Poultry Science

Developing an automatic warning system for anomalous chicken dispersion and movement using deep learning and machine learning

Bo-Lin Chen,[1] Ting-Hui Cheng,[1] Yi-Che Huang, Yu-Lun Hsieh, Hao-Chun Hsu, Chen-Yi Lu, Mao-Hsiang Huang, Shu-Yao Nien, and Yan-Fu Kuo[2]

Department of Biomechatronics Engineering, National Taiwan University, Taipei, Taiwan

ABSTRACT Chicken is a major source of dietary protein worldwide. The dispersion and movement of chickens constitute vital indicators of their health and status. This is especially evident in Taiwanese native chickens (**TNC**s), a local variety which is high in physical activity when healthy. Conventionally, the dispersion and movement of chicken flocks are observed in patrols. However, manual patrolling is laborious and time-consuming. Moreover, frequent patrols increase the risk of carrying pathogens into chicken farms. To address these issues, this study proposes an approach to develop an automatic warning system for anomalous dispersion and movement of chicken flocks in commercial chicken farms. Embendded systems were developed to acquire videos of chickens from overhead view in a chicken house, in which approximately 20,000 TNCs were raised for a period of 10 wk. Each video was 5-min in length. The videos were transmitted to a remote cloud server and were converted into images. A You Only Look Once—version 7 tiny (**YOLOv7-tiny**) object detection model was trained to detect chickens in the images. The dispersion of the chicken flocks in a 5-min long video was calculated using nearest neighbor index (**NNI**). The movement of the chicken flocks in a 5-min long video was quantified using simple online and real-time tracking algorithm (**SORT**). The normal ranges (i.e., 95% confidence intervals) of chicken dispersion and movement were established using an autoregressive integrated moving average (**ARIMA**) model and a seasonal autoregressive integrated moving average with exogenous factors (**SARIMAX**) model, respectively. The system allows farmers to check up on the chicken farm only when the dispersion or movement values were not in the normal ranges. Thus, labor time can be saved and the risk of carrying pathogens into chicken farms can be reduced. The trained YOLOv7-tiny model achieved an average precision of 98.2% in chicken detection. SORT achieved a multiple object tracking accuracy of 95.3%. The ARIMA and SARIMAX achieved a mean absolute percentage error 3.71% and 13.39%, respectively, in forecasting dispersion and movement. The proposed approach can serve as a solution for automatic monitoring of anomalous chicken dispersion and movement in chicken farming, alerting farmers of potential health risks and environmental hazards in chicken farms.

Key words: Convolutional neural network (CNN), Embedded system, Simple online and real-time tracking (SORT), Taiwanese native chickens (TNCs), You only look once (YOLO)

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INTRODUCTION

Chicken is a major source of dietary protein worldwide. In 2022, 122 million tons of chicken products were produced globally (Food and Agriculture Organization, 2022). In Taiwan, approximately 680,000 metric tons of chicken products were produced in 2021, which accounted for 27.63% of the total animal husbandry sales for the year and generated revenue of $53.1 billion New Taiwan dollars (Council of Agriculture, Executive Yuan, Taiwan, 2022). Notably, Taiwanese native chickens (**TNCs**) accounted for around 30% of total domestic chicken production, representing a large industry sector with different systems than conventional broilers. The growth of the chicken industry has not seen any signs of slowing down yet. However, with the increasing emphasis on animal welfare, the chicken industry has encountered some challenges within chicken farming.

The dispersion and movement are 2 preliminary diagnostic indicators to assess the health and welfare of chicken stocks (Ben Sassi et al., 2016; Sakamoto et al., 2020). TNCs are high in physical activity when healthy,

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[1]These authors have contributed equally to this work.

[2]Corresponding author: ykuo@ntu.edu.tw

Figure 1. Configuration of the chicken farm: (A) feeding pipeline, (B) nipple drinkers, and (C) cooling pad system.

and thus are predominantly raised using floor rearing method with high stocking density (Figure 1). In Taiwan, a typical commercial chicken farm is approximately 100 × 15 m^2 in dimension, allowing TNCs to move around freely. Frequent movement of TNCs is desired because exercise improves the meat quality of chickens and improves their economic value. Also, TNCs are usually raised for 10 wk. Because of the high physical activity, high degrees of freedom for moving around, and long raising periods of time, litter in certain areas of a chicken farm can accumulate moisture or ammonia. Chickens avoid these areas and distribute unevenly. Also, the accumulated moisture or ammonia increases the chance of chicken leg deformities, such as lameness and footpad dermatitis (Karaarslan and Nazlıgül, 2018), ultimately affecting chicken movement (Sørensen et al., 2000) and eventually influencing the meat quality of chicken (El-Deek and El-Sabrout, 2019). Thus, monitoring the dispersion and movement of chicken flocks is crucial.

Conventionally, evaluating the dispersion and movement of chicken flocks is conducted by experienced farm patrolmen. The behavior of a chicken flock is dynamic. Frequent observation of chicken dispersion and movement is needed. However, patrolling is time-consuming and labor-intensive, and the observation can be subjective. In addition, frequent manual patrolling increases the risk of introducing pathogens into the chicken farm (Hermans et al., 2012). Furthermore, due to a shortage in the labor force, the frequency of patrols in Taiwan has decreased significantly (Goh et al., 2023). From 2016 to 2020, the agricultural labor force in Taiwan declined by 1.1% on average annually (Directorate General of Budget, Accounting and Statistics, Executive Yuan, Taiwan, 2021). Moreover, middle-aged and older individuals accounted for over 80% of the total labor force (Huang, 2015). Therefore, developing an automatic approach for observing the dispersion and movement of chicken flocks in chicken farming is an urgent issue.

Recently, convolutional neural networks (**CNN**) have become a powerful tool for solving complex machine-vision problems. CNNs comprise millions of neurons that execute convolutional and pooling operations (O'Shea and Nash, 2015). A properly trained CNN can directly detect specific objects in complex images, such as images with a high degree of variation in illumination (Figure 2) (Pal et al., 2021). Zhuang and Zhang (2019) detected broilers from chicken farm images and identified the health status of the broilers by applying a CNN model of an improved feature fusion single-shot multibox detector architecture. Wang et al. (2019) detected egg breeders from self-breeding cage images and identified their behavior by employing a CNN model of You Only Look Once—version 3 (**YOLOv3**; Redmon and Farhadi, 2018) architecture. Liu et al. (2021) detected broilers in a poultry house and identified the health of the broilers by utilizing a CNN model of YOLOv4 architecture. Jaihuni et al. (2023) detected broilers in an experimental farm and monitored their behaviors by using a CNN model of YOLOv5 architecture.

By integrating tracking algorithms with detection algorithms, a solution is provided for effectively quantifying animal movements. Zhang et al. (2019) utilized 3 CNN algorithms to detect pigs on a commercial pig farm and tracked their trajectories using a discriminative correlation filter (Danelljan et al., 2017). Cowton et al. (2019) detected pigs on a farm using a faster region-based CNN (**Faster R-CNN;** Ren et al., 2015) model and tracked them by applying a simple online and real-time tracking (**SORT**) algorithm (Bewley et al., 2016) and DeepSORT algorithm (Wojke et al., 2017). Chickens in a chicken coop were localized using a Faster R-CNN model and were tracked by executing minimum distance matching and color feature matching (Lin et al., 2018). Sun et al. (2019) employed YOLOv3 to detect broilers in a breeding house and subsequently tracked them using a Kalman filter (Kalman, 1960) and the Hungarian algorithm (Kuhn, 1955).

The movement and dispersion of chicken flocks change with age and the time of day (i.e., time-series data). Autoregressive moving average models are machine learning models for analyzing time-series data. Several studies have applied these models to predict animal behaviors and production. The migration of silver eels was forecasted using seasonal autoregressive integrated moving average with exogenous factors (**SARIMAX;** Box et al., 2015). To mitigate the eels' mortality, turbines of hydroelectric power plants were turned down when the predicted migration rates exceeded a certain threshold (Trancart et al., 2013). Salau and Krieter (2021) determined the resource usage of dairy cows, including lying cubicles, moving area, licking stone, cow brush water, and feeding trough, using autoregressive integrated moving average (**ARIMA;** Box et al., 2015). The daily milk production of cows was predicted using ARIMA (da Rosa Righi et al., 2020). Khatib et al. (2021) gathered early egg production in India and forecasted future values using ARIMA. Uzundumlu and Dilli (2022) employed ARIMA to predict the production of chicken meat in the top chicken-producing countries. Given that the dispersion and movement of chicken

