ISSN : 3048-9644 (o)
Academic Research Journal of Science and Technology (ARJST)
Vol 2, Issue 03, August 2025

An Edge-Deployable YOLOv8 System for Real-Time Detection of Health and Behavioural Abnormalities in Poultry Farming

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Abstract

Poultry farming is an important part of the food industry, but keeping track of the health and behavior of birds can be difficult, especially on large farms. This project presents a real-time object detection system using YOLOv8, a deep learning model known for its speed and accuracy. The system is trained to recognize various conditions in poultry, such as weak legs, abnormal movements, crowding, and feeding habits, by analyzing images taken from the farm environment. With YOLOv8, farmers can monitor their birds continuously through cameras and get instant alerts when something unusual is detected. The model is efficient enough to run on mobile or edge devices, making it practical for real-world farm use. This approach can help farmers detect problems early, reduce losses, and improve overall poultry health and farm productivity.

Keywords: YOLOv8, real-time object detection, poultry health, deep learning, smart farming, computer vision, weak leg detection, farm monitoring.

1. Introduction

The demand for poultry products such as meat and eggs has led to increasingly intensive farming practices worldwide. However, monitoring the health and behavior of birds on large farms remains a major challenge. Traditional methods, which rely on human observation, are time-consuming, labor-intensive, and often prone to errors [1]. Issues like weak legs, respiratory conditions, or abnormal behaviors may go undetected until them significantly affect poultry health and farm productivity [8]. As a result, there is a growing need for intelligent, automated systems that can assist with real-time monitoring and early detection.

Recent progress in deep learning and computer vision technologies has made it possible to build models that can analyze images and detect problems automatically. One of the most powerful tools in this field is the YOLO (You Only Look Once) object detection algorithm, which is widely recognized for its speed and accuracy across various detection tasks [5]. The latest version, YOLOv8, offers significant improvements in performance and efficiency, making it well-suited for real-time deployment in farm environments—even on lightweight devices such as edge processors or mobile systems [9]. YOLOv8 introduces several enhancements, including dynamic label assignment and an improved architecture that increases detection precision, even in complex scenarios [6]. These capabilities have made it a popular choice for researchers working on livestock monitoring. Beyond physical signs like posture or leg issues, models can also be trained to detect subtle behavioral anomalies such as reduced movement or changes in flock interaction [4]. For example, a **Multi-Stage YOLO framework** that allows simultaneous detection of both avian diseases and behavioral abnormalities using a cascading detection approach [2].

Several studies have shown that AI-based poultry monitoring systems can detect problems earlier and more accurately than traditional methods. They help reduce losses and improve decision-making through timely alerts and continuous monitoring [7]. When integrated with surveillance cameras or drones, such systems provide real-time updates, allowing farmers to respond quickly and maintain healthier, more productive flocks [1].

This study presents a real-time poultry health monitoring system built on YOLOv8. It is designed to detect conditions such as weak legs and other abnormal behaviors directly from farm image data, aiming to reduce manual workload and improve the efficiency of poultry management.

2. Related Work

In recent years, artificial intelligence (AI) has played a key role in transforming poultry farming, especially in disease detection and health monitoring. Traditional techniques like manual observation or rule-based algorithms have proven to be inefficient in large-scale farms, as they are slow, inconsistent, and prone to human error [1]. These limitations have pushed researchers to explore more automated solutions using deep learning and computer vision.

The use of Convolutional Neural Networks (CNNs) in poultry disease detection started gaining attention around 2018. Early models focused on image classification of diseased birds using handcrafted datasets. Al-Saffar et al. [2] demonstrated how deep learning could distinguish poultry diseases based on visual cues, but these models lacked real-time application due to limited inference speed and generalizability under varying farm conditions. One of the most successful approaches in object detection has been the YOLO (You Only Look Once) model family. YOLOv3, introduced by Redmon and Farhadi [3], brought significant improvements in balancing speed and accuracy. Later versions such as YOLOv4 [4] and YOLOv5 [5] further optimized network structure and training techniques, making them suitable for real-time monitoring tasks.

