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Broiler Behavior Recognition Based on YoloV5 for Health Monitoring

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Abstract

In large-scale broiler farms, broilers get sick or even die every day due to infection with pathogens, which must be treated to prevent huge loss. But monitoring such large-scale broiler cages can result in high labor cost. Fortunately, computer vision technology has the potential to do the job. However, the current image recognition models for broiler chicken still has challenging problems that need to be tackled, such as the complexity of scenes, the sticky and obscured targets of the broilers. This study proposes a YOLOv5-based model for behavior recognition and health monitoring of intensively farmed broilers. The results showed that the MAP (Mean Average Precision, IoU=0.5) of the model proposed in this study reached 92.60% for behavior detection of caged broilers, which improved 24.28%, 11.07%, 7.55% compared with traditional models such as YOLOv3, YOLOv4, and Faster RCNN, respectively. The detection speed reached 69.44 FPS(Frame Per Second), which meets the requirements of real-time detection. Besides, we analyzed the time series data of the broiler's behavior acquired with the recognition model to determine the health status of it. Comparison experiments was conducted between healthy and diseased broiler flocks. The results suggest that the abnormalities in the timing of broilers behavior during feeding can be used as a basis for assessing the health status of the flock. This study provides an automatic and effective method for identifying the behavior and monitoring the health of broilers under intensive breeding mode, and provides a basis for analysis of flock behavior and judgment of health status.

Keywords: *broiler, health monitoring, behavior recognition, deep learning*

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I. Introduction

With the improvement of people's living standards, the quality of broiler and eggs is required to be higher and higher, and people want to eat more healthy food [1]. In order to meet the growing market demand, the farming model of broilers is also constantly improving [2]. Intensive breeding mode has great advantages in land occupation area, breeding cost, social benefits, etc [3], and is adopted by many large breeding enterprises [4]. Although the intensive breeding mode has technical advantages, there are still some problems in the actual breeding process: it is not convenient for breeders to patrol because of many layers of broiler cages and the large breeding density, which is easy to cause that sick and dead broilers cannot be found in time, further causing disease spread and environmental pollution [5,6]. As shown in Figure 1, a diseased broiler that were not found in time was pecked to death by other broilers, resulting in environmental pollution.

Figure 1. Picture of a diseased broiler pecked to death by others.

Precision Livestock Farming (PLF) integrates artificial intelligence, sensing technology, and communication technology to continuously and automatically monitor the health and welfare of animals remotely [7,8]. PLF collects animal behavior information and biological indicators through sensors and uploads them to the host computer [9]. Then analyzes the comprehensive information to discriminate the health and welfare of animals [10,11]. Image sensing technology is increasingly used in precision animal husbandry because of its advantages of simple operation, non-destructive detection and fast discrimination [8,12]. Mehdizadeh [13] used computer vision techniques to study the kinematic characteristics of broiler broilers during feeding. The locating of the broiler's eye in the video was done by chromatic aberration principle to obtain the area of interest and reduce the redundant information, then the beak tip was detected by Otsu algorithm, and the amplitude, speed and acceleration of the movement of the beak tip were analyzed to identify its feeding behavior. However, the traditional image processing methods are difficult to effectively solve the problems of adhesion and occlusion between broiler flocks, and the recognition accuracy of images collected when the light is too dark will be too low [14].

With the development of artificial neural network technology and computer hardware, object detection algorithm based on deep learning has been well applied in animal behavior recognition and health detection [15,16]. The object detection based on depth learning mainly undertakes two tasks, which are to classify and locate objects in the image. Target detection algorithms are mainly divided into Two-stage target detection algorithm and One-stage target detection algorithm. The realization of Two-stage target detection algorithm is divided into two stages: target region extraction and classification recognition. Its representative algorithms are RCNN [17], Fast RCNN [18], Faster RCNN [19], SPPNet [20], etc. As the name implies, the network structure of this algorithm has the characteristics of two-stage, which makes the detection accuracy higher but the detection speed slower. One-stage target detection algorithm does not need to extract the target region that may contain the object to be detected, but directly divides the image into different size grids. Its representative algorithms are mainly series of YOLO (You Only Look Once) [21,22]. One-stage target detection algorithm can achieve the prediction of different size targets, and has better performance in detection speed and training speed [22,23].

In summary, in order to realize broiler behavior recognition and health monitoring in intensive farming environment, and to solve the problems of individual broiler targets sticking, obscuring and poor detection in complex scenes, this study constructs a YOLOv5-based broiler behavior recognition and health monitoring model for intensive farming. The model combined with the characteristics of broiler behavior in intensive farming environment, and evaluated the health status of broilers by identifying and outputting the occurrence time and center-of-mass distribution of different broiler behaviors.

II. Materials and Methods

Experiment environment and equipment

The experiment was conducted at the breeding base of Hunan Agricultural Equipment Research Institute, and the environment of the experimental site is shown in Figure 2. The broilers in the experiment lived in three-layered H-type laminated cages with individual cage dimensions of 700 mm x 700 mm x 450 mm (L x W x H). To ensure sufficient feeding space for each broiler, five broilers were housed in each compartment (average living space of per roiler was 4.41 x 107 mm3). The cages were arranged back-to-back, with a water supply pipe between the positive and negative cages. Each cage has two nipple-shaped water dispensers to supply water throughout the day. The cages are equipped with a push-in door and a food trough in front of the cage. The daily feeding time is 9:00 am. Broilers can drink and feed freely. A conveyor belt at the bottom of each layer is used to clean broiler manure regularly. Incandescent lamps are used for lighting in the broiler house during the experiment, with 18 h of light per day. The broiler house is cooled by wet curtain-fan system to maintain the ambient temperature at about 25℃. The image acquisition equipment was a Hikvision H16, installed at a distance of 560 mm from the cage net. To obtain a better view the lens is set in the center plane of the cage and tilted downward at an angle of 30° to the horizontal (as shown in the Figure 3). The daily behavior of broilers was recorded by video recording method during 8:00-24:00. The disturbance of the broilers by the staff should be avoided during the filming period [24]. The sick broilers we selected were naturally diseased, they walked less, preferred to lie down, moved slowly and were accompanied by some motor impairment. They were unable to maintain a standing position when walking and need to spread their wings to support their bodies as they moved forward. Most of them had some appetite, but their growth process was slow or stagnant.