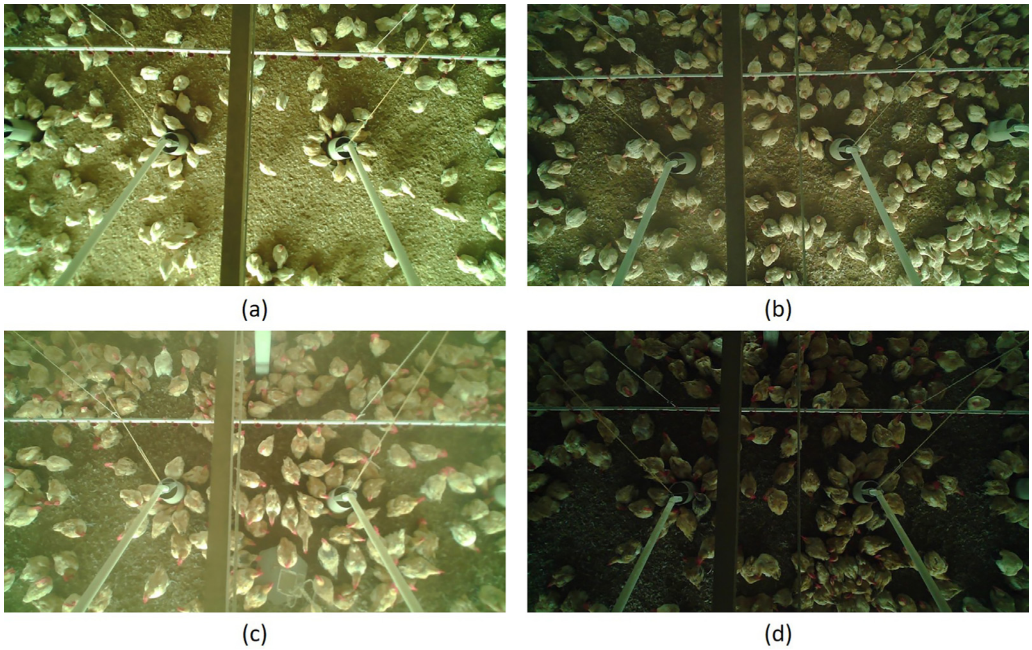

Figure 2. Images acquired on a naturally illuminated chicken farm under various illumination conditions: (a) high illumination, (b) high contrast, (c) low illumination, and (d) dark illumination. The images also show various chicken dispersion levels.

flocks show time-series patterns, autoregressive moving average models should be suitable for modeling and forecasting these 2 indicators.

In this study, we propose an approach to develop an automatic warning system for anomalous dispersion and movement of TNCs in a commercial chicken farm. For the remainder of this manuscript, the term "chicken" specifically refers to red-feathered TNC, which is a popular variety in Taiwan. A tracking-by-detection strategy was employed by combining a chicken localization deep learning model with tracking algorithms. Chicken dispersion and movement were then explicitly quantified and analyzed for 2 batches raised in different seasonal periods. This study compared the chicken dispersion and movement between 2 batches and used machine learning forecasting models to identify outliers. These forecasting models enable the automatic detection of anomalous dispersion and movement events that can assist chicken farmers in identifying potential health risks and environmental hazards.

MATERIALS AND METHODS

Overview of the Proposed Method

The proposed method for automatically monitoring chicken dispersion and movement consisted of: a) embedded systems for capturing overhead view videos in chicken farms, b) deep learning model to localize chicken in the video, c) 2 algorithms to quantify the dispersion and movement of chicken flocks, d) machine learning models to forecast the chicken dispersion or movement, and e) anomalous dispersion and movement warnings (Figure 3). A customized embedded system was

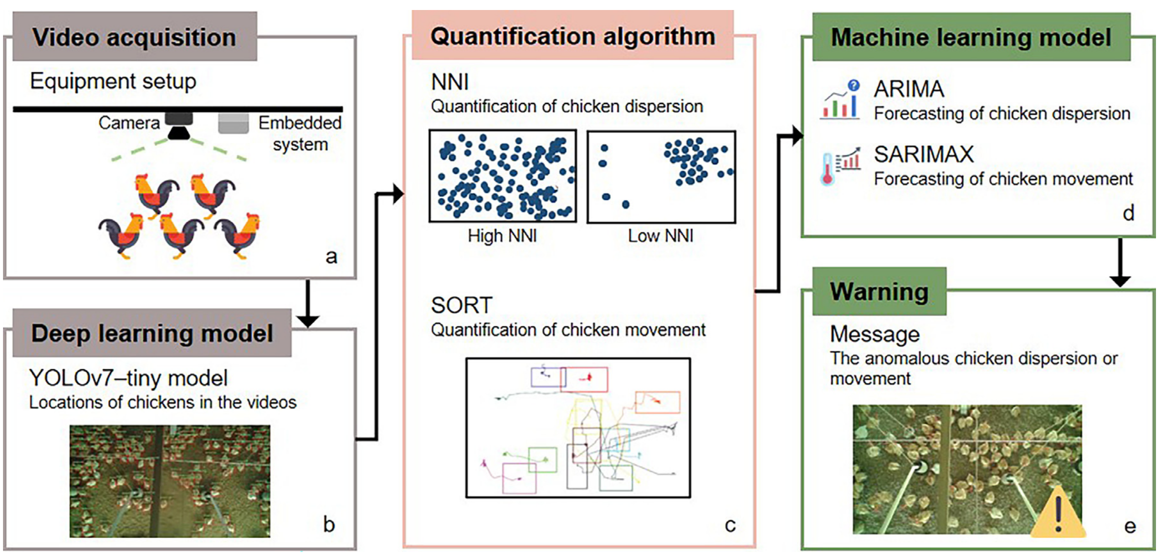

Figure 3. Schematic of the proposed automatic chicken movement monitoring approach.

developed to record overhead view videos and collect environmental information on the farm. The videos and environmental information were streamed back to a remote cloud server through 4G cellular connection. The locations of chickens were identified using YOLOv7-tiny (Wang et al., 2022). The dispersions of the chicken flocks were next quantified using nearest neighbor index (**NNI**; Clark and Evans, 1954). The movements of chicken flocks were also quantified using chicken locations in consecutive frames and SORT. The dispersion and movement of the chicken flocks throughout their growth were modeled using an ARIMA model and a SARIMAX model, respectively. The dispersions or movements outside the 95% confidence intervals of the ARIMA and SARIMAX predictions were considered warnings.

Experimental Site

Chicken images were collected from the Hsin-Ho chicken farm (size: approximately 113 × 15 m^2) of Leadray Livestock Co., Ltd. (Huwei, Yunlin, Taiwan; Figure 1). The chicken farm is equipped with feeding pipelines, nipple drinkers, and a cooling pad system. To achieve natural illumination, the sidewalls of the chicken farm are partially composed of transparent glass. Thus, the illumination conditions of the images collected on the farm varied considerably (Figure 2). The farm had approximately 20,000 red-feathered TNCs (Pham et al., 2013) at the time of the study. The chickens are usually raised for 80 d before being slaughtered.

Video Collection and Image Annotation

Six embedded systems were customized to record videos and collect environmental information on the chicken farm. Each embedded system comprised a single-board computer (Raspberry Pi 3 Model B+; Raspberry Pi Foundation, Cambridge, UK), a wide-angle distortion-free USB camera (KS2A17; Shenzhen, China), and a humidity and temperature sensor (SHT20; Sensirion, Stäfa, Switzerland). Given that chickens are diurnal animals and the chicken house is naturally illuminated, cameras without night-vision functions were chosen.

The embedded system was installed 3 m above the litter in the chicken farm to record videos of the chicken flocks from an overhead view. The system acquired videos at a resolution of 1,920 × 1,080 pixels and a frame rate of 5 frames per second (**fps**). A camera covered an area of approximately 5.3 × 3 m^2. A video of 5 min was saved as a file. The videos were acquired continuously between 06:00 and 18:00. However, due to processing delays for video storage and transmission, only approximately 9 videos were acquired and stored each hour, resulting in a total of approximately 108 videos daily (between 06:00 and 18:00) per embedded system. The humidity and temperature of the chicken farm were measured at 1-min intervals. The videos and environmental information were uploaded to cloud storage via 4G cellular connection.

Videos were collected in 2020 and 2021. In 2020, the videos of chicken flocks were collected to train the model for chicken detection and tracking. A total of 11,712 h of videos were collected when the chickens were at the ages between 4-wk-old and 10-wk-old. Subsequently, images were converted from the videos. To prevent overfitting, structural-similarity index measure (**SSIM**; Wang et al., 2004) was used to exclude images with high levels of similarity. A threshold of 0.8 was used for SSIM. A 1,000 images were collected. Among the images, 800 and 200 were used for training and testing, respectively. The chickens visible in the images, whether entirely or partially, were annotated. A total of 146,516 chickens were annotated in the images. On average, each image contained 162.43 chickens, with a standard deviation of 36.79 chickens. The annotation was performed by the authors using LabelImg (Tzutalin, 2015).

In 2021, videos of chicken flocks were collected to develop the proposed method for long-term modeling and warning of chicken dispersion and movement. In 2021, 2 batches of chickens were raised: winter batch (January to March) and summer batch (May to July). Videos of chicken flocks aged between 4 and 10 wk were collected. The collection was performed continuously between 06:00 and 18:00 throughout these 2 periods. The chicken flocks younger than 4-wk-old were raised in a specific area with heat lamp. The chicken flocks older than 10-wk-old were gradually sent for slaughter. Thus, the video collected when the chicken flocks younger than 4-wk-old or older than 10-wk-old were disregarded. Certain videos were missing due to unstable internet connection or maintenance of the embedded system. A total of 371.0 h of videos were collected. The dispersion and movement of each 5-min video were subsequently quantified using the proposed approaches.

