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Detecting broiler chickens on litter floor with the YOLOv5-CBAM deep learning model

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A B S T R A C T

For commercial broiler production, about 20,000–30,000 birds are raised in each confined house, which has caused growing public concerns on animal welfare. Currently, daily evaluation of broiler wellbeing and growth is conducted manually, which is labor-intensive and subjectively subject to human error. Therefore, there is a need for an automatic tool to detect and analyze the behaviors of chickens and predict their welfare status. In this study, we developed a YOLOv5-CBAM-broiler model and tested its performance for detecting broilers on litter floor. The proposed model consisted of two parts: (1) basic YOLOv5 model for bird or broiler feature extraction and object detection; and (2) the convolutional block attention module (CBAM) to improve the feature extraction capability of the network and the problem of missed detection of occluded targets and small targets. A complex dataset of broiler chicken images at different ages, multiple pens and scenes (fresh litter versus reused litter) was constructed to evaluate the effectiveness of the new model. In addition, the model was compared to the Faster R-CNN, SSD, YOLOv3, EfficientDet and YOLOv5 models. The results demonstrate that the precision, recall, F1 score and an mAP@0.5 of the proposed method were 97.3%, 92.3%, 94.7%, and 96.5%, which were superior to the comparison models. In addition, comparing the detection effects in different scenes, the YOLOv5-CBAM model was still better than the comparison method. Overall, the proposed YOLOv5-CBAM-broiler model can achieve real-time accurate and fast target detection and provide technical support for the management and monitoring of birds in commercial broiler houses.

1. Introduction

Poultry provides a valuable source of proteins but face a number of challenges worldwide. Among the many challenges is the welfare concerns of the birds under intensive management systems (Chai et al., 2018, 2019). Due to the large number of chickens reared at any given time in a house, accurate and efficient monitoring of birds can improve their health and welfare status (Li et al., 2021; Okinda et al., 2020). Currently, most broiler houses are monitored manually, however, this approach could be both laborious and erroneous. Automatic broiler monitoring system could collect individual bird data within a flock and provide critical information to aid digital management (Subedi et al., 2023a, 2023b; Yang et al., 2022).

Computer vision technology (CVT) is widely used to monitor farm animals because it is non-invasive (Qin et al., 2021; Wang et al., 2022; He et al., 2016). The CVT together with machine vision methods have achieved target detection based on the features of the target area (e.g., color, shape, texture). The ability to effectively acquire these visual features will affect the accuracy of target detection (Tharwat et al., 2014; Awad et al., 2013; Andrew et al., 2017). The feature acquisition method, external environment (e.g., light intensity and occlusion), shooting angle and image quality chosen are crucial parameters that will affect target detection. Therefore, it is important to innovate animal target detection algorithms that are less affected by the natural environment.

Deep learning technology has powerful feature representation capabilities, fast processing speed, and can resolve problems associated with external interferences. Thus, deep learning algorithms are appropriate models for developing an automatic, efficient and intelligent tool for animal farming (Qiao et al., 2021). Deep learning technologies have been applied to the study of large animals (pigs, sheep, cattle), such as object

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detection, individual tracking, behavior recognition and body condition evaluation (Chen et al., 2021; Xue et al., 2021; Tian et al., 2019; Qiao et al., 2019; Shen et al., 2020; Alvarez et al., 2019; Guo et al., 2021a, 2022). However, the size of the chicken and the sheer numbers that are raised in a single house (e.g., 20,000–30,000 chickens on litter floor of 2000–2500 m^2) pose challenges in applying deep learning techniques in monitoring individual chickens (Guo et al., 2020). Yang et al. (2022) built a YOLOv5x-hens model, which detection is highly efficient and over 95% accurate. Fang et al. (2020) proposed poultry tracking algorithm TBroiler tracker which has good performance in overlap rate, pixel error and failure rate, and its hybrid tracking performance evaluation (MTPE) is 0.730. Fang et al. (2021) analyzed the behavior of broiler using DNNs.

The tests showed that the accuracy of standing, walking, running, eating, resting and tidying behavior recognition was 0.7511, 0.5135, 0.6270, 0.9361, 0.9623 and 0.9258, respectively. Although the above research has made some progresses, however, there is a lack of poultry research at different ages, feeding environments, and densities. And object detection is the premise of behavior recognition and target tracking, and it is also the data basis for providing target area information. Therefore, target detection of broiler groups in multiple scenarios is of great significance. Among the deep learning algorithms, YOLO series is one of the fast and high precision algorithms for multi-target detection at present (Subedi et al., 2023a, 2023b; Ge et al., 2021;Bochkovskiy et al., 2020). When targets are small or occluded YOLO can result in missed or false detections. There are attention mechanisms in deep learning that can reduce information loss and improve the detection performance of occlusion and small object.(Yang et al., 2023; Li et al., 2020; Fukui et al., 2019).

In the current study, we incorporated a convolutional block attention module (CBAM) into YOLOv5 to enhance the algorithm's ability to extract image features. To do this, we used a complex dataset of broiler images (e.g., birds at different ages, fresh and reused litter and multiple pens) to train and test the model. The proposed YOLOv5-CBAM improved the acquisition ability of small object features and the accuracy of small target detection.

2. Material and methods

2.1. Data acquisition

The data for this study came from an experimental broiler house at the Poultry Research Center of the University of Georgia, USA (Guo et al., 2020; Guo et al., 2021b). Two different litter types (fresh pine shavings and reused litter previously used to raise three flocks of broilers) were selected as application scenes for broiler detection. For the two litter scenes, 70 images were selected from d2, d9, d16, and d23, respectively, for a total of 560 images. In addition, to evaluate the detection performance of the model under multiple pens scenes, the image samples shown in Fig. 1c were constructed, in which 70 images were selected for d16 and d23. Finally, 700 images were obtained and randomly assigned at a ratio of 5:2 into training and testing set, respectively. Fig. 1 are examples of broiler images from different scenes.

