Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 14, No. 1, 2025

Image Recognition Method for Corn Northern Leaf Blight of Unmanned Aerial Vehicles Based on Deep Learning

Xianyuan Liu, Wei Su

Jilin Institute of Chemical Technology, Jilin 132000, China

Abstract: Aiming at the problems of high complexity, false detection and missing detection of maize big spot based on UAV image, an improved algorithm for maize big spot detection was proposed. The algorithm is based on EMA and the improved YOLOv8-BiFPN feature pyramid network. By adding the efficient multi-scale EMA attention mechanism module, the capturing ability of detail information is improved, thus enhancing the feature extraction ability of the model. The YOLOv8 structure is improved into YOLOV8-BIFPN feature pyramid network by integrating BiFPN structure, which can extract context information more efficiently. By introducing WloU loss function, low quality samples in training data are filtered effectively, and the generalization ability of the model is improved. In this paper, the accuracy P was increased by 2.7%, the recall rate R was increased by 4.7%, the average accuracy mAP50 was increased by 3.1%, and the model size was reduced by 2.78M. Compared with other YOLO algorithms, the proposed method has significant advantages in the detection of corn big spot disease.

Keywords: EMA Attention Mechanism; UAV image; YOLOv8-BiFPN; Corn Large Spot Disease.

1. Introduction

In China's agricultural structure, corn is the largest crop, accounting for nearly 40% of the total grain output, with a planting area of 650 million mu. It is the foundation of grain production, the link between crop cultivation and breeding, more than 60% of its output is used for the production of feed, and it plays an important role in the economy, sustainable agriculture, and the development of rural livelihoods, and is also key to ensuring food security and promoting sustainable social and economic development. However, in recent years, the frequent occurrence of corn diseases, especially the large spot disease, poses a major threat to corn leaves, affecting photosynthesis and thus threatening the yield and quality of corn.

Due to the inefficiency, high cost, subjectivity, and lack of timeliness of traditional manual detection methods, machine vision technology is introduced to achieve rapid and effective identification of diseases, thereby formulating control measures to reduce the negative impact of diseases, ensuring food security, and promoting sustainable agricultural development. With the development and cost reduction of UAV technology, its flexibility and accessibility have been widely applied in various fields, and its aerial photography images play an important role in target detection. Combined with machine vision technology, it can achieve rapid and effective disease detection, providing innovative scientific and technological means for agricultural production.

At present, YOLOv8, as a more advanced target detection model, has shown great potential in the agricultural field, especially in crop disease detection. Lu et al. proposed the YOLOv8_Rice model, which significantly improved the recognition ability of small-sized and irregularly shaped disease types by optimizing the attention mechanism and introducing deformable convolution. In addition, He et al. proposed the EDS-YOLOv8 algorithm, which significantly improved the accuracy of dense weed detection. Sun et al. proposed a lightweight network to improve the YOLOv8 model, effectively reducing the model's parameter volume and computational complexity while maintaining accuracy in the detection of tobacco pests in complex environments. Deng Pengfei et al. used the fusion structure of Inception and VGG as the feature extraction model, and compressed the model through transfer learning, channel pruning, and knowledge distillation, achieving rapid identification of corn diseases. Ye et al. proposed an improved YOLOv8 lightweight pest image recognition model, which significantly improved the performance of small target detection by introducing BiFormer attention mechanism and GELAN network. Liu et al. proposed a feature-enhanced detection algorithm based on SSD, integrating the residual structure of the ResNet50 network into the backbone network, improving the detection ability for small targets. The YOLOv8 model has also been applied to agricultural resource monitoring and yield estimation. Yu et al. proposed a model based on improved YOLOv8, using PConv technology to improve model detection accuracy in complex situations.

With the development of agricultural automation and intelligence, the application of YOLOv8 algorithm models in agricultural robots and intelligent agricultural equipment is also becoming more and more widespread. Guo et al. used the improved YOLOv8 algorithm model to achieve early detection of harmful plants by combining multi-source image data. Zhu Qi et al. proposed a DSCS-YOLO-based apple surface defect detection method, designed a DSCS shallow-deep feature selection module based on the Dense module and SE module, improved the original decoupling head with ELU activation function, and used the Wise-IoU loss function for nonlinear gain, achieving dynamic focused learning of the network. Liu et al. proposed a lightweight apple detection algorithm Faster-YOLO-AP based on improved YOLOv8, which is specifically designed for edge computing devices to achieve real-time object detection. Wang et al. proposed a YOLOv8+ model for strawberry maturity detection and classification, providing technical support for intelligent harvesting systems. Zhang et al. improved the YOLOv8 algorithm by introducing Mish activation function and DenseBlock structure, improving the accuracy and robustness of agricultural pest and disease detection. Zhu et al. proposed the Poly-YOLOv8 model and designed a new loss calculation algorithm, improving the model's detection ability for polygonal targets.