Image Calibration

The conversion factor from pixel to physical distance was determined to quantify the spatial dispersion of chicken flocks and their movement. For this process, 4 binary square fiducial markers were placed in the field of view of a camera (Figure 4). The positions of the markers were detected using the OpenCV library ArUco

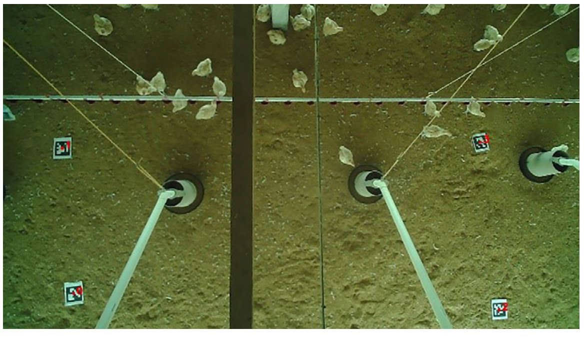

Figure 4. Detection results of ArUco markers.

(Garrido-Jurado et al., 2014). The conversion factor α was defined as:

$$\alpha = \frac{l_r}{l_p}, \tag{1}$$

where l_r and l_p are the physical distance and pixel distance, respectively, between 2 markers. The average conversion factor of the marker pairs was used.

Automated Chicken Detection

YOLOv7-tiny, a lightweight version of YOLOv7 (Wang et al., 2022), was used to detect chickens in the collected images. YOLOv7-tiny was chosen because of its optimized memory usage, efficient processing time, and satisfactory performance. With these characteristics, YOLOv7-tiny has great potential to be used on edge devices. See Discussion section for more details. YOLOv7-tiny comprises a backbone CNN, a neck, and a head (Figure 5). The backbone CNN and neck generate feature maps from an input image. The head then makes predictions for classes, bounding boxes, and confidence scores of objects of interest (i.e., chickens) using the feature maps. Subsequently, nonmaximum suppression (Neubeck and van Gool, 2006) with a threshold of 0.65 was applied to the output of the head to reduce the number of bounding boxes for the same object. The dimensions of the input images to the YOLOv7-tiny model were set to 416 × 416 pixels.

The YOLOv7-tiny model was trained using the PyTorch framework. During training, a region of interest (**RoI**; e.g., a region in an input image that comprised a chicken) was labeled as positive if the intersection-over-union (**IoU**) between the RoI and ground truth (**GT**) was higher than 0.65. Online image augmentations were implemented to enhance the robustness of the YOLOv7-tiny model to be trained. The augmentation operations included hue, saturation, brightness, horizontal flipping, mosaic, and mix-up. The augmentation operations of hue, saturation, and brightness were applied to increase the diversities of the images in color. The 3 operations were applied by multiplying random values of 1 ± 0.71, 1 ± 0.458, and 1 ± 0.015, respectively, to the hue, saturation, and brightness of a training image. The augmentation operations of horizontal flipping, mosaic, and mix-up were applied to increase the diversities of the images in object (i.e., chickens) arrangements. The 3 operations were applied to a training image with probabilities of 0.415, 0.8, and 0.0362, respectively, in horizontal flipping, mosaic, and mix-up. Stochastic gradient descent (**SGD**; LeCun et al., 1989) was used as the optimizer. The momentum and weight decay of SGD were set to 0.9 and 0.0005, respectively. The batch size was set to 16. The model was trained for 200 epochs with an initial learning rate of 0.001. The learning rate decay factor of 0.01 was applied at the third training epoch. A graphics processing unit (GeForce Titan RTX, NVIDIA; Santa Clara, USA) was used to expedite the training process.

Spatial Dispersion of Chicken Flocks

The spatial dispersion of chicken flocks was quantified using the NNI proposed by Clark and Evans (1954). The NNI represents the ratio of the mean observed distance between chickens $d_o \in \mathbb{R}$ to the expected mean distance between chickens $d_e \in \mathbb{R}$ in an image:

$$\text{Dispersion} = d_o / d_e, \tag{2}$$

The mean observed distance between chickens d_o is defined as:

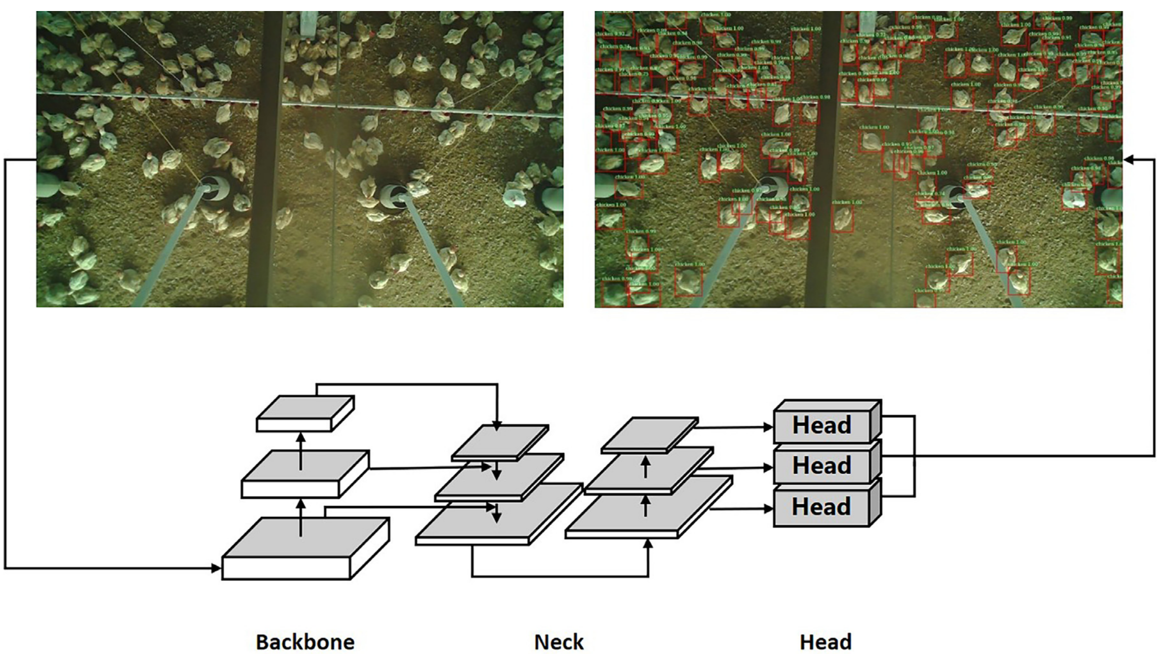

Figure 5. Architecture of YOLOv7-tiny.

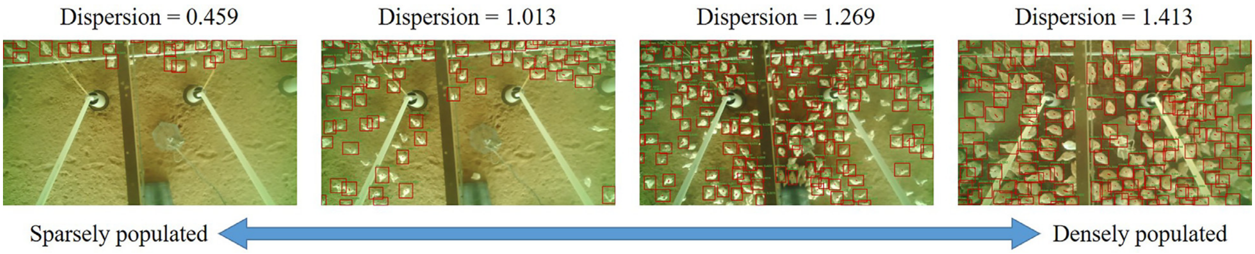

Figure 6. Dispersion values of chicken images with various spatial dispersion levels.

$$d_0 = \frac{\sum_{i=1}^{N} d_i}{N}, \tag{3}$$

where d_i is the distance between a chicken and its nearest neighbor, and $N \in \mathbb{N}$ is the number of chickens in the image. The expected mean distance between chickens $d_e \in \mathbb{R}$ is defined as:

$$d_e = \frac{0.5}{\sqrt{\frac{N}{A}}}, \tag{4}$$

where $A \in \mathbb{R}$ is the total number of pixels in the image. Figure 6 presents the dispersion values derived from chicken images with different levels of spatial dispersion, ranging from sparsely populated to densely populated images. A dispersion value was calculated for a video of 5-min in length by averaging the dispersion values of each frame, yielding a total of 108 dispersion values daily.

Movement of Chicken Flocks

Chickens detected in consecutive frames by the YOLOv7-tiny model were tracked using the SORT algorithm. The SORT algorithm comprises a Kalman filter and Hungarian algorithm. In this study, the Kalman filter was used to estimate the centroid coordinates, bounding box dimensions (area and aspect ratio), and changes in the centroid coordinates and bounding box dimensions of chickens in a subsequent frame by using the same information on chickens in the previous frame. The Hungarian algorithm was implemented to optimize the linear assignment of the same chickens in 2 consecutive frames. The distances between the chicken bounding boxes in the specific IoU were used as the metric for executing the tracking algorithm. The threshold of IoU was set to 0.3 to distinguish 2 chickens in consecutive frames. The association between 2 chickens in consecutive frames was rejected if the IoU was less than 0.3. Each tracking iteration was performed for a video of 5-min length, yielding a total of 108 movement readings daily.

