Intelligent Poultry Health Recognition Using an Improved YOLOv8

Yajie Liu[1], Zhi Liu[1,*], Qingxun Meng[1], Yuxi Huang[2], Md Gapar Md Johar[3]

[1]School of Information Engineering, Henan Vocational University of Science and Technology, Zhoukou, China

[2]Faculty of Health Management, North Henan Medical College, Xinxiang, China

[3]Software Engineering and Digital Innovation Centre, Management and Science University, Shah Alam, Malaysia

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Abstract

Intelligent poultry health recognition is crucial in precision livestock farming. Nevertheless, existing methods suffer from limited precision and practicality due to complex backgrounds and small detection targets. This study aims to develop an improved YOLOv8-based poultry health recognition model to enhance detection precision and robustness in real poultry farming environments. In this study, YOLOv8 is improved at both the data and network levels. At the data level, multi-strategy data augmentation is applied. At the network level, the neck network of YOLOv8 is reconstructed by integrating the large-small (LS) block to enhance multi-scale feature fusion capabilities. Experimental results indicate that both improvement levels increase precision by 4.4% and 4.5%, respectively. Moreover, the model achieves overall improvements of 5.4% in precision and 9.9% in mAP@0.5:0.95 compared with the original YOLOv8 algorithm. In this study, the developed model effectively improves poultry health recognition performance and demonstrates practical value for practical poultry farming applications.

Keywords: poultry health, YOLOv8, data augmentation, object detection, abnormal posture

1. Introduction

The poultry farming sector is a vital part of global agriculture and a cornerstone of food security and rural economic development [1]. Owing to the constant growth in the world population, the demand for poultry-derived products is expected to increase by 50% by 2050 to meet the future demands [2]. The sustainability of poultry operations depends on the provision of optimal poultry welfare and health; hence, early detection of poultry diseases is essential for effective disease prophylaxis and management.

Poultry disease control and prevention remain pertinent challenges for the poultry farming industry. Poultry epizootics can cause significant economic loss to farmers. Pathogenic microorganisms and viruses may spread to the entire flock if infected poultry are not identified and quarantined in time [3]. Conventional poultry management, however, is labor-intensive and requires manual surveillance, which is time-consuming, resource-intensive, and highly dependent on farmers' experiential acumen, making it prone to inaccuracies. Moreover, manual inspection may cause physiological stress to chickens [4].

To address these limitations, the industry is moving toward digitalization, automation, and intelligence [5]. Technologies related to the Internet of Things (IoT), artificial intelligence (AI), and big data analytics have played leading roles in the agri-socio-economic context, enabling productivity optimization within the Industry 4.0 paradigm [6]. In recent years, YOLO-based studies have been widely applied in real-time detection tasks, highlighting the importance of balancing accuracy and real-time performance [7].

* Corresponding author. E-mail address: 402097323@qq.com

Precision livestock farming (PLF) has emerged alongside advances in technology and has attracted industry managers and academic researchers. PLF can support optimal growth and health of the poultry. It contains two types: invasive and non-invasive methods. Invasive monitoring of poultry health is performed using various sensors attached to the poultry, whereas non-invasive methods are preferred nowadays as they do not disturb or stress the poultry. Overall, PLF aims to explore technological solutions in practical operations to enhance sustainability. For example, sensor-based systems have been developed to identify poultry behaviors; however, wearable sensors attached to the neck may still cause discomfort, especially at the beginning of the wearing period [8].

Computer vision technology is a non-invasive and well-established method for monitoring and detecting sick poultry in livestock farming systems. Researchers have conducted vision-based experiments to detect turkey injuries by identifying key points on the turkey, where timely detection and intervention can improve turkey welfare and prevent potential massive losses [9]. In recent years, convolutional neural network (CNN)-based computer vision technology has gained significant attention and is being widely explored and utilized, especially in the field of poultry health management [10-12]. A poultry behavior classification experiment was carried out using various deep learning algorithms, including YOLOv5 and Faster R-CNN. Among these methods, the YOLOv5 algorithm achieved the best performance, enabling real-time poultry health monitoring. These studies indicate that artificial intelligence can provide technological support for enhancing the management of modern poultry farming and improving poultry welfare [13].

By leveraging the benefits of advanced technologies, deep learning has shown significant potential for early disease detection in poultry and for improving management efficiency [14]. Moreover, the identification of poultry health status by intelligent systems is a critical component of precision livestock farming. However, existing precision livestock farming studies still lack computer vision-based recognition of poultry abnormal postures, an insufficient image dataset, and low recognition precision, which limits their practical applications. Hence, further studies are needed to address dataset sample imbalance and improve detection precision, thereby enhancing model robustness and practical deployment feasibility. This study proposes a new approoch for posture-based health recognition in real poultry-rearing environments. The main contributions of this study are described below:

(1) A poultry health identification dataset is constructed, and multiple data augmentation strategies are designed to enhance sample diversity and model generalization.

(2) An improved YOLOv8n-based poultry health recognition model is proposed by integrating the C2f_LSBlock computational block to improve the detection performance.

(3) Data-level and network-level optimizations are combined to enhance the robustness of poultry health recognition under complex rearing environments.

The rest of this manuscript is organized as follows: Section 2 presents the theoretical foundation by conducting a thorough literature review. Section 3 describes the research methodology, including the experimental design, dataset preparation, and the improved YOLOv8 architecture. Experimental results are presented in Section 4. Section 5 contains a discussion of the findings. Finally, Section 6 summarizes the study and discusses directions for future research.

2. Related Works

In PLF, deep learning-based image recognition applications have emerged for poultry health monitoring and early disease detection. These technologies enable comprehensive, non-contact, and real-time monitoring of poultry health across multiple dimensions, including body temperature, posture, behavior, feces, and vocalizations. Such approaches facilitate the intelligent identification of diseased poultry.

