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A deep learning method for monitoring spatial distribution of cage-free hens

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ABSTRACT

The spatial distribution of laying hens in cage-free houses is an indicator of flock's health and welfare. While larger space allows chickens to perform more natural behaviors such as dustbathing, foraging, and perching in cage-free houses, an inherent challenge is evaluating chickens' locomotion and spatial distribution (e.g., real-time birds' number on perches or in nesting boxes). Manual inspection of hen's spatial distribution requires closer observation, which is labor intensive, time consuming, subject to human errors, and stress causing on birds. Therefore, an automated monitoring system is required to track the spatial distribution of hens for early detection of animal welfare and health concerns. In this study, a non–intrusive machine vision method was developed to monitor hens' spatial distribution automatically. An improved You Only Look Once version 5 (YOLOv5) method was developed and trained to test hens' distribution in research cage-free facilities (e.g., 200 hens per house). The spatial distribution of hens the system monitored includes perch zone, feeding zone, drinking zone, and nesting zone. The dataset contains a whole growth period of chickens from day 1 to day 252. About 3000 images were extracted randomly from recorded videos for model training, validation, and testing. About 2400 images were used for training and 600 images for testing, respectively. Results show that the accuracy of the new model were 87–94% for tracking distribution in different zones for different ages of hens/pullets. Birds' age affected the performance of the model as younger birds had smaller body size and were hard to be detected due to blackness or occultation by equipment. The performance of the model was 0.891 and 0.942 for baby chicks (≤10 days old) and older birds (> 10 days) in detecting perching behaviors; 0.874 and 0.932 in detecting feeding/drinking behaviors. Miss detection happened when the flock density was high (>18 birds/m^2) and chicken body was occluded by other facilities (e.g., nest boxes, feeders, and perches). Further studies such as chicken behavior identification works in commercial housing system should be combined with the model to reach an automatic detection system.

1. Introduction

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

In the past years, computer vision has gained fast – paced advances from human detection to animal monitoring (Aydin et al., 2010; Porto et al., 2015; Lao et al., 2012, 2016; Subedi et al., 2023a). The computer vision system provides a non – intrusive method in livestock monitoring (i.e., swine, cattle, and sheep) (Hitelman et al., 2022; Li et al., 2014; Nasirahmadi et al., 2017). For poultry housing, computer vision or deep learning models (e.g., convolutional neural network - CNN) have been applied to track individual bird for analyzing behaviors (Fang et al., 2020; Pereira et al., 2013; Subedi et al., 2023a). Some studies have focused on chickens' floor distribution (i.e., feeding, drinking and walking zones) (Aydin et al., 2010; Guo et al., 2020a, 2021; Yang et al., 2022). The CNN image processing algorithms showed high accuracy in monitoring floor distribution (two dimensions). Guo et al. (2022) compared

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different CNN models (i.e., ResNet-152, ResNeXt-101 and ECA-DenseNet-264) in monitoring broilers' behaviors. The models showed 88–97% of accuracies. The YOLO (you only look once) is a one-stage CNN algorithm that has been applied to monitor poultry behaviors (Guo et al., 2022; Yang et al., 2022; Jocher et al., 2021). Ding et al. (2019) developed detector to monitor heat stress conditions of broilers by using YOLOv3 (Ding et al., 2019). Ye et al. (2020) proposed a CNN algorithm (YOLO + multilayer residual module (MRW) to detect white feather broilers stunning states. Subedi et al. (2023a) developed You Only Look Once version 5 (YOLOv5)-pecking models to track hens' pecking behaviors and improved accuracy of the model to 85–90%.

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

2. Material and methods

2.1. Experimental design and data collection

About 800 day-old chicks (Hy-Line W-36) were raised in four research chamber rooms (each was measured as 7.3 m long × 6.1 m wide × 3 m high) at the Poultry Science Center at the University of Georgia (UGA). Cameras (Swann Communications, Santa Fe Spring, CA) were installed with two different angles (i.e., vertically and horizontally) to record the spatial distribution of birds (Fig. 1). The recorded videos were transferred to massive hard devices for analyzing video quality and converting to JPG format in the Department of Poultry Science at UGA.

