settings are critical to their success. In addition, the pioneering advancements in computer vision technologies hold immense promise for poultry health management.

Groundbreaking methods in poultry health management are showcased using thermographic imaging and the novel technique of converting audio files to images for stress analysis. This process involves analyzing the transformed images with pretrained CNN, achieving significant accuracy in stress detection (van den Heuvel et al., 2022). Integrating virtual reality (VR) and eye-tracking technology could also represent a future direction for enhancing poultry disease detection, offering precise monitoring and analysis capabilities. A study presents a VR system using eye-tracking to diagnose neurodegenerative diseases, successfully eliciting diagnostic eye movements and enhancing remote, accurate detection of conditions like Parkinson's (Orlosky et al., 2017). The integration of advanced computer vision with multi-modal sensory data underscores a future where adaptable and scalable solutions become the cornerstone of poultry health management and animal welfare.

Table 1.2. Main computer vision techniques for welfare indicators detection.

Technique	Target	Sensor	Bird type	Reference
Residual network (ResNet)	Sick bird	Digital camera	Broiler	Zhang et al. (2020)
CNNs	Manure	Top view camera	Chicken	Zhu et al. (2021)
Logistic regression	Comb	Google Search	/	Bakar et al. (2023)
Dense convolutional Network	Chicken	Top view camera	Broiler	Cao et al. (2021)
U^2-Net	Plumage	Side view camera	Layer	Heo et al. (2023)

Threshold segmentation	Muscle	Vertical view camera	Broiler	Chen et al. (2022)
Visual geometry group network (VGGNet) and ResNet	Avian pox, Infectious Laryngotracheitis, Newcastle, and Marek	Digital camera	Chicken	Quach et al. (2020)
Chan-Vese model	Head and body	Side view camera	Caged chicken	Xiao et al. (2017)
Xception	Eimeria	/	/	Boufenar et al. (2022)
Decision Tree	Slouching, eye foaming, lethargy, feather loss, color paling, and raling	Side view camera	Caged chicken	Quintana et al. (2022)
U-Net and Pix2pixHD.	Chicken	Side view camera	Caged chicken	Yang et al. (2023e)
CNNs	Crowdedness	Kinect sensor	Cage-free chicken	Pu et al. (2018)
CNNs	Locomotion, perching, feeding, drinking, and nesting.	Top view camera	laying-hen	Nakarmi et al. (2014)
CNNs	Breeder	Top view camera	Broiler	Pereira et al. (2013)

Mask R-CNN YOLOv4	Postures	Top view camera	Broiler	Joo et al. (2022)
YOLOv3	egg breeders	Top view camera	Hens	Wang et al. (2020)
Matlab	Flock movement	Top view camera	Broiler	Neves et al. (2015)
Improved Sparrow Search Algorithm and Support Vector Machine	Aggressive behaviors	High-definition cameras	Taihang chickens	Li et al. (2023b)
Matlab	Eating behaviors	High-speed camera	Broiler	Mehdizadeh et al. (2015)
YOLOv5 and deep sort	Mobility	Top view camera	Broiler	Jaihuni et al. (2023)

1.3.5 Integrating Robotics and Computer Vision

The integration of robotics and computer vision in poultry processing reveals a landscape of innovative technologies aimed at enhancing efficiency and animal welfare. Misimi et al. (2016) introduced the GRIBBOT, a 3D vision-guided robot for harvesting of chicken fillets, which represents a significant step toward automating the manual processes currently in place (Misimi et al., 2016). This innovation is paralleled by developments in ethological research, where robots like PoulBot were used to study and influence the behavior of domestic chicken chicks, thereby advancing our understanding of animal-robot interactions (Gribovskiy et al., 2018). Chen et al. (2018) described a machine vision method for recognizing visceral contours in poultry carcasses, which greatly improves the accuracy of processing and highlights the potential for automation in tasks that were traditionally challenging to mechanize (Chen and Wang, 2018). Concurrently, *PoultryBot* demonstrates the feasibility of using autonomous robots for tasks such as floor egg collection in commercial poultry houses, despite a need for further refinement in collection mechanisms and navigation systems (Vroegindeweij et al., 2018). The advancements in evisceration are showcased by six degrees of freedom robot system, which used robotics and machine vision to achieve high accuracy in poultry incisions for evisceration (Chen et al., 2021a).

In the realm of egg handling, a study has developed a sophisticated method involving an improved three-channel convolutional neural network (T-CNN) and you only look once (YOLOv5) technique for egg detection and segmentation (Zhang et al., 2023a). The method includes median filtering, OTSU method (OTSU) for segmentation, and the Kirsch operator for edge extraction, followed by feature extraction via T-CNN and classification using a support vector machine (SVM). The technique achieved a 95.65% accuracy rate in egg recognition, with a low misrecognition rate, demonstrating its efficacy for potential use in automated goose egg picking systems (Zhang et al., 2023a). This is complemented by the development of robots designed for the removal of broiler mortality, and autonomous egg picking systems that promise to reduce manual labor significantly while enhancing production efficiency. Livestock robots capable of picking and classifying eggs on farms are equipped with various sensors and virtual instrument devices, indicating a shift towards multifunctional farm automation (Wang et al., 2019).

Recent advancements highlight the importance of robotics in various sectors. High-throughput robotics help detect antimicrobial-resistant bacteria, linking robotics with public health (Truswell et al., 2023). Machine vision, using an improved region-based active contour method, accurately positions viscera, showcasing the potential of image processing in complex chicken slaughtering tasks (Chen et al., 2021b). Additionally, pick-and-place systems for handling deformable poultry pieces from cluttered bins highlight the need to evaluate robotic adaptability to meet varying demands in the food industry (Raja et al., 2023). The selective compliance articulated robot arm (SCARA) robot with a pneumatic gripper is specifically designed for egg handling in the poultry sector, showcasing automation's potential to increase production speed and reduce manual labor (Prakash et al., 2021). Moreover, smart mobile robots for free-range farms and real-time recognition studies of egg-collecting robots in free-range duck sheds exhibit the growing influence of machine learning models, like YOLOv5s, on robotic efficiency and environmental adaptability (Chang et al., 2020; Fei et al., 2023). Lastly, the studies explored sophisticated integrations of machine vision and robotics tailored to specific needs within the poultry sector. Chen et al. (2019) constructed an eviscerating robot system for the poultry processing sector, enhancing production efficiency, ensuring production efficiency and ensuring the health standards of poultry products and reducing labor intensity using parallel robots and machine vision, with a visual system developed on MATLAB. Gribovskiy et al. (2010) delved into the realm of ethology and robotics, where a mobile robot, PoulBot, was designed to interact with and influence chick behavior, showing young chicks accept robot as member as new insights for both scientific research and potential improvements in poultry welfare. This project utilized video and audio data, along with advanced data analysis systems, to build formal models of animal behavior for implementation in robots (Gribovskiy et al., 2010; Chen et al., 2019).

Future studies in poultry farming could revolutionize the sector by leveraging voice-controlled robotics and VR for enhanced human-machine interaction. The potential of voice-controlled machinery, as demonstrated by the Raspberry Pi project, indicates significant benefits in terms of automation. Using smartphone devices to control agricultural machinery could greatly improve efficiency and reduce labor needs in the poultry sector. The incorporation of Raspberry Pi 3 and its built-in Wi-Fi capability could serve as a cornerstone for internet-based automation, streamlining operations through simple voice commands. Furthermore, this system necessitates the use of a microSD card loaded with Raspbian OS to boot the Raspberry Pi. The integration of these technologies effectively transforms a conventional farm into a 'smart farm', where tasks are automated, and efficiency is greatly enhanced. The system's design takes into consideration ease of use, with a focus on creating a seamless interface for farmers who may not have extensive technical knowledge. The use of voice commands signifies a move towards more natural forms of human-machine interaction, reducing the learning curve and increasing accessibility (Chavan et al., 2019). In addition, further advancement could integrate VR-based robotics, taking advantage of immersive teleoperation systems to bridge the physical and virtual worlds in poultry environments. By using algorithms for real-time 3D reconstruction of unstructured agricultural scenes, operators could remotely guide robots through complex tasks within a virtual representation of the actual environment (Fadzli et al., 2023). This immersive approach could facilitate precise control over farming activities, from feeding and health monitoring to egg collection, while minimizing human presence and disruption to the birds. Such synergistic application of voice control and VR in robotics could lead to breakthroughs in operational productivity and animal welfare, ushering in a new era of precision farming in the poultry sector. With these technologies, future research could develop sophisticated models that simulate entire poultry operations, allowing for the optimization of workflows and the exploration of novel farming strategies before their real-world implementation (Chen et al., 2020b). Collectively, these studies signify a transformative period in the poultry sector, marked by rapid technological advancements. The convergence of robotics, computer vision, and ethology is not only enhancing production and efficiency but also contributing to better animal welfare and global health outcomes by enabling early detection of animal abnormal behaviors and removing unnormal birds in time, ensuring higher standards of food safety. As these technologies evolve, they hold the potential to address some of the most pressing challenges in the sector, including labor shortages, food safety, and disease surveillance. Figure 1.8 shows computer vision-based robotics and their roles of poultry sector.

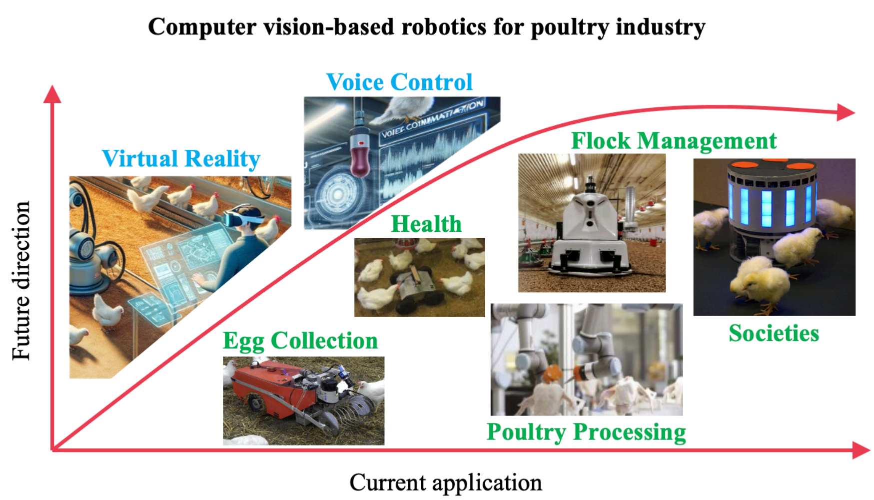

Figure 1.8. Enhancing poultry sector security with computer vision-based robotics (Source: Ren et al. (2020), Gribovskiy et al. (2010), Park et al. (2022) and Vroegindeweij et al. (2018)).

1.3.6 Case Studies: Successful Implementations Around the Globe

To understand the application of computer vision in the poultry sector, we examined cases from commercial farms, including enclosed broiler houses, free-range, and cage-free environments. In enclosed broiler houses, significant advancements have been made using computer vision and deep learning. A study conducted by Mortensen et al. (2016) describes a 3D camera-based system utilizing a Kinect camera for broiler weight prediction, achieving an average error of 7.8%. This technology shows promise for broader applications such as activity analysis and health monitoring (Mortensen et al., 2016). Additionally, Eijk et al. (2022) detailed a study employing computer vision algorithms, including Mask R-CNN and U-Net models, to monitor broiler interactions with resources like feeders and drinkers, enhancing farm management and welfare practices (van der Eijk et al., 2022). Furthering these developments, Cakic et al. (2023) 's research introduces the use of high-performance computing (HPC) and deep learning to create predictive models for smart poultry farms. These models, effective in tasks like chicken counting, dead chicken detection, weight assessment, and uneven growth detection, were implemented on edge AI devices. Utilizing Faster R-CNN architectures for chicken detection and Mask R-CNN for segmentation, the study demonstrated high accuracies, paving the way for real-time farm monitoring. This underscores the potential of integrating HPC, deep learning, and edge computing in smart agriculture solutions, especially in poultry farming. Figure 1.9 illustrates the practical application observed in these case studies of enclosed broiler houses.

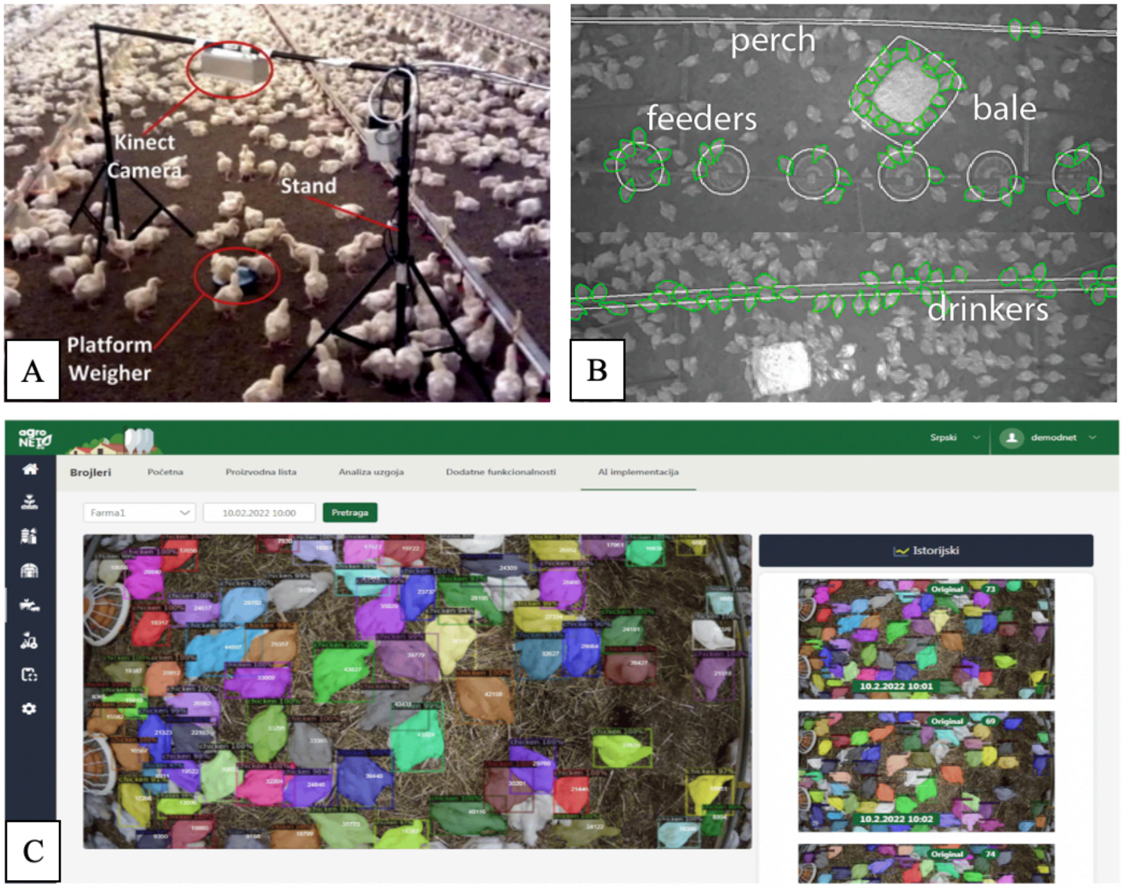

Figure 1.9. Case study of broilers: (A) body weight prediction (Mortensen et al., 2016), (B) broiler interaction monitoring (van der Eijk et al., 2022), and (C) broiler detection interface developed using HPC (Cakic et al., 2023).

In free-range chicken houses, advanced computer vision and deep learning have significantly improved farm management and animal welfare. Cao et al. (2021) discussed the development of the locally constrained dense fully convolutional network (LC-DenseFCN) model, a deep learning method for chicken counting with a 97% accuracy rate. This model utilized densely connected convolutional networks (DenseNet) as the backbone network and a unique LC-Loss function for accurate, real-time counting in dense environments(Cao et al., 2021). Yao et al. (2020) focused on chicken gender classification, achieving a 96.85% accuracy using YOLOv3 for detection and a VGG-19 based classifier (Yao et al., 2020). Liu et al. (2021)

detailed an automated system for detecting and removing dead chickens, integrating a visible light camera and YOLOv4 algorithm into a robotic system, enhancing biosecurity with a 95.24% precision rate (Liu et al., 2021). Figure 1.10 shows the practical application observed in these case studies of free-range chicken houses. The integration of such systems not only streamlines operations but also ensures high standards of care and well-being for the chickens by providing them with a healthier living and well-managed environment that is conducive to their health and productivity.

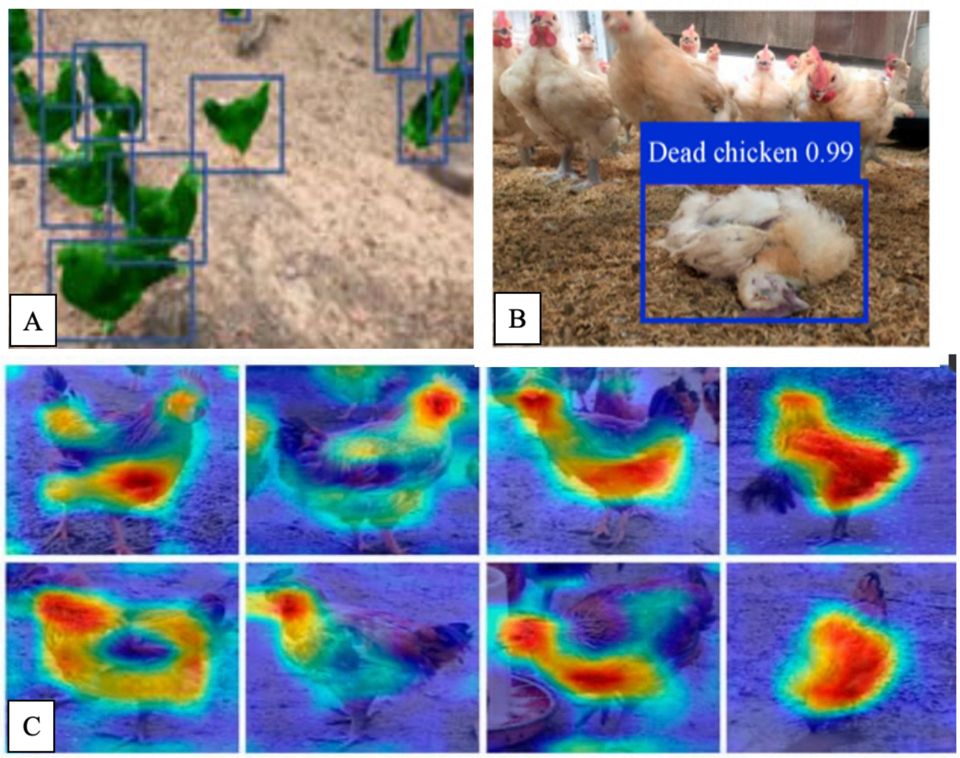

Figure 1.10. Case study of free-range chickens: (A) chicken counting (Cao et al., 2021), (B) dead chicken removal (Liu et al., 2021), and (C) chicken gender detection (Yao et al., 2020).

In cage-free hen houses, innovative computer vision and deep learning methodologies address specific poultry management challenges. Lamping et al. (2022) introduced ChickenNet, a system for assessing the plumage condition of laying hens. It extends the Mask R-CNN framework and was tested with different image resolutions, achieving a 98.02% mAP for hen detection and 91.83% for plumage condition prediction (Lamping et al., 2022). Subedi et al. (2023) described the development of deep learning models (YOLOv5s-egg, YOLOv5x-egg, YOLOv7-egg) for detecting floor eggs in cage-free environments. The YOLOv5x-egg model, in particular, showed a 90% precision and 92.1% mAP, indicating its potential utility in varying conditions for automatic floor egg monitoring (Subedi et al., 2023b). These advancements in computer vision and deep learning demonstrate significant potential for enhancing welfare monitoring and operational efficiency in cage-free poultry farming. Figure 1.11 depicts the practical application observed in these case studies of cage-free houses.

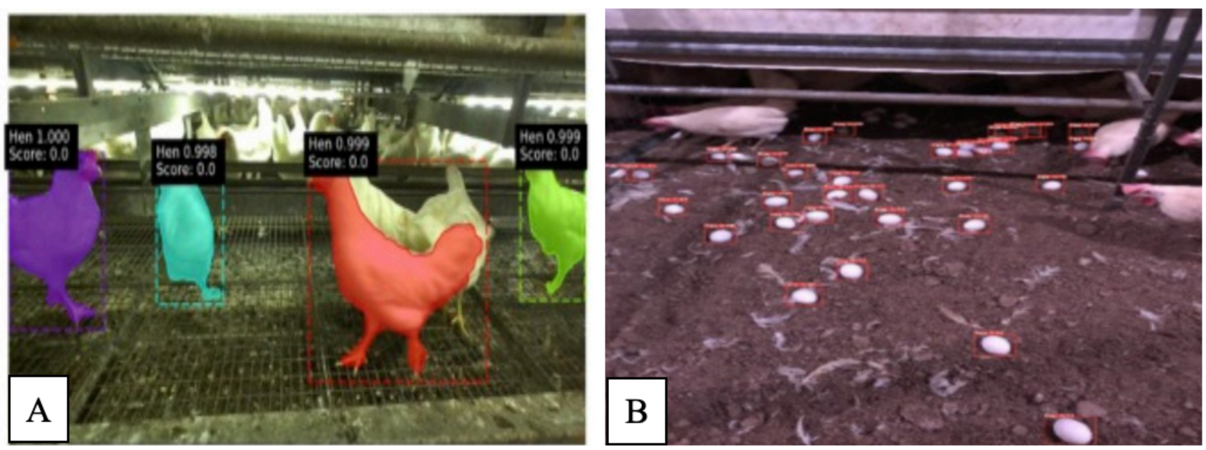

Figure 1.11. Case study of cage-free chickens: (A) plumage condition assessment(Lamping et al., 2022), and (B) floor egg detection (Subedi et al., 2023b).

1.4 FUTURE TECHNOLOGIES ON THE HORIZON

Recent techniques from fields such as chat generative pre-trained transformer (ChatGPT), autonomous vehicles (AVs), and large voice models like speech audio language music open neural network (SALMONN), contextual speech model with instruction-following/in-context-learning capabilities (COSMIC), and multi-modal music understanding and generation (M2UGen), provide a wealth of inspiration for the poultry sector, suggesting new avenues for optimizing the environmental conditions and overall management of poultry houses, leading to enhanced growth rates, better health outcomes, and reduced waste. The data processing and natural language capabilities of ChatGPT, as applied in precision agriculture, could offer poultry farmers advanced tools for managing health, nutrition, and environmental controls, allowing for enhanced decision-making through simplified interaction with complex datasets (Biswas, 2023; Genç, 2023; Potamitis, 2023). Similarly, occlusion management techniques from self-driving car technology, utilizing light detection and ranging (LiDAR) and YOLOv2 algorithms, could revolutionize poultry monitoring systems, enabling precise tracking of individual birds and swift correction of visual occlusion errors, even under challenging conditions such as low light or high-density settings (Yahya et al., 2020). The use of training simulators, inspired by the car learning to act (CARLA) simulator for autonomous vehicles, could be developed for the poultry sector to train algorithms in virtual environments that mirror actual farm conditions, improving the predictability and management of flock dynamics. Additionally, the real-time processing power of end-to-end deep learning, akin to CNN approaches in AVs, could be applied to instantly process visual data from farms, ensuring accurate health assessments and headcounts. Techniques for image classification and semantic segmentation, crucial for navigation in AVs, could be adapted to segment and classify different areas of poultry farms, enhancing detection and reducing errors in bird counting (Liang et al., 2020; Tippannavar et al., 2023). Furthermore, the integration of SALMONN's audio processing capabilities could provide insights into the respiratory health indicators of poultry (Tang et al., 2023), while COSMIC's emergent instruction-following capabilities could enable farmers to seamlessly translate sensor data into actionable insights (Pan et al., 2023). M2UGen's prowess in multi-modal generation suggests potential for creating stimulating or calming farm environments, innovating control interfaces for farming equipment, and providing interactive staff training using natural language (Hussain et al., 2023). Collectively, these advanced technologies can significantly enhance poultry farming operations, leading to better animal welfare-characterized by good nutrition, comfortable living conditions, robust health, natural living, and humane handling, provided they are used responsibly in conjunction with human expertise and in adherence to the Animal Welfare Act.

1.5 LARGE VISION MODELS FOR POULTRY SCIENCE

In the swiftly advancing domain of artificial general intelligence (AGI), the advent of the segment anything model (SAM) stands out as a vanguard development (Kirillov et al., 2023). Unveiled by Meta AI in 2023, SAM revolutionizes the field with a pioneering, zero-shot segmentation approach (Ahmadi et al., 2023). As a universal image segmentation model, SAM adeptly addresses majority of segmentation challenges within new and complex datasets, employing the sophisticated art of prompt engineering. SAM's architecture is a paragon of large vision models, meticulously engineered to navigate the intricate landscape of segmentation tasks with unparalleled agility and precision. By initiating the use of prompt-based segmentation in its preparatory phase, SAM not only enhances the pre-training paradigm but also redefines it, laying down a novel standard that underscores the transformative adaptability of vision models. This innovation is particularly pertinent to the poultry sector, where SAM can be further tailored with adaptors and improvements. Its capacity to analyze and interpret diverse visual information holds the promise of revolutionizing the way we monitor and manage poultry health, behavior, and overall welfare. With its robust segmentation capabilities, SAM could offer unprecedented insights into the nuanced environments of poultry farming, enabling more efficient and humane practices.

1.5.1 SAM for Tracking

SAM's foray into tracking applications, particularly within the field of video object segmentation (VOS), has proven to be a game-changer. This innovative tracking method, known as track anything model (TAM) (Yang et al., 2023d), integrates SAM with the established tracker XMem to segment and follow any object in video footage. In the context of poultry science, this technology holds significant promise; for instance, it can be tailored to track the speed and movement of chickens within a farm setting (Yang et al., 2023c). Users initiate the tracking by selecting an object, prompting SAM to generate a segmentation mask, which XMem then uses to track the object's movement through the video based on temporal and spatial data. This ability to monitor in real-time and make immediate adjustments is invaluable for farmers and researchers aiming to understand chicken behavior. However, TAM faces challenges in zero-shot scenarios where it must perform without pre-existing data, a situation often encountered in poultry environments when new or occluded behaviors emerge. Despite these challenges, the integration of SAM into poultry management practices heralds a new era of precision farming, offering insights that could lead to enhanced productivity and improved animal welfare.

1.5.2 3D-SAM-adapter

The SAM has garnered acclaim for its proficiency in general-purpose semantic segmentation, demonstrating a strong ability to generalize across a variety of everyday images. However, challenges arise when SAM is tasked with identifying objects characterized by small size, irregular shape, and low contrast, due to its foundational design for 2D imagery which doesn't capture the complex 3D spatial information. To address these challenges, the 3D-SAM-adapter, an innovative solution that modifies the original 2D SAM to interpret volumetric data, effectively enhancing its performance and enabling it to bridge the dimensional divide between 2D and 3D data interpretation (Gong et al., 2023). This adaptation has shown significant performance improvements over traditional methods. Recognizing the requirements of the poultry industry, the application of the adapted 3D SAM model for estimating poultry body weight and volume through 3D imaging represents a novel approach (Pleuss et al., 2019; You et al., 2021). Accurate measurement of these parameters is vital for effective health monitoring and growth management in poultry farming. By employing the 3D SAM model, there's potential to transform body weight estimation practices, offering poultry scientists and farmers a tool that could outperform conventional methods in both precision and efficiency. This advancement paves the way for more informed decision-making in poultry nutrition and welfare, leading to optimized farm operations and enhanced animal health.

1.5.3 MobileSAM

The SAM is known for its comprehensive image segmentation capabilities, but its performance can be hampered by the considerable computational weight of its image encoder. This issue has been ingeniously addressed by MobileSAM, which implements a knowledge distillation technique to distill the capabilities of the original SAM's heavy-duty image encoder, ViT-H, into a more lightweight version. This streamlined encoder retains compatibility with SAM's mask decoder while offering a significant reduction in size-over 60 times smaller than the original-without compromising on performance. Incorporating these innovations, MobileSAM stands out as especially beneficial for mobile applications, significantly advancing the practical deployment of SAM in various settings, including poultry farming (Zhang et al., 2023b). By minimizing the need for heavy computational resources, MobileSAM can be trained in less than a day on a single GPU, making it an ideal candidate for deployment in poultry farms where computational resources can be limited (Sigut et al., 2020). This adaptation not only ensures that the technology is accessible and cost-effective for farmers but also opens new avenues for real-time monitoring and management of poultry health, behavior, and productivity directly from mobile devices.

1.6 CURRENT TECHNOLOGY LIMITATIONS

Integrating computer vision in poultry farming represents a cutting-edge approach to agricultural management, leveraging deep learning and sophisticated hardware to optimize production. However, this integration is fraught with challenges. Firstly, the cost and complexity of digital signal processors (DSPs), field-programmable gate arrays (FPGAs), and graphics processing units (GPUs) present substantial barriers(Feng et al., 2019). These barriers are not solely financial but also technical, as leveraging these technologies requires a depth of programming and hardware knowledge often absent in farm settings. For instance, DSPs, essential for real-time processing tasks like grading poultry eggs, are priced between $500-$2,000 but demand familiarity with digital signal processing and embedded system programming (HajiRassouliha et al., 2018). FPGAs, ranging from $1,000-$3,000, offer configurability crucial for tasks such as sorting eggs. However, they necessitate expertise in hardware description languages and the ability to manage complex logic networks. The price reflects their versatility and capability to perform parallel processing tasks effectively (Monmasson et al., 2011). GPUs, which fall within the $1,500-$15,000 range, are the powerhouse for behavior classification through deep learning. They require a substantial investment not only in the hardware but also in developing and optimizing algorithms, which often involves knowledge of high-level programming languages and machine learning libraries (Rozemberczki et al., 2021). Table 1.3 encapsulates the common price ranges for these critical hardware types, highlighting the associated costs and technical requirements for their application in poultry farming. Beyond the hardware, the implementation of custom codes, especially those written in assembly language, further complicates the integration process. Assembly language coding for DSPs or FPGAs demands a granular level of control and an understanding of the processor architecture. It can optimize the performance for specific tasks (e.g., meat discrimination) but at the cost of increased development time and expertise (Arsalane et al., 2016). Such codes are meticulously tailored to the hardware, ensuring efficient execution of tasks but creating a steep learning curve for those not versed in low-level programming.

Table 1.3: Price range overview of essential computer vision hardware for poultry farming.

Hardware type	Price	Use case in poultry farming
DSPs	$500 - $2,000 (HajiRassouliha et al., 2018)	Grading of Poultry Eggs (Wang et al., 2010)
FPGAs	$1,000 - $3,000	Sorting eggs (Akkoyun et al., 2023)
GPUs	$1,500 – $15,000	Behavior classification (Pu et al., 2018)

Secondly, establishing a reliable connection between hardware and the computational model on farms is complex, given the need for robust infrastructure to handle data transmission and processing. For instance, in a poultry farm, computer vision systems may be deployed for monitoring the health and growth of chicken, detecting behavioral patterns, or automating the counting and sorting processes (Chmiel et al., 2011). Each of these applications generates a vast amount of data that must be processed in real time to be effective. This data flow demands high-bandwidth, low-latency communication channels to transfer video feeds from the cameras to the processors without significant delay. Moreover, the computational models that analyze this visual data must be hosted on hardware that can process information rapidly and accurately.

Typically, this would involve servers equipped with high-performance GPUs or FPGAs that can execute complex machine learning algorithms (Afif et al., 2020). These servers must be connected to the farm's network infrastructure in a way that ensures continuous operation despite the environmental challenges present in such settings, like temperature fluctuations, dust, and humidity (El-Medany, 2008). Additionally, the hardware must be calibrated to handle the peculiarities of the farm's environment. For example, variations in lighting conditions throughout the day can affect the accuracy of image recognition and object detection algorithms. Therefore, the hardware and software must be adaptable and robust enough to maintain performance regardless of these variables.

Lastly, the practical deployment of computer vision technologies in poultry farming is significantly challenged by the environmental factors inherent to such agricultural settings. The presence of dust, for example, can occlude camera lenses and interfere with the image quality being fed into vision algorithms, leading to reduced accuracy in detecting or classifying birds or behaviors (Guo et al., 2023). Similarly, variable lighting conditions can dramatically affect image capture; the stark contrast between bright daylight, the shadows of an indoor and light density setting may require algorithms to have dynamic range capabilities and adjustment mechanisms to maintain consistent performance (Zhou and Lin, 2007). Water lines and other farm equipment can also introduce visual noise that confuses the models. For instance, reflections or refractions from water surfaces can lead to false detections or misclassifications. The movement and presence of equipment like feeders and drinkers can obstruct the view or be mistakenly identified as part of the chicken by the vision system (Li et al., 2021b), necessitating sophisticated background subtraction techniques and object tracking algorithms that are robust to such changes. Moreover, behavioral analysis of poultry, an application of computer vision, can be affected by these disturbances. The detection of abnormal behaviors indicative of diseases or stress requires continuous and clear observation of the poultry, which can be disrupted by the environmental factors. To counteract these challenges, computer vision systems in poultry farming must be designed with advanced features such as: (1) to cope with the changes in lighting, cameras must have mechanisms that adjust their settings dynamically for optimal image capture (Kromanis and Kripakaran, 2021); (2) cameras and processing units must be protected and sealed against dust and moisture to ensure longevity and consistent operation (Mohd Ansari Shajahan et al., 2021); (3) algorithms must be trained on datasets that include the range of environmental conditions expected in a poultry farm to improve their robustness (Yang et al., 2023b). These improvements can enhance the reliability and effectiveness of computer vision applications in poultry farming, ensuring that the potential benefits of these technologies can be fully realized in such a complex ecosystem.

1.7 CONCLUSIONS

This review highlights the transformative role of computer vision in poultry management, emphasizing a shift towards technology-driven approaches. By integrating classical machine learning and advanced deep learning frameworks like CNNs, significant improvements in animal welfare and farm operations have been achieved. Challenges such as complex backgrounds and bird occlusions are avoided by the use of non-visible light and depth-based sensors, enhancing monitoring accuracy and efficiency.

Advancements span from egg quality assessment to health monitoring, reducing manual labor and boosting productivity. The use of multimodal systems integrating diverse sensors further extends these capabilities. However, adapting to real farm conditions and the need for extensive annotated datasets remain challenges.

Future innovations, including voice-activated robotics and virtual reality, promise greater efficiency and sustainability in poultry farming. Continued research and development in flexible, scalable, and ethical solutions merging human expertise with automation will fundamentally transform the sector, contributing to global food security and animal welfare.

1.8 OBJECTIVES OF THE DISSERTATION

The main objective of this dissertation was to explore the use of computer vision, thermal cameras, machine learning, and robotics to improve hen management, monitor behavior, and enhance welfare in cage-free hen houses. The detailed objectives were:

(a) Evaluate the performance of traditional CNN models (e.g., YOLO series, EfficientNetV2, SegFormer, SETR) and large vision models (LVM) (e.g., Segment Anything Model, Track Anything Model) in detecting key production and welfare indicators, including poultry locomotion, dust bathing, feeding, drinking, and perching behaviors, which are crucial for maintaining both hen welfare.

(b) Investigate the application of advanced computer vision and thermal camera technologies for monitoring poultry floor distribution, predicting bird body weight, detecting floor eggs, and identifying deceased chickens in dimly lit or hard-to-reach areas within the poultry house.

(c) Integrate CNN models with intelligent robotic systems (e.g., bionic quadruped robots) to enhance the automation of poultry management tasks, including the detection of floor eggs and dead chickens, advancing the poultry industry toward more ethical, efficient, and sustainable production practices.

This dissertation consists of individual chapters, each published or to be published in different journals and summarized in Chapter 7. Each chapter stands as one or two independent publications featured in various academic journals.

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CHAPTER 2

MACHINE VISION SYSTEMS FOR MONITORING HEN FLOOR DISTRIBUTION IN CAGE-FREE LAYER HOUSES [2]

[2] Yang, X., Bist, R., Subedi, S., & Chai, L. (2023). A deep learning method for monitoring spatial distribution of cage-free hens. Artificial Intelligence in Agriculture, 8, 20-29. https://www.sciencedirect.com/science/article/pii/S2589721723000120. Reprinted here with permission of the publisher.

ABSTRACT

The spatial distribution of laying hens in cage-free houses is an indicator of flock's health and welfare. While larger space allows chickens to perform more natural behaviors such as dustbathing, foraging, and perching in cage-free houses, an inherent challenge is evaluating chickens' locomotion and spatial distribution (e.g., real-time birds' number on perches or in nesting boxes). Manual inspection of hen's spatial distribution requires closer observation, which is labor intensive, time consuming, subject to human errors, and stress causing on birds. Therefore, an automated monitoring system is required to track the spatial distribution of hens for early detection of animal welfare and health concerns. In this study, a non–intrusive machine vision method was developed to monitor hens' spatial distribution automatically. An improved You Only Look Once version 5 (YOLOv5) method was developed and trained to test hens' distribution in research cage-free facilities (200 hens per house). The spatial distribution of hens the system monitored includes perch zone, feeding zone, drinking zone, and nesting zone. The dataset contains a whole growth period of chickens from day 1 to day 252. About 3000 images were extracted randomly from recorded videos for model training, validation, and testing. About 2400 images were used for training and 600 images for testing, respectively. Results show that the accuracy of the new model were 87-94% for tracking distribution in different zones for different ages of hens/pullets. Birds' age affected the performance of the model as younger birds had smaller body size and were hard to be detected due to blackness or occultation by equipment. The precision of the model was 0.891 and 0.942 for baby chicks (≤10 days old) and older birds (> 10 days) in detecting perching behaviors; 0.874 and 0.932 in detecting feeding/drinking behaviors. Miss detection happened when chicken body was occluded by other facilities (e.g., nest boxes, feeders, and perches). Further studies such as chicken behavior

identification works in commercial housing system should be combined with the model to reach a smart detection system.

Keywords: Cage-free system; Precision farming; Spatial distribution; Deep learning.

2.1 INTRODUCTION

Poultry distribution and activities are key information in assessing animal's welfare and flock production (Li et al., 2017; Guo et al., 2020a, 2020b, 2022). In cage-free laying hen houses, chickens have more space to move and perform natural behaviors as compared to conventional cage houses (Ben Sassi et al., 2016; Wang et al., 2017; Chai et al., 2018, 2019; Li et al., 2020; Bist and Chai, 2022; Castro et al., 2022). While larger space allows chickens to perform more natural behaviors such as dustbathing, foraging, and perching in cage-free houses, an inherent challenge is evaluating chickens' health, welfare, and specific behaviors such as locomotion and spatial distribution (e.g., real-time birds' number on perches or in nesting boxes) (Chai et al., 2019; Oliveira et al., 2019; Bist et al., 2023). Au automated monitoring system is required to track the spatial distribution of hens for early detection of animal welfare and health concerns (Subedi et al., 2023).

In the past years, computer vision has gained fast – paced advances from human detection to animal monitoring (Aydin et al., 2010; Porto et al., 2015; Lao et al., 2016; Subedi et al., 2023). The computer vision system provides a non-intrusive method in livestock monitoring (i.e., swine, cattle, and sheep) (Hitelman et al., 2022; Li et al., 2014; Nasirahmadi et al., 2017). For poultry housing, computer vision or deep learning models (e.g., convolutional neural network - CNN) have been applied to track individual bird for analyzing behaviors (Pu et al., 2018; Fang et al., 2020; Pereira et al., 2013; Subedi et al., 2023). Some studies have focused on chickens' floor distribution (i.e., feeding, drinking and walking zones) (Aydin et al., 2010; Guo et al., 2020a, 2021; Yang et al., 2022). The CNN image processing algorithms showed high accuracy in monitoring floor distribution (two dimensions). Guo et al. (2022) compared different CNN models (i.e., ResNet-152, ResNeXt-101 and ECA-DenseNet-264) in monitoring broilers' behaviors. The models showed 88-97% of accuracies. The YOLO (you only look once) is a one-stage CNN algorithm that has been applied to monitor poultry behaviors (Guo et al., 2022; Yang et al., 2022). Anlan et al. (2019) developed detector to monitor heat stress conditions of broilers by using YOLOv3(Anlan et al., 2019; Ding et al., 2019). Ye et al. (2020) proposed a CNN algorithm (YOLO + multilayer residual module (MRW) to detect white feather broilers stunning states. Sachin et al. (2023) developed You Only Look Once version 5 (YOLOv5)-pecking models to track hens' pecking behaviors and improved accuracy of the model to 85-90%(Jocher, 2020).

However, existing models have limitations (i.e., low speed detection and one-time total number of detected chickens is restricted in tracking spatial distribution of chickens (i.e., floor distribution + vertical distribution). Vertical distribution patterns of chickens are critical information for understanding hens' performance and behaviors in cage-free housing system, an emerging egg production system in the US and EU countries (Chai et al., 2019). The objectives of this study were to: (1) develop a deep learning method for monitoring the spatial distribution of cage-free hens/pullets; (2) quantify the real-time birds' number in different zones automatically; and (3) optimize the performance of the model by incorporating camera angles, chicken ages and flock densities.

2.2 MATERIALS AND METHODS

2.2.1 Experimental Design and Data Collection

About 800 day-old chicks (Hy-Line W-36) were raised in four research chamber rooms (each was measured as 7.3 m long × 6.1 m wide × 3 m high) at the Poultry Science Center at the University of Georgia (UGA). Cameras (Swann Communications, Santa Fe Spring, CA) were installed with two different angles (i.e., vertically and horizontally) to record the spatial distribution of birds (Figure 2.1). The recorded videos were transferred to massive hard devices for analyzing video quality and converting to JPG format in the Department of Poultry Science at UGA.

Figure 2.1. Experimental setup for collecting laying hens' spatial distribution dataset.

Feeders, nipple drinkers, nest boxes (Bestnestbox company, Hudson, Ohio, USA) and a A-frame hen perch were installed in each of research chamber rooms by referring the dimension suggested by commercial farms (Chai et al., 2019). The research room was divided virtually into perching, nesting, drinking, feeding zones for the deep learning algorithm to identify the distribution of chickens (Figure 2.2). Husbandry and management were following Hy-line W-36 management guides. Animal management was approved by the Institutional Animal care and Use Committee (IACUC) at the University of Georgia.

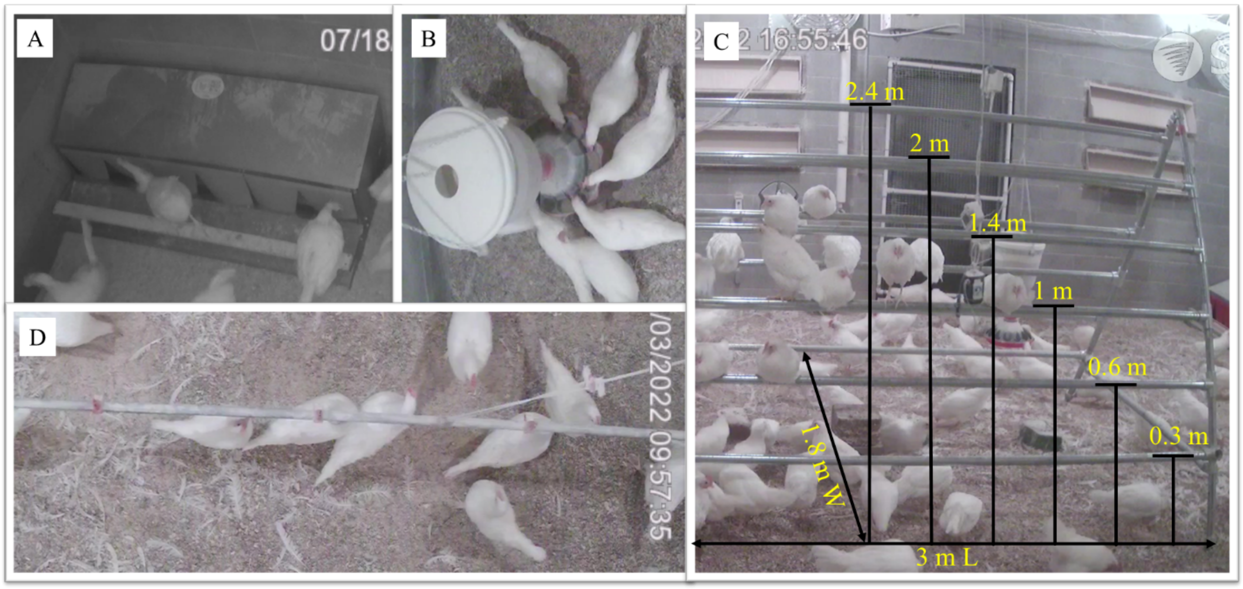

Figure 2.2. The definition of different zones. A. nesting zone; B. feeding zone; C. perching zone (3 m long, 1.8 m wide, 6 different heigh for birds to perch from 0.3 m to 2.4 m); and D. drinking zone.

2.2.2 Methods for Chicken Detection

In this study, an improved YOLOv5 model was developed for chicken detection. The architecture consisted of three parts, i.e., backbone, neck, and head (Figure 2.3). The improved YOLOv5 model is based on CNN network that can take in an input image and capture its spatial characters (learnable weights) to train the network to detect object (Liu et al., 2022). In backbone, four different models are used to extract basic features. In neck, feature pyramids and attention mechanism module were utilized to recognize same target under separate size and scales. Besides, three attention mechanism modules were added to enhance small targets detection. In model head, three individual feature maps were used to detect target (i.e., hens in different zones). According to Figure 2.3, there are four main modules in backbone for extracting features from given pictures, including FOCUS, Conv + Bottle Neck + Hard Switch (CBH), cross stage partial (CSP) and spatial pyramid pooling (SPP). After each module, the pixels of pics changed from 608 × 608 pixels to 76 × 76 pixels, 38 × 38 pixels, and 19 × 19 pixels (Zhang et al., 2022). With these decreased feature maps, the neck network applies CSP and CBH to generate feature pyramids to aggregate on the features and submit it to head. However, during the pass progress, the contextual information will decrease. To obtain more accurate information and minimize the information loss, an attention mechanism was introduced to this improved YOLOv5 method (with red background in Figure 2.3). The attention mechanism is combined with C3Ghost and Ghost modules to enhance the dominated channel attention(Woo et al., 2018). The aim of C3Ghost module is to reduce heavy computational burden as the Ghost applied into YOLOv5 neck network.

