



Automated, real-time monitoring of bird and flock movement and behaviour 2.0

Final Project Report | APRIL 2025

A report for Australian Eggs Limited
by Zhen Luo, Litao Yu, Richard Shephard,
Qiang Wu and Jian Zhang

© 2025 Australian Eggs Limited. All rights reserved.

ISBN 978-1-920835-84-2

Project Title: Automated, real-time monitoring of bird and flock movement and behaviour 2.0

Australian Eggs Limited Project Number INNO017

The views expressed and the conclusions reached in this publication are those of the author and not necessarily those of persons consulted. Australian Eggs Limited shall not be responsible in any way whatsoever to any person who relies in whole or in part on the contents of this report.

This publication is copyright. However, Australian Eggs Limited encourages wide dissemination of its research, providing that it is clearly acknowledged. For any other enquiries concerning reproduction, contact the Sustainability Program Manager on 02 9409 6999.

Researcher/Author Contact Details

Name: Zhen Luo, Litao Yu, Richard Shephard, Qiang Wu, and Jian Zhang
Address: Faculty of Engineering and Information Technology
The University of Technology Sydney
15 Broadway, Ultimo NSW 2007
Phone: +61 (0)2 9514 3829
Fax: N/A
Email: jian.zhang@uts.edu.au

In submitting this report, the researcher has agreed to Australian Eggs Limited publishing this material in its edited form.

Australian Eggs Limited Contact Details:

Australian Eggs Limited
ABN: 66 102 859 585
Suite 6.02, Level 6, 132 Arthur St North Sydney NSW 2060

Phone: 02 9409 6999
Fax: 02 9954 3133
Email: research@australianeggs.org
Website: www.australianeggs.org.au

Published in April 2025

Foreword

The poultry industry is at a critical crossroads, where optimising productivity while ensuring the welfare of laying hens has become increasingly important. Traditional methods of monitoring hen behaviours are labour-intensive and often fail to capture the continuous data necessary for informed decision-making, highlighting the need for innovative solutions. Precision Livestock Farming (PLF) technologies have emerged as a key response, offering automated, real-time monitoring systems that are both cost-effective and capable of providing continuous observation. The advanced computer vision and deep learning techniques were utilised to track and analyse hen behaviours, correlating these with daily environmental data such as temperature, food and water consumption. By providing a non-invasive, accurate method of continuous observation, this project not only sheds light on the relationship between hen behaviours and welfare but also demonstrates the potential for data-driven decision-making in modern poultry farming, marking a significant step forward in enhancing both animal welfare and farm productivity.

This project was funded from industry revenue, which is matched by funds provided by the Australian Government.

This report is an addition to Australian Eggs Limited's range of peer reviewed research publications and an output of our R&D program, which aims to support improved efficiency, sustainability, product quality, education and technology transfer in the Australian egg industry.

Most of our publications are available for viewing or downloading through our website:

www.australianeggs.org.au

Printed copies of this report are available for a nominal postage and handling fee and can be requested by phoning (02) 9409 6999 or emailing research@australianeggs.org.au.

Acknowledgments

The authors would like to thank Egg Farm A in QLD and Egg Farm B in NSW, for outstanding support in all areas including the use of infrastructure, excellent communication, and teamwork. Richard Shephard (Herd Health Pty Ltd), Rod Jenner (Rosetta Management Consulting Pty Ltd) and Noella Powell (Australian Eggs) all provided outstanding help in conducting the field work.

About the Authors

Zhen Luo

Zhen Luo received his Master's degree from the University of New South Wales in 2023. He is currently working with Professor Jian Zhang as a research engineer at the Multimedia Data Analytics Lab (MDAL), part of the Global Big Data Technologies Centre (GBDTC) at the University of Technology Sydney, Ultimo, NSW, Australia. His research interests include image processing, deep learning, and computer vision.

Dr Litao Yu

Litao Yu received the PhD degree from the University of Queensland, QLD Australia in 2016. He then worked as a research fellow with the QUT Centre of Robotics, Queensland University of Technology, Brisbane QLD in 2017, and as a research fellow with the Institute of Integrated and Intelligent Systems, Griffith University, Brisbane from 2018 to 2019. He is a research fellow with Multimedia Data Analytics Lab (MDAL), Global Big Data Technologies Centre (GBDTC), and the University of Technology Sydney (UTS), Ultimo, NSW Australia. His research interests include image processing, machine learning and multimedia content analysis.

A/Professor Qiang Wu

Qiang Wu is an Associate Professor in computer vision, image processing pattern recognition, machine learning and multimedia processing. The application fields where the research outcomes are applied span over video security surveillance, biometrics, video data analysis, human-computer interaction. His research outcomes have been published in many premier international conferences including ICCV, ECCV, CVPR and the major international journals such as IEEE TIP, IEEE TCSVT, IEEE TMM and PR. He is also a principal investigator and/or a technical leader in several industry research projects collaborating with Meat & Livestock Australia (MLA), Canon, Toshiba, Microsoft, Nokia and Westpac Bank.

Dr Richard Shephard

Richard Shephard is an adjunct professor in the Faculty of Engineering and IT at the University of Technology Sydney (UTS). As an adjunct appointment, he collaborated with Professor Jian Zhang's research team in developing this project and, as sub-contractor, he worked on this project. Richard is a veterinary epidemiologist and farm management consultant with wide experience across many animal production industries in Australia and internationally. He worked for ten years as a clinical veterinarian in mixed (mainly cattle) practice, and completed an epidemiology PhD in syndromic surveillance systems for extensive cattle production. Richard also provides farm management advice for commercial farms in the fields of animal health, nutrition, economics, and optimisation. He is the Independent Scientist advising the Live Export Research and Development Advisory Committee (a program jointly managed by Meat & Livestock Australia and LiveCorp). Previously, he managed the InCalf program for dairy Australia. Richard has over 30 peer reviewed publications in animal health, production, disease management, surveillance, and epidemiology. Richard specialises in translational research in agriculture, focusing on ensuring technology informs actionable decisions by commercial farmers.

Professor Jian Zhang

Jian Zhang is a Professor in the Faculty of Engineering and IT at the University of Technology Sydney (UTS) working on cutting-edge research in the areas of computer vision, pattern recognition and data analysis, large-scale image and video content analysis and retrieval, and multimedia and social media signal processing. As the director of the Multimedia Data Analytics Lab (MDAL) in the Global Big Data Technologies Centre of UTS, Jian built an award-winning cross-disciplinary UTS research and engineering team, uniquely focusing on computer vision research for the agriculture-food sector. He led the establishment of a solid UTS project pipeline from his lab research to technology development and commercialisation pathway. These projects are funded by Australian Rural Research and Development Corporations (RDCs), including Meat & Livestock Australia/LiveCorp and Australia Eggs.

Table of Contents

Foreword	iii
Acknowledgments	iv
About the Authors	iv
List of Figures.....	vii
Abbreviations.....	viii
Executive Summary	ix
Overall Conclusions	x
1 Literature and patent review.....	1
1.1 Literature review	1
1.2 Patent review.....	2
2 Camera placement and data collection.....	3
3 Model development for behavioural analysis	6
3.1 Model development	6
3.2 Performance evaluation.....	6
4 Case study: behavioural analysis	9
4.1 Video data collecting	9
4.2 Statistical metrics.....	9
4.3 Cross-source data integration	10
5 Discussion and future improvement	15
6 References.....	17
7 Plain English Summary	19
Appendix 1 – Epidemiological analysis	21
Introduction.....	21
Data	22
Exploratory analysis.....	22
Predictive model.....	32

List of Figures

Figure 1	Network topology of camera placement for video data collection.....	3
Figure 2	One placement of video camera on the Egg Farm A, QLD.....	4
Figure 3	One placement of video camera on the Egg Farm B, NSW.....	4
Figure 4	Sample frames of the collected video data	5
Figure 5	Detection visualisation on Egg Farm B, NSW.....	7
Figure 6	Detection visualisation on Egg Farm A, QLD.....	7
Figure 7	Tracking visualisation on Egg Farm B, NSW	8
Figure 8	Tracking visualisation on Egg Farm A, QLD	8
Figure 9	Illustration of hourly statistics focusing on average eating & drinking time (C107, NSW)	11
Figure 10	Illustration of hourly statistics focusing on snapshot eating & drinking (C107, NSW)	11
Figure 11	Illustration of hourly statistics focusing on average eating & drinking time (C110, NSW)	12
Figure 12	Illustration of hourly statistics focusing on snapshot eating & drinking (C110, NSW)	12
Figure 13	Illustration of hourly statistics focusing on average drinking time (C109, QLD)	13
Figure 14	Illustration of hourly statistics focusing on snapshot for drinking behaviour (C109, QLD)	13
Figure 15	Illustration of hourly statistics focusing on average eating time (C113, QLD)	14
Figure 16	Illustration of hourly statistics focusing on snapshot for eating behaviour (C113, QLD)	14

Abbreviations

AI	Artificial intelligence
CNN	Convolution neural network
CV	Computer vision
DL	Deep learning
EE	Effective eating
GPU	Graphic processing unit
IoU	Intersection-over-union
IR	Infrared
LTL	Latency to lay
ML	Machine learning
NOL	Number of laying
OA	Occupied area
RFID	Radio-frequency identification
THI	Temperature-humidity index

Executive Summary

The poultry industry is increasingly focused on improving the welfare of laying hens while optimising production efficiency. This project aimed to address these goals by developing an advanced system for automated, real-time monitoring and analysis of bird behaviours on commercial egg farms. Our R&D efforts have resulted in the creation of the Flock Behaviour Data Analysis Platform, a prototype system that leverages computer vision and deep learning techniques to track and analyse the activities of hens, such as eating and drinking.

We recorded video footage from several strategically placed cameras in sheds at Egg Farm B in NSW and Egg Farm A in Queensland. These cameras focused on monitoring the birds' drinking and eating behaviours. In parallel, we collected daily operational data from the farms, including temperature, feed consumption and water consumption, to cross-reference with the video-derived behaviour metrics. The integration of these diverse data sources allowed us to develop a comprehensive understanding of how environmental and operational factors influence flock behaviour and overall welfare.

Our analysis involved computing key metrics such as activity duration and the proportion of birds engaging in specific behaviours over time. These metrics were visualised and correlated with daily operational records, revealing potential links between environmental factors such as 24/7 temperature and bird welfare. The insights gained from this analysis highlight the system's ability to identify deviations from normal behaviour, which can serve as early indicators of potential welfare issues or suboptimal management practices.

The Flock Behaviour Data Analysis Platform has demonstrated significant potential to enhance farm management by providing a scalable, non-invasive, and automated method for monitoring large flocks of hens. By eliminating the need for continuous human observation, this system offers a practical solution for large-scale commercial operations, enabling farmers to make data-driven decisions that improve both hen welfare and farm productivity.

This project underscores the importance of combining innovative technologies with practical farm management strategies to achieve better welfare outcomes for poultry, and it lays the groundwork for future advancements in the field of Precision Livestock Farming.

Overall Conclusions

In this project, we have successfully demonstrated the integration of video observations and daily data records for bird flock monitoring on commercial egg farms. Our advanced computer vision techniques provide automated detection and tracking of laying hen behaviours, offering critical insights into their wellbeing, welfare, and production risks. The system eliminates the need for continuous human monitoring, making it a practical solution for large-scale operations.

An epidemiological analysis report is attached as Appendix 1 to this report.

The findings highlight the potential to better understand the impact of environmental factors on bird behaviour and epidemiological issues. The correlation between video-derived statistics and daily data records provides valuable insights for optimising farm management practices. These insights help identify potential welfare issues related to management practices and environmental conditions, showcasing the system's potential to enhance hen welfare on commercial egg farms.

Our ongoing work aims to refine our understanding and improve the system's robustness.

1 Literature and patent review

1.1 Literature review

Computer vision is the construction of explicit, meaningful descriptions of physical objects from images or video streams. Continuous monitoring of bird health and welfare requires the description of the birds' state based on recorded/analysed information. Recently, computer vision-based techniques have drawn broad attention in automated analysis of tracking, identifying and monitoring the flock or individual behaviours in large groups. The visual sensors used for computer vision-based techniques mainly include the 2D-camera, 3D-camera and thermal camera, and the systems built on these sensors are slightly different. In this report, we review the computer vision and image processing techniques that have been used to build automated analytic systems for the purpose of reducing human labour and improving the management efficiency. Most computer vision applications for bird behaviour monitoring rely heavily on some core components for automated analysis: image/video data acquisition, instance recognition, tracking and data statistics. The computational models are mainly based on the scene, shape, motion or appearance.

The 2D-camera is commonly used in various monitoring applications. With image processing and machine learning techniques, the system can automatically recognise the visual patterns in video streams. Recently, many researchers have applied these techniques for monitoring birds' behaviours. Lao et al. (2012) proposed to use traditional image processing and machine learning techniques to recognise individual laying hens [1]. Nakarmi et al. designed an automated system that combines RFID and computer vision, for tracking and analysing laying hens [22]. They applied an object detection algorithm in frame-to-frame correspondence, while an RFID-transponder was placed on the lower part of a hen's leg to provide an individual identification. Wang et al. (2016) proposed a hen-tracking method based on a hybrid support vector machine with three steps: initialisation, 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 [2]. Zhuang et al. (2018) proposed to use the k-means clustering algorithm to detect sick broilers for early warning [3]. Dawkins et al. (2012) used optical flow for welfare assessment, which has a potential for flock and group level assessment of general activity and distribution [4]. In Dawkins et al. (2021) [5], the authors analysed 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. Derakhshani et al. (2022) proposed to use an inertia sensor (3-DOF motion tracker) to classify the behaviour of laying hens [6]. Recently, the success of deep learning in computer vision has greatly changed automated monitoring systems for animal behaviour. For example, Guo et al. (2020) designed a machine vision-based method for monitoring broiler chicken floor distribution, using artificial neural networks [7]. Neethirajan et al. adopted very similar techniques with our previous system for chicken detection, tracking and counting [23]. Rodenburg et al. (2017) used the sensor technology and genomics to breed for laying hens that exhibit less damaging behaviour [8]. Del Valle et al. (2021) proposed a novel computer vision method to analyse the poultry birds' movements for thermal comfort, which is used to measure the unrest index [9].

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 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. Aydin (2017) proposed a 3D-based model for assessing inactivity of broilers to detect lameness [14]. 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. Mortensen et al. (2016) used the 3D-camera for broilers' weight estimation at both the individual and group level, showing a high correlation between the 3D feature representations and broiler's weights, allowing the consistent and continuous monitoring of growth rate and indirect feed consumption rates [10]. 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, a thermal camera needs extensive calibration. Zaninelli et al. (2016; 2017; 2018) proposed several methods for monitoring laying hens based on IR technology and pattern recognition [11,12,13]. The frames recorded by an IR camera are 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, the IR camera is not economically feasible for building low-cost monitoring systems.

