Monitoring cage-free laying hens on litter floor with machine vision

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Abstract

Real-time and automatic detection of chickens (e.g., laying hens and broilers) is the cornerstone of precision poultry farming based on image recognition. However, such identification becomes more challenging under cage-free situation compared to caged hens. In this study, we developed a deep learning model (*YOLOv5x-hens*) based on *YOLOv5*, an advanced convolutional neural network (CNN), to monitor hens' behaviors in cage-free facilities. More than 1000 images were used to train the model and additional 200 images were adopted to test it. The one-way ANOVA and Tukey HSD analysis were conducted using JMP software (JMP Pro 16 for Mac, SAS Institute, Cary, North Caronia) to determine whether there are significant differences between the predicted number of hens and the actual number of hens under various situations (i.e., age, light intensity, and observational angles). The difference was considered significant at $p<0.05$. Our results show that the evaluation metrics (Precision, Recall, F1 and mAP@0.5) of the YOLOv5x-hens model were 0.96, 0.96, 0.96 and 0.95, respectively, in detecting hens on the litter floor. The newly developed YOLOv5x-hens was tested with stable performances in detecting birds under different lighting intensities, angles, and ages over 8 weeks. For instance, the model was tested with 95% accuracy after birds were 8 weeks old. However, younger chicks such as one-week old birds were hard to be tracked (e.g., only 25% accuracy) due to interferences of equipment such as feeders, drink lines, and perches. According to further data analysis, the model performed efficiently in real-time detection with an overall accuracy more than 95%, which is the key step for individual birds' tracking for evaluation of production and welfare. However, there are some limitations for the current version of the model. Error detections came from highly overlapped stock, uneven light intensity, and images occluded by equipment (i.e., drinking line and feeder). Future research is needed to address those issues for a better detection. The current study established a novel CNN deep learning model in research cage-free facilities for hens' detection, which provides technical basis for developing a machine vision system for tracking individual birds for evaluation of animals' behaviors and welfare status in commercial cage-free houses.

Keywords: egg production, cage-free system, precision farming, deep learning algorithms

Introduction

Daily routine evaluation of chickens (e.g., broilers and layers) are critical for maintaining animals' health and welfare in commercial poultry houses (Guo et al., 2020a, 2020b, 2021). For laying hen production, it is becoming more challenging under cage–free production systems (Figure 1) as compared to conventional caged hens (Figure 2) because the birds are free to move in a larger space and perform some natural behaviors on the litter floor such as dustbathing and foraging. In recent years, computer vision has been used to monitor farm animals considering the benefit of non-invasive(Abas et al., 2016). In using computer vision, cameras or ground robots are used to collect images or videos of animals (i.e., cattle, pig, and poultry). Collected data (i.e., images and videos) are analyzed with machine learning or deep learning models, which need to be specifically programmed for extracting object features (e.g., chickens' profile and body features) and predict the target class, and thus determine the accuracy of the classification (Faroqi et al., 2020; Li et al., 2021). However, most of these deep learning methods for poultry detection are focused on broilers. Few studies were investigated cage-free layers. With the increasing of cage-free systems in USA and EU countries, it is critical to develop an automatic method for detecting laying hens on the litter floor of cage-free houses(Lin et al., 2020; Guo et al., 2020; Yang et al., 2022; Subedi et al., 2023).

Figure 1: Cage-free hen house (photo credit: Vencomatic Group).

Figure 2: Conventional cage (manure belt) hen house (photo credit: Big Dutchman).

Materials and methods

Experimental facilities

To develop an automatic imaging system for tracking laying hens on the litter floor, 800 Hy- Line W-36 laying hens are reared evenly in the four rooms (Figure 3; each was measured as 24 ft long, 20 ft wide, and 10 ft high) on the UGA Research Poultry Farm. Waterproof HD cameras (Figure 2) were installed at the ceiling and the side wall in each room to collect chickens' video data. To protect the lens glasses and record clear video, a lens cleaning cloth was used to wipe dustand keep lens glasses clean periodically (weekly). Footage data was saved on video recorder temporarily on the farm and transferred to massive hard drives for storage in the data hub in the Department of Poultry Science at the University of Georgia timely.

