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

FINAL PROJECT REPORT | 31 DECEMBER 2021

A report for Australian Eggs Limited by Dr. Litao Yu, Dr. Jingsong Xu, Dr. Richard Shephard, A/Prof. Qiang Wu and Prof. Jian Zhang.

Australian eggs

Foreword

Pile-ups (or piling) is a root cause of smothering events, which can be a serious problem in commercial egg farms. Automated pile-up monitoring can provide a farmer-friendly way to detect and therefore prevent or reduce smothering events.

Specifically, a video-based monitoring system can automatically estimate flock density and bird movement patterns in layer flocks. This provides early warning opportunity for farmers of impending pile-ups.

Warnings in real-time allow producers to take corrective action to prevent smothering.

Video monitoring can also automatically record and identify bird individual behaviours (including eating, drinking, interactions with other birds and egg laying). These additional measurements increase the value of automated video content analysis and so contribute to reductions in labour costs yet improving labour efficiency. This flows through to improvements in egg productivity.

This work aims to combine computer vision and AI models with farm video systems, to enable non-intrusive and continuous monitoring for commercial egg farms.

Summary

This project investigated the possibility of designing an automated flock movement analysis system for commercial egg farms. The system is based on advanced AI techniques, to enable continuous, hands-free, and non-intrusive flock density and movement monitoring. The possible application of the system is many-fold but includes giving an immediate warning of birds' piling up for possible smothering protection.

Summaries of bird activity and their distribution reveal the density and movement patterns of flocks which give reliable information on crowd behaviour in the shed of egg farms. Such information can give early warnings of smothering, where large numbers of hens pile up (often resulting in smothering). To observe these important flock activities in this project, the following objectives applied:

a) Collect video data from an egg farm with sufficient data samples with manual annotations. This is the prerequisite for training the data-driven models.

b) Develop the animal detection, segmentation, tracking and crowd counting models for flock density estimation, crowd counting and individual behaviour analysis.

c) Based on the detection and tracking models, identify some pre-defined activities, and do the corresponding statistics.

d) Validate the functions of the monitoring system and conduct the case studies.

The research was conducted in Windsor NSW at a commercial Egg Farm, and the experiments were conducted in the Multimedia data Analytics Lab located in the UTS Tech Lab for an 18-month period. The video data collection was conducted by setting several cameras in both indoor and outdoor environments of the shed. Based on the collected data and manual annotation, several AI models were built including for bird detection, segmentation, tracking and crowd counting.

The AI models that were developed and tested are summarized as follows:

a) **Bird detection** – This model detects each hen.

b) **Instance segmentation** – This model locates each instance and the contours of the birds, describing their motion.

c) **Bird tracking** – This model works in conjunction with the bird detection model to estimate the location of each hen in the frame sequence.

d) **Crowd counting** – This model estimates the number of birds in the observation area.

The above models were trained and tested on the validation split of the datasets. In our preliminary study, the models of object detection and segmentation achieve 94% and 92% accuracies for the indoor environment.

The crowd counting algorithm further improves the accuracy by 1.5%. Applying the trained models to the daily routine videos captured in the shed, the system can also automatically identify the bird individual behaviour, which were defined in the Ethogram we developed, to give immediate statistical reports.

Overall conclusions

Welfare and productivity gains by automated analysis of laying-hen flock activity using video streams, supporting hands-free and continuous monitoring of flock and individual behaviours.

Early warning of some flock activities, such as pile-ups, can prevent or reduce smothering incidences, and provides insight into risk factors for these rare events.

Applied artificial intelligence (AI) and computer vision techniques through our video system can summarise bird activities, their occurrence and distribution within the flock.

Specifically, we have developed a low-cost and easy-to-use system for layer farms.

Our video system has recorded more than 1000 hours of data from a Windsor egg farm during the project.

We used our large-scale video data to train AI models to estimate the density of birds and characterise bird and flock movements, some of which precede pile-ups.

The system provides early-warning capability.

Our system can also monitor and record individual bird behaviours such as eating, drinking, interactions with other birds and egg laying to generate a daily distribution of behaviours.

This information can be examined for correlations between patterns and egg production adverse welfare activities.

Finding predictive patterns supports control leading to improved bird welfare and productivity.

The current project has built baseline video technology (platform technology) that we can use for the next stage of the project (stage 2) that will focus on flock-based behaviour assessment and measurement, specifically for bird welfare monitoring and to identify productivity improvement predictors for egg farms.

About the Authors

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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 a research fellow with the Institute of Integrated and Intelligent System, Griffith University, Brisbane from 2018 to 2019. He is currently a research fellow with Multimedia Data Analytics Lab (MDAL), Global Big Data Technologies Centre (GBDTC), University of Technology Sydney, Ultimo NSW Australia. His research interests include image processing, machine learning and multimedia content analysis.

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Professor Jian Zhang
Jian Zhang is a Professor in the Faculty of Engineering and IT at 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.

Acknowledgments
The authors would like to thank Windsor Egg Farm 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.

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ABBREVIATIONS

AI Artificial intelligence
DL Deep learning
RFID Radio-frequency identification
ROI Region of interest
HOG Histogram of oriented gradients
SVM Support vector machine
NOL Number of laying
LTL Latency to lay
OA Occupied area
EE Effective eating
IR Infrared
THI Temperature-humidity index
CNN Convolution neural network
IoU Intersection-over-union
GPU Graphic processing unit
MAE Mean average error

Contents

1 Literature and patent review

1.1 Literature review

It is expected that the global demand for livestock products will increase by 70% by the year 2050 [1]. As one of the most high-protein and environmentally friendly sources, egg production is an important human food source. Intensive egg production enables economical, nutritious, and readily available human food. However, one of the challenges is how to ensure the production systems meet the birds' needs, including comfort, health, and positive experiences. In Australia, 95% of the human population is concerned about animal welfare with 91% desiring better ways to monitor and improve animal welfare [2]. There is an increased understanding and focus on animals' sentience and the need to ensure farm animals have "lives worth living". This applies to the Australian egg industry where research shows the community believes that hens are entitled to positive and rewarding lives [3]. Good hen welfare also promotes better egg quality and productivity [4].

The flock activities, such as group running and pilling up, are important indicators of bird's flock movement and crowd behaviour status. The comprehensive analysis of such indicators on commercial farms is currently labour-intensive if this work is done manually. Thus, some sensors such as wearable devices (e.g., RFID, accelerometers), microphones, and thermometers, are used for data collection to analyse the welfare status. Among them, acoustic analysis is mostly used at the flock level, while wearable sensors are used to track individual behaviours. However, in the poultry industry, wearable devices are not widely used due to cost, size, weight, and practicality limitations.

Automated video analysis can provide universal, non-intrusive, continuous, and real-time monitoring. Video techniques have been used in livestock management for more than a decade. Here we summarize these techniques with traditional image processing methods, as well as the advanced deep learning-based computer vision methods [5,6].

Traditional image processing methods follow the paradigm of pre-processing, region-of-interest (ROI) computation and classification. The pre-processing is mainly to prepare the digital image for feature extraction, including grey-scale transformation and resolution adjustment. Applying some feature descriptors such as Histogram of Oriented Gradients (HOG) on the processed image, we can compute the ROI with a classification method, such as Support Vector Machines (SVM) to locate the animal instances. Using the webcam or Kinect cameras, Aydin et. al adopted background subtraction to detect the region containing the bird(s) for 250 broilers [7,8,9], where the number of laying events (NOL) and latency to lay (LTL) can be computed. In [10], the authors defined a set of variables for broiler chicken behavioural analysis, where they used image segmentation methods to compute the occupied area and activity index.

