IMPROVED YOLOv8-BASED AUTOMATED DETECTION OF WHEAT LEAF DISEASES /
基于改进 YOLOv8 的小麦叶片病害自动检测

Na MA, Yanwen LI, Miao XU, Hongwen YAN*[1]
College of Information Science and Engineering, Shanxi Agricultural University, Taigu/China
Tel: +86-0354-6288165; E-mail: yhwhxh@126.com
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ABSTRACT
Stripe rust, leaf rust, and powdery mildew are important leaf diseases in wheat, which significantly affect the yield and quality of wheat. Their timely identification and diagnosis are of great significance for disease management. To achieve convenient identification of wheat leaf diseases based on mobile devices, an improved YOLOv8 method for wheat leaf disease detection is proposed. This method incorporates the CBAM (Convolutional Block Attention Module) attention mechanism module into the feature fusion network to enhance the network's feature expression ability. Experimental results show that the improved YOLOv8 model has an accuracy, recall rate, and mean average precision (mAP) of 95%, 98.3%, and 98.8% respectively for wheat leaf disease detection, with a model memory usage of 5.92 MB. Compared with the Faster R-CNN, YOLOv5, YOLOv7, and YOLOv8 models, the mAP has been improved by 66.76, 48, 13.2, and 1.9 percentage points respectively, and it also has the lowest model memory usage. The research demonstrates that the improved YOLOv8 model can provide an effective exploration for automated detection of wheat leaf diseases.

摘要
小麦条锈病、叶锈病和白粉病是小麦叶部重要病害，严重影响小麦的产量和品质，其及时识别和诊断对于病害管理具有重要意义。为实现基于移动端的小麦叶部病害图像便捷识别，提出一种改进的yolov8 小麦叶部病害检测方法。该方法在特征融合网络中加入CBAM 注意力机制模块以提高网络的特征表达能力。实验结果表明，改进的yolov8 模型对小麦叶片病害检测的精确率、召回率和平均精度均值（Mean average precision，mAP）分别为 95%、98.3% 和 98.8%，模型内存占用量为 5.92MB。对比 Faster R-CNN、YOLOv5、YOLOv7 和 YOLOv8 模型，平均精度均值mAP 分别提升了66.76、48、13.2、1.9 个百分点，模型内存占用量方面也最优。研究表明改进的 YOLOv8 模型能够为小麦叶片病害实现自动化检测提供有效探索。

INTRODUCTION
Wheat is an important cereal crop and the second most consumed grain globally, second only to rice. It is a staple food for over one-third of the world's population. The yield of wheat is influenced by various factors such as climate, temperature, soil, pests, bacteria, and other biotic and abiotic factors *(Li et al., 2023; Sereda et al., 2023)*. Then, diseases also have a significant impact on the yield and quality of wheat (*Chai et al., 2022).* Most wheat diseases occur on the leaves, with powdery mildew, leaf rust, and stripe rust being the most common ones. All of these are fungal diseases that can cause significant yield losses in wheat *(Khan et al., 2022; Kartikeyan et al., 2021)*. However, due to the small size and difficult observation of early-stage diseases, farmers lacking professional knowledge, timely prevention and control of wheat diseases is not possible. Therefore, achieving accurate identification of wheat diseases and providing guidance for agricultural production in an efficient manner is one of the key factors for the development of modern agriculture.

The rapid and accurate identification of wheat disease types using computer vision technology has important application value in the prevention and control of wheat diseases. Traditional computer vision recognition of crop diseases usually involves multiple steps, such as preprocessing of disease images, lesion segmentation, feature extraction and selection, and classification using classifiers such as Support Vector Machine (SVM) and neural networks. *Sahu et al.* proposed a novel Hybrid Random Forest Multi-Class SVM (HRF-MCSVM) method for detecting plant leaf diseases *(Sahu et al., 2023)*.

Rahmanet et al. used the Gray-Level Co-occurrence Matrix (GLCM) algorithm to calculate 13 different statistical features of tomato leaves. The obtained features were classified into different diseases using Support Vector Machine (SVM) *(Rahmanet et al., 2023)*.