Feeders, nipple drinkers, nest boxes (Bestnestbox company, Hudson, Ohio, USA) and a A-frame hen perch were installed in each of research chamber rooms by referring the dimension suggested by commercial farms (Chai et al., 2019). The research room was divided virtually into perching, nesting, drinking, feeding zones for the deep learning algorithm to identify the distribution of chickens (Fig. 2). Husbandry and management were following Hy-line W-36 management guides. Animal management was approved by the Institutional Animal care and Use Committee (IACUC) at the University of Georgia.

2.2. Methods for chicken detection

In this study, an improved YOLOv5 model was developed for chicken detection. The architecture consisted of three parts, i.e., backbone, neck, and head (Fig. 3). The improved YOLOv5 model is based on CNN network that can take in an input image and capture its spatial characters (learnable weights) to train the network to detect object (Liu et al., 2022). In backbone, four different models are used to extract basic features. In neck, feature pyramids and attention mechanism module were utilized to recognize same target under separate size and scales. Besides, three attention mechanism modules were added to enhance small targets detection. In model head, three individual feature maps were used to detect target (i.e., hens in different zones). According to Fig. 3, there are four main modules in backbone for extracting features from given pictures, including FOCUS, Conv + Bottle Neck + Hard Switch (CBH), cross stage partial (CSP) and spatial pyramid pooling (SPP). After each module, the pixels of pics changed from 608 × 608 pixels to 76 × 76 pixels, 38 × 38 pixels, and 19 × 19 pixels (Zhang et al., 2022). With these decreased feature maps, the neck network applies CSP and CBH to generate feature pyramids to aggregate on the features and submit it to head. However, during the pass progress, the contextual information will decrease. To obtain more accurate information and minimize the information loss, an attention mechanism was introduced to this improved YOLOv5 method (with red background in Fig. 3). The attention mechanism is combined with C3Ghost and Ghost modules to enhance the dominated channel

Fig. 1. Experimental setup for collecting laying hens' spatial distribution dataset.

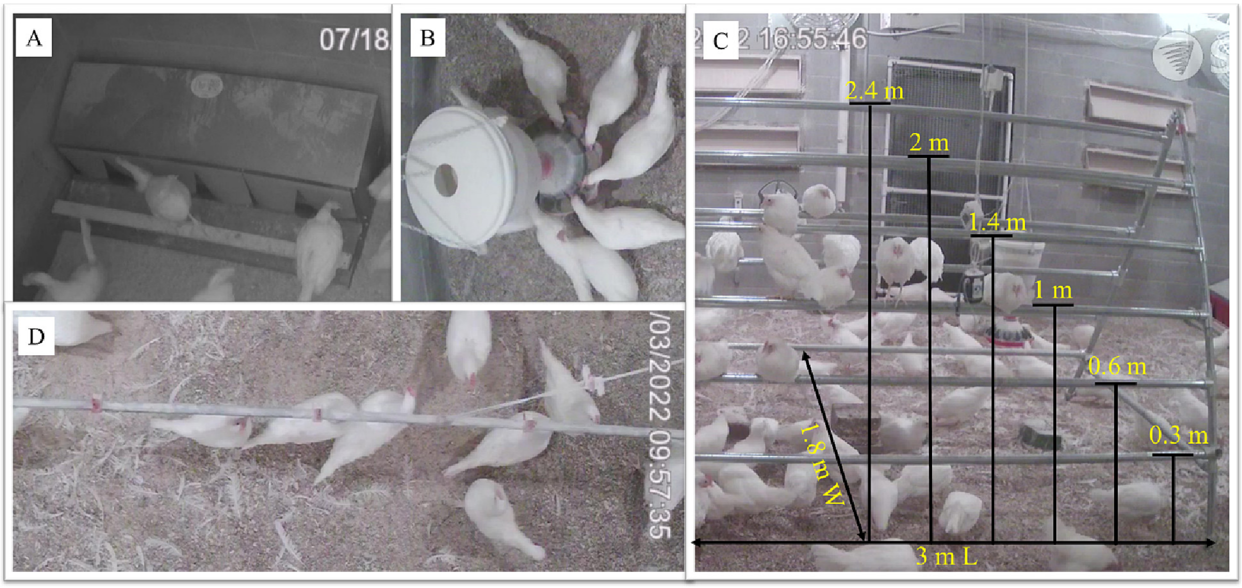

Fig. 2. The definition of different zones. A. nesting zone; B. feeding zone; C. perching zone (3 m long, 1.8 m wide, 6 different heigh for birds to perch from 0.3 m to 2.4 m); and D. drinking zone.

attention(Woo et al., 2018). The aim of C3Ghost module is to reduce heavy computational burden as the Ghost applied into YOLOv5 neck network.