The aforementioned methods have some issues with real-time and accuracy in detection speed and model precision. In response to these issues, this paper improves the YOLOv8n as the benchmark algorithm to achieve UAV image corn large spot disease detection, and the main improvements and innovations to the YOLOv8 algorithm are as follows: first, a new attention mechanism module is introduced to improve recognition accuracy, then the new feature pyramid network structure adopts cross-scale connection methods and weighted feature methods to effectively integrate multi-scale features, fully solving the problem of large scale differences and feature loss, in addition, the introduction of a new loss function effectively reduces the negative impact of low-quality samples, further enhancing the model's generalization performance.

2. Improved YOLOv8 Algorithm

The YOLOv8 algorithm is known for its fast speed and high accuracy, and has been widely applied. The innovation of the YOLOv8 model structure first uses a deep convolutional neural network as its feature extractor, which greatly helps in capturing richer image features. At the same time, multi-scale feature fusion technology is introduced into the algorithm, making it more effective in handling targets of different sizes and improving the algorithm's ability to detect small targets. YOLOv8 also optimizes the loss function by introducing new regularization terms and adjusting the predicted bounding box, further improving the accuracy of detection. YOLOv8 has achieved simultaneous improvement in recognition speed and detection accuracy through these improvements. The optimization of YOLOv8 has achieved good results in target detection tasks.

2.1. Maize Large Spot Disease Recognition Algorithm Model

To improve the detection accuracy of maize large spot disease, this paper proposes an improved optimization plan based on the YOLOv8 network architecture. The model is based on the YOLOv8 base algorithm and is improved and optimized, as shown in Figure 1.

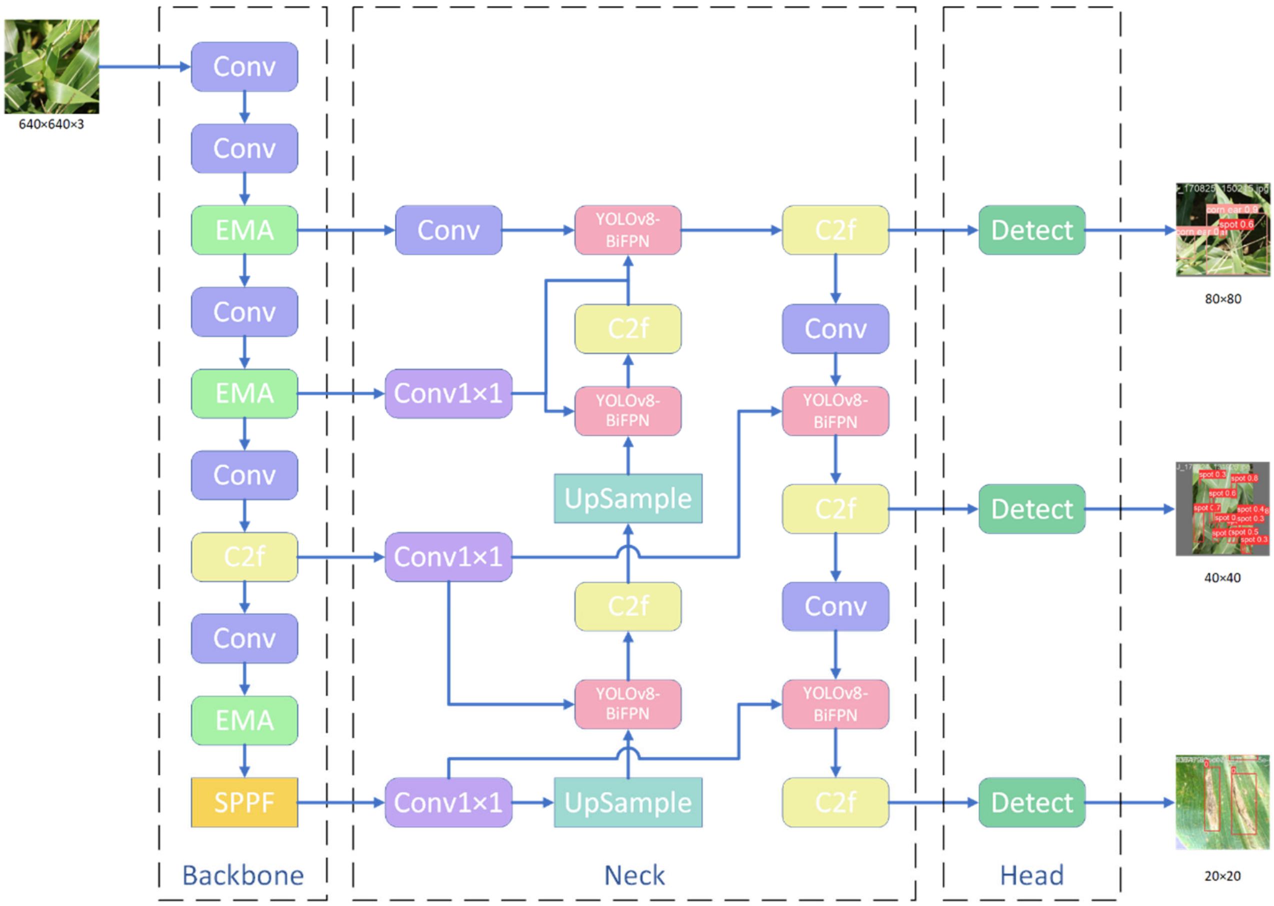


Figure 1. Improved and optimized YOLOv8 network structure

The specific improvements of the improved model compared to the pre-improved model are as follows.

