APPLICATION OF DEEP LEARNING FOR MONITORING WELFARE AND BEHAVIORS OF CAGE FREE LAYING HENS

by

Sachin Subedi

(Under the Direction of Lilong Chai)

ABSTRACT

This study uses deep learning models to monitor and evaluate cage-free hens' welfare and behaviors. Our first project used YOLOv5 (i.e., version 5 of You Only Look At Once, an innovative deep learning model for target detection) deep learning models to track feather pecking (FP) behaviors in hens for improving early detection and minimizing the spread of FP. The YOLOv5x-pecking model performed better than YOLOv5s-pecking, achieving higher precision, recall, and mean average precision. The second project involved detecting floor eggs using YOLOv5-egg, YOLOv5x-egg, and YOLOv7-egg models. All three models detected eggs with high accuracy, while the YOLOv5x-egg model achieved the highest precision and mean average precision. The third project involved classifying the different behaviors of birds inside poultry houses using a serials of deep learning models based on YOLOv5 and YOLOv7. The YOLOv5s_BH model had the best performance in terms of precision, recall, and mean average precision compared to the other two models. These deep learning models developed in this study provide references for developing real-time automatic monitoring systems for tracking pecking damages and floor eggs and monitoring bird activity inside poultry houses to enhance welfare and reduce economic losses for egg producers.

INDEX WORDS: Deep Learning, hen welfare, cage-free production, real-time monitoring

APPLICATION OF DEEP LEARNING FOR MONITORING WELFARE AND BEHAVIORS

OF CAGE FREE LAYING HENS

by

SACHIN SUBEDI

B.V.Sc. & A.H., Agriculture and Forestry University, Nepal, 2018

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment

of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2023

APPLICATION OF DEEP LEARNING FOR MONITORING WELFARE AND BEHAVIORS

OF CAGE FREE LAYING HENS

by

SACHIN SUBEDI

Major Professor: Lilong Chai
Committee: Casey Ritz
Prafulla Regmi

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
August 2023

DEDICATION

To my family and loved ones

ACKNOWLEDGEMENTS

I want to say thank you to all the people who helped me finish my project. First, I want to thank my major professor Dr. Lilong Chai for choosing me to work on this project and helping me until I finished it. I also want to thank the Department of Poultry Science, my committee members Dr. Casey Ritz and Dr. Prafulla Regmi, who helped me finish the project, and I am thankful for their advice. I appreciate Ramesh Bahadur Bist and Xiao Yang for helping me with the farm work and data collection. Lastly, thank my friends, family, and loved ones for supporting me.

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

LITERATURE REVIEW

1.1 Cage-free Housing and Management

The European Commission aimed to eliminate cages for farmed animals by 2027 (Duncan, 2001). Thus, there is a need to redesign the poultry housing systems using an enhanced understanding of the range of behavior and locomotion of laying hens and broilers. In addition, there is a high demand from the public and the primary restaurants or grocers to improve poultry welfare and provide products like cage-free eggs (Neethirajan, 2022). Traditional cage-based farming suppresses the natural behaviors of birds; as a result, poultry welfare policies are increasing (Chang et al., 2020) (Hewson, 2003). Cage-free housing systems are an alternative to traditional battery cage systems, often used in egg production. This housing system provides a more spacious environment for hens, allowing them to engage in natural behaviors such as walking, perching, and laying their eggs in nests (Hartcher & Jones, 2017, Ochs et al., 2018). However, cage typed housing system was criticized for lack of available space, bone fragility in birds, and the lack of possibilities to perform natural behaviors (Craig & Swanson, 1994).

The main benefits of cage-free housing systems are improved animal welfare and reduced stress levels for the hens (Hartcher & Jones, 2017). In cage-free systems, hens can move around freely, reducing stress and improving their overall quality of life. In terms of egg production, cage-free systems have been shown to have similar or even higher egg production rates compared to traditional battery cages. Hens in traditional battery cages are often confined to small spaces and unable to engage in natural behaviors, which can cause physical and psychological stress. In traditional cages, hens experience extreme behavioral restriction, and the lack of movement causes metabolic disorders, high rates of disuse osteoporosis, and the birds experience severe frustration due to the prevention of normal behaviors such as nesting (Duncan, 2001). In addition, caged-laying hens sometimes show paralysis around peak production, called cage layer fatigue due to the fractures of the fourth and fifth thoracic vertebrae causing spinal cord compression (Riddell et al., 1968). The condition of cage layer fatigue can be solved by housing them on a bedded floor and providing them with perches (Leeson et al., 1995). Hens are strongly motivated to find the nesting area after nesting behavior has been triggered. Adding nest boxes in a cage-free housing system is helpful for the birds to express nesting behavior naturally. (Duncan & Kite, 1987). Caged houses suppress body maintenance activities of birds like head shaking, head-scratching, tail wagging, feather-ruffling, dust bathing, bill wiping, and unilateral wing-leg stretching (Duncan et al., 1998). Housing birds in cages with wired floors causes hyperkeratosis of toe pads in birds (Duncan, 2001). The birds in cage-free housing systems typically have higher feed conversion ratios than traditional cage systems due to more movement inside the poultry houses and heat losses related to feather cover and environmental temperature (Tauson, 2005a).

Despite the benefits of cage-free housing systems, they also have some challenges. For example, cage-free systems require more space, which can increase the cost of production. Additionally, the hens in cage-free systems may be more susceptible to injuries from other hens, as they can interact with each other more freely. Furthermore, due to the availability of perching areas in cage-free hen houses, birds have higher risks of breaking their furculum and keel bones, so the appropriate design of perching areas is recommended (Freire et al., 2003). Finally, occupational hazards due to poor air quality in cage-free hen houses, such as the presence of ammonia and dust, are prevalent, so proper mitigating measures such as use of electrostatic ionization should follow to ensure good air quality inside the house (Tauson, 2005, Ritz et al., 2006). Access to litter implies higher potential risks of both endoparasites and ectoparasitic infestations among the birds in the litter floor system (Höglund et al., 1995). Injuries landing in perches and contact with litter and moisture are more prevalent in cage-free birds (Tauson & Abrahamsson, 1994). Feather pecking behavior is also widespread in cage-free laying birds, and Severe feather pecking has been estimated to occur in 40%-50 % of cage-free flocks (Coton et al., 2019, Subedi et al., 2023a).

1.2 Precision monitoring of poultry

Precision poultry farming is a technology-driven system that includes continuous and real-time monitoring, extensive data collection, and analysis that assists poultry producers in management decisions and can provide early detection of disease, and production insufficiencies (Rowe et al., 2019). In addition, precision poultry farming provides evidence-based strategies to improve management and decision-making (Li et al., 2021a). Introducing artificial intelligence (AI) in poultry farming and management can improve multiple aspects of the poultry industry such as quick detection of welfare issues (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 (Okinda et al., 2020). There was an application of automatic monitoring systems to study poultry behaviors in group settings (Li et al., 2020e). With the increasing number of cage-free systems in the USA and EU countries, an automatic method was developed for detecting laying hens in cage-free houses (Yang et al., 2022).

Leroy et al., 2005 aimed to measure the behavior of individually recorded laying hens by identifying six behaviors (standing, sitting, sleeping, grooming, scratching, pecking). There is a low classification rate, only 21% for pecking behavior, compared to other behaviors like feeding or drinking. Li et al., 2020e found that poultry feeding and drinking behaviors help indicate feed and water resources utilization by birds and their health status, thus providing critical welfare and economic implications for poultry production. They develop a model that will show the number of birds near the feeder and drinker with an accuracy of 89%. Similarly, developing a model that will quantify the number of birds showing feather pecking will be helpful for farmers and the industry. The novel convolutional neural network-based model tracked the feather pecking behavior in cage-free laying birds (Subedi et al., 2023a). The model provides a basis for developing a real-time automatic model for tracking pecking damages in commercial cage-free houses to protect the health and welfare of laying hens.

Leroy et al., 2006 used a computer vision system to quantify only individual hens that show scratching behaviors. Classification of the behavior of birds in flocks is needed to mimic commercial cage-free conditions. Using machine vision techniques, Guo et al. (2020) examined how poultry behavior is affected by different areas, such as feeding, drinking, and resting zones, and potential interference and obstructions in these areas. Each area where the birds show their activity was visualized using machine vision methods. A machine vision-based monitoring system to classify poultry behavior found the accuracies as 70.3%, 92.09%, 96.04%, and 99.7%, respectively (Pereira et al., 2013, Wang et al., 2020, Pu et al., 2018, Zhuang & Zhang, 2019). Using acoustic data, a convolutional neural network-based model was developed to identify chicken distress calls automatically (Mao et al., 2022). A Mask Region-Based Convolutional Neural Network was developed for detecting preening behaviors in birds. (Li et al., 2020c).

Cluster analysis (unsupervised machine learning) was used to see how free-range hen systems use aviary systems and free-range (Sibanda et al., 2020). This study was to characterize the aviary system's flock sub-populations (clusters) and range usage. A fully automated monitoring technique was developed to measure the activity of broiler chickens with different gait score levels (Aydin et al., 2010). The study assessed the relationship between gait scores obtained by human experts and an automatic image monitoring system. The optical flow method was used to monitor the broiler behavior (Dawkins et al., 2012). This method used a combination of cameras and statistics to analyze poultry behavior and provide the basis for automated assessment of broiler chicken welfare. An automated method to detect problems in a broiler house using cameras and image analysis software was developed (Kashiha et al., 2013). In this work, the image analysis software translated images collected from top-view cameras into an animal distribution index. The real-time prediction of broilers' distribution index helps detect management problems in poultry houses like feeding, drinking, heating, and ventilation systems. An algorithm that indicates the response to the thermal environment was developed to describe the behavioral pattern of broiler breeders, like clustering, preening, foraging and pecking (Nääs et al., 2012). An object detection method was innovated for monitoring broilers and tracking spatial distribution inside poultry houses (Novas & Usberti, 2017). Image-processing algorithms were developed to detect broiler feeding and drinking behaviors (Li et al., 2020e).

To assess lameness in broilers, a 3D vision camera was used, and an algorithm was developed for evaluating the sitting and standing positions of broiler chickens (Aydin, 2017). The group behavior of yellow feather broilers under heat stress was detected using the YOLOv3 algorithm (Anlan Ding et al., 2019). Therefore, this deep learning method could be helpful for farmers to reduce the heat stress of broilers and improve production performance. A Single shot

MultiBox detector (SSD), the InceptionV3 classification model, was innovated to classify the health status of broilers using colors and texture features (Zhuang & Zhang, 2019). Using information from an optical flow analysis to monitor chicken flock behavior can be very helpful in early warning of *Campylobacter* infection (Colles et al., 2016). Optical flow uses the rate of change of brightness in different parts of images temporally and spatially, which can be used for long-term continuous monitoring of large flocks of animals like egg-laying hens. A machine vision system, "Nest-Usage-Sensor," was developed to look at nesting behavior and laying performances in a free-range housing system (Zaninelli et al., 2018). This technology allows the quantification of hens in the nest. Radio-Frequency Identification Technology was used to analyze ranging patterns in free-range laying hens (Campbell et al., 2018). This study analyzed RFID data of hen movement in and out of pop-holes in an experimental free-range system to show evidence of pop-hole-following behavior among individuals within the group and associations between individual hens in simultaneous time spent indoors or outdoors. The multi-Object Tracking algorithm, an SSD detector, was used to visualize a free-range poultry rearing system (Khairunissa et al., 2021) and in turkeys (Ju et al., 2021). The unrest behavior of poultry was observed using Unrest Index to estimate the thermal comfort of poultry (Del Valle et al., 2021). Furthermore, the evaluation of cluster and unrest behaviors of laying hens in response to different light intensities, wavelengths, and light duration was done using a camera, sensors, and machine learning algorithms (Fernandes et al., 2021). The walking duration of birds under restricted feedings was estimated using R-CNN-based object detectors (Li et al., 2021b).

The use of machine learning and computer applications to produce results with good evaluation metrics (precision, accuracy, and recall) is essential in the automated detection of poultry behavior. Automated tracking platforms help manage abnormal poultry behavior using deep learning models (Neethirajan, 2022, Subedi et al., 2023a). Daily animal welfare inspection by poultry farm workers is labor-intensive, time-consuming, and subjective to human errors (Li, Huang et al., 2021). Researchers have investigated robotic applications on hen floor egg reduction, production performance, stress response, bone quality, and behavior (Li et al., 2022d). 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. Floor eggs in cage free housing system were tracked using YOLO-based models with 90% precision (Subedi et al., 2023b). This task requires the development of an automatic tool or method to monitor real-time animal welfare in commercial poultry houses.

1.3 Application of Deep Learning and Machine Vision in Poultry Farming

In recent years, the rise of machine vision through deep learning constitutes a significant improvement in detecting and counting livestock, including poultry (Geffen et al., 2020). Deep learning in poultry science involves using advanced machine learning techniques involving neural networks to analyze and interpret large amounts of poultry-related data. It involves training computer algorithms to learn patterns and make predictions that help farmers and animal scientists make informed behavior detection and animal welfare monitoring decisions. Computer vision is a field of artificial intelligence (AI) that enables computers and systems to derive meaningful information from digital images, videos, and other visual inputs and take actions or make recommendations based on that information (Lei et al., 2022). Image classification, object localization, and object detection are all various types of object recognition techniques for extracting information from an image. For example, for extracting information from an image, methods like image classification, object localization, and object detection can be used. The image classification method helps in assigning a specific class for an object inside the picture; object localization localizes the object in the picture by drawing the bounding box, and object detection is a combined technique where multiple objects can be detected within an image given by an output containing several bounding boxes and multiple classes (Vahab et al., 2019).

Machine vision systems include cameras, recording units, processing units, and deep learning models (Li et al., 2021a). For example, the activity of birds inside the poultry house, i.e., behaviors, are captured by a camera mounted on the ceiling and wall of the house. Next, recording units acquire the data through images and videos. Finally, the images and videos are processed using high-performance computers or cloud-based computing systems like Oracle Cloud Infrastructure. The deep learning models use image processing technology to extract the desired objects and give results after training and prediction. However, the model requires numerous annotated image data to learn for obtaining expected results.

Convolutional neural networks (CNN) are a class of artificial neural networks applicable for image recognition and object detection designed for images (Lei et al., 2022). Multiple convoluted layers extract useful features from the input, i.e., the image, into the hidden units in the form of a tile-like image tensor known as the kernel (He et al., 2014). First, the kernel decides to get particular pixels for the weights used in the learning (O'Shea & Nash, 2015). Next, the pooling layer summarizes information from convoluted layers, which also act as specific regions of pixels used for downsampling. Finally, a fully connected layer comprehends intricate connections between high-level features and converts them into a feature vector (O'Shea & Nash, 2015). The classification layer in the output layer then categorizes the image based on the feature vector.

Deep learning-based models can be divided into one-stage and two-stage methods. Two-stage models, such as R-CNN and Feature Pyramid Network (FPN), first use a region proposal network to identify the potential object regions and then use a fine-tuned network to determine the categories of these regions (Ren et al., 2015). Unfortunately, despite achieving high accuracy in object detection, the inference time for these models can still make them unsuitable for real-time detection requirements in some cases (Shang et al., 2018). In addition, optimizing each component of a two-stage pipeline is more complicated. To address these challenges, faster one-stage-stage models such as Single Shot Multibox Detector (SSD), RetinaNet, and You Only Look Once (YOLO) have been developed as alternatives (Wang et al., 2020).

YOLO, cutting-edge real-time object detection technology, has evolved, with the latest version being YOLOv8. This model is part of a series known as YOLOv1 – YOLOv8 and has been constantly improved by researchers through evaluations on two benchmark datasets, Pascal VOC and Microsoft COCO.

1.3.1 YOLOv5 model for poultry detection

The YOLOv5 model employs CSPDarknet53 as its backbone, incorporating a Spatial Pyramid Pooling layer, a PANet as its neck, and YOLO detection as the Head (J. Guo et al., 2020). YOLOv5 builds its backbone with CSPDarknet by integrating the Cross-Stage Partial Network (CSPNet) into Darknet (Bochkovskiy et al., 2020). This enhances the network's depth and improves feature extraction capabilities. Furthermore, incorporating CSPNet reduces parameters and FLOPS (floating-point operations per second), improving inference speed, accuracy, and reduced model size (Shen et al., 2022). In addition, the Neck Network, which includes the Path Aggregation Network (PANet), addresses the challenge of low-level feature propagation in original feature pyramid networks (FPN) (Liu et al., 2018). PANet also more efficiently leverages information from lower layers for more accurate object detection (Xu et al., 2021).

The Head network in YOLO models comprises three parts: bounding box loss, classification loss, and confidence loss. The loss functions for the classification loss and confidence loss are based on binary cross-entropy. In contrast, Intersection over Union (IoU) loss is used for the bounding box loss (Zheng et al., 2021). The YOLOv5 family includes ten versions of models named YOLOv5l, YOLOv5m, YOLOv5n, YOLOv5s, YOLOv5x, YOLOv5l6, YOLOv5m6, YOLOv5n6, YOLOv5s6, and YOLOv5x6 + TTA which vary in feature extraction modules and convolution kernels (Jocher et al., 2020, Horvat et al., 2022). YOLOv5s is a lightweight algorithm that is easier to use and train but cannot accurately handle the detection of small objects in a complex environment (Idrissi et al., 2022). YOLOv5x model is more powerful and flexible in detecting small-size objects such as chickens (Subedi et al., 2023a). The Ultralytics team has open-sourced the model and made it available on GitHub with pre-trained weights from the COCO dataset.

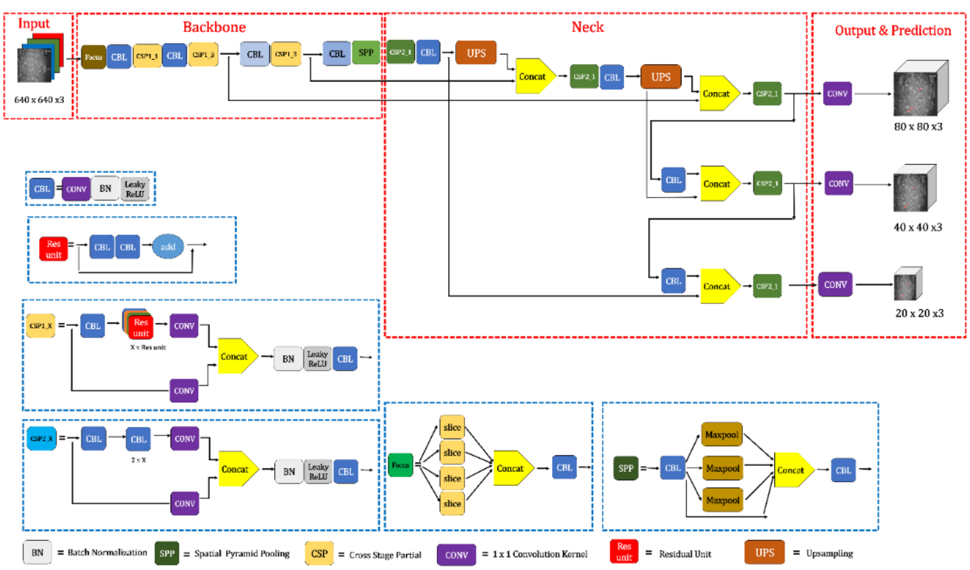


Figure 1.1: YOLOv5 architecture

1.3.2 YOLOv7 for poultry detection

The YOLOv7 model has four components: the input, the backbone layer, the Head, and the output. The input of YOLOv7 is similar to that of YOLOv5. The backbone layer of YOLOv7 includes Bconv layers, E-ELAN layers, and MP layers. The BConv layer performs convolution, batch normalization (BN), and activation functions (Wang et al., 2022). The E-ELAN layer enhances the network's learning capacity by using expanding, shuffling, and merging cardinality methods, allowing the deep network to learn and converge more efficiently without disrupting the original gradient path (Chen et al., 2022). Finally, the MP layer downsamples the input to half its length and width, utilizing BConv layers for both halves. The Head of YOLOv7 is similar to YOLOv5 but has a few differences (C.-Y. Wang et al., 2022). The E-ELAN module replaces the CSP module, and the downsampling module is changed to the MPConv layer (Z. Yang et al., 2022). The head layer comprises several SPPCPC layers, BConv layers, MPConv layers, Catconv layers, and RepVGG block layers that produce three heads in succession (Yang et al., 2022).

The SPPCSPC layer is formed using pyramid pooling and the CSP structure, and the information is concatenated. The Catconv layer performs the same function as the E-ELAN layer, allowing deeper networks to learn and converge more efficiently. The operation of the Catconv layer is similar to the E-ELAN layer, enabling deeper networks to learn and connect more efficiently (Z. Yang et al., 2022) (Lv et al., 2022). Hyperparameters are adjustable settings chosen before training a model based on the data's characteristics and the algorithm's capabilities to improve the effectiveness of the learning process. For Convolutional Neural Networks, hyperparameters often include the number of nodes, layers, epochs, batch size, learning rate, momentum, and loss function. The network's ability to learn complex features is tied to the number of layers, also known as the network's depth. Each layer consists of several nodes, with the number of nodes in the first and last hidden layer typically matching the number of input features and predicted classes, respectively.

The batch size determines the number of data samples processed before updating the weights and computing the gradient, which can be equal to the size of the training set or smaller. When the batch size is smaller than the training set, the algorithm iterates over multiple batches before making predictions. However, having a batch size that is too small can result in fluctuating predictions, while a larger batch size allows for a higher learning rate but may cause memory errors. The number of epochs determines how many times the algorithm will iterate over the entire training dataset. At the same time, the loss function is chosen based on the desired output and used to evaluate the performance of the weights.

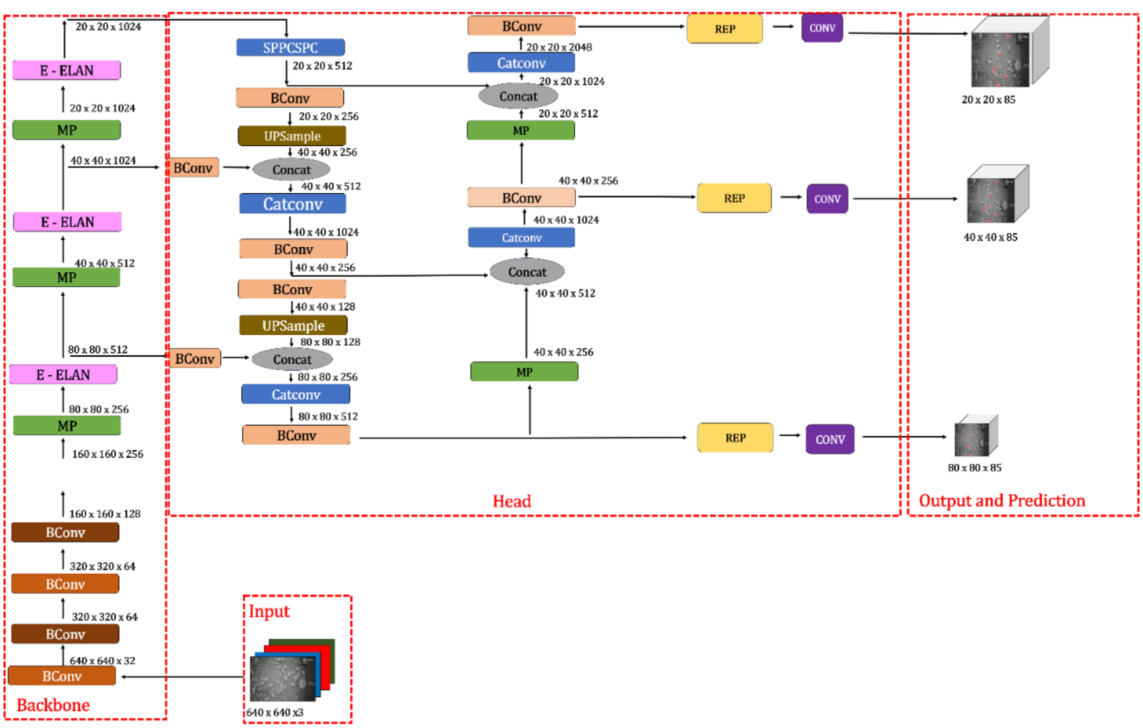


Figure 1.2: YOLOv7 architecture

The object detection task is represented by the object class/label, the bounding box, and the confidence score. The confidence score is between 0 and 1 and describes how confident the model is about the prediction. The detection is compared to the ground-truth bounding box and the label from the annotation to assess the prediction. Intersection over Union (IOU) is used to measure how close the predicted bounding box is to the ground-truth bounding box.

1.3.3 Evaluation metrics

The confusion matrix 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 YOLO models (Lv et al., 2022). TP is when the classifier predicted TRUE (i.e., the image has the class), and the correct class was TRUE (i.e., the image has the class). TN is when the model predicted FALSE (i.e., no class), and the correct class was FALSE. FP is when the classifier predicted TRUE, i.e., the image has a class, but the correct class was FALSE. Finally, FN is when the classifier predicted FALSE, but images have the class.

Table 1.1. The confusion matrix

	Predicted positive	Predicted negative
Actual positive	True positive (TP)	False negative (FN)
Actual negative	False positive (FP)	True negative (TN)

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. Precision describes how well the model can identify relevant objects and answer the question: when the model guesses, how often does it guess correctly?

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

Recall (Sensitivity) is the ratio of correctly predicted positive observations to all observations in the actual class. It answers the question, has the model guessed every time it should have guessed?

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

Mean average precision (mAP) was calculated by Eq. 3:

$$mAP = \sum_{i=1}^{N} P(i)\ x\ \Delta R(i)$$

P(*i*) is precision, and *Δ*R(*i*) is the change in recall from the *i*th detection.

1.4 REFERENCES

Anlan Ding, Xuhui Zhang, Xiuguo Zou, Yan Qian, Heyang Yao, Shikai Zhang, & Yuning Wei. (2019). A Novel Method for the Group Characteristics Analysis of Yellow Feather Broilers Under the Heat Stress Based on Object Detection and Transfer Learning:. *INMATEH - Agricultural Engineering*, *58*(3), 49–58. https://doi.org/10.35633/INMATEH-59-06

Aydin, A. (2017). Using 3D vision camera system to automatically assess the level of inactivity in broiler chickens. *Computers and Electronics in Agriculture*, *135*, 4–10. https://doi.org/10.1016/j.compag.2017.01.024

Aydin, A., Cangar, O., Ozcan, S. E., Bahr, C., & Berckmans, D. (2010). Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. *Computers and Electronics in Agriculture*, *73*(2), 194–199. https://doi.org/10.1016/j.compag.2010.05.004

Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). *YOLOv4: Optimal Speed and Accuracy of Object Detection* (arXiv:2004.10934). arXiv. https://doi.org/10.48550/arXiv.2004.10934

Campbell, D. L. M., Horton, B. J., & Hinch, G. N. (2018). Using Radio-Frequency Identification Technology to Measure Synchronised Ranging of Free-Range Laying Hens. *Animals*, *8*(11), Article 11. https://doi.org/10.3390/ani8110210

Chang, C.-L., Xie, B.-X., & Wang, C.-H. (2020). Visual Guidance and Egg Collection Scheme for a Smart Poultry Robot for Free-Range Farms. *Sensors*, *20*(22), Article 22. https://doi.org/10.3390/s20226624

Chen, J., Liu, H., Zhang, Y., Zhang, D., Ouyang, H., & Chen, X. (2022). A Multiscale Lightweight and Efficient Model Based on YOLOv7: Applied to Citrus Orchard. *Plants*, *11*(23), Article 23. https://doi.org/10.3390/plants11233260

Colles, F. M., Cain, R. J., Nickson, T., Smith, A. L., Roberts, S. J., Maiden, M. C. J., Lunn, D., & Dawkins, M. S. (2016). Monitoring chicken flock behaviour provides early warning of infection by human pathogen Campylobacter. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1822), 20152323. https://doi.org/10.1098/rspb.2015.2323

Craig, J. V., & Swanson, J. C. (1994). Review: Welfare Perspectives on Hens Kept for Egg Production1. *Poultry Science*, *73*(7), 921–938. https://doi.org/10.3382/ps.0730921

Dawkins, M. S., Cain, R., & Roberts, S. J. (2012). Optical flow, flock behaviour and chicken welfare. *Animal Behaviour*, *84*(1), 219–223. https://doi.org/10.1016/j.anbehav.2012.04.036

Del Valle, J. E., Pereira, D. F., Mollo Neto, M., Gabriel Filho, L. R. A., & Salgado, D. D. (2021). Unrest index for estimating thermal comfort of poultry birds (Gallus gallus domesticus) using computer vision techniques. *Biosystems Engineering*, *206*, 123–134. https://doi.org/10.1016/j.biosystemseng.2021.03.018

Duncan, I. J. H. (2001). The pros and cons of cages. *World's Poultry Science Journal*, *57*(4), 381–390. https://doi.org/10.1079/WPS20010027

Duncan, I. J. H., & Kite, V. G. (1987). Some investigations into motivation in the domestic fowl. *Applied Animal Behaviour Science*, *18*(3–4), 387–388. https://doi.org/10.1016/0168-1591(87)90240-1

Duncan, I. J. H., Widowski, T. M., Malleau, A. E., Lindberg, A. C., & Petherick, J. C. (1998). External factors and causation of dustbathing in domestic hens. *Behavioural Processes*, *43*(2), 219–228. https://doi.org/10.1016/S0376-6357(98)00017-5

Fernandes, A. M., de Lucca Sartori, D., de Oliveira Morais, F. J., Salgado, D. D., & Pereira, D. F. (2021). Analysis of Cluster and Unrest Behaviors of Laying Hens Housed under Different Thermal Conditions and Light Wave Length. *Animals*, *11*(7), Article 7. https://doi.org/10.3390/ani11072017

Freire, R., Wilkins, L. J., Short, F., & Nicol, C. J. (2003). Behaviour and welfare of individual laying hens in a non-cage system. *British Poultry Science*, *44*(1), 22–29. https://doi.org/10.1080/0007166031000085391

Geffen, O., Yitzhaky, Y., Barchilon, N., Druyan, S., & Halachmi, I. (2020). A machine vision system to detect and count laying hens in battery cages. *Animal*, *14*(12), 2628–2634. https://doi.org/10.1017/S1751731120001676

Guo, J., Han, K., Wang, Y., Zhang, C., Yang, Z., Wu, H., Chen, X., & Xu, C. (2020). *Hit-Detector: Hierarchical Trinity Architecture Search for Object Detection* (arXiv:2003.11818). arXiv. https://doi.org/10.48550/arXiv.2003.11818

Guo, Y., Chai, L., Aggrey, S. E., Oladeinde, A., Johnson, J., & Zock, G. (2020). A Machine Vision-Based Method for Monitoring Broiler Chicken Floor Distribution. *Sensors*, *20*(11), Article 11. https://doi.org/10.3390/s20113179

Hartcher, K. M., & Jones, B. (2017). The welfare of layer hens in cage and cage-free housing systems. *World's Poultry Science Journal*, *73*(4), 767–782. https://doi.org/10.1017/S0043933917000812

He, K., Zhang, X., Ren, S., & Sun, J. (2014). *Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition* (Vol. 8691, pp. 346–361). https://doi.org/10.1007/978-3-319-10578-9_23

Hewson, C. J. (2003). What is animal welfare? Common definitions and their practical consequences. *The Canadian Veterinary Journal*, *44*(6), 496–499.

Höglund, J., Nordenfors, H., & Uggla, A. (1995). Prevalence of the Poultry Red Mite, Dermanyssus gallinae, in Different Types of Production Systems for Egg Layers in Sweden. *Poultry Science*, *74*(11), 1793–1798. https://doi.org/10.3382/ps.0741793

Horvat, M., Jelečević, L., & Gledec, G. (2022, September 23). *A comparative study of YOLOv5 models performance for image localization and classification*.

