Monitoring mislaying behaviors of hens with deep learning models

R. B. Bist[1], X. Yang[1], S. Subedi[1] and L. Chai[1,*]
[1]*Department of Poultry Science, College of Agricultural and Environmental Sciences, University of Georgia, Athens, GA 30602, USA*
[*]Corresponding author: Lilong Chai, lchai@uga.edu

Abstract

Floor egg-laying behavior (FELB) is one of most concerned problematic behaviors in commercial cage-free (CF) housing systems, leading to increased mislaid eggs, which range from 0.1-10% of total daily egg production. In addition, mislaid eggs on the litter floor are more likely to be contaminated and damaged, resulting in economic loss and egg safety concerns. Several management strategies, such as light systems, nest boxes, perches, and robots, have been tested and implemented to control floor eggs. Robots have shown good performance in reducing floor eggs, but these robots lack a detection system to target FELB and non-FELB (NFELB). Therefore, the primary objectives of this research were to develop and test new deep-learning model to detect FELB and evaluate the model's performance in four research CF facilities using five different YOLOv5 models (YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x). According to the model performances based on a dataset of around 3000 images, YOLOv5m and YOLOv5x-FELB model size had shown the highest and similar precision (99.9%), recall (99.2%), mAP@50 (99.5%), and F1-score (99.6). However, YOLOv5m-NFELB model sizes resulted in slightly higher precision and lower recall than YOLOv5n, YOLOv5s, YOLOv5l, and YOLOv5x. Thus, the newly developed and trained YOLOv5m model has acceptable in detecting FELB and NFELB in research houses with 720 Hy-Line W-36 hens.

Keywords: machine vision, YOLOv5, floor egg laying, laying hen, cage-free housing

Introduction

The poultry egg industry is shifting from conventional caged (CC) to cage-free (CF) housing due to various welfare concerns and public demand to improve the behavior and welfare issues (Chai et al., 2017, 2018, 2019; Bist et al., 2022a, 2022b, 2022c). Providing CF housing helps improve bird welfare while inheriting the serious challenges of mislaid eggs due to floor egg-laying behavior (FELB) of laying hens. Floor laying is natural behavior observed in laying hens where they sit on the floor and lay their eggs. However, laying eggs on the floor increases labor demand and economic losses to the producer because floor eggs have higher chances of contamination with harmful bacteria (Parisi et al., 2015) and are not considered table eggs or for direct sale (Holt et al., 2011). In addition, floor eggs have a higher chance of getting broken and eaten by laying hens.

Several strategies have been implemented to reduce floor eggs. Some of the examples were used of the nest box (Chai, 2021), perch (Gunnarsson, 1999; Bist et al., 2023b), light systems (Chai, 2021), and the introduction of experienced hens (Oliveira et al., 2019) to reduce floor eggs. However, the mislaid egg problem still needs to be solved. It was found that by providing proper training and management practices, the mislaid eggs account for 0.1%-2% of daily (Vroegindeweij et al., 2018). In extreme cases, mislaid eggs can reach 5%-10% of total daily egg production. In both cases, the mislaid eggs need to be collected manually daily, which is expensive and time-consuming. That is why robots were trained to reduce workload and increase productivity and profitability. The robot moves randomly inside the house and helps reduce floor eggs by making hens stop laying on the floor. By moving randomly, the robot can reduce floor eggs but is unable to control them entirely because the robot, without detection, will be unable to detect the right FELB. That is why the robot should be inbuilt with technology that consists of a machine or deep learning model to detect the FELB and target those birds mostly to avoid them laying on the floor. The objective of this research is to; i) develop and test a new deep-learning model to detect FELB; ii) Compare the performances of the five YOLOv5 network models.

Materials and methods

Experimental design

The experiment was conducted in the four identical CF housing at the University of Georgia poultry research facility, Georgia state, USA. About 180 Hy-line W36 birds (total 720 laying hens) were raised in each house (Figure 1) measuring 7.3m L × 6.1m W × 3m H. Each house was provided with a feeder, drinkers, and other enrichment like perch, bedding materials, and nest boxes. The indoor temperature, relative humidity, light duration and intensity, and ventilation rates were controlled with the help Chore-Tronics Model 8 controller. This research was monitored and approved by the Institutional Animal Care and Use Committee (IACUC) present at the University of Georgia (UGA).