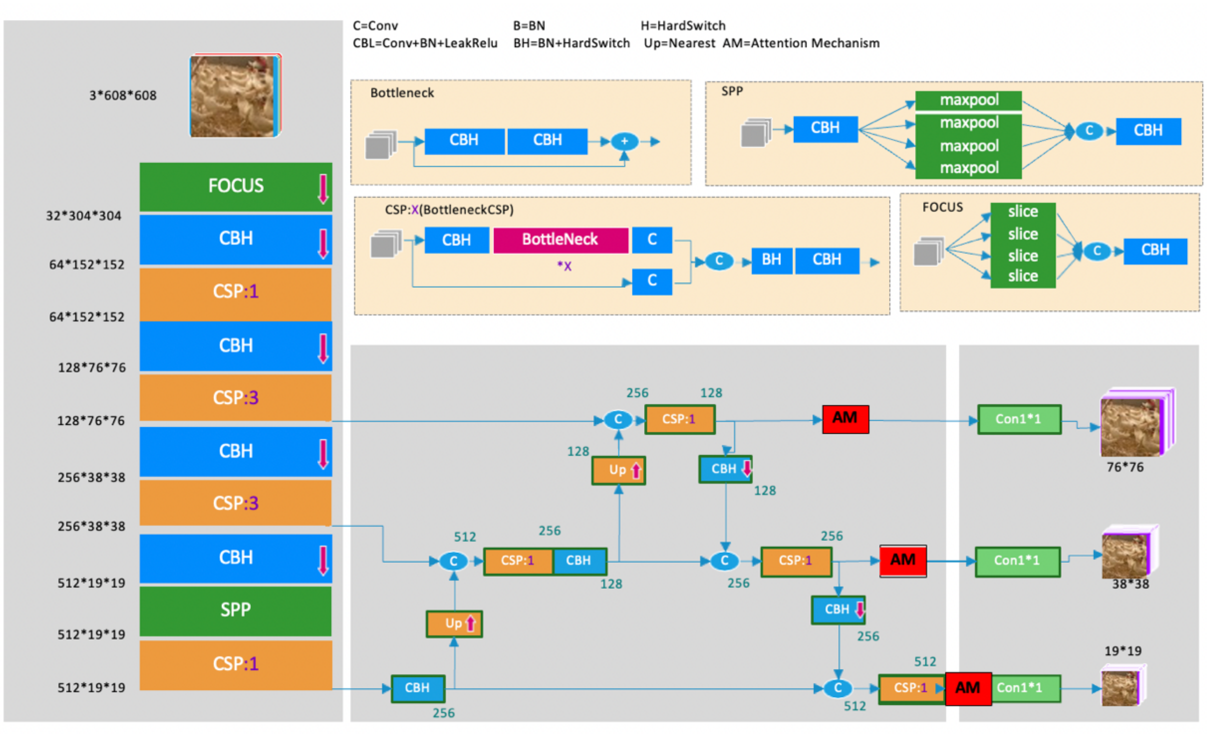

Figure 2.3. The network structure of improved YOLOv5 for tracking spatial distribution of chickens in cage-free houses.

The Ghost module focuses on generating more feature maps by using fewer parameters. In this study, the Ghost was adopted to process hen's feature maps(Han et al., 2020). The original hen's feature map is blurry after YOLOv5 neck network. However, with the Ghost module, the channel number of hen's feature maps improved, and an enhanced hen's feature pyramid developed. The structure of it is shown in Figure 2.4. In the neck, the three dimension of input feature map is a × b × c, after the neck, the output feature map is a1 × b1 × c1, and the size of kernel is n × n, where a and a1 are heights of feature map, b and b1 are widths of feature map. Comparing to the convolutional layer, the Ghost module processes the ordinary convolution in two steps. During the convolutional layer, the basic number of floating-point operation (FLOPs) is a1 × b1 × c1 × c × n × n, which is usually over 105 when the channel number c is 256 and multiplies the filter number c1. The overload FLOPs lead the critical information of inputted imagines (Ren et al., 2022). In the two steps of Ghost module, a cheap transformation procedure was utilized in generating intrinsic feature maps and needs fewer filters. Therefore, the new structure can obtain a notable performance.

$$FLOPs = \mathrm{a1} \times \mathrm{b1} \times \mathrm{c1} \times \mathrm{c} \times \mathrm{n} \times \mathrm{n} \qquad \text{Eq.1}$$

where a1, b1, and c1 are the output feature map's height, width, and channels after the convolution operation. C represents the number of channels in the feature map input. N represents the size of the convolutional kernel employed during the convolution operation.

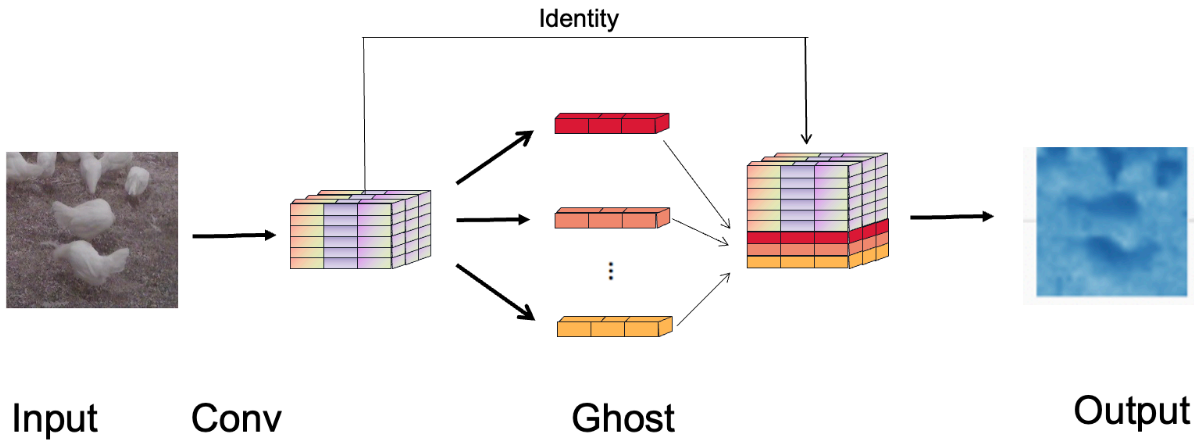

Figure 2.4. A demonstration of two steps Ghost module that used in this study for processing poultry images.

2.2.3 Methods for Tracking Chickens in Different Zones

A whole vision dataset (horizontal and vertical) and an interface were used to recognize spatial distribution of birds in different zones (Figure 2.5). The graphical user interface (GUI) was developed with Python binding for the Qt5 application framework (PyQt5) (Figure 2.6), which enhances the process of selecting target zones (nesting, perching, feeding and drinking) (Xie et al., 2022). The zones of each bird in the picture were designed firstly, then the whole area in the image was used as the reference area to estimate the number of birds in the selected zones, the equation is showed below.

$$\tilde{N}_i = \frac{n_i}{n}, 1 \leq i \leq x \qquad \text{Eq. 2}$$

Where $\tilde{N}_i$ (birds/m^2) is the average number of the target zones after normalization, n_i is the number of the target zones in the ith picture, n (m^2) is the reference value of whole spatial area, and x is the number of zones recognized in the picture.

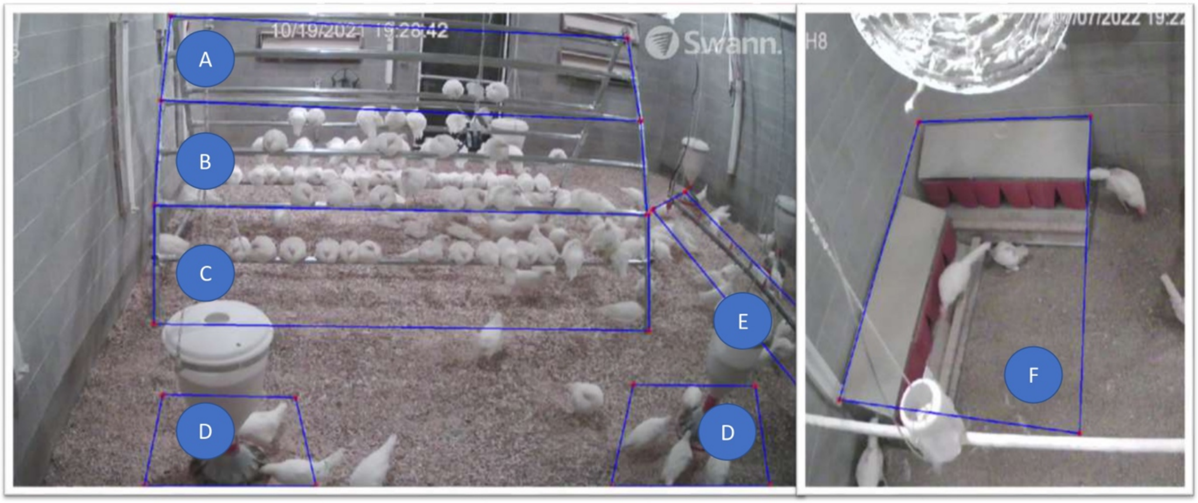

Figure 2.5. The selected zones in the picture. The blue bullet A to C represents the different high perching zone varying from 7.9 ft to 0 ft; the two blue bullet D represent the feeding zone; the blue bullet E represents drinking zone; the blue bullet F represents the nesting zone.

Figure 2.6. The GUI developing by PyQt5 (b is pullets/hens > 10 days; s – baby chicks ≤ 10 days).

2.2.4 Dataset and Setting

A laying hens' dataset was constructed to evaluate the performance of the improved YOLOv5 on the detection of birds. The dataset contains whole growth period of bird from 1 week to 36 weeks (baby chicks to hens) and consisting of 3000 pics that were extracted randomly from recorded videos. All the pics were labeled by LabelImg Windos_v1.6.1 version. Birds under 2 weeks of age were labeled as baby chicks, and birds 2 weeks or older were labeled as pullets/hens. 2400 pics and 600 pics were used during training section and testing section separately. The training was run under window operating system for 300 epochs with a learning rate 0.01 and a batch size of 16. The confidence threshold is set to 0.25, which means that objects with a similarity of 0.25 or above can be considered interesting and marks will be assigned.

2.2.5 Model Evaluation and Statistical Analysis

To compare the performance of improved YOLOv5 with other methods, the precision, recall and F1 score were used as evaluation parameters. The equations of them are showed below:

$$Precision\ (100\%) = \frac{TP}{(TP+FP)} \times 100 \qquad \text{Eq. 3}$$

$$Recall\ (100\%) = \frac{TP}{(TP+FN)} \times 100 \qquad \text{Eq. 4}$$

$$F1\ score\ (100\%) = \frac{(2*Precision*Recall)}{(Precision+Recall)} \times 100 \qquad \text{Eq. 5}$$

The true positive (TP) is the test result correctly predicts the presence of a characteristic, false positive (FP) is the test result wrongly indicates an attribute is present and false negative (FN) is the test result that falsely predicts a particular condition is absent.

To assess model performance under different situations (i.e., ages, various high of perching zone, flock density and the distributional zones), a one-way ANOVA and Turkey HSD were conducted by JMP software. The significant difference was set at 0.05.

2.3 RESULTS AND DISCUSSIONS

2.3.1 Model Performance in Detecting Chickens

To evaluate the model performance and explore optimal setting parameters, the YOLOv5-x method and several training parameters were applied. These parameters include image size (e.g., 640 and 320) and datasets (e.g., individual type dataset and mixed type dataset). The summary outcomes are shown in Table 2.1. Five experiments were conducted to explore the best model performance among whole chicken group by setting different parameters (image size, dataset, and attention mechanism). image size represents the inputted image, and the epochs represents the training times. Individual type dataset has two categories (i.e., baby chicks (< 1 week old) and pullet/hens that are older than 1 week), mixed type dataset is all age of chickens is considered as one type. We separate baby chicks from pullets/hens because 1 week or young chicks had smaller body size and have more challenges to be detected than older birds.

Table 2.1. The adjustment methods and results.

Model	Dataset	Image Size	Epochs	Precision	Accuracy	F1 score
YOLOv5-h1	Baby chicks	640	200	63.0% (s)	23.5% (s)	34.2% (s)
	Pullets/hens			76.0% (b)	80.1% (b)	77.8% (b)
YOLOv5-h2	Baby chicks	640	200	62.5% (s)	33.8% (s)	43.9% (s)
	Pullets/hens			83.6% (b)	84.6% (b)	84.1% (b)
YOLOv5-h3	Baby chicks	320	200	65.8% (s)	22.5% (s)	33.5% (s)
	Pullets/hens			71.4% (b)	83.6% (b)	77.0% (b)
YOLOv5-h4	Mixed type	320	200	91.7% (all)	80.2% (all)	85.6% (all)
YOLOv5-h5	Mixed type	320	200	90.2% (all)	91.6% (all)	90.9% (all)

Note: *s*-baby chicks ≤ 10 days; *b*-Pullets/hens > 10 days. YOLOv5-h1 means the experiment parameters are image size 640, dataset is individual type; YOLOv5-h2 means the experiment parameters are image size 640, dataset is individual type with attention mechanism; YOLOv5-h3 means the experiment parameters are image size 320, dataset is individual type; YOLOv5-h4 means the experiment parameters are image size 320, dataset is mixed type; YOLOv5-h5 means the experiment parameters are image size 320, mixed type means dataset is mixed type with attention mechanism.

During the experiments, the loss function values toward to be stable when the epoch approached to 200, so the epoch was 200. From the Table 2.1, we discovered a) improved YOLOv5 method had better detection comparing to original YOLOv5 on both individual and mixed datasets, b) mixed dataset has better performance comparing to individual dataset when trained with improved YOLOv5 and original YOLOv5 methods, c) increase the imagine size improved the overall model precision. These confirmed our setting parameters. The Receiver Operating Characteristic (ROC) curve shows the sensitivity and specifity of different detector.

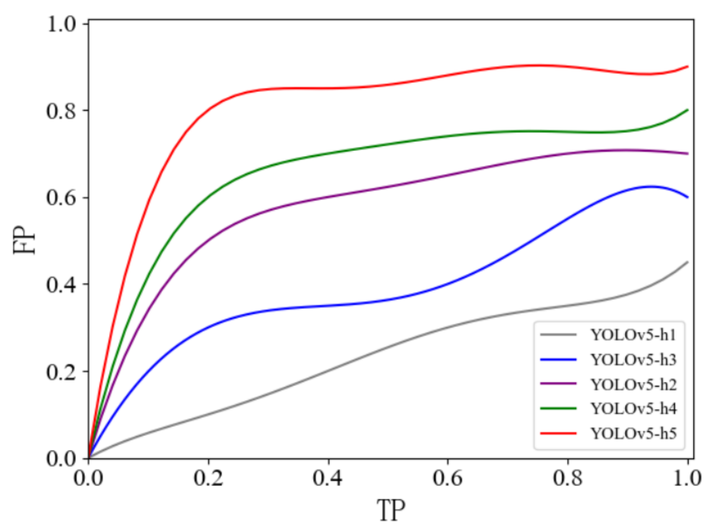

Figure 2.7. ROC curve comparison results of different detector based on deep learning.

2.3.2 Chicken Distribution Identification in Perching Zones

Figure 2.8 shows the birds detected by improved YOLOv5 model. In the perching zone (Figure 2.8A), the model monitored perched chickens from 0 to 2.4 m and summed up them to three different levels (the number of hens in three levels were 7, 61, and 17 from bottom to top of the perch frame), respectively. For baby chicks' perching (Figure 2.8B), there were 8 hardwood perching boards. The number of detected chicks in each perching board was 2, 3, 1, 5, 4, 1, 6 and 4, respectively, from far to close in the Figure 2.8B.

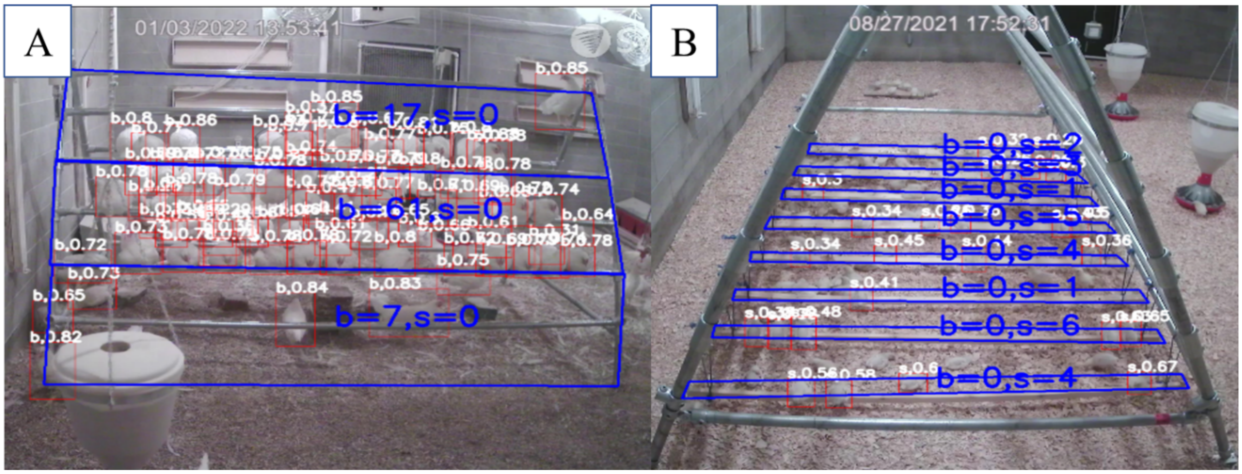

Figure 2.8. Chickens' distribution in perching zones detected by improved YOLOv5. (A) adult hens (133 days of old) detected; (B) baby chicks detected (8 days of old). The letter *b* in blue means older birds (> 10 days old) and the letter *s* in blue represents baby chicks (≤ 10 days old).

To test the performance of improved YOLOv5 model in monitoring birds in perching zones, about 200 images were randomly selected (chickens' age ranged from week 1 to week 20) to test the model (Table 2.2). The performance of the model was 0.891 and 0.942 for baby chicks (≤10 days old) and older birds (> 10 days), respectively. The miss detection rates of hens and baby chicks were 0.054 and 0.102, respectively. Errors or miss detections were caused by high density chickens (pilling or crowding) and interreferences of perch frame and feeders. In general, the mew model fitted well in the perching zone (R_{ture} > 0.89).

Table 2.2. Tested performance of improved YOLOv5 on perch zone.

Zone	Target Chickens	True Detection	Miss Detection			False	R_{true}	R_{miss}	R_{false}
			Overlap	Occlusion	others				
Perch (*s*)	1987	1872	46	41	20	8	0.942	0.054	0.004
Perch (*b*)	866	772	30	27	31	6	0.891	0.102	0.007

Note: R_{true}, R_{miss} and R_{false} rates were evaluated by true detection number/target chickens' number, miss detection number/target chickens' number and false detection number/target chickens' number respectively; *s* means baby chicks; *b* means hens.

A back propagation (BP) neural network algorithm was used to identify the chicken distribution in drinking and feeding zones, the missed detection also comes from chicken crowding behaviors and collusion problems (Yang et al., 2022). Other flaws in our method are original from the horizonal vison factor (when baby chicks are too small under horizontal scale, the miss detection happens) and designed perch zone (when the perch zone is designed narrower than the real situation, there will be less perch chicks included into the perch zone, so the chicks were missed). The false detection rates were 0.004 and 0.007 respectively. This were also the common drawback of other vision based algorithms (Abdanan Mehdizadeh et al., 2015).

2.3.3 Chicken Distribution in Feeding and Drinking Zones

Figure 2.9 demonstrates the distribution of detected birds in feeding zones monitored by improved YOLOv5 model. For each pic, the number of chickens in targeted areas were analyzed. From Figure 2.9A, we can identify the distribution of baby chicks (i.e., 10 days old) in feeding zone in 100% accuracy. For Figure 2.9B and 2.9C, the model detected larger chickens (i.e., 122 day old) in 100% accuracy as well. From Figure 2.10A and 2.10B, the distribution of 122 days old of hens in drinking areas collected from two different angles. The detection efficiency was 100% in the Figure 2.10B as there was no osculation. For Figure 2.10A, the feeder (low right corner) could block some chickens during the study.

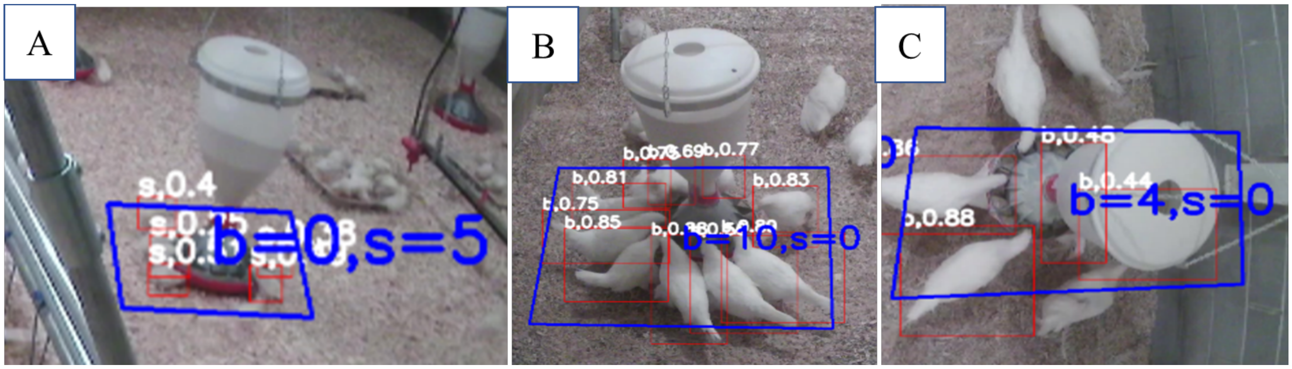

Figure 2.9. Chickens' distribution in the feeding zone at different ages (A-chickens were 10 days old; B and C-chickens were 122 days old (*b* means birds were > 10 days; *s* means birds were ≤10 day).

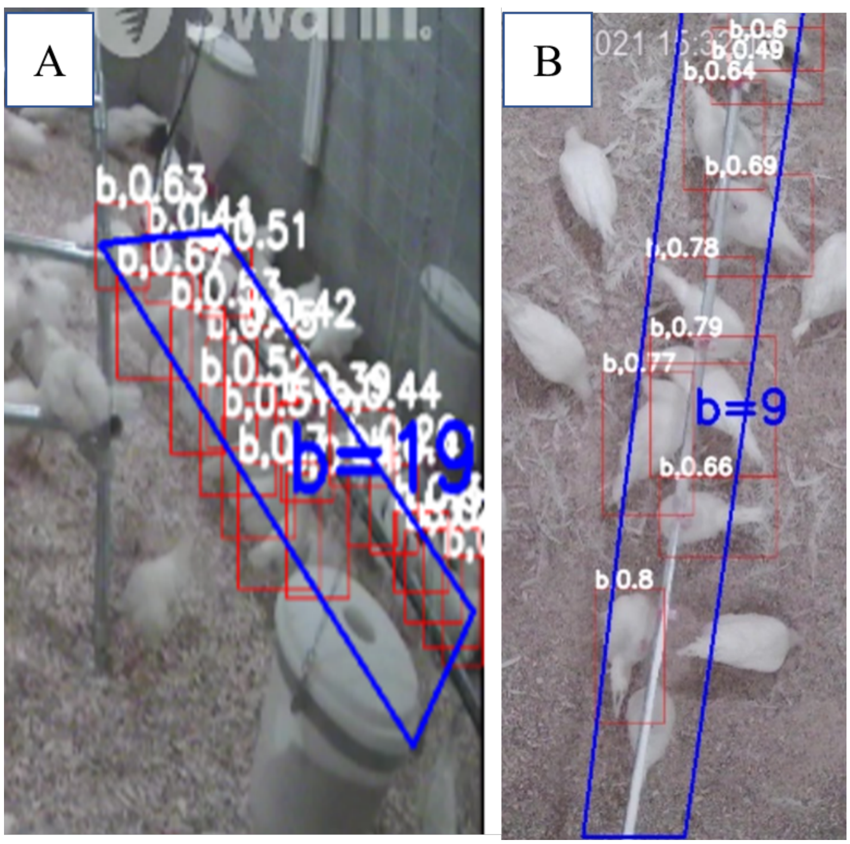

Figure 2.10. The distribution of chickens (i.e., 122 days old) in the drinking zone at different angles: chickens in A (side view in 45 degree) and B (top view) (*b* means birds were > 10 days; *s* means birds were ≤10 day).

To investigate a larger number of chickens, we used about 200 images to test the model performance in feeding and drinking zones (Table 2.3). The overall accuracy for baby chicks and older chickens were 0.874 and 0.932, respectively. Comparing to accuracy of perch zones, detecting baby chicks of feeding and drinking zones was more challenging due to smaller size of body and interferences of equipment. When a higher number of birds were assembled at the same feeder or drinker, birds standing in front of the feeder or drinker had higher possibility to be recognized than those close at sides of feeder and drinker. In addition, lighting affected image quality and model's performance. Apart from these, birds' density has been reported affect deep learning model's performance (Maselyne et al., 2016).

Table 2.3. Tested performance of improved YOLOv5 on feeding and drinking zones.

Birds	Target Chickens	True Detection	Miss Detection			False detection	R_{true}	R_{miss}	R_{false}
			Overlap	Occlusion	others				
s	1027	898	20	19	19	71	0.874	0.056	0.069
b	768	716	17	15	15	6	0.932	0.061	0.008

Note: R_{true}, R_{miss} and R_{false} rates were evaluated by true detection number/target chickens' number, miss detection number/target chickens' number and false detection number/target chickens' number respectively; *s* means baby chicks ≤ 10 days; *b* means older birds > 10 days.

2.3.4 Chicken Distribution in Nesting Zone

In this study, most hens started to lay their first eggs at around 18 weeks of age. The nesting behaviors of hens was analyzed with our newly developed model because it's important identify if there are floor eggs or not (Gonzalez-Mora et al., 2022). Monitoring hens' distribution in nesting zones helps to minimize losses from laying eggs on the floor. Figure 2.11 shows the distribution of detected hens in nesting zones with our improved YOLOv5 model. Figure 2.11A is the original image of nesting area. Figure 2.11B demonstrates the detected hens in nesting zone. The model performed with over 90% accuracy in detecting hens in nesting zones.

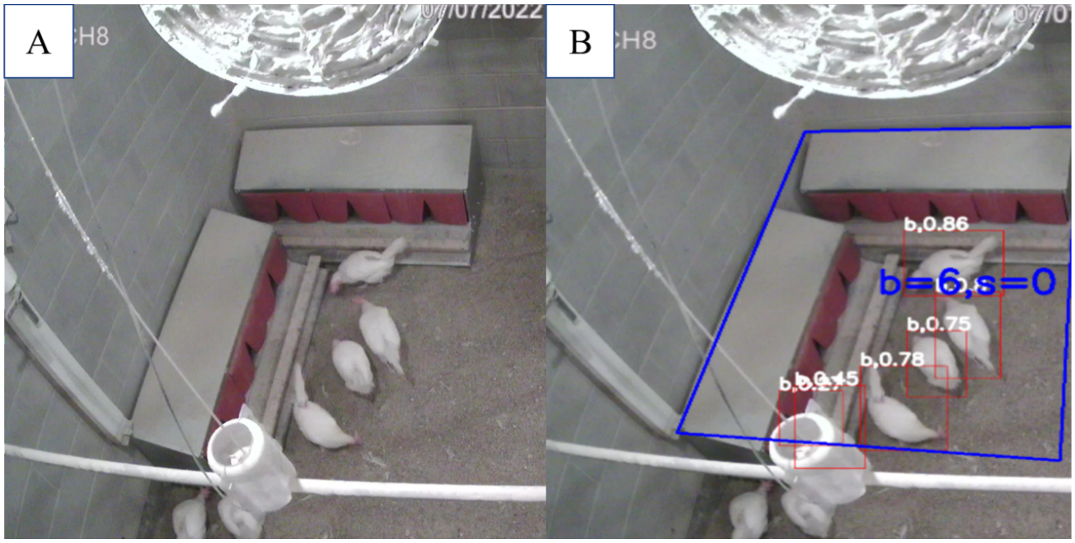

Figure 2.11. Chicken distribution in nesting zone. (A) original image of nesting area and (B) detected nesting area.

To evaluate model's performance in nesting zone for hens' detection systemically, over 200 images were randomly selected from video dataset to improve targeted hens' dataset (Table 7). The tested accuracy rate in nesting zone reached 0.906, which is slightly less than that in other zones (i.e., perching, feeding, and drinking zones), because there was an equipment hanging above the nesting zone.

Table 2.4. Tested performance of improved YOLOv5 on nesting zone.

zone	Target Chickens	True Detection	Miss Detection			False detection	R_{true}	R_{miss}	R_{false}
			Overlap	Occlusion	others				
Nest (*b*)	873	791	8	13	7	54	0.906	0.061	0.008

Note: R_{true}, R_{miss} and R_{false} rates were evaluated by true detection number/target chickens' number, miss detection number/target chickens' number and false detection number/target chickens' number respectively; *b* means hens. There were no baby chicks (*s*) because only hens would lay eggs.

2.4 CONCLUSIONS

In this study, an improved deep learning model was developed based on YOLOv5 structure to monitor cage-free hens' spatial and floor distributions, including the real-time number of birds in perching zone, feeding zone, drinking zone, and nesting zone. The accuracies of the new model were 87-94% for all ages of chickens across zones. Birds' age affected the performance of the model as younger birds had smaller body size and were hard to be detected due to blackness or occluded by equipment. The performance of the model was 0.891 and 0.942 for baby chicks (≤10 days old) and older birds (> 10 days) in detecting perching behaviors; 0.874 and 0.932 in detecting feeding/drinking behaviors. The different zones in the chicken house (perch zone, feeding zone, drinking zone, and nesting zone) are related to specific behaviors of the chickens. For example, some chickens are expected to perch during the night, while during the day they move around the house and visit the feeding and drinking zones. Nesting behavior occurs when hens are about to lay eggs. The current findings provide references for automatically monitoring cage-free laying hens' spatial distribution in all age level (from baby chicks to hens). More future chicken behavior identification works could be combined with the model to reach an automatic detection system.

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CHAPTER 3

IMAGING TECHNOLOGIES FOR MONITORING BODY WEIGHT OF PULLETS AND LAYERS[3]

[3] Yang, X., Dai, H., Wu, Z., Bist, R. B., Subedi, S., Sun, J., ... & Chai, L. (2024). An innovative segment anything model for precision poultry monitoring. Computers and Electronics in Agriculture, 222, 109045. https://www.sciencedirect.com/science/article/pii/S0168169924004368. Reprinted here with permission of the publisher.

ABSTRACT

In recent years, artificial intelligence (AI) advancements have influenced the agricultural industry, particularly with the emergence of large foundation models. One such model, the Segment Anything Model (SAM) developed by Meta AI Research, has benefited object segmentation tasks. While SAM has demonstrated success in various agricultural applications, its potential in the poultry industry, specifically regarding cage-free hens, remains largely unexplored. This study aims to evaluate SAM's zero-shot segmentation performance for chicken segmentation tasks, including part-based segmentation and the utilization of infrared thermal images. Additionally, it investigates SAM's ability to predict weight and track chickens. The results highlight SAM's superior performance compared to SegFormer and SETR for both whole and part-based chicken segmentation. SAM demonstrated remarkable performance improvements, achieving a mean intersection of union (mIoU) of 94.8% when using the total points prompts. These findings contribute to the understanding of SAM's potential in poultry science, paving the way for future advancements in chicken mask segmentation and tracking using large foundation model.

Key words: Visual Foundation Model, Segmentation, Precision Poultry Farming, Machine vision.

3.1 INTRODUCTION

In recent years, the field of artificial intelligence has seen significant advancements in large-scale foundation models, which have revolutionized many fields, including agriculture(Eli-Chukwu, 2019; Li et al., n.d.; Lu et al., 2023; Wang et al., 2021). Combining natural language processing (NLP) and computer vision, these models stretch the limits of language comprehension and generation in agriculture with notable examples such as OpenAI's GPT4. These models' impressive capabilities extend to applications such as the administration of unmanned aerial vehicles (UAVs)(de Curtò et al., 2023), robotic grippers(Stella et al., 2023), and weather forecasting(Ashraf Vaghefi et al., 2023). Their success has prompted researchers to investigate visual learning, at first concentrating on pre-training methods to extract rich representations or linguistic descriptions from images and later on specialized foundation models for semantic segmentation tasks(Luo et al., 2022; Zhang and Zhou, 2023).

The Segment Anything Model (SAM) from Meta AI Research is a revolutionary object segmentation utility that employs a cutting-edge foundation model. SAM demonstrates extraordinary zero-shot segmentation capabilities by supporting visual cues such as points, boxes, and masks(Kirillov et al., 2023). This is due to its extensive data training. In contrast to conventional models, SAM's distinct prompt capability makes it highly versatile and accurate in object segmentation, which has applications in numerous fields, including agriculture. It enables researchers and practitioners to enhance detection of pests and leaf diseases, as well as crop segmentation(Chen et al., 2023; Ji et al., 2023; Tang et al., 2023).

Despite its effectiveness, SAM remains underutilized in the poultry industry, particularly for cage-free hens. There is a need for automated methods to detect laying hens on the litter floor due to the growing adoption of cage-free housing systems in the egg industry to improve avian welfare and comply with regulations(Bist et al., 2023b, 2023a; Subedi et al., 2023; Yang et al., 2022, 2023a). In this context, the advanced capabilities of SAM offer promising solutions for enhancing the precision and efficacy of various analysis duties.

This study evaluates SAM's zero-shot segmentation performance and investigates its potential for object tracking, particularly chicken mask segmentation. We evaluate SAM's ability to segment chickens in various contexts, including part-based segmentation and thermal infrared imaging. To evaluate its efficacy, we compare SAM's results to the most advanced domain-specific models currently available. In addition, we examine the feasibility of integrating SAM with other multi-object tracking (MOT) techniques. Through these investigations, we hope to gain a greater understanding of SAM's capabilities and efficacy in addressing challenges associated with poultry segmentation, body weight estimation, and tracking.

3.2 MATERIALS AND METHODS

3.2.1 Experimental Setup

A total of 800 Hy-line W-36 chickens were used for the study. The birds were reared evenly in four cage – free rooms at the Poultry Research Center from the department of poultry science of the University of Georgia (UGA), USA. Every room is equipped with six suspended feeders, one drinking system, and a moveable A-frame roost for birds to behave their natural roosting habits (Figure 3.1).

Figure 3.1. An overview of cage–free chicken house.

The environmental conditions were regulated by an automated system (CHORE-Time Controller, Milford, IN, USA) with settings based on Hy-Line W-36 commercial layer management guidelines. Team members inspected the growth and environmental conditions of the hens daily to maintain a safe rearing environment. In addition, to enhance the biosecurity, six disinfection pens were placed at two main doors and four individual doors before entering farm and each rearing house. The animal use and management were approved by the Institutional Animal Care and Use Committee (IACUC) of the UGA (Li et al., 2023).

3.2.2 Poultry Image and Body Weight Data Acquisition

A thermal image system was designed to obtain body weight and thermal pictures of chicken (Figure 3.2). There are three parts of the collector, a digital scale to measure body weight, a cardboard box (L81.28 centimeters × W45.72 centimeters × H43.18 centimeters) for chicken to stand and a professional thermal imager (FLIR T540, Wilsonville, Oregon, USA) with adjustable lens (14°-24°) to collect thermal images of chickens. To ensure the quality of the image acquisition, the camera was secured at 1.5 m above from the weighting plate. Every month (from May 2022 to Dec 2022) 80 chickens (1/10 of whole flock) were randomly selected to take body weight and capture thermal pictures of each chicken four times to record different chicken positions. In addition, to compare the predicting accuracy of different datasets, a FLIR Thermal Studio software was used to extract the original pictures. Therefore, each thermal image corresponds with its own original image (Figure 3.3) and two datasets (original dataset vs thermal dataset) were established.

To track different types of birds, excluding cage-free hens, a broiler house was equipped with a Swann Communications HD camera (model PRO-1080MSFB), which was strategically positioned on the ceiling, at a height of 2.5 meters from the ground. These cameras were set to record at a rate of 15 frames per second, offering a resolution of 1440 × 1080 pixels. The footage captured by these cameras was then stored as AVI files on a Swann Communications DVR (model DVR-4580), ensuring detailed documentation in broiler houses' development and behavior throughout the study period. Therefore, we collected images.

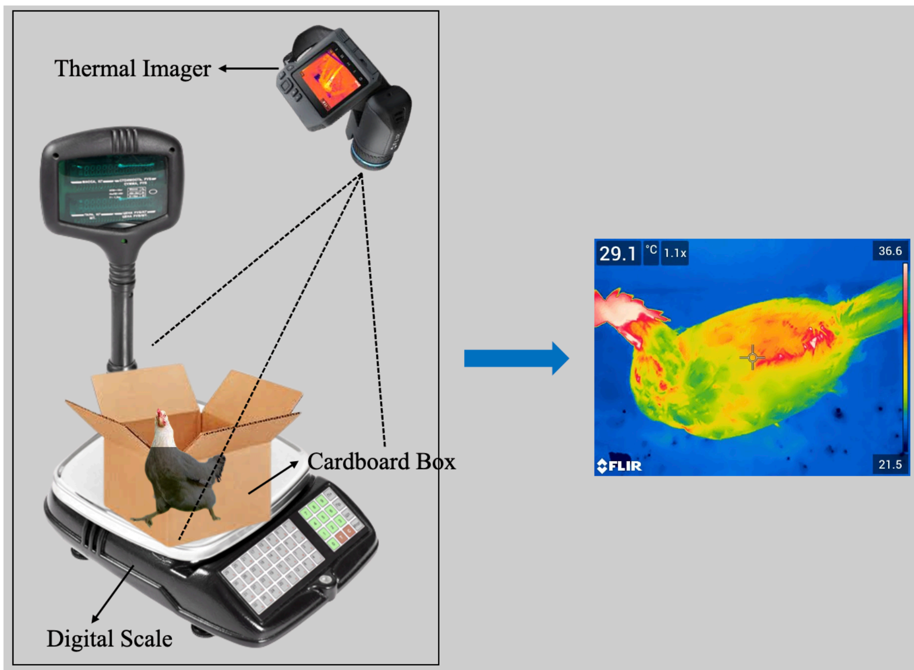

Figure 3.2. The infrared thermal system.

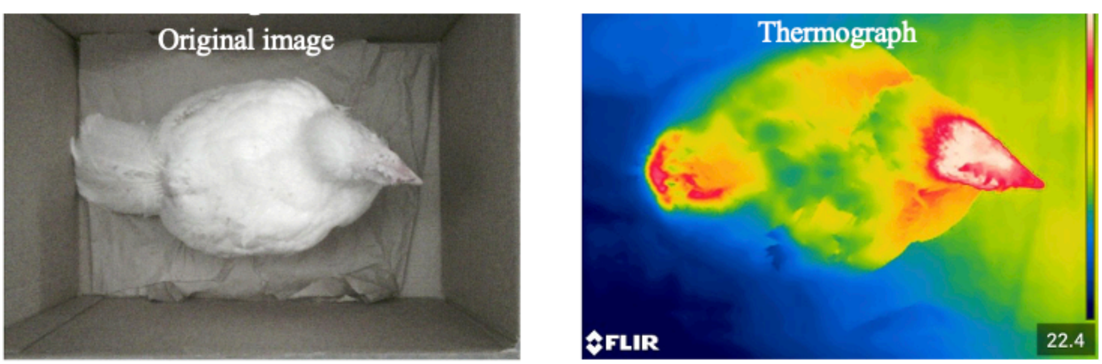

Figure 3.3. An example of raw thermal image and thermograph of chicken.

3.2.3 Chicken Body Weight Data Cleaning

During the process of weighing and capturing images of chickens, various factors can potentially affect the quality of the data collected (Latshaw and Bishop, 2001). This includes the presence of distracting elements such as feathers and droppings in the cardboard box used for placing chickens, as well as active chicken behavior, such as walking or attempting to fly out of the box, which may result in outliers. To mitigate these challenges, this study applied data cleaning techniques including image segmentation and data scaling. Image segmentation was used to isolate the chicken from the background, making it easier to detect and remove feathers and droppings from the images. By segmenting the images, the focus is placed solely on the chicken, reducing the impact of irrelevant elements. Data scaling was also applied to resize the data to a common range (Zhang and Zhou, 2023). This helps to reduce the impact of outliers and ensure that the model is not biased towards features with a larger scale. By scaling the data, the focus is placed on the underlying patterns in the data, rather than any outliers that may have been introduced during the collection process. Overall, the use of data cleaning techniques, such as image segmentation and data scaling, can greatly improve the quality of data collected in a poultry farm and provide more accurate results.

3.2.4 Chicken Segment Methods

To explore the zero-shot segmentation performance of SAM, two state-of-the-art (SOTA) methods (SegFormer and SETR) were utilized to compare with it(Liu et al., 2022; Xie et al., 2021). SegFormer and SETR are two of the latest methods in the field of semantic segmentation. SegFormer is a type of Transformer-based model designed specifically for semantic segmentation. Its hybrid design combines the advantages of both Transformers and convolutional neural networks (CNNs) and hence has been found to perform well on segmentation tasks. SETR is another transformer-based model used for semantic segmentation tasks. SETR uses a pure transformer-based approach and was one of the first such methods showing that transformers can be used directly for dense prediction tasks without the need for CNN-based architectures. Therefore, by choosing SegFormer and SETR as the comparison benchmarks, the efficacy of SAM can be validated.

State-of-the-art models, designed for tasks like semantic segmentation, require training on datasets where each image pixel is assigned a specific label. This enables the model to effectively perform on similar tasks by learning from these pixel-level labels. In our study, we built a chicken weight dataset, which consists of 4 labels (a (semantic segmentation of chickens based on original pictures), b (part-based segmentation of chickens based on original pictures), c (semantic segmentation of chickens based on thermal pictures), d (part-based segmentation of chickens based on thermal pictures)). By comparing four different segmentation labels and their respective accuracies in predicting chicken weight, we can determine which label is most applicable for this task.

In contrast to conventional methods, SAM employs an innovative prompt-enabled model architecture and a large, diverse training dataset. This method inaugurates a marketable segmentation task. To facilitate data collection and improve the performance of the model, a cyclical process was created using a proposed data engine. SAM was trained on a massive dataset consisting of more than one billion masks derived from 11 million licensed images, allowing it to learn a vast array of features and patterns. This extensive training enables SAM to adapt to and excel in new tasks, even without task-specific instruction. As shown in Figure 4, SAM consists of three essential components: an image encoder, a prompt encoder, and a mask decoder. The image encoder, which is built on the ViT backbone and pre-trained using the masked autoencoder (MAE) method, takes an image and outputs the image embedding to be combined with the subsequent prompt encoding (Dai et al., 2023; J. Wang et al., 2023). The prompt encoder divides its output into dense and sparse segments. Using a convolutional neural network (CNN), the dense segment encodes mask prompts. The mask decoder ultimately interprets all embeddings and predicts the masks. SAM supports both automatic and manual testing modes. The automatic mode requires only an image input, and automatically generates all predicted masks. Manual mode, on the other hand, requires additional user-supplied hints, including one point and total points, to provide SAM with more object segmentation data. The structure of SAM is shown below (Figure 3.4). To compare the three segmentation methods, we used a ground truth from human labeling with Labelme software (macOS), employing the Polygons function to draw the mask of the chicken, later outputting it as a JSON file as a benchmark. A predefined set of chicken head, tail, and body was taught by examples of the chicken pictures. Later, two people worked individually on each picture, and if the mean Intersection over Union (mIoU) error between their results was more than 2%, a new cycle of intra-comparison would be conducted until the requirements were met.

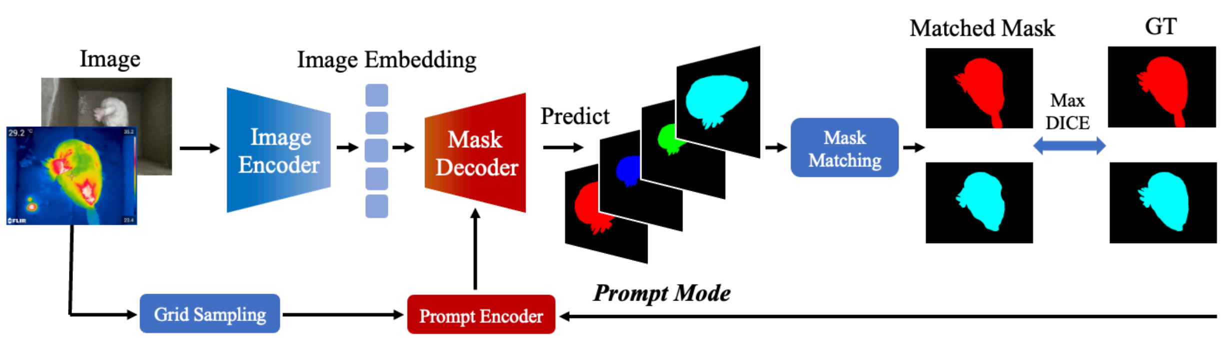

Figure 3.4. the structure of SAM in chicken segmentation tasks.

3.2.5 Chicken Body Weight Prediction Methods

Predicting chicken weight through computer vision poses several challenges that must be addressed. One of the challenges is the accuracy of measurements of the chicken's dimensions, such as body length and width. This is due to the difficulty of obtaining high-quality images or accurately identifying and measuring the chicken in the image. In this study, we use 1500 pictures labeled with body weights. One additional challenge is the wide diversity in the sizes and shapes of chickens, including variations in head position and tail state (Marino, 2017). In certain images, the chicken's head is positioned in a way that partially covers or overlaps its body, resulting in a visual effect where parts of the body are hidden or obscured. Simultaneously, the chicken's tail is in an open state, with the feathers spread out or extended (Liu et al., 2023). This open tail state contributes to the overall appearance of the chicken, influencing the total number of pixels accounted for after segmentation, as depicted in Figure 3.5. Addressing these complexities requires the implementation of sophisticated machine learning algorithms capable of accommodating various factors such as body color, shape, size, and age. These factors can potentially affect chicken weight estimation (Milosevic et al., 2019).

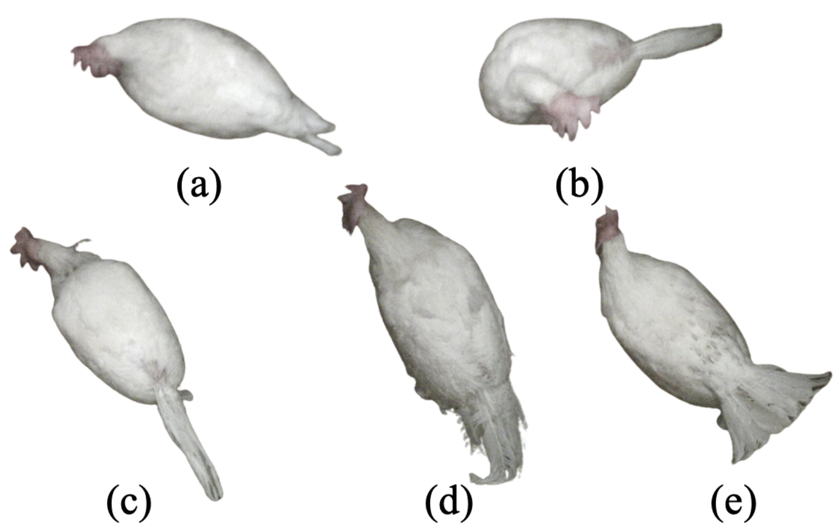

Figure 3.5. Shapes of chickens: (a) head position doesn’t overlap back, (b) head position overlaps the partial body, (c) open tail state (0%), (d) open tail state (50%) and (e) open tail state (100%).

