Intelligent Detection of Crop Pests and Diseases Based on Deep Learning: Rice Pests and Tomato Leaf Diseases

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Abstract. At the critical stage of the development of smart agriculture, integrating mechanical vision and deep learning technologies to achieve precise monitoring of tomato leaf diseases and rapid identification of rice pests is of great significance for enhancing agricultural production efficiency and ensuring food security. However, existing image recognition technologies face numerous challenges, such as difficulties in extracting image features under complex lighting conditions, poor recognition performance in multi-object and multi-scale scenarios, and large computational costs and low recognition accuracy due to blurred boundaries in dynamic images. There is an urgent need to construct intelligent solutions that can adapt to complex agricultural scenarios. This paper focuses on two specific application scenarios: rice pest and disease monitoring and tomato leaf disease monitoring, and evaluates the mainstream object detection models and their improvement schemes in recent years. The research mainly reviews the progress of improved models based on multiple versions of the YOLO series in the past half year. These improved models have effectively enhanced detection performance in complex environments by optimizing network structures (such as introducing lightweight designs and feature fusion mechanisms), providing new algorithmic ideas for addressing the aforementioned challenges.

Keywords: Deep learning, Rice disease detection, Tomato leaf disease detection, YOLO, Convolutional neural network.

1 Introduction

With the continuous improvement of global agricultural production intensification, precise prevention and control of crop diseases and pests have become a core link in ensuring food security and economic benefits. Tomatoes, as an important economic crop worldwide, have a wide variety of leaf diseases and often present multi-scale concurrent characteristics, such as early blight and late blight, with significantly different lesion morphologies. When these diseases occur simultaneously, it is easy to cause confusion in their characteristics, and traditional methods are difficult to achieve efficient identification. While rice is a staple food crop, there are over 200 types of pests and diseases. Moreover, its field environment is complex and the plant density is high, and pests (such as rice leafhoppers and second-generation rice borers) have the

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characteristics of being small in size (often less than 5mm), similar in shape, and aggregating in groups, making detection in dense backgrounds extremely difficult.

These two scenarios respectively represent the typical detection dilemmas of economic crops and staple food crops: Tomato diseases need to solve the problem of scale adaptability for multiple targets and multiple lesions; Rice pests need to break through the bottleneck of positioning and classification of tiny targets in complex backgrounds. This difference makes it difficult for a single technical route to be comprehensive, and it is urgent to systematically sort out the evolving paths of advanced algorithms.

In terms of technological development, detection methods based on deep learning are gradually replacing manual identification. For the challenge of small target detection in rice pests, researchers focus on feature enhancement and lightweight design: Ji Zhiyong et al. combined the CA attention mechanism with the BiFPN structure, significantly improving the feature capture ability of YOLOv5s for small targets, but increasing the computational complexity [1]; Gui Yupeng et al. optimized YOLOv8 through the context-guided module and depth separable convolution, achieving efficient deployment on mobile devices [2]; Li Xin [3] introduced polarized self-attention in YOLOv7-tiny, balancing the accuracy and speed for unbalanced samples [3]; Li Long et al. integrated the significant deformable convolution (SD_Conv) and the lightweight Slim-Neck into YOLOv8, achieving a balance between hardware compatibility and accuracy [4]. Wang Yanling et al. used the mature AlexNet for transfer learning on the ImageNet image dataset and proposed a method of fixing the underlying network and keeping the parameters unchanged, fine-tuning the parameters of the higher layers, with an average accuracy rate of 95.62% [5]. Wang Zhiqiang et al. proposed a hybrid model that integrates multi-scale features and coordinate attention mechanisms, improving the recognition accuracy to 94.11%, with a significant reduction in parameter quantity, achieving a reasonable and efficient balance between accuracy and computational cost [6]. This paper aims to systematically review deep learning technologies and the latest progress in crop and pest disease detection, focusing on the core challenges of specific scenarios such as the multi-scale and multi-target recognition of tomato diseases and the target detection and classification of rice pests in complex small targets. In response to existing methods, the differences in accuracy, efficiency, and scene adaptability. This paper focuses on analyzing the improvement strategies based on the YOLO series algorithms. And explores the application potential of technologies such as multi-scale transfer learning. By comparing the advantages and limitations of different technical routes. This paper aims to provide differentiated algorithm choices and optimization directions for precise pest control in crops and economic crops, promoting the development of efficient and lightweight detection models for practical agricultural scenarios. It provides theoretical support and practical paths for the large-scale application of intelligent pest detection in agriculture.