However, the number of birds within the observation area and the effective eating (EE) needs to be manually counted on the monitor. Li et al. [11] adopted an infrared (IR) camera to identify foreground regions, where the number of hens is counted. These traditional image processing methods are restricted by the hand-crafted visual features, which do not generalise well in the different visual environments. Also, these visual feature extractions and model training are independent procedures, which is a bottleneck to improving the overall performance. The method proposed in [11] only achieves the overall accuracy of identification of 71%. Based on the observation of the static images, bird activities such as laying, perching, wing flapping and dust bathing were analysed [12].

However, the activities usually have temporal patterns, which is even more difficult in traditional image processing methods. [13] used colour-based segmentation to segment birds from the background then identify the diseased birds. Guo et al. applied similar techniques to predict the number of birds within an observation area [14].

The optical flow, defined as the apparent motion of individual pixels on the image plane, which then in aggregate describe the (bird) motion in frame sequences. This therefore will identify moving objects, so it can be used for the movements of animals. The measures in optical flow include spatial mean, skewness, variance, and kurtosis of the estimated flow velocities [15,16,17]. Based on these properties, Silvera et al. applied optical flow for bird lameness assessments [18]. Fernandez et al. used the activity index (the percentage of pixels that changed between two images) and the occupation index (the percentage of pixels containing birds) to develop a welfare score [19].

Due to the technical limitations of low descriptive ability of optical flow, the above research outcomes based on traditional image processing can hardly use in broader applications in animal behaviour monitoring. Most of the methods are characterized by low-level image features, which gap the high-level semantic modelling thus leading to low accuracy. Furthermore, the low-level features are not robust enough for field use within different (commercial) visual environments where issues include changes due to variable illumination and weather. Specifically, when it comes to crowded animal environments, automated recognition performance drops dramatically.

These reasons make the current systems unable to provide satisfactory performance for precise poultry farming in commercial environments.

Deep Learning (DL) is a data-driven technique that combines feature learning and model training. In image processing, DL methods directly process the image through a deep neural network then output the desired patterns. In the past few years, significant progress of DL has been made in computer vision, including large-scale classification, object detection and instance segmentation.

For example, the fine-tuned YOLOv3, SSD and Faster-RCNN can be used to detect bird behaviours [20] and sick broilers [21]. The detection model and other sensor signals such as temperature-humidity index (THI), can be jointly used to monitor heat stress [22]. Pu et al. proposed to use a convolutional neural network (CNN) on images captured by Kinect to classify group behaviours into “not crowded”, “slightly crowded” and “fairly crowded” categories [23].

With the advanced deep learning models and the ongoing hardware evolvement, now it is much more affordable to deploy the data-driven models for automated egg farm management. However, the power of deep learning techniques in poultry management has not been fully evaluated, due to the lack of applicable data.

Based on current deep learning techniques, this project is to provide real-time monitoring and automated flock behavioural pattern analysis. Specifically, the system aims to implement the following functions: 1) individual bird detection; 2) individual bird activity classification and 3) flock movement description.

1.2 Patent review

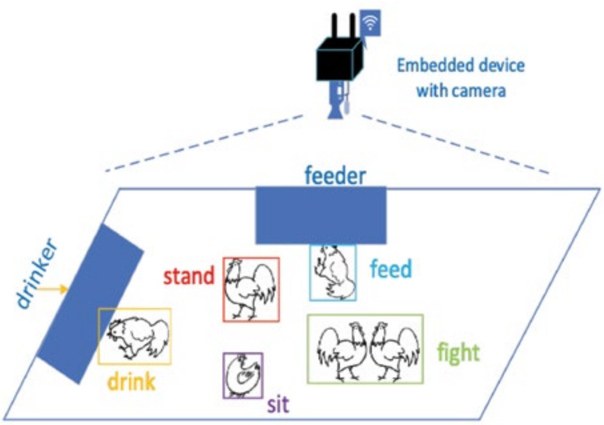
A few related patents that describe the methods for animal detection and behavioural analysis focus on quadruped livestock species, which are mainly about the animal measurement functions, such as individual identification, weight estimation, lameness detection and meat quality assessment through multispectral imaging. In the commercial poultry industry, [24] describes a system for livestock individual behavioural analysis using optical signals. In [25], the author introduced a system to analyse animal behaviour. The patent [26] proposes to apply image processing techniques to detect dead chickens. [27] describes a method for cattle gait analysis.

2 Data collection

2.1 Hardware design

For effective monitoring, a top-view video camera is mounted to capture the video footage. Such a view setting can avoid occlusion and enlarge the observation area. The video camera is connected to a desktop, which provides computation and communication functions. The data collection platform in a shed is illustrated in *Figure 1.* The live video feed can be saved locally but can also be processed simultaneously in a mini computation centre to provide data insights. The height of the platform is adjustable to allow full coverage of the observation area.

Figure 1: The hardware configurations for the data collection.



We set up the cameras in the Windsor Egg Farm, NSW and recorded the video data footage from 15/03/2021 to 16/06/2021. The cameras used in the data collection are illustrated in *Figure 2*. The cameras are from different vendors and were set up with different view angles for different tasks. We set the cameras in both indoor and outdoor environments, to collect videos in different visual conditions for data diversity. These settings are shown in Figure 3. In this project, 4K cameras 1 and 2, PTZ cameras 3 and 4, fisheye camera 5 and standard indoor cameras 6 and 7 are used. The following is a brief introduction of these cameras:

- The 4K camera can capture videos with a resolution of up to 3840 x 2160 pixels (4k, Ultra HD). We used the 1920x1080 resolution (1080p, Full HD) setting for video recording.
- The PTZ camera has remote control foundations for panning, tilting, and zooming.
- The standard camera is a widely used RGB video camera.
- The Fisheye camera has a 360-degree view but has some distortions on recorded images/videos.

Table 1 details the collected datasets (#1 - #12), and *Figure 4* shows the image samples from the datasets. Among them (a) and (b) are from camera 1 (4K). (c) and (d) are from camera 2 (4K). (e), (f) and (g) are from camera 3 (PTZ). (h) and (i) are from camera 4 (PTZ). (j) is from camera 5 (fisheye). (k) and (l) are from cameras 6 and 7 for indoor environments.

Figure 2: The cameras used for data collection.

Figure 3: Camera settings for indoor and outdoor environments.

Table 1: Details of the collected dataset.

#Dataset	Camera	Type	Location	View-angle	#Days	Mode
1	1	4K	Indoor	1	36	1080P/30fps
2			Indoor	2	8	1080P/30fps
3	2	4K	Indoor	1	21	1080P/30fps
4			Indoor	2	8	1080P/30fps
5	3	PTZ	Indoor	1	26	1080P/30fps
6			Outdoor	1	15	1080P/30fps
7			Outdoor	2	8	1080P/30fps
8	4	PTZ	Outdoor	1	42	1080P/30fps
9			Outdoor	2	8	1080P/30fps
10	5	Fisheye	Indoor	1	12	1920x1920/15fps
11	6	Indoor	Indoor	1	4	1080P/30fps
12	7	Indoor	Indoor	1	4	1080P/30fps

Figure 4: Sample video frames from different camera settings for 12 datasets (from #1 to #12) listed in *Table 1*.