Figure 2. Scene map of the experiment site.

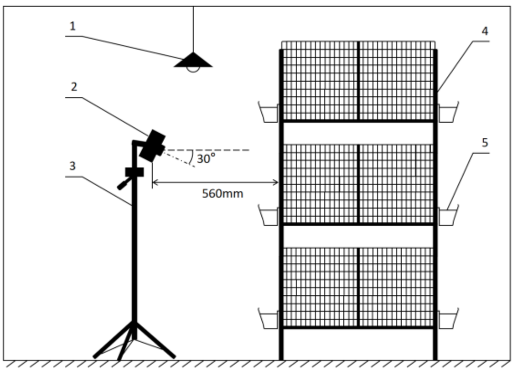


Figure 3. Schematic diagram of broiler house layout: (1) light source of broiler house,(2) image acquisition equipment, (3) tripod, (4) stacked broiler cages, (5) food trough.

Dataset preparation and labeling

We write a program to capture images from recorded videos, especially retaining images with too bright or dark lighting, overlapping blur and excessive adhesion. When the broiler visual recognition system performs real-time monitoring, the recognition effect is mainly affected by factors such as light intensity and overlapping obscuration of broilers. In order to improve the generalization ability of the model the original data set is processed using a data enhancement algorithm and different processing effects is shown in Figure 4.

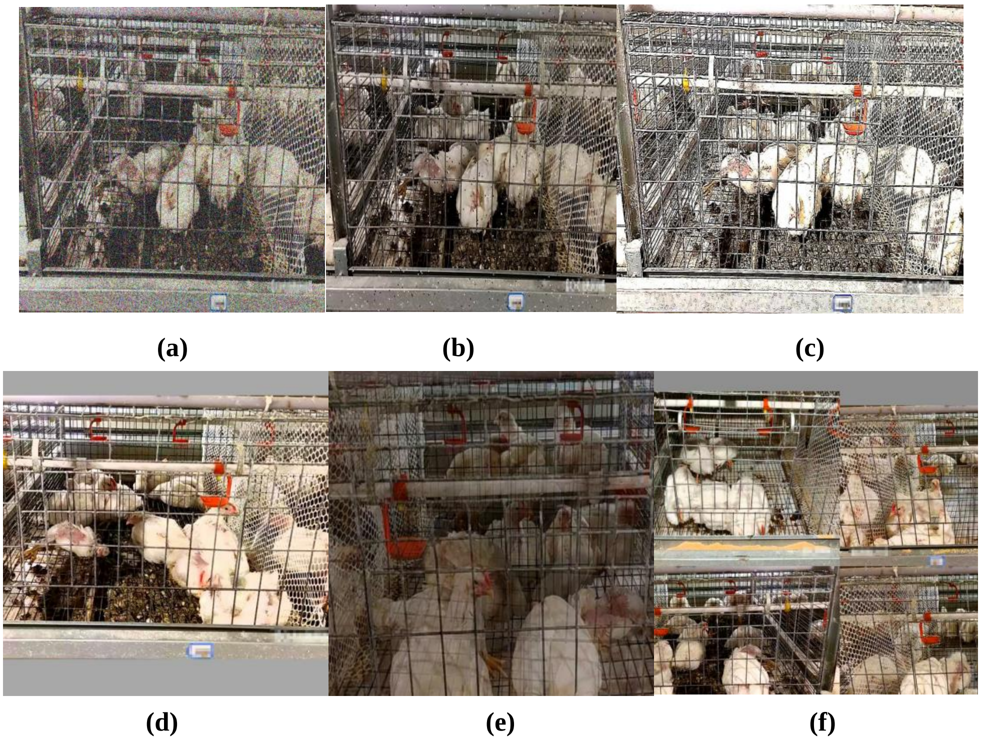


Figure 4. Schematic diagram of image enhancement algorithm: (a) gaussian noise, (b) random noise, (c) edge enhancement, (d) random, (e) mixup, (f) mosaic.

In order to enhance the algorithm's recognition of images that are not bright enough and not uniform in brightness and to reduce the influence of the image sensor's own noise and excessive temperature on the image, the data set is processed by the algorithms of random noise, gaussian noise and edge enhancement [25]. Then the data is augmented by three algorithms, random, mixup and mosaic, so as to enhance the recognition accuracy and generalization of the recognition model. Random data augmentation refers to first acquiring the image and target frame information, flipping the image randomly and scaling it up or down to a certain size, correcting the target frame information to the new image and pasting the new image to a random position on the gray canvas. Mixup is an algorithm for mixing class enhancement of images, which can mix images between different classes in a linear interpolation to construct a new training samples. Mosaic data enhancement reads four images at a time, flips, scales, and changes the color gamut of each of the four images and arranges them in four directions to combine the images and frames together.

