Flock Behaviour Analysis using Computer Vision and Deep Learning Techniques on Egg Farms

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Thesis submitted in fulfilment of the requirements for the degree of
Master of Science in Computing Sciences (Research)
under the supervision of Jian Zhang

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Certificate of Original Authorship

I, Zhen Luo, declare that this thesis is submitted in fulfilment of the requirements for the award of Master of Science in Computing Sciences (Research), in the School of Electrical and Data Engineering at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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Abstract

Laying hen behaviour is a vital indicator of welfare, health, and production performance, making its continuous and objective monitoring a central challenge in modern poultry farming. Traditional qualitative methods are labor-intensive and limited in their ability to capture subtle or long-term behavioural changes. Similarly, existing computer vision approaches often perform well under laboratory conditions but struggle to adapt to commercial farms, where high stocking densities, environmental variability, and complex interactions present significant challenges. Addressing these limitations is essential for advancing precision livestock farming and improving both animal welfare and productivity. This thesis develops a comprehensive framework that integrates deep learning, computer vision techniques to provide robust, real-time monitoring of laying hens, while incorporating temperature data to support the analysis and interpretation of laying hen behaviours. First, a non-invasive monitoring system was designed to quantify the duration and frequency of key behaviours, enabling the detection of subtle welfare-related changes. Unlike qualitative observation, this system provides objective, continuous measurements that support the identification of eating, drinking, or other activities. To advance algorithm development, this work introduces ChickenbehaviourView, the first top-down, multi-task chicken behaviour dataset, consisting of 16,991 annotated instances across 98 video sequences. The dataset enables benchmarking for detection, tracking, and behaviour recognition tasks, providing a valuable resource for the research community. Benchmark experiments demonstrate the feasibility of applying state-of-the-art models, while environmental data such as shed temperature were integrated with behaviour metrics, offering new insights into how external conditions shape welfare outcomes. Building on these advances, a prototype monitoring system was deployed under commercial farm conditions, demonstrating improved scalability and reliability compared to prior laboratory-focused studies. By incorporating multi-angle video analysis, deep learning algorithms, and multimodal data fusion, the system reveals hidden behavioural patterns and provides a more holistic view of flock dynamics. This approach supports precise interventions, reduces reliance on manual observation, and minimizes animal stress by enabling fully automated monitoring. Overall, this thesis contributes both methodological advances and practical tools for the poultry industry. It bridges the gap between controlled research environments and real-world deployment, advancing the technical frontier of behaviour monitoring while supporting the goals of sustainable and welfare-focused poultry production. Beyond laying hens, the proposed framework holds promise for broader applications across livestock systems, with important implications for the ecological sustainability, and animal health.

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Chapter 1

Introduction

Global demand for poultry products continues to rise, driven by population growth and heightened expectations for food quality, safety, and sustainability. At the same time, public concern for farm-animal welfare has intensified, prompting commercial egg producers to seek systems capable of monitoring hens more effectively, more continuously, and with greater scientific rigour. Laying hens express a wide repertoire of behaviours—eating, drinking, perching, exploring, and social interactions—that collectively serve as key indicators of welfare, health, and productivity. Understanding how these behaviours vary across time, temperature, stocking density, and management conditions is essential for both welfare-focused farming and profitable egg production.

Yet, despite their importance, current welfare-monitoring practices remain overwhelmingly qualitative. Manual observations are labour-intensive, subjective, and impractical in commercial sheds housing 25,000–50,000 hens. RFID-based systems, while providing individual-level tracking, are intrusive, restricted to adult hens, and unsuitable for large-scale flock-level behavioural assessment. Even recent advances in computer vision have largely focused on behaviour classification rather than behaviour quantification. They can recognise whether a bird is eating or drinking, but very few systems can measure how long hens perform these activities, what proportion of the flock is active at any given moment, or how these behaviours change over time. Consequently, commercial farms still lack reliable, continuous measurements of where, when, and for how long hens eat or drink—two behaviours that directly influence nutrient intake, heat stress, and egg production. This explains why nearly all existing studies remain qualitative, offering categorical labels instead of quantitative, welfare-relevant metrics.

Critically, previous research has only been able to qualitatively analyse hen behaviour, not quantitatively. This limitation prevents early detection of welfare risks, restricts evidence-based management, and hinders the development of precision-livestock technologies suitable for real-world commercial deployment. Eating and drinking are also instantaneous behaviours that last only fractions of a second, making them difficult to detect reliably in crowded, dynamic environments. These technical barriers have long impeded progress toward achieving automated, quantitative behavioural monitoring at flock scale.

To address these challenges, this thesis integrates modern computer vision, deep learning, and operational farm data to develop a continuous, automated, and quantitative behaviour-monitoring system for commercial egg farms. The system bridges the gap between academic research—often trialled in clean, controlled laboratory environments—and the complex visual

conditions of large commercial sheds, where occlusion, dust, crowding, and variable lighting present persistent challenges.

1.1 Research Objectives and Overview

The overarching research question addressed in this thesis is:

How can deep learning and computer vision techniques be effectively applied to monitor, quantify, and analyze laying hen behaviours in commercial farm environments to improve welfare and productivity?

To answer this question, the thesis pursues the following objectives:

1. Develop a comprehensive, top-down video dataset of laying hen behaviours, annotated for detection, tracking, and behavioural classification.
2. Design and implement a real-time prototype system integrating state-of-the-art detection and tracking models for automated monitoring of individual and group behaviours.
3. Quantitatively analyze hen behaviours in relation to environmental factors, providing actionable insights for welfare and productivity management.

The structure of the thesis is organized to address these objectives progressively:

- Chapter 2 provides a comprehensive literature review of deep learning and computer vision applications in poultry science and other livestock domains. It examines current methods for behaviour recognition, detection, and tracking, highlighting technological gaps and opportunities for precision livestock farming.
- Chapter 3 introduces **ChickenbehaviourView**, the first top-down, multi-task video dataset for laying hen behaviour analysis. This dataset enables detection, tracking, and behavioural classification, serving as a benchmark for both academic research and practical farm applications.
- Chapter 4 details the development of the detection and tracking models used in the prototype system. It evaluates different backbone and head architectures, compares state-of-the-art detectors, and integrates ByteTrack for robust multi-object tracking under commercial farm conditions.
- Chapter 5 presents quantitative behavioural analyses derived from the prototype system. It demonstrates the relationship between hen activities—such as eating and drinking—and environmental factors, providing insights for welfare assessment and operational decision-making. Comparative analyses with prior studies emphasize the innovations and scalability of the approach.
- Chapter 6 summarizes the outcomes of this research, discusses implications for precision livestock farming, and outlines recommendations for future work, including extending behavioural coverage, integrating multimodal data, and deploying the system at scale.

1.2 Contributions of This Thesis

This thesis addresses these limitations through a set of novel datasets, models, and analytical tools designed specifically for large-scale commercial poultry environments.

1.2.1 A Novel Behaviour Dataset: *ChickenbehaviourView*

This work introduces *ChickenbehaviourView*, the first top-down, multi-task video dataset focusing on eating, drinking, and other behaviours in commercial egg farms. The dataset contains 16,991 annotated instances across two farms in New South Wales and Queensland. It enables benchmarking of detection, tracking, and behaviour-recognition models under real-world commercial complexity.

1.2.2 A Real-Time Automated Behaviour Monitoring System

A complete system is developed to detect hens, track individuals, and classify their behaviours in real time. By combining NanoDet for lightweight detection and ByteTrack for stable identity preservation, the system achieves robust performance despite crowding and occlusion. It represents one of the first end-to-end computer vision systems deployed in Australian commercial egg farms.

1.2.3 Introduction of Two Quantitative Behaviour Metrics

To enable flock-level behavioural analysis, two new metrics are proposed:

- **Average activity time:** quantifies how long hens engage in a given behaviour.
- **Proportion of active birds:** measures how many hens are eating or drinking at each time period.

These metrics transform qualitative recognition into quantitative behavioural monitoring.

1.2.4 Integration with Environmental and Production Data

Video-derived statistics are correlated with temperature, feed and water consumption, egg production, and mortality records. This cross-source integration reveals patterns associated with heat stress, diurnal feeding cycles, and operational performance.

1.2.5 Demonstration of Commercial Feasibility

Unlike studies performed in controlled laboratory settings, the system developed in this thesis is evaluated on months of continuous commercial recordings, demonstrating resilience to real-world challenges such as dust, feed dusting, camera blur, and flock movement.

1.3 Summary

This Introduction chapter has outlined the motivation, context, and research direction underpinning this thesis. The growing global demand for high-quality poultry products, together with heightened expectations for animal welfare, has created an urgent need for technologies capable of monitoring laying hens continuously, objectively, and at commercial scale. However, current welfare-assessment methods remain predominantly qualitative, labour-intensive, and unsuitable for the large flock sizes typical of commercial egg farms. Existing computer vision research, although promising, has focused largely on behaviour classification rather than quantification, and has rarely been applied in dense, visually complex production environments.

Against this backdrop, this thesis advances a new direction in precision livestock farming by focusing on the quantitative measurement of eating and drinking behaviours—two fundamental indicators of welfare, nutrition, and productivity. The chapter has introduced the central research objectives: building a dedicated behaviour dataset for laying hens, developing a real-time detection-and-tracking system tailored to commercial sheds, and generating quantitative behavioural metrics that can be correlated with environmental and operational records. These objectives address critical gaps in current practice and form the foundation for behaviour-aware, data-driven farm management.

The key contributions outlined—including the creation of the *ChickenbehaviourView* dataset, the development of a robust automated monitoring system, the introduction of quantitative behaviour metrics, and the integration of cross-source farm data—together demonstrate both scientific novelty and practical relevance. By bridging the divide between controlled laboratory experiments and large-scale commercial operations, this thesis lays the groundwork for scalable, real-world deployment of computer vision systems in the poultry industry.

The subsequent chapters expand upon these contributions in detail, beginning with a comprehensive review of the literature on deep learning and behavioural analysis in livestock, followed by the dataset construction, model development, behavioural quantification, and final conclusions.

Chapter 2

Literature Review

2.1 Introduction

In poultry science area especially for the chicken, the rapid increase in the number of papers on deep learning and computer vision over the past few years reflects the growing interest of the public in deep learning for a variety of poultry animals. In this review, we would explore recent milestones in the application of computer vision systems and deep learning algorithms in poultry science. The aim of this review is to provide an overview of how deep learning can advance the use of computer vision systems in poultry science, improve the prediction of chicken phenotypes, and enable data-driven management decisions.

2.2 Deep learning methods development in poultry science

2.2.1 Deep learning methods development in chicken

detection

The most common poultry animal to do the related research is chicken. Moreover, laying hen and broiler are two different study areas. Deep learning applications for broilers and laying hens are advancing rapidly in the poultry industry, with each category having a different focus [1]. In the field of broiler farming, deep learning techniques are used to monitor the growth, health and welfare of broilers to ensure optimal yields are achieved. Computer vision techniques allow broilers to track their weight, size and gait to detect problems such as lameness or abnormal growth in a timely manner. These technologies enable precision feeding strategies by analyzing feeding behaviour and adjusting diets to optimize growth rates. In addition, deep learning-based automation systems can detect early signs of disease, such as respiratory diseases, by analyzing movement patterns and behavioural changes in broilers. Deep learning algorithms can also accurately estimate the weight of broilers, helping farmers to rationalize feed intake, optimize the growth process and reduce waste.

Deep learning models are increasingly used in poultry farming to monitor broilers for early signs of health problems such as reduced activity, difficulty standing, or lameness. By analyzing video streams, these systems detect abnormal behaviours, identify potential diseases,

and issue early warnings, enabling farmers to intervene sooner and reduce the risk of transmission. They also track flock dynamics in crowded environments, flagging aggressive interactions or stress-related behaviours that threaten welfare and productivity. This data-driven approach minimizes human intervention, lowers animal stress, and enhances output. In processing plants, deep learning assists in meat quality assessment. Image analysis of texture, color, and fat distribution allows automatic classification, ensuring consistent quality and reducing waste. On the farm, the technology extends to monitoring feeding and drinking patterns. Abnormal intake triggers alerts, helping farmers adjust strategies and maintain optimal nutrition. At the group level, activity density and feeding frequency are tracked to detect negative behaviours such as fighting or feather pecking, as well as growth issues like feed competition. By automating data collection, farmers gain real-time insights without disturbing the birds, directly improving welfare. For laying hens, applications shift toward productivity and welfare monitoring. Models track individual egg-laying patterns, feed consumption, and water intake, while predicting egg production rates based on behaviour and environmental data. Sudden drops in feeding, drinking, or laying frequency can signal disease, allowing for rapid intervention. Body size monitoring provides further health indicators, particularly during peak laying periods. Automated feeding adjustments ensure hens receive the correct nutrients at different physiological stages, supporting both health and egg production. Deep learning also helps address welfare concerns in layers, including feather pecking, roosting, and nesting behaviours. By analyzing these patterns, farmers can adapt housing and feeding conditions to reduce stress, improving both welfare and egg quality. Automated egg sorting systems rely on image recognition to rapidly screen eggs for size, shape, color, and defects, enhancing efficiency and ensuring consistent standards. In both broiler and layer systems, the integration of multimodal sensor data—such as thermal and 3D imaging—with convolutional neural networks drives the automation of poultry management. These technologies simultaneously improve productivity, welfare, and food safety, while lowering costs and supporting sustainable farming.

In Australia, the practice of free-range egg production has grown rapidly, driven by consumer perceptions that free-range systems promote better hen welfare [2]. Growing public concern about poultry welfare highlights the important link between animal welfare, product quality and consumer health [3]. Maintaining high standards of animal welfare is not only essential for the healthy development of poultry, but also reduces the incidence of disease and therefore improves the quality of livestock products. Poultry in free-range systems have greater opportunities to express natural behaviours compared to those in caged systems. Hen behaviour in particular is one of the key indicators of welfare, and research has shown that hens in good health and positive moods tend to produce more good quality eggs [4]. However, current methods for monitoring these behaviours are mostly manual, labor-intensive and prone to bias [5]. With the demand for poultry products expected to increase by 70 percent year-on-year by 2050 [6], there is an urgent need for automated and accurate systems to monitor poultry activity. These systems are critical to the effective management of poultry health and welfare, especially as natural resources such as fresh water, feed are stretched [7]. Through data-driven behavioural analysis, farmers can optimize welfare conditions for laying hens, leading to improved productivity and product quality. Behaviour is one of the key indicators in animal welfare assessment, which can be considered from multiple perspectives, including the animal's emotional state, health condition and physiological needs. Traditional welfare assessment methods rely on manual observation, which is subjective, time-costly, and discontinuous in monitoring intervals, making it difficult to get a comprehensive understanding of the real-time condition of animals. However, with the development of science and technology, automated technologies offer new possibilities for real-time, continuous detection of poultry behaviour. These technologies are

able to monitor behavioural changes around the clock without interfering with the normal life of the animal, enabling farmers to take timely interventions to improve animal welfare. Research has shown that sensor-based systems such as video surveillance, infrared sensors, accelerometers and weight sensors are capable of recording and analyzing poultry behavioural patterns continuously and accurately. These systems not only detect individual activities such as eating, drinking, exercising and social behaviour, but also identify abnormal behaviour in a group, helping farmers to detect potential health problems. With automated behavioural monitoring technology, farm managers can adjust the environment, optimize feed allocation and address health risks based on real-time data, thereby improving the efficiency and sustainability of the entire farming system. In addition, advances in sensor technology have laid the foundation for the development of precision livestock systems. By integrating data from different sensors, precision animal husbandry systems enable accurate management of individual animals, which not only improves animal welfare but also optimizes production efficiency. In the future, with the further improvement of the technology, such systems are expected to be popularized in larger-scale commercial farms, driving the entire livestock industry in the direction of intelligent, data-driven development.

Traditional methods for identifying and analyzing hen behaviours include using radio frequency identification (RFID) systems, where each hen is equipped with a silicone leg band containing a unique ID microchip to track activity patterns and durations [8]. This method is invasive, as it requires capturing each hen to secure the device on their legs. In addition, leg bands are only available for adult birds, thus limiting the age range for monitoring purposes. This challenge highlights the need for Precision Livestock Farming (PLF) technology, which enables non-intrusive, real-time monitoring [9]. The goal of PLF is to automate the continuous monitoring of animal health and welfare. Specifically, automated systems that incorporate advanced Artificial Intelligence (AI) models present a practical solution for welfare monitoring. By precisely tracking hen behaviours, farmers can gain valuable insights into the health, welfare, and productivity of laying hens, thereby enhancing the accuracy of welfare assessments [10]. Before deep learning technology came out, conventional machine learning methods were the mainstream for animal behaviour analysis. One of these methods uses a hybrid support vector machine, which involves three steps: initialization, tracking, and updating of instances. However, this approach is significantly affected by the physical scale of the observation area, the number of moving hens, and directional changes. Another direction is using the infrared (IR) camera instead of 2D cameras which can effectively avoid the variation of natural light and shadows. This kind of camera is sensitive to the temperature, humidity, dust particles and other environmental factors, so it needs extensive calibration. Moreover, IR camera is not economically friendly to build low-cost monitoring systems [11][12][13].

In recent years, deep learning based approaches have become increasingly prevalent as decision support tools in precision farming [14]. A Kinect camera was used to automatically monitor the behaviour of flock in a commercial environment by combining a computer vision system with an innovative convolutional neural network (CNN) approach, the accuracy reaches 99.17% [15]. The You Only Look Once (YOLO) model is a widely used detector applied in animal science studies (Borges Oliveira et al., 2021). The authors used YOLOv5 model to automatic detect brown hens [16] and mislaying behaviour in cage-free hens [17] while others used YOLOv7 model to track floor eggs [18]. The structure of YOLOv5 is shown in Figure 2.1.