1.2 Patent review

Compared to the proliferation of 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 innovation at the level of individual models or methods.

Berckmans et al. (2014) applied real-time image analysis to monitor animals' presence and eating position for nutriment ingestion [15]. This method is not limited to egg hens, but also other farm animals such as pigs and cows. Ying et al. (2002) applied machine vision to determine chicken sex as a binary classification problem [16]. Similarly, Pan et al. (2015) proposed to use hyperspectral images of chicken embryo hatching, analysing 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 [19]. Another patent using image analysis for gender determination is Karimpour (2017) [20]. Liang et al. (2000) 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 [17]. This system provides functions that are similar to our projects, but the techniques applied are fundamentally different. Yanai et al. (2014) built a health monitoring system by combining acoustic and visual information to assess the existence and/or progress of a disease in animal groups [18]. Gary et al. (2015) designed a spectral imaging system for remote and non-invasive detection [21], which can be considered as a specific image processing technique for bird monitoring.

These patents basically applied some computer vision methods for different purposes within the poultry industry, based on a few existing technologies. The fundamental difference between this project and the above-mentioned patents is that this research does not have explicit objectives related to any specific or defined purpose. Instead, we aim to apply computer vision and machine learning techniques to discover the unknown activity patterns of birds, then we try to use semantic analysis in order to correlate them to animal welfare issues.

2 Camera placement and data collection

The automated analysis of video-based bird behaviour monitoring focuses on developing computational models that can efficiently process visual data reflecting the birds' activities, such as movement paths, speeds, and other behaviour patterns. Data collection is crucial for these data-driven models, as the computational models rely on extensive visual data supplemented by manual annotations. The detection model identifies and describes each bird within the camera's field of view, and the combined individual behaviours reveal the overall flock activity patterns.

We collected data from two egg farms, Farm B in NSW and Farm A in QLD. All cameras used in this project were AXIS IP cameras with resolutions of either 1920x1080 or 1280x720, operating at a default frame rate of 30 frames per second. To create a small network, we utilised several switches for power supply and video signal transmission, connecting them to a router. The video data was then transmitted to a desktop workstation, and due to the large amount of video collected over a few weeks, we stored the footage on an external hard drive. The overall network setup for both farms is shown in Figure 1.

After ensuring that the experimental site met animal ethics standards, we installed multiple cameras in a shed to capture a top-down view of the birds' activities from various angles, utilising the cameras' built-in recording capabilities. The cameras were positioned approximately 2.2 meters above the ground, each covering an area of about 12 square meters. The collected videos, totalling around 2 TB in storage, provided ample data to develop a detection and tracking model within a controlled visual environment (with minimal changes in lighting and fixed camera angles). Egg Farm A, which houses around 10,000 laying hens in a single shed, had a similar camera setup as Egg Farm B. The camera placements are depicted in Figure 2. Another example placement for Egg Farm B is shown in Figure 3. These are two example placements of all the top-down view cameras in the different egg farms.

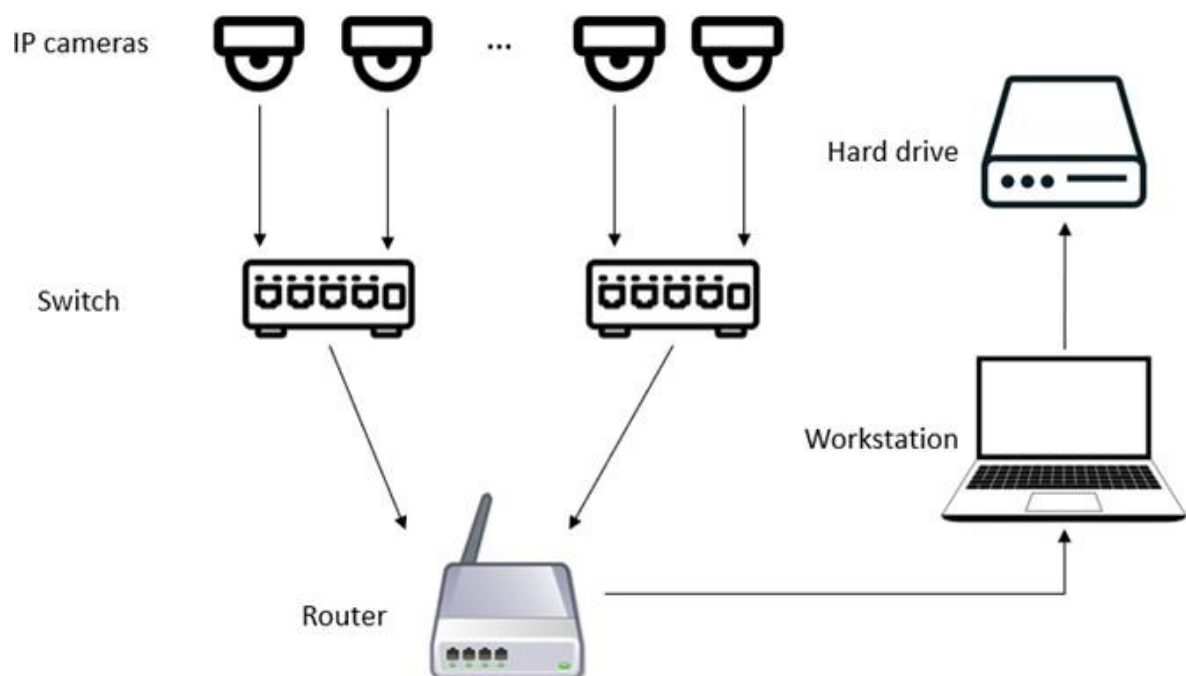


Figure 1 Network topology of camera placement for video data collection



Figure 2 One placement of video camera on the Egg Farm A, QLD

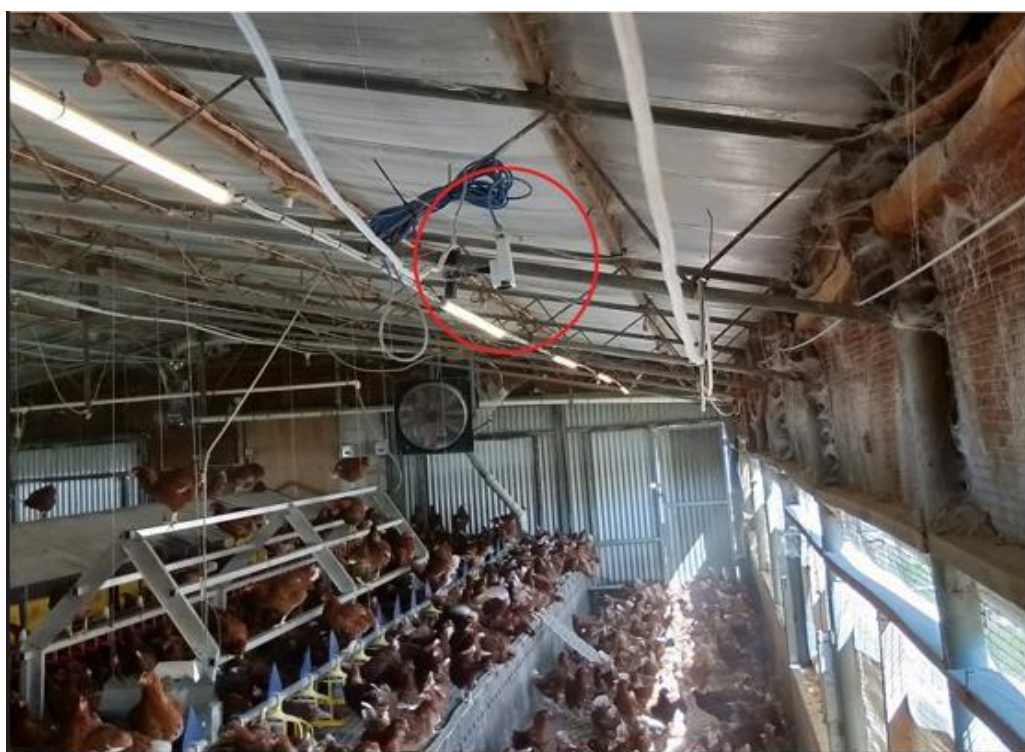


Figure 3 One placement of video camera on the Egg Farm B, NSW

Although the laying hens on the two egg farms have similar activities in terms of their behavioural patterns, their statistical properties may differ due to the habitat environments. In Figure 4 we illustrate some data samples collected from the two egg farms. From multiple views to record the laying hens' behaviours, we collected diversified data samples to build a robust computational model, to accurately analyse the activity patterns and provide strong data support to improve animal welfare.

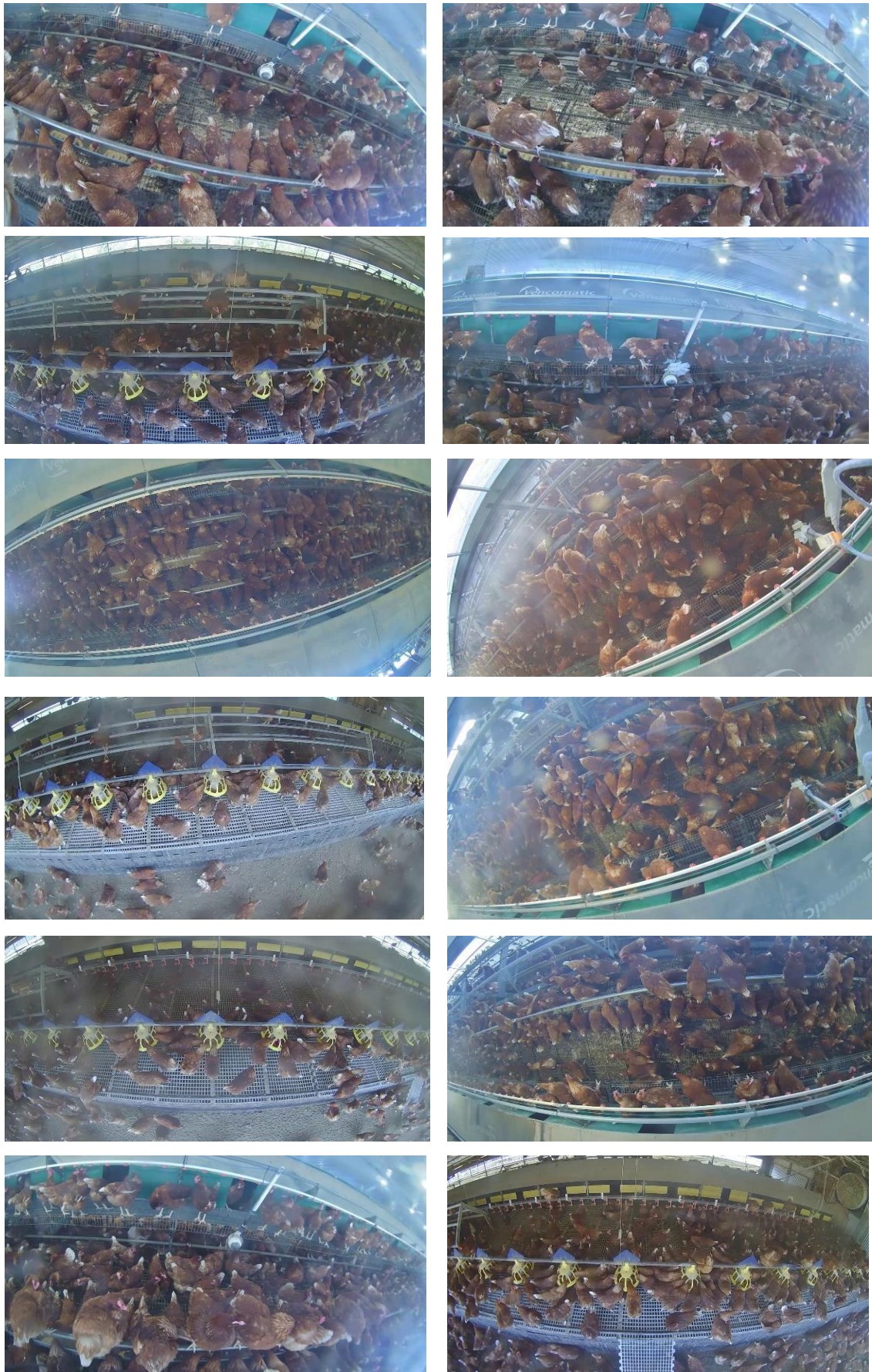


Figure 4 Sample frames of the collected video data

3 Model development for behavioural analysis

We describe the process of building the detection and tracking model, to identify bird activities. Based on the video data collected from the two egg farms in the previous stage, we sampled the frames from the videos that observe the birds in different views, then annotated all the observable instances, as well as the activities. The detection and tracking model is light weight, which can monitor the birds' behaviours with high accuracy in real-time.

However, it must be understood that during the evaluation process, when our model attempted to detect whether a bird was eating or drinking, it could only identify the physical actions associated with these behaviours. For example, it could detect when a bird lowered its head into the food container (trough) or tilted its neck back to sip from the water tap. However, the model was unable to accurately determine whether the bird was actually eating or drinking.

3.1 Model development

The first step in training the model involved annotating sampled frames from a diverse video dataset, which included various visual environments with differing scales, illuminations, occlusions, and deformations. There are three activities: eating, drinking, and others. To maintain data quality, areas where birds were too crowded to be visually identified were excluded. The detection model, trained on this annotated data, was then evaluated on a test set, achieving an average precision of 86.3%, despite challenging conditions such as high bird density and significant occlusions. Under less challenging conditions, the precision could reach 94.2%. To analyse group behaviour patterns beyond static images, we also tracked each bird, assigning unique IDs and monitoring their activities as they moved through the observation area.

3.2 Performance evaluation

We experimented with the model by deploying it on both pre-recorded videos and live cameras at NSW Egg Farm B and QLD Egg Farm A, with detection and tracking visualisations shown in Figures 5–8. Detected bird activities — eating, drinking, and others — were represented by green, blue, and red dots, respectively, with numbers indicating tracked instances and trajectories showing their movements. Despite occasional miss-detections and classifications, the system demonstrated satisfactory robustness and stability. The miss-tracking rate was 0.0127 per second, meaning that about 1.27% of instances were lost due to factors like illumination, crowdedness, and occlusion. However, a key limitation was the model's inability to accurately distinguish between actual eating or drinking and the physical actions associated with these behaviours.