Figure 1: Experimental setup in research cage-free houses.

Image data acquisition and labeling

This study used a night-vision network camera (PRO-1080MSB, Swann Communications USA Inc., Santa Fe Springs, LA, USA) to obtain an image dataset for the main data acquisition tool. Each room consists of 6 cameras mounted ~3m above the litter floor and 2 cameras above the ground floor placed at 0.5m from the ground. The data acquisition time was between 5:00 hrs-21:00 hrs every day with the help of a digital video recorder (DVR-4580, Swann Communications USA Inc., Santa Fe Springs, LA, USA) from 25-50 WOA. The video files were stored in .avi format with a resolution of 1920 × 1080 pixels with a sampling rate of 15 frames per second (fps). Video data were converted into images (.jpg) with the help of Free Video to JPG Converter App (ver. 5.0), then labeled using the image labeler website (Makesense.AI) in YOLOv5 format. About 70%, 20%, and 10% of total images (3600 images) were used for training, validation, and testing, respectively. Images were analyzed using Oracle Cloud (Python 3.11.0, 64 OCPU count, 100 Gbps network bandwidth, 1024GB memory, 2 drives of 7.68 TB NVMe SSD storage, and 4 NVIDIA® A10 GPU count). The two classes (FELB and Non-FELB) were compared and used for identification for the model detection. Non-FELB is the behavior or activities performed by the birds, like feeding, drinking, sitting, preening, nesting, dustbathing, pecking, and foraging.

Description of the YOLOv5 model

Before the discovery of the YOLO model, the R-CNN series algorithm was widely used to achieve high detection accuracy of the target object (Tang et al., 2021). However, the R-CNN series cannot meet real-time detection requirements with faster speed because of its two-stage network structure. That is why in 2016, Joseph Redmon and his team developed the single-stage object detection network (YOLOv1 model), which can detect objects with higher accuracy and speed and run efficiently in a real-time detection module (Redmon et al., 2016). After the massive success of the YOLOv1 model, the series of YOLO models created like YOLOv2, YOLOv3, YOLOv4, and YOLOv5 with various versions with various feature extraction modules, convolutional network, and parameters (Horvat et al., 2022).

The YOLOv5 model comprises three main parts backbone, neck, and head (Sachin et al., 2022; Yang et al., 2022). Each part function differently. When the head takes input data, it passes down to the backbone for feature extraction. The backbone of the YOLOv5 uses cross stage partial (CSP) Darknet53 convolutional neural network, which uses residual and dense blocks. CSP network helps to reuse denseNet's features and tackle the excessive amount of redundant gradient data (Wang et al., 2020). After tackling, an excessive amount of redundant gradient information was reduced by truncating the gradient flow. Thus, it helps in the feature extraction process.Similarly, the neck of the YOLOv5 consists of two major changes: Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PANet). This PANet variant was modified by incorporating the bottleNeck CSP network strategy. The PANet features a pyramid network and helps to enhance the flow of information. In addition, it also helps in proper pixel localization in mask prediction. Similarly, SPP helps improve the network's speed by aggregating the information it receives as input and returns as a fixed length of output without lowering the network speed (He et al., 2015). Finally, the Head structure in YOLOv3, YOLOv4, and YOLOv5 are the same, which consists of three convolution layers and helps to obtain multi-scale prediction as output. These layers help to predict the scores, the object classes, and the location of the bounding boxes (x, y, height, width) (Jocher, 2022). The predicted results were finally taken out through output through convolutional kernels.

Model evaluation

First, the image was trained and validated for the model evaluation to get the necessary outputs. YOLOv5 produces three outputs: the detected objects' classes, bounding boxes, and objectness scores. As a result, it computes the class loss and the objectness loss using BCE (Binary Cross Entropy). The location loss is computed using the CIoU (Complete Intersection over Union) loss. The loss function in YOLOv5 helps to improve detection efficiency by positioning errors. Handling objects of different sizes need to be strengthened, so loss functions play an important role in solving this issue. The equation of final loss is generated from the following equation;

$$Loss = \lambda_{\&} L_{\text{`êë}} + \lambda_{*} L_{\text{[é"}} + \lambda_{+} L_{\text{ê[`}} \tag{1}$$

Similarly, for the model evaluation, Python 3.9 was used for descriptive statistics and statistical analysis. Precision, recall, F1 score, and mAP were measured for validating data and calculated with the help of the following formulas;

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{4}$$

$$mAP = \frac{\sum_{!R\&}^{i} APi}{C} \tag{5}$$

where, TP, FP, and FN indicate true positive, false positive, and false negative values, respectively. Similarly, APi and C represent the average precision of the ith category and the total number of categories, respectively.