Abnormal body temperature is commonly associated with poultry diseases, such as avian influenza, Newcastle disease, and fowl cholera. Therefore, body temperature is a significant indicator of sick poultry detection. A non-contact YOLOv8n-integrated edge computing device was implemented for detecting diseased chickens using poultry head temperature assessment, achieving 91.6% precision [15]. In addition, a thermal-imaging-based YOLOv11n model was trained using 1222 images to detect feather damage regions in laying hens, achieving 81%, 73%, and 84% for precision, recall, and mAP@0.5, respectively [16].

Poultry vocalization is associated with health status and serves as an important health assessment indicator. The researchers developed a model to detect and classify vocalizations of laying hens using a recurrent neural network (RNN), which achieved a 92.75% F1 score for poultry voice detection across different activities [17]. Another study proposed a convolutional neural network (CNN) based poultry distress identification model, named light-VGG11, which reached a detection precision of up to 94.58% using poultry audio recordings [18]. Furthermore, a k-nearest neighbor (kNN)-based optimal model was established for the recognition of broiler sound signals. The constructed model could accurately identify 4 broiler activities: crow, cough, purr, and flapping wings by analyzing 60 sound features, with up to 99.12% recognition accuracy achieved [19].

An IoT edge-computing-based poultry sound analysis system with a machine-learning-integrated microcontroller was designed to classify six different voice categories, achieving 92% accuracy and providing a low-cost solution for real-world scenarios [20]. F. Sattar constructed a deep learning-based poultry vocalization detection model using 4000 audio clips to detect respiratory diseases, attaining an accuracy of 83.42% [21]. In addition, a non-invasive acoustic technology-based CNN model was trained using 3,000 vocalization samples to distinguish laying hens, roosters, and other sounds in a commercial caged poultry house, achieving a precision of 98% [22].

Chicken droppings from healthy and diseased chickens differ in shape and color. Therefore, fecal characteristics are closely linked to their health condition, and veterinarians usually identify fecal appearance during disease diagnosis. A faster region-based convolutional neural network (Faster R-CNN)-based deep learning recognition model was illustrated to detect abnormal chicken droppings. The experiments showed that the trained model could accurately classify and localize the target droppings, achieving up to 98.8% accuracy [23]. Sakib et al. proposed an IoT-based hardware for poultry fecal image acquisition, in which a deep learning model was integrated into the microcontroller to distinguish poultry fecal images into four categories intelligently [24]. Additionally, based on YOLOv3 to YOLOv9 different versions, intelligent poultry manure recognition models were developed using 5,688 images to classify five digestive disease categories, achieving up to 99.4% accuracy with YOLOv8m [25].

Apart from physiological indicators, poultry behavior monitoring plays a crucial role in optimizing poultry welfare and early detection of sick poultry. For example, a three-stage CNN-based pipeline model was created to detect chicken lameness using 16,500 images, achieving up to 97.5% test precision and addressing the significance of deep learning-based computer vision applications [26]. Besides, a surveillance system for detecting abnormal behavior based on poultry heatmap images was proposed using deep learning technology [27]. In addition, dead chicken detection models were developed using YOLOv8n, YOLOv9c, YOLOv10n, and YOLOv11n based on 3,413 synthetic images for complex cage-free farming environments. Among these models, YOLOv9c achieved the highest detection accuracy of 98.3%, whereas YOLOv11n achieved the fastest inference speed of 2.8 ms per frame [28]. Furthermore, a YOLOv9-based intelligent poultry health recognition system was developed using 903 images to classify chickens as healthy or sick through behaviors and postures, achieving 88.7%, 97%, 82%, and 88% for precision, recall, F1-score, and mAP@0.5, respectively [29].

Poultry health can be assessed through physiological characteristics, such as body temperature, droppings, vocalizations, and behaviors. With the rapid advancement of deep learning techniques, intelligent poultry health models, particularly one-stage YOLO detectors, have been developed to enable precision livestock farming. However, existing studies lack sufficient exploration of posture-based health identification. Furthermore, detection accuracy still faces challenges in complex poultry farming environments. Therefore, this study proposes an improved YOLOv8 algorithm to achieve intelligent health assessment through abnormal poultry postures. A summary of related studies is presented in Table 1.

Table 1 Summary of recent related works

No.	Author	Year	Modality	Method	Dataset	Main Results	Limitations
1	Wang et al.	2025	To monitor poultry health through head temperature.	YOLOv8n	2,896 images	Achieved 91.6%, 92.5%, 92.0%, and 96.0% for precision, recall, F1 score, and mAP@0.5, respectively.	Focused only on head temperature.
2	Dahal et al.	2026	To assess poultry damage regions through body temperature.	YOLOv11n	1,222 images	Achieved 81%, 73%, and 84% for precision, recall, and mAP@0.5, respectively.	Focused on regions of poultry damage, rather than direct disease monitoring.
3	Sattar.	2026	To monitor poultry health through vocalization.	Wavelet scattering transform (WST) and a long short-term memory (LSTM) network	4,000 audio clips	Achieved 83.42% accuracy.	Limited validation in real farm environments.
4	Lin et al.	2025	To classify roosters and laying hens through vocalization.	CNN	3,000 audio clips	Achieved an accuracy of 98%.	Focused on environmental adaptation and stress responses rather than direct disease diagnosis.
5	Qin et al.	2026	To monitor poultry health through feces.	YOLOv3-YOLOv9	5,688 images	Achieved up to 99.4% accuracy with YOLOv8m.	Limited validation across different poultry farm environments.
6	Garg and Goel	2026	To recognize lame chickens through movement patterns and leg posture.	YOLOv5n	16,500 images	Achieved a precision of 97.5%.	Focused only on lameness recognition, rather than overall poultry health assessment.
7	Bumbálek et al.	2025	To identify dead chickens through abnormal posture.	YOLOv8n, YOLOv9c, YOLOv10n, and YOLOv11n.	3,413 images	Achieved up to 98.3% detection accuracy for YOLOv9c.	Based on synthetic images rather than real farm data.
8	Risma et al.	2026	To classify chickens as healthy or sick through behavior characteristics.	YOLOv9	903 images	Achieved 88.7%, 97%, 82%, and 88% for precision, recall, F1-score, and mAP@0.5, respectively.	Limited dataset size and insufficient generalization validation.