In this context, Random Forest (RF) Regression is utilized for chicken weight prediction (Breiman, 2001). Random Forest Regression is a powerful algorithm that can handle complex, non-linear relationships between features and target variables. One advantage of using Random Forest Regression for chicken weight prediction is that it provides feature importance scores. These scores help determine the most significant factors that contribute to chicken weight prediction, allowing researchers to understand which features have the most influence on the outcome. A chicken bodyweight dataset containing 1500 chicken images from hens was employed, and it was split into three distinct sets. The training set consisted of 900 images, the validation set contained 300 images, and the remaining 300 images were allocated for testing purposes. It employs an ensemble learning method that combines the predictions from multiple decision trees, which are trained on randomly selected subsets of the data. This combination reduces variance and enhances the overall accuracy of the model. Additionally, Random Forest can handle missing or incomplete data and performs effectively when there is a combination of continuous and categorical variables. The structure of RF is shown below (Figure 3.6).

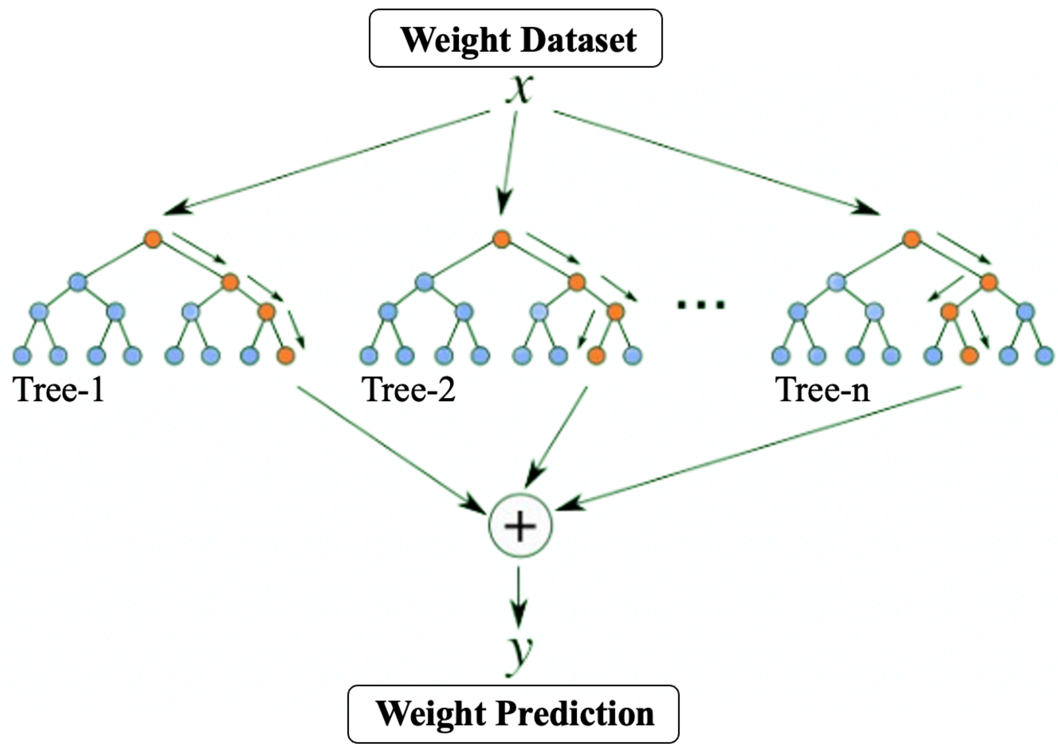

Figure 3.6. Random forest algorithm (Çavuşoğlu, 2019).

3.2.6 Evaluation Metrics

In this study, we utilize the mean intersection of union (mIoU) as a benchmark to assess and compare the performance of SAM against state-of-the-art (SOTA) methods.

$$mIoU = (\sum_{i=1}^{n} Area\ of\ Overlap \,/ \sum_{i=1}^{n} Area\ of\ Union)/n$$

where n represents the number of classes.

To compare which label performs better in chicken weight prediction, coefficient of determination (R^2) was used.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

where SS_{res} represents the residual sum of squares and SS_{tot} means the total sum of squares.

The detection performance of each tracking method is evaluated using various metrics, including assembly accuracy (AssA), ID F1 score (IDF1), number of identity switches (IDs), higher order tracking accuracy (HOTA), multiple object tracking accuracy (MOTA), and detection accuracy (DetA). The equations for calculating these metrics are as follows:

$$AssA = (C/T)$$

where C represents the number of correctly assembled trajectories and T represents the total number of ground truth trajectories.

$$\mathrm{IDF1} = 2 * (\mathrm{Precision} * \mathrm{Recall}) / (\mathrm{Precision} + \mathrm{Recall})$$

Where precision is defined as the ratio of the number of correctly identified trajectories to the number of identified trajectories. Recall is defined as the ratio of the number of correctly identified trajectories to the total number of ground truth trajectories(Subedi et al., 2023).

$$IDs = Number\ of\ identity\ switches$$

$$HOTA = Number\ of\ correctly\ localized\ detections\ /\ Total\ number\ of\ detections$$

$$MOTA = 1 - (FP + FN + IDs)\ /\ Total\ number\ of\ ground\ truth\ objects$$

$$DetA = Number\ of\ correctly\ localized\ detections\ /\ Total\ number\ of\ detections$$

Broken trajectory is a common issue in our study, affecting the tracking of individual chickens. Initially, we calculated the averaged embedding similarity between broken trajectory pairs using cosine similarity (CS) and concatenated those whose averaged embedding similarity is greater than a predetermined threshold(Ma et al., 2020). Comparing with the ground truth, we discovered that while embedding similarity alone can correctly identify a portion of a trajectory with a high degree of similarity, it still has limitations when the movements of multiple objects have a very high degree of similarity. We introduced the location information and computed the distance error to solve this problem further. We combined distance error and embedding similarity to make assembly decisions for trajectories. We also calculate the distance (D) between the two trajectories to ensure that they do not represent separate objects with similar actions. Then, we merged the two measures to generate the assembling decision score (ADS).

$$CS(e^a, e^b) = \frac{\sum_{i=1}^{n} e_i^a \times e_i^b}{\sqrt{\sum_{i=1}^{n} e_i^a e_i^a} \sqrt{\sum_{i=1}^{n} e_i^b e_i^b}}$$

where e^a and e^b are two trajectories, e_i is the *i*th element of vector A.

$$D(t^a, t^b) = \sum_{i=1}^{n} |t_i^a - t_i^b|$$

where t_i^a and t_i^b represent the *i*th elements of the trajectory embeddings.

$$ADS = \alpha CS(e^a, e^b) + \beta D(t^a, t^b)$$

where the two coefficients were empirically set to be 0.2 and 0.8, respectively.

3.3 RESULTS

3.3.1 Comparison of Segmentation Approaches

Four separate experiments (SegFormer, SETR, SAM (one point), and SAM (total points)) were produced to identify the most effective approach for chicken segmentation tasks. For the models requiring training, SegFormer and SETR, a chicken dataset consisting of 1500 images (original images and thermal images) was utilized. The dataset was divided into three sets: 900 images for training, 300 images for validation, and 300 images for testing purposes. The models were trained for 300 epochs using the Python 3.7 version and the PyTorch deep learning library. The training process was conducted on hardware equipped with an NVIDIA-SMI graphics card with a capacity of 16 GB. In the case of SAM, a default pre-trained model (ViT-H SAM model) was used and tested under two different prompt modes (one point and total points) using the same testing set. The "one point" prompt mode refers to providing a single point or location within the object of interest to guide the segmentation process. This mode aims to capture the specific details and characteristics of the object based on prompt point. On the other hand, the "total points" prompt mode involves providing multiple points or locations that encompass the entire object. This mode considers a broader context by considering various aspects and features of the object throughout its entirety. SAM outperformed both SegFormer and SETR in both the overall and part-based segmentation benchmarks, as shown in Table 3.1.

Table 3.1: A comparison of SAM and state-of-the-art (SOTA) methods (SegFormer and SETR) in terms of mean Intersection over Union (mIoU).

Method	Semantic segmentation of chickens		Part-based segmentation of chickens	
	Original image	Thermogram	Original image	Thermogram
SegFormer	43.22	23.44	35.34	0.22

SETR	42.90	35.34	29.91	0.28
SAM (one point)	92.50	88.95	86.17	72.20
SAM (total points)	94.80	91.74	85.64	80.08

Particularly when using the total points prompts, SAM demonstrated remarkable performance improvements, achieving a mIoU of 94.8%. It was observed that the mIoU obtained from original images was found to be 15% (average) higher than that obtained from thermograms. This suggests that the utilization of original images provides more favorable conditions for accurate segmentation, thereby yielding superior results compared to thermal images. This is due to the presence of various color pixels in thermograms and the lack of a clear boundary between the chicken and the background, posing challenges for accurate chicken recognition by all models. Regarding semantic segmentation and arbitrary parts, the models performed better in recognizing semantic segments compared to arbitrary parts, excluding the tail. This can be attributed to the similarity in color between the tail and the chicken body, which persists under both natural light and thermal conditions, making it difficult to distinguish the tail alone (Li et al., 2021). Consequently, recognizing the entire chicken body proved to be a relatively easier task. Figure 3.7 presents a qualitative comparison of the performance of SegFormer, SETR and SAM. It is clear that the SAM produced the best result. Besides, SAM (total points) outperforms SAM (one point). Thus, in the rest of this paper, chicken segmentation tasks produced by SAM (total points).

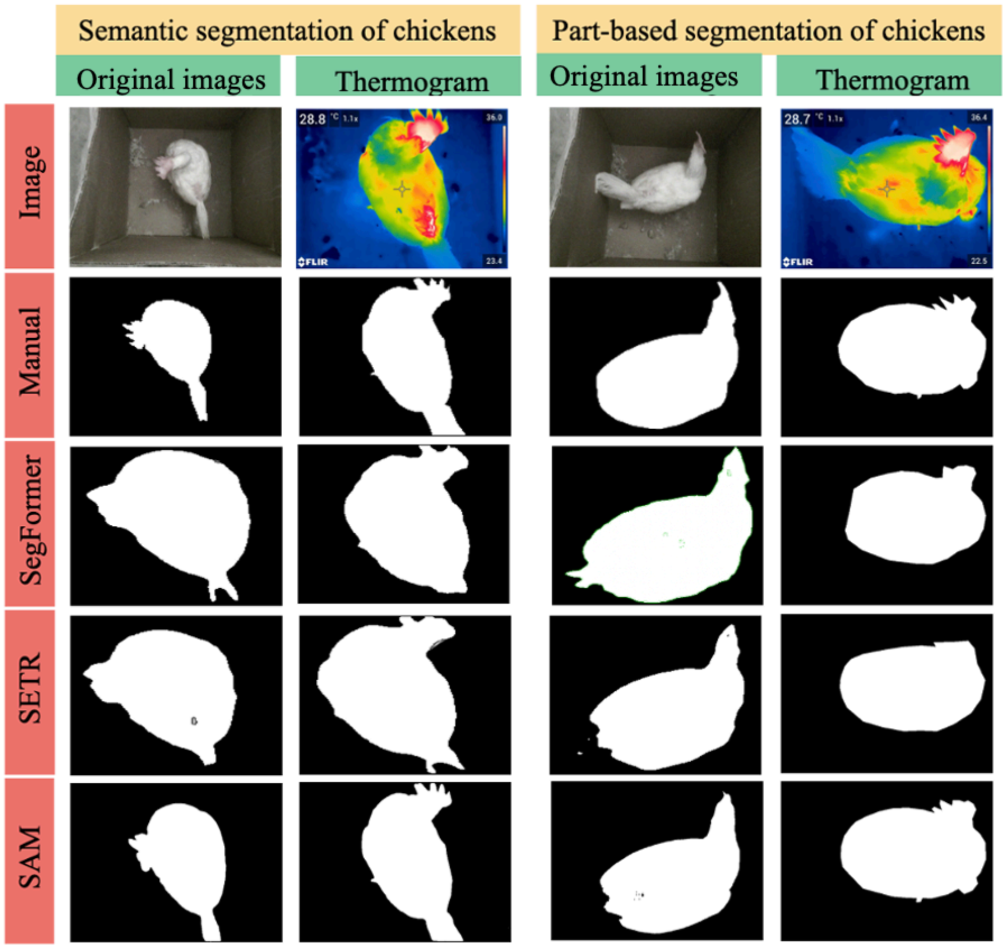

Figure 3.7. Visual comparison of segmentation results. State-of-the-art methods (SegFormer and SETR) are compared with SAM approach applied to diverse chicken datasets (Yang et al., 2023b).

3.3.2 Chicken Weight Prediction Using SAM

The combined R^2 value of the SAM and RF techniques in predicting chicken weights is 0.83. Figure 3.8A provides insights into the impact of each label on the overall precision. Notably, the utilization of thermal images with semantic segmentation (label c) yields the highest R^2 value of 0.89, outperforming the other three labels. Additionally, Figure 3.8B, the correction plot, showcases the correlation between any two labels. Significantly, labels a and b exhibit the strongest correlation, scoring an impressive 0.91. These findings underscore the exceptional performance of thermal images with semantic segmentation in the task of chicken weight prediction, as well as the noteworthy correlation between labels a and b. Knowing that both full and part-based segmentation from original images provide similar information for weight prediction with potential reduction in data processing requirements. If the tail is not needed, it could be omitted from analysis to save computational resources without losing predictive power.

To further explore SAM and its applications, a chart of average absolute residual values across different body weight ranges was generated (Figure 3.9) based on label c dataset. The residuals decrease as the body weight increases, which indicates that predictions are more accurate for heavier body weights. The highest residual is observed in the 1801-1900g range, with a value of approximately 28.58g, while the lowest is in the 2200-2300g range, at about 4.44g. This trend suggests that the model's accuracy in predicting the body weight improves for heavier entities. Additionally, the analysis of predicted body weight and residuals versus actual body weight, in conjunction with the previously discussed average absolute residuals, offers a comprehensive overview of the predictive SAM's performance. Figure 3.10 demonstrates a strong correlation between actual and predicted body weights, as indicated by a root mean square error (RMSE) of 25.26g. Figure 3.11, which illustrates the residuals, presents them scattered around the zero line, suggesting that the SAM's errors are random rather than systematic. The previously noted downward trend in average absolute residuals is contextualized by these graphs, confirming that the SAM's accuracy indeed improves for larger body weights. This improvement is made evident by the lower residuals in these weight ranges and an RMSE value that indicates the errors are not only smaller on average but also less variable as body weight increases.

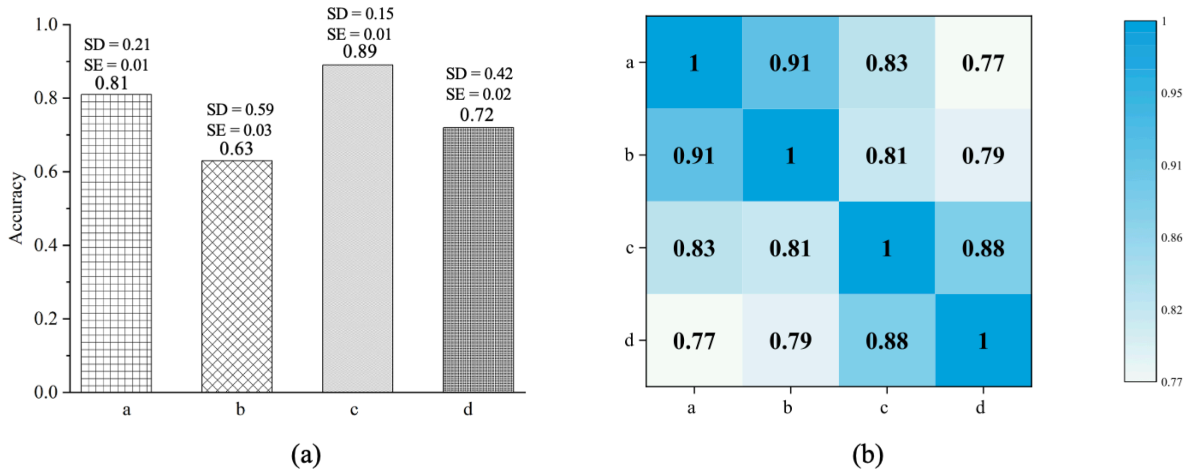

Figure 3.8. Accuracy impact A and correlation analysis B of labels in chicken body weight prediction (labels (a (semantic segmentation of laying hens based on original pictures), b (part-based segmentation of chickens based on original pictures), c (semantic segmentation of chickens based on thermal pictures), d (part-based segmentation of chickens based on thermal pictures)). Standard error (SE) and standard deviation (SE).

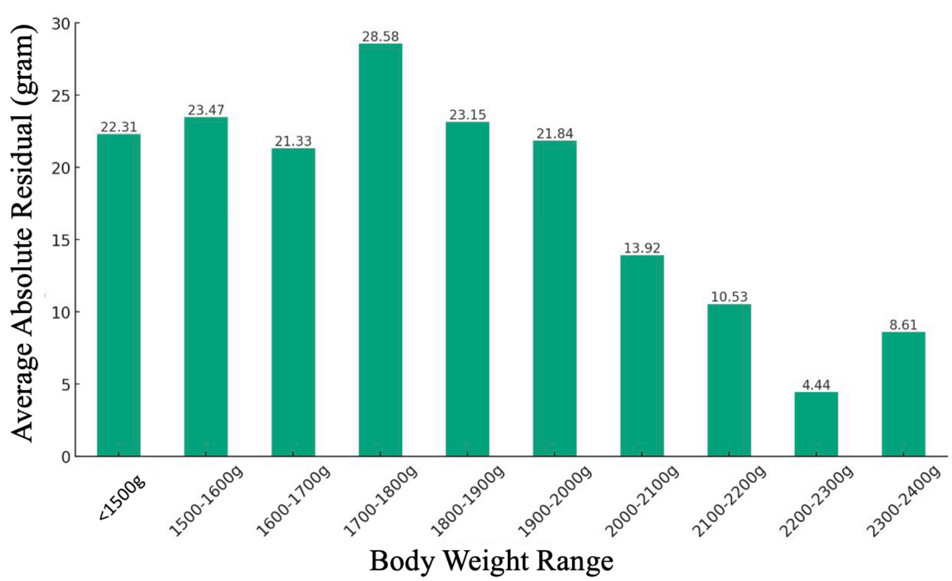

Figure 3.9. Variation in average absolute residuals across different body weight ranges.

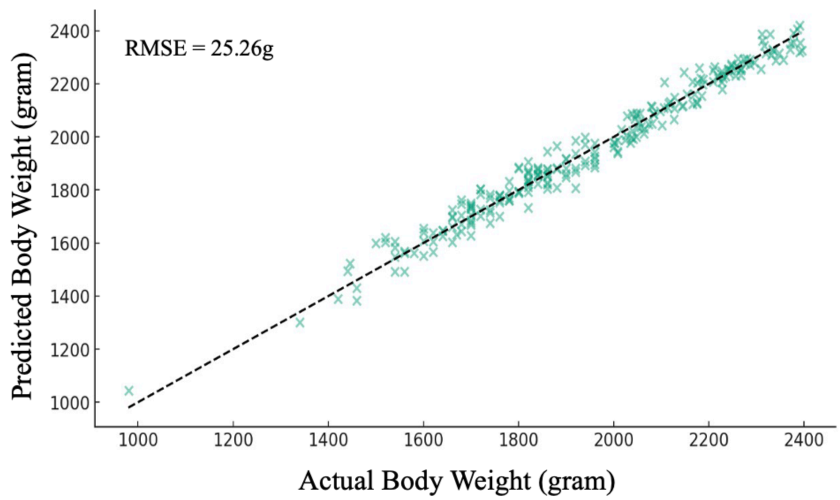

Figure 3.10. Physical difference between predicted and actual body weights with indicated RMSE.

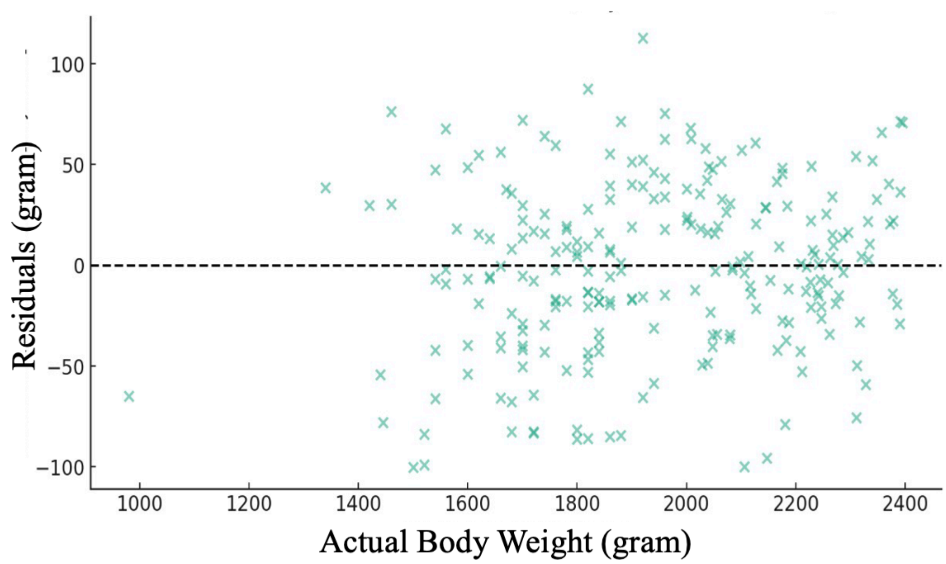

Figure 3.11. Distribution of prediction residuals across actual body weight ranges.

3.4 DISCUSSIONS

3.4.1 Discussion of Chicken Segmentation Approaches of Chicken Segmentation Approaches

In this study, SAM outperformed SegFormer and SETR in four distinct segmentation tasks, including part-based and total segmentation using either original or thermal images.

Specifically, SAM's total points prompt mode attained the highest level of precision. This outstanding performance can be attributed to several factors. First, SAM employs its segmentation attention mechanism, which effectively captures fine-grained details and complex image patterns. This attention mechanism enables SAM to focus on relevant regions and features, resulting in more accurate segmentation (L. Zhang et al., 2023). Alternatively, it is noteworthy that SAM outperformed the other models without requiring additional training. This indicates that the architecture and design of SAM have inherent segmentation capabilities, eliminating the need for extensive fine-tuning or specialized training. This quality renders SAM a more feasible and effective option for segmentation applications(Kirillov et al., 2023). In addition, the use of thermogram images for segmenting target chicken did not increase segmentation accuracy overall. This could be due to a number of factors. Thermogram images capture the heat distribution and are sensitive to temperature variations, which may not correlate directly with the shape or boundaries of the poultry being analyzed. Consequently, relying solely on thermogram images for segmentation may introduce noise or irrelevant information, resulting in a reduction in overall precision (Resendiz-Ochoa et al., 2017; X. Zhang et al., 2023). Comparing part-based segmentation, it was discovered that whole-chicken segmentation exhibited superior performance across the board. This is because part-based segmentation may present difficulties in accurately identifying and delineating the boundaries between poultry parts. The segmentation of a whole chicken provides a more comprehension of the object by capturing its overall shape and structure, which facilitates improved segmentation results(Ahmadi et al., 2023; Chen and Bai, 2023; Jing et al., 2023). To further discuss the performance of SAM, we compare our study with various research. The table 3.2 shows the results of related studies conducted on the chicken segmentation using computer vision, compared with the result obtained in the present study. In a study involving the segmentation of meat carcasses by a meat dataset (108,296 images), EfficientNet-B0 obtained a mIoU of 89.34% (Gorji et al., 2022). MSAnet obtained a mIoU of 87.7% when used to segment caged poultry in a dataset of 300 images (Li et al., 2021). Mask R-CNN obtained a mIoU range of 83.6% to 88.8% when used to segment hens from a dataset of 1700 images (Li et al., 2020). The method used in this study, SAM, achieved a mIoU of 88.06% for poultry segmentation, putting it on par with or even surpassing the performance of other methods without the development of target dataset, indicating its capability to accurately delineate chicken regions in images. These results demonstrate the efficacy of SAM for this particular task and its potential for broader applications in computer vision tasks involving chicken segmentation.

Table 3.2. Comparison of segmentation accuracy.

Methods	Dataset (constructed by authors)		mIoU (%)
	Number	Type	
EfficientNet-B0	108,296	meat carcasses	89.34
MSAnet	300	caged chickens	87.7
mask R-CNN	1700	hens	83.6-88.7
SAM (this study)	/	/	88.06

Note: Multi-Similarity and Attention Network (MSANet) and Region-Based Convolutional Neural Network (R-CNN).

3.4.2 Discussion of Chicken Weight Prediction

In predicting chicken weights, label c, which represents the use of thermal images with semantic segmentation, obtains the highest accuracy of 0.89. This finding indicates that incorporating thermal images and employing semantic segmentation techniques significantly improves the accuracy of the comparison with the segmentation from the original image.

Thermal images predominantly detect areas with temperature variations, which can be used to predict the weight of chickens. Comparing thermal images to the original images, the segmentation mask derived from thermal images tends to emphasize the chicken's center more (Brenner et al., 2023). As a result of the presence of vital organs and metabolic activity, the central region typically has a higher average temperature. We can effectively extract the thermal patterns and temperature-related characteristics of the central body region by employing thermal images and semantic segmentation techniques. This emphasis on the central portion of the poultry reduces the impact of temperature variations in non-central areas, such as the tail feathers, which may have less of an effect on the overall weight prediction. Strong correlation of 0.91 between labels a and b indicates a significant relationship between semantic segmentation of chickens from original images (label a) and part-based segmentation of chickens from original images (label b). This correlation suggests that these two labeling methods provide complementary information and predict chicken weights with a high degree of concordance. If we know that labels a and b are highly correlated, we can potentially use their combined information to enhance weight prediction even further. By combining semantic segmentation from the original images (label a) and part-based segmentation from the original images (label b), we can potentially derive a more comprehensive understanding of the features and structure of chickens, resulting in improved predictive performance. This correlation suggests that the two labeling methods capture similar characteristics of the poultry, which strengthens potential accuracy in weight prediction. For chicken shape, if the head overlaps with the body and the open tail state is more than 50%, the model tends to overestimate body weight. Amraei et al. (2018) utilized the Transform Function (TF) model to measure the body weight of broiler chickens (Amraei et al., 2018). During the processing of the chicken dataset, they employed a technique to remove the tail, resulting in a remarkable accuracy of 0.98. However, it should be noted that this method required a substantial number of annotated pictures, specifically 2440, which can be challenging to obtain in practice. On the other hand, Mollah et al. (2010) employed image software called IDRISI 32 to determine the surface area of broiler chicken bodies (Mollah et al., 2010). They further developed a linear equation to estimate the weight of chickens, achieving an impressive accuracy of 0.99. Nonetheless, this approach also relied on a significant dataset of 1200 basic chicken samples. In comparison, although the SAM+RF method's accuracy falls slightly short of the aforementioned techniques, it is important to consider that the SAM was not pretrained in weight prediction task. By implementing a custom image segmentation model based on YOLOX and SAM, it is possible to enhance the accuracy of weight prediction. This approach allows for further improvements and fine-tuning, which can potentially bridge the accuracy gap observed in the initial results (Kirillov et al., 2023).

3.5 CONCLUSIONS

This article presents the development and evaluation of SAM, a novel computer vision model for laying hens segmentation, body weight prediction, and tracking. The findings demonstrate SAM's superiority over existing methods in both semantic and part-based segmentation. Moreover, the combination of SAM with RF and thermal camera proves promising for chicken weight prediction, while integrating SAM with YOLOX and Byte-Tracker enables real-time tracking of individual broiler bird movements. However, the study also highlights several limitations of SAM, including challenges related to flock density, occlusion, and chicken behaviors. To address these limitations, the article proposes future research directions that involve exploring arbitrary chicken parts, developing models for sorting and monitoring chicken weight, and integrating SAM with additional computer vision models to monitor chicken behaviors. Ultimately, the article emphasizes SAM's potential to improve chicken welfare and optimize poultry production operations.

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CHAPTER 4

AUTOMATIC METHODS FOR DETECTING FLOOR EGGS AND LAYING HENS BEHAVIORS IN CAGE-FREE HOUSES [4,5]

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ABSTRACT

Defective eggs diminish the value of laying hen production, particularly in cage-free systems with a higher incidence of floor eggs. To enhance quality, machine vision and image processing have facilitated the development of automated grading and defect detection systems. Additionally, egg measurement systems utilize weight-sorting for optimal market value. However, few studies have integrated deep learning and machine vision techniques for combined egg classification and weighing. To address this gap, a two-stage model was developed based on real-time multitask detection (RTMDet) and random forest networks to predict egg category and weight. The model uses convolutional neural network (CNN) and regression techniques were used to perform joint egg classification and weighing. RTMDet was used to sort and extract egg features for classification, and a Random Forest algorithm was used to predict egg weight based on the extracted features (major axis and minor axis). The results of the study showed that the best achieved accuracy was 94.8% and best R2 was 96.0%. In addition, the model can be used to automatically exclude non-standard-size eggs and eggs with exterior issues (e.g., calcium deposit, stains, and cracks). This detector is among the first models that perform the joint function of egg-sorting and weighting eggs, and is capable of classifying them into five categories (intact, cracked, bloody, floor, and non-standard) and measuring them up to jumbo size. By implementing the findings of this study, the poultry industry can reduce costs and increase productivity, ultimately leading to better quality products for consumers.

Poultry behavior is an important indicator of their welfare, health, and production performance. For instance, the welfare of layers and broilers such as walking ability, breast blisters and hock burn are measurable through behavior monitoring. In the previous research, most of laying hen studies focused on basic behaviors such as drinking, feeding, and walking of broilers. However, with the transition to the cage-free houses, more natural behaviors need to be monitored for welfare assessment. In this study, a six-behavioral classifier (i.e., feeding, drinking, walking, perching, dust bathing, and nesting) was developed based on multiple CNN models (e.g., efficientNetV2 and YOLOv5-cls). Furthermore, a cage-free birds' dataset containing 12,000 pictures was collected and annotated in a lifespan scale (e.g., from 1 week to 50 weeks of age), from which 9,600 images were used as training dataset and the rest were used for validation. The best performance model YOLOv5-cls-m achieved an average accuracy of 95.3%, which is 5.01% higher than that of efficientNetV2-l. Drinking behavior of chicks was monitored with the highest accuracy (97.8%) while nesting behavior had a detection precision of 92.5%. In terms of chickens' age, the classifier has a better accuracy for smaller chicks (< 10 days) than larger chickens older than 10 days (96.4% vs 94.3%). The results show that the classifier is a useful tool to segregate cage-free bird behaviors in various life periods and environments.

Keywords: Laying hen production; Egg quality; Defect detection; Egg weight; Deep learning; Poultry production; Cage-free housing; Animal welfare; Artificial intelligence; Behavior monitoring.

4.1 INTRODUCTION

Eggs are a nutritious food source for humans and are widely consumed across the world, but their high fragility makes them vulnerable to defects during production (Nematinia and Abdanan Mehdizadeh, 2018). Defects such as cracks, dirty spots on the eggshell, and blood spots inside the egg can decrease the quality and market value of eggs. To address this issue, researchers have developed automatic methods for grading eggs and determining defects. In the past, machine vision and image-processing technology have been applied to egg-quality detection and grading in the USA and abroad. Researchers have built gray-machine-vision systems and trained neural networks using egg image histograms to classify eggs into cracked and grade A (Patel et al., 1998, 1994). They have also established conventional neural networks (CNN) for the detection of blood spots, cracks, and dirt stains and developed an expert system for egg-sorting based on these networks (Omid et al., 2013; Turkoglu, 2021). The average accuracy of these systems exceeds the USDA requirements (Bist et al., 2023b). Therefore, the use of computer vison to grade eggs automatically has the potential to improve the potential efficiency and quality of the egg production process, leading to higher-quality eggs for consumers and increased market value for producers.

Egg weight is another important aspect of egg quality associated with the egg grade and market value (Sanlier and Üstün, 2021). The manual measurement of eggs at the digital scale is a time-consuming and tedious process. To improve the efficiency of the egg weighting process, automated egg measurement systems have been developed. Payam et al. (2011) used the ANFIS model to predict egg weight according to the number of pixels of eggs reaching 0.98 R-squared (R2) (Javadikia et al., 2011), which is more efficient and accurate compared to manual methods. Jeerapa et al. (2017), using the Support Vector Machine (SVM) technique to predict brown chicken eggs from a single egg image, yielded the correlation coefficient of 0.99 (Thipakorn et al., 2017). Raoufat et al. (2010) built a computer vison system to measure egg weights by artificial neural networks (ANN); their algorithms showed a high accuracy (R2 = 0.96) (Asadi and Raoufat, 2010).

Previous works in this area primarily focused on using computer vision techniques such as convolutional neural networks (CNNs) and image classification algorithms for egg classification (Apostolidis et al., 2021; Dong et al., 2021). These methods have shown promising results in classifying eggs based on their size, shape, and color. However, few studies have combined deep learning and machine learning regression techniques for joint egg classification and weighing, especially including floor eggs collected from cage-free poultry farms. This can be useful for producers who want to ensure consistent quality across all types of eggs and consumers who want to purchase high-quality eggs. Another reason for this is that the egg industry is shifting from cage to cage-free (Berkhoff et al., 2020; Hansstein, 2011; Lilong Chai et al., 2022; Lusk, 2019). Therefore, introducing floor eggs is beneficial for application in the cage-free egg in-dustry.

In this study, an automatic system was developed at the University of Georgia, aiming to fill this gap by integrating deep learning and supervised machine learning technologies to perform joint egg classification and weighting. The system uses an up-dated and powerful CNN, called real-time multitask detection (RTMDet), to extract egg features for classification (Lyu et al., 2022), and a classic Random Forest (RF) algorithm to regress egg-weight data based on the extracted features (Breiman, 2001). The objects of this study were as follows: (1) develop an egg classifier to sort eggs through their size and surface; (2) build a regressor to predict egg weights through their geometrical attributes; (3) combine egg-sorting and the measuring of egg weights into one two-stage model; (4) test the model with standard eggs and second eggs. This two-stage model is expected to result in improved accuracy and efficiency compared to existing methods.

Global population has reached about 8 billion in 2023 and is projected to increase further to 9.7 billion in 2050, which requires a 50 percent growth in animal-derived products to meet the demand of the world (Avendano et al., 2020). To achieve this goal, precision livestock production is introduced to monitor and manage animal production and health. It involves the application of sensors, data collection, and analytics of big data, which optimizes animal production and product quality, while minimizing the utilization of limited natural resources. A major component of precision poultry farming is the observation of animal behaviors to assess the well-being and health of the chicken flock (Bist et al., 2023; Tullo et al., 2019; Werkheiser, 2018).

Animal behavior is an indicator of emotional state and well-being. The common welfare indicators of layers and broilers include walking ability, breast blisters, hock burn, heart failures, and pecking damages that are measurable through monitoring behaviors (Webster et al., 2008; Subedi et al., 2023a, b). For example, chickens may exhibit behaviors such as pecking, scratching, and dust bathing when they are content and relaxed (Subedi et al., 2023; Yang et al., 2022b). On the other hand, if a chicken is stressed or anxious, it may result in behaviors such as feather plucking, pacing, and vocalizing. To monitor chicken behaviors, two main approaches were used previously: contact monitoring with body carried sensors (e.g., planted sensors and RFID) and non-contact monitoring (e.g., cameras and audio sensors) (Castro et al., 2023). Direct observation involves observing birds in their natural environment in person. This method allows researchers to recognize the behavior of animals in their natural habitat and to gain a better understanding of their behaviors.

Non-contact monitoring evolves the observation using sensors, cameras, and other technology to monitor birds from a distance (Engel et al., 2014; Mollenhorst et al., 2005). Unlike direct observation, this method enables researchers to observe chicken without disturbing them, and to collect data on their behavior over time. It also improves the farm biosecurity because of the non-invasive method. Computer vision strategy has seen broad utilization for animals' monitoring. In traditional computer vision world, visual techniques are employed to identify poultry behaviors by extracting pre-defined characters and applying them with supervised, unsupervised, semi-supervised and reinforced learning (Khan et al., 2021). A high accuracy of detection relies on the characters extracted. In recent years, the emergence of deep learning has been remarkable. Deep learning is a type of machine learning that uses artificial neural networks to learn from data. It is a powerful tool for solving complex problems in computer vision (Gikunda and Jouandeau, 2019). Convolutional neural network (CNN) is one of the most popular deep learning methods, which enables farmers to gain insights into the behaviors and health of their animals. In the animal science field, deep learning techniques such as CNNs have been increasingly utilized to analyze a diverse range of data related to animal behavior, welfare, and health. These techniques have proven to be highly effective in various applications, including detecting and analyzing images of animals to identify signs of injury, disease, or stress. Its applications in poultry industry are broad. (Nasiri et al., 2020) achieved an automatic sorting system for unclean eggs by CNN model. The testing result shows the average accuracy is 94.84%. You only look once (YOLO) is a popular object detection algorithm in computer vison due to its accuracy and speed. (Wang et al., 2019) developed a detector based on YOLO network to detect and pick up sick birds in crowded conditions with 84.3% accuracy. Li et al. (2020b) used a fast R-CNN method to monitor drinking behaviors of layer under different light colors, reaching the detection rate of the model is 88.2%.

However, most of the previous studies were based on broilers and caged layers (Guo et al., 2020, 2021, 2022). The egg production in US and EU is shifting from either conventional cage or enriched colony systems to cage-free system (aviary housing). In addition, almost all the current research focused on some time periods of chicken (Brannan and Anderson, 2021; Gonzalez-Mora et al., 2022). When the study targeted on cage-free birds at a lifespan scale, more challenges need to be addressed. This research gap highlights the need for studies that focus on the behavior and welfare of cage-free birds throughout their entire lifespan, contributes to the development of more accurate and efficient deep learning models, and can provide substantial benefits to the agricultural industry and animal welfare organizations. Incorporating deep learning models containing characters of multiple birds' behaviors under cage-free houses at different growth periods will enhance the accuracy of the prediction and welfare of chicken. Accurate prediction of the behavior and welfare of cage-free birds can enable farmers and animal welfare organizations to take targeted measures to enhance the birds' health and well-being. In particular, this approach can lead to improved productivity and reduced costs by minimizing disease outbreaks and maximizing the efficiency of interventions. The objectives of this study were to (1) develop a behavioral classifier for monitoring cage-free hens applied behaviors (e.g., feeding, drinking, walking, perch, dust bathing, and nesting); and (2) test the performance of newly developed deep models on behavior monitoring in research poultry houses.

4.2 MATERIALS AND METHODS

4.2.1 Egg Collection

In this study, 800 Hy-line W-36 hens were used to produce cage-free eggs with free access to fresh water and feeds (Figure 4.1). The eggs were collected daily and stored at a temperature around 24 °C for the next sorting process, and were then graded according to size and quality. A binary classification (standard and defect eggs) was first introduced to classify the eggs manually. The standard eggs were those that were clean, and sizes ranged from small (50–55 g) to jumbo (70 g and above), while the non-standard eggs were those that were bloody, cracked, had an unusual egg shape (too long, too round or dis-torted), and a size less than small or more than jumbo (Figure 4.2) (Subedi et al., 2023a; Thipakorn et al., 2017). This classification was applied to determine the quality of the eggs and to ensure that only the best quality eggs were utilized for measuring egg weight.

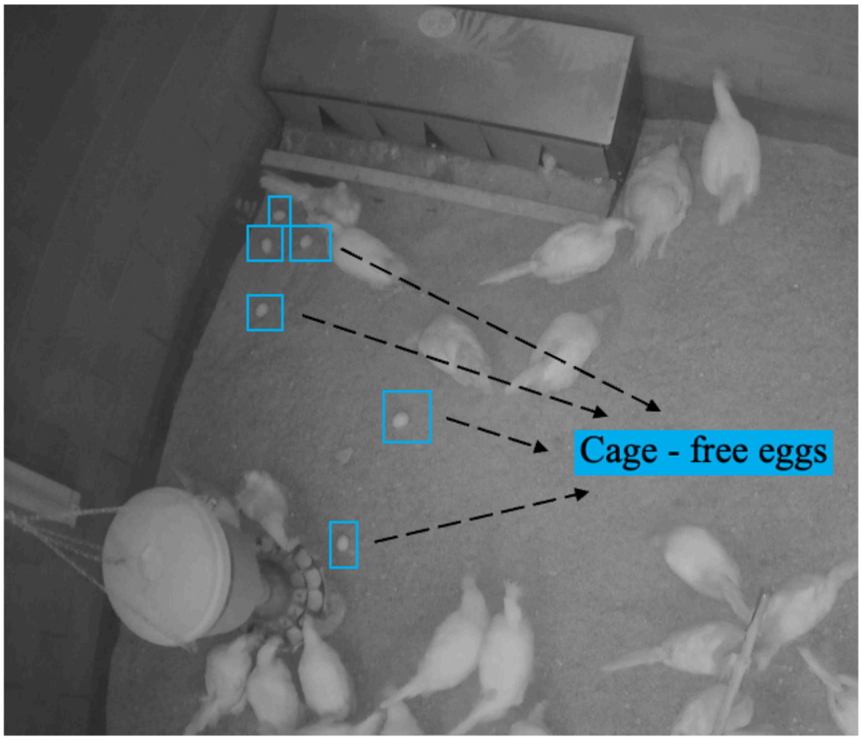


Figure 4.1. The production of cage-free eggs.

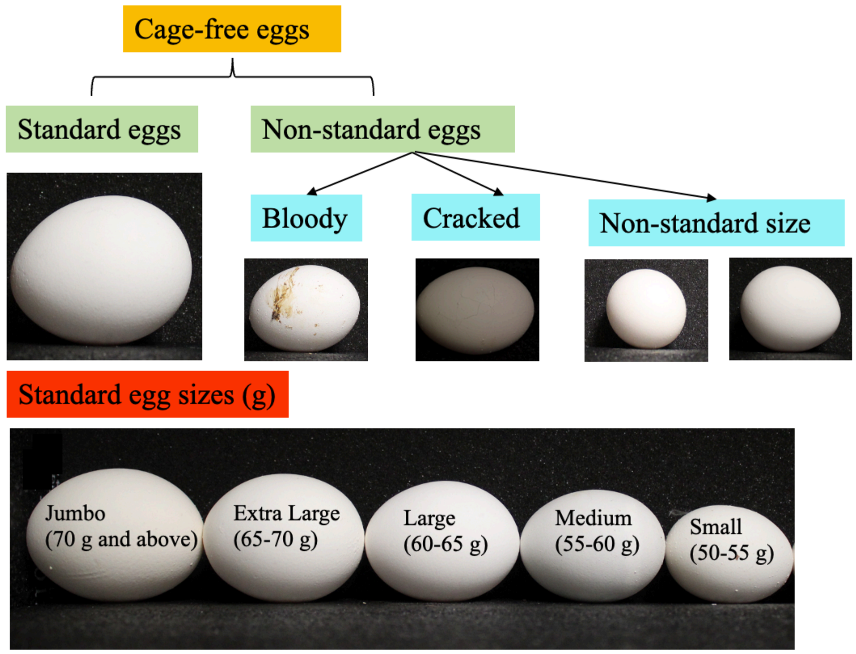


Figure 4.2. The classification of cage-free eggs and visualization of standard egg sizes (g).

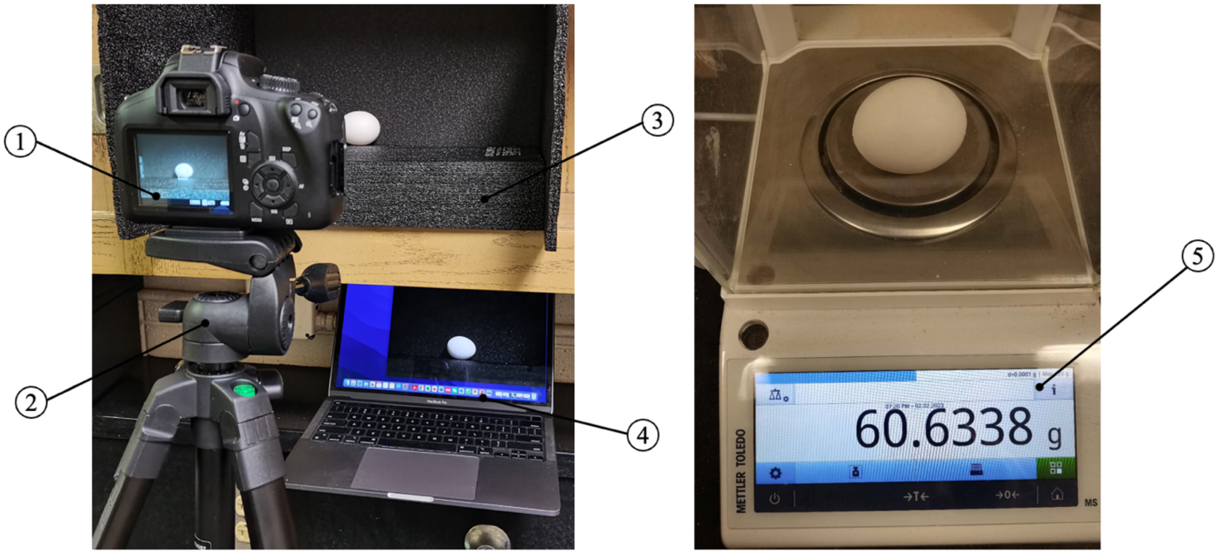
4.2.2 Experimental Arrangement and Equipment

In this study, 800 Hy-Line W-36 commercial layers were randomly assigned to four rooms, each of 7.3 m × 6.1 m × 3 m (length × width × high) in the University of Georgia (UGA), m house, Poultry Research Center (Athens, GA, USA). The room is shown in Figure 4.3. Each room has six hanging feeders, four nest boxes, one water pip mounted nipple drinkers and a trapezoid frame hen perch to promote chicken's natural habits. The feeders were filled two times per week and the water was provided 24 hours every day. Chickens were able to eat and drink freely. To monitor and capture the behavioral data of birds, the top-view and side-view cameras were installed on the celing and side wall of each room separately. The video data were collected 24 hours per day from August 17th 2021 to September 1, 2022. Every three days, the videos were transformed into a massive hard drive for safe storage at Department of Poultry Science in the UGA.

Figure 4.3. Experimental arrangement of cage-free research houses.

4.2.3 Egg Samples Acquisition System

An egg samples' collection system was constructed to collect images and weights of different classes of eggs at the department of poultry science at the University of Georgia (UGA), USA. Figure 4.4 demonstrates the egg sample acquisition setup, including the camera, tripod, egg base, computer, and digital scale. Details are shown in Table 4.1. The system is designed to accurately collect and record data on the different classes of eggs. The camera, which is mounted on a tripod, takes images of the eggs placed on the designated egg base. The digital scale measures the weight of the eggs, and the computer stores the collected data and images. The combination of the camera, scale, and computer allows for a comprehensive and efficient egg sample collection process. The collected data and images were used to develop an automatic system for classifying and weighting the eggs using computer vision.



(a) (b)

Figure 4.4. The egg samples' acquisition system for classifying eggs (a) and weighing eggs (b): (1) camera; (2) tripod; (3) egg base; (4) computer; (5) digital scale.

Table 4.1. The details of the egg sample acquisition setup.