Images were manually labeled using the LabelImg tool and four behaviors were distinguished and labeled, including lying, standing, eating and drinking. The criteria for determining broiler behavior are shown in Table 1. LabelImg tool, an open source graphic image labeling tool software from Github (https://github.com/heartexlabs/labelImg, accessed on September 25, 2022), is used to label images and generate corresponding XML files.

Table 1. Judgment standards of cage-reared broiler behaviors.

Behavior	Judgment Standard for Broiler Behavior
Lying	Broiler torso close to bottom of cage and head tucked in, legs bent or covered by body
Standing	Broiler torso away from the bottom of the cage, head extended or turned, legs spread
Eating	Broiler with their necks out of the cage and their heads near or in the trough
Drinking	Broiler standing, head extended and close to the nipple-shaped water dispensers

YoloV5 Network Structure

YOLOv5 is a One-stage target detection algorithm whose network structure is shown in Figure 5. YOLOv5 is divided into five main models, YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLO5x, for different sizes of inputs and network depth and width [26]. Among them, the Yolov5s' network model has a smaller depth and a smaller width of the feature map [27].

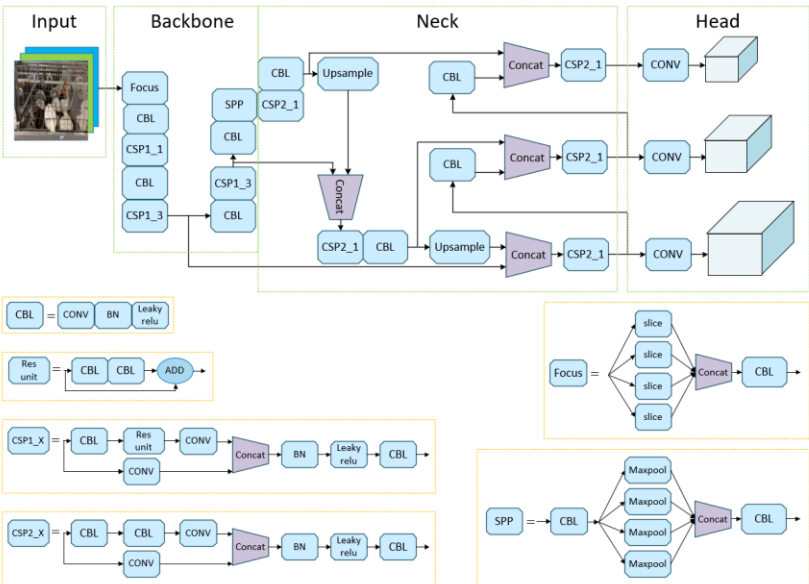


Figure 5. Diagram schematic of YOLOv5 network structure.

Yolov5 mainly consists of Input, Backbone, Neck, Head four parts [28]. The core function of Input is to perform Mosaic data enhancement, adaptive anchor frame calculation and adaptive image scaling on the input image. The Backbone part uses the Focus structure to perform the key slicing operation. Original images are input to the Focus structure, the slicing operation is performed to generate the feature map, and then the convolution operation with 32 convolution kernels is performed to finally generate the new feature map. By this way, the number of feature maps is reduced and the number of channels becomes more [29].

YOLOv5 is designed with two CSP structures, taking YOLOv5s as an example, the CSP1_X structure is applied to Backbone and the CSP2_X structure is applied to Neck. The convolution kernel in front of each CSP module is 3x3 size and the step size is 2, which can play the role of downsampling [30]. The CSP module first divides the feature mapping of the base layer into two parts, then merges them through the cross-stage hierarchy to reduce the computational effort and ensure the accuracy. The Neck part uses the structure of FPN+PAN [31]. FPN fuses the high-level feature information by upsampling to obtain the feature map for prediction. A bottom-up feature pyramid containing two PAN structures is also added behind the FPN layer. Based on these, YOLOv5 chooses the CSP2 structure instead of the normal convolution used in the Neck part of YOLOv4 in order to enhance the network feature fusion [32].

Data Set Training

The behavior of broilers under intensive breeding environment is divided into four categories: lying, standing, eating and drinking. The 2468 images collected at different angles and light intensities at different times, are randomly divided into training set, validation set and test set in the ratio of 8:1:1 to construct image dataset for broiler behavior detection under intensive breeding environment.

This experiment is based on Windows 10, 64-bit operating system, Intel (R) Core (TM) i9-10920X CPU@3.50GHz, NVIDIA TITAN RTX GPU, PyTorch 1.8.1 deep learning framework, Pycharm integrated development environment, Python 3.8 development language, CUDA 11.1 parallel computing framework and cuDNN acceleration library. This training includes 300 epochs, the batch size is set to 6, the lr0 (initial learning rate) is set to 0.01.

III. Results

Training results of YoloV5 model

The behavioral training set of broiler broilers in intensive farming environment is used for training, and the model is validated using the validation set after each training. The variation of the loss function values during the training process is shown in Figure 6.

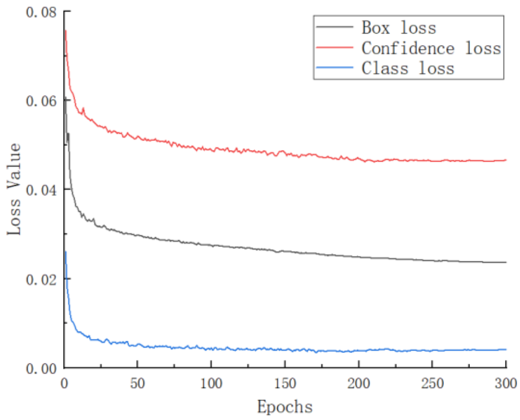


Figure 6. Variation of loss function values with epochs.

