

Detecting Broiler Chickens with an Innovated Deep Learning Model

Lilong Chai

Department of Poultry Science, University of Georgia, Athens, GA, 30602

Introduction

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 subjective to human errors. Therefore, there is a need for an automatic tool to detect and analyze the behaviors of chickens and predict their welfare status. 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 precision animal farming. However, the size of the chicken and the sheer numbers that are raised in a single house pose challenges in applying deep learning techniques in monitoring individual chickens. In the current study, we integrated the convolutional block attention module (CBAM) into YOLOv5 to enhance the algorithm's ability to extract image features.

Methods

This study was conducted in an experimental broiler house at the Poultry Research Center of the University of Georgia, Athens, USA. High-definition cameras (PRO-1080MSFB, Swann Communications, Santa Fe Springs, CA) were mounted on the ceiling (2.5 m above floor) to capture video (15 frame/s, 1440 pixels \times 1080 pixels) from November 26, 2019 to January 14, 2020 (Guo et al., 2020 and 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, a total of 700 images were obtained and

Learning for Life Agriculture and Natural Resources • Family and Consumer Sciences • 4-H Youth ugaextension.com randomly divided at a ratio of 5:2 into training and testing set, respectively. Figure 1 are examples of broiler images from different scenes.



c. Broiler images from multiple pens floor Fig. 1. Examples of broiler images from different scenes.

Results

We used datasets consisting of broiler images at different ages, raised on two types of litter and multiple pens to test the applicability and effectiveness of YOLOv5-CBAM. The detection results of broiler with different models 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%) and SSD (60.8%, 94.0%, 73.8% and 88.5%). The results show that the overall performance of the proposed YOLOv5-CBAM was the best. 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. In addition, the 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) and SSD (3.1 Frame/s).

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
YOLOv5	96.6	92.1	94.3	96.3	62
YOLOv5-CBAM	97.3	92.3	94.7	96.5	55

Figures 2 and 3 show detection results of broilers with YOLOv5 and YOLOv5-CBAM on fresh pine shaving floor and reused litter floor, respectively. 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* is the actual number of broilers, and *j* is the number of broilers detected broilers. The YOLOv5-CBAM detected broilers with a higher precision than YOLOv5, and in the case of crowded or small targets, it could still provide better detection results.





(d) Birds at day 23

Fig. 2. Detection results using YOLOv5 and YOLOv5-CBAM in fresh pine shavings.



Results of YOLOv5

Original image

(b) Birds at day 9

Results of YOLOv5 -CBAM



(d) Birds at day 23 Fig. 3. Detection results using YOLOv5 and YOLOv5-CBAM in reused litter.

Summary

In this study, we developed a YOLOv5-CBAM-broiler model and tested its performance for tracking broilers on litter floor. The proposed model consisted of two parts: (1) basic YOLOv5 model for bird or broiler feature extraction and target detection; and (2) the convolutional block attention module (CBAM) to improve the feature extraction ability 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 and YOLOv5 models. The results demonstrate that the proposed approach achieved a precision of 97.3%, a recall of 92.3%, an F1 score of 94.7%, and an mAP@0.5 of 96.5%, which outperformed Faster R-CNN, SSD and YOLOv5-CBAM model was still better than the comparison method. Overall, the proposed deep learning-based broiler detection approach can achieve real-time accurate and fast target detection and provide technical support for the management and monitoring of birds in commercial broiler houses.

Further reading: *Guo, Y., S. E. Aggrey, X. Yang, A. Oladeinde, Y. Qiao, L. Chai. (2023)* Detecting broiler chickens on litter floor with the YOLOv5-CBAM deep learning model. *Artificial Intelligence in Agriculture,9: 36-45.* <u>https://doi.org/10.1016/j.aiia.2023.08.002</u>.