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[1] *Na MA, As. Lect. M.S. Eng.; Yanwen LI, Lect. M.S. Eng.; Miao XU, Lect. M.S. Eng.; Hongwen Yan*, Prof. Ph.D. Eng.*

Kumar et al. used median filtering technique for preprocessing rice leaf diseases. The proposed prototype achieved an accuracy of approximately 98.8% in detecting and classifying rice leaf diseases *(Kumar et al., 2022)*. However, with the popularity of large-scale cultivation and the accelerated spread of crop pathogens, traditional methods of manually extracting features for input into classifiers are gradually being eliminated *(Thakur et al., 2022)*. Firstly, they are highly dependent on the quality of the original disease images, and the selection of the most appropriate preprocessing and segmentation methods depends on the nature of the dataset. Secondly, manual selection of features requires strong agricultural expertise and a limited number of selected features, in the face of massive data, then it is difficult to effectively construct the appropriate model using these traditional machine learning methods, which will greatly limit the progress of disease identification.

In recent years, with the generation of large-scale labelled data and the rapid improvement of computer processing power, deep learning technology has developed rapidly. Classification, target detection, image segmentation and other deep learning methods have become the latest technology for automatic detection of crop diseases *(Orchi et al., 2021; Chen et al., 2020)*. Agarwal et al. utilized convolutional neural networks to detect and classify diseases on tomato leaves. The average accuracy of the proposed model was 91.2% *(Agarwal et al., 2020)*. Jiang et al. proposed an improved VGG16 model and a multi-task transfer learning approach that can simultaneously identify diseases on rice leaves and wheat leaves, providing a reliable method for identifying leaf diseases in multiple plants *(Jiang et al., 2021)*. Parasa et al. designed an optimized framework based on ant-lion for YOLOv-5, which can generate images affected by diseases without impacting the original image *(Parasa et al., 2023)*. Fang et al. combined residual modules and initial modules to construct a lightweight multi-scale CNN model. They incorporated CBAM and ECA modules into the residual modules to increase the model's focus on diseases and reduce the impact of complex backgrounds on disease recognition. The proposed method achieved an accuracy rate of 98.7% in wheat disease identification *(Fang et al., 2023)*.

The above research shows that deep learning can achieve certain effects in crop and plant disease detection methods. However, existing models have the following issues: most methods with high detection accuracy have high model computational complexity and slow detection speed, while methods with low model computational complexity and fast detection speed have lower detection accuracy. YOLOv8 is the latest version of YOLO series of target detection algorithms, and compared to the previous version, YOLOv8 has a faster inference speed, higher accuracy, and is easier to train and adjust. Therefore, for the problem of wheat leaf disease, adopting the latest YOLOv8 model as the base model and improving it to be better applied to wheat leaf disease detection, realize efficient automated disease detection, improve detection accuracy, reduce prevention and control costs, and be able to ensure the quality and safety of agricultural products, is of great application prospect and social significance, and provides technical support for the development of intelligent identification system of wheat disease based on mobile terminal.

MATERIALS AND METHODS

Data acquisition and pre-processing

The experimental data was collected from the wheat experimental field of Shanxi Agricultural University, from 2020 to 2023. A total of 825 images of three types of wheat leaf diseases, including powdery mildew, stripe rust, and leaf rust, were collected using the vivo Z3i smartphone in complex natural environments. Among them, 306 images of powdery mildew, 320 images of leaf rust, and 304 images of stripe rust were collected. The data collection is shown in Figure 1.

a.powdery mildew

b.stripe rust

c.leaf rust

Fig.1 - Partial Data Collection

Due to the insufficient sample size of the wheat disease dataset to achieve convergence during model training, data augmentation techniques were employed to improve the training effectiveness of the network model and enhance its generalization ability. In this study, various data augmentation methods, including Gaussian blur, horizontal flip, vertical flip, non-uniform scaling, random translation, perspective transformation, and random cropping, were randomly combined to augment the dataset. Through data augmentation, a total of 1530 images of powdery mildew on wheat leaves, 1600 images of wheat leaf rust, and 1520 images of wheat stripe rust were obtained.

Use LabelImg to annotate the wheat leaf disease image dataset and save the annotations in .txt format. Label the disease regions on wheat leaves and set the labels as wheat powdery mildew, leaf rust, and stripe rust. A total of 2200 were annotated for wheat powdery mildew, 1725 for leaf rust, and 2070 for stripe rust.