The performance is good enough due to the advanced deep learning technologies. A tracker equipped with simple online and real-time tracking algorithm (SORT) is able to automatic monitor anomalous chicken dispersion and movement in the chicken farm. The author adopted

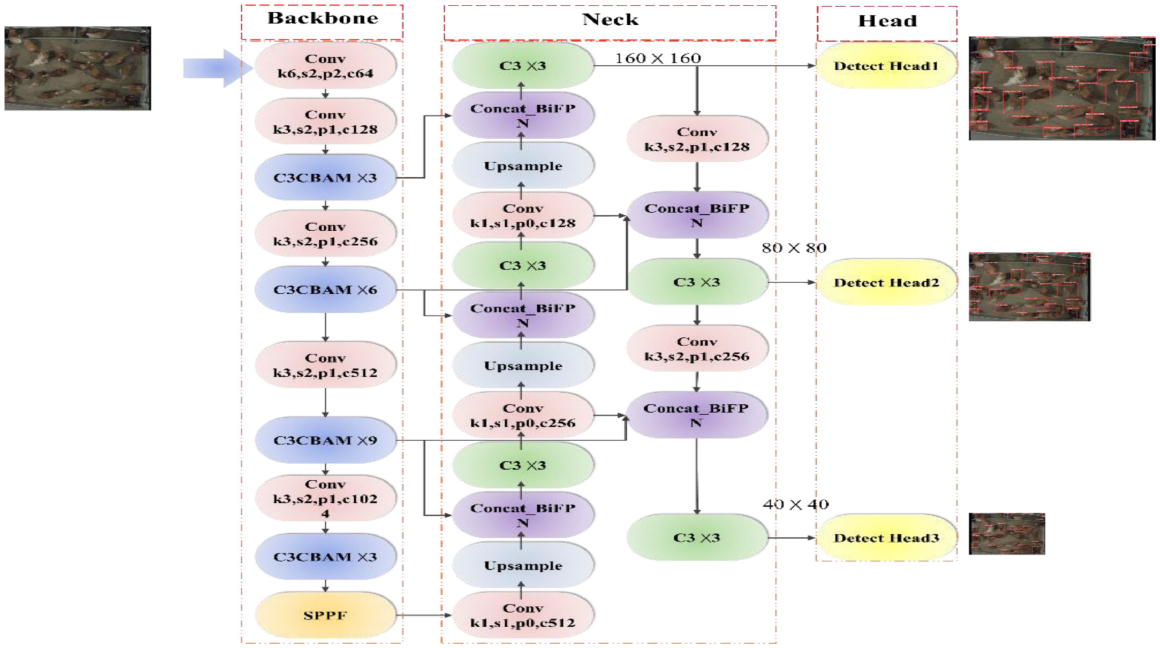


Figure 2.1: Overall structure of YOLOv5-C3CBAM-BiFPN network.

the same algorithm to evaluate tracking performance for individual broilers in terms of time and distance [19]. The most advanced chicken activity tracker combined YOLOv8 and DeepSORT models to solve the piling and smothering problems in the flock [20]. A classifier based on YOLOv5 model can successfully identify some behaviours of laying hen in various life periods and environments [21][22]. YOLOv7 and YOLOv8 are adopted in tracking perching behaviour of cage-free laying hens from different ages. This method achieves high accuracy [23]. At the meantime, same methods are used for tracking dustbathing behaviour of cage-free laying hens [24]. They just test different YOLO models and find the best one which can achieve highest accuracy. A modified algorithm for head features of caged chickens' detection based on cyclic consistent migration neural network is inspired from YOLOv8. It successfully removes the cages and get more completed outline images, provides valuable insights for future animal science researchers aiming to deploy enhanced detection equipment [25].

Overall, the widespread application of deep learning in chicken farming has greatly enhanced the automated management of the farming process, not only improved accuracy and efficiency, but also bringing about far-reaching impacts. Through deep learning technology, farms are able to monitor the health, behaviour and growth of chickens in real time, accurately capturing differences and abnormalities between individual broilers or laying hens. This precise monitoring not only reduces reliance on manual labor and lowers labor costs, but also reduces the risk of human error and ensures that each chicken grows under optimal conditions. The application of deep learning technology has also greatly boosted breeding productivity. More importantly, the application of deep learning in farming not only promotes productivity but also improves animal welfare. In the long run, the application of deep learning in chicken farming opens up opportunities for sustainability across the industry. By optimizing the use of resources, reducing waste, improving animal welfare and enhancing food safety, farms are able to achieve higher productivity without increasing the burden on the environment. This data-driven approach to farming helps to reduce the environmental impact of agriculture and drive the industry towards a more environmentally friendly and sustainable direction, laying a solid foundation for future food safety and farm operations.

2.2.2 Deep learning methods development in cow detection

Unlike the small objects like chicken, cows are much bigger than chicken and many researchers also do the research on cows combining with deep learning and computer vision methods. A deep learning network named FLYOLOv3 were proposed to identify the cow images in different lighting conditions and detect the head, leg, and back areas accurately. It can successfully detect different parts of the cow, and it compares to YOLOv3 and Faster R-CNN, achieving the highest average precision which is 99.45%. It approves the FLYYOLOv3 is the best [26]. This is the front view of the cows. For the different view like top-down view, a DCNN model are generated to do the cow identification. The proposed model can achieve the accuracy of 86.8% for the detection and 97.01% for the individual identification [27]. It is useful in cattle counting situation and can get the exact number of the loaded cows. It can benefit the real world. Differ to the focusing on the cow itself, another computer vision system equipping with the RGB-D camera is designed to measure individual cow feed intake. These findings highlight the potential of using low-cost cameras for accurately measuring individual feed intake in modern dairy farms [28]. Moreover, it is a real time system and does not need too much computation resource. A single GPU is enough for serval cameras and inferencing. Another research is detecting the position of the eyes of the cows and udders by using thermal cameras. It enhances the performance of the accuracy of the detection accuracy and makes a new way of research by the temperature of the animal [29]. This algorithm achieves an overall mean average precision of 96.8%. And it is capable to reach 99 frames per second. It can automatically identify cow mastitis. In order to improve the accuracy of behavioural recognition in dairy cows through modern data analytics, a comprehensive behavioural recognition and computational scheme has been proposed. The method uses observed sensor data to develop predictive models based on a recursive learning paradigm. The analysis focuses on identifying data patterns over continuous and discrete time intervals. In order to detect anomalous behaviours and perform behavioural modelling, similarity and dispersion metrics are used to accommodate different input sequences. The identified patterns are enhanced and adapted based on observed behavioural changes and process mapping. Pattern classification is performed for continuous and discrete sequences when behavioural changes are detected, resulting in significant improvement in recognition accuracy [30]. Some other research focuses on complex cattle behaviour patterns equipped with accelerometer data. It can successfully capture the behaviour of cattle such as walking, lying and grazing. And it can achieve over 96% accuracy [31]. Lameness, an abnormality in the way an animal walks or moves, often due to pain, injury, or dysfunction in the muscles, joints, bones, or nerves of the legs or feet is usually seen in dairy cows. It is important to find it out because lameness can lead to reduced milk production, lower fertility, and higher treatment costs, making it a key welfare and economic issue for farmers. Proper detection, diagnosis, and treatment are essential to managing and preventing lameness. YOLOv3 deep learning algorithm is developed by long short-term memory and support vector machine to do the intelligent detection [32]. The technical route is shown in Figure 2.2. A newly deep learning-based framework with improved techniques for multi-cattle tracking using video is aiming to provide greater performance through all existing methods in tracking. It can successfully track multiple cattle over a series of frames. It outperforms most popular tracking algorithms and achieve high accuracy [33]. A knowledge-driven deep learning model for efficient diagnosis of dairy cow diseases is proposed with hybrid framework. The F1 value of the model can reach 94.89% [34]. A newly deep learning model trained on autonomous data effectively forecast cattle heat stress [35]. It overcomes the limitations of the climate-based indices.

Overall, the application of deep learning technology in cattle farming not only dramatically

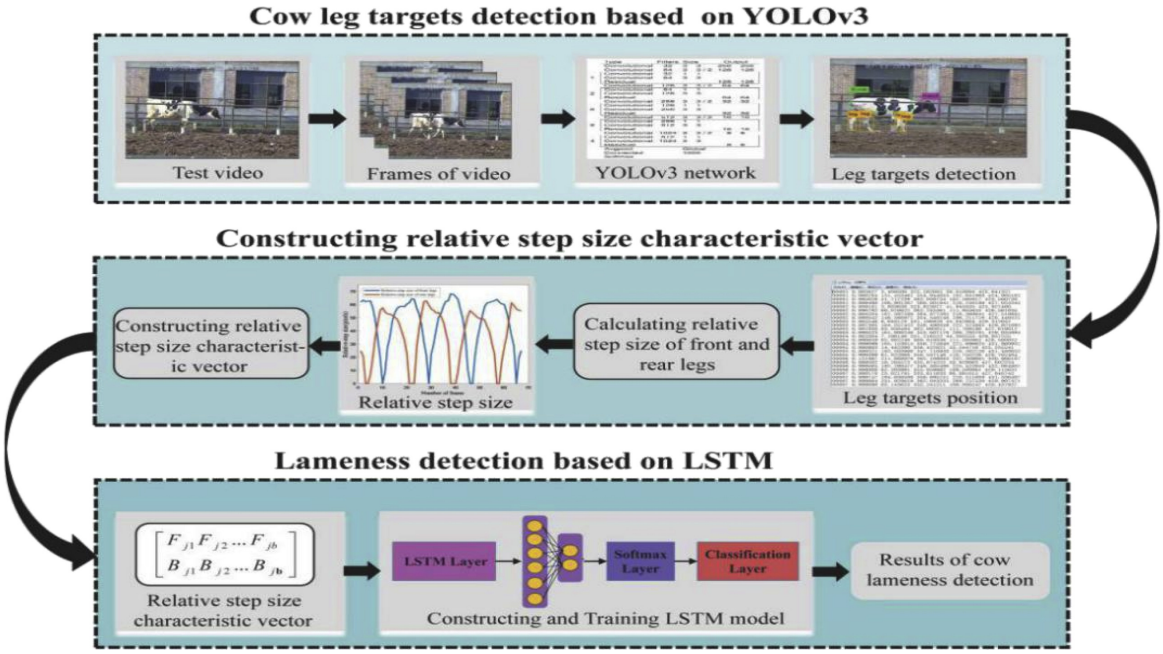


Figure 2.2: Technical route of the YOLOv3 method.

improves health management, productivity optimization and animal welfare, but also helps farmers achieve more refined and automated management. By reducing manual intervention, lowering feeding costs and improving herd health, deep learning technology brings more benefits and sustainability possibilities to modern farming.

2.2.3 Deep learning methods development in other animals' detection

The application of deep learning technology in animal husbandry is not only limited to chickens and cows but is also widely used in the breeding of other animals, such as pigs, sheep and fish, which has greatly contributed to health monitoring, production optimization, and the improvement of animal welfare in these fields. Some other big animals such as sheep and pig are similar like cows. The research for the deep learning method to dig the potential of improving animal welfare is various.

In large-scale agricultural production management, pig counting is a necessary step. A modified Counting Convolutional Neural Network (Counting CNN) model is developed to count pigs. The Mean Absolute Error (MAE) per image is 1.67 and it outperforms the competing algorithms [36]. Another research is using normal 2D camera, detecting pigs' posture and behaviour. The mean average precision is 80.2% and the average precision is 67.7% [37]. A smart pig weights estimate tool based on deep learning model is designed to provides some references for intelligent weighing researchers. It is implemented from Faster-RCNN and it uses a top-view depth cameras as the input and output [38]. Three deep learning-based detector methods, including faster regions with convolutional neural network features (Faster R-CNN), single shot multibox detector (SSD) and region-based fully convolutional network (R-FCN), combined with Inception V2, Residual Network (ResNet) and Inception ResNet V2 feature extractions of RGB images were proposed for posture detection of individual pigs by using deep learning and machine vision approaches. The mean average precision is more than 0.93. The average precision is all over than 0.92 [3]. EnsemblePigDet, which is implemented from YOLOv4, is developed

to accurately detect pig in commercial pig farms. It tries to deal with the overexposed regions and refine the model to improve the detection accuracy of the baseline [39]. An automatic sheep classifier is used to assist sheep farmers to differentiate between breeds. The average accuracy is 95.85% [40]. Just like other animals, there are also some researchers focusing on sheep behaviours recognition. A deep learning model based on YOLOv5 is adopted and the precision is 96.7% while the recall is 95.6%. It is a powerful tool for improving the breeding management level and ensuring sheep health [41]. A modified YOLOv3 algorithm is used to accurately detect the face of the sheep. The mean average precision is 96.4% and it is higher than the baseline model with the original dataset [42].

Fish is also a worthy exploring research area. An Autonomous Underwater Vehicle (AUV) is specially designed to detect the fish in the ocean and outer space combined with deep learning algorithms. The proposed method can replace human to do some dangerous detection under the ocean. Equipped with the advanced technology, the robot can fulfill human being's curiosity in the sea and extend the knowledge for human [43]. In application field, a mask R-CNN based deep learning method is used to automatically segment fish to do the fish size measurement. The key point is that there are many overlapping and occlusions in cluttered images, which need the advanced segmentation tools to deal with these different situations perfectly [44]. In the marine environment, it is very complex. It is necessary to call for the image processing techniques to do the fish species classification in unconstrained underwater environment. A convolution neural network model in a hierarchical feature combination is set up to solve the problem. The correct classification rate is more than 90% [45]. Deep learning technology can also automatically screen high-quality individuals to improve farming efficiency and ensure high-quality fish products. However, there are still many challenges for smart fishing farming. First thing is that the trained model needs lots of the labelled data to train. Without perfect data to feed the model, it can not achieve high performance. Moreover, test data and validation data is also needed labelling, otherwise it will fail to successfully evaluate the model. The key point for the deep learning model is extracting features from the dataset. Nevertheless, it is still useful for the fish area and provide strong support in the related area [46]. In addition to land and aquatic animals, the application of deep learning in insect farming has also evolved, especially in industrial insect farming for analyzing the growth rate, reproduction rate and health of insects. By monitoring insect behaviour and environmental conditions in real time, deep learning can help to optimize the farming environment and improve the yield and quality of insect products, especially in areas such as feed production and organic waste treatment, where this kind of fine-tuned management is particularly important [47].

Overall, the application of deep learning technology in a variety of animal farming not only improves the automation of the production process, but also brings about a more precise and efficient management approach. By reducing human intervention, deep learning not only reduces the cost of farming, but also improves animal welfare and reduces the stress response of animals in the farming process. This technology helps farmers control the health of their animals in real time and adjust production strategies to ensure the sustainable development of their farms. In addition, deep learning significantly improves food safety. With a comprehensive, automated monitoring system, farmers can better prevent disease outbreaks, reduce contamination and losses, and ensure consistent product quality. In the future, deep learning technology will continue to play a role in the wider field of farming, driving the development of smart agriculture and making livestock farming more refined, efficient and sustainable. This will not only have a profound impact on agricultural production globally, but will also improve food safety and animal welfare, while providing additional solutions to the challenges posed by

climate change and limited resources.

2.3 Camera applications in animal science

With the development of the technology, the cameras are also improved a lot. For the video-based research of animal science, the camera becomes the important part of the coming research in animal science. Different cameras have different purpose in different situations. It has different advantages and disadvantages as well. It must be chosen carefully for deep learning methods. Computer vision consists of generating explicit, meaningful descriptions of physical objects from images or video streams. In the poultry farming industry, continuous monitoring of poultry health and welfare requires interpretation of poultry conditions based on recorded and analyzed data. Recently, computer vision techniques have gained significant attention in automating the tracking, identification and monitoring of individual and group behaviour in large poultry flocks. The main vision sensors used in these techniques include 2D cameras, 3D cameras, and thermal imaging cameras, with systems varying slightly depending on the type of sensor used. Most computer vision applications for bird behaviour monitoring rely heavily on a number of core components for automated analysis: image/video data acquisition, instance recognition, tracking and data statistics. Computational models are largely based on scene, shape, motion or appearance. Image processing technology has become a key tool for automated monitoring of animal behaviour and is an essential part of research, providing valuable insights into animal welfare, health status, weight prediction and long-term tracking. In the poultry industry, this technology is widely used to detect and monitor large-scale flocks through automated systems that operate continuously without direct human intervention, thus effectively reducing animal stress. Due to the non-invasive nature of image processing technology, continuous behavioural monitoring can be achieved, capturing data in real time on a variety of activities such as feeding, drinking, movement patterns and social interactions. A major advantage of image processing technology in poultry farming is its ability to automatically record and identify different behaviours of chickens. This automation greatly reduces the need for human intervention and significantly improves operational efficiency. By combining computer vision technology, farms can more accurately assess the health and welfare of their flocks with this integrated and efficient monitoring tool. The continuous operation of the system ensures that any critical behavioural changes are not overlooked, and the data generated can be used to optimize management strategies, prevent disease outbreaks and improve overall animal welfare. As a result, this technology has become an indispensable tool for modern data-driven poultry farming, significantly improving the accuracy and efficiency of farm management [48](N. Li et al., 2019).

The 2D-camera is commonly used in various monitoring applications. With image processing and machine learning techniques, the system can automatically recognize the visual patterns in video streams. Recently, many researchers have applied these techniques for monitoring birds' behaviours. The author proposed to use traditional image processing and machine learning techniques to recognize individual laying hens [49]. Another author designed an automated system that combines RFID and computer vision, for tracking and analyzing laying hens. They applied an object detection algorithm in frame-to-frame correspondence, while an RFID-transponder is placed on the lower part of a hen's leg to provide an individual identification. The author proposed a hen-tracking method based on a hybrid support vector machine with three steps: initialization, tracking and updating of an instance. However, this method is heavily affected by the physical scale of the observation area, number of moving instances

and directional changes [50]. Another author proposed to use k-means clustering algorithm to detect sick broilers for the early warning [51]. The author used optical flow for welfare assessment, which has a potential for flock and group level assessment of general activity and distribution [52]. In [53], the authors analyzed optical flow to compute the average level of activity with measures of variation and cumulating information over time, differences between flocks become apparent within the first few days of life and are correlated with welfare outcomes in later life in UK and Switzerland. The author proposed to use inertia sensor (3-DOF motion tracker) to classify the behaviour of laying hens [54]. Recently, the success of deep learning in computer vision has greatly changed the way of automated monitoring system for animal behaviour. For example, the author designed a machine vision-based method for monitoring broiler chicken floor distribution, based neural networks [55]. The author adopted very similar techniques with the previous system for chicken detection, tracking and counting [52]. The author used the sensor technology and genomics to breed for laying hens that can reduce the damaging behaviour [48]. Another author proposed a novel computer vision method to analyze the poultry birds' movements for thermal comforts, which is used to measure the unrest index [56].

The above methods proposed for poultry behaviour analysis are based on either traditional image processing or recently developed deep learning methods for computer vision. The automated analysis on 2D image representations (or video streams) is the most straightforward way to monitor the animal behaviour via a video camera and a computational backend. These methods are designed for different purposes, which shows the great potential of AI computational models for the improvement of animal welfare.

The 3D camera can provide depth information in addition to the 2D images. The author proposed a 3D-based model for assessing inactivity of broilers to detect lameness [57]. The core idea is to mount a top-down Kinect camera, to measure broilers' posture and activity indices in a test corridor, observing the lying events and the latency to lie down. Other authors used the 3D camera for boilers' weight estimation at both individual and group level, showing the high correlation between the observation area and weight, allowing the consistent and continuous monitoring of growth rate and indirect feed consumption rates [58]. Here the 3D depth data representation differs from the concept of point cloud in computer vision. The depth information provides an additional channel to describe the visual properties of birds. However, in many cases, the benefit brought by this sensor is limited, especially when monitoring the group activity of birds. The infrared (IR) camera, or thermal imaging camera takes the image using infrared radiation, so using this imaging technology can effectively avoid the variation of natural light and shadows. However, due to the sensitivity of temperature, humidity, dust particles and other environmental factors, thermal camera needs extensive calibration. The frames recorded by an IR camera is essentially represented by grey-scale images, which can be easily processed by modern computer vision models. Also, due to the robustness to natural light, the variation of visual representation is much lower compared to 2D cameras. However, IR camera is not economically friendly to build low-cost monitoring systems.

