Research on Real-time Detection Method of Rice Diseases and Pests Based on Improved YOLOv10s Model

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Abstract

As one of the world's most important food crops, rice's yield and quality are largely threatened by pests and diseases, necessitating a highly accurate, fast-responding, and adaptable intelligent detection method to support pest and disease control and sustainable agricultural development. This paper addresses the problems of low accuracy, poor real-time performance, and sensitivity to occlusion interference in complex field environments with existing methods, proposing a real-time detection method for rice pests and diseases based on an improved YOLOv10s model. First, a high-quality image dataset of 3100 images covering seven typical pests and diseases—rice blast, bacterial leaf blight, sheath blight, leaf spot, rice stem borer, rice borer moth, and rice green bug—was constructed, encompassing various real-world scenarios. A stratified sampling combined with five-fold cross-validation strategy was used for data partitioning to enhance the model's generalization ability. Secondly, to address the limitations of the receptive field and feature modeling in the YOLOv10s model, SAConv and SEAM structures were introduced. The former enhances spatial modeling capabilities through Multi-holes Rate Switchable Convolution Module, while the latter enhances the perception of fine-grained features and occluded targets based on a channel-Spatial joint attention mechanism. Furthermore, the MPDIoU bounding box regression loss function was introduced to optimize target box position prediction from a geometric perspective, significantly improving localization accuracy and training stability. Experimental results show that the improved model achieves an mAP of 93.1% and an inference speed of 176.4 FPS while maintaining a relatively low computational cost (20.3 GFLOPs) and parameter size (7.1 MB), significantly outperforming mainstream detection models such as YOLOv5s, YOLOv8s, and Faster-RCNN. It possesses good engineering deployment potential and field application value, providing an efficient and scalable solution for intelligent identification of agricultural pests and diseases.

Keywords: Rice diseases and pests, Target detection, YOLOv10s, Atrous convolution, Attention mechanism, Real-time recognition

1 Introduction

As the staple food source for nearly half of the world's population, rice's yield and quality are directly related to food security, agricultural economic stability, and social well-being. According to statistics from the Food and Agriculture Organization of the United Nations (FAO), the global annual rice planting area exceeds 160 million hectares, with Asia contributing more than 85% of the output. In populous countries such as China, India, and Indonesia, rice is a strategic crop that ensures food self-sufficiency [1-4]. However, throughout the entire growth cycle of rice, diseases and pests have always been the key bottleneck restricting yield improvement—common diseases and pests such as rice blast, sheath blight, and rice stem borer can lead to a 20%-40% reduction in yield per unit area in years of outbreaks, and in severe cases, even cause total crop failure [5-12]. With the intensification of global warming and the frequent occurrence of extreme weather, the spread and outbreak frequency of pests and diseases have further expanded. The drawbacks of the traditional prevention and control model of "emphasizing treatment and neglecting early warning" have gradually become prominent. How to achieve early, accurate and rapid detection of pests and diseases has become a core problem that urgently needs to be solved in the field of modern agriculture [13-15].

In the development of pest and disease detection technology, manual field inspection and traditional image processing methods have long dominated. Manual field inspection relies on the experience and judgment of agricultural technicians. By visually observing the color of leaves, the morphology of lesions and the traces of pests, the types of pests and diseases can be identified. This method is simple to operate and has low cost, and still has certain application value in small-scale farmland [16-20]. Traditional image processing methods acquire leaf images through image acquisition equipment, and then use algorithms such as grayscale, filtering and threshold segmentation to extract the features of pest and disease areas, and then combine texture, shape or color features for classification and identification. For example, Joshi et al. [21] proposed a method for detecting rice leaf diseases using K-Nearest Neighbor (KNN) and minimum distance classifier (MDC), with accuracies of 87.02% and 89.23%, respectively. Sun et al. [22] used simple linear iterative clustering (SLIC) combined with support vector machine (SVM) to detect tea diseases. This method can effectively extract tea leaf diseases from complex backgrounds, with an accuracy of 98.5%. Pantazi et al. [23] used local binary patterns (LBPs) for feature extraction and used a single-class classification method for classification. The model solved the conflict problem between single-class classifiers and achieved an accuracy of 95% in identifying grape leaf diseases. Bachhal et al. [24] proposed a PRF-SVM algorithm. The model consists of PSPNet, ResNet50 and fuzzy support vector machine (Fuzzy SVM). The average accuracy of this method in detecting and classifying various corn leaf diseases reached 96.67%. Xiong et al. [25] proposed an EResNet-SVM model, which achieved an accuracy of 99.30% in identifying 8 typical plant diseases and pests (7 plant diseases and 1 normal plant disease), which is 5.90% higher than the original ResNet18. Compared with manual field inspection, the objectivity and standardization of these methods have been improved, but there are still obvious shortcomings in their applicability in complex fields.

In recent years, deep learning technology has made breakthrough progress in the field of target detection with its powerful feature adaptive learning ability, providing a new solution for high-precision detection of rice pests and diseases. The target detection framework based on convolutional neural network (CNN) has been widely used in agricultural pest and disease detection tasks. For example, Cheng et al. [17] used CNN and deep residual learning to identify agricultural pests in complex farmland backgrounds. The accuracy of this method is much higher than that of SVM and BP neural network. Compared with ordinary CNN, the recognition accuracy is further improved. For 10 types of agricultural pests in complex backgrounds, the recognition accuracy reached 98.67%. Zheng et al. [26] proposed a deep residual network for multi-scale feature extraction based on Res2Net structure. The hierarchical residual connection was used to replace the original 3×3 convolution kernel, increasing the receptive field of each network layer, which can extract multi-scale features in a finer granular manner, realizing the effective recognition of rice pests in natural backgrounds, with an average recognition accuracy of 92.023%. Zhang et al. [3] proposed the ResViT-Rice model, which uses ResNet as the backbone network and introduces encoder components and convolutional block attention modules from the converter architecture. It achieves accurate detection of rice leaf spot and brown spot. The detection accuracy of the model reached 99.87%. Guan et al. [27] proposed the GC-Faster RCNN detection framework, which integrates channel-wise correlations and spatial dependencies hybrid attention mechanism to cope with the challenge of pest identification in complex environments. Compared with the original Faster RCNN model, the accuracy and recall of the GC-Faster RCNN model were improved by 4.5% and 16.6%, respectively. Haruna et al. [28] improved the detection performance of region-based Faster-RCNN for major diseases of rice leaves by adopting style generative adversarial network adaptive discriminant enhancement method (SG2-ADA) and Laplacian filter variance technology. The detection accuracy of the model reached 93%.

