Machine Learning in Chicken Counting – Smart Solutions for Modern Livestock

Pham Van Viet, Nguyen Trung Kien,
Le Van Luong, Nguyen Hai Nam
Khoa Trí tuệ nhân tạo, FPT University, Hanoi, Vietnam
vietpvhe180096@fpt.edu.vn, kienkakakak@gmail.com,
trinhptthe160790@fpt.edu.vn, namnhhe180706@fpt.edu.vn

Abstract: Manual counts on traditional farms might sound easy but actually pose various challenges. Manual counting involves farmers looking at and recording how many chickens are in which area. This takes a lot of time and can build up large errors—particularly when dealing with hundreds or thousands of flocks. The environment inside the farm does not usually offer ideal conditions for observation due to low lighting, dust, the constant movement of the chickens themselves, and physical obstructions like feeders and cage partitions which further reduce visibility. Problems also arise from overlapping chickens and crowded conditions that usually lead to miscounts. Its solution results in applying artificial intelligence, particularly in using state-of-the-art computer vision models as an integral aspect of smart agriculture. Among the leading models available today is YOLOv8 (You Only Look Once, version 8), among one of the most effective tools toward detecting as well as counting objects within poultry environments—such as chickens. With the same angle, that objects are missed when obscured by other objects in the images or videos is just an insinuating aspect assured of by YOLOv8, and it does this with accuracy.
Instant processing-since this model operates based on real-time monitoring, YOLOv8 can count chickens directly on the farm from the live camera feeds and hence farmers can check on the number as well as the condition of their flocks from anywhere at any time.This is perhaps why YOLOv8 has been preferred over the rest in smart chicken counting: because it processes lightly in a powerful manner, and small data sets are also used during training yet compelling results come out from it.However, to put this into practice demands quite some level of AI and programming skills, a feat that has remained very challenging for many students. It is against this background that we are proposing the design of a very practical learning kit that will help students approach chicken counting techniques using YOLOv8 in a very intuitive, visual, and cheap way, reference source code, and practice exercises based on the project-based learning approach.

Keywords: aquaculture automation, computer vision, chicken detection, chicken counting, grazing monitoring, machine learning .

1. Introduction

The poultry industry is facing very serious challenges in its efforts to meet the growing demand of consumers for their products while at the same time meeting increasingly higher standards for food safety [1–2]. Among the many problems being faced are, first, a shortage of skilled labor; second, controlling diseases; and third, enhancing productivity even with large-scale operations. Accurate chicken counting within a flock forms the major factors that can determine efficiency in poultry farming; therefore, monitoring, management, and timely operational decisions depend on it. Conventional techniques, such as hand tallying and standard sensors, require much time, are not accurate in many cases and cannot be effectively used on a large scale of industrial farms. These problems would be taken care of by an intelligent system our research group designed and implemented machine learning plus computer vision technologies to automate the process of counting chickens in real-time environments [3–4]. It applies the YOLOv8 object detection model—presently one of the most leading-edge as well as greatly efficient models available—merged with semi-supervised learning in addition to active learning. This drastically reduces over 80% of the time taken in data labeling, traditionally known as one of the most labor-intensive steps in model training when compared with traditional means. Hence proved by experimental results that it can identify various breeds of chickens together with their behavioral analysis attaining an accuracy value possible up to 90.4% F1-score at 92.5%.

The setup does not end with just counting chickens. It involves sensors and image analysis technologies that will help in monitoring the behavior and health condition of individual birds[5–6]. Abnormalities can be detected at an early stage through a change in movement patterns, abnormal behavior, or any stress indicators of the birds; thus, the system will be able to send alerts for timely intervention to mitigate against disease outbreak risks and economic losses[7–8]. This capability is especially crucial in the context of ongoing threats from infectious diseases like avian influenza.

It is a global practice to modernize agriculture, hence AI tools are becoming an essential part of the poultry process. This assists not only in promoting productivity and efficiency but also supports the quality assurance of products, traceability, and public health as well. The massive use of intelligent systems such as ours is geared toward farm management revolutions and very important components of national strategies on sustainable agriculture and food safety [9].

The product is designed to suit AI learning or its associated areas such as Image Processing and Deep Learning. Since this device is compact, it becomes very handy to use for classroom group activities. Details of the item shall be put forward in this paper.