In this paper, three loss functions are used to evaluate the convergence of the model: box loss, confidence loss, class loss, where box loss is used to describe the error between the prediction box and the calibration box, confidence loss is used to calculate the confidence level of the network, and class loss is used to calculate whether the anchor box is correctly classified with the corresponding calibration box. The class loss is used to calculate whether the anchor box is correctly classified with the corresponding calibration [33]. As shown in Figure 6, with the increase of Epochs, all loss functions gradually decrease and finally stabilize. regression box loss is close to 0.024, confidence loss is close to 0.047, and classifification loss converges to about 0.004. Thus, it can be seen that after After 300 Epochs of training, the loss function of the model converges to the ideal level.

To evaluate the effectiveness of model for detecting the behavior of broilers under intensive farming, Precision, Recall, AP (Average Precision), and MAP (Mean Average Precision) were selected as indicators in this study and calculated as follows.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

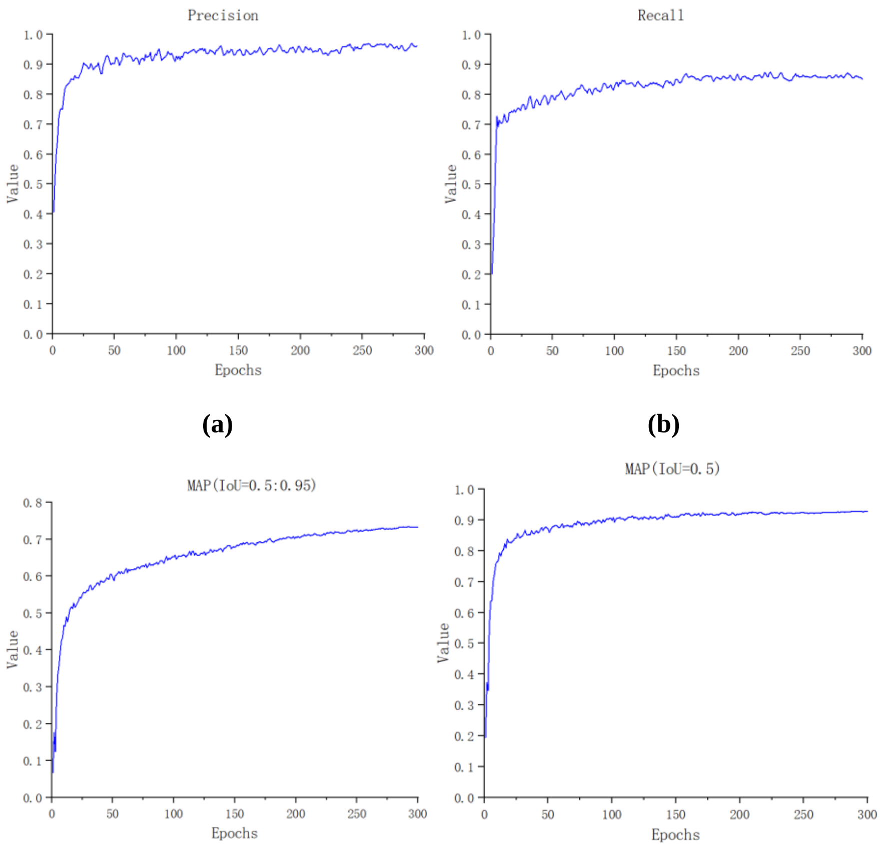
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{AP} = \int_0^1 \text{P(R)dR} \tag{3}$$

$$\text{MAP} = \frac{\sum_{i=1}^{k} \text{AP}_i}{k} \tag{4}$$

Where TP denotes positive samples whose behaviors were correctly identified, FP denotes negative samples misidentified as existing categorized behaviors, and FN denotes positive samples misidentified as other behaviors; P denotes Precision, R denotes Recall [34]; and k denotes the number of categories of behaviors [35].

After each round of training, the model was tested against the test set using the model, and the changes of the four indicators Precision, Recall, MAP (IoU=0.5:0.95) and MAP (IoU=0.5) during the training process are shown in Figure 7. As the number of training epochs increases, the values of the four metrics gradually increase and finally oscillate in a certain range and stabilize. Precision stabilizes around 0.96, Recall stabilizes around 0.85, MAP (IoU=0.5:0.95) stabilizes around 0.73, and MAP (IoU=0.5) stabilizes around 0.92. It shows that the model has high accuracy in detecting broiler behavior in intensive farming environment. The best results of the model on the test set during the training process selected in this paper are shown in Table 2.



(a) **(b)** **(c)** **(d)**

Figure 7. Variation of evaluation index values of the model in the test set with epochs: (a) curve of Precision, (b) curve of Recall, (c) curve of MAP (IoU=0.5:0.95), (d) curve of MAP (IoU=0.5).

Table 2. Best test results of YOLOv5.

Evaluation Index	Classification			
	Drinking	Eating	Lying	Standing
Precision	96.20%	97.40%	95.40%	91.40%
Recall	82.80%	89.60%	90.20%	82.10%
AP	91.00%	95.00%	95.10%	89.50%
mAP	92.60%			

As can be seen from Table 2, the recognition performance of the model for all four behaviors can meet the detection accuracy requirements. The Precision of the four behaviors were 96.20% for drinking, 97.40% for eating, 95.40% for lying , and 91.40% for standing.AP of the above four behaviors were 91.00% for drinking, 95.00% for eating, 95.10% for lying, and 89.50% for standing.Figure 8-9 shows some of the behavioral detection results, and the prediction frame consists of categories and confidence levels (drinking abbreviated to drink, other behaviors are similar). Figure 8 shows the detection results at different angles. The top half of Figure 9 shows the comparison of detection results at different densities, and the bottom half shows the comparison of detection results at different brightnesses. It can be seen that the above four behaviors of broiler in intensive breeding environment can be accurately identified under different densities, angles and light intensities.