Improved YOLOv8 model

Collecting wheat leaves in natural environments is challenging as they are prone to branch and leaf obstructions, which can decrease the accuracy of wheat leaf disease detection. In 2023, Ultralytics released an updated version of YOLO, the YOLOv8 model, which has higher accuracy *(Hussain et al., 2023)*. Therefore, this study adopts the YOLOv8 model to achieve automatic detection of wheat leaf diseases. To improve the accuracy and speed of wheat leaf disease detection, the YOLOv8 model will be further improved to obtain an optimal model that can be deployed for applications.

YOLOv8 model

The YOLOv8 model is divided into two parts: the Backbone network and the Head network. YOLOv8 incorporates the excellent features of previous generations of networks. The Backbone network and Neck part follow the idea of CSP, replacing the C3 module in YOLOv5 *(Xu et al., 2023)* with a more feature-rich C2f module. The convolution structure in the upsampling stage of PAN-FPN in YOLOv5 is removed. The features outputted from different stages of the Backbone are directly fed into the upsampling operation. The model provides different-sized models of N/S/M/L/X scales, which can meet the needs of different industries and domains.

The process of YOLOv8 detection is as follows:

The input image is passed through a backbone network to extract features.

The feature map is refined and fused through multiple downsampling and upsampling layers.

The feature map is then used for prediction, generating predicted bounding boxes and class probabilities for each grid cell.

Finally, post-processing operations such as non-maximum suppression (NMS) and threshold filtering are applied to obtain the final object detection results.

The improvements in YOLOv8 are as follows:

1. Backbone: YOLOv8 still follows the concept of CSP (Cross Stage Partial) used in YOLOv5, but replaces the C3 module with the C2f module, achieving further lightweight design. YOLOv8 also utilizes the SPPF (Spatial Pyramid Pooling Fusion) module used in YOLOv5 architecture.

Figure 2 shows the C3 structure diagram, while Figure 3 shows the C2F structure diagram. In Figure 3, the input Tensor of each Bottleneck has only half the number of channels compared to the previous level, resulting in a significant reduction in computational complexity. On the other hand, the increase in gradient flow can also noticeably improve the convergence speed and effectiveness.

2. PAN-FPN: YOLOv8 still employs the PAN (Path Aggregation Network) concept, but removes the convolutional structure in the upsampling stage of PAN-FPN used in YOLOv5. Additionally, the C3 module is replaced with the C2f module in YOLOv8.

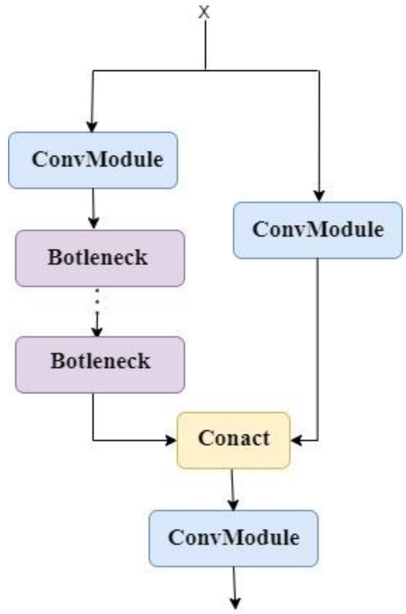

Fig. 2 - C3 model

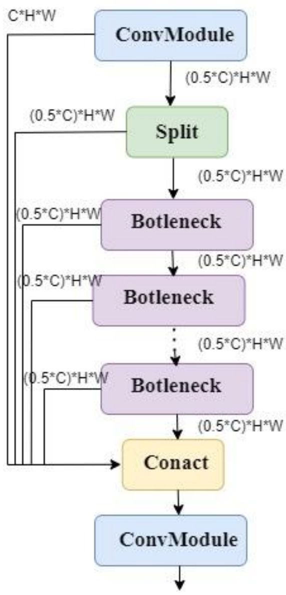

Fig. 3 - C2F model

3. Head changes: The most significant change in the Head part is that it transforms from the previous coupled head to a decoupled head, and it goes from Anchor-Based in YOLOv5 to Anchor-Free in YOLOv8. The head structure of YOLOv5 is shown in Figure 4, and the head structure of YOLOv8 is shown in Figure 5. From the figures, it can be observed that YOLOv8 no longer has the objectness branch as in the previous version. It only consists of decoupled classification and regression branches. Additionally, its regression branch utilizes the integral representation proposed in the Distribution Focal Loss.