With the increasing demand for efficient and deployable solutions in the agricultural field, single-stage target detectors (such as SSD and YOLO series) have received more and more attention due to their faster inference speed and lower computational complexity. For example, Yin et al. [29] proposed the JujubeSSD method based on the SSD network. This method uses deformable convolutional networks (DCN) to replace traditional convolutional layers, which enhances the learning of target detail features and the ability to identify weak information. In addition, in order to solve the problem of difficulty in identifying the lesion area on jujube fruit caused by the different sizes and shapes, the path aggregation feature pyramid network (PAFPN) and the balanced feature pyramid (BFP) were integrated into the SSD network. The recognition accuracy of the model reached 97.1%. Lyu et al. [30] improved the performance of small object detection of grain pests by introducing a top-down feature fusion strategy into the SSD algorithm. Combined with K-means clustering to calculate the prior bounding box of grain pests, the performance of small object localization of grain pests was improved. The mAP of the optimized model reached 96.89%. Fang et al. [31] proposed the RRDD-Yolov11n model for rice diseases, using the SCSABlock attention module to optimize multi-semantic fusion, and introduced the CARAFE upsampling module to solve the limitations of the original upsampling module in reconstructing rice disease-related features, thereby increasing the mAP to 88.3%. Qiang et al. [32] proposed the YOLO-PEST model based on the YOLOv5s architecture. In the feature fusion process, the model integrates the ConvNeXt module to improve the detection accuracy of small objects through multi-scale feature extraction. In addition, the CoTAttention mechanism is introduced to enhance the robustness of the model under complex environmental conditions. The mAP reaches 97%. Yang et al. [15] proposed the YOLO-RP lightweight rice pest detection method based on the YOLO11n model. The model simplifies the module by integrating a high-resolution P2 detection head, a lightweight partial convolution detection head (LPCHead), a reparameterizable multi-branch module (DBELCSP), and a structure-aware wavelet pooling module (WaveletPool). The model size is only 2.8MB, and the mAP reaches 90.99%. Pan et al. [33] proposed the SSD-YOLO improved rice disease detection method based on YOLOv8 . The squeeze and excitation network (SENet) attention mechanism was introduced to optimize the bottleneck structure of YOLOv8. The lightweight dynamic upsampling module DySample was used to solve the problem of high similarity between rice diseases and background. The Shape Intersection over Union (ShapeIoU) loss was used to replace the CIoU loss function, thereby improving the model performance in complex environments. The mAP of the model in identifying rice brown spot disease, rice bacterial leaf blight and bacterial leaf blight reached 87.52%, 99.48% and 98.99%, respectively. Zhou et al. [34] embedded a ternary attention mechanism into the YOLOv8n model to achieve cross-dimensional interaction between channel and spatial dimensions. The Global-to-Local Spatial Aggregation module (GLSA) was used to improve the neck of YOLOv8n and enhance the effectiveness of feature representation. The Wavelet Transform Convolution (WTConv) was used to improve the C2f-BottleNeck of the original model and expand the network's perceptual range. The model achieved an average accuracy of 80.9% for fifteen common rice diseases and pests.

Although significant progress has been made in detection accuracy, feature representation, and multi-scale fusion, existing methods typically rely on highly complex architectures to achieve high accuracy. This results in high computational costs, making it difficult to balance accuracy and real-time performance, thus limiting lightweight deployment in resource-constrained agricultural scenarios. To address these issues, this paper proposes an improved model based on YOLOv10s. By introducing the SAConv module, SEAM module, and MPDIoU loss function, the model's ability to extract and identify features of multiple types and scales of rice diseases and pests in complex environments is optimized. The aim is to achieve high-precision, real-time detection of rice diseases and pests in the field, providing technical support for early warning and precise control of rice diseases and pests, helping to improve the quality and efficiency of agricultural production, and ensuring food security.

2 Introduction to the YOLOv10s algorithm

YOLOv10s, as the next-generation object detection framework in the YOLO series, integrates efficient convolutional modules and attention mechanisms in its structural design, further improving the model's ability to balance accuracy and speed. Its overall network structure consists of three parts: the Backbone, the Neck and the Head, as shown in Fig 1. The Backbone introduces a C2f module to achieve cross-stage information flow, an SCDown module for spatial-channel decoupling downsampling, a CIB module to improve the compactness and lightweight nature of feature representation, an SPPF module to expand the receptive field, and a PSA module to enhance the model's ability to focus on key features in both spatial and channel dimensions. The Neck adopts a PANet-like structure, achieving full integration of deep and shallow semantic information through multi-scale upsampling and feature fusion operations, effectively improving the model's ability to detect small targets. The Head is designed as a dual-branch head structure. During training, both one-to-one and one-to-many matching strategies are enabled to strengthen the supervision signal, while only the one-to-one head is retained during inference to improve inference efficiency and control computational load.

Compared to its predecessors like YOLOv5 and YOLOv8, YOLOv10s achieves key improvements in several aspects. Its Anchor-Free mechanism eliminates the anchor box design, simplifying label preprocessing and training. Simultaneously, the NMS-Free mechanism avoids the target miss problem caused by redundant box suppression. This structure not only reduces dependence on hyperparameters but also improves model training stability and inference speed, making it particularly suitable for deployment in edge agriculture equipment with high real-time requirements, such as unmanned field vehicles and agricultural drones. In actual pest and disease detection scenarios, targets are typically small in size, complex in shape, and subject to strong background interference. YOLOv10s, with its modular, scalable network design and greater sensitivity to small targets, demonstrates higher robustness and adaptability in complex field scenarios such as high-density plants, low-light environments, and multiple targets adhering together. Furthermore, its highly compatible network structure provides an ideal foundation for subsequent integrated modules.

In summary, YOLOv10s outperforms previous models in terms of detection performance, structural flexibility, and engineering deployment adaptability, making it the preferred foundational model for real-time identification of rice diseases and pests.

Fig 1. YOLOv10s model structure diagram

Note: Split is a split operation; Concat is a concatenation operation; Conv2d is a convolution operation; BatchNorm is a batch normalization operation; SiLU is an activation function; MSHA is a multi-head self-attention module; FFN is a feedforward network; MaxPool is a max pooling operation; Upsample is an upsampling operation; One-to-one Head is a one-to-one matching detection head; One-to-many Head is a one-to-many matching detection head.