Figure 8. Detection results at different angles.

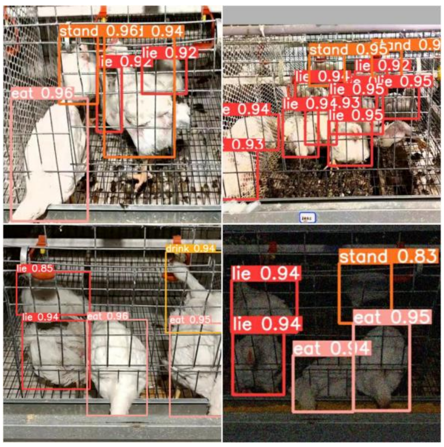


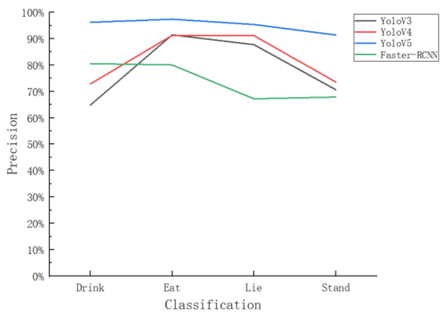
Figure 9. Detection results at different densities and light intensities.

Performance comparison of different target detection algorithms

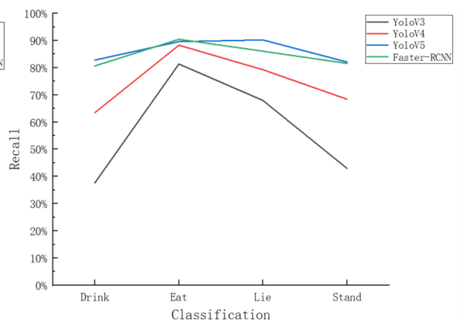
The algorithms for deep learning-based target detection are developing rapidly and there are many kinds. In this study, we selected the representative Faster RCNN algorithm among Two- stage target detection algorithms and the representative YoloV3, YoloV4, and YoloV5 algorithms among One-stage target detection algorithms to experiment for performance comparison, respectively. The experiments of the above algorithms used a unified dataset of broiler behavior detection under intensive farming environment, and the training steps were similar to YoloV5. Finally the best trained model was used for broiler behavior detection respectively. The experimental results are shown in Table 3.

Table 3. Comparison of the performance of the models.

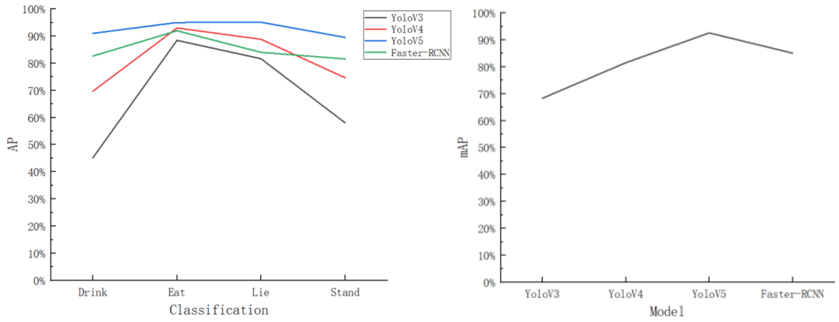
Model	Classification	Precision	Recall	AP	MAP (IoU=0.5:0.95)	FPS
YoloV3	Drinking	64.81%	37.63%	45.14%	68.32%	51.76
	Eating	91.46%	81.34%	88.44%		
	Lying	87.75%	67.96%	81.67%		
	Standing	70.67%	42.98%	58.05%		
YoloV4	Drinking	72.84%	63.44%	69.67%	81.53%	53.36
	Eating	91.26%	88.29%	92.98%		
	Lying	91.17%	79.26%	88.81%		
	Standing	73.58%	68.42%	74.65%		
YoloV5	Drinking	96.20%	82.80%	91.00%	92.60%	69.44
	Eating	97.40%	89.60%	95.00%		
	Lying	95.40%	90.20%	95.10%		
	Standing	91.40%	82.10%	89.50%		
Faster RCNN	Drinking	80.56%	80.65%	82.64%	85.05%	16.69
	Eating	80.04%	90.46%	91.97%		
	Lying	67.21%	86.09%	84.01%		
	Standing	67.88%	81.58%	81.58%		



(a)



(b)



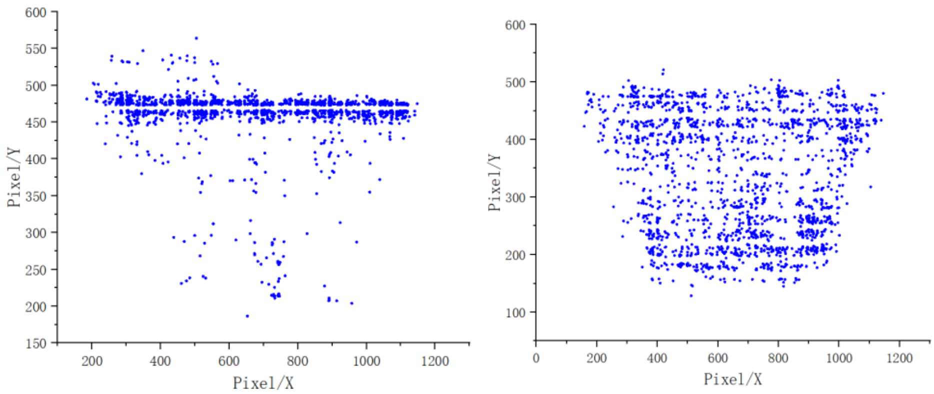
(c) (d)