Compared to the proliferate research outcomes of computer vision techniques on bird behaviour analysis, there are fewer patents available. This might be because of the systematic integration of multiple techniques for specific purposes registered as patents rather than the model innovation of the proposed methods. The author applied real-time image analysis to monitor animals' presence and eating position for nutriment ingestion [10]. This application is not limited to egg hens, but also other farm animals such as pigs and cows. The author applied machine vision to determine the chicken sex as a binary classification problem. Similarly, another author pro-

posed to use hyperspectral images of chicken embryo hatching, analyzing difference of spectral response between a male embryo and a female embryo, extracting a spectral value within a wavelength range of 600-900 nm as an input value of a neural network, and judging the gender of the chicken embryo [59]. The author invented a system with a video camera coupled to a computer in which the computer is configured to automatically provide object segmentation and identification, object motion tracking (for moving objects), object position classification, and behaviour identification [60]. This system provides similar functions with our projects, but the techniques applied are fundamentally different. The author built a health monitoring system by combining acoustic and visual information to assess the existence and/or progress of a disease in animal groups [61]. Existing studies usually set clear learning objectives for specific problems, such as recognizing specific behaviours such as eating, drinking or exercising. However, unlike these studies, future directions may no longer be limited to single-purpose monitoring, but more extensive use of computer vision and machine learning techniques to explore the complex behavioural patterns of poultry and reveal new biological or welfare information from them.

Future research in poultry science will focus on uncovering unknown behavioural patterns of individuals and groups using automated systems, rather than pursuing narrowly defined objectives. By combining multi-angle video, multimodal sensor data, and deep learning, these systems can analyze postures, trajectories, and group dynamics to reveal hidden traits linked to welfare, health, and environmental factors. This integrated approach enables more precise interventions to improve productivity and animal well-being. Camera technologies—ranging from 2D and 3D imaging to thermal cameras—are central to this shift. When paired with advanced algorithms, they provide accurate, real-time monitoring of animal behaviour and health, reducing reliance on manual observation. Each camera type contributes unique advantages, from routine behavioural tracking to health-specific applications, forming the foundation of precision livestock management. Looking ahead, advances in multimodal fusion, self-supervised learning, and large-scale annotation will allow monitoring systems to operate effectively in complex farm environments. By integrating diverse sensor data, researchers can achieve a deeper understanding of animal behaviour and welfare, supporting a more data-driven, sustainable, and welfare-focused livestock industry with broad implications for food security and animal health.

2.4 Conclusion

In this review, we have described modern applications of advanced deep learning and computer vision techniques for poultry science. Understanding the fundamentals of these algorithms is critical to developing more efficient systems. In conclusion, the rapid development of deep learning methods in the field of poultry science, especially in computer vision systems, has greatly improved the ability to monitor, analyze, and predict key poultry phenotypes, which has provided an extremely critical aid to the development of the field of poultry science. The use of deep learning and computer vision methods as an aid in the field of poultry science has taken the field to a higher level of development. By using deep learning algorithms such as Mask R-CNN, Faster R-CNN, YOLO, and advanced network architectures such as ResNet, Transformer, and others, researchers have been able to achieve accurate individual identification, behavioural analysis, and biometrics on a variety of livestock species. These technological tools provide real-time, non-invasive data to make farm management more efficient, as well as providing vital support for breeding programmed optimization, animal health monitoring and welfare interventions. Such technological advances not only reduce the cost of manual han-

dling, but also reduce the stress on animals due to human contact, increasing the sustainability of agricultural production and improving animal well-being. However, despite the stellar performance of these existing techniques, deep learning still faces several challenges in practical applications. Firstly, the details of algorithm implementation often lack a comprehensive description, especially in terms of hyperparameter tuning, the use of pre-training weights, and the selection of deep learning backbone networks. Due to the specificity of the field of poultry science, many commonly used deep learning methods cannot be directly applied in this field, and deep learning methods need to be adapted to make them suitable for this field. In addition, computational efficiency when dealing with large-scale data still needs to be further optimized in order to cope with the huge amount of data and the complex operating environment in animal husbandry. In the field of poultry science, a large amount of data is usually required as a training set for deep learning models. Future research should not only focus on these technical details, but also explore how to extend the detection range of the system to cover more complex behaviours and phenotypes. Meanwhile, by integrating environmental monitoring data, such as temperature, humidity, air quality and light conditions, a more comprehensive understanding of the influencing factors behind animal behaviour can be gained, thus improving the accuracy of animal welfare monitoring. With the continuous advancement of technology and the constant development of the times, the application of deep learning methods in poultry science is promising. It will help promote the development of precision animal husbandry and achieve a more efficient, sustainable and animal welfare-focused production management model through real-time data analysis and intelligent decision-making. This shift will not only bring economic benefits but will also play an important role in ecological protection and animal health, laying a solid foundation for future innovation in animal husbandry. By integrating classical machine learning methods with advanced deep learning frameworks (e.g., Convolutional Neural Networks, CNN), several aspects of animal welfare and farm operations have been significantly improved. Non-visible light and depth-based sensor technologies have effectively solved traditional monitoring challenges such as complex background interference and poultry shading, dramatically improving the accuracy and efficiency of monitoring. These technologies have been applied in a wide range of fields, from egg quality assessment to health monitoring, and have made significant progress, not only reduced manual labor, but also significantly improved productivity.

In addition, the introduction of multimodal systems has further enhanced these monitoring capabilities. By integrating multiple sensors, such as thermal imaging, depth cameras and acoustic sensors, such systems are able to not only acquire richer environmental data but also capture poultry behaviour and physiology more comprehensively. Multimodal data fusion has allowed the systems to perform better when dealing with complex farm environments, enabling more comprehensive real-time monitoring. However, how to adapt these systems to the dynamic conditions of real farms and how to cope with the large, annotated datasets required for deep learning remain ongoing challenges.

Future technological innovations, such as voice-activated robots and virtual reality (VR) technologies, are expected to further enhance the efficiency and sustainability of poultry farming. Voice-activated robots can reduce human intervention and intelligently manage animal behaviour, while virtual reality technology can provide farm managers with a new way to remotely monitor and simulate operations. Meanwhile, the continued development of flexible, scalable and ethical solutions that effectively combine human expertise with automated systems may fundamentally change the entire poultry farming industry. The development of these technologies will not only help to increase the efficiency of global food production, but also

significantly improve animal welfare, ultimately contributing positively to global food security and sustainable development [62]. The future is promising in the development of the deep learning and computer vision in animal science. It is worthy to keep trying with the deep learning methods into poultry science. It is glad to see that many researchers gather together to use the modern AI technology to solve the real-world problems in poultry science.

Chapter 3

ChickenbehaviourView: A Multi-task Top-down View Chicken Behaviour Dataset for Smarter Precision Livestock Farming

3.1 Introduction

In this Chapter, ChickenbehaviourView dataset is presented. Nowadays, the public's attention to poultry welfare is increasing rapidly, because people realize that the quality of animal welfare has a great impact on the quality of livestock products , which in turn affects the health of consumers [2]. Ensuring good animal welfare not only promotes healthy growth of poultry, but also reduces the incidence of disease. There is a strong interrelationship between poultry health, product quality and good welfare conditions [63]. It is believed that hens in a good healthy condition and with improved emotions typically produce higher quantities of eggs with superior quality [4]. Hen behaviours are one of the important indicators for evaluating hen welfare, and behavioural research has become a common way for evaluating animal welfare.

Conventional methods of identifying and analyzing hen behaviours often rely on radio frequency identification (RFID) systems. Each hen is equipped with silicone leg bands containing a unique ID microchip that helps track activity patterns and duration while monitoring [8]. One of the advantages of using RFID chips is that it can provide specific data related to individual hens, rather than focusing on the behaviour of the entire flock. However, this method is invasive because it requires capturing each hen and securing the device on their legs. In addition, leg bands are only available for adult birds, thus limiting the age range for monitoring purposes. As a result, the information gained through RFID chips provides limited insights for hen behaviours analysis. And there are typically 25,000-50,000 laying hens in each shed on commercial egg farms, which is a large scale, it is not feasible to equip each hen with a silicone leg band to observe their behaviours in real time.

That's why we call for the Precision Livestock Farming (PLF) technology, which brings a non-intrusive and real-time monitoring system. The purpose of PLF is to monitor animal health and welfare automatically and continuously [9]. In particular, automated-monitoring systems incorporating advanced Artificial Intelligence (AI) models provide a practical solution

for welfare monitoring. By monitoring of hen behaviours precisely, farmers can gain insight into the health, welfare and productivity of each hen, thus improving the accuracy of welfare assessments. Although several chicken-related datasets exist, few specifically target behavioural analysis. With the growing emphasis on poultry welfare, there is a clear and urgent need for a dedicated chicken behaviour dataset to support further research and development in this specific area.

To address such limitation, we construct ChickenbehaviourView, the first multi-task video chicken behaviour dataset using top-down views. Our ChickenbehaviourView dataset offers comprehensive and carefully annotated data, including **(1)** bounding boxes of chickens for detection and tracking tasks, and **(2)** detailed annotations of eating, drinking and other behaviours to support welfare assessment. By providing these rich, multi-level annotations, ChickenbehaviourView serves as a valuable resource for both the research community and the livestock industry. It enables the development, adaptation, and evaluation of advanced models tailored to behavioural monitoring in poultry. This, in turn, promotes the advancement and real-world deployment of smarter Precision Livestock Farming AI systems, addressing diverse industry needs and application scenarios. We also build a prototype monitoring system by leveraging state-of-the-art detection and tracking models. Furthermore, we correlate the duration of specific hen behaviours with shed temperature to enable deeper investigation into the welfare status of the flock.

3.2 ChickenbehaviourView Dataset

3.2.1 Camera Placement and Data Acquisition

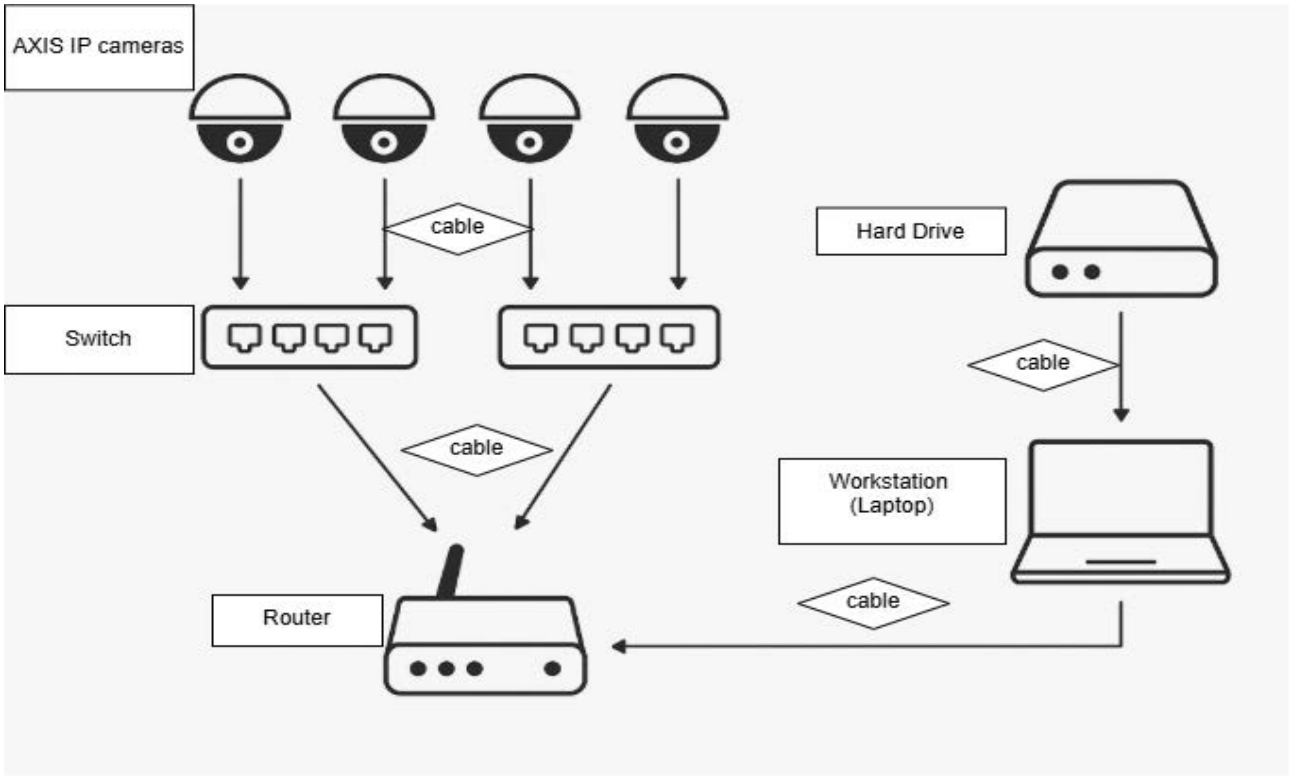


Figure 3.1: The network topology of camera placement for video data collection.

The data for this study was collected from two commercial egg farms located in New South

Wales (NSW) and Queensland (QLD), Australia. Both farms were equipped with AXIS IP cameras operating at either 1920×1080 or 1280×720 resolution, with a default frame rate of 30 frames per second (FPS). The cameras were connected through a series of switches that supplied power and transmitted video signals, which were then linked to a router to form a local network infrastructure. Recorded footage was transmitted in real time via cable to a desktop workstation. Given the large volume of data generated over several weeks, an external hard drive was employed for additional storage capacity. The overall network setup at the two farms is depicted in Figure 3.1.

In compliance with animal ethics guidelines, a total of four cameras were installed across the two farms. The cameras were positioned to provide a top-down view of the hens' activities from multiple perspectives. Each unit was mounted at a height of approximately 2.2 meters, covering an observation area of roughly 12 square meters. The cameras were scheduled to operate daily from 6:00 a.m. to 6:00 p.m., capturing daytime behaviours such as eating and drinking. The placement of one camera within the NSW farm is shown in Figure 3.2. And another placement of the camera within the QLD farm is shown in Figure 3.3.

Over the course of data collection, approximately 2 TB of video footage was acquired. To facilitate model development, the video was segmented into five-minute clips, ensuring manageable file sizes while maintaining temporal continuity. The controlled visual environment—characterized by fixed camera angles and minimal variation in illumination—provided a consistent and reliable dataset for the detection and tracking of hen behaviours. This setup ensured comprehensive observation across both farms while supporting efficient data acquisition for the study's objectives.



Figure 3.2: One placement of video camera (in red circle) on egg farm in NSW.

3.2.2 Data Selection and Annotation

A total of 158 frames from the collected video dataset were densely annotated, resulting in 16,991 instances of hens engaged in eating, drinking, and other activities. These frames were randomly selected then converted to JPG format by using video to JPG conversion software. The annotation tool is LabelMe [64]. Blurry images were discarded to maintain data quality, and areas where hens were too crowded for visual inspection were excluded. The sampled

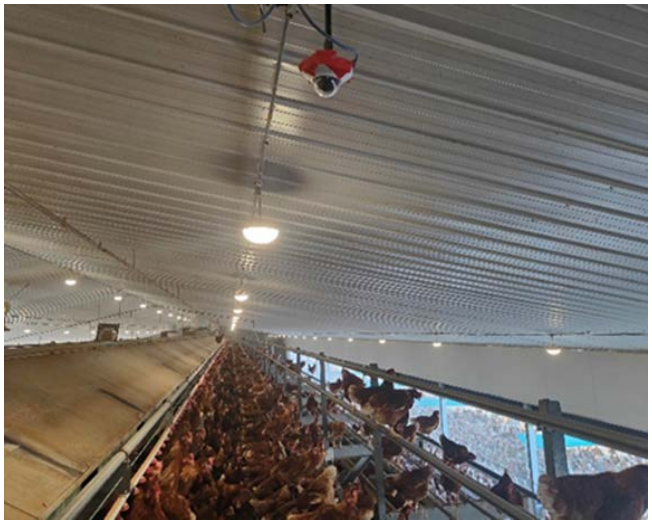


Figure 3.3: One placement of video camera on egg farm in QLD.

frames represented a range of visual environments, including different scales, lighting conditions, occlusions, and distortions. Annotations were manually created by labeling the images with bounding boxes around observable hens and categorizing their activities. The details of annotated behaviours are shown in Table 3.1. And the percentage distribution of annotated behaviours in our dataset is shown in Figure 3.4. As shown in the pie chart, 'Others' dominates the dataset, accounting for the majority of annotations, while 'Eat' and 'Drink' form comparatively small proportions.

This imbalance is expected and reflects the natural behaviour of laying hens. Most of a hen's daily activity consists of walking, standing, resting, and interacting with the flock, while actual eating and drinking occur intermittently and for relatively short durations. Consequently, the frequency of visually observable eating or drinking events is naturally lower than the frequency of all non-feeding behaviours combined.

Beyond behavioural patterns, technical factors in the annotation and detection process also contribute to the smaller proportion of eating and drinking samples. Eating and drinking are instantaneous behaviours: Drinking often occurs in very brief actions where the hen quickly pecks the water nipple, making the capture window extremely short. Eating can also be rapid, with birds dipping their head into the trough for only a moment before lifting it again. These short and subtle motions reduce the number of frames where the behaviour is clearly visible and therefore reduce the number of images that can be labelled as eat or drink.

Furthermore, a significant model limitation emerged during the evaluation process. When our model attempted to differentiate eating or drinking behaviours, it could only detect the physical postures associated with these actions—such as a hen lowering its head into the trough or tilting its head back near the water tap. However, the model was unable to determine with certainty whether the bird was actually eating or drinking. In many cases, similar head movements occur for reasons unrelated to consumption—for instance, exploratory pecking, social interactions, or simply passing by the feeder. As a result, only instances where behaviour was visually unambiguous were annotated, further reducing the number of usable eating and drinking samples. Together, these behavioural and technical factors explain why the Eat and Drink categories are substantially smaller than the Others category in the dataset.

Some examples of the annotated frames are shown in Figure 3.5 and Figure 3.6. The red

bounding boxes represent eating behaviour while blue means drinking and green means neither eating nor drinking.

Despite the careful annotation process, it is important to acknowledge that the dataset size—158 annotated frames with 16,991 labelled instances—is relatively limited for training deep learning models. Compared to large-scale benchmarks such as COCO or ImageNet, this dataset may not fully capture the diversity of visual variations present in real-world commercial environments. This limitation is primarily due to the high cost and time required for manual annotation, particularly in dense flock scenes where each frame may contain hundreds of birds requiring precise labelling.

To mitigate this constraint, several strategies were adopted. First, each annotated frame contains a large number of instances, which partially compensates for the limited number of images by providing dense supervision. Second, data augmentation techniques—including scaling, flipping, and brightness variation—were applied to increase the diversity of training samples and improve model generalization.

Nevertheless, the limited dataset size remains a constraint, particularly for capturing rare behaviours such as drinking, which are both infrequent and visually subtle. Future work should focus on expanding the dataset with additional annotated frames, incorporating semi-supervised or self-supervised learning techniques, and exploring automated or weakly supervised annotation methods to reduce manual labelling effort. These approaches would further improve the robustness and scalability of behaviour recognition models in commercial egg farm environments.

Table 3.1: Counts of annotated behaviours in the dataset

Behaviour	**Count**
Others	10469
Eat	5605
Drink	917
Total	**16991**

3.2.3 Comparison with existing datasets

Although there are some existing chicken datasets, most of them are primarily designed for object detection [65] or re-identifying individual chickens [66][67], with an emphasis on individual identity rather than behavioural patterns. One notable exception is a dataset focused on chicken behaviour in cage-free poultry houses [68], but it is limited to detect two abnormal behaviours, namely inactive broiler and huddling behaviour. Also there is another dataset building the world's first chicken gender classification database annotated manually [69]. Moreover, there is an article presenting a comprehensive dataset featuring ten distinct hen breeds, sourced from various regions, capturing the unique characteristics and traits of each breed [70].