3. Methodology

Unlike previous studies that focused on a single optimization approach, this study adopted two strategies to improve the robustness of the trained model for real poultry rearing environments. First, data augmentation techniques were used to address the limited sample size and class imbalance issues of the original dataset. Second, an improved YOLOv8 network was designed by leveraging C2f_LSBlock to enhance the feature extraction and multi-scale feature fusion capabilities for complex backgrounds and posture variations.

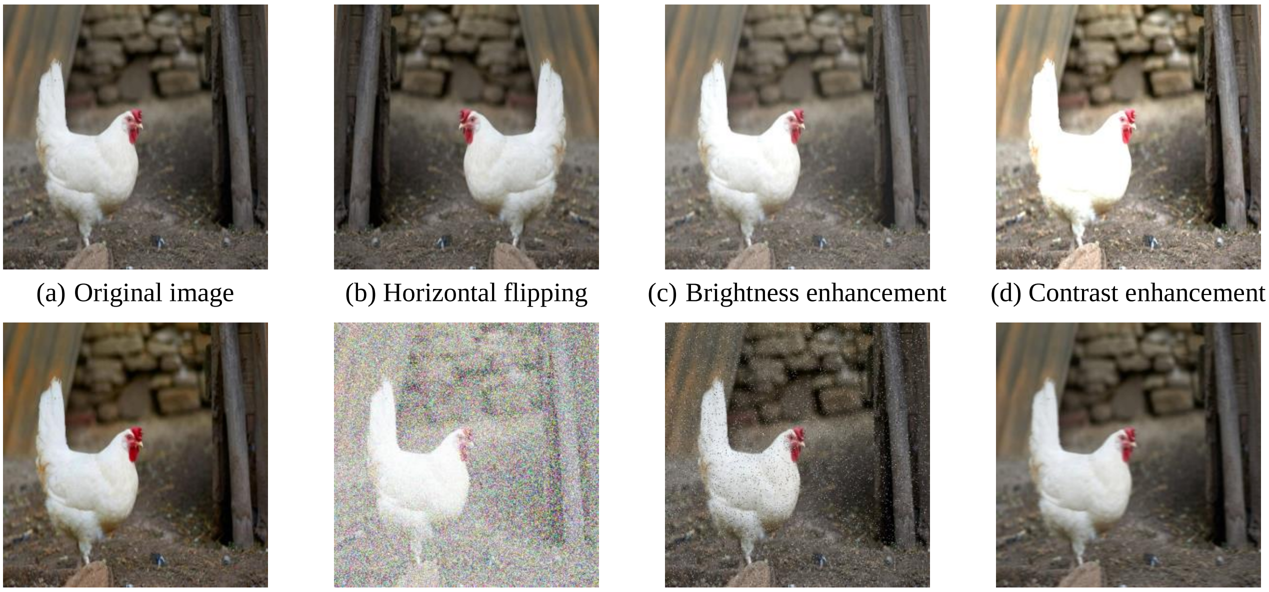
3.1 Dataset Preparation

This study constructed an image dataset for deep learning training. A total of 2,000 images of white-feather broiler chickens were collected from Agro Business Sdn. Bhd., Malaysia, using a Raspberry Pi Camera Module 3. The distribution of the original dataset images is depicted in Table 2.

Table 2 Original dataset specifications

Dataset Partition	Class	Number	Total	Percentage
Training	Healthy	1,000	1,600	80%
	Sick	600		
Validation	Healthy	100	200	10%
	Sick	100		
Testing	Healthy	100	200	10%
	Sick	100		

To improve the generalization ability and robustness of the model, this study performed data augmentation on the collected base samples. The poultry individual detection dataset was expanded through operations such as flipping, contrast adjustment, adding salt-and-pepper (S & P) noise, Gaussian noise, motion blurring, and luminance adjustment. These augmentation techniques helped alleviate the issues of limited sample size and class imbalance. Fig. 1 illustrates the effects of different augmentation methods.



(a) Original image (b) Horizontal flipping (c) Brightness enhancement (d) Contrast enhancement

(e) Saturation enhancement (f) Gaussian noise injection (g) S & P noice injection (h) Motion blur

Fig. 1 Effect of image augmentation

After data augmentation operations, a total of 5,000 images were created for the experiment, including 2,000 basic images and 3,000 data-augmented images. All images were set to the standard size of 640 × 640 pixels. The dataset partition is summarized in Table 3. Among the dataset, 4,000 images were used for training, while 500 were for validation, and another 500 images for testing.

Table 3 Augmented dataset specifications

Dataset Partition	Class	Number	Total	Percentage
Training	Healthy	2,000	4,000	80%
	Sick	2,000		
Validation	Healthy	250	500	10%
	Sick	250		
Testing	Healthy	250	500	10%
	Sick	250		

3.2 Image Annotation

The LabelImg data annotation tool was utilized to manually label all images with assistance from veterinarians. The dataset contains two classes: “healthy” and “sick”. Chickens with abnormal visual characteristics, such as drooping wings, loose feathers, inverted neck posture, and paralysis, were classified as the sick class, while the remaining samples were categorized as healthy. Additionally, the coordinates and classes of the labeled boxes were exported to a text file to create a poultry individual detection dataset in the YOLO format. Finally, all the annotated images were manually verified by the research team.