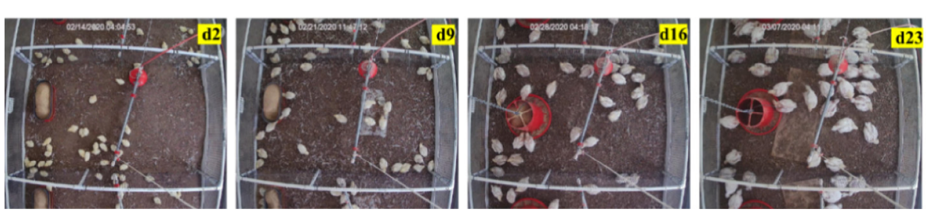
2.2. YOLOv5-CBAM model for broiler detection

In the current study, we propose a YOLOv5-CBAM-broiler model (Fig. 2). This method added CBAM attention modules to the backbone and neck layers of YOLOv5 to improve the feature representation capability.

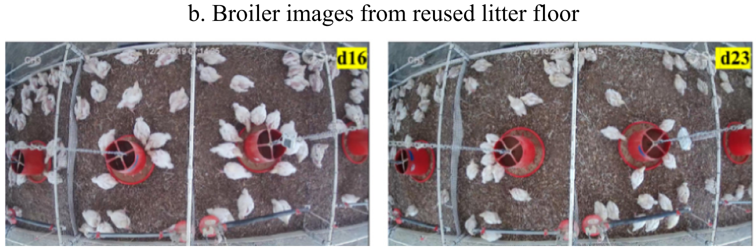
2.2.1. The YOLOv5 network

Jocher et al. (2020) developed the YOLOv5 algorithm and demonstrated that it was more accurate and faster compared to the previous YOLO model. The YOLOv5s network consists of three parts: backbone, neck, and prediction. Broiler chicken images were used as input for the backbone to obtain image features, the neck part was used to integrate the extracted feature information and generate feature maps, and the prediction part was used to generate bounding boxes and predict categories for the generated feature maps. The detailed process is provided as a supplementary material.

a. Broiler images from fresh pine shavings floor



b. Broiler images from reused litter floor



c. Broiler images from multiple pens floor

Fig. 1. Examples of broiler images from different scenes.

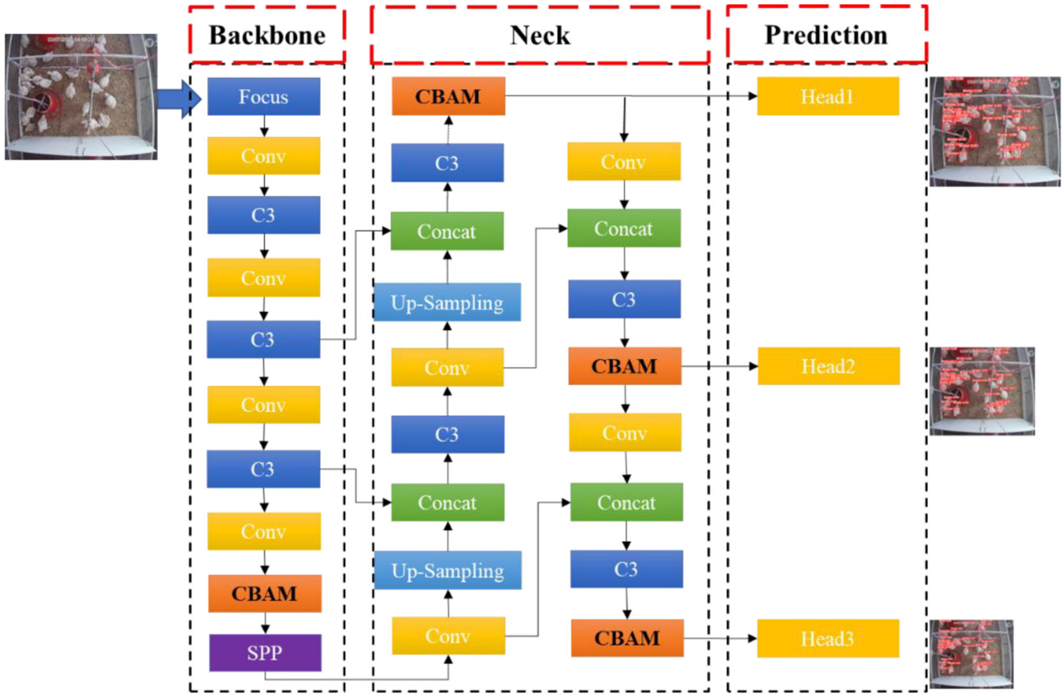


Fig. 2. The overall structure of YOLOv5-CBAM network.

The Backbone part of the model is used to extracted different fine-grained features from images, as shown in Fig. 2, the original backbone network is composed of Focus, Conv, C3 and Spatial Pyramid Pooling (SPP). The bird image size in the YOLOv5s model was 416 × 416 × 3, which became 208 × 208 × 12 through the focus slicing operation, and the final feature map size became 208 × 208 × 32 after convolution with 32 convolution operation kernels. C3 is used to extract broiler image features. In the Backbone part, the C3 module contains detailed location information, but less semantics. The SPP is used to concatenate feature maps of different sizes together as an output (He et al., 2015). In the Neck part, the C3 module extracts features, which contains less location information, but more semantics. After the feature information of occluded or small targets are processed by C3 modules, the target position information is rough, and the feature information can be easily lost. The Head part predicts the processed broiler image features in three different scales, generates bounding boxes and predicts the class of objects. The Head part in YOLOv3 was used as YOLOv5 Head.