Parts	Details
Camera	Canon EOS 4000D (Tokyo, Japan)
Tripod	BOSCH BT 150 (Gerlingen, Germany)
Egg base	ESS—8010 (Wasco, CA, USA)
Computer	Apple MacBook Pro (M1, 2020) (Cupertino, CA, USA)
Digital scale	Mettler Toledo MS104TS/00 (Greifensee, Switzerland)

4.2.4 Egg Data Processing

Once the egg image data was collected, two key processing steps: preprocessing the diffraction patterns and performing hierarchical clustering on the data. These steps involve refining the diffraction patterns and organizing the data into clusters based on their similarities (Zhang et al., 2022). Preprocessing involves removing background noise, normalizing the signal intensity, and correcting for any artifacts in the data. This step ensures that the diffraction patterns are clean and reliable for analysis. Hierarchical clustering is a method for grouping similar data points into clusters based on their similarity (Nazari et al., 2015). The algorithm starts by considering each data point as its own cluster, and then iteratively merges clusters until a desired number of clusters is reached or a stopping criterion is met (Figure 4.5). This approach can be used to identify patterns in the egg data, such as different eggshell types (bloody, cracked and distorted) or quality grades (small size to jumbo size).

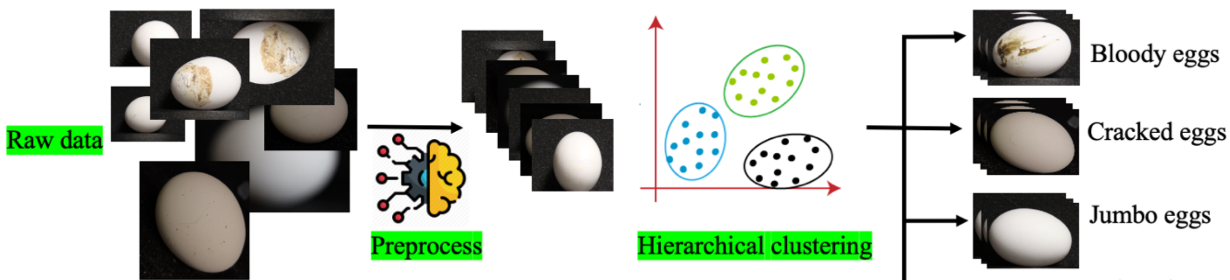


Figure 4.5. The flow of egg data processing.

4.2.5 Egg Sorting Method

To develop a real-time automatic egg-quality checking system that meets the future requirements of the egg industry by utilizing deep learning for small object classification, specifically egg classification, during the grading process, a new family of original real-time models using you only look once (YOLO) for object classification, referred to as RTMDet, was utilized. RTMDet is introduced with improved small-object detection abilities. The appealing enhancements come from the large-kernel depth-wise convolutions and soft labels in the dynamic label assignments. This approach enables a comprehensive egg analysis, encompassing factors such as egg size and eggshell type. The large-kernel depth-wise convolutions improve the model's global context-capturing ability, while reducing the model depth to maintain a fast inference speed. The training strategies are revisited to improve accuracy with a better combination of data augmentations and optimization. Soft targets are introduced instead of hard labels in the dynamic label assignment process, improving discrimination and reducing noise in label assignment.

The overall architecture of the RTMDet classifier is broken down into three parts: the backbone, neck, and head. The backbone component is similar to that of YOLO, which is a recent advance in object detection, and is regularly equipped with a cross-stage partial network darknet (CSPDarkNet). This backbone consists of four stages, each of which is composed of several basic neural layers. These layers are designed to extract hierarchical features from the input data, capturing both low-level and high-level visual information. The neck merges the multi-scale feature pyramid from the backbone and improves it through bottom-up and top-down feature flow. It facilitates the fusion of information across different scales, enabling the model to effectively handle objects of various sizes. This ability is especially relevant when considering parameters such as the major axis and minor axis of the eggs. The major axis corresponds to the longer diagonal of the egg, providing insights into its overall length and shape. On the other hand, the minor axis represents the shorter diagonal, which helps to assess the width of the eggs. The detection head then identifies the object bounding boxes and categorizes them using the feature map at each scale. By analyzing the feature maps at different scales, the detection head can accurately localize objects and assign corresponding class labels (standard, bloody, floor, cracked and non-standard). This design is well-suited to both standard and small objects and can be expanded to instance segmentation through the implementation of kernel and mask feature production modules (Lyu et al., 2022). To provide a clearer representation of the system architecture, a diagram of the RTMDet macro-architecture is shown in Figure 4.6 (Lyu et al., 2022).

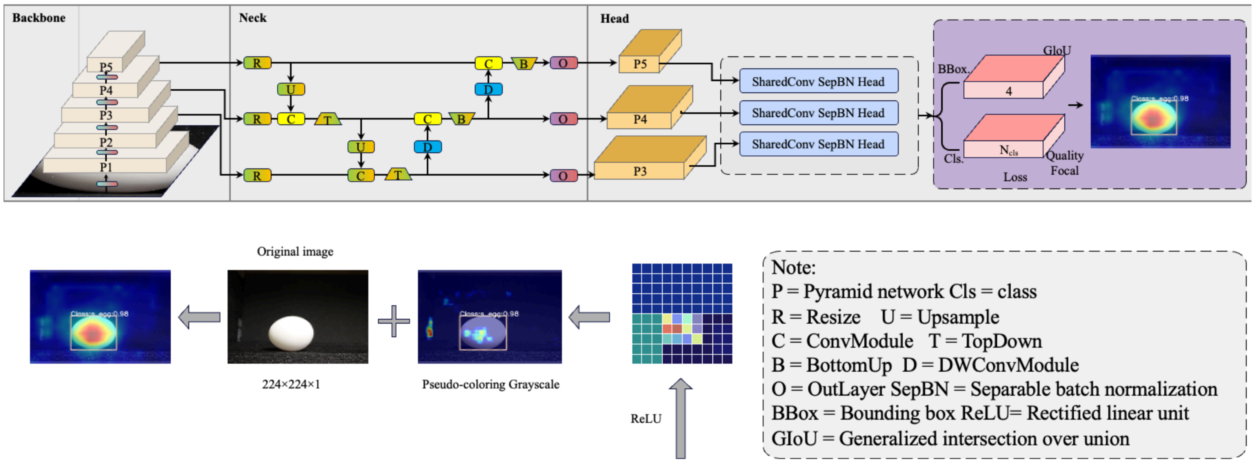


Figure 4.6. The structure of egg classification based on RTMDet architecture.

Large-Kernel Depth-Wide Convolution Approach

Large-kernel depth-wise convolutions involve the use of more extensive filters in depth-wise convolutional layers within a convolutional neural network (CNN) (Zhang and Zhou, 2023). The purpose of using these larger kernels is to gain a better understanding of the contextual information contained in the input data and enhance the representation power of the model. Depth-wise convolutions are frequently utilized in CNNs to reduce computational complexity and boost efficiency. Nevertheless, they have limitations in capturing significant scale context and spatial information. With the use of large-kernel depth-wise convolutions, this constraint can be overcome. The advantages of using large-kernel depth-wise convolutions include improved model ability when applied to real-world objects, a more comprehensive capturing of the data and their surroundings, and enhanced accuracy on benchmark datasets. In the context of egg classification, this approach allows for a more comprehensive analysis of various parameters, including egg size, eggshell type, and other spatial characteristics. Furthermore, large-kernel depth-wise convolutions allow for a reduction in the number of parameters and computation, while still delivering a similar performance to models with more parameters.

Soft Labels

In deep learning, soft labels refer to the use of continuous, rather than binary, values as target outputs. The purpose of using soft labels is to provide the model with additional information and to encourage smoothness in the model predictions (Ma et al., 2020; Subedi et al., 2023a). By employing soft labels, the model can generate predictions that provide more subtlety and precision in the classification task. Instead of solely assigning eggs to specific classes with binary labels, the soft labels enable the model to express varying degrees of confidence or probabilities for each class. This allows for a more detailed understanding of the eggs' characteristics and their association with different classes. In addition, the use of soft labels can result in more robust models because the model is able to discover correlations between the input data and the desired outputs, even if the relationship is not obvious. In our study, soft labels are applied in problems with multi-class classification or multi-label classification (i.e., unclean eggs, standard eggs, and no standard eggs), where the model must predict the presence of multiple target classes (Wang et al., 2021, 2023). In addition, on the basis of simplified optimal transport assignment (SimOTA), an advanced cost function calculation for soft labels was presented to reduce training loss, and its loss function is described below.

$$f(C) = \alpha_1 f(C_{cls}) + \alpha_2 \, f\left(C_{reg}\right) \tag{1}$$

where $\mathrm{f(C)}$ is loss fuction, $\mathrm{f(C_{cls})}$ is the classification loss, $\mathrm{f(C_{reg})}$ is the regression loss, and two coefficients, α_1 and α_2, were empirically set.

$$f(C_{cls}) = CE\left(P, Y_{soft}\right) \times (Y_{soft} - p)^2 \tag{2}$$

where $\mathrm{CE}(\mathrm{P}, \mathrm{Y}_{\mathrm{soft}})$ represents the cross-entropy (CE) loss between the predicted probabilities (P) and the soft labels ($\mathrm{Y}_{\mathrm{soft}}$).

$$f(C_{reg}) = -\,log(IoU) \tag{3}$$

where −log (IoU) means the negative logarithm of the intersection over union (IoU).

4.2.6 Egg Weight Prediction Method

Predicting egg weight through computer vision leads to several challenges that must be addressed. One of the challenges is the accuracy of measurements of the egg's dimensions, such as the major and minor axis. This is due to the difficulty of obtaining high-quality images or accurately identifying and measuring the egg in the image. Another obstacle is the diversity in the shapes and sizes of eggs (small-jumbo), which requires the implementation of complex machine learning algorithms that can account for various factors, including eggshell color, shape, size, and birth date, that may affect egg weight. Random Forest Regression is utilized for egg-weight prediction due to its ability to handle complex, non-linear relationships between features and target variables using an ensemble learning method that combines predictions from multiple decision trees, which are trained on randomly selected subsets of the data. This combination reduces variance and enhances the overall accuracy of the model. Furthermore, Random Forest can handle missing or incomplete data and perform effectively when there is a combination of continuous and categorical variables (Breiman, 2001; Riley et al., 2021). Lastly, feature importance scores are provided by Random Forest, which helps determine the most significant factors that contribute to egg weight prediction. The structure of RF is shown below (Figure 4.7) (Khan et al., 2021).

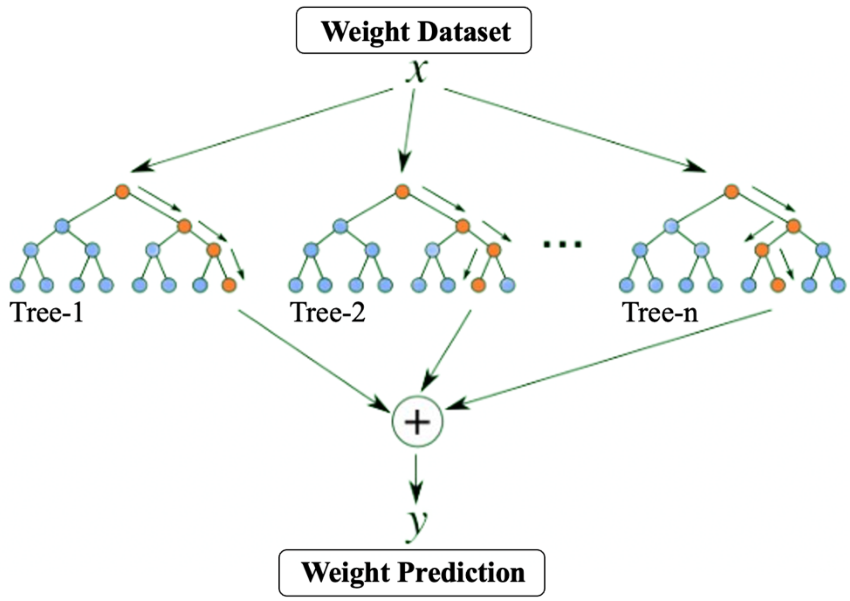


Figure 4.7. Random forest algorithm.

4.2.7 Computer Vision System

In this study, we aim to integrate computer vision technologies, deep learning and machine learning, into a single implementation for the purpose of jointly performing egg-sorting and weighting functions. The input egg images will first be processed through RTMDet, a deep learning technique that surpasses conventional CNN models, to extract egg features for classification. After obtaining the segmented mask of the egg, we identify four cutting points on the mask, namely, the top, bottom, left, and right points. These points are then used to form a new rectangle. Within this rectangle, the longer diagonal corresponds to the major axis, while the shorter diagonal corresponds to the minor axis. The weighting function will then utilize a classic Random Forest algorithm to regress egg weight data based on the egg features (major axis and minor axis) extracted by binary image. Figures 4.8 and 4.9 show the whole flow (Chieregato et al., 2022).

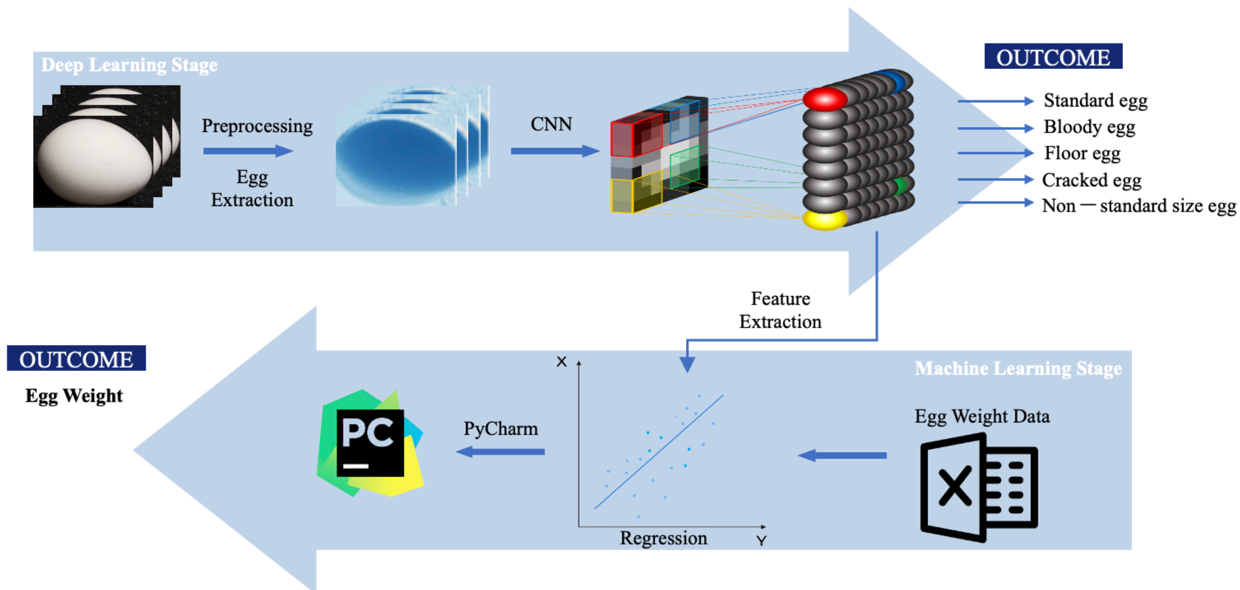


Figure 4.8. A streamlined approach to egg quality classification using computer vision.

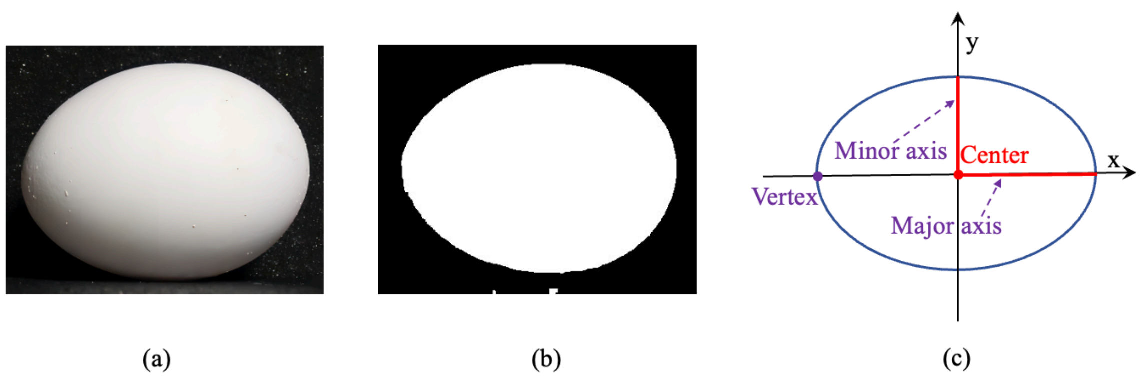
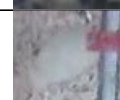
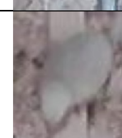
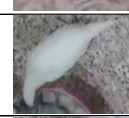
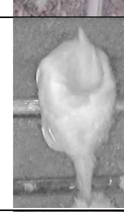


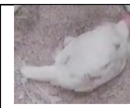
Figure 4.9. The processes of calculating egg parameters: (a) original image; (b) binary image; (c) geometric image.

4.2.8 Behavior Dataset Description and Labeling

A behavior dataset was developed by ImageJ (The National Institutes of Health, Bethesda, MD, USA) with its crop function. The crop function returns a subset of target object with different behaviors. In our study, eleven behavioral datasets were created based on birds' age and their acts. For chicks (1-4 weeks), five basic behaviors were defined, including feeding, drinking, perch, walking and dust bathing. For chickens (older than 4 weeks), except the common acts they keep since young, one more behavior (nesting) because of natural chicken brood was added. Therefore, there are eleven behaviors in total, which represent birds' welfare at discrete chicken growth stages in the research. The details of the definition of each act are shown below.

Table 4.2. The definitions of different behaviors.

Categories	Definition	examples
feeding	Birds less than 4 weeks & head above the feeder	
drinking	Birds less than 4 weeks & head closes to the nipples	
perch	Birds less than 4 week & feet on wood	
walking	Birds less than 4 weeks & body moving on the litter	
dust bathing	Birds less than 4 weeks & body rolling around in the litter	
feeding	Birds more than 4 weeks & head above the feeder	
drinking	Birds more than 4 weeks & head close to the nipples	
perch	Birds more than 4 week & feet on perch frame	
walking	Birds more than 4 weeks & body moving on the litter	

dust bathing	Birds more than 4 weeks & body rolling around in the litter	
nesting	Birds more than 4 weeks & body sits on the eggs for most of the time	

4.2.9 Behavior Data Augmentation Technique

Data augmentation is a technique aimed to improve the amount of data available for enhancing the training performance of deep learning models. It is a process of creating synthetic data from existing data points artificially by applying different transformations. In our study, due to the shortage of nesting datasets, four augmentation approaches were applied to increase the diversity including blur (blur the input image), scaling (change the dimensions of the input image), contrast (brighten the darker areas of the input image) and rotation (rotate the input image randomly) (Perez and Wang, 2017). The examples of the data augmentation techniques are shown in Figure 2. After data augmentation process, 12000 images were generated, of which 9600 divided into training dataset and the rest was used for validation set. The training and validation sets were spitted into a 4: 1 ratio. Each class in the dataset consists of 1092 pictures, with the exception of the "dust bathing" class, which contains 1080 pictures due to the greater difficulty in collecting images of this behavior.

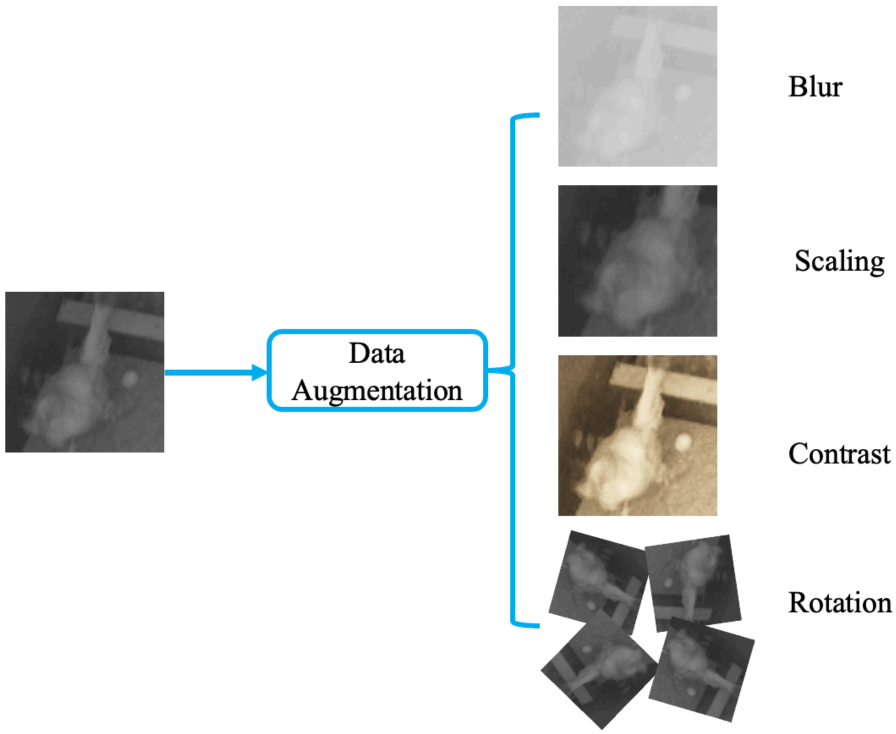


Figure 4.10. The results of data augmentation techniques.

4.2.10 Behavior Data Segmentation Method

During this time, there are many online tools and software to solve the problems of image segmentation. A cropping method is provided by ImageJ, unlike other software, which leaves a black area after cropping the target image out of the whole scene, ImageJ could use the selected rectangle to crop where we are interested repeatedly. After cropping, duplicate the selected area and rename it automatically to a given folder for the permeant storage (Figure 4.11). ImageJ is broadly used because of its time-saving and easy use for beginners who are not familiar with complex code.

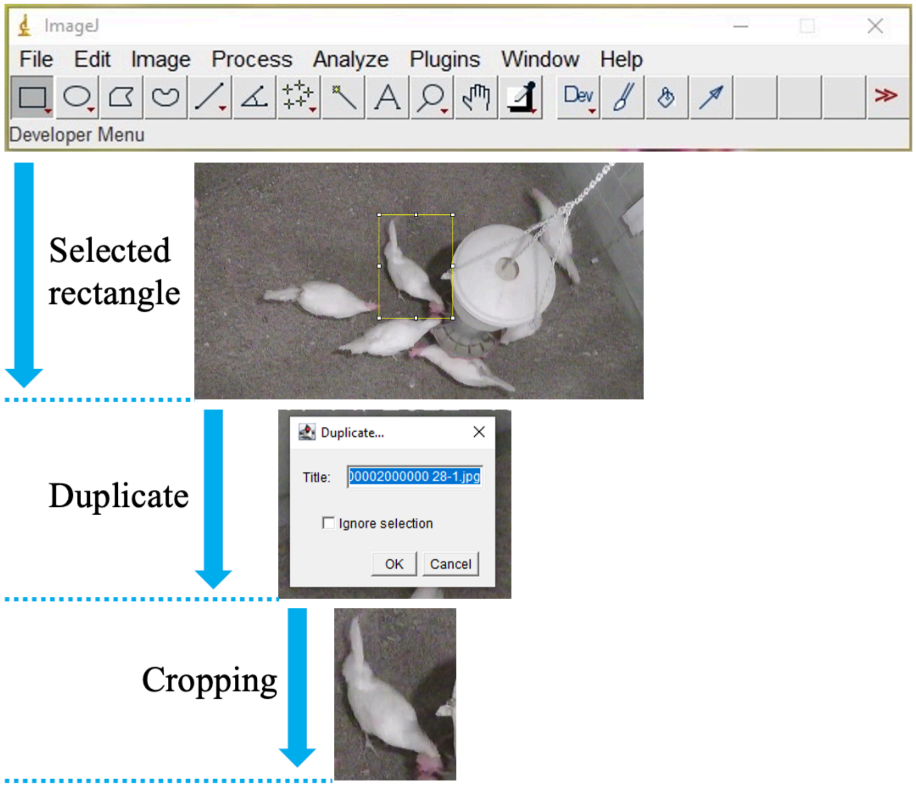


Figure 4.11. The diagram of image segmentation.

4.2.11 Methods of Image Classification for Laying Behaviors

To classify the behaviors of birds, the newest v6.2 YOLOv5-cls method (accuracy superiority) and a standard efficientNetV2-B0 model (speed superiority) were applied in the study. Both models reach excellent accuracy on classification tasks. Beyond accurate performance, however, training speed and parameter efficiency are further factors considered for applying model to wider environments, which are usually with moderate computing resources. Therefore, the comparison of the two methods on the performance of birds' behavioral classification could make a balance and objective evaluation on the overall application of models.

The algorithm of YOLOv5-cls is shown in Figure 4.12. The YOLOv5-cls network includes two parts, backbone and head. The backbone network is the core part to extract the high, middle, and low feature maps from input images by FOCUS, cross stage partial (CSP), contextual block separable (CBS) and spatial pyramid pooling fast (SPPF) structures (Redmon et al., 2016). The CBS module has two primary components: a separate convolution layer and a context aggregation layer. The separable convolution layer employs depth wise separable convolutions to decrease the number of parameters and enhance computational efficiency. To capture contextual information, the context aggregation layer aggregates features from neighboring pixels. Multiple CBS modules are frequently employed in CNN backbone architectures to extract increasingly complex image features. Depending on the network design and task being performed, the specific roles of the six CBS modules in the backbone architecture may vary, but in general, they are used to capture increasingly complex and abstract features at different stages of the network. The head network consists of three convolution layers that predicts the objects classes with probabilities. In addition, to prevent model from growing over-confidence, label smoothing is used in the behavioral classification task.

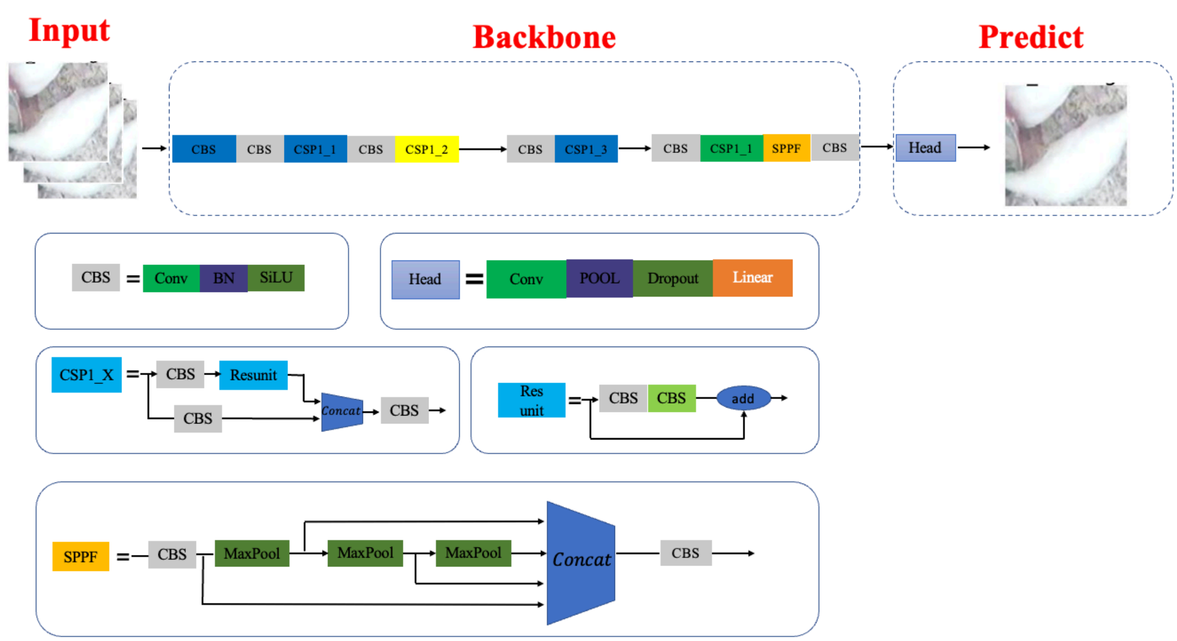


Figure 4.12. The YOLOv5-cls architecture.

In YOLOv5, the function of FOCUS is to slice the picture before it inputs into backbone (Wang et al., 2020). The detailed operations are: a) every pixel was given a value, which is similar to down sampling, b) four pics were generated and each of them were complementary to prevent information lose, c) the input channel is expanded by four times, d) the sliced pics were composited to 12 channels, e) a double down sampling feature map was obtained after a final convolution layer (Figure 4.13). Taking a 640 × 640 × 3 image as an example. After slice operation, it becomes a 320 × 320 × 12 feature map. Then after a convolution layer, its feature map size is 320 × 320 × 32. By reducing layers, FOCUS structure increases the forward and backward speed (Mao et al., 2022). Algorithm 1 describes how to encode (Table 4.3).

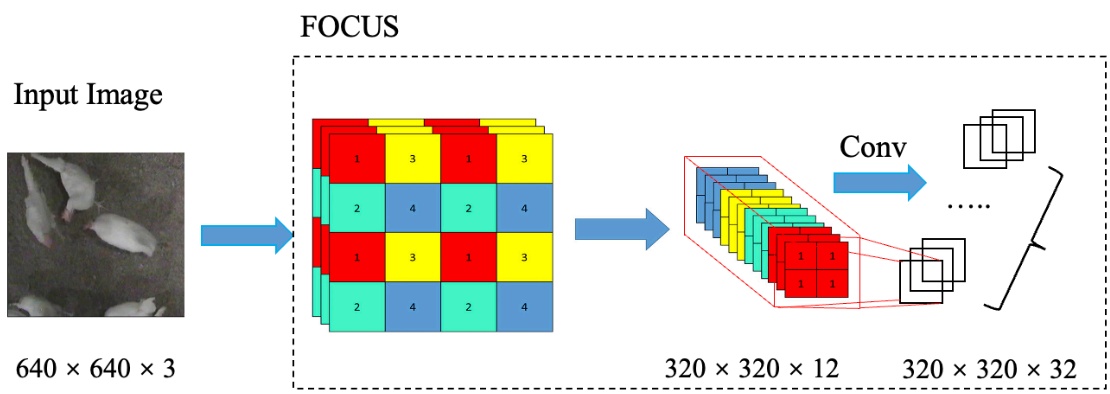


Figure 4.13. Illustration of FOCUS structure.

Table 4.3. Algorithm 1-FOCUS summary.

Algorithm 1: FOCUS

```
class Focus(nn.Module):
   # Focus wh information into c-space
   def __init__(self, c1, c2, k=1, s=1, p=None, g=1, act=True):  # ch_in, ch_out, kernel, stride,
padding, groups
      super(Focus, self).__init__()
      self.conv = Conv(c1 * 4, c2, k, s, p, g, act)      # input channels become 4 times here

   def forward(self, x):  # x(b,c,w,h) -> y(b,4c,w/2,h/2)
      return self.conv(torch.cat([x[..., ::2, ::2], x[..., 1::2, ::2], x[..., ::2, 1::2], x[..., 1::2, 1::2]], 1))
```

The CSP-Darknet module is applied in YOLOv5. It is designed to strengthen the learning capability of neural network by reducing computations. The CSP module partitions the original input layer into two parts and convolutes them separately. Then a cross-stage hierarchy is used to merge the gradient flows (Figure 4.14). With the network optimization, CSP retains the information of feature maps along with less computational tasks (Yang et al., 2015). In addition, CSP network can greatly reduce memory costs by compressing the feature maps through cross-channel pooling. Algorithm 2 outlines the detailed operations (Table 4.4).

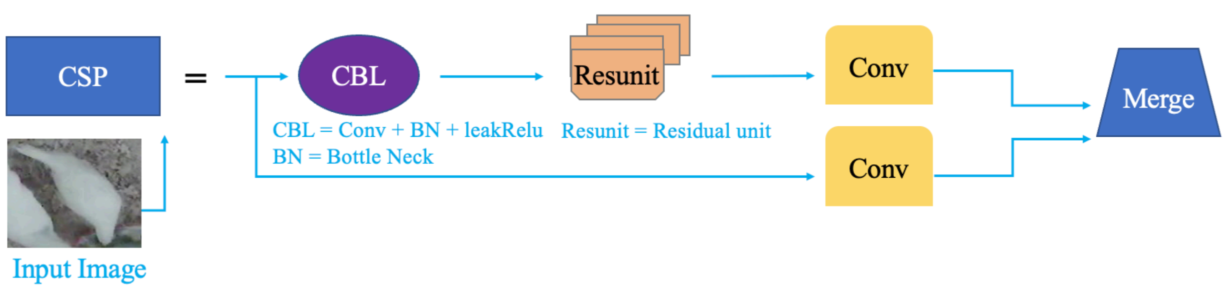


Figure 4.14. Illustration of CSP structure.

Table 4.4. Algorithm 2-CSP summary.

Algorithm 2: CSP

```
class BottleneckCSP(nn.Module):
    #CSP structure
    def __init__(self, c1, c2, n=1, shortcut=True, g=1, e=0.5):  # ch_in, ch_out, number, shortcut,
groups, expansion
        super().__init__()
        c_ = int(c2 * e)  # hidden channels
        self.cv1 = Conv(c1, c_, 1, 1)
        self.cv2 = nn.Conv2d(c1, c_, 1, 1, bias=False)
        self.cv3 = nn.Conv2d(c_, c_, 1, 1, bias=False)
        self.cv4 = Conv(2 * c_, c2, 1, 1)#CBL
        self.bn = nn.BatchNorm2d(2 * c_)  # applied to cat(cv2, cv3)
        self.act = nn.SiLU()
        self.m = nn.Sequential(*(Bottleneck(c_, c_, shortcut, g, e=1.0) for _ in range(n)))
        #nn.Sequential
def forward(self, x):
        y1 = self.cv3(self.m(self.cv1(x)))
        y2 = self.cv2(x)
        return self.cv4(self.act(self.bn(torch.cat((y1, y2), dim=1))))
```

SPPF is another pooling strategy, to maintain the classification accuracy. In general, CNN network consists of two parts: convolutional section and full-connected section. During full-connected layer process, all input images should have fixed same size, which leads to geometric distortion and classification accuracy can be forced (Ji et al., 2022). SPPF network partitions the whole image into several portions and extracts individual feature maps from each portion before the full-connected convolutional layer (Figure 4.15). In other words, SPPF module aggregates all the image features at a deeper stage in advance to prevent the arbitrary sizes. In this study, the use of SPP enabled the efficient and accurate extraction of features from images of cage-free birds engaging in various behaviors, enabling the development of a deep learning model with high classification accuracy. Algorithm 4.5 presents the work.

Label smoothing has been adopted efficiently to improve the performance of deep learning networks across many state-of-the-art image classification tasks. It is a regularization method to prevent over-confident and calibration error (Lienen and Hüllermeier, 2021; Xu et al., 2020). For image classification assignments, traditional one-hot approach defines the correct class probability as 1 and the incorrect class probability as 0 in the training dataset. During learning process, the method encourages the cross-entropy between the true class and the rest, which results in the final predicted logits tending to be infinite. Moreover, the infinite increase of the logit difference between the true and false labels makes the model lack adaptability and become over-confident.

$$y_i = \begin{cases} 1, & i = target \\ 0, & i = targrt \end{cases} \qquad \text{Eq. 1}$$

Where i is the class type.

$$H(y,p) = -\sum_i^K y_i log p_i \qquad \text{Eq. 2}$$

$$p_i = \frac{\exp(z_i)}{\sum_j^K \exp(z_j)} \qquad \text{Eq. 3}$$

Where p_i is the probability of i-th class, z_i is the logistic value of i-th class, z_j is the sum of logit values, K is the sum of total classes, j is the starting count and p represents each class type.

Label smoothing combines the uniform distribution with an updated label to replace the regular one-hot encoded label. By artificially softening labels, the smoothed distribution of the labels is equitant to add noise to the real distribution, preventing the model from being over-confident about the correct label. Therefore, the difference between output values of the predicted positive and negative classes could be reduced, thereby avoiding overfitting, and improving the generalization ability of the model.

$$\hat{y}_i = y_{hot}(1-\alpha) + \alpha/K \qquad \text{Eq. 4}$$

$$\hat{y}_i = \begin{cases} 1-\alpha, \ i = target \\ \alpha/K\,, \ i \neq target \end{cases} \qquad \text{Eq. 5}$$

Where $\hat{y}_i$ represents the predicted probability of a class i, y_{hot} is the original label vector for class i, K is the total number of classes, α is the hyperparameter and $\hat{y}$ is updated label.

The efficientNetV2 is a new family of CNN that has faster training speed (increased by 11 times) and less parameter (reduced by 15%) than prior methods as well as improving recognition accuracy (Figure 4.15). In efficientNetV1, accuracy, parameter and floating-point operations per second (FLOPs) are focused on. In efficientNetV2, however, authors further pay attention to the training speed by adopting new network module Fused-MBConv and progressive learning. Fused-MBConv is projected in 2019 to better use modern accelerators. It extends the conv1 × 1 in MBConv to conv3 × 3. When applied in early blocks, the training speed is significantly increased. Three Fused-MBConv modules and three MBConv modules are arranged in the backbone to strike a balance between computational efficiency and model performance. The Fused-MBConv modules combine multiple kinds of convolution operations into a single operation, thereby enhancing computational efficiency. However, this can result in a loss of precision. Therefore, the Fused-MBConv modules are positioned at the beginning of the backbone, where the input images have a higher spatial resolution and are less sensitive to minor differences in feature extraction. Combining depthwise convolutions, pointwise convolutions, and squeeze-and-excitation operations, the computationally more expensive MBConv modules extract features more precisely than their predecessors. The EfficientNetV2 architecture strikes a balance between computational efficiency and precision by alternating between the Fused-MBConv and MBConv modules. The precise configuration of three Fused-MBConv modules and three MBConv modules is probably the result of empirical testing and architectural optimization. Progressive learning strategy is proposed to combat a drop in accuracy when training images with various sizes. To cooperate with different image sizes, a rooted regularization in earlier work is not suitable now. Therefore, an adaptive regularization is advanced. The flexible regularization adaptively allocates augmentations and computations based on different image size (Demiray et al., 2021; Tan and Le, 2021). In general, smaller image size has the best training accuracy with moderate augmentation and less computational tasks, but for larger image size, significant augmentation is required to reach the best model performance. Progressive learning with gradual regularization assigns different types of regularization. In the early training epochs, images with smaller size shares weak regularization. Then, increaser progressively grows image size as well as regularization. In this way, efficeintNetV2 learns representations simply and fast.

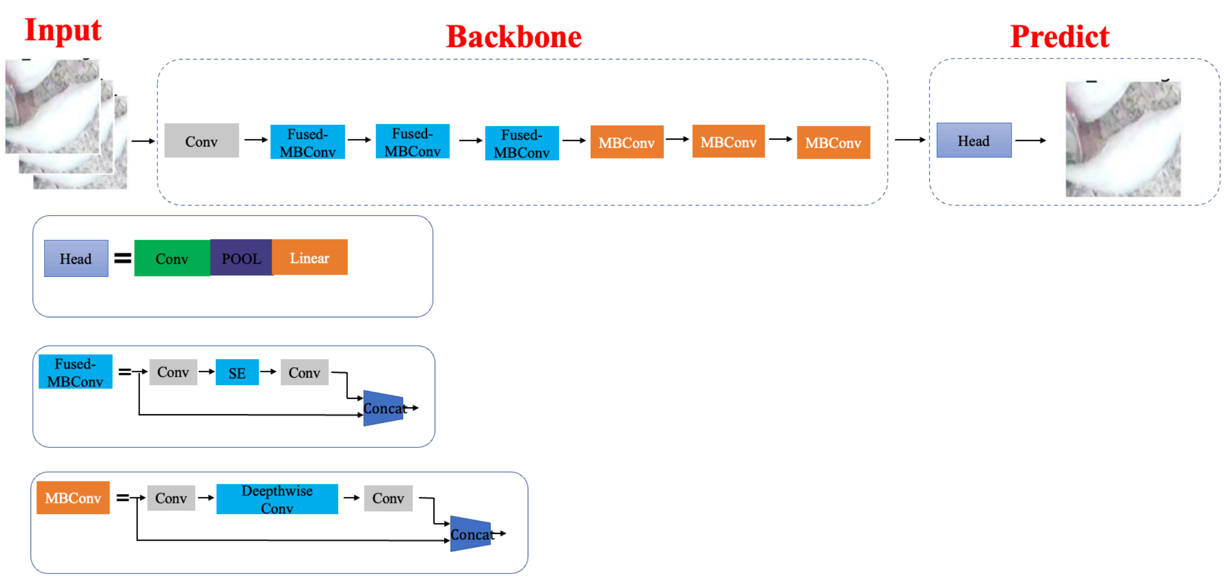


Figure 4.15. The effcientNetV2 architecture.

4.2.12 Performance Evaluation

In this research, a dataset was created using 2100 egg images, which were then randomly divided into training and testing sets with a ratio of 4:1. To better analyze and compare performance across egg classes, the confusion matrix was created to derive standard parameters in classification tasks (Wu et al., 2020). The confusion matrix is a two-dimensional table that summarizes RTMDet model's performance by comparing the predicted and actual class labels. Each row of the matrix represents occurrences in a predicted class, while each column represents instances in an actual class. The elements of the confusion matrix represent the number of cases identified correctly versus incorrectly. The four elements of true positives (*TP*), false positives (*FP*), true negatives (*TN*), and false negatives (*FN*) are used to calculate evaluation metrics such as precision, recall, F1-score, and average precision (*AP*) for egg grading in deep learning (Subedi et al., 2023b; Yang et al., 2022). To further explore the performance of Random Forest, coefficient of determination (R^2) is utilized to evaluate the goodness of fit of the regression model.

$$precision = \frac{TP}{TP + FP} \tag{4)}$$

$$recall = \frac{TP}{TP + FN} \tag{5)}$$

$$F1 - score = \frac{2 \times (precision \times recall)}{(precision + recall)} \tag{6)}$$

$$AP = \int_{\gamma=0}^{1} p(r)dr \tag{7)}$$

where $p(r)$ means the precision–recall curve.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$ 8)

where SS_{res} represents the residual sum of squares and SS_{tot} means the total sum of squares.

To benchmark the performance of classifiers, accuracy (mean average precision, mAP), GPU time, frames per second (FPS) and loss function values were focused on. Accuracy is the primary one used to evaluate how model correctly predicts all classes. GPU time is the actual time that processed the code, which indicated the computational performance of the algorithms. FPS is a standard one to evaluate the speed of methods(Ma et al., 2020; Zhang and Zhou, 2023). In terms of loss function, it is a metric associated with how algorithms modeling dataset and optimum result.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \qquad \text{Eq. 6}$$

Where AP_k is the average precision of class k, n is the total number of classes.

$$loss\ function = l_{cls} + l_{obj} \qquad \text{Eq. 7}$$

$$l_{cls} = \lambda_{class} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{obj} \sum_{C \in classes} P_i(c) \log(\hat{p}_l(c)) \qquad \text{Eq. 8}$$

$$l_{obj} = \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{noobj} (c_i - \hat{C}_l)^2 + \lambda_{obj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{obj} (c_i - \hat{C}_l)^2 \text{ Eq. 9}$$

Where $I_{i,j}^{obj}$ connects with whether targets locate at the anchor box (i, j) or not, $P_i(c)$ is the likelihood of target, and p̂l (c) is the actual value of the class. The sum of the two consists of the total number of classes C.

4.3 RESULTS

4.3.1 CNN Model Comparison

Four individual experiments (RTMDet-s, RTMDet-m, RTMDet-l and RTMDet-x) were conducted to discover the optimal classifier for egg-sorting. All experiments trained 300 epochs based on Python 3.7 version, PyTorch deep learning library and a hardware with NVIDIA-SMI (16 GB) graphics card. A summary of the model comparison is listed below (Table 4.5). In terms of accuracy, RTMDet-x reached an accuracy of 94.80%, which was better than any other comparison model. Correspondingly, the training loss and validation loss values of RTMDet-x were also the smallest among all the tested models because fewer loss values mean minor errors in neural networks. In terms of floating-point operations per second (FLOPS), RTMDet-s with fewer parameters have minimal FLOPS compared with other methods, which means they requires less computational time to perform a forward or backward pass in a neural network, and therefore have a broader further application in robots with limited computational resources (Jeyakumar et al., 2022). In addition, RTMDet-x also outperformed any other comparison model in map@0.75 and map@0.95 because of the additional parameters required for the computer to perform classification. Figure 4.16 shows the detailed comparison results of the model indicators for different deep learning classifiers. These findings demonstrated that RTMDet-x achieved the best performance in terms of egg classification.