2 Rice Disease Detection Based on Deep Learning

2.1 Basic Information about Rice Diseases

As shown in Figure 1, brown planthoppers suck the sap of rice plants and spread viruses, causing severe damage to the plants. As shown in Figure 2, rice bugs pierce the grains with their mouthparts to suck the juice, resulting in empty grains or moldy grains. Regarding the leaves, as shown in Figure 3, leaf roller larvae often spin silk to wrap the leaves and hide within them to feed on the leaf flesh. As shown in Figure 4, the larvae of sand moths (or rice aphids) feed along the veins, causing the leaves to be incomplete. Moreover, as shown in Figure 5, the larvae of leaf rollers bore into the rolled leaves, and as shown in Figure 6, green leafhoppers also weaken the growth of the plants by sucking the sap of the leaves. In terms of diseases, as shown in Figure 7, rice blight can form brown spindle-shaped lesions and cause the leaves to die, and as shown in Figure 8, brown spot disease will also cause brown spots on the leaves, affecting photosynthesis.

Fig. 1. Brown planthopper [7].

Fig. 2. RiceBug [7].

Fig. 3. Leaf-folder [7].

Fig. 4. StemBorer [7].

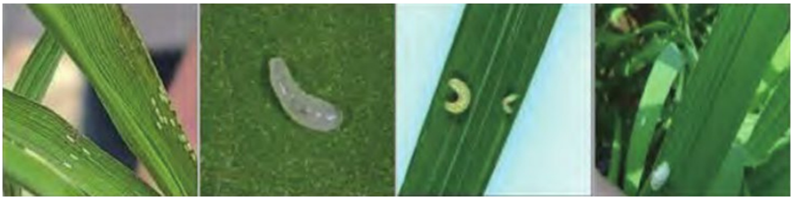

Fig. 5. WhorlMaggot [7].

Fig. 6. GreenLeafhopper [7].

Fig. 7. Rice blast [7].

Fig. 8. Brown spot [7].

2.2 Improved Model for Monitoring Rice Pests and Diseases

In response to the challenges of detecting rice pests in complex scenarios, Xiong Gan et al. proposed an improved algorithm QMDF-YOLOv11 based on YOLOv11. This model enhances multi-scale feature fusion by designing a lightweight neck network QS-RepGFPN, introducing dynamic convolution to improve geometric deformation adaptability, and adopts an adaptive fusion detection head QASFFHead to optimize cross-scale information interaction. On the RicePests dataset, QMDF-YOLOv11 achieved an mAP@0.5 of 94.57%, with a computational cost of only 8.4 GFLOPs and a parameter count of 4.29×10^6. It outperformed mainstream models such as YOLOv5s and YOLOv8s in terms of accuracy and lightweight design, especially maintaining strong robustness in severely occluded and low-light conditions [7]. To address the issues of complex backgrounds, large model computation and parameter quantities, and difficult deployment in real scenarios for rice pest recognition, Gui Yupeng et al. proposed a lightweight improved model YOLOv8-Rice. This model first replaces the original C2f module with a context-guided module (Context Guided Block) to jointly extract local features and global context, enhancing feature representation capabilities; then, it uses depthwise separable convolution to reduce computation and parameter quantities; and simultaneously employs GroupNorm2d normalization method to further improve the lightweight effect. Experiments show that YOLOv8-Rice maintains a high accuracy while increasing mAP@0.5 to 94.1%, with a parameter count of only 0.888M, a computational cost of 3.1 GFLOPs, significantly outperforming the original model, and is suitable for deployment on mobile and embedded devices [8]. To address the problems of weak feature extraction ability of lightweight models in rice disease detection, complex environments with low accuracy, and difficult deployment on edge devices, researchers proposed a lightweight recognition model YOLOv8-DiDL. This method enhances the capture ability of small target features through the introduction of the inverted residual mobile module (iRMB), improves adaptability to geometric deformations by using the C2f-DCNv2 module, and optimizes computational efficiency by using the DySample dynamic upsampling algorithm, while introducing the LSKA attention mechanism in the feature fusion part to strengthen multi-scale information extraction. Experiments show that this model achieves accuracy, recall rate, and mAP of 91.4%, 83.5%, and 90.8% respectively, significantly improving over the original YOLOv8, with a weight reduction of 97.8%, computational efficiency improvement of 7.4%, and excellent lightweight and real-time detection performance [9].