To improve the detection accuracy of the original model for broiler targets at different growth stages and feeding scenes, we herein propose an improved YOLOv5 network model, as shown in Fig. 2. The CBAM module was added to Backbone and Neck and placed after the C3 module. The CBAM module can strengthen the learning of occlusion or small target feature information during the network training process through the channel and spatial attention modules.

2.2.2. The CBAM attention module

In the target detection task of broiler chickens at different growth stages and in different scenes, occlusion or small targets occupy fewer pixels, and their feature information is easily lost in the deep network, which leads to missed and false detection of targets. The CBAM module can effectively increase the weight of the occlusion or small targets in the entire feature map through channel and spatial attention modules, making the information easier to be learned by the network (Woo et al., 2018). The broiler image features extracted from the C3 module were denoted as F, and the channel attention map was generated by using the channel relationship between features, which was multiplied by F to form a new feature F′ to enhance the features related to the target area of bird. Then, the spatial attention feature map was generated by using the internal spatial relationship between features, which multiplied with F′ to obtain F″, which strengthened the weight of broiler target area features from the channel and spatial relationship between features. As shown in Fig. 3.

2.2.2.1. Channel attention module. The channel attention module information is extracted using max pooling and average pooling, respectively, and then filtered, activated and normalized to improve the ability to extract channel information.

As shown in Fig. 3a. First, the feature map $F \in R^{(C\times H\times W)}$ is inputted, and the feature map of size $C \times H \times W$ is transformed into $C \times 1 \times 1$ using maximum pooling and average pooling. Then the feature map is entered into the neural network MLP, the number of neurons in the first layer is C/r, r is the decline rate, and the activation function is *Relu*. The number of neurons in the second layer is C, and then the results are combined through the addition operation. The weight coefficient $M_c \in R^{(C\times 1\times 1)}$ is obtained through the *sigmoid* function, as shown in Eq. (1).

$$M_c(F) = \sigma\left(W_1\left(W_2\left(F^c_{avg}\right)\right) + W_1\left(W_2\left(F^c_{max}\right)\right)\right) \quad (1)$$

where, σ is the sigmoid function; F^c_{avg} and F^c_{max} represent the feature maps after average and maximize pooling; W_1 and W_2 represent the weights of two layers of a multilayer perception. Then, the channel attention feature map F' is obtained by multiplying M_c with the original feature map F.

2.2.2.2. Spatial attention module. The spatial attention mechanism focuses on local information. The information is filtered by pooling, and then the important information is extracted by convolution from the filtered information. As shown in Fig. 3b. Using F' as input into the spatial attention module, it is also pooled with maximum and average, stacked by the *Concat* operation, and then the weight coefficient $M_s \in R^{(1\times H\times W)}$ is obtained by convolution operation and *sigmoid*, as shown in eq. (2).

$$M_s(F') = \sigma\left(f^{7\times 7}\left(\left[F'^S_{avg}; F'^S_{max}\right]\right)\right) \quad (2)$$

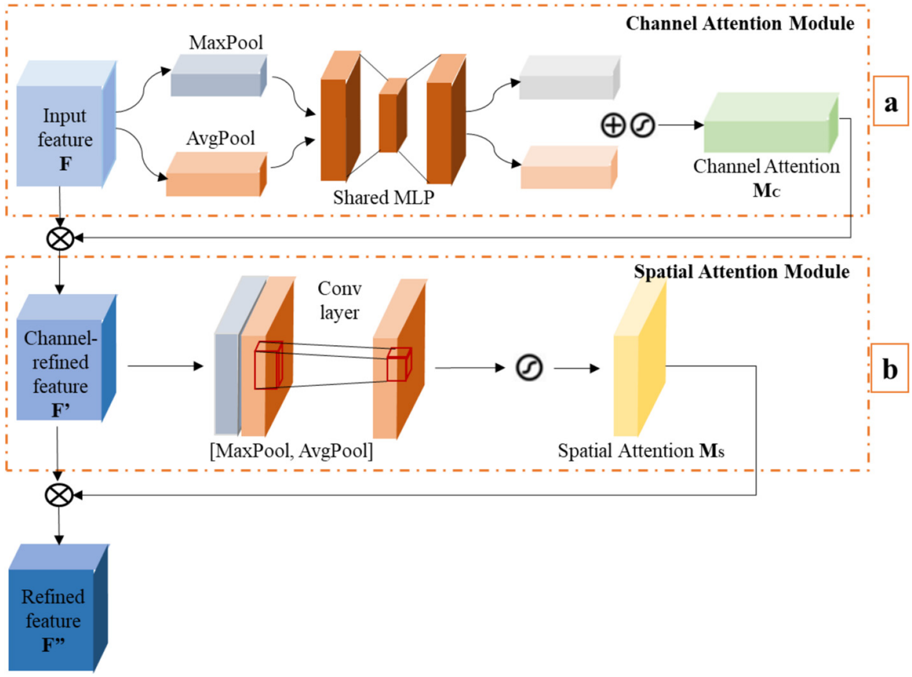


Fig. 3. The structure of the CBAM module.

where, σ is the sigmoid function; F'^{s}_{avg} and F'^{s}_{max} represent the feature maps of size $1 \times H \times W$ after average and maximize pooling; $f^{7\times7}$ represents 7×7 convolution. Lastly, the M_s and F′ are multiplied to obtain the final attention feature map F''.

2.3. Performance evaluation

In the current study, precision, recall, F1 score, mean average precision (mAP) and Frames Per Second (FPS) were adopted as the metrics of the detection accuracy, as shown in the following equations:

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

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

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

$$AP = \int_0^1 P(r)dr \quad (6)$$

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP(i) \quad (7)$$

where, TP, FP and FN are the numbers of true positive samples, false positive samples and false negative samples, respectively. The mAP is the mean of all classified AP (Average Precision). n represents the number of object categories ($n = 1$). FPS refers to the number of images identified within 1 s.