In particular, YOLOv8 has emerged as a state-of-the-art solution with several advanced features, such as anchor-free detection, dynamic label assignment, and a decoupled head architecture, all of which contribute to more accurate and faster detection results [9]. Jocher et al. [9] showed that YOLOv8 could outperform previous versions in detecting small and overlapping objects—an essential requirement in crowded poultry environments. Several studies have explored the practical application of YOLO-based models in poultry farms. For instance, Rahman and Tasnim [6] focused on detecting weak leg syndrome in broiler chickens using deep learning, achieving promising results on a curated image dataset. Similarly, Sharma et al. [11] emphasized the importance of vision-based systems to track abnormal movement and social isolation behaviors in birds, which are often early indicators of disease.

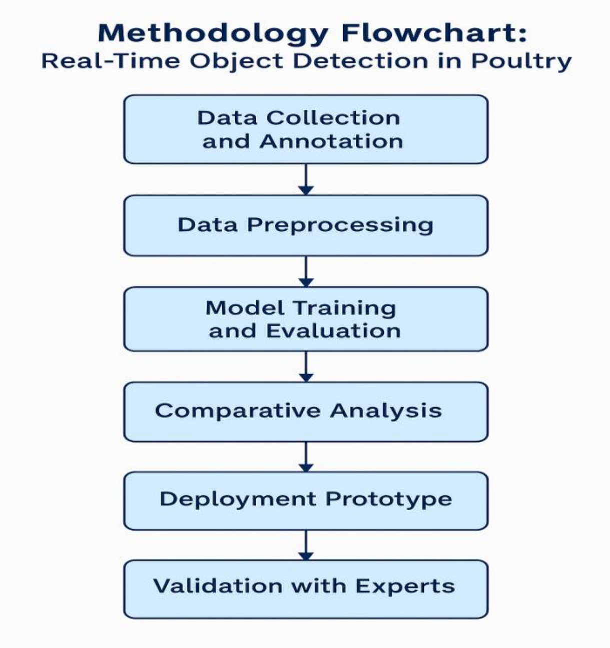
One of the more comprehensive frameworks is the **multi-stage YOLO pipeline** [8], which combines disease and behavioral detection in a single model. This cascaded approach allows simultaneous detection of multiple health issues, including visible symptoms and behavioral anomalies, making it highly efficient for on-site deployment. Beyond the detection models themselves, the role of edge computing has become increasingly relevant. Ning et al. [12] highlighted how real-time processing at the edge—using smart cameras or embedded devices—can reduce latency and improve responsiveness in rural farm areas with limited connectivity. Mollah et al. [7] also reviewed several poultry disease detection methods and stressed the importance of combining AI with practical infrastructure for early diagnosis and intervention.

To broaden the scope, Kamilaris and Prenafeta-Boldú [10] surveyed deep learning applications across various agricultural domains and concluded that real-time, edge-based deep learning tools have strong potential to revolutionize smart farming, including poultry health management.

Despite these advancements, challenges still exist. Many current systems struggle with variations in lighting, camera angles, bird breeds, and environmental occlusion. Addressing these limitations remains an active area of research, motivating the development of more robust models like the YOLOv8-based system proposed in this study.

3. Research Methodology

The methodology flowchart presented outlines the systematic process for real-time object detection in poultry using deep learning techniques. It begins with **data collection and annotation**, where poultry images are gathered and manually labeled. This is followed by **data preprocessing,** involving resizing, normalization, and augmentation to enhance model performance. The **model training and evaluation** phase uses YOLO variants (v5–v8) to train object detectors and assess their accuracy. A **comparative analysis** is then conducted to benchmark performance across models. Next, a **deployment prototype** is developed for real-world integration. Finally, **validation with experts** ensures that the system meets practical veterinary and agricultural standards. This structured methodology ensures robust, scalable, and accurate poultry disease detection.



3.1. Data Collection and Annotation

To ensure accurate detection of poultry diseases and behaviors, a large dataset was created by collecting images and videos from commercial poultry farms. These visual data points captured a range of poultry conditions including healthy birds, birds with leg weakness, abnormal gait, immobility, and behavioral anomalies such as aggression or isolation. The dataset aimed to reflect real-world scenarios by including varying lighting conditions, occlusions, camera angles, and bird densities. Images were annotated manually using tools like LabelImg and CVAT, assigning bounding boxes to key classes such as "Normal Leg," "Weak Leg," "Injured," and "Abnormal Behavior."