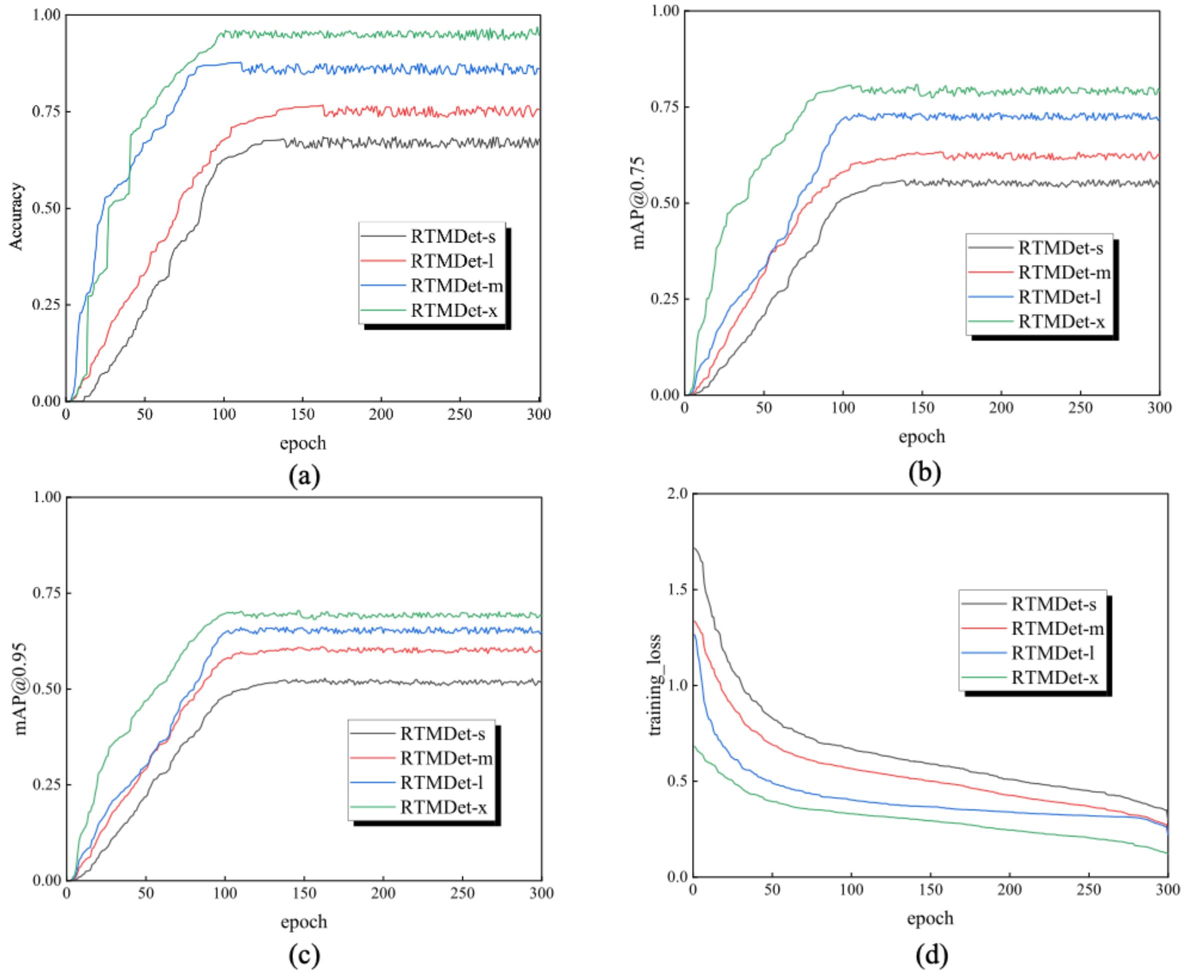


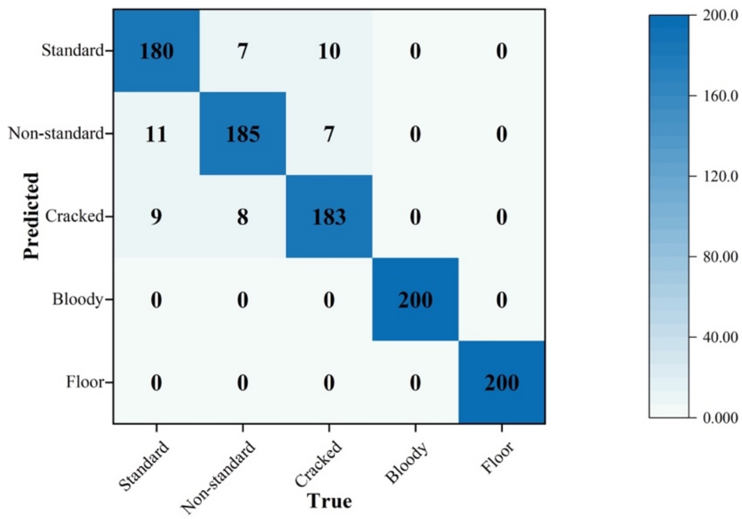
Figure 4.16. Model comparison: (a) accuracy, (b) mAP@0.75, (c) mAP@0.95 and (d) training loss.

Table 4.5. Summary of model comparison.

Model	Accuracy (%)	mAP@0.75 (%)	mAP@0.95 (%)	Params (M)	FLOPS(G)	Training Loss
RTMDet-s	67.8	55.8	52.3	8.89	14.8	0.30
RTMDet-m	75.6	62.6	60.1	24.71	39.27	0.23
RtMDet-l	86.1	72.1	64.8	52.3	80.23	0.21
RtMDet-x	94.8	79.2	69.1	94.86	141.67	0.12

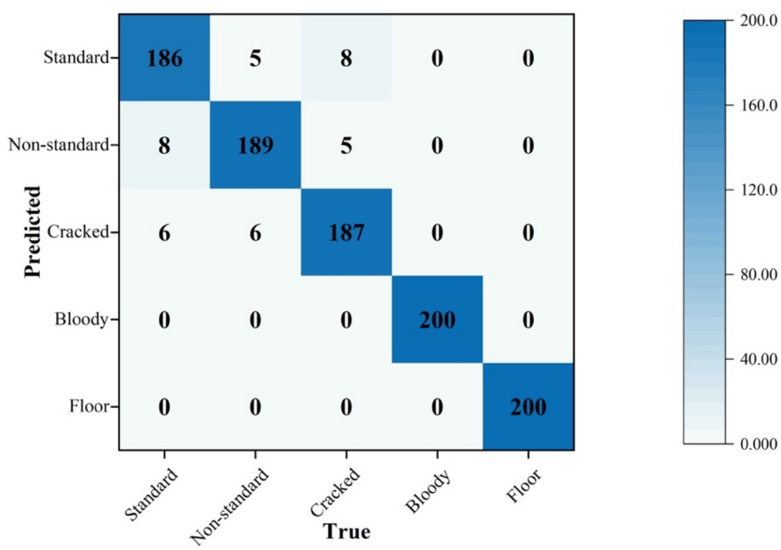
4.3.2 Regression Results for Detecting Eggs

To compare the classification performances of multiple deep learning models on the classification of eggs, the confusion matrix was adopted (Figure 4.17). Each type of egg was tested by different models 200 times.



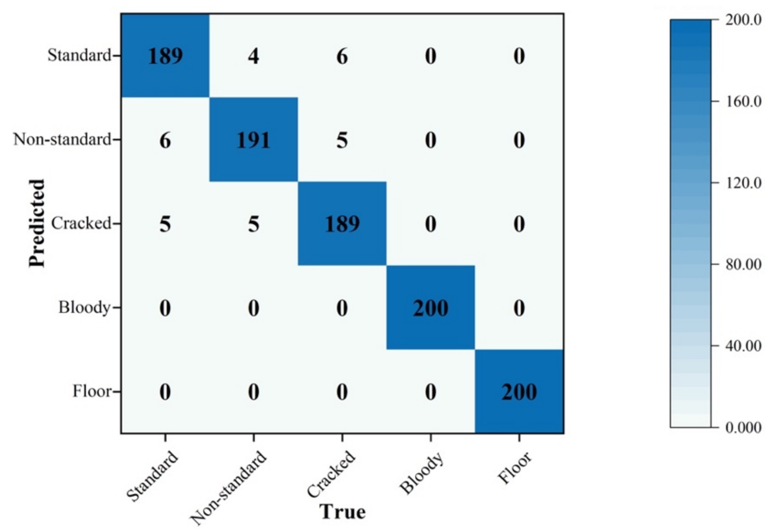
Standard
Non-standard
Cracked
Bloody
Floor
Predicted
True
180
7
10
0
0
11
185
7
0
0
9
8
183
0
0
0
0
0
200
0
0
0
0
0
200
200.0
160.0
120.0
80.00
40.00
0.000

(**a**)

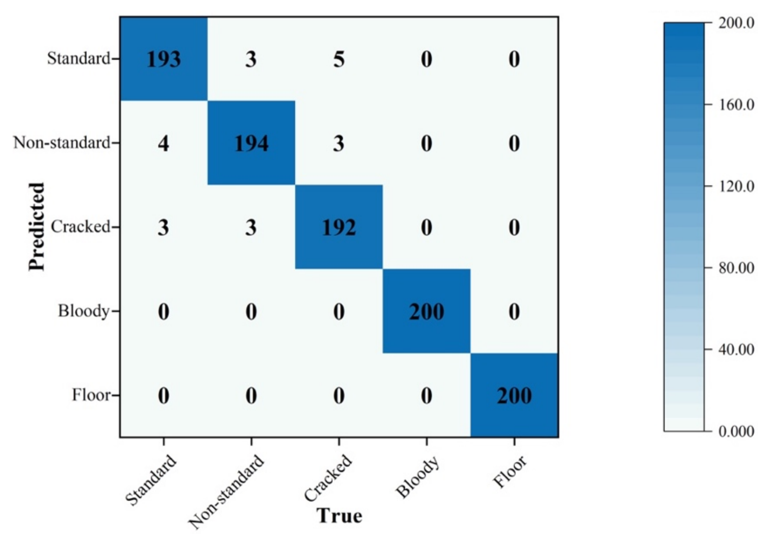


Standard
Non-standard
Cracked
Bloody
Floor
Predicted
True
186
5
8
0
0
8
189
5
0
0
6
6
187
0
0
0
0
0
200
0
0
0
0
0
200
200.0
160.0
120.0
80.00
40.00
0.000

(**b**)



(c)



(d)

Figure 4.17**.** Confusion matrix of classifiers for different types of eggs ((a)-(d) represent RTMDet-s, RTMDet-m and RTMDet-l and RTMDet-x, respectivly).

The prediction results are shown in the confusion matrix, where the gradually changing shade of blue represents the accuracy of true predictions (cells filled with deeper blue have more accurate predictions). The number in each cell represents the results of the models (Li et al., 2023). The average true scores (along the diagonal line from the top-left corner of the matrix to the bottom-right corner) of RTMDet-x are the highest among the whole confusion matrix of classifiers, which indicates that RTMDet-x has a better true prediction rate. The scores off the diagonal (false scores) represent the instances where the predicted class does not match the true class. The average false scores of RTMDet-s are higher than those of other classifiers, which means its performance could be improved. In terms of type error, no type error was observed in the classes of bloody eggs and floor eggs. The reason for this is their significant characters; for example, bloody eggs have clear bloody spots and only floor eggs have a litter background. However, when classifiers detect eggs using standard, non-standard, and cracked eggs, some errors exist due to the similarities within the minor axis and major axis, and the difficulties in detecting microcracks and cracks located on the bottom or sides not shown by the camera (Bist et al., 2023a). However, the results were still acceptable because there are not many non-standard eggs or cracked eggs on commercial poultry farms (varying between 1 and 5% of the total) (KHABISI et al., 2012). In general, the RTMDet-x classifier is the best experimental classifier with the highest accuracy. In addition, to visualize how RTMDet-x classifies eggs and extracts feature maps, heatmap and gradient-weighted class-activation mappings were outputted (Figure 4.18). To understand the model's decision-making process and identify important regions in the input images, the gradient-weighted class activation mapping (Grad-CAM) technique was utilized (Selvaraju et al., 2017). Grad-CAM produces a heatmap that highlights the regions contributing significantly to the model's predictions. By extracting the feature map from the last convolutional layer of the input egg image, a Grad-CAM heatmap is created. The feature map channels are then weighted using a class gradient computed with respect to the feature map. This weighting process emphasizes regions that strongly influence the model's predictions. Experimental findings demonstrate the CNN-based model's ability to effectively extract features from areas with blood spots and broken parts, even when the defects are minor. This showcases the model's capacity to accurately identify egg abnormalities and make precise predictions.

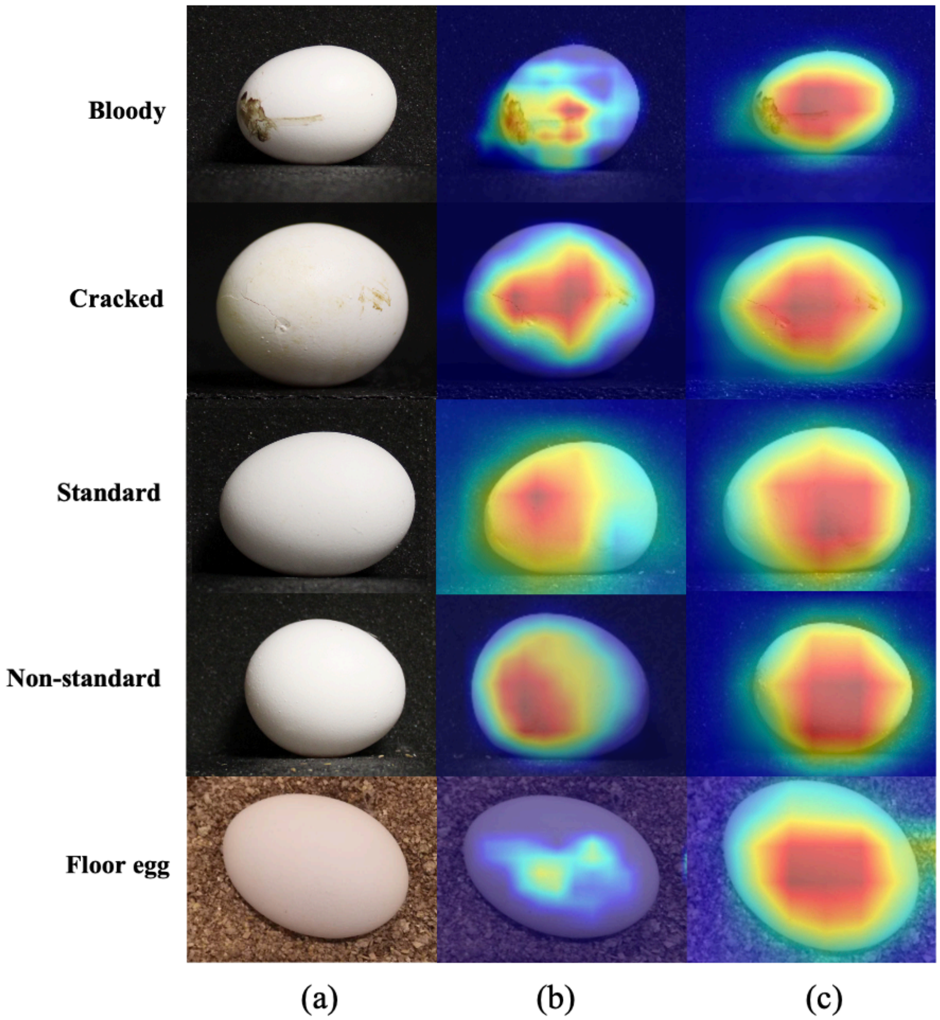


Figure 4.18. Visualization of CNN: (**a**) original image, (**b**) heatmap and (**c**) gradient-weighted map.

In this study, a random forest (RF) regressor was used to predict standard eggs (from small to jumbo size) because only standard eggs (consistent size and weight) can be sold to consumers by commercial poultry farms. As shown in Figure 4.19a, the predicted weight, using minor and major axis features using the RF regressor, showed an R^2 value of 0.96, which suggests that the predicted weights were highly correlated with the actual weights of the eggs. To further analyze the best performance of RF regressor, we classified standard eggs into five types (small, medium, large, extra-large and jumbo) and test each type 100 times using an RF regressor. In addition, the time of eggs is another important factor affecting egg weight; therefore, we also include this when comparing the predicted weight using minor and major axes obtained using the random forest regressor and the actual weight of the eggs on different storage days ($R^2 = 0.92$) (Figure 4.19b). By comparing the predicted weight obtained using the random forest regressor with the actual weight of the eggs under different storage conditions, the study was able to evaluate the robustness of the regressor in accounting for storage effects. Our storage conditions (24 °C) had a minimal impact on egg diameter, which remains highly correlated with egg weight (Gogo et al., 2021). As a result, the RF regressor can continue to accurately predict egg weight. The stable storage temperature ensures that the regressor's accuracy in estimating egg weight remains unaffected. The results suggest that the regressor is able to accurately predict egg weight under different storage conditions, which can be useful for optimizing egg production and storage practices (Kim et al., 2022).

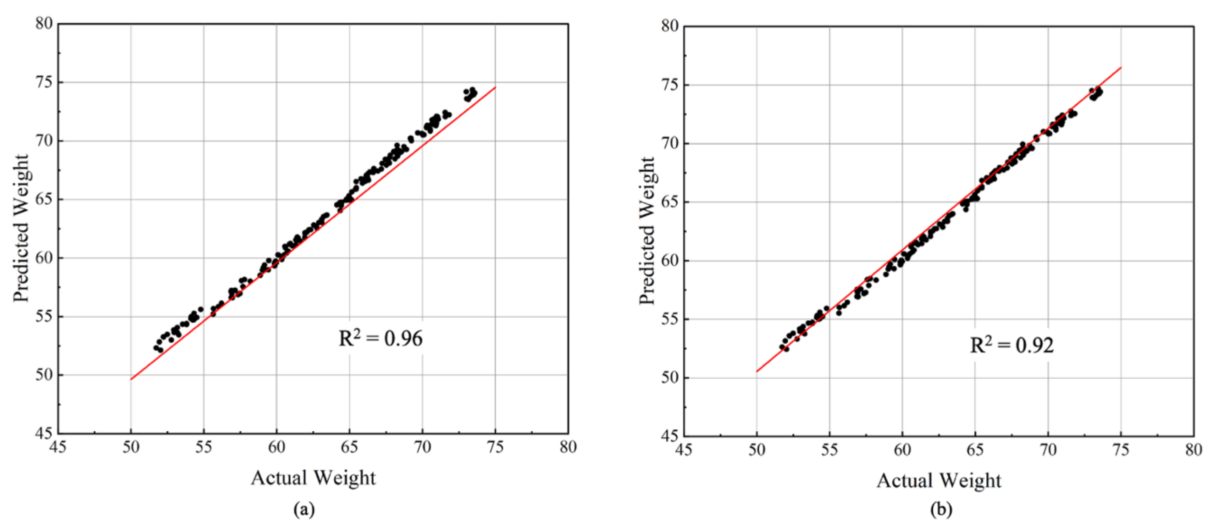


Figure 4.19. Regression models with (b) or without (a) storage date factor.

4.3.3 Results of Weighing Eggs

To further test the model under egg scales ranging from small to jumbo, each category randomly selected 100 pictures to test the robustness and precision of the regressor. The results are shown in Figure 4.20. The error bar at the top of each stacked bar graph represents the standard error of each class and the height of the green bar represents the absolute error between real weights and predicted weights. From the graph, we can find the height of the error bar for small, medium and jumbo eggs is lower than that for large and extra-large eggs, which indicates that the regressor has a better prediction performance for large and extra-large eggs. This may because the large and extra-large eggs have medium values according to the regression model; in a large dataset, the relationship between the precited variables and the response variables is more complex, resulting in the risk of overfitting and more prohibitive computational costs. However, the data in the medium values may be less affected by measurement error or other types of noise than very small or very large values (Li et al., 2017; Radlak et al., 2019). This can help to improve the accuracy of the regressor predictions. In addition, for some types of data, preprocessing can be simplified for medium values. For example, scaling or normalization may not be as critical for medium values as it is for very small or very large values. In addition, medium values may be complex enough to require a more sophisticated model, but not so complex that the model becomes difficult to interpret. This can help strike a balance between model performance and interpretability.

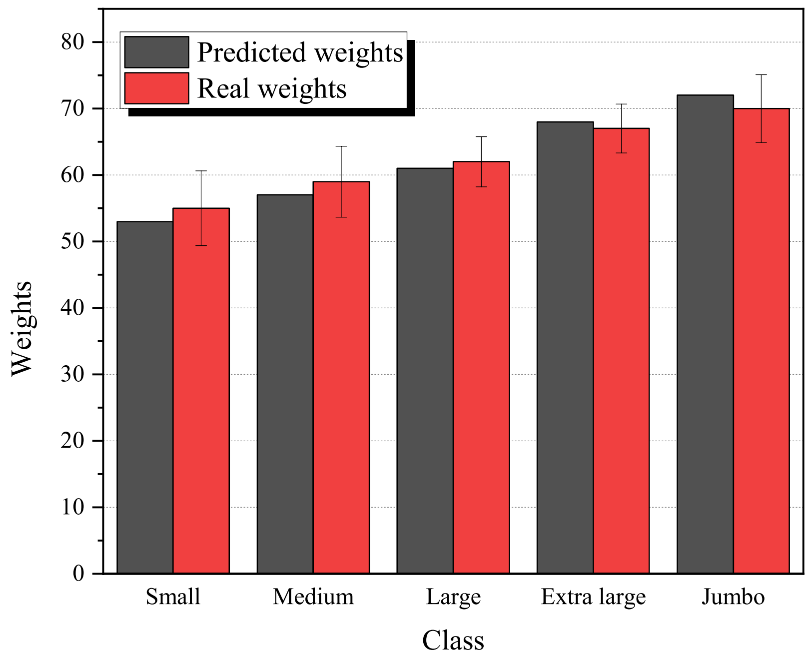


Figure 4.20. Egg weight prediction from small to jumbo.

4.3.4 Model Comparison for Laying Behaviors

Six individual experiments (efficient-s, efficient-m, efficient-l, YOLOv5-tiny, YOLOv5-s and YOLOv5-m) were conducted to discover the optimal classifier for birds' behaviors. The suffix "tiny" in YOLOv5 refers to a version of the model with fewer layers and reduced computational requirements. The suffixes "s" and "m" refer to small and medium-sized YOLOv5 models, respectively. Similarly, the suffixes "s", "m", and "l" in the efficient architecture denote small, medium, and large versions of the model, respectively. The checkpoint differences between these models are presented in Table 4.6. All experiments trained 300 epochs based on Python 3.7 version, PyTorch deep learning library and a hardware with NVIDIA-SMI (16GB) graphics card. The summary of model comparison is listed below (Table 4.7). In terms of accuracy, YOLOv5-m reached an accuracy of 95.33%, which was better than any other comparison models. Correspondingly, the training loss and validation loss values of YOLOv5-m were also smallest among the whole tested models because less loss values mean minor errors in neural networks. In terms of GPU time, YOLOv5-tiny with less parameters have the minimum training time compared with other methods. EfficientNetV2 series algorithms with additional Fused-MBConv and progressive learning modules, which expands the overall computational process causing more GPU time (Fayek et al., 2020). In addition, YOLOv5 also outperformed EfficientNetV2 in FPS because of reduced parameters for computer to perform (Ren et al., 2022). Figures 4.21-4.26 shows the detailed comparison results of the model indicators for different deep learning classifier. In the case of Efficient models, the greater the model's size, the greater its precision. However, this increased precision comes at the expense of a slower GPU and frame rate. In contrast to the Efficient-s model, the Efficient-l model has the highest accuracy but takes longer to train and process frames. The YOLOv5 models, on the other hand, are more accurate than the Efficient models and have lower training and validation losses. This demonstrates greater model performance than the Efficient models. Nevertheless, YOLOv5 models have lower FPS than Efficient models. The YOLOv5-tiny model has the highest FPS but the lowest accuracy, indicating that it may be better suited for applications that require rapid processing but less precision. These findings demonstrated YOLOv5-m achieved the best performance in birds' behavioral classification.

Table 4.6. The summary of checkpoint comparison.

Model	Size (pixels)	Parameters (M)	FLOPs (B)	Learning rate	Batch size
Efficient-s	224	5.3	1.0	0.01	8
Efficient-m	224	7.8	1.5	0.01	8
Efficient-l	224	9.1	1.7	0.01	8
YOLOv5-tiny	224	2.5	0.5	0.01	8
YOLOv5-s	224	5.4	1.4	0.01	8
YOLOv5-m	224	12.9	3.9	0.01	8

Table 4.7. The summary of model comparison.

Model	Accuracy (%)	GPU time (h)	FPS	Training loss	Validation loss
Efficient-s	72.32	2	50	1.71	2.48-1.53
Efficient-m	79.63	2.5	29	1.60	2.46-1.43

Efficient-l	90.32	2.8	17	0.99	2.45-0.68
YOLOv5-tiny	74.46	1	100	1.24	2.47-1.21
YOLOv5-s	91.12	1.3	74	0.57	2.49-0.46
YOLOv5-m	95.33	1.5	64	0.23	2.50-0.18

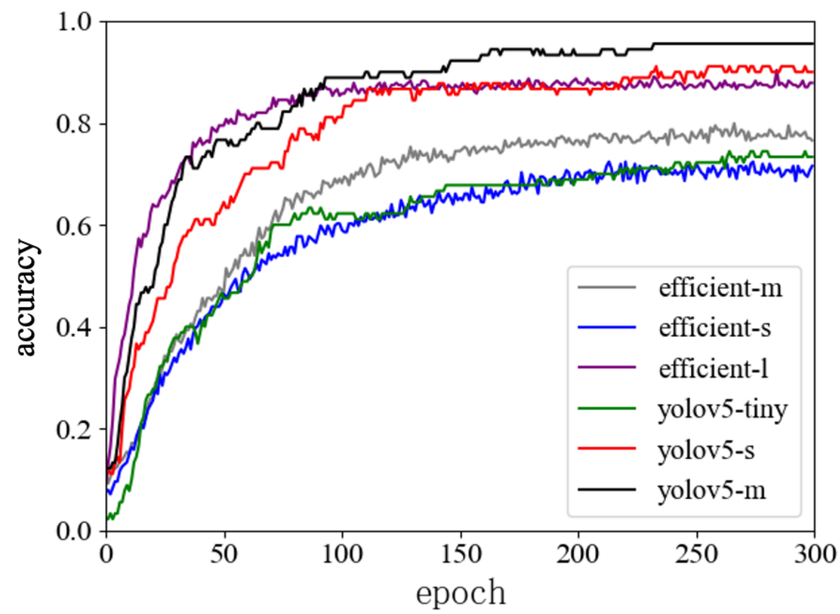


Figure 4.21. Accuracy comparison results for different classifier based on deep learning.

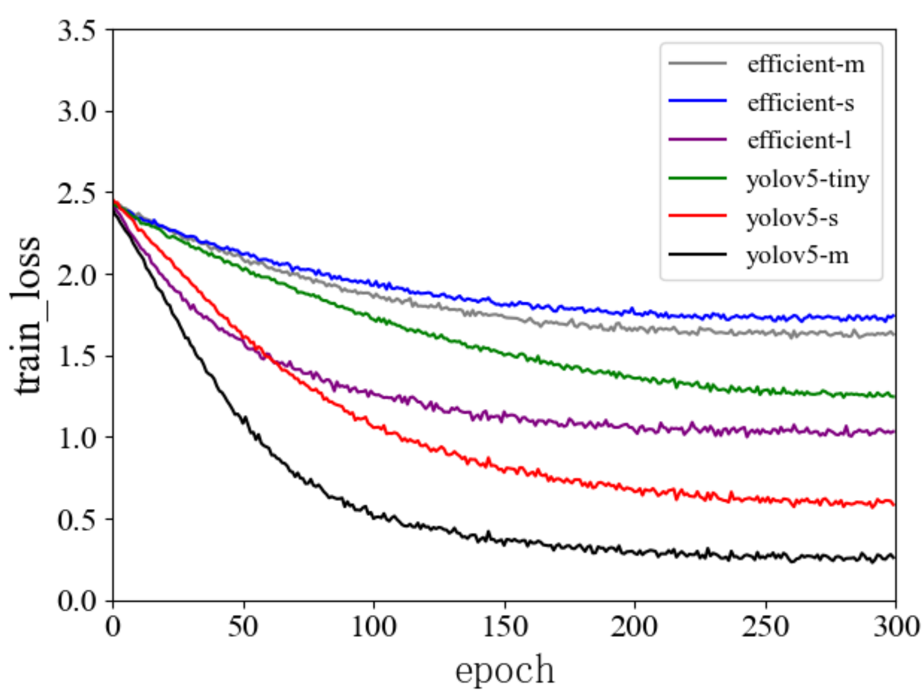


Figure 4.22. Training loss comparison results for different classifier based on deep learning.

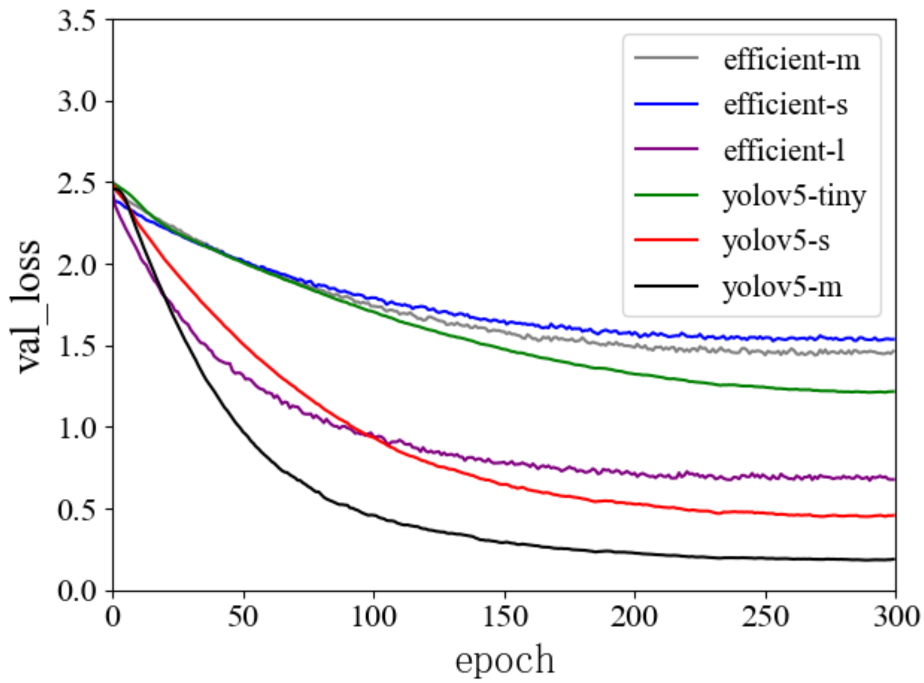


Figure 4.23. Validation loss comparison results of different classifier based on deep learning.

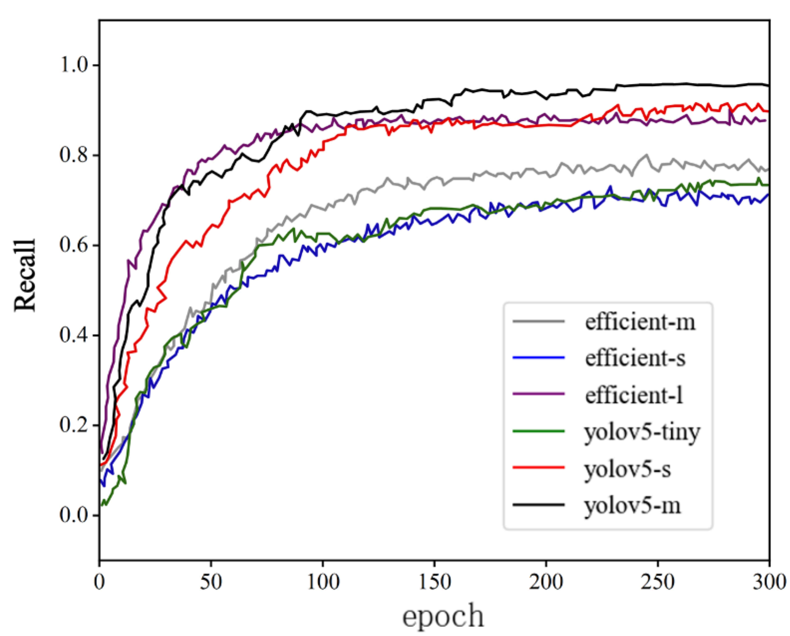


Figure 4.24. Recall comparison results of different classifier based on deep learning.

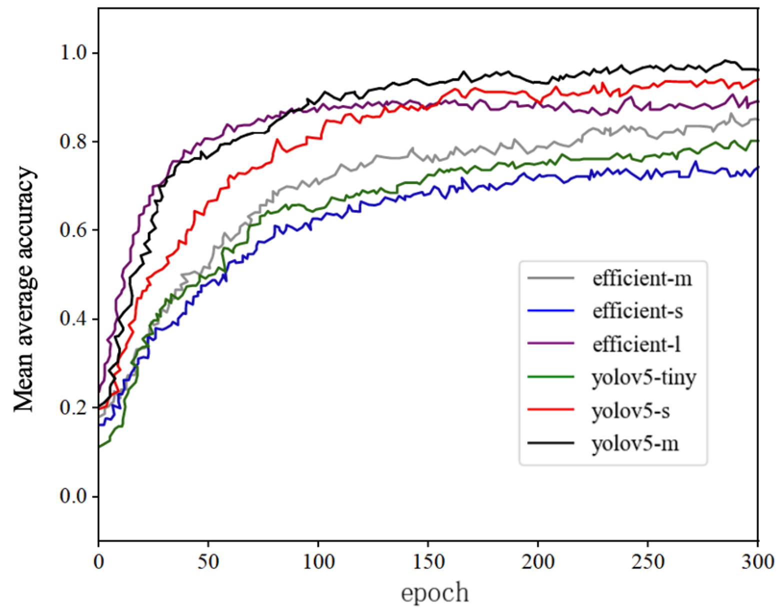


Figure 4.25. Mean average accuracy comparison of different classifier based on deep learning.

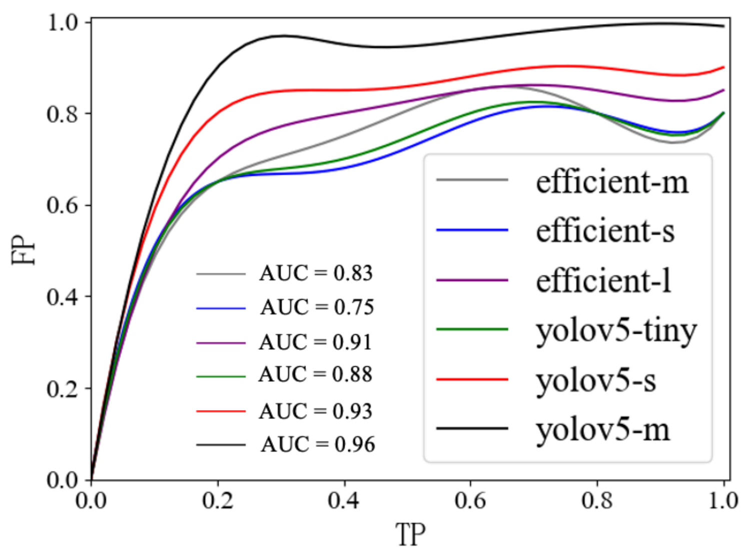
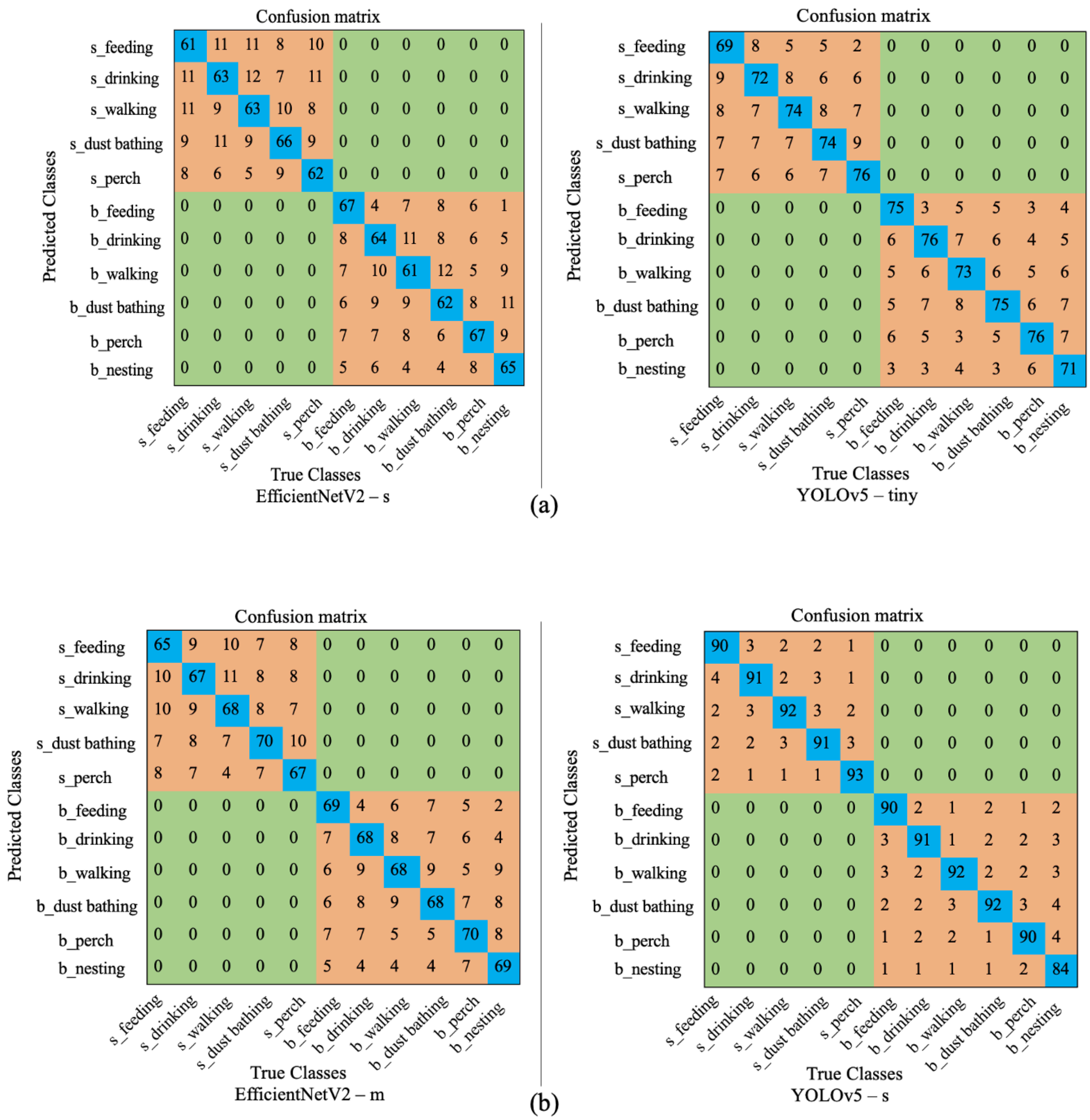


Figure 4.26. ROC curve comparison results of different classifier based on deep learning.

4.3.5 Results of Classification of Behaviors in Cage-Free Laying Hens

To compare the classification performances of multiple deep learning models on cage-free birds' behaviors, the confusion matrix is adopted (Figure 4.27). Each behavior is tested by different models 100 times.



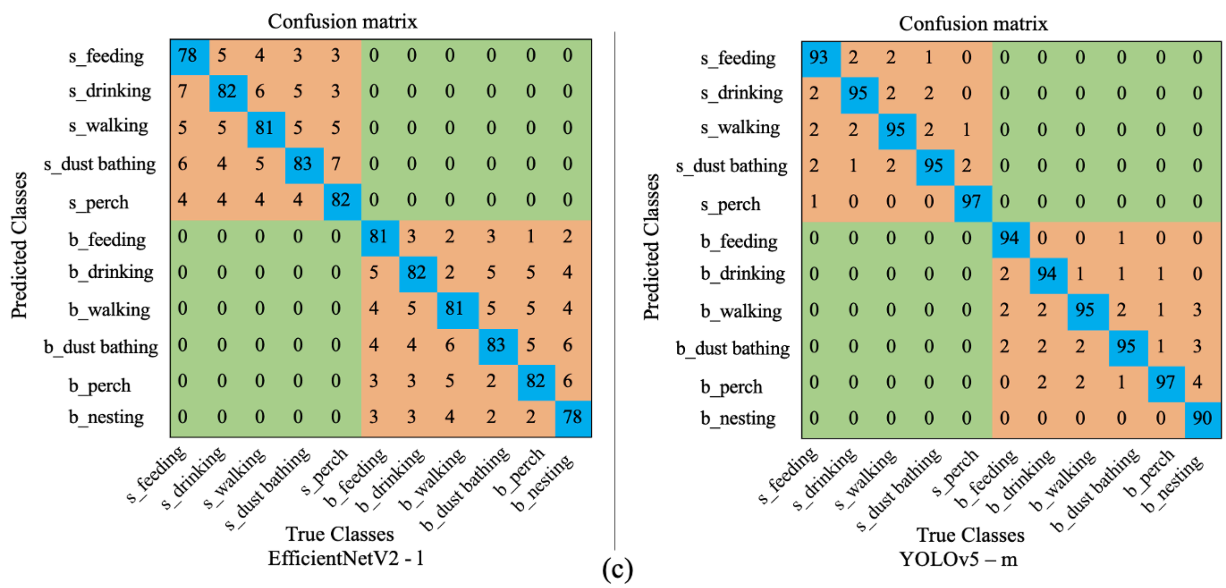


Figure 4.27. Confusion matrix of classifiers at cage-free birds' behaviors (s means chicks and b means chickens).

The prediction results are shown in confusion matrix, where three colors (blue, orange, and green) represent true predictions, false prediction, and type error (chicks were predicted as chickens or chickens were predicted as chicks). The number in each cell scores the results of the models. The average scores of YOLOv5 in blue cells are 10 more than that of efficientNetV2 in blue cells, which indicates YOLOv5 has better true prediction rate. In terms of orange cells, the misidentification scores vary from 9 to 1.5 (efficientNetV2-s has the maximum score on average and YOLOv5-m has the minimum score on average), which shows progressive improvements from efficientNetV2 methods to YOLOv5 methods. In addition, no type error was observed in the study since all the scores of different algorithms in green cells are 0, the reason being the significant changes between chicks and chickens, for example, feather color and body size. In terms of the recognition of behavioral classification of cage-free birds, all the behaviors except b_nesting (chicken nesting) have relatively higher accuracy comparing with average precision.

Nesting behavior is broody hen sits on eggs for 21 days until eggs hatch(Hedlund and Jensen, 2021). Due to the planform similarity within nesting, perch, and dust bathing, it is impenetrable for classifiers to detect nesting behavior. However, it is still acceptable result because there are not many broody hens at commercial polytree farms. In general, YOLOv5-m classifier is best among whole experimental classifiers with its highest accuracy.

4.3.6 Detection Results of Yolov5-m Algorithm for Behaviors

In the study, YOLOv5-m classifier has the best performance at detecting behaviors of cage-free birds comparing with other models. Therefore, a further investigation of multiple cage-free birds behavior types was conducted through YOLOv5-m model. The accuracy of different behavior patterns was shown in Figure 4.28. The average classification accuracy is around 0.95 from which s_drinking (chicks drinking) has the highest prediction confidence while the lowest accuracy comes from b_nesting pattern. Compared with chicks, chickens grow one more reproduction behavior (nesting) except basic behaviors (e.g., feeding, drinking, perch, walking and dust bathing). It might be the reason the average accuracy of classification of chicken behaviors is weaker than that of classification of chick behaviors. Broody hens prefer to hatch at dark areas, which limits the power detection of nesting behavior. The top 4 most efficient behavioral classification are s_drinking (0.978), b_dust bathing (chicken dust bathing) (0.960), s_feeding (chick feeding) (0.960) and s_walking (chick walking) (0.960). It is evident that chick behavioral classification outperforms the chicken behavioral classification. The discrepancies could come from the body size differences between chick and chickens. Feeders, drinkers, perch frames and other farm equipment maintain the fixed range. When birds live inside poultry houses, birds with bigger body size are prone to be occluded by facilities, which will cause false or missing classification. Therefore, it might be the other reason accounts for small birds achieve more precise recognition. In addition, the detection of perch behavior is not as accurate as expected. In our study, a special A shape frame (see in Figure 4.3) was developed for chickens to perch. However, sometimes chickens prefer to perch above drinking column or near air inlet ventilation window, such unforeseen situations cause a decrease in the precision of the classifier.

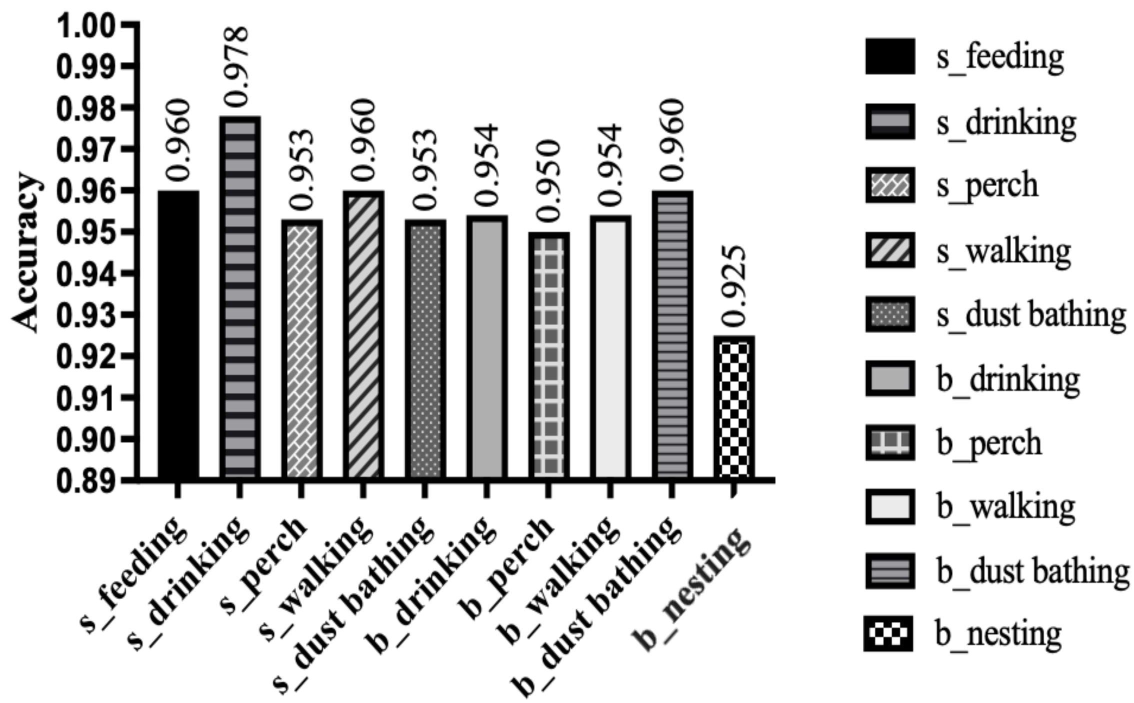


Figure 4.28. The accuracy of classification of muti-behaviors (s means chicks and m means chickens).

Birds' age plays a pivotal role for cage-free hens because the lifespan of hens at commercial farms is between 96 and 144 weeks for producing more eggs. In our study, 6 time points (1 week, 10 weeks, 20 weeks, 30 weeks, 40 weeks, and 50 weeks) were used to test the classifier accuracy under different bird's life period. After 50 weeks, most chickens stop growth, therefore, 6 time points is enough to evaluate the performance of classifier under whole chicken life expectancy. Figure 4.29 is a summary of the results. The average precision is varying from

0.943 (50 weeks) to 0.964 (1 week), which shows similar outcome as we discovered at confusion matrixes. Behaviors of small chicks are easier to be classified. In terms of time points in the middle, all the average accuracy of classifier is around 0.95, which indicates the chicken rearing in the poultry houses gets steady growth. Figure 4.30 presents some examples recognized by YOLOv5-m classifier among the 6 time points of cage-free chickens. After 18 weeks, hens begin to lay eggs. Therefore, nesting behavior wasn't calculated before that time.