Different from existing chicken datasets, our ChickenbehaviourView video dataset provides carefully labeled annotations of bounding boxes for chicken eating and drinking behaviours. The ChickenbehaviourView dataset includes diverse types of annotations tailored to support the training of a wide range of models aimed at advancing precision livestock farming. It serves as a challenging and valuable benchmark for both academic researchers and industry practitioners to develop, adapt, and evaluate state-of-the-art techniques for smarter, behaviour-aware poultry management.

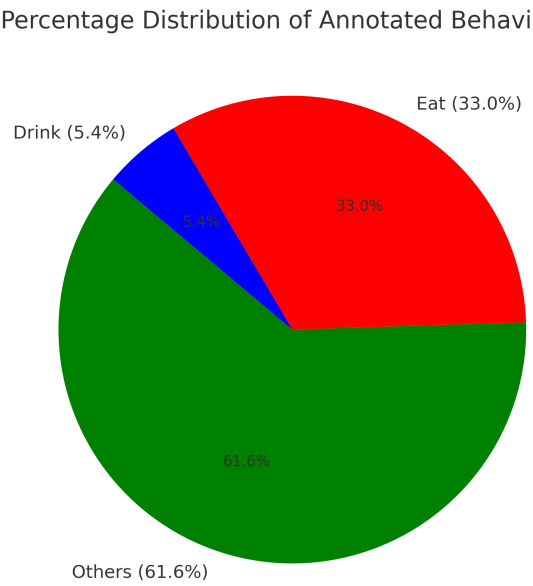


Figure 3.4: The percentage distribution of annotated behaviours in our dataset.

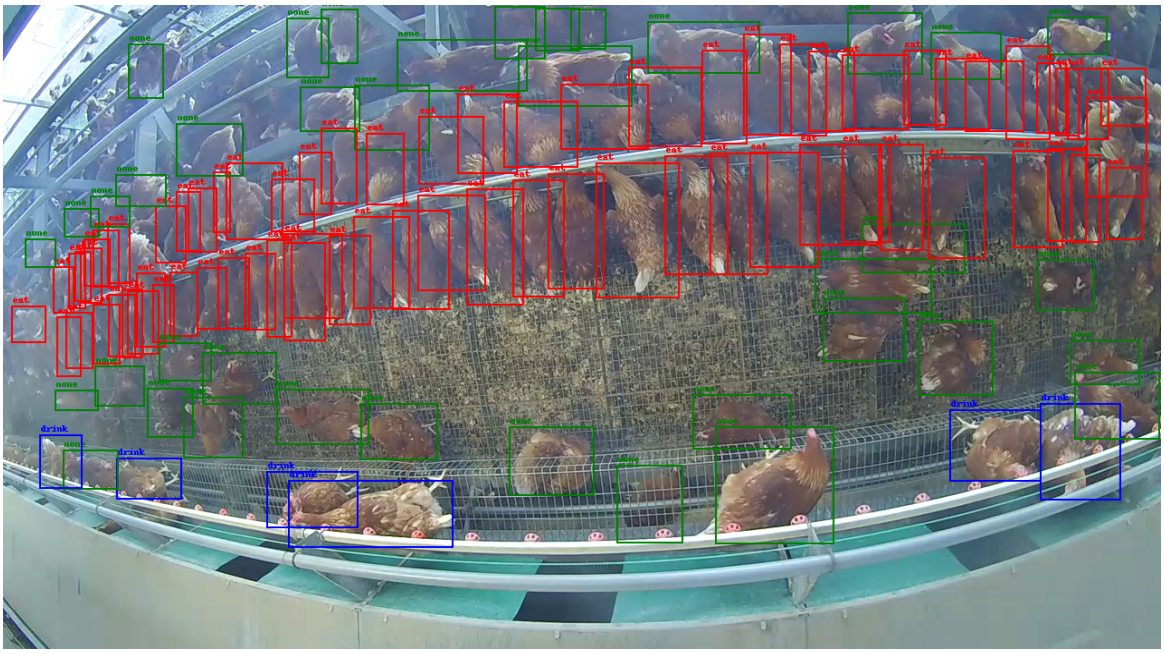


Figure 3.5: Example of annotations in a frame of the video sequence (QLD egg farm).

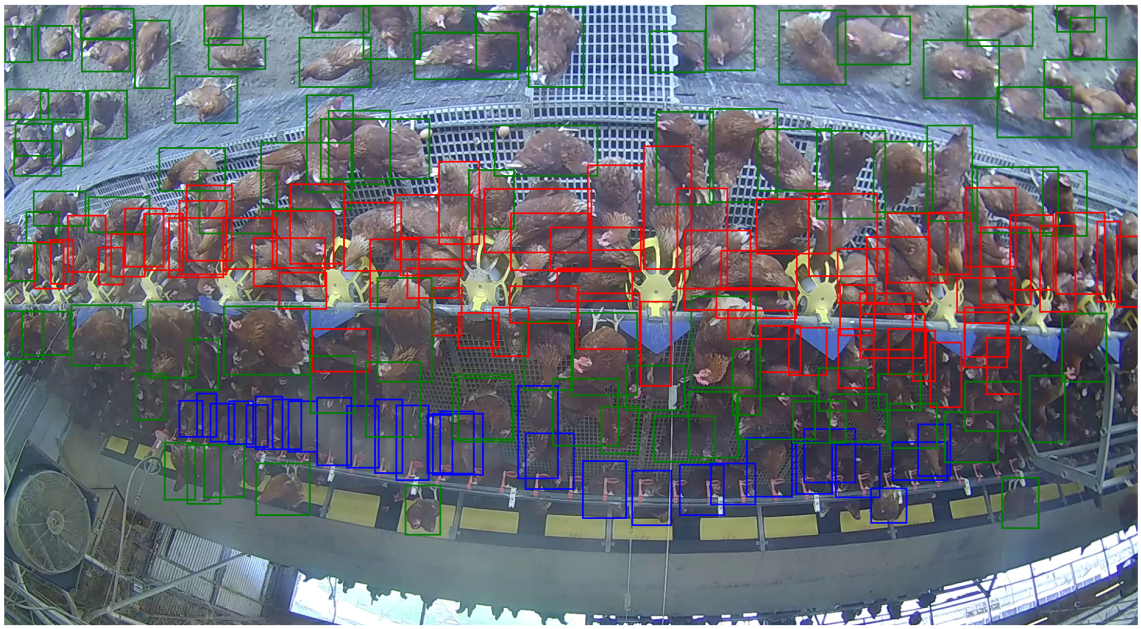


Figure 3.6: Example of annotations in a frame of the video sequence (NSW egg farm).

3.2.4 Commercial video datasets

Beyond the annotated frames, the dataset also includes hundreds of video segments made available to both the research community and industry stakeholders. These videos play a crucial role in the quantitative behavioural analysis presented in later chapters. The initial collection phase took place at an egg farm in NSW, where video data were recorded between 01/11/2023 and 23/12/2023 using two cameras (ID C107 and C110) positioned inside the shed. These recordings enabled detailed observation of flock activity over an extended period and provided the foundation for a more precise analysis of laying hen behaviours. Each camera captured both the feeding and drinking zones, and the recordings were divided into 5-minute clips, which served as the basic analytical unit. Hourly summaries of key behaviours—specifically eating and drinking—were then computed from these clips. To monitor daytime activity patterns, recordings were collected following a 12-hour schedule, from 06:00 to 18:00, using Axis network cameras.

The detection and tracking model in this study was applied to all video clips, generating structured log files that documented every identifiable bird and its behaviour. Each log corresponded to a single 5-minute clip and contained several hundred entries, with each entry representing a timestamped observation of a bird, recorded in the format XX:YY, where XX denotes a unique bird ID and YY denotes the behaviour label (eating, drinking, or other). Using the fixed frame interval, we calculated the duration of each behaviour for every bird present within the camera's field of view.

Initially, four cameras placed at different angles were planned for analysis; however, two became unusable—one due to hardware failure and the other due to severe lens blurring. As a result, subsequent data collection was relocated to a farm in QLD, where high-quality recordings were available from cameras C109 and C113. These videos were further supported by operational records provided by the farm manager, including daily egg production data, enabling an exploration of potential correlations between behavioural trends and production outcomes.

Camera C113 primarily monitored feeding behaviour, whereas camera C109 focused on drinking activity. Both cameras recorded continuously from 01/01/2024 to 03/05/2024. Due to intermittent blurring, only footage from 01/01–22/01 and 28/01–01/02 from C113 was suitable for analysing feeding behaviour. Camera C109 remained consistently clear throughout the study; however, it was manually repositioned at one point, shifting the view temporarily toward the feeding area. As a consequence, C109 reliably captured drinking behaviour from 01/01–27/02, and feeding behaviour from 28/02–04/03. The details of chicken dataset collected at both egg farms are shown in Table 3.2.

The data collected from these two egg farms provides a comprehensive foundation for developing and evaluating the proposed detection, tracking, and behavioural analysis system. Across both sites, cameras were strategically positioned in different locations and at varying heights, capturing a diverse range of environmental conditions, stocking densities, and behavioural contexts. Although some cameras experienced hardware failures, lens blur, or changes in viewing angle, the remaining streams still offered extensive footage—covering several hundred hours—that effectively supports both model training and downstream behavioural quantification. Importantly, the two farms contributed complementary perspectives: NSW egg farm provided large-scale, long-duration recordings with broad behavioural coverage, while QLD egg farm supplied cleaner, more targeted observations useful for validating detection and tracking performance. Together, these datasets enable a robust assessment of flock-level behaviour in real commercial environments and form a critical basis for building reliable, scalable precision-livestock monitoring tools.

Table 3.2: Summary of the chicken dataset collected at both egg farms.

Camera	**Farm**	**Period**	**Frames (approx.)**	**Behaviours**
C107	NSW	01/11/23 – 23/12/23	∼68.7M	Eat, Others
C109	QLD	01/01/24 – 04/03/24	∼81.6M	Eat, Drink, Others
C110	NSW	01/11/23 – 23/12/23	∼68.7M	Eat, Drink, Others
C113	QLD	01/01/24 – 05/03/24	∼83.0M	Eat, Others

3.3 Conclusion

In this chapter, we introduced ChickenbehaviourView, the first top-down, multi-task chicken behaviour dataset specifically designed to advance automated welfare assessment and behaviour recognition in commercial poultry environments. By integrating high-resolution video recordings from two operational egg farms in NSW and QLD, capturing diverse environmental settings, flock densities, and behavioural contexts, the dataset provides a rich and realistic foundation for developing robust AI models suited for real-world deployment. Through dense annotations of 158 frames containing 16,991 labelled instances—including eating, drinking, and other behaviours—ChickenbehaviourView delivers a level of behavioural detail not present in existing poultry datasets, most of which focus solely on object detection or re-identification rather than welfare-relevant behavioural monitoring.

A key strength of the dataset lies in its explicit behavioural annotations using top-down video views, a perspective shown to be highly effective for minimizing occlusion and enabling more consistent detection across crowded flock environments. The inclusion of both annotated frames

and extensive video sequences ensures that the dataset supports a wide range of AI tasks, including object detection, multi-object tracking, behaviour classification, and temporal behaviour analysis. The combination of annotated images and long-duration commercial video recordings also allows future research to explore advanced topics such as sequence modelling, domain adaptation, semi-supervised learning, and behaviour quantification under varying environmental conditions.

From an academic perspective, ChickenbehaviourView establishes a valuable benchmark for the computer vision and precision livestock farming research communities. The dataset provides a challenging testbed characterised by real-world noise, occlusion, illumination variation, and complex flock dynamics—conditions seldom captured in lab-based poultry datasets. Researchers can use this dataset to develop and validate novel architectures, loss functions, and multimodal approaches aimed at improving behaviour recognition accuracy and system robustness. Furthermore, the dataset's multi-task structure enables investigations into joint detection–tracking–behaviour modelling, cross-domain generalisation, and fine-grained behavioural inference, promoting interdisciplinary research spanning machine learning, agriculture, and animal health sciences.

For industry practitioners, ChickenbehaviourView offers direct practical value. As commercial egg farms increasingly adopt Precision Livestock Farming technologies, there is a growing demand for AI systems capable of automating welfare monitoring, detecting early signs of stress or illness, and supporting data-driven decision-making. The dataset reflects authentic farm conditions—including flock size, lighting variations, dust levels, and behavioural diversity—making it highly suitable for training models intended for deployment in production environments. By providing high-quality labelled data for essential welfare indicators such as eating and drinking, the dataset enables AI developers and farm technology providers to build more accurate and reliable monitoring systems. These systems can empower farmers to reduce manual labour, increase productivity, implement timely interventions, and ultimately enhance welfare standards in large-scale operations.

In summary, ChickenbehaviourView represents a significant step toward bridging the gap between academic research and real-world poultry farming applications. Its comprehensive annotations, commercial realism, and focus on behaviour make it a robust and valuable resource for advancing automated welfare monitoring. We anticipate that this dataset will play an important role in accelerating innovation in Precision Livestock Farming, supporting both cutting-edge research and practical on-farm solutions aimed at creating healthier, more sustainable, and welfare-conscious poultry production systems.

Chapter 4

Model Development for the Behavioural Analysis

4.1 Introduction

In this chapter, we present the development of a comprehensive computer vision system for monitoring laying hen behaviour in commercial egg farms. The primary goal is to design and implement an automated framework capable of accurately detecting, tracking, and analyzing individual hen activities in real time. The system integrates state-of-the-art object detection models, multi-object tracking, and quantitative behavioural metrics to provide actionable insights into flock welfare, resource utilization, and productivity.

Section 4.2 describes the model development, including the selection and evaluation of detection backbones and heads, comparison of advanced object detectors, and the integration of ByteTrack for reliable multi-object tracking under challenging farm conditions. Section 4.3 outlines the statistical metrics used to quantify hen behaviour at both individual and flock levels, including average activity time and the proportion of birds performing specific activities. Together, these sections highlight the system's capability to combine real-time monitoring with quantitative behavioural analysis, providing a foundation for precision poultry farming and welfare assessment.

4.2 Model development

4.2.1 Detection model

The detection model forms the core of the automated monitoring system for laying hen behaviour in commercial egg farms. Accurate detection of individual hens is essential for both welfare assessment and productivity analysis. To develop an effective detector, we evaluated a range of backbone and head combinations and benchmarked state-of-the-art object detectors, analyzing both accuracy and computational efficiency. We randomly split the dataset into training, validation and testing as the normal percentage 70% : 10% : 20%.

A central design requirement of the proposed behaviour-monitoring system is its ability to perform inference in real time. Commercial egg farms typically operate with 25,000–50,000 hens per shed, producing continuous video streams for up to twelve hours per day. As a result,

the detection model must process thousands of frames per hour without accumulating delays. If the detector is too slow, behavioural events—especially short and instantaneous ones—cannot be measured accurately, and the system becomes unsuitable for continuous monitoring.

Critically, eating and drinking behaviours in laying hens occur within very short durations, sometimes lasting less than a second. Especially for drinking behaviour, it can be considered as drinking behaviour when hen tilted its neck back to sip from the water tap. It is an instant movement. A detector running below real-time speed (e.g., fewer than 20–25 FPS) may miss these brief events or capture them only partially, leading to incorrect quantification of activity time. This highlights that high inference speed is not merely a computational preference; it is essential to the functional validity of the behavioural metrics developed in this thesis.

Furthermore, heavy backbones such as ResNet-50 [71], ResNet-101 [72] significantly increase computational load and memory requirements, resulting in long inference times that are incompatible with on-farm deployment. They also increase hardware cost and energy consumption, making long-term monitoring impractical. For these reasons, the model design in this thesis prioritises lightweight backbones that offer a favourable trade-off between representational capacity and efficiency.

Inference efficiency is a core feature of the monitoring system. It directly influences the system's ability to detect behaviours reliably, quantify activity durations, and provide timely insights for welfare assessment. This motivated the evaluation of lightweight models such as ResNet-18 [73], ShuffleNetV2 [74], and MobileNetV2 [75], which are more suitable for real-world commercial operation than deeper, more computationally demanding architectures.

Table 4.1: Comparison of different backbone and head combinations on dataset.

Backbone	**Head**	**mAP@50**	**processing time(ms/per image)**
ResNet-18	FCOS	0.584	48.66
ResNet-18	GFL	0.613	49.43
ResNet-18	ATSS	0.488	47.75
MobileNetV2	FCOS	0.388	48.03
MobileNetV2	GFL	0.452	47.21
MobileNetV2	ATSS	0.134	54.25
ShuffleNetV2	FCOS	0.503	48.82
ShuffleNetV2	GFL	0.538	47.35
ShuffleNetV2	ATSS	0.148	48.12

Table 4.1 summarizes the performance of three backbone networks (ResNet-18 [73], MobileNetV2 [75], ShuffleNetV2 [74]) combined with three detection heads (FCOS [76], GFL [77], ATSS [78]) on the chicken behaviour dataset. Across all settings, ResNet-18 consistently outperformed the two lightweight alternatives, confirming that moderate network depth provides sufficient representational capacity for subtle behavioural recognition tasks where visual cues are small or partially occluded. The best performance was achieved by ResNet-18 + GFL, yielding an mAP@50 of 0.613 with an average inference time of 49.43 ms per image. This indicates that the combination of a balanced feature extractor and an anchor-free head with adaptive quality prediction (GFL) effectively captures fine-grained spatial and confidence variations.

In contrast, ShuffleNetV2 + GFL achieved a slightly lower accuracy (mAP@50 = 0.538) but with comparable inference speed (47.35 ms), demonstrating the trade-off between computational efficiency and feature expressiveness. The relatively strong performance of ShuffleNetV2

Table 4.2: YOLOv5n Evaluation Metrics Table

Class	Precision (P)	Recall (R)	mAP50	mAP50-95
all	0.635	0.498	0.526	0.239
eat	0.615	0.566	0.568	0.249
drink	0.608	0.392	0.460	0.234
none	0.684	0.537	0.550	0.233

compared to MobileNetV2 suggests that its channel split and feature reuse strategy preserves more discriminative information, even with fewer parameters.

MobileNetV2, however, showed notable underperformance across all heads, particularly when combined with ATSS, which recorded only 0.134 mAP@50. This is likely due to a mismatch between the model's lightweight feature maps and the anchor-based ATSS head, which relies heavily on well-structured multi-scale feature hierarchies. The smaller receptive field and weaker gradient flow in MobileNetV2's inverted residual blocks may further limit its ability to localize fine-scale behaviours.

Comparing across heads, the results reveal that GFL is better than FCOS and ATSS is worst in both accuracy and stability. GFL's generalized focal loss and quality-aware regression improve robustness to label noise and class imbalance—conditions present in this dataset, where the drink category is notably underrepresented. ATSS, though effective on large-scale datasets like COCO, underperforms here because its anchor assignment strategy struggles with small, dense targets typical of flock behaviour scenes.

Overall, these results emphasize that the backbone–head coupling plays a decisive role: deeper but efficient backbones paired with adaptive, anchor-free heads achieve the optimal balance between accuracy and speed. Lightweight networks can approach similar real-time inference rates but require careful loss design or feature enhancement to reach competitive detection accuracy.