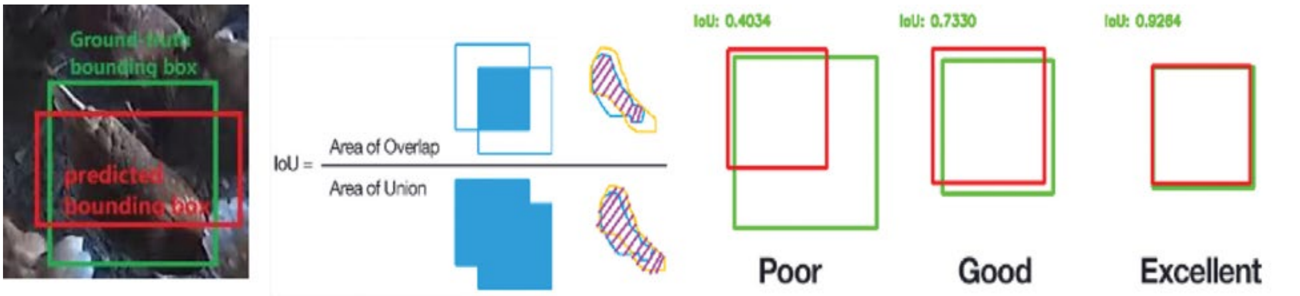
2.2 Video data collection

The video data collected on the egg farm as shown in Table 1 is the cornerstone in building the system for automated monitoring and video content analysis. With the massive data that records diversified bird instances and activities, we must first manually annotate the monitoring objects (e.g., bird instances and non-birds such as a human in the shed) as well as their behaviours (e.g., eating, drinking and egg-laying). This was achieved by working with the animal scientists on the team. These annotated data samples are then used to train AI models that are deployed in the system to assist farm managers with different functions. For example, providing the bird density statistics in real-time and giving early warnings of hazardous incidents.

3 Task identification

Figure 5: Bird detection from video frames.

Figure 6: The computation of IoU for bird detection.



To implement the flock activity monitoring system, we developed and linked five modules together to provide the operating final system. The modules are bird detection, bird instance segmentation, crowd counting, bird tracking and bird behaviour classification. In each module we defined the technical requirements from the perspective of computer vision and machine learning, and linked the various modules together into a workflow system.

3.1 Bird detection

Individual bird detection is the cornerstone in the whole computational framework, which aims to locate each bird in an image and compute a bounding box. This is a supervised learning process, which requires manual annotation from the sampled frames from the video footage. *Figure 5* illustrates the bird detection in a video frame, where each bird is assigned by a bounding box, and the number of bounding boxes is just the number of observable birds in the frame.

For general object detection tasks, we usually use Intersection-over-Union (IoU) as the evaluation metric to compare the predicted instances and ground-truth. The high IoU score means accurate object localization. *Figure 6* illustrates how the object detector computes the location of the bird.

The predicted and ground-truth bounding boxes are marked by red and green rectangle bounding boxes, respectively. The IoU score is the ratio between the overlapped area and their union. The range of IoU is between 0 and 1. The IoU score 0 means the predicted instance and ground truth are totally unmatched, while the IoU score of 1 indicates the perfect match.

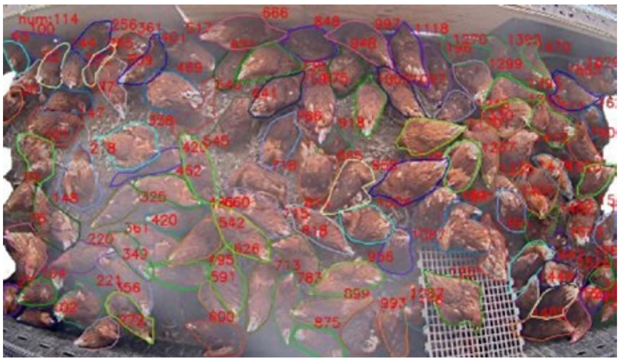
Besides the IoU score that is used for object localisation, average precision (AP) is used to measure if the detected object is the desired one. This metric is used when there is more than one category (e.g., bird and mammal) to be detected.

3.2 Bird segmentation

For the detected birds, segmentation is to mask all pixels that cover the whole body of each bird, providing more details about the bird's motions. By doing this, the system can observe some specific visual properties that the detection model cannot. For example, orientations of the movement. *Figure 7* illustrates the instance segmentation of the birds in the shed.

The evaluation of instance segmentation is similar to object detection. For each instance, the IoU score is computed via the ratio between the pixel intersections and the unions.

Figure 7: An illustration of bird instance segmentation.



3.3 Crowd counting

Crowd counting aims to estimate the total number of instances in a pre-defined observation area. This learning target can be implemented by object detection or instance segmentation but does not need the regression of bounding boxes or drawing the contours that cover the individual instances.

Figure 8 illustrates the crowd counting in a single frame, where each bird is labelled by a dot. Real-time crowd counting can be used to estimate the bird density, which is a key indicator of piling up those leads to smothering.

Figure 8: An illustration of crowd counting.

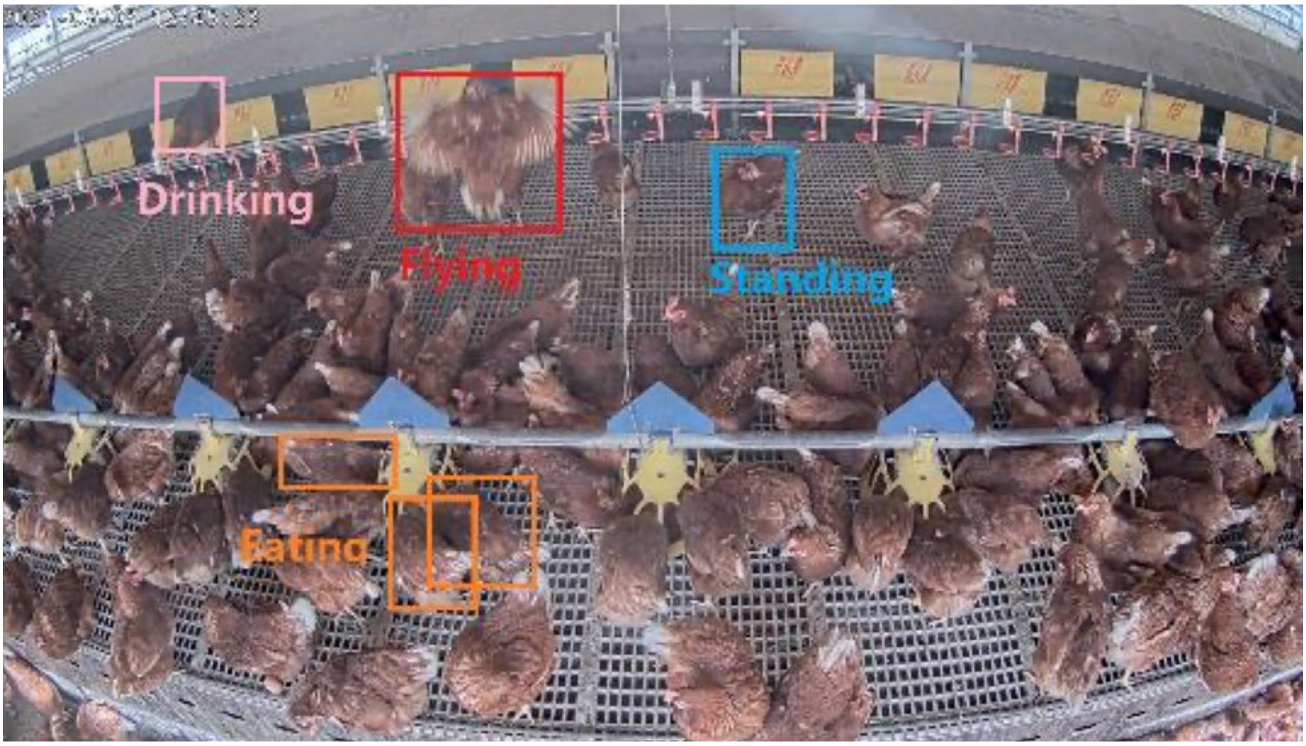
3.4 Bird tracking

Bird tracking aims to compute a moving trajectory of each bird within a frame sequence of videos. This term is usually bound with bird detection. The tracking sketches the movement of each bird within the observation area, which dynamically describes the activities.