3 Proposed method

3.1 SAConv model

In this study, the SAConv[35] (Switchable Atrous Convolution) module is introduced, as shown in Fig 2. It aims to enhance the model's ability to perceive the features of rice pests and diseases in complex backgrounds. Traditional convolution is limited by a fixed receptive field, making it difficult to take into account both local details and global context information. Especially in scenarios where the scale of pest and disease areas varies greatly, the morphology is blurred, and the integration with the leaf background is high, the problem of insufficient feature extraction is likely to occur. SAConv introduces convolution operations with different dilation rates in parallel on the same input features, and combines a learnable switching function to dynamically adjust the convolution response under different receptive fields, thereby achieving adaptive fusion of local details and global semantics, effectively expanding the receptive field of the model. Specifically, the SAConv structure consists of three parts: a pre-global context module, a switchable atrous convolution core module, and a post-context enhancement module. It can achieve joint expression of multi-scale information while keeping the computational cost controllable. By replacing the 3×3 standard convolution of the SCDown module in the YOLOv10s network with the SAConv module, the model gains stronger spatial modeling and target boundary perception capabilities. It exhibits higher robustness and discriminative power in multi-scale pest and disease detection and occlusion interference environments, providing effective support for improving the recognition accuracy of rice pest and disease detection in complex scenarios.

$$y=S(x)\cdot\mathrm{Conv}(x,w,r)+(1-S(x))\cdot\mathrm{Conv}(x,w+\Delta w,r) \qquad (1)$$

Where x and y represent the input and output feature maps, $\mathrm{Conv}(x,w,r)$ represents the convolution operation with weights w and a dilation rate of r, Δw is trainable weights, $S(\cdot)$ is the switching function that fuses the convolution results with different dilation rates.

Fig 2. SAConv structure diagram

Note: r is the hole rate; S is the switching function.

3.2 SEAM Model

In this study, SEAM[36] (Separated and Enhanced Attention Module) is introduced, as shown in Fig 3. It aims to improve the robustness and occlusion adaptation of the model in the detection of rice pests and diseases in complex agricultural scenarios. Traditional CNN often have problems such as insufficient feature expression and insufficient response in important regions when facing complex environments such as occlusion, background interference or blurred target boundaries, which affects the detection accuracy. SEAM introduces the synergistic effect of channel attention and spatial attention mechanisms by jointly modeling the channel dimension and spatial dimension of the feature map, and weights each channel and each spatial position, thereby enhancing the network's attention to key feature regions.

The SEAM structure mainly consists of depthwise separable convolutional modules, residual connection structures, and a fully connected attention mechanism. First, the input feature map is compressed into channel vectors through global average pooling, and multi-scale feature capture is achieved through patch embedding of different sizes. Then, through channel-wise depthwise separable convolution operations, the independence between channels is preserved while reducing the number of parameters and computational overhead, effectively improving the accuracy and efficiency of feature extraction. Next, pointwise convolution is used to fuse channel information, generating channel attention weights, and a fully connected network further enhances the response to important channels. These attention weights are ultimately applied to the original input feature map, achieving enhanced responses in key regions and suppression of redundant features.

Fig 3. SEAM structure diagram

In the introduced SEAM, the CSMM (Channel-Spatial Multi-scale Module), as one of its core components, plays a crucial role in improving the model's ability to represent the details of rice pests and diseases and its multi-scale adaptability. The CSMM module significantly enhances the representation of key regions in the feature map by constructing a joint modeling spatial-channel attention mechanism, making it particularly suitable for handling difficult scenarios commonly encountered in agricultural vision tasks, such as small-area pests and diseases with varied shapes and complex backgrounds.

The CSMM module consists of multiple multi-scale patch embedding branches with different receptive fields. Each branch encodes the input features in parallel using local receptive regions of different sizes (e.g., patch size=6, 7, 8), thereby achieving perceptual modeling of the target at different scales. This structural design effectively alleviates the problem of insufficient target response capability of traditional convolution at fixed scales and enhances the model's adaptability to the morphological differences exhibited by pests and diseases at different stages (e.g., early spots versus late-stage large lesions).

As shown in Fig 4, within each CSMM branch, the input feature map is first mapped to a unified token space through patch embedding, and then the GELU activation function and Batch Norm normalization layer are used sequentially to improve feature stability and nonlinear expression ability. The core processing component is Depthwise Convolution, which improves local detail modeling capabilities while maintaining low parameter complexity, particularly in terms of texture clarity and boundary preservation. The residual connection structure effectively enhances the model's training stability and robustness to complex image perturbations while maintaining the integrity of the information pathway. Subsequent Pointwise Convolution enables cross-channel information interaction, further integrating the contextual semantics between channels.

In the rice pest and disease detection model constructed in this paper, the CSMM module in SEAM is directly used in the feature enhancement stage, fusing with the mid-to-high-level features output by the YOLOv10s backbone network to form a representation with higher semantic expressiveness and detail preservation ability. Through the introduction of this module, the model exhibits stronger feature discrimination ability and target localization accuracy when facing complex field backgrounds, overlapping occlusions, and fine-grained blurring of pests and diseases, providing a solid structural foundation for improving overall detection performance.

Fig 4. CSMM structure diagram

Furthermore, the residual connection structure in SEAM weights and superimposes the input features with the output after depthwise convolution, effectively mitigating the gradient vanishing problem in deep network training and improving the stability and generalization ability of feature representations. Thanks to these mechanisms, SEAM significantly improves the model's ability to detect occluded pests and diseases in complex scenes, enhancing fine-grained feature recognition, and is particularly suitable for handling target information loss caused by leaf occlusion and changes in light in field environments. In summary, the introduction of SEAM provides crucial support for improving the model's detection accuracy and robustness against rice pests and diseases in multi-scale, occluded, and high-background-interference scenarios.

3.3 Improved Model Structure Diagram

To improve the YOLOv10s model's ability to detect rice pests and diseases in complex field backgrounds, this paper introduces SAConv and SEAM on the basis of the original network structure, as shown in Fig 5. These two structural improvements significantly enhance the model's spatial modeling ability and attention expression ability. Specifically, in the Backbone stage, the SCDown module in the original YOLOv10s was replaced by the SCDown_SAConv module. The latter effectively solves the problem of traditional convolutions being limited by a fixed receptive field and struggling to balance local and global features by applying convolutions with different dilation rates in parallel on the same input features and introducing a learnable switching function to adaptively adjust the multi-scale receptive field. The SAConv module, while maintaining controllable computational overhead, achieves effective fusion of local texture details and contextual semantics, significantly improving the model's generalization ability and robustness in multi-scale pest and disease target detection. Furthermore, the SEAM module is introduced in the Neck and Head stages to further enhance the mid-to-high-level semantic features extracted by the backbone network. SEAM highlights key region responses and suppresses redundant features by jointly modeling channel attention and spatial attention in feature maps. Its core component, CSMM, achieves efficient modeling of pest and disease regions of different scales and complex morphologies through multi-branch patch embedding and depthwise separable convolutions, exhibiting stronger discriminative ability under conditions of occlusion, illumination interference, and background fusion. The residual connection structure in SEAM further improves the stability of feature representation and the feasibility of deep training.