Long-Term Analysis of Chicken Dispersion and Movement

An ARIMA model was used to predict chicken dispersion and the dispersion's safe zone throughout the chickens' growth period. According to the observed data (Figure 10), dispersion values increased along with the growth of chickens. Thus, dispersion was considered as a time-series variable. The ARIMA model predicted the mean dispersion value of a day using the daily mean dispersion values of the past days. An ARIMA model has 3 parameters: the order of the autoregressive model, the degree of differencing, and the moving-average model. The degree of differencing was set to 1, since the dispersion values were not stationary. The order of the autoregressive model and the order of the moving-average model were set to 3 and 4, respectively, using the partial autocorrelation function, autocorrelation function, and Akaike information criterion. The ARIMA model also predicted the 95% confidence interval of the mean dispersion value of a day based on the distribution of the dispersion values of the past days. The 95% confidence interval of the mean dispersion value was defined as the safe (green) zone. The dispersion values outside the 95% confidence interval were defined as yellow warnings. If the yellow warnings persisted for an hour, the dispersion values were further redefined as red warnings.

A SARIMAX model was employed to predict chicken movement and determine the safe zone for their movement throughout their growth period. The chicken's movement displayed a seasonal pattern, with peak activity in the morning and a decrease around noon daily (Figure 10 and Figure 11). Therefore, the movement was recognized as a time-series variable characterized by seasonal patterns. The SARIMAX model predicted the mean movement values of an hour using the hourly mean movement values of the past days. The hourly mean movement values fluctuated throughout the day, along with the temperature changes. Therefore, the temperature was considered an external variable to forecast. Moreover, the SARIMAX model includes 7 parameters, the order of the autoregressive model, the moving-average model, the seasonal autoregressive model, the seasonal moving-average model, the degree of differencing, seasonal differencing, and the period of the seasonality. The degree of differencing and seasonal differencing were set to 0 and 1, respectively, since the movement values with seasonal patterns were not stationary. The order of the autoregressive model, moving-average model, seasonal autoregressive model, and seasonal moving-average model were set to 0, 0, 3, and 2, respectively, using partial autocorrelation function, autocorrelation function, and Akaike information criterion. The period of the seasonality was set to 12 due to the maximum amount of hourly mean movement values collected per day. The SARIMAX model predicted the 95% confidence interval of the movement values of a day based on the distribution of the movement values of the past days. The 95% confidence interval of the movement values was defined as the safe (blue) zone. The movement values outside the 95% confidence interval were defined as yellow warnings. If the yellow warnings persisted for an hour, the movement values were further redefined as red warnings.

RESULTS

Training of the Chicken Detection Model

The total loss, bounding box loss, classification loss, an average precision at an IOU threshold of 0.5 (AP@50; Everingham et al., 2010) and classification accuracy during the training of the YOLOv7-tiny model were illustrated (Figure 7). The total loss and classification accuracy reached 0.3 and 98.2%, respectively, by the end of the training. This observation provides evidence that the model successfully acquired and assimilated the discernible attributes of the chickens depicted in the images.

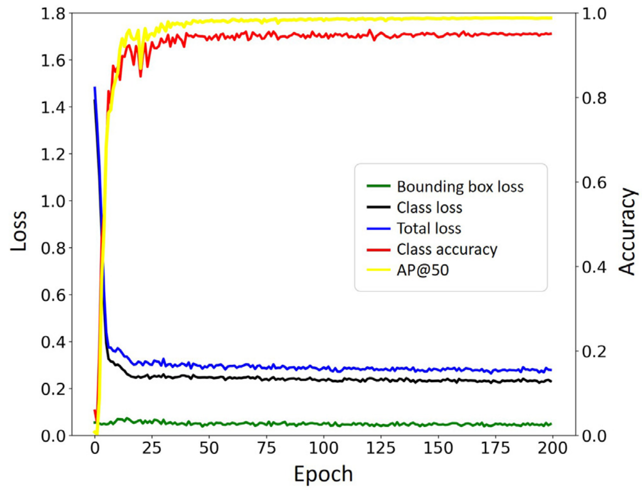

Figure 7. Training loss and accuracy of YOLOv7-tiny model.

Performance of the Chicken Detection Model

The performance of the trained YOLOv7-tiny model was evaluated using the 200 test images and receiver operating characteristic (**ROC**) analysis (Fawcett, 2006). In the analysis, the threshold for the confidence score was set to 0.25. A detection was considered a true positive if the IoU between a bounding box proposed by the model and a GT exceeded 0.65; otherwise, it was considered a false positive (**FP**). Figure 8 illustrates the chicken detection performance of the model. Chickens were successfully detected under various illumination and contrast. The trained YOLOv7-tiny model achieved an overall precision of 89.78%, an overall recall of 93.33%, an overall F1-score of 91.48%, and an AP@50 of 94.24% (Table 1).

Performance in Chicken Tracking

The performance of the SORT algorithm (Table 2) was evaluated using a video, multiple object tracking (**MOT**) metrics (Milan et al., 2013), and identification (**ID**) metrics (Ristani et al., 2016). The video contained 225 consecutive frames (45 s). A total of 114 GT objects

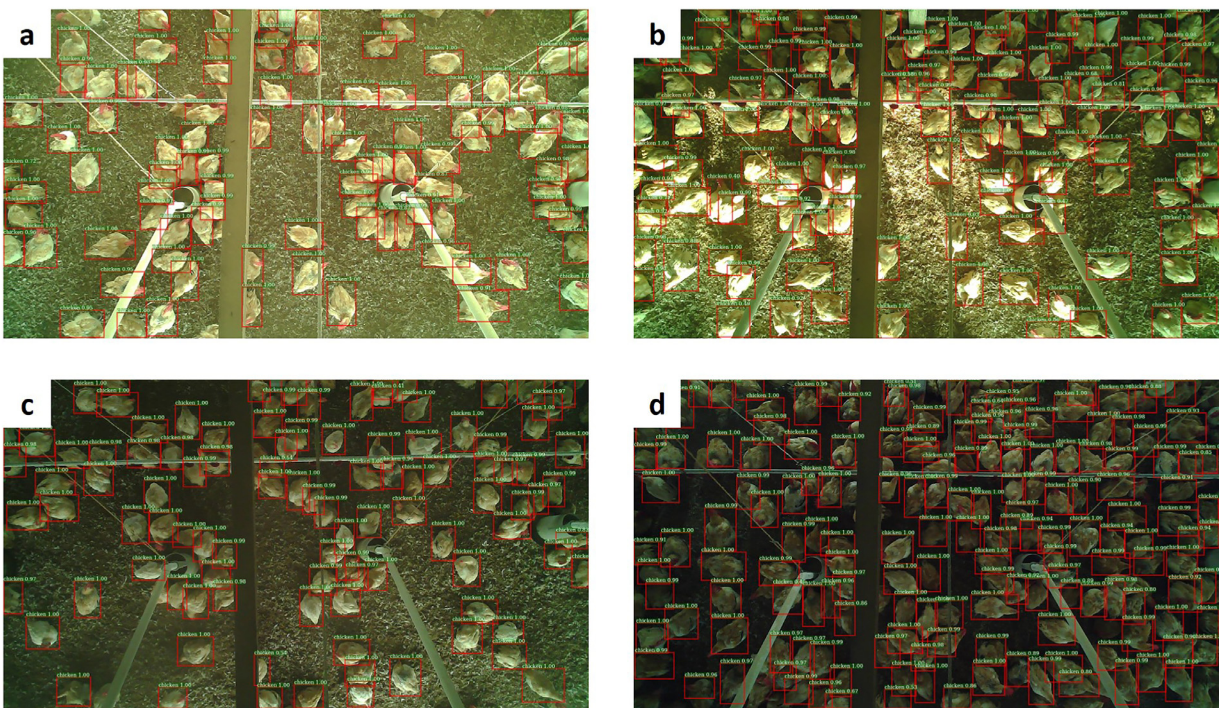

Figure 8. Detection results under various illumination conditions: (a) high illumination, (b) high contrast, (c) low illumination, and (d) dark illumination.

Table 1. ROC analysis of trained YOLOv7-tiny model.

Illumination conditions	Precision (%)	Recall (%)	F1-score (%)	AP (%)
High illumination	90.26	93.67	91.93	94.52
High contrast	90.22	91.36	90.79	93.48
Low illumination	90.12	95.52	92.74	95.72
Dark illumination	88.53	92.46	90.45	93.26
Overall	89.78	93.33	91.48	94.24

ROC = receiver operating characteristic; F1-score = harmonic mean of precision and recall; AP = Average precision.

(i.e., chickens) appeared in the video. Since the field of view of the camera could not encompass the whole chicken farm, chickens moving in and out the view area of the camera affected the number of GT chickens in each frame. In the video, the number of GT chickens in each frame ranged between 95 and 101, with an average of 98.0. Figure 9 depicts the SORT results. Regarding the MOT metrics, SORT achieved a MOT accuracy (**MOTA**) of 94.5% and MOT precision (**MOTP**) of 84.4%. For the ID metrics, SORT achieved an identification precision of 94.5%, identification recall of 93.9%, and identification F1-score (**IDF1**) of 94.3%. The processing speed for chicken tracking using an Intel Xeon E5-2620 CPU was 19.1 fps.