2.Related Work

Estimating the number of objects in an image or video involves processing visual data to determine how many items appear within a specific scene. According to current research, object counting techniques are typically grouped into three types: those that rely on detecting individual objects, those that use density estimation, and those that apply segmentation methods. The approach used for counting chickens in this study is based on object detection.

2.1. Counting by Detection

The coming of AI technology, more specifically machine learning technologies, brought a wave of modernization to the livestock sector [10–11].Present detection methods in caged poultry dwell mostly on two major aspects; accurate live chicken detection and prompt identification of dead chickens.Hao et al. designed a dead broiler detector by adopting the YOLOv3 network for large-scale poultry operations in China.While this setup significantly minimized breeder workload due to its static rather than dynamic inspection method, it could not utilize multi-frame analysis capabilities to reduce the effects of occlusion and because there was not enough dataset on dead chickens leading to both missed and false detections [12]. Although these studies have advanced technologically, they are still limited by factors such as efficiency and practicality.

3. Materials and Methods

Right now, the documentation that comes with the product is still pretty basic. Most of it is just shared as attachments without much detail. Since we want to develop this product further and make it a main product, we decided to look at the problems and solutions we discussed earlier. One of our priorities is to make the documentation fit better with what students are learning at universities nowadays. Because of that, we also made some changes to the design of the practical exercises so they are easier for students to follow and more useful for their studies.

3.1 Data collection

In agricultural technology, including tasks like chicken counting, the quality and diversity of the datasets impact the performance of an object detection model. For the YOLOv8-based detection system, it was essential to obtain datasets of chickens with images under different scenarios so as to evaluate training as thoroughly as possible.

This study focused on acquiring datasets from both self-sourced and publicly available data. We obtained images and videos of chickens within commercial cage systems using HD cameras that simulated natural light variations and different degrees of occlusion. These images collected during different times of the day captured a chicken's multiple angles, poses, flock densities, and various environmental conditions as greatly as possible to create a robust The detection model.

The Labeling tool was used as the annotating tool of choice to draw bounding boxes and polygons in the YOLO format around chicken instances. Careful consideration was made for the overlapping chickens, and partially visible birds which frequently appear in high-density cages.

Alongside self-collected data, datasets such as PoultryNet and those available on Roboflow were incorporated and evaluated. Such datasets provided self-collected datasets with challenges like motion blur or exceptional occlusion that were underrepresented.

Figure. 1. *Crowded and cramped ,Gaussian noise images*

3.2. Data Pre-Processing

This subsection outlines the methods employed to ensure that the annotations created were of a high enough quality for effective training of the object detection model. The dataset was intended to include the body and head features of chickens as they are seen from an angle and from above, enabling accurate and reliable training of the model.

The raw data was reviewed and filtered to eliminate abnormal frames resulting from random captures or poor image quality. Abnormal frames were removed as, caused by random captures or poor quality images. During annotation, the chicken's body and head were the primary focus, as these crucial components for object detection accuracy. The videos were captured from fixed angled and top down viewpoints to realistically mimic conditions on a farm, which is an essential step to increase the model’s practicality.

Chickens were seen congregating closely or were partially blocked from view in many situations. To solve these issues, the contour of interest was marked out in a manner that included additional area beyond the body or head. If the head was covered, then the bounding box was drawn to include parts of the neck and the lower body region close to the feeding trough to make sure that object detection was done correctly. While this might pose a small risk of introducing some erroneous detections, it was much more helpful in reducing the risk of valid detections being missed.

We drew bounding boxes and polygons over the target areas in Roboflow where annotation took place. A portion of the labeled images was used to train Roboflow's auto-labeling model, accelerating labeling for the rest of the dataset. All auto-generated annotations were subsequently verified for consistency and accuracy by human reviewers.