Fig 5. Improved YOLOv10s model structure diagram

Note: SAConv is Switchable Atrous Convolution; SEAM is Separated and Enhanced Attention Module.

3.4 MPDIoU loss function

To further improve the bounding box localization accuracy and training convergence stability of the model in the rice pest and disease detection task, the CIoU loss function used in the original YOLOv10s model was replaced with the MPDIoU (Minimum Points Distance Intersection over Union) loss function[37]. This improvement strategy aims to solve the problems of insufficient modeling of the geometric relationship of the bounding box and excessive freedom in the optimization process when CIoU is used to deal with different target shapes and scales. In particular, in complex agricultural images with diverse target sizes and blurred boundaries, CIoU has certain limitations in terms of regression accuracy and robustness.

MPDIoU reconstructs the positional relationship measurement mechanism between bounding boxes from a geometric perspective by introducing the concept of minimum point distance. As shown in Equation (4), MPDIoU, based on the calculation of the intersection-union ratio of the predicted box B and the ground truth box A, introduces the minimum Euclidean distance metric between the top left and bottom right corners (corresponding to d_1^2、d_2^2 in Equations (2) and (3)), and combined with the normalization term w^2+h^2(the sum of squares of the width and height of the image) to scale the distance error, thereby achieving precise control over the differences in the position of the bounding box corners.

$$d_1^2=(x_1^B-x_1^A)^2+(y_1^B-y_1^A)^2 \quad (2)$$

$$d_2^2=(x_2^B-x_2^A)^2+(y_2^B-y_2^A)^2 \quad (3)$$

$$\mathrm{MPDIoU}=\frac{A\cap B}{A\cup B}+\frac{d_1^2}{w^2+h^2}+\frac{d_2^2}{w^2+h^2} \quad (4)$$

Where A represents the ground truth bounding box; B represents the predicted bounding box; (x_1^A, y_1^A) , (x_2^A, y_2^A) are the top left and bottom right corners of the ground truth bounding box; (x_1^B , y_1^B) , (x_2^B , y_2^B) are the top left and bottom right corners of the predicted bounding box; d_1 is the distance between the top left corners of the two boxes; d_2 is the distance between the bottom right corners of the two boxes; w is the image width; h is the image height; $\cap$ represents the intersection operation; $\cup$ represents the union operation.

MPDIoU through modeling the minimum distance of boundary points, can more accurately drive the model to learn the true location distribution of pests and diseases, mitigating problems such as predicted box drift and large size fitting errors, thereby significantly improving target detection and localization accuracy. This loss function not only reduces unnecessary degrees of freedom in the bounding box regression process, helping to accelerate the model's convergence speed, but also improves robustness and stability in small and dense target detection tasks.

4 Implementation details and evaluation metrics

4.1 Introduction to the dataset

In order to construct a high-quality rice disease and pest image detection dataset, this study used web crawling technology to obtain a large number of rice disease and pest image samples from public resources, covering seven major disease and pest types: rice blast, bacterial leaf blight, sheath blight, leaf spot, rice stem borer, rice borer moth, and rice green bug. Combined with some pre-collected field samples, after image screening and deduplication, a diverse and representative image dataset was constructed, with a total of 3100 images. This dataset includes various scenarios such as single pests and diseases, co-occurrence of multiple pests and diseases, multi-target adhesion, and complex backgrounds, effectively improving the robustness and generalization ability of the model in various field environments. Fig 6 shows typical image examples of different pest and disease states. Considering the diverse sources of images and the differences in original resolution, which may affect the detection performance of the model during training and inference, all images were standardized to 640×640 pixels during the data preprocessing stage to enhance the consistency and adaptability of the model input. Subsequently, the LabelImg tool was used to annotate each image, with annotation types including "Rice blast", "Bacterial leaf blight", "Sheath blight", "Leaf spot", "Rice stem borer", "Rice borer moth", and "Rice green bug". Regarding sample distribution, the seven image categories account for the following percentages in the overall dataset: rice blast (15%), bacterial leaf blight (15%), sheath blight (15%), leaf spot (15%), rice stem borer (13%), rice borer moth (13%), and rice green bug (14%). To ensure class balance in the image data during training and improve the stability and representativeness of the model evaluation results, a stratified sampling combined with five-fold cross-validation strategy was adopted in the data partitioning stage, dividing the total dataset into five subsets according to class proportions. In each round of training, four subsets serve as the training set, and the other subset serves as the test set, alternating five rounds of training to reduce performance bias caused by randomness in partitioning. Furthermore, in each round of training, a training subset and a validation subset are further divided in a 4:1 ratio for model parameter optimization and model selection, respectively, effectively controlling the risk of overfitting and ensuring a steady improvement in model performance.

Fig 6. Typical image examples of rice diseases and pests. (a) Rice blast. (b) Bacterial leaf blight. (c) Sheath blight. (d) Leaf spot. (e) Rice stem borer. (f) Rice borer moth. (g) Rice green bug.

4.2 Experimental platform

The training and validation experiments of the proposed improved YOLOv10s rice disease and pest detection model were all completed under the Windows 11 operating system environment. The hardware platform configuration was an NVIDIA GeForce RTX 3090 GPU with 24 GB of video memory; the system disk capacity was 20 GB, and a 50 GB NVMe high-speed solid-state drive was used for data read and write to ensure efficient data caching and access speed during model training. The deep learning framework selected was PyTorch 2.0.1, and CUDA 11.8 was used to accelerate computation.

During the training phase, the model was trained for a total of 150 epochs using Stochastic Gradient Descent (SGD) as the optimizer. To obtain the optimal combination of hyperparameters, a grid search method was employed to systematically traverse and evaluate multiple parameter combinations, ultimately determining the following optimal training parameter settings:

Initial Learning Rate:	0.001
Batch Size:	16
Weight Decay:	0.0005
Momentum:	0.937

To effectively mitigate the risk of overfitting and improve the model's generalization ability, several control strategies were introduced during training: First, data augmentation techniques were used to significantly enhance the diversity of training images, including image rotation, brightness perturbation, MixUp, and Mosaic methods; second, the lightweight model YOLOv10s was used as a pre-trained network to guide the model in learning general visual features, which helps to accelerate convergence and improve initial performance; in addition, an Early Stopping strategy was introduced during training, automatically terminating training when the validation set performance did not show significant improvement within 10 consecutive training epochs, thereby avoiding overfitting of the model to the training set.