Jocher, G., Changyu, L., Hogan, A., L. Y., changyu98, Rai, P., & Sullivan, T. (2020). *ultralytics/yolov5: Initial Release*. Zenodo. https://doi.org/10.5281/zenodo.3908560

Ju, S., Erasmus, M. A., Zhu, F., & Reibman, A. R. (2021). Turkey Behavior Identification Using Video Analytics And Object Tracking. *2021 IEEE International Conference on Image Processing (ICIP)*, 1219–1223. https://doi.org/10.1109/ICIP42928.2021.9506541

Kashiha, M., Pluk, A., Bahr, C., Vranken, E., & Berckmans, D. (2013). Development of an early warning system for a broiler house using computer vision. *Biosystems Engineering*, *116*(1), 36–45. https://doi.org/10.1016/j.biosystemseng.2013.06.004

Khairunissa, J., Wahjuni, S., Soesanto, I. R. H., & Wulandari, W. (2021). Detecting Poultry Movement for Poultry Behavioral Analysis using The Multi-Object Tracking (MOT) Algorithm. *2021 8th International Conference on Computer and Communication Engineering (ICCCE)*, 265–268. https://doi.org/10.1109/ICCCE50029.2021.9467144

Leeson, S., Diaz G., G. J., & Summers, J. D. (1995). *Poultry metabolic disorders and mycotoxins*. University Books. https://scholar.google.com/scholar_lookup?title=Poultry+metabolic+disorders+and+mycotoxins&author=Leeson%2C+Steven.&publication_year=1995

Lei, Y., Dong, P., Guan, Y., Xiang, Y., Xie, M., Mu, J., Wang, Y., & Ni, Q. (2022). Postural behavior recognition of captive nocturnal animals based on deep learning: A case study of Bengal slow loris. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-11842-0

Leroy, T., Vranken, E., Struelens, E., Sonck, B., & Berckmans, D. (2005, January 1). *Computer vision based recognition of behavior phenotypes of laying hens*. 2005 ASAE Annual International Meeting. https://doi.org/10.13031/2013.19471

Li, G., Huang, Y., Chen, Z., Chesser, G. D., Purswell, J. L., Linhoss, J., & Zhao, Y. (2021a). Practices and Applications of Convolutional Neural Network-Based Computer Vision Systems in Animal Farming: A Review. *Sensors*, *21*(4), Article 4. https://doi.org/10.3390/s21041492

Li, G., Hui, X., Chen, Z., Chesser, G. D., & Zhao, Y. (2021b). Development and evaluation of a method to detect broilers continuously walking around feeder as an indication of restricted feeding behaviors. *Computers and Electronics in Agriculture, 181*, 105982. https://doi.org/10.1016/j.compag.2020.105982

Li, G., Hui, X., Lin, F., & Zhao, Y. (2020c). Developing and Evaluating Poultry Preening Behavior Detectors via Mask Region-Based Convolutional Neural Network. *Animals*, *10*(10), Article 10. https://doi.org/10.3390/ani10101762

Li, G., Hui, X., Zhao, Y., Zhai, W., Purswell, J. L., Porter, Z., Poudel, S., Jia, L., Zhang, B., & Chesser, G. D. (2022d). Effects of ground robot manipulation on hen floor egg reduction, production performance, stress response, bone quality, and behavior. *PLOS ONE*, *17*(4), e0267568. https://doi.org/10.1371/journal.pone.0267568

Li, G., Zhao, Y., Purswell, J. L., Du, Q., Chesser, G. D., & Lowe, J. W. (2020e). Analysis of feeding and drinking behaviors of group-reared broilers via image processing. *Computers and Electronics in Agriculture*, *175*, 105596. https://doi.org/10.1016/j.compag.2020.105596

Liu, S., Qi, L., Qin, H., Shi, J., & Jia, J. (2018). Path Aggregation Network for Instance Segmentation. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 8759–8768. https://doi.org/10.1109/CVPR.2018.00913

Lv, B., Wu, L., Huangfu, T., He, J., Chen, W., & Tan, L. (2022). Traditional Chinese Medicine Recognition Based on Target Detection. *Evidence-Based Complementary and Alternative Medicine*, *2022*, e9220443. https://doi.org/10.1155/2022/9220443

Mao, A., Giraudet, C. S. E., Liu, K., De Almeida Nolasco, I., Xie, Z., Xie, Z., Gao, Y., Theobald, J., Bhatta, D., Stewart, R., & McElligott, A. G. (2022). Automated identification of chicken distress vocalizations using deep learning models. *Journal of The Royal Society Interface*, *19*(191), 20210921. https://doi.org/10.1098/rsif.2021.0921

Nääs, I. de A., Laganá, M., Mollo Neto, M., Canuto, S., & Pereira, D. F. (2012). Image analysis for assessing broiler breeder behavior response to thermal environment. *Engenharia Agrícola*, *32*(4), 624–632. https://doi.org/10.1590/S0100-69162012000400001

Neethirajan, S. (2022). Automated Tracking Systems for the Assessment of Farmed Poultry. *Animals*, *12*(3), Article 3. https://doi.org/10.3390/ani12030232

Novas, R. V., & Usberti, F. (2017). Live Monitoring in Poultry Houses: A Broiler Detection Approach. *2017 30th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*. https://doi.org/10.1109/SIBGRAPI.2017.35

Ochs, D. S., Wolf, C. A., Widmar, N. J. O., & Bir, C. (2018). Consumer perceptions of egg-laying hen housing systems. *Poultry Science*, *97*(10), 3390–3396. https://doi.org/10.3382/ps/pey205

Okinda, C., Nyalala, I., Korohou, T., Okinda, C., Wang, J., Achieng, T., Wamalwa, P., Mang, T., & Shen, M. (2020). A review on computer vision systems in monitoring of poultry: A welfare perspective. *Artificial Intelligence in Agriculture*, *4*, 184–208. https://doi.org/10.1016/j.aiia.2020.09.002

O'Shea, K., & Nash, R. (2015). *An Introduction to Convolutional Neural Networks* (arXiv:1511.08458). arXiv. https://doi.org/10.48550/arXiv.1511.08458

Pereira, D. F., Miyamoto, B. C. B., Maia, G. D. N., Tatiana Sales, G., Magalhães, M. M., & Gates, R. S. (2013). Machine vision to identify broiler breeder behavior. *Computers and Electronics in Agriculture*, *99*, 194–199. https://doi.org/10.1016/j.compag.2013.09.012

Pu, H., Lian, J., & Fan, M. (2018). Automatic Recognition of Flock Behavior of Chickens with Convolutional Neural Network and Kinect Sensor. *International Journal of Pattern Recognition and Artificial Intelligence*, *32*(07), 1850023. https://doi.org/10.1142/S0218001418500234

Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *Advances in Neural Information Processing Systems*, *28*. https://papers.nips.cc/paper/2015/hash/14bfa6bb14875e45bba028a21ed38046-Abstract.html

Riddell, C., Helmboldt, C. F., Singsen, E. P., & Matterson, L. D. (1968). Bone Pathology of Birds Affected with Cage Layer Fatigue. *Avian Diseases*, *12*(2), 285–297. https://doi.org/10.2307/1588228

Ritz, C. W., Mitchell, B. W., Fairchild, B. D., Czarick, M., & Worley, J. W. (2006). Improving In-House Air Quality in Broiler Production Facilities Using an Electrostatic Space Charge System. *Journal of Applied Poultry Research*, *15*(2), 333–340. https://doi.org/10.1093/japr/15.2.333

Rowe, E., Dawkins, M. S., & Gebhardt-Henrich, S. G. (2019). A Systematic Review of Precision Livestock Farming in the Poultry Sector: Is Technology Focussed on Improving Bird Welfare? *Animals*, *9*(9), Article 9. https://doi.org/10.3390/ani9090614

Shang, L., Yang, Q., Wang, J., Li, S., & Lei, W. (2018). Detection of rail surface defects based on CNN image recognition and classification. *2018 20th International Conference on Advanced Communication Technology (ICACT)*, 45–51. https://doi.org/10.23919/ICACT.2018.8323642

Shen, H., Dong, Z., Yan, Y., Fan, R., Jiang, Y., Chen, Z., & Chen, D. (2022). Building roof extraction from ASTIL echo images applying OSA-YOLOv5s. *Applied Optics*, *61*(11), 2923–2928. https://doi.org/10.1364/AO.451245

Sibanda, T. Z., Welch, M., Schneider, D., Kolakshyapati, M., & Ruhnke, I. (2020). Characterising Free-Range Layer Flocks Using Unsupervised Cluster Analysis. *Animals: An Open Access Journal from MDPI*, *10*(5), E855. https://doi.org/10.3390/ani10050855

Subedi, S., Bist, R., Yang, X., & Chai, L. (2023a). Tracking pecking behaviors and damages of cage-free laying hens with machine vision technologies. *Computers and Electronics in Agriculture*, *204*, 107545. https://doi.org/10.1016/j.compag.2022.107545

Subedi, S., Bist, R., Yang, X., & Chai, L. (2023b). Tracking Floor Eggs with Machine Vision in Cage-free Hen Houses. *Poultry Science*, 102637. https://doi.org/10.1016/j.psj.2023.102637

T. Leroy, E. Vranken, A. Van Brecht, E. Struelens, B. Sonck, & D. Berckmans. (2006). A COMPUTER VISION METHOD FOR ON-LINE BEHAVIORAL QUANTIFICATION OF INDIVIDUALLY CAGED POULTRY. *Transactions of the ASABE*, *49*(3), 795–802. https://doi.org/10.13031/2013.20462

Tauson, R. (2005a). Management and housing systems for layers – effects on welfare and production. *World's Poultry Science Journal*, *61*(3), 477–490. https://doi.org/10.1079/WPS200569

Tauson, R. (2005b). Management and housing systems for layers – effects on welfare and production. *World's Poultry Science Journal*, *61*(3), 477–490. https://doi.org/10.1079/WPS200569

Tauson, R., & Abrahamsson, P. (1994). Foot and Skeletal Disorders in Laying Hens: Effects of Perch Design, Hybrid, Housing System and Stocking Density. *Acta Agriculturae Scandinavica, Section A — Animal Science*, *44*(2), 110–119. https://doi.org/10.1080/09064709409410189

Vahab, A., Naik, M. S., & Raikar, P. G. (2019). *Applications of Object Detection System*. *06*(04).

Wang, C.-Y., Bochkovskiy, A., & Liao, H.-Y. M. (2022). *YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors* (arXiv:2207.02696). arXiv. https://doi.org/10.48550/arXiv.2207.02696

Wang, C.-Y., Mark Liao, H.-Y., Wu, Y.-H., Chen, P.-Y., Hsieh, J.-W., & Yeh, I.-H. (2020). CSPNet: A New Backbone that can Enhance Learning Capability of CNN. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 1571–1580. https://doi.org/10.1109/CVPRW50498.2020.00203

Wang, T., Yang, F., & Tsui, K.-L. (2020). Real-Time Detection of Railway Track Component via One-Stage Deep Learning Networks. *Sensors*, *20*(15), Article 15. https://doi.org/10.3390/s20154325

Xu, R., Lin, H., Lu, K., Cao, L., & Liu, Y. (2021). A Forest Fire Detection System Based on Ensemble Learning. *Forests*, *12*(2), Article 2. https://doi.org/10.3390/f12020217

Yang, X., Chai, L., Bist, R. B., Subedi, S., & Wu, Z. (2022). A Deep Learning Model for Detecting Cage-Free Hens on the Litter Floor. *Animals*, *12*(15), Article 15. https://doi.org/10.3390/ani12151983

Yang, Z., Ni, C., Li, L., Luo, W., & Qin, Y. (2022). Three-Stage Pavement Crack Localization and Segmentation Algorithm Based on Digital Image Processing and Deep Learning Techniques. *Sensors*, *22*(21), Article 21. https://doi.org/10.3390/s22218459

Zaninelli, M., Redaelli, V., Luzi, F., Mitchell, M., Bontempo, V., Cattaneo, D., Dell'Orto, V., & Savoini, G. (2018). Development of a Machine Vision Method for the Monitoring of Laying Hens and Detection of Multiple Nest Occupations. *Sensors*, *18*(1), Article 1. https://doi.org/10.3390/s18010132

Zheng, D., Li, L., Zheng, S., Chai, X., Zhao, S., Tong, Q., Wang, J., & Guo, L. (2021). A Defect Detection Method for Rail Surface and Fasteners Based on Deep Convolutional Neural Network. *Computational Intelligence and Neuroscience*, *2021*, e2565500. https://doi.org/10.1155/2021/2565500

Zhuang, X., & Zhang, T. (2019). Detection of sick broilers by digital image processing and deep learning. *Biosystems Engineering*, *179*, 106–116. https://doi.org/10.1016/j.biosystemseng.2019.01.003

CHAPTER 2

TRACKING PECKING BEHAVIORS AND DAMAGES OF CAGE-FREE LAYING HENS WITH MACHINE VISION TECHNOLOGIES[1]

[1] Subedi, S, Bist, R, Yang, X, and Chai, L. 2023. *Computers and Electronics in Agriculture, 204,* 107545. Reprinted here with permission of the publisher.

ABSTRACT

Abstract: Feather pecking (FP) is one of the primary welfare issues in commercial cage-free hen houses as that can also cause economic losses for egg producers. A beak trimming is highly criticized in Europe and the USA, alternative methods are needed for pecking monitoring and management. Early detection of FP behaviors and damages on the bird is key to prevent it from spreading or increasing as feather pecking is a learned behavior. The objectives of this study were to develop a machine vision method, testing the performance of new models in tracking the pecking behaviors of hens and potential damages to birdsin the cage-free facilities and improve the detection accuracy of the model. Two YOLOv5 based deep learning models, i.e., YOLOv5s-pecking and YOLOv5x-pecking, were developed and compared in tracking FP behaviors of laying hens cage-free facilities. According the performance based on a dataset of 1924 images (1300 for training, 324 for validation, and 300 for testing), YOLOv5x-pecking model had a 3.1%, 8.6%, and 5.4% higher performance in precision, recall, and Map than YOLOv5s-pecking model, respectively. However, YOLOv5s-pecking model size is 80% smaller, and thus used 75% less GPU memory and 80% less time in model training than YOLOv5x-pecking model for the same dataset. Therefore, YOLOv5s-pecking model was considered to be of with superior performance. This study was among the first to apply YOLOv5 models to track problematic behaviors of cage-free hens. The model provides a basis for developing a real-time automatic model for tracking pecking damages in commercial cage-free houses to protect the health and welfare of millions laying hens.

Keywords: Egg production; cage-free housing; precision farming; animal welfare.

2.1 INTRODUCTION

The European Commission decided to eliminate cages for farmed animals by the year 2027 (Mcdougal, 2021). Thus, there is a need for redesigning the laying hen housing systems using an enhanced understanding of the range of behavior and locomotion of laying hens and broilers. In the USA, there is a high demand from the general public and the primary restaurants or grocers to improve poultry welfare and give products like cage-free (CF) eggs (Chai et al., 2017, 2018, 2019; Oliveira et al., 2019). However, one of the significant problems in the case of CF poultry farming is feather pecking (FP) and associated damages and losses (Coton et al., 2019). Feather pecking is a behavior in which a bird pecks at the feathers of another bird, and it is an indicator of a welfare problem in the bird that develops the behavior. Feather pecking is abnormal behavior in laying hens. It causes welfare concerns as severe cases involve forcefully pecking and pulling out feathers, leading to feather loss, tissue damage, pain, and potential cannibalism resulting in death (Fijn et al., 2020). Records of FP in laying hen flocks from the last 20 years show a prevalence of between 24% and 94% (Mens et al., 2020). It is also a significant economic problem for poultry farmers. Beak trimming is one of the prophylactic measures; however, it does not remedy the cause but only minimizes resulting injuries. Beak trimming is a currently highly criticized practice regarding animal welfare in Europe and the USA as it is a painful practice that influences beak-related behavior (Schwarzer et al., 2021). One possibility for minimizing the problem is the early detection of FP to prevent it from spreading as pecking is a behavior that could be learned by other chickens (Cloutier et al., 2002). Direct observation of pecking behavior, either live or by video recording, is the most precise measure of FP (Kjaer, 2002). Direct observation with high precision is a relatively time-consuming and expensive method. Prediction and detection of pecking behavior in previous studies acoustic data, peckometer and statin gauges were not found to be success due to high density of chickens in commercial houses (Albentosa et al., 2003; Bessei et al., 1999). By monitoring the conditions of FP using modern tools like real time computer vision detection methods and big data collection, we may be able to detect the pecking conditions and stops it before it becomes a serious problem. Daily animal welfare inspection by poultry farm workers is labor-intensive, time-consuming, and subjective to human errors. This task requires the development of an automatic tool or method that can monitor real-time animal welfare in commercial poultry houses. An automatic pecking activity detection in birds can be a valuable tool to identify changes in flock behavior that are potentially indicative of upcoming welfare problems such as cannibalism (Gonzalez et al., 2020).

Researchers used equipment like peckometer to compare the frequency of pecks and pulls between two different breeds of turkeys in a specific test pen (Busayi et al., 2006; Gonzalez et al., 2020). A peckometer was used to record the frequency of both pecks and pulls exerted by the turkeys above a predefined but unspecified force. However, the peckometer could not assist in quantifying the number of birds that are pecking and the number of birds that are being pecked which made early warning or detection of the condition not possible. In turkeys, use of statin gauges to record oscillations resulting from pecking or pulling was also experimented (Bessei et al., 1999). Pecking activity was also detected using sound or acoustic data from grouped-housed turkeys (Gonzalez et al., 2020). The disturbances in the poultry house from stirring fans for ventilation could make isolation of chicken vocalizations difficult for further analysis. Using image data rather than sound could be a viable alternative to detect FP, however, an automatic detection system of pecking activity using an imaging method suitable for long-term recording under near-farming conditions is not yet available.

Image processing technology is a non-invasive and economical solution for monitoring poultry behaviors. An image-based system commonly consists of image/video acquisition systems and algorithms for animal behavior identifications. Appropriate image processing algorithms in computer vision are essential for poultry monitoring in the farm environment for the precise detection or tracking of birds (Okinda et al., 2020). Using these methods in livestock farming has led to options to monitor the health, disease, normal and undesired behaviors of animals on large-scale farms with high performance (Okinda et al., 2020). There was an application of automatic monitoring systems to study poultry behaviors in group settings (Li et al., 2020). Leroy et al. (2005) aimed to measure the behavior of individually laying hens by identifying six different behaviors (i.e., standing, sitting, sleeping, grooming, scratching, pecking). Nevertheless, there was a low classification rate, only 21% for pecking behavior compared to other behaviors such as feeding and drinking. Li et al. (2020) found that poultry feeding and drinking behaviors help indicate utilization of feed and water resources by birds and their health status, thus providing critical welfare and economic implications for poultry production. They developed a model that show the number of birds near feeders and drinkers with an accuracy of 89%. Similarly, developing a model that will quantify the number of birds showing FP will be helpful for egg farmers and the industry. Leroy et al. (2006) used a computer vision system to quantify individual hens' behaviors that show scratching behaviors. The classification algorithm can recognize the scratching behavior of a single caged hen. Guo et al. (2020) studied the interference and obstruction of poultry behaviors and various zones like feeding, drinking, and resting with machine vision methods. The various area where the birds show their activity was visualized using machine learning. Pereira et al. (2013), Wang et al. (2020), Pu et al. (2018), and Zhuang and Zhang (2019) used machine vision-based monitoring systems to classify poultry behaviors and found the accuracies of 70.3%, 92.1%, 96 %, and 99.7%, respectively. The use of machine learning and computer applications to produce results with good evaluation metrics (e.g., precision, accuracy, and recall) is essential in the automated detection of poultry behaviors. Automated tracking platforms help manage abnormal poultry behaviors (Neethirajan, 2022). The use of machine vision and sensor technologies offers poultry management personnel easy management by avoiding subjectivity and inaccuracies in decision-making (Neethirajan, 2022).

Early studies proved that poultry welfare evaluation could be conducted with computer or machine vision-based methods. However, no existing system/method can track, identify, and locate individual birds with the FP. The objectives of this research were to develop a machine vision method to 1) detect the pecking behaviors and damages of laying hens; 2) test the performance of the method in research CF houses; and 3) improve the detection accuracy of the model. We aimed to track, identify, and locate birds showing the FP behavior with the newly developed detection system in cage-free hen houses.

2.2 MATERIAL AND METHODS

Experimental setup

The experiment was conducted in research cage-free research facilities on the University of Georgia poultry research farm in Athens, GA. Eight hundred W36 Hy-Line hens were raised in four identical cage-free facilities (200 birds each room from day 1; Figure 2.1), each was measuring 7.3 m L × 6.1 m W × 3 m H. Nest boxes, feeders, drinkers, and perches were equipped in each cage-free facility by following sizes recommended by the Hy-Line management guides. Pine shavings were uniformly spread on the floor (5 cm depth) before bird arrival and commercial feed was provided ad libitum. Environmental management was controlled by the automatic environment system and the set points were followed as recommended by the Hy-Line W-36 commercial layer management guides (e.g., air temperature was 21 – 23°C, light intensity was 20 lux during egg laying; and lighting was 19L:5D). We checked the growth and environmental conditions of hens every day as suggested by UGA Poultry Research Center Standard Operating Procedure Form. The animal use and management were approved by the Institutional Animal Care and Use Committee (IACUC) at the University of Georgia, USA.

Figure 2.1. Research cage-free facility (200 hens per room; 7.3 m L × 6.1 m W × 3 m H).

Data collection and preparation

For pecking detection, four night-vision network cameras (PRO-1080MSB, Swann Communications USA Inc., Santa Fe Springs, LA, USA) were mounted above the drinking system, feeders, and perches at ~3 m above the ground to capture top-view videos. 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 2.2. Imaging system and data collection

Pecking Behavior Definition and Labelling

Feather pecking (FP) is defined as the pecking, pulling out, and eating of feathers (Rodenburg et al., 2013). Based on the definition, we manually labeled each pecking hen that had the features in Figure 2.3. A dataset of 1924 images (i.e., 1300 for training, 324 for validations, and 300 for testing) from 22-28 weeks of age was created to analyze the feather pecking behavior. Images contain pecking hens with events from approaching towards birds and injuring them were used for the labelling. The labelling was conducted in an open-source labeling software (Makesense.AI). We created the bounding box around region of interest (i.e., pecking behavior). The dataset was split into two folders (i.e., training and validation datasets) in the ratio 70:30. These two folders were divided into two subfolders “Images” and “Labels”. The annotation file was obtained in *.txt* format (text file).

Figure 2.3. Example of pecking behavior and damages in layers

Training of laying hens' images with YOLOv5 models

YOLO (You Only Look Once) is a single stage object detector or algorithm developed in 2015 (Bochkovskiy et al., 2020). Compared to R-CNNs and Fast/Faster R-CNNs, YOLO has a higher accuracy and speed as use of Single Stage Detectors (SSDs) that helps in improving 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 flavors. TinyYOLO, YOLOv2, YOLOv3, YOLOv4, YOLOv5 and YOLOx scaled-YOLO, YOLO with various backends, etc. The most popular flavor of YOLO used in industry was YOLOv3. Now it's the Ultralytics implementation of YOLOv5 (Bochkovskiy et al., 2020). YOLOv5 consists of 10 versions of models named YOLOv5l, YOLOv5m, YOLOv5n, YOLOv5s, YOLOv5x, YOLOv5l6, YOLOv5m6, YOLOv5n6, YOLOv5s6 and YOLOv5x6 + TTA which vary in feature extraction modules and convolution kernels (Jocher et al., 2020, Horvat et al., 2022). In this study, we have used YOLOv5s and YOLOv5x models in our dataset. YOLOv5s is a lightweight algorithm that is easier to use and train but cannot accurately handle the detection of small objects in a complex environment (Idrissi et al., 2022). YOLOv5x model is more powerful and flexible in detecting small-size objects such as chickens (Yang et al., 2022). Pretrained YOLO models especially on COCO (Common Objects in Context) dataset are readily available and easy to use. COCO is a large image dataset designed for object detection, segmentation, person key points detection, stuff segmentation, and caption generation. For laying hens' images/videos, the dataset has annotations for bounding box and image segmentation with one object classes named Pecking. In the newly innovated model, images collected at multiple locations and scales with high scoring regions of the image were considered in tracking/detections. Taking the whole image of hens at test time and evaluating predictions using single network is a major advantage of YOLO over classifier-based systems (Guo et al., 2022). In the YOLO model of this study, 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 confidences of each box with the Probability that box has an object (Pecking). 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 or Pecking.

Architecture of YOLOv5 pecking model

The models (YOLOv5s-pecking and YOLOv5x-pecking) was developed based on YOLOv5s network, which consists three parts: a backbone for feature extraction, a neck for feature fusion, and an output for object detection. The backbone network was CSPDarkNet53 with four feature maps of different sizes, and it was used for poultry feature extraction in this study (Bochkovskiy et al., 2020; Shen et al., 2022). The function of the neck network was extracting feature maps (e.g., pecking behaviors or damages) to obtain rich informative features and reduce losses. The neck was directly leveraged into the model backbones for enhancing the richness and semantic representation of the extracted features for objects of difference shapes and sizes. Neck helps to generate feature pyramids to generalize well on object scaling. It helps to identify the same object with different sizes and scales. The feature pyramid structures of Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) were used in the poultry feature fusion process (Liu et al., 2018; Shen et al., 2022). FPN structure conveys strong semantic features from the top feature maps into the lower feature maps and the PAN structure conveys strong localization features from lower feature maps into higher feature maps. By using PAN as the neck of the model, the input was the feature map output from the backbone, which was feature-fused to obtain features with richer semantic information to be sent to the model head for object detection. Model head helps to perform the final detection part. It applies anchor boxes on features and generates final output vectors with class probabilities, objectness, scores, and bounding boxes. From these new feature maps, the output network part performed poultry or pecking behaviors detection and classification. In this architecture, the focus module is used to slice images and concatenate them to better extract the features during down-sampling. The CBL module consists of three parts: convolution, normalization, and a Leaky Rectified Linear Unit (ReLu) activation function. There are two kinds of cross- stage partial (CSP) networks in YOLOv5 that are similar in structure: one CSP is used in the backbone network and the other is in the neck. With cross-layer connectivity to connect the front and back layers of the network, the CSP network can improve the inference speed while maintaining precision by reducing model size (Wang et al., 2020). Although CSP networks are similar to each other, there is one or three residual units in the CSP network of the backbone, while the CSP network in neck residual units is replaced by CBL modules. In addition, the Spatial Pyramid Pooling (SPP) module executes the maximum pooling with different kernel sizes and fuses features through concatenating them together (He et al., 2014). The Concat module represents the tensor concatenation operation.

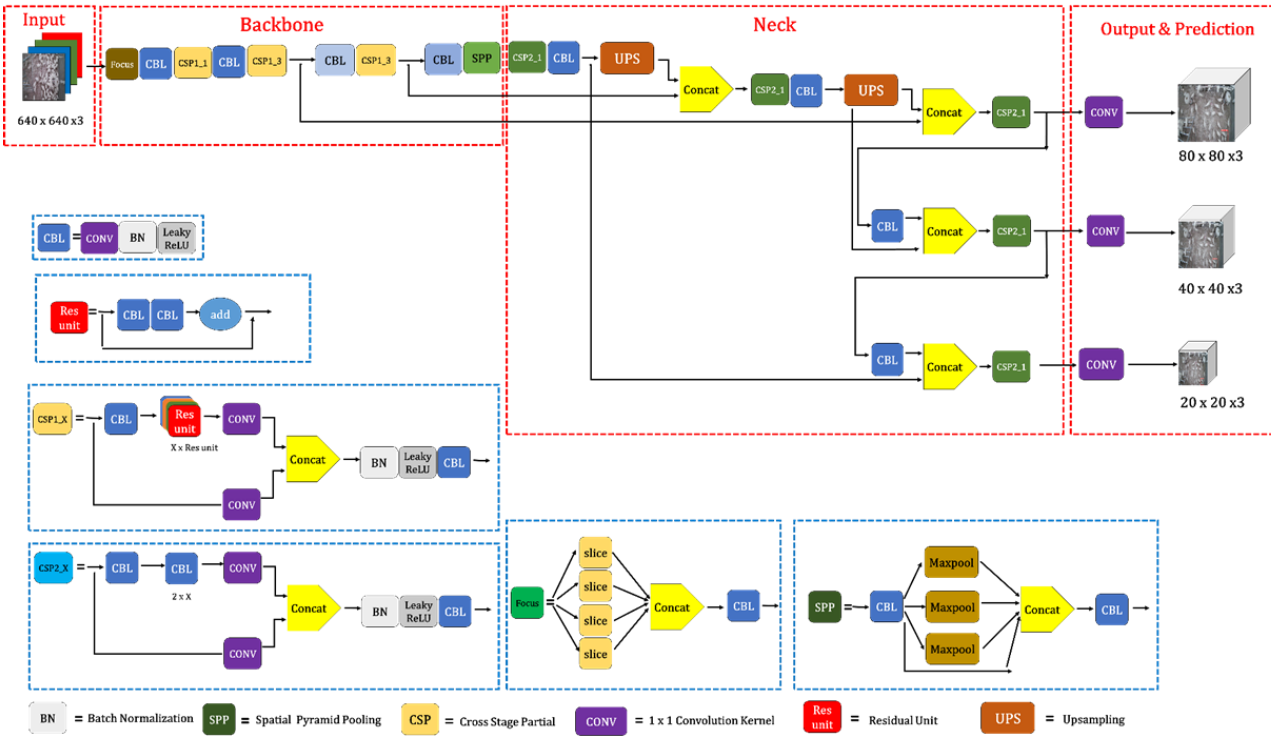


Figure 2.4. YOLOv5 architecture that was used for this study.

Detection training and validation

The dataset was input into the pretrained COCO weights detectors for training, and the training loss was continuously calculated during the training process as illustrated in the Figure 2.5. After that, a modified "yaml" class file and pre-trained learning weights have been employed during the training (Hossain et al., 2022).The training detectors was periodically stored in specific training iteration and validated with the validation dataset. The training and validation losses were compared (Heaton, 2017).

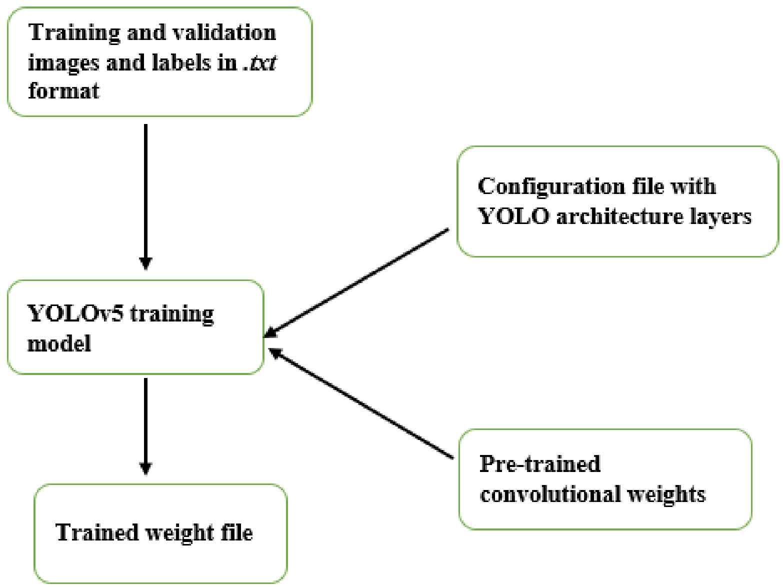


Figure 2.5. YOLOv5 training pipeline

Implementation and execution of YOLOv5s-pecking model was performed in the anaconda distribution using PyTorch machine learning library with 3.9 version. The experiments have been carried out on Oracle Cloud Infrastructure. VM. GPU3.1 with 16 GB GPU memory has been used to enhance neural network training performances. The file named "dataset.yaml" is a customized yolov5 file that contains information about images and labels. We used image batch size of 16 in training of 300 epochs.

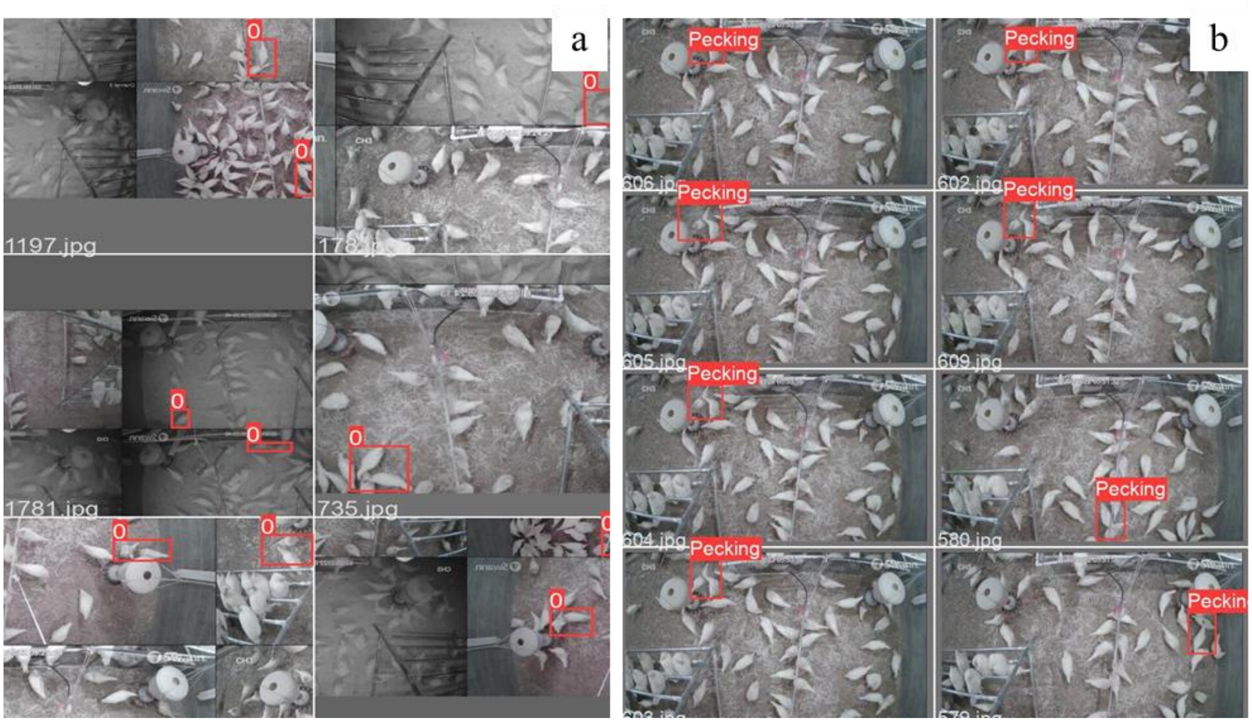


Figure 2.6. Model training (a) and validation (b).