2.4. Network training parameters

In this study, all model tests were performed on a computer equipped with a GeForce GTX 1080 Ti GPU, I9-7920× CPU@2.9 GHz. Parameter settings: $416 \times 416 \times 3$ input size, 1000 training period, 16 batch size, 0.0013 learning rate. Other parameters are their default settings.

I Faster R-CNN (Ren et al., 2015), SSD (Liu et al., 2016), YOLOv3 (Redmon and Farhadi, 2018), EfficientDet (Tan et al., 2020) and YOLOv5s (Liu et al., 2021) serve as comparison models.

3. Results

3.1. Performance of new detection model

We used datasets consisting of broiler images at different ages, raised on two types of litter and multiple pens to test the performance of YOLOv5-CBAM. The detection results of broiler with different models

Table 1
Performance comparison of different algorithms (%).

Method	Precision	Recall	F1	mAP@0.5	FPS (Frame/s)
Faster-rcnn	79.7	95.4	86.8	90.6	2.6
SSD	60.8	94.0	73.8	88.5	3.1
YOLOv3	83.7	83.0	83.3	70.6	18.9
EfficientDet	97.0	47.0	64.0	59.6	36
YOLOv5	96.6	92.1	94.3	96.3	62
YOLOv5-CBAM	97.3	92.3	94.7	96.5	55

Table 2
Comparison of detection accuracy in different scenes.

Method Precision	Fresh pine shavings				Reused litter				Multiple pens	
	d2	d9	d16	d23	d2	d9	d16	d23	d16	d23
Precision of YOLOv5	95.1	99	98.6	92.8	94.3	99	99.1	98.7	92.2	98.6
Precision of YOLOv5-CBAM	96.1	99.3	99.3	94	95.2	98.9	99.3	99.3	92.5	98.8

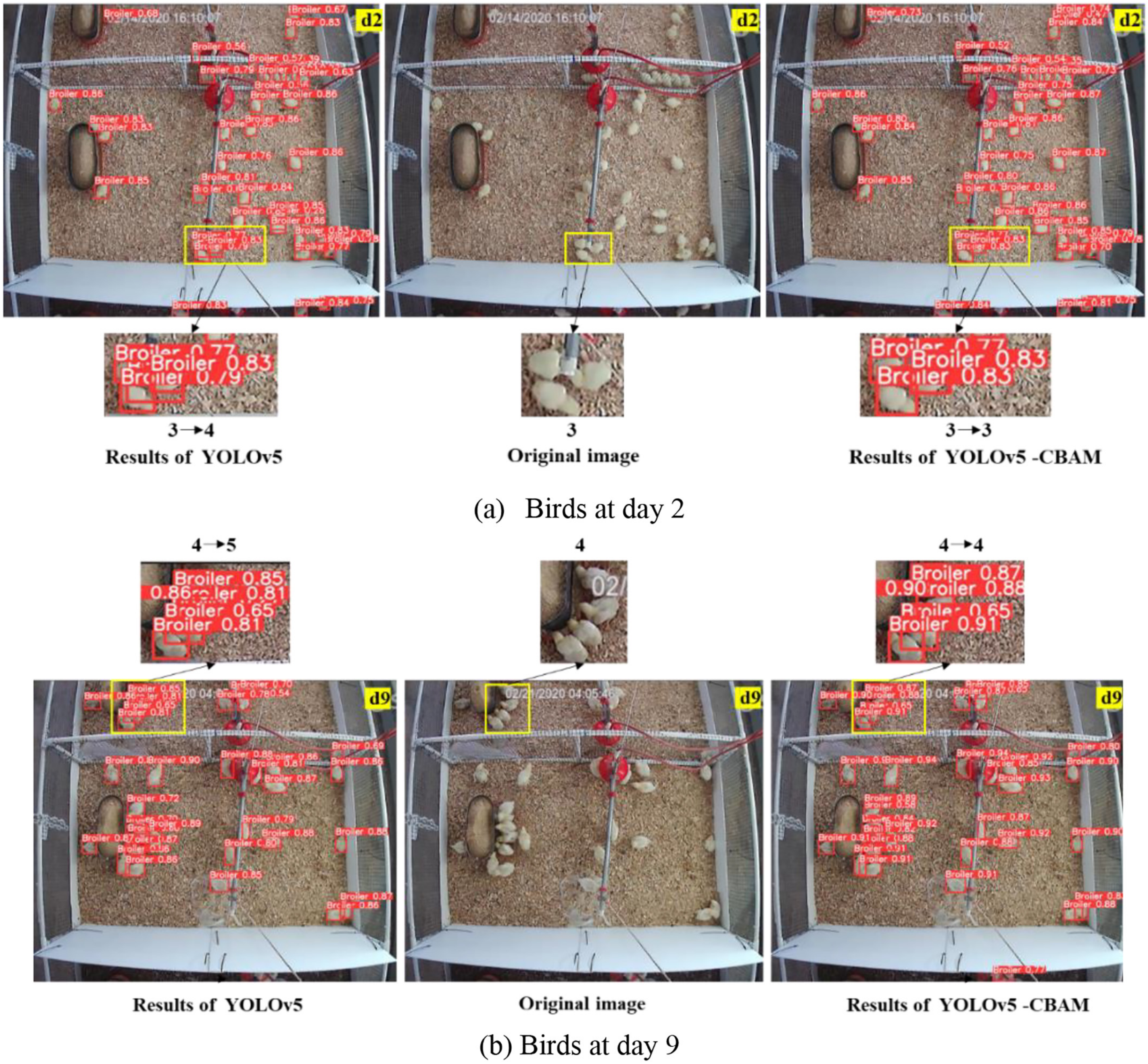
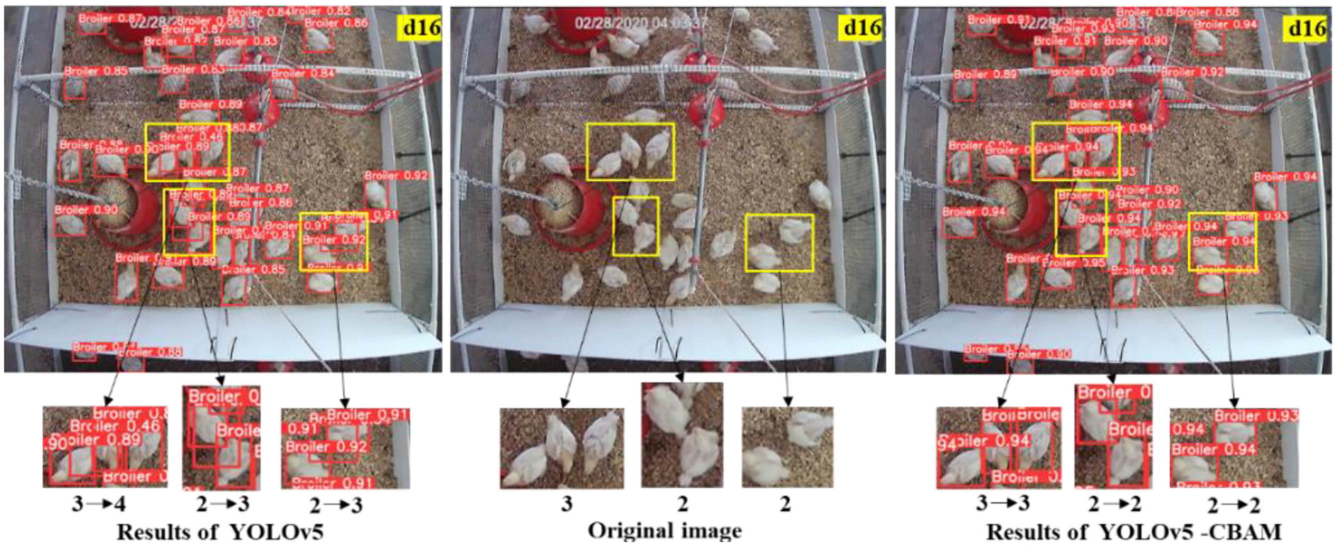


