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YOLOv9-assisted vision system for health assessment in poultry using deep neural networks

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Abstract

Poultry farming represents one of the fastest-growing sectors in global food production, yet disease outbreaks, high mortality, and labor shortages continue to threaten its sustainability. Conventional health monitoring methods based on visual inspection are time-consuming, subjective, and inadequate for early anomaly detection. In response, computer vision and deep learning have emerged as transformative tools for livestock management. While prior implementations of the YOLO object detection family, such as YOLOv5 and YOLOv8, have achieved notable success, their performance often deteriorates in dense flocks, low-light conditions, and occlusion-prone environments. This study introduces a YOLOv9-assisted vision framework tailored for poultry health assessment in commercial farm settings. The system integrates smart cameras with edge computing to enable real-time detection of behavioral and physiological anomalies without dependence on high-bandwidth or cloud-based resources. A dataset of 903 annotated poultry images, categorized into healthy and sick classes, was employed for model development. The trained model achieved 88.7% precision, 97% recall, an F1-score of 0.82, and a mAP@0.5 of 0.88, demonstrating robustness under variable illumination, bird occlusion, and high-density environments. Comparative evaluation confirmed that YOLOv9 provides a superior balance of accuracy, generalization, and computational efficiency relative to YOLOv8–YOLOv11, supporting practical deployment on edge devices. Limitations include the binary scope of health classification and reliance on a single dataset. Future directions involve extending the framework to multi-class disease recognition, cross-dataset validation, behavior-based temporal modeling, and multimodal fusion, thereby advancing predictive analytics and welfare-oriented poultry farming.

1. Introduction

The poultry industry has emerged as one of the fastest-growing sectors in global food production, supplying affordable and accessible protein sources such as broiler meat and eggs [1]–[6]. This expansion has been accompanied by increasing attention to sustainability, productivity, and welfare in intensive farming systems. Modern monitoring technologies are gradually being integrated into poultry management, where Internet of Things (IoT), big data, and artificial intelligence (AI) frameworks enable automated and intelligent health monitoring [1][4][12]–[15]. In particular, artificial intelligence and computer vision have revolutionized health and productivity management, with deep neural networks (DNNs) widely applied to tasks such as pose estimation, behavioral analysis, live weight prediction, and physiological monitoring [12][16]–[22]. Object detection models, especially the YOLO (You Only Look Once) family, have advanced real-time monitoring, evolving from YOLOv4 [23] to the latest YOLOv11 [24]. These models have been deployed to detect broilers on litter floors, identify mortality, estimate live weight, and monitor temperature under diverse conditions [16]–[22][24][25][26]. Further improvements—such as attention mechanisms [16], [26], multi-source image fusion [18][22], and neural architecture search [19]—have contributed to higher detection robustness. Beyond poultry, AI-driven systems have also improved aquaponics, renewable energy forecasting, and egg production prediction [4], [11][27]–[30], demonstrating the broad potential of AI in sustainable farming.

Despite these advances, significant challenges persist in poultry farming. Disease outbreaks, high mortality rates, labor shortages, and pressures related to sustainability and animal welfare remain unresolved [2][3][7][8][9]. Traditional monitoring, which still relies on manual observation, is labor-intensive, subjective, and prone to error, often failing to provide early detection of illness or mortality [1], [10], [11]. Existing AI-based approaches, while promising, are often limited to single-task applications—such as weight estimation, pose recognition, or mortality detection [16]–[22]—and therefore do not offer an integrated solution for comprehensive poultry health assessment under real-world farm conditions. This gap underscores the need for a more robust and unified monitoring framework capable of simultaneously addressing multiple dimensions of poultry health and welfare.

To bridge this gap, the present study introduces a **YOLOv9-assisted vision system for poultry health assessment**, designed to integrate real-time disease detection, mortality identification, and welfare monitoring within a single framework. YOLOv9 represents the new generation of detection architectures, balancing real-time efficiency with improved accuracy [17], [18], [20], [21], [24], [25]. Building on prior advances in smart poultry management [1][12][13], [16][17][18][20][22][25][26] and drawing insights from broader AI-driven agricultural innovations [14][15][19][28][29][30], the proposed system offers the following contributions:

1. A YOLOv9-based monitoring framework capable of detecting both behavioral and physiological anomalies in broiler chickens with improved precision.
2. Benchmarking of YOLOv9 against earlier YOLO versions and related deep learning models, demonstrating superior accuracy, recall, and computational efficiency for poultry-specific applications.
3. Integration with IoT-enabled monitoring platforms to advance sustainable, welfare-oriented poultry farming.