Backbone Network: Three multi-scale attention EMA modules are introduced to capture detail information and improve the model's feature extraction capability, while retaining the original SPPF module in the model, which can solve the problem of repeated feature extraction of images by convolutional neural networks, speed up the generation of candidate boxes, and save computational costs.

Neck Network: A lightweight YOLOv8-BiFPN feature pyramid network structure is proposed by fusing BiFPN and the original YOLOv8 structure to enhance the model's multi-scale feature fusion capability and improve the network's detection accuracy for small targets.

Head Network: The original network loss function is optimized with WIoU Loss, introducing a dynamic non-monotonic focusing mechanism to improve the model's generalization capability.

In summary, this design method improves the existing algorithm, achieving high detection speed and model lightweight while improving detection accuracy, thereby enhancing the extraction capability of maize large spot disease features and enhancing the stability of the detection process.

2.2. Backbone Network Improvement.

By introducing the EMA (Efficient Multi-Scale Attention) attention module, the ability of the attention mechanism to obtain local important information is improved. EMA, as a multi-scale efficient attention mechanism, reshapes the channel dimension while maintaining the original channel dimension, improving computational ability while minimizing the loss of channel information. EMA is mainly responsible for global information encoding, can manage the channel weights of multiple parallel subnetworks, and promotes cross-dimensional information integration between these subnetworks, thereby producing output features. Its structure is shown in Figure 2. When the input features $\mathbf{X} \in R^{C\times H\times W}$ are divided into N sub-features $\mathbf{X} = [\mathbf{X}_0, \mathbf{X}_i, \cdots \mathbf{X}_{N-1}], \mathbf{X}_i \in \mathrm{R}^{C//C\times H\times W}$ according to the EMA channel number, let N<<C, and assume that the learned weights can enhance the feature representation of key areas in all sub-features. EMA uses a 3x3 branch and two 1x1 branches as parallel paths to obtain feature weights, which can obtain multi-scale features while avoiding dimensionality reduction. This study replaces the three C2f in the backbone network with EMA.

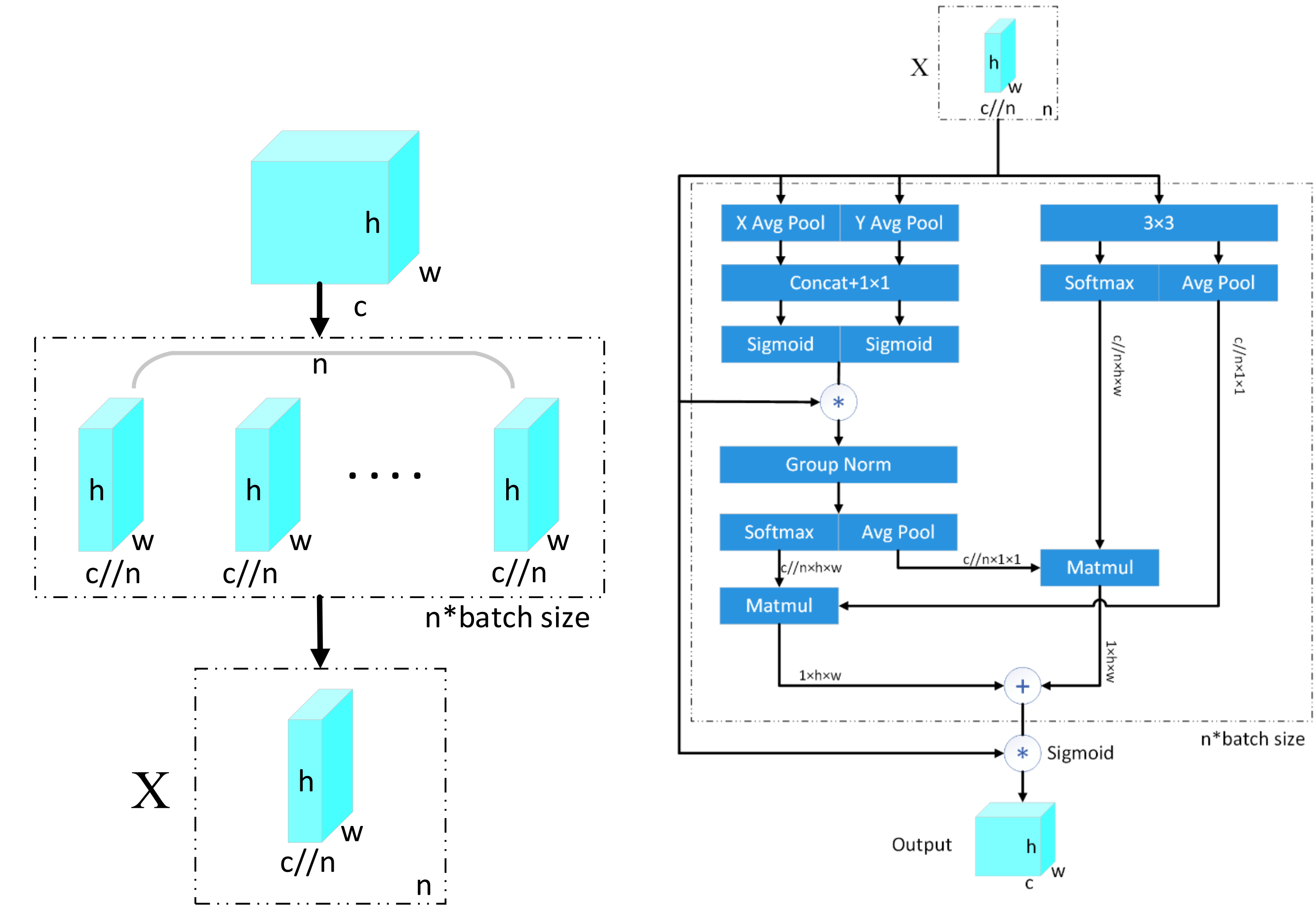
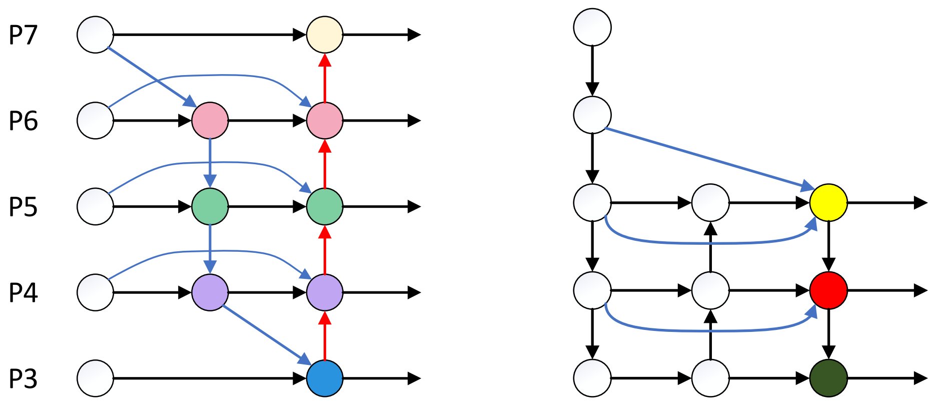