The Ghost module focuses on generating more feature maps by using fewer parameters. In this study, the Ghost was adopted to process hen's feature maps(Han et al., 2020). The original hen's feature map is blurry after YOLOv5 neck network. However, with the Ghost module, the channel number of hen's feature maps improved, and an enhanced hen's feature pyramid developed. The structure of it is shown in Fig. 4. In the neck, the three dimension of input feature map is a × b × c, after the neck, the output feature map is a1 × b1 × c1, and the size of kernel is n × n, where a and a1 are heights of feature map, b and b1 are widths of feature map. Comparing to the convolutional layer, the Ghost module processes the ordinary convolution in two steps. During the

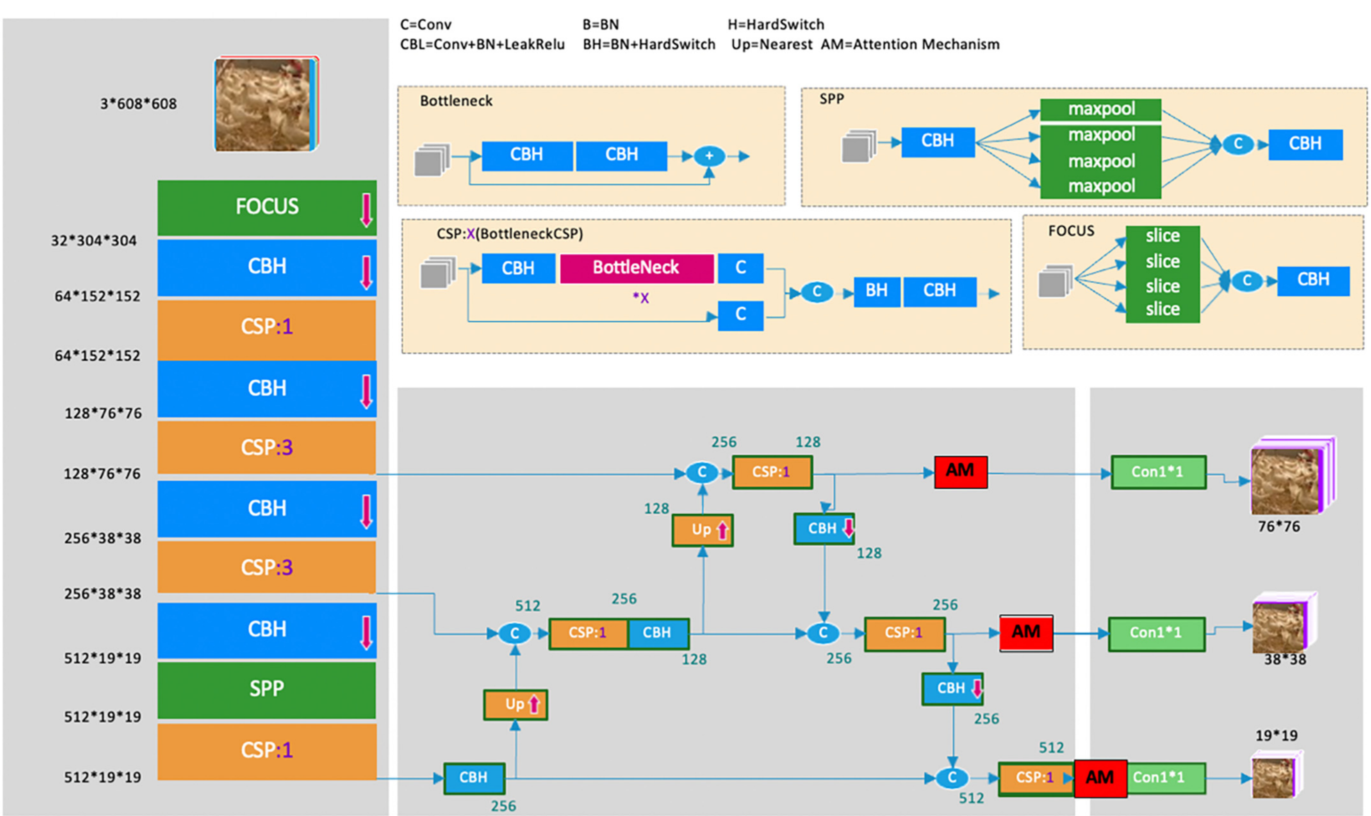

Fig. 3. The network structure of improved YOLOv5 for tracking spatial distribution of chickens in cage-free houses.

