Floor egg detection with machine vision in cage-free houses

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Abstract

In the USA, the primary restaurants or grocers have pledged to buy cage-free (CF) eggs only by 2025 or 2030. However, CF production has several concerns such as floor eggs. Floor eggs have a high chance of contamination by manure resulting in a food safety concern. Manual collection of floor eggs is labor intensive. The objectives of this study were to develop a machine vision method and test the performance in detecting eggs on litter floors timely. The YOLO (You Only Look Once), an advanced object detection technology with very high precision and speed compared to CNN-based algorithms (e.g., R-CNN, Faster R-CNN, Mask R-CNN, etc.), was used as a model structure. In this study, we trained "YOLOv5s" network to detect floor eggs of laying hens in research cage-free facilities. Datasets were trained with a batch size of 16 for 200 epochs using Virtual Machine GPU 3.1 provided by Oracle Cloud Infrastructure (OCI) with 6 Oracle CPUs and 90 GB of memory. Results show that the trained algorithm can detect the floor eggs with a precision of 87.9%, recall 86.8%, and mean average precision (mAP) of 90.9 %. Errors were led by image quality as there was dust accumulation on cameras. Cleaning camera frequently can enhance the accuracy of the model.

Keywords: Cage-free system; deep learning; floor eggs; artificial intelligence.

Introduction

In the USA, the primary restaurants or grocers have pledged to buy cage-free (CF) eggs only by 2025 or 2030 (Xin and Liu, 2017; Chai et al., 2017, 2018, 2019). Cage-free housing system allows birds to move freely inside the poultry housing with perches and nesting areas so that they can show their behaviors like perching and foraging (Ochs et al., 2018). However, CF production has several concerns such as floor eggs. The mislaid eggs on the floor are called floor eggs, which causes an increase in dirty eggs contaminated with feces and litter, even an increase in broken eggs as the bird's peck some eggs (Jones et al., 2015; Li et al., 2020). This affects the overall quality of eggs along with hen-day production. In addition to degrading the overall quality of eggs, the manual collection is very labor extensive and time-consuming. One possibility to solve this problem is the use of technology. For example, the detection of floor eggs as an object with the help of deep learning and object detection can be used. This type of technique can be used for developing a robotic egg-picking system.

Introducing artificial intelligence (AI) in poultry farming and management can improve multiple aspects of the poultry industry (Guo et al., 2020a, 2020b, 2021, 2022; Neethirajan, 2022). Machine learning techniques include object classification, detection, recognition, and tracking. Using these methods in livestock farming has led to options to monitor the health, disease, and normal and undesired behavior of animals in large-scale farms with high performance (Okinda et al., 2020). There was an application of automatic monitoring systems to detect and study floor eggs in a cage-free setting (Li et al., 2020). A deep-learning model for detecting cage-free hens with an accuracy of around 96 % was used (Yang et al., 2022). Deep learning was used to classify six different behaviors (standing, sitting, sleeping, grooming, scratching, pecking) of laying hens (Leroy et al., 2005). YOLOv5 model was used to detect the feather pecking behavior in cag-free laying hens (Subedi et al., 2023a). A computer vision system to quantify individual hens' behaviors that show scratching behaviors (Leroy et al., 2006). The interference and obstruction of poultry behaviors and various zones like feeding, drinking, and resting with machine vision methods were also studied (Guo et al., 2020). Early studies proved that floor eggs could be detected with computer or machine vision-based methods. Researchers have investigated robotic applications on hen floor egg reduction, production performance, stress response, bone quality, and behavior (Li et al., 2022). A vision-based floor-egg detector was developed based on three convoluted neural networks, i.e., single-stage detectors (SSD), faster R-CNN, and R-FCN, with the faster R-CNN detector having precision, recall, and accuracy 91.9%–100% in floor egg detection.

The objectives of this research were to develop a machine vision method to 1) detect the floor eggs in cage-free housing systems, 2) test the method's performance in research CF houses, and 3) figure out how to improve the detection accuracy of the model. In addition, we aimed to identify and locate floor eggs and test a newly developed automatic floor egg detection system based on image data analysis.

Materials and methods

Experimental setup

We conducted our experiment at a research layer house on Athens's University of Georgia poultry research farm. The Institutional Animal Care and Use Committee (IACUC) of the University of Georgia, USA, approved animal use and management. Hy-Line hens (800 W-36) were raised in four cage-free houses (200 birds in each room from day 1), each measuring 7.3 m long × 6.1 m wide × 3 m high. Pine shavings were uniformly spread on the floor (5 cm depth) before bird arrival, and commercial feed was provided ad libitum. We followed layer management guidelines for Hy-Line W-36 commercial layers. An automatic environment system controlled the rearing condition, and set points were 21 – 23°C for air temperature during egg laying with 19L:5D lighting period and 20 lux intensity. In addition, daily hens' growth and environmental conditions were checked as suggested by the UGA Poultry Research Center Standard Operating Procedure Form.