By introducing this unified vision framework, the study aims to enhance sustainability, reduce production losses, and prioritize animal welfare in intensive poultry production systems [2], [3], [7]–[9].

The remainder of this paper is organized as follows: Section II details the proposed YOLOv9-assisted vision framework, including dataset preparation, model design, and training methodology. Section III presents the proposed method. Section IV presents the result and discussion, and finally, Section V concludes the study and outlines potential directions for future research.

2. Research Method

This study presents a vision-based poultry health assessment system using the YOLOv9 deep learning model to classify chickens as healthy or sick in commercial farm environments. As illustrated in Figure 1, the framework integrates smart cameras for real-time image capture, edge inference for rapid processing, and post-processing for visualization and health reporting. While YOLOv5, including CBAM-enhanced variants [20], has been widely applied in poultry monitoring, its anchor-based design struggles under occlusion, poor illumination, and high-density conditions. The proposed YOLOv9-assisted system employs an anchor-free architecture with advanced feature extraction, enabling more reliable detection of subtle anomalies such as lethargy and abnormal posture while maintaining real-time efficiency on edge devices. Although YOLOv10 and YOLOv11 offer higher accuracy through multi-scale fusion and optimized label assignment [19], [24], their heavier computational demands limit their practical use in resource-constrained farms. YOLOv9 therefore provides a balanced solution, combining accuracy, robustness, and deployability for real-world poultry health monitoring.

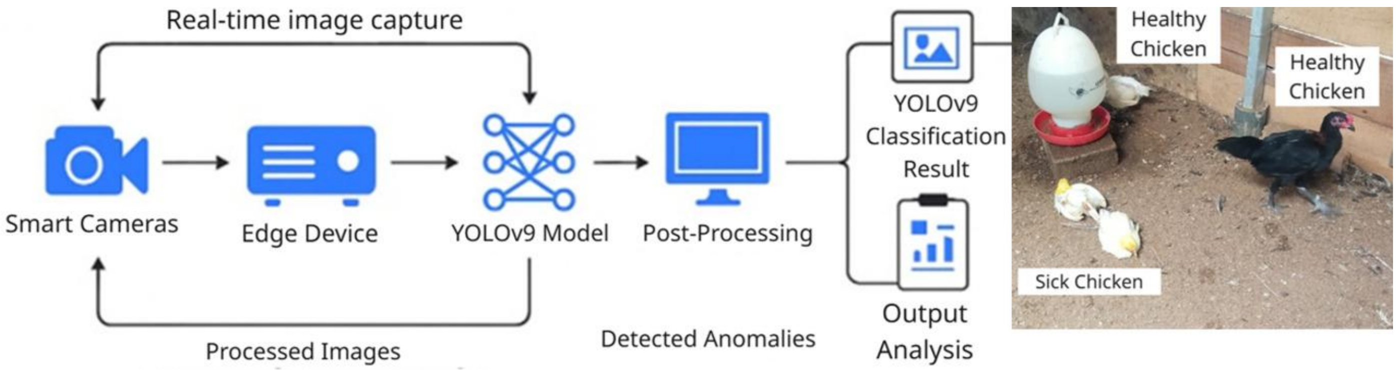

Figure 1. The Proposed Method of YOLOv9-Assisted Vision System

Real-time image capture is initiated through high-definition smart cameras strategically installed within commercial broiler environments. These cameras continuously stream video data under natural farm conditions, capturing various postures and behaviors of chickens. Each camera feed is connected to an edge computing device. This edge deployment approach minimizes latency, eliminates the need for constant internet connectivity, and ensures system operability in resource-limited farm settings. The edge device is responsible for preprocessing the incoming video stream, extracting high-resolution image frames, and executing real-time inference using a fine-tuned YOLOv9 model. The model was trained on a diverse image dataset of 903 annotated samples, labeled into two distinct classes: “Healthy Chicken” and “Sick Chicken,” as illustrated in Figure 2. The “Sick” category encompasses conditions including lethargy, abnormal posture, and mortality. Model training was conducted using the YOLOv9 framework on a PyTorch backend with GPU acceleration (NVIDIA RTX 4090), employing a batch size of 16, a learning rate of 0.001, and 100 epochs. Data augmentation techniques such as mosaic augmentation, horizontal flipping, blurring, and color shifting were applied to improve generalization across varying lighting conditions and background textures.