Figure 2. EMA structure diagram "n" represents grouping, "X Avg Pool" represents one-dimensional horizontal global pool, "Y Avg Pool" represents one-dimensional vertical global pool

2.3. Neck Improvement

To improve the detection accuracy of small targets such as large spot disease lesions, YOLOv8 has successfully integrated the advantages of PAN (Path Aggregation Network) and FPN (Feature Pyramid Network) structures, and this paper further introduces the concept of BiFPN (Bidirectional Feature Pyramid Network), proposing an innovative YOLOv8-BiFPN feature fusion network through new cross-scale connection methods and feature fusion methods, the detailed network structure is shown in Figure 3.



(a)BiFPN (b)YOLOv8-BiFPN

Figure 3. BiFPN, YOLOv8-BiFPN feature network structure

The construction method of the FPN feature pyramid is top-down, which can capture detailed information of images at different scales, thereby enhancing the performance and semantic information robustness of the algorithm. Nevertheless, the issue of semantic information differences at different levels in FPN still exists in YOLOv8. The construction method of PAN adds a bottom-up feature transmission method to FPN, effectively enhancing the transmission of low-level positioning features to the high level, and constructing a fused feature pyramid. YOLOv8 further optimizes on the basis of PAN, by removing nodes that do not participate in feature fusion, both simplifying the network and improving efficiency. However, these improvements still have certain limitations in small target detection. Small targets are easily disturbed by large targets during feature extraction, and inconspicuous feature information is also easily ignored by the network, leading to the gradual loss of key information of small targets, thereby affecting the accuracy of detection.

The BiFPN facilitates the connection of nodes at the input and output ends within the same level via an edge, thereby eliminating nodes incapable of feature integration. Moreover, it incorporates weighted feature fusion techniques, which supplant the conventional feature concatenation approach, thus more effectively preserving the hierarchical structure of features. In this study, an enhancement to the BiFPN is proposed, introducing a novel cross-layer connection methodology. Specifically, for the second and third layers of the network, 3×3 and 1×1 convolutional operations are respectively integrated to adjust the dimensions of the feature maps to 80×80, and subsequently merge these with the outputs of the corresponding layers. Additionally, a 1×1 convolutional layer is inserted between the input and intermediate nodes, and a weighted fusion strategy is employed, which not only reduces the number of model parameters but also more effectively retains a greater amount of original feature information.