Performance Metrices of the new model

For descriptive statistics and statistical analysis, Python 3.9 was used. Sensitivity/recall, precision and mAP were calculated for the validation data. Precision is the ratio of correctly predicted positive observations (Eq. 1), i.e., Pecking, to the total predicted positive observations. High precision relates to the low false-positive rate.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad \text{Eq. 1}$$

Recall (Sensitivity) is the ratio of correctly predicted positive observations to all observations in actual class – Pecking (Eq.2).

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad \text{Eq. 2}$$

Mean average precision (mAP) was calculated by Eq. 3:

$$mAP = \sum_{i=1}^{N} P(i)\ x\ \Delta R(i) \qquad \text{Eq. 3}$$

Where, P(i) is the precision, and ΔR(i) is the change in recall from the ith detection. For all above, metrics, a closer to 100% value reflects a better performance of the detectors. Figure 2.6 shows the training and validation processes.

2.3 RESULTS AND DISCUSSIONS

Model performance in pecking detection

The confusion matrix 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-pecking and YOLOv5x-pecking. In this study, TP was 0.56 for YOLOv5s-pecking and 0.63 for YOLOv5x-pecking, respectively, when classifier predicted TRUE (i.e., the image has the Pecking), and correct class was TRUE (i.e., the image has the Pecking) (Figure 2.7). TN was 0 for both models, cases when model predicted FALSE (i.e., no Pecking), and correct class was FALSE (i.e., images do not have a Pecking). FP was 1 for both models (Type I error) that classifier predicted TRUE i.e., image has Pecking, but correct class was FALSE (i.e., image did not have Pecking). FN was 0.28 for YOLOv5s-pecking and 0.37 for YOLOv5x-pecking (Type II error), respectively, which indicates that classifier predicted FALSE (i.e., image do not have Pecking), but images do have the Pecking behavior.

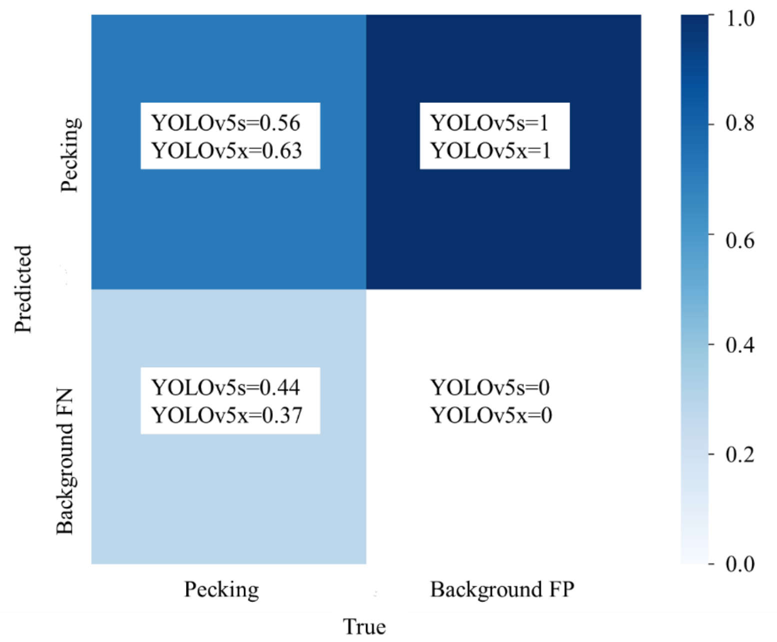


Figure 2.7. Confusion matrices of the YOLOv5s-pecking vs. YOLOv5x-pecking model.

As we trained models with single class (i.e., Pecking) and each image had a background, and thus both YOLOv5s-pecking vs. YOLOv5x-pecking models are expected to predict labelled targets only. There were FPs from the background meaning background should have been classified as a “class” mistakenly by models. Similarly, background FNs are probably objects that weren't classified as anything, which should have been unsteadily.

Model performance in computing system use

Figure 2.8 shows the characteristics of YOLOv5 models such as GPU memory usage, model size, and training time. YOLOv5s-pecking model size is 80% smaller, it used 75% less GPU memory and took 80% less training time than YOLOv5x-pecking model for the same dataset. This information is critical as that affects computer system selection and data analysis speed. YOLOv5s-pecking model has superior performance than YOLOv5x-pecking model.

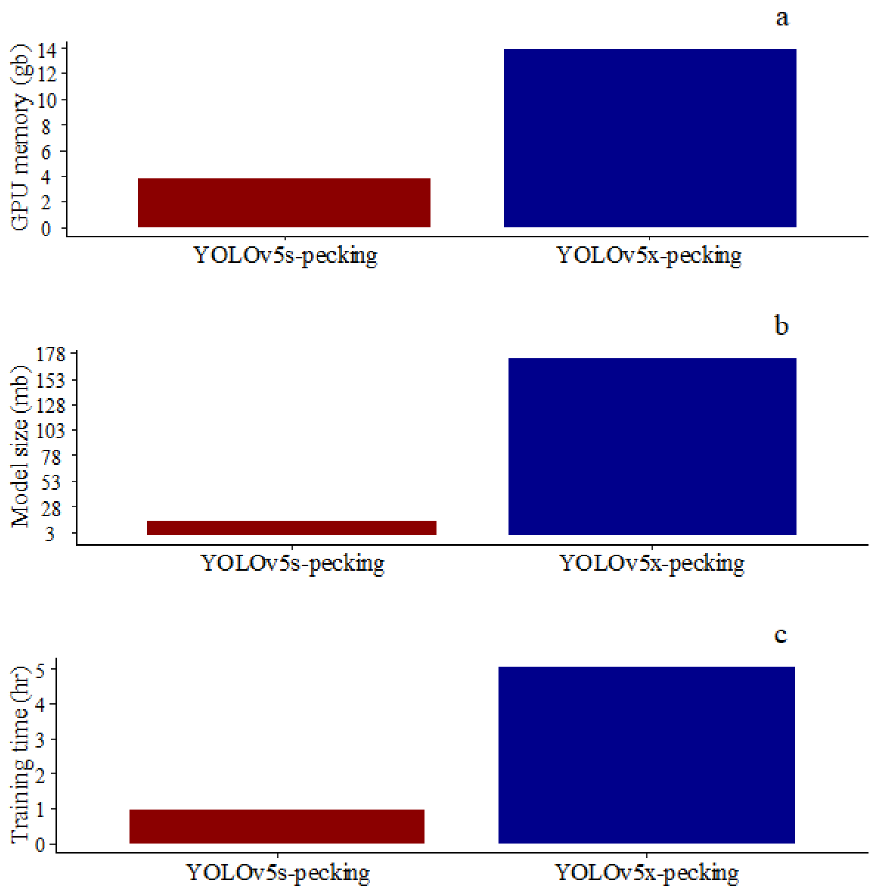


Figure 2.8. YOLOv5s vs. YOLOv5x models in memory size, model size, and training time.

Performance of pecking models in data training and validation

The training and validation process loss function rapidly decreased while running in 300 epochs (Figure 2.9 & Figure 2.10). 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). It is the average mAP over different IoU thresholds, ranging 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).

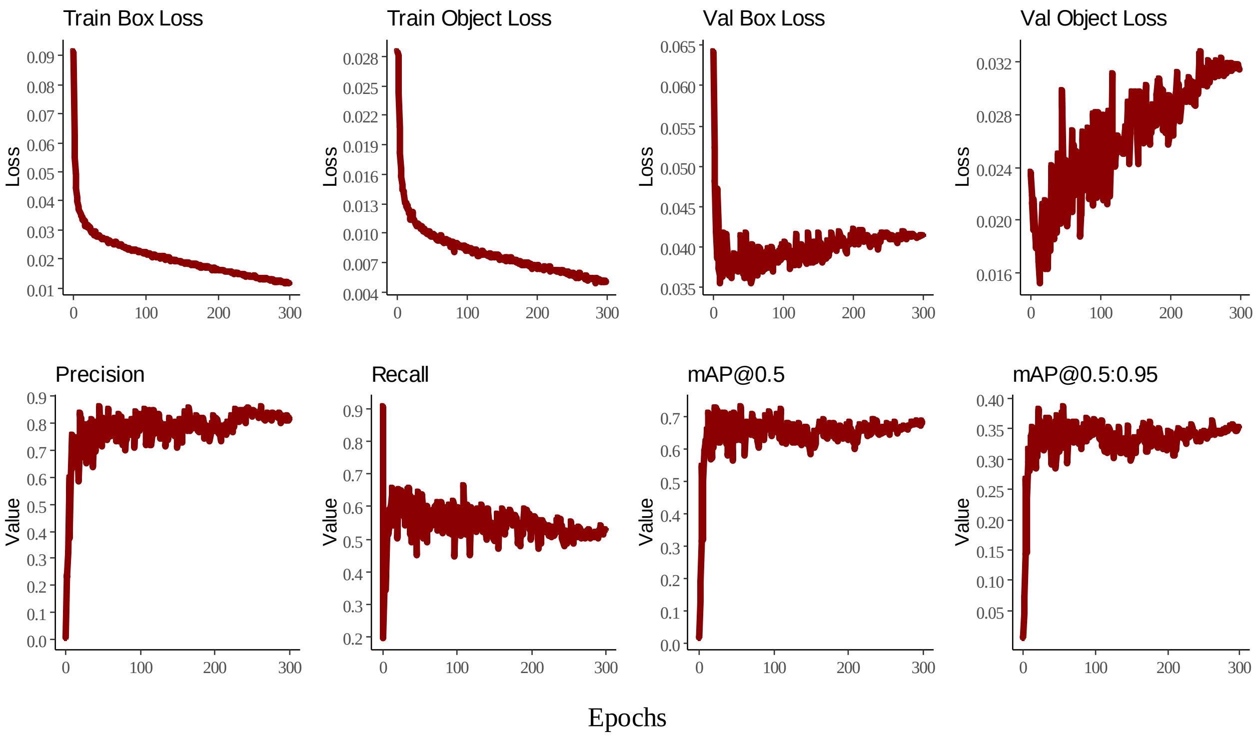


Figure 2.9. Training results of the YOLOv5s-pecking model.

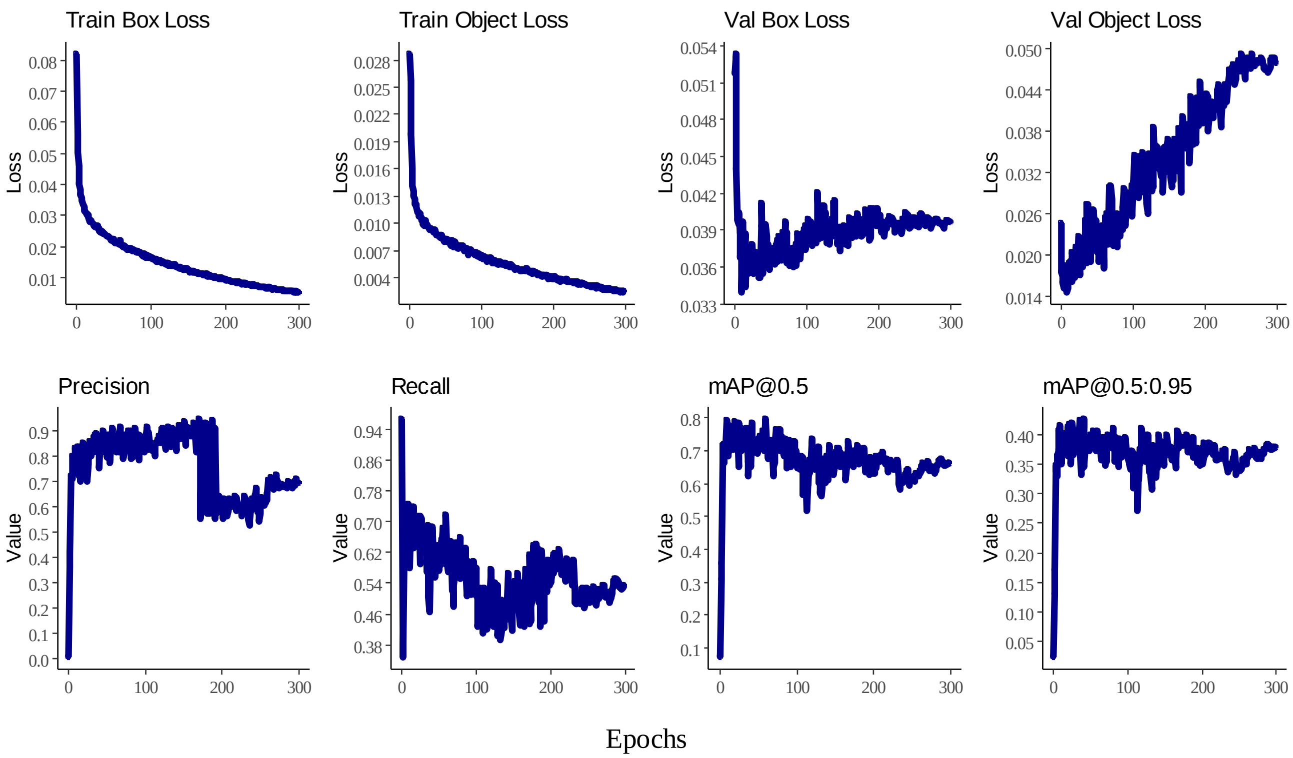


Figure 2.10. Training results of the YOLOv5x model.

Models' Performance Curves after Training

The precision, recall, and PR curve (Precision × Recall) were tested with respect to confidence scores. In Figure 2.11, the pecking detection precision of YOLOv5s-pecking model was low at the beginning, and then increased gradually with the increasing of confidence score. The precision reached 100% when confidence scores was 0.882. For the YOLOv5x-pecking model, the precision was gradually increased 100% when confidence score was 0.852.

The recall for the pecking class (Figure 2.12) was 74% for the YOLOv5s-pecking model at the beginning, and then decreased with the increase of confidence score to 0.9. For the YOLOv5x-pecking model, the recall was similar to YOLOv5x-pecking model at 78% at the beginning, and gradually decreased with the increasing of confidence score to 0.9.

Precision × Recall curve was investigated to evaluate the performance of the Pecking detection of the YOLOv5-pecking models when the confidence score changes for each class. It helps to assess pecking prediction ability when the precision maintains a significant value with the increase in the recall (Hossain et al., 2022). Figure 2.13 shows that cross values (Precision X Recall) for Pecking class and mAP of all classes for YOLOv5s-pecking is 73.3%, which was lower than the 78.7% as generated by YOLOv5x-pecking model.

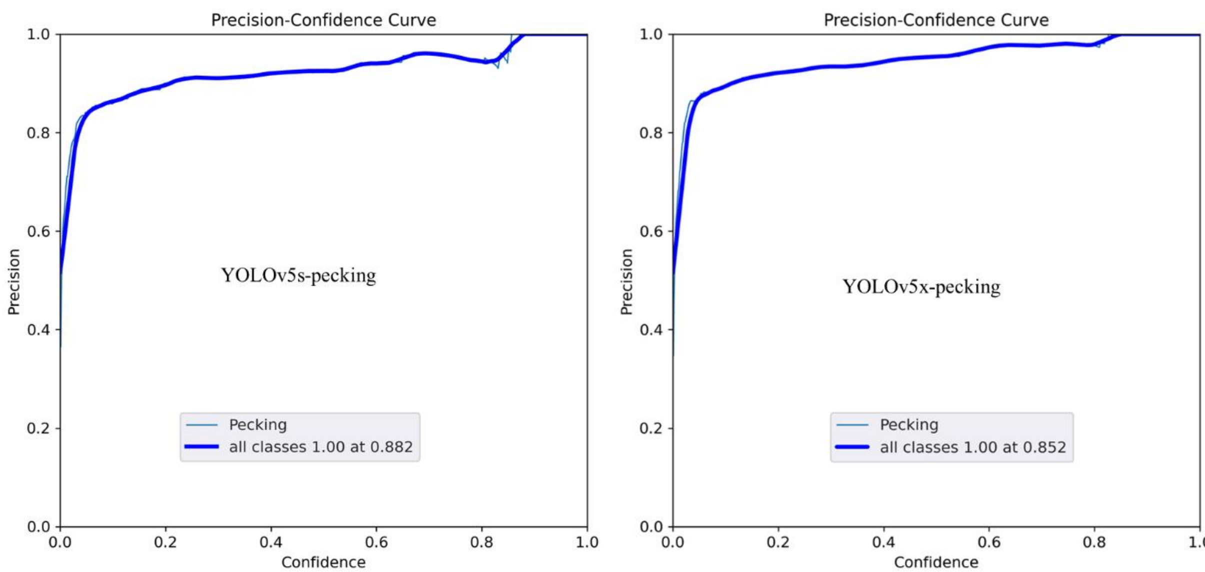


Figure 2.11. The precision of the YOLOv5s vs. YOLO-v5x in pecking detection.

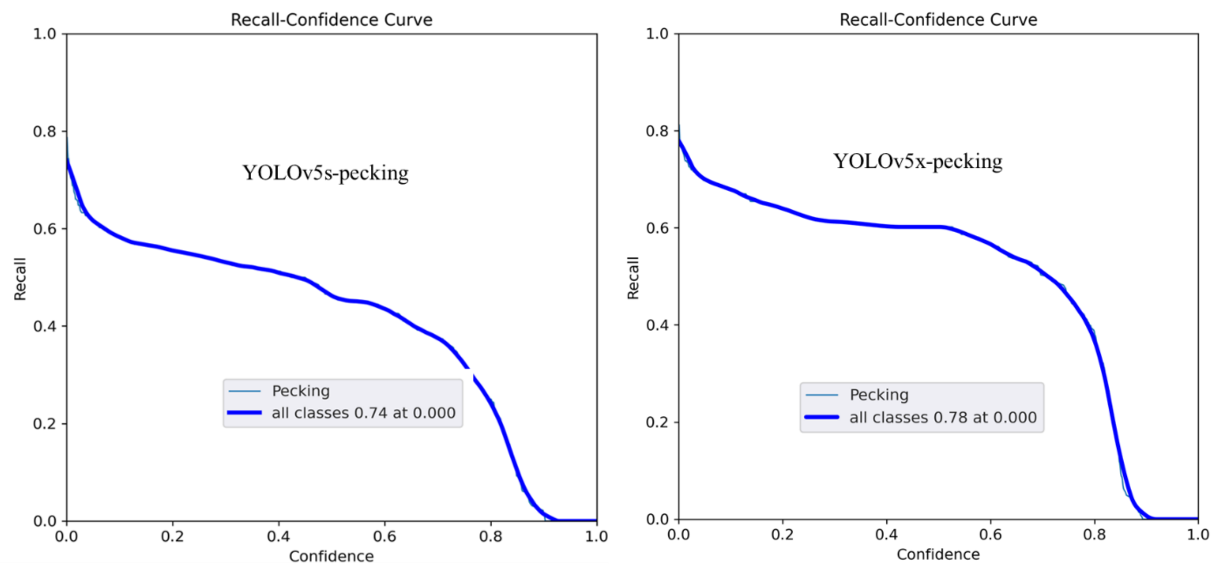


Figure 2.12. The Recall of the YOLOv5s vs. YOLO-v5x in pecking detection.

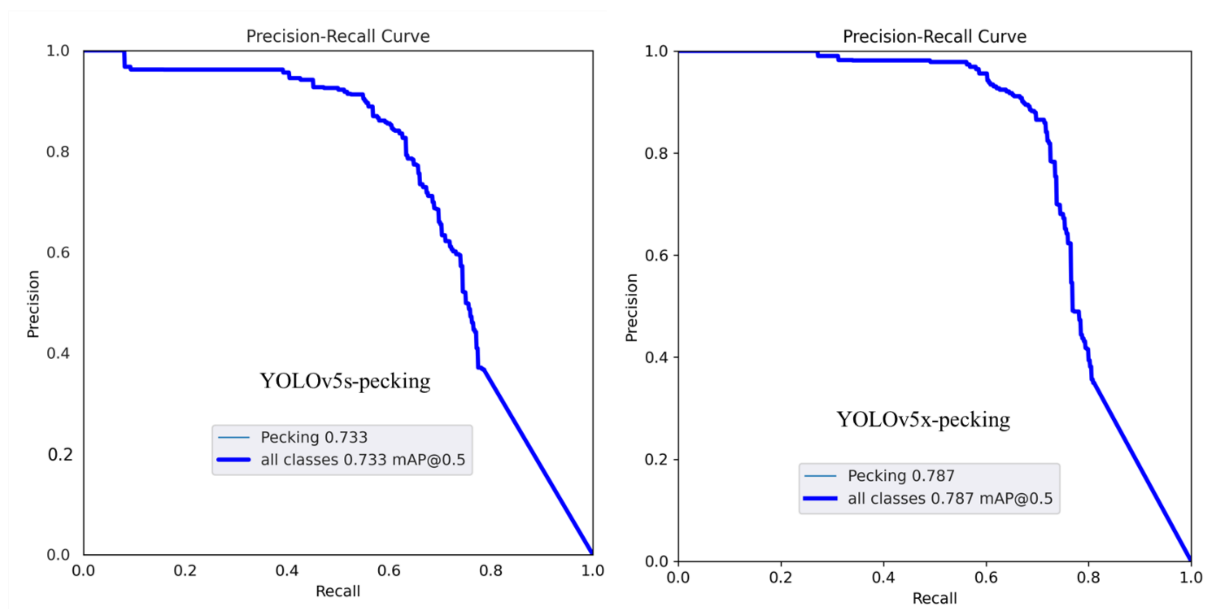


Figure 2.13. The Precision X Recall of the YOLOv5s vs. YOLO-v5x in pecking detection.

Testing results of New Models in Detecting Pecking Behaviors

The optimized model after training was used to detect the condition of pecking in new unlabeled images (300 images) that were not used for validation and testing. Figure 2.14 shows some example of automatic detection. Table 2.1 shows the comparison summery between the YOLOv5s-pecking and the YOLOv5x-pecking model: the YOLOv5s-pecking model can detect the FP behaviors with a precision of 85.2%, recall of 60.2%, and mean average precision (mAP) of 73.3 %; the YOLOv5x-pecking model can detect the FP behaviors with a precision of 88.3%, recall of 68.8%, and mean average precision (mAP) of 78.7 %; YOLOv5x-pecking model detected FP behaviors with a higher accuracy, precision, mAP, and recall than YOLOv5s-pecking.

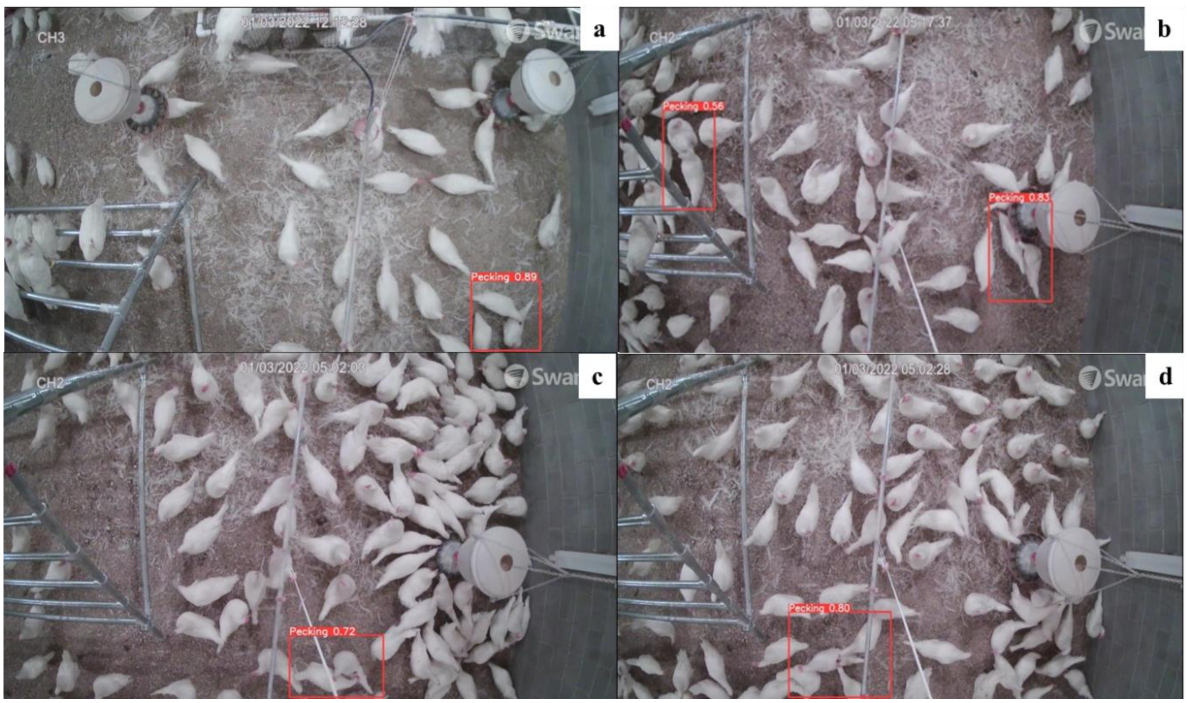


Figure 2.14. Performance of YOLOv5-pecking model in pecking tracking: a – pecking in rest zone, b – pecking in feeding zone, c – pecking in in drinking zone; d – two birds are pecking one bird.

Table 2.1. Results of comparing YOLOv5s and YOLOv5x models for pecking detection

Model	YOLOv5s-pecking			YOLOv5x-pecking		
Parameters	7.1 million			86.1 million		
Layers	157			322		
Class	Precision	Recall	mAP@0.5	Precision	Recall	mAP@0.5
Pecking	85.2	60.2	73.3	88.3	68.8	78.7

However, models generated errors at different contents during situation when a bird's head was overlapping with another bird's back or when birds were piling or crowding together. In addition, dusty environment affected data collection, then we cleaned the camera periodically (weekly) for enhancing performance of the model (Yang et al., 2022). Besides, equipment (e.g. perch, feeders, and drinking lines) was observed to affect imaging system and accuracy, which has been previous reported in broiler houses as well (Guo et al., 2021). For instance, we analyzed the videos recorded by the camera installed above the perch, but pecking was not observed very often on the perches because most of pecking behaviors happened on the floor area. As perches blocked the hens' images on the floor, we used data collected by cameras installed at other locations. In addition, model performance is affected by the stocking density because crowding behaviors could lead to higher errors in object detection. In cage-free housing either in an experimental setup or commercial setup, head-body overlapping is very common. Using a mobile camera may enable to obtaining images from different angles and address the head-body overlapping issues (Guo et al., 2021).

This study was among the first to apply the YOLOv5 modified models to track problematic behaviors (i.e., pecking) and damages in the cage-free hen house, an emerging laying hen housing system in the USA and EU countries. It is predicted that 70% of total laying hens in the US (320 million hens) and 100% of hens in EU countries (370 million hens) will be under cage-free production by 2025-2030 (Chai eta l., 2018, 2019; McDougal, 2021). Severe feather pecking has been estimated to occur in 40%- 50% of cage-free flocks. Therefore, the model provides a basis for developing a real-time automatic model for tracking pecking damages in commercial cage-free houses to protect the health and welfare of hundreds of millions laying hens.

2.4 CONCLUSION

Feather pecking (FP) is one of the primary welfare issues in commercial cage-free hen houses as that reduce the well-being of birds and cause economic losses for egg producers. YOLOv5 based deep learning models of "YOLOv5s-pecking" and "YOLOv5x-pecking" were developed and compared in tracking FP behaviors of laying hens cage-free facilities. According the performance based on a dataset of 1924 images (1300 for training, 324 for validation, and 300 for testing) that were collected from 22-28 weeks of hens' age, the YOLOv5s-pecking model detected the FP behaviors with a precision of 85.2%, recall of 60.2%, and mean average accuracy (mAP) of 73.3 %. Meanwhile, the YOLOv5x-pecking model detected the FP behaviors with a precision of 88.3%, recall of 68.8%, and mean average precision (mAP) of 78.7%. YOLOv5x-pecking model had a 3.1%, 5.6%, and 5.2% higher performance in precision, recall, and Map than YOLOv5s-pecking model. However, YOLOv5s-pecking model size is 80% smaller, it used 75% less GPU memory and took 80% less training time than YOLOv5x-pecking model for the same dataset. Therefore, YOLOv5s-pecking model was considered with superior performance than

YOLOv5x-pecking model. This study was among the first to apply YOLOv5 models to track problematic behaviors of cage-free hens. The model provides a basis for developing a real-time automatic model for tracking pecking behaviors and damages in commercial cage-free houses to protect the health and welfare of hundreds of millions laying hens.

Acknowledgments

This project is supported by the Egg Industry Center; Oracle for Research Grant, Oracle America (Award Number: 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) & Enhancing Poultry Production Systems through Emerging Technologies and Husbandry Practices (GEO00894; Accession Number: 1021518).

2.5 REFERENCES

Albentosa, M. J., Kjaer, J. B., & Nicol, C. J. (2003). Strain and age differences in behaviour, fear response and pecking tendency in laying hens. British Poultry Science, 44(3), 333–344. https://doi.org/10.1080/00071660310001598085

Bessei, W., Reiter, K., Bley, T., & Zeep, F. (1999). Measuring pecking of a bunch of feathers in individually housed hens: first results of genetic studies and feeding related reactions. Lohmann Information, 22, 27-31.

Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). YOLOv4: Optimal Speed and Accuracy of Object Detection (arXiv:2004.10934). arXiv. https://doi.org/10.48550/arXiv.2004.10934

Chai, L., Xin, H., Wang, Y., Oliveira, J., Wang, K., & Zhao, Y. (2019). Mitigating Particulate Matter Generation in a Commercial Cage-Free Hen House. Transactions of the ASABE, 62(4), 877-886.

Chai, L., Zhao, Y., Xin, H., Wang, T., & Soupir, M. L. (2018). Mitigating airborne bacteria generations from cage-free layer litter by spraying acidic electrolysed water. Biosystems Engineering, 170, 61-71.

Cloutier, S., Newberry, R., Honda, K., & Alldredge, J. R. (2002). Cannibalistic behaviour spread by social learning. Animal Behaviour, 63, 1153–1162. https://doi.org/10.1006/anbe.2002.3017

Coton, J., Guinebretière, M., Guesdon, V., Chiron, G., Mindus, C., Laravoire, A., Pauthier, G., Balaine, L., Descamps, M., Bignon, L., Huneau-Salaün, A., & Michel, V. (2019). Feather pecking in laying hens housed in free-range or furnished-cage systems on French farms. British Poultry Science, 60(6), 617–627. https://doi.org/10.1080/00071668.2019.1639137

Fijn, L. B., van der Staay, F. J., Goerlich-Jansson, V. C., & Arndt, S. S. (2020). Importance of Basic Research on the Causes of Feather Pecking in Relation to Welfare. *Animals : An Open Access Journal from MDPI*, *10*(2), 213. https://doi.org/10.3390/ani10020

Gonzalez, J. J., Nasirahmadi, A., & Knierim, U. (2020). Automatically Detected Pecking Activity in Group-Housed Turkeys. Animals, 10(11), 2034. https://doi.org/10.3390/ani10112034

Guo, Y., Aggrey, S. E., Oladeinde, A., Johnson, J., Zock, G., & Chai, L. (2021). A Machine Vision-Based Method Optimized for Restoring Broiler Chicken Images Occluded by Feeding and Drinking Equipment. Animals, 11(1), 123. https://doi.org/10.3390/ani11010123

Guo, Y., Chai, L., Aggrey, S. E., Oladeinde, A., Johnson, J., & Zock, G. (2020). A Machine Vision-Based Method for Monitoring Broiler Chicken Floor Distribution. Sensors, 20(11), 3179. https://doi.org/10.3390/s20113179

Guo, Z., Wang, C., Yang, G., Huang, Z., & Li, G. (2022). MSFT-YOLO: Improved YOLOv5 Based on Transformer for Detecting Defects of Steel Surface. Sensors, 22(9), 3467. https://doi.org/10.3390/s22093467

He, K., Zhang, X., Ren, S., & Sun, J. (2014). Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition (Vol. 8691, pp. 346–361). https://doi.org/10.1007/978-3-319-10578-9_23

Heaton, J. (2017). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning: The MIT Press, 2016, 800 pp, ISBN: 0262035618. Genetic Programming and Evolvable Machines, 19. https://doi.org/10.1007/s10710-017-9314-z

Horvat, M., Jelečević, L., & Gledec, G. (2022, September 23). A comparative study of YOLOv5 models performance for image localization and classification.