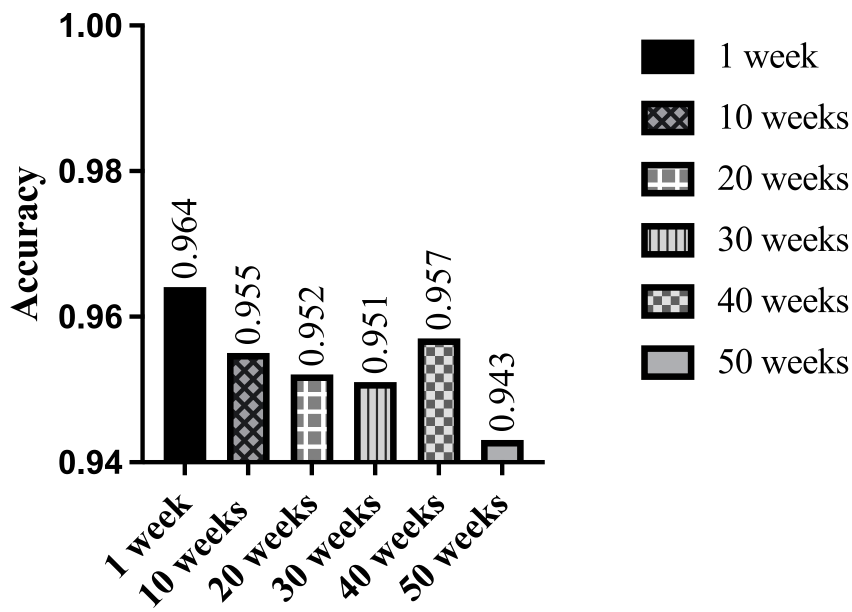
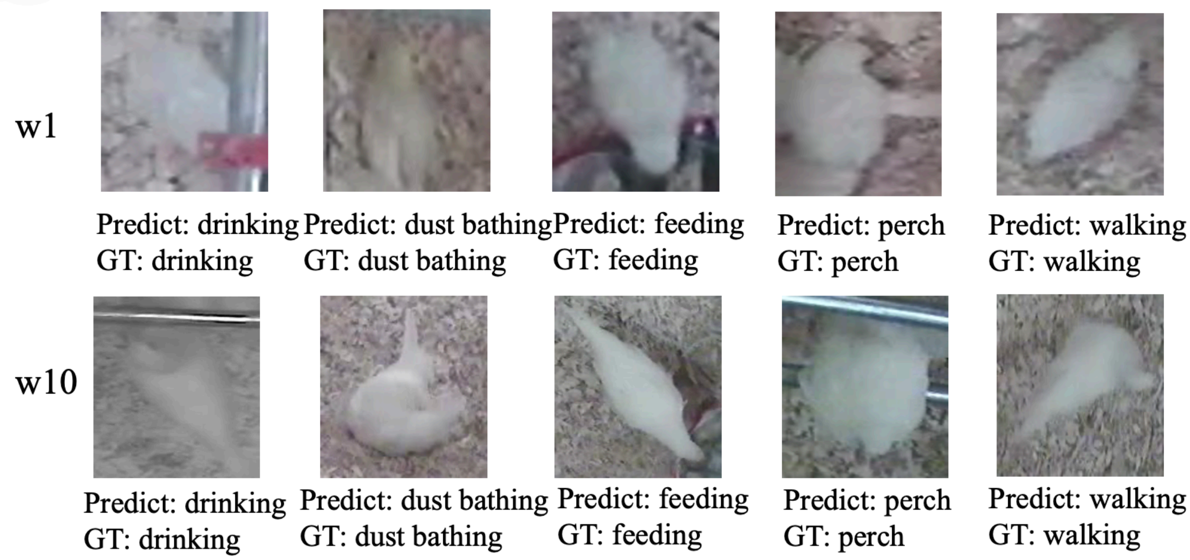
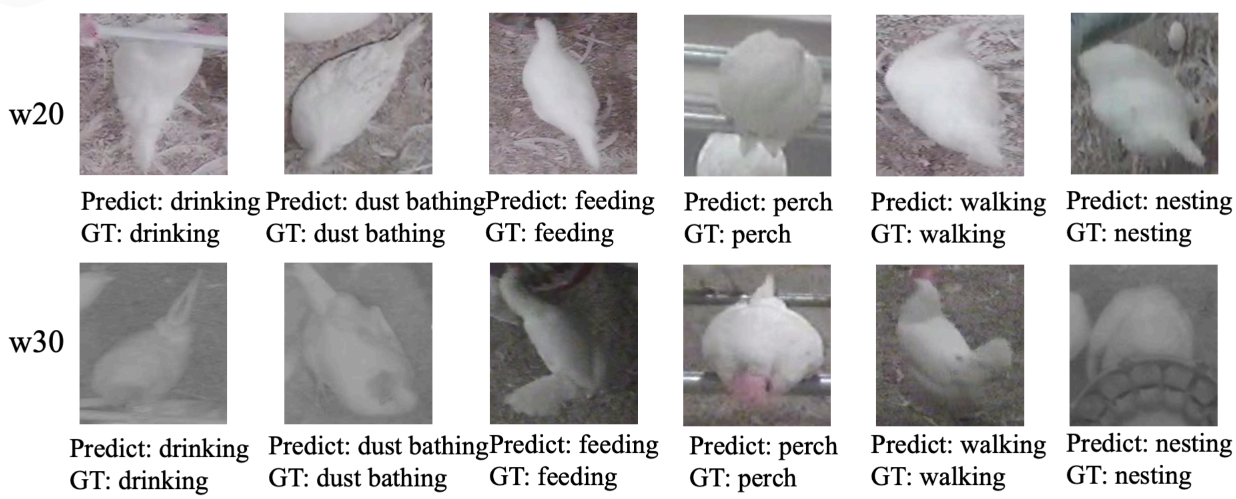


Figure 4.29. the average accuracy of the classifier tested under 6 time points of chicken lifespan.


w1
Predict: drinking
GT: drinking
Predict: dust bathing
GT: dust bathing
Predict: feeding
GT: feeding
Predict: perch
GT: perch
Predict: walking
GT: walking
w10
Predict: drinking
GT: drinking
Predict: dust bathing
GT: dust bathing
Predict: feeding
GT: feeding
Predict: perch
GT: perch
Predict: walking
GT: walking


w20
Predict: drinking
GT: drinking
Predict: dust bathing
GT: dust bathing
Predict: feeding
GT: feeding
Predict: perch
GT: perch
Predict: walking
GT: walking
Predict: nesting
GT: nesting
w30
Predict: drinking
GT: drinking
Predict: dust bathing
GT: dust bathing
Predict: feeding
GT: feeding
Predict: perch
GT: perch
Predict: walking
GT: walking
Predict: nesting
GT: nesting

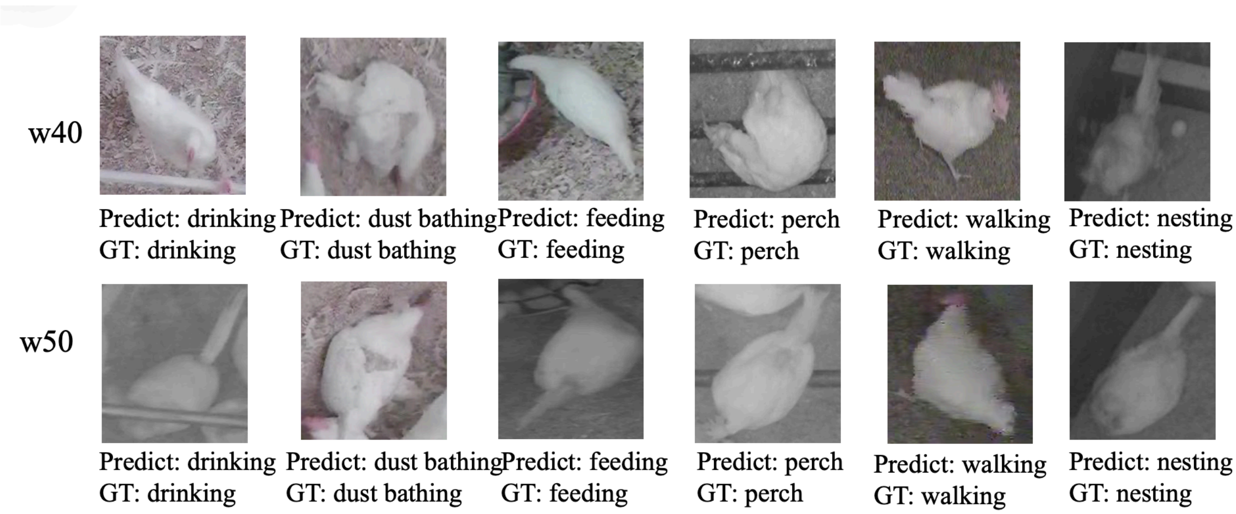


Figure 4.30. Classification of cage-free birds' behaviors (w1 means 1 week, w10 means 10 weeks, w20 means 20 weeks, w30 means 30 weeks, w40 means 40 weeks, w50 means 50 weeks and GT represents ground truth).

4.4 DISCUSSION

4.4.1 Discussion of Egg Classification Accuracy

In this study, five classes of eggs were investigated to build a classifier to sort eggs. For floor and bloody eggs, there is no misunderstanding in the classification of them and other classes. This is due to the clear features of floor and bloody eggs (Bist et al., 2023c). For floor eggs, the eggs are laid in the litter, so, in computer vision, the white eggs are surrounded by brown litter, which is a unique feature compared to other egg classes. This improves the egg classifier's accuracy when sort it. As for bloody eggs, because of the red spots that appear on white eggshells, there is a clear indicator that the CNN model can use to extract feature maps, and the egg classifier also has a high sorting accuracy. More false classifications are obtained for standard, non-standard and cracked eggs. This is because the classifier uses minor and major axes to differentiate egg size, and non-standard eggs have more abnormal shapes, such as being too long or too round, which means there might be unusual minor and major axes that the classifier misunderstands (Turkoglu, 2021). In addition, cracked eggs are also not easy for the classifier to detect. This is due to the limitations of camera angles. In this study, we only use the front view of eggs for egg classification tasks. Therefore, some cracks on the eggshell on the back or side view of might be ignored, and cracked eggs will be classified as other types of eggs.

To further discuss the performance of the classifier, we compare our study with various other pieces of research. Table 4.8 shows the results of some studies conducted on the classification of eggs using computer vision and compares these with the results obtained in the present study. Pyiyadumkol et al. (2017) developed a sorting system based on the machine vision technique to identify cracks in unwashed eggs (Priyadumkol et al., 2017). The egg images were captured under atmospheric and vacuum pressure. The cracks were detected using the difference between images taken under atmospheric and vacuum conditions. A combination of machine vision methods and the support vector machine (SVM) classifier was presented in Wu et al. (2017) to detect intact and cracked eggs (Wu et al., 2017). Guanjun et al. (2019) introduced a machine vision-based method for cracked egg detection (Guanjun et al., 2019). A negative Laplacian of Gaussian (LoG) operator, hysteresis thresholding method, and a local fitting image index were used to identify crack regions. Amin et al. (2020) proposed a CNN model using hierarchical architecture to classify unwashed egg images based on three classes, namely intact, bloody, and broken (Nasiri et al., 2020). In our study, we introduced more classes, floor and non-standard eggs, to cover all the normal egg categories while maintaining a high level of accuracy through the use of the large-kernel depth-wide convolution approach and soft labels, and cooperation with other optimizations such as anchor-free object detection and deformable convolutional networks, which further improve accuracy and efficiency in multi-classification tasks.

Table 4.8. Comparison of classification accuracy.

Study	Class					Accuracy (%)
	Intact	Crack	Bloody	Floor	Non-Standard	
Priyadumkol et al. (2017)(Priyadumkol et al., 2017)	✓	✓	–	–	–	94
Wu et al. (2017)(Wu et al., 2017)	✓	✓	–	–	–	93
Guanjun et al. (2019)(Guanjun et al., 2019)	✓	✓	–	–	–	92.5
Amin et al. (2020)(Nasiri et al., 2020)	✓	✓	✓	–	–	94.9
Our study	✓	✓	✓	✓	✓	94.8

4.4.2 Discussion of Egg Weight Prediction Accuracy

Five different graded eggs were predicted and their average absolute error ranged from 0.9 to 1.8 g. Overall, large and extra-large grades have more accurate prediction than small, medium and jumbo eggs. One reason why a larger egg grade (such as large and extra large) may lead to more accurate predictions than smaller grades (such as small and medium) is that larger eggs generally have a higher mean weight than smaller eggs. This means that there is less variation in egg weight within the larger grades, which can make it easier for the regression model to accurately predict the weight of these eggs. On the other hand, smaller eggs and jumbo grades typically have a wider range of weights, which can make it more difficult for the regression model to accurately predict their weights. Additionally, smaller eggs and jumbo grades may also have more variability in their physical characteristics (such as shell thickness and yolk size), which can further complicate the prediction process.

To further investigate the performance of the regressor, we compared our regressor with other egg weight regressors. Table 4.9 shows the results of some studies conducted on the regression models.

Cen et al. (2006) developed an egg weight detector by an indicator composed of R, G, B intensity and egg diameters (Cen et al., 2006). An equation was created by the re-gression model, and a 97.8% correlative coefficient was achieved. Similarly, Alikhanow et al. (2015) constructed several equations based on different variables (egg area, egg volume, egg minor axis or major axis) (D et al., 2015); the most significant parameter was egg area, reaching 94.3% R2. Other researchers also used computer vison to predicted egg weight based on the regression model, but they used the multi-flow production line in real-time to cooperate with industrial applications. The identical objects' measurements under a multi-light source was found to be around 95.0% (Akkoyun et al., 2023). In our study, we extended the previous egg weight prediction for the upper litter from extralarge to jumbo, but our regressor maintained a high accuracy with non-line regression because a random forest model is an ensemble of decision trees trained on random subsets of the egg weight data and features (major and minor axis). The random forest model's final prediction is a weighted average of the egg-weight predictions of the individual trees. Since each decision tree in a random forest can model the non-linear relationships between the input features and the target variable, the random forest model, as a whole, can account for nonlinearities in the egg-weight data.

Table 4.9. Comparison of different regressor accuracies.

Study	Egg Size					R^2 (%)
	Small	Medium	Large	Extra Large	Jumbo	
Cen et al. (2006)(Cen et al., 2006)	✓	✓	✓	✓	–	97.8

Alikhanow et al. (2015)(D et al., 2015)	✓	✓	✓	✓	–	94.3
Faith et al. (2023)(Akkoyun et al., 2023)	✓	✓	✓	✓	–	95.0
Our study	✓	✓	✓	✓	✓	96.0

4.4.3 Discussion of Jointly Performing Egg-Sorting and Weighting Functions

In our study, we combine egg classification and weighing tasks into one two-stage model. The approach is to train two distinct models, one for classification and one for regression, and then combine their predictions at the time of inference. First, train a classification model to predict each input's egg class label. Then, using the predicted class labels to filter the inputs, train a regression model using only the filtered inputs. Use the egg classification model to sort eggs and the corresponding regression model to predict the weight of eggs at same time (Figure 4.32). The overall performance of the two-stage model is good, but other factors restrict its application, including potential errors in filtering and increased complexity. The classification model is used to filter the regression model's inputs. If the classification model's predictions are inaccurate, it may erroneously exclude inputs that the regression model could have used. This can result in a reduction in the accuracy of the final prediction. In addition, the two-stage model approach requires the training of two distinct models and additional processing steps at the time of inference to combine the predictions. This could make the overall architecture more complicated and increase the required computational resources.

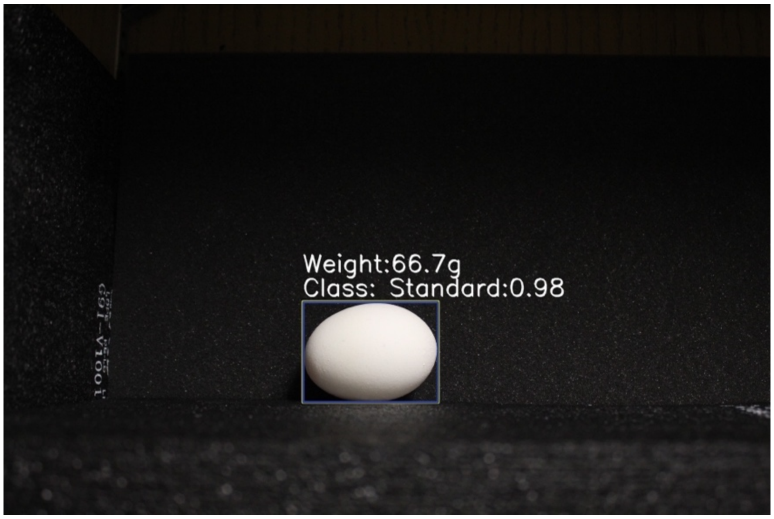


Figure 4.32. The egg has been classified as 'Standard' and its predicted weight is 66.7 g.

4.4.4 Future Studies for Detecting Floor Eggs

Despite the research's high performance in sorting egg quality based on egg surface and weight, some further studies could the model be applied to real-world situations: (a) using emerging nonvolatile memory (NVM) to reduce memory footprint and latency (Wen et al., 2022), which is crucial for mobile application; (b) extending the model to egg datasets with more diversity (other egg colors, egg multiplication and other spices) to fulfill the application environment; (c) using a 360-degree camera to prevent misidentification in cracked and bloody eggs; (d) optimize the sorting and weighing process to reduce the time required to complete the task without sacrificing accuracy; (e) enhancing the accuracy of egg segmentation by leveraging the segment-anything model (Yang et al., 2023).

4.4.5 Model and Atypical Result Analysis for Laying Hens Behaviors

The aim of this research is to ameliorate the accuracy and extend the behavioral classification in poultry farms especially cage-free chicken farms by cropping images of birds acting different behaviors from 1 week to 50 weeks and then applying image argumentation technology to enhance dataset size and quality. On the other hand, in terms of the methods based on the newest classification algorithms, the operation of CNN extracting image features improves the processing speed as well as precision by pooling the instantaneous field of the feature maps and encouraging distortions and translations (YOLOv5-s model reached 100 FPS, which is 5 times than the standard of real-time detection. YOLOv5-m achieved 95.3% accuracy, which is 5% higher than that of EfficientNetV2-l networks). In addition, our model achieved 6 behaviors of cage-free birds under a half lifespan of commercial chickens. Except basic behaviors (feeding, drinking, walking), our study connects cage-free birds by adding their special behaviors to the research (perch, dust bathing and hatch)(Rehman et al., 2018; Shields and Greger, 2013). the latter two behaviors are welfare indicators of cage-free birds. Furthermore, when applying the best model into different time periods of chicken, the recognition accuracy remains incredible. Finally, to make headway of the application of the classifier to poultry farms where high computational GPU is not always available (Islam et al., 2019). A light structure CNN efficientNetV2 is introduced to cooperate with the obstacle. The efficientNetV2 removes expensive batch normalization and imposes a progressive learning strategy assigning different types of regularization to reduce requirements of computing platforms. The result of effcientNetV2 method achieved 90.32% accuracy, which met the demand of classification with less parameters compared to YOLOv5-m network (24M vs 42M).

Despite the study achieved outstanding accuracy, there are also some flaws in the classifier. As showed in Figure 12 YOLOv5-m confusion matrix, the false detection rate of hatch behavior is apical and commonly hatch is misidentified as other class such as perch behavior. Broody hens tend to lay eggs at dim areas (Shimmura et al., 2010). For example, the corner of the wall and below the feeder. In addition, the vertical view of hatch and perch are similar, which also challenges the classification of hatch behavior. To address the problem, a typical approach is to brighten dark image by expanding the exposure time, which helps natural light concentrate to the sensor and light the image. In addition, the cage-free poultry houses are so dusty, the dust particles floating in the air and attached to camera, which also causes dark pics. Therefore, a regular dust clean at cameras is necessary. Perch behavior is misclassified as drinking behavior sometime, which is the other aspect the classifier can be improved (Appleby et al., 1992; Liu et al., 2018). The misclassification comes from the similarity of drinking line and frame column. A possible solution is to change the color of drinking line (they are both slivery now). Therefore, the classifier could clearly divide two columns as individual one. In summary, the classifier could be improved through two main aspects: brighten the dark area where hens hatch and change the color of similar facilities, which are also key elements for the classifier to recognize the behaviors of birds in poultry houses.

4.4.6 Compared with Related Research for Laying Behaviors

To compare our research with previous work, accuracy is selected as the parameter to evaluate the classification performance among existing research because accuracy is the most basic and common value that assess models. Table 4.10 shows accuracy values of similar research. In terms of the deep learning algorithms, detection (Pu et al., 2018), classification (Guo et al., 2022) and segmentation (Li et al., 2020) are utilized at different research. Since the models were based on different dataset of behaviors, accuracy is set as a reference index for impartial compartments. Detecting method to classify flock behaviors at three depths of images (non-crowded, litter crowded and extremely crowded) gained excellent 99.17% accuracy. However, the application of it might be narrow cause the training is based on single scene where limited chickens encouraged the accuracy because single mission was uncomplicated to process during validation period. The average accuracy of segmentation of behaviors was 87%. Although it is acceptable outcome, the chicken segmentation can mark the boundaries of target preening chickens, which locates and distinguishes chickens into preening birds and non-preening birds. Classification is another popular approach to categorize various observations. A collection of similar objects could be classified accurately. For example, both studies (Guo et al., 2022) achieved more than 90% accuracy. Besides, 4 and 6 behavioral categories classification were reached respectively by Guo et al. (2022) and ours. Overall, image classification is the most stabilized approach for a multiply chicken behavior classification as well as superior performance.

Table 4.10. The accuracy of comparable experiments.

	Pu (2018)	Li (2020)	Guo (2022)	Ours
Accuracy	99.17%	87%	90%	95.33%
Bird type	layer	hens	broiler	Cage-free bird
Bird species	/	Hyline Brown	Cobb 500	Hy-line W36
Bird numbers	3087	30	80	800
Bird age (day)	/	260-266	1-50	1-350
Method	detection	segmentation	classification	classification
model	CNN	mask R-CNN	DenseNet-264	YOLOv5-cls

4.4.7 Future Studies for Laying Hens Behaviors

Despite the research accomplished high performance, its classification ability for different poultry farms and special cases still requires further study because bird species and environmental setting (i.e.., litter color and other different facilities) also impacts model performance. Poultry farms are different from each other including light intensity, floor area, and most importantly the chickens breed. Different breeds of chickens are performing differently (Chai et al., 2019; Oliveira et al., 2019). Therefore, the deep learning model need to incorporate new farm information prior to application. In addition, the overall accuracy could be improved by three aspects: increasing the horizontal hatch and perch behavioral dataset, collecting eggs frequently to prevent hens from nesting eggs and self-attention module, which allows the transformer to aggregate various parts of the same input to the sequence and find out which objects should pay more attention. Besides, six behaviors classification is not a terminal task because cage-free birds act more natural behaviors such as fighting, laying eggs and so on. A comprehensive classifier could be established by including all chicken behaviors. Finally, the algorithm can be applied to other animals (i.e., cattle, swine or sheep) because they are bigger than chicken, which means they are easier to be detected by CNN.

4.4 CONCLUSIONS

In this study, a two-stage model was developed based on RTMDet and random forest networks to predict egg category and weight. The results show that the best classification accuracy was 94.80% and 96.0% for the R2 regression model. The model can be installed on the egg-collecting robot to sort eggs in advance and collect our target eggs specifically. In addition, the model can be used to automatically pick out non-standard size eggs and eggs with surface defects (blood-stained or broken). Furthermore, 1000 egg pictures were utilized to test the detector's performance for different egg types and egg weight scales. The results showed that the detector has a better classification performance for standard and non-standard size eggs, and large (55-60 g) and extra-large (60-65 g) egg weights led to more reliable predictions. This detector is one of the first models that performs the joint function of egg sorting and weighting. By implementing the findings of this study, the poultry industry can reduce costs and increase productivity, ultimately leading to bet-ter-quality products for consumers.

In this study, multiple behavioral classifiers were developed based on efficientNetV2 and YOLOv5-cls networks for monitoring laying hens' behavior in cage-free facilities. Results show that the average accuracy of each classifier ranges from 72.32% to 95.33%. The classifier can be applied to recognize various behaviors of hens' behavior from 1-50 weeks of old, including feeding, drinking, walking, perch, dust bathing, and nesting effectively. This classifier is among the first model that included cage-free hens' perching and dust bathing behaviors, which are special indicators of chicken welfare especially in cage-free poultry farms because such natural behaviors need open space to act, which is not commonly met in traditional cage eggs industry. Drinking behavior has the highest performance among whole classification types (97.8%). In addition, although perch detection moderates average accuracy of the classifier, 92.5 % true prediction was achieved. Furthermore, 6 time points of birds' lifespan from 1 week to 50 weeks were tested to evaluate the classifier under time scale. The model has better performance at 1 week than other time periods. The results provide actionable approach to classify cage-free birds' behaviors in a lifespan scale without invasion. This study was among the first to monitor as many as six behaviors of cage-free hens with deep learning technologies at the same time. Those behaviors are valuable information for assessing animals' welfare.

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CHAPTER 5

DEEP LEARNING ALGORITHMS FOR TRACKING INDIVIDUAL LAYERS HENS FOR LOCOMOTION ANALYSIS[6]

[6] Yang, X., Bist, R. B., Paneru, B., & Chai, L. (2024). Deep Learning Methods for Tracking the Locomotion of Individual Chickens. Animals, 14(6), 911. https://www.mdpi.com/2076-2615/14/6/911. Reprinted here with permission of the publisher.

ABSTRACT

Poultry locomotion is an important indicator of animal health, welfare, and productivity. Traditional methodologies such as manual observation or the use of wearable devices encounter significant challenges, including potential stress induction and behavioral alteration in animals. This research introduced an innovative approach that employs an enhanced track anything model (TAM) to track chickens in various experimental settings for locomotion analysis. Utilizing a dataset comprising both dyed and undyed broilers and layers, the TAM model was adapted and rigorously evaluated for its capability in non-intrusively tracking and analyzing poultry movement by intersection over union (mIoU) and the root mean square error (RMSE). The findings underscore TAM's superior segmentation and tracking capabilities, particularly its exemplary performance against other state-of-the-art models, such as YOLO (you only look once) models of YOLOv5 and YOLOv8, and its high mIoU values (93.12%) across diverse chicken categories. Moreover, the model demonstrated notable accuracy in speed detection, as evidenced by an RMSE value of 0.02 m/s, offering a technologically advanced, consistent, and non-intrusive method for tracking and estimating the speed of chickens. This research not only substantiates TAM as a potent tool for detailed poultry behavior analysis and monitoring but also illuminates its potential applicability in broader livestock monitoring scenarios, thereby contributing to the enhancement of animal welfare and management in poultry farming through automated, non-intrusive monitoring and analysis.

Keywords: Poultry locomotion; Deep learning; Track anything model; Animal welfare; Non-intrusive tracking

5.1 INTRODUCTION

Precision livestock farming (PLF) has rapidly evolved into a key field, merging modern technology with traditional animal farming to improve animal welfare and streamline production processes (Morrone et al., 2022). In poultry farming, it is essential to monitor and understand bird movement and behavior closely. This not only ensures the well-being of the animals but also helps improve production in a sustainable environment (Li et al., 2021; Siriani et al., 2022; Yang et al., 2022). Chickens display a variety of behaviors, including different movement patterns, social interactions, and reactions to their surroundings. This requires advanced systems to track and analyze them effectively.

Deep learning, an advanced form of machine learning, is becoming a key tool for analyzing and predicting patterns in large and complex datasets (Gorji et al., 2022; Liu et al., 2021). In animal behavior studies, deep learning helps provide a detailed understanding of movement, interactions between species, and overall health (Bist et al., 2023). In poultry farming, the use of deep learning offers more than just a glimpse into bird behaviors. It acts as a powerful tool to closely observe and track their activities (Ben Sassi et al., 2016). Regarding post-observational monitoring, a slew of algorithms has found their footing in this domain, with you only look once (YOLO) being at the forefront. For instance, in large-scale poultry farms, the surveillance of thousands of chickens for health, activity, and behavioral patterns becomes pivotal (Tong et al., 2023). YOLO's rapid detection capabilities can identify early signs of disease or distress in chickens by recognizing subtle behavioral changes, thereby aiding farmers in timely interventions (Liu et al., 2021). In addition, the proposed Chick Track model uses deep learning to detect chickens, count them, and measure their movement paths, providing spatiotemporal data and identifying behavioral anomalies from videos and images (Neethirajan, 2022). However, while YOLO has shown commendable performance in a variety of scenarios, it is not exempt from limitations. For effective use in poultry farming, it demands rigorous training on domain-specific data to fine-tune its detection and tracking capabilities. The nuances of poultry behavior, their interactions, and variations in physical appearances require YOLO to be trained with vast and diverse datasets. But even with comprehensive training, the model might still face challenges in tracking individual entities within dense flocks, especially under varying environmental conditions (Elmessery et al., 2023). It is in this context that the track anything model (TAM) emerges as a promising candidate. This research aims to harness the potential of TAM, enhancing its capabilities to not just track individual chickens in a flock, but to analyze their complex locomotion patterns in real-time (Ahmadi et al., 2023; Lu et al., 2023; X. Yang et al., 2023). By bridging the gaps left by previous models and incorporating the strengths of YOLO's detection capabilities, TAM is poised to offer a holistic solution to the multifaceted challenges in avian behavior analysis.

In this research, an innovative approach involving the strategic dyeing of chickens was adopted to augment the model's capability to distinctly identify and track individual entities within the flock. The dyed chickens, exhibiting distinct and consistent coloration, serve as a unique identifier, facilitating improved tracking and identity preservation by the algorithms. The research further explores the adaptation of TAM, integrating a speed detection function, thereby providing a comprehensive tool for detailed poultry behavior analysis and monitoring. Through rigorous evaluations and comparative analyses, this research aims to underscore the efficacy and potential of TAM and its adaptation, TAM-speed, in providing a multifaceted solution for real-time poultry behavior tracking and analysis, thereby contributing to the advancement of precision livestock farming.

The objectives of this study were to: (1) develop a tracker model for monitoring the speed of individual chicks based on the TAM; (2) compare the TAM-speed model with state-of-the-art models such as YOLO, which are trained using images of chickens; and (3) test the performance of these newly developed models under various production conditions.

5.2 MATERIALS AND METHODS

5.2.1 Data Acquisition

The dataset was obtained from two different experimental chicken houses (i.e., broilers and layers houses) in the Poultry Research Center at the University of Georgia (UGA), USA. Chickens were subjected to dyeing to assess the detection differences between dyed and undyed samples. Broilers were dyed with specific colors (green, red, and blue) and laying hens with another set (green, red, and black). Figure 5.1 illustrates the experimental chicken houses alongside their dyed counterparts. HD cameras (PRO-1080MSFB, Swann Communications, Santa Fe Springs, CA, USA) were affixed at a 3 m height on ceilings and walls in each room, capturing chicken behavior at 18 FPS with a 1440 × 1080 resolution. Lens maintenance involved weekly cleaning for clarity (Subedi et al., 2023). Image data were initially stored on Swann video recorders and subsequently transferred to HDDs (Western Digital Corporation, San Jose, CA, USA) at UGA's Department of Poultry Science.

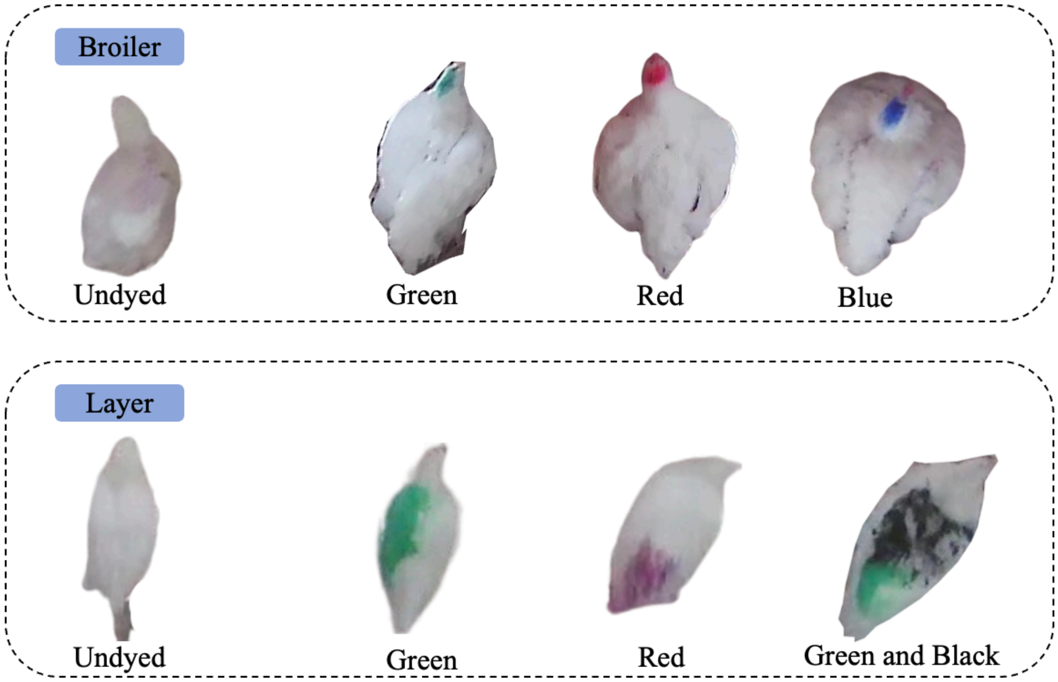

Figure 5.1. Contrast of dyed and undyed broilers and layers in experimental settings.

5.2.2 Marking Approach

Chickens were first subjected to a random selection process to determine which individuals would be used for the experiment. Once chosen, these chickens were dyed using the all-weather Quick Shot dye (LA-CO INDUSTRIES, INC, Elk Grove Village, IL, USA). The selection of dye colors aims to reduce feather flecking in dyed chickens (Shi et al., 2019). The application process required a coordinated effort from a two-person team: while one individual gently held and restrained the bird to ensure its safety and ease of application, the other expertly applied the spray dye to the specific targeted areas on the chicken's body, ensuring consistent and even coverage. This methodology was designed to minimize stress to the chickens while achieving a uniform application of the dye.

5.2.3 Model Innovation for Tracking Chickens

In our study, we utilized the track anything model (TAM) to monitor chicken locomotion. Recognizing the versatility of TAM, we further enhanced it with a speed detection function, enabling the real-time measurement of each chicken's velocity (J. Yang et al., 2023). In the preprocessing phase, we utilized the XMem video object segmentation (VOS) technique to discern the masks of chickens across subsequent video frames (Cheng and Schwing, 2022). XMem, renowned for its efficiency in standard scenarios, usually generated a predicted mask. However, when this forecast was suboptimal, our system captured both the prediction and key intermediate parameters, namely the probe and affinity. In instances where the mask quality fell below expectations, the SAM technique was harnessed to further refine the XMem-proposed mask using the said parameters as guidance. Recognizing the limitations of automated systems in intricate situations, we also factored in human oversight, allowing manual mask adjustments during real-time tracking to ensure optimal accuracy (Figure 5.2). The TAM architecture was structured such that preprocessed frames of size 1440 × 1080 served as input. Within the model, convolutional neurons were dedicated to extracting essential features like shape and color patterns. Crucially, by integrating TAM's inherent capabilities with our innovations, we developed a layer that not only estimated chicken trajectories but also calculated their speed using the change in positional coordinates across frames and the associated time differential (Sun et al., 2006). The output then presented both the chicken's position and speed. We later benchmarked our enhanced TAM with a speed detection model (TAM-speed) against several state-of-the-art simple online and real-time tracking (SORT) models including observation-centric SORT (OC-SORT) (Cao et al., 2023), deep association metric SORT (DeepSORT) (Wojke et al., 2017), ByteTrack (Zhang et al., 2022), and StrongSORT (Du et al., 2023), focusing on criteria such as tracking accuracy, speed measurement accuracy, frame processing rate, and model robustness in scenarios with dense poultry populations. For the models like OC-SORT, DeepSORT, ByteTrack, and StrongSORT, the comparison with TAM was primarily based on their tracking function. However, when it came to comparing TAM with you only look once version 5 (YOLOv5) and you only look once version 8 (YOLOv8), our motivation was distinct. YOLOv5 and YOLOv8 are renowned for their advanced segmentation capabilities, which are crucial for detailed object recognition and delineation in complex environments (Wei et al., 2023). By comparing TAM with these YOLO versions, we aimed to evaluate how our model fares in terms of segmentation accuracy, efficiency, and reliability. Given the intricate patterns and overlapping scenarios often observed in poultry behavior, a robust segmentation function can significantly enhance the precision of tracking. Thus, understanding how TAM stands against the segmentation prowess of YOLOv5 and YOLOv8 can provide insights into potential areas of improvement and adaptation for our model. This adaptation of the TAM model aims to provide a comprehensive solution for real-time poultry behavior tracking, potentially paving the way for broader applications in livestock monitoring.

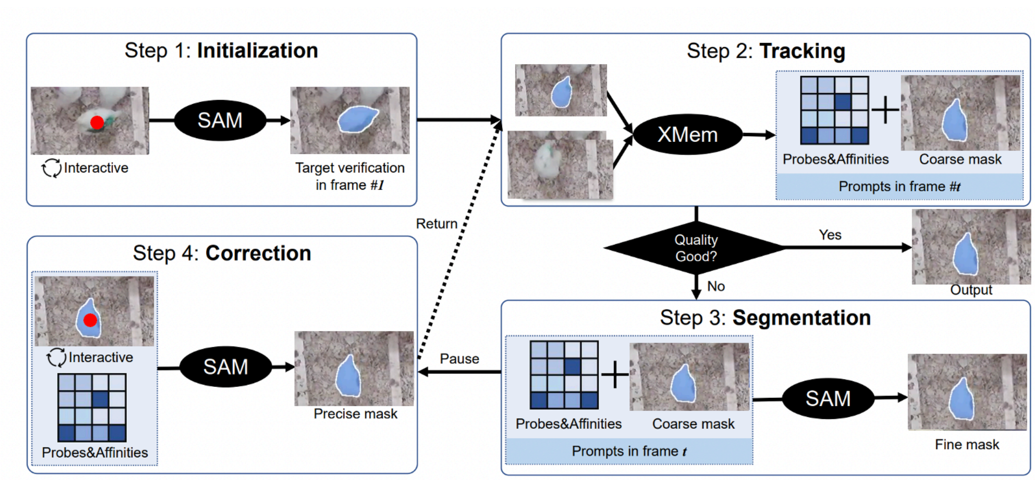

Figure 5.2. Pipeline of the track anything model (TAM) applied to chicken tracking (J. Yang et al., 2023).

5.2.4 Methods of Speed Calculation in Chicken Tracking

Video analysis often encounters challenges in measuring the velocity of chickens due to distortions from camera perspectives. A video, which comprises continuous frames, enables the calculation of "pixel speed" by evaluating the chicken's pixel displacement across frames within a time interval of 55.56 milliseconds (ms) at 18 FPS. However, the chicken's motion can appear distorted in 2D frames due to 3D environmental dynamics. Our solution transforms the video frame to a top-down perspective, using open source computer vision library (OpenCV)'s perspective transformation capabilities based on known rectangle coordinates in the original frame (Figure 5.3) (Culjak et al., 2012). This transformation eliminates horizontal discrepancies and relates vertical pixel shifts to the chicken's actual distance traveled. Using this method and the time between frames, we were able to estimate individual chickens' average velocity, which also indicates their real-time walking/running speed in closely spaced frames.

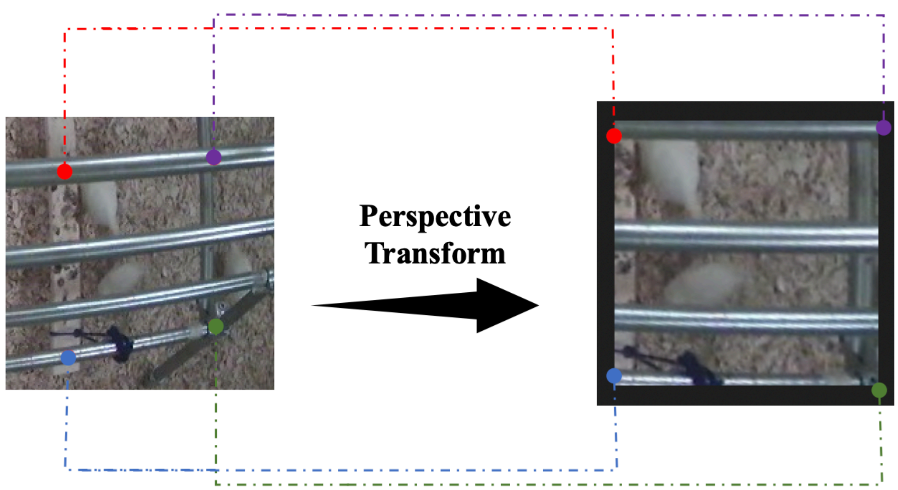

Figure 5.3. An illustration of a perspective transformation utilizing the OpenCV library.

So, the equation to compute the actual speed V for chickens:

$$\boldsymbol{V} = \frac{\boldsymbol{\Delta Y \times W}}{(\boldsymbol{M - N}) \times \mathbf{55.56\ ms}}$$

where:

$\boldsymbol{\Delta Y}$ is the vertical pixel displacement of the chicken in the top-down view.

W is the actual physical distance represented by one pixel in the top-down view.

M and N are the frame numbers where the chicken's position was recorded.

5.2.5 Model Evaluation Metrics

In our endeavor to optimize the track anything models for monitoring chicken locomotion, rigorous model evaluations were centered on specific metrics to ensure precise and consistent tracking of individual chickens across video sequences. The multiple objects tracking accuracy (MOTA) gauges the accuracy of the tracking model, considering discrepancies like false positives, misses, and identity switches. The identification F1 score (IDF1) becomes paramount in assessing the model's proficiency in recognizing and consistently maintaining the identity of each chicken throughout sequences. IDF1 is computed as the harmonic mean of identification precision (IDP) and identification recall (IDR). IDP evaluates how many detections of a particular chicken identity are correct, while IDR calculates the proportion of actual detections for a chicken identity. Furthermore, the identity switches (IDS) metric quantifies instances when the system erroneously alters a chicken's identity. The frames per second (FPS) metric serves as a testament to the model's real-time monitoring efficacy, elucidating its processing speed (Zhang et al., 2023). When comparing TAM with YOLO, the mean Intersection over Union (mIoU) becomes essential. mIoU is a metric that evaluates the overlap between the predicted segmentation and the ground truth, providing insights into the model's segmentation accuracy. In the context of TAM-speed detection accuracy, the root means square error (RMSE) is employed to quantify the model's prediction accuracy in determining the chickens' speed (Li et al., 2017). RMSE represents the square root of the average squared differences between the observed actual speed and the speed predicted by the model. Through this lens, the TAM-speed model's efficacy in accurately detecting and predicting the chickens' speed was rigorously evaluated, ensuring that the model not only proficiently tracks the chickens but also precisely gauges their speed, thereby providing a comprehensive tool for detailed poultry behavior analysis and monitoring. For each metric, we calculated the average from test results based on a test dataset across different models. These average values were then utilized to compare the performance among the various models.

$$MOTA = 1 - \frac{(FalsePositives + Misses + IdentitySwitches)}{TotalGroundTruthObjects}$$

$$IDF1 = \frac{2 \times (IDP \times IDR)}{(IDP \times IDR)}$$

$$IDP = \frac{TruePositives}{TruePositives + FalsePositives}$$

$$IDR = \frac{TruePositives}{TruePositives + Misses}$$

$$FPS = \frac{TotalFrames}{TotalTime(inseconds)}$$

$$mIoU = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Prediction_i \cap GroundTruth_i}{Prediction_i \cup GroundTruth_i}\right|$$

where N is the number of classes, $Prediction_i$ is the predicted segmentation for class i, and $GroundTruth_i$ is the ground truth for class i.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where n is the total number of observations, $\boldsymbol{y_i}$ is the actual speed of the chicken in the ith observation, and $\hat{y}_i$ is the predicted speed of the chicken in the ith observation.

5.3 RESULTS

5.3.1 Comparison of Segmentation Approaches

In our rigorous comparative analysis of segmentation methodologies for chicken tracking analysis, we evaluated YOLOv5, YOLOv8, and TAM. The chicken dataset, encompassing 1000 images, served as the foundation for this analysis. For the models necessitating training phases, specifically YOLOv5 and YOLOv8, a distribution of 600 images was allocated for training, 200 for validation, and the residual 200 for testing. The training regimen was orchestrated within a Python 3.7 environment, harnessing the capabilities of the PyTorch deep learning library, facilitated by an NVIDIA-SMI graphics card with a 16 GB capacity. Our segmentation efficacy evaluation spanned four distinct chicken categories: undyed broilers, undyed layers, dyed broilers, and dyed layers. A recurrent theme was the enhanced segmentation precision observed in dyed chickens, attributed to the pronounced color contrast introduced by dyeing, which counteracted the challenges posed by the chromatic resemblance between the chickens' white plumage and the light brown litter. Despite the distinction between broilers and layers, no significant segmentation performance variance was observed, suggesting challenges predominantly driven by color rather than morphology. Among the methodologies, TAM, leveraging its pre-trained model, consistently outperformed both YOLOv5 and YOLOv8. This superiority can be attributed to TAM's architectural robustness, its adeptness at high-dimensional feature extraction, and the efficacy of its pre-trained model (J. Yang et al., 2023), which potentially aligns better with the challenges presented by the chicken dataset. The forthcoming mIoU values in Table 5.1 will further detail TAM's segmentation prowess, and a visual representation in Figure 5.4 underscores its potential as a leading choice for future chicken segmentation research.

Table 5.1. A comparison of TAM and YOLOv5 and YOLOv8 in terms of mean intersection over union (mIoU).

Method	Semantic Segmentation of Broilers		Semantic Segmentation of Layers	
	Undyed	Dyed	Undyed	Dyed
YOLOv5	81.26%	85.63%	80.79%	85.51%
YOLOv8	83.44%	86.91%	82.59%	87.72%
TAM	93.15%	95.13%	92.17%	94.82%

Notes: Track anything model (TAM) and you only look once (YOLO).

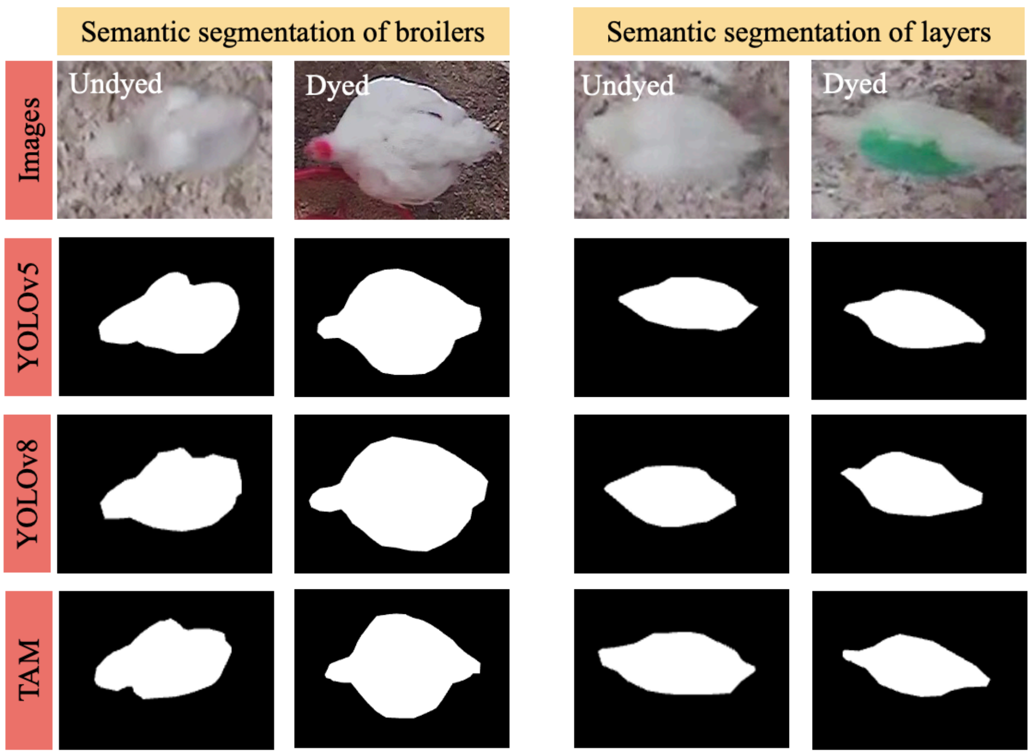

Figure 5.4. Visual comparison of segmentation results. YOLOv5 and YOLOv8 are compared with the TAM approach applied to diverse chicken datasets.