Figure 9 shows the locations of one tracked bird along a trajectory over the different timestamps in a video clip.

Figure 9: An illustration of bird tracking.

Figure 10: Different observable bird behaviours.



3.5 Bird behaviour classification

The behaviours in the cage-free system can reveal the bird's health status as well as the living environment. In this project, our collaborator Rodney Jenner and Richard Shephard developed a comprehensive Laying Hen Ethogram, which covers 32 bird behaviours, including resting, eating, drinking, running, panting, flying, perching, egg-laying, dust bathing, fighting, feather pecking, etc. that is able to be used as a set of visual rules allowing automated (video-based) classification of bird behaviour and activity. *Figure 10* shows some behaviour samples that can be monitored from the recorded video footage.

The task of activity classification is to assign a categorical label when observing a bird's motion. Note that in *Figure 10*, the image contains multiple bird instances as well as the background. Also, the classification does not consider location information. To accurately monitor each bird's behaviours, the classification should be conducted in conjunction with bird detection (or instance segmentation) and bird tracking.

The activities can be either static observable or should be identified by temporal analysis. In this project, we focus on the case study of simple activities that can be observed from a single frame of the video.

4 System implementation

4.1 Bird detection

To conduct the bird detection experiment, we labelled 5751 birds from 53 images from datasets #1 and #5, then randomly split the data into a training dataset and validation dataset, respectively. The training dataset is used to obtain the AI model, while the validation dataset is used to test the true performance. In machine learning, the high performance on the validation dataset signifies the trained model has better generalization ability. Without the validation, the trained model can 'over-fit' the data. Practically, a model that has been over-fit will provide near-perfect accuracy on the training dataset but has very low performance when comes to the unknown data. Managing and controlling for over-fitting is vitally important in developing AI systems on large training data sets.

4.2 Bird segmentation

A bird is a non-rigid object (since it can scratch its head, legs, and wings, etc.), which cannot be analysed by the detection model. To get the accurate bird body activity identification, bird segmentation provides more detailed information for this task. It does this by masking all body parts pixels on detected birds, and it is this fine-grained pixel-level approach that improves predictive accuracy of bird motion.

To train the segmentation model, we selected the video footage from camera 6 for performance evaluation. In detail, we labelled 1707 instances from 137 images, in which 109 images with 1357 birds are used for model training and the rest instances were used for validation.

After the training, the models obtained the overall segmentation accuracies of 94.5% and 92%.

4.3 Crowd counting

Given a video frame, crowd counting estimates the likelihood of a bird instance of every pixel. The crowd counting can be directly implemented by object detection, where we can count the number of bounding boxes for such a purpose. However, the regression of bounding boxes for bird instances are redundant. Also, in our preliminary study, applying object detection to count the bird numbers is comparably less accurate. So, in our experiment, we also built a direct crowd counting model.

The details of the data are summarised in *Table 2*. Note that this split setting (indoor and outdoor) will be used in the ablation study in the next section. In the evaluation, we just use the mean average error (MAE) for the performance evaluation, which is the ratio between the number of miscounts and the total number of instances in a frame. The MAE values are 7.3% and 5.8% based on bird detection and crowd counting models, respectively.

Table 2: Details of training and testing dataset for crowd counting.

	Indoor		Outdoor	
	#images	#instance	#images	#instance
Train	116	12077	122	8426
Val	30	2808	31	2063
Σ	146	14885	153	10489

Table 3: Details of training and testing dataset for bird behaviour classification.

	Eating	Drinking	Egg-laying	Others
Train	1167	1064	563	2421
Val	292	266	114	606
Σ	1459	1330	677	3027

4.4 Bird tracking

The bird tracking is also built on the object detection model. When handling a sequence of frames in video footage, once a bird is detected, we apply a matching process aligned to each instance in the continuous frames in video streams. We tested the bird tracking model in a 5-minutes video in dataset #1, which achieves 95% accuracy. These algorithmic tweaks were essential to adapt automated video analysis algorithms and approaches to work in the challenging chicken farm environment.

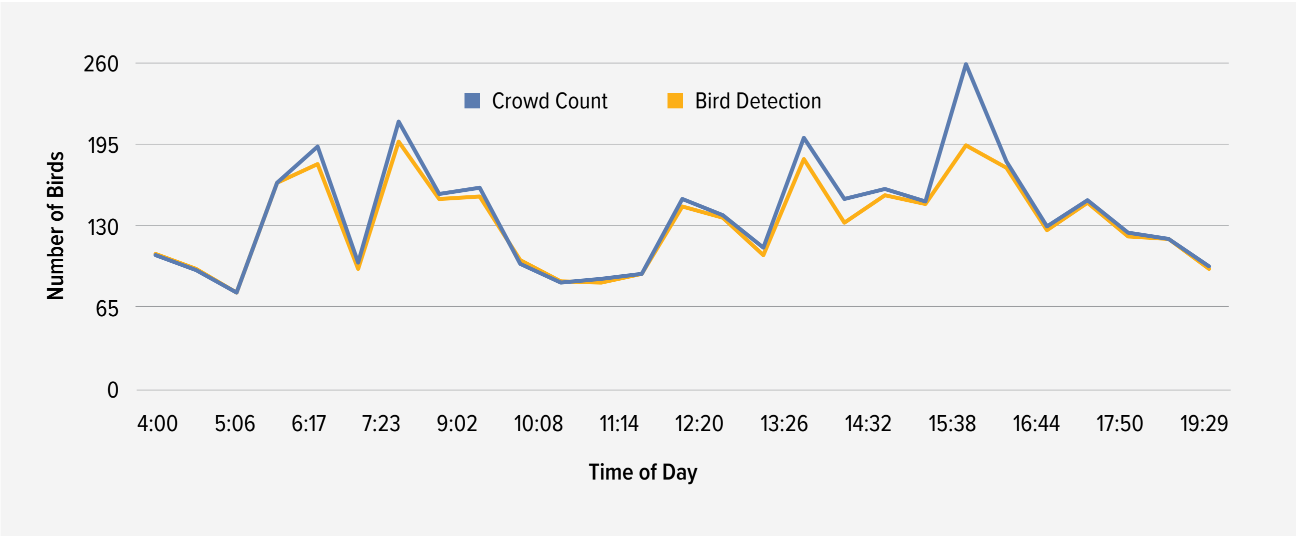
4.5 Behaviour classification

Datasets #2 and #4 capture the feeding, drinking, and egg-laying areas. Here we apply the supervised learning technique to analyse the individual behaviours. The annotated data of the categories are summarized in *Table 3*. All the data samples are annotated manually, where the training data (Train – line 2) is used to build the model, while the validation data (Val – line 3) is used to test the model effectiveness. The ∑ is the sum of the Train and Val data. Using the pre-trained model can effectively improve the model generalization ability and accelerate model training and refinement. After fine-tuning the model, the behaviour classification accuracy is 95.4% on the validation dataset.