Hossain, A., Islam, M. T., & Almutairi, A. F. (2022). A deep learning model to classify and detect brain abnormalities in portable microwave based imaging system. Scientific Reports, 12(1), 6319. https://doi.org/10.1038/s41598-022-10309-6

Jocher, G., Changyu, L., Hogan, A., Rai, P., & Sullivan, T. (2020). ultralytics/yolov5: Initial Release. Zenodo. https://doi.org/10.5281/zenodo.3908560

Kjaer, J. (2002, September 6). Recording of feather pecking and selection against feather pecking.

Li, G., Zhao, Y., Purswell, J. L., Du, Q., Chesser, G. D., & Lowe, J. W. (2020). Analysis of feeding and drinking behaviors of group-reared broilers via image processing. Computers and Electronics in Agriculture, 175, 105596. https://doi.org/10.1016/j.compag.2020.105596

Liu, S., Qi, L., Qin, H., Shi, J., & Jia, J. (2018). Path Aggregation Network for Instance Segmentation. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 8759–8768. https://doi.org/10.1109/CVPR.2018.00913

McDougal, T. (2021). European Parliament votes to ban the use of cages by 2027. (2021, June 14). Poultry World. https://www.poultryworld.net/poultry/european-parliament-votes-to-ban-the-use-of-cages-by-2027/

Mens, A. J. W., van Krimpen, M. M., & Kwakkel, R. P. (2020). Nutritional approaches to reduce or prevent feather pecking in laying hens: Any potential to intervene during rearing? World's Poultry Science Journal, 76(3), 591–610. https://doi.org/10.1080/00439339.2020.1772024

Neethirajan, S. (2022). Automated Tracking Systems for the Assessment of Farmed Poultry. Animals, 12(3), 232. https://doi.org/10.3390/ani12030232

Okinda, C., Nyalala, I., Korohou, T., Okinda, C., Wang, J., Achieng, T., Wamalwa, P., Mang, T., & Shen, M. (2020). A review on computer vision systems in monitoring of poultry: A welfare perspective. Artificial Intelligence in Agriculture, 4, 184–208. https://doi.org/10.1016/j.aiia.2020.09.002

Busayi, R.M., Channing, C. E., & Hocking, P. M. (2006). Comparisons of damaging feather pecking and time budgets in male and female turkeys of a traditional breed and a genetically selected male line. Applied Animal Behaviour Science, 96(3), 281–292. https://doi.org/10.1016/j.applanim.2005.06.007

Schwarzer, A., Plattner, C., Bergmann, S., Rauch, E., Erhard, M., Reese, S., & Louton, H. (2021). Feather Pecking in Non-Beak-Trimmed and Beak-Trimmed Laying Hens on Commercial Farms with Aviaries. Animals, 11(11), 3085. https://doi.org/10.3390/ani11113085

Shen, H., Dong, Z., Yan, Y., Fan, R., Jiang, Y., Chen, Z., & Chen, D. (2022). Building roof extraction from ASTIL echo images applying OSA-YOLOv5s. Applied Optics, 61(11), 2923–2928. https://doi.org/10.1364/AO.451245

Tulbure, A.-A., Tulbure, A.-A., & Dulf, E.-H. (2022). A review on modern defect detection models using DCNNs – Deep convolutional neural networks. Journal of Advanced Research, 35, 33–48. https://doi.org/10.1016/j.jare.2021.03.015

Wang, C.-Y., Mark Liao, H.-Y., Wu, Y.-H., Chen, P.-Y., Hsieh, J.-W., & Yeh, I.-H. (2020). CSPNet: A New Backbone that can Enhance Learning Capability of CNN. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 1571–1580. https://doi.org/10.1109/CVPRW50498.2020.00203

Yang, X., Chai, L., Bist, R. B., Subedi, S., & Wu, Z. (2022). A Deep Learning Model for Detecting Cage-Free Hens on the Litter Floor. Animals, 12(15), 1983. https://doi.org/10.3390/ani12151983.

Zhang, K., Wang, C., Yu, X., Zheng, A., Gao, M., Pan, Z., Chen, G., & Shen, Z. (2022). Research on mine vehicle tracking and detection technology based on YOLOv5. Systems

Science & Control Engineering, 10(1), 347–366.

https://doi.org/10.1080/21642583.2022.2057370

CHAPTER 3

TRACKING FLOOR EGGS WITH MACHINE VISION IN CAGE-FREE HEN HOUSES[1]

[1] Subedi, S, Bist, R, Yang, X, and Chai, L. 2023. *Poultry Science, 102(6),* 102637
Reprinted here with permission of the publisher.

ABSTRACT

Abstract: Some of the major restaurants and grocery chains in the USA have pledged to buy cage-free (CF) eggs only by 2025 or 2030. While CF house allows hens to perform more natural behaviors (e.g., dust bathing, perching and foraging on the litter floor), a particular challenge is floor eggs (mislaid eggs on litter floor). Floor eggs have high chances of contamination. The manual collection of eggs is laborious and time-consuming. Therefore, precision poultry farming technology is necessary to detect floor eggs. In this study, three new deep learning models, i.e., YOLOv5s-egg, YOLOv5x-egg, and YOLOv7-egg networks, were developed, trained, and compared in tracking floor eggs in four research cage-free laying hen facilities. Models were verified to detect eggs by using images collected in two different commercial houses. Results indicate that the YOLOv5s-egg model detected floor eggs with a precision of 87.9%, recall of 86.8%, and mean average precision (mAP) of 90.9%; the YOLOv5x-egg model detected the floor eggs with a precision of 90%, recall of 87.9%, and mean average precision (mAP) of 92.1 %; and the YOLOv7-egg model detected the eggs with a precision of 89.5%, recall of 85.4%, and mean average precision (mAP) of 88%. All models performed with over 85%detection precision; however, model performance is affected by the stocking density, varying light intensity, and images occluded by equipment like drinking lines, perches, and feeders. The YOLOv5x-egg model detected floor eggs with higher accuracy, precision, mAP, and recall than YOLOv5s-egg and YOLOv7-egg. 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.

Keywords: Cage-free system; animal behaviors; mislaid eggs; computer vision.

3.1 INTRODUCTION

The way to raise poultry in the US is shifting towards a cage-free housing system due to various welfare considerations. There is a high demand from the public and the some of the major grocery chains and restaurants to improve poultry welfare and give products like cage-free eggs (Chai et al., 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). In cage-free housing and aviary housing, there are many forage areas for the birds and the eggs laid there are called floor eggs (Jones et al., 2015; Oliveira et al., 2019). In the laying industry under cage-free housing, the eggs are mainly laid around the foraging area, which causes an increase in dirty eggs contaminated with feces and litter, even an increase in broken eggs because hens were observed to peck eggs on the floor more than in the nesting boxes(G. 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 to guide sensing for a robotic egg-picking system.

Introducing sensing technologies and artificial intelligence (AI) (e.g., deep learning and compute vision) in poultry farming and management can improve multiple aspects of the poultry industry (Li et al., 2017; Neethirajan, 2022; Castro et al., 2023). Machine learning techniques include object classification, detection, recognition, and tracking (Wurtz et al., 2019). Using these methods in livestock farming has led to opportunities to monitor the health, disease, as well as the behavior of animals in large-scale farms with high performance (Lao et al., 2016; Okinda et al., 2020). Various works are done in the live video monitoring of broilers to look for their behaviors, movement, and spatial distribution patterns. A fully automated monitoring technique was developed to measure the activity of broiler chickens with different gait score levels (Aydin et al., 2010). The study assessed the relationship between gait scores obtained by human experts and an automatic image monitoring system. The optical flow method was used to monitor the broiler behavior (Dawkins et al., 2012). This method used a combination of cameras and statistics to analyze poultry behavior and provide the basis for automated assessment of broiler chicken welfare. Activity sensors (three-axis accelerometers) were used to continuously monitor the hen's movement before, during, and after infestation with mites (Murillo et al., 2020). In this study, the frequency of behaviors in individual birds was identified using the trained algorithm. Mites cause skin lesions, so there is an increased frequency of preening behaviors in birds. (Zhuang & Zhang, 2019). Using information from optical flow analysis to monitor chicken flock behavior can be very helpful in early warning of *Campylobacter* infection (Colles et al., 2016). Optical flow uses the rate of change of brightness in different parts of images temporally and spatially, which can be used for long-term continuous monitoring of large flocks of animals like egg-laying hens. A machine vision system, "Nest-Usage-Sensor," was developed to look at nesting behavior and laying performances in a free-range housing system (Zaninelli et al., 2018). This technology allows the quantification of hens in the nest. Radio-Frequency Identification Technology was used to analyze ranging patterns in free-range laying hens (Campbell et al., 2018). This study analyzed RFID data of hen movement in and out of pop-holes in an experimental free-range system to show evidence of pop-hole-following behavior among individuals within the group and associations between individual hens in simultaneous time spent indoors or outdoors.

Li et al. (2020b) developed and applied an automatic monitoring system to detect floor eggs in a lab-scale cage-free setting (Li et al., 2020b). A YOLOv5 deep-learning model for detecting cage-free hens was developed with an accuracy of 96% (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). 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., 2022a). 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. A recent study trained and optimized YOLOv5s and YOLO5x models for tracking pecking behaviors and damages of cage-free hens (Subedi et al., 2023). The precision of both models reached 85%.

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) explore ways 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 in research and commercial houses based on image data analysis.

3.2 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. 800 W36 Hy-Line hens 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.

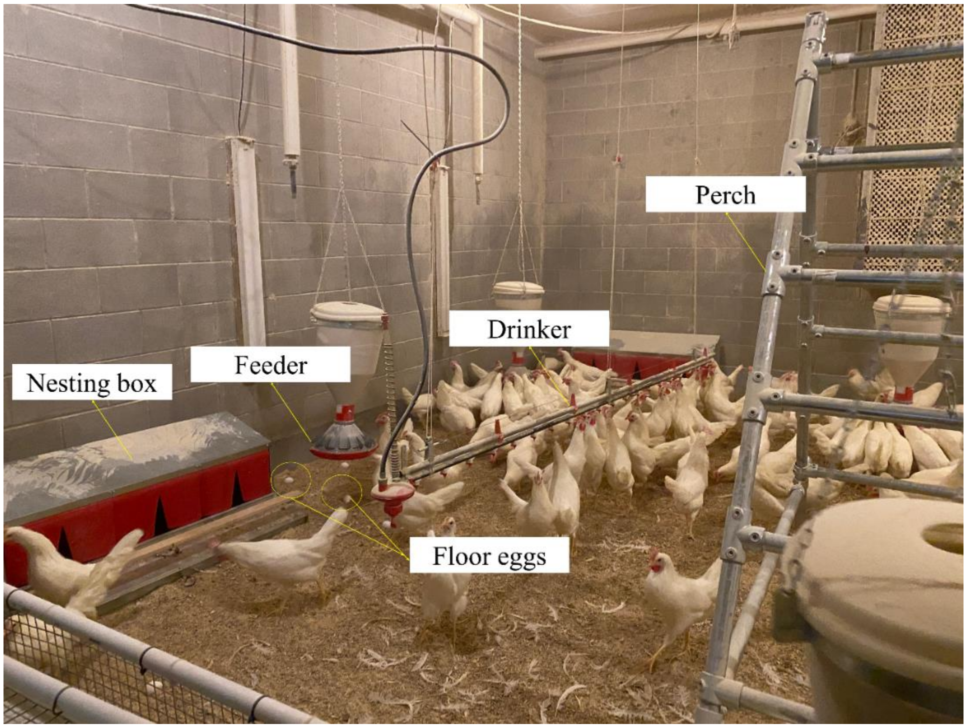


Figure 3.1. Research cage-free facility (200 hens per room; 7.3 m L × 6.1 m W × 3 m H).

An automatic environment system controlled the rearing condition, and set points were 21 – 23°C for air temperature and 30 lux for light intensity during Egg laying with 19L:5D lighting.

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. 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 3.2. Imaging system and data collection.

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 (i.e., eggs). 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 of "Images" and "Labels". Finally, we got the annotation file in .txt format (text file).

Convolutional Neural Network (CNN)

Convolutional neural networks (CNN) are a class of artificial neural networks applicable for image recognition and object detection designed for images (Lei et al., 2022). Multiple convoluted layers extract useful features from the input, i.e., the image, into the hidden units in the form of a tile-like image tensor known as the kernel (He et al., 2014). First, the kernel decides to get particular pixels for the weights used in the learning (O'Shea & Nash, 2015). Next, the pooling layer summarizes information from convoluted layers, which also act as specific regions of pixels used for downsampling. Finally, a fully connected layer comprehends intricate connections between high-level features and converts them into a feature vector (O'Shea & Nash, 2015). The classification layer in the output layer then categorizes the image based on the feature vector.

Transfer learning

Transfer learning is helpful for rapidly retraining a model on new data without training the entire network from scratch. It accomplishes this by leveraging useful features from one or more source datasets to train the target object (Dawei et al., 2019). Instead of retraining the complete network, transfer learning involves keeping some initial weights fixed while the optimizer updates the remaining weights to minimize the loss. This technique is more resource-efficient than standard training and leads to faster training times, although it may decrease the final model's accuracy (Pan & Yang, 2010). Furthermore, when pre-trained networks are used, transfer learning can be employed to adjust the network more efficiently for the target problem (Lubich et al., 2019). This can be achieved by extracting the features from the pre-trained network, employing the same architecture, or freezing some layers while training the others (Pan & Yang, 2010). For example, in image recognition, where the initial layers usually extract general features of images, such as colors, shapes, and edges, transfer learning can be utilized by freezing these layers. This enables the pre-trained initial layers from a larger base dataset to be applied to the target dataset (Ray et al., 2023). The performance of the layers trained on a larger dataset is then leveraged to increase the overall performance of a network trained on a smaller dataset. The remaining layers of the target network are then responsible for extracting the specific features linked to the target dataset (Ray et al., 2023).

Hyperparameter tuning

Hyperparameters refer to the parameters that can be manually set before training the model to enhance the effectiveness of the learning process by adjusting the model's capacity and data characteristics (Agrawal, 2021). Tuning the hyperparameters is crucial when developing a high-performing model. It is important to note that weight or model parameters adjusted by the algorithm during training are not considered hyperparameters. Hyperparameters vary depending on the model, and convolutional neural networks typically include the number of nodes and layers, epochs, batch size, learning rate, momentum, and loss function (Agrawal, 2021). The network's depth, determined by the number of layers, plays a significant role in the model's ability to learn complex features. The first and last hidden layers usually have the same nodes as the input features and classes to predict, respectively. The batch size specifies the number of data samples the model should pass through before updating the weights and computing the gradient. It can be the same as the size of the training set or smaller. A small batch size may cause prediction fluctuations, while a large batch size can lead to memory errors (Smith, 2018). The number of epochs determines how many times the algorithm will iterate over the entire training dataset. The choice of loss function depends on the desired output, which is used to evaluate the weight's performance.

The COCO (Common Objects in Context) dataset is a high-quality dataset for computer vision with 117, 264 pictures, including 80 object classes and 7.4 bounding boxes per image on average (Lin et al, 2014). The COCO dataset is often used during transfer learning to fine-tune pre-trained models for object detection and segmentation tasks. Transfer learning with the COCO dataset involves utilizing a pre-trained model trained on a large dataset, such as ImageNet, and fine-tuning it on the COCO dataset to improve its performance on object detection and segmentation tasks (Girish et al., 2021). Using the COCO dataset, which contains over 330,000 images with more than 2.5 million object instances labeled with bounding boxes and masks, the fine-tuned model can learn to identify objects in a wide range of contexts and backgrounds, making it more accurate and robust (Bu et al., 2021). The hyperparameters used during training on the COCO dataset are carefully tuned to optimize the model's performance for object detection and segmentation tasks. When training on the COCO dataset, hyperparameters are set to optimize the model's performance.

ARCHITECTURE OF DEEP LEARNING MODELS

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 (Jocher et al., 2020). 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 and YOLOv7 is widespread (Bochkovskiy et al., 2020). Pretrained YOLO models, especially on the COCO dataset, are readily available and easy to use (Jocher et al., 2020). 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 eggs 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 egg 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).

YOLOv5 egg model (YOLOv5s-egg and YOLOv5x-egg)

The models of YOLOv5s-egg and YOLOv5x-egg were developed based on the YOLOv5 network, which consists of three parts: a backbone, a neck, and an output for object detection (Figure 3). The backbone network is CSPDarkNet53, with four feature maps of different sizes, and was used for feature extraction (Bochkovskiy et al., 2020, p. 4; Shen et al., 2022). 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.

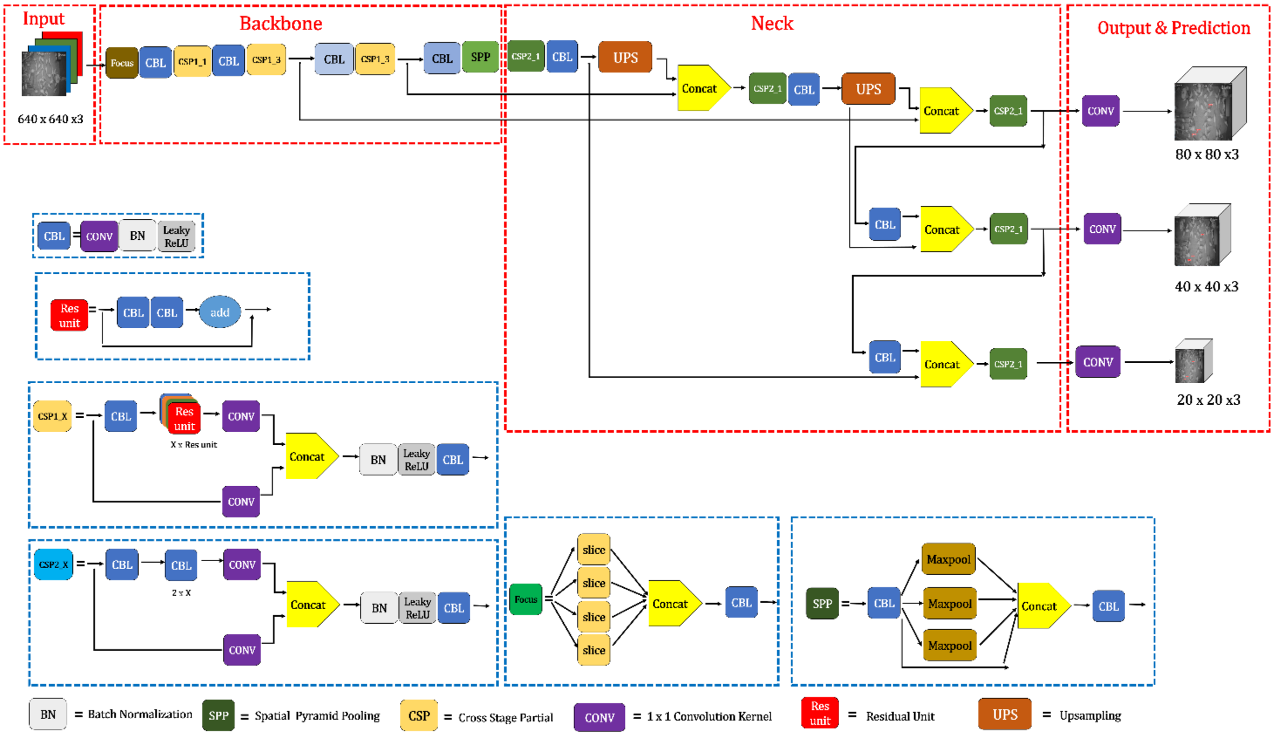


Figure 3.3 The YOLOv5-egg architecture (model input, head, backbone, model neck, and output & prediction) for tracking floor eggs in this study.

YOLOv7- egg model

The model of YOLOv7-egg was developed based on the YOLOv7 network, which consists of an input, backbone layer, Head, and output. Inputting the image in YOLOv7 is similar to YOLOv5 (Z. Yang et al., 2022). The backbone layer of YOLOv7 consists of Bconv layers, E-ELAN layers, and MP layers. The BConv layer consists of convolution, BN, and activation functions. The E-ELAN uses methods such as expanding, shuffling, and merging cardinality to improve the learning ability so that the deep network can learn and converge more efficiently without destroying the original gradient path (Wang et al., 2022) Yang et al., 2022). MP layer consists of input and output channels in which the output length and width are half the input length and width, and both halves consist of the BConv layer. The Head is similar to YOLOv5, but differences are that the E-ELAN module replaces the CSP module in YOLOv7, and the Down

Sampling module is changed to the MPConv layer. The entire head layer comprises SPPCPC layers, several BConv layers, several MPConv layers, several Catconv layers, and RepVGG block layers that output three heads subsequently (Yang et al., 2022). The SPPCSPC layer is obtained using the pyramid pooling operation and the CSP structure. The output information is concat. The function of the Catconv layer is the same as that of the E-ELAN layer, which also allows deeper networks to learn and converge more efficiently. The operation of the Catconv layer is the same as that of the E-ELAN layer, allowing deeper networks to learn and connect more efficiently (Yang et al., 2022).

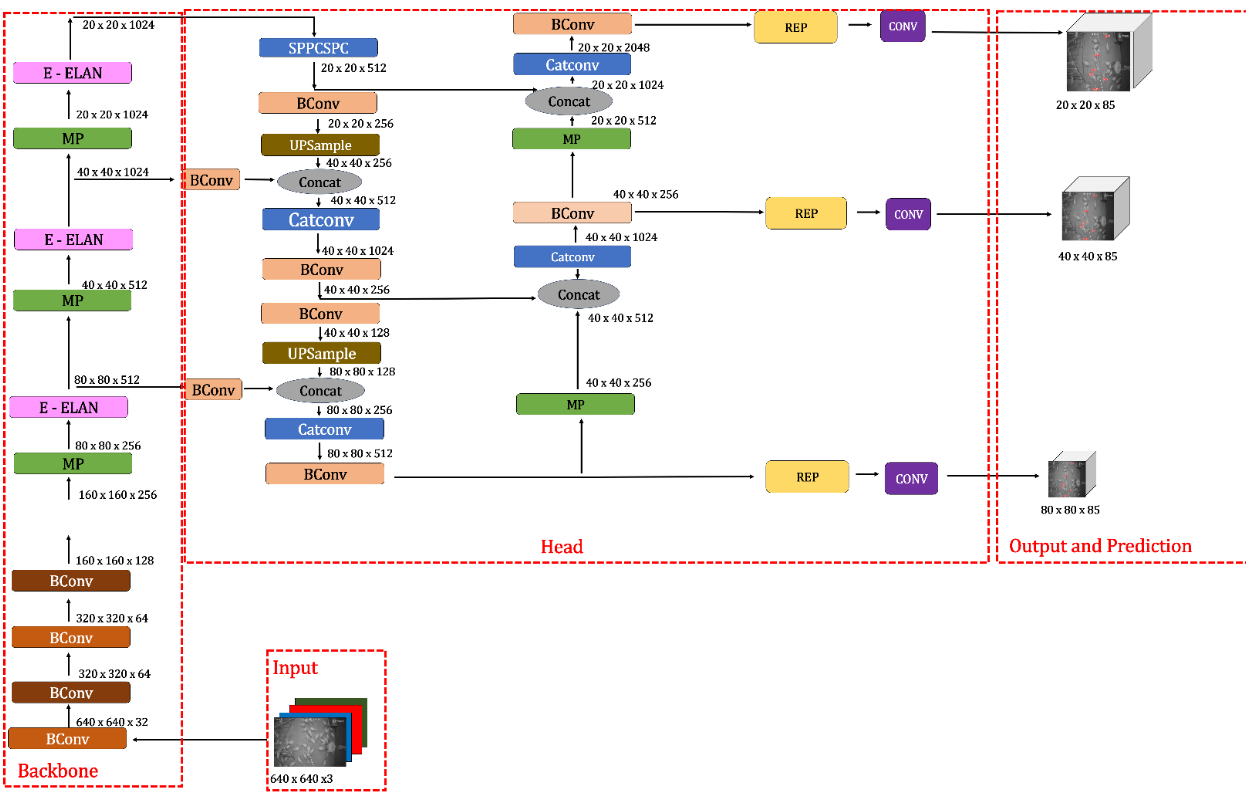


Figure 3.4. The YOLOv7-egg architecture used for tracking floor eggs in this study.

Detection Training and Validation

The floor egg dataset was trained using COCO weights, and losses during training were continuously calculated. A modified "yaml" file is a customized YOLOv5s, YOLOv5x, and

YOLOv7 file that contains information about images and labels for training and validation were modified (Hossain et al., 2022). Implementation and execution of the YOLOv5 model were done in anaconda distribution using PyTorch machine learning library with a 3.9 version. The experiments have been carried out with Oracle Cloud Infrastructure. VM GPU3.2 to enhance neural network training performances.

Evaluation metrics

Precision, Recall, and mean average precision (mAP) provide an essential reference index to evaluate the model's performance.

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:

$$mAP = \sum_{i=1}^{N} P(i)\ x\ \Delta R(i)$$

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

3.3 RESULTS AND DISCUSSIONS

Model performance in floor eggs detection

The confusion matrix (Figure 3.5) 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-egg, YOLOv5x-egg and YOLOv7-egg:

1) The TP was 0.94 for YOLOv5s-egg, 0.89 for YOLOv5x-egg, and 0.87 for YOLOv7-egg, respectively, 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 for all three models, 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 for all three models (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 for YOLOv5s-egg, 0.11 for YOLOv5x-egg, and 0.13 for YOLOv7 (Type II error), respectively, which indicates that the classifier predicted FALSE (i.e., the image does not have Egg), but images do have the floor eggs.

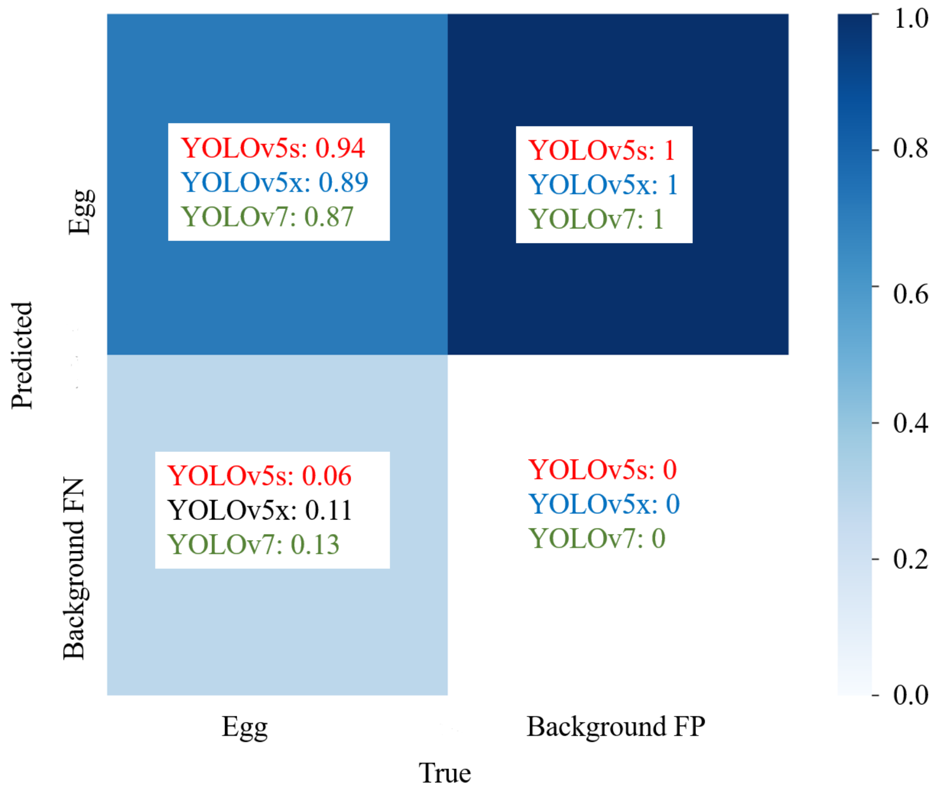


Figure 3.5. Confusion matrices of the YOLOv5s, YOLOv5x, and YOLOv7 models for floor eggs tracking.

Model performance in computing system use

The Figure 3.6 shows the characteristics of YOLOv5s, YOLOv5x, and YOLOv7 models, such as GPU memory usage, model size, and training time. For example, although the YOLOv5s-egg model size is smaller than YOLOv5x-egg and YOLOv7-egg models, it uses less GPU memory. In addition, YOLOv7-egg took more training time than other models for the same dataset. This information is critical as that affects computer system selection and data analysis speed.

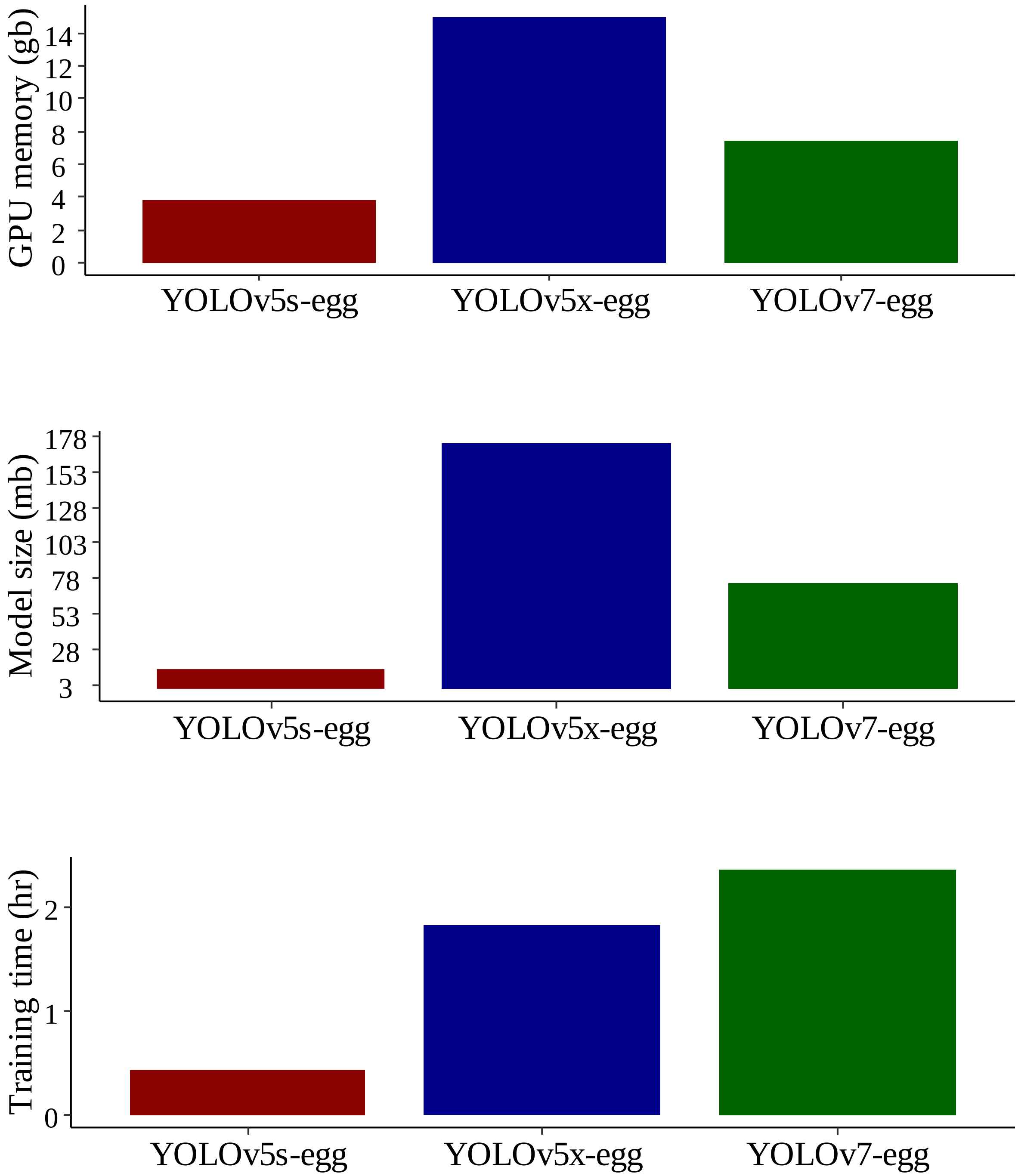


Figure 3.6. YOLOv5s, YOLOv5x and YOLOv7 models in memory size, model size, and training time.

Performance of egg detection models in data training and validation

Total training loss: All three models' total training loss function rapidly decreased while running in 200 epochs (Figure 3.7). The precision, recall, and mean average precision are shown in Figures 8-10.