3.3 Improved YOLOv8 Algorithm

In this study, YOLOv8 was selected as the base deep learning model for training. The overall structure of the improved YOLOv8 comprises three main components: the backbone, improved neck, and head. The backbone and head structures of the original YOLOv8 model were retained, whereas the neck network was enhanced to improve feature extraction ability and reduce computational complexity.

The backbone network is responsible for extracting detailed image features, serving as the foundation for subsequent network operations. The backbone network of the original YOLOv8 was retained in the improved YOLOv8 model. The backbone network contains different computational blocks, such as convolution (Conv) layers, the original C2f block, and the spatial pyramid pooling-fast (SPPF) block, to extract features at multiple levels.

The neck network integrates multi-level features extracted from the backbone using a path aggregation network and a feature pyramid network. In the original YOLOv8 neck architecture, deep feature extraction modules composed of convolutional layers and non-linear activation functions are utilized to enhance feature representation capability. This increased depth also increases the model’s complexity and computational load.

To address these limitations, the LSNet algorithm was incorporated into the proposed YOLOv8 architecture. LSNet constructs a lightweight visual network architecture based on the “see large, focus small” strategy, in which LS convolutions combine large-kernel perception with small-kernel aggregation.

In this study, the complete LSNet network was not adopted; instead, only the LS Block was integrated into the original C2f module. Consequently, the LS Block can effectively capture extensive perceptual information while achieving precise feature aggregation for dynamic and complex visual representations, thereby enabling more adept processing of visual information. Fig. 2 shows the structure of the LS Block.

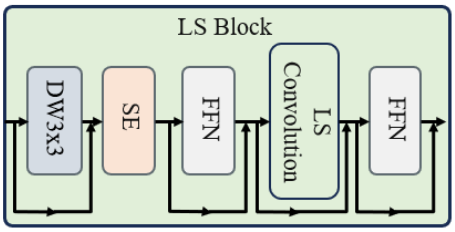
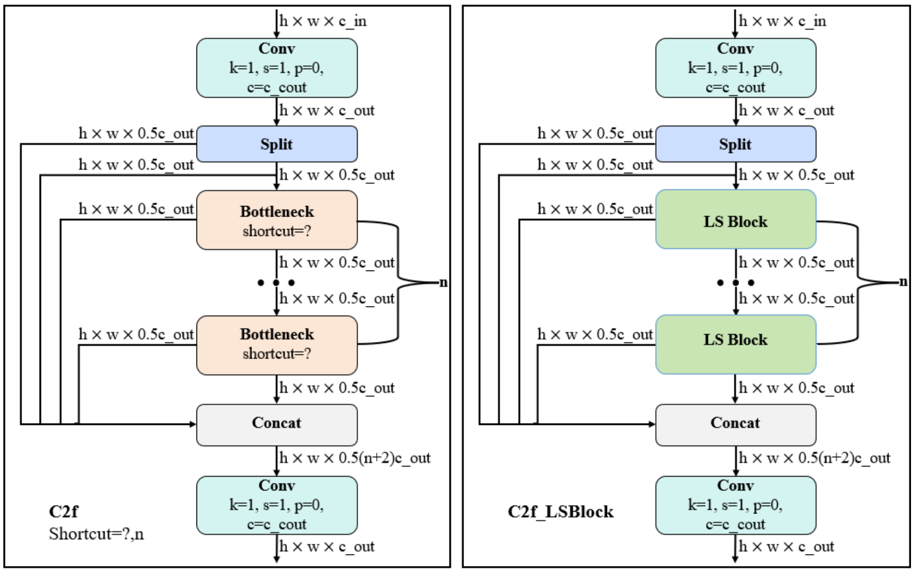


Fig. 2 Structure of the LS Block

Therefore, the original YOLOv8 C2f block was restructured by incorporating the LS Block, thereby reducing parameters while preserving feature extraction capabilities. The C2f block of original YOLOv8 has been reconfigured into a lightweight variant named C2f_LSBlock. In this paper, the C2f block of the original YOLOv8 neck network is replaced with C2f_LSBlock. Fig. 3 illustrates the differences between the original C2f block and the proposed C2f_LSBlock.



(a) C2f block (b) C2f_LSBlock

Fig. 3 Structure comparison between C2f block and C2f_LSBlock

As shown in Fig. 3, the bottleneck modules were substituted with the LS Block to construct C2f_LSBlock. The improved YOLOv8 architecture was then established by substituting the C2f module in the original YOLOv8 neck network with a restructured C2f_LSBlock computational module. Consequently, C2f_LSBlock enhances feature extraction capability as well as its contextual feature representation capability, thereby improving recognition performance and robustness. Fig. 4 depicts the overall framework of improved YOLOv8.