5 Case study:

Density estimation and individual behavioural analysis

Figure 11: The number of birds observed in different times of the day (indoor).



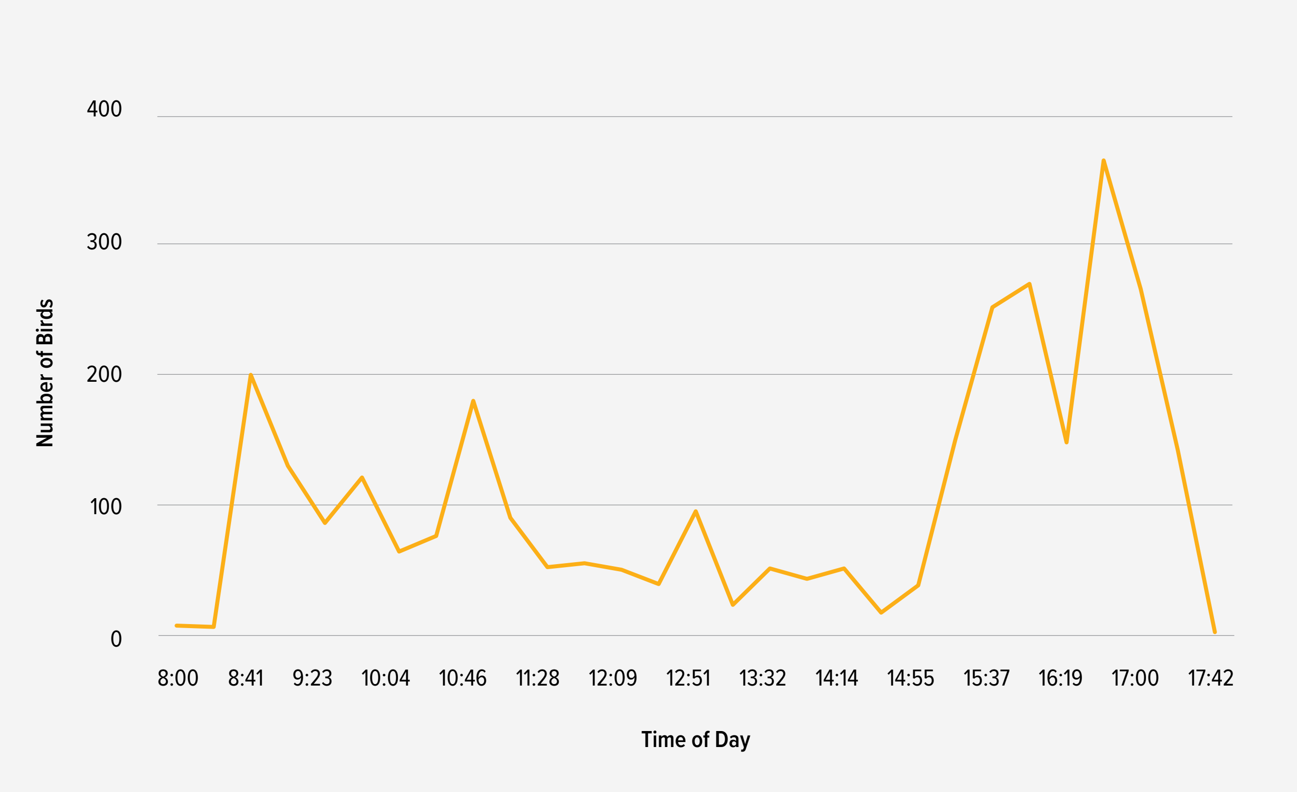
5.1 Indoor density estimation

Density estimation can be implemented by either bird detection or crowd counting. We applied the trained model and tested on the video footage taken on 18/04/2021 from dataset #1 for the entire day to give the periodical statistics, as shown in *Figure 11*. The light in the shed was turned on at 4:00 AM and was turned off at 8:00 PM. So, we just count the bird numbers during this period as a case study. The diagram shows a few density peaks, with more than 200 birds within the observation area. We checked the video footage and found out different reasons for some sudden density changes. For example, at 7:25 AM, the sudden increase of birds is because of a staff intervention, who walked in the shed and impacted the movement of the birds. At around 3:28 PM, a burst of sudden sunshine appeared in the shed, causing the birds to huddle together.

Figure 12 shows a visualization of the two methods. The numbers counted by detection and crowd counting are 213 and 219, respectively. The reason for the discrepancy is the re-counting in the dense areas of the frame. With fast computer processors, the model can run in real-time, providing live statistics for immediate notifications. Also, when the shooting area is not crowded, both study algorithms gave comparable results. When there is crowding to the point that it is difficult to distinguish the individual boundaries of birds, the crowd counting algorithm shows to outperform 1.5% than object detection in terms of the counting accuracy.

Figure 12: The visualisations of bird counting based on object detection and crowd counting. (A) The snapshot in a video frame; (B) The visualisation of all detected birds, annotated by the red bounding boxes; (C) The visualisation of dense counting, where each dot annotates a bird instance.

Figure 13: The number of observable birds at different times of the day (4K camera, outdoor).