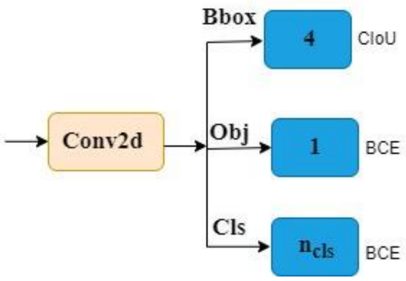

Fig. 4 - Yolov5 coupled head

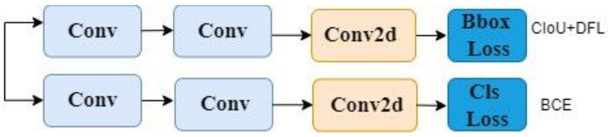

Fig. 5 - Yolov8 decoupled head

4. Loss function: YOLOv8 uses the VFL (Varifocal Loss) as the classification loss and combines DFL (Distribution Focal Loss) with CIOU (Complete Intersection over Union) Loss as the regression loss.

5. Sample Matching: YOLOv8 discards the previous IOU matching or unidirectional proportion assignment approach and instead uses the Task-Aligned Assigner matching method.

CBAM Attentional Mechanisms

CBAM (Convolutional Block Attention Module) attention mechanism is a module used for image recognition tasks. It introduces two sub-modules, channel attention and spatial attention, into convolutional neural networks to enhance the capturing ability of key features, as shown in Figure 6. The channel attention module adjusts the channel weights of feature maps by learning the relationships between channels, in order to extract the most representative features. This module first obtains the global features of each channel through global average pooling layer, and then calculates the channel weights through a fully connected layer. Finally, the channel weights are applied to the feature maps to adjust the importance of each channel.

The spatial attention module adjusts the spatial weights of feature maps by learning the relationships in the spatial dimension, in order to extract the most representative spatial information. This module first generates spatial feature maps through a convolutional layer, and then calculates the weights for each spatial position through a fully connected layer. Finally, the spatial weights are applied to the feature maps to adjust the importance of each spatial position.

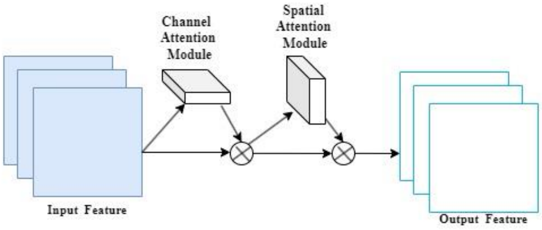

Fig. 6 - CBAM channel attention module

Improved YOLOv8

CBAM can enhance the feature capturing capability of the YOLOv8 model. By introducing two sub-modules, channel attention and spatial attention, CBAM can adjust the channel weights and spatial weights of the feature map to extract the most representative features and spatial information. By embedding the CBAM module in the YOLOv8 network, the detection accuracy and performance of the model can be improved.

Incorporating CBAM into the backbone layer of YOLOv8, the network architecture is shown in Figure 7.