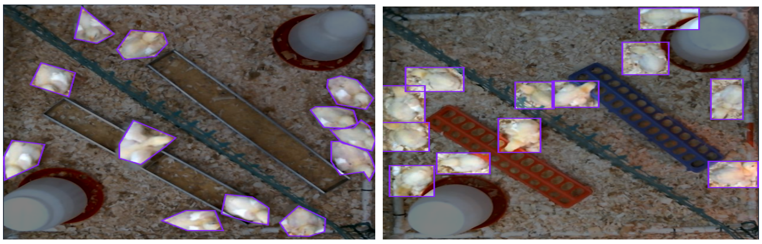


Figure. 2. *LabelIng images*

3.3. Overall Process Flow Diagram

The general process of running YOLOv8 for chicken counting follows a structured workflow for the attainment of accurate and efficient detection. It starts with image or video data collected in real-life conditions from caged chicken farms. Preprocessing includes cleaning and resizing as well as augmenting, and manually annotating the chickens labeling who they are. This annotated dataset trains the YOLOv8 model so it recognizes chickens in complex crowded environments. During training, validation, and optimization of model performance are carried out continuously. After being trained, the model can be used on new input images or video frames to detect chickens and count their number by inference. Results are post-processed through such methods as non-maximum suppression (NMS) that eliminate duplicate detections. The outputs—the number of chickens plus visual bounding boxes—can both be displayed for monitoring, analysis, or plugging into farm management systems.

The diagram of YOLOv5 (default setup) describes net architecture as comprising three major components: Backbone, Neck, and Head. After minor standardization pre-processing, images run through a feature extraction process in the backbone followed by feature fusion processing in the neck. This information is then processed by the head network to generate a model along with detection results inclusive of class, score, location, and size.

3.4. Overall Flow of the Visual Algorithm

This paper gives a caged chicken counting algorithm which has two major steps: object detection and filtering with threshold. The video input from the camera is first processed through an optimized model of YOLOv8s so that some key elements, including chicken heads and fence structure can be identified and localized yielding their pixel-based coordinates.

After detection, the recognition results are subjected to threshold filtering. An algorithm then runs a loop to check the positional relationship between recognized chicken heads and fences thereby achieving isolation and counting of chickens in every specified cage area. As a final output, the number of chickens per cage is provided accurately. Figure 3 shows a complete flow of work for this counting system.

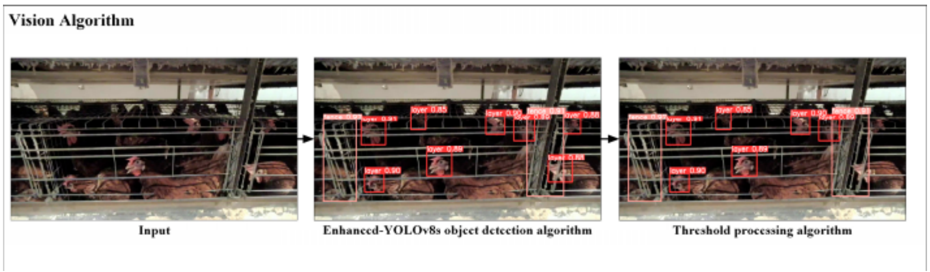
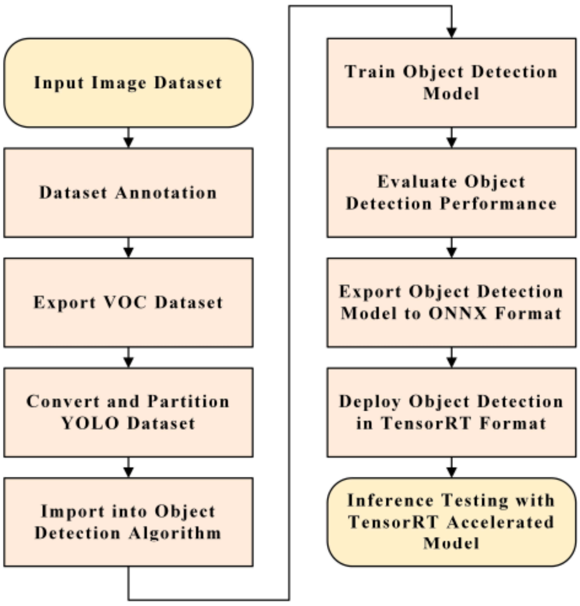


Figure. 3. *Flowchart of the caged chicken counting algorithm is a two-step process consisting first of object detection then followed by threshold processing.*

3.5. Evaluation Criteria

This section discusses the steps required to execute the object finder strategy, mostly discussing model modification and application in robot systems. In order for the model to function effectively and be dependable when employed, it carefully considers preparing it for real-time application.