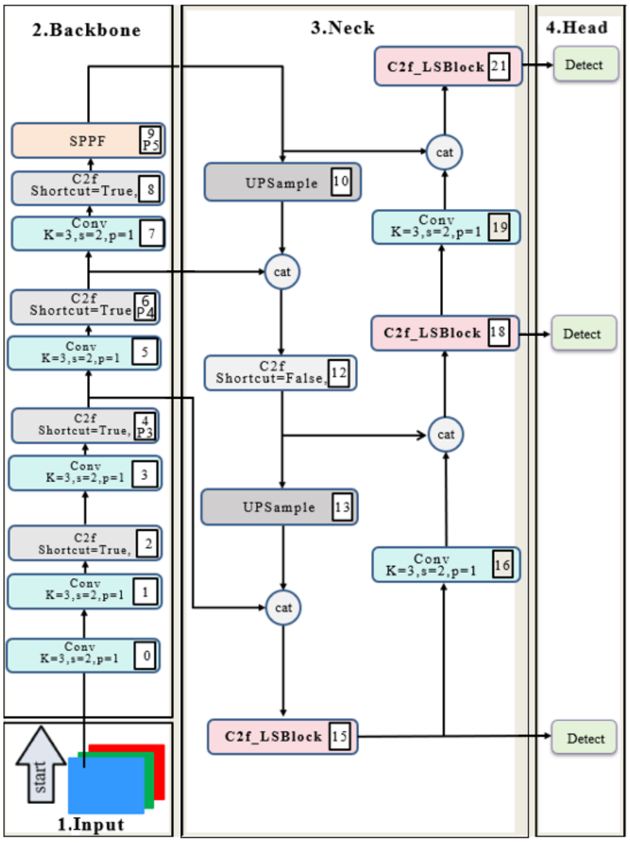


Fig. 4 Overall framework of improved YOLOv8

As shown in Fig. 4, the modified computational blocks are located in the neck network of the improved YOLOv8. To reduce model complexity and enhance poultry health detection performance, the reconstructed C2f_LSBlock modules were used to replace the original C2f blocks in the neck network, while the remaining modules were retained without modification.

The head network architecture of the improved YOLOv8 remains the same as the original YOLOv8, retaining an anchor-free decoupled head structure. Detection accuracy and convergence speed are enhanced when classification and regression tasks are carried out independently.

3.4 Evaluation Metrics

During training, the model undergoes performance evaluation on the validation dataset after each training epoch using object detection metrics, including precision, recall, and mean average precision (mAP). The calculation methods for each evaluation metric are defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F_1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{3}$$

In the above formulas, true positive (TP) refers to the number of correctly classified positive samples, true negative (TN) represents the number of samples correctly classified as negative samples, false positive (FP) refers to the number of incorrectly classified positive samples, and false negative (FN) refers to the number of incorrectly classified negative samples. Precision measures the proportion of correctly predicted positive samples among all predicted positives, while Recall measures the proportion of correctly identified positive samples among all actual positives. Average precision (AP) is defined as the area under the precision-recall (P-R) curve, and mAP is the arithmetic mean of AP values across all categories.

4. Experimental Setup and Results

This experiment was conducted on a CP12 vCPU Intel® Xeon® Silver 4214R CPU (2.40 GHz), with 16GB RAM, an RTX 4080 GPU, CUDA 11.3, Python 3.8.10, and PyTorch 1.11.0. This setup was employed to evaluate the algorithm's accuracy, efficiency, and the system's robustness. Before model training, the following parameters were configured: no pre-trained weight file was used; stochastic gradient descent (SGD) was selected as the optimizer; the learning rate was set to 0.01; the batch size was set to 16; and the number of epochs was set to 100. The hyperparameter configuration is summarized in Table 4.

Table 4 Hyperparameter configuration

Hyperparameters	Value
Training Size	640 × 640
Epoch	100
Batch Size	16
Learning Rate (lr0)	0.01
Optimizer	SGD

After 100 epochs of training, the learning behavior of the improved YOLOv8 network using the augmented dataset is shown in Fig. 5, which presents the box loss (box_loss), classification loss (cls_loss), and distribution focal loss (dfl_loss) for the training and validation datasets. These curves reflect the convergence performance and training stability of the improved YOLOv8 model.

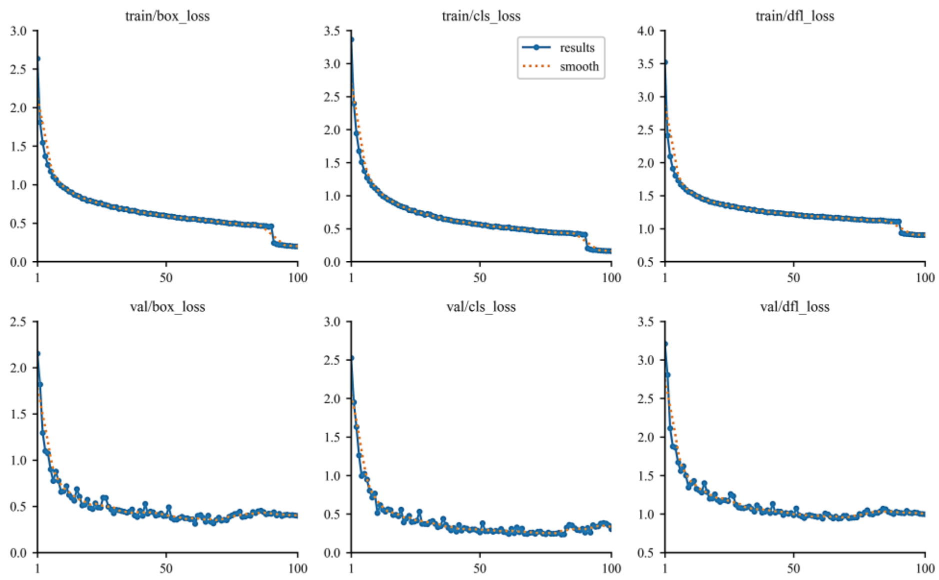


Fig. 5 Loss values of the improved YOLOv8 model using the augmented dataset.

From Fig. 5, the training and validation loss curves decreased rapidly in the early stages. The curves gradually converged as the number of training epochs increased, indicating that the model effectively learned the data and finally achieved stable convergence. In addition, the consistency between training and validation curves suggests that no significant overfitting was observed.

4.1 Ablation Experiment

To validate the effectiveness of the proposed improvements, ablation experiments were carried out on the original and augmented poultry image datasets. To systematically compare the impact of different improvement strategies on model performance, four algorithmic improvement schemes were designed and compared under identical experimental settings. The correspondence between each algorithmic scheme and its designation is detailed in Table 5.