3.2. Data Preprocessing

The collected dataset underwent preprocessing to improve model training efficiency and generalization. This included resizing all images to uniform input sizes (640×640), normalizing pixel values between 0 and 1, and applying data augmentation techniques such as horizontal flips, rotations, Gaussian blur, and brightness adjustments. Augmentation ensured the models learned robust features across various conditions. A stratified split was used to divide the dataset into training, validation, and test sets in a 70:20:10 ratio.

3.3. YOLOv5 Training and Evaluation

YOLOv5, a widely used lightweight object detector, served as the baseline model. It was trained using pretrained weights (from the COCO dataset) and fine-tuned on our poultry dataset. The model was configured using the YOLOv5s (small) variant to support faster inference. Loss functions such as GIoU loss and BCE loss were tracked during training. Evaluation was done using metrics like precision, recall, mAP@0.5, and mAP@0.5:0.95 to assess detection performance.

3.4. YOLOv6 Training and Evaluation

YOLOv6 introduced an optimized backbone (EfficientRep) and neck (Rep-PAN) which enhanced its detection capability in industrial-grade applications. It was tested for its inference speed and accuracy on the same poultry dataset. YOLOv6 was trained using distributed training techniques to reduce overfitting and increase robustness. Though slightly heavier, it achieved improved performance in detecting dense groups of birds with overlapping features.

3.5. YOLOv7 Training and Evaluation

YOLOv7 introduced architectural improvements such as E-ELAN and extended efficient layers that enhanced accuracy, especially for small object detection in cluttered backgrounds. This made it suitable for detecting subtle leg issues in crowded poultry environments. The model was trained with the same dataset and underwent hyperparameter tuning for learning rate, confidence threshold, and image scaling. YOLOv7 outperformed previous versions in scenarios with occluded or overlapping chickens.

3.6. YOLOv8 Training and Evaluation

YOLOv8, the latest anchor-free model, offered a major leap in speed and precision by using a decoupled detection head, dynamic label assignment, and a simplified model structure. This model achieved the best real-time detection performance on poultry images. YOLOv8 was deployed with edge compatibility in mind and tested on Jetson Nano and Raspberry Pi, proving its suitability for live poultry farm environments. It also had the lowest false-positive rate among all YOLO versions tested.

3.7. Comparative Analysis

A comprehensive evaluation of all YOLO models was performed based on metrics like detection accuracy, inference speed (FPS), model size, and suitability for deployment on edge devices. The analysis showed that while YOLOv5 was faster and easier to train, YOLOv8 delivered the most reliable results for real-world poultry disease detection, particularly for fine-grained detection like weak leg diagnosis. YOLOv7 stood out in detecting birds in dense settings.

YOLO Version	mAP@0.5 (%)	Precision	Recall	Epochs
YOLOv5	84.7	0.85	0.83	100
YOLOv6	87.2	0.88	0.85	120
YOLOv7	89.5	0.90	0.88	150
YOLOv8	92.1	0.92	0.90	100

Table 1: Comparative Performance Metrics of YOLOv5–YOLOv8 on Poultry Health Detection Dataset