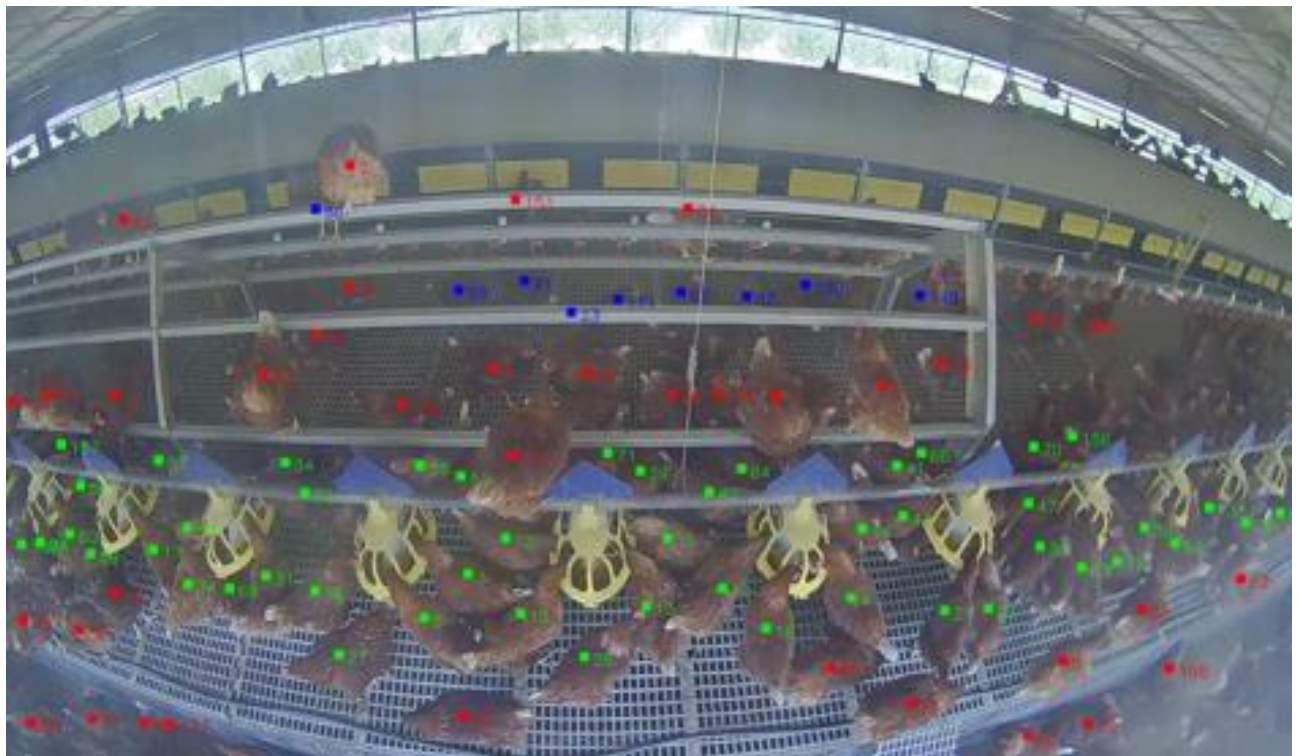


Figure 5 Detection visualisation on Egg Farm B, NSW

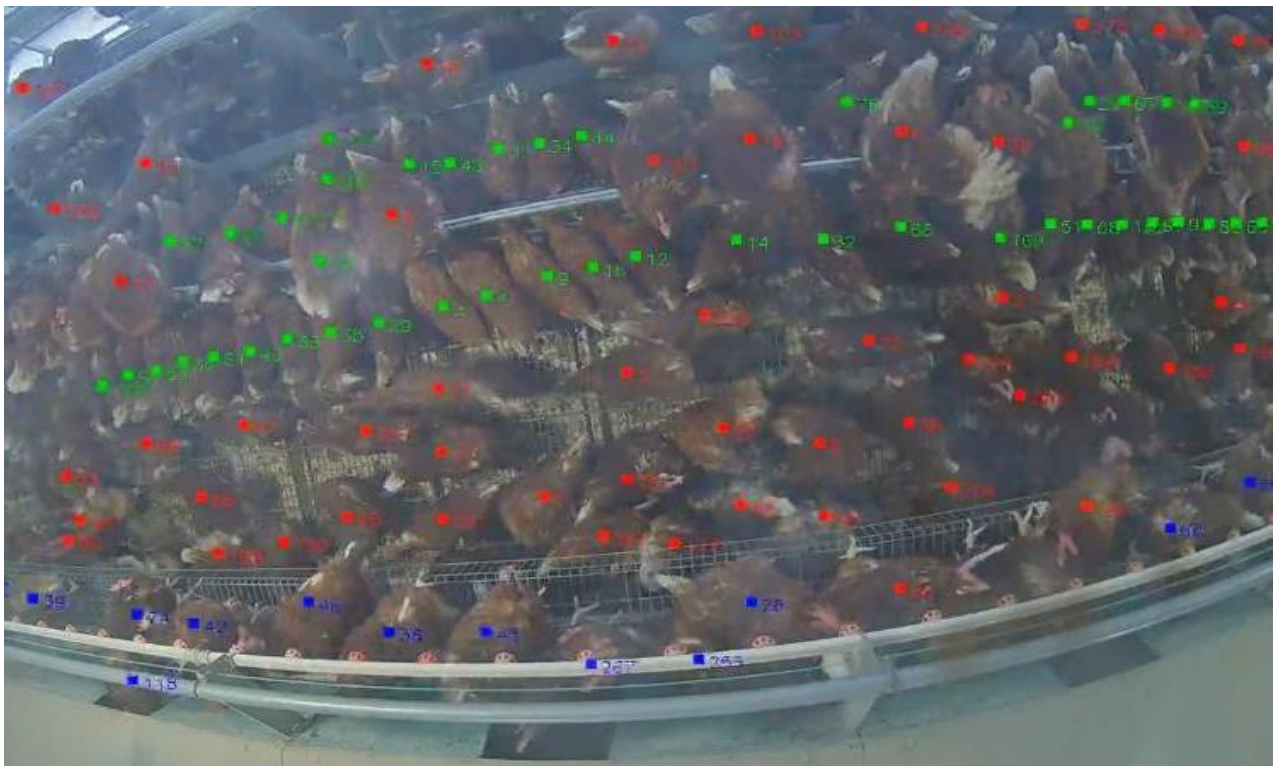


Figure 6 Detection visualisation on Egg Farm A, QLD

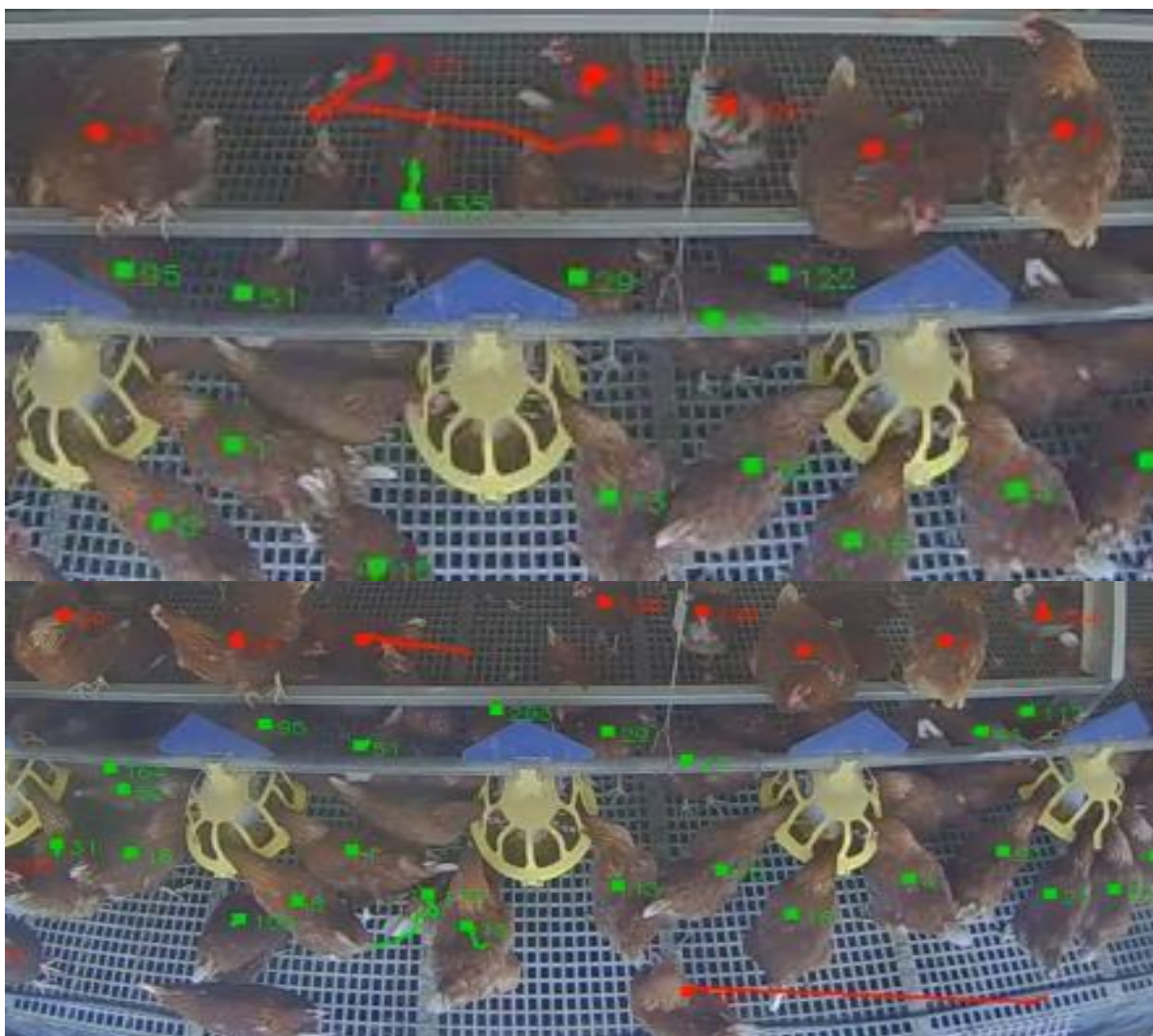


Figure 7 Tracking visualisation on Egg Farm B, NSW

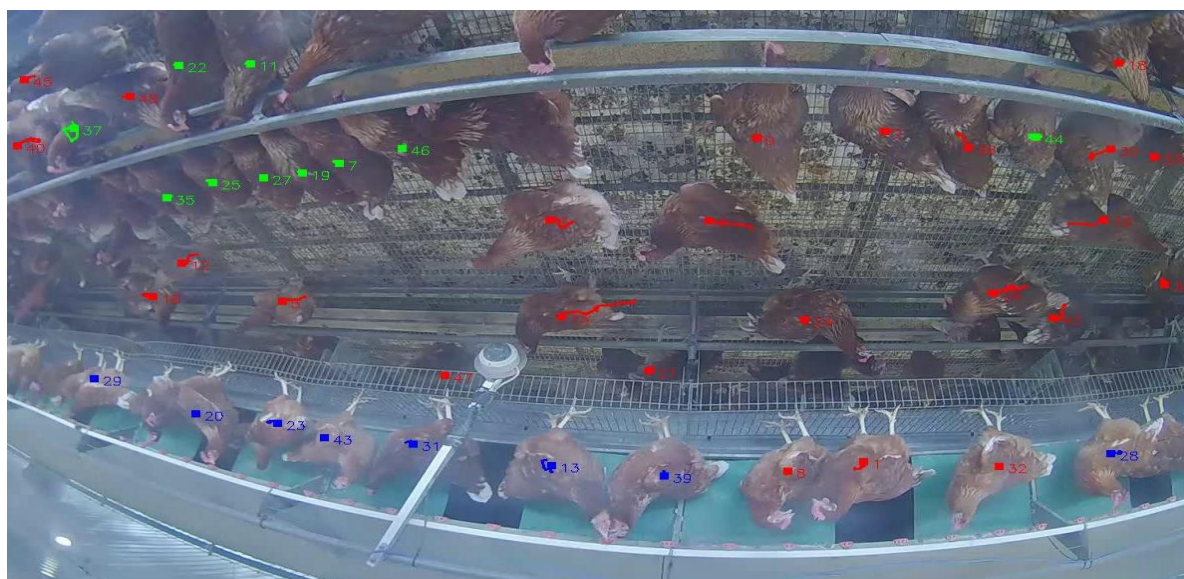


Figure 8 Tracking visualisation on Egg Farm A, QLD

4 Case study: behavioural analysis

4.1 Video data collecting

We first recorded videos at Egg Farm B from 1 November to 23 December 2023. Then, we recorded videos from 5 January to 5 March 2024 at Egg Farm A. After that, we use our AI model to inference and collect eating and drinking behaviours data. Finally, we could visualise them and do some preliminary studies.

4.2 Statistical metrics

We have jointly considered the monitoring capabilities of the system prototype and the practical requirements. Following discussions with Richard Shephard and Rod Jenner, we linked the activities of birds with the following two metrics – activity statistical measurement and average activity time. Before introducing the two metrics, we set the following pre-conditions: (1) the bird that exits the observation area and then re-enters it will be considered as a new bird, i.e. the bird ID is re-assigned; (2) the metrics are only in the salient observation area due to the crowd of birds.

The first metric is to compute the average activity time of the flock. Taking eating as an example, assuming the system provides the log within 5 minutes, based on the tracking IDs, we can count how many birds spend ≤ 1 minute eating, how many birds spend ≤ 5 minutes, etc.

Based on all the trackable birds within a period, we can calculate the average activity time of the flock. This metric is used to measure the average time one bird spends on an activity, which is computed as follows:

$$\frac{\sum N_i T_i}{\sum N_i}$$

where N_i is the number of birds for i -th group, in which each bird spends T_i time on eating. For example, 20 birds spend 1 minute eating, and 15 birds spend 2 minutes eating, the average eating time of the two groups is:

$$\frac{20 \times 1 + 15 \times 2}{20 + 15} = 1.43.$$

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. Within the i -th snapshot, we count the total number of birds N_i and the number of birds that conduct an activity (e.g. eating) M_i , so the average proportion is calculated over a period, e.g. 1 hour. For example, we sample the frames every second for five minutes, so $i = 1, 2, \dots, 300$. The average proportion of eating is:

$$\frac{\sum M_i}{\sum N_i}$$

This metric is calculated multiple times during a period, and the average value is recorded.

4.3 Cross-source data integration

The statistical results obtained from the automated analysis were cross-referenced with the daily data records provided by the two NSW and QLD egg farms. This correlation aimed to identify potential relationships between flock behaviour and environmental factors. The daily data provided by Egg Farm B contains feed consumption, water consumption, eggs, minimal temperature, and maximal temperature. The daily data provided by Egg Farm A contains the following factors: bird number, mortality, feed consumption, water consumption, 1st grade eggs, floor egg numbers, minimal temperature, and maximal temperature.

The average eating and drinking time visualisations for Egg Farm B in NSW (for 8 and 13 December 2023) are shown in Figures 9 and 11, while the snapshot eating and drinking data are shown in Figures 10 and 12.