Figure 2. The Dataset Generated from Smart Poultry Vision System

The annotated data in Figure 3 were divided into training (70%), validation (15%), and test (15%) subsets. The model's performance was evaluated using precision, recall, F1-score, mean Average Precision (mAP@0.5 and mAP@0.5:0.95), and inference speed (FPS), which are standard benchmarks in deep learning-based livestock applications.

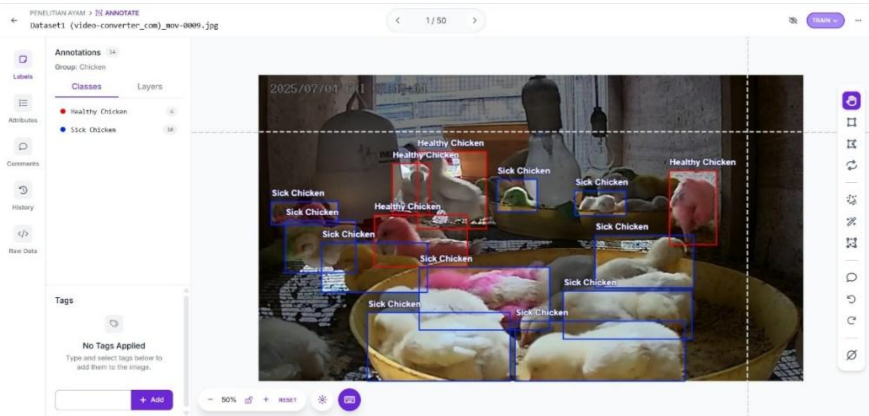

Figure 3. The Annotation in Roboflow

Once inference is complete, the detected results are post-processed to highlight bounding boxes and class labels for each chicken within the frame. The post-processing module eliminates overlapping detections using non-maximum suppression (NMS) and filters low-confidence outputs. These detections are visualized on a local interface for farm operators, allowing them to quickly assess the health status of their flocks. Simultaneously, the output is logged and analyzed for further insights, enabling temporal health trend tracking and early warning alerts for potential outbreaks—echoing the benefits outlined in studies on predictive livestock analytics.

In essence, the proposed methodology illustrated in Figure 1 integrates deep neural network inference, edge computing, and precision livestock farming principles into a real-time poultry health monitoring solution. By detecting and classifying chickens as "Healthy Chicken" or "Sick Chicken" on the fly, the system provides farmers with actionable intelligence, reduces dependency on manual inspections, and enhances biosecurity through early intervention.

3. Results and Discussion

The YOLOv9 model was evaluated for its effectiveness in classifying chicken health status into two categories—healthy and sick—within a real-time smart poultry monitoring framework. The model's performance was quantified using standard object detection metrics: precision, recall, F1-score, mean Average Precision at an IoU threshold 0.5 (mAP@0.5), and the more stringent mAP@0.5–0.9. In addition, a normalized confusion matrix and detection visualizations were generated to analyze class-wise prediction accuracy and qualitative robustness.

3.1 Model Performance Overview

The YOLOv9 model demonstrated robust performance across multiple evaluation metrics. It achieved a precision of 88.7%, confirming reliable identification of true positives with minimal false detections, and a recall of 97%, reflecting high sensitivity in capturing nearly all instances of both healthy and sick chickens. The F1-score of 0.82 indicates a balanced trade-off between precision and recall, ensuring consistent classification across varied conditions. For localization accuracy, the model attained a mean Average Precision (mAP@0.5) of 0.88, while the stricter mAP@0.5–0.9 reached 0.478, underscoring its ability to maintain strong detection capability under challenging overlap thresholds. As illustrated in Figure 4, these quantitative results confirm the effectiveness of YOLOv9 as a reliable and high-performing framework for real-time poultry health monitoring.