2.4. Loss Function

The WIoU loss function is used to replace the original loss function to improve the prediction accuracy of anchor frames. The WIoU v3 loss function dynamically allocates gradient gains to suppress harmful gradients generated by low-quality images, overcoming the insufficient localization performance of the YOLOv8n network, allowing the network to more accurately locate lesions in joint misalignment detection, thereby reducing errors and improving the model's recognition accuracy and generalization capability.

$$L_{WIoUv1} = R_{WIoU} L_{IoU} \quad (1)$$

$$R_{WIoU} = \exp\left(\frac{(x - x_{gt})^2 + (y - y_{gt})^2}{(W_g^2 + H_g^2)^*}\right) \quad (2)$$

WIoU loss function is a loss function used for bounding box regression in target detection, which optimizes the quality assessment of anchor frames during training by dynamically allocating gradient gains. Compared with the CIoU loss function, the WIoU v3 loss function introduces a dynamic non-monotonic mechanism, which uses "outlier degree" instead of IoU for anchor frame quality assessment and provides a wise gradient gain allocation strategy. This strategy reduces the competitiveness of high-quality anchor frames while also reducing the harmful gradients generated by low-quality examples, allowing WIoU to focus more on ordinary quality anchor frames and improve the overall performance of the detector.

3. Experimental Data and Evaluation Metrics

3.1. Dataset

The corn large spot disease image acquisition platform is composed of a UAV-mounted camera. Table 1 shows the corresponding equipment models and parameter configurations.

Table 1. UAV Platform Parameters

Numble	Name	Scheme 2
1	UAV	DJI Mavic Air 2s
2	Image Resolution	6000×4000
3	Maximum Flight Time	34 minutes
4	Camera Sensor	1/2 inch CMOS, 48mp

To construct the corn large spot disease disease dataset, this study used the LabelImg tool to accurately label 4000 corn leaf disease images. To improve the generalization capability of the model during evaluation, the dataset was divided in a ratio of 8:1:1 to form the training set, test set, and validation set. A total of 3200, 400, and 400 images were obtained, meeting the needs for comprehensive training and model evaluation. This annotation and division process aims to provide the model with accurate enough training data to improve its performance in practical applications.

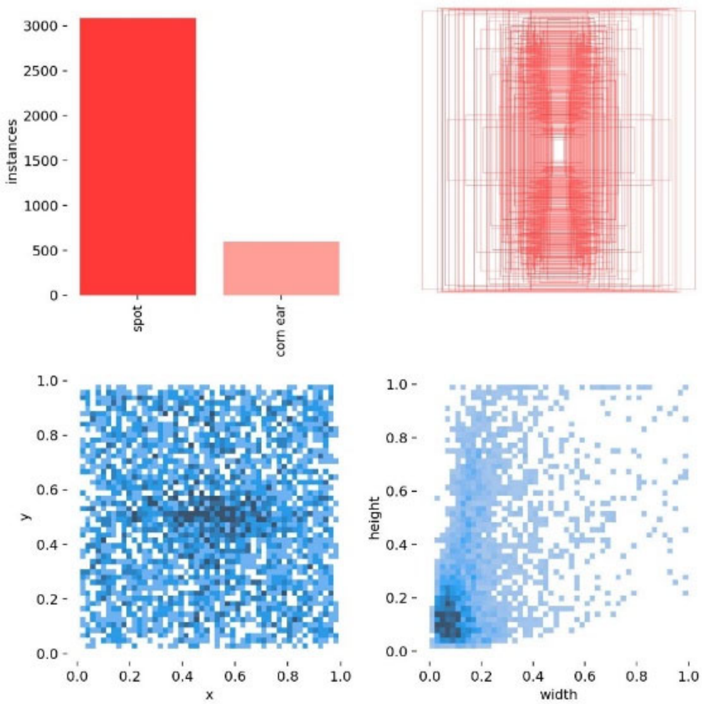


Figure 4. Dataset Annotation File Statistics

3.2. Experimental Environment and Parameter Configuration

Table 2. YOLOv8 Model Training Environment

Configuration	Parameter
CPU	Intel(R) Core(TM) i7-12700
Memory	32G
GPU	NVIDIA GeForce RTX4070
Video Memory	12G
Training Environment	CUDA 12.4
Operating System	Windows10 (64-bit)
Development Environment	Python3.11 Pytorch2.3

Parameter Settings: The training period is set to 150 epochs, under which the model can reach a converged state; the learning rate is set to 0.01, and the number of images processed per batch is 16, ensuring that the GPU can operate at full power; the input image size is 640×640 pixels, and the images are scaled to a uniform size to improve processing speed.

3.3. Evaluation Metrics

In this paper, the following evaluation metrics are mainly used to measure the performance of the model: precision (P), recall rate (R), average precision (mAP), F1 score, model parameter quantity (Params), total floating-point operations (FLOPs). These metrics together form a comprehensive evaluation system, and the related formulas are as follows:

$$\mathrm{P}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{3}$$

$$\mathrm{R}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{4}$$

$$\mathrm{AP}=\int_0^1 P(R)dR \tag{5}$$

$$\mathrm{mAP}=\frac{\sum_{i=0}^{n} AP_i}{n} \tag{6}$$

$$F1=\frac{2PR}{P+R} \tag{7}$$

Precision and recall rate can be measured using true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). AP represents the average precision on each category, which can measure the model's performance on different categories, and mAP is the average value of all APs, which can measure the model's performance on all categories. The definition of mAP is shown in formula (6). mAP50 is the total category average precision when the IoU threshold is set to 0.5.