We further provide two views of the data visualisation for data from Egg Farm A in QLD (for 7 January and 3 February 2024). The first view summarises the hourly drinking activities, as illustrated in Figures 13 and Figure 14. The horizontal axis represents the hour. The bar charts describe the two metrics, average drinking times and proportions of drinking sampled from the videos. The horizontal axis represents the hour during the observation period (from 6:00 AM to 6:00 PM), and in Figure 13 the left vertical axis represents the drinking time (seconds). In Figure 14, the left vertical axis represents the percentage ratio of the drinking birds out of the total number of birds in the image captured by the camera. In Figures 13 and 14, the right vertical axis represents the temperature. The curves (red ink) are the hourly statistics for the temperature in the shed.

As shown in these figures, for example, on 03 February 2024, the drinking behaviour happened mainly in the morning. We put all of these statistics into a web demo, and we could see the trends with more days to make the results more convincing.

The second view summarises eating activities at different times of each day, as illustrated in Figures 15 and 16. Differently from the first view, here we focus on the hourly eating statistics. The bar charts reflect the two proposed metrics of bird flock eating behaviour at different times of the day (from 6:00 AM to 6:00 PM). Hourly statistics (e.g. consumption, egg numbers) can be further correlated to environmental data such as temperature and production. We can see that the average eating time is usually more than the average drinking time. This is because the camera can only record the birds being engaged to eat. For the drinking part, birds suck water from a tap, and the action would occur very quickly. But for the eating part, birds put their head down in the food container (trough). From the camera's top-down view, it is hard to check whether this hen is eating or not. Nevertheless, we can still analyse the trend of their eating and drinking behaviour from the collected data and find some correlations between them.

These findings could enhance our understanding of how environmental factors affect hen behaviours in commercial egg farms. The correlation between video-derived statistics and daily records offers valuable insights for improving farm management. These natural variations provide a useful baseline for monitoring deviations from normal behaviour. We can further refine the baseline by analysing more data and other factors (e.g. density of flock, breed and age of hens) to provide a more valuable reference for commercial egg farms and farmers. Additionally, we can record the weights of eggs laid by the hens each day. By comparing this important information with the statistics generated from the collected data and the environmental factors, we can find out some correlations and try to improve both the quantity and quality of the eggs, thereby enhancing the commercial egg farm's economic outcome.

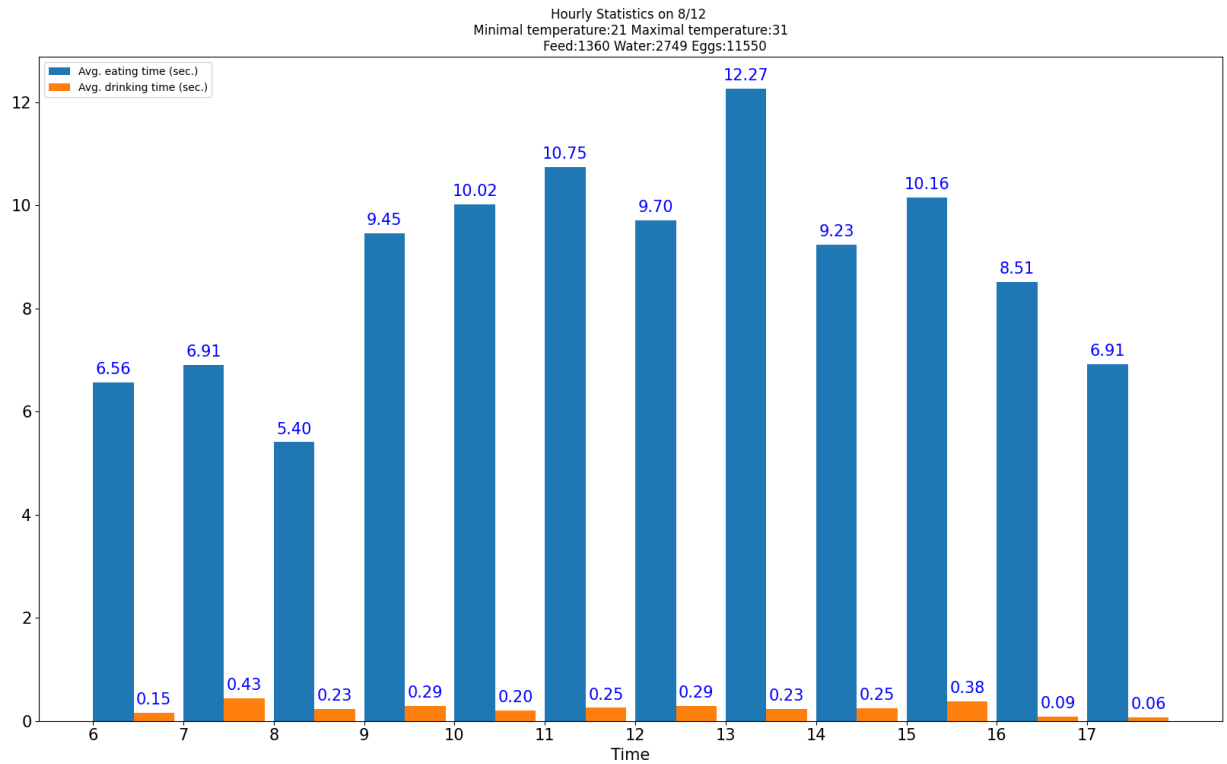


Figure 9 Illustration of hourly statistics focusing on average eating & drinking time (C107, NSW)

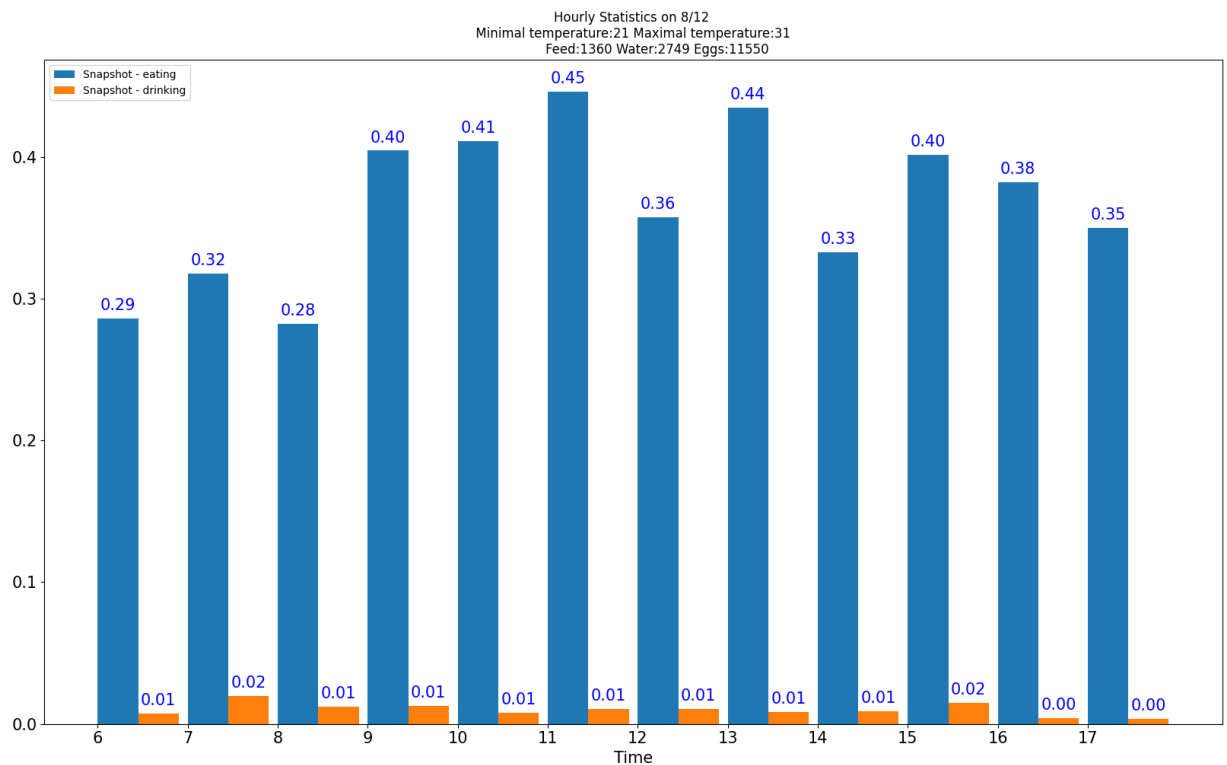


Figure 10 Illustration of hourly statistics focusing on snapshot eating & drinking (C107, NSW)

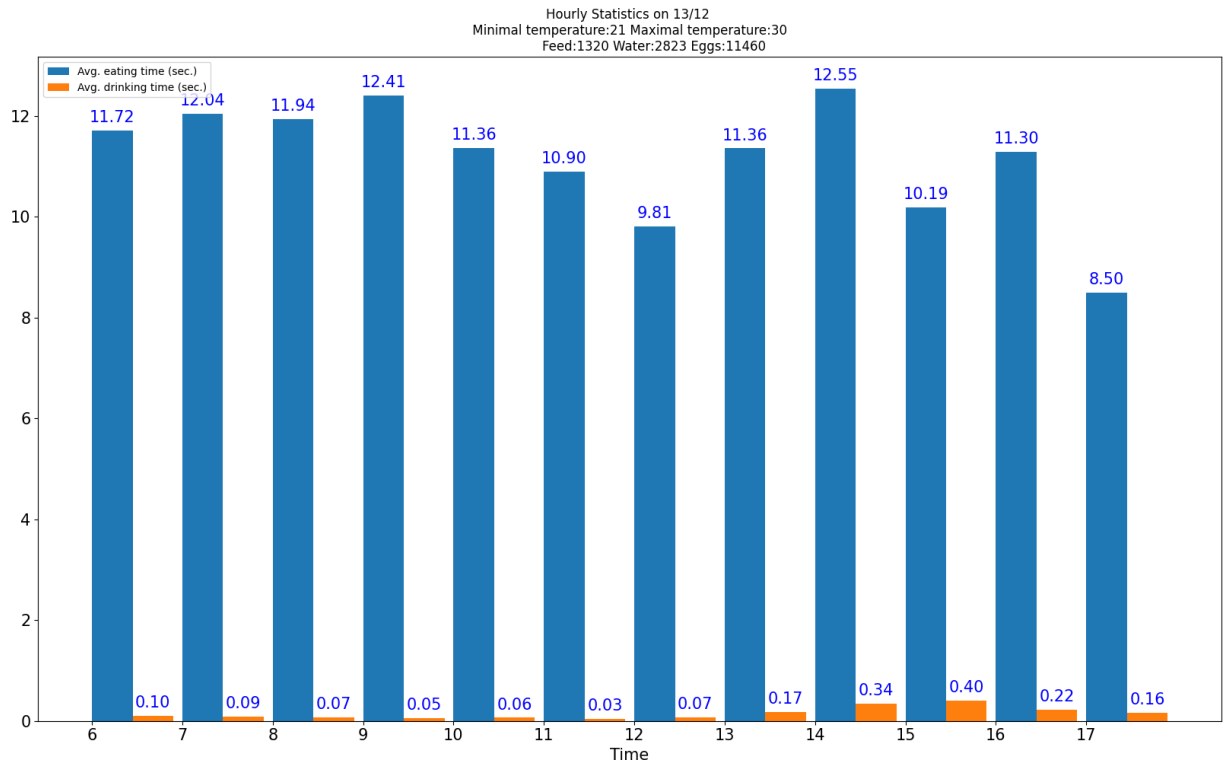


Figure 11 Illustration of hourly statistics focusing on average eating & drinking time (C110, NSW)

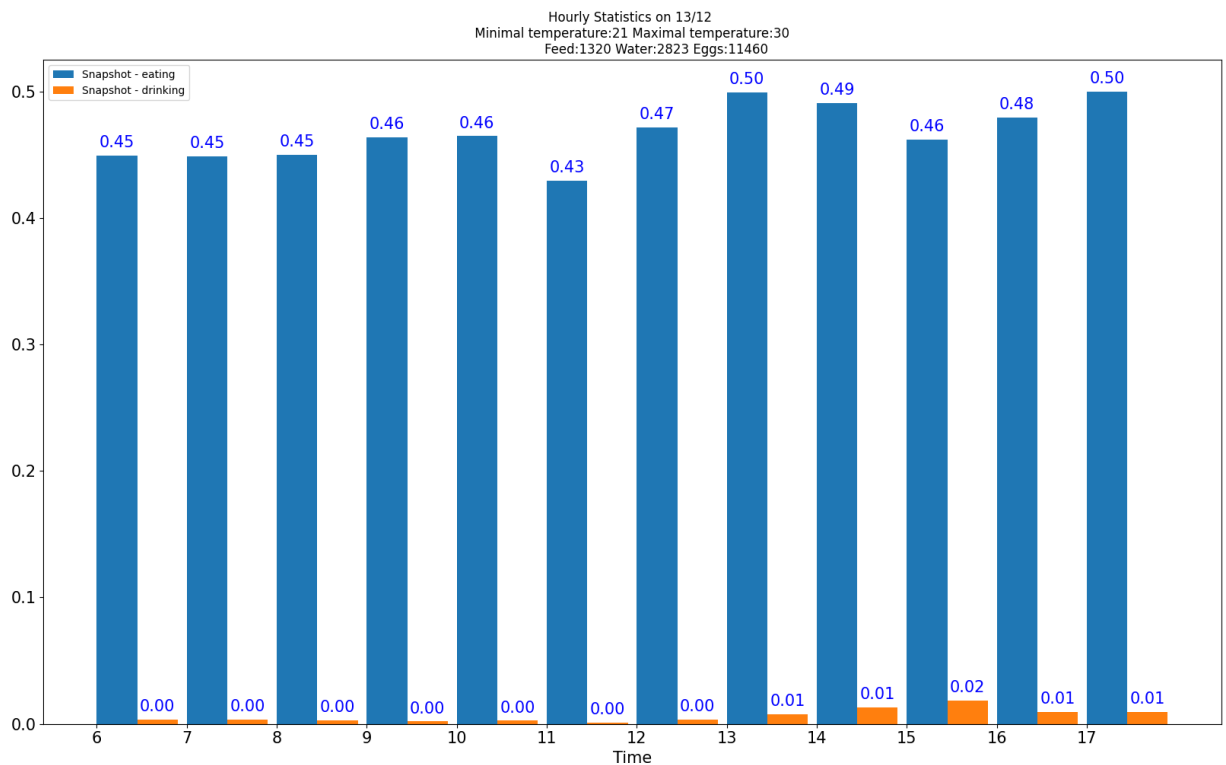


Figure 12 Illustration of hourly statistics focusing on snapshot eating & drinking (C110, NSW)