Figure 3: Research cage-free facilities (24 ft long, 20 ft wide, and 10 ft high).

Figure 4: Monitoring cameras.

Data analysis model

Videos recorded at birds' age of 8-16 weeks (as this is a transition period from pullet to layers) were used for data analysis to make sure the method would be applicable for both hens and pullets. After removing blurred images, about 1200 images were labeled for model trainingand test (Figure 5) (Yang et al., 2022).

Figure 5: Image labeling for hens on the floor.

The YOLOv5x model was adapted and innovated by integrating hens' image information asa new model "YOLOv5x-hens" for detecting birds on the litter floor. The YOLOv5x model is one of the four most commonly used models for object detection in YOLOv5, which is a newer version of YOLO (You only look once) model, a deep learning-based object detection algorithm.

Results and discussion

Impact of lighting on the model

About 200 images were used to test the performance of YOLOv5x-hens under different levels of light intensity (10 lux and 30 lux; Figure 6). The accuracies at 10 lux and 30 lux were 95.15% and 95.02%, respectively.

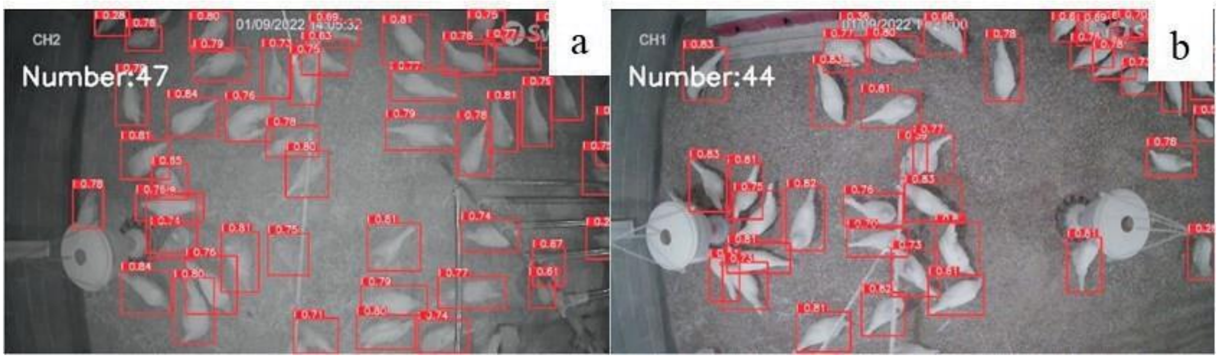

Figure 6: Number of chickens identified under different level of light intensity by our model:10lux (a) vs. 30 lux (b).

Impact of birds' density on the model

About 300 images were used to test model accuracy under different levels of flock density (Figures 7 and 8): of low density (0–5 birds/m^2), moderate density (5–9 birds/m^2), and high density (9–18 bird/m^2). For the three different densities, there was no difference in accuraciesunder low and middle densities (95.60% and 95.58%).

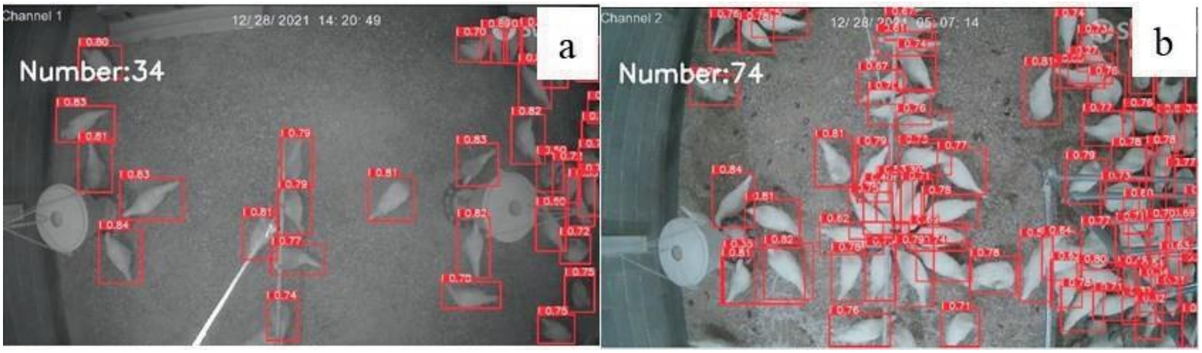

Figure 7: Number of chickens identified under low density and moderate density by our model:low density (a) vs. moderate density (b).