Beyond backbone-head combinations, we evaluated the performance of three widely used detection frameworks: YOLOv5n[79], YOLOv8n[80], and NanoDet[81] (Tables 4.2, 4.3, 4.4). YOLOv8n achieved the highest overall precision (0.737) and mAP50 (0.692), outperforming YOLOv5n and NanoDet across most behaviour classes, including eating and drinking. YOLOv5n achieved moderate accuracy, with overall mAP50 of 0.526, while NanoDet provided slightly lower mAP50 (0.474) but demonstrated strong performance for the drinking class (mAP50 = 0.524), indicating its ability to capture specific behaviours effectively.

Processing time is a critical factor for deployment in commercial egg farms, where continuous monitoring generates thousands of images daily. As shown in Table 4.5, NanoDet is the most computationally efficient detector, processing an image in 30.12 ms on average, compared to 35.47 ms for YOLOv8n and 49.21 ms for YOLOv5n. The combination of low latency and acceptable accuracy makes NanoDet particularly suitable for real-time applications, ensuring that large volumes of video data can be analyzed without significant delays.

Selecting a detection model requires balancing accuracy, processing speed, and scalability. While YOLOv8n provides the highest precision, its slightly higher computational cost may limit real-time performance in large-scale operations. ResNet-18 with GFL heads offers high accuracy but is more resource-intensive than lightweight alternatives. NanoDet, though slightly

Table 4.3: YOLOv8n Evaluation Metrics Table

Class	Precision (P)	Recall (R)	mAP50	mAP50-95
all	0.737	0.617	0.692	0.359
eat	0.779	0.677	0.753	0.382
drink	0.651	0.646	0.655	0.364
none	0.781	0.528	0.668	0.331

Table 4.4: NanoDet Evaluation Metrics Table

Class	Precision (P)	Recall (R)	AP50	mAP50
all	0.641	0.512	0.629	0.474
eat	0.658	0.534	0.633	0.473
drink	0.672	0.498	0.682	0.524
none	0.593	0.503	0.573	0.427

less precise overall, delivers a favorable trade-off between accuracy and speed, making it the ideal choice for our prototype system deployed in commercial egg farms.

Furthermore, accurate detection is foundational for subsequent tracking and quantitative analysis. The ability to precisely identify individual birds allows the system to calculate behavioural metrics, such as average activity time and proportion of active birds, which are critical for assessing flock welfare, resource utilization, and productivity trends.

In conclusion, the evaluation of backbones, detection heads, and state-of-the-art detectors demonstrates that NanoDet provides a robust, efficient, and scalable solution for real-time hen behaviour detection. Its integration into the monitoring system ensures that large flocks can be continuously observed with minimal human intervention, providing reliable input for both welfare assessment and operational decision-making in commercial poultry environments. How Nanodet worked in our prototype system is illustrated in Figure 4.1.

NanoDet is a real-time anchor-free detection model that delivers the comparable performance as the YOLO series and is just as easy to train and port to the mobile site. It is derived from a fully convolutional one-stage object detector (FCOS[76]), and it uses generalized focal loss (GFL[77]) as classification and regression loss. The model has been significantly lightweighted to fit the real-time monitoring. In order to mitigate the potential loss of accuracy due to lightweighting, an assign guidance module (AGM) with a dynamic soft label assigner (DSLA) is introduced in the training phase [82]. The AGM consists of only four 3x3 convolutional layers and is normalized using group normalization (GN[83]). The AGM, used only during training, does not impact inference speed, ensuring efficiency. It predicts classification probabilities and detection bounding boxes, which the DSLA module uses to calculate matching costs, comprising classification, regression, and distance costs.

It is important to note that the assign guidance module (AGM) is only introduced during the training phase and is completely removed during inference. The purpose of AGM, together with the dynamic soft label assigner (DSLA), is to improve label assignment quality by providing more accurate supervision signals. Specifically, it helps the model learn better classification confidence and bounding box regression by considering both spatial alignment and prediction quality during training.

Table 4.5: Detector time Table

Detector	processing time (ms/per image)
YOLOv5n	49.21
YOLOv8n	35.47
Nanodet	30.12

If the AGM is removed during inference, there is no impact on the model structure or computational cost, since it is not involved in the forward prediction process. However, if AGM were not used during training, the model would rely on standard label assignment strategies, which are less adaptive to the characteristics of small, dense, and overlapping objects such as hens in commercial farm environments. This would likely result in lower detection accuracy, especially for challenging cases such as occluded birds or subtle behaviours.

Therefore, AGM improves the quality of learned representations during training, while its removal during inference ensures that the model maintains high efficiency and real-time performance. This design allows NanoDet to achieve a favourable balance between accuracy and computational cost, which is essential for deployment in practical monitoring systems.

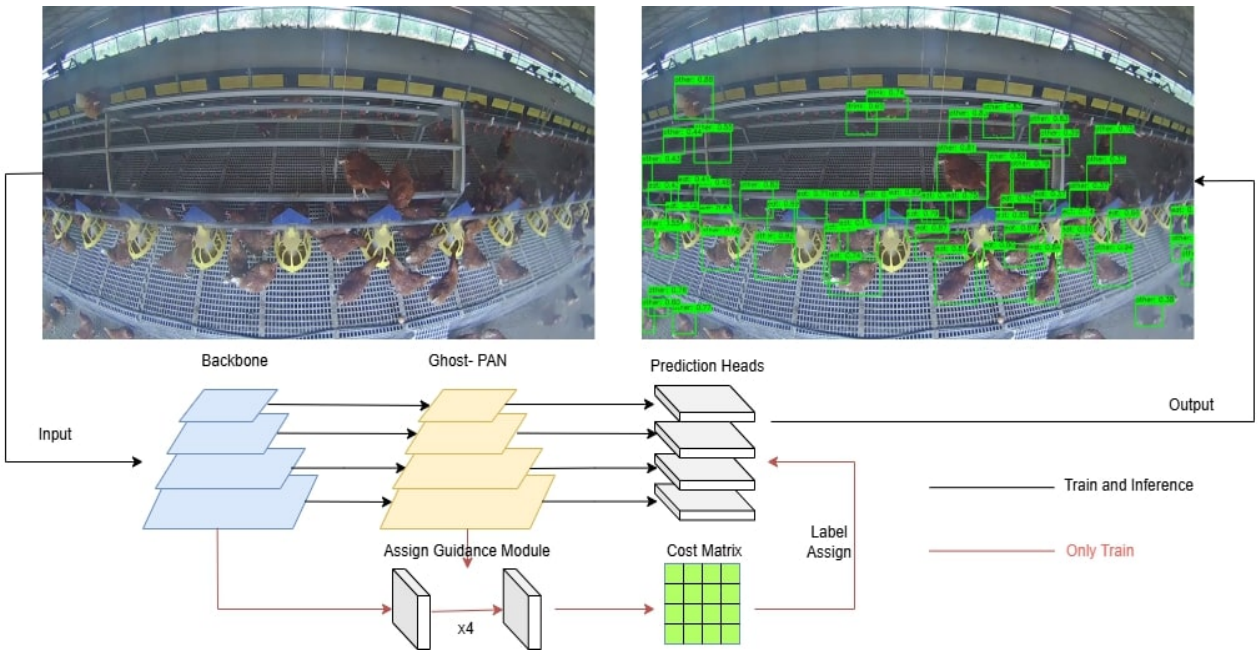


Figure 4.1: How we adopted Nanodet in our prototype system.

The detection model identifies individual hens and their activities, but tracking across multiple frames is essential for analyzing group behaviour patterns. Incorporating a tracking component enhances accuracy and enables the measurement of time spent on behaviours like drinking and eating, allowing for deeper behavioural analysis.

4.2.2 Tracking model

Multi-object tracking (MOT) is a key aspect of computer vision, responsible for tracking multiple objects simultaneously across recorded videos or live streams. In this study, a MOT

method called ByteTrack [84] is specifically adopted for tracking hens in video frames, especially in challenging environments such as commercial egg farms. These environments are often characterized by low light, dust and occlusion, which can make tracking difficult. The main advantage of ByteTrack is that it is able to correlate all detected bounding boxes, including those with low detection scores, to ensure that hens with low detection confidence - often due to partial occlusion or low visibility - are not discarded during the tracking process.

The tracking process follows the detection phase. The detection model is applied to each frame of the video sequence to identify hens and assign confidence scores to the bounding boxes. Typically, detections with higher scores are more reliable, while detections with lower scores may be less accurate due to factors such as occlusion or lighting conditions. However, instead of discarding low-scoring detections, ByteTrack uses a two-stage correlation strategy. The first stage associates high-confidence detections with existing tracklets to ensure primary tracking of the most reliable hen detections.

After the initial high-confidence correlation, ByteTrack performs a second stage of low-score detection recovery. It compares the low confidence bounding box to the existing minor tracks and uses their similarity to recover real objects that may have been missed by low scores in the first phase. This secondary correlation step is crucial in egg farm environments where hens are often overlapped or partially hidden by objects such as feeders or other hens. By exploiting these similarities, the system maintains continuous tracking of hens even under difficult conditions.

In addition to accuracy, ByteTrack is designed to be computationally efficient. It avoids relying on complex appearance or motion models and instead focuses on accurate detection and byte-level correlation. This efficiency makes the model suitable for real-time tracking, thus enabling real-time monitoring of hen behaviour with minimal computational resources.

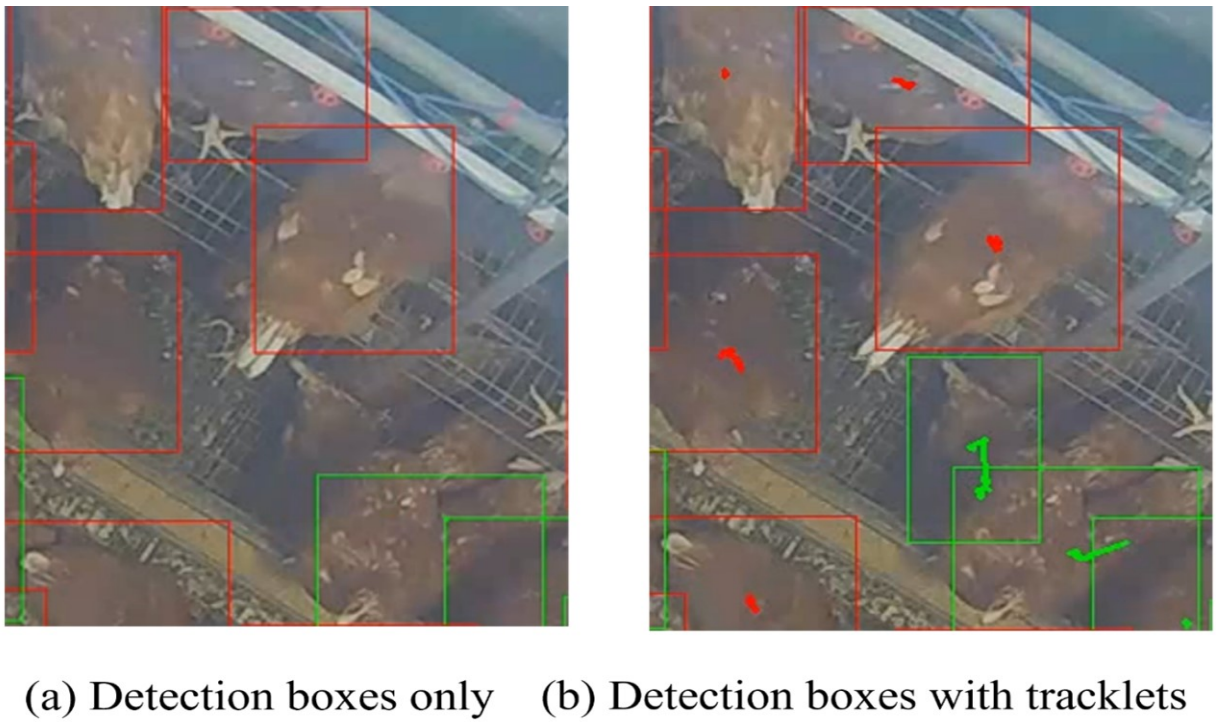


Figure 4.2: Comparison between detection only and detection plus tracking.

To demonstrate the benefits of integrating the tracking feature, a comparison was made be-

tween the detection-only and detection-plus-tracking scenarios in Figure 4.2. These two images are taken from the same frame in the same video. In the detection-only case, as shown in Figure 4.2(a), one hen was missed and had no detection box due to occlusion by other hens. However, after incorporating the tracking model, as seen in Figure 4.2(b), the system successfully retrieved the occluded hen through trajectory matching, highlighting the improved reliability of the system in complex environments.

In addition, it is important to clarify how ByteTrack maintains identity consistency and reduces mis-tracking in dense environments. ByteTrack leverages a motion-based tracking mechanism, where each detected hen is associated with a trajectory (tracklet) that is updated frame by frame. A Kalman filter is used to predict the position of each tracked hen in the next frame based on its previous movement. This prediction is then matched with new detections using an Intersection-over-Union (IoU) similarity metric, ensuring that the closest spatial match is selected. The association process is further optimized using the Hungarian algorithm, which minimizes matching errors across all detections.

The key strength of ByteTrack lies in its two-stage association strategy. By first matching high-confidence detections and then incorporating low-confidence detections, the algorithm is able to recover partially occluded or low-visibility hens that would otherwise be missed. This significantly reduces identity switching and track fragmentation, especially in crowded scenes where multiple hens overlap. However, it should be noted that ByteTrack does not include an appearance-based re-identification (ReID) module. As a result, when a hen leaves the camera view and later re-enters, it is typically assigned a new ID. Despite this limitation, the method remains highly reliable for short-term tracking within the observation area and is well-suited for real-time behavioural analysis in commercial egg farm environments.

4.2.3 System overview

The visualization of the system is shown in Figure 4.3. Each detected hen in the observation area has a unique ID and their movement trajectory is generated from a series of frames. The color of the ID indicates the current activity of the hen: green for eating, blue for drinking, and red for neither eating nor drinking. Due to the large number of hens in the frame, as well as obvious occlusions and overlaps, displaying each hen in a bounding box would clutter the image and hinder visualization. For this reason, the center point of each bounding box is used to represent each detected hen.

If a hen leaves the camera's field of view, the system stops monitoring the behaviour of that individual. When the hen returns to the camera's coverage area, the system assigns a new unique ID and restarts the detection and tracking process. Despite occasional misidentifications, the system demonstrates robust and stable performance, automatically recording observations in real time. This feature holds promises for improving hen welfare and is an excellent analysis tool for commercial egg farms.

4.2.4 Limitations of Mointoring System

Despite the strong performance of the proposed detection and tracking framework, several practical limitations remain when deploying the system in commercial egg farms. First, camera deviations—often caused by accidental physical contact, dust accumulation on the lens, or slight shifts during cleaning—can lead to changes in the viewing angle. Even small deviations may alter the apparent scale and orientation of hens, occasionally resulting in misdetections or

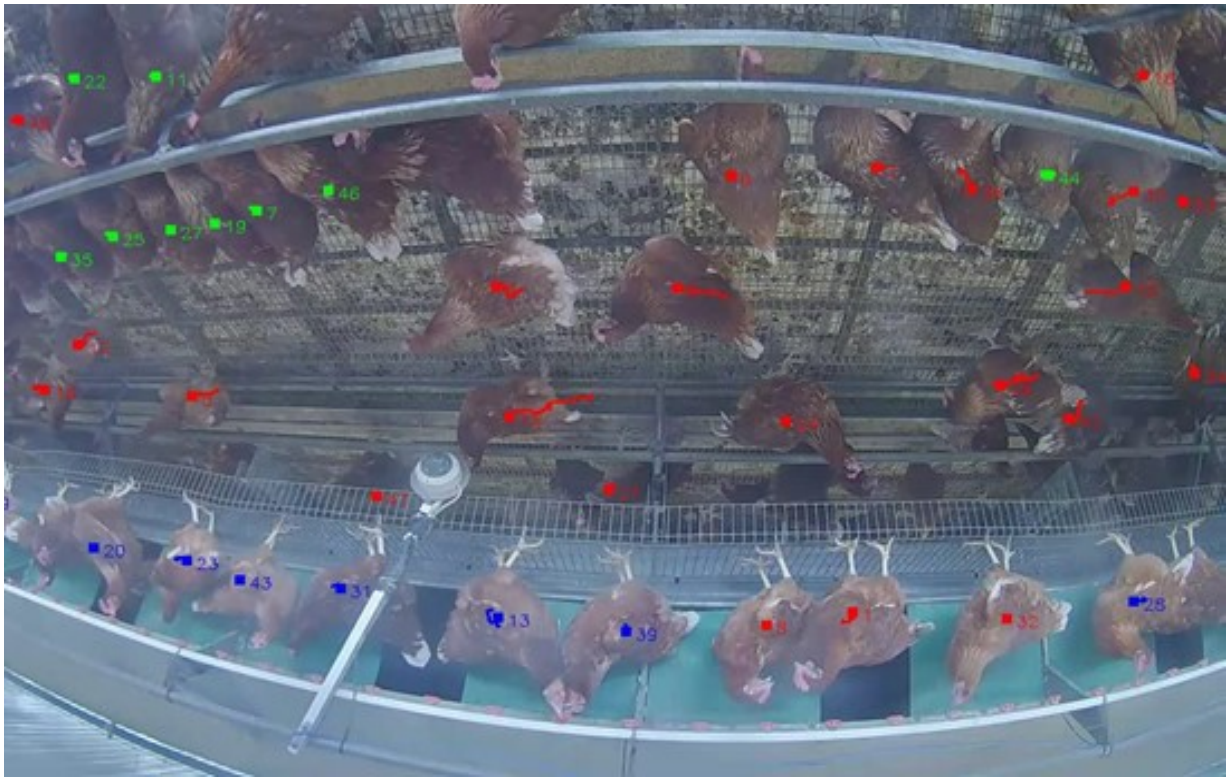


Figure 4.3: The visualization of hen activity monitoring system

ambiguous behavioural classifications. This issue is particularly evident for behaviours such as eating and drinking, where subtle head movements must be distinguished from non-consumptive actions.

Second, although the tracking component successfully maintains short-term identity consistency within the observation area, we still need to face the biggest challenge in tracking system: the re-identification (ReID) problem. As a result, when a hen leaves the camera's field of view and later re-enters, it is assigned a new ID. This prevents the construction of long-term behavioural histories for individual hens and limits the analysis to flock-level metrics rather than individual-level welfare monitoring. Given the density and dynamic movement patterns in commercial sheds, implementing a reliable ReID framework remains a challenging but important direction for future work.

Finally, the system's behaviour classification depends on visual cues captured from a top-down perspective, where drinking and eating are instantaneous and often occluded actions. This increases the likelihood of ambiguous detections, especially when birds crowd around feeders or drinkers. Although the prototype system provides robust group-level statistics, fine-grained behavioural interpretation at the individual level is still constrained by these visual and algorithmic limitations.

4.3 Defining Statistical Metrics

To evaluate the system's real-time monitoring capabilities, statistical metrics were established to extract meaningful insights from the generated data files. During real-time monitoring, the system outputted data files documenting all observed hens and their activities. Each file corresponded to a video clip and consisted of several hundred data rows, with each row

representing an observation at a specific timestamp. The activities were recorded in the format 'XX: YY', where "XX" denoted the unique bird ID, and "YY" indicated the activity (eating, drinking, or other behaviours).