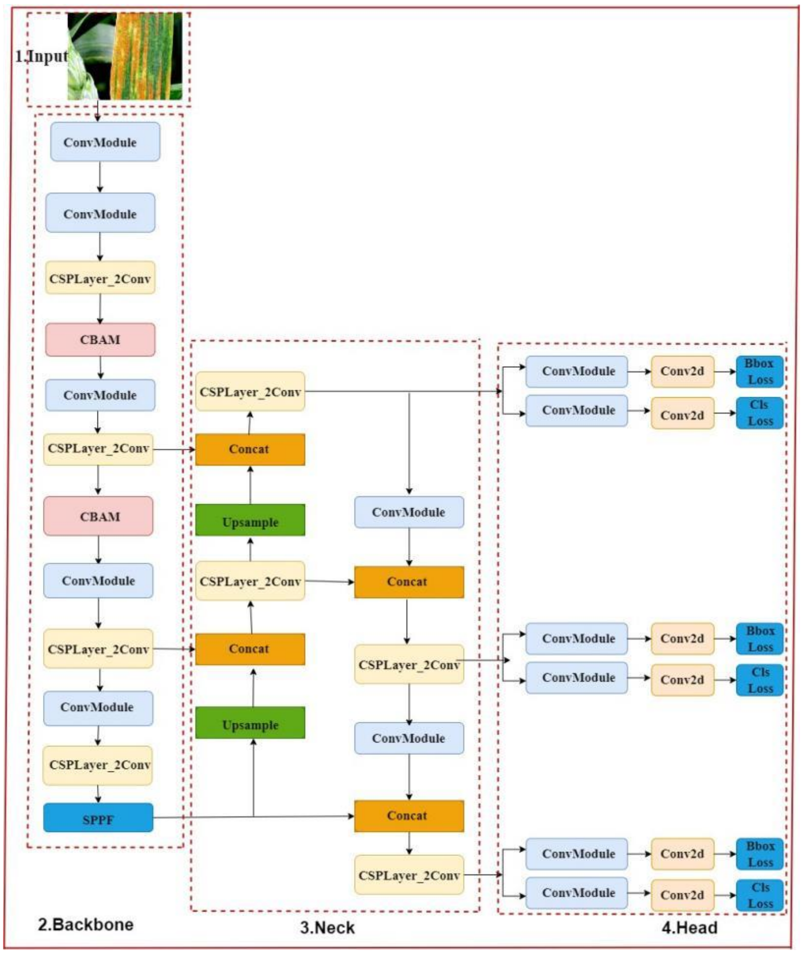

Fig. 7 - Improved YOLOv8 network structure

Model Evaluation Metrics

In this study, Precision (P), Recall (R), Average Precision (AP), and Mean Average Precision (mAP) are used to evaluate the performance of wheat leaf disease detection. The calculations are as follows:

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

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

where:

TP (True Positive) represents the number of correct predictions as positive samples.

FP represents the number of incorrect predictions as positive samples.

FN represents the number of incorrect predictions as negative samples.

Average Precision (AP): It is calculated by computing the precision-recall curve and taking the area under the curve (AUC). AP represents the average precision across all recall levels.

Mean Average Precision (mAP): It is the average of AP values calculated for each class or category. mAP provides an overall evaluation of the detection performance across different classes.

RESULTS

The operating system used for the experiment is Windows 10. The CPU model is Intel(R) Core(TM) i7-13700F @2.10GHz. The GPU model is NVIDIA GeForce RTX 4080. The system has 32GB of RAM and a 1TB mechanical hard drive. The programming language used is Python 3.9. The deep learning framework used is PyTorch 2.0.1. GPU acceleration libraries used are CUDA 11.8 and CUDNN 8.8.0.

The annotated data mentioned above is randomly divided into a training set and a test set in an 8:2 ratio. The improved YOLOv8 algorithm is used to evaluate the test set, which consists of 306 wheat leaf powdery mildew images, 320 wheat leaf rust images, and 304 wheat leaf stripe rust images. Among these images, there are 440 annotated wheat leaf powdery mildew instances, 345 annotated wheat leaf rust instances, and 414 annotated wheat leaf stripe rust instances.

In this study, the input image size is set to 640*640 pixels. The frozen training approach is used, with an initial learning rate of 0.0001, a momentum of 0.9, a batch size of 16, and a total of 100 iterations.

Detection results of different wheat diseases under the improved YOLOv8 model

To evaluate the performance of the improved YOLOv8 model, the wheat disease leaf samples in the test set were tested and the detection results, including TP, FP, and FN values, are shown in Table 1. From the table, it can be observed that out of the 440 marked wheat powdery mildew leaf samples, 440 were correctly detected as wheat powdery mildew, while 20 were falsely detected. Out of the 345 marked wheat leaf rust samples, 327 were correctly detected, 29 were falsely detected, and 18 were mistakenly detected as wheat leaf rust. As for the 414 marked wheat stripe rust samples, 414 were correctly detected as wheat stripe rust, while 11 were falsely detected.

Table 1

TP, FP, and FN values for different disease detection

Disease	TP	FP	FN
Wheat Powdery Mildew	440	20	0
Wheat Leaf Rust	327	29	18
Wheat Stripe Rust	414	11	0

Therefore, according to the precision, recall, and Mean Average Precision (mAP) calculation formulas, the detection results of different wheat leaf diseases by the algorithm in this paper are shown in Table 2. From Table 2, it can be observed that the average precision of the algorithm in this paper (mAP) can reach 98.8%, with the Precision of 95% and the recall of 98.3%.