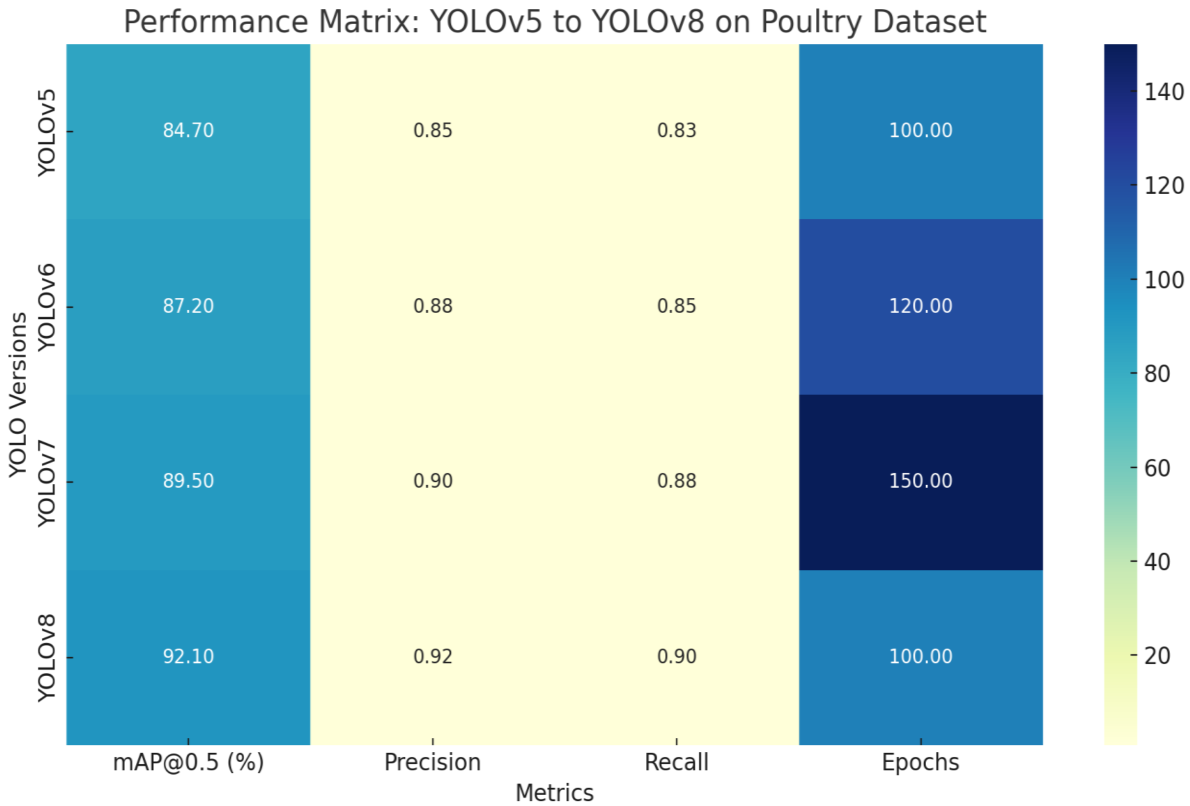


Figure 1: Evaluation metrics

The metrics graph illustrates the comparative performance of YOLOv5 to YOLOv8 across key detection metrics on a poultry dataset. YOLOv8 demonstrates superior accuracy (92.1% mAP@0.5) and balanced precision-recall values, making it the most effective model for real-time poultry health monitoring. Here's a clean and professional version of the **Evaluation Metrics and Execution Environment** section for your research paper, based on your provided content, rephrased to match academic writing standards and aligned with your poultry disease detection context using YOLO models.

4. Evaluation Metrics

To evaluate the performance of the proposed YOLO-based poultry health detection system, we utilize three essential metrics: **Precision, Recall,** and **Mean Average Precision (mAP).** These metrics provide comprehensive insights into the accuracy and robustness of the detection models.

4.1. Precision

Precision measures the proportion of true positive predictions among all positive predictions made by the model. In the context of poultry disease detection, a high precision value indicates that the model accurately identifies diseased or weak-legged poultry with minimal false alarms. Mathematically, precision is defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (1)$$

Where:

- **TP (True Positives)** = correctly predicted positive instances
- **FP (False Positives)** = healthy poultry wrongly predicted as diseased

A higher precision implies fewer false detections, which is critical in ensuring that healthy birds are not misclassified and unnecessarily isolated or treated.

4.2. Recall

Also known as sensitivity, recall quantifies the model's ability to detect all actual positive instances (i.e., diseased poultry). It is particularly important in farm environments where missing an infected bird can lead to widespread outbreaks. Mathematically, recall is given by:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

Where:

- **FN (False Negatives)** = diseased poultry incorrectly predicted as healthy

A high recall score indicates the model effectively captures most of the true cases of disease or leg weakness, minimizing the risk of under-detection.