Table 5 Model Specifications

No.	Algorithm	Improved Strategy
Model 1	Original YOLOv8n	None
Model 2	YOLOv8n + Backbone C2f_LSBlock	C2f_LSBlock applied only in the backbone.
Model 3	YOLOv8n + Neck C2f_LSBlock	C2f_LSBlock applied only in the neck.
Model 4	YOLOv8n + Backbone and Neck C2f_LSBlock	C2f_LSBlock applied to both the backbone and neck.

As listed in Table 5, Model 1 serves as the original YOLOv8 baseline model. Model 2 replaces the original C2f block with C2f_LSBlock only for the backbone network, while Model 3 applies the replacement only in the neck network. Model 4 replaces the original C2f block with the C2f_LSBlock for both the backbone and neck networks. Among these models, Model 3 represents the final improved YOLOv8 model in this study.

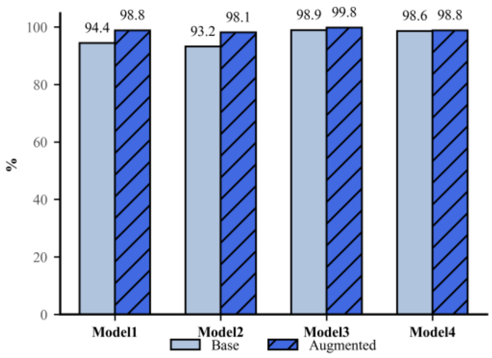
YOLOv8n was used as the baseline model, and the ablation experiments incorporated data augmentation and the C2f_LSBlock strategy at both the data and network levels. Furthermore, all ablation experiment models were developed from scratch on the same hardware and with the same hyperparameter configurations. Table 6 summarizes the training performance of Models 1–4 under two training schemes: without data augmentation (“–”) and with data augmentation (“√”).

Table 6 Results of ablation experiments

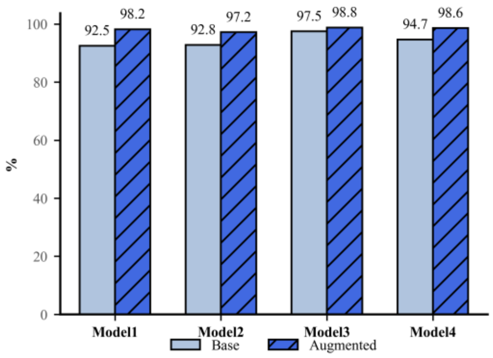
Model	Augmented data	Precision (%)	Recall (%)	mAP@0.5 (%)	mAP@0.5:0.95 (%)
Model 1	—	94.4	92.5	98.0	85.7
Model 1	√	98.8	98.2	99.5	95.0
Model 2	—	93.2	92.8	96.3	84.6
Model 2	√	98.1	97.2	99.1	93.8
Model 3	—	98.9	97.5	98.7	89.7
Model 3	√	99.8	98.8	99.5	95.6
Model 4	—	98.6	94.7	97.8	86.9
Model 4	√	98.8	98.6	99.5	92.2

The results presented in Table 6 were calculated as the average across three independent training runs. Metrics include precision, recall, mAP@0.5, and mAP@0.5:0.95. Model 1 demonstrated the most significant performance improvement on the augmented dataset, with precision, recall, mAP@0.5, and mAP@0.5:0.95 increasing by 4.4%, 5.7%, 1.5%, and 9.3%, respectively. Model 2 likewise benefited from the data augmentation strategy, with the four metrics improving by 4.9%, 4.4%, 2.8%, and 9.2%, respectively. In contrast, Model 3 exhibited relatively smaller improvements, with precision, recall, mAP@0.5, and mAP@0.5:0.95 improving by 0.9%, 1.3%, 0.8%, and 5.9%, respectively. Model 4 showed corresponding improvements of 0.2%, 3.9%, 1.7%, and 5.3%. These results indicate that different improvement strategies have varying effects on poultry health detection performance.

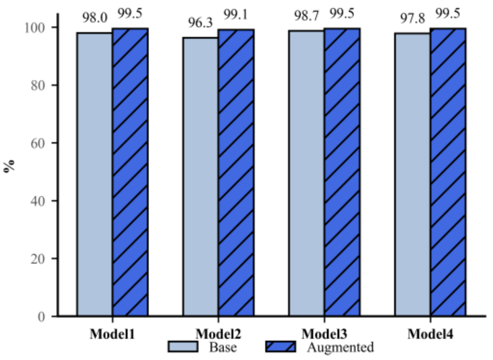
Overall, the Model 3, in which the original C2f module is replaced with C2f_LSBlock in the neck network, achieved the greatest detection improvement: its precision exceeds Model 1 by 4.5% on the original dataset. Furthermore, when further evaluated on the augmented dataset, Model 3 achieved overall improvements of 5.4% in precision and 9.9% in mAP@0.5:0.95 compared with the baseline model. To provide a more intuitive visualization of the ablation experiment results in Table 6, Fig. 6 compares the precision, recall, mAP@0.5, and mAP@0.5:0.95 metrics for Models 1–4 on both the original and augmented datasets.



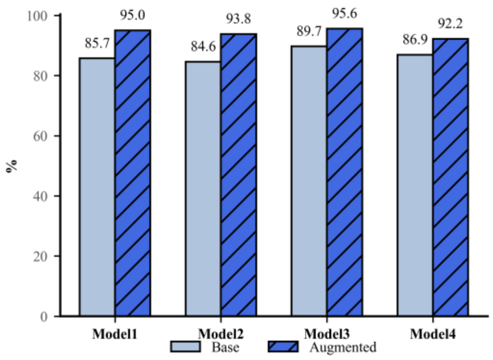
(a) Precision



(b) Recall



(c) mAP@0.5



(d) mAP@0.5:0.95

Fig. 6 Performance comparisons of ablation experiments

As shown in Fig. 6, the data augmentation strategy significantly improved performance across all ablation experiments, particularly recall and mAP. Among all models, Model 3 achieved the best performance for precision, recall, and mAP@0.5–0.95 of 98.9%, 97.5%, and 89.7%, respectively, on the original dataset. These results verify the effectiveness of the C2f_LSBlock in enhancing feature extraction capabilities and multi-scale feature fusion. Moreover, performance differences were observed when applying different network architectures under baseline and improved strategies.