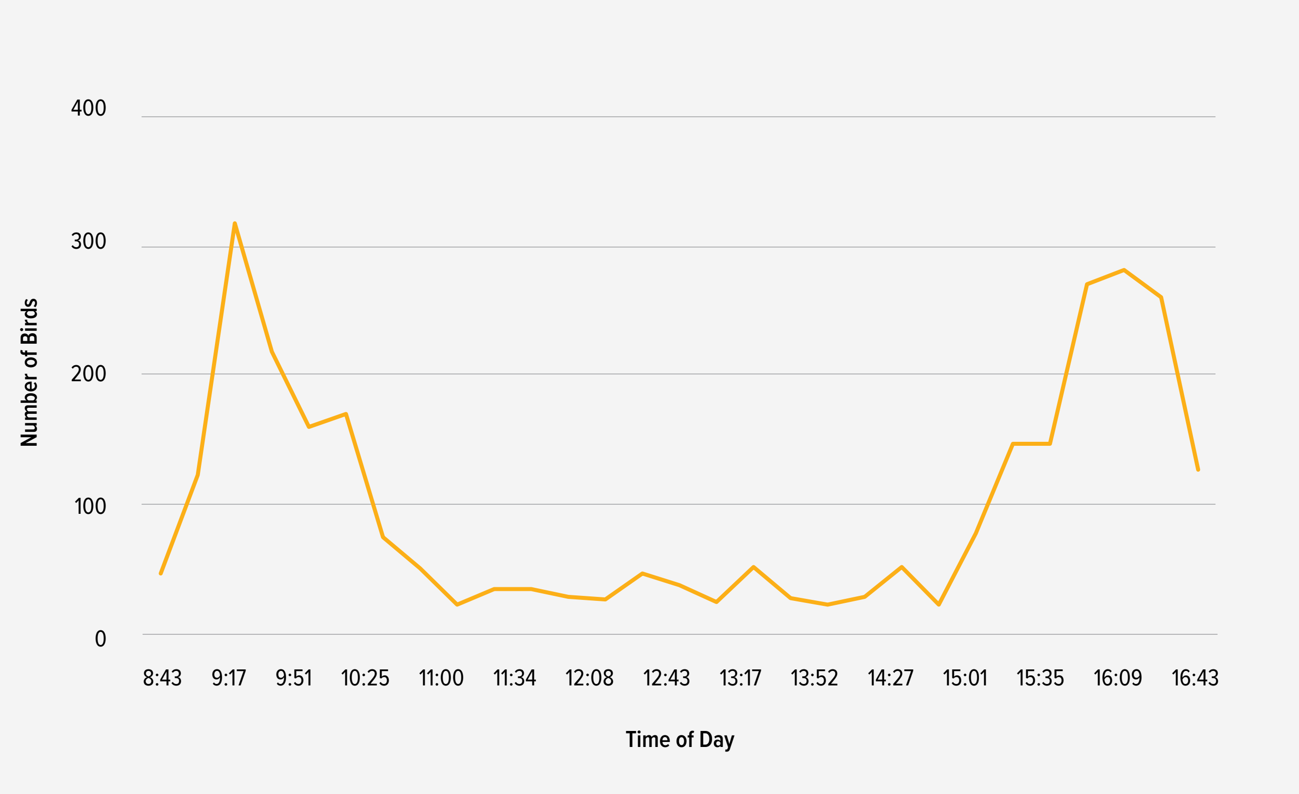


5.2 Outdoor density estimation

Our two outdoor cameras were mounted on a 4m high pole, covering a comparably large visible area (approximately 50m2). We performed the crowd counting algorithm on the video footage taken on 13/05/2021 from dataset #6 and give the counting results in different periods, as is shown in *Figure 13*. The counted number of birds changes dramatically during the entire day because in the free-range scenario, birds can walk freely in or out of the shed. *Figure 14* shows the screenshot for a few density peaks around 4:39 PM and the counting results.

Figure 14: The visualisation of dense counting at 4:39 PM on 13/05/2021 (outdoor).

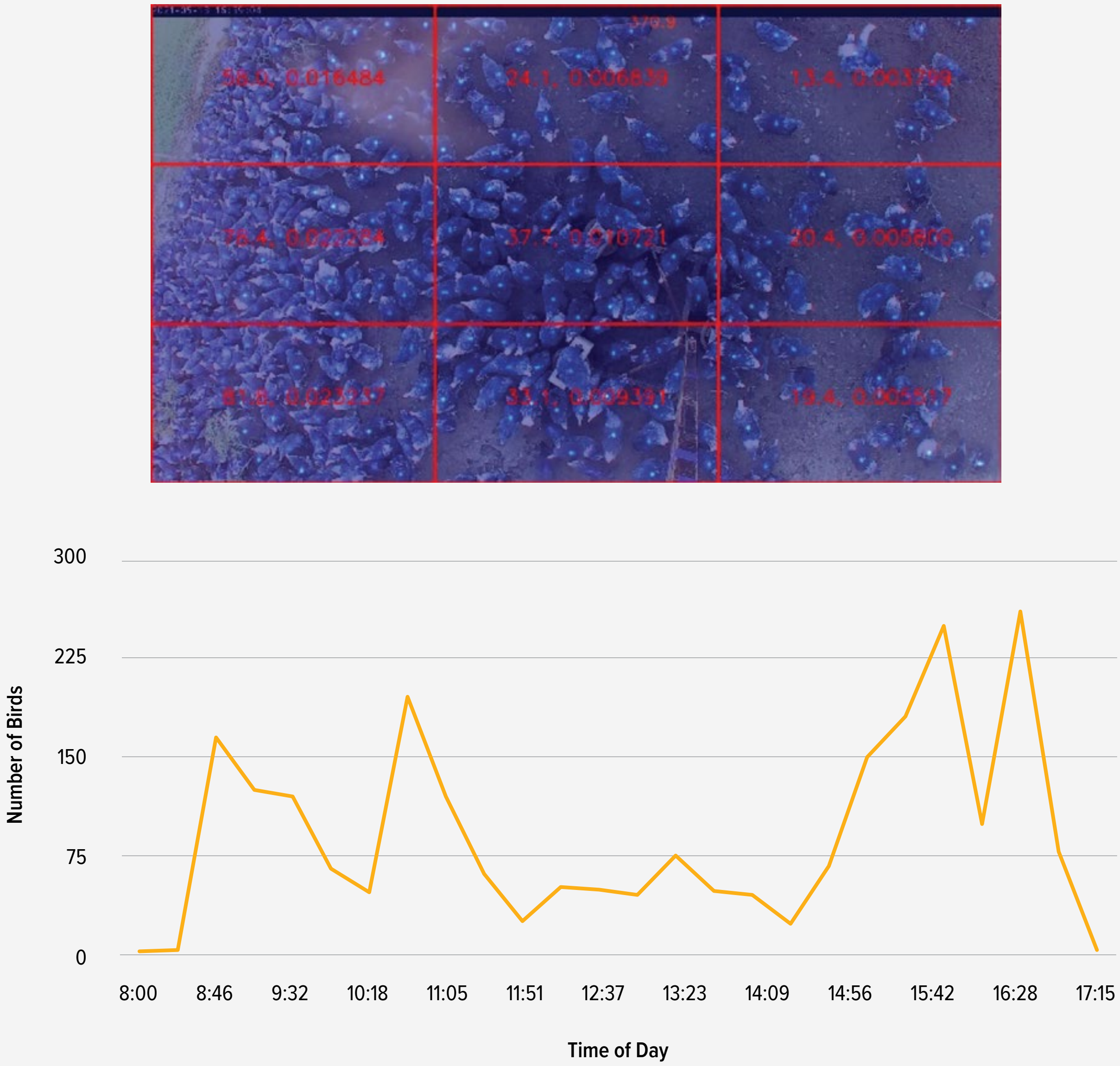
Figure 15: The number of observable birds at different times of the day (PTZ camera, outdoor).



Figures 15 and *16* show another crowd counting example taken by a PTZ camera (05/26/2021) from dataset #8. This camera targets a doorway area of outdoor of the shed. This example shows a clear density pattern that more birds are gathering before 10:00 AM and after 3:00 PM. It might be possible that the traffic of entering and exiting more frequently at these times. A further investigation needs to be conducted.

Figure 16: The visualisation of dense counting at 4:39 PM on 13/05/2021 (outdoor).

Figure 17: The density estimation at different times of the day, based on equal-sized windows.