4.3 Evaluation metrics

The model performance was evaluated using metrics such as precision (P), recall (R), mean average precision (mAP) , and computational cost. Precision (P) refers to the proportion of true positive samples among the predicted positive samples. Recall (R) refers to the proportion of predicted positive samples among the true positive samples. Mean average precision (mAP) is a better indicator of overall performance than the unstable fluctuations of P and R. P, R, and mAP are given by formula (5-7):

$$p = \frac{T_P}{T_P + F_P} \times 100\% \tag{5}$$

$$R = \frac{T_P}{T_P + F_N} \times 100\% \tag{6}$$

$$mAP = \int_0^1 P(R)dR \times 100\% \tag{7}$$

Where: TP represents the number of correctly detected targets; FP represents the number of incorrectly detected targets; FN represents TP that was not detected.

Meanwhile, this study uses the Computational Cost and the number of parameters to measure the complexity of the model, and uses the frame rate to evaluate the real-time detection performance of the model.

5 Experimental results and discussion

5.1 Ablation test

Table 1 shows the ablation test results of the YOLOv10s model under different improvement schemes. A comprehensive analysis from the dimensions of detection accuracy, computational complexity, and model efficiency shows that each improved module significantly improves performance while maintaining the model's lightweight nature. The baseline model YOLOv10s achieved an mAP of 88.7%, with precision and recall of 87.6% and 86.2%, respectively. Introducing the SAConv module further improved the mAP to 89.7% and precision to 89.1%, demonstrating the effectiveness of switchable atrous convolution in expanding the receptive field and enhancing feature representation. Further introducing the SEAM module increased the model's mAP to 91.3% and recall to 89.8%, indicating its significant advantages in capturing fine-grained target features and improving response in occluded regions. When SAConv and SEAM were used together, detection accuracy was further improved, with mAP reaching 92.8%, and precision and recall increasing to 91.8% and 90.6%, respectively, validating the complementarity of the two mechanisms in spatial modeling and detail enhancement. Finally, by introducing the MPDIoU loss function, the model performance reached its optimal level, with mAP increasing to 93.1%, Precision and Recall reaching 92.1% and 91.4% respectively, representing improvements of 4.4%, 4.5%, and 5.2% compared to the baseline model. Simultaneously, the computational cost was only 20.3G, while the frame rate remained at 176.4 frames per second, demonstrating strong real-time processing capabilities.

Table 1. Ablation test Results

model	**Precision/%**	**Recall/%**	**mAP/%**	**Computation/GB**	**parameter size/MB**	**frame rate/fps**
YOLOv10s	87.6±0.01	86.2±0.03	88.7±0.04	21.6	8.1	160.1
YOLOv10s+ SAConv	89.1±0.02	87.6±0.03	89.7±0.02	20.6	7.6	165.1
YOLOv10s+SEAM	90.5±0.01	89.8±0.03	91.3±0.05	20.4	7.3	170.1
YOLOv10s+ SAConv +SEAM	91.8±0.03	90.6±0.04	92.8±0.01	20.3	7.1	176.4
YOLOv10s+ SAConv + SEAM + MPDIoU Loss	**92.1**±0.03	**91.4**±0.02	**93.1**±0.01	**20.3**	**7.1**	**176.4**

5.2 Comparative tests

Table 2 presents the performance comparison results of the improved model and current mainstream object detection models (including SSD, Faster R-CNN, YOLOv5s, YOLOv7, YOLOv8s, YOLOv9s, YOLOv10s, and YOLOv11s) on the same rice pest and disease image test set. In terms of detection accuracy, OUR model performed best among all compared models, achieving an mAP of 93.1%, and precision and recall of 92.1% and 91.4%, respectively. While maintaining high-precision detection capabilities, it effectively enhanced the stability and completeness of the model's object regression. Compared with representative high-precision lightweight models such as YOLOv8s and YOLOv11s, OUR model improves mAP by 8.8%, demonstrating superior feature representation and spatial modeling capabilities. In terms of computational efficiency, OUR model has a computational complexity of 20.3 GFLOPs, roughly on par with YOLOv10s (21.6 G), but lower than YOLOv8s (28.6 G) and YOLOv11s (26.3 G). This effectively controls computational resource consumption while maintaining high performance, validating the significant computational efficiency advantages of the SAConv and SEAM modules in improving receptive field and detail modeling capabilities. Regarding model size, OUR model has a parameter count of 7.1 MB, the smallest in the table, approximately half that of YOLOv8s (13.4 MB), and significantly lower than Faster-RCNN (43.5 MB) and SSD (54.3 MB), demonstrating a highly compact structure and excellent model deployment and mobile adaptability. Furthermore, in terms of inference speed, OUR model ranks first among all models with a speed of 176.4 FPS, which is significantly better than YOLOv9s (108.4 FPS) and YOLOv11s (140.8 FPS). This fully verifies its high real-time performance and low latency characteristics in practical applications, meeting the needs of real-time detection of pests and diseases and edge deployment.

Table 2. Comparative test results

model	**Precision/%**	**Recall/%**	**mAP/%**	**Computation/GB**	**parameter size/MB**	**frame rate/fps**
SSD	77.2±0.04	71.3±0.05	75.3±0.01	62.4	54.30	46.5
Faster-RCNN	79.6±0.03	78.3±0.02	76.5±0.07	251.8	43.5	38.4
YOLOv5s	80.6±0.04	79.6±0.03	82.2±0.01	**16.5**	7.2	80.2
YOLOv7	82.3±0.05	80.1±0.02	83.9±0.06	101.3	38.4	90.7
YOLOv8s	84.7±0.04	82.6±0.05	84.3±0.01	28.6	13.40	100.3
YOLOv9s	80.1±0.01	79.5±0.02	82.4±0.04	24.6	7.9	108.4
YOLOv10s	87.6±0.01	86.2±0.03	88.7±0.04	21.6	8.1	160.1

YOLOv11s	82.4±0.03	83.6±0.01	84.3±0.02	26.3	9.9	140.8
YOLOv10s+ SAConv + SEAM + MPDIoU Loss	**92.1**±0.03	**91.4**±0.02	**93.1**±0.01	20.3	**7.1**	**176.4**

5.3 Overall Performance Comparison

Fig 7 shows the trends of three key performance indicators (MPIs) of different object detection models during 150 training epochs, namely precision, recall, and mAP. The figure shows that the performance of each model increases rapidly in the early stages of training (epochs 0 – 30), and then gradually stabilizes, demonstrating good convergence.