Figure 10. The results of different algorithms: (a) chart of Precision of four behaviors, (b) chart of Recall of four behaviors, (c) chart of AP of of four behaviors, (d) chart of MAP (IoU=0.5:0.95) of four behaviors.

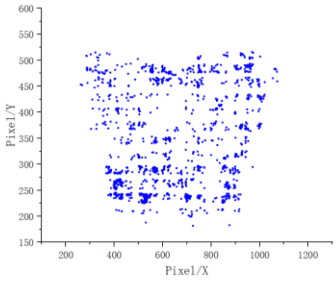
From Figure 10, it can be seen that for the detection of four behaviors yolov5 has the best overall performance of each performance to meet the accuracy of recognition. YOLOv5's Precision of detecting four behaviors is 96.20% for drinking, 97.40% for eating, 95.40% for lying, and 91.40% for standing, and the AP is 91.00% for drinking, 95.00% for eating, 95.10% for lying, and 89.50% for standing. Among them, eating and drinking have obvious features during training, so they can obtain better recognition accuracy. Due to the imbalance of lying behavior in the training set, the recognition accuracy of the model for lying behavior is significantly higher than that of standing behavior. Due to the high frequency and distinct behavioral characteristics of the feeding behavior samples, all models had better prediction results for feeding behavior, 91.46%, 91.26%, 97.40%, and 80.04%, respectively.There are poorer prediction results for standing behavior, 70.67%, 73.58%, 91.40%, and 67.88%, respectively, which was also due to the unbalanced sample size and ambiguous characteristics of standing behavior. In MAP YOLOv5 has the highest value which means better overall performance. Better still, YOLOv5 also has a higher FPS (Frame Per Second) which means fast enough to achieve real-time detection.

Behavior analysis of healthy broiler flocks

The health condition of the broiler flock will be reflected in its behavioral distribution, so the videos are taken for the healthy broilers, and their daily status is divided into three parts: feeding stage, activity stage and rest stage for analysis. The 360 frames are randomly selected from each stage of the video, and the behavior of individual target broilers is identified by deep learning algorithm, and the location information of the target is outputted by the algorithm to get the distribution of the center of mass of the healthy flocks under each stage.



(a) **(b)**

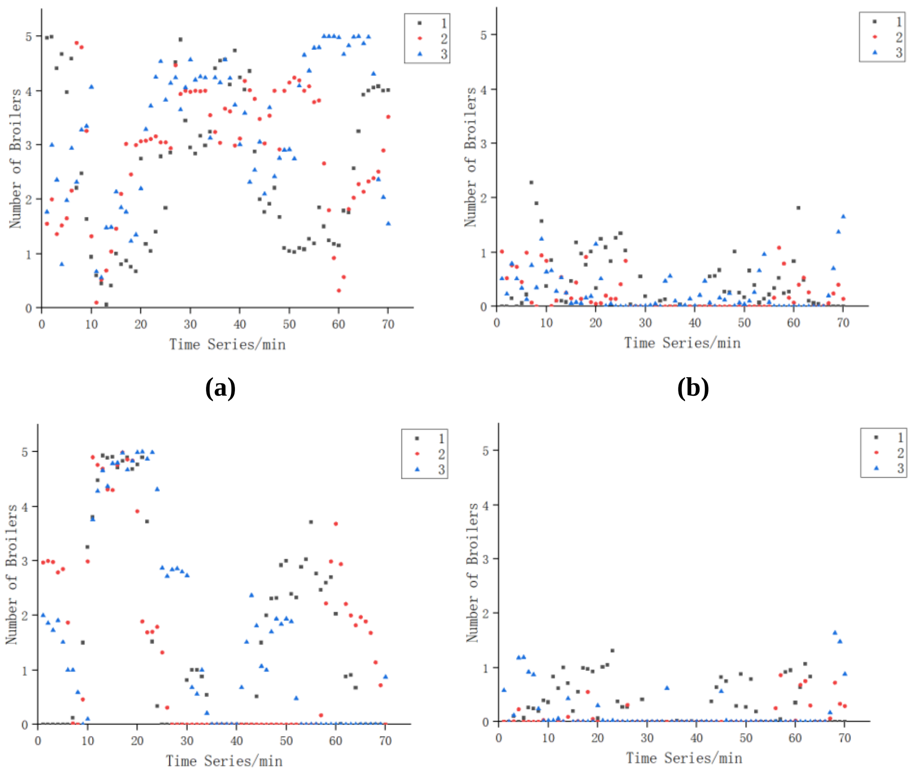


(c)

Figure 11. Centroid distribution of broilers at each stage: (a) feeding stage, (b) activity stage, (c) rest stage.

In the feeding stage, the distribution of individual broilers is more concentrated, most of the broilers feeding behavior gathered near the trough, a very small number of individuals will move away from the trough; in the activity stage after feeding, individual broilers have more freedom of movement, behavior is not affected by other individuals, there are more standing, walking, drinking and other behaviors, the distribution is more scattered; after entering the resting stage, the behavior of the broilers is mainly lying down, there will be part of the situation of piling up, more piling up occurs in the position close to the cage around.