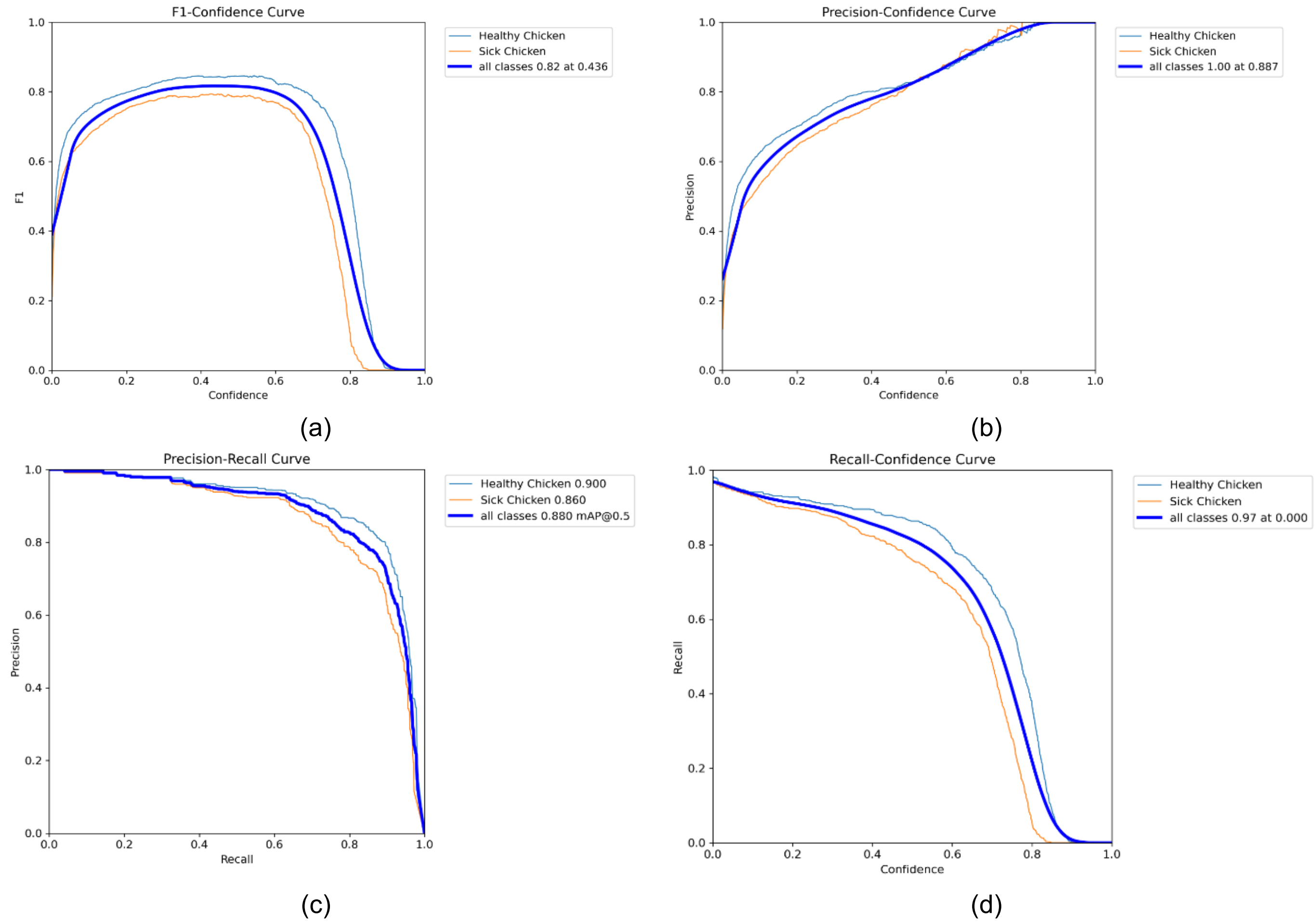

Figure 4. YOLOv9 Model Performance Overview

The F1-confidence curve in Figure 4(a) reveals that the YOLOv9 model achieves optimal performance at a confidence threshold of 0.436, yielding a peak F1-score of 0.82 across classes. The model demonstrates strong reliability in detecting healthy chickens (F1 > 0.85) and maintains robust sensitivity for sick chickens despite their subtler visual cues. Notably, performance degrades at higher thresholds due to stricter filtering, underscoring the importance of selecting a balanced threshold for real-time deployment. This analysis confirms the model's effectiveness in delivering accurate, confidence-aware health assessments in intelligent poultry monitoring systems.