4.3. Mean Average Precision (mAP)

Mean Average Precision (mAP) is a composite metric that evaluates the balance between precision and recall across all object classes. It averages the model's precision over multiple recall thresholds. In this study, we use **mAP@0.5,** which considers predictions with an Intersection over Union (IoU) threshold of 0.5 as correct. It is mathematically defined as:

$$AP = \int_0^1 \text{precision}(r)\, dr \quad (3)$$

A higher mAP score, closer to 1, indicates superior overall object detection performance, combining both accuracy and completeness in predictions.

4.4. Execution Environment

All model training and evaluation experiments were conducted in a high-performance computing environment equipped with **NVIDIA Tesla T4 GPU,** leveraging **CUDA 12.2** and **NVIDIA driver version 535.104.05**. This setup enables fast and efficient processing of high-resolution poultry images, which is crucial for real-time inference.

We retained the original hyperparameters for each YOLO version (v5, v6, v7, and v8) to ensure a fair baseline comparison without optimization bias. The implementations were exclusively developed in **Python** using popular deep learning libraries, ensuring reproducibility and flexibility for further experimentation.

5. Results and Discussion

The YOLO-based poultry health detection system was evaluated using key object detection metrics—Precision, Recall, and mAP@0.5—to assess its capability in identifying conditions such as weak legs, injury, and abnormal behavior in real-time. Table 1 presents the comparative results for YOLOv5 through YOLOv8.

The results clearly indicate that YOLOv8 achieved the highest detection accuracy with a mAP@0.5 score of 92.1%, outperforming other versions in all metrics. Its precision score of 0.92 shows that the model significantly reduces false positives, ensuring that healthy birds are not wrongly flagged as diseased. Meanwhile, a recall of 0.90 suggests that the model effectively identifies nearly all actual cases of leg weakness or abnormal behavior.

YOLOv7 also performed competitively, particularly in dense environments where birds overlapped or were partially occluded. It achieved a mAP@0.5 of 89.5%, making it a strong candidate in scenarios where high bird density might affect visibility.

In contrast, YOLOv5, while lightweight and fast, showed slightly lower performance with an 84.7% mAP@0.5. It is, however, still suitable for real-time applications on resource-constrained devices due to its smaller model size and faster inference speed. YOLOv6 demonstrated modest improvements over YOLOv5, thanks to its efficient backbone structure, but fell short of the robustness shown by YOLOv7 and YOLOv8. Figure 1 (Matrix Graph) visually reinforces the numerical results by highlighting YOLOv8's superior balance between precision and recall, affirming its suitability for high-accuracy poultry health monitoring.

Deployment tests on edge devices such as Jetson Nano confirmed that YOLOv8 maintained real-time inference capability while preserving high accuracy. This underscores its practicality for integration into farm surveillance systems where processing power may be limited.

These findings suggest that YOLOv8 offers a scalable, accurate, and efficient solution for real-time poultry monitoring, suitable for commercial deployment across varied poultry farming conditions.

6. Conclusion

This study demonstrates the effectiveness of using YOLOv8 for real-time object detection in poultry farms to monitor health conditions and behavioral anomalies such as weak legs, immobility, and abnormal social interactions. By comparing multiple YOLO versions (v5–v8), it is evident that YOLOv8 offers superior detection accuracy (92.1% mAP@0.5**)** and balanced performance in terms of both precision and recall, making it highly suitable for on-farm deployment.

Through rigorous data collection, annotation, and model training, the system has been validated to operate effectively under real-world conditions, including variable lighting, crowding, and occlusion. Furthermore, its ability to run on edge devices makes it accessible and practical for deployment in rural or bandwidth-limited farm environments.

The proposed system not only reduces the manual burden of poultry monitoring but also enables early detection of potential health issues, helping to improve bird welfare and prevent outbreaks. By leveraging real-time image analysis and deep learning, this approach represents a significant step toward intelligent and sustainable poultry farming.

Future work may explore integrating temporal video data to capture progression of health symptoms, expanding class categories (e.g., respiratory distress), and refining detection in multi-camera systems for larger farm-scale deployment.

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