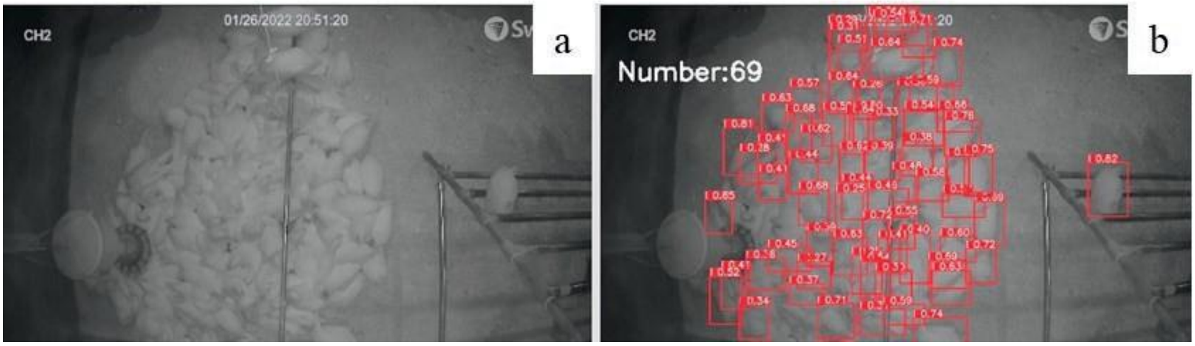

Figure 8: Number of chickens identified under high density by our model: original image of highdensity (a) vs. identified high density (b) (Yang et al., 2022).

<u>Impact of cameras' angle on the model</u>

In the current study, cameras were installed on the celling (vertical angle) and sidewall (horizontal angle). A total of 200 images were used for evaluating the effect of angles on imagequality. The model performances between these two angels are slightly different. It performed better with vertical (96.33%) than horizontal (82.24%) monitoring angles (Figure 9).

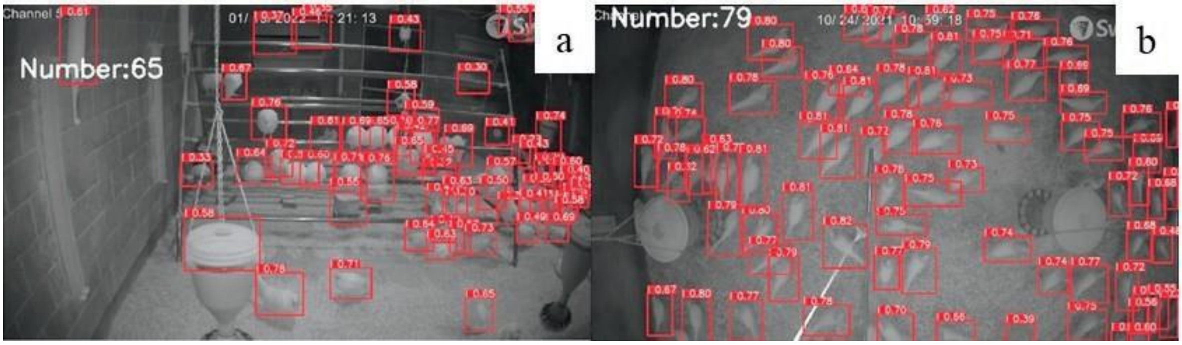

Figure 9: Number of chickens identified under horizontal angle and vertical angle by our model:horizontal angle (a) and vertical angle (b).

Conclusions

In this study, a machine vision system and deep learning model *YOLOv5x-hens* was built and evaluated at the University of Georgia research cage-free hen houses to track hens (e.g., real-timenumber of hens in different locations) on the litter floor. The *YOLOv5x-hens* model performed efficiently in real-time detection under different lighting intensities, angles, bird density, and agesover 8 weeks. However, some misidentifications happened due to the hens pilling on the floor, uneven light intensity, and images occluded by equipment (i.e., drinking line and feeder). Further research will be conducted to address those issues such as higher bird density and moreoccultations to mimic the situation in the commercial cage-free houses.

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