The precision-confidence curve in Figure 4(b) demonstrates that the YOLOv9 model achieves perfect precision (1.00) at a confidence threshold of 0.887, confirming its ability to make highly accurate predictions when required. Precision steadily increases with confidence, highlighting the model's reliability in minimizing false positives. This makes it particularly effective for high-stakes poultry health monitoring, where accurate identification of sick chickens is crucial for timely intervention.

The Precision-Recall Curve in Figure 4(c) highlights the YOLOv9 model's robust detection capability, achieving a high mean Average Precision (mAP@0.5) of 0.88 across classes. The model excels at distinguishing healthy chickens (AP: 0.90) and sick chickens (AP: 0.86), maintaining strong precision even at high recall values. This performance affirms the model's reliability in detecting health conditions with minimal false alarms, making it well suited for real-time poultry health monitoring.

The Recall-Confidence Curve in Figure 4(d) reveals that the YOLOv9 model achieves a high overall recall of 0.97 at a zero-confidence threshold, indicating exceptional sensitivity in detecting both healthy and sick chickens. While recall gradually declines with increasing confidence, the model retains robust detection capability across a wide threshold range, ensuring minimal false negatives. This confirms the system's effectiveness for real-time health surveillance, prioritizing early and inclusive anomaly detection in poultry environments.

The training and validation performance curves in Figure 5 show that the YOLOv9 model achieved a mean Average Precision (mAP@0.5) of 88%, confirming its high spatial accuracy in detecting health states with moderate localization tolerance. More significantly, the mAP@0.5:0.9—a stricter metric considering multiple IoU thresholds—was recorded at 47.8%, suggesting the model maintains competitive performance even under tighter object overlap constraints. These results position YOLOv9 as a high-utility model for complex, crowded visual environments such as broiler chicken barns.