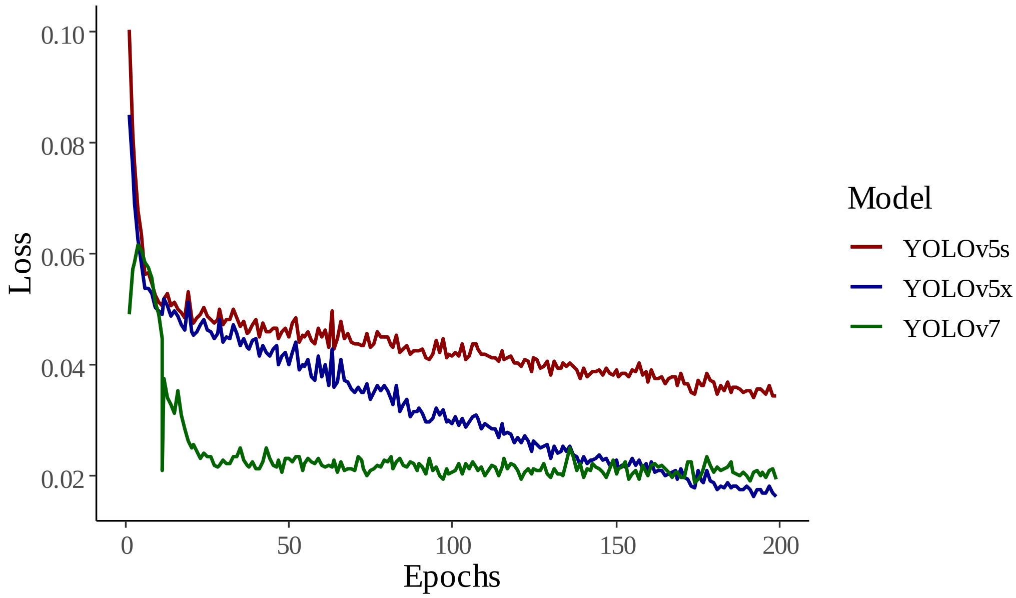


Figure 3.7. Total training losses from all three models while training floor egg dataset.

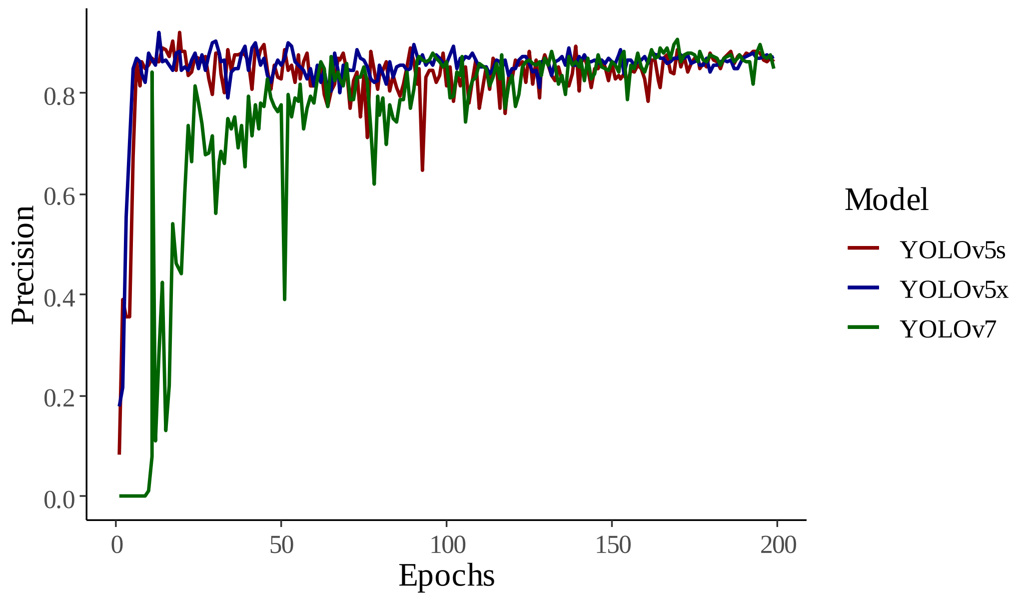


Figure 3.8. Precision from all three models while training floor egg dataset.

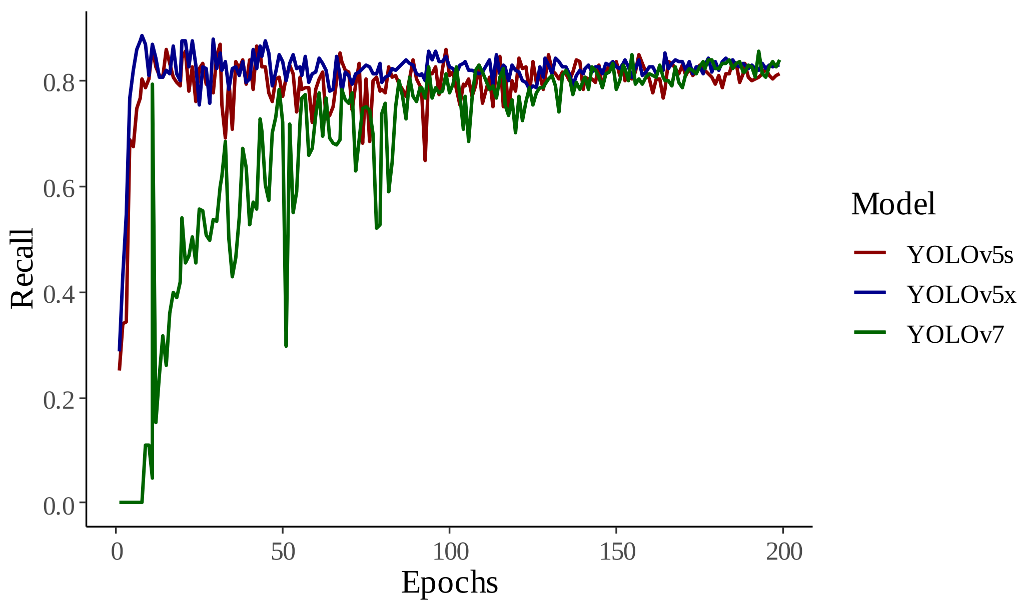


Figure 3.9: Recall from all three models while training the floor egg dataset

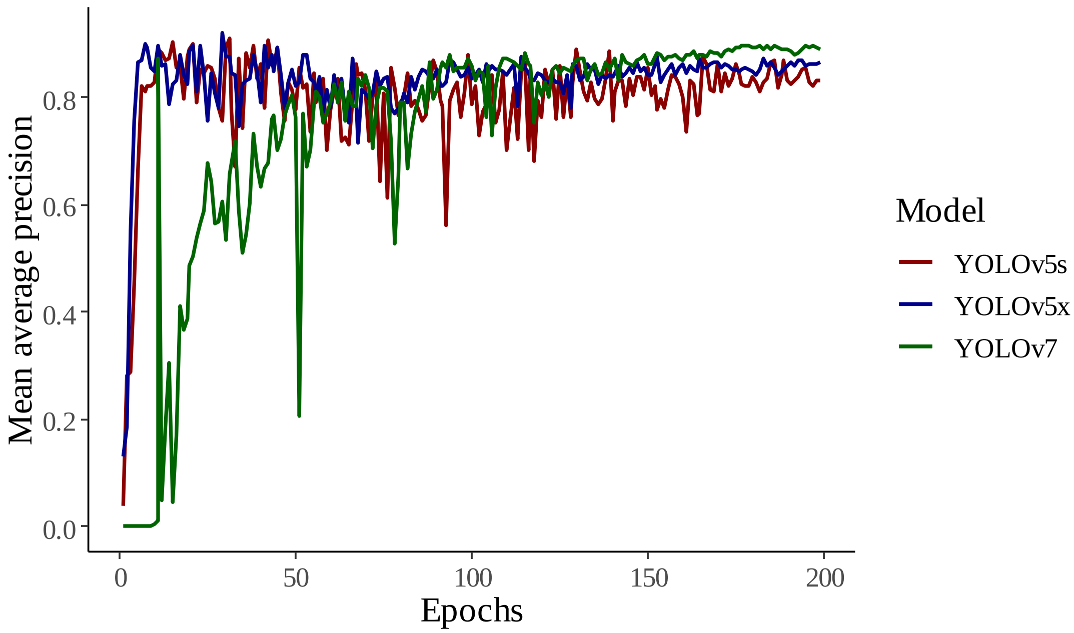


Figure 3.10: mAP from all three models while training floor egg dataset

Models' Performance Curves after Training

The precision, recall, and PR curve (Precision × Recall) were tested concerning confidence scores. In Figure 3.11, the egg detection precision of the YOLOv5s-egg model was low at the beginning and then increased gradually with the confidence score. For example, the precision reached 100% when the confidence score was 0.73. For the YOLOv5x-egg model, the precision gradually increased 100% when the confidence score was 0.75. Also, for the YOLOv7-egg model, the precision gradually increased by 100% when the confidence score was 0.724.

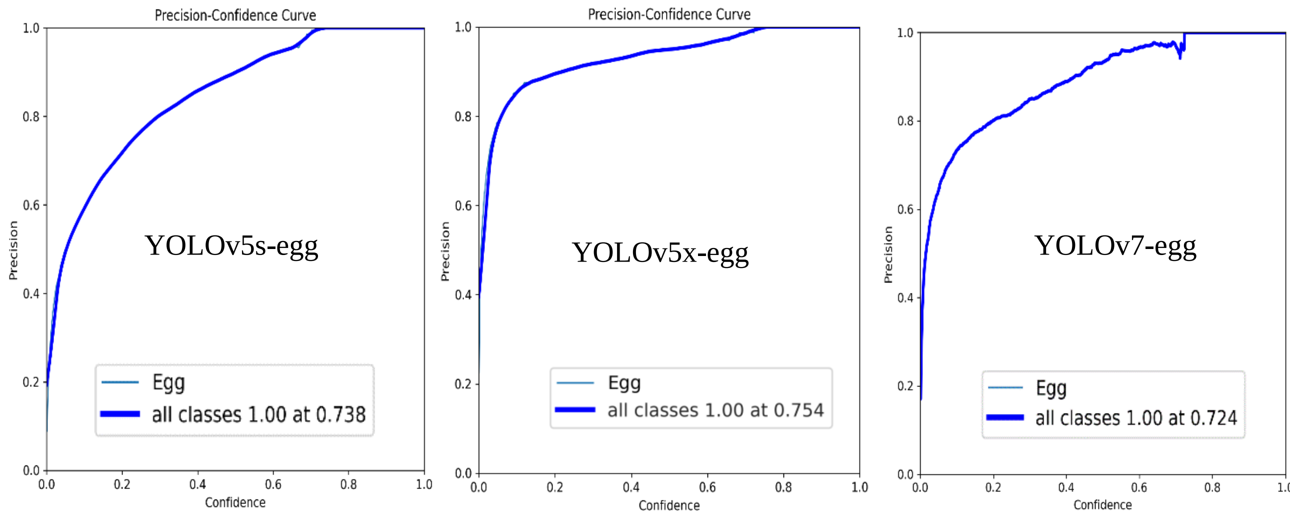


Figure 3.11. The precision of the YOLOv5s-egg, YOLO-v5x-egg, and YOLOv7-egg in floor eggs detection.

The recall for the egg class (Figure 3.12) was 97% for the YOLOv5s-egg model at the beginning and then decreased with the increase of confidence score to 1. For the YOLOv5x-egg model, the recall was similar to the YOLOv5s-egg model at 95% at the beginning and gradually decreased with the increasing confidence score to 1. For the YOLOv7-egg model, the 96% at the beginning gradually reduced with the increasing confidence score to 1.

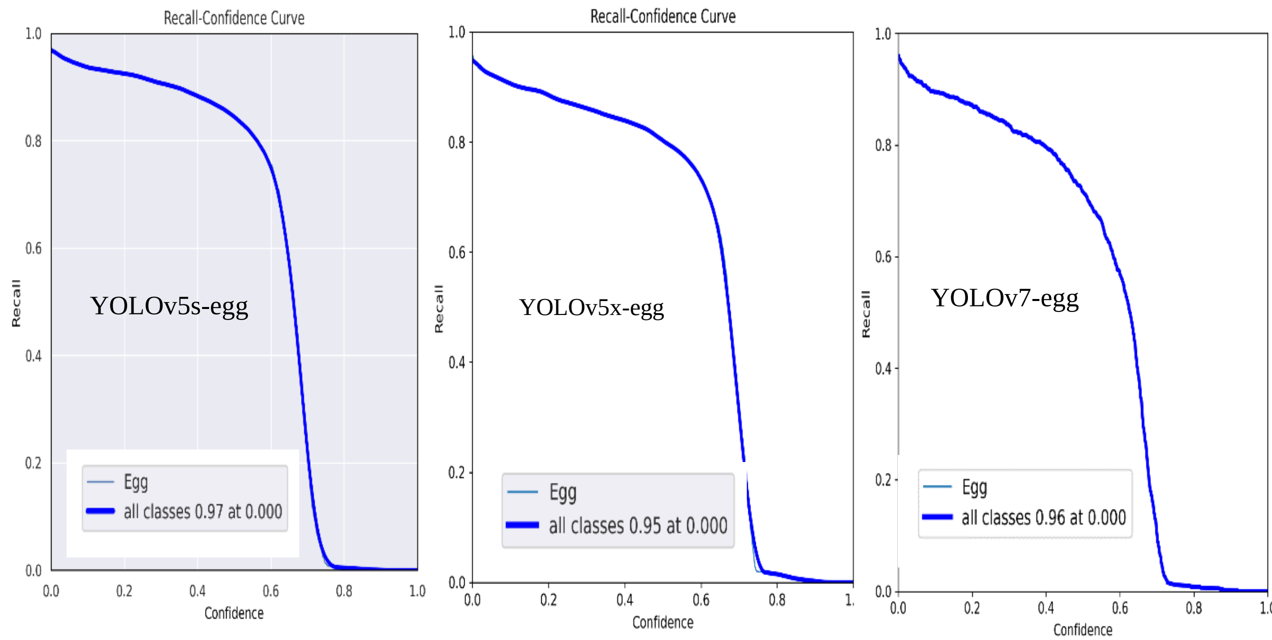


Figure 3.12. The recall of the YOLOv5s-egg, YOLO-v5x-egg, and YOLOv7-egg in floor eggs detection.

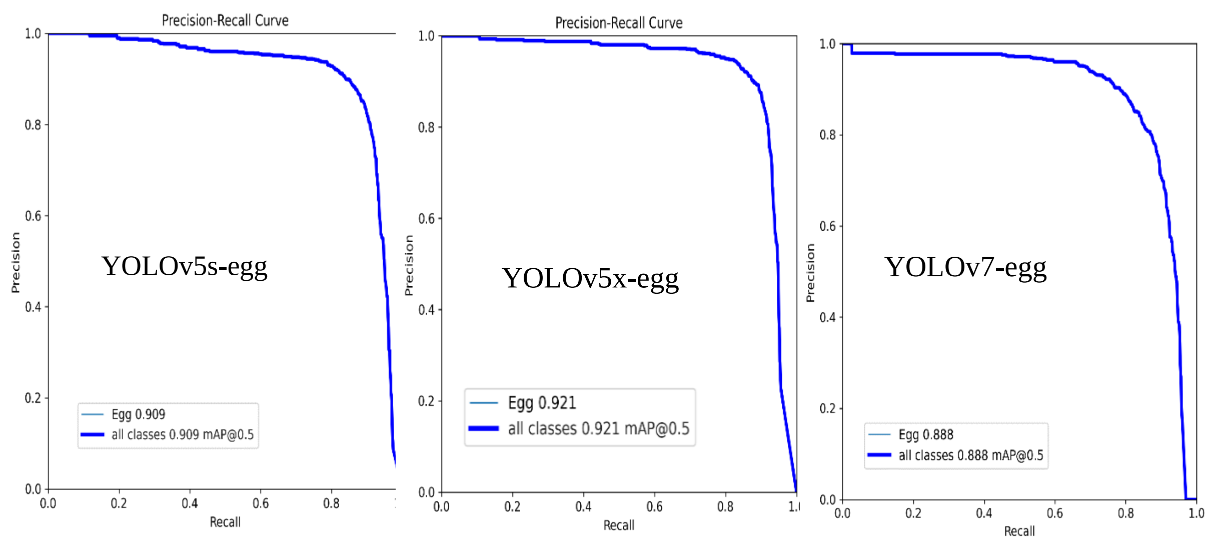


Figure 3.13. The Precision X Recall of the YOLOv5s-egg, YOLO-v5x-egg, and YOLOv7-egg in floor eggs detection.

The precision × Recall curve was investigated to evaluate the performance of the Egg detection of all three models when the confidence score changes for each class. It helps to assess egg prediction ability when the precision maintains a significant value with the increase in the recall (Hossain et al., 2022). The Figure 3.13 shows that cross values (Precision X Recall) for the egg class and mAP of all classes for YOLOv5s-egg is 90.9%, YOLOv5x-egg is 92.1%, and YOLOv7 is 88.8%

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 3.14 & 3.15 shows some examples of the automatic detection of floor eggs. The YOLOv5s-egg, the YOLOv5x-egg, and the YOLOv7-egg models were compared with the following observations (Table 1): 1) the YOLOv5s-egg model can detect the eggs with a precision of 87.9%, recall of 86.8%, and mean average precision (mAP) of 90.9%; 2) the YOLOv5x-egg model can detect the eggs with a precision of 90%, recall of 87.9%, and mean average precision (mAP) of 92.1 %; 3) the YOLOv7-egg model can detect the eggs with a precision of 89.5%, recall of 85.4%, and mean average precision (mAP) of 88%; and 4) the YOLOv5x-egg model detected floor eggs with higher accuracy, precision, mAP, and recall than YOLOv5s-egg and YOLOv7-egg.

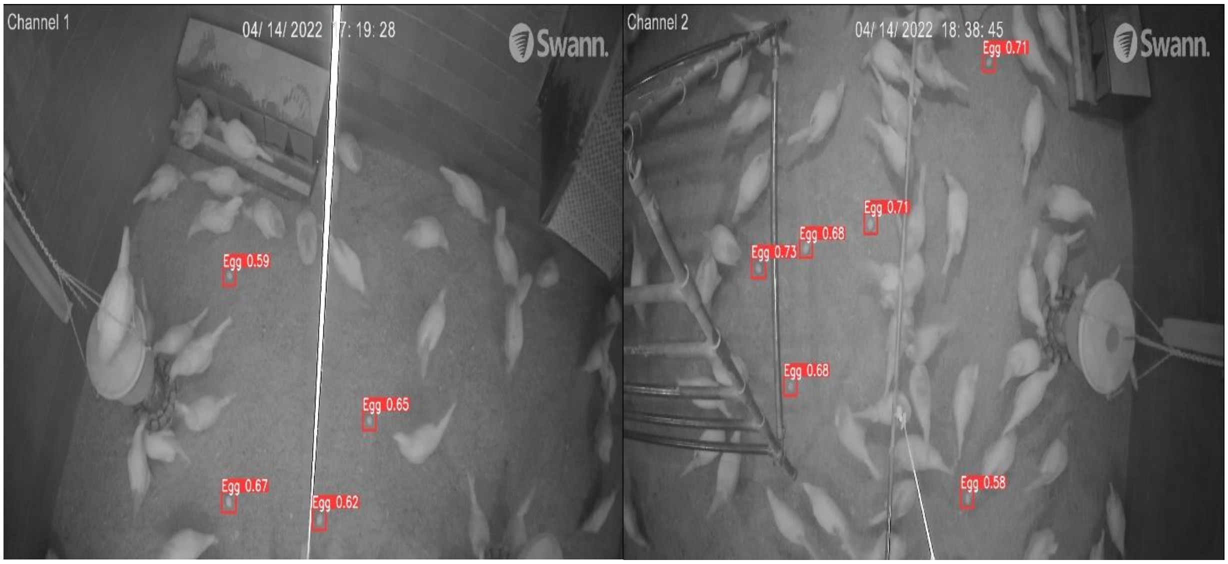


Figure 3.14. Performance of all three models in floor eggs (UGA farm).

Figure 3.15. Performance of three models in floor houses (Commercial farms: left – organic farm in the USA; middle and right – cage-free farm in the USA).

Table 2.1. Results of comparing YOLOv5s, YOLOv5x and YOLOv7 models for egg detection.

Model	**YOLOv5s-egg**			**YOLOv5x-egg**			**YOLOv7-egg**		
Parameters	7.1 million			86.1 million			37 million		
Layers	157			322			-		
Class	**Precision**	**Recall**	**mAP@50**	**Precision**	**Recall**	**mAP@50**	**Precision**	**Recall**	**mAP@50**
Egg	0.879	0.868	0.909	0.9	0.879	0.921	0.895	0.854	0.88

Quantification of detected eggs

We found that YOLOv5x-egg performed better in terms of accuracy, precision, mAP, and recall than YOLOv5s-egg and YOLOv7-egg. In addition, YOLOv5x-egg detected the floor eggs more accurate than other two models, but it took a longer inference time to detect due to the large model size (Table 2.2).

Table 2.2. Comparing the actual number of eggs with the YOLOv5x-egg model.

Test Image Name	Actual Count	Counting by our model			Inference Time (milliseconds)		
		YOLOv5s-egg	YOLOv5x-egg	YOLOv7-egg	YOLOv5s-egg	YOLOv5x-egg	YOLOv7-egg
1	4	3	4	3	21.2	37.4	17.9
2	4	4	4	4	14.2	30.5	18.1
3	9	8	8	8	15.1	30.1	18.0
4	6	5	6	6	14.3	30.1	18.0
5	8	7	8	9	14.3	30.2	18.7

This study adopted advanced CNN deep learning (i.e., YOLOv5 and YOLOv7) for tracking floor eggs, which will be an applicable tool for egg producers to pinpoint location of floor eggs for a timely collection in the cage-free facilities. The European Commission aimed to eliminate cages for farmed animals by 2027. Meanwhile, the primary restaurants or grocers in the USA have pledged to buy cage-free (CF) eggs only by 2025 or 2030 (Chai et al., 2019; Oliveira et al., 2019). Prior to address the floor egg issues, it is challenging for egg producers to transit to CF productions in EU and USA. As the commercial house is about 150 m long and 40-50 m wide, it is suggested to use mobile imaging system for collecting images from different locations periodically at a specific high. In addition, an APP will be developed for tracking results of floor eggs.

3.4 CONCLUSION

In this study, three new deep learning models, i.e., YOLOv5s-egg, YOLOv5x-egg, and YOLOv7-egg networks, were developed, trained, and compared in tracking floor eggs in four research cage-free laying hen rooms. Models were verified to detect eggs by using images collected two different commercial houses. All models perform well in precision and detection; however, model performance is affected by the stocking density, varying light intensity, and images occluded by equipment like drinking lines, perches, and feeders. The YOLOv5x-egg model detected floor eggs with higher accuracy, precision, mAP, and recall than YOLOv5s-egg and YOLOv7-egg. 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

The Egg Industry Center supports this project; Oracle for Research Grant, Oracle America (Award Number: 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) & Enhancing Poultry Production Systems through Emerging Technologies and Husbandry Practices (GEO00894; Accession Number: 1021518).

3.5 REFERENCES

Agrawal, T. (2021). *Hyperparameter Optimization in Machine Learning: Make Your Machine Learning and Deep Learning Models More Efficient*. Apress. https://doi.org/10.1007/978-1-4842-6579-6

Aydin, A., Cangar, O., Ozcan, S. E., Bahr, C., & Berckmans, D. (2010). Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. *Computers and Electronics in Agriculture*, *73*(2), 194–199. https://doi.org/10.1016/j.compag.2010.05.004

Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). *YOLOv4: Optimal Speed and Accuracy of Object Detection* (arXiv:2004.10934). arXiv. https://doi.org/10.48550/arXiv.2004.10934

Bu, X., Peng, J., Yan, J., Tan, T., & Zhang, Z. (2021). GAIA: A Transfer Learning System of Object Detection that Fits Your Needs. *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 274–283. https://doi.org/10.1109/CVPR46437.2021.00034

Campbell, D. L. M., Horton, B. J., & Hinch, G. N. (2018). Using Radio-Frequency Identification Technology to Measure Synchronised Ranging of Free-Range Laying Hens. *Animals*, *8*(11), Article 11. https://doi.org/10.3390/ani8110210

Colles, F. M., Cain, R. J., Nickson, T., Smith, A. L., Roberts, S. J., Maiden, M. C. J., Lunn, D., & Dawkins, M. S. (2016). Monitoring chicken flock behaviour provides early warning of infection by human pathogen Campylobacter. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1822), 20152323. https://doi.org/10.1098/rspb.2015.2323

Dawei, W., Limiao, D., Jiangong, N., Jiyue, G., Hongfei, Z., & Zhongzhi, H. (2019). Recognition pest by image-based transfer learning. *Journal of the Science of Food and Agriculture*, *99*(10), 4524–4531. https://doi.org/10.1002/jsfa.9689

Dawkins, M. S., Cain, R., & Roberts, S. J. (2012). Optical flow, flock behaviour and chicken welfare. *Animal Behaviour*, *84*(1), 219–223. https://doi.org/10.1016/j.anbehav.2012.04.036

Girish, S., Maiya, S. R., Gupta, K., Chen, H., Davis, L., & Shrivastava, A. (2021). *The Lottery Ticket Hypothesis for Object Recognition* (arXiv:2012.04643). arXiv. http://arxiv.org/abs/2012.04643

Guo, Y., Chai, L., Aggrey, S. E., Oladeinde, A., Johnson, J., & Zock, G. (2020). A Machine Vision-Based Method for Monitoring Broiler Chicken Floor Distribution. *Sensors*, *20*(11), Article 11. https://doi.org/10.3390/s20113179

Guo, Z., Wang, C., Yang, G., Huang, Z., & Li, G. (2022). MSFT-YOLO: Improved YOLOv5 Based on Transformer for Detecting Defects of Steel Surface. *Sensors*, *22*(9), Article 9. https://doi.org/10.3390/s22093467

He, K., Zhang, X., Ren, S., & Sun, J. (2014). *Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition* (Vol. 8691, pp. 346–361). https://doi.org/10.1007/978-3-319-10578-9_23

Hossain, A., Islam, M. T., & Almutairi, A. F. (2022). A deep learning model to classify and detect brain abnormalities in portable microwave based imaging system. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-10309-6

Jocher, G., Changyu, L., Hogan, A., L. Y., changyu98, Rai, P., & Sullivan, T. (2020). *ultralytics/yolov5: Initial Release*. Zenodo. https://doi.org/10.5281/zenodo.3908560

Jones, D. R., Cox, N. A., Guard, J., Fedorka-Cray, P. J., Buhr, R. J., Gast, R. K., Abdo, Z., Rigsby, L. L., Plumblee, J. R., Karcher, D. M., Robison, C. I., Blatchford, R. A., & Makagon, M. M. (2015). Microbiological impact of three commercial laying hen housing systems1 1Research support provided in part by a grant from the Coalition for a Sustainable Egg Supply (Kansas City, MO). *Poultry Science*, *94*(3), 544–551. https://doi.org/10.3382/ps/peu010

Lei, Y., Dong, P., Guan, Y., Xiang, Y., Xie, M., Mu, J., Wang, Y., & Ni, Q. (2022). Postural behavior recognition of captive nocturnal animals based on deep learning: A case study of Bengal slow loris. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-11842-0

Leroy, T., Vranken, E., Struelens, E., Sonck, B., & Berckmans, D. (2005, January 1). *Computer vision based recognition of behavior phenotypes of laying hens*. 2005 ASAE Annual International Meeting. https://doi.org/10.13031/2013.19471

Li, G., Hui, X., Zhao, Y., Zhai, W., Purswell, J. L., Porter, Z., Poudel, S., Jia, L., Zhang, B., & Chesser, G. D. (2022a). Effects of ground robot manipulation on hen floor egg reduction, production performance, stress response, bone quality, and behavior. *PLOS ONE*, *17*(4), e0267568. https://doi.org/10.1371/journal.pone.0267568

Li, G., Xu, Y., Zhao, Y., Du, Q., & Huang, Y. (2020b). Evaluating Convolutional Neural Networks for Cage-Free Floor Egg Detection. *Sensors*, *20*(2), Article 2. https://doi.org/10.3390/s20020332

Li, H., Zhou, Q., Mao, Y., Zhang, B., & Liu, C. (2022). Alpha-SGANet: A multi-attention-scale feature pyramid network combined with lightweight network based on Alpha-IoU loss. *PLOS ONE*, *17*(10), e0276581. https://doi.org/10.1371/journal.pone.0276581

Lin, T. Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., ... & Zitnick, C. L. (2014). Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13* (pp. 740-755). Springer International Publishing.

Liu, S., Qi, L., Qin, H., Shi, J., & Jia, J. (2018). Path Aggregation Network for Instance Segmentation. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 8759–8768. https://doi.org/10.1109/CVPR.2018.00913

Lubich, J., Thomas, K., & Engels, D. W. (2019). *Identification and Classification of Poultry Eggs: A Case Study Utilizing Computer Vision and Machine Learning*. *2*(1).

Neethirajan, S. (2022). Automated Tracking Systems for the Assessment of Farmed Poultry. *Animals*, *12*(3), Article 3. https://doi.org/10.3390/ani12030232

Ochs, D. S., Wolf, C. A., Widmar, N. J. O., & Bir, C. (2018). Consumer perceptions of egg-laying hen housing systems. *Poultry Science*, *97*(10), 3390–3396. https://doi.org/10.3382/ps/pey205

Okinda, C., Nyalala, I., Korohou, T., Okinda, C., Wang, J., Achieng, T., Wamalwa, P., Mang, T., & Shen, M. (2020). A review on computer vision systems in monitoring of poultry: A welfare perspective. *Artificial Intelligence in Agriculture*, *4*, 184–208. https://doi.org/10.1016/j.aiia.2020.09.002

O'Shea, K., & Nash, R. (2015). *An Introduction to Convolutional Neural Networks* (arXiv:1511.08458). arXiv. https://doi.org/10.48550/arXiv.1511.08458

Pan, S. J., & Yang, Q. (2010). A Survey on Transfer Learning. *IEEE Transactions on Knowledge and Data Engineering*, *22*(10), 1345–1359. https://doi.org/10.1109/TKDE.2009.191

Ray, A., Kolekar, M. H., Balasubramanian, R., & Hafiane, A. (2023). Transfer Learning Enhanced Vision-based Human Activity Recognition: A Decade-long Analysis. *International Journal of Information Management Data Insights*, *3*(1), 100142. https://doi.org/10.1016/j.jjimei.2022.100142

Shen, H., Dong, Z., Yan, Y., Fan, R., Jiang, Y., Chen, Z., & Chen, D. (2022). Building roof extraction from ASTIL echo images applying OSA-YOLOv5s. *Applied Optics*, *61*(11), 2923–2928. https://doi.org/10.1364/AO.451245

Smith, L. N. (2018). *A disciplined approach to neural network hyper-parameters: Part 1 -- learning rate, batch size, momentum, and weight decay* (arXiv:1803.09820). arXiv. http://arxiv.org/abs/1803.09820

Subedi, S., Bist, R., Yang, X., & Chai, L. (2023). Tracking pecking behaviors and damages of cage-free laying hens with machine vision technologies. *Computers and Electronics in Agriculture*, *204*, 107545. https://doi.org/10.1016/j.compag.2022.107545

T. Leroy, E. Vranken, A. Van Brecht, E. Struelens, B. Sonck, & D. Berckmans. (2006). A COMPUTER VISION METHOD FOR ON-LINE BEHAVIORAL QUANTIFICATION OF INDIVIDUALLY CAGED POULTRY. *Transactions of the ASABE*, *49*(3), 795–802. https://doi.org/10.13031/2013.20462

Tulbure, A.-A., Tulbure, A.-A., & Dulf, E.-H. (2022). A review on modern defect detection models using DCNNs – Deep convolutional neural networks. *Journal of Advanced Research*, *35*, 33–48. https://doi.org/10.1016/j.jare.2021.03.015

Wang, C.-Y., Bochkovskiy, A., & Liao, H.-Y. M. (2022). *YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors* (arXiv:2207.02696). arXiv. http://arxiv.org/abs/2207.02696

Wang, C.-Y., Mark Liao, H.-Y., Wu, Y.-H., Chen, P.-Y., Hsieh, J.-W., & Yeh, I.-H. (2020). CSPNet: A New Backbone that can Enhance Learning Capability of CNN. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 1571–1580. https://doi.org/10.1109/CVPRW50498.2020.00203

Wurtz, K., Camerlink, I., D'Eath, R. B., Fernández, A. P., Norton, T., Steibel, J., & Siegford, J. (2019). Recording behaviour of indoor-housed farm animals automatically using machine vision technology: A systematic review. *PLOS ONE*, *14*(12), e0226669. https://doi.org/10.1371/journal.pone.0226669

Yang, X., Chai, L., Bist, R. B., Subedi, S., & Wu, Z. (2022). A Deep Learning Model for Detecting Cage-Free Hens on the Litter Floor. *Animals*, *12*(15), Article 15. https://doi.org/10.3390/ani12151983

Yang, Z., Ni, C., Li, L., Luo, W., & Qin, Y. (2022). Three-Stage Pavement Crack Localization and Segmentation Algorithm Based on Digital Image Processing and Deep Learning Techniques. *Sensors*, *22*(21), Article 21. https://doi.org/10.3390/s22218459

Zaninelli, M., Redaelli, V., Luzi, F., Mitchell, M., Bontempo, V., Cattaneo, D., Dell'Orto, V., & Savoini, G. (2018). Development of a Machine Vision Method for the Monitoring of Laying Hens and Detection of Multiple Nest Occupations. *Sensors*, *18*(1), Article 1. https://doi.org/10.3390/s18010132

Zhuang, X., & Zhang, T. (2019). Detection of sick broilers by digital image processing and deep learning. *Biosystems Engineering*, *179*, 106–116. https://doi.org/10.1016/j.biosystemseng.2019.01.003

CHAPTER 4

MULTIPLE BEHAVIOR CLASSIFICATION OF CAGE-FREE LAYING HENS USING DEEP LEARNING[1]

[1] Subedi, S, Bist, R, Yang, X, Li, Li, G, and Chai, L. 2023. Submitted to *Artificial Intelligence in Agriculture*

ABSTRACT

Abstract: The welfare status of hens in cage-free houses is reflected in different behaviors they perform, such as feeding, drinking, pecking, perching, bathing, preening, foraging, etc. We developed and tested a deep-learning method to track and classify poultry behaviors using the models we developed. YOLO (You Only Look Once) is an advanced object detection technology with many advantages, like high accuracy, fast speed, and small size. A YOLO-based deep learning model, i.e., YOLOv5s_BH, YOLOv5x_BH, and YOLOv7_BH, was developed to track the poultry behaviors of laying hens in cage-free facilities. A dataset of 1500 training images, 500 validation images, and 50 test images was collected to build the model for tracking behaviors. After training our model on the behavior dataset, results show that the model can automatically and effectively detect poultry behaviors with a predicted bounding box, including an objectness score ranging from 0 to 1 in test images. The YOLOv5s_BH showed good precision performance, achieving 78.1%, which is higher than both the YOLOv5x_BH and YOLOv7_BH by 1.9% and 2.2%, respectively. On the other hand, the YOLOv5s_BH has a recall of 71.7%, which is better than both the YOLOv5x_BH and YOLOv7_BH by 1.9% and 2.8%, respectively. Additionally, the YOLOv5s_BH has a mean average precision (mAP) of 74.6%, which is higher than the YOLOv5x_BH and YOLOv7_BH by 2.6% and 9%, respectively. Model performance is affected by the stocking density, varying light intensity, and images occluded by equipment like drinking lines, perches, and feeders. This study provides a reference for cage-free producers that poultry behaviors can be monitored automatically.