5.3.2 Assessing the Performance of Chicken Tracking

Navigating through the intricate domain of chicken tracking, a comparative analysis was conducted, scrutinizing various algorithms, each harboring a unique blend of detection and tracking capabilities. The algorithms under the lens included YOLOv5+DeepSORT, YOLOv5+ByteTrack, YOLOv8+OC-SORT, YOLOv8+StrongSORT, and TAM, each meticulously paired to harness the strengths of YOLO's object detection and the respective tracking proficiencies of the algorithms. YOLOv5 was paired with both DeepSORT and ByteTrack, leveraging its enhanced detection capabilities with DeepSORT's deep association metrics and ByteTrack's byte-level tracking, respectively, to maintain persistent identities of chickens, especially amidst occlusions and flock interactions. The dyed chickens, with their distinct colors, provided a vibrant scenario to evaluate the color-based tracking of these algorithms. The color distinction in dyed chickens inherently offers a unique identifier that facilitates improved tracking and identity preservation by the algorithms. In experiments, dyed chickens consistently demonstrated superior MOTA and IDF1 scores across all algorithms, indicating enhanced tracking accuracy and identity preservation, respectively. For instance, YOLOv5+DeepSORT exhibited a MOTA of 92.13% and IDF1 of 90.25% for dyed chickens, compared to slightly lower percentages for undyed ones. This trend was consistent across all algorithms, underscoring the pivotal role of distinct coloration in enhancing tracking performance (Bidese Puhl, 2023).

In the case of YOLOv8, it was paired with OC-SORT and StrongSORT, evaluating their potential to minimize identity switches and maintain tracking accuracy amidst the dynamic and interactive poultry house environment. The algorithms were evaluated based on the TAM, ensuring a balanced assessment of both accuracy and computational efficiency, focusing on metrics such as MOTA, IDF1, and IDS. In the context of dyed chickens, YOLOv5+DeepSORT exhibited commendable tracking accuracy, leveraging the color features effectively, yet faced challenges in maintaining identities during occlusions. YOLOv5+ByteTrack showcased robustness in handling identity switches but at a computational cost, reflected in a lower FPS. YOLOv8+OC-SORT demonstrated enhanced tracking accuracy in scenarios of chicken interactions and occlusions due to its observation-centric approach, while YOLOv8+StrongSORT, maintaining a high MOTA, faced challenges in dense chicken populations, leading to a higher IDS ("Early Warning System for Open-beaked Ratio, Spatial dispersion, and Movement of Chicken Using CNNs," n.d.). Considering the comparative values provided in experiments and illustrated in Table 5.2, TAM emerges as the superior model, substantiating its position as the best model among those evaluated. It boasts the highest MOTA, indicating the highest accuracy in tracking while minimizing misses and false positives. It achieves the highest IDF1 score, showcasing its proficiency in maintaining consistent identities throughout the tracking period. Furthermore, TAM registers the lowest number of Identity Switches (IDS), reflecting its capability to preserve identities accurately across frames with minimal switches. This unique capability of TAM to provide accurate tracking alongside its superior tracking accuracy underscores its unparalleled utility in comprehensive poultry behavior analysis, thereby substantiating its position as the best model among the ones evaluated. This assessment reveals a trade-off between tracking accuracy and computational efficiency, suggesting that advancements in TAM could potentially enhance poultry tracking in future applications.

Table 5.2. Comparative analysis of tracking algorithms for dyed and undyed chickens.

Notes: Track anything model (TAM), you only look once (YOLO), multiple objects tracking accuracy (MOTA), identification F1 score (IDF1), identity switches (IDS), and frames per second (FPS).

Algorithm	Condition	MOTA (%)	IDF1 (%)	IDS	FPS
YOLOv5+DeepSORT	Dyed	92.13	90.25	15	18
YOLOv5+DeepSORT	Undyed	88.47	86.32	25	18
YOLOv5+ByteTrack	Dyed	93.21	91.47	14	15
YOLOv5+ByteTrack	Undyed	89.36	87.14	22	15
YOLOv8+OC-SORT	Dyed	95.67	93.12	12	17
YOLOv8+OC-SORT	Undyed	91.78	89.12	20	17
YOLOv8+StrongSORT	Dyed	94.56	92.34	13	18

YOLOv8+StrongSORT	Undyed	90.12	88.45	23	18
TAM-*speed*	Dyed	97.45	95.67	10	16
TAM-*speed*	Undyed	94.78	92.34	18	16

Notes: Track anything model (TAM), you only look once (YOLO), multiple objects tracking accuracy (MOTA), identification F1 score (IDF1), identity switches (IDS), and frames per second (FPS).

5.3.3 Evaluating Velocity Measurement

In the meticulous pursuit of accurate and reliable chicken tracking, TAM-*speed* has been subjected to a thorough evaluation, particularly focusing on its capability to accurately detect and quantify the speed of chickens within a controlled environment. In our experiments, where the average speed of the chickens was measured to be 0.05 m/s, the precision with which TAM-*speed* could predict and validate these speed measurements became paramount. Utilizing the RMSE as a pivotal metric to quantify the average discrepancies between the speeds predicted by TAM-*speed* and the actual observed speeds, a comprehensive analysis was conducted. Given that RMSE provides a high penalty for larger errors, it serves as a stringent metric, ensuring that the model's predictions are not only accurate on average but also do not deviate significantly in individual predictions. In our analysis, dyed chickens, with their distinct and consistent coloration, provided a somewhat stable basis for the tracking algorithm to latch onto, potentially minimizing the instances where tracking was lost or inaccurately assigned. The RMSE for dyed chickens was recorded at a laudable 0.02 m/s, indicating a high degree of accuracy in speed detection. The distinct coloration likely assisted the model in maintaining a consistent track, thereby enabling more accurate speed calculations over a sequence of frames. Conversely, undyed chickens, with their more variable and less distinct visual features, posed a slightly more complex scenario for TAM-*speed*. The RMSE for undyed chickens was marginally higher, recorded at 0.025 m/s. This subtle elevation in error might be attributed to the challenges in maintaining consistent tracking amidst the visually similar undyed chickens, potentially leading to brief losses in tracking or misidentifications, which in turn, could slightly skew the speed calculations (Okinda et al., 2020). Despite these discrepancies, it is crucial to note that in the dynamic and somewhat unpredictable environment of a poultry house, numerous variables can influence the chickens' speed, such as their age, size, and overall health, as well as external factors like lighting and noise levels. Despite the challenges, TAM-*speed* has showcased a commendable capability in speed detection, providing predictions that, while subject to error, still provide valuable insight into the locomotion and behavior of the chickens. The utility of such a model extends beyond mere speed detection, offering potential insights into the health and well-being of the poultry by monitoring their mobility and activity levels (Fang et al., 2020). In conclusion, while TAM-*speed* demonstrates a notable accuracy in speed detection, it is imperative to continually refine the model, considering the myriad of variables that can influence the speed and behavior of chickens. Future iterations of the model might benefit from additional training data, encompassing a wider range of scenarios and conditions, to further enhance its predictive accuracy and reliability in diverse poultry house environments. Table 5.3 summarizes the velocity changes among dyed and undyed chickens. Figure 5.5 displays a visualization of speed and track detected by TAM-*speed*.

Table 5.3. Comparative analysis of velocity for dyed and undyed chickens.

Algorithm	Condition	RMSE (m/s)	Velocity Range (m/s)
TAM-*speed*	Dyed	0.02	0.00–0.21
TAM-*speed*	Undyed	0.025	0.00–0.21

Figure 5.5. Track and detection speed of broilers (the green number indicates the tracking number, while the black number represents speed).

5.4 DISCUSSIONS

5.4.1 Chicken Segmentation Approaches

In the present exploration, TAM has notably eclipsed both YOLOv5 and YOLOv8 in a variety of tracking tasks, particularly those involving chickens in dyed condition. Specifically, TAM's integrated mode, which amalgamates tracking and speed measurement, has showcased unparalleled precision across diverse tracking scenarios. This exemplary performance can be attributed to several pivotal factors. Firstly, TAM utilizes a specialized tracking mechanism that adeptly captures intricate movement patterns and complex trajectories, enabling it to focus on pertinent features and trajectories, thereby facilitating more accurate tracking. Moreover, it is worth noting that TAM surpassed other models without necessitating additional training or extensive fine-tuning. This implies that the architecture and design of TAM inherently possess robust tracking capabilities, negating the need for exhaustive model adjustments or specialized training datasets. This inherent proficiency not only underscores TAM as a more practical and effective option for tracking applications but also highlights its potential to be applied in various poultry tracking scenarios without the need for exhaustive model adjustments or specialized training datasets. In addition, the segmentation of dyed chickens consistently exhibited superior performance across all algorithms when compared to undyed chickens. This can be attributed to the distinct colors of the dyed chickens, which provide a more discernible feature for the model to track, thereby reducing identity switches and enhancing tracking accuracy (Wang et al., 2023). This nuanced capability of TAM to adeptly manage variations in object features further solidifies its position as a versatile and reliable model for chicken tracking applications. Comparing the tracking of whole chickens, it was observed that tracking dyed chickens demonstrated superior performance across all metrics. This is because tracking dyed chickens may provide additional distinctive features for the model to latch onto, thereby facilitating improved tracking results. The tracking of a dyed chicken provides a more comprehensive understanding of the object by capturing its overall shape and structure, which facilitates improved tracking results. Table 5.4 presents a comparative analysis of TAM with various research studies in the domain of chicken tracking using computer vision. For instance, EfficientNet-B0 achieved a mIoU of 89.34% in a study involving the segmentation of meat carcasses using a dataset of 108,296 images (Gorji et al., 2022). Similarly, MSAnet secured a mIoU of 87.7% for segmenting caged poultry across a 300-image dataset (Li et al., 2021), while Mask R-CNN recorded a mIoU between 83.6% and 88.8% for segmenting hens in a 1700-image dataset (Li et al., 2020). Contrarily, TAM demonstrated a mIoU of 93.12% for poultry tracking, potentially outperforming other methods even without a specialized target dataset. This highlights TAM's ability to accurately trace chicken movements within images and underscores its efficacy and potential applicability in broader computer vision tasks related to chicken tracking.

Table 5.4. Comparison of segmentation accuracy.

Methods	Dataset (Constructed by Authors)		mIoU (%)
	Number	Type	
EfficientNet-B0	108,296	meat carcasses	89.34
MSAnet	300	caged chickens	87.7
mask R-CNN	1700	hens	83.6–88.7
TAM (this study)	/	/	93.12

5.4.2 The Precision of Velocity Measurement in Poultry Tracking

In the realm of poultry tracking, the implementation of speed detection, particularly through computer vision, remains a relatively unexplored territory. The TAM-*speed* model, however, has emerged as a pioneering approach in this domain, offering a novel perspective in estimating the velocity of broiler and layers. This model, while primarily focused on tracking, also encapsulates the capability to measure speed, providing a dual functionality that is both innovative and crucial for comprehensive poultry behavior analysis. In contrast, the field of vehicle speed detection has witnessed substantial advancements, with numerous methodologies being developed and refined over the years. A common approach within this domain involves the utilization of a perspective transformer, which aids in estimating the speed of vehicles by analyzing the change in position of a vehicle over consecutive frames, considering the camera's perspective (Wu et al., 2023; Zhang et al., 2023). This method, while effective for vehicles, presents unique challenges when applied to poultry due to the erratic and non-linear movement patterns exhibited by chickens. Comparatively, other methods of speed detection in poultry have traditionally relied on wearable equipment or radio speed detection techniques. Wearable devices, while providing accurate data, may influence the natural behavior and movement of the chickens due to the physical burden and potential stress induced by the equipment (Fujinami et al., 2023; Siegford et al., 2016). On the other hand, radio speed detection, which typically involves tracking the radio frequency identification (RFID) tags attached to the chickens, may offer valuable data but is often constrained by its dependency on the proximity and orientation of the RFID tags, potentially limiting the accuracy and consistency of the data collected (Chien and Chen, 2018; Doornweerd et al., 2023; Zhang et al., 2016). TAM-*speed*, in this context, offers a non-intrusive, consistent, and technologically advanced method of not only tracking but also estimating the speed of chickens without the need for physical contact or proximity-based technology. It leverages computer vision to analyze movement and estimate speed, providing a wealth of data that are both accurate and comprehensive, without influencing the natural behaviors of the poultry.

5.4.3 Limitations and Future Works

TAM and its derivative, TAM-*speed*, exhibit a notable limitation in their substantial computational and memory demands, especially when applied to scenarios involving the tracking of numerous entities over extended durations. In specific test cases, even when utilizing the robust NVIDIA A100 GPU, which is equipped with a substantial 96 GB of memory and is renowned for its computational prowess, the models encountered difficulties in sustaining tracking for periods exceeding 2 min, particularly when tasked with simultaneously tracking more than 20 individual chickens. This computational demand not only restricts the duration and scale of tracking but also poses significant barriers to its application in real-world, large-scale poultry farms where continuous monitoring of larger flocks is imperative for effective management and research.

In future endeavors, leveraging distributed computing can mitigate TAM's computational demands, enabling the analysis of larger poultry populations and extended tracking durations. Additionally, incorporating edge computing strategies, where initial data processing occurs on local devices, could alleviate the computational load on the central model, ensuring efficient and timely poultry behavior analysis. Furthermore, implementing adaptive sampling techniques, which dynamically adjust the TAM model's sampling rate based on scene complexity, could optimize computational resource allocation, ensuring detailed analyses during complex behaviors while conserving resources during simpler scenarios (Xie et al., 2023).

5.6 CONCLUSION

The track anything model and its adaptation, TAM-*speed*, have emerged as potent tools for analyzing chicken locomotion and behavior, demonstrating superior performance in tracking and segmenting dyed chickens compared to other models like YOLOv5 and YOLOv8. TAM achieved a mean Intersection over Union (mIoU) of up to 95.13%, showcasing its architectural robustness and effective pre-trained model. Furthermore, TAM-*speed* exhibited commendable speed detection capabilities, with an RMSE of 0.02 m/s for dyed chickens, providing valuable insights into poultry behavior and potential health indicators. This research underscores TAM's potential as a multifaceted tool for comprehensive poultry behavior analysis without requiring extensive training or fine-tuning, paving the way for advanced applications in precision livestock farming.

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CHAPTER 6

ROBOTIC SYSTEM FOR CAGE-FREE FLOCK MANAGEMENT [7]

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ABSTRACT

Floor eggs and dead chickens present new challenges as the egg industry transitions from caged to cage-free housing due to animal welfare concern. In this study, convolutional neural network (CNN) models and the intelligent bionic quadruped robot were used to detect floor eggs and dead chickens in cage-free housing environments. A dataset comprising 1200 images was used to develop detection models, which were split into training, testing, and validation sets in a 3:1:1 ratio. Five different CNN models were developed based on YOLOv8 and the robot's 360° panoramic depth perception camera. The final results indicated that YOLOv8m exhibited the highest performance, achieving a precision of 90.59%. The application of the optimal model facilitated the detection of floor eggs in dimly lit areas such as below the feeder area and in corner spaces, as well as dead chickens within the flock. This research underscores the utility of bionic robotics and convolutional neural networks for poultry management and precision livestock farming.

Keywords: Poultry management; Robotics; Computer vision; Deep learning, Convolutional neural networks

6.1 INTRODUCTION

Animal welfare policies are receiving increased global attention. In poultry farming, traditional battery cages severely restrict hens' natural behaviors, leading to disuse osteoporosis (Chang et al., 2020). Even with improved environments and managed activities, hens in cages are deprived of expressing most of their natural behaviors (Hewson, 2003). Consequently, many countries are actively formulating policies and trade measures to protect animal welfare in poultry production systems (Shields and Duncan, 2009). The egg industry is shifting to cage-free houses to improve bird welfare, providing sufficient space for hens to engage in natural behaviors. For example, legislation in California mandates that all eggs sold must come from hens in cage-free houses (Mullally and Lusk, 2018). However, the transformation to cage-free systems presents new challenges, including managing floor eggs and the increased time required to inspect the entire house for deceased chickens (5%-15%) (Bist et al., 2023b; Li et al., 2020). Automatic floor egg collection and removal of deceased chickens are primary concerns for egg producers in cage-free housing. One potential solution is to utilize robots for these tasks (Ren et al., 2020a).

Mobile robot technology has been extensively developed and applied in the agricultural industry (Rubio et al., 2019). Most robots utilize a two-wheeled differential drive method for directional control. They collect environmental information via multiple sensors, enabling target tracking and obstacle avoidance in unknown environments (Gopalakrishnan et al., 2004). In the poultry sector, Vroegindeweij et al. (Vroegindeweij et al., 2014) proposed a path-planning method using the PoultryBot to collect floor eggs, reducing the need for manual egg picking. Bao et al. (Bao et al., 2021) introduced an AI-based sensor method for monitoring dead and sick chickens using foot rings and a ZigBee network, achieving 95.6% accuracy and reducing costs by 25% over four years compared to manual inspection. In the ever-evolving landscape of mobile robotics, the incorporation of advanced object recognition technologies is pivotal in enhancing robotic capabilities and operational efficiency, particularly in intelligent bionic quadruped robots (Hentout et al., 2019). Reese et al. (Reese et al., 2024) investigated the integration of object recognition in autonomous quadruped robotics using Red-Green-Blue (RGB) cameras and You Only Look Once version 8 (YOLOv8) in “Unitree Go 1” robots, optimizing sensor use for defense, surveillance, and industrial monitoring applications. Angulo et al. (Martinez Angulo et al., 2024) explored the implementation of Chat Generative Pre-trained Transformer (ChatGPT) with the “Unitree Go 1” Robot Dog using voice prompts. They developed an interface that connects the ChatGPT Application Programming Interface (API) with the Unitree Go 1 Software Development Kit (SDK), facilitating user-friendly control and software development. Our research focuses on the integration of advanced object recognition technologies within the “Unitree Go 1”, a quadrupedal robotic dog. This platform hosts a network of interconnected sensors and cameras, including Forward-Looking Infrared (FLIR), Light Detection and Ranging (LiDAR), and Depth Camera, for both autonomous and manually controlled applications. The study explores the synergistic effects of combining these technologies to enhance the capabilities and operational efficiency of the “Unitree Go 1”(Sharma et al., 2016).

At the heart of our proposed system for object detection with the “Unitree Go 1” are Convolutional Neural Networks (CNNs) (Jiang et al., 2020). Besides the “Unitree Go 1”, some custom-designed robots utilize robotic arms, a conveyor belt, and a storage cache to remove deceased chickens. Additionally, a robotic bin-picking pipeline for chicken fillets employs 3D reconstruction of the environment using depth data from an RGB-D camera. Both systems are based on advanced computer vision techniques and CNNs (Jonker, 2023; Liu et al., 2021). CNNs utilize patterns in images to recognize objects, classes, and categories, making them suitable for various applications. Among these, the YOLO series stands out for its effectiveness in precision livestock farming. These algorithms can automatically extract target features from images, eliminating the need for manual observation and enhancing the model's generalizability (Li et al., 2021). Seo et al. (Seo et al., 2019) demonstrated improved accuracy and processing time for real-time pig surveillance by combining YOLO object detection with image processing techniques. They utilized infrared and depth information to effectively separate touching pigs. Similarly, Tong introduced a real-time poultry disease detector by integrating scale-aware modules and slide weighting loss into YOLOv5. This enhancement significantly improved detection accuracy and health status recognition in chickens, facilitating automated monitoring (Tong et al., 2023). Given the high performance of YOLO in object detection for precision livestock farming, it has the potential to detect floor eggs and dead chickens in various cage-free housing environments. By combining the YOLO detection model with the “robot dog”, the system could efficiently identify and collect floor eggs as well as remove dead chickens (Yang et al., 2024). This integration enhances the functionality and applicability of automated monitoring and management in livestock farming.

The objectives of this study were to: (1) develop a detector based on YOLOv8 and the robotic method (i.e., Unitree Go 1 robot) for monitoring floor eggs and deceased chickens in research cage-free houses; (2) train the YOLOv8 model using images and videos of dead hens and floor eggs collected by the robot wide-angle and RGB cameras; and (3) test the performance of the newly developed models under various production conditions.

6.2 MATERIALS AND METHODS

6.2.1 Birds’ Management

The robotic monitoring system was tested at the University of Georgia (UGA)’s Poultry Research Center. Each research house, measuring 7.3 m in length, 6.1 m in width, and 3 m in height, housed 200 Lohmann White Leghorn Chickens (22-24 weeks age). Initially, the robot was placed in the henhouse with limited movement to avoid startling the chickens. Over time, as the chickens became more accustomed to its presence, the robot's activity levels were slowly increased. The houses were equipped with lights, perches, nest boxes, feeders, and drinkers, with floors covered in pine shavings. Indoor conditions, including light intensity and duration, ventilation rates, temperature, and relative humidity, were managed using a Chore-Tronics Model 8 controller (CHORE-Time Controller, Milford, IN, USA). The feed, a soy-corn mixture, was manufactured at the UGA feed mill every two months to ensure freshness and prevent mildew. Team members monitored the hens' growth and environmental conditions daily, following the UGA Poultry Research Center Standard Operating Procedure. This experiment adhered to the animal care and use guidelines established by UGA's Institutional Animal Care and Use Committee (IACUC).

6.2.2 Robotic System for Collecting Dead Chickens and Egg Samples

In this study, we utilized the "Unitree Go1" dog (Unitree, Binjiang District, Hangzhou, China), which is the world's first intelligent bionic quadruped robot companion at the consumer level. It is the first full-size general-purpose humanoid robot capable of running and featuring 360° panoramic depth perception. This robot boasts an extensive joint movement range with up to 34 joints, incorporating force-position hybrid control technology to simulate human hand operations for precise tasks (Kim et al., 2024). This capability enables it to potentially remove dead chickens and pick up eggs in the future. Figure 6.1 presents its three-dimensional view. The Go 1 is equipped with a built-in advanced AI processing unit, comprising a 16-core top CPU and a GPU (384 cores, 1.5 TFLOPS) for deploying AI models, such as chicken detection and chicken body weight prediction (Roh, 2023). The YOLOv8 model was integrated into the robot's AI unit, allowing it to analyze live video feeds captured by the robot's cameras to identify dead chickens and eggs in real-time. (Figure 6.2) We controlled the robot dog using its dedicated controller and the official application (unitree.com/app/go1/). The robotic dog was deployed twice daily, in the morning and evening, to inspect the entire poultry house. The inspection route was pre-set by human operators using the robot's controller, guiding the robot from the entrance door around the perimeter of the house and across all sections, ensuring comprehensive coverage of the entire facility. Figure 6.3 illustrates the experimental setup. The robotic dog demonstrates several movement patterns, including turning, jumping, side-stepping, and more (Long et al., 2023). During our sample collection process, we primarily utilized climbing when encountering steps, as well as turning and walking to search for dead chickens and eggs and to capture sample images.

Figure 6.1. Three-dimensional views of the "Unitree Go 1" robotic dog (Front, Side, and Top).

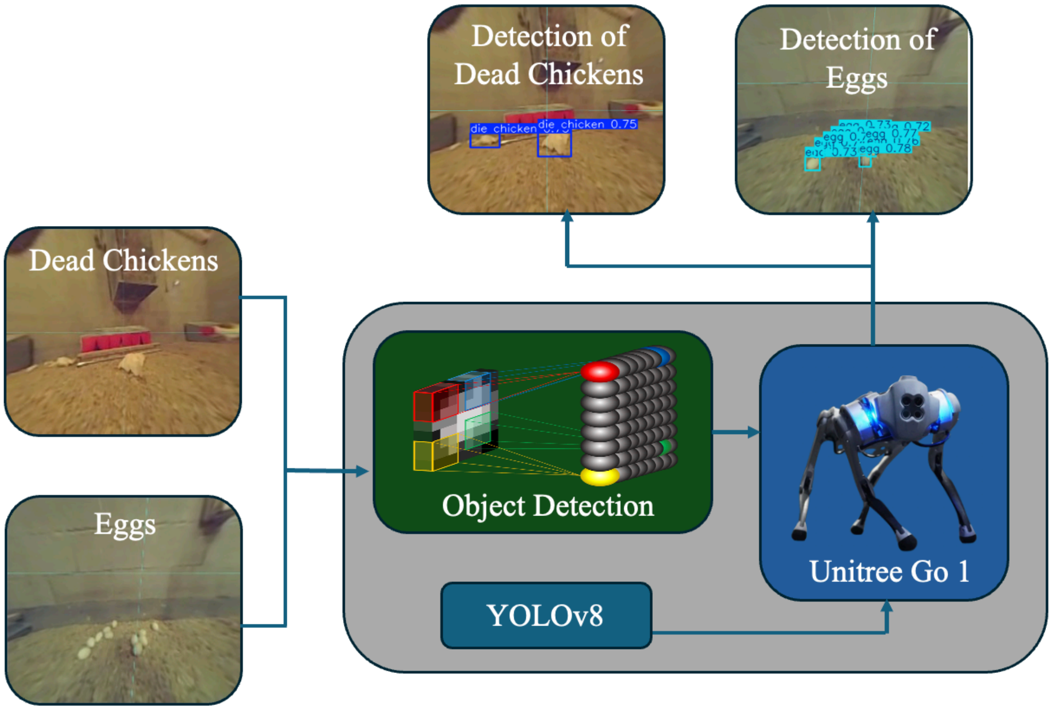

Figure 6.2. Overview of the automated detection system for poultry management using YOLOv8 and Unitree Go 1 Robotic.

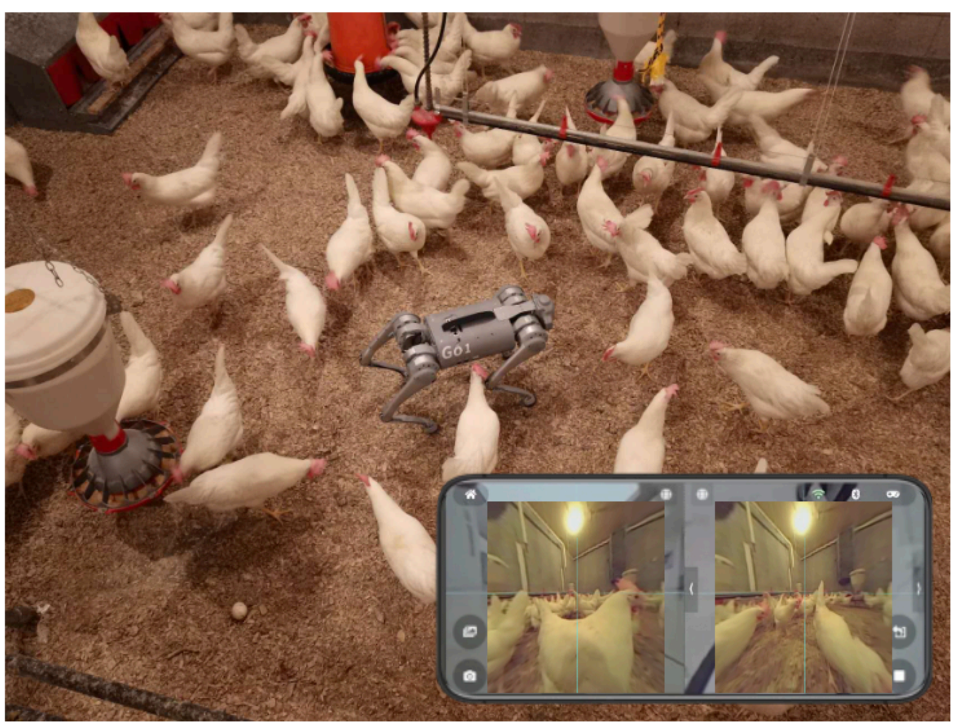

Figure 6.3. The robot dog in walking mode collecting chicken and egg images in the research poultry house.

6.2.3 Data Processing and Analysis

Bird and egg images were extracted from the robot dog and annotated using V7 Darwin, an online annotation tool provided by V7labs (V7, 8 Meard St, London, United Kingdom). This tool supports various formats, including JPG, PNG, TIF, MP4, MOV, SVS, DICOM, NIfTI, and more, enabling the consolidation of training data in one place (Vidal et al., 2021). In this study, we created two classes: dead chickens and good eggs. For each image, we first checked the quality to ensure that it captured our target objects. Using the bounding box tool, we created boxes around the target objects. After a final review, we marked the images as completed (Figure 6.4).

Figure 6.4. Examples of image labeling by V7 Darwin.

6.2.4 Detection Methods

In our detection tasks, identifying small targets like chickens and eggs presents challenges such as limited feature availability and a low proportion of annotated areas for small targets. Additionally, the challenge is exacerbated by the limited dataset of 300 original images. To address these challenges, we first employed data augmentation methods like copy-paste enhancement, which involves randomly duplicating small targets multiple times within the image (pure cropping) or copying a region containing multiple small targets (cropping with background context), applying various transformations (scaling, flipping, rotating, etc.) during pasting. Additionally, we used over-sampling by duplicating the same image file multiple times and applying scaling and stitching techniques to combine multiple image files into one (Zou et al., 2021). These data augmentation methods expanded the dataset size and increased its diversity, artificially boosting the proportion of small targets in the dataset to ensure the network can effectively learn their features. After data augmentation, we obtained 1200 images, which we split into training, testing, and validation sets in a 3:1:1 ratio. In this study, we adapted You Only Look Once version 8 (YOLOv8) to detect chickens and eggs, utilizing one of the five most used models for object detection within the YOLOv8 family (i.e., YOLOv8s, YOLOv8n, YOLOv8m, YOLOv8l, and YOLOv8x) (Safaldin et al., 2024). The backbone network, which is the foundation of the model, is responsible for extracting features from the input image, and these features are the basis for subsequent network layers to perform object detection. In YOLOv8, the backbone network uses a structure similar to Cross Stage Partial Darknet (CSPDarknet) (Sohan et al., 2024). The head network is the decision-making part of the object detection model, responsible for producing the final detection results, while the neck network lies between the backbone and head networks, playing a role in feature fusion and enhancement. Other modules include the ConvModule, which contains convolutional layers, batch normalization (BN), and activation functions (e.g., Sigmoid Linear Unit (SiLU)) for feature extraction; DarknetBottleneck, which increases network depth through residual connections while maintaining efficiency; and the CSP layer, a variant of the Cross Stage Partial structure that improves model training efficiency through partial connections (Hussain, 2023). The design of the YOLOv8 network is shown in Figure 6.5.

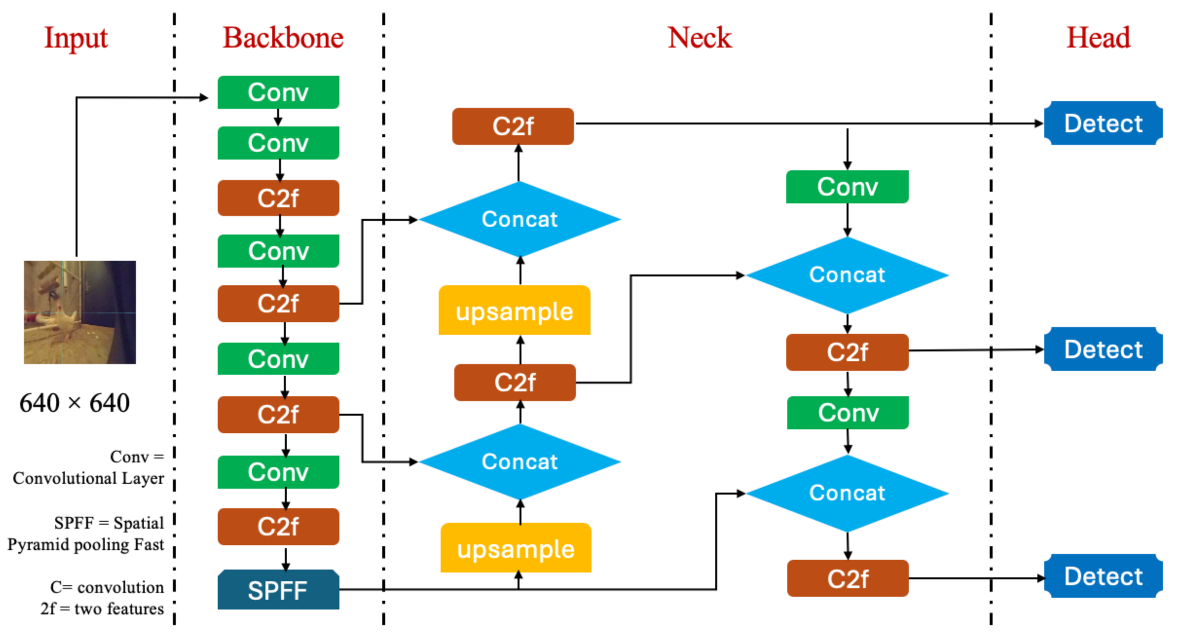

Figure 6.5. YOLOv8 network structure diagram.

6.2.5 Model Evaluation

To benchmark the performance of classifiers, we focused on precision, recall, mean average precision (mAP), frames per second (FPS), and loss function values (Equations 1-3). Precision measures the accuracy of detected objects, indicating the proportion of correct detections, while recall assesses the model's ability to identify all instances of objects in the images. The mAP, which evaluates the model's bounding box predictions on the validation dataset, is determined by plotting precision and recall values at different confidence thresholds. Additionally, FPS is used to evaluate the speed of the methods, providing a measure of their efficiency. Finally, the loss function serves as a metric indicating how well the algorithms train the neural network model based on the dataset and achieve optimal results, tying together the overall performance evaluation.

$$Precision = \frac{TP}{(TP+FP)} \qquad \text{Eq. 1}$$

$$Recall = \frac{TP}{(TP+FN)} \qquad \text{Eq. 2}$$

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \qquad \text{Eq. 3}$$

APk denotes the average precision for class k, where n is the number of classes. In chicken detection, True Positive (TP) correctly identifies a chicken, False Positive (FP) incorrectly identifies a non-chicken as a chicken, and False Negative (FN) fails to identify a chicken. mAP@0.5 refers to the mean average precision calculated at an Intersection over Union (IoU) threshold of 0.5. A loss function measures how well a model accomplishes its task by comparing its predicted dead chickens and eggs to the actual output. "l_{cls}" measures the discrepancy between the predicted class probabilities and our labels, while "l_{obj}" measures the confidence score assigned to each predicted bounding box, indicating whether it contains an object or not, as Equations 4-6.

$$loss\ function = l_{cls} + l_{obj} \qquad \text{Eq. 4}$$

$$l_{cls} = \lambda_{class} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{obj} \sum_{C \in classes} P_i(c) \log(\hat{p}_l(c)) \qquad \text{Eq. 5}$$

$$l_{obj} = \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{noobj} (c_i - \hat{C}_l)^2 + \lambda_{obj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{obj} (c_i - \hat{C}_l)^2 \qquad \text{Eq. 6}$$

In the equation, $I_{i,j}^{obj}$ indicates whether the targets are located at the anchor box (i, j), $P_i(c)$ represents the probability of the target class c, and $\hat{p}_i(c)$ denotes the actual value of the class. The summation across these terms encompasses the total number of classes C.

6.3 RESULTS AND DISCUSSIONS

6.3.1 Influence of Robotics on Chicken Activity

In this study, we recorded the entire process of chickens' interactions with a robotic entity, over the course of one hour. The observation focused on their initial reactions and subsequent behavior changes, documenting phases of fear, curiosity, aggregation, and normalization (Ren et al., 2020b). The robot was positioned in our observation area, which included half a drinking line (camera view), two feeders, and one nesting box, representing a typical section of a cage-free house. We recorded the number of chickens around the robot in this area. Upon first encountering the robot, the chickens exhibited immediate flight responses, resulting in widespread panic within the flock, accompanied by dust and feathers flying. Initially, only two chickens remained at the edge of the observation area. Within 20 minutes, the chickens' panic subsided, and curiosity began to dominate. Consequently, the number of chickens in the observation area rapidly increased from 2 to 37. This number continued to rise steadily, reaching 51 chickens by the 40-minute mark. After 40 minutes, more interactive behaviors, such as jumping and pecking at the robot, were observed (Vroegindeweij et al., 2018a). Gradually, the chickens began to treat the robot as a normal object in their environment, with approximately 57 chickens present in the observation area by the end of the hour. This observation illustrates the process by which chickens overcome their initial fear and the time required for a flock to acclimate to the presence of a robotic entity. These findings can inform researchers aiming to integrate robotics into poultry environments, highlighting the optimal time frame for chickens to become comfortable interacting with robots while maintaining their welfare (Figure 6.6).

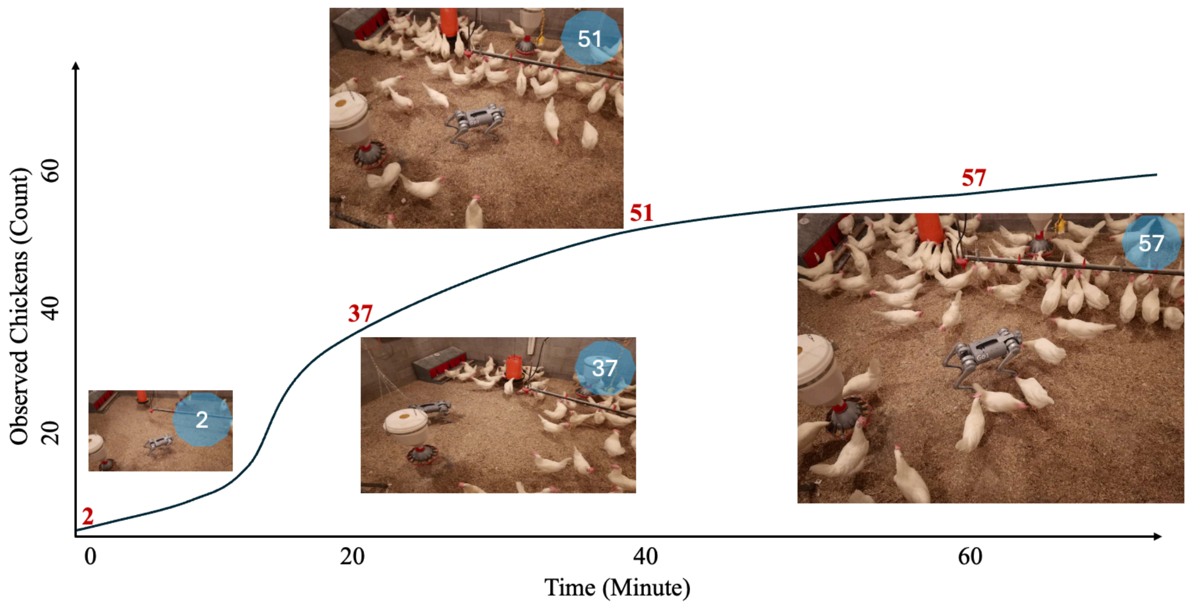

Figure 6.6. Time series of chicken interaction with the robot.

6.3.2 Model Comparison

Five individual experiments (YOLOv8s, YOLOv8n, YOLOv8m, YOLOv8l, and YOLOv8x) were conducted to identify the optimal detector for floor egg and dead chicken detection. The suffixes “s,” “n,” “m,” “l,” and “x” in YOLOv8 refer to different versions of the model, with varying numbers of layers and computational requirements. Specifically, 's' represents the smallest model with the fewest layers and parameters, while “x” denotes the largest model with the most layers and parameters. The '“n,” “m,” and “l,” versions fall between these two extremes, corresponding to nano, medium, and large models, respectively (Wu and Dong, 2023). All experiments were trained for 100 epochs using Python 3.7 and the PyTorch deep learning library, on hardware equipped with an NVIDIA-SMI (16 GB) graphics card. A summary of the model comparison is presented in Table 6.1.

Table 6.1. The summary of model comparison for dead chickens and egg detection.

Model	Precision (%)	Recall (%)	FPS	mAP@0.5	Class_loss	Box_loss
YOLOv8s	85.39	79.32	74	85.08	0.94	2.01
YOLOv8n	85.49	79.89	69	85.17	0.90	1.98
YOLOv8m	90.59	79.34	63	85.40	0.92	2.02
YOLOv8l	88.10	80.72	48	86.29	0.88	2.05
YOLOv8x	87.97	78.52	41	85.31	0.89	2.01

In terms of accuracy, YOLOv8m achieved 90.59%, outperforming all other models. This superior performance can be attributed to the small size of floor eggs and chickens in our images, which cover less than 10% of the image area (Rekavandi et al., 2022). Lower-stride models like YOLOv8m generally perform better with small objects because they retain more detail from the input image, which is crucial for accurate detection and classification. Consequently, YOLOv8m is more effective for detecting floor eggs and deceased chickens (Terven et al., 2023). In terms of recall, the values ranged from 78.52% to 80.52%, showing only a 2% maximum difference among the five models. This minimal variation in recall indicates that all models are similarly effective at identifying the presence of floor eggs and deceased chickens (Juba and Le, 2019). For FPS, YOLOv8s demonstrated the highest speed due to its fewer layers and reduced number of parameters compared to the other models (Held et al., 2016). In addition, mAP@0.5 shows the precision-recall trade-off at an IoU threshold of 0.5. YOLOv8l, YOLOv8m, and YOLOv8x have the top three mAP@0.5 scores, at 86.29%, 85.40%, and 85.31%, respectively. Although YOLOv8n and YOLOv8s have slightly lower mAP@0.5 values, all models perform reasonably well in detecting the bounding boxes for floor eggs and dead chickens. As for Class_loss and Box_loss, all models have Class_loss values close to 0.90 and Box_loss values close to 2.00. This indicates that their ability to classify floor eggs and deceased chickens, as well as the errors in the predicted bounding box locations, are similar (Jiang et al., 2022). These findings demonstrate that YOLOv8m achieved the best performance in detecting floor eggs and deceased chickens (see Figures 6.7-6.11).

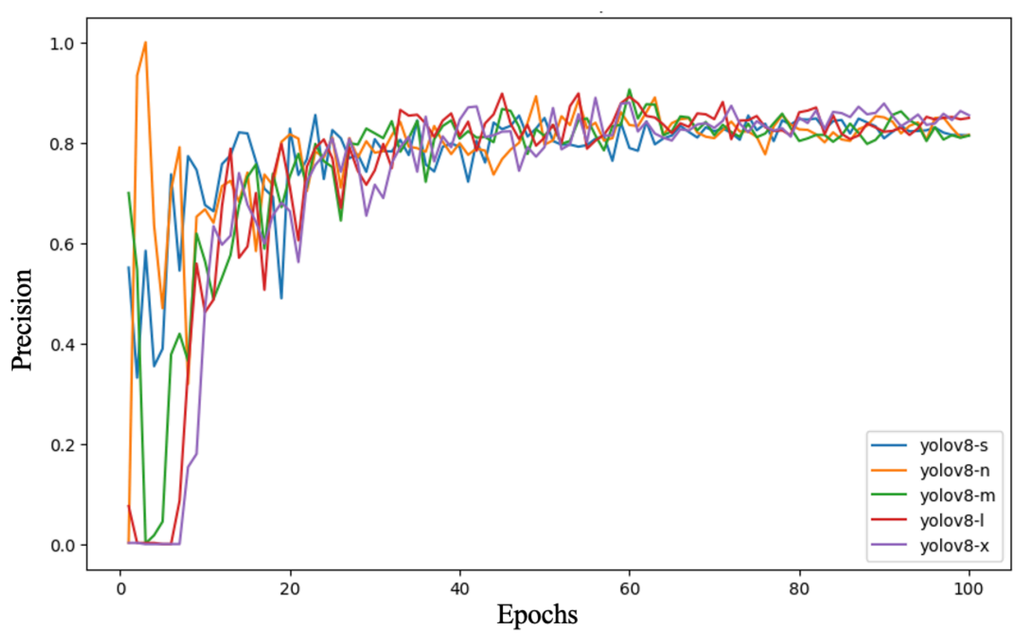

Figure 6.7. Precision comparison results of different detectors for dead chickens and floor eggs.

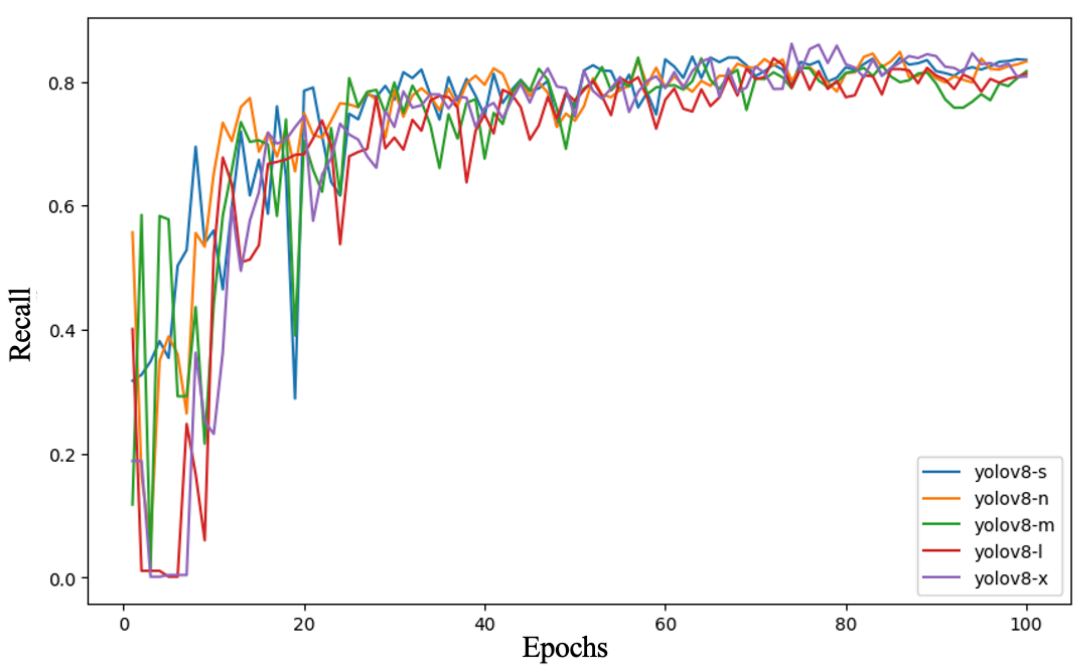

Figure 6.8. Recall comparison results of different detectors for dead chickens and floor eggs.