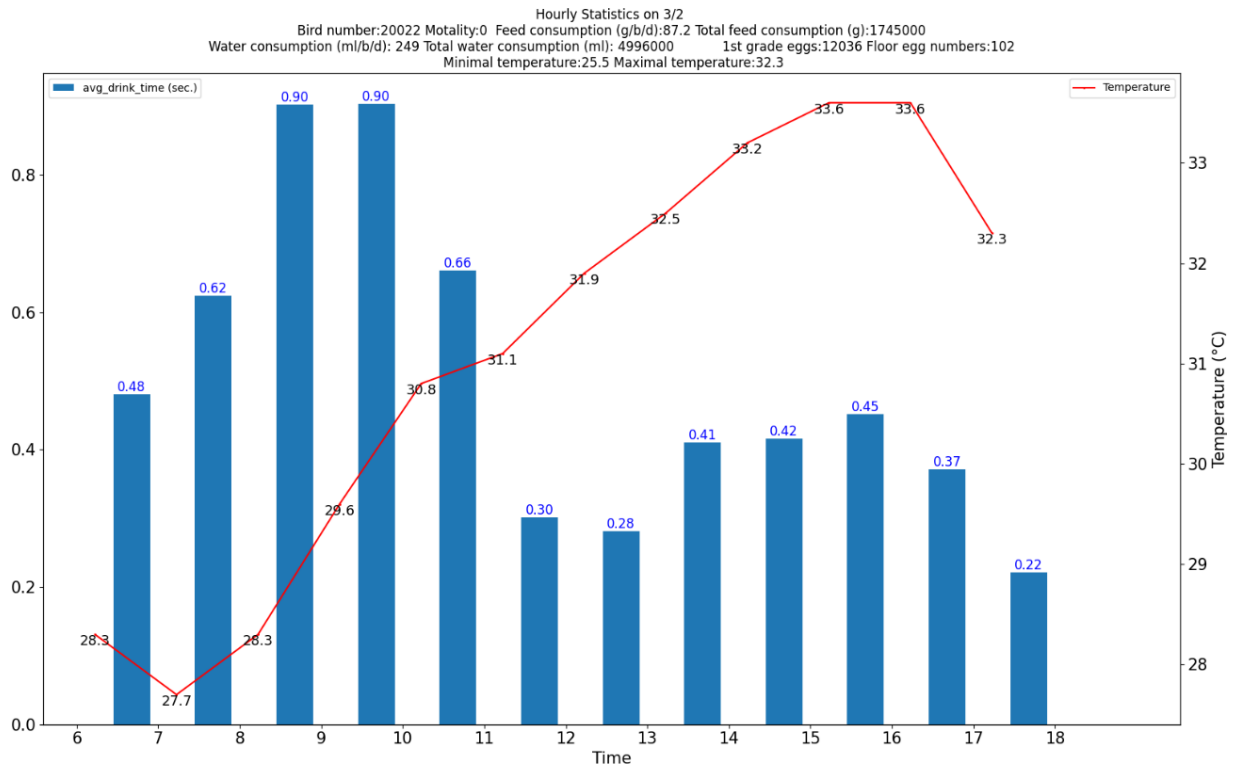


Figure 13 Illustration of hourly statistics focusing on average drinking time (C109, QLD)

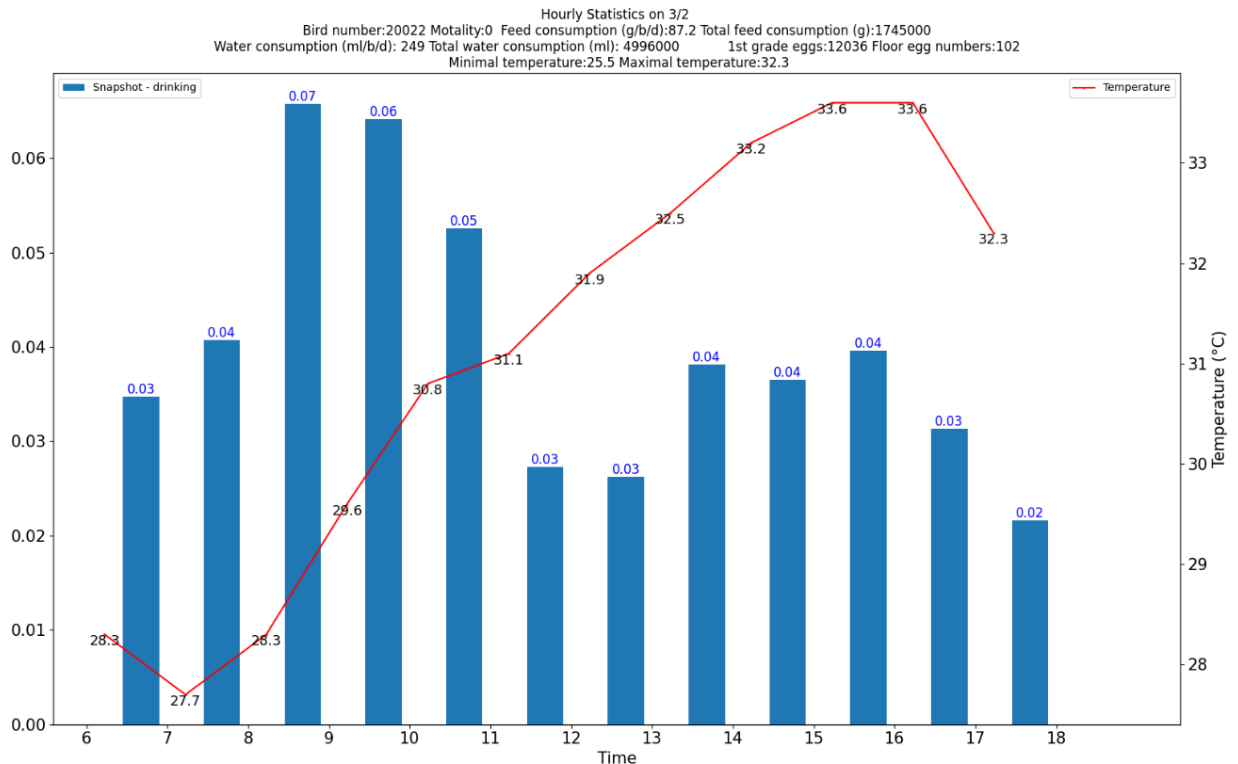


Figure 14 Illustration of hourly statistics focusing on snapshot for drinking behaviour (C109, QLD)

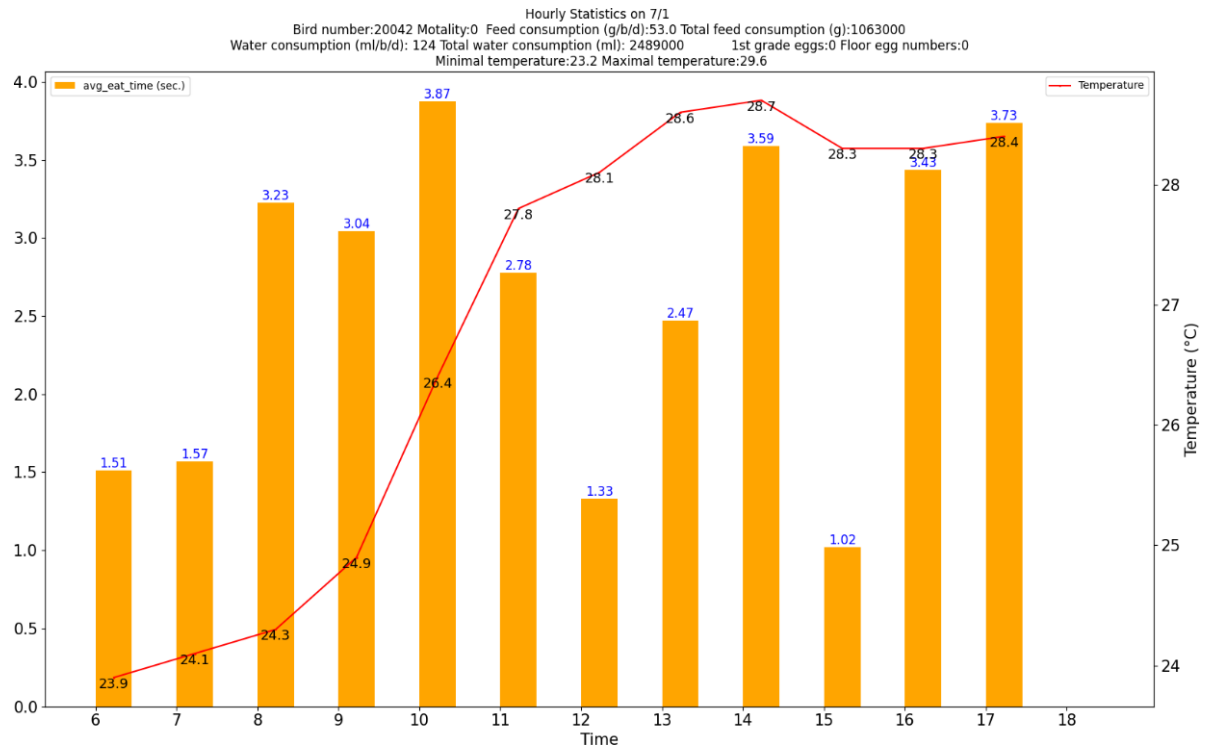


Figure 15 Illustration of hourly statistics focusing on average eating time (C113, QLD)

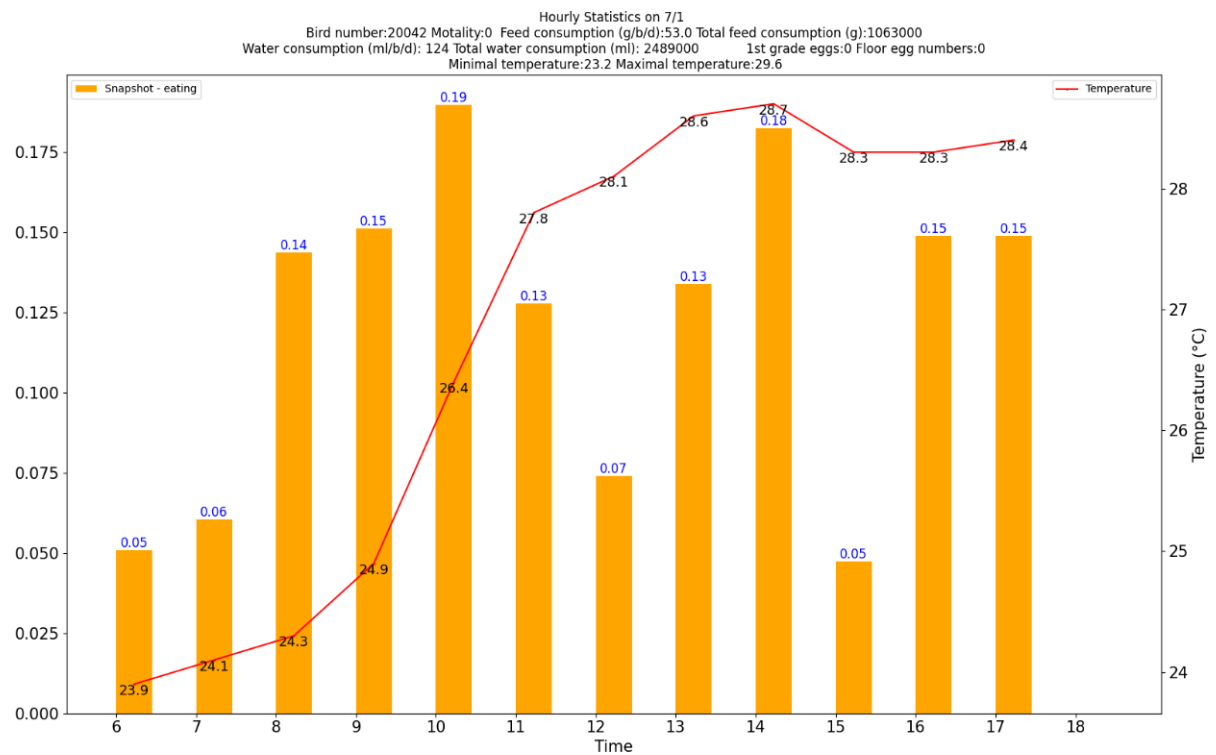


Figure 16 Illustration of hourly statistics focusing on snapshot for eating behaviour (C113, QLD)

5 Discussion and future improvement

This project has successfully demonstrated the potential of integrating advanced computer vision and deep learning technologies with daily operational data to monitor and analyse bird behaviours on commercial egg farms. By automating the detection and tracking of individual hens and correlating their activities with environmental and operational factors, we have developed a robust system that can significantly enhance the management and welfare of laying hens.

One of the key strengths of this system is its ability to provide continuous, real-time monitoring without the need for constant human oversight. The system's capacity to analyse large volumes of video data and extract meaningful patterns in bird behaviour is crucial for identifying welfare issues that may otherwise go unnoticed. For example, by tracking the time each bird spends eating or drinking, the system can detect deviations from normal behaviour that might indicate health problems or suboptimal environmental conditions.

The correlation between video-derived behaviour metrics and daily operational data, such as temperature, feed consumption, and egg production, provides valuable insights into the impact of environmental factors on bird welfare. Our findings suggest that fluctuations in these factors can significantly influence flock behaviour, which in turn affects productivity and overall flock health. These insights can help farmers make informed decisions to optimise both the welfare of the hens and the efficiency of the farm.

However, there are still challenges to be addressed in refining this system. For instance, while the detection and tracking model has shown a high level of accuracy, there were instances of miss-tracking, particularly in crowded or low-visibility conditions, which compromised its reliability. Furthermore, during the evaluation process, a significant limitation became apparent: the model could only detect the physical actions of birds, such as lowering their heads into the food container (trough) or tilting their necks back to sip, but it could not reliably determine whether the birds were actually eating or drinking. They are more likely to be engaged in eating or drinking. Enhancing the model's ability to accurately differentiate between these activities, along with improving its robustness in challenging conditions, will be critical for ensuring reliable and precise monitoring across different farm environments.

Additionally, our current focus has been on monitoring basic activities such as eating and drinking. Future improvements should aim to expand the range of behaviours that the system can detect, including more complex activities like perching, social interactions, and stress-related behaviours. Understanding these behaviours will provide a more comprehensive view of hen welfare and allow for more targeted interventions.

Another area for improvement is the integration of more sophisticated environmental sensors and data analytics techniques. By incorporating data on factors such as air quality, lighting, and noise levels, the system could provide a more detailed understanding of the factors that influence hen behaviour and welfare. The ongoing collection and analysis of video and operational data will further refine our understanding of how these environmental factors relate to bird behaviour, helping to establish baselines for normal behaviour. These baselines could be crucial for detecting early signs of potential welfare issues. As the system evolves, it has the potential to become a vital tool for epidemiological studies, aiding in the identification of risk factors for disease outbreaks and other health problems within poultry populations.