Table 2

Detection results of different wheat leaf diseases

Disease	Precision [%]	Recall [%]	AP [%]
Wheat Powdery Mildew	95.7	1	99.5
Wheat Leaf Rust	91.9	94.8	97.7
Wheat Stripe Rust	97.4	1	99.1
Average	95.0	98.3	98.8

Partial detection examples are shown in Figure 8. From Figure 8, it can be seen that the algorithm proposed in this paper can accurately detect various types of wheat diseases. Figures 8(a)(b)(c) show that the algorithm can detect the targets well, whether it is with or against the light, in single leaf without obstruction.

Figures 8(d)(e)(f) show that the algorithm can also accurately detect wheat disease leaves in the case of multiple targets and obstructions. In summary, the improved YOLOv8 model can accurately detect different types of wheat disease leaves, and it has good detection performance for single targets, multiple targets, obstructions, and lighting effects.

Fig. 8 - Partial detection results

a *- leaf rust single target + backlit*, ***b*** *- powdery mildew single target + backlit*, ***c*** *- stripe rust single target + frontlit*, ***d*** *- leaf rust multiple targets + frontlit*, ***e*** *- powdery mildew multiple targets + frontlit;* ***f*** *- stripe rust multiple targets + backlit*

Comparison of improved YOLOv8 model and YOLOv8 model for wheat disease detection results

For each type of wheat leaf disease detection, the TP value represents the number of correctly detected instances of that disease, while the FP value represents the number of incorrectly detected instances of that disease. The comparison of TP/FP in wheat disease leaf detection results between the improved YOLOv8 model and YOLOv8 model is shown in Figure 9, where a represents the detection results of improved YOLOv8 algorithm for wheat powdery mildew, b represents the detection results of YOLOv8 algorithm for wheat powdery mildew, c represents the detection results of improved YOLOv8 algorithm for wheat leaf rust, d represents the detection results of YOLOv8 algorithm for wheat leaf rust, e represents the detection results of improved YOLOv8 algorithm for wheat stripe rust, and f represents the detection results of YOLOv8 algorithm for wheat stripe rust. It can be seen that for wheat powdery mildew and leaf rust, the improved algorithm in this study has an increase of 4 and 7 in TP values, and the decrease of 8 and 27 in FP values, respectively. Although the improvement in TP values is not significant, there is a significant difference in FP values, which highlights the advantage of the improved algorithm in this study.

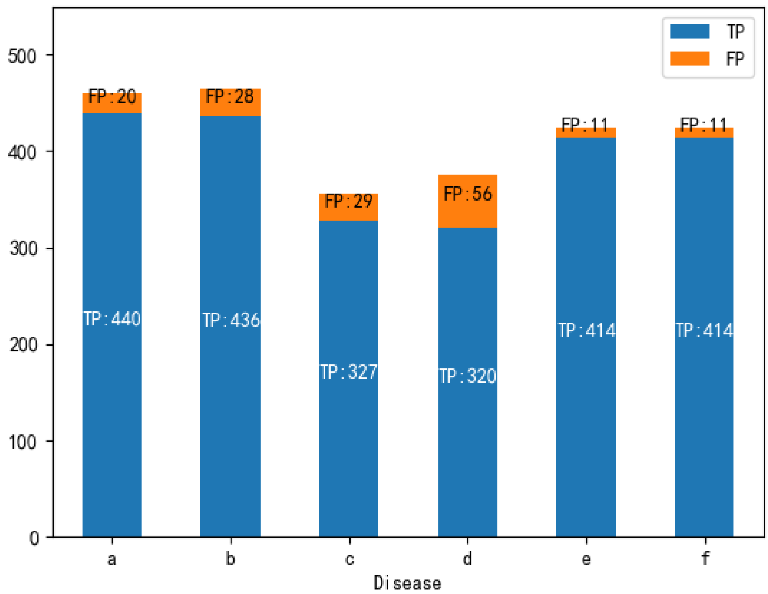

Fig. 9 - Comparison of TP/FP values for different algorithms

The detection results of improved YOLOv8 model and YOLOv8 model for different wheat leaf diseases are shown in Table 3. It can be observed that the improved algorithm in this study has improved precision and recall for wheat powdery mildew and leaf rust, and has also improved the AP values for all three wheat diseases. The mAP value for wheat disease detection has increased from 0.969 to 0.988, showing a 1.9% improvement.