To allow integration with robotic platforms, the model was initially converted into Open Neural Network Exchange (ONNX) format and then further converted into TensorRT format. The latter is well-optimized for low-computing-resource devices as well as power consumption; thus, efficiency and responsiveness of the model would be enhanced. With the help of NVIDIA's Jetpack software suite, which offers an out-of-the-box deep learning environment, the deployment process is also straightforward. Figure 4 displays the entire model teaching and sharing job flow.



.***Figure. 4.*** *Comprehensive diagram of model training, transformation and deployment for efficient integration*

3.6. Evaluation Criteria

In order to thoroughly analyze the effectiveness of the proposed object detection algorithm, some evaluation benchmarks were set. These benchmarks measure the model's detection, effectiveness, and efficiency in systems embedded within devices on different levels, both qualitatively and quantitatively. The most important benchmarks are: Precision (P), Recall (R), F1 Score, Average Precision (AP_{0.5:0.95}), Frames Per Second (FPS) alongside some model complexity metrics. Furthermore, for practical applicability, particularly in the monitoring of fowls, auxiliary poultry related metrics such as Sample Selection Rate, Chicken Selection Rate, and Chicken Recognition Rate were added to better represent the poultry-centered use of the model.

Prediction accuracy is described using a Precision metric, which defines Precision (P) as the share of positive predictions that were correct over the entire predicted positive cases which encompasses True Positives alongside False Positives (TP + FP). Increased precision means that the model is making significantly fewer mistakes with false alarms. Such precision is calculated as follows:

$$P = TP/(FP+TP) \tag{1}$$

Recall (R), on the other hand, focuses on the fraction of positives that are actually tagged as positive by the model. It consists of True Positives and False Negatives (FN) and higher numbers mean less misses. It is computed as:

$$R = TP/(FN+TP) \qquad (2)$$

For a more balanced evaluation containing both Recall and Precision, F1 Score is computed. It is their harmonic mean, which comes in handy when there is a disproportionate ratio of classes.The F1 Score is calculated as:

$$F1 = 2 \cdot P+(R \cdot P)/(P+R) \qquad (3)$$

4. Results

In this section, we present the main performance assessment of the chicken counter based on YOLOv8. The appraisal covers the entire training process, starting from convergence behaviour and extending through detection performance across numerous epochs. We adopt commonly accepted object detection metrics: mean Average Precision at IoU = 0.5 (mAP@0.5), Precision, and Recall. Together, these metrics deliver an integrated perspective on the model's ability to identify individual chickens within both cluttered and restricted settings. To confirm stability and generalization, we visualize and scrutinize the results over all 50 training epochs.

4.1. Model Performance Analysis

As illustrated in Figure 5, the YOLOv8 model's performance was monitored throughout 50 training epochs using three primary metrics: mAP@50, Precision, and Recall.

Starting at about 0.973 and steadily rising to almost 0.978 by epoch 50, mAP@50 stayed high throughout the training process. This shows that even in situations when there is partial occlusion and crowding, the model can locate and categorize chickens with high accuracy across frames.

Precision values also increased, from 0.954 to consistently about 0.967 by the final epoch. This means that the model got progressively less wrong by producing incorrect positives as training progressed, improving its belief in correctly labeling chickens.

Recall, which denotes the model's ability to capture all real chickens in the scene, started lower at approximately 0.918 but plateaued at a consistent rate of approximately 0.941. Although more erratic than mAP and Precision, the recall plot exhibits greater sensitivity in capturing chickens in varying environmental and spatial settings.

Overall, these trends point to the fact that the model is well-trained and possesses good performance in terms of detection accuracy and robustness, and therefore is viable to real-time poultry monitoring in real farm conditions.

Figure. 5. *Model performance across 23 epochs measured using mAP and mAP@50:95.*

4.2. Box Loss Trend

At figure 6, the graph illustrates the trend of the train/box_loss metric over 50 training epochs. At the beginning of training, the box loss fluctuates around a relatively high value, peaking at around 1.32 in the first 5 epochs. This suggests that the model initially has difficulty predicting the bounding boxes accurately.

As training progresses, the box loss decreases, indicating that the model is learning and improving its predictions. At time 40, the box loss drops significantly, indicating a clear improvement in performance. By the end of training (time 50), the box loss stabilizes at a much lower level, around 1.03.