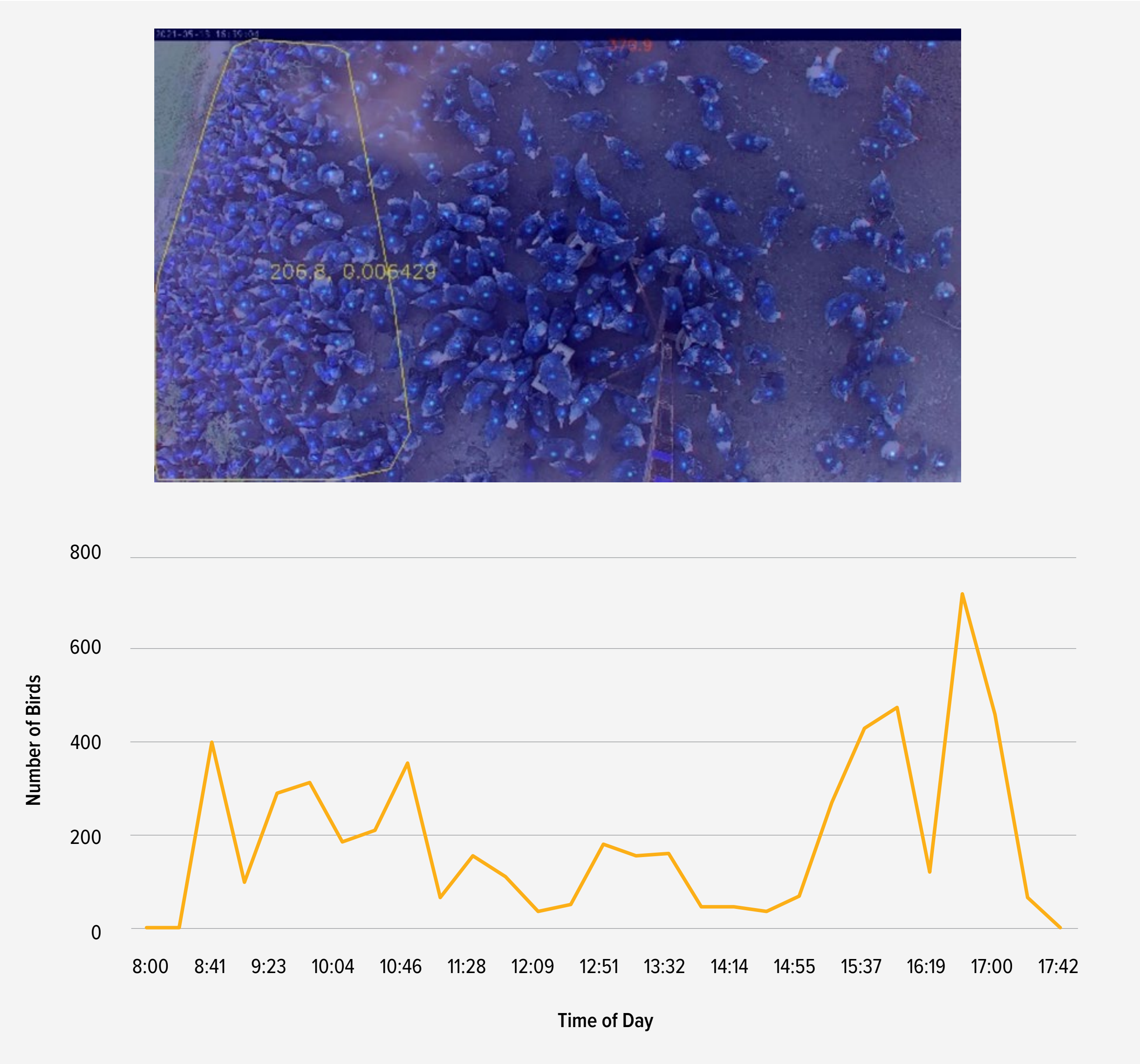


5.3 Region analysis

Region analysis aims to dynamically estimate the density of birds in different regions of an observation area, which is particularly important to monitor the pilling behaviours leading to smothering. Here we propose two solutions based on equal-sized windows and clustering, respectively.

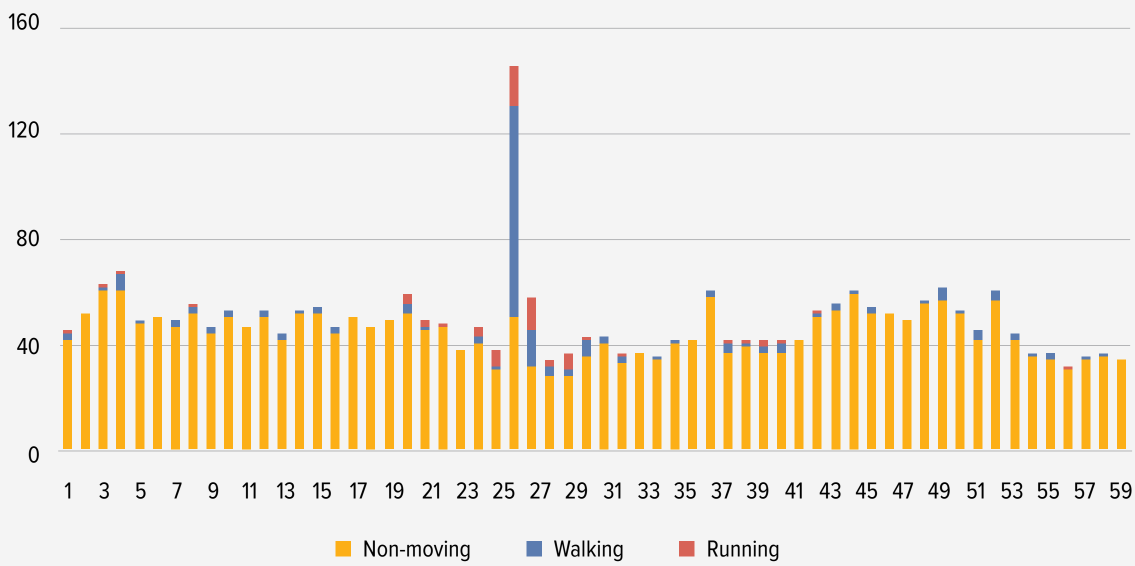
The first solution is to partition an observable region with equal-sized windows, thus the density (e.g., number of birds per square meter) within each window can be separately estimated. Using this scheme, a sample density statistic result for the entire day is illustrated in *Figure 17*.

Figure 18: The density estimation at different times of the day, based on auto-clustering.



The second solution is to perform the clustering on the density map of the whole image to segment different regions automatically. The regions with estimated densities are illustrated in *Figure 18*.

Figure 19: The moving distribution at different times of the day, and the snapshot at the peak time.



5.4 Case study: individual behaviour analysis

To support laying hen ethogram monitoring, we set cameras angles for datasets #2, #4, #7 and #9 that cover both indoor and outdoor areas. Two 4K cameras were adjusted to shoot eating and drinking areas (indoor) while one PTZ camera out-door was adjusted to shoot the doorway and the other PTZ camera was zoomed to focus on fine motion monitoring.

We plot the distribution of the number of birds with different moving behaviours from 07:00 AM-08:00 AM taken on 08/04/2021 from dataset #1, as is shown in *Figure 19*. The figure shows that most birds move slowly while a few birds run around 7:25 AM where a staff entered the shed that caused the sudden movement.

Figure 20: The focus areas of bird individual activities.

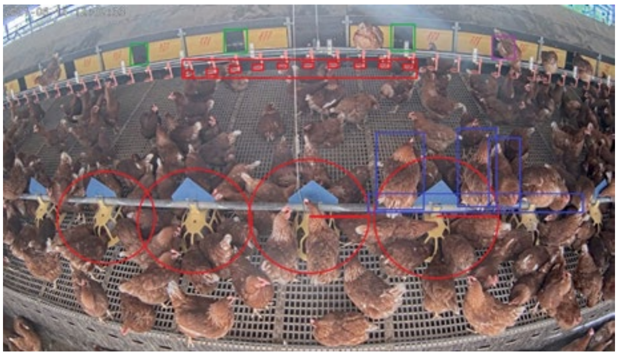


Figure 21: The average feeding time distribution within 1 hour.