Table 3

Detection Results of Improved YOLOv8 Model and YOLOv8 Model

	Disease	Precision[%]	Recall[%]	AP[%]
YOLOv8	Wheat Powdery Mildew	94	99.1	99.3
	Wheat Leaf Rust	85.1	92.8	92.4
	Wheat Stripe Rust	97.4	1.00	99.0
	average	92.2	97.3	96.9
Improved YOLOv8	Wheat Powdery Mildew	95.7	1	99.5
	Wheat Leaf Rust	91.9	94.8	97.7
	Wheat Stripe Rust	97.4	1	99.1
	average	95	98.3	98.8

Analysis of Comparative Results of Different Object Detection Networks

To qualitatively evaluate the detection results of the improved YOLOv8 model, the improved model was compared with the Faster R-CNN model *(Ren et al., 2015)*, YOLOv5 model *(Jiang et al., 2022)*, YOLOv7 model *(Wang et al., 2023)*, and the original YOLOv8 model on the test set of wheat leaf disease images. The detection results of the 5 models are shown in Table 4. It can be seen that the improved YOLOv8 algorithm in this paper achieves the best detection results for three types of wheat leaf diseases, and the model size is relatively small.

Table 4

Detection Results of Different Models

Model	AP [%] Wheat Powdery Mildew	AP [%] Wheat Leaf Rust	AP [%] Wheat Stripe Rust	mAP [%]	Size of the Weight Files（MB）
Faster R-CNN	0.28	0.42	0.27	32.04	108
Ylov5	0.357	0.956	0.212	50.8	14.3
Yolov7	0.957	0.629	0.982	85.6	71.3
Yolov8	0.993	0.924	0.990	96.9	5.92
Improved Yolov8	0.995	0.977	0.991	98.8	5.92

In order to further demonstrate the detection results of five different object detection models for wheat leaf disease, detection on three types of wheat leaf diseases in the test set was conducted.

The comparison of the detection results is shown in Figure 10 and Figure 11.

powdery mildew single leaf spot *leaf rust single leaf spot* *stripe rust single leaf spot*

a.Original image

b.Improved YOLOv8

c.YOLOv8

d.YOLOv7

e.YOLOv5

f.Faster R-CNN

Fig.10 - Single-target prediction results of five models

leaf rust multiple leaf spot *powdery mildew multiple leaf spot* *stripe rust multiple leaf spot*