Long-Term Observation of Chicken Dispersion and Movement

The mean dispersions, mean movements, and their 95% confidence intervals for the videos collected in 2021 were illustrated (Figure 10). The results indicate that the mean dispersions increased gradually (Winter batch: $r = 0.933$; Summer batch: $r = 0.892$) and the mean movement decreased gradually (Winter batch: $r = -0.314$; Summer batch: $r = -0.303$) as the chickens grew. The mean movement decreased steadily on a weekly basis (ANOVA; Winter batch: $F = 135.935$, $P < 0.001$; Summer batch: $F = 320.524$, $P < 0.001$) (t test; Winter batch: $t_{\text{wk 4 vs. wk 10}} = 20.289$, $P_{\text{wk 4 vs. wk 10}} < 0.001$; Summer batch: $t_{\text{wk 4 vs. wk 10}} = 17.777$, $P_{\text{wk 4 vs. wk 10}} < 0.001$).

The movements and temperatures by hour from 06:00 to 18:00 in the 2 batches were illustrated (Figure 11). The figure shows that the movements peaked in the morning and bottomed around noon. Scheffé's multiple comparison tests indicated that the mean movements of the chickens between 12:00 and 14:00 were significantly lower than that of those between 6:00 and 10:00 (ANOVA; $F = 1515.007$, $P < 0.001$). The indoor mean temperatures, however, had an opposite trend.

Long-Term Modeling and Warning of Chicken Dispersion and Movement

The proposed approach was applied to model the chicken dispersions and to generate warnings when anomalous chicken dispersions were observed (Figure 12). The ARIMA model achieved a mean absolute percentage error (**MAPE**) of 3.71%. The predicted dispersions followed the increasing trend of dispersion values when the chickens grew. Anomalous (i.e., yellow- and red-warning) dispersion values were also successfully identified. In the winter batch, 7.4% of the dispersion values were in the yellow-warning zone. Within the summer batch, 5.4% of the dispersion values fell within the yellow-warning zone, while 1.4% of the values crossed into the more critical red-warning zone.

The proposed approach was applied to model the chicken movements and to generate warnings when anomalous chicken movements were observed (Figure 13). The SARIMAX model achieved a MAPE of 13.39%. The predicted movements followed the decreasing trend of movement values as the chickens grew. As a result, anomalous (i.e., yellow- and red-warning) movement values were successfully identified. In the winter batch, 11.6% and 1.2% of the movement values were in the yellow-warning zone and red-warning zone, respectively. In the summer batch, 5.2% of the movement values were in the yellow-warning zone.

DISCUSSION

Performance of the Chicken Detection Model Under Various Illumination

The precision−recall curves (Manning and Schutze, 1999) of the trained YOLOv7-tiny chicken detection model under various illuminations were illustrated (Figure 14). Based on the precision−recall curves, the performance of the trained YOLOv7-tiny chicken detection model was slightly affected by illumination conditions. The model exhibited suboptimal performance under the low-illumination condition (Table 1). Nevertheless, chickens are diurnal animals; therefore, detecting chickens under dark conditions may not be necessary if natural illumination is used.

Table 2. Performance of SORT on chicken video sequence.

Object	GT	MT	ML	ID_{sw} (%) ↓	Frag (%) ↓	FP (%) ↓	FN (%) ↓	MOTA (%) ↑	MOTP (%) ↑	IDP (%) ↑	IDR (%) ↑	IDF1 (%) ↑
Chicken	114	108	2	0.3	0.5	1.9	2.6	95.3	84.4	94.5	93.9	94.3

GT = number of ground truths; MT = number of mostly tracked trajectories; ML = number of mostly lost trajectories; ID_{sw} = number of identity switches; Frag = track fragmentations; FP = number of false positives; FN = number of false negatives; MOTA = multiple object tracking accuracy; MOTP = multiple object tracking precision; IDP = identification precision; IDR = identification recall; IDF1 = identification F1-score; ↑/↓ = higher/lower scores denote better performance.

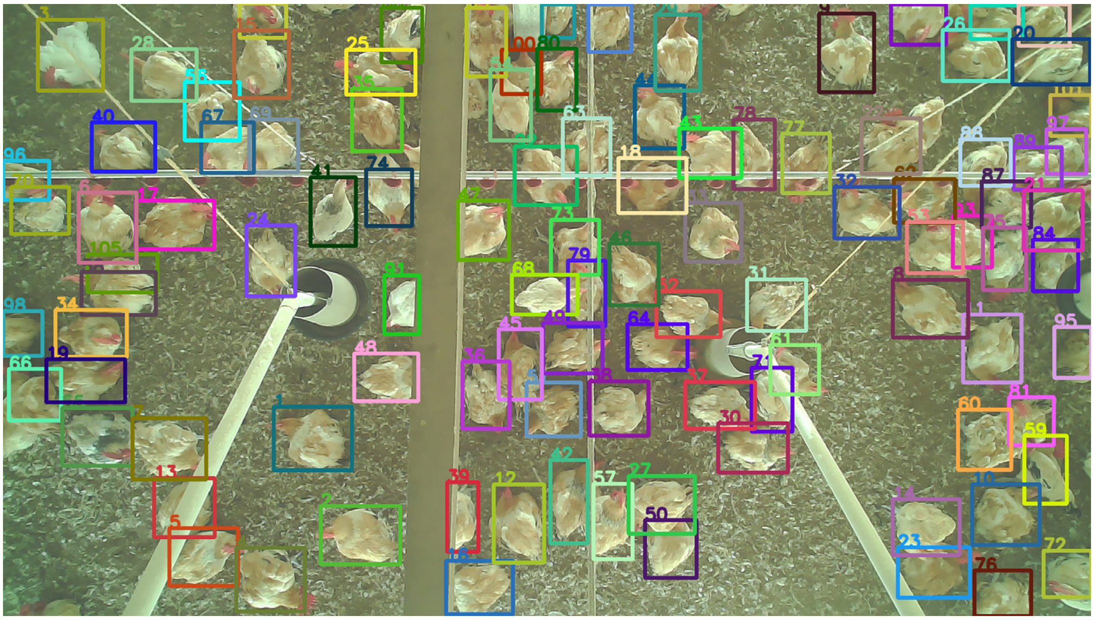

Figure 9. Chicken tracking using SORT algorithm.

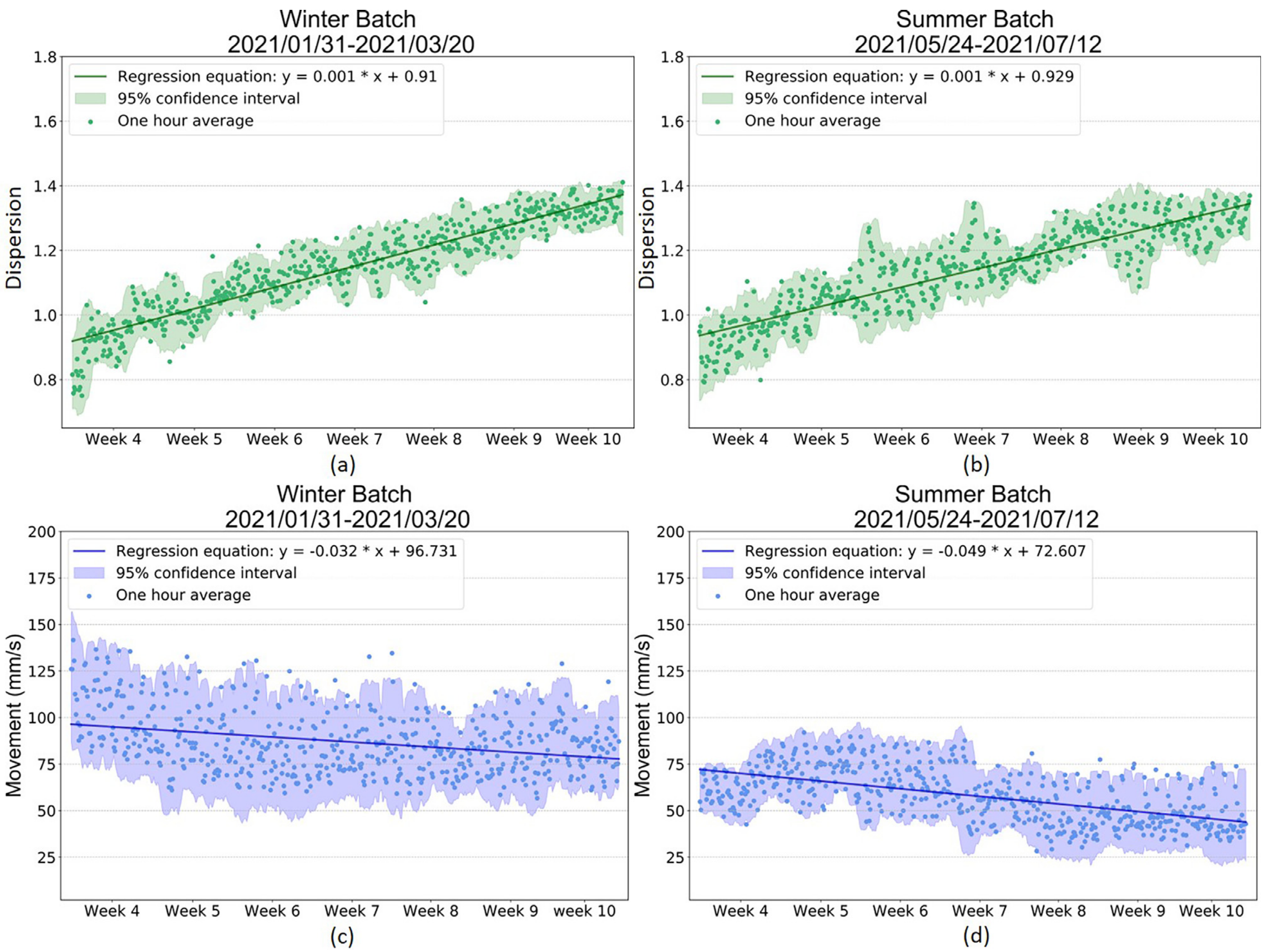

Figure 10. Dispersion observations in the (a) winter and (b) summer batches and movement observations in the (c) winter and (d) summer batches.