4. Experimental Results and Analysis

4.1. Ablation Study

To ensure the rationality of the ablation study comparison, all participating models are trained based on the same dataset and parameter environment. In this study, YOLOv8n is used as the benchmark algorithm to implement a series of improvement measures, and the corresponding ablation experiments are completed. The results of the experiments are shown in Table 1.

Table 3. Ablation Study Results

Experiment	Improvement Backbone	Improvement Neck	Improvement Loss	P/%	R/%	mAP 50/%	Params /M	FLOP s/G	F1/%
1	×	×	×	80.1	73.4	77.2	9.31	20.4	76.6
2	√	×	×	81.1	74.2	78.1	10.35	21.5	77.5
3	×	√	×	80.1	75.4	77.7	7.51	16.7	77.8
4	×	×	√	79.8	73.8	77.4	11.13	21.7	76.7
5	√	√	×	81.4	74.7	78.8	6.72	16.3	77.9
6	√	×	√	80.3	73.6	77.5	10.72	21.5	76.8
7	×	√	√	81.7	76.9	79.2	7.48	16.7	79.2
8	√	√	√	82.8	78.1	80.3	6.53	16.1	80.4

In-depth analysis of the experimental results: Experiment 2 integrated the EMA attention mechanism into the backbone network, and most performance indicators have improved, indicating that the optimization of the backbone network has enhanced the model's feature extraction capability and improved detection accuracy. Experiment 3 integrated the YOLOv8-BiFPN structure into the neck of YOLOv8n, and compared with the original algorithm, all performance indicators have significantly improved except for precision, ensuring that the detection accuracy is improved while the model is simplified. Considering that precision is not a core indicator of model evaluation, it can be considered that the improvement of the network neck is very successful. Finally, experiment 4 used WIoU as a new method for bounding box regression, and compared with the benchmark algorithm, it successfully improved the network's detection accuracy without increasing the model's complexity.

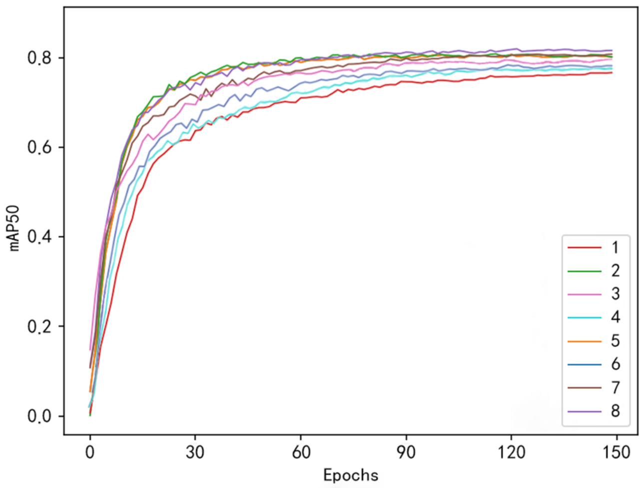


Figure 5. Ablation Study mAP50 Comparison

In the YOLOv8n and the improved backbone network structures, after introducing the WIoU loss function, the mAP50 increased by 0.2% and 0.3% respectively, the recall rate increased by 0.4% and 0.2% respectively, but the precision decreased, indicating that the improvement effect is not significant. However, when WIoU was applied to the improved neck network structure, the mAP50 significantly increased by 2%, the recall rate increased by 3.5%, and the precision also improved, reaching 1.6%. These comparative results indicate that the WIoU loss function performed better in the network optimized with the neck structure, implying that the WIoU loss function is more suitable for networks that have undergone multi-scale feature fusion. Experiment No. 8 shows that after integrating all the improvements proposed in this paper into YOLOv8n, compared with the original algorithm, the method proposed in this paper increased the mAP50 by 3.1%, precision by 2.7%, recall rate by 4.7%, reduced the parameter volume by 2.78 million, reduced the total floating-point operations by 4.3G, and increased the F1 score by 3.8%. These improvements make the algorithm superior to YOLOv8n in all performance indicators. As shown in Figure 5, which compares the changes in mAP50, it not only shows the improvement in detection accuracy but also the simplification of the model, meeting the needs for real-time and accuracy.

4.2. EMA Quantity Comparison Experiment

There are 4 C2f modules in the YOLOv8 backbone network. Adding different quantities of EMA will have different effects on the model. This experiment compares the model by adding different quantities of EMA modules after the C2f modules in the YOLOv8 backbone network. The results are shown in Table 2.