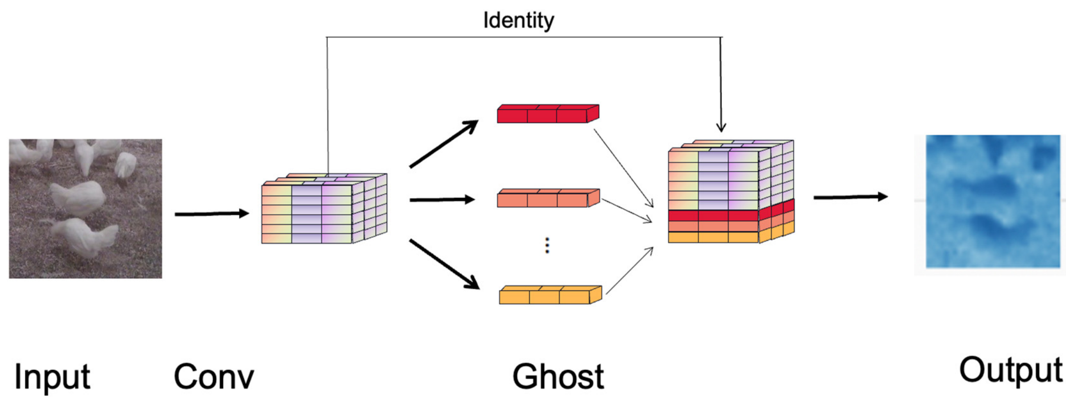

Fig. 4. A demonstration of two steps Ghost module that used in this study for processing poultry images.

convolutional layer, the basic number of floating-point operation (FLOPs) is a1 × b1 × c1 × c × n × n, which is usually over 105 when the channel number c is 256 and multiplies the filter number c1. The overload FLOPs lead the critical information of inputted imagines (Ren et al., 2022). In the two steps of Ghost module, a cheap transformation procedure was utilized in generating intrinsic feature maps and needs fewer filters. Therefore, the new structure can obtain a notable performance.

$$FLOPs = \mathrm{a1} \times \mathrm{b1} \times \mathrm{c1} \times \mathrm{c} \times \mathrm{n} \times \mathrm{n} \tag{1}$$

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

2.3. Methods for tracking chickens in different zones

A whole vision dataset (horizontal and vertical) and an interface were used to recognize spatial distribution of birds in different zones (Fig. 5). The graphical user interface (GUI) was developed with Python binding for the Qt5 application framework (PyQt5) (Fig. 6), which enhances the process of selecting target zones (nesting, perching, feeding and drinking) (Xie et al., 2022). The zones of each bird in the picture were designed firstly, then the whole area in the image was used as the reference area to estimate the number of birds in the selected zones, the equation is showed below.

$$\tilde{N}_i = \frac{n_i}{n}, \quad 1 \le i \le x \tag{2}$$

(See Fig. 7.)

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

2.4. Dataset and setting

A laying hens' dataset was constructed to evaluate the performance of the improved YOLOv5 on the detection of birds. The dataset contains whole growth period of bird from 1 week to 36 weeks (baby chicks to hens) and consisting of 3000 pics that were extracted randomly from recorded videos. All the pics were labeled by LabelImg Windos_v1.6.1 version. Birds under 2 weeks of age were labeled as baby chicks, and birds 2 weeks or older were labeled as pullets/hens. 2400 pics and 600 pics were used during training section and testing section separately. The training was run under in Python Qt5 application framework for 300 epochs with a learning rate 0.01 and a batch size of 16. The

Fig. 5. The selected zones in the picture. The blue bullet A to C represents the different high perching zone varying from 7.9 ft. to 0 ft.; the two blue bullet D represent the feeding zone; the blue bullet E represents drinking zone; the blue bullet F represents the nesting zone.