Keywords: Deep learning, Cage-free housing, animal welfare, precision management,

4.1 INTRODUCTION

Traditional cage-based farming of laying hens provides limited opportunities for birds to express different behaviors in their repertoire; as a result, poultry welfare policies and corresponding public concerns led to the reintroduction of cage-free systems (Hewson, 2003). Hens in cage-free systems can express behaviors like preening, foraging, perching, and dust bathing (Vestergaard et al., 1997; Xu et al., 2022; Subedi et al., 2023). Chicken behavior can provide clues to their health, and welfare status and there is a need to develop capabilities to detect behavioral abnormalities without increasing the need for manual labor. For that, automated systems are needed. Modern technologies, including computers, sensors, cloud computing, machine learning (ML), and artificial intelligence (AI), are causing significant transformations in various industries. These technologies are contributing to increased efficiency and significant gains in industries, resulting in a decrease in human labor and an increase in productivity and profitability (Neethirajan, 2020). For instance, using these technologies has decreased regular bird monitoring by human labor in commercial poultry farming, leading to increased productivity and profitability (Okinda et al., 2020). There is an increasing trend of computer vision tools and deep learning techniques in solving various problems in hematology, cell biology, agriculture, and livestock. For example, computer vision encompasses mathematics and computer science to provide image-based automated process control. It allows continuous and real-time measurements during a poultry production cycle in a fully automated, non-invasive way by extracting patterns from raw images, classifying them, and making predictions based on those patterns (Loddo & Di Ruberto, 2021; Black et al., 2020).

Six behaviors of laying hens, namely standing, sitting, sleeping, grooming, feeding, and drinking, were classified using deep learning (Leroy et al., 2005), with classifying the latter two behaviors with an accuracy of 89 % (Li et al., 2020). Another computer vision system was developed to quantify and visualize scratching behaviors of individual hens (Leroy et al., 2006). The effects of interference and obstruction of various zones on poultry behaviors of feeding, drinking, and resting were studied with machine vision methods (Guo et al., 2020). The image classification methodology was developed to identify broiler breeders' behaviors using machine vision techniques and has shown a higher than 70% success rate (Pereira et al., 2013). The behaviors studied for the experiment were wing spreading, bristling, drinking, scratching, resting, stretching, preening, and mounting. In addition, flock behaviors (crowding near feeders) were recognized using CNN architecture with an accuracy of 99.17% (Pu et al., 2018). A machine vision method was a practical tool for tracking abnormal behaviors in poultry, like pecking (Subedi et al., 2023a). Cage-free laying hens and floor eggs were also detected using deep-learning models (Yang et al., 2022a; Subedi et al., 2023b). Mask Region-Based Convolutional Neural Network was developed for detecting preening behaviors in birds (Li et al., 2020). An improved deep learning model was created utilizing the YOLOv5 architecture to keep track of the spatial and floor patterns of cage-free hens, which included tracking the real-time quantity of birds in various zones such as perching, feeding, drinking, and nesting (Yang et al., 2023). The model's accuracy ranged from 87% to 94% across all chicken ages and zones.

The automatic detection of poultry behaviors helps identify deviations from normal behavior patterns that has the potential to notify producers in real time (Massari et al., 2022). Early detection of unexpected changes in activity and behaviors can benefit poultry's well-being. The objectives of this research were to develop a deep learning model to 1) detect the poultry behaviors in cage-free housing systems, 2) test the model's performance in experimental setting, and 3) examine improvement strategies on the detection accuracy of the model. In this study, we classify different poultry behaviors (Feeding, Drinking, Perching, Preening, Perching, Dust Bathing, and Foraging). In particular, we compare three deep learning models (YOLOv5s, YOLOv5x, YOLOv7) from multiple behavior classification.

4.3 MATERIAL AND METHODS

Experimental Station

We conducted our experiment at a research layer house on the poultry research farm at the University of Georgia, Athens, Georgia State. The Institutional Animal Care and Use Committee (IACUC) of the University of Georgia, USA, approved animal use and management. A total of 800 W36 Hy-Line hens were raised in four cage-free research rooms (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*. In each research room, equipment such as feeders, nipple drinkers, nest boxes, and an A-frame hen perch was installed. We followed layer management guidelines of Hy-Line W-36 commercial layers. An automatic environment system controlled the rearing condition, and set points were 21 – 23 °C for air temperature and 30 lux for light intensity during photoperiod with a 19L:5D lighting program. 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 on the wall at ~3 m above the ground to capture top-view videos and footage from sideways. In addition, different bird behaviors 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 4.1. Imaging system and data collection.

Definition of laying hens' behaviors and Labeling

We manually labeled the seven behaviors (Feeding, Drinking, Perching, Preening, Dust Bathing, Pecking and Foraging) from laying hens to create bounding boxes based on the definition given in the ethogram in Table 1. A dataset of 2050 images (1500 for training, 500 for validations, and 50 for testing) was created to develop the behavior detector and classifier. The labeling was conducted in open-source software (Makesense.AI), and we created the bounding box around the region of interest. The dataset was split into two folders, i.e., training and validation. These two folders were divided into two subfolders, Images, and Labels. Finally, we got the annotation file in .txt format (text file).

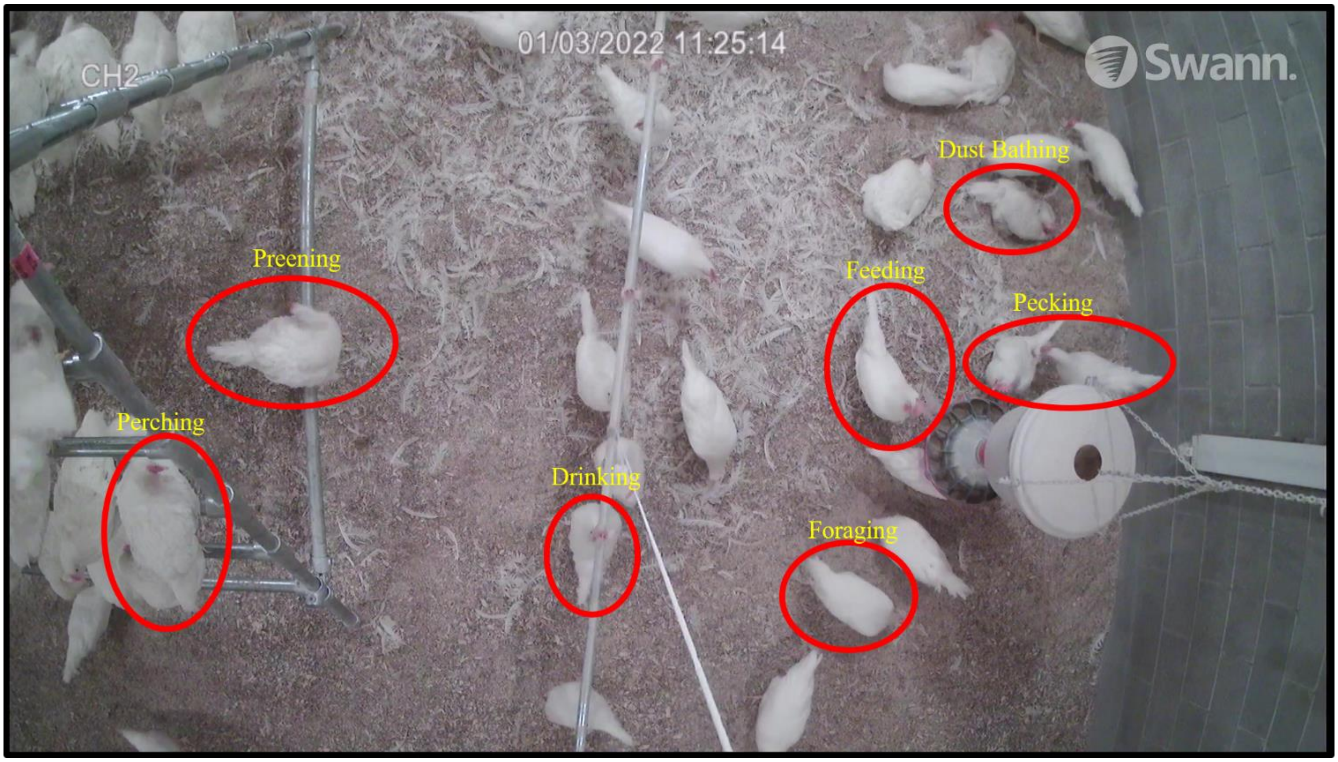


Figure 4.2. Different behaviors of laying hen.

Table 4.1: Ethogram of behaviors observed in the experiment

Behavior	Description	References
Feeding	Birds approach feeders for feeding	(Scanes et al., 1987)
Drinking	Birds approach drinkers to drink	(Wood-Gush, 1955)

Perching	Birds roost on the elevated structure	(Wood-Gush & Duncan, 1976)
Preening	Birds bend and twist their bodies to access their uropygial glands, using their beaks to clean and groom their feathers	(Florentino Pereira et al., 2013; Wood-Gush, 1955)
Dust Bathing	Birds crouching down to bath in the litter and use their wings to throw dust	(van Liere & Bokma, 1987; Wood-Gush, 1955)
Pecking	Birds peck at the feathers of another bird	(Savory, 1995)
Foraging	Birds scratch or peck the ground	(Ferreira et al., 2020)

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, YOLOv8, YOLO with various backends, etc. The most popular model of YOLO used in the industry was YOLOv3. The Ultralytics implementation of YOLOv5 and YOLOv7 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, semantic/instance segmentation, and caption generation. For laying hens' images/videos, the dataset has annotations for bounding boxes and image segmentation with one object class named with one of the behaviors (Feeding, Drinking, Perching, Preening, Perching, Dust Bathing, and Foraging). In the newly innovated model, images collected at multiple locations and scales with high-scoring regions were considered in tracking/detection. Taking the whole image of an object at test time and evaluating predictions using the single network is a significant advantage of YOLO over classifier-based systems (Z. 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 with dimensions of (x, y, w, h) and the confidence of each box with the Probability that box has target behavior (Feeding, Drinking, Perching, Preening, Perching, Dust Bathing, and Foraging). 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., Feeding, Drinking, Perching, Preening, Perching, Dust Bathing, and Foraging.

Architecture of YOLOv5_BH model (YOLOv5s_BH and YOLOv5x_BH)

The model of YOLOv5_BH and YOLOv5x_BH was developed based on the networks of YOLOv5s and YOLOv5x, which consists of three parts: a backbone, a neck, and an output for object detection. The backbone network is CSPDarkNet53, with four feature maps (Feeding, Drinking, Perching, Preening, Perching, Dust Bathing, and Foraging) of different sizes, and was used for feature extraction (Bochkovskiy et al., 2020; Shen et al., 2022). The neck serves as a feature aggregation mechanism that combines the features produced in the backbone, in order to prepare for the detection process in the detection head. The feature pyramid structures of the Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) are used in the fusion process (Shen et al., 2022; Liu et al., 2018). 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., 2022). 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.

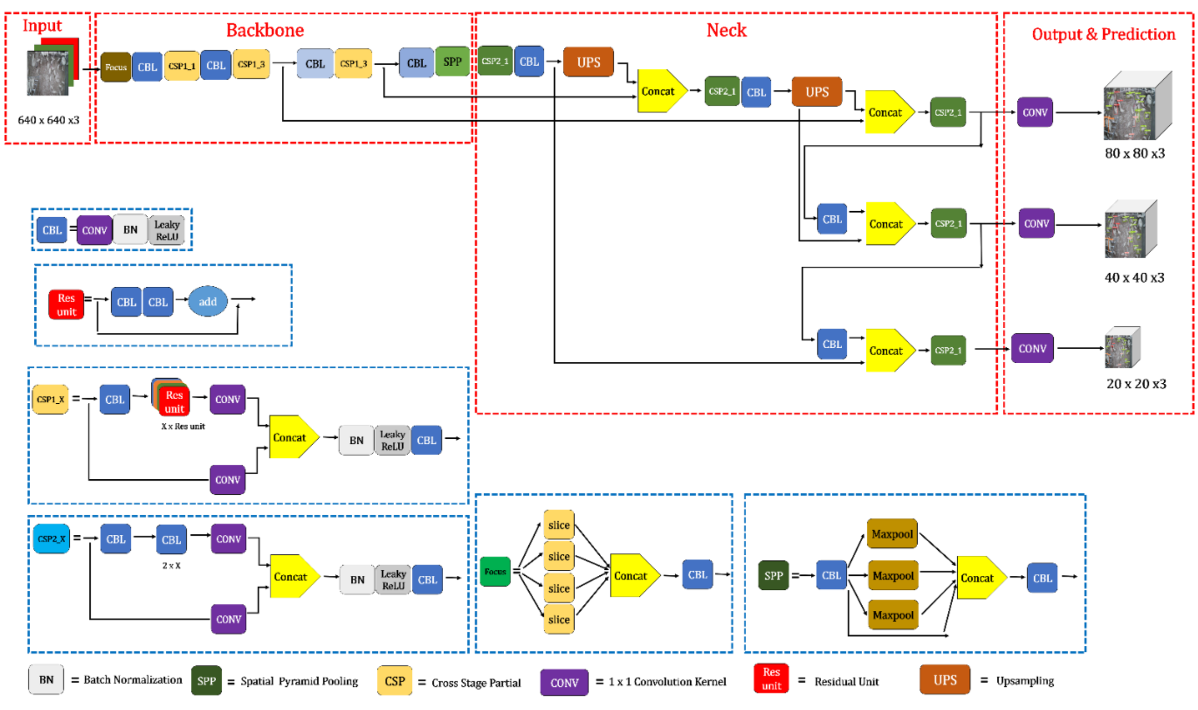


Figure 4.3. YOLOv5_BH architecture was used for this study.

Architecture of YOLOv7_BH model

The model of YOLOv7_BH was developed based on the YOLOv7 network, which consists of an input, backbone layer, Head, and output. Inputting the image in YOLOv7 is similar to YOLOv5 (Yang et al., 2022). The backbone layer of YOLOv7 consists of Bconv layers, E-ELAN layers, and MP layers. The BConv layer consists of convolution, BN, and activation functions. The E-ELAN uses methods such as expanding, shuffling, and merging cardinality to improve the learning ability so that the deep network can learn and converge more efficiently without destroying the original gradient path (Wang et al., 2022; Yang et al., 2022b). MP layer consists of input and output channels in which the output length and width are half the input length and width, and both halves consist of the BConv layer. The Head is similar to YOLOv5. The only differences between the YOLOv5 and YOLOv7 are that the E-ELAN module replaces the CSP module in YOLOv7, and the downsampling module is changed to the MPConv layer. The entire head layer comprises SPPCPC layers, several BConv layers, several MPConv layers, several Catconv layers, and RepVGG block layers that output three heads subsequently (Yang et al., 2022b). The SPPCSPC layer is obtained using the pyramid pooling operation and the CSP structure. The output information is concat. The function of the Catconv layer is the same as that of the E-ELAN layer, which also allows deeper networks to learn and converge more efficiently. The operation of the Catconv layer is the same as that of the E-ELAN layer, allowing deeper networks to learn and connect more efficiently (Yang et al., 2022b).

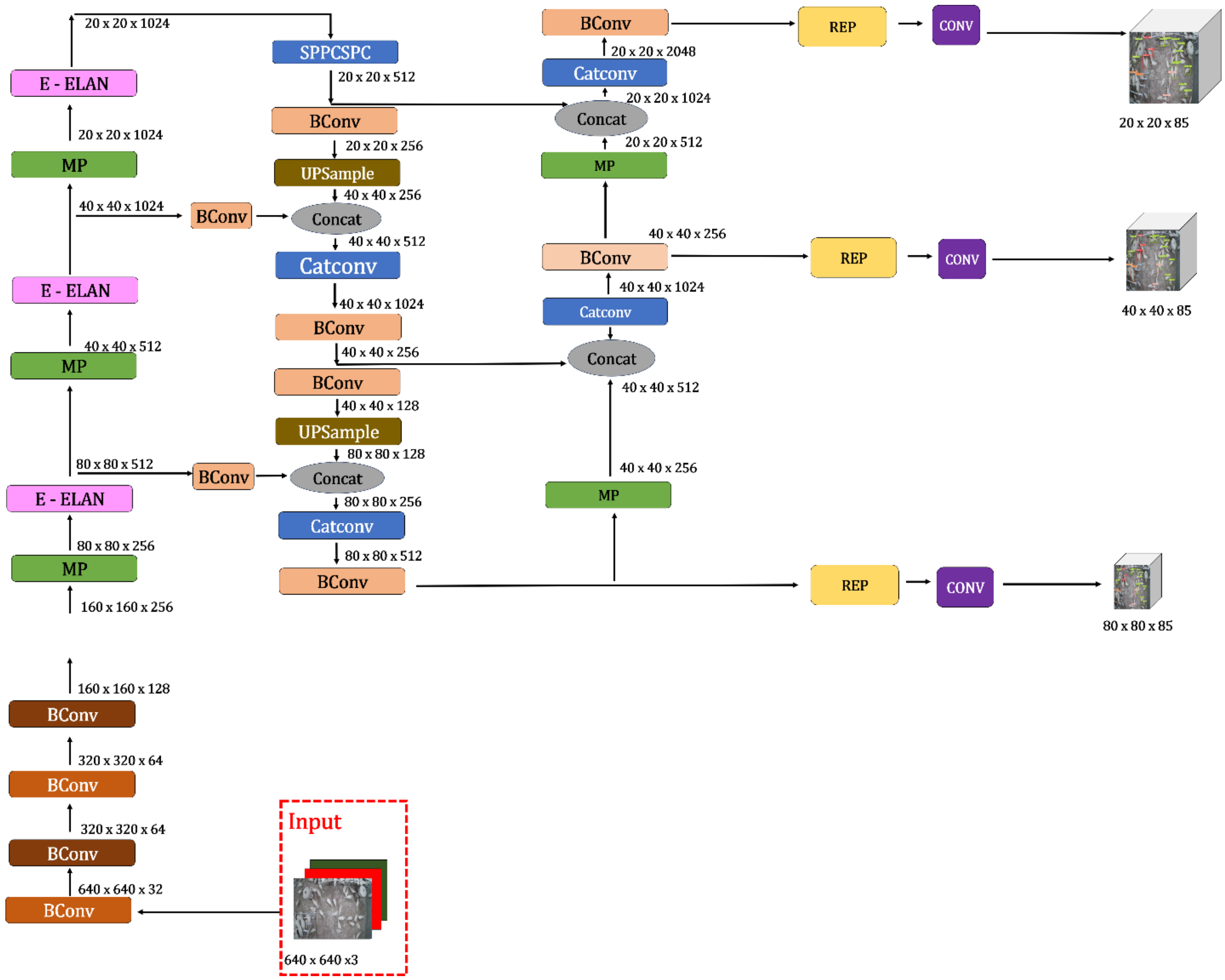


Figure 4.4. YOLOv7_BH architecture was used for this study.

Detection Training and Validation

The behavior dataset was trained using COCO weights, and losses during training were continuously calculated. A modified "yaml" file is customized for all three models containing information about images and modified labels for training and validation (Hossain et al., 2022). The system is running on Oracle Linux 7, with a Tesla V100-SXM2 GPU. Python 3.8 is the programming language used, along with PyTorch 2.0 for deep learning tasks. The NVIDIA driver version is 510.108.03, and CUDA is version 11.6. We used an image batch size of 16 with 1000 training epochs to train our dataset.

Evaluation metrics

Precision, Recall and mean average precision (mAP) provide an essential reference index to evaluate the model's performance.

Precision represents the proportion of all predicted positive samples that were correctly detected. It is the ratio of correctly predicted positive observations, i.e., Behaviors ((Feeding, Drinking, Perching, Preening, Dust Bathing, Pecking and Foraging)) 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 – Behaviors (Feeding, Drinking, Perching, Preening, Dust Bathing, Pecking and Foraging).

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

Mean average precision (mAP) was calculated as follows:

$$mAP = \sum_{i=1}^{N} P(i)\ x\ \Delta R(i)$$

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

4.3 RESULTS AND DISCUSSION

Model performance in computing system use

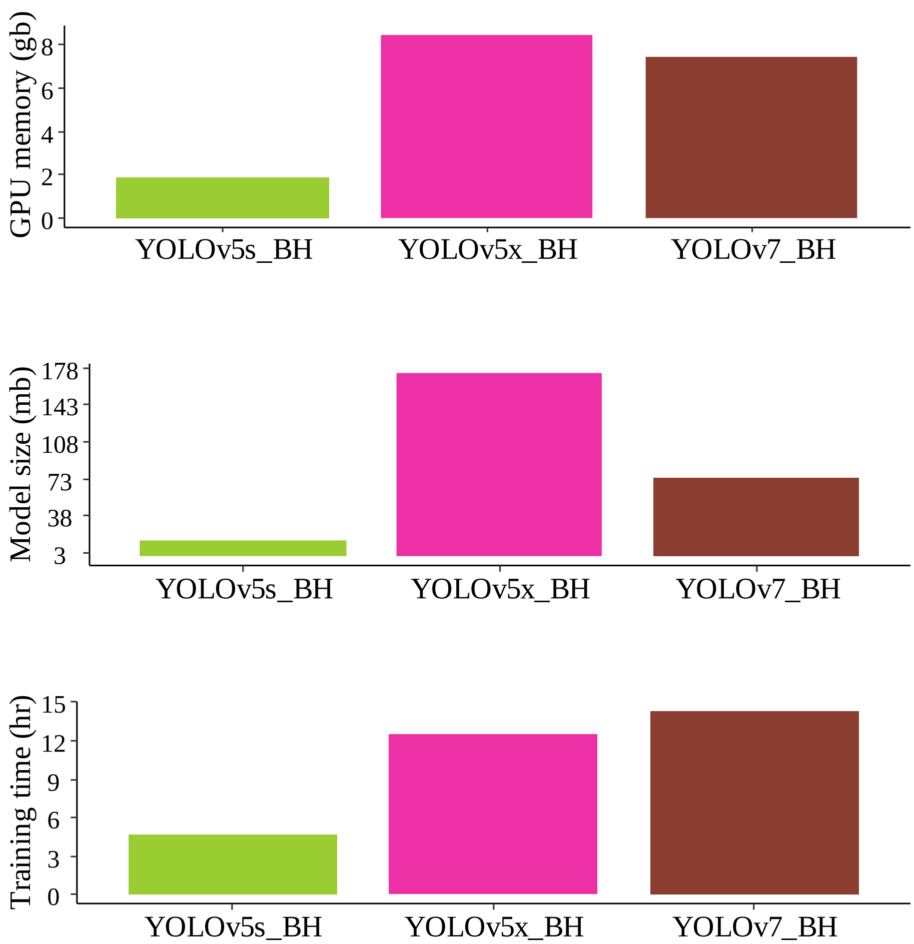


Figure 4.5. YOLOv5s_BH, YOLOv5x_BH, and YOLO7_BH models in memory size, model size, and training time.

Figure 4.5 illustrates the attributes of YOLOv5s, YOLOv5x, and YOLOv7 models, including their usage of GPU memory, model size, and the duration of their training time. Regarding the duration of the training process, YOLOv5s_BH required nearly 5 hours, whereas

YOLOv5x_BH and YOLOv7_BH had a longer training time of 12.5 hours and 14 hours, respectively. YOLOv5x_BH is the biggest model, measuring 173.1 mb, while YOLOv7_BH comes in second with a size of 74.8 mb, and YOLOv5s_BH is the smallest with a size of 14.4 mb. YOLOv5s_BH stands out as the most efficient model regarding both time and GPU usage, but it has the smallest size among the three models. YOLOv5x_BH, on the other hand, is the largest model with the highest GPU usage, while YOLOv7_BH requires less GPU usage compared to YOLOv5x_BH. This information is crucial as it can affect the selection of computer systems and the speed of data analysis.

Performance of behaviors detection models in data training and validation

a) Total training loss

All three models' full training loss function decreased while running in 1000 epochs (Figure 4.6). The total loss in the YOLO model is the sum of these three loss functions (Box/Localization loss, Classification loss, and Objectness loss) used to optimize the model's performance. In addition, the total loss is used to update the model weights during backpropagation to minimize the loss and improve the model's accuracy on the training data.

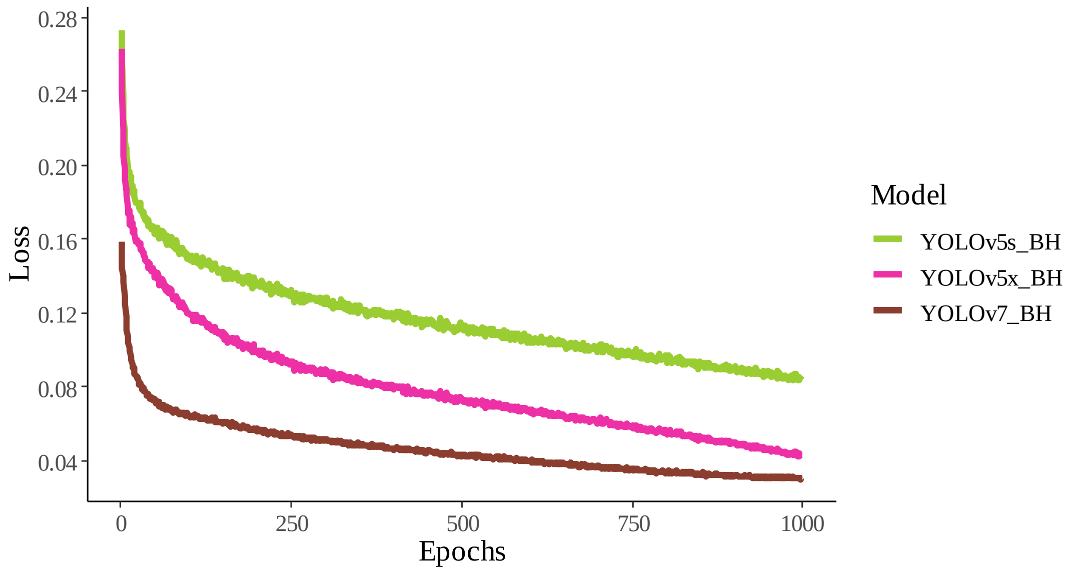


Figure 4.6. Total training losses from all three models while training behavior dataset

b) Precision

Precision is the ratio of true positive detections to the total number of positive detections. It measures the accuracy of the detection algorithm. The Figure 4.7 shows the precision of the model on a poultry behavior classification over 1000 epochs of training.

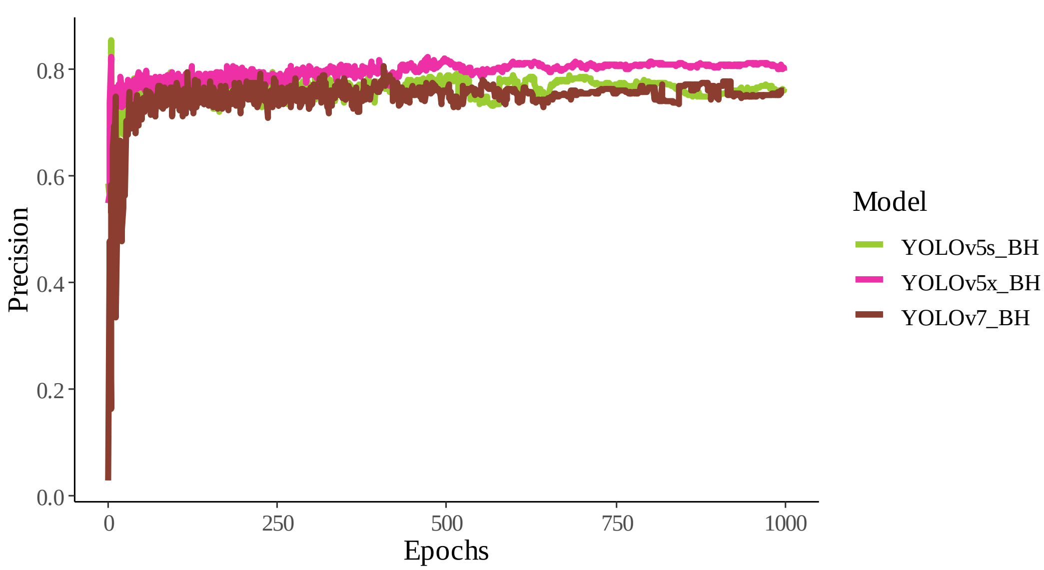


Figure 4.7. Precision from all three models while training behavior dataset

c) Recall

Recall is the ratio of true positive detections to the total number of actual positive instances. Figure 4.8 shows the recall of the model on a poultry behavior classification over 1000 epochs of training.

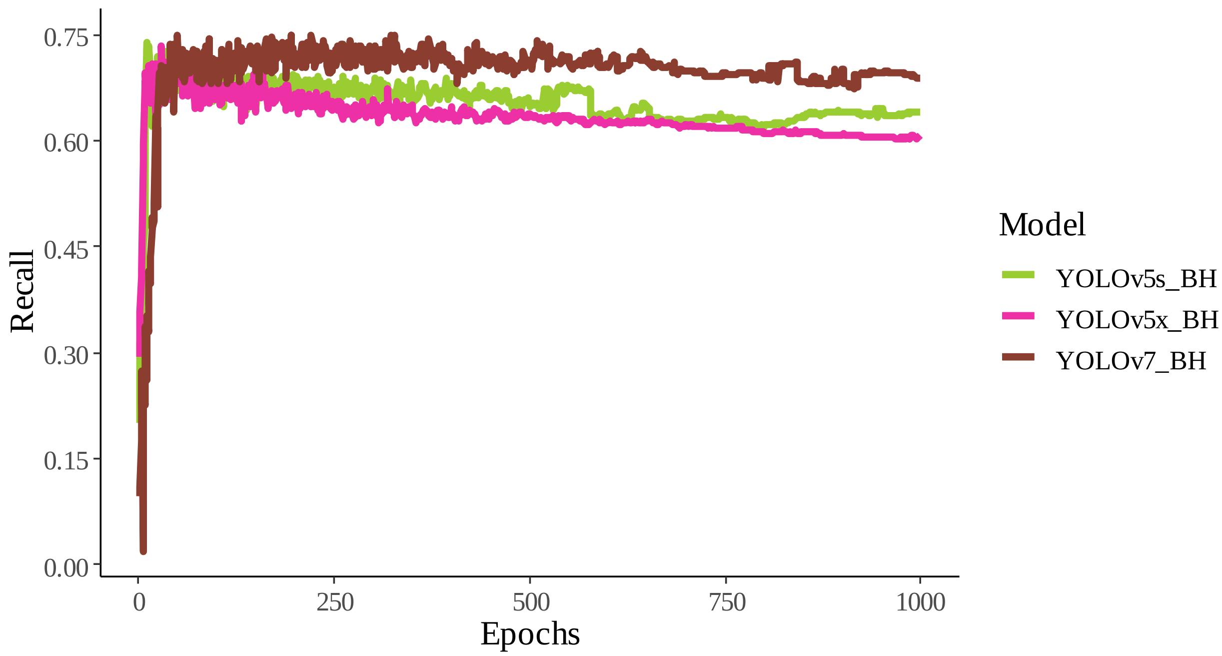


Figure 4.8. Recall from all three models while training the behavior dataset.

d) Mean average precision

mAP (mean Average Precision) is a measure that combines both precision and recall. It is the average precision calculated at various levels of recall. The Figure 4.9 shows the mAP of the model on a poultry behavior classification over 1000 epochs of training.