Fig. 4. Detection results using YOLOv5 and YOLOv5-CBAM in fresh pine shavings.

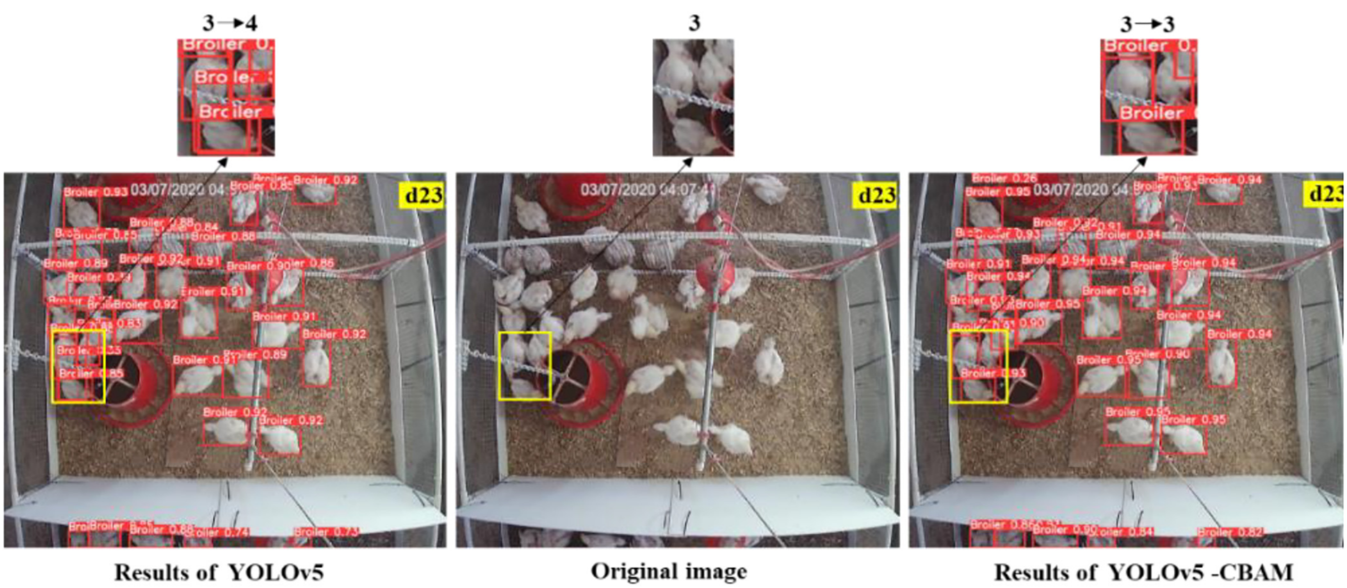
are shown in Table 1. From Table 1, the precision, recall, F1 and mAP@ 0.5 of YOLOv5-CBAM were 97.3%, 92.3%, 94.7% and 96.5%, which was higher than that of YOLOv5 (96.6%, 92.1%, 94.3% and 96.3%), Faster R-CNN (79.7%, 95.4%, 86.8% and 90.6%), SSD (60.8%, 94.0%, 73.8% and 88.5%), YOLOv3 (83.7%, 83.0%, 83.3% and 70.6%) and EfficientDet (97.0%, 47.0%, 64.0% and 59.6%). Adding the CBAM module to YOLOv5 network improved the performance of the broiler detection model. It also showed that the model YOLOv5-CBAM was suitable for the detection of broilers at different growth stages, in different litters type and multiple pens. IThe FPS of YOLOv5-CBAM was 55 Frame/s, which was lower than YOLOv5 (62 Frame/s), but higher than Faster R-CNN (2.6 Frame/s),SSD (3.1 Frame/s), YOLOv3 (18.9 Frame/s) and EfficientDet (36 EfficientDet). It can be seen that the accuracy of YOLOV5-CBAM has also been improved while maintaining a high processing speed, and it can be applied to target detection or small target detection of birds at different feeding densities.