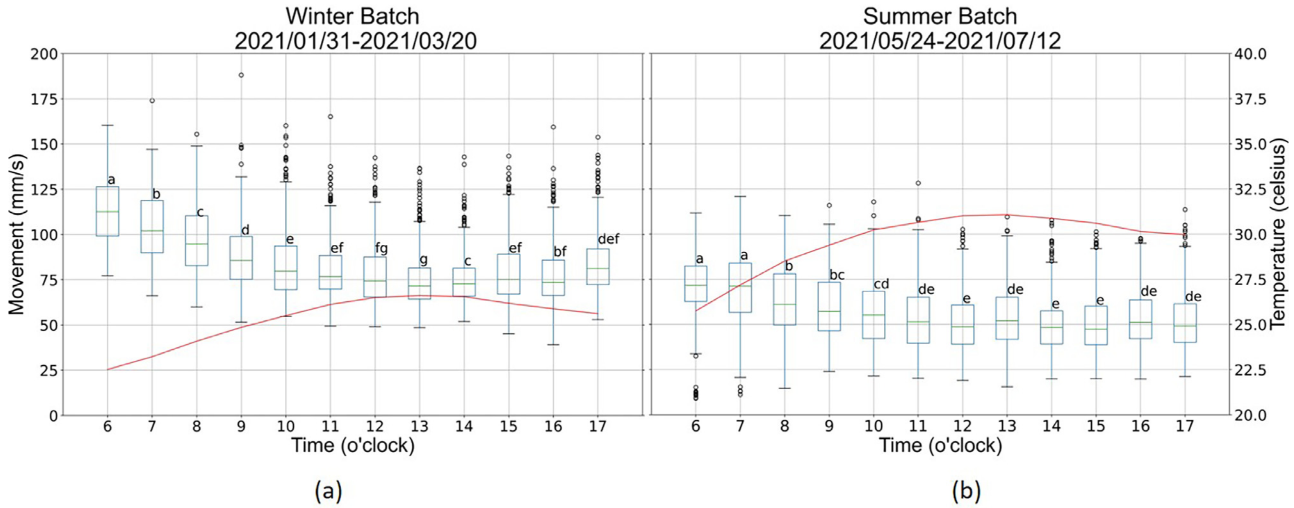

Figure 11. Daily chicken movement and temperature distributions in the (a) winter and (b) summer batches. The alphabets at the top of the box plots denote the groups of Scheffé's multiple comparison tests.

Analysis in False-Negative Chicken Detection

False-negative (**FN**) detection of chickens were examined (Figure 15). Overlapping and occlusion were the 2 major sources of FN detections. Occasionally, a high degree of overlap between 2 chickens in an image caused these 2 chickens to be misidentified as 1 chicken (blue dashed boxes in Figure 15a–c). The chickens occluded by pipelines, pillars, or drinkers in the images were often undetected (yellow dashed boxes in Figure 15d–f). Additionally, when several chickens were clustered together in an image, 1 chicken may be repeatedly detected as multiple chickens (black dashed boxes in Figure 15g–i).

Analysis in Unsuccessful Chicken Tracking

Unsuccessful tracking of the chickens in the tracking evaluation video was further examined (Figure 16). The tracking errors included FPs, FNs, and identity switches ($\mathbf{ID_{sw}}$). FPs were mainly caused by multiple detections of the same chicken by the trained YOLOv7-tiny model (I and II in Figure 17a). FNs occurred when the trained YOLOv7-tiny model failed to detect chickens because of occlusions (III and IV in Figure 17b). These FPs and FNs could be reduced by improving the performance of the chicken detection model. Occasionally, chicken detection bounding boxes exhibited a high degree of overlap with each other, causing ID_{sw} of the chickens (V and VI in Figure 17c). The phenomenon of ID_{sw} may not be avoidable in a crowded chicken farm.

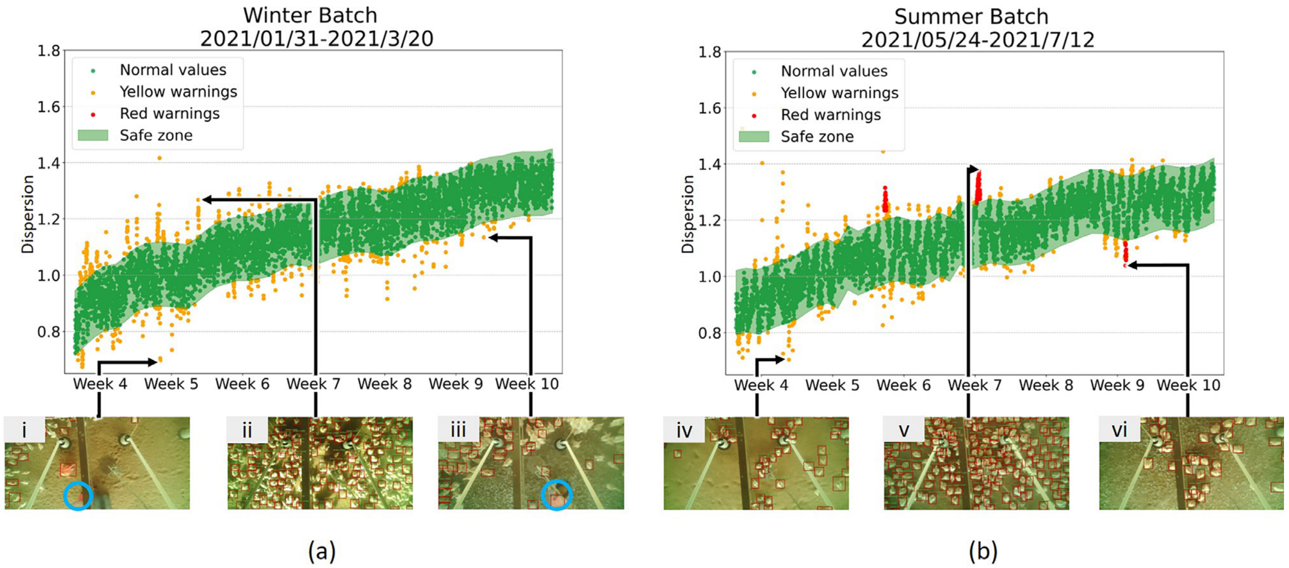

Figure 12. Dispersion monitoring results in the (a) winter and (b) summer periods. The dispersion values of i, iii, and iv were yellow warnings below the safe zone. The dispersion value of ii was a yellow warning above the safe zone. The dispersion value of vi was a red warning below the safe zone. The dispersion values of v was a red warning above the safe zone.

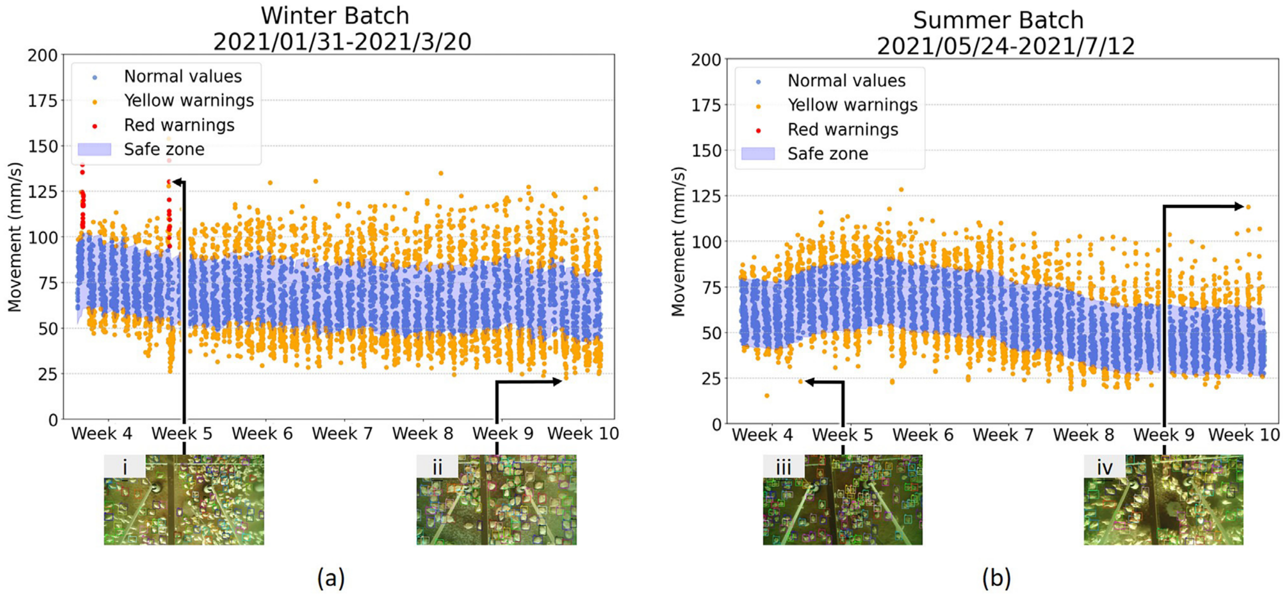

Figure 13. Movement monitoring results in the (a) winter batch and (b) summer batch. The movement values in ii and iii were yellow warnings below the safe zone. The movement value of iv was a yellow warning above the safe zone. The movement value of i was a red warning above the safe zone. See the Appendix for the videos of i, ii, iii, and iv.