In terms of accuracy (Fig 7(a)), OUR model maintained its lead throughout the entire training process, with its precision eventually stabilizing at around 0.92, significantly outperforming other models. Among them, the accuracy of YOLOv10s, YOLOv8s, and YOLOv11s reached a high level in the mid-to-late stages, but there was still a significant gap compared with the OUR model. Traditional models such as SSD and Faster-RCNN showed limited accuracy improvement throughout the entire training cycle, exhibiting significant performance bottlenecks.

In terms of recall (Fig 7(b)), OUR model also performed best, exceeding 0.9 after about 40 training iterations and remaining stable in subsequent iterations, indicating its higher completeness in detecting pests and diseases. YOLOv10s and YOLOv8s, as the current mainstream lightweight models, also showed strong recall capabilities, but their performance was slightly inferior under high-density target or occlusion conditions. In contrast, the recall rates of SSD and Faster-RCNN hovered between 0.7 and 0.78 for a long time, indicating that their adaptability to small targets and complex backgrounds was relatively weak.

Regarding the mean accuracy (Fig 7(c)), OUR model achieved an mAP of over 0.93 in the later stages of training, demonstrating the best performance among all models and exhibiting good stability and generalization ability. In contrast, the mAP of YOLOv10s and YOLOv8s remained stable at around 0.88 and 0.84, respectively. Although better than traditional models, their ability to represent multi-scale features and fine-grained targets in complex scenes is still insufficient, limiting further improvement in their detection performance. Models such as YOLOv9s and YOLOv11s performed only moderately, while models such as YOLOv5s, SSD, and Faster-RCNN consistently maintained an accuracy below 0.83, indicating their limited ability to model complex features in current agricultural images.

Fig 7. Training process curves. (a) Precision trend. (b) Recall trend. (c) mAP trend.

5.4 Test effects

Fig 8 shows the visualization results of the YOLOv10s basic model and the improved model (OUR) on four typical rice diseases: rice blast, bacterial leaf blight, sheath blight, and leaf spot. The visualization results provide a direct comparison of the differences between the different models in terms of target localization accuracy, confidence prediction, and small target recognition capabilities.

In rice blast images, YOLOv10s detected some lesion areas, but suffered from low confidence and missed detections. OUR model significantly improved the recognition confidence (e.g., prediction values reached 0.93 and 0.90) and completely covered all lesion areas, demonstrating stronger fine-grained recognition capabilities. In bacterial leaf blight samples, OUR model not only detected more targets but also more accurately located them, effectively alleviating the localization offset and missed detection issues of YOLOv10s in situations with dense multi-target populations. In images of rice sheath blight, both models can accurately identify lesion areas, but OUR model's predicted bounding box boundary fits the target contour better, and its confidence score (reaching a maximum of 0.93) is significantly higher than YOLOv10s, indicating that it models the structural features of striped lesions more comprehensively. In images of leaf spot, OUR model also shows a more sensitive response to small lesions, with a more complete number of detection boxes and higher confidence, effectively reducing the risk of false positives and false negatives under low contrast.

Fig 8. Visualization results of detection on typical rice diseases. (a) YOLOv10S. (b) OUR.

Fig 9 shows the visualization results of the YOLOv10s base model and the improved model (OUR) on three typical rice pests: rice stem borer, rice borer moth, and rice green bug. In the detection task of these three typical rice pests, OUR model outperforms YOLOv10s in terms of both localization accuracy and confidence level. Taking the rice stem borer as an example, although YOLOv10s can complete the recognition task, it suffers from bounding box offset and a low confidence level (0.84). In contrast, OUR model not only has a boundary highly consistent with the insect's outline, but also improves the confidence level to 0.93, demonstrating its advantage in modeling elongated insect structures. Similarly, in the detection of the rice borer moth , the detection box of YOLOv10s was relatively loose and had obvious redundant coverage, with a confidence level of only 0.84; while OUR model's boundary was closer to the actual insect body, with a confidence level increased to 0.94, demonstrating a stronger ability to perceive complex wing textures and blurred edges. For the rice green bug, a target with strong camouflage against a green background, YOLOv10s showed detection bias and insufficient confidence (0.86), while OUR model not only accurately located the target, but also improved the confidence level to 0.95, effectively enhancing robustness in low-contrast environments.

Fig 9. Visualization results of detection on typical rice pests. (a) YOLOv10S. (b) OUR.

The above experimental results fully verify the significant advantages of the improved YOLOv10s model proposed in this paper in the task of detecting rice diseases and pests. By introducing the SAConv module to enhance the spatial receptive field, the SEAM module to improve detail modeling capabilities, and the MPDIoU loss function to optimize bounding box regression accuracy, the model achieves simultaneous improvements in accuracy, recall, and mAP while maintaining efficient training convergence. In complex visual scenes such as blurred target edges, large scale variations, and dense target density, the improved model can more accurately and stably complete target localization and classification tasks, demonstrating superior comprehensive performance and engineering deployment potential, and providing more reliable technical support for intelligent crop health monitoring systems.

5.5 Discussion

This study aims to address the challenges of diverse types of rice pests and diseases, significant morphological differences, and frequent leaf occlusion in complex field environments by proposing a multi-structure improved model based on YOLOv10s. By introducing the SAConv, SEAM attention module, and MPDIoU regression loss function, the accuracy, localization precision, and robustness of pest and disease target detection are effectively improved without significantly increasing computational burden. The model outperforms mainstream detection algorithms such as YOLOv5s and YOLOv8s on several key performance indicators.

The introduced SAConv module enhances the model's ability to express multi-scale features of rice diseases and pests through multi-holes rate convolutional fusion and a learnable switching function mechanism, especially in samples with significant differences in the size of diseases and pests and blurred textures. The SEAM module further introduces a multi-scale attention mechanism in both spatial and channel dimensions, enabling the model to more accurately distinguish between disease and pest areas and background interference, and exhibits good adaptability and stability in situations with leaf occlusion and multiple targets adhering together. The combined use of both significantly improves the model's feature extraction ability and perceptual resolution in complex visual environments.

Furthermore, the MPDIoU loss function enhances the geometric consistency between the predicted and ground truth boxes by introducing a minimum distance constraint on the key points of the bounding box, thereby improving the accuracy of boundary fitting. Compared to CIoU, its optimization path is smoother, making it particularly suitable for targets with ambiguous boundaries and large scale differences, such as rice pests and diseases.