When further trained on the augmented dataset, Model 3 achieved the best overall performance, with precision, recall, mAP@0.5, and mAP@0.5–0.95 reaching 99.8%, 98.8%, 99.5%, and 95.6%, respectively. These results demonstrate that improvements at both the data and network levels have positive effects, and that combining the two further enhances the detection performance and robustness of the proposed model.

To further evaluate the computational complexity of the trained model, Table 7 presents the training results of Parameters and giga floating point operations (GFLOPs) for Models 1-4 using the augmented dataset images. As shown in Table 7, Models 2-4 all exhibited lower parameters and GFLOPs than those of the baseline Model 1, indicating that model complexity was reduced by integrating various network architecture improvement strategies.

Table 7 Complexity Comparison Results

No.	Parameters	GFLOPs
Model 1	3,006,038	8.1
Model 2	2,862,902	7.7
Model 3	2,867,990	7.8
Model 4	2,724,854	7.5

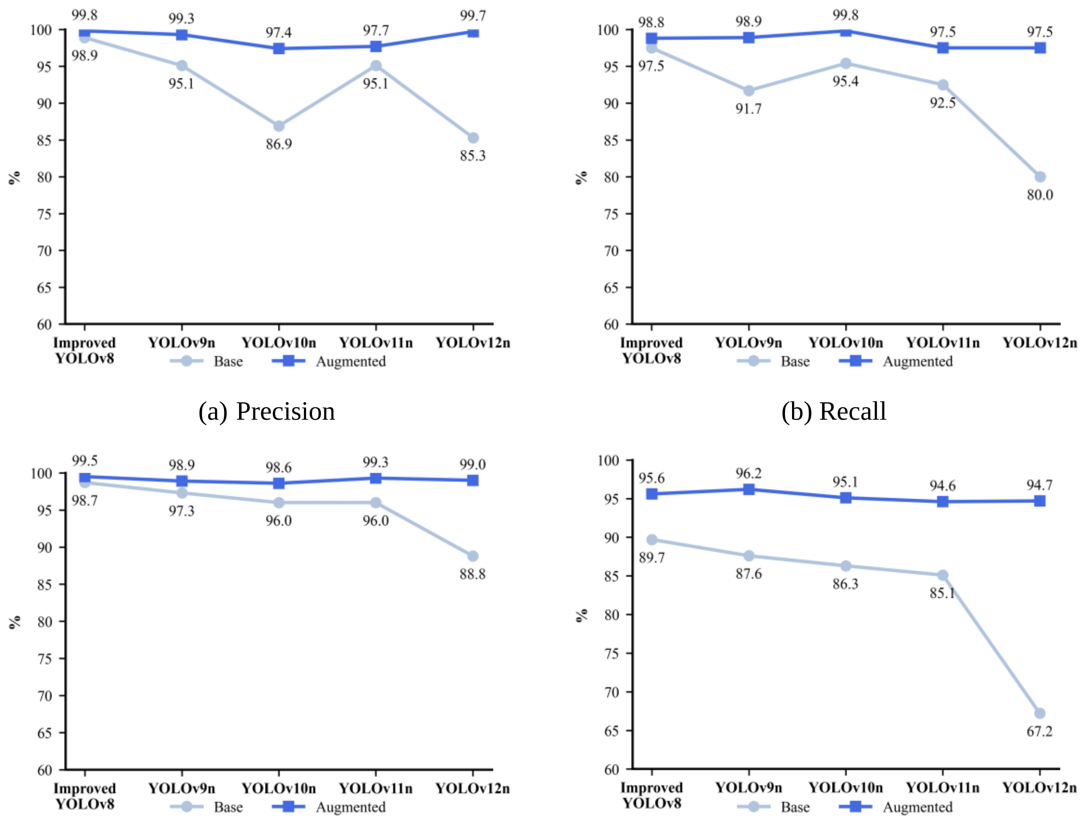
Specifically, the number of parameters decreased to 2,862,902, 2,867,990, and 2,724,854 for Models 2–4, respectively. Correspondingly, the GFLOPs decreased to 7.7, 7.8, and 7.5 for Models 2–4, respectively. Furthermore, based on Tables 6 and 7, Model 3 achieved the optimal balance between complexity and performance. In particular, compared with Model 1, Model 3 reduced the number of parameters and GFLOPs by 4.6% and 3.7%, respectively. These results further indicate that Model 3 still maintained effective feature extraction and detection capabilities while reducing computational overhead.

4.2 Comparison Experiment

In the comparative experiments, the performance of the proposed improved YOLOv8 was compared with that of the original YOLOv8n, YOLOv9n, YOLOv10n, YOLOv11n, and YOLOv12n using comprehensive evaluation metrics across the original and augmented datasets. All models were trained from scratch using the same datasets without loading pretrained weights. Additionally, all comparative experiments were conducted on the same machine with identical hyperparameter configurations. Fig. 7 shows an overview of the performance of all the algorithms using two datasets.