Data collection and preparation

We mounted six night-vision network cameras (PRO-1080MSB, Swann Communications USA Inc., Santa Fe Springs, LA, USA) above the drinking system, feeders, and perches and in the wall at ~3 m above the ground to capture top-view videos and footage from sideways (Figure 1). In addition, different areas of eggs laid and hens' activities were continuously monitored, and videos were stored in digital video recorders (DVR-4580, Swann Communications USA Inc., Santa Fe Springs, LA, USA). The video files (.avi format) were recorded with a resolution of 1920 × 1080 pixels at a sample rate of 15 frames per second (fps) and converted to image files (.jpg) using Free Video to JPG Converter (ver. 5.0).

Figure 1: Data collection using camera and video recorder.

Definition of floor egg and Labeling

In cage-free housing and aviary housing, there are many forage areas for birds and the eggs laid there are called floor eggs (Jones et al., 2015). We manually labeled each Egg from the laying hen to create a bounding box based on the definition. A dataset of 1050 images (750 training, 250 validations, and 50 test) was created to analyze the floor eggs laid. A day of videos, 16 h in one day, was used. The images containing eggs laid were used for the labeling. The labeling was conducted in open-source software (Makesense.AI), and we created the bounding box around the region of interest (Subedi et al., 2023a, 2023b). The dataset was split into two folders, i.e., training and validation, set in the ratio 70:30. These two folders were divided into two subfolders, Images, and Labels. Finally, we got the annotation file in .txt format (text file).

You Only Look Once (YOLO) model

YOLO (You Only Look Once) is a single-stage object detector algorithm developed in 2015 by researchers Joseph Redmon and Ali Farad. Compared to R-CNNs and Fast/Faster R-CNNs, YOLO has higher accuracy and speed using Single Stage Detectors (SSDs) that helps improve the speed and eliminates the use of Region Proposal Network (Tulbure et al., 2022). YOLO has had tremendous success in real-world applications and has sprung many different versions of models. TinyYOLO, YOLOv2, v3, v4, v5, and YOLOx scaled-YOLOv7, YOLO with various backends, etc. The most popular model of YOLO used in the industry was YOLOv3. The Ultralytics implementation of YOLOv5 is widespread (Bochkovskiy et al., 2020). Pretrained YOLO models, especially on the COCO dataset, are readily available and easy to use. COCO is a large image dataset for object detection, segmentation, person key points detection, stuff segmentation, and caption generation. For laying hens' images/videos, the dataset has annotations for bounding boxes and image segmentation with one object class named Egg. In the newly innovated model, images collected at multiple locations and scales with high-scoring regions of the image were considered in tracking/detection. Taking the whole image of hens at test time and evaluating predictions using the single network is a significant advantage of YOLO over classifier-based systems (Guo et al., 2022). In YOLO, the individual hens' image was split into a grid (S x S - 7 x 7), and then each cell predicted the bounding boxes (x, y, w, h) and the confidence of each box with the Probability that box has an object (Egg). Then each cell has bounding boxes and the associated probabilities of each box having an object. Each cell predicted a class probability. Each cell provided the probability of the object class, e.g., P (Egg).

Architecture of the YOLOv5s model

The model of YOLOv5s was developed based on the YOLOv5 network, which consists of three parts: a backbone, a neck, and an output for object detection. The backbone network is CSPDarkNet53, with four feature maps of different sizes, and was used for feature extraction (Shen et al., 2022; Bochkovskiy et al., 2020). The neck helps extract feature maps (eggs) to obtain information and reduce loss directly connected to the backbones. The feature pyramid structures of the Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) are used in the fusion process (Liu et al., 2018; Shen et al., 2022). FPN structure conveys powerful semantic features from the top feature maps into the lower feature maps, and the PAN structure gives strong localization features from lower feature maps into higher feature maps. By using PAN as the neck of the model, the input is the feature map output from the backbone, which is feature-fused to obtain features with richer semantic information to be sent to the Head for detection. Head helps to perform the final detection part, which generates final output vectors with class probabilities, objectness, scores, and bounding boxes. The CBL module consists of convolution, normalization, and a Leaky Rectified Linear Unit (ReLu) activation function. There are two kinds of cross-stage partial (CSP) networks, one in the backbone network and the other in the neck. The CSP network can improve the inference speed while maintaining precision by reducing model size. (Wang et al., 2020). In addition, the Spatial Pyramid Pooling (SPP) module also executes the maximum pooling with different kernel sizes and fuses features by concatenating them together (He et al., 2014). The Concat module represents the tensor concatenation operation.

Evaluation metrics

Precision, Recall, and mean average precision (mAP) provide an essential reference index to evaluate the model's performance (Subedi et al., 2023a). Precision represents the proportion of all predicted positive samples that were correctly detected. It is the ratio of correctly predicted positive observations, i.e., Egg, to the total predicted positive observations.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

The recall represents the proportion of all positive samples successfully detected. It is the ratio of correctly predicted positive observations to all observations in the actual class – Egg.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Mean average precision (mAP) was calculated as follows:

$$mAP = \text{æ}_{\text{!@ \&}}^{7} P(i)\ x\ \Delta R\ (i)$$

P(*i*) is the precision, and *ΔR*(*i*) is the change in recall from the *i*th detection. For all the above metrics, closer to 100% value reflects a better performance of the detectors.