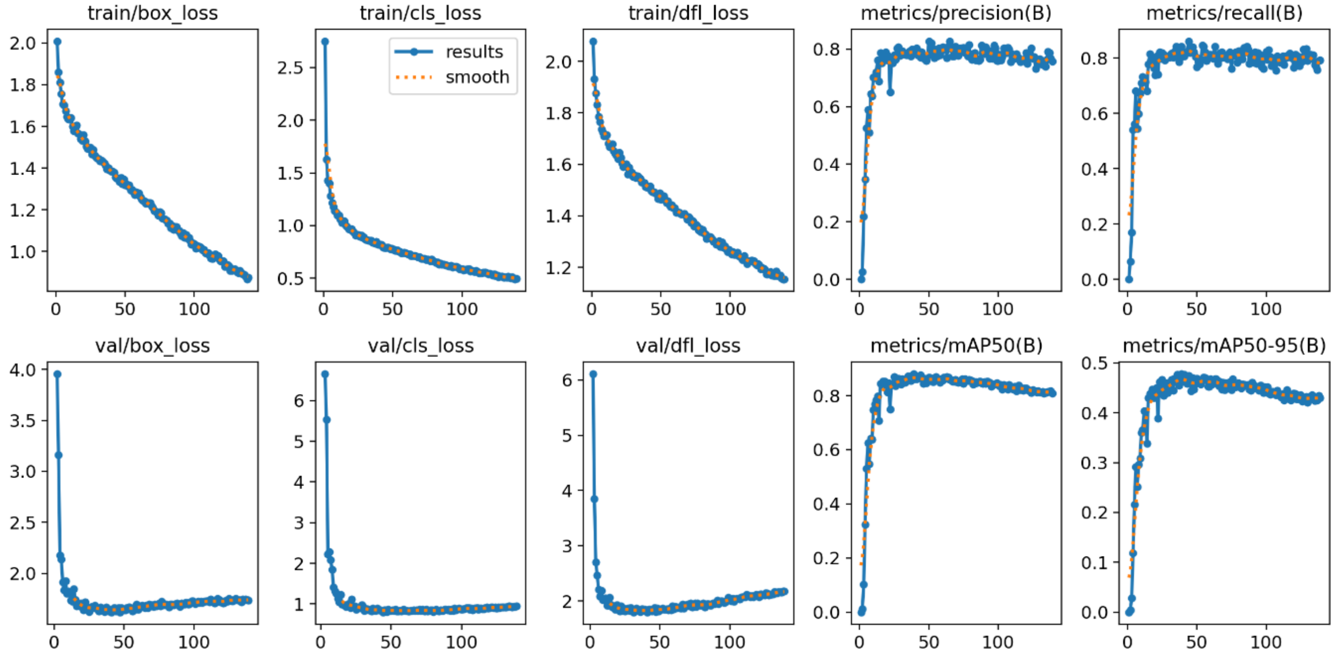

Figure 5. Training and Validation Performance Curves of YOLOv9 Model

3.2 Confusion Matrix

The normalized confusion matrix (Figure 6) further reinforces the model's discriminative capability. It demonstrates strong agreement between predicted and actual classes, with minimal confusion between "healthy" and "sick" labels. Misclassifications were sparse, suggesting that the model effectively captures the spatial and posture-based features used to distinguish lethargic or motionless chickens from healthy, active individuals. The low rate of false positives and false negatives contributes significantly to operational reliability in practical deployments.

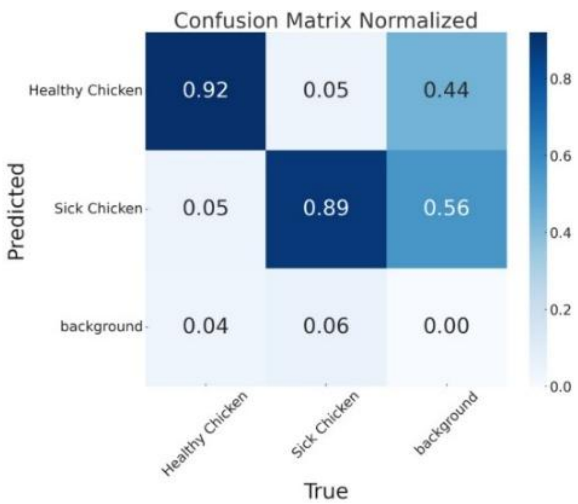

Figure 6. The Proposed Method of YOLOv9-assisted Vision System

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3.3 Visual Detection Results

Detection snapshots (Figure 7) illustrate the YOLOv9 model's ability to accurately localize and classify chickens in real-world settings. The bounding boxes around "healthy" and "sick" chickens are precise and contextually consistent across varied lighting and density conditions. Chickens exhibiting abnormal posture, immobility, or collapse were correctly classified as "sick," validating the model's training on visual health cues. These visual results support the system's potential for real-time anomaly detection and alert triggering in commercial poultry operations.