Table 4. EMA Quantity Comparison Experiment Results

Method	mAP50%	Params/M	FLOPs/G
YOLOv8n	77.2	9.31	20.4
1EMA	77.4	9.34	20.9
2EMA	77.6	9.36	21.2
3EMA	77.8	9.38	21.5
4EMA	77.8	9.41	21.9

From the experimental data in Table 2, it is known that adding the EMA attention mechanism can improve the model's feature extraction capability and thereby improve detection accuracy, but at the same time, it causes an increase in the number of parameters, which will slow down the model's computation speed. Therefore, as the number of EMA introductions increases, a balance point needs to be sought between the number of parameters and the improvement of accuracy. When adding up to 3 EMA mechanisms, accuracy is improved and the increase in the number of parameters is within an acceptable range. However, after adding 4 EMA mechanisms, the accuracy did not significantly improve, and the number of parameters continued to increase. Therefore, adding 3 EMA mechanisms in the backbone network can achieve an ideal balance between speed and accuracy improvement.

4.3. Comparative Experiment

To fully evaluate the advantages of the improved YOLOv8 algorithm proposed in this paper in the detection of corn large spot disease, this paper compares the improved algorithm with the YOLOv8n benchmark algorithm and other representative network models in the field, including Faster-RCNN, SSD, RetinaNet, YOLOv5, YOLOv6, YOLOv7-tiny, and YOLOv8, as shown in Table 3.

Table 5. Comparative Experiment Results of Different Models

Model	P/%	R/%	mAP50/%	F1/%	Params/M	FLOPs/G
Faster R-CNN	74.1	78.5	75.6	76.2	76.73	95.7
SSD	80.4	77.4	79.4	78.9	24.71	57.2
RetinaNet	74.6	73.1	74.7	73.8	18.9	60.4
YOLOv5	75.3	76.4	76.3	75.8	6.51	15.8
YOLOv6	77.1	73.7	77.3	75.4	9.50	17.5
YOLOv7-tiny	78.5	76.9	77.7	78.2	6.14	12.1
YOLOv8	80.1	73.4	77.2	76.6	9.31	20.4
Improved YOLOv8n	82.8	78.1	80.3	80.4	6.53	16.1

The results of the comparative experiment show that the improved algorithm proposed in this paper has achieved the highest level in terms of precision and mAP50 values. The algorithm not only has excellent performance but also the fastest detection speed, and the parameter volume is not much different from other models. Compared with the benchmark algorithm YOLOv8n, the improved algorithm shows significant advantages in all indicators. Considering all performance indicators, the comprehensive performance of the improved algorithm proposed in this paper is the best, with good detection ability for corn large spot disease in UAV images, and good performance in both speed and accuracy. To intuitively show the superiority of this algorithm, the mAP50 change curve is compared, and the experimental results are shown in Figure 6. From Figure 6, it can be seen that all algorithms can converge through continuous iteration, but the curve of the improved YOLOv8n is significantly higher than other algorithms, proving that the improved YOLOv8 algorithm has effectively improved detection accuracy.

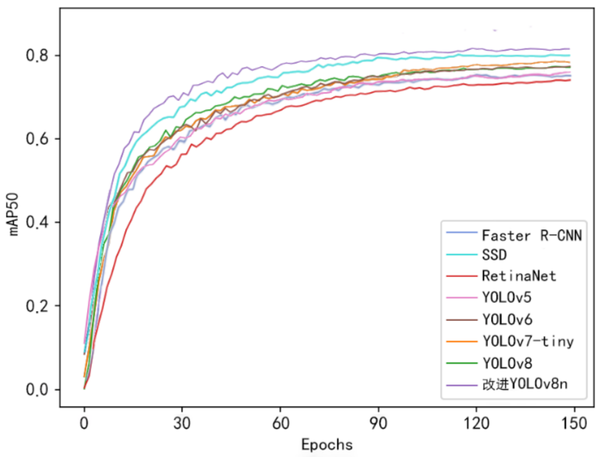


Figure 6. Comparison of mAP50 for Different Models

5. Summary

In this study, considering the high complexity and low distinguishability of the morphological and color features of corn large spot disease lesions, an improved YOLOv8 corn large spot disease detection model was proposed, specifically for detecting corn large spot disease. The model's training was based on a mixed dataset, which was composed of some public dataset images and our own collected corn large spot disease UAV images. The following are the main conclusions of this study: First, a corn large spot disease image dataset under natural conditions was successfully constructed, and its data integrity and reliability were ensured, which is crucial for model training and evaluation. Second, the EMA attention mechanism was added to the backbone network, the YOLOv8-BiFPN was designed to optimize the model's neck structure, and a new WIoU loss function was introduced to improve the YOLOv8 algorithm, making it specifically applicable to the detection of corn large spot disease in UAV images. Finally, compared with the benchmark algorithm YOLOv8n, the proposed algorithm shows superiority in many aspects, in comparison with other advanced methods, it has the best comprehensive performance, meeting the requirements for real-time and accuracy. In future research, we plan to increase the types of diseases and the number of samples to improve the model's accuracy and recognition ability. In addition, we will continue to explore the combination and optimization improvement of different network models to further improve the model's training speed and accuracy.