3.2. Detection results in different scenes

Table 2 lists the detection precision of YOLOv5 and YOLOv5-CBAM at different growth stages, on different litter types and in multiple pens. In this sample dataset, the precision of YOLOv5-CBAM in each scene was slightly higher than that of YOLOv5 (Table 2). The precision of detection at d2 in fresh and reused litter was lower than d9 and d16. This is because broilers on d2 were small, and the feature extraction was not sufficient for crowded and occluded targets. This may have resulted in missed detections or false positive and negative detections. Nevertheless, the precision of YOLOv5-CBAM (96.1%, 95.2%) at d2 was slightly higher than YOLOv5 (95.1%, 94.3%). The detection precision of hens on d23 was lower in the scene of fresh pine shavings than the reused litter scene (as shown in Fig. 1), which could be caused by changes in chickens' crowding or pilling behaviors on different litter floors. When overcrowded, the target information of broilers could be lost, and thus



(c) Birds at day 16



(d) Birds at day 23

Fig. 4 (*continued*).

lead to missed or false detection. In addition, the selection of samples will also affect the performance of the test, and the accuracy of the model detection will be reduced when the birds in the sample are too crowded or heavily occluded. This is also the reason for the reduced accuracy of YOLOv5-CBAM in d23. Although the precision of YOLOv5-CBAM in each scene was slightly higher than YOLOv5 (Table 2), the overall performance was better than YOLOv5 (Table 1). YOLOv5-CBAM has been improved at different ages, different litter and different population densities, and the generalization performance of the model has also been improved, which can be applied to object detection in different feeding environments. It also provides technical support for the accurate detection of commercial broiler breeding.

Fig. 4, Fig. 5, and Fig. 6 shows detection results of YOLOv5 and YOLOv5-CBAM in different scenes (floor types). In Figs. 4 to 6, the first column is the detection results of YOLOv5, the second column is the original images, and the third column is the detection results of YOLOv5-CBAM. i → j in the Figs. 4 to 6, i is the actual number of broilers, and j is the number of broilers detected broilers. It can be observed from Figs. 4 to 6 that in different scenes, YOLOv5-CBAM can detect broilers better than YOLOv5, and in the case of crowded or small targets, it can still provide better detection results. For example, in Fig. 4, YOLOv5 will falsely detect broilers under crowded conditions, while YOLOv5-CBAM performed better under crowded condition. However, when the broilers were overcrowded, that is, the broilers overlap and block each other significantly, YOLOv5-CBAM also has false detection (d23 in Fig. 5), but it was lower than YOLOv5. In the case of multiple pens, the edge of the sample image is distorted, and the broiler appears smaller in the field of view, and the occlusion is more substantial and resulted in false detections by the model (Fig. 6).