Results and discussion

The training and validation of each model process loss function decrease rapidly when run at 100 epochs and 16 batches. The train box loss, train object loss, and val box loss values decreased while val object loss, precision, recall, mAP_0.5, and mAP_0.5:0.95 increased, giving a better performance model. The precision, recall, and precision-recall curves were detected and evaluated based on confidence interval (CI). The FELB precision for the YOLOv5m and YOLOv5x were highest among other models, with a precision of 99.9% (Figure 2). Overall, precision reached above 100% when CI reached above 0.80 for both YOLOv5-FELB or NFELB models. Similarly, recall, mAP_0.5, and mAP_0.5:0.95 were highest in the YOLOv5m model. The performance of five different models is well-described in Figure 3 (Bist et al., 2023a).

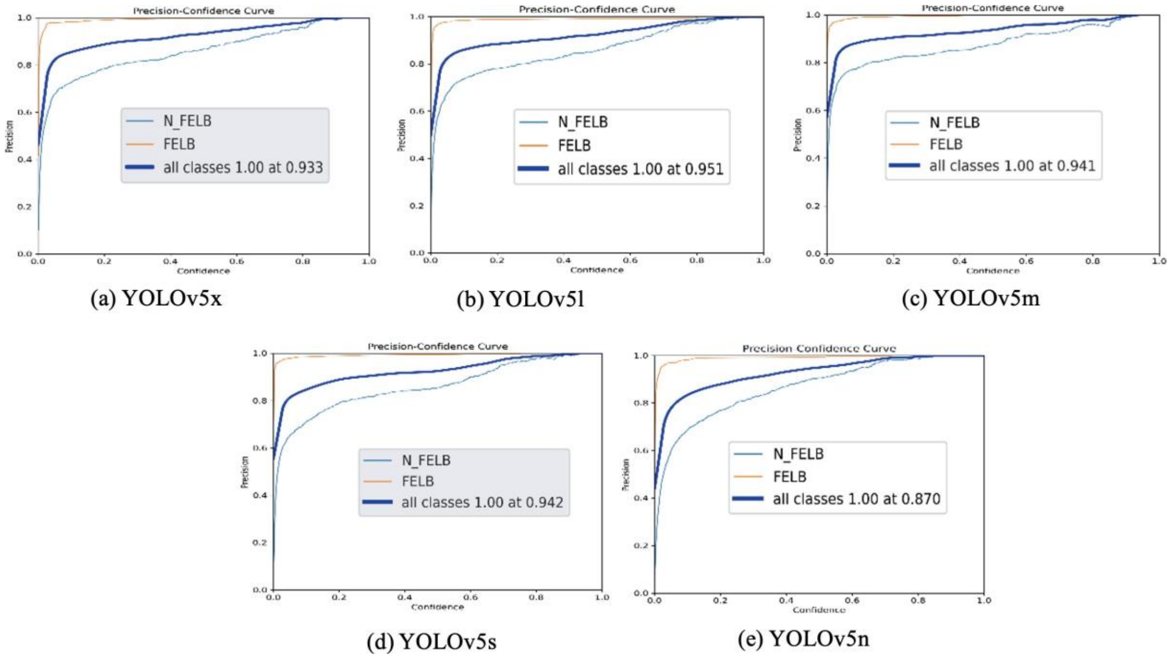

Figure 2: The precision of the five YOLOv5 models in FELB and NFELB detection.

Figure 3: Confusion matrices of the five YOLOv5 models for FELB and NFELB.

Conclusions

The YOLOv5m and YOLOv5x-FELB model sizes had shown the highest and similar precision, recall, mAP@50, and F1-score, while YOLOv5x-FELB had the lowest processing speed. Similarly, YOLOv5m-NFELB model sizes resulted in higher precision and lower recall than others. The speed of data processing and training was higher in the YOLOv5s model. Overall, by comparing each model and their performance, YOLOv5m-FELB or NFELB outperforms.

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