As shown in Fig. 7, different YOLO versions exhibited varying responses across the original and augmented datasets. Overall, all compared models yielded better performance on the augmented dataset than on the original dataset, indicating that augmented data was effective for this poultry health detection task. However, the improved YOLOv8 achieved the most stable and superior performance on both datasets. On the original dataset, the improved YOLOv8 achieved optimal results for all four performance metrics: precision, recall, mAP@0.5, and mAP@0.5:0.95, with results of 98.9%, 97.5%, 98.7%, and 89.7%, respectively. It also significantly outperformed the other comparison models on overall results (Fig. 7(a)-(d)). In contrast, YOLOv12n achieved the lowest performance across all four metrics, particularly for mAP@0.5:0.95 at 67.2%.

Furthermore, all models demonstrated performance improvements on the augmented dataset. Notably, YOLOv10n and YOLOv12n obtained significant precision gains of 10.5% and 14.4%, respectively, compared with training on the original dataset. The improved YOLOv8 model reached a detection precision of 99.8%. Overall, these experiments show that data augmentation techniques address problems arising from a lack of features in the original samples and data imbalance. In addition, the improved YOLOv8 showed relatively small fluctuations between training on the original dataset and on the augmented dataset, further suggesting that the data augmentation strategy improves the generalization and detection robustness of the trained models. Therefore, the proposed method demonstrates strong potential for intelligent poultry health monitoring, enabling precision livestock farming.



(a) Precision (b) Recall

(c) mAP@0.5 (d) mAP@0.5:0.95

Fig. 7 Performance comparisons among different algorithms

As shown in Fig. 7, the experimental results demonstrate that the improved YOLOv8 algorithm outperforms other algorithms in terms of precision, recall, and mAP metrics. The findings further validate the feasibility and effectiveness of the improved YOLOv8 model for intelligent poultry health recognition.

To further evaluate the overall recognition performance of the final improved YOLOv8n (Model 3) for Healthy and Sick chickens, the normalized confusion matrix of Model 3 is depicted in Fig. 8. The results indicate the distribution of correct and misclassified outcomes and further demonstrate the ability of Model 3 to distinguish between Healthy and Sick classes.

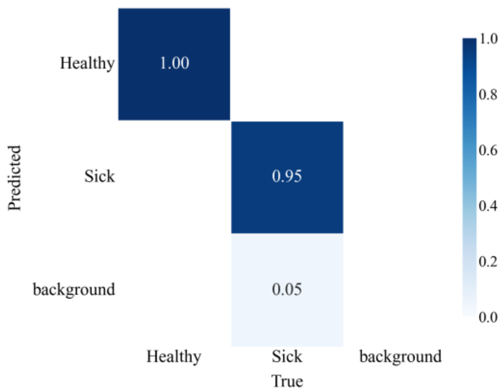


Fig. 8 Normalized Confusion Matrix of final improved YOLOv8n

As illustrated in Fig. 8, the recognition rates for the Healthy and Sick classes reached 1.00 and 0.95, respectively. The results indicated that the trained model possesses a strong capability to distinguish between Healthy and Sick classes, although a small number of Sick cases were still misclassified. The few errors mainly involved Sick being classified as background.

5. Discussion

A systematic optimization process has been conducted at both the data level and the network level to develop an intelligent poultry health recognition system based on an improved YOLOv8. Experimental results verify the effectiveness and feasibility of the proposed architecture. From the data perspective, after the data augmentation strategies are implemented, the recognition precision of the original YOLOv8 and the improved YOLOv8 increased by 4.4% and 0.9%, respectively. This demonstrates that well-designed data augmentation not only reduces overfitting and enriches feature distributions but also equips the structurally enhanced model with more discriminative training samples, thereby improving the latent performance of the network.

From the network perspective, the enhanced YOLOv8 is proposed by using the reconstructed C2f_LSblock instead of the original C2f block in the neck network. The improved YOLOv8 is shown to achieve 4.5% higher precision than the original on the image dataset. This indicates that the LS Block enhances the feature extraction ability of fine-grained representations by efficient modeling of local features and multi-channel information exchange.

Besides, the overall detection precision of the improved YOLOv8 algorithm increased by 5.4% when trained on the augmented dataset, indicating that improvements at both the data and the network levels can synergistically enhance model detection performance. As a result, the proposed model in this study efficiently improves the precision of poultry health recognition and the robustness of model detection, providing a feasible and scalable approach for deploying real-time automated health monitoring systems in poultry farming. However, the poultry images in this study were collected from Malaysia. Considering that poultry farming environments vary across different rearing farms, including farm size, farm layout, breeds, poultry age, backgrounds, lighting intensity, and farming density, further validation on new scenarios is necessary to verify the generalization ability of the proposed model.

6. Conclusion

This study utilized computer vision technology for non-invasive poultry health conditions. An improved YOLOv8n-based model was developed to detect poultry health status through body posture analysis. The findings of this study are summarized below:

(1) Data augmentation techniques were used to enrich the diversity of the dataset images, increasing precision, recall, mAP@0.5, and mAP@0.5:0.95 by 4.4%, 5.7%, 1.5%, and 9.3%, respectively, using the same baseline YOLOv8n.

(2) The proposed C2f_LSBlock enhanced feature extraction and multi-scale fusion capabilities in the improved YOLOv8n architecture, increasing precision, recall, and mAP@0.5:0.95 by 1%, 0.6%, and 0.6%, respectively, compared with the original YOLOv8n using the augmented dataset.

(3) The ablation and comparative experiments demonstrated the effectiveness of data and network-level improvements. Overall, the proposed model increased precision and mAP@0.5:0.95 by 5.4% and 9.9%, respectively, over the original YOLOv8n algorithm.

This study demonstrated that deep learning-based non-invasive poultry health identification enables precision livestock farming. The proposed method showed the potential practical value for precision livestock farming. In future work, the trained model will be further explored for deployment on edge devices, such as Raspberry Pi, to evaluate its real-time detection performance. Furthermore, the dataset will be expanded by collecting images from various real poultry farms.

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Conflicts of Interest

The authors declare no conflict of interest.

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