The monitoring capabilities of the system prototype were evaluated in conjunction with practical requirements. Bird activities were associated with two key metrics: average activity time and activity statistical measurement. These metrics were designed to provide practical indicators for flock management, offering actionable insights into behaviour trends and welfare conditions.

The first metric is to compute the average activity time of the flock. Based on the generated files, this metric is computed as follows:

$$\bar{T} = \frac{\sum_i N_i T_i}{\sum_i N_i} \tag{4.1}$$

where N_i is the number of birds in the i-th group, and T_i represents the time each bird spends on a specific activity, such as eating. This metric provides insights into group-level behaviour patterns. A lower average activity time may indicate competition for resources or potential welfare challenges within the flock, whereas a higher value may reflect efficient resource utilization and favorable welfare conditions. It allows farm managers to assess overall flock activity and detect significant deviations or anomalies.

The second metric is the average proportion of birds that conduct a specific activity, over the sampled frames of the video stream within a period. We call these sampled frames snapshots. For the i-th snapshot, let N_i denote the total number of birds and M_i the number of birds engaged in the activity (e.g., eating). The average proportion over a given period, such as one hour, is computed as:

$$\bar{P} = \frac{\sum_i M_i}{\sum_i N_i} \tag{4.2}$$

This metric is calculated multiple times throughout the period, and the mean value is used to generate behavioural statistics. It captures group dynamics, illustrating how resources are utilized and whether activities are evenly distributed among the flock. Consistent proportions indicate uniform resource access and balanced flock behaviour, whereas variations may signal stress or uneven resource utilization.

Both metrics offer valuable insights into flock-level behaviour and resource usage. The average activity time measures the overall time commitment to specific behaviours, while the activity statistical measurement highlights the distribution of these activities across the flock.

Together, these metrics address practical challenges in poultry management, enabling a comprehensive understanding of flock behaviour. This quantitative framework helps identify irregularities and trends, facilitating data-driven interventions to improve resource allocation, enhance welfare, and optimize productivity in commercial farming environments.

4.4 Conclusion

This chapter has presented the development and evaluation of an automated system for detecting and tracking laying hen behaviours in commercial egg farms. The detection model

evaluation demonstrated that the choice of backbone and head architecture significantly influences accuracy and computational efficiency. Among the tested configurations, ResNet-18 with the GFL head achieved the highest detection accuracy, while lightweight networks such as ShuffleNetV2 provided competitive performance with faster inference times. Comparisons among state-of-the-art detectors revealed that YOLOv8n achieved the highest precision, whereas NanoDet offered the optimal trade-off between accuracy and processing speed, making it particularly suitable for real-time monitoring in large-scale commercial environments.

The integration of the ByteTrack multi-object tracking algorithm enhanced the system's reliability, enabling accurate identification of hens even under occlusion or partial visibility. Visualization of tracked hens, combined with unique IDs and trajectory representations, allows clear interpretation of individual and group-level behaviours, while minimizing visual clutter in dense flocks.

To quantify behaviour, two primary statistical metrics—average activity time and the proportion of active birds—were developed. These metrics provide insight into flock-level dynamics, resource utilization, and potential welfare issues, enabling early detection of abnormal behaviours or environmental stressors. By combining detection, tracking, and quantitative metrics, the system provides a robust, real-time tool for precision poultry management.

In summary, the developed system demonstrates that advanced computer vision models, coupled with efficient tracking and behavioural analytics, can deliver actionable insights for welfare assessment and operational optimization. It provides a scalable framework that can be deployed in commercial egg farms to continuously monitor individual and flock behaviours, supporting data-driven interventions, improved resource allocation, and enhanced productivity while promoting animal welfare.

Chapter 5

Flock behavioural Analysis

5.1 Introduction

In this chapter, we present the results and analysis from the prototype system we developed to monitor laying hen behaviour in commercial egg farms. The primary focus is on quantifying hen activities, such as eating and drinking, and analyzing their correlation with environmental factors, such as temperature. By leveraging advanced object detection and tracking models, we can automatically collect behavioural data, providing valuable insights into the welfare and productivity of hens.

The study aims to offer a comprehensive understanding of how environmental conditions influence hen behaviour, providing farm operators with actionable data to optimize welfare and improve operational efficiency. The analysis is based on real-time video data collected from two commercial egg farms in New South Wales (NSW) and Queensland (QLD), Australia. We examine the relationship between hourly and daily activity statistics and explore how factors like temperature can impact key behaviours. This chapter also includes a comparison with related studies in the field, highlighting the strengths and innovations of our approach.

5.2 Quantitative behavioural Analysis

Based on the object detection and tracking model, we recorded hen activities and analyzed behaviour patterns. As shown in Figure 5.1, it demonstrates the hourly statistics of hen activities on January 8, 2024 with the camera C109. The blue bar represents the average eating time while the orange bar shows the average drinking time. The red line represents average temperature each hour. A preliminary conclusion suggests that hens are more active in the morning when temperatures are lower. As temperatures increase significantly, both average eating and drinking times decrease. On this day, as the temperature peaks at 28.8°C at 2 pm, the average drinking and eating times reach their lowest. In contrast, when temperatures are lower in the morning, these times are higher. The average drinking time is notably shorter than the average eating time because drinking behaviour in chickens involves quickly pecking at the water tap, resulting in brief, sudden interactions. The average eating and drinking rates are shown in Figure 5.2. It is similar to the previous figure, but instead of average eating and drinking times, this figure shows the average eating and drinking rates. The trend of average eating and drinking rates remains the same as before, though the fluctuations are less pronounced. To

detail the correlation between environmental factors and activities, we extend hourly statistics to daily statistics.

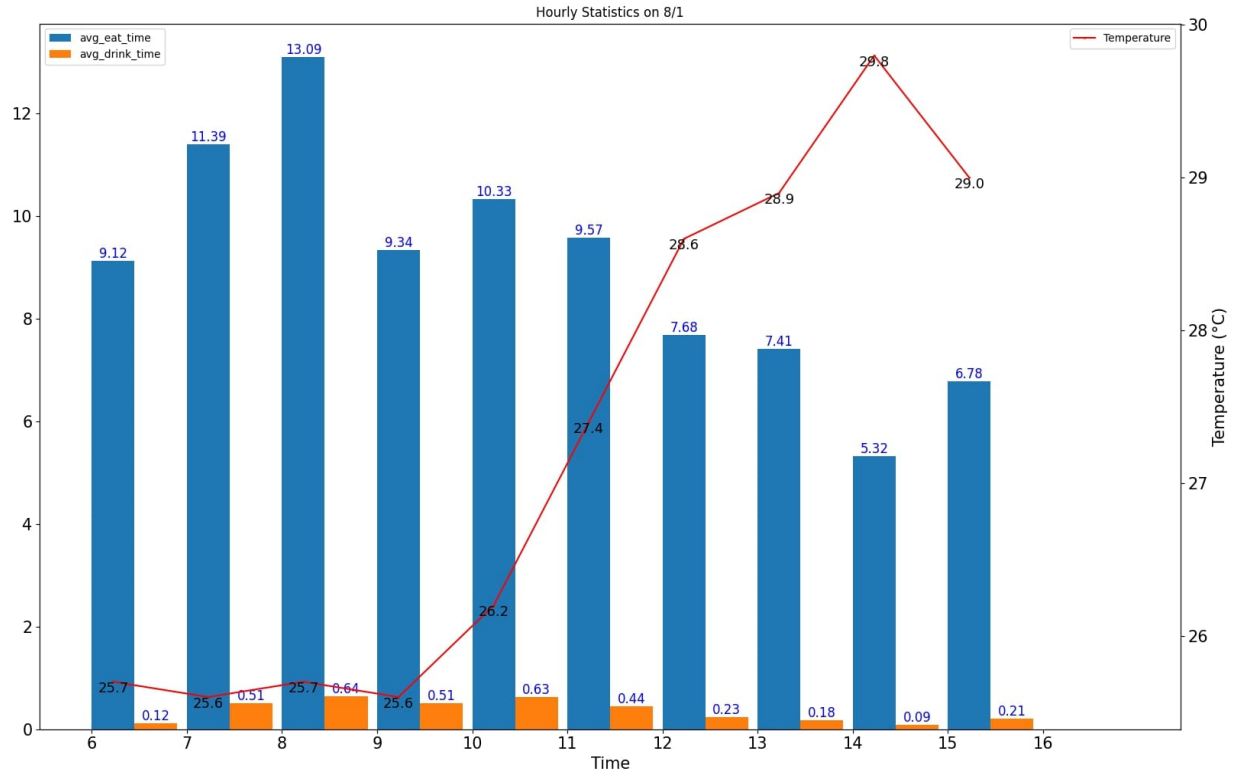


Figure 5.1: The hourly statistics of hen activity times

From the collected data, it appears that the peak drinking and eating periods of the hens are generally concentrated in the morning between 8 and 9 a.m. Therefore, we visualized the data collected from January 5, 2024, to January 19, 2024, focusing on the period from 8 a.m. to 9 a.m. The statistics are illustrated in Figure 5.3. The green line represents the average eating time of hen during that hour, the orange line represents the average drinking time of hen during that hour, and the bar graph records the average temperature in the shed during that time of day. Since the time the hen spends on eating is usually much longer than the time the hen spends on drinking, in order to see the trend of the line graph more clearly and to analyze the correlation between the hen's behaviour and the temperature, we divide the recorded eating time uniformly by 10 to make the fluctuation of the line graph more obvious. From the data shown in the graph, it can be seen that on the days with lower temperatures (24.6°C on the 6th of January and 24.3°C on the 7th of January), the eating time of hen was much more than on the days with higher temperatures (28.6°C on the 15th of January and 28.8°C on the 16th of January). This can be proved in a previous study [85]. It shows that laying hens kept at 30°C showed poor performance and had altered nutrient digestibility compared to those housed at 24°C, which means that when the temperature is high, the hen's appetite and digestive system is not as good as it is when the temperature is low.

Typically, hens tend to eat less and drink more as temperature rises [86]. We are able to reach this conclusion through quantitative analysis, as opposed to the traditional qualitative approach. In our data graph, there is a trend for the average time spent on eating to drop as the temperature increases, with the average drinking time going up instead. In the first few days, with temperatures between 24 and 27 degrees Celsius, the hens' average drinking

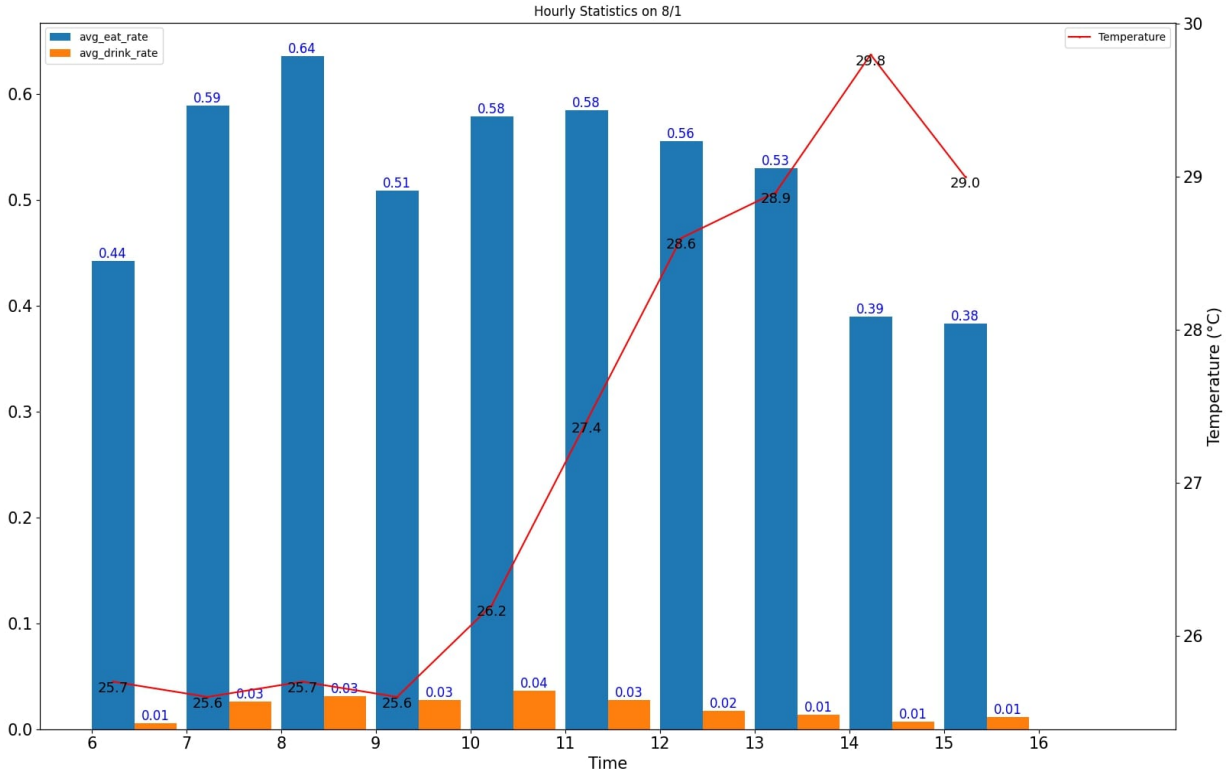


Figure 5.2: The hourly statistics of hen activity rates

time fluctuated slightly and remained relatively stable. However, as the temperature rose from 27.8°C on the 14th of January to 28.8°C on the 16th of January, the hens' average drinking time gradually increased.

This could be an alarm for farmers that a significant decrease in the average time hens spend on eating can lead to a reduced nutrient conversion rate, ultimately affecting hen's health status and egg production. The increased average drinking time of hens will result in the increased water intake, which would raise the water content of the feaces, thus making the shed wet, which is not conducive to the growth of hens, and the eggs will be easily tainted. In hot summers in Queensland, when the temperature is high and the chicken's water intake increases, the hen's feaces tend to be too thin, which ultimately seriously affects the health condition of the hen and egg production. If this issue is not addressed promptly, the prolonged discomfort could lead to higher mortality rates among hens in commercial egg farms, significantly impacting overall production and animal welfare.

5.3 Cross-source data integration

To obtain a more holistic understanding of hen behaviour under real commercial conditions, the behavioural metrics extracted from the automated video analysis were integrated with daily operational data provided by the two collaborating egg farms in NSW and QLD. This cross-source integration allowed us to investigate how behavioural patterns correspond to environmental fluctuations, management conditions, and production outcomes. In essence, the behavioural indicators derived from the video serve as the real-time, fine-grained observations of the flock, while the farm-level data provide the broader context within which these behaviours occur.

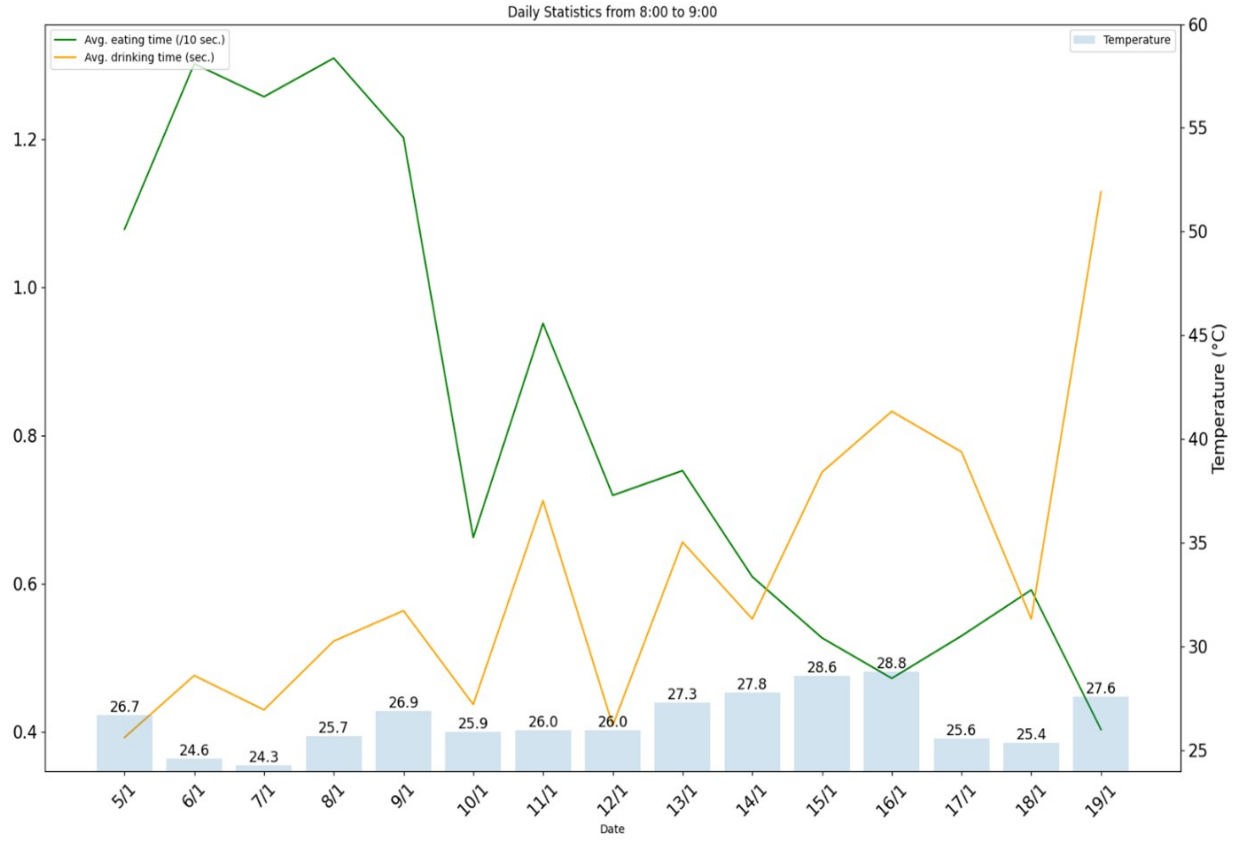


Figure 5.3: The daily statistics of hen activity times

The NSW farm supplied daily records that included bird numbers, mortality counts, feed consumption, water consumption, the number of first-grade eggs, the number of floor eggs, and the minimum and maximum temperatures recorded inside the shed. Meanwhile, the QLD farm provided daily summaries of feed intake, water usage, egg numbers, and corresponding temperature measurements. These datasets vary in structure but together form a complementary set of indicators that reflect the overall operational conditions in each farm. By linking this information with the time-stamped behavioural summaries generated from video analysis, we were able to evaluate behaviour not in isolation but as part of a dynamic production system.

The hourly behavioural metrics for one of the NSW cameras (C107) are shown in Figures 5.4 and 5.5. Figure 5.4 presents the average eating and drinking time per bird, offering insight into how long hens are engaged in these activities. Figure 5.5 illustrates the snapshot-based proportions of eating and drinking, providing an estimate of how many hens are performing these behaviours at different times of the day. When viewed together, these plots reveal distinct behavioural rhythms. Eating tends to peak during the cooler early hours, while drinking is generally infrequent and highly variable. These trends align with known thermoregulatory behaviours in poultry: hens often consume more feed when temperatures are mild, and water intake increases as temperatures rise. The hourly behavioural metrics for one of the NSW cameras (C110) are shown in Figures 5.6 and 5.7.