Patterns in Chicken Dispersion and Movement

An increasing pattern in chicken dispersion was observed (Figure 10). The space of the chicken farm was limited, and the space between the chickens reduced as they grew. Consequently, the reduction in space availability resulted in an increasing trend in dispersion and a decreasing trend in movement. A decreasing pattern in chicken movement was observed (Figure 10a and b). On average, the mean movement values of the chickens aged between 4 and 7 wk were 92.4 mm/s and 67.3 mm/s, respectively, for the winter and summer batches. By contrast, the mean movement values of the chickens aged between 8 and 10 wk were 83.2 mm/s and 51.3 mm/s, respectively, for the winter and the summer batches. A negative correlation between movement and temperature was observed (Figure 10c and d). Statistical test indicates that the summer and winter movements significantly differed (t test: t = 31.362, P < 0.001). The indoor mean temperatures of the summer and winter batches were 28.4°C and 25.2°C, respectively. The high temperatures in summer may reduce the movement of chicken flocks. By contrast, the temperature did not seem to have caused any variation in chicken dispersion. A negative correlation between hourly movement and temperature was observed (Figure 11). The correlation coefficients between hourly movement and temperature were −0.500 and −0.298, respectively, for the winter and summer batch. These observations support that dispersion is time-series data and movement is time-series data with seasonal patterns.

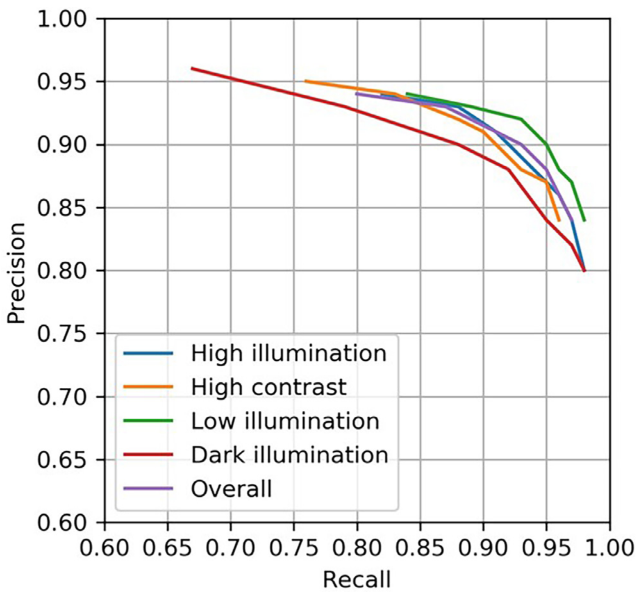

Figure 14. Precision−recall curves derived for YOLOv7-tiny model.

Case Analysis in Anomalous Chicken Dispersion and Movement

Given the inherent active nature of TNCs, our study specifically examines warning cases involving dispersion and movement values falling beyond the safe zone. Drawing from chicken management experience, instances categorized as yellow warnings may pose potential threats to the chicken flock or individual birds, whereas red warning cases could lead to irreversible damage. Analyzing these warning cases provides demonstrations of enabling timely actions to secure chicken welfare.

In chicken dispersion, certain dispersion values below the safe zone were observed. Figure 12i, iii, and iv demonstrates numbers of chickens grouped on one side of the farm, resulting in low dispersion values of 0.703, 1.171, and 0.721, respectively, which fell in the yellow-warning zone. Nonetheless, it was the presence of a farmworker (indicated by blue circles in Figure 12i and iii)

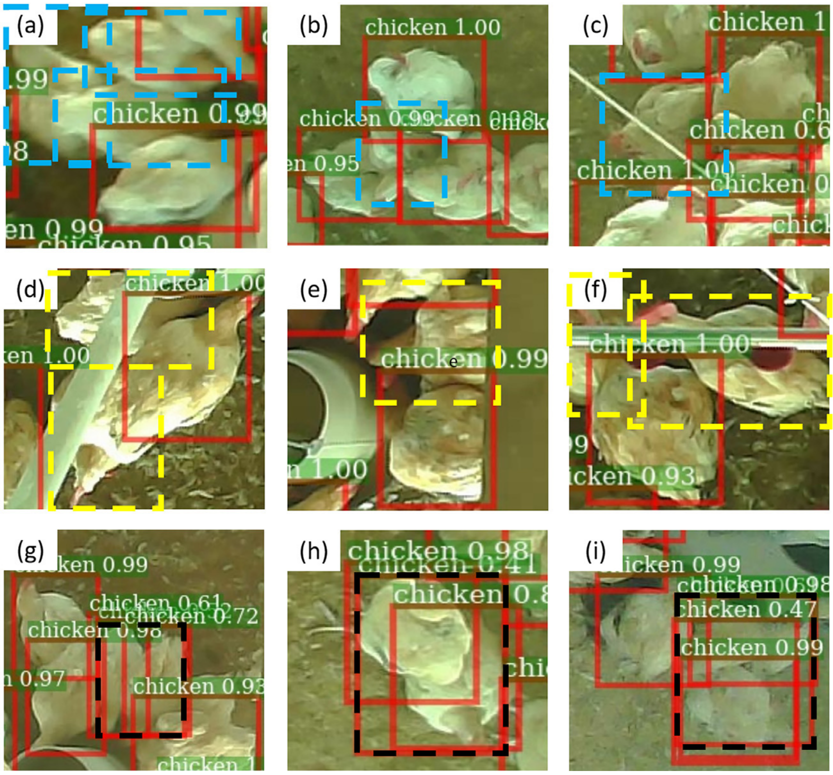

Figure 15. False detection cases: (a), (b), and (c): 2 overlapping chickens falsely recognized as 1 chicken; (d), (e), and (f): chickens blocked by a pipeline, pillar, or drinker were not detected; And (g), (h), and (i): 1 chicken was repeatedly detected as multiple chickens when several chickens gathered together.

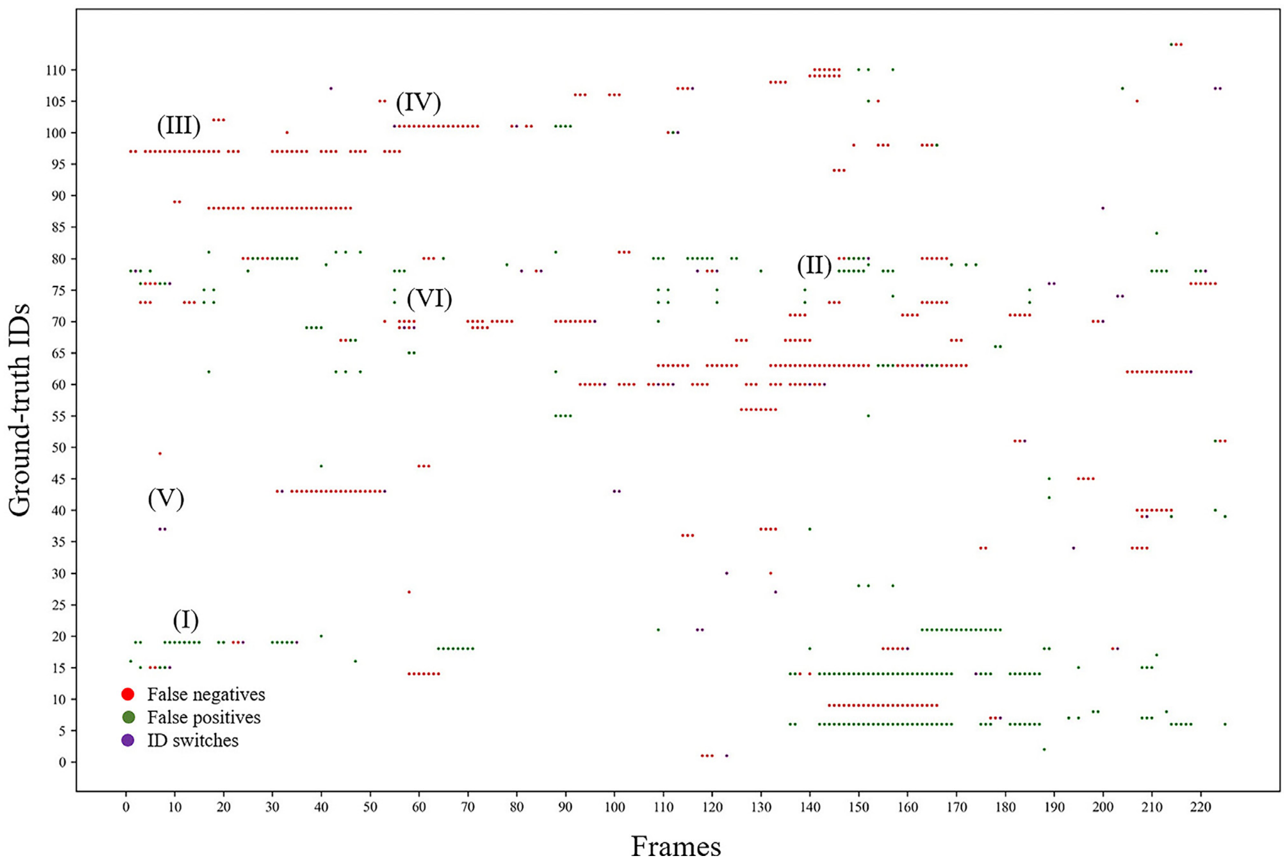

Figure 16. Chicken tracking errors in each frame. The red, green, and purple dots denote FNs, FPs, and ID_{sw}, respectively.