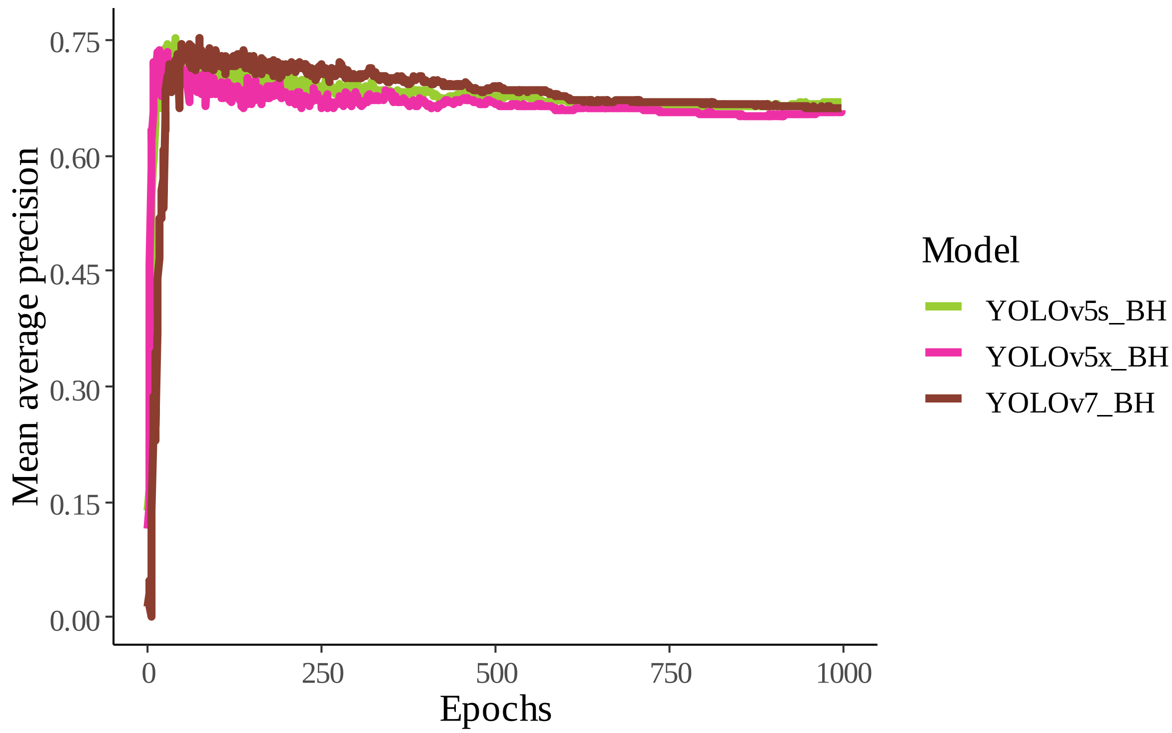


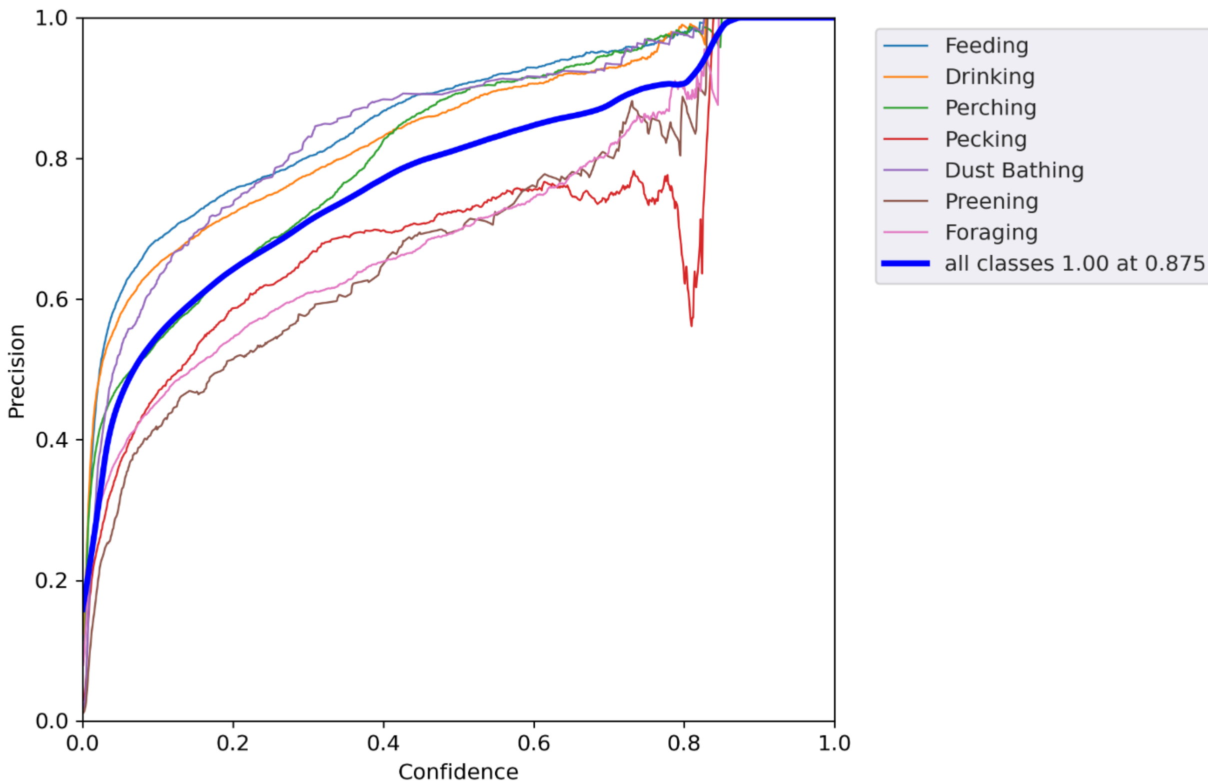
Figure 4.9. mAP from all three models while training behavior dataset.

Models' Performance Curves after Training

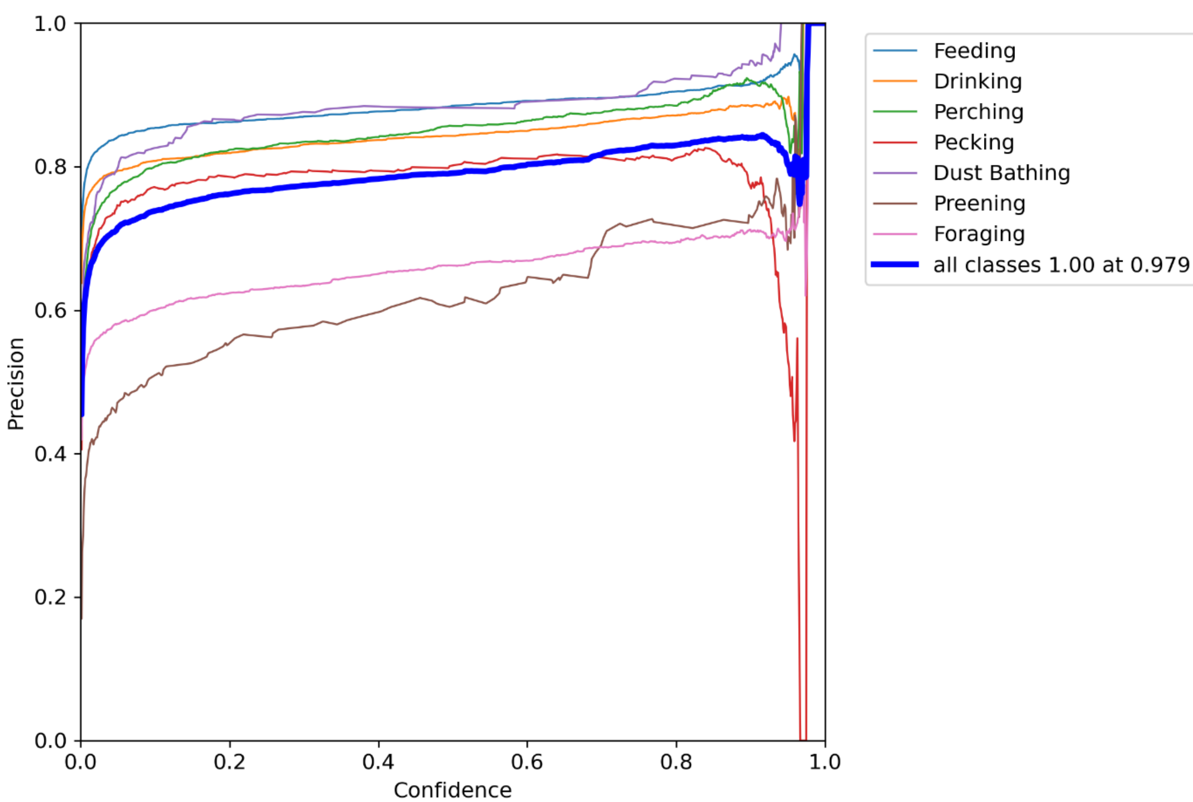
The precision, recall, and PR curve (Precision × Recall) were tested concerning confidence scores.

a) Precision Curves:

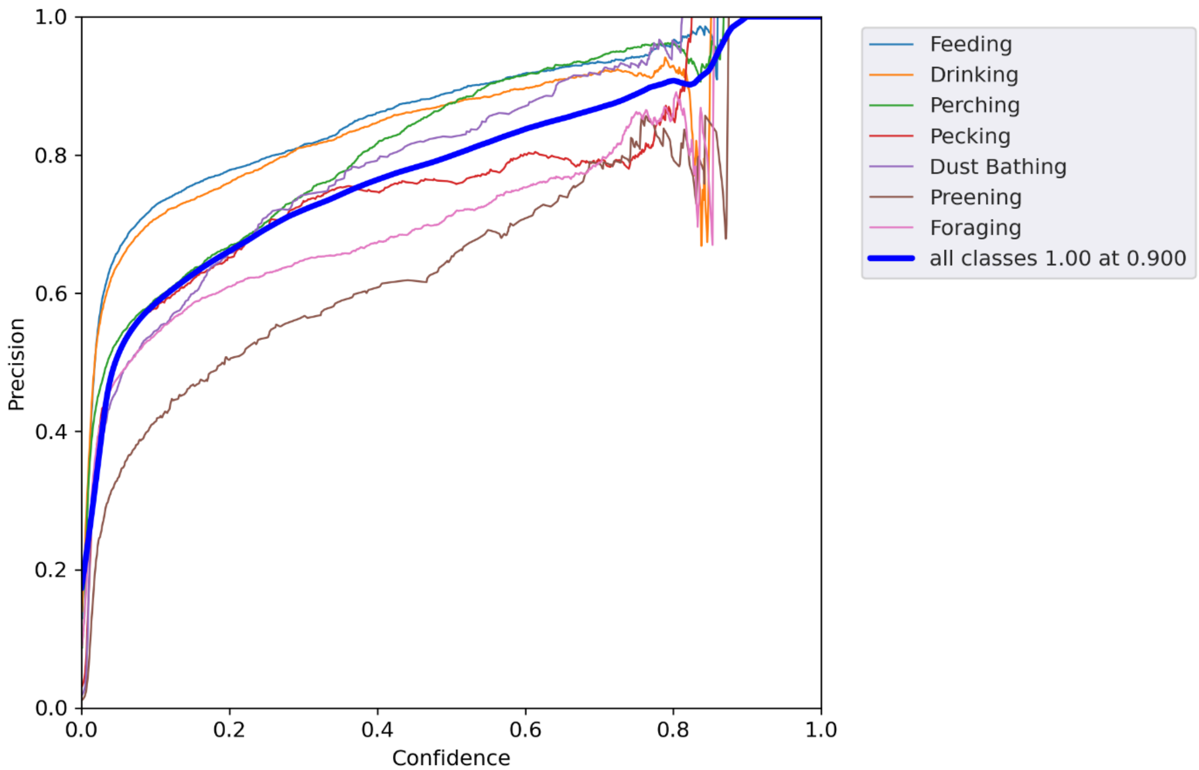
In precision curve the behavior detection precision of the YOLOv5s_BH model was low at the beginning and then increased gradually with the confidence score. In Figure 4.10 a), the precision reached 100% when the confidence score was 0.875. In Figure 4.10 b), the YOLOv5x_BH model, the precision gradually increased 100% when the confidence score was 0.9. Also, in Figure 4.10 c) the YOLOv7_BH model, the precision gradually increased by 100% when the confidence score was 0.979.



a) Precision Curve of YOLOv5s_BH



c) Precision Curve of YOLOv7_BH

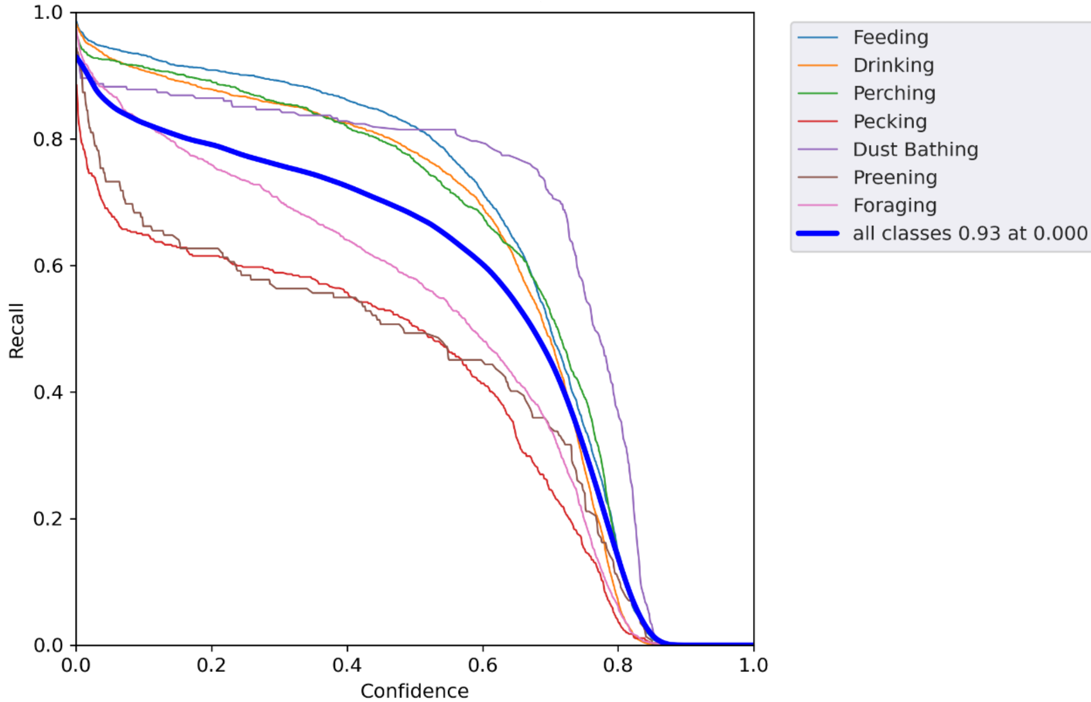


b) Precision Curve of YOLOv5x_BH

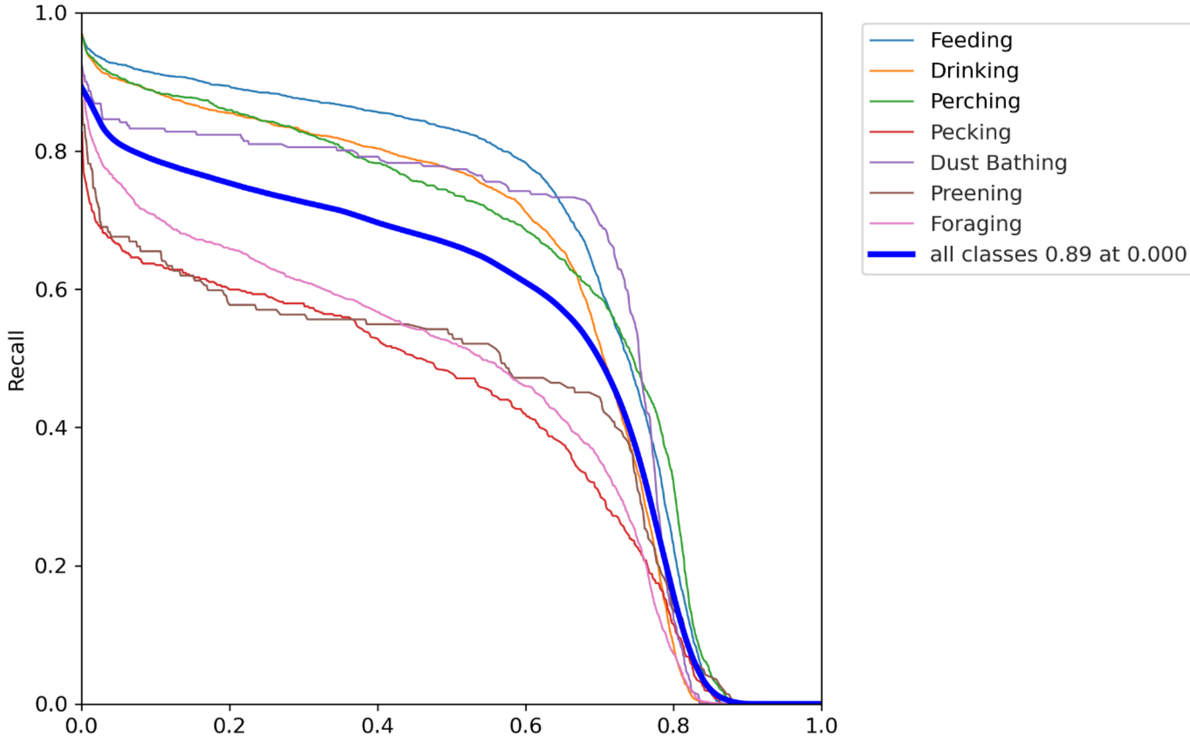
Figure 4.10. The precision curve of the YOLOv5s_BH, YOLO-v5x_BH, and YOLOv7_BH in behavior detection.

b) Recall Curves:

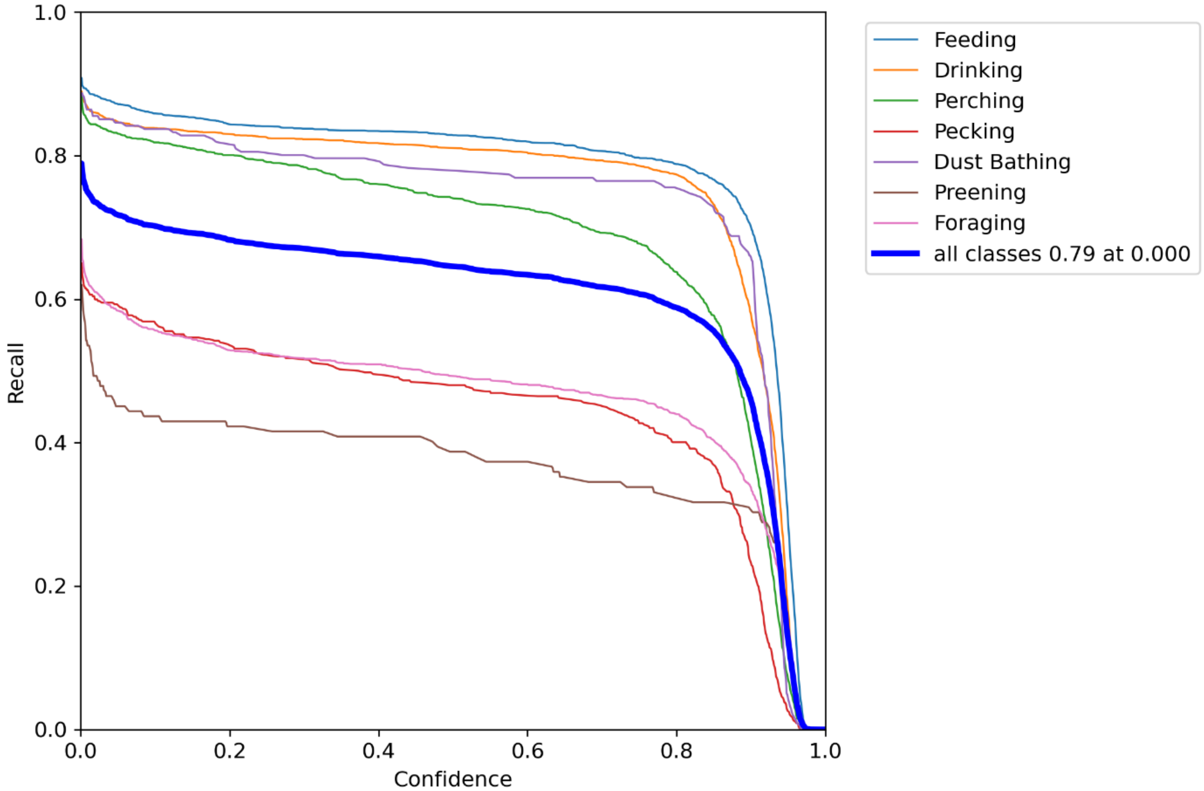
In Figure 4.11 a) the recall for the behavior classes was 93% for the YOLOv5s_BH model at the beginning and then decreased with the increase of confidence score to 1. For the YOLOv5x_BH model, the recall was similar to the YOLOv5s_BH model at 89% at the beginning and gradually decreased with the increasing confidence score to 1 in Figure 4.11 b). In Figure 4.11 c), the YOLOv7_BH model, the 79% at the beginning gradually reduced with the increasing confidence score to 1.



a) Recall Curve of YOLOv5s_BH



b) Recall Curve of YOLOv5x_BH

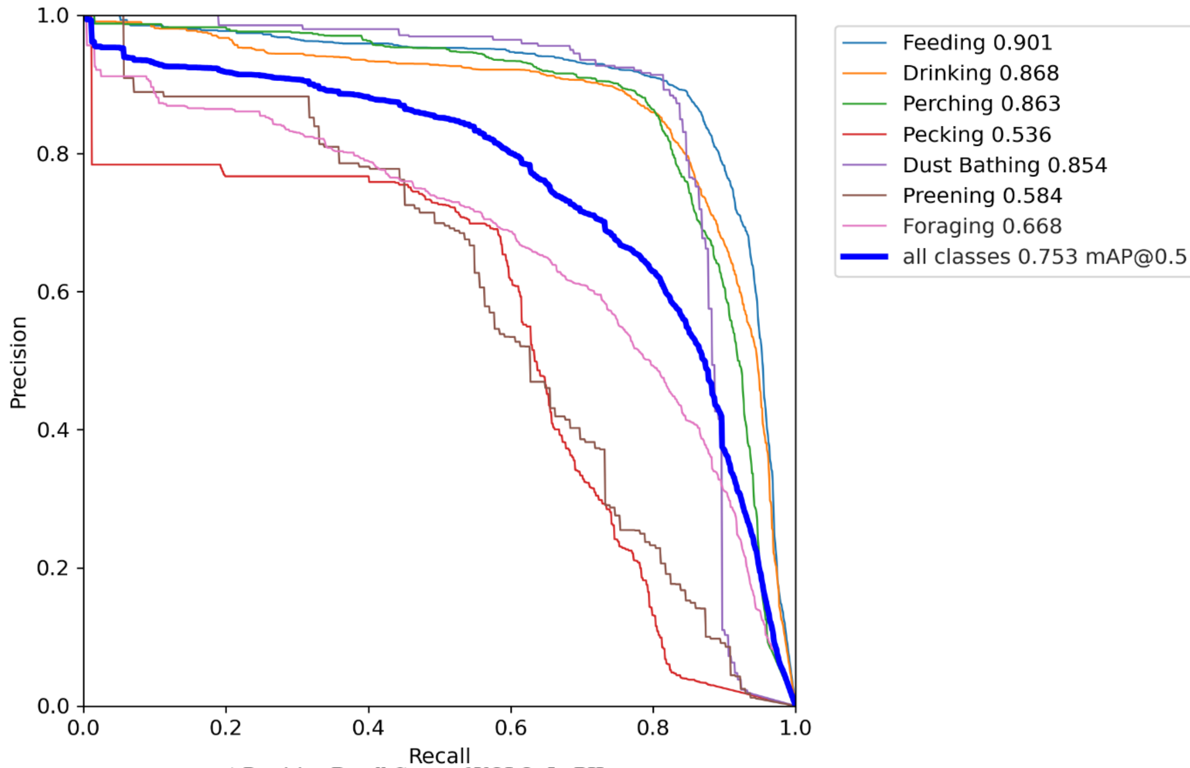


c) Recall Curve of YOLOv7_BH

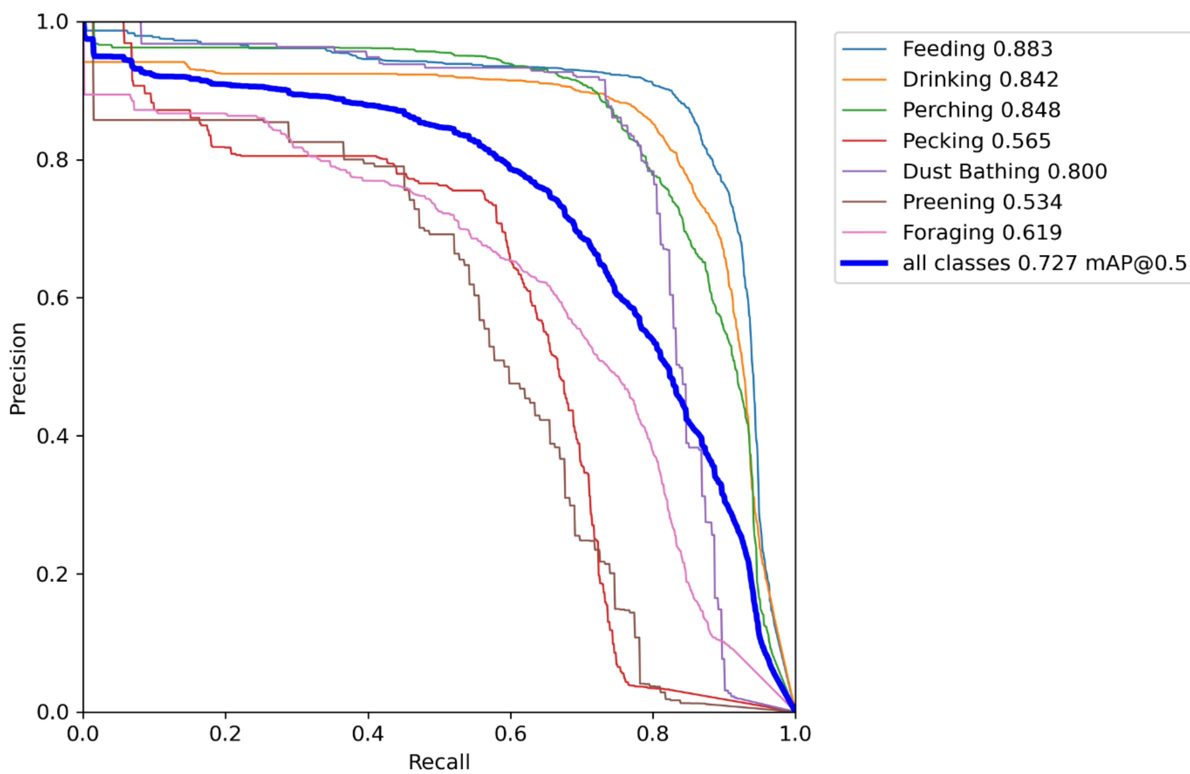
Figure 4.11. The recall curve of the YOLOv5s_BH, YOLOv5x_BH, and YOLOv7_BH in behavior detection.

c) **Precision-Recall Curves:**

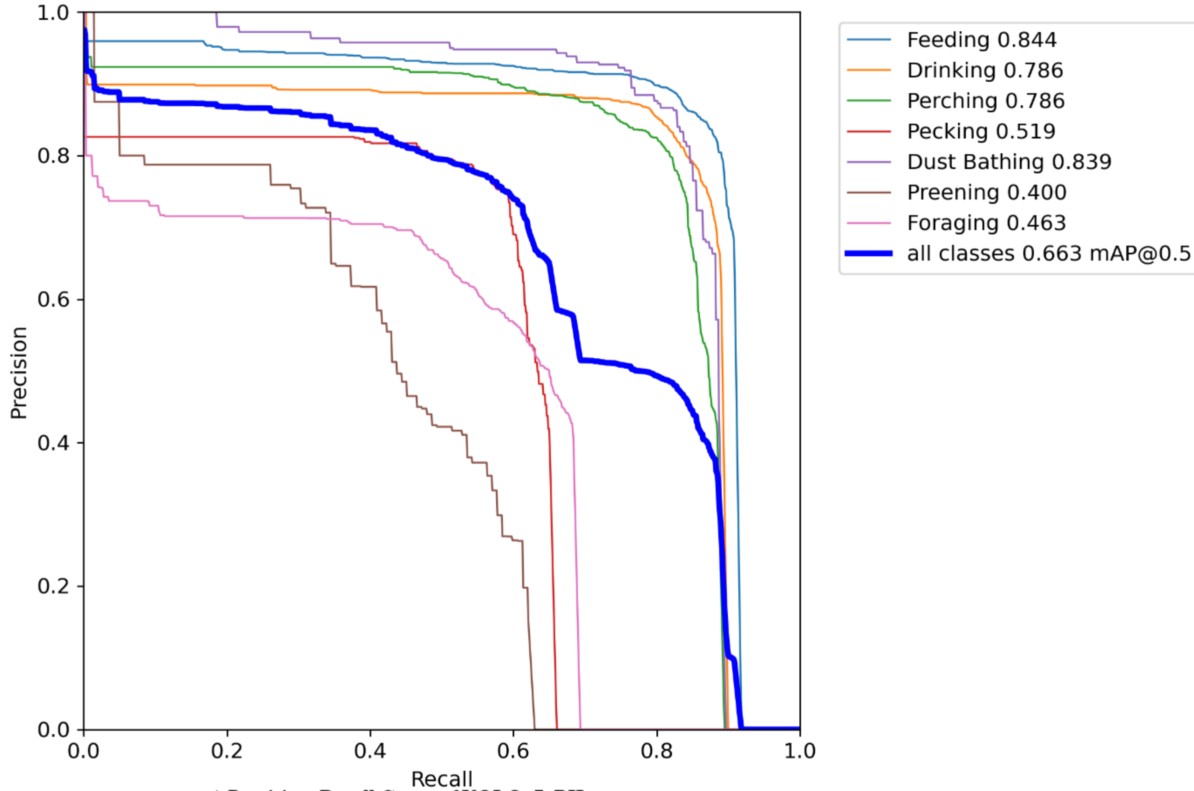
The precision × Recall curve was investigated to evaluate the performance of the behavior detection of all three models when the confidence score changes for each class. It helps to assess behaviors prediction ability when the precision maintains a significant value with the increase in the recall . Figure 4.12 a, b and c show that cross values (Precision X Recall) for the behavior class and mAP of all classes for YOLOv5s_BH is 75.3%, YOLOv5x_BH is 72.7%, and YOLOv7_BH is 66.3%.



a) Precision-Recall Curve of YOLOv5s_BH



b) Precision-Recall Curve of YOLOv5x_BH

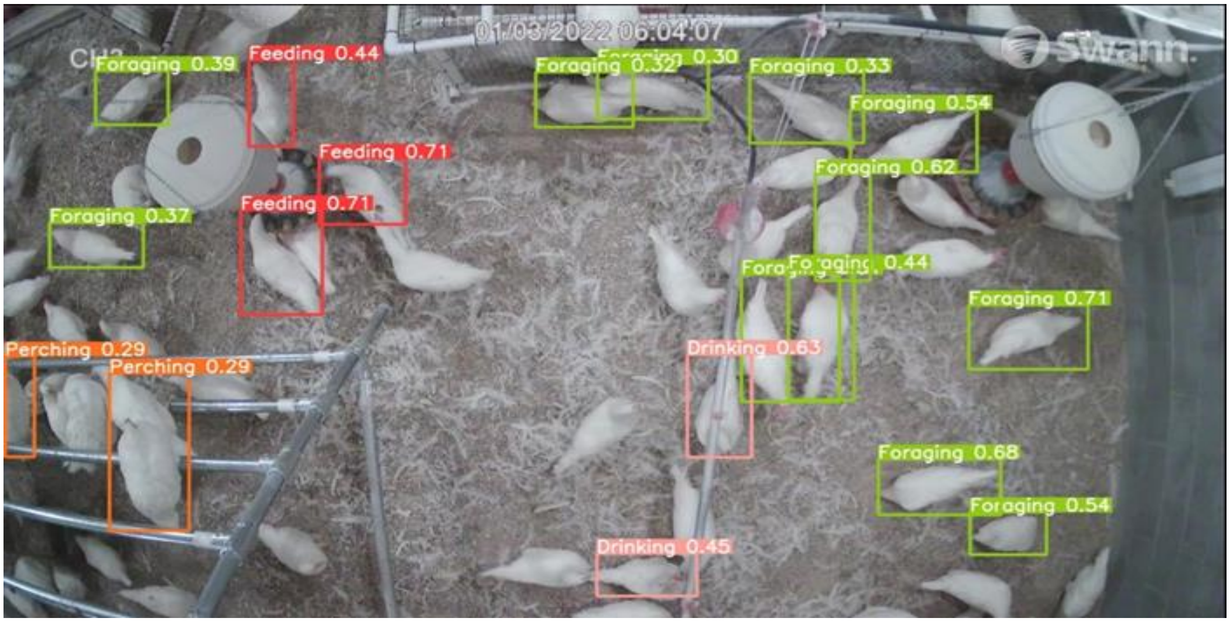


c) Precision_Recall Curve of YOLOv7_BH

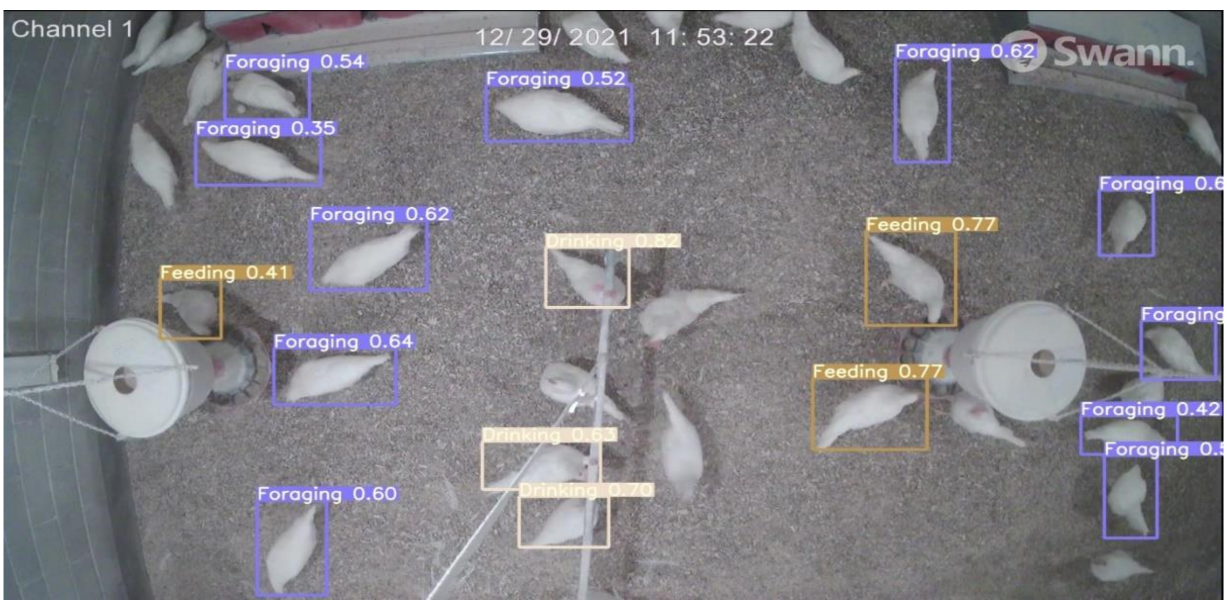
Figure 4.12. The Precision X Recall curve of the YOLOv5s_BH, YOLO-v5x_BH, and YOLOv7_BH in behavior detection.