References

[1] Han Dongfeng, Li Feng, Qin Quan, et al. A refined identification method for summer corn planting area based on GEE and Sentinel-1/2 data[J]. Journal of Marine Meteorology, 2024, 44(03): 122-132.

[2] Xu Xingbin. Characteristics of corn disease occurrence and control techniques[J]. Modern Agriculture, 2024, (08): 47-49.

[3] Dai Linhua, Li Yuansong, Shi Rui. Improved YOLOv8n algorithm for rice leaf disease detection[J]. Journal of Hubei University for Nationalities (Natural Science Edition), 2024, 42(03): 382-388.

[4] Meng Wei, Wang Jinghui. Progress in the application of UAV technology in forest pest and disease monitoring[J/OL]. Forest Science and Communication, 1-6 [2024-10-10].

[5] Lu, Y., Yu, J. H., Zhu, X. F., Zhang, B. F., & Sun, Z. F. (2024). YOLOv8-Rice: a rice leaf disease detection model based on YOLOv8. PADDY AND WATER ENVIRONMENT.

[6] He, C. C., Wan, F. X., Ma, G. J., Mou, X. B., Zhang, K. K., Wu, X. F., & Huang, X. P. (2024). Analysis of the Impact of Different Improvement Methods Based on YOLOV8 for Weed Detection. AGRICULTURE-BASEL.

[7] Sun, D. Z., Zhang, K., Zhong, H. S., Xie, J. X., Xue, X. Y., Yan, M. L., Wu, W. B., & Li, J. H. (2024). Efficient Tobacco Pest Detection in Complex Environments Using an Enhanced YOLOv8 Model. AGRICULTURE-BASEL.

[8] Deng Pengfei, Guan Zheng, Wang Yuyang, et al. A method for corn disease recognition based on transfer learning and model compression[J]. Computer Science, 2022, 49(S2): 444-449.

[9] Ye, R., Gao, Q., Qian, Y., Sun, J. H., & Li, T. (2024). Improved YOLOv8 and SAHI Model for the Collaborative Detection of Small Targets at the Micro Scale: A Case Study of Pest Detection in Tea. AGRONOMY-BASEL.

[10] LIU W J, QIANG J, LI X X, et al. UAV Image Small Object Detection Based on Composite Backbone Network[J]. Mobile Information Systems, 2022(15):1-11.

[11] Yu, X., Yin, D. M., Xu, H. G., Espinosa, F. P., Schmidhalter, U., Nie, C. W., Bai, Y., Sankaran, S., Ming, B., Cui, N. B., Wu, W. B., & Jin, X. L. (2024). Maize tassel number and tasseling stage monitoring based on near-ground and UAV RGB images by improved YoloV8. PRECISION AGRICULTURE.

[12] Guo, B. L., Ling, S. K., Tan, H. Y., Wang, S., Wu, C. L., & Yang, D. S. (2024). Detection of the Grassland Weed Phlomoides umbrosa Using Multi-Source Imagery and an Improved YOLOv8 Network. AGRONOMY-BASEL.

[13] Zhu Qi, Zhou Deqiang, Sheng Weifeng, et al. A DSCS-YOLO-based apple surface defect detection method [J]. Journal of Nanjing Agricultural University, 2024, 47(03): 592-601.

[14] Liu, Z. F., Abeyrathna, R. M. R. D., Sampurno, R. M., Nakaguchi, V. M., & Ahamed, T. (2024). Faster-YOLO-AP: A lightweight apple detection algorithm based on improved YOLOv8 with a new efficient PDWConv in orchard. COMPUTERS AND ELECTRONICS IN AGRICULTURE.

[15] Wang, C. L., Wang, H. M., Han, Q. Y., Zhang, Z. G., Kong, D. D., & Zou, X. J. (2024). Strawberry Detection and Ripeness Classification Using YOLOv8+ Model and Image Processing Method. AGRICULTURE-BASEL.

[16] Zhang, L. J., Ding, G. C., Li, C. R., & Li, D. M. (2024). DCF-Yolov8: An Improved Algorithm for Aggregating Low-Level Features to Detect Agricultural Pests and Diseases. AGRONOMY-BASEL.

[17] Zhu, R. X., Hao, F. Q., & Ma, D. X. (2024). Research on Polygon Pest-Infected Leaf Region Detection Based on YOLOv8. AGRICULTURE-BASEL.

[18] OUYANG D L, HE S, ZHANG G Z, et al. Efficient Multi Scale Attention Module with Cross-Spatial Learning[C] // Proceedings of the IEEE International Conference on Acoustics Vancouver : IEEE,2023:12021-12031.

[19] Tan M, Pang R, Le Q V. Efficientdet: Scalable and efficient object detection[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020: 10781-10790

[20] Tong Z, Chen Y, Xu Z, et al. Wise-IoU: bounding box regression loss with dynamic focusing mechanism[J]. arXiv preprint arXiv:2301.10051, 2023.