In order to investigate the behavioral changes of broilers during feeding, three cages were randomly selected and the videos were intercepted 10 min before feeding and 60 min after feeding for detection. The four behaviors of broiler lying, standing, eating and drinking were identified and the number of broilers with each behavior was recorded with time series as shown in Figure 12.



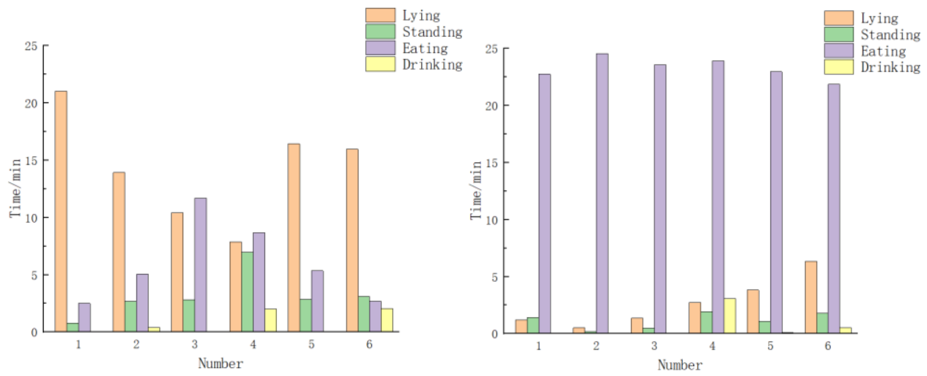
(a) **(b)**

(c) **(d)**

Figure 12. Statistics on the number of broilers with different behaviors: (a) lying, (b) standing, (c) eating, (d) drinking.

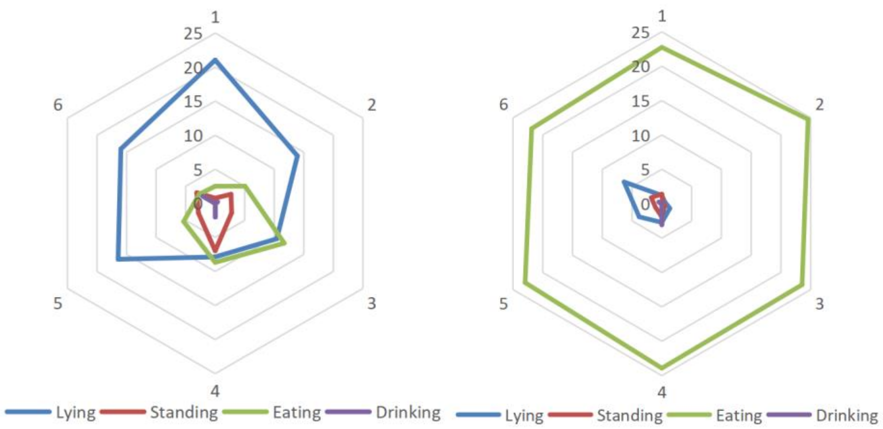
It can be seen that the number of different behaviors of broilers before and after feeding has a large change from Figure 12.Ten min before feeding, the behavior of broilers is mainly lying yet broilers of drinking is less. Broilers have a strong desire to feed after a night's rest and will frequently approach the trough to look for food, if there is leftover feed in the trough from the previous day then a few broilers will carry out eating behavior at this time.Other broilers are mainly resting, at this moment the whole flock is in the resting stage. Within 5 min after feeding by the keeper, the flock quickly gathered in front of the trough and the number of eating broilers increased rapidly, with an average of 4.6broilers/min. After a period of continuous eating, the number of eating broilers began to decline. After 20-30 min of feeding most broilers finished eating and the number of lying broilers began to increase gradually, while standing and drinking behavior started to appear frequently.

For further analysis, six cages containing five broilers each were randomly selected to record videos for 5 min each before and after feeding for detection. The time of the same behavior of broilers in the same cage within 5 minutes were identified and superimposed to obtain the time when the different behaviors occurred in the 6 cages before and after feeding, as shown in Figure 13. The distribution of the time of different behaviors occurring before and after feeding is shown in Figure 14.



(a) **(b)**

Figure 13. Statistics of different bahavior occurrence time: (a) bahavior occurrence time before feeding, (b) bahavior occurrence time after feeding.



(a) **(b)**

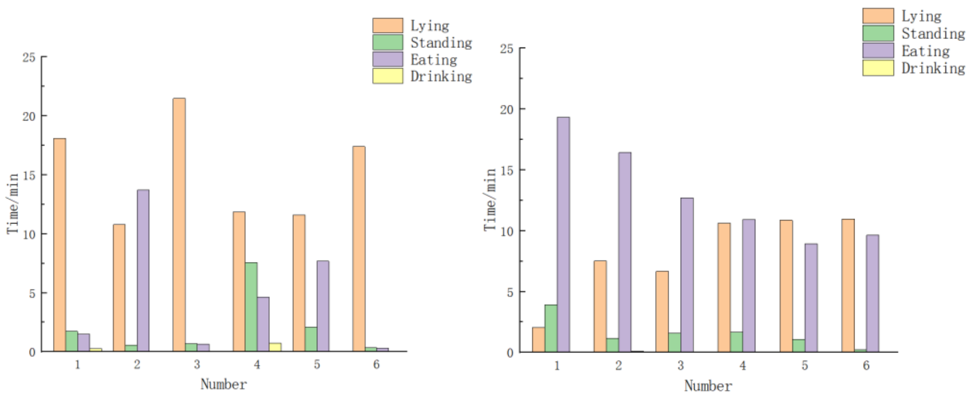
Figure 14. Time distribution of different behaviors: (a) distribution of behaviors before feeding, (b) distribution of behaviors after feeding.