Fig. 6. The GUI developing by PyQt5 (b is pullets/hens >10 days; s – baby chicks ≤10 days).

confidence threshold is set to 0.25, which means that objects with a similarity of 0.25 or above can be considered interesting and marks will be assigned.

2.5. Model evaluation and statistical analysis

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

$$Precision\ (100\%) = \frac{TP}{(TP + FP)} \times 100 \tag{3}$$

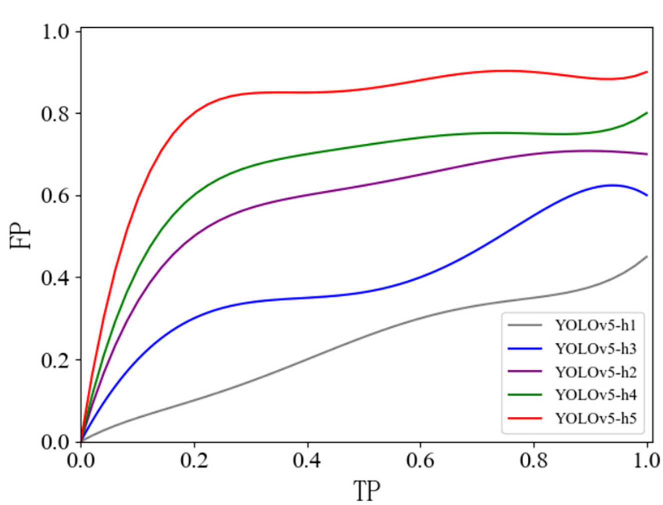

Fig. 7. ROC curve comparison results of different detector based on deep learning.

$$Recall\ (100\%) = \frac{TP}{(TP + FN)} \times 100 \tag{4}$$

$$F1\ score\ (100\%) = \frac{(2*Precision*Recall)}{(Precision + Recall)} \times 100 \tag{5}$$

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

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

3. Results and discussions

3.1. Model performance in detecting chickens

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

Table 1
The adjustment methods and results.

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

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

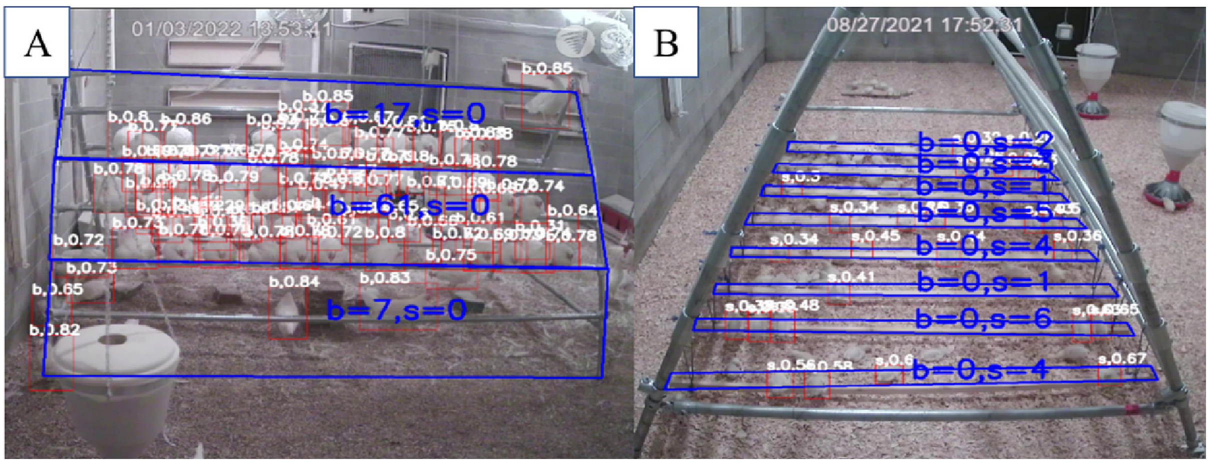

Fig. 8. Chickens' distribution in perching zones detected by improved YOLOv5. (A) adult hens (133 days of old) detected; (B) baby chicks detected (8 days of old). The letter *b* in blue means older birds (> 10 days old) and the letter *s* in blue represents baby chicks (≤ 10 days old).