Ablation experiments and comparative experiments further demonstrate that SAConv, SEAM, and MPDIoU have a complementary effect in improving detection performance. The synergistic combination of the three enables the YOLOv10s model to achieve optimal performance in multiple metrics such as mAP, precision, recall, and FPS. Among them, mAP is improved to 93.1%, precision and recall reach 92.1% and 91.4% respectively, and the frame rate is maintained at 176.4 FPS, balancing the dual requirements of high accuracy and real-time performance.

It should be noted that although this study has achieved significant improvements in the accuracy and real-time performance of rice disease and pest detection, the current model still mainly relies on single-modal RGB image input. Under conditions such as extreme lighting, severe occlusion, complex reflections, and local low contrast, the detection performance may still be affected to some extent. More importantly, this study mainly verifies the effectiveness of the proposed model for detecting typical rice diseases and pests under single-modal RGB image conditions, but has not yet systematically evaluated the model's domain transfer performance under cross-regional, cross-variety, and cross-collection device conditions. Therefore, the current results reflect the model's effectiveness under given data distribution and experimental scenarios, while its broader cross-domain generalization ability still needs further verification with larger-scale, multi-source data.

Future research can be further developed in the following aspects: First, combine multimodal sensing information such as thermal infrared and hyperspectral to improve the model's target discrimination ability and anti-interference performance in complex environments; second, introduce three-dimensional structural modeling or temporal information analysis methods to enhance the understanding of dynamic pest targets and complex spatial distribution characteristics; third, based on the deployment needs of agricultural edge terminals, further research on model compression, network pruning, knowledge distillation, and inference acceleration can be carried out to improve the feasibility of model application on resource-constrained devices. Through the above work, it is hoped that the method proposed in this paper can be further promoted from laboratory verification to stable application in actual agricultural intelligent monitoring scenarios.

6 Conclusion

This study proposes a real-time detection method for rice diseases and pests based on an improved YOLOv10s model, aiming to solve the problems of low accuracy and poor real-time performance of traditional detection methods in complex field environments. The structural improvements and loss function optimization proposed in this study significantly improve the model's detection performance and engineering adaptability. The main conclusions are as follows:

(1) By introducing the SAConv module to enhance multi-scale spatial modeling capabilities and combining it with the SEAM module to improve the perception of disease and pest occlusion areas, significant breakthroughs have been achieved in feature extraction and representation.

(2) The MPDIoU loss function exhibits stronger geometric constraint capabilities in localization tasks, especially in scenarios such as blurred edges of pests and diseases, and multi-target adhesion, demonstrating higher localization accuracy and stability.

(3) On a dataset of 3100 images from multiple scenes and multiple pests and diseases, the improved model, while maintaining low computational cost (20.3 GFLOPs) and small parameter count (7.1 MB), achieved an mAP of 93.1% and an inference speed of 176.4 FPS, comprehensively outperforming mainstream algorithms such as YOLOv5s, YOLOv8s, and Faster-RCNN.

(4) The improved model has advantages such as high accuracy, fast speed and compact structure, providing a good model foundation and technical support for subsequent deployment in agricultural edge terminals such as field inspection vehicles and plant protection drones, showing strong engineering application potential and promotion value.

The proposed improved YOLOv10s model provides an efficient, accurate, and low-cost solution for intelligent identification of rice pests and diseases, which is of great significance for promoting the construction and application of intelligent monitoring systems for agricultural pests and diseases. Future development can further combine multi-source data fusion, lightweight deployment, and cross-variety transfer learning to expand the model's practicality and adaptability, providing solid support for the intelligent development of agriculture.

7 Author Contributions

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8 Data Availability Statement

Data is contained within the article or supplementary material.All relevant data are on Figshare: https://doi.org/10.6084/m9.figshare.32049591

References

1. Behnassi, M.; Baig, M.B.; Sraïri, M.T.; Alsheikh, A.A.; Risheh, A.W.A.A. Food Security and Climate-Climate Smart Food Systems—An Introduction. In Food Security and Climate-Smart Food Systems; Springer: Cham, Switzerland, 2022; pp. 1 – 13.

2. Falsafi, P.; Baig, M.B.; Reed, M.R.; Behnassi, M. The Nexus of Climate Change, Food Security, and Agricultural Extension in Islamic Republic of Iran. In Food Security and Climate-Smart Food Systems; Springer: Cham, Switzerland, 2022; pp. 241 – 261.

3. Zhang, Y.; Zhong, L.; Ding, Y.; Yu, H.; Zhai, Z. ResViT-Rice: A Deep Learning Model Combining Residual Module and Transformer Encoder for Accurate Detection of Rice Diseases. Agriculture 2023, 13, 1264.

4. Tilman, D.; Balzer, C.; Hill, J.; Befort, B.L. Global Food Demand and the Sustainable Intensification of Agriculture. Proc. Natl. Acad. Sci. USA 2011, 108, 20260 – 20264.

5. Yuen, K.W.; Hanh, T.T.; Quynh, V.D.; Switzer, A.D.; Teng, P.; Lee, J.S.H. Interacting effects of land-use change and natural hazards on rice agriculture in the Mekong and Red River deltas in Vietnam. Nat. Hazards Earth Syst. Sci. 2021, 21, 1473 – 1493.

6. Sekiya, N.; Nakajima, T.; Oizumi, N.; Kurosawa, C.; Tibanyendela, N.; Peter, M.A.; Natsuaki, K.T. Agronomic practices preventing local outbreaks of rice yellow mottle virus disease revealed by spatial autoregressive analysis. Agron. Sustain. Dev. 2022, 42, 1 – 15.

7. Ng, L.C.; Sariah, M.; Sariam, O.; Radziah, O.; Zainal Abidin, M.A. Bio-efficacy of microbial-fortified rice straw compost on rice blast disease severity, growth and yield of aerobic rice. Australas. Plant Pathol. 2012, 41, 541 – 549.

8. Chukwu, S.C.; Rafii, M.Y.; Ramlee, S.I.; Ismail, S.I.; Hasan, M.M.; Oladosu, Y.A.; Magaji, U.G.; Akos, I.; Olalekan, K.K. Bacterial leaf blight resistance in rice: A review of conventional breeding to molecular approach. Mol. Biol. Rep. 2019, 46, 1519 – 1532.

9. Chhabra, R.; Sharma, R.; Hunjan, M.S.; Sharma, V.K.; Sharma, P.; Chauhan, S.K. Microstructural and metabolic variations induced by Bipolaris oryzae inciting brown spot disease of rice. Cereal Res. Commun. 2023.

10. Barnwal, M.K.; Kotasthane, A.S.; Magculia, N.; Mukherjee, P.K.; Savary, S.; Sharma, A.K.; Singh, H.B.; Singh, U.; Sparks, A.H.; Variar, M.; et al. A review on crop losses, epidemiology and disease management of rice brown spot to identify research priorities and knowledge gaps. Eur. J. Plant Pathol. 2013, 136, 443 – 457.