Overall, the chart shows a successful training process, with consistent improvement and no signs of overfitting or divergence in the bounding box regression performance.

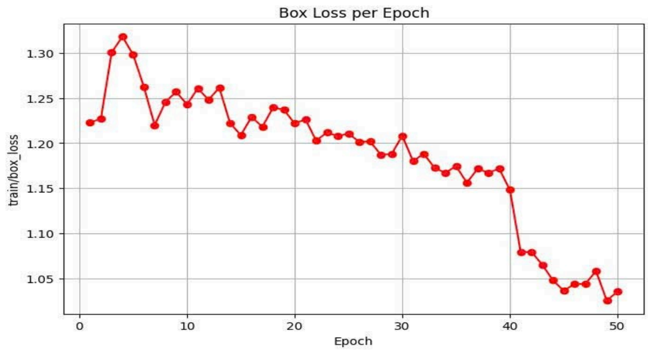


Figure. 6. *Box loss trend showing consistent reduction over the training epochs.*

4.3. Class Loss Trend

Figure 7 illustrates the trend of train/cls_loss (classification loss) over 50 training epochs. At the beginning of training, the class loss fluctuates and peaks around 0.61, indicating that the model initially struggles to accurately classify the detected objects.

As training continues, the attenuation gradually decreases, with a more pronounced decrease after epoch 30. A sharp decrease is observed after epoch 40, indicating a significant improvement in the model's classification performance. By epoch 50, the class attenuation stabilizes at around 0.47.

Overall, Figure 7 reflects a successful training process with consistent learning and improved classification accuracy over time. The lack of divergence or overfitting further confirms that the model is generalizing effectively during training.

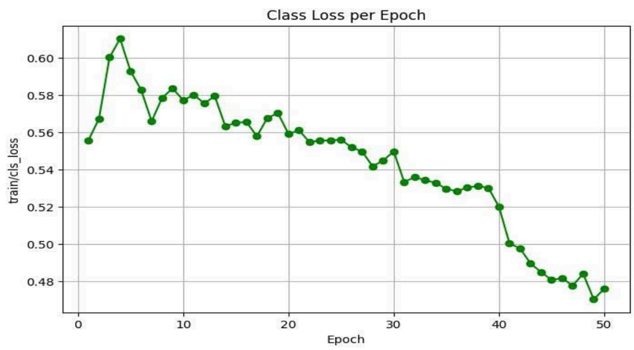


Figure. 7. *Class loss significantly reduces in early epochs and stabilizes at a low value.*

4.4. Objectness Loss Trend

As can be seen from Figure 8, objectness loss—which is the measure of how well the model identifies the presence of objects as opposed to background—starts very high, at about 0.92. It throws up a few jitters in the beginning (say about epochs 1-20), minor peaks and troughs, but since the trend is downward, it finally manages to go below 0.89 by epoch 50.

Though there is noisiness, a gradual decrease in objectness loss would purportedly mean better and more accurate understanding of where the objects are located within the input data for this model. This also means that confidence as well as accuracy regarding region information about the presence of an object has improved; hence, learning has taken a positive direction in training.

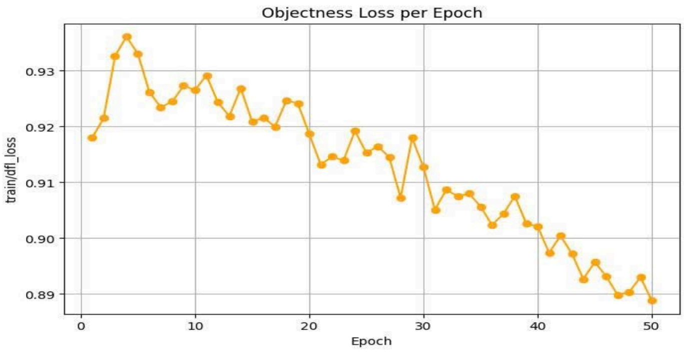


Figure. 8. *Objectness loss decreases significantly, indicating improved object presence detection.*

5. Conclusion

In the field of automatic chicken counting in caged environments, this study presents an intelligent solution based on the YOLOv8 object detection model. Thanks to the advanced neural network architecture and real-time inference capabilities, YOLOv8 can accurately identify chicken heads even in complex conditions such as overlapping chickens, high stocking density, or partially obscured by the cage structure. To increase stability over time, the detection results are also processed through a multi-frame thresholding algorithm, which helps to filter out noise and maintain stable counting results over consecutive frames.