During the experiments, the loss function values toward to be stable when the epoch approached to 200, so the epoch was 200. From the Table 1, we discovered a) improved YOLOv5 method had better detection comparing to original YOLOv5 on both individual and mixed datasets, b) mixed dataset has better performance comparing to individual dataset when trained with improved YOLOv5 and original YOLOv5 methods, c) increase the imagine size improved the overall model precision. These confirmed our setting parameters. The Receiver Operating Characteristic (ROC) curve shows the sensitivity and specifity of different detector (Fig. 7).

4. Chicken distribution identification in perching zones

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

To test the performance of improved YOLOv5 model in monitoring birds in perching zones, about 200 images were randomly selected (chickens' age ranged from week 1 to week 20) to test the model (Table 2). The performance of the model was 0.891 and 0.942 for baby chicks (≤10 days old) and older birds (> 10 days), respectively. The miss detection rates of hens and baby chicks were 0.054 and 0.102, respectively. Errors or miss detections were caused by high density chickens (pilling or crowding) and interreferences of perch frame and feeders. In general, the mew model fitted well in the perching zone ($Rture = 0.891$ and 0.942).

A back propagation (BP) neural network algorithm was used to identify the chicken distribution in drinking and feeding zones, the missed detection also comes from chicken crowding behaviors and

Table 2
Tested performance of improved YOLOv5 on perch zone.

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

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

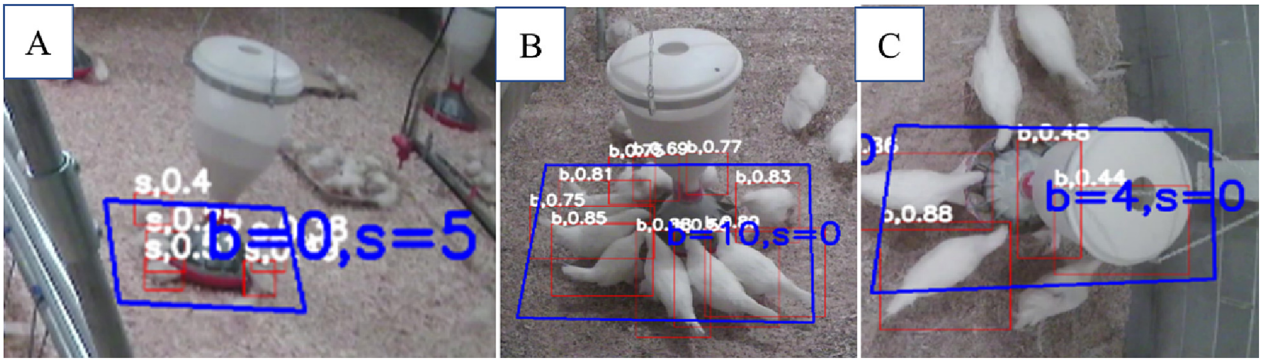

Fig. 9. Chickens' distribution in the feeding zone at different ages (A – chickens were 10 days old; B and C – chickens were 122 days old (*b* means birds were > 10 days; *s* means birds were ≤ 10 day).

collusion problems(Yang et al., 2022). Other flaws in our method are original from the horizonal vison factor (when baby chicks are too small under horizontal scale, the miss detection happens) and designed perch zone (when the perch zone is designed narrower than the real situation, there will be less perch chicks included into the perch zone, so the chicks were missed). The false detection rates were 0.004 and 0.007 respectively. This were also the common drawback of other vision based algorithms (Abdanan Mehdizadeh et al., 2015).

4.1. Chicken distribution in feeding and drinking zones

Fig. 9 demonstrates the distribution of detected birds in feeding zones monitored by improved YOLOv5 model. For each pic, the number of chickens in targeted areas were analyzed. From Fig. 9A, we can identify the distribution of baby chicks (i.e., 10 days old) in feeding zone in 100% accuracy. For Fig. 9B and C, the model detected larger chickens (i.e., 122 day old) in 100% accuracy as well. From Fig. 10A and B, the distribution of 122 days old of hens in drinking areas collected from two different angles. The detection efficiency was 100% in the Fig. 10B as there was no osculation. For Fig. 10A, the feeder (low right corner) could block some chickens during the study.