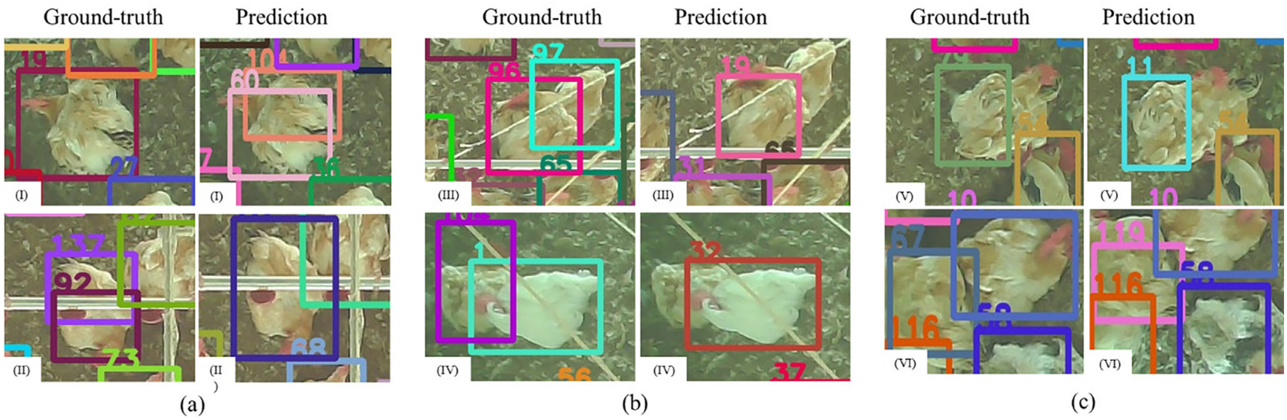

Figure 17. Tracking errors: (a) FPs, (b) FNs, and (c) ID_{sw}. The roman numerals correspond to the roman numerals in Figure 16.

passing by the flock of chickens that led to their temporary dispersion. In Figure 12vi, chickens clustered for an hour, resulting in a dispersion value 1.068, which fell in the red-warning zone. Certain dispersion values above the safe zone were observed. In Figure 12ii, chickens were spread evenly in the farm, leading to a dispersion value 1.268, which fell on the yellow-warning zone. In Figure 12v, a group of chickens were overcrowded for 2 h, resulting in a high dispersion value of 1.375, which fell in the red-warning zone.

In chicken movement, certain movement values below the safe zone were observed. The mean movement value of all the chickens was calculated for each video. In Figure 13ii and iii, most chickens were stationary on the litter, resulting in mean movement values of 22.6 mm/s and 15.4 mm/s per chicken, respectively. See the Appendix for the videos. Certain movement values above the safe zone were also observed. In Figure 13iv, a flock of chickens ran from the right side of the camera view to the left side, leading to a mean movement value of 118.8 mm/s per chicken. In Figure 13i, a flock of chickens kept moving in the camera view, resulting in a high mean movement value of 141.8 mm/s per chicken.

Compared with manual patrol method, the proposed method objectively quantifies essential behaviors (i.e., dispersion and movement) of chicken flocks and provides warning to farmers when anomalous behaviors are observed. This method reduces labor costs and improves chicken welfare.

Comparison Between Three YOLOv7 Models in Chicken Detection

Three models were trained to compare their performance in chicken detection, including YOLOv7, YOLOv7x, and YOLOv7-tiny. The models were trained using the images and methods mentioned in Materials and Methods. The trained models were hosted on a graphics processing unit (RTX A6000, NVIDIA; Santa Clara) for comparison purposes (Table 3). YOLOv7-tiny required considerably lower memory consumption compared with YOLOv7x and YOLOv7. YOLOv7-tiny also had the shortest inference time. Considering that a 5-min video is composed of 1,500 images (e.g., frames), the cumulative inference time of YOLOv7 and YOLOv7x for a video can be considerably large. YOLOv7 outperformed YOLOv7-tiny in AP@50; however, the difference is less than 1%. Thus, YOLOv7-tiny was selected as the model in this study due to its optimized memory usage, efficient processing time, and satisfactory performance.

Comparison With Related Studies

Several systems that monitor chicken farms have been proposed. Certain studies focused on monitoring environmental factors, such as temperature, humidity, ammonia concentration, and carbon dioxide concentration (Syahrorini et al., 2020; Liani et al., 2021). By contrast, our study directly monitored chicken behaviors (i. e., dispersion and movement) using machine vision, which are 2 direct indicators that reflect the wellness of chickens. Certain other studies quantified the dispersion (Yang et al., 2023) and movement (Neethirajan, 2022) of chickens using machine vision (YOLOv5). By contrast, our approach further forecasted the dispersion and movement of chickens and developed a warning system using autoregressive moving average models. Certain other studies monitored chickens in small-scale experimental coops (Lin et al., 2020; Tao and Xiaoyan, 2020). By contrast, our study was conducted in a commercial chicken farm, where thousands of chickens were raised.

Practical Implications of the Proposed Method

The proposed system enables automatic monitoring the dispersion and movement of chicken flocks in commercial chicken farms. The monitoring of the 2 vital traits is continuous and is in real-time. The system facilitates the early detection of potential issues in chicken farms. Alerts can be generated in a timely manner when the dispersion or movement values move out from the safe zone to the warning zone, ensuring that farmers can take prompt actions to minimize negative impacts to

Table 3. Performance of 3 YOLOv7 models.

Performance metrics	YOLOv7	YOLOv7x	YOLOv7-tiny	YOLOv7-tiny (no augmentation)
AP@50	0.9853	0.9828	0.9824	0.9241
Memory consumption (MB)	74.8	142.1	2.2	
Inference time (ms)	12.7	15.3	7.8	
Processing time for quantifying a 5-min video (s)	24.62	26.95	15.27	

chicken flocks from potential health risks or environmental hazards. Also, the dispersion and movement of chicken flocks can be recorded automatically and can be available to chicken farms. These data can help chicken farmers to further improve their management in chicken farming.

Future Work

The proposed approach provides a solution for monitoring chicken dispersion and movement and for determining unusual chicken dispersion and movement automatically. Although this study proves that monitoring chicken flocks and detecting unusual events in chicken farms via machine vision is practical and useful, future research is still needed for chicken farmers to receive warnings when the events occur. One possibility is to develop a mobile application to receive alerts of unusual events. The mobile application can then push the alerts to chicken farmers in real-time. Another approach is to send the alerts through short message service of cell phones. Once chicken farmers can monitor their chickens without entering chicken farms, the risk of carrying pathogens into chicken farms can be minimized.

CONCLUSIONS

The dispersion and movement of TNCs are 2 essential factors that concern chicken farmers. Manually observing chicken dispersion and movement is time-consuming and labor-intensive. To address the challenges of labor shortage in chicken farming, this study proposed a system for automatically detecting anomalous dispersion and movement of chicken flocks in commercial chicken farms. A YOLOv7-tiny model was trained to localize chickens in images of overhead view and reached an AP@50 of 98.2%. The dispersion and movement of chicken flocks, respectively, were subsequently quantified using NNI and SORT algorithms. The SORT algorithm achieved a MOTA of 95.3%, a MOTP of 84.4%, and an IDF1 of 94.3%. Chicken dispersion and movement were observed as time-series data in a long-term experiment. ARIMA and SARIMAX models, respectively, were thus implemented to model chicken dispersion and movement and to automatically detect anomalous dispersion and movement events. ARIMA and SARIMAX models achieved a MAPE of 3.71% and 13.39%, respectively, in predicting the trends of chicken dispersion and movement. Dispersion and movement values, respectively, beyond the 95% confidence intervals predicted by ARIMA and SARIMAX were regarded as anomalous events. The anomalous events in the long-term experiment were successfully detected. The proposed approach objectively and automatically records and monitors the dispersion and movement of chicken flocks. The records can help chicken farms to improve their management in chicken farming. Also, chicken farmers only need to visit their farms when alerts of anomalous dispersion or movement values are triggered. Thus, the proposed approach can alleviate labor costs in chicken farming.

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DISCLOSURES

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yan-Fu Kuo reports financial support was provided by Council of Agriculture. Yan-Fu Kuo reports a relationship with Council of Agriculture that includes: funding grants.

SUPPLEMENTARY MATERIALS

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.psj.2023.103040.

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