The mean values of lying, standing, eating, drinking time were calculated as 14.27 min, 3.19 min, 5.99 min, 0.76 min and 2.65 min, 1.14 min, 23.27 min, 0.62 min respectively before and after 5 minutes of feeding. Before feeding the broilers were in the resting stage and less active, where the mean value of lying time was up to 14.27 min. Some time after feeding, the flock was in the feeding stage and became active. The mean value of lying time decreased to 2.65 min, and the mean value of eating time increased, which was 23.27 min after the increase.

The radar plot clearly shows that before feeding, without disturbance, the broilers were not very active and resting, with occasional eating behaviors. After feeding, the flock became active and eating was the main behavior. The major differences in the behavior of broilers before and after feeding were lying behavior and eating behavior. Therefore, the timing of the occurrence of eating and lying behavior can be used as a criterion to determine whether the flock is feeding normally.

Behavior comparison of broilers pre and post feeding under different health conditions

To analyze the target behavior of broilers at different health levels, six control groups were added to the experiment, 1 sick broiler, 2 sick broilers, and 3 sick broilers, respectively. And two data sets were selected for each condition, where the sick broilers were randomly selected naturally sick broilers. We photographed and recorded each broiler cage before and after feeding. The behavioral time of control groups are shown in Figure 15.



(a) **(b)**

Figure 15. Statistics of behavioral time of control groups: (a) bahavior occurrence time before feeding, (b) bahavior occurrence time after feeding.

The results of the control group showed that the behavior of broilers before feeding was still mainly lying with occasional eating behavior, after feeding lying behavior decreased and eating behavior increased. With the increase of the number of sick broilers in the cage, the occurrence of eating behavior within 5 min after feeding showed a decreasing trend and lying behavior showed an increasing trend. The mean value of standing time before feeding was 3.19 min in healthy flocks and 2.17 min in diseased flocks, which indicate that the occurrence of standing behavior in diseased flocks was less than that in healthy flocks before feeding. The mean value of eating time was 23.27 min and the mean value of lying time was 2.65 min after feeding for healthy flocks. Using them as thresholds and comparing them with the control group respectively, it was found that the cages containing diseased broilers had significantly lower time of eating than 90% of the threshold value for healthy flocks and there was a substantial increase in the time of lying behavior. For group 2 data the flock with more eating time before feeding was analyzed for the reason that the dying broilers did not eat feed the previous day resulting in more leftover feed in the trough, thus causing more eating behavior in other healthy broilers before feeding.

IV. Conclusion

Today's broiler cages of intensive farming model have more floors, and it is not convenient for farmers to inspect too high or too low floors, which can easily lead to sick broilers not being detected in time. Therefore, the use of camera technology can easily capture the locations that are difficult for farmers to reach, reducing work intensity, improving work efficiency, and also reducing human interference with poultry. This study shows that the YOLOv5-based broiler behavior recognition and health monitoring model can identify the behavior of adhesive and masked broilers in intensive farming environment, and can evaluate the health level of the flock by analyzing the behavior recognition results. The MAP (IoU=0.5:0.95) of the model proposed in this study for broiler behavior detection in intensive farming reached 92.60%, which is 24.28%, 11.07%, and 7.55% higher than the traditional models such as YOLOv3, YOLOv4, and Faster RCNN, respectively; the AP of the model for detecting four behaviors were 91.00% for drinking, 95.00% for eating, 95.10% for lying, 89.50% for standing, and the detection speed can reach 69.44fps, which can meet the requirements of real-time detection on the basis of the detection accuracy. On this basis, the time of occurrence of the four behaviors of caged broilers during feeding was recorded. The comparison results showed that the differences in lying and eating behaviors of healthy broilers before and after feeding were large. The lying behavior decreased significantly and the eating behavior increased significantly within 5 min after feeding. Further, in this paper, a comparison experiment was conducted between healthy and diseased flocks, and it was found that there were significant differences in eating and lying behaviors between diseased flocks and healthy flocks within 5 min after feeding. As the number of sick broilers in the cage increased, the time of eating behavior decreased and lying behavior increased. When the mean value of eating behavior and the mean value of lying behavior after feeding were used as thresholds in healthy flocks and compared with diseased control flocks, it was found that the time of eating behavior in cages containing diseased broilers was significantly lower than 90% of the threshold value in healthy flocks, and the time of lying behavior of diseased flocks also increased significantly. Therefore, abnormalities in the time of occurrence of lying behavior and eating behavior during feeding can be used as criteria for assessing the health of the flock.

The behavior identification and health assessment method of intensively farmed broilers based on YoloV5 has a certain reference value for subsequent behavior identification and poultry health assessment, promoting the development of poultry health detection under intensive farming model. However, there are still many representative issues that need to be addressed and more exploratory work is needed. In future research, we can improve the speed of detection while ensuring the accuracy of identification, so that the efficiency of real-time detection can be improved. At the same time, the identification accuracy of sick broilers can be improved, and the criteria for assessing the health level of broiler flocks can be refined to be able to achieve a quantitative assessment of the overall health level of flocks. Future work will further integrate animal behavior and deep learning and apply them to more areas of other poultry and livestock to improve the scientific and applicability of the research.

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