We extended this comparison to the QLD farm using cameras C109 and C113. The first set of visualisations, Figures 5.8 and 5.9, highlight drinking behaviour across different hours of the day. The bar charts represent both the average drinking time and the proportion of hens observed drinking, while the temperature curve shows the corresponding environmental con-

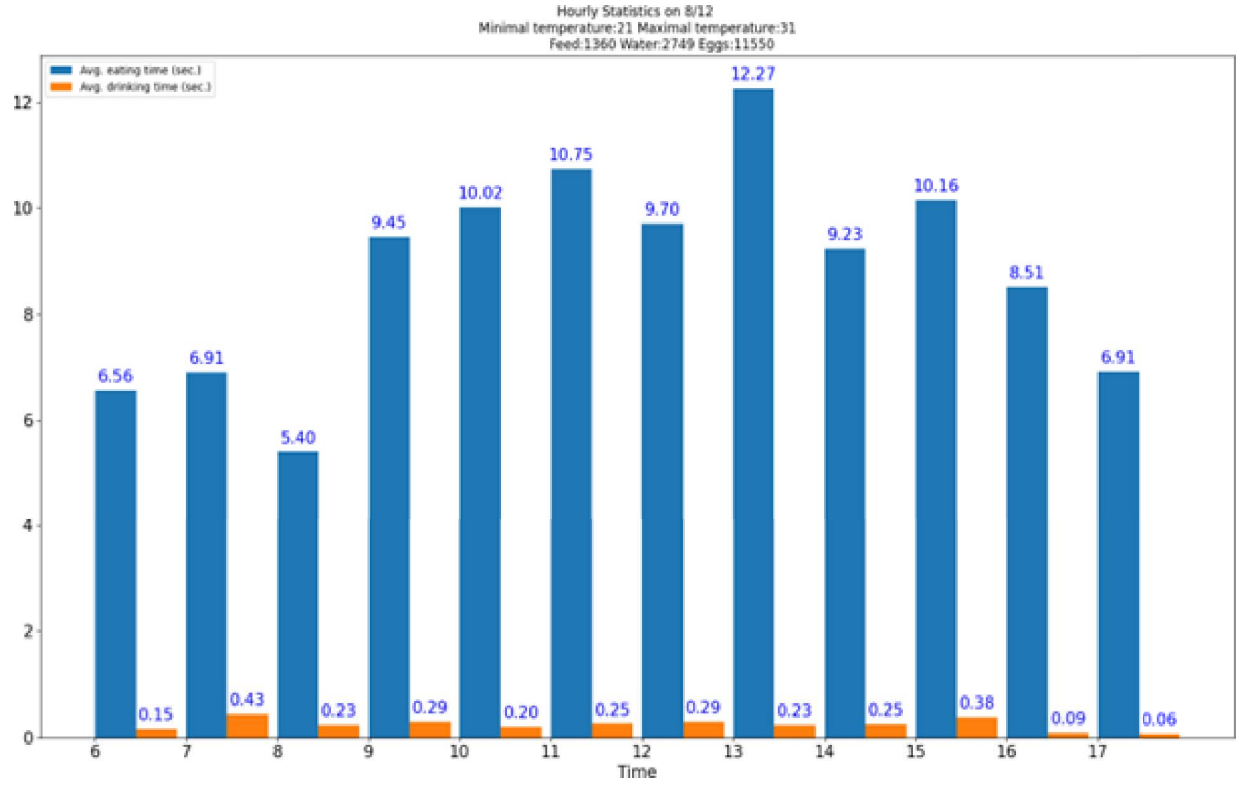


Figure 5.4: The illustration of hourly statistics focusing on average eating and drinking time. (C107, NSW)

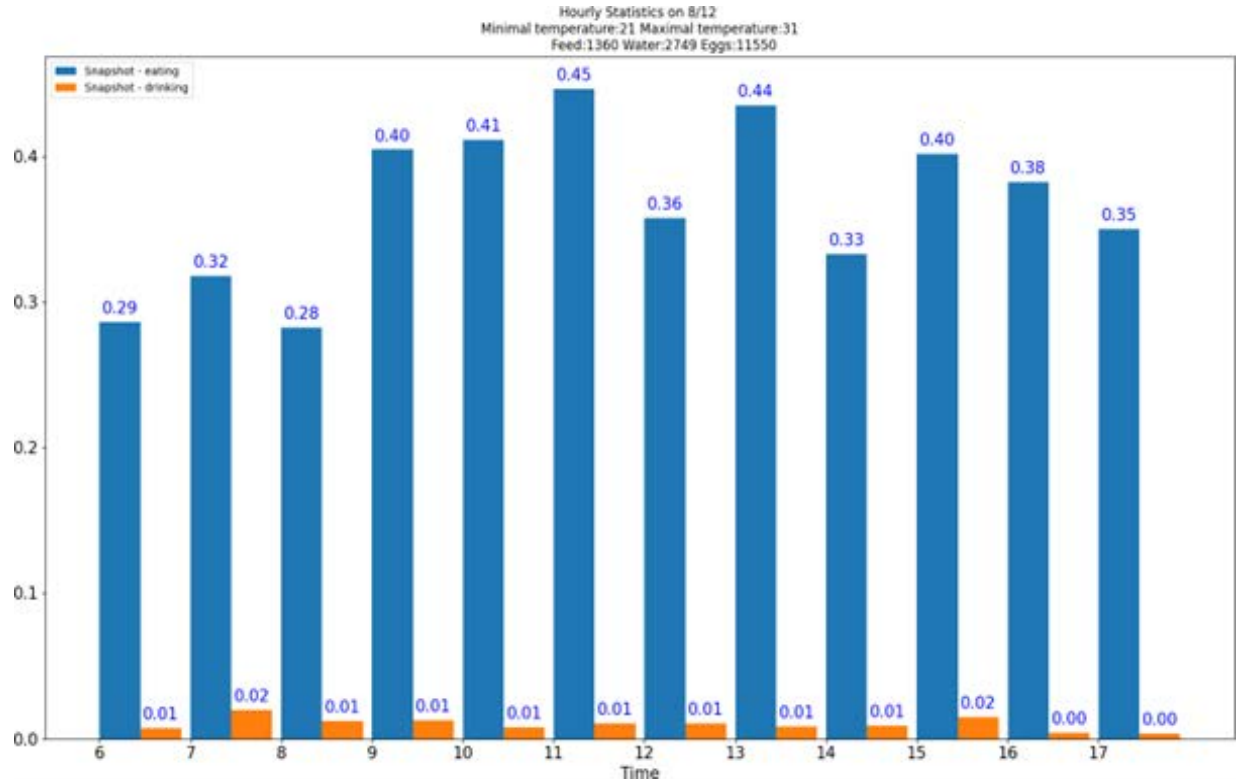


Figure 5.5: The illustration of hourly statistics focusing on snapshot eating and drinking. (C107, NSW)

ditions. For instance, on 03/02/2024, drinking was most prominent during the morning when temperatures were still rising. After midday, as shed temperatures climbed above 32°C, drinking activity declined sharply. This pattern demonstrates a measurable behavioural response to increasing environmental heat load. When viewed over several days through our interactive web dashboard, consistent patterns emerge: drinking spikes in the morning and early afternoon before being suppressed by higher ambient temperatures later in the day.

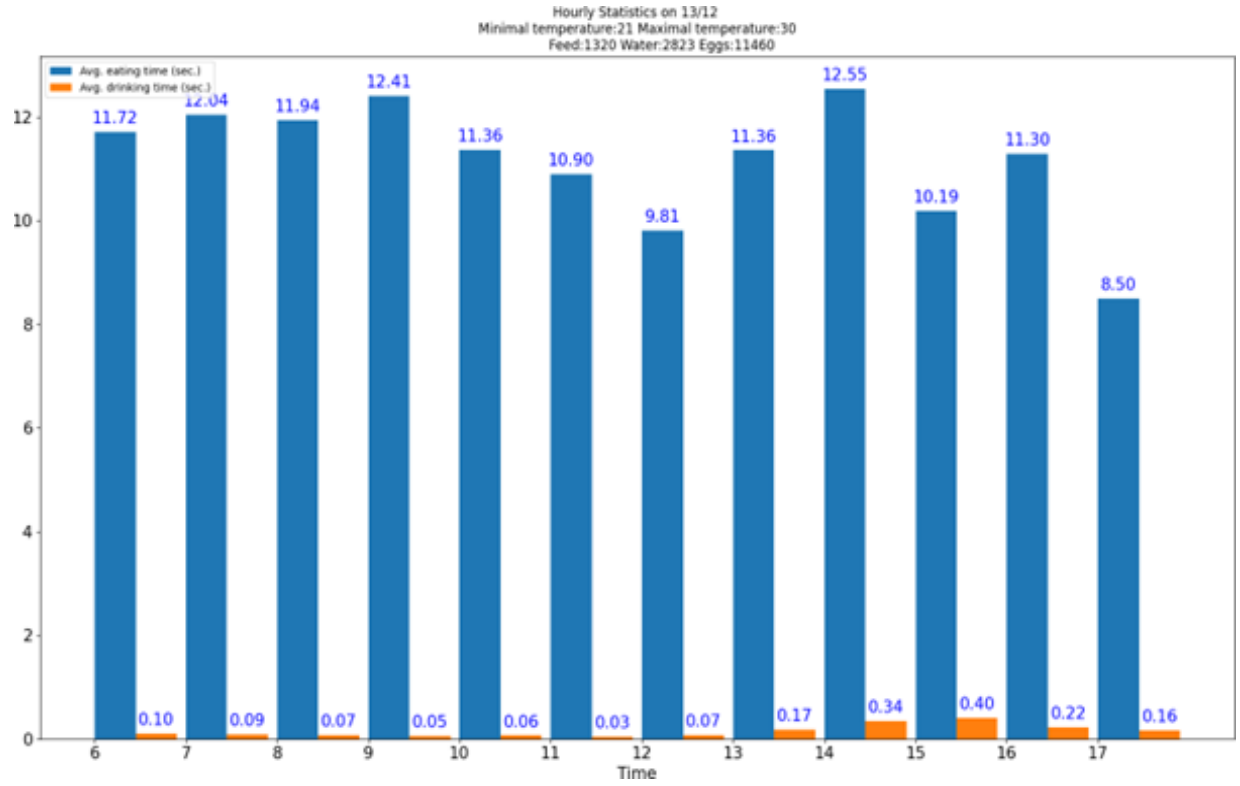


Figure 5.6: The illustration of hourly statistics focusing on average eating and drinking time. (C110, NSW)

The eating-focused visualisations, provided in Figures 5.10 and 5.11, illustrate a different type of relationship with environmental conditions. Unlike drinking, which is composed of very brief and intermittent behaviours, eating involves sustained interactions with the feeder where hens lower their heads into the trough for longer durations. However, these continuous interactions introduce a layer of observation complexity: because the feeder blocks the view of the hen's beak from the top-down camera perspective, the system can only infer eating behaviour from head orientation and proximity. While this limitation means that some eating behaviours may be underestimated, the overall temporal pattern still remains clear. Eating tends to follow a predictable daily cycle, rising in the morning, fluctuating at midday, and declining slowly towards late afternoon.

It is also important to highlight the practical limitations associated with detecting drinking behaviour. Drinking events are extremely short—hens typically take only a fraction of a second to peck the water nipple—and may occur while the head is partially obscured by other hens or by the water line itself. As a result, many drinking events are difficult for any vision-based system to capture reliably. These biological and observational constraints help explain why drinking durations appear much shorter than eating durations in our dataset. Despite this, the relative changes over time still provide valuable behavioural indicators.

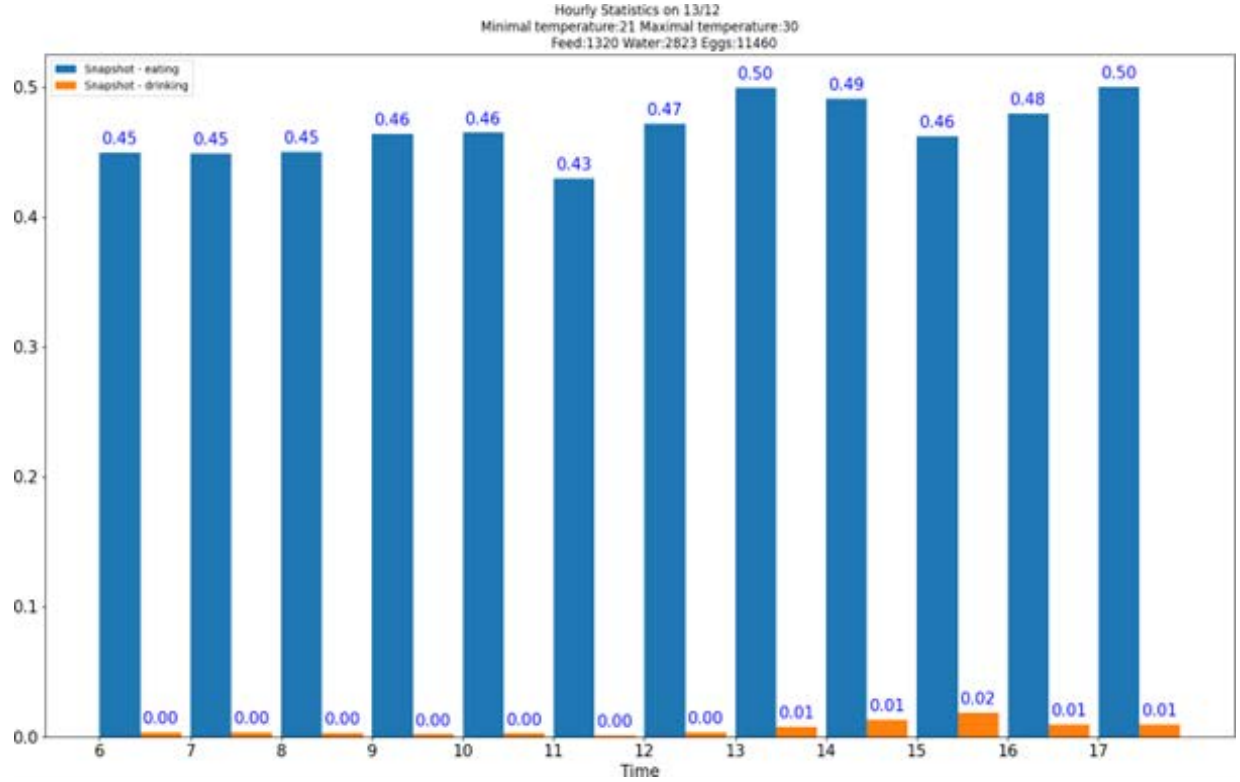


Figure 5.7: The illustration of hourly statistics focusing on snapshot eating and drinking. (C110, NSW)

The integration of these behavioural and environmental datasets yields several important insights. First, the combined visual and operational data consistently show that behaviour is sensitive to temperature fluctuations. As temperatures rise, eating tends to decrease while drinking may briefly increase before dropping off, reflecting the birds' attempts to regulate their internal temperature. Second, by comparing these behavioural shifts with egg production records, farm operators may begin to identify early indicators of reduced productivity or emerging welfare challenges. Third, the visualisations establish a behavioural baseline for each flock. Any significant deviation from this baseline—such as unusually low feeding activity or prolonged declines in drinking—could signal heat stress, illness, or disruptions in feed or water availability.

Moving forward, this cross-source analytical framework can be enriched by incorporating additional variables such as stocking density, ventilation rates, litter quality, or hen age. For example, integrating egg weights with feeding trends could reveal subtle links between nutrition intake and product quality. Adding humidity or ammonia measurements could provide deeper understanding of environmental stressors. With more comprehensive multi-modal data, future research can move beyond descriptive analysis toward predictive modelling, supporting early-warning systems for welfare or production risks.

In summary, the integration of video-derived behavioural metrics with farm operational records provides a powerful means of understanding flock dynamics in commercial egg farms. This approach not only reveals how hens respond to changes in their environment but also lays the foundation for data-driven decision-making in precision livestock farming. By identifying correlations between behaviour, environment, and productivity, farm managers can intervene earlier, adjust management strategies more effectively, and ultimately improve both welfare

and production outcomes.

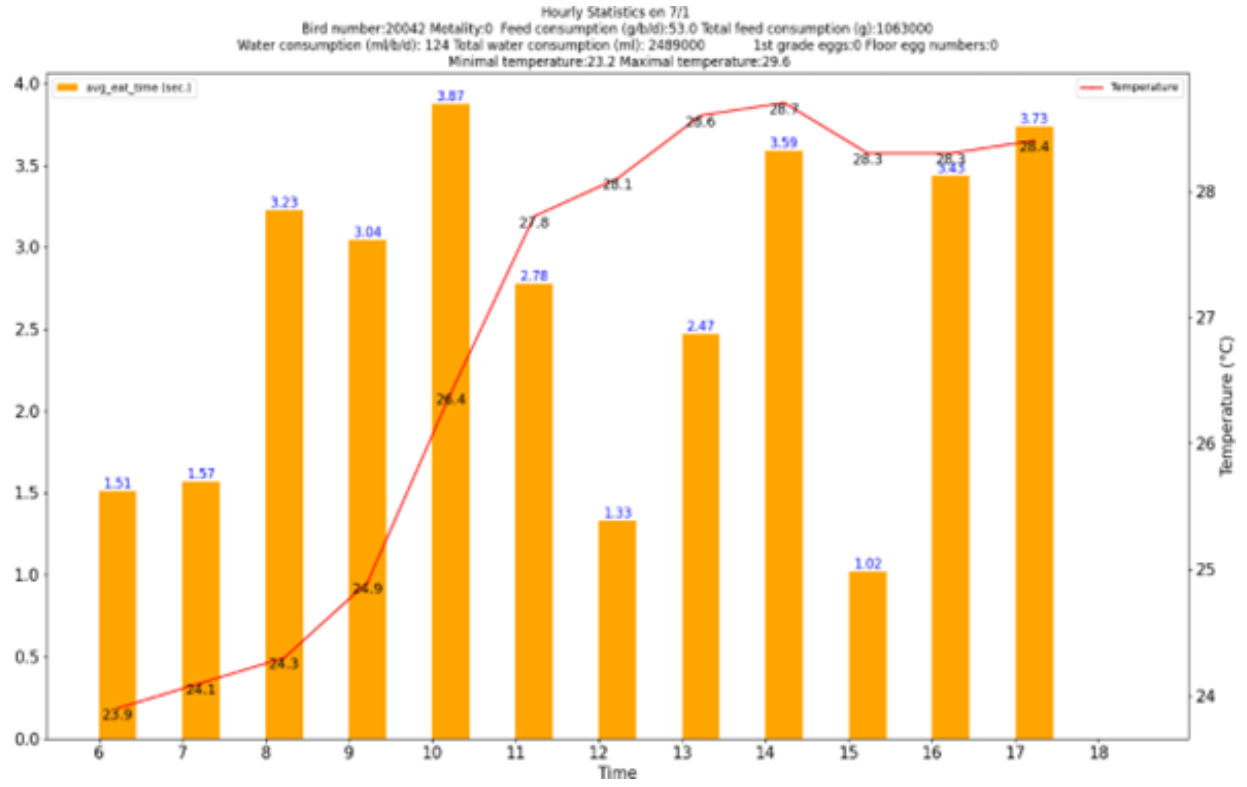


Figure 5.8: The illustration of hourly statistics focusing on average drinking time (C109, QLD)

5.4 Comparison with Related Studies

Table 5.1 summarizes comparable studies, highlighting the varying challenges of behaviour identification across settings. At the individual level, identification is relatively straightforward due to minimal occlusions or obstructions. In lab environments, where chicken density is moderate, identification remains effective thanks to controlled conditions and sparser positioning. However, commercial settings present significant challenges due to higher densities, frequent occlusions, and complex environments. There are typically 25,000-50,000 laying hens in each shed on commercial egg farms, which is a large scale. The number of laying hens in each viewed area on commercial egg farms is much more than lab level. Visibility in commercial egg farm sheds is often hindered by poor lighting, primarily caused by dust, and shading from hens clustering together or being obscured by other hens or objects like feeders, complicating accurate behaviour detection. Research in chicken deep learning applications focuses primarily on broilers and laying hens, each with distinct objectives [1]. In our research, we mainly focused on laying hens on commercial egg farms.