a.Original image

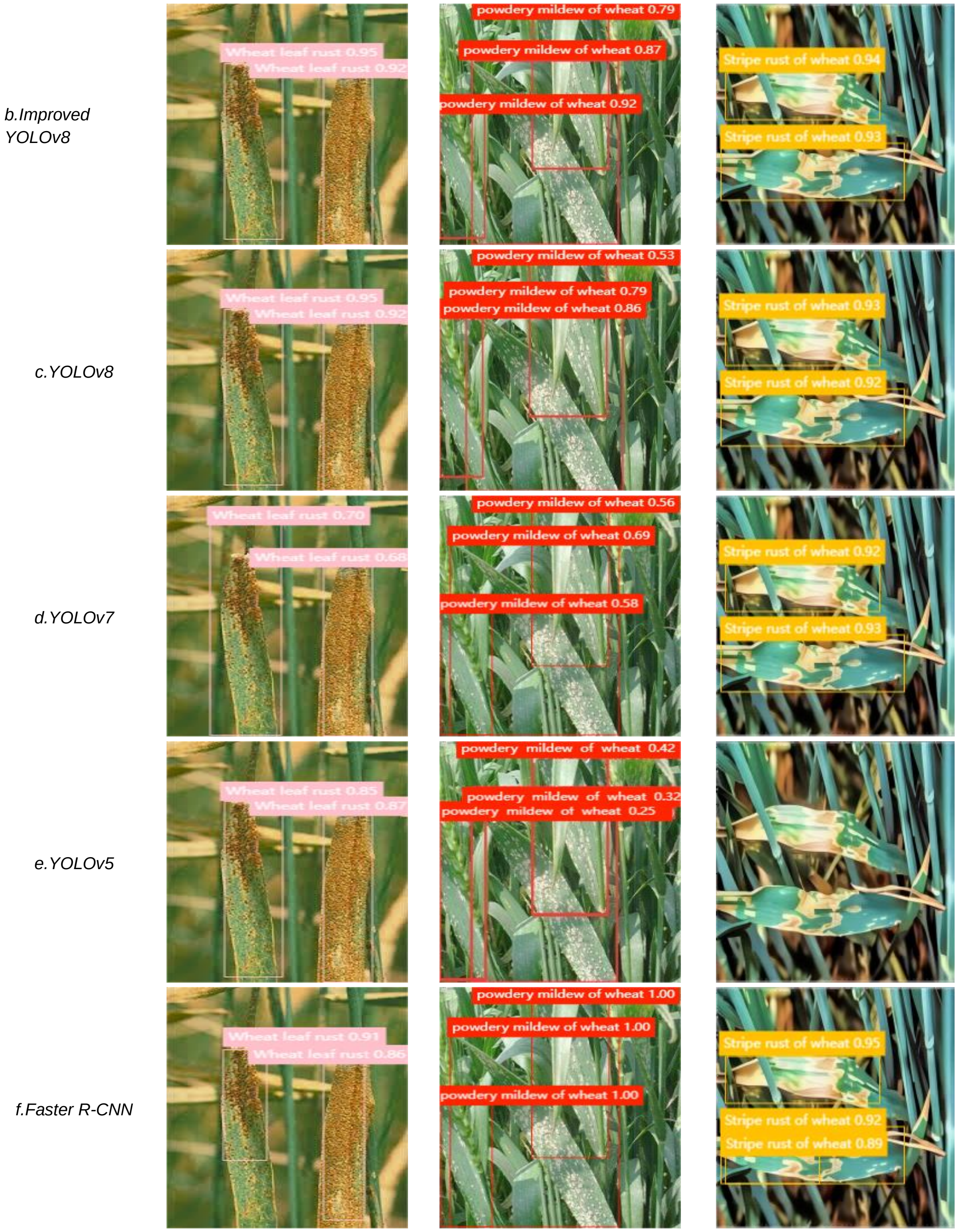

Fig.11 - Multi-target prediction results of five models

From the recognition results of the improved YOLOv8 model in Figure 10(b) and 11(b), it can be seen that the improved YOLOv8 model can accurately detect diseases in single-object, multi-object, and occluded scenarios, with high detection accuracy. From the YOLOv8 recognition results in Figure 10(c) and 11(c), it can be observed that the YOLOv8 model can detect disease leaves in both single-object and multi-object scenarios, but in some cases, the recognition rate is not as high as the improved YOLOv8 model. From the YOLOv7 recognition results in Figure 10(d) and 11(d), it can be seen that the YOLOv7 model can detect wheat disease targets in single-object detection, but with low recognition accuracy. In multi-object detection, there are cases of misjudgment.

From the YOLOv5 recognition results in Figure 10(e) and 11(e), it can be seen that the YOLOv5 model has missed detections in both single-object and multi-object detection. From the Faster R-CNN recognition results in Figure 10(f) and 11(f), it can be seen that the Faster R-CNN model has inaccurate detection ranges in both single-object and multi-object detection, and there are cases of repeated detections in multi-object detection. In conclusion, the improved YOLOv8 model in this paper has the best detection performance for wheat leaf disease.

CONCLUSIONS

(1) This study focuses on powdery mildew, leaf rust, and stripe rust of wheat leaves and proposes an improved YOLOv8 model for wheat leaf disease detection. The CBAM attention mechanism is introduced into the YOLOv8 model to improve its detection performance.

(2) To evaluate the performance of the improved YOLOv8 model, this paper compares the detection results of the original YOLOv8 model and the improved YOLOv8 model on the three types of wheat leaf diseases. The quantitative analysis of the detection results shows that the improved model increases the mAP value of wheat leaf disease detection from 0.969 to 0.988, with an improvement of 1.9 percentage points.

(3) Under the same experimental conditions, compared with the Faster R-CNN, YOLOv5, YOLOv7, and YOLOv8 models, the improved model achieves better results on the wheat leaf disease dataset, with an average precision (mAP) improvement of 66.76, 48, 13.2, and 1.9 percentage points, respectively. The experiments fully demonstrate that the improved YOLOv8 model has good performance in wheat disease detection.

The wheat leaf disease detection based on the improved YOLOv8 model has the advantages of small size, high accuracy, and fast recognition speed. It is convenient for deployment on machines for real-time detection, lightweight, and portable, providing a good reference for the application of wheat disease recognition on mobile devices. However, since there are very few samples in the collected data with multiple diseases simultaneously, further research is needed for the simultaneous detection of multiple wheat diseases.

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