To investigate a larger number of chickens, we used about 200 images to test the model performance in feeding and drinking zones (Table 3). The overall accuracy for baby chicks and older chickens were 0.874 and 0.932, respectively. Comparing to accuracy of perch zones, detecting baby chicks of feeding and drinking zones was more

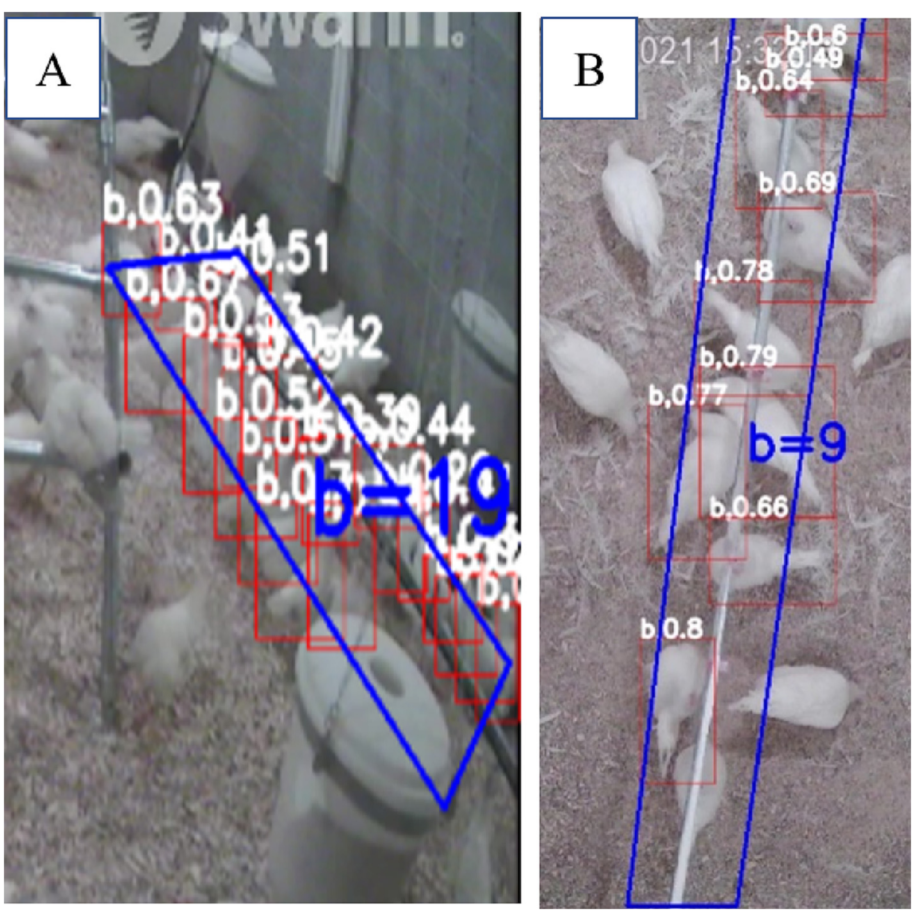

Fig. 10. The distribution of chickens (i.e., 122 days old) in the drinking zone at different angles: chickens in A (side view in 45 degree) and B (top view) (*b* means birds were > 10 days; *s* means birds were ≤ 10 day).

Table 3
Tested performance of improved YOLOv5 on feeding and drinking zones.