Quantitative evaluation shows that the system achieves high efficiency with mAP@50 (mean Average Precision at IoU 50%) of 97.78%, accuracy of 96.26%, and recall of 94.1%. These results demonstrate the robustness of the model in accurately detecting and tracking individual chickens, with low miss and false alarm rates in a variety of real-world scenarios.The combination of deep learning technology with edge deployment has resulted in significant improvements in operational efficiency, traceability, and animal welfare in industrial poultry farming. Future research will focus on optimizing system performance under changing lighting and environmental conditions, as well as integrating predictive models for early anomaly detection and intelligent decision support. Overall, the application of YOLOv8 in chicken counting demonstrates the great potential of artificial intelligence in agricultural automation, providing a reliable and scalable solution for modern livestock management.

6. References

1. Banhazi, T.M.; Lehr, H.; Black, J.L.; Crabtree; Schofield ; Tscharke ; Berckmans, D. Precision livestock farming: An international review of scientific and commercial aspects. *Int. J. Agric. Biol. Eng.* **2012**, *5*, 1–9. [CrossRef] 2. Jiang, B.; Tang, W.; Cui, L.; Deng, X. Precision Livestock Farming Research: A Global Scientometric Review. *Animals* **2023**, *13*, 2096. [CrossRef]
2. Olejnik, K.; Popiela ; Opali´nski, S. Emerging precision management methods in poultry sector. *Agriculture* **2022**, *12*, 718. [CrossRef]
3. Wu, Z.; Zhang ; Fang, C. Research on machine vision online monitoring system for egg production and quality in cage environment. *Poult. Sci.* **2025**, *104*, 104552. [CrossRef]
4. Fang ; Zhuang ; Zheng, H.; Yang ; Zhang, T. The Posture Detection Method of Caged Chickens Based on Computer Vision. *Animals* **2024**, *14*, 3059. [CrossRef]
5. Vaswani .; Shazeer ; Parmar, N.; Uszkoreit ; Jones, L.; Gomez ; Polo Sukhoi. Attention is all you need. *Adv. Neural Inf. Process. Syst.* **2017**, *30*, 5998–6008.
6. Jiang, K.; Xie ; Yan ; Wen, X.; Li, D.; Jiang ; Wang, J. An attention mechanism-improved YOLOv7 object detection algorithm for hemp duck count estimation. *Agriculture* **2022**, *12*, 1659. [CrossRef]
7. Cao ; Xiao, Z.; Liao ; Yao, Y.; Wu, K.; Mu, J.; Pu, H. Automated chicken counting in surveillance camera environments based on the point supervision algorithm: LC-DenseFCN. *Agriculture* **2021**, *11*, 493. [CrossRef]
8. Li, X.; Zhao ; Wu ; Huang ; Wen, J.; Sun ; Gao, Y. Y-BGD: Broiler counting based on multi-object tracking. *Comput. Electron. Agric.* **2022**, *202*, 107347. [CrossRef]
9. De Luna ; Yang, Q.; Azusa.; Ito, S.; Idrus ; Iman, R.H.; Sinclair, M. Cage egg producers' perspectives on the adoption of cage-free systems in China, Japan, Indonesia, Malaysia, Philippines, and Thailand. *Front. Vet. Sci.* **2022**, *9*, 1038362. [CrossRef]
10. Berckmans, D. General introduction to precision livestock farming. *Anim. Front.* **2017**, *7*, 6–11. [CrossRef]
11. Papakonstantinou ; Voulgarakis ; Terzidou, G.; Fotos ; Giamouri, E.; Papatsiros, V.G. Precision Livestock Farming Technology: Applications and Challenges of Animal Welfare and Climate Change. *Agriculture* **2024**, *14*, 620. [CrossRef]
12. Hao ; Fang ; Duan, E.; Yang ; Wang ; Wang, H. A dead broiler inspection system for large-scale breeding farms based on deep learning. *Agriculture* **2022**, *12*, 1176. [CrossRef]