In conclusion, the development of the prototype platform represents a significant advancement in the field of poultry farming. By seamlessly integrating cutting-edge technology with practical farm management needs, this system has the potential to revolutionise how commercial egg farms monitor

and enhance animal welfare. Importantly, the prototype system is ready for real-time operation, meaning that it can be deployed immediately to provide valuable, data-driven insights on a large scale. Continued research and development will be essential for further refining its capabilities and ensuring its widespread adoption across the industry, but the system is already poised to make a tangible impact on poultry farming today.

6 References

- [1] Lao, F., Teng, G., Li, J., Yu, L. and Li, Z., 2012. Behaviour recognition method for individual laying hen based on computer vision. *Transactions of the Chinese Society of Agricultural Engineering*, 28(24), pp.157- 163.
- [2] Wang, C., Chen, H., Zhang, X. and Meng, C., 2016. Evaluation of a laying-hen tracking algorithm based on a hybrid support vector machine. *Journal of Animal Science and Biotechnology*, 7(1), pp.1-10.
- [3] Zhuang, X., Bi, M., Guo, J., Wu, S. and Zhang, T., 2018. Development of an early warning algorithm to detect sick broilers. *Computers and Electronics in Agriculture*, 144, pp.102-113.
- [4] Dawkins, M.S., Cain, R. and Roberts, S.J., 2012. Optical flow, flock behaviour and chicken welfare. *Animal Behaviour*, 84(1), pp.219-223.
- [5] Dawkins, M.S., Wang, L., Ellwood, S.A., Roberts, S.J. and Gebhardt-Henrich, S.G., 2021. Optical flow, behaviour and broiler chicken welfare in the UK and Switzerland. *Applied Animal Behaviour Science*, 234, p.105180.
- [6] Derakhshani, S.M., Overduin, M., van Niekerk, T.G. and Groot Koerkamp, P.W., 2022. Implementation of Inertia Sensor and Machine Learning Technologies for Analyzing the Behavior of Individual Laying Hens. *Animals*, 12(5), p.536.
- [7] Guo, Y., Chai, L., Aggrey, S.E., Oladeinde, A., Johnson, J. and Zock, G., 2020. A machine vision-based method for monitoring broiler chicken floor distribution. *Sensors*, 20(11), p.3179.
- [8] Rodenburg, T.B., Bennewitz, J., De Haas, E.N., Košťál, L., Pichová, K., Piette, D., Tetens, J., Van Der Eijk, J., Visser, B. and Ellen, E.D., 2017. The use of sensor technology and genomics to breed for laying hens that show less damaging behaviour.
- [9] Del Valle, J.E., Pereira, D.F., Neto, M.M., Gabriel Filho, L.R.A. and Salgado, D.D.A., 2021. Unrest index for estimating thermal comfort of poultry birds (*Gallus gallus domesticus*) using computer vision techniques. *Biosystems Engineering*, 206, pp.123-134.
- [10] Mortensen, A.K., Lisouski, P. and Ahrendt, P., 2016. Weight prediction of broiler chickens using 3D computer vision. *Computers and Electronics in Agriculture*, 123, pp.319-326.
- [11] Zaninelli, M., Redaelli, V., Tirloni, E., Bernardi, C., Dell'Orto, V. and Savoini, G., 2016. First results of a detection sensor for the monitoring of laying hens reared in a commercial organic egg production farm based on the use of infrared technology. *Sensors*, 16(10), p.1757.
- [12] Zaninelli, M., Redaelli, V., Luzi, F., Bontempo, V., Dell'Orto, V. and Savoini, G., 2017. A monitoring system for laying hens that uses a detection sensor based on infrared technology and image pattern recognition. *Sensors*, 17(6), p.1195.
- [13] Zaninelli, M., Redaelli, V., Luzi, F., Mitchell, M., Bontempo, V., Cattaneo, D., Dell'Orto, V. and Savoini, G., 2018. Development of a machine vision method for the monitoring of laying hens and detection of multiple nest occupations. *Sensors*, 18(1), p.132.
- [14] Aydin, A., 2017. Using 3D vision camera system to automatically assess the level of inactivity in broiler chickens. *Computers and Electronics in Agriculture*, 135, pp.4-10.
- [15] Daniel Berckmans, Arda AYDIN and Claudia BAHN, 2014, Automated monitoring of animal nutriment ingestion, Worldwide Patent, No. WO2014153626A3.
- [16] Yibin Ying and Meidui Dong, 2002, Automatic testing method and system for chicken sex, China Patent, No. CN1413458A.
- [17] Yiqing Liang, Linda Crnic, Vikrant Kobla and Wayne Wolf, 2000, US Patent, No. US20040131254A1.

- [18] Ehud Yanai and Ron Elazari-Volcani, 2014, System and methods for health monitoring of anonymous animals in livestock groups, US Patent, No. US8677941B2.
- [19] Leiqing Pan, Pengcheng Hu, Kang Tu, Wei Zhang, Ye Sun and Zijun Li, 2015, Gender determination method for chicken hatching egg incubation early embryo based on hyperspectral image, China Patent, No. CN104316473A.
- [20] Ramin Karimpour, 2017, System and method of determining the health & gender of a chick, Worldwide Patent, No. WO2017083654A1.
- [21] Gary L. McQuilkin and Gregory L. Engelke, 2015, Spectral imaging system for remote and noninvasive detection of target substances using spectral filter arrays and image capture arrays, US Patent, No. US20170089761A1.
- [22] Nakarmi, A.D., Tang, L. and Xin, H., 2014. Automated tracking and behavior quantification of laying hens using 3D computer vision and radio frequency identification technologies. *Transactions of the ASABE*, 57(5), pp.1455-1472.
- [23] Neethirajan, S., 2022. ChickTrack—A quantitative tracking tool for measuring chicken activity. *Measurement*, 191, p.110819.

7 Plain English Summary

Project Title:	Automated, real-time monitoring of bird and flock movement and behaviour 2.0
Australian Eggs Limited Project No.	1I017
Researchers Involved	Z. Luo, L. Yu, R. Shephard, J. Zhang, and Q. Wu
Organisations Involved	The University of Technology Sydney
Phone	+61 2 9514 3829
Fax	N/A
Email	jian.zhang@uts.edu.au
Objectives	Final performance of AI system for flock behaviour analysis on participating egg farms. Results of the epidemiological study to identify flock level risk factors. Commercial opportunities of the prototyped system. Next steps and recommendations.
Background	The public's attention to poultry welfare is increasing rapidly because people realise that the quality of animal welfare has a great impact on the quality of livestock products, which in turn affects the health of consumers. 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.
Research	Hen behaviours are one of the important indicators for evaluating hen welfare, and behavioural research has become a common way for evaluating animal welfare. Given the current focus on improving poultry welfare, there is an urgent need for data-centric behavioural analytics support for commercial egg farms. Such systems can provide valuable insights into hen behaviour, helping farmers optimise welfare conditions and, consequently, enhance both productivity and product quality.
Outcomes	A prototype system called the Flock Behaviour Data Analysis Platform.
Implications	Our robust system monitors flock activities on commercial egg farms using video cameras and desktop workstations, eliminating the need for continuous human monitoring. This system enables automated detecting and tracking the behaviours of laying hens, providing critical insights into wellbeing, welfare, and production risks through the analysis of collected data. The statistics help to identify the potential welfare issues related to management practices and environmental conditions, demonstrating the system's potential to enhance hen welfare on large-scale commercial egg farms.

Key Words	Deep learning; computer vision; animal welfare
Publications	[1] The paper `Vision-based multi-bird tracking for animal welfare on commercial egg farms` has been accepted as an oral presentation by Australian Poultry Science Symposium (APSS) 2024. [2] The paper `Robust Automated-monitoring System for Laying Hen Behaviours on Commercial Egg Farms` has been submitted to the IEEE Visual Communications and Image Processing (IEEE VCIP 2024) Conference.

Appendix 1 – Epidemiological analysis

Australian Eggs Limited Project No 11017

Richard Shephard, Rod Jenner & Jian Zhang

23 August 2024

Introduction

Summary data was provided for analysis. This included hourly averages and hourly snapshot estimates of eating and drinking obtained from analysis of video camera images. Each farm provided some shed performance and environmental data at day level of aggregation¹.

Data

De-identified data was analysed. Two farms participated, one located in Queensland and one in New South Wales. Each farm provided a shed for analysis and each shed contained two cameras. Both farms supplied video and operation data. The operation data from NSW farm are as follows:

The operation data from QLD egg farm are as follows:

DATE	BIRD NUMBERS	MORTALITY	FEED CONSUMPTION g/b/d	TOTAL FEED CONSUMPTION KG	WATER CONSUMPTION ml/b/d	TOTAL WATER CONSUMPTION LITRES	1st GRADE EGGS	FLOOR EGG NUMBERS	MIN TEMPERATURE	MAX TEMPERATURE
------	--------------	-----------	------------------------	---------------------------	--------------------------	--------------------------------	----------------	-------------------	-----------------	-----------------

The operation data from NSW egg farm are as follows:

DATE	BIRD NUMBERS	TOTAL FEED CONSUMPTION KG	TOTAL WATER CONSUMPTION LITRES	1st GRADE EGGS	TEMPERATURE
------	--------------	---------------------------	--------------------------------	----------------	-------------

Video data was provided at hourly timepoints², and this was supplemented with daily operation data as mentioned above. Analysis was conducted in the R Environment for Statistical Computing.

Based on the QLD operation data, we observed that from 5/1-16/2/2024, birds did not produce eggs as expected. The QLD farm staff informed us that the birds had just completed their rearing period (week 17) and were loaded into the shed within the last two weeks. Consequently, the egg production increased rapidly during this period. For example, in a shed housing 20000 birds, the egg count was 0 from 5/1/2024 to 9/1/2024, 3 eggs on 10/1/2024, 888 eggs on 17/1/2024 and 5,256 eggs on 24/1/2024. According to the operation data sheet for this shed, the expected daily egg production would normally be around 16,000 or more. By 16/2/2024, egg production reached a stable level 16,000 eggs per day.

To efficiently monitor bird behaviour, we needed to regularly clean the camera housing glass with a

¹ Each farm provided different variables; the consistent set included daily shed minimum and maximum temperatures, egg production, feed and water intakes.

² Within the range of recording times (6:00–17:00).

soft eyeglass cleaning cloth due to the heavy dust in the shed. Depending on the camera's position, the glass should be cleaned every two weeks, or even more frequently. Since video recording started on 5/1/2024, the camera housing glass needed to be cleaned by 20/1/2024. However, due to the long physical distance between UTS and the QLD egg farm for UTS team to travel there, dust accumulated on the housing glass. Upon reviewing the video data after 16/2/2024 (more than 1.5 months after the camera installation), it was noticed that significant noise was caused by dust on the camera lens, resulting in large blurs in the images, as shown in Figure 1. This significantly reduced the accuracy of the video analysis.



Figure 1 Example of blurred images (dust) negatively impacting the analysis of visual bird behaviours (eating and drinking)

Given these two issues with QLD data – 1) the unstable egg production due to the early production period (before 16/2/2024) and 2) the heavy image noise, such as blurring effects on the video footage -- correlation analysis between egg product and video metrics such as eating and drinking behaviours become very difficult and could potentially lead to misleading conclusions. As a result, several data analyses for QLD were withheld.

Exploratory analysis

The main camera variables were Average Eating Time, Average Drinking Time, Snapshot Eating and Snapshot Drinking recorded by each camera and at several time points

Both the NSW and QLD farm provided daily egg production, daily minimum and maximum temperature, total shed feed and water consumption. The QLD farm also provided total shed bird numbers, daily mortality and egg production which was further classified into floor eggs and grade 1 eggs³. From this, daily feed and water consumption per bird and the daily proportion of hens producing an egg were available.

Two cameras operated within the NSW shed. The distribution of video parameter results for this shed are presented in Figure . It appears likely that camera field-of-view effects produce different results for each of the variables measured. This has implications for use of the technology as a monitoring tool. Each camera must generate its own baseline data. Unless standardised fittings can be developed, it seems unlikely that industry-standard performance ranges can be produced and disseminated; each camera must act as its own control.

However, it must be understood that during the evaluation process, when our model attempted to detect whether a bird was eating or drinking, it could only identify the physical actions associated with these behaviours. For example, it could detect when a bird lowered its head into the food container (trough) or tilted its neck back to sip from the water tap. The model was unable to accurately

³ The NSW farm provided a longer time series of data than the QLD farm.

determine whether the bird was actually eating or drinking. This is informative in itself, as there is potentially a measure of eating efficiency when this data is examined against shed feed consumption.

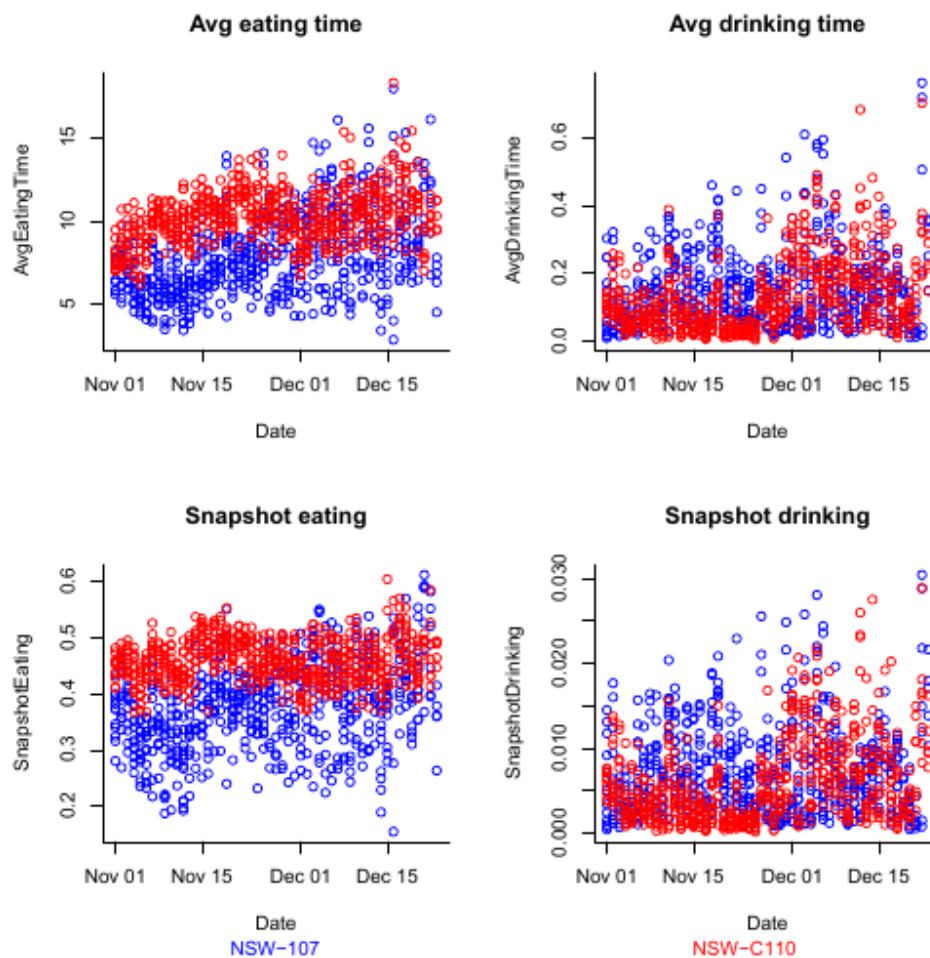


Figure 2 Comparison of video parameters from two cameras operating in the same shed across the same dates and times (NSW farm)

There were differences between farms (sheds) and time of day within sheds for average eating times (see Figure 33 for the NSW farm and Figure 4 for the QLD farm). Feeding times were most variable early in the morning for both the NSW and QLD sheds, with feed intake increasing in the afternoon for the QLD shed but not for the NSW shed. There was an upwards trend in average eating times across the production cycle in the NSW shed, but this was not apparent for the QLD shed (although fewer consecutive days were recorded from the QLD farm than for the NSW farm). Absolute differences in average eating time between the farms are significant, but this may be a camera position effect.