Results and discussion

Model performance in floor eggs detection

The confusion matrix (Figure) is made up of four components, i.e., True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), in assessing the performance of YOLOv5s: The TP was 0.94 when the classifier predicted TRUE (i.e., the image has the Egg), and the correct class was TRUE (i.e., the image has the Egg); 2) The TN was 0, cases when the model predicted FALSE (i.e., no Egg), and the correct class was FALSE (i.e., images do not have an Egg); 3) FP was 1 (Type I error) that classifier predicted TRUE, i.e., the image has Egg, but the correct class was FALSE (i.e., the image did not have Egg); and 4) The FN was 0.06, which indicates that the classifier predicted FALSE (i.e., the image does not have Egg), but images do have the floor eggs (Subedi et al., 2023b).

Performance of YOLOv5s in data training and validation

The training and validation process loss function rapidly decreased in 300 epochs**.** Box loss is bounding box regression loss (Mean Squared Error), and object loss is the confidence of object presence is the objectness loss (Binary Cross Entropy). mAP@0.5: 0.95 represents the average map at different IOU thresholds (from 0.5 to 0.95, step 0.05). (0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95). The average mAP over different IoU thresholds ranges from 0.5 to 0.95. The 'mAP_0.5' is the mean Average Precision **(mAP)** at IoU (Intersection over Union) threshold of 0.5. It indicates an average map with a threshold greater than 0.5 (Zhang et al., 2022; (Subedi et al., 2023b).

Testing results of new models in detecting floor eggs

The optimized model, after training, was used to detect the floor eggs in new unlabeled images. The Figure 2 shows some examples of the automatic detection of floor eggs. The YOLOv5s model could detect the eggs with a precision of 87.9%, recall of 86.8%, and mean average precision (mAP) of 90.9%. The uncertainties or errors were caused by dust accusation on cameras, interferences of equipment (e.g., feeders and drinkers), and birds' body.

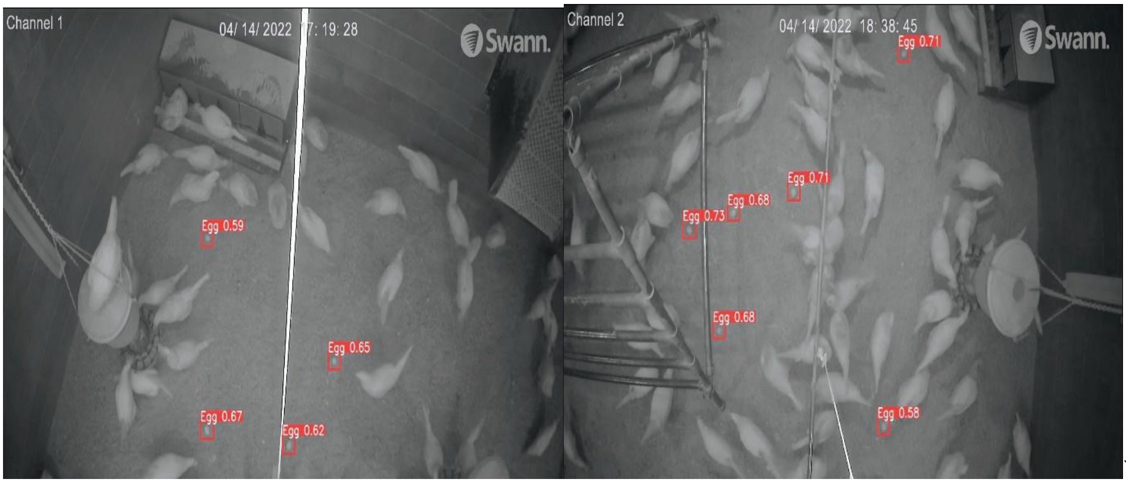

Figure 2: Performance of YOLOv5s in floor eggs (Subedi et al., 2023b).

Conclusions

In this study, an advanced object detection technology (i.e., the YOLO model) was used as the model structure for developing YOLOv5s network to detect floor eggs in research cage-free houses. The YOLOv5s performed well in terms of accuracy, precision, mAP, and recall. This study provides a reference for cage-free producers that floor eggs can be monitored automatically. Future studies are guaranteed to test the system in commercial houses. Furthermore, the detection of floor eggs as an object with the help of deep learning and object detection can be used for developing a robotic egg-picking system.

Acknowledgments

This project is supported by the Egg Industry Center; Georgia Research Alliance – Venture Fund; Oracle America (Oracle for Research Grant, Award #: CPQ-2060433); UGA College of Agricultural and Environmental Sciences Dean's research grant; and USDA-Hatch projects: Future Challenges in Animal Production Systems: Seeking Solutions through Focused Facilitation (GEO00895; Accession Number: 1021519) and Enhancing Poultry Production Systems through Emerging Technologies and Husbandry Practices (GEO00894; Accession Number: 1021518).

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