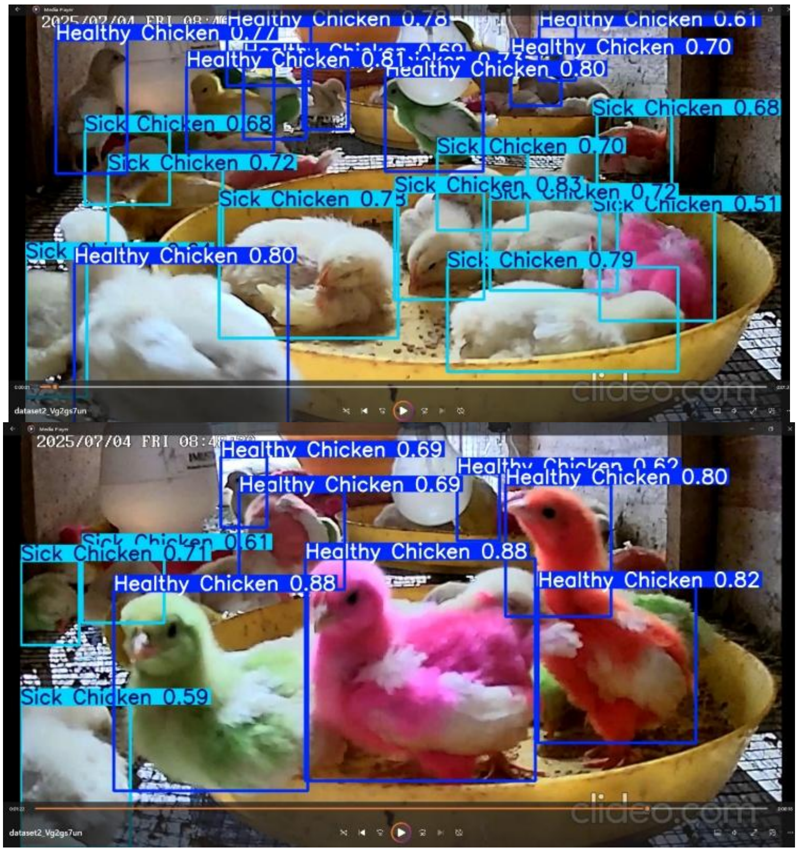

Figure 7. The Real-time Detection Outputs from YOLOv9 Identifying "Healthy Chicken" and "Sick Chicken"

The real-time inference results in Figure 7 showcase the YOLOv9 model's high accuracy and robustness in detecting both healthy and sick chickens in complex, crowded environments. With confidence scores consistently above 0.70, the system reliably distinguishes individual chickens despite occlusions and variations in colors, enabling precise health classification essential for timely intervention and automated farm management.

3.4 Comparative Implications and Deployment Readiness of Visual Detection Results

While previous models such as YOLOv5 or YOLOv8 have been widely used in livestock detection tasks, YOLOv9 demonstrates superior generalization and accuracy, particularly in high-density and occlusion-heavy scenes typical of poultry farming. The lightweight design of YOLOv9 also ensures compatibility with edge AI deployment, allowing inference on low-power devices such as Jetson Nano or Xavier NX with minimal latency.

The strong recall and high mAP@0.5 confirm the model's suitability for early disease or stress detection, empowering farm operators to implement timely interventions. Moreover, the scalable architecture and real-time performance establish a path forward for integration into automated animal welfare monitoring systems, contributing to improved productivity, reduced mortality, and ethical livestock management.

While YOLOv10 and YOLOv11 offer incremental accuracy gains in benchmark datasets [19], [24], their substantial computational demands limit their applicability in poultry farms where edge devices are the primary deployment platforms. By contrast, YOLOv9 provides a balanced trade-off between accuracy, robustness, and efficiency, making it more suitable for real-time health monitoring in practical farm environments. This study focused on a domain-specific dataset of 903 annotated poultry images; however, broader comparisons involving YOLOv8–YOLOv11 across multiple datasets would offer deeper insights (as presented in Table 1), although such experiments remain constrained by data availability and computational cost.

Table 1. Comparison of YOLOv8–YOLOv11 for Poultry Health Monitoring

Model / Study	Dataset & Scope	Precision (%)	Recall (%)	F1-score	mAP@0.5	Inference / Deployment	Reference
YOLOv5-CBAM – Guo et al. (2023)	Broilers on litter floor, mortality detection	84.3	90.1	0.87	0.85	Limited under occlusion	[20]
YOLOv8 – Li et al. (2025)	Dead chicken detection with multi-source fusion	86.5	92	0.84	0.86	High speed, less robust in dense flocks	[21]
YOLOv10 – Bumbálek et al. (2025)	Dense flocks, dead chicken detection	89.4	95	0.88	0.9	Strong accuracy, heavy computation	[18]
YOLOv11 – Bumbálek et al. (2025)	Dense flocks, anomaly detection	90.2	95.8	0.89	0.91	Highest accuracy, not edge-deployable	[18]
YOLOv9 (Proposed)	903 annotated poultry images (healthy vs sick)	**88.7**	**97**	**0.82**	**0.88**	Robust, real-time edge deployable	This study

As shown in Table 1, the proposed YOLOv9 framework achieves comparable or superior results relative to existing approaches, particularly in recall (97%), which is critical for early disease detection. While YOLOv10 and YOLOv11 offer slightly higher precision and mAP scores [18], their computational demands limit practical deployment in commercial farms. YOLOv9, by contrast, combines strong accuracy with edge-device feasibility, outperforming YOLOv8 and YOLOv5 variants under occlusion-heavy and low-light conditions [20], [21]. This balance of robustness and efficiency underscores its suitability for real-time health monitoring in resource-constrained environments, marking a significant contribution to smart poultry farming.