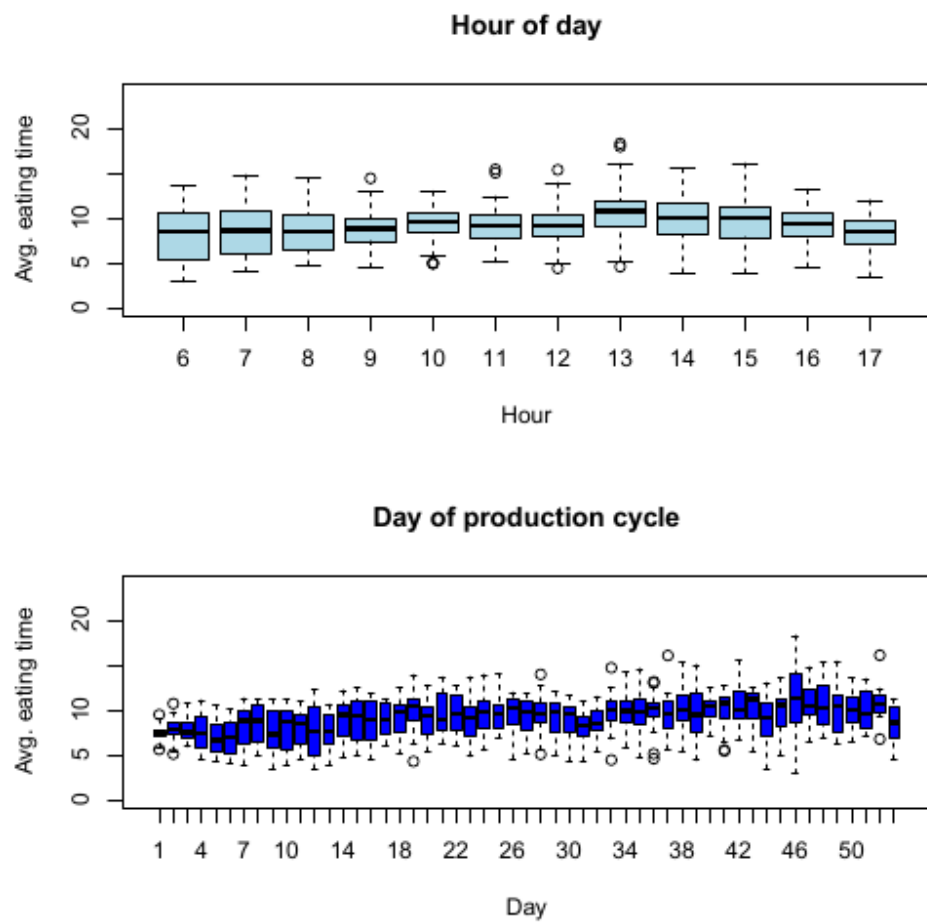


Figure 3 Boxplot of average eating time by time of day and date for the NSW farm

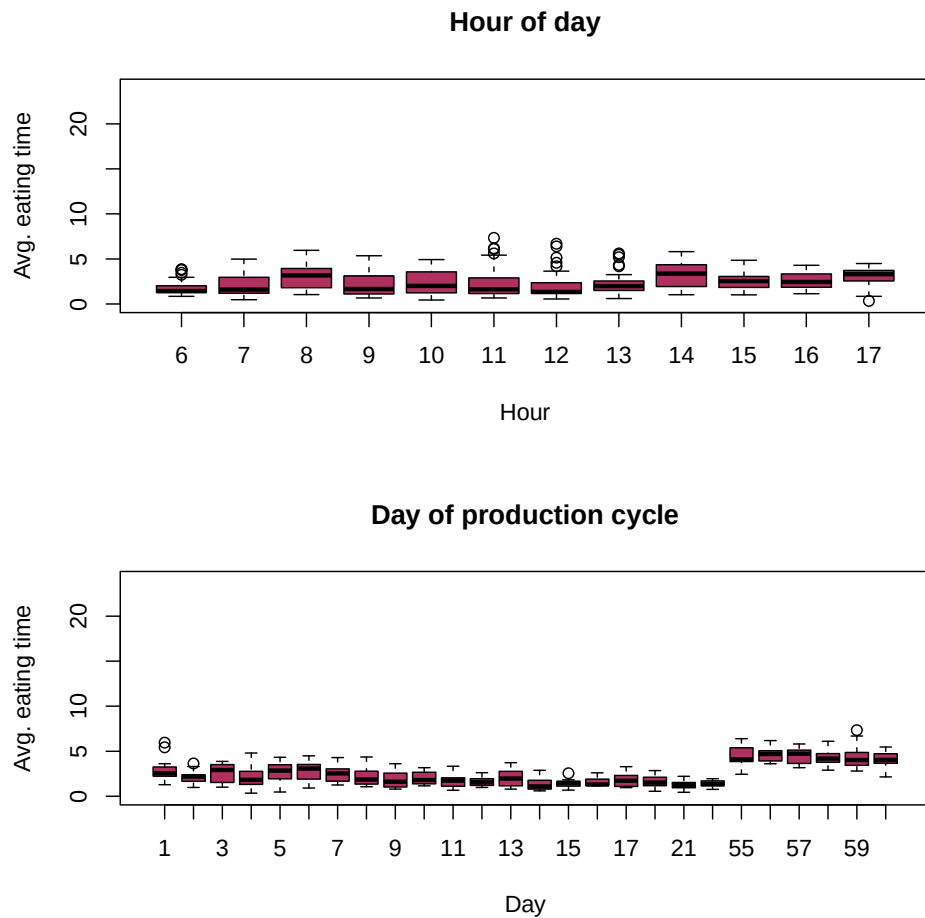


Figure 4 Boxplot of average eating time by time of day and date for the QLD farm

The change in average eating time and the total shed egg production for the NSW farm is presented in Figure 5. The NSW farm experienced an upwards trend in average eating time and a sudden decline in egg production beginning around the end of November.

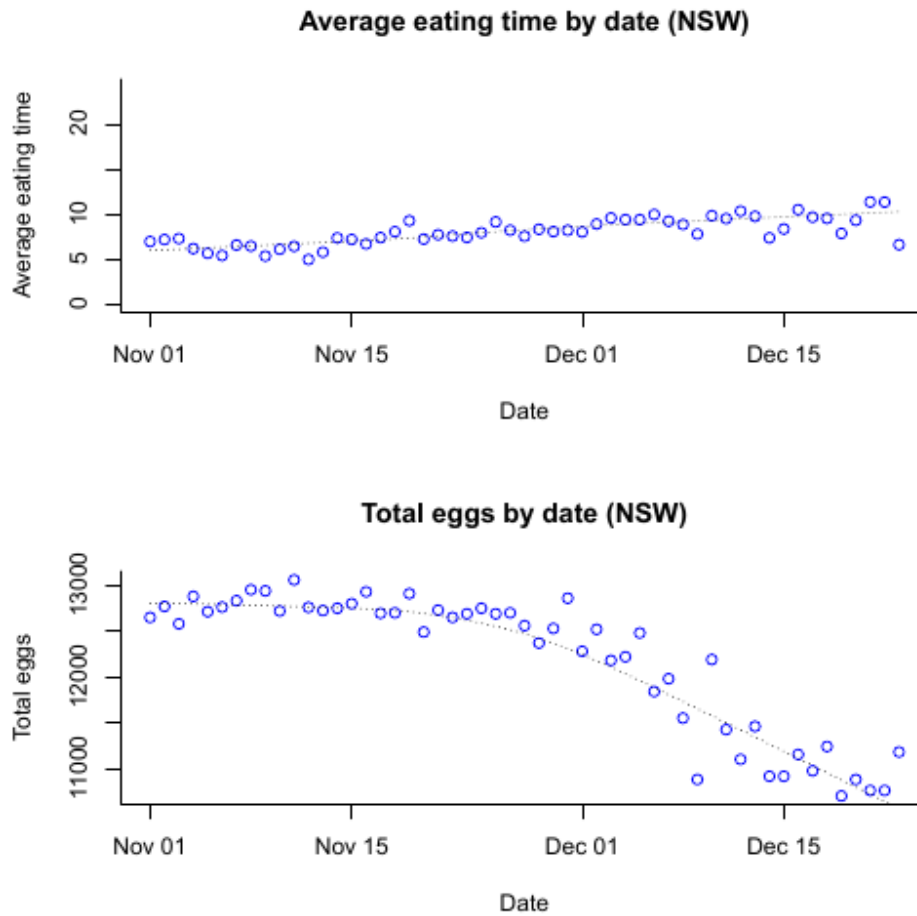


Figure 5 Eating time and total shed egg production for the NSW farm

The relationship between daily egg production and average eating time was explored (see Figure 17 for NSW), and between total shed feed consumption and average eating time (Figure 7 for NSW). There seems to be a paradoxical relationship between average eating time and (decreased) shed egg production and decreased total shed feed intake in the NSW farm that was not mirrored in the QLD farm.

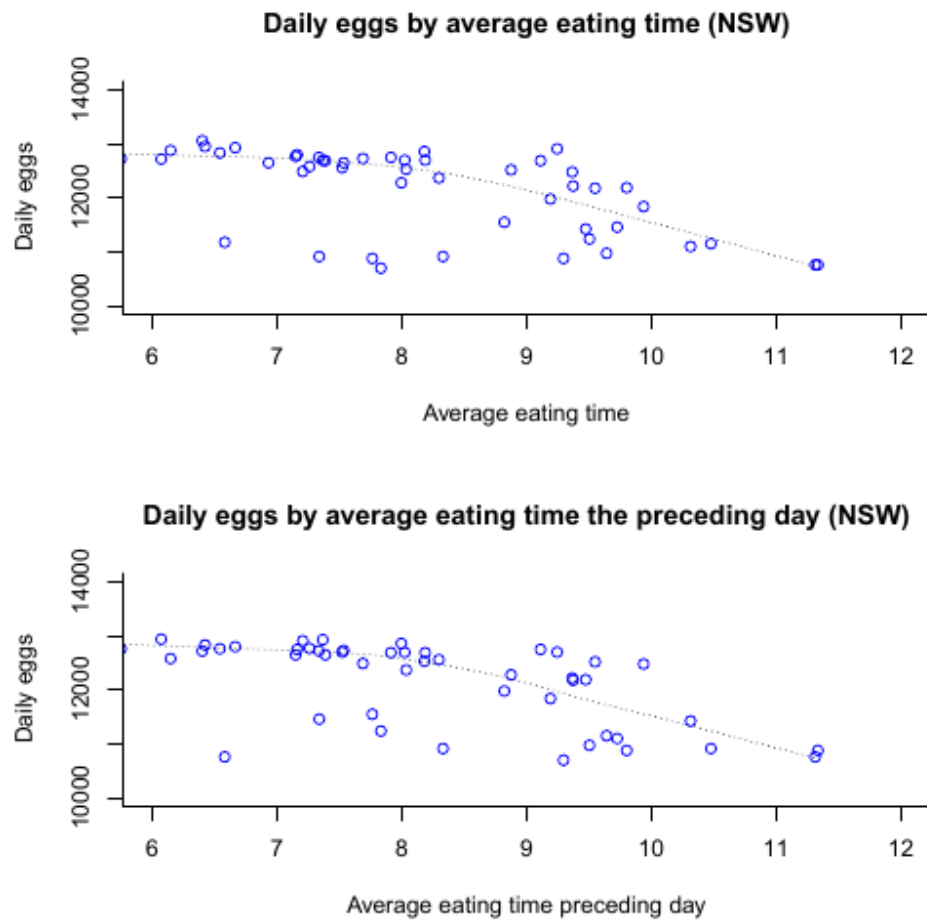


Figure 17 Daily shed egg production by average eating time for the NSW farm

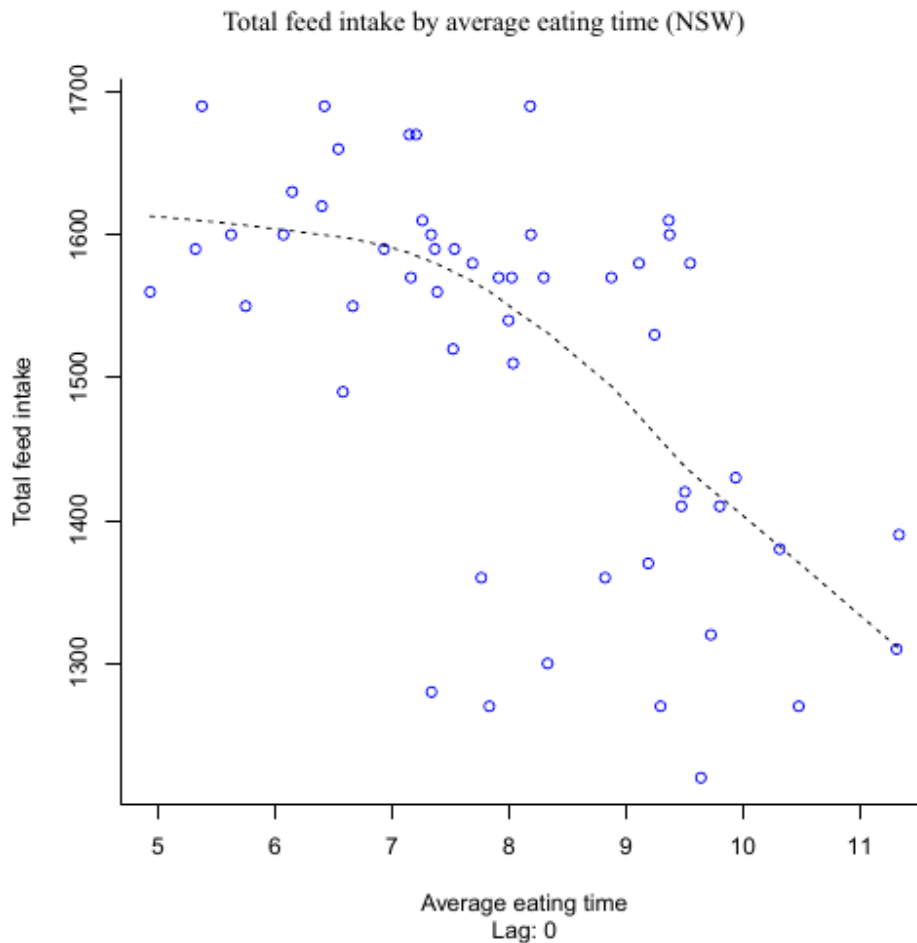


Figure 7 Total shed feed intake by average eating time for the NSW farm

One issue may be that the timing of these inflexion points in the NSW farm is confounded with another (unmeasured) variable, such as a disease. If a confounding variable is present and producing this observation, then the relationships between the video variables (average eating time, etc.) and total shed feed consumption and total shed egg production are correlations and not causal relationships. We have no evidence to include or exclude causality from this study. One question may be if the video variables provide early warning of the presence of the (yet unknown) variable driving egg production down.