Testing results of New Models in Detecting Laying Behaviors

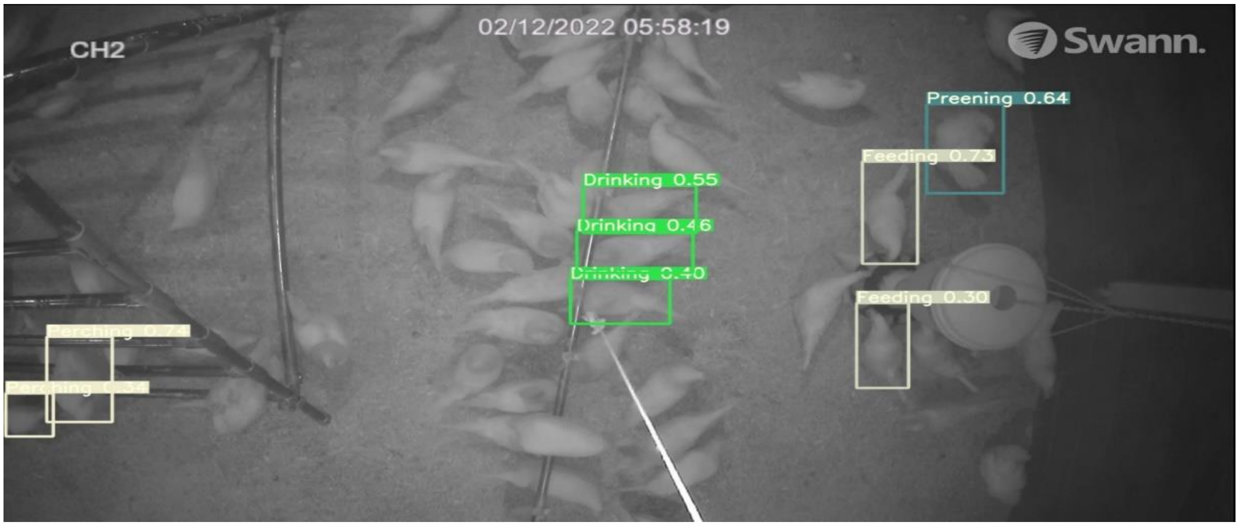
The optimized model, after training, was used to detect the laying hens behaviors in new unlabeled images. The Figure 4.13 (a, b and c and d) shows some examples of the automatic detection of behaviors. Table 2 shows the comparison summary between the YOLOv5s_BH, the YOLOv5x_BH model, and the YOLOv7_BH: the YOLOv5s_BH model can detect the behaviors with a precision of 78.1%, recall of 71.7%, and mean average precision (mAP) of 75.3%; the YOLOv5x_BH model can detect the behaviors with a precision of 76.2%, recall of 69.8%, and mean average precision (mAP) of 72.7 %; the YOLOv7_BH model can detect the behaviors with a precision of 75.9%, recall of 68.9%, and mean average precision (mAP) of 66.3%; YOLOv5s_BH model detected behaviors with higher precision, recall and mAP than YOLOv5x_BH and YOLOv7_BH.



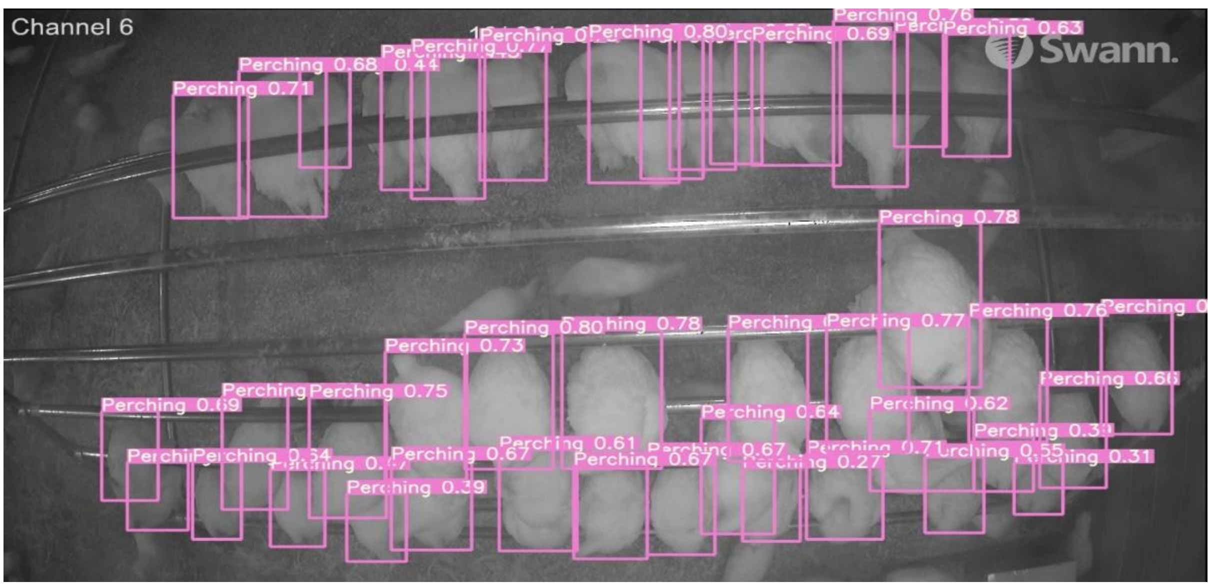
a) Feeding, Foraging, Perching and Drinking behaviors were detected.



b) Feeding and Foraging behaviors were detected



c) Detection (Perching, Feeding and Drinking) of behaviors in an image affected by dust



d) Perching behaviors detected by our models

Figure 4.13. Performance of all three models in test dataset.

Table 4.2. Results of comparing YOLOv5s_BH, YOLOv5x_BH and YOLOv7_BH models for behavior detection.

Model	**YOLOv5s_BH**			**YOLOv5x_BH**			**YOLOv7_BH**		
Parameters	7.1 million			86.1 million			37 million		
Layers	157			322			-		
Class	**Precision**	**Recall**	**mAP@50**	**Precision**	**Recall**	**mAP@50**	**Precision**	**Recall**	**mAP@50**
Behaviors	0.781	0.717	0.753	0.762	0.698	0.727	0.759	0.689	0.663

Evaluation metrics of all three models in Detecting Laying Behaviors

Precision: Precision measures how accurate our behavior detector is when it predicts the presence of a behavior. It is calculated as the ratio of true positives (correctly predicted behaviors) to the sum of true positives and false positives (incorrectly predicted behaviors). From the Figure 4.14, we can see that the highest precision is achieved for Dust Bathing with YOLOv5s_BH (0.887), followed by Feeding with YOLOv5s_BH (0.877) and Dust Bathing with YOLO7_BH (0.867). On the other hand, the lowest precision is achieved for Preening with YOLOv7_BH (0.542).

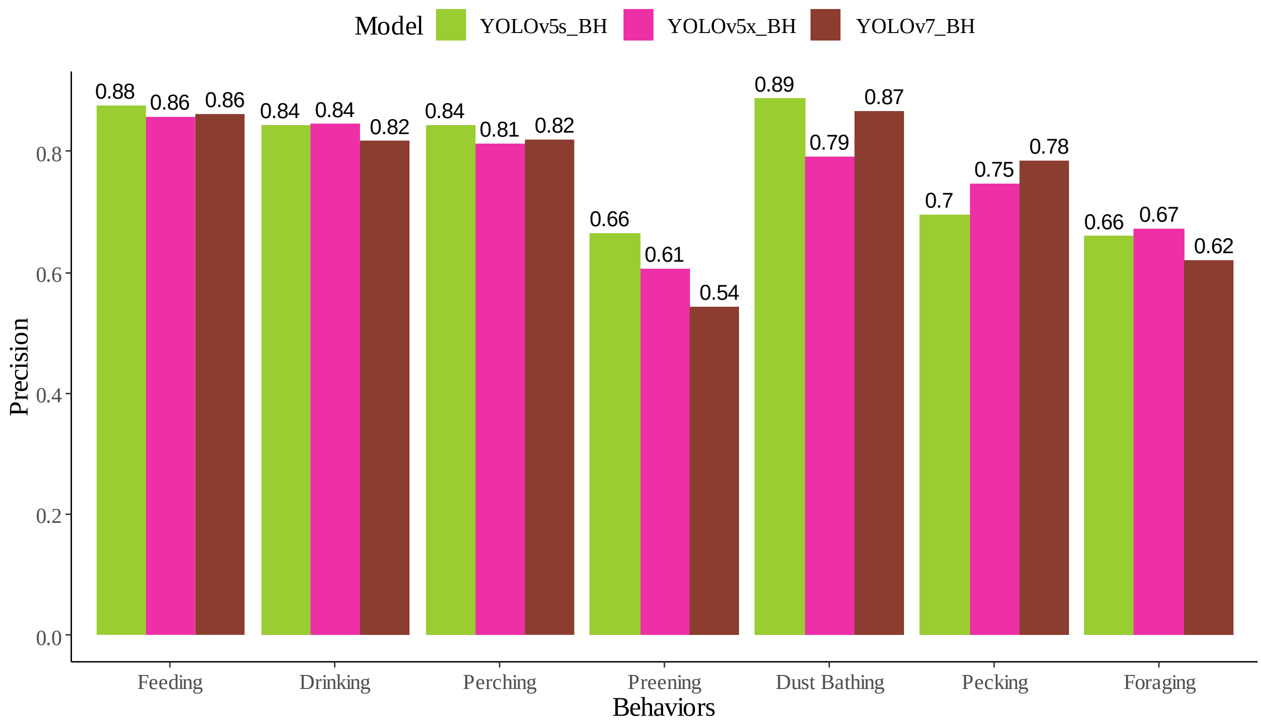


Figure 4.14: Precision of all models in Behavior detection

Recall: Recall measures how well the behavior detector can detect all the behaviors in an image. It is calculated as the ratio of true positives to the sum of true positives and false negatives (missed behaviors).

From the Figure 4.15, we can see that the highest recall is achieved for all Feeding behaviors with YOLOv5x_BH (0.858), YOLOv5s_BH (0.854) and YOLOv7_BH (0.849). On the other hand, the lowest recall is achieved for Preening with YOLOv7_BH (0.43).

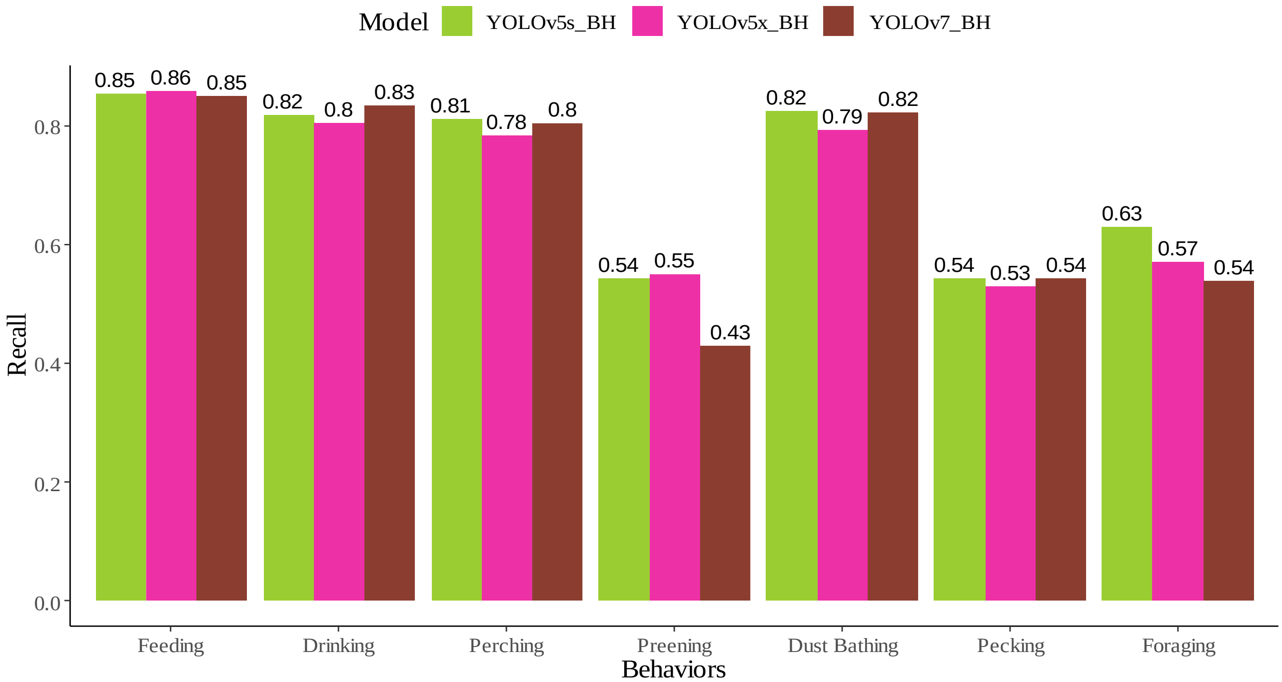


Figure15: Recall of all models in Behavior detection

Mean average precision: Object detection models often use a mean average Precision (mAP) metric to balance precision and recall. The mAP is the average of the precision-recall curve over all the behavior categories in the dataset.

From the Figure 4.16, we can see that the highest mAP is achieved for Feeding with YOLOv5s_BH (0.901), followed again by Feeding with YOLOv5x_BH (0.883) and Drinking with YOLOv5s_BH (0.868). On the other hand, the lowest mAP is achieved for Preening with YOLOv7_BH (0.4).

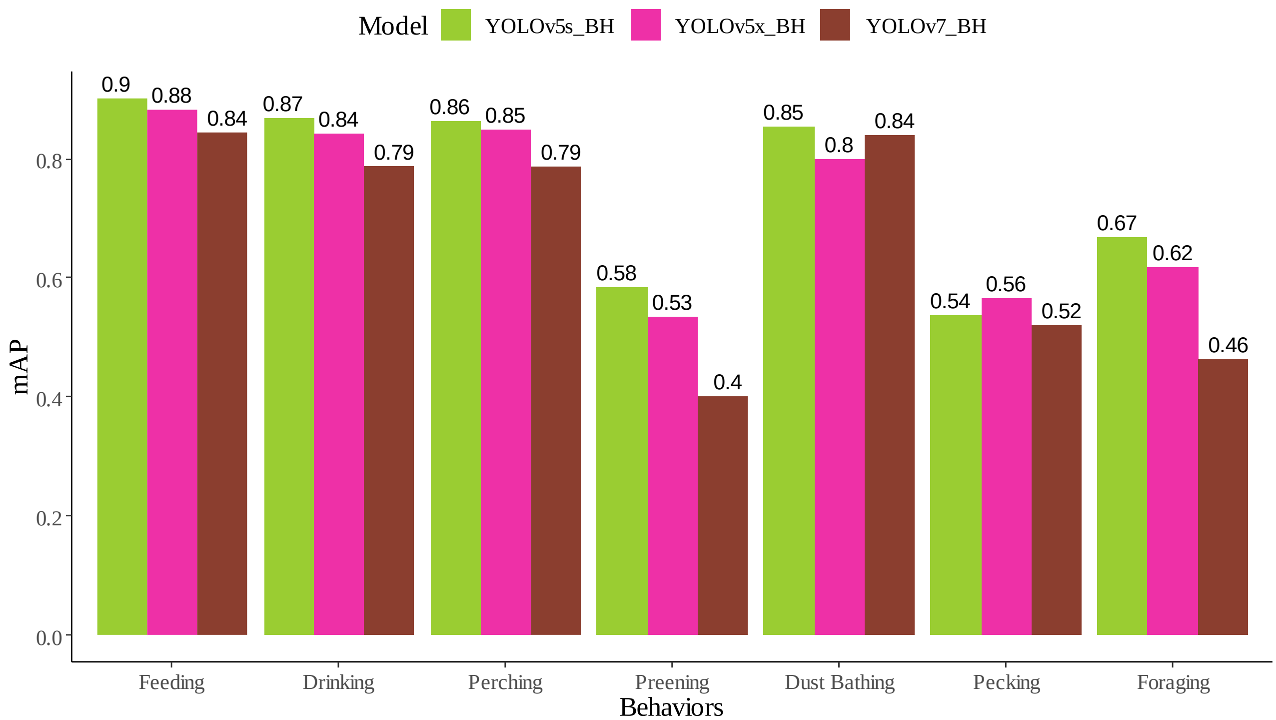


Figure 16: mAP of all models in Behavior detection.

In summary, the YOLOv5s_BH model seems to perform better than YOLOv5x_BH and YOLOv7_BH models for most behaviors. Feeding and Dust Bathing are the behaviors with the highest overall performance in terms of precision, recall, and mAP. Preening and Foraging are the behaviors with the lowest overall performance in terms of precision, recall, and mAP.

4.4 CONCLUSION

Precision poultry farming technology is necessary to detect laying hen behaviors automatically. An advanced object detection technology (i.e., the YOLO model) was used as the model structure. In this study, three new deep learning models, "YOLOv5s_BH", “YOLOv5x_BH”, and “YOLOv7_BH " networks were developed to detect and classify behaviors in a four-room research cage-free floor facility at the University of Georgia. Our model automatically detects and classifies behaviors in cage-free facilities. Furthermore, the smallest model, YOLOv5s_BH, performed well in terms of precision, recall and mAP as compared to the YOLOv5x_BH and YOLOv7_BH. The YOLOv5s_BH model had a 1.9%, 1.9%, and 2.6 % higher performance in precision, recall, and mAP than the YOLOv5x_BH model respectively. Also, the YOLOv5s_BH model had a 2.2%, 2.8%, and 9 % higher performance in precision, recall, and mAP than the YOLOv7_BH model, respectively. This study provides a reference for cage-free producers that poultry behaviors could be monitored automatically. Future studies are guaranteed to test the system in commercial houses.

Acknowledgments

This study was sponsored by the Egg Industry Center; Georgia Research Alliance – Venture Fund; UGA COVID Research Recovery Fund; UGA Office of Global Engagement - Global Research Collaboration Grant; UGA Provost and PSO Rural Engagement Fund; Oracle for Research Grant, Oracle America (Award Number: CPQ-2060433); and USDA-NIFA AFRI/ CARE program (2023-68008-39853).

References

Bist, R. B., Subedi, S., Chai, L., Regmi, P., Ritz, C. W., Kim, W. K., & Yang, X. (2023). Effects of Perching on Poultry Welfare and Production: A Review. *Poultry*, *2*(2), Article 2. https://doi.org/10.3390/poultry2020013

Black, K. M., Law, H., Aldoukhi, A., Deng, J., & Ghani, K. R. (2020). Deep learning computer vision algorithm for detecting kidney stone composition. *BJU International*, *125*(6), 920–924. https://doi.org/10.1111/bju.15035

Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). *YOLOv4: Optimal Speed and Accuracy of Object Detection* (arXiv:2004.10934). arXiv. https://doi.org/10.48550/arXiv.2004.10934

Ferreira, V. H. B., Barbarat, M., Lormant, F., Germain, K., Brachet, M., Løvlie, H., Calandreau, L., & Guesdon, V. (2020). Social motivation and the use of distal, but not local, featural cues are related to ranging behavior in free-range chickens (Gallus gallus domesticus). *Animal Cognition*, *23*(4), 769–780. https://doi.org/10.1007/s10071-020-01389-w

Florentino Pereira, D., Miyamoto, B., Maia, G., Sales, G., Magalhães, M., & Gates, R. (2013). Machine vision to identify broiler breeder behavior. *Computers and Electronics in Agriculture*, *99*, 194–199. https://doi.org/10.1016/j.compag.2013.09.012

Guo, Y., Chai, L., Aggrey, S. E., Oladeinde, A., Johnson, J., & Zock, G. (2020). A Machine Vision-Based Method for Monitoring Broiler Chicken Floor Distribution. *Sensors*, *20*(11), Article 11. https://doi.org/10.3390/s20113179

Guo, Z., Wang, C., Yang, G., Huang, Z., & Li, G. (2022). MSFT-YOLO: Improved YOLOv5 Based on Transformer for Detecting Defects of Steel Surface. *Sensors*, *22*(9), Article 9. https://doi.org/10.3390/s22093467

He, K., Zhang, X., Ren, S., & Sun, J. (2014). *Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition* (Vol. 8691, pp. 346–361). https://doi.org/10.1007/978-3-319-10578-9_23

Hewson, C. J. (2003). What is animal welfare? Common definitions and their practical consequences. *The Canadian Veterinary Journal*, *44*(6), 496–499.

Hossain, A., Islam, M. T., & Almutairi, A. F. (2022). A deep learning model to classify and detect brain abnormalities in portable microwave based imaging system. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-10309-6

Li, G., Hui, X., Lin, F., & Zhao, Y. (2020b). Developing and Evaluating Poultry Preening Behavior Detectors via Mask Region-Based Convolutional Neural Network. *Animals*, *10*(10), Article 10. https://doi.org/10.3390/ani10101762

Li, G., Zhao, Y., Purswell, J. L., Du, Q., Chesser, G. D., & Lowe, J. W. (2020a). Analysis of feeding and drinking behaviors of group-reared broilers via image processing. *Computers and Electronics in Agriculture*, *175*, 105596. https://doi.org/10.1016/j.compag.2020.105596

Liu, S., Qi, L., Qin, H., Shi, J., & Jia, J. (2018). Path Aggregation Network for Instance Segmentation. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 8759–8768. https://doi.org/10.1109/CVPR.2018.00913

Loddo, A., & Di Ruberto, C. (2021). On the Efficacy of Handcrafted and Deep Features for Seed Image Classification. *Journal of Imaging*, *7*(9), Article 9. https://doi.org/10.3390/jimaging7090171

Massari, J. M., de Moura, D. J., de Alencar Nääs, I., Pereira, D. F., & Branco, T. (2022). Computer-Vision-Based Indexes for Analyzing Broiler Response to Rearing Environment: A Proof of Concept. *Animals*, *12*(7), Article 7. https://doi.org/10.3390/ani12070846

Neethirajan, S. (2020). The role of sensors, big data and machine learning in modern animal farming. *Sensing and Bio-Sensing Research*, *29*, 100367. https://doi.org/10.1016/j.sbsr.2020.100367

Okinda, C., Nyalala, I., Korohou, T., Okinda, C., Wang, J., Achieng, T., Wamalwa, P., Mang, T., & Shen, M. (2020). A review on computer vision systems in monitoring of poultry: A welfare perspective. *Artificial Intelligence in Agriculture*, *4*, 184–208. https://doi.org/10.1016/j.aiia.2020.09.002

Pu, H., Lian, J., & Fan, M. (2018). Automatic Recognition of Flock Behavior of Chickens with Convolutional Neural Network and Kinect Sensor. *International Journal of Pattern Recognition and Artificial Intelligence*, *32*(07), 1850023. https://doi.org/10.1142/S0218001418500234

Savory, C. j. (1995). Feather pecking and cannibalism. *World's Poultry Science Journal*, *51*(2), 215–219. https://doi.org/10.1079/WPS19950016

Scanes, C. G., Campbell, R., & Griminger, P. (1987). Control of Energy Balance during Egg Production in the Laying Hen. The Journal of Nutrition, 117(3), 605–611. https://doi.org/10.1093/jn/117.3.605

Shen, H., Dong, Z., Yan, Y., Fan, R., Jiang, Y., Chen, Z., & Chen, D. (2022). Building roof extraction from ASTIL echo images applying OSA-YOLOv5s. *Applied Optics*, *61*(11), 2923–2928. https://doi.org/10.1364/AO.451245

Subedi, S., Bist, R., Yang, X., & Chai, L. (2023a). Tracking pecking behaviors and damages of cage-free laying hens with machine vision technologies. *Computers and Electronics in Agriculture*, *204*, 107545. https://doi.org/10.1016/j.compag.2022.107545

Subedi, S., Bist, R., Yang, X., & Chai, L. (2023b). Tracking Floor Eggs with Machine Vision in Cage-free Hen Houses. *Poultry Science*, 102637. https://doi.org/10.1016/j.psj.2023.102637

T. Leroy, E. Vranken, A. Van Brecht, E. Struelens, B. Sonck, & D. Berckmans. (2006). A computer vision method for on-line behavioral quantification of individually caged poultry. *Transactions of the ASABE*, *49*(3), 795–802. https://doi.org/10.13031/2013.20462

Tulbure, A.-A., Tulbure, A.-A., & Dulf, E.-H. (2022). A review on modern defect detection models using DCNNs – Deep convolutional neural networks. *Journal of Advanced Research*, *35*, 33–48. https://doi.org/10.1016/j.jare.2021.03.015

van Liere, D. W., & Bokma, S. (1987). Short-term feather maintenance as a function of dust-bathing in laying hens. *Applied Animal Behaviour Science*, *18*(2), 197–204. https://doi.org/10.1016/0168-1591(87)90193-6

Vestergaard, K. S., Skadhauge, E., & Lawson, L. G. (1997). The Stress of Not Being Able to Perform Dustbathing in Laying Hens. *Physiology & Behavior*, *62*(2), 413–419. https://doi.org/10.1016/S0031-9384(97)00041-3

Wang, C.-Y., Bochkovskiy, A., & Liao, H.-Y. M. (2022). *YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors* (arXiv:2207.02696). arXiv. http://arxiv.org/abs/2207.02696

Wood-Gush, D. G. M. (1955). The behaviour of the domestic chicken: A review of the literature. *The British Journal of Animal Behaviour*, *3*(3), 81–110. https://doi.org/10.1016/S0950-5601(55)80001-9

Wood-Gush, D. G. M., & Duncan, I. J. H. (1976). Some behavioural observations on domestic fowl in the wild. *Applied Animal Ethology*, *2*(3), 255–260. https://doi.org/10.1016/0304-3762(76)90057-2

Xu, D., Shu, G., Liu, Y., Qin, P., Zheng, Y., Tian, Y., Zhao, X., & Du, X. (2022). Farm Environmental Enrichments Improve the Welfare of Layer Chicks and Pullets: A Comprehensive Review. *Animals*, *12*(19), Article 19. https://doi.org/10.3390/ani12192610

Yang, X., Bist, R., Subedi, S., & Chai, L. (2023). A deep learning method for monitoring spatial distribution of cage-free hens. *Artificial Intelligence in Agriculture*. https://doi.org/10.1016/j.aiia.2023.03.003

Yang, X., Chai, L., Bist, R. B., Subedi, S., & Wu, Z. (2022a). A Deep Learning Model for Detecting Cage-Free Hens on the Litter Floor. *Animals*, *12*(15), Article 15. https://doi.org/10.3390/ani12151983

Yang, Z., Ni, C., Li, L., Luo, W., & Qin, Y. (2022b). Three-Stage Pavement Crack Localization and Segmentation Algorithm Based on Digital Image Processing and Deep Learning Techniques. *Sensors*, *22*(21), Article 21. https://doi.org/10.3390/s22218459

CHAPTER 5

SUMMARY

The conventional caged housing system restrains the laying hens from displaying their natural behaviors. This has led to raising concerns about poultry welfare policies among the public. As a solution, there is a shift towards cage-free bird rearing, which allows them to express their normal behaviors such as preening, foraging, perching, and dust bathing. Consequently, there is a requirement for the agricultural industry to improve its ability to identify any deviations in the behavior, health, and welfare of chickens without relying on manual labor. This can be achieved by adopting automated systems.

In our first study, we developed a machine vision method for tracking the feather-pecking behaviors of hens and potential damages in cage-free facilities. Feather pecking (FP) is one of the primary welfare issues in commercial cage-free hen houses, as that can seriously reduce the well-being of birds and cause economic losses for egg producers. Two YOLOv5-based deep learning models, i.e., YOLOv5s-pecking and YOLOv5x-pecking, were developed and compared in tracking FP behaviors of laying hens cage-free facilities. The YOLOv5x-pecking model performs well, achieving 88.1% precision, 68.8 recall, and 78.7 % mAP, which is higher than the YOLOv5s-pecking model by 3.1%, 8.6%, and 5.4% respectively.

Our second research project involved developing a machine vision technique for tracking floor eggs in cage-free facilities. We developed, trained, and compared three deep learning models based on YOLO, namely YOLOv5s-egg, YOLOv5x-egg, and YOLOv7-egg, to track floor eggs in cage-free facilities. The YOLOv5s-egg model detected floor eggs with 87.9% precision, 86.8% recall, and a mean average precision (mAP) of 90.9%. The YOLOv5x-egg model detected floor eggs with 90% precision, 87.9% recall, and a mAP of 92.1%. The YOLOv7-egg model detected eggs with 89.5% precision, 85.4% recall, and a mAP of 88%.

For our third research project, we developed three new deep learning models, named "YOLOv5s_BH," "YOLOv5x_BH," and "YOLOv7_BH," to identify and categorize seven different behaviors of laying birds (Feeding, Drinking, Perching, Pecking, Dust Bathing, Preening, and Foraging) in cage-free facilities at the University of Georgia. Among these models, the YOLOv5s_BH model performed the best in terms of precision (78.1%), recall (71.7%), and mean average precision (75.3%) when compared to the YOLOv5x_BH and YOLOv7_BH models. Specifically, the YOLOv5s_BH model had 1.9%, 1.9%, and 2.6% higher precision, recall, and mAP, respectively, than the YOLOv5x_BH model. Furthermore, the YOLOv5s_BH model had 2.2%, 2.8%, and 9% higher precision, recall, and mAP, respectively, than the YOLOv7_BH model.

Although all the models showed impressive precision in detecting behaviors, their performance was influenced by the stocking density, different levels of lighting, and obstructions in the images, such as drinking lines, perches, and feeders. Our use of YOLOv5 models to track problematic behaviors of cage-free hens was one of the earliest attempts. This model lays the groundwork for creating a real-time automated system that can monitor pecking behaviors and identify damages in commercial cage-free hen houses, thus safeguarding the welfare and health of laying hens. In addition, the findings of our study serve as a helpful reference for cage-free producers, demonstrating that poultry behaviors can be monitored automatically.