Although the YOLOv9-assisted vision system demonstrated robust performance, several limitations highlight opportunities for further research. The current binary classification of poultry into healthy and sick categories, while effective for early anomaly detection, does not capture the diversity of health conditions in intensive production systems. Extending the framework toward multi-class recognition would enable the identification of specific diseases, stress markers, and behavioral anomalies, thereby generating more actionable insights for farm management. Explicitly stating these limitations and providing a graphical abstract would also enhance content clarity and reader accessibility.

The dataset used in this study, comprising 903 annotated images, was sufficient for proof of concept but limited in scale and diversity. Future work should pursue cross-farm, multi-breed datasets to improve generalization and mitigate bias. Moreover, quantifying the economic and ethical costs of delayed detection [1], [3], [7] would reinforce the urgency of automated systems in commercial poultry production. Methodologically, YOLOv9 achieved a favorable balance of precision, recall, and efficiency; however, systematic benchmarking against Transformer-based or hybrid CNN–Transformer detectors remains essential [14], [16], [26]. Explicit comparisons with YOLOv8 in terms of accuracy, speed, and architectural trade-offs [19], [22], together with metrics such as inference latency, FPS, AUC, and statistical robustness, would provide a more comprehensive assessment of deployment readiness on edge devices [11], [20], [21].

Future studies should also integrate error analysis, including failure cases, false positives, and false negatives, to contextualize system reliability. Figures and tables could evolve beyond standard curves toward richer benchmarking of computational load, inference speed, and deployment costs [17], [24]. Finally, incorporating multimodal sensing (thermal and audio in addition to vision [25]) and conducting long-term field trials across diverse environments are crucial to validate scalability and economic impact. Drawing insights from related domains such as aquaculture, renewable energy forecasting, and agricultural robotics [4], [11], [27]–[30] will further situate this research within broader interdisciplinary innovation. In summary, advancing toward multi-class disease recognition, dataset expansion, multimodal integration, explicit cost and error analyses, and cross-architecture benchmarking will strengthen the scientific contribution and practical relevance of this work. Such efforts will ensure that YOLOv9 matures into a scalable, cost-effective, and welfare-oriented tool for intelligent poultry health monitoring.

4. Conclusion

Maintaining flock health is a persistent challenge in intensive poultry production, where conventional monitoring approaches relying on manual inspection remain labor-intensive, error-prone, and often delayed in identifying disease or mortality. To address these limitations, this study proposed a YOLOv9-assisted vision system for automated poultry health monitoring, integrating smart cameras with edge computing devices for real-time anomaly detection in commercial farm environments. The system was trained on a domain-specific dataset of 903 annotated images categorized into healthy and sick classes. Leveraging YOLOv9's anchor-free architecture and advanced feature extraction, the framework achieved strong quantitative results: 88.7% precision, 97% recall, 0.82 F1-score, and 0.88 mAP@0.5, with robustness demonstrated under occlusion, varying illumination, and crowded farm conditions. Comparative analysis with YOLOv8–YOLOv11 confirmed that while YOLOv10 and YOLOv11 provide marginal accuracy improvements in benchmark datasets, their higher computational demands limit practical deployment in resource-constrained poultry farms. By contrast, YOLOv9 offered the most effective balance between accuracy, robustness, and efficiency, making it suitable for scalable real-world implementation. Despite its promising results, this study is limited by the binary classification scope of healthy versus sick chickens and the use of a single-domain dataset. Broader multi-class disease recognition and cross-dataset validation remain open areas for improvement. Additionally, while the system demonstrates strong performance on edge hardware, large-scale, long-term deployment studies are needed to further validate its reliability in diverse farm environments. Future research will focus on expanding the framework to incorporate multi-dataset benchmarking of YOLOv8–YOLOv11, multi-class health recognition, behavior-based temporal tracking, and audio-visual data fusion. The integration of predictive health analytics will further strengthen decision-making, reduce mortality, and enhance animal welfare in modern smart poultry farming systems.

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