11. Subedi, B.; Poudel, A.; Aryal, S. The Impact of Climate Change on Insect Pest Biology and Ecology: Implications for Pest Management Strategies, Crop Production, and Food Security. J. Agric. Food Res. 2023, 14, 100733.

12. Ahmad, I.; Yang, Y.; Yue, Y.; Ye, C.; Hassan, M.; Cheng, X.; Wu, Y.; Zhang, Y. Deep Learning Based Detector YOLOv5 for Identifying Insect Pests. Appl. Sci. 2022, 12, 10167.

13. Bari, B.S.; Islam, M.N.; Rashid, M.; Hasan, M.J.; Razman, M.A.M.; Musa, R.M.; Majeed, A.P.A. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. PeerJ Comput. Sci. 2021, 7, e432.

14. Wang, Y.; Wang, H.; Peng, Z. Rice diseases detection and classification using attention based neural network and bayesian optimization. Expert Syst. Appl. 2021, 178, 114770.

15. Yang, X.; He, Q.; Xie, X.; Dong, M. YOLO-RP: A Lightweight and Efficient Detection Method for Small Rice Pests in Complex Field Environments. Symmetry 2025, 17, 1598.

16. Zhao, C.J. Agricultural knowledge intelligent service technology: A review. Smart Agric. 2023, 5, 126 – 148, (In Chinese with English Abstract).

17. Cheng, X.; Zhang, Y.; Chen, Y.; Wu, Y.; Yue, Y. Pest Identification via Deep Residual Learning in Complex Background. Comput. Electron. Agric. 2017, 141, 351 – 356.

18. Masood, M.; Nawaz, M.; Nazir, T.; Javed, A.; Alkanhel, R.; Elmannai, H.; Dhahbi, S.; Bourouis, S. MaizeNet: A deep learning approach for effective recognition of maize plant leaf diseases. IEEE Access 2023, 11, 52862 – 52876.

19. De Rossi, R.L.; Guerra, F.A.; Plazas, M.C.; Vuletic, E.E.; Brücher, E.; Guerra, G.; Reis, E. Crop damage, economic losses, and the economic damage threshold for northern corn leaf blight. Crop Prot. 2022, 154, 105901.

20. Yang, S.; Xing, Z.; Wang, H.; Dong, X.; Gao, X.; Liu, Z.; Zhang, X.; Li, S.; Zhao, Y. Maize-YOLO: A new high-precision and real-time method for maize pest detection. Insects 2023, 14, 278.

21. Joshi, A.A.; Jadhav, B.D. Monitoring and controlling rice diseases using Image processing techniques. In Proceedings of the International Conference on Computing, Analytics and Security Trends (CAST), Pune, India, 19 – 21 December 2016; pp. 471 – 476.

22. Sun, Y.; Jiang, Z.; Zhang, L.; Dong, W.; Rao, Y. SLIC_SVM Based Leaf Diseases Saliency Map Extraction of Tea Plant. Comput. Electron. Agric. 2019, 157, 102 – 109.

23. Pantazi, X.E.; Moshou, D.; Tamouridou, A.A. Automated Leaf Disease Detection in Different Crop Species through Image Features Analysis and One Class Classifiers. Comput. Electron. Agric. 2019, 156, 96 – 104.

24. Bachhal, P.; Kukreja, V.; Ahuja, S.; Lilhore U.K.; Simaiya, S.; Bijalwan, A.; Alroobaea, R.; Algarni, S . Maize leaf disease recognition using PRF-SVM integration: a breakthrough technique. Scientific Reports, 2024, 14, 10219.

25. Xiong, H.T.; Li, J.; Wang, T.W.; Zhang, F.; Wang Z.Y .EResNet-SVM: an overfitting-relieved deep learning model for recognition of plant diseases and pests. Journal of the Science of Food and Agriculture, 2024, 104, 6018-6034.

26. Zheng, X.R.; Zheng, P.; Wang, W.X.; Cheng, Y.H.; Su, Y.F. Rice pest recognition based on multi-scale feature extraction depth residual network. South China Agric. Univ. 2023, 44, 438 – 446.

27. Guan, B.; Wu, Y.; Zhu, J.; Kong, J.; Dong, W. GC-Faster RCNN: The Object Detection Algorithm for Agricultural Pests Based on Improved Hybrid Attention Mechanism. Plants 2025, 14, 1106.

28. Haruna, Y.; Qin, S.; Mbyamm Kiki, M.J. An Improved Approach to Detection of Rice Leaf Disease with GAN-Based Data Augmentation Pipeline. Appl. Sci. 2023, 13, 1346.

29. Yin, Z.B.; Liu, F.Y.; Geng, H.; Xi, Y.J.; Zeng, D.B.; Si, C.J.; Shi, M.D. A High-Precision Jujube Disease Spot Detection Based on SSD during the Sorting Process. PLoS ONE 2024, 19, e0296314.

30. Lyu, Z.; Jin, H.; Zhen, T.; Sun, F.; Xu, H. Small Object Recognition Algorithm of Grain Pests Based on SSD Feature Fusion. IEEE Access 2021, 9, 43202–43213.

31. Fang, K.; Zhou, R.; Deng, N.; Li, C.; Zhu, X. RLDD-YOLOv11n: Research on rice leaf disease detection based on YOLOv11. Agronomy 2025, 15, 1266.

32. Qiang, J.; Zhao, L.; Wang, H.; Xu, T.; Jia, Q.; Sun, L. YOLO-PEST: a novel rice pest detection approach based on YOLOv5s. Plant Methods, 2025, 21(1): 121.

33. Pan, C.; Wang, S.; Wang, Y.; Liu, C. SSD-YOLO: a lightweight network for rice leaf disease detection. Computers and Electronics in Agriculture, 2025, 229: 108762.

34. Zhou, T.; Wei, L. YOLO-DP: A detection model of fifteen common rice diseases and pests. Comput Electron Agric, 2025, 15:35968.

35. Qiao, S.; Chen, L.; Yuille, A. Detectors: Detecting objects with recursive feature pyramid and switchable atrous convolution //Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2021: 10213-10224.

36. Yu, Z., Huang, H., Chen, W., Su, Y., Liu, Y., Wang, X. Yolo-facev2: A scale and occlusion aware face detector. Pattern Recognition, 2024, 155: 110714.

37. Siliang, M.; Yong, X. Mpdiou: A loss for efficient and accurate bounding box regression. arXiv 2023. arXiv preprint arXiv:2307.07662.