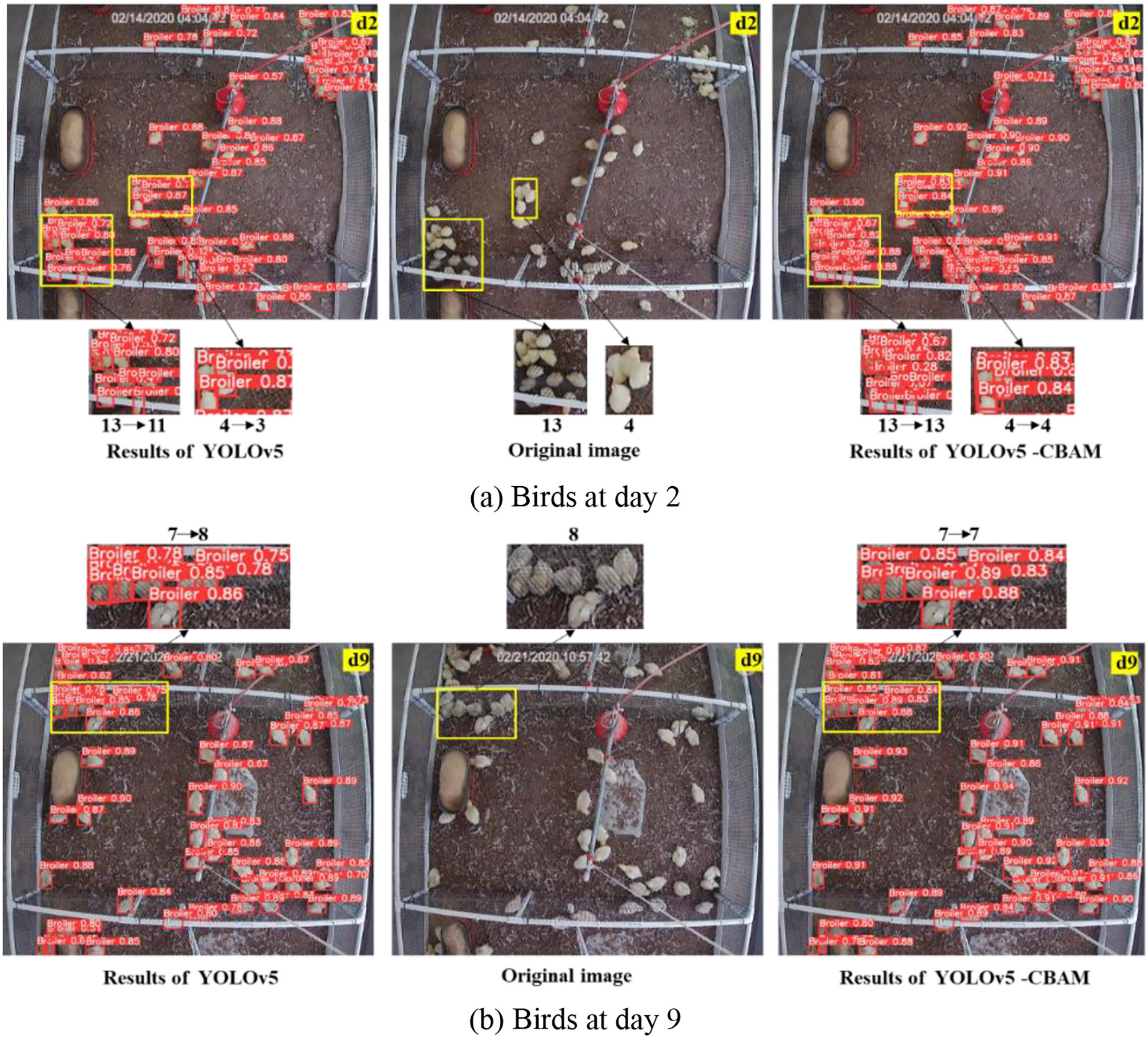


Fig. 5. Detection results using YOLOv5 and YOLOv5-CBAM in reused litter.

4. Discussion

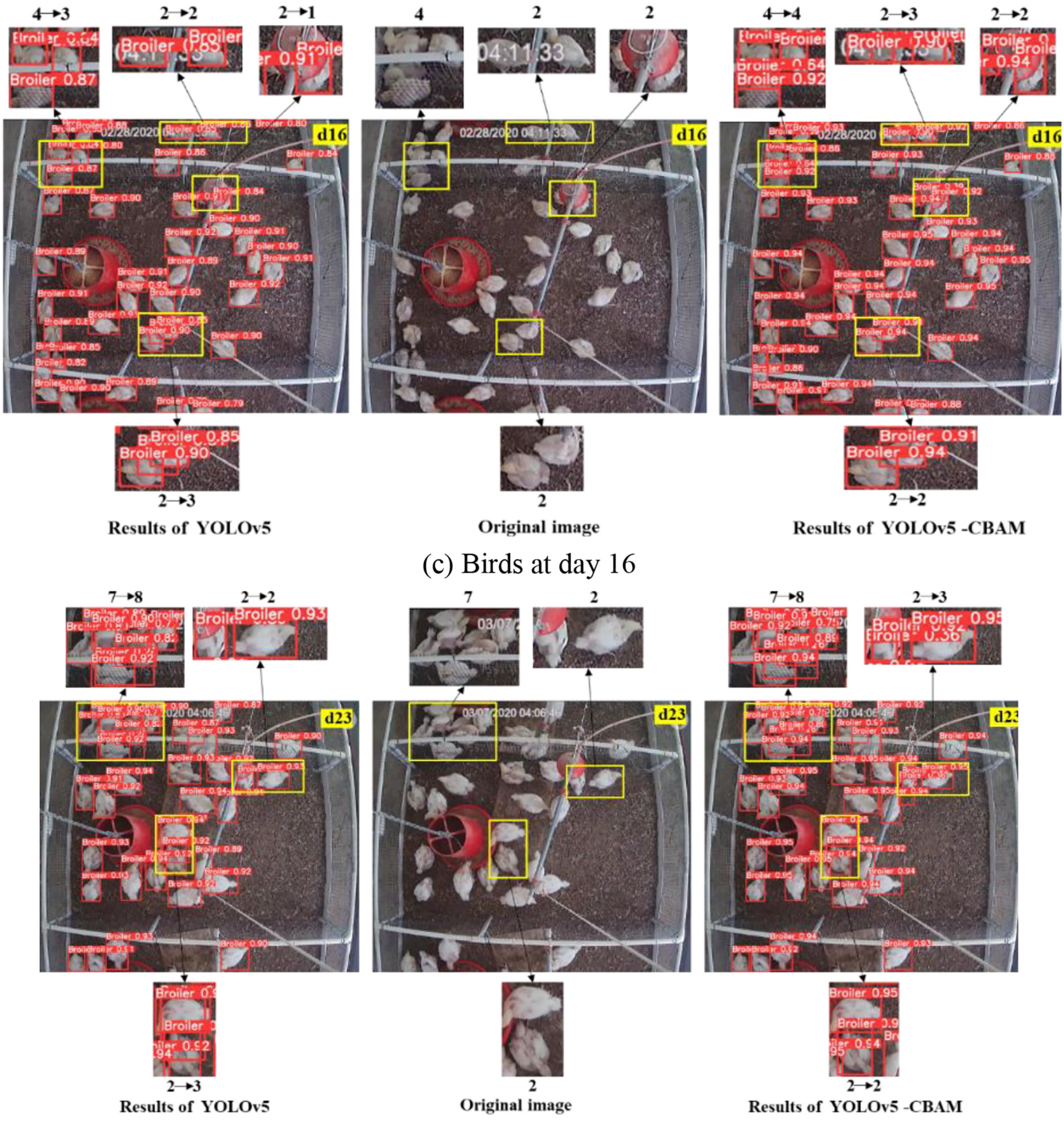
The YOLOv5-CBAM-broiler modle in the current study has a precision of 97.3% for broiler detection on the litter floor, which is higher than that of Faster R-CNN, SSD and YOLOv5 models. The introduction of CBAM attention mechanism can suppress the general features and enhance the important features, thus effectively reducing the missed or false detections. From Table 2 and Figs. 4 to 6, it can be found that adding the CBAM module to YOLOv5 network can improve the detection performance of the model against small or blocked targets. However, when the broilers are significantly blocked or there is a substantial distortion in the image, YOLOv5-CBAM has the phenomenon of false detection or missing detection.