Most methods employ YOLO series models [22][87][23][24][68] as the primary detector, supplemented by additional methods to enhance performance for chicken behaviour analysis. Some approaches integrate traditional machine learning methods, such as support vector machine (SVM)[88], while earlier studies relied on older deep learning models like DenseNet[89]. With advancements in classification models, behaviour identification has evolved from basic behaviours like standing and walking to more complex actions such as threatening and flapping, and even abnormal behaviours like inactivity and huddling. Our method utilizes the advanced

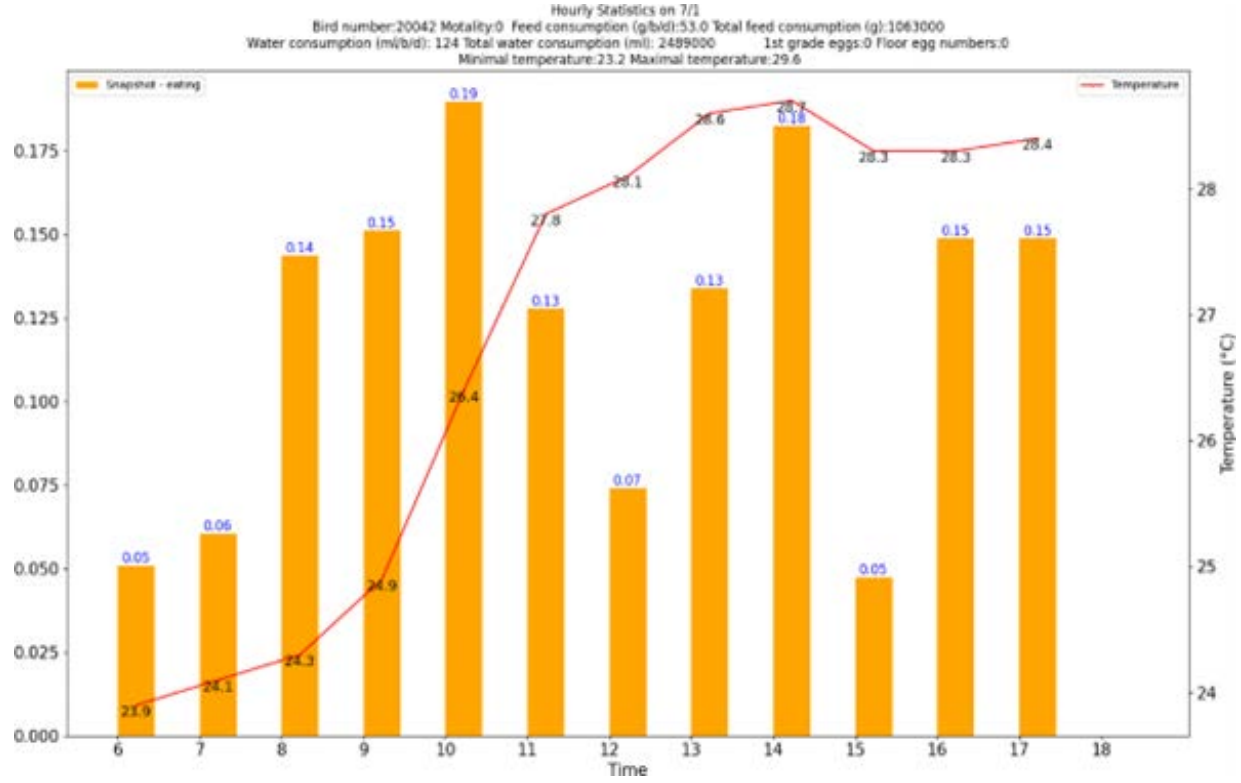


Figure 5.9: The illustration of hourly statistics focusing on snapshot for drinking behaviour (C109, QLD)

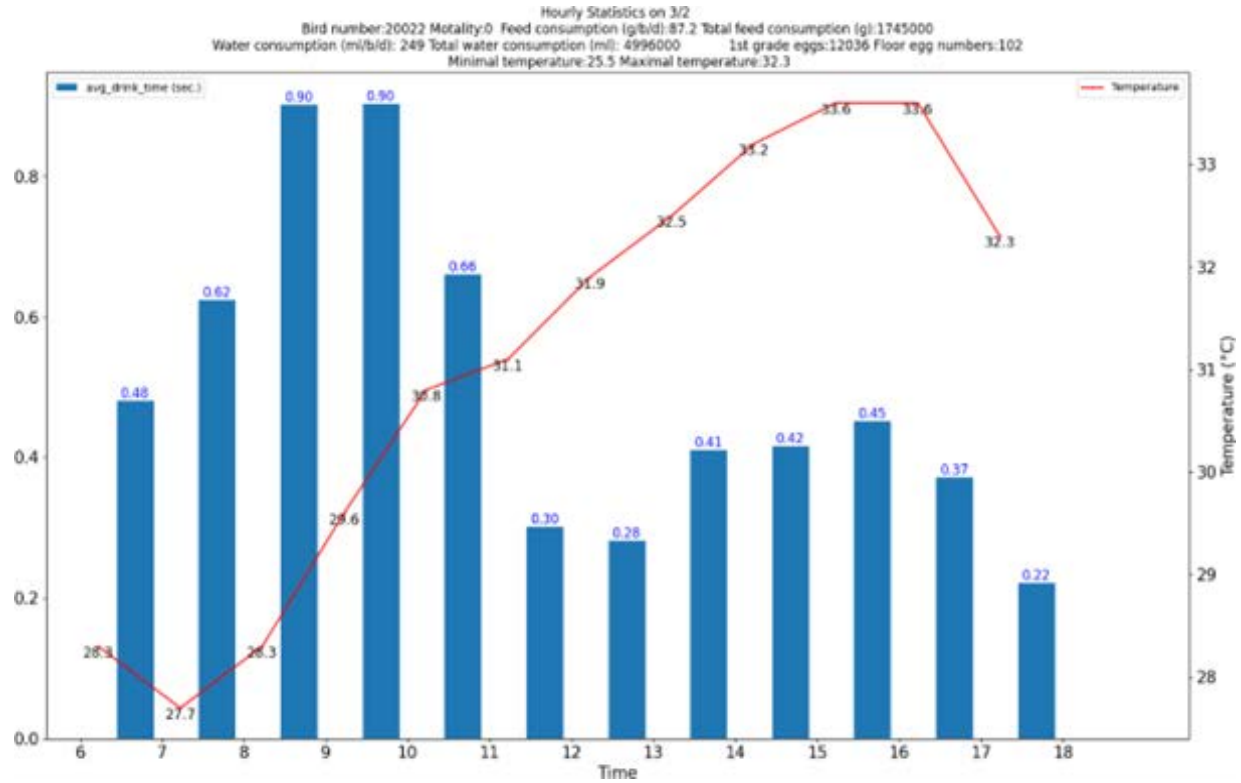


Figure 5.10: The illustration of hourly statistics focusing on average eating time (C113, QLD)

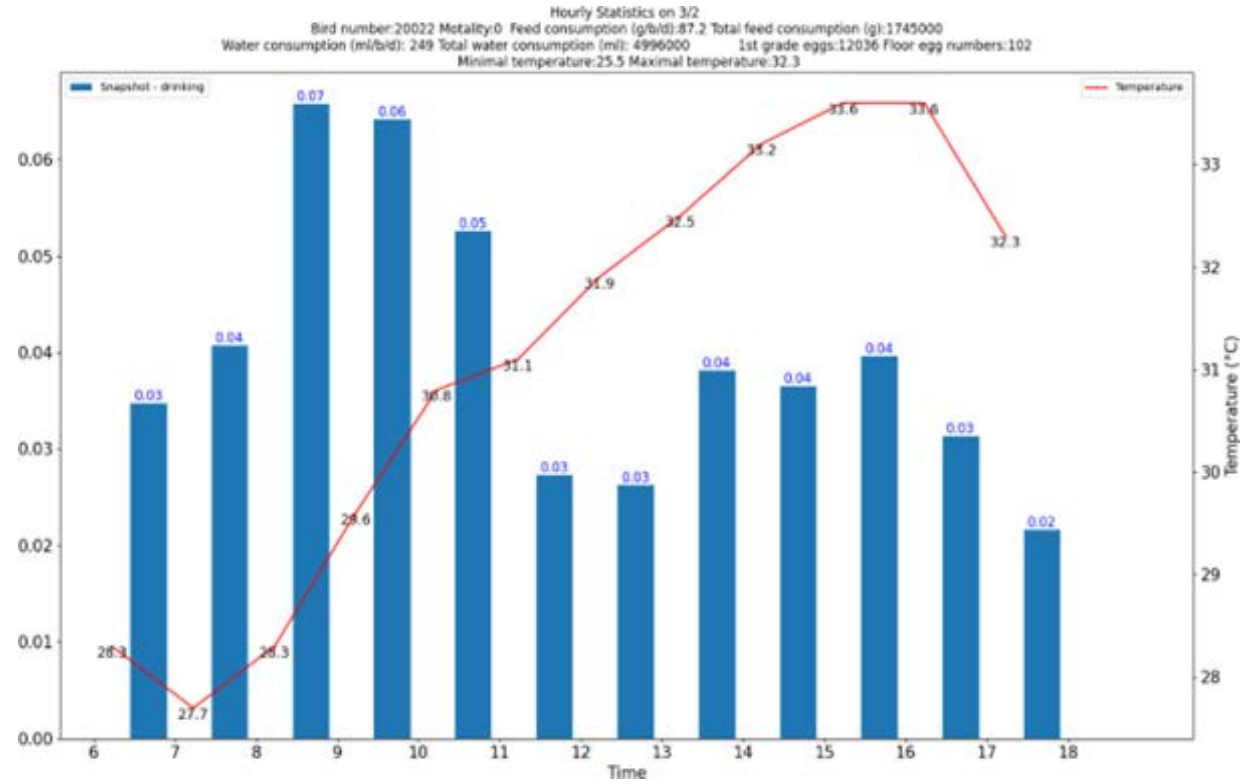


Figure 5.11: The illustration of hourly statistics focusing on snapshot for eating behaviour (C113, QLD)

NanoDet detector, enhanced with DSLA and AGM to boost performance. Additionally, we integrate the ByteTrack algorithm to assist in building a robust prototype system.

Previous studies primarily focus on identifying basic chicken behaviours, with some capable of recognizing more complex activities like dustbathing and perching. Our methodology advances beyond basic identification by enabling the quantification of activity duration and exploring potential behavioural correlations. This approach sets a new standard in poultry behaviour research, offering a scalable and effective solution for future studies.

5.5 Conclusion

This chapter has demonstrated the effectiveness of our prototype system in quantifying hen behaviour and analyzing the impact of environmental factors in commercial egg farms. By combining real-time video analysis with deep learning-based detection models, we were able to capture and track hen activities such as eating and drinking, revealing clear patterns related to temperature fluctuations. The findings suggest that hens are more active in the cooler morning hours, with eating and drinking times decreasing as temperatures rise. These insights are crucial for optimizing farm management practices, as they help identify potential welfare concerns that could affect both the health of the hens and the quality of egg production.

Moreover, we have advanced beyond traditional qualitative assessments by introducing quantitative behavioural analysis, which enables more precise and data-driven monitoring of hen welfare. This approach not only enhances the accuracy of behaviour recognition but also provides valuable baseline data that can be used to detect deviations from normal behaviour. We further compared our method with existing studies, highlighting how our system goes beyond

Table 5.1: Summary of comparable experiments on poultry behaviour

Study	**Bird type**	**behaviour type**	**Model**	**Identification level**	**Quantitative analysis**
(Y. Guo et al., 2022)[89]	Broiler	Feeding, drinking, standing, and resting	DenseNet-264	Individual level	No
(Yang et al., 2023)[22]	Cage-free bird	Drinking, dust bathing, eating, perching, walking, and nesting	YOLOv5-cls	Individual level	No
(L. Li et al., 2024)[88]	Laying hen	Threatening, fighting and evading	ISSA-SVM	Individual level	No
(Chang et al., 2024)[87]	Broiler	Standing, walking, resting, eating, preening, and flapping	YOLOv4 + fuzzy logic inference	Lab level	No
(Paneru et al., 2024a)[23]	Laying hen	Dustbathing	YOLOv7-DB	Lab level	No
(Paneru et al., 2024b)[24]	Laying hen	Perching	YOLOv8x-PB	Lab level	No
(Ehsan et al, 2024)[68]	Broiler	Abnormal behaviours (i.e. inactivity, and huddling)	YOLOv4 + Centroid	Commercial level	No
Ours	Laying hen	Eating and drinking	NanoDet + ByteTrack	Commercial level	Yes

basic behaviour recognition to offer a scalable solution for commercial settings.

While the results are promising, future work should focus on expanding the range of detected behaviours and integrating additional environmental sensors to enhance the depth of the analysis. The findings in this chapter contribute significantly to the ongoing effort to create smarter, more efficient systems for poultry welfare management, offering a foundation for future innovations in precision livestock farming.

Chapter 6

Conclusions and Future Work

6.1 Summary of Outcomes

This thesis has demonstrated the potential of integrating advanced computer vision and deep learning techniques with poultry farming practices to improve the monitoring of laying hen behaviour, welfare, and productivity. The research addressed key limitations of existing methods, particularly the heavy reliance on qualitative assessments and the lack of scalable, real-time solutions suited to commercial farm conditions.

A major contribution of this work is the construction of ChickenbehaviourView, the first top-down, multi-task chicken behaviour video dataset. Comprising nearly 17,000 annotated instances across multiple video sequences, this dataset provides an essential resource for benchmarking detection, tracking, and behaviour recognition models. It has already enabled the evaluation of state-of-the-art algorithms and laid the foundation for practical applications of deep learning in commercial egg production.

In parallel, a prototype monitoring system was developed using advanced detection and tracking methods such as NanoDet and ByteTrack. The system achieved a satisfied accuracy under real farm conditions, demonstrating its feasibility for real-time, automated monitoring of large flocks. Beyond technical performance, the prototype linked behavioural data—such as eating and drinking duration—with environmental factors, including shed temperature, feed consumption, and egg production. These correlations provided valuable insights into the influence of external conditions on welfare and productivity, offering farm operators actionable information for management decisions.

Together, these contributions advance the field of precision livestock farming by bridging the gap between laboratory studies and practical farm deployment. They show that continuous, non-invasive, and data-driven monitoring can significantly improve welfare assessment while reducing reliance on manual labor.

6.2 System Limitations

While the automated monitoring system demonstrates strong potential for commercial deployment, several limitations must be acknowledged. Camera misalignment, dust accumulation, and minor shifts during routine farm operations introduce noise into the visual stream, occasionally causing misdetections or uncertain behavioural interpretation. Developing automated camera

calibration or self-correction mechanisms would help maintain consistent detection performance over long-term deployment.

Another key limitation is the re-identification (ReID) problem. Although the current tracker maintains identity consistency within each continuous clip, individuals cannot be reliably tracked across longer time spans or after leaving and re-entering the field of view. This restricts the system to flock-level behavioural quantification and prevents longitudinal welfare analysis for specific hens. Incorporating the most advanced tracking models—potentially using colour patterns, body morphology, or temporal embedding—represents an important avenue for future research.

Finally, the classification of eating and drinking behaviours remains constrained by the top-down viewpoint, instantaneous nature of these behaviours, and frequent occlusions. Enhancing temporal modelling, integrating multi-view cameras, or combining visual data with environmental sensors (e.g., feed or water actuator activity) could improve classification reliability. Addressing these challenges will enable the system to evolve from flock-level analytics toward more detailed, welfare-focused behavioural monitoring.

6.3 Recommendations & Future Work

Although the system developed in this study represents a significant advancement in automated poultry monitoring, several areas remain open for further improvement and future exploration. One key limitation is the current behavioural scope of the system, which has so far focused primarily on detecting fundamental activities such as eating and drinking. Expanding detection to more complex behaviours—including perching, social interactions, stress-related actions, and aggressive encounters—will provide a more comprehensive picture of flock welfare and enable more targeted interventions.

Another important recommendation is to enhance the system's ability to differentiate between similar activities. For example, while head movements into feeders or drinkers can be reliably detected, distinguishing between actual feeding or drinking and other non-consumptive actions remains a challenge. More refined temporal modeling, supported by multimodal data such as acoustic or physiological signals, will be necessary to achieve greater classification accuracy and ensure meaningful behavioural insights.

The robustness of the system in challenging environments also warrants further attention. Farm conditions often involve crowding, variable lighting, and occlusions, all of which can compromise detection and tracking accuracy. Future work should explore more resilient algorithmic approaches, such as self-supervised learning, domain adaptation, and improved model generalization, to ensure consistent performance across diverse commercial settings.

In addition, the integration of multimodal environmental data presents a valuable opportunity for extending the system's capabilities. Incorporating information such as air quality, humidity, light intensity, and acoustic signals could yield a richer understanding of the factors influencing hen welfare. By fusing these data sources with behavioural metrics, future systems may achieve earlier and more accurate detection of stress, illness, or suboptimal living conditions.

Long-term deployment will also allow the establishment of behavioural baselines for flocks, creating benchmarks against which anomalies can be identified with greater precision. These baselines could prove valuable not only for real-time monitoring but also for epidemiological

studies, offering new tools for identifying risk factors associated with disease outbreaks and other health challenges.

Finally, for the system to achieve widespread industry adoption, issues of scalability, cost-effectiveness, and ease of deployment must be addressed. Practical integration with existing farm management platforms, combined with validation through partnerships with commercial producers, will be critical for ensuring that these technologies move beyond research prototypes to become standard tools in precision livestock farming.

6.4 Concluding Remarks

In summary, this thesis has demonstrated that advanced deep learning and computer vision techniques can play a transformative role in modern poultry farming. By developing a novel dataset, benchmarking state-of-the-art models, and deploying a prototype monitoring system under commercial conditions, this work has shown how technology can provide continuous, real-time insights into laying hen behaviour and welfare.

The outcomes highlight not only the feasibility of automated welfare monitoring but also its potential to improve productivity, reduce costs, and support sustainable farming practices. Importantly, the integration of behavioural data with environmental factors has revealed valuable connections that can guide more precise management interventions.

While challenges remain—particularly in expanding behavioural coverage, improving robustness, and integrating multimodal sensing—the research provides a strong foundation for future innovation. The continued refinement of these systems will enable the poultry industry to transition toward precision livestock farming models that are more efficient, welfare-focused, and environmentally sustainable.

Ultimately, this thesis contributes to the growing body of knowledge that seeks to harmonize technological advancement with animal welfare, underscoring the role of intelligent, data-driven systems in shaping the future of agriculture.

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