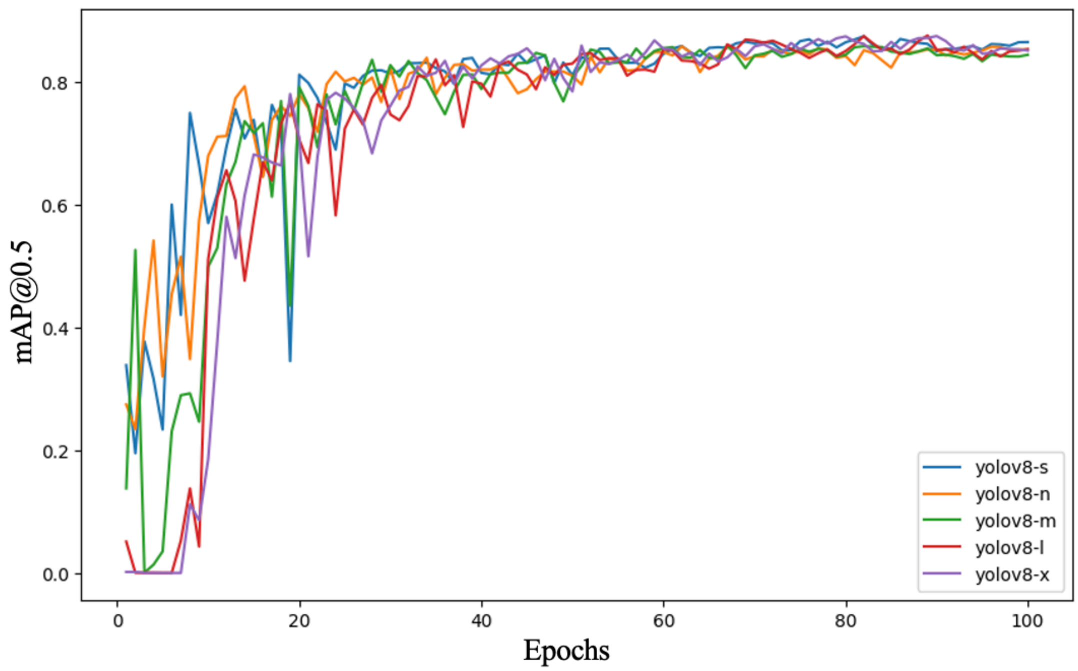

Figure 6.9. The mAP@0.5 comparison results of different detectors for dead chickens and floor eggs.

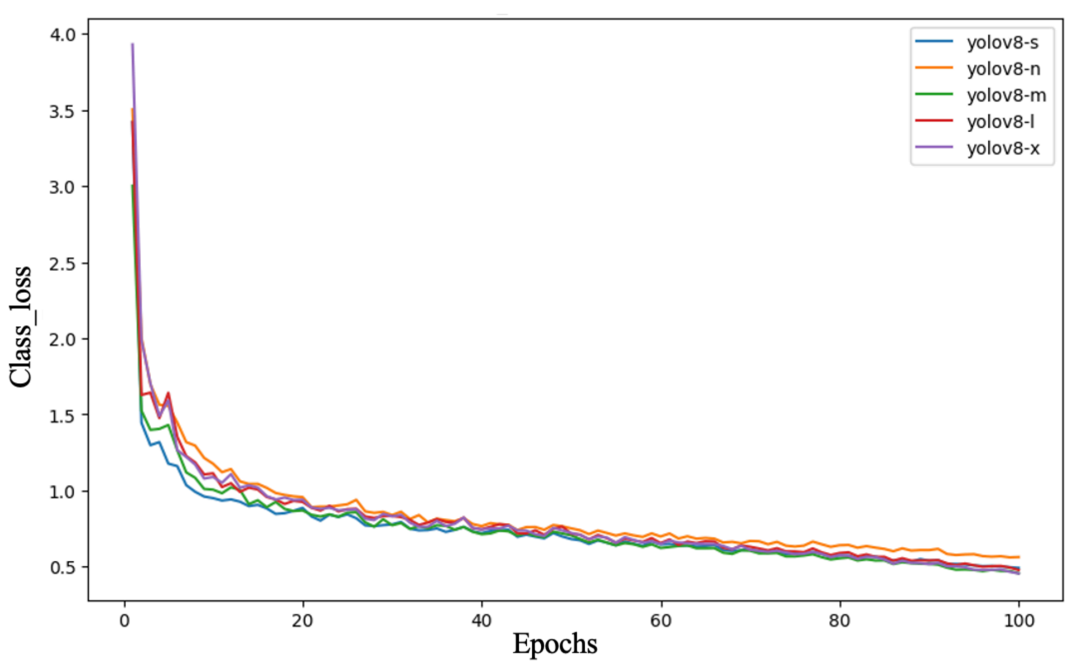

Figure 6.10. Class_loss comparison results of different detectors for dead chickens and floor eggs.

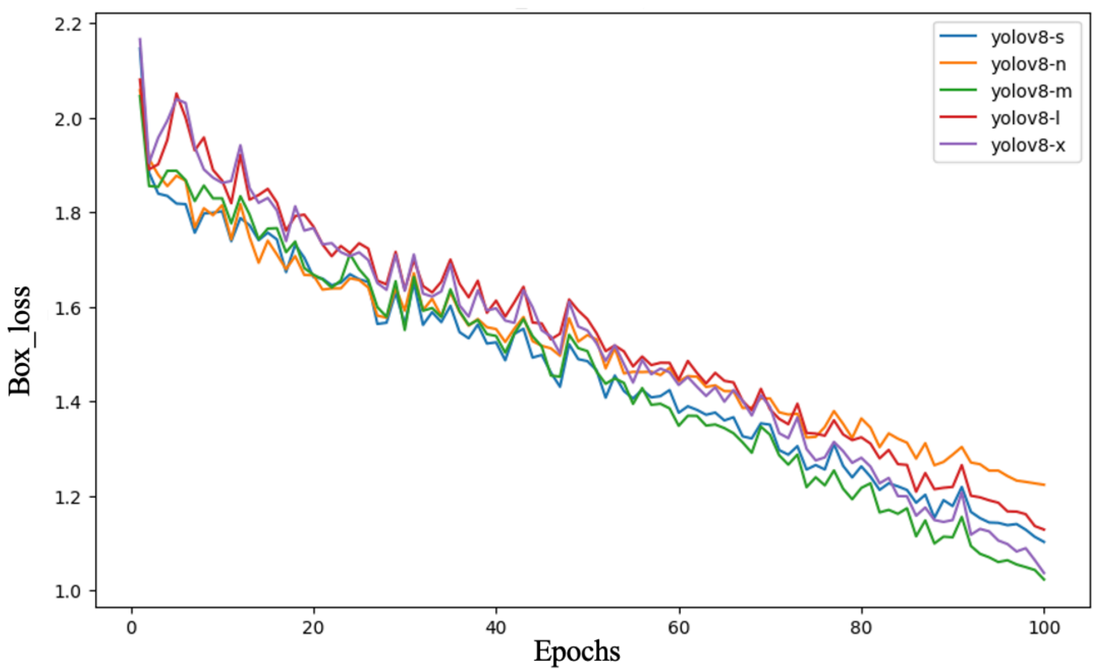

Figure 6.11. Box_loss comparison results of different detectors for dead chickens and floor eggs.

6.3.3 YOLOv8m Algorithm Detection

In the study, the YOLOv8m detector demonstrated the best performance in detecting floor eggs and dead chickens compared to other models. Consequently, a further investigation was conducted using the YOLOv8m model in conjunction with the robot in cage-free houses. In cage-free houses, floor eggs are primarily found in dark areas such as below the feeder area and in corner spaces. YOLOv8m, when paired with the robot, performs well in detecting floor eggs in these dimly lit areas. This is because these areas are not completely dark but have lower than normal light intensity, which does not hinder the model's detection capability (Yang et al., 2022). Additionally, the robustness of the YOLOv8m model allows it to detect floor eggs effectively as long as the images capture the eggs. However, there are some misdetections when the robot is too far from the eggs, such as eggs located under perches where the robot cannot reach. To mitigate this, it is recommended to either remove the perches or design higher perches on the first layer to accommodate the robot's detection capabilities (Bist et al., 2023a). Regarding the detection of dead chickens, there is no particular location where dead birds are commonly found. However, dead chickens often become mixed with the floor litter after death, which does not affect the model's detection performance (Bist et al., 2023b). When chickens die, their bodies and feet become stiff, and their heads often lie in the litter, creating unique features that make it easier to detect dead chickens. Consequently, the model can detect dead chickens using the robot. Nonetheless, occlusions can sometimes occur, such as when a dead chicken carcass is covered by other chickens (Bist et al., 2023c; Subedi et al., 2023). Therefore, the robot should inspect the entire house at least once daily to prevent carcass decomposition and address animal biosecurity concerns. Figures 6.12 and 6.13 illustrate the detection results using the robot in cage-free houses.

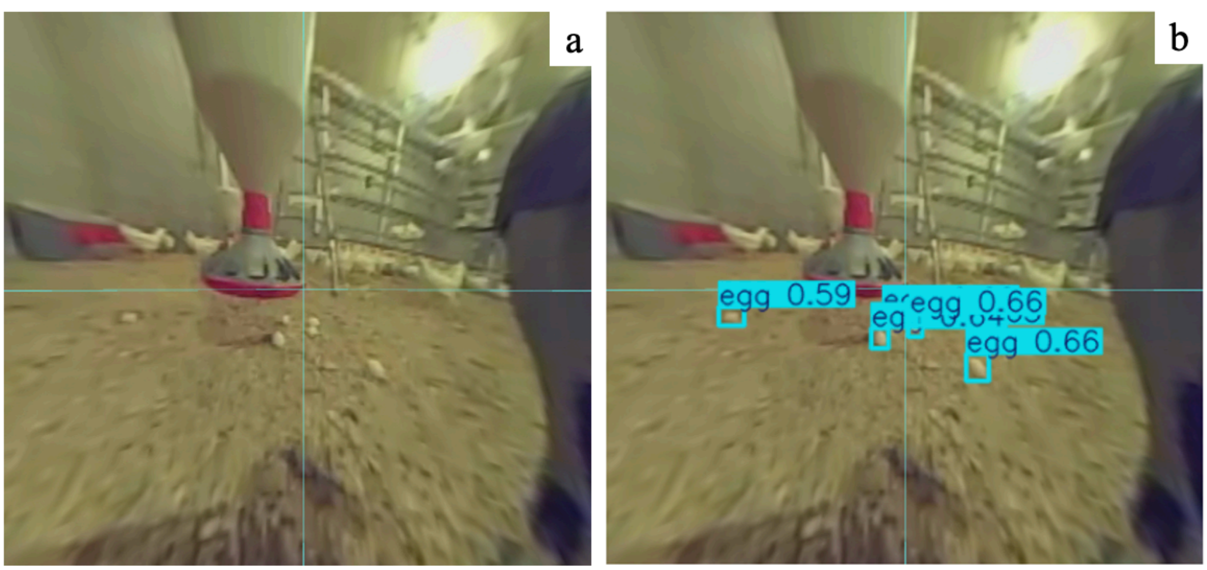

Figure 6.12. Floor eggs identified by our model: original image (a) vs. identified floor eggs (b).

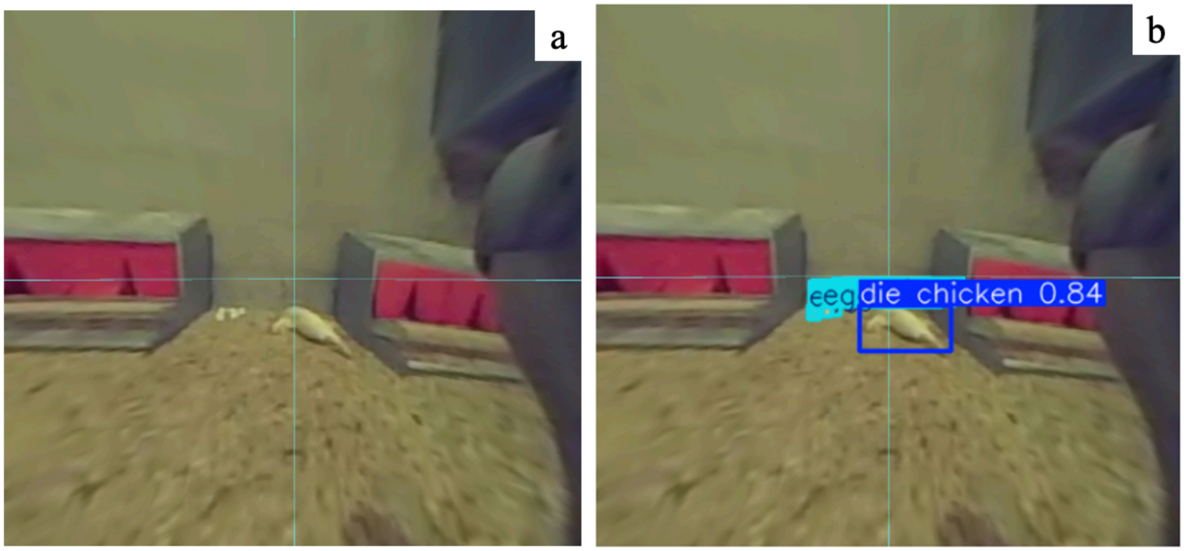

Figure 6.13. Floor eggs and death chickens identified by our model: original image (a) vs. identified floor eggs and death chickens (b).

6.3.4 Compare with Related Studies

To compare our research with previous work, we selected some recent studies on using robotics to detect eggs and deceased chickens. For egg collection, there are two primary methods: CNN and traditional sensing systems. One study featured a robot equipped with a YOLOv3-based deep-learning egg detector, a robotic arm, a two-finger gripper, and a hand-mounted camera. The YOLOv3 detected eggs on a simulated litter floor in real-time, providing coordinates and dimensions for accurate gripper manipulation (Li et al., 2021). Another study introduced the PoultryBot, which utilizes various sensing systems, including a laser scanner with a 20-meter depth and 270-degree view, a digital camera for area visualization, and wheel encoders to measure rotation and movement. The localization technique involves a particle filter that estimates the robot's pose using prediction, update, and resampling phases (Vroegindeweij et al., 2016). Both systems demonstrated more than 90% accuracy in floor egg detection. However, when it came to picking up eggs, the sensing systems achieved only 43% success, while the

CNN maintained a high accuracy of 93% in egg collection (Vroegindeweij et al., 2018b). In our study, we also employed CNN to detect eggs, aiming to advance egg collection development using the robot. Compared to the study by Li et al. (2021), our data is based on cage-free houses, thus demonstrating greater potential for applications in cage-free egg collection. Regarding the detection of deceased chickens, CNN remains the mainstream method. Studies utilizing YOLOv3 and YOLOv4 for detecting dead broilers have achieved detection accuracy as high as 99%, though these studies were conducted in stacked-cage broiler houses and sometimes required multiple robotics combinations for high precision (Hao et al., 2022; Lei et al., 2022a). In cage-free houses, our study can detect both deceased chickens and floor eggs simultaneously using an Intelligent Bionic Quadruped Robot. This comprehensive solution addresses the challenges of cage-free environments, such as floor eggs and the increased time required to inspect the entire house for deceased chickens. Therefore, employing CNN with a Quadruped Robot like "Unitree Go 1" has the potential to efficiently collect floor eggs and remove deceased chickens in a single system.

6.3.5 Future Studies

Despite the significant advancements in detecting floor eggs and deceased chickens, the robotic ability to pick up eggs and remove dead chickens remains an ongoing area of research. For egg collection, most studies integrate computer vision with mechanical arms. One common approach involves using a soft suction mechanism to pick up eggs. This design ensures that the eggs are handled delicately to prevent breakage during collection. Additionally, soft rubber grippers are employed to gently grasp and lift the eggs without causing damage. Once the eggs are picked up, they need to be stored in a tank within the robot for later retrieval (Chang et al., 2020; Wang et al., 2019). Therefore, an additional mechanical arm and a storage tank can be incorporated into the robot dog system to facilitate the collection and storage of floor eggs. On the other hand, removing dead chickens presents a more complex challenge due to their greater weight and size compared to floor eggs (Zhang et al., 2023; Zhou et al., 2023). A stronger mechanical arm, or alternatively, a separate robot equipped with a multi-target path routing scheme, can be utilized (Lei et al., 2022b). This secondary robot would collect the dead chickens using location data provided by the robotic system.

6.4 Conclusions

In this study, a multiple detector for floor eggs and dead chickens was developed based on YOLOv8 networks embedded in a robotic system for picking up eggs and removing dead chickens in cage-free facilities. Results show that the average accuracy of each detector ranges from 85.39% to 90.59%, with the best model being YOLOv8m, which achieved a precision of 90.59%. The detector can effectively recognize various floor eggs on the litter or under feeders and detect dead chickens in corners or around healthy chickens. This detector can be further combined with mechanical arms, such as soft suction mechanisms or soft rubber grippers, to pick up floor eggs. It can also be equipped with a secondary robot to remove dead chickens using location information provided by the robot. The results provide an actionable approach to detecting floor eggs and dead chickens in cage-free houses using a single system without intrusion. This study demonstrates the potential of using intelligent bionic quadruped robots to address the issues of floor eggs and dead chickens in cage-free houses. These advancements provide valuable information for using robotics to help improve the management of cage-free chickens.

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CHAPTER 7

SUMMARY

The dissertation presents a comprehensive investigation into the use of innovative technologies and strategies to improve conditions within cage-free poultry farming systems. The research findings are significant, addressing the challenges of poultry management, sustainable egg production, and automation in modern farming. This study demonstrates the potential of precision farming technologies to tackle critical issues such as floor egg management and animal welfare.

Welfare Enhancement: By combining traditional convolutional neural network (CNN) models (e.g., YOLO series, EfficientNetV2, SegFormer, and SETR) with large vision models (LVM) (e.g., Segment Anything Model and Track Anything Model) and thermal cameras, the study successfully tracked chickens' spatial distribution and predicted bird body weight with high accuracy ($R^2 = 0.90$). Moreover, behaviors like locomotion, feeding, drinking, and dust bathing were accurately classified, providing valuable insights into hen welfare. By integrating these technologies, the study offers a more nuanced understanding of how environmental factors impact both hen welfare.

Floor Egg Management: One of the key achievements of this research was demonstrating how CNN and robotic systems effectively detect floor eggs with 94.8% accuracy. The study used intelligent bionic quadruped robots, which were instrumental in detecting floor eggs in dimly lit areas, such as beneath feeders and in corner spaces. This novel application of robotics provides a promising solution to a common issue in cage-free systems, potentially reducing economic losses and labor costs associated with mislaid eggs.

Animal Welfare Monitoring and Dead Chicken Detection: The study further explored the use of advanced robotic systems for identifying dead chickens within the flock. Combined with LVM and CNN models, the robots provided a groundbreaking approach welfare monitoring, offering automated systems for detecting welfare concerns such as footpad dermatitis.

Conclusion: This dissertation underscores the transformative potential of integrating precision farming technologies with computer vision and robotics to improve production efficiency and welfare standards in cage-free poultry farming. The successful application of CNN and LVM models, alongside intelligent robots, marks a significant advancement towards the automation of poultry management. The findings advocate for a holistic approach, where AI-driven technologies enhance production while ensuring ethical treatment of animals. This research sets a new benchmark for the future of cage-free farming, advancing the industry with more efficient, automated, and sustainable practices.

APPENDIX A

CURRICULUM VITAE

A.1 EDUCATION

- **Sep 2021-Dec 2024 University of Georgia, Athens, GA, USA**

  GPA: 3.90/4.0, **PhD Candidate of Poultry Science**

- **Sep 2018-Jun 2020 China Agricultural University, Beijing, China**

  GPA: 3.22/4.0, **Master of Science in Animal Science** Granted in June 2020

- **Sep 2014-Jun 2018 South China Agricultural University, Guangzhou China**

  GPA: 3.62/5.0, **Bachelor of Science in Animal Science** Granted in June 2018

A.2 RESEARCH INTERESTS / SUMMARY

- Focused on precision farming, interested in developing models helping manage chicken farm and improve poultry welfare based on computer vision;
- Additional interest includes optimizing feed formula for feed mills and dealing with practical problems such as feed waste and waste disposal in farms;
- Conducted several field trips and internships in farms and feed mills, has been practicing solving front-line difficulties with professional knowledge.

A.3 RESEARCH TECHNIQUES AND SKILLS

- Computer Vision: Python, deep learning, object recognition, classification, and segmentation by neural network
- Real-time PCR: Detection of microorganisms in rumen fluid and feces
- Gas Chromatograph: Determination of rumen fluid volatile fatty acids

- Proximate Analysis: Including moisture, ash, crude protein, ether extract, neutral detergent fiber, acid detergent fiber and so on
- Other skills: Using thermal camera and SLR camera, collecting rumen fluid by a flexible esophageal tube; Design feed formula

A.4 RESEARCH AND INTERNSHIP EXPERIENCES

Sep 2021-Present, *Research Assistant*

University of Georgia **Athens**

- Rear 800 cage-free chickens at Poultry Research Center and installed video systems, light control systems to collect image data
- Measuring chicken body weight based on thermal camera and deep learning for less labor of weighting birds
- Detecting cage-free chicken and calculating total number of recognized chickens to improve real-time detection of chicken using deep learning
- Classifying behaviors of chicken automatically via convolutional neural network and utilizing these behavioral indicators to improve chicken welfare
- Monitoring wild birds by computer vision to prevent high pathogenic avian influenza (HPAI)
- Breeding Athens Canadian Random Bred (ACRB)
- Helping extension (International Poultry Short Course, 4-H) at department of poultry science

Sep 2020-May 2021, *Lab assistant*

Sinovac Life Science Co., Ltd. **Beijing**

- Worked as a lab assistant to evaluate the effectiveness of the vaccines

Mar 2019-Jun 2019, ***Assistant Experimenter Intern***

Hong' An High-Quality Beef Cattle Technology Breeding Co., Ltd. Yangxin

- Part of the graduation experiment for my master's degree, researched with doctoral students
- Targeted to solve the problem of high tannin content in sorghum as the feed for cattle
- Conducted Latin Square Experiment on Simmental bull, utilized the theoretical basis that polyethylene glycol can eliminate the toxic and side effects of tannin, increased the use of tannin-rich feed for beef cattle, which allowed sorghum to become a roughage resource that could feed grass-eating livestock like cattle, sheep, and camels in large quantities
- Reduced nitrogen emissions in animal feces with a certain proportion of polyethylene glycol and tannin in their feed

Jun2018-Aug 2018, ***Member, Elite Cattlemen Summer Program***

DeLaval Beijing and College of Animal Science and Technology, China Agricultural University Beijing

- Joined as a member of the Elite Cattlemen Summer Program, merit-based, highly selective
- Acquired theoretical lessons and production training at DeLaval, Beijing, in English; studied comprehensive and systemic solutions including traditional and fully automatic milking systems, milk quality and animal health maintaining, milk refrigeration, cow comfort, ranch supplies, feeding, manure treatment, barn facilities, and ranch management support systems, covering all aspects of ranch operations
- Applied the knowledge to help dairy farmers to take care of cows and produce dairy products

Sep 2017-Mar 2018, ***Academic Research***

Undergraduate Thesis, *The Distribution of Glucose Transporters at the Placenta of Sow*, South China Agricultural University, Guided by Associate Professor Fang Chen Guangzhou

- Extracted RNA from different parts of the pig placenta, conducted real-time PCR, and explored the distributionsof the glucose transporter
- Provided a theoretical basis for the use of glucose in pregnant sows, discussed the distribution of glucose carriers in the pig placenta preliminarily, prepared basic data for future research on the function of glucose transporters

Jul2017-Aug 2017, *Assistant ExperimenterIntern*

Changjiang Food Group Co., Ltd. Foshan

- Performed piglet fattening experiments and learned to design experiments on production issues
- Fed 300 piglets for one month, grouped them based on their initial weight, compared four feed produced by different companies by analyzing feed intake

Aug 2016, *Field Study*, *Farm Breeding Intern*

Guangdong Wen's Foodstuffs Group Co.,Ltd. Zhaoqing

- Learned breeding techniques, and experienced the whole process from breeding the pigs to selling the pigs
- StudiedWen's unique family cooperation model, provided farmers the unified piglets, vaccines, feed, and other technical instructions, helped them sow more piglets, reduce feed costs, and improve maturity rate

Jun2015-Jun 2017, *Pet Breeding Intern, Team Leader*

College of Animal Science, South China Agricultural University Guangzhou

- Undergraduate Innovation and Entrepreneurship Program for the breeding of mammals and ornamental birds
- Visited the pet laboratory three times a week, successfully bred two litters of Chinchillas, a litter of Russian blue cats, and a litter of Garfield cats, witnessed the yellow Opaline, pink Bourke's Parrot, and other Ploceidae breeding offspring in the lab
- Exhibited on pet culture festival, presented achievements to primary schools students nearby

Aug2014, *Feeding Intern*

ZhongshanJianbang Feed Technology Co., Ltd **Zhongshan**

- Understood the process of feed production, assisted workers to produce the feed, involved in the production and packaging of premixed feed, an average of 300 bags, each 20kg, were produced each day

A.5 PROJECTS

[1] 2023-2024: Post Vaccination Performance Model Development with Zoetis (the world's largest producer of medicine and vaccinations for pets and livestock). $100,000 (leader).

[2] 2023-2026: Precision farming practices for sustainable egg production. USDA-NIFA. $300,000 (participant).

[3] 2023-2024: A Precision Tracking System in Food Supply Chain. UGA. $37,500 (participant).

[4] 2022-2024: An automatic imaging system for poultry welfare evaluation. Georgia Research Alliance. $50,000 (participant).

[5] 2022-2024: Cloud computing for cage-free egg production. Oracle America. $100,000 (gifts

- computers/cloud credits). (Participant).

[6] 2020-2023: An integrated method for air quality management in cage-free houses. Egg Industry Center. $100,000 (participant).

A.6 PUBLICATIONS (31 peer-reviewed papers, 1 M.S. thesis, 29 conferences papers and 9 first author international conference presentations)

Peer Reviewed Journal Articles

[1] **Yang, X**., Dai, H., Wu, Z., Bist, R. B., Subedi, S., Sun, J., ... & Chai, L. (2024). An innovative segment anything model for precision poultry monitoring. Computers and Electronics in Agriculture, 222, 109045, doi.org/10.1016/j.compag.2024.109045.

[2] **Yang, X**., Bist, R. B., Paneru, B., & Chai, L. (2024). Deep Learning Methods for Tracking the Locomotion of Individual Chickens. Animals, 14(6), 911, doi.org/10.3390/ani14060911.

[3] **Yang, X**., Bist, R. B., Paneru, B., Liu, T., Applegate, T., Ritz, C., ... & Chai, L. (2024). Computer Vision-Based cybernetics systems for promoting modern poultry Farming: A critical review. Computers and Electronics in Agriculture, 225, 109339, doi.org/10.1016/j.compag.2024.109339.

[4] **Yang, X**., Bist, R. B., Paneru, B., & Chai, L. (2024). Deep Learning Methods for Tracking the Locomotion of Individual Chickens. Animals, 14(6), 911, doi.org/10.3390/ani14060911.

[5] **Yang, X.,** Bist, R. B., Subedi, S., Wu, Z., Liu, T., Paneru, B., & Chai, L. (2024). A Machine Vision System for Monitoring Wild Birds on Poultry Farms to Prevent Avian Influenza. AgriEngineering, 6(4), 3704-3718, doi.org/10.3390/agriengineering6040211.

[6] **Yang, X**., Bist, R., Subedi, S., & Chai, L. (2023). A deep learning method for monitoring

spatial distribution of cage-free hens. Artificial Intelligence in Agriculture, 8, 20-29, doi.org/10.1016/j.aiia.2023.03.003.

[7] **Yang, X**., Bist, R., Subedi, S., Wu, Z., Liu, T., & Chai, L. (2023). An automatic classifier for monitoring applied behaviors of cage-free laying hens with deep learning. Engineering Applications of Artificial Intelligence, 123, 106377, doi.org/10.1016/j.engappai.2023.106377.

[8] **Yang, X**., Bist, R. B., Subedi, S., & Chai, L. (2023). A computer vision-based automatic system for egg grading and defect detection. Animals, 13(14), 2354, doi.org/10.3390/ani1314.

[9] **Yang, X**., Chai, L., Bist, R. B., Subedi, S., & Wu, Z. (2022). A deep learning model for detecting cage-free hens on the litter floor. Animals, 12(15), 1983, doi.org/10.3390/ani1215.

[10] **Yang X**., Jinchang Zhang, Bidur Paneru, Jiakai Lin, Ramesh Bist, Guoyu Lu, Lilong Chai, Monitoring Dead Chickens and Floor Eggs with Robotic Technologies. (Submitted)

[11] Bist, R. B., **Yang, X**., Subedi, S., & Chai, L. (2024). Automatic detection of bumblefoot in cage-free hens using computer vision technologies. Poultry Science, 103(7), 103780, https://doi.org/10.1016/j.psj.2024.103780.

[12] Bist, R. B., **Yang, X**., Subedi, S., Ritz, C. W., Kim, W. K., & Chai, L. (2024). Electrostatic particle ionization for suppressing air pollutants in cage-free layer facilities. Poultry Science, 103(4), 103494, https://doi.org/10.1016/j.psj.2024.103494.

[13] Bist, R. B., **Yang, X**., Subedi, S., Paneru, B., & Chai, L. (2024). Enhancing Dust Control for Cage-Free Hens with Electrostatic Particle Charging Systems at Varying Installation Heights and Operation Durations. AgriEngineering, 6(2), 1747-1759, https://doi.org/10.3390/agriengineering6020101.

[14] Bist, R. B., **Yang, X**., Subedi, S., Paneru, B., & Chai, L. (2024). An Integrated Engineering Method for Improving Air Quality of Cage-Free Hen Housing. AgriEngineering, 6(3), 2795-2810, https://doi.org/10.3390/agriengineering6030162.

[15] Li, W., Zhang, X., Li, J., **Yang, X**., Li, D., & Liu, Y. (2024). An explanatory study of factors influencing engagement in AI education at the K-12 Level: an extension of the classic TAM model. Scientific Reports, 14(1), 13922, https://doi.org/10.1038/s41598-024-64363-3.

[16] Paneru, B., Bist, R., **Yang, X**., & Chai, L. (2024). Tracking perching behavior of cage-free laying hens with deep learning technologies. Poultry Science, 103(12), 104281, https://doi.org/10.1016/j.psj.2024.104281.

[17] Bist, R. B., **Yang, X**., Subedi, S., Bist, K., Paneru, B., Li, G., & Chai, L. (2024). An automatic method for scoring poultry footpad dermatitis with deep learning and thermal imaging. Computers and Electronics in Agriculture, 226, 109481, https://doi.org/10.1016/j.compag.2024.109481.

[18] Saeidifar, M., Li, G., Chai, L., Bist, R., Rasheed, K. M., Lu, J., ... & **Yang, X**. (2024). Zero-shot image segmentation for monitoring thermal conditions of individual cage-free laying hens. Computers and Electronics in Agriculture, 226, 109436, https://doi.org/10.1016/j.compag.2024.109436.

[19] Guo, Y., Aggrey, S. E., **Yang, X**., Oladeinde, A., Qiao, Y., & Chai, L. (2023). Detecting broiler chickens on litter floor with the YOLOv5-CBAM deep learning model. Artificial Intelligence in Agriculture, 9, 36-45, https://doi.org/10.1016/j.aiia.2023.08.002.

[20] Bist, R. B., **Yang, X**., Subedi, S., & Chai, L. (2023). Illuminating Solutions for Reducing Mislaid Eggs of Cage-Free Layers. AgriEngineering, 5(4), 2170-2183, https://doi.org/10.3390/agriengineering5040133.

[21] Lu, H., Xue, M., Nie, X., Luo, H., Tan, Z., **Yang, X**., ... & Wang, T. (2023). Glycoside hydrolases in the biodegradation of lignocellulosic biomass. 3 Biotech, 13(12), 402, doi.org/10.1007/s13205-023-03819-1.

[22] Bist, R. B., Subedi, S., Chai, L., Regmi, P., Ritz, C. W., Kim, W. K., & **Yang, X**. (2023). Effects of perching on poultry welfare and production: a review. Poultry, 2(2), 134-157, https://doi.org/10.3390/poultry2020013.

[23] Bist, R. B., Subedi, S., **Yang, X**., & Chai, L. (2023). Effective Strategies for Mitigating Feather Pecking and Cannibalism in Cage-Free W-36 Pullets. Poultry, 2(2), 281-291, https://doi.org/10.3390/poultry2020021.

[24] Bist, R. B., Subedi, S., **Yang, X**., & Chai, L. (2023). A novel YOLOv6 object detector for monitoring piling behavior of cage-free laying hens. AgriEngineering, 5(2), 905-923, https://doi.org/10.3390/agriengineering5020056.

[25] Bist, R. B., Subedi, S., **Yang, X**., & Chai, L. (2023). Automatic detection of cage-free dead hens with deep learning methods. AgriEngineering, 5(2), 1020-1038, https://doi.org/10.3390/agriengineering5020064.

[26] Subedi, S., Bist, R., **Yang, X**., & Chai, L. (2023). Tracking pecking behaviors and damages of cage-free laying hens with machine vision technologies. Computers and Electronics in Agriculture, 204, 107545, doi.org/10.1016/j.compag.2022.107545.

[27] Bist, R. B., Subedi, S., Chai, L., & **Yang, X**. (2023). Ammonia emissions, impacts, and mitigation strategies for poultry production: A critical review. Journal of Environmental Management, 328, 116919, doi.org/10.1016/j.jenvman.2022.116919.

[28] Bist, R. B., **Yang, X**., Subedi, S., & Chai, L. (2023). Mislaying behavior detection in cage-free hens with deep learning technologies. Poultry Science, 102(7), 102729,

https://doi.org/10.1016/j.psj.2023.102729.

[29] Bist, R. B., **Yang, X**., Subedi, S., Sharma, M. K., Singh, A. K., Ritz, C. W., ... & Chai, L. (2023). Temporal variations of air quality in cage-free experimental pullet houses. Poultry, 2(2), 320-333, doi.org/10.3390/poultry2020024.

[30] Subedi, S., Bist, R., **Yang, X**., & Chai, L. (2023). Tracking floor eggs with machine vision in cage-free hen houses. Poultry Science, 102(6), 102637, https://doi.org/10.1016/j.psj.2023.102637.

[31] Xie, B., **Yang, X**., Yang, L., Wen, X., & Zhao, G. (2021). Adding polyethylene glycol to steer ration containing sorghum tannins increases crude protein digestibility and shifts nitrogen excretion from feces to urine. Animal Nutrition, 7(3), 779-786, https://doi.org/10.1016/j.aninu.2021.03.002.

A.7 M.S. THESIS

[32] **Yang, X**. 2020. Effects of adding different levels of polyethylene glycol to sorghum diets on rumen fermentation, rumen microflora, nutrient digestibility and plasma biochemical indicators of beef cattle.

A.8 CONFERENCE PAPERS/ABSTRACT

[1] **Yang, X**, L. Chai, R. Bist, S. Subedi, and Z. Wu. Monitoring cage-free laying hens with deep learning models. 2023 US Livestock Farming Conference. Knoxville, TN, May 21-24 Full Paper accepted.

[2] Bist, R. B, **X. Yang**, and S. Subedi, L. Chai. Monitoring floor egg laying behaviors of cage-

free hens with machine vision. 2023 US Livestock Farming Conference. Knoxville, TN, May 21-24. Full Paper accepted.

[3] Subedi, S., L. Chai, R. Bist, **X. Yang**. Floor Egg Detection with Machine Vision in Cage-free Hen Houses. 2023 US Livestock Farming Conference. Knoxville, TN, May 21-24. Full Paper accepted.

[4] **Yang, X**., Bist, R., Subedi, S., L. Chai. Tracking cage-free laying hens on litter floor with machine vision. 2023 International Poultry Scientific Forum (IPSF), Jan. 22-23, Atlanta, GA.

[5] Bist, R., Yang, X., Subedi, S., L. Chai*. Monitoring mislaying behaviors of cage-free hens with deep learning. 2023 International Poultry Scientific Forum (IPSF), Jan. 22-23, Atlanta, GA.

[6] Subedi, S., **Yang, X**., Bist, R., L. Chai. Detecting Floor Eggs with Machine Vision Technologies. 2023 International Poultry Scientific Forum (IPSF), Jan. 22-23, Atlanta, GA.

[7] **Yang, X**., L. Chai, R. Bist, and S. Subedi. 2022. Litter quality in cage-free houses. 2022 ASABE Annual International Meeting. Paper# 2200925 (doi:10.13031/aim.202200925).

[8] Bist, R. L. Chai, **Yang, X**., S. Subedi. 2022. Air quality in cage-free hen houses during pullets production. 2022 ASABE Annual International Meeting. Paper# 2200329 (doi:10.13031/aim.202200329).

[9] Bist, R. B, S. Subedi and **X, Yang**, L. Chai. Detecting cage-free hens bumblefoot with deep learning models. 2023 Poultry Science Association (PSA) Annual Meeting. Jul 9-13. Philadelphia, PA.

[10] Bist, R. B, S. Subedi and **X, Yang**, L. Chai. Synergistic effect of electrostatic particle ionization and bedding management on particulate matter and ammonia reduction in cage-

free hen houses 023 Poultry Science Association (PSA) Annual Meeting. Jul 9-13. Philadelphia, PA.

[11] **Yang, X**., Bist, R., Subedi, S., L. Chai. A automatic system for grading and sorting cage-free eggs based on computer vision. 2023 Poultry Science Association (PSA) Annual Meeting. Jul 9-13. Philadelphia, PA.

[12] Bist, R.B., Chai, L., **Yang, X**. and Subedi, S., 2023. Effects of artificial dusk lighting on perching behaviors of cage-free laying hens. In *2023 ASABE Annual International Meeting* (p. 1). American Society of Agricultural and Biological Engineers.

[13] Bist, R.B., Chai, L., **Yang, X**. and Subedi, S., 2023. Cage Free Hens' Feather Pecking Management. In *2023 ASABE Annual International Meeting* (p. 1). American Society of Agricultural and Biological Engineers.

[14] Subedi, S., Bist, R., **Yang, X**., L. Chai.Multiple Behavior Classification of Cage-free Laying Hens using Deep Learning. 2023 International Conference on Integrative Precision Agriculture. May 18-19. Athens, GA.

[15] **Yang, X**., Bist, R., Subedi, S., L. Chai. A computer vision based automatic system for egg grading and defect detection. 2023 International Conference on Integrative Precision Agriculture. May 18-19. Athens, GA

[16] Bist, R. B, S. Subedi and **X, Yang**, L. Chai. An integrated engineering method for mitigating air pollutant emissions from cage-free hen houses. 2023 UGA Cleantech Symposium.

[17] Bist, R. B, S. Subedi and **X, Yang**, L. Chai. Bedding management for suppressing particulate matter in the cage-free layer house. 2022 *ASABE Annual International Meeting*.

[18] **Yang, X**., L. Chai, R. Bist, and S. Subedi. Detecting cage-free laying hens on litter floor with machine vision. 2022 Poultry Science Association (PSA) Annual Meeting. July. 11-14,

San Antonio, TX.

[19] **Yang, X**., L. Chai, R. Bist, and S. Subedi. Monitoring litter quality in cage-free facilities with W-36 pullets. 2022 Poultry Science Association (PSA) Annual Meeting. July. 11-14, San Antonio, TX.

[20] Bist, R. B, S. Subedi and **X, Yang**, L. Chai. Bedding management for suppressing particulate matter in the cage-free layer house. 2022 oultry Science Association (PSA) Annual Meeting. July. 11-14, San Antonio, TX.

[21] Bist, R. B, B, Paneru, S. Subedi and **X, Yang**, L. Chai.Tracking dustbathing behavior of cage-free laying hens with machine vision technologies. Jan 30-Feb 1, Atlanta, GA.

[22] **X, Yang**, Bist, R. B, S. Subedi and B, Paneru, L. Chai.Deep learning algorithms for tracking individual chicken for locomotion analysis. Jan 30-Feb 1, Atlanta, GA.

[23] Bist, R. B, **X, Yang**, S. Subedi and B, Paneru, L. Chai.Automatic detection and scoring of footpad dermatitis in poultry utilizing YOLOv8-FPD models. Jan 30-Feb 1, Atlanta, GA.

[24] Paneru, B., Bist, R., **Yang, X.**, & Chai, L. (2024). Using Machine Learning to Detect Dustbathing Behavior of Cage-free Laying Hens Automatically. In 2024 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. June 28-August 1, Anaheim, CA.

[25] Bist, R. B., Bist, K., **Yang, X.**, Paneru, B., & Chai, L. (2024). Automatic Detection and Scoring of Footpad Dermatitis in Laying Hens Using Machine Learning Models. In 2024 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. June 28-August 1, Anaheim, CA.

[26] Paneru, B., Bist, R., **Yang, X.**, & Chai, L. (2024). Detecting Perching Behavior of Cage-Free Laying Hens with Machine Vision Technologies. In 2024 ASABE Annual International

Meeting (p. 1). American Society of Agricultural and Biological Engineers. June 28-August 1, Anaheim, CA.

[27] **Yang, X.**, Bist, R., Paneru, B., & Chai, L. (2024). Advanced Machine learning Techniques for Monitoring Poultry Movement Patterns. In 2024 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. June 28-August 1, Anaheim, CA.

[28] Bist, R. B., Bist, K., **Yang, X.**, Paneru, B., & Chai, L. (2024). Machine Learning Model for Detection, Segmentation, and Tracking of Individual Cage-free Laying Hens. In 2024 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. June 28-August 1, Anaheim, CA.

[29] Bist, R. B., Regmi, P., **Yang, X.**, Subedi, S., Paneru, B., & Chai, L. (2024). Comparative Assessments of Cage-free Pullet Age, Activities, and Impacts on Dust Concentration Using Accelerometer-Based Activity Sensors. In 2024 ASABE Annual International Meeting (p. 1). American Society of Agricultural and Biological Engineers. June 28-August 1, Anaheim, CA.

A.9 PRESENTATIONS

[1] **Yang, X**, L. Chai, R. Bist, S. Subedi. Monitoring litter quality in cage-free facilities with W-36 pullets. 2022 International Poultry Scientific Forum (IPSF), Jan. 22-23, Atlanta, GA. (Post Presentation).

[2] **Yang, X**., Bist, R., Subedi, S., L. Chai. Tracking cage-free laying hens on litter floor with machine vision. 2023 International Poultry Scientific Forum (IPSF), Jan. 22-23, Atlanta, GA. (Oral Presentation).

[3] **Yang, X**., L. Chai, R. Bist, and S. Subedi. Detecting cage-free laying hens on litter floor with machine vision. 2022 Poultry Science Association (PSA) Annual Meeting. July. 11-14, San Antonio, TX. (Oral Presentation).

[4] **Yang, X**., Bist, R., Subedi, S., L. Chai. A deep learning method for detecting cage- free hens on the litter floor. 2022 Poultry Science Graduate Research Forum Department of Poultry Science UGA. May 4. Athens GA. (Oral Presentation).

[5] **Yang, X**, L. Chai, R. Bist, S. Subedi, and Z. Wu. Monitoring cage-free laying hens with deep learning models. 2023 US Livestock Farming Conference. May 21-24. Knoxville, TN (Oral Presentation).

[6] **Yang, X**., Bist, R., Subedi, S., L. Chai. A computer vision based automatic system for egg grading and defect detection. 2023 International Conference on Integrative Precision Agriculture. May 18-19. Athens, GA (Poster Presentation).

[7] **Yang, X**., Bist, R., Subedi, S., L. Chai. A automatic system for grading and sorting cage-free eggs based on computer vision. 2023 Poultry Science Association (PSA) Annual Meeting. Jul 9-13. Philadelphia, PA (Oral Presentation).

[8] **Yang, X**., Bist, R., Subedi, S., L. Chai. Deep learning algorithms for tracking individual chicken for locomotion analysis. 2024 International Poultry Scientific Forum (IPSF), Jan. 30-Feb 1, Atlanta, GA. (Oral Presentation).

[9] **Yang, X.**, Bist, R., Paneru, B., & Chai, Advanced Machine learning Techniques for Monitoring Poultry Movement Patterns. 2024 American Society of Agricultural and Biological Engineers (ASABE) Annual International Meeting. June 28-August 1, Anaheim, CA. (Oral Presentation)

A.10 AWARDS AND HONORS

- Poultry science forum 3rd prize, 2022
- Student Hackathon Poultry Track Competition 1st Prize, 2023
- Graduate student summer research grand, 2023
- Gainesville Spring Chicken Scholarship Award 1st Prize, 2023
- AOC Graduate Academic Achievement Award, 2024
- AOC Student Research Presentation Award, 2nd Prize, 2024

A.11 REVIEW

- The First Workshop on DL-Hardware Co-Design for AI Acceleration 2023
- IEEE Transactions on Neural Networks and Learning Systems 2 times (Impact factor: 10.4)
- Frontiers in Bioengineering and Biotechnology (Impact factor: 5.7)
- 2nd U.S. Precision Livestock Farming Conference 2 times
- Process Biochemistry 3 times (Impact factor: 7.9)
- Computers and electronics in Agriculture 5 times (Impact factor: 8.3)
- Artificial Intelligence in Agriculture (Impact factor: 8.0)
- Biosystems Engineering (Impact factor: 5.1)
- British Poultry Science (Impact factor: 2.0)
- PeeJ Computer Science 17 times (Impact factor: 3.8)
- Frontiers in Medicine (Impact factor: 3.9)

- Frontiers in Immunology (Impact factor: 7.3)
- Animals 17 times (Impact factor: 3.20)
- Discover Oncology 2 times (Impact factor: 4.7)
- Frontiers in Immunology (Impact factor: 7.3)
- BMC Bioinformatics 10 times (Impact factor: 3.0)
- Computational and Mathematical Methods 2 times (Impact factor: 0.9)
- Animals (Impact factor: 3.2)
- PLOS ONE 7 times (Impact factor: 3.7)
- Poultry Science (Impact factor: 4.4)
- Briefings in Functional Genomics 2 times (Impact factor: 4.0)
- Applied Sciences 4 times (Impact factor: 2.7)
- Electronics 13 times (Impact factor: 2.9)
- Machines 2 times (Impact factor: 2.6)
- Algorithms 2 times (Impact factor: 2.3)
- Vehicles 2 times ((Impact factor: 2.2)
- Computers (Impact factor: 2.80)
- Signals
- Medicine (Impact factor: 2.6)
- American Society of Agricultural and Biological Engineers (Impact factor: 1.5)
- Internal Journal of Molecular Sciences (Impact factor: 5.6)

- Engineering Open Access 21 times (Impact factor: 1.2) (**Served as editor**)
- Journal of Nursing & Healthcare 14 times (Impact factor: 1.9) (**Served as editor-in-chief**)

A.12 MEMBERSHIPS

- Poultry Science Association (PSA)
- World's Poultry Science Association (WPSA)
- American Society of Agricultural and Biological Engineers (ASABE)
- Association of Overseas Chinese Agricultural, Biological, and Food Engineers (AOCABFE)

A.13 GRANT APPLIED

1. **UGA- Summer Research Grant.** " A computer vision-based automatic system for egg grading and defect detection." (Funded: $1500; 2023).
2. **Greenacres Grand from Greenacres Foundation.** "Develop an automatic system to grade and weight table eggs with an innovative machine vision system in cage-free hen houses" (Unfunded; 2023)
3. **Graduate Student Travel Grant** from the Graduate School at the University of Georgia (Funded: $900; 2024).