The datasets samples used for model development consisted of different image scenes of broilers at different ages, raised on litter types and multiple pens. Therefore, the overall sample contains broilers of different sizes, crowding, occlusion, equipment interference, etc., which will affect the detection performance. In addition, broilers have multiple angles and poses in the scene, which will also affect the detection accuracy, as shown in Figs. 4 to 6. To sum up, it can be concluded that the selection and number of samples will also affect the results.

YOLOv5-CBAM has a small model, high detection accuracy, and FPS of 55 frames/s. It has good real-time performance and can be installed on portable embedded platforms to develop mobile object detection equipment, such as mobile robots. In addition, this method has achieved good detection results in different scenarios, and the samples of different varieties can be further enriched to further train the model in the later stage, which is expected to achieve multi-target detection under different varieties.

5. Conclusions

To detect broilers in different scenes (e.g., different ages, raised on different litter types and multiple pens), we proposed using the



(d) Birds at day 23

Fig. 5 (*continued*).

YOLOv5-CBAM-broiler model. The proposed approach integrates CBAM into YOLOv5 and improved the overall detection performance, especially in the case of small targets or occlusions. In addition, the results show that YOLOv5-CBAM could detect broilers of different ages effectively and provides the basis for real-time target detection for intelligent poultry management.

CRediT authorship contribution statement

Yangyang Guo: Data curation, Investigation, Writing - original draft. **Samuel E. Aggrey:** Resources, Supervision. **Xiao Yang:** Investigation. **Adelumola Oladeinde:** Resources, Supervision. **Yongliang Qiao:** Data curation. **Lilong Chai:** Conceptualization, Resources, Supervision.

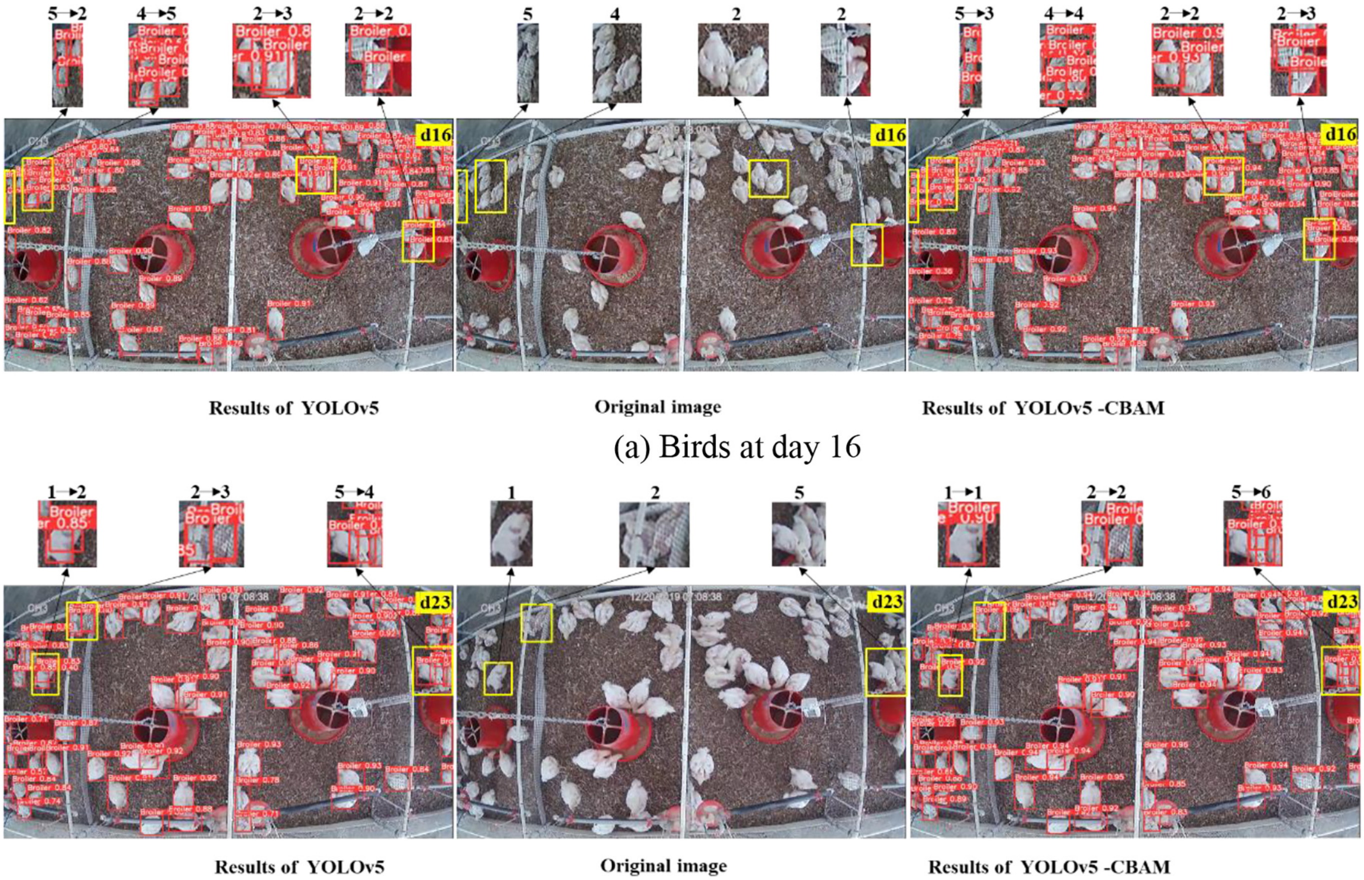


Fig. 6. Detection results using YOLOv5 and YOLOv5-CBAM in multiple pens.

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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