There was no clear relationship between average eating time and the proportion of birds producing an egg per day, but there is some paradoxical (inverse) relationship between average eating time and total feed intake. Does this suggest that as shed feed intake decreases, birds that are feeding have less pressure to move away from the feeders and so record greater average eating times? Does this provide useful information for management? This requires further examination.

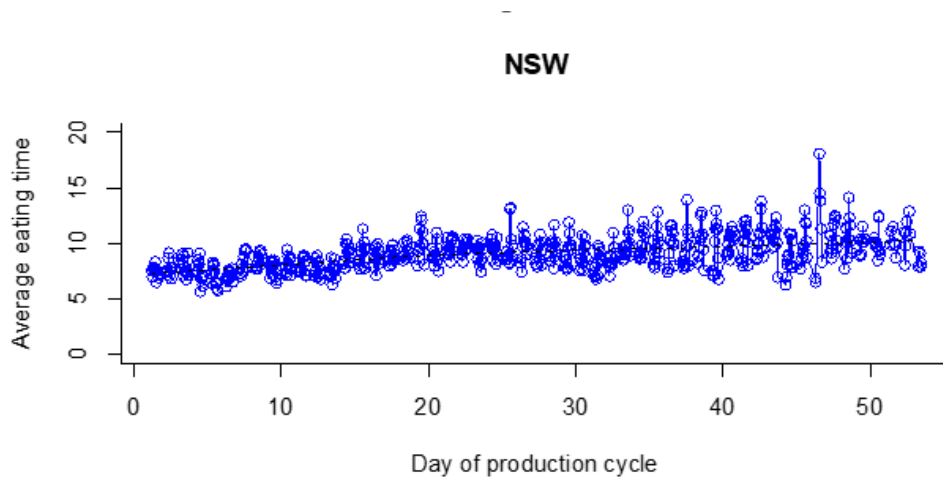


Figure 8 Trends in average eating time by time of day and day within the production cycle for the NSW shed

There was a gradual increase in average eating time and in variability of average drinking time as the production cycle progressed in the NSW shed. The average drinking time and the number of birds seeking to drink in the afternoon (snapshot drinking) increased over time. But this trend was not observed in the mornings. Exponentially-weighted moving averages (EWMA) for the key variables were calculated and plotted to identify trends in each parameter (see Figure to **Error! Reference source not found.1**).

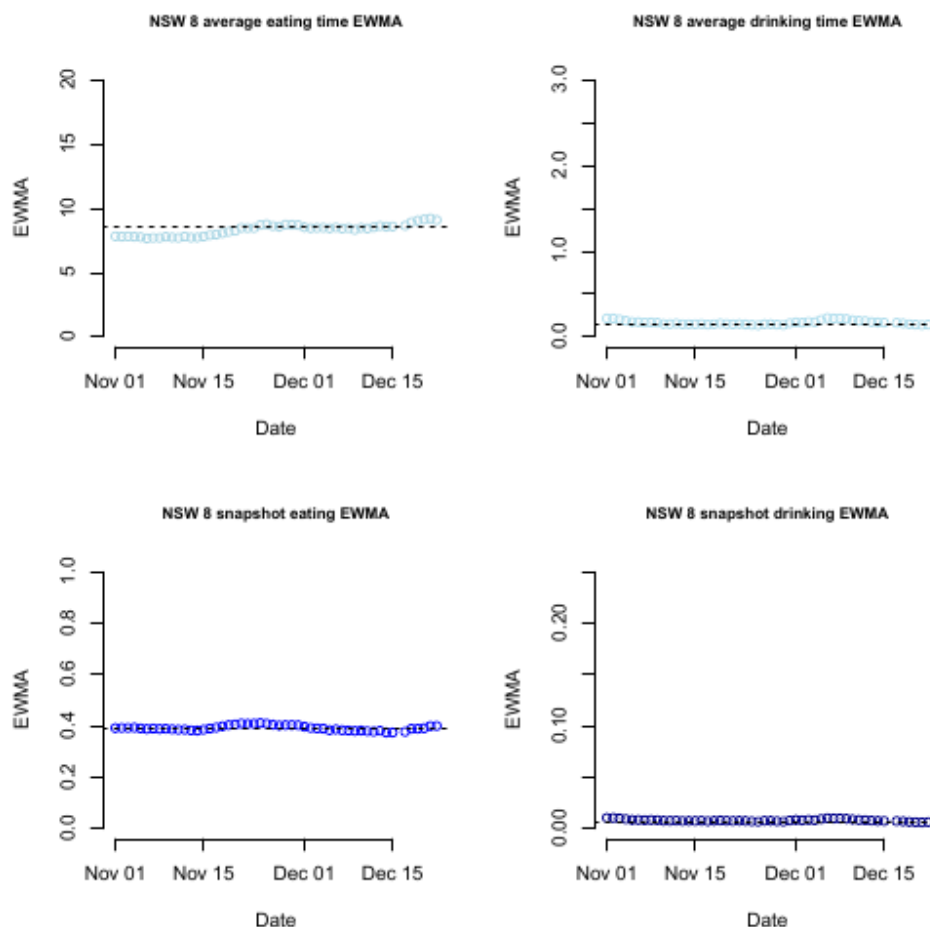


Figure 9 Exponentially-weighted moving average (EWMA) plots for the video variables for the

NSW shed (8 AM)

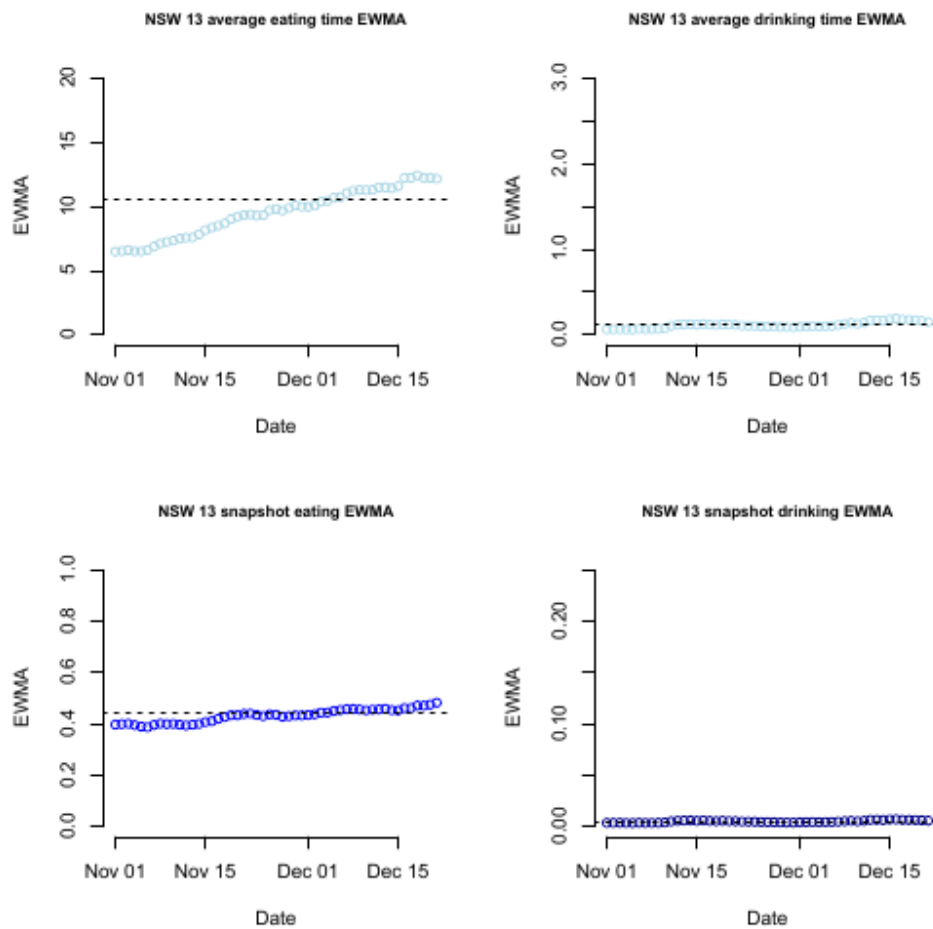


Figure 10 Exponentially-weighted moving average (EWMA) plots for the video variables for the NSW shed (1 PM)

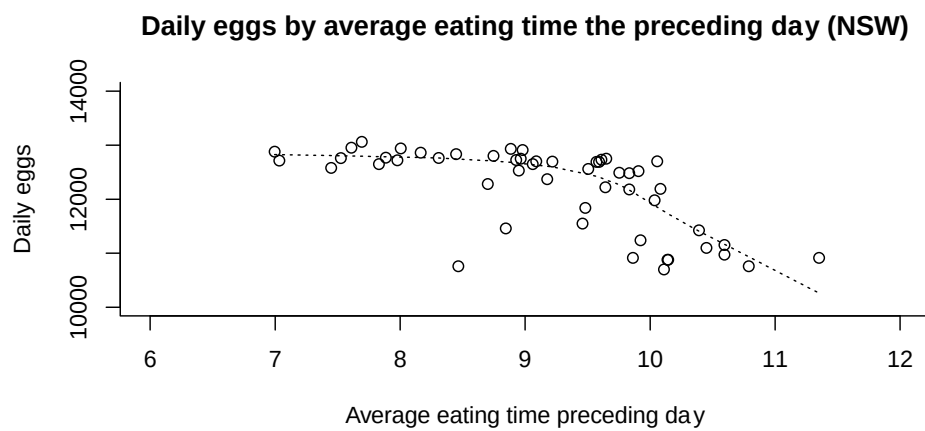


Figure 11 Daily eggs by average daily eating time today and for the preceding day (lag 1) for NSW

Egg production had a curvilinear relationship to average eating time in the NSW shed. There was a paradoxical decline in shed egg production as average eating time today and in the preceding day increased past 10:00am.

Predictive model

A regression model was constructed to explore the relationship between predictor variables. This was a basic regression model that predicts shed daily egg output (NSW) using non-video derived variables (that existed before this project) and that were correlated with egg production (namely the day of the production cycle⁴), and total shed feed. This is presented below.

Call:

```
lm(formula = Eggs ~ 1 + DayNo + Feed, data = nswAllDay)
```

Residuals:

Min	1Q	Median	3Q	Max
-565.34	-213.67	83.04	191.28	602.04

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	7808.6197		891.3519	8.760
DayNo	-20.5358		4.4242	-
Feed	3.2630	0.5233		6.236

9.40e-08 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 286.1 on 50 degrees of freedom

Multiple R-squared: 0.8645, Adjusted R-squared: 0.8591

F-statistic: 159.5 on 2 and 50 DF, p-value: < 2.2e-16

The NSW farm base model had good predictive power, explaining approximately 86% of the variation in daily shed egg production.

A final model from the inclusion of key video-based variables into the base model above was developed. Improvement in model fit and the statistical significance of predictor terms were used to select the most parsimonious model. Variables that did not add to the predictive power of the model were excluded (like average drinking and snapshot variables).

This model is presented below.

⁴ Day of the production cycle was arbitrarily set to day 1 when the camera first went in.

Call:

lm(formula = Eggs ~ 1 + (DayNo + AvgEatingTime + Feed)^2, data = nswAllDay)

Residuals:

Min	1Q	Median	3Q	Max
-633.84	-80.17	21.93	141.56	453.25

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5024.242	4788.712	1.049	0.300
DayNo	-225.242	50.929	-4.423	5.92e-05 ***
AvgEatingTime	1600.680	622.005	2.573	0.0134 *
Feed	4.501	2.871	1.568	0.1237
DayNo:AvgEatingTime	-5.921	2.582	-2.294	0.0264 *
DayNo:Feed	0.1580	0.031	5.078	6.76e-06 ***
AvgEatingTime:Feed	-0.9329	0.378	-2.466	0.0175 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 219.3 on 46 degrees of freedom

Multiple R-squared: 0.9268, Adjusted R-squared: 0.9172

F-statistic: 97 on 6 and 46 DF, p-value: < 2.2e-16

This model was an improvement on the base model, now explaining 93% of the variation in total daily eggs harvested per shed. Importantly, the model is a significantly better fit than above (see below), and the model residuals were without systematic patterns.

Analysis of Variance Table

Model 1: Eggs ~ 1 + (DayNo + AvgEatingTime + Feed)^2

Model 2: Eggs ~ 1 + DayNo + Feed

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	46	2212245				
2	50	4092328	-4	-1880083	9.773	8.300e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

We conclude that there is corrective information in the total amount of feed eaten and in how the birds consume their feed (i.e. average eating time). It should be noted that the day of the production cycle should control for shed stage-of-lay effects.

We have identified a pattern between average eating time and shed performance (total feed intake and daily egg production) in the NSW shed that seems contradictory. It has been noted that the AI model was unable to accurately determine whether the bird was actually eating or drinking, only identifying the physical actions associated with these behaviours. Therefore, we have no insight into why average eating time (eating behaviour in general) is so influential – could this be related to bird aggression, with some birds dominating the feeding sites and thereby preventing other birds from gaining full access to feed? We also do not know what action we can take to change eating behaviour favourably; the first step in control is understanding the phenomenon. Measuring eating and drinking efficiency may prove to be a useful metric.

One finding of note is that each camera will need to act as its own control given differences in positioning, shed layout, bird population, etc. The use of statistical process control techniques, with internal reference points, are likely to be required for the video-based system to have sufficient sensitivity and specificity for detecting change.