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

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

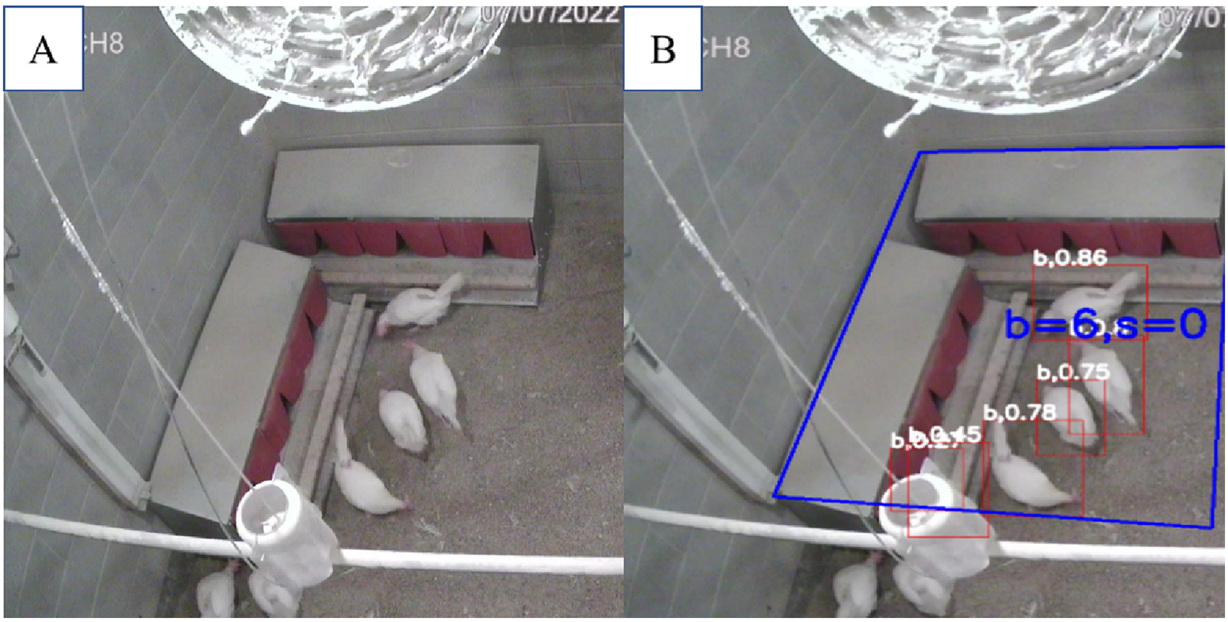

Fig. 11. Chicken distribution in nesting zone. (A) original image of nesting area and (B) detected nesting area.

challenging due to smaller size of body and interferences of equipment. When a higher number of birds were assembled at the same feeder or drinker, birds standing in front of the feeder or drinker had higher possibility to be recognized than those close at sides of feeder and drinker. In addition, lighting affected image quality and model's performance. Apart from these, birds' density has been reported affect deep learning model's performance (Maselyne et al., 2016).

4.2. Chicken distribution in nesting zone

In this study, most hens started to lay their first eggs at around 18 weeks of age. The nesting behaviors of hens was analyzed with our newly developed model because it's important identify if there are floor eggs or not (Gonzalez-Mora et al., 2022). Monitoring hens' distribution in nesting zones helps to minimize losses from laying eggs on the floor. Fig. 11 shows the distribution of detected hens in nesting zones with our improved YOLOv5 model. Fig. 11A is the original image of nesting area. Fig. 11B demonstrates the detected hens in nesting zone. The model performed with over 90% accuracy in detecting hens in nesting zones.

To evaluate model's performance in nesting zone for hens' detection systemically, over 200 images were randomly selected from video dataset to improve targeted hens' dataset (Table 4). The tested accuracy rate in nesting zone reached 0.906, which is slightly less than that in others zones (i.e., perching, feeding, and drinking zones), because there was an equipment hanging above the nesting zone.

Comparing to other computer vision-based tools for monitoring nesting zone, our model has a higher precision. For instance, a 0.825 of accuracy was reported in a research focusing on monitoring eggs and birds in nesting zone (Lubich et al., 2019; Hui et al., 2021). In previous studies, the best YOLO model reached an accuracy of 0.885. In this study, our improved YOLOv5 model performed better than most of existing YOLO models and other CNN models. However, the model missed some detections under high density of hens' flock due to occlusion of hanging line or equipment on nesting boxes and zones. Further studies are need to enhance model's performance, especially under

Table 4
Tested performance of improved YOLOv5 on nesting zone.

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

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

environment of high density of laying hens because commercial house tend to have thousands hens on the floor (Huang et al., 2022; Subedi et al., 2023a).

5. Conclusions

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

Authors credit statement

Lilong Chai (L.C.) contributed the research method and resources; Xiao Yang (X.Y.) conducted the experiment and collected the data; X.Y., Ramesh Bist (R.B.) and Sachin Subedi (S.S.) contributed to the data collection; X.Y. and L.C wrote the main manuscript. All authors reviewed the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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