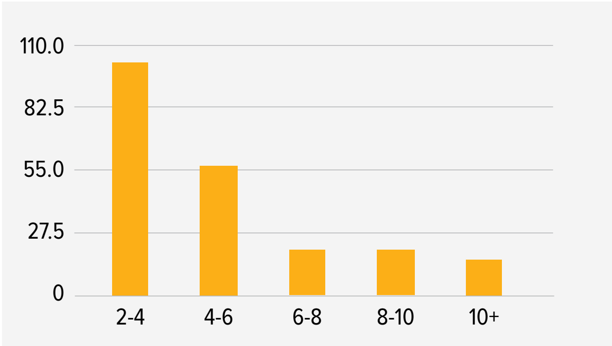
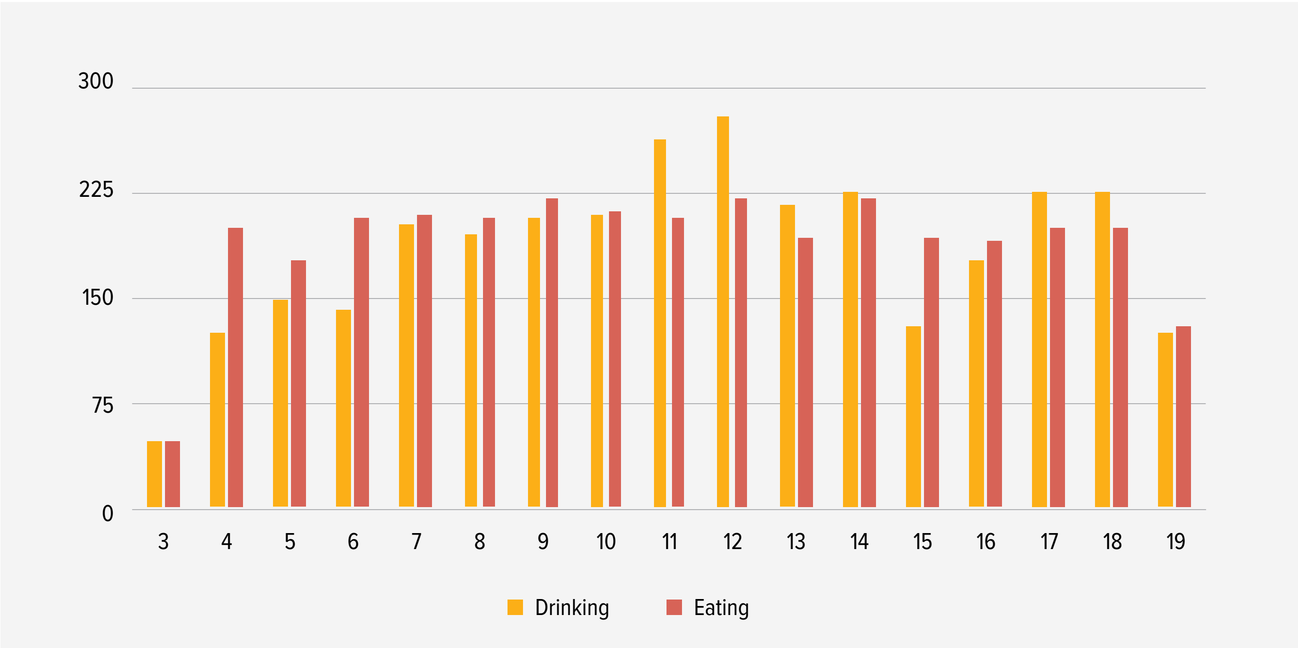


Figure 22: The number of birds drinking and eating within the observation area in an entire day.



We further experimented with the individual activity analysis: eating and drinking. The two terms, according to the Ethogram, are defined as:

1. **Eating**: The bird is actively eating food from the feeding system. Particles of food are picked up in the beak and thrown back into the mouth. Gulping motion with no chewing.
2. **Drinking:** The bird is actively taking in water from the watering system, either pecking at a nipple drinker system or scooping water in its beak from a cup or bell-type system. The scooping motion is followed by the head being raised to allow the water to run to the back of the throat.

From the technical perspective of computer vision, we define the bird action recognition based on our video dataset as follows:

1. If a bird puts its head inside the feeder, it will be classified as eating.
2. If a bird's head is inside the drinker, it will be classified as drinking.

In the experiment setting, we focused on the surrounding areas of feeder and drinker, i.e., only the birds that fall in the specific areas (red circles and rectangles in *Figure 20*) are observed and classified.

Based on the trained models for detecting and tracking individual birds, we conducted a case study on video footage taken on 14/06/2021. We first plotted the distribution of feeding time between 12:00 PM and 1:00 PM in *Figure 21*. We can see that within the 1-hour observation, most birds spent 2-4 minutes eating, with fewer than 60 birds taking more than 6 minutes to eat. In *Figure 22*, we report the number of birds drinking and eating in different periods of an entire day. From the two distributions, we can see that between 4:00 AM and 6:00 PM, the number of birds eating is almost constant. The peak period for drinking occurs between 11:00 AM and 12:00 PM. These natural variations provide useful baselines for monitoring deviations to normal behaviours. The baselines can be further refined with more data and more variety in farm conditions (e.g., shed, density, breed, age, and production system etc.).

5.5 Discussion

In this project, we have developed a low-cost and automated video monitoring system that can be installed in commercial egg farms.

By applying advanced AI and computer vision techniques, our system can automatically estimate flock density and track bird movement in real-time for pile-ups monitoring.

This will alert farmers about possible smothering incidents. We have recorded more than 1000 hours of video and tested our system in/out- door of the shed at Windsor Egg Farm, NSW with high accuracy performance in density estimation, bird tracking and segmentation.

For individual behaviour classification, we have developed vision-based AI model to identify eating, drinking and egg lying individually based on the Ethogram defined by ROSETTA MANAGEMENT CONSULTING PTY LTD in conjunction with Herd Health Pty Ltd (A/Prof Richard Shephard).

The developed system has potential for impending pile-up warnings, thereby helping to prevent smothering incidents.

The outcomes of our current project include: a large-scale video dataset, flock density estimation, image-based bird segmentation and video-based bird and their flock movement tracking and individual behaviour classification algorithms.

Together, these allow identification and characterisation of robust flock baselines.

This supports our plans to progress to stage 2 of the project, with focus on expanding commercial application.

We propose to expand development of the video-based system to allow real-time monitoring of flock health, behaviour, and production.

By better characterising the behaviour and relationships between inputs and behaviours on outputs (such as egg production and bird welfare), the system will enhance egg farm performance. More timely interventions and bring added production and better bird welfare.

Our non-intrusive system allows real-time measurement, assessment and analysis of bird and flock behaviours and production, thereby presenting as a platform technology for industry.

Our solution, using computer vision and machine learning, has compelling advantages over existing management systems and brings capacity to control wide and varied aspects of egg production.

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ISBN 978-1-920835-60-6

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

Australian Eggs Limited Project Number: 31HS102UT/1I011

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Published in October 2022

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 output of our R&D program, which aims to support improved efficiency, sustainability, product quality, education and technology transfer in the Australian egg industry.

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