3 Tomato Leaf Disease Detection Based on Deep Learning

3.1 Basic Information about Tomato Leaf Diseases

Common diseases of tomato leaves include, as shown in Figure 9, bacterial spot disease, which initially presents as water-soaked small spots, gradually expanding into black-brown lesions. In humid conditions, it appears oily, dries out when dry, and can cause leaf yellowing and falling off; as shown in Figure 10, early blight occurs when water-soaked dark-brown lesions appear, expanding into nearly circular concentric patterns, easily causing premature leaf death, and a gray-black mold layer grows on the stem; as shown in Figure 11, late blight usually starts at the leaf tip or edge, presenting as dark-green water-soaked spots, turning brown and growing white mold on the underside of the leaf, and the stem becomes soft and wilted; as shown in Figure 12, leaf mold disease initially presents as pale yellow irregular spots, with white mold appearing on the back and gradually turning dark purple-black, affecting photosynthesis; as shown in Figure 13, leaf spot disease initially appears as small gray-white round spots, with dark brown edges, producing small black dots when humidity is high, and can cause continuous necrosis when severe; as shown in Figure 14, spider mite damage causes yellow-white spots on the leaf surface, expanding and causing leaf chlorosis and falling off, with the plant growth stunted; as shown in Figure 15, target spot disease initially presents as light-brown water-soaked small spots, expanding into circular or irregular shapes, with concentric patterns, and gray-brown depressions appear on the fruit surface; as shown in Figure 16, chlorosis curly leaf virus disease is manifested as smaller growth point leaves, yellowing and curling, leaf margins turning up, plant stunted, and significantly affecting fruiting; as shown in Figure 17, tomato mosaic virus disease is divided into mild mosaic and severe mosaic. The former has green mottling on the leaves but normal morphology, while the latter has yellow-green alternating patterns, deformity and distortion, stunted plants, and poor flower bud differentiation.

Fig. 9. Bacterial spot disease [10].

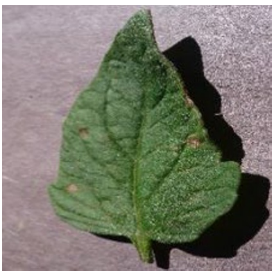

Fig. 10. Early disease [10].

Fig. 11. Late blight [10].

Fig. 12. Leaf rot disease [10].

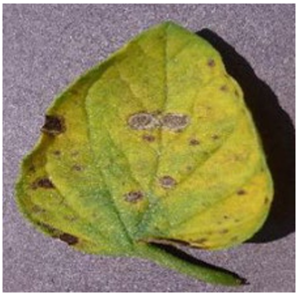

Fig. 13. Leaf spot disease [10].

Fig. 14. Spider mite damage [10].

Fig. 15. Target spot disease [10].

Fig. 16. Yellowing leaf virus disease [10].

Fig. 17. Tomato mosaic virus disease [10].

3.2 Improved Model for Identification and Detection of Tomato Leaf Diseases

In the tomato disease detection task, the YOLOv8sCBAM model enhances its ability to focus on the lesion areas and select features by introducing the CBAM attention mechanism at the key feature layers of the Backbone network. This significantly reduces the interference from complex backgrounds. The model performs exceptionally well in multiple metrics such as recall rate (0.973), precision rate (0.969), mAP@0.5 (0.991), and F1-score (0.970). It particularly demonstrates remarkable robustness in scenarios involving small target detection, concurrent multiple lesions, and occlusion.

Although the model's size increases slightly (24.6 MB), its overall detection accuracy is significantly improved compared to the baseline model, still meeting the requirements for lightweight deployment. In contrast, YOLOv11s achieves good balanced performance with a smaller model size (18.7 MB) and lower computational cost (mAP@0.5: 0.979; F1: 0.930), especially suitable for real-time inference on edge devices. Traditional two-stage models like Faster R-CNN have acceptable recall rates (0.943), but low precision rates (0.817), and are large (108 MB). SSD has severe missed detection problems (recall rate 0.432). None of these models can meet the dual requirements of light weight and high accuracy. To address the issues of small target missed detection, similar feature similarity among diseases, and scarce samples in tomato leaf disease detection, Hou Wenhui et al. proposed a detection model based on super-resolution enhancement and YOLOv8 improvement. This method first uses a super-resolution adversarial network to reconstruct the image, enhancing the features of small target diseases; then, it builds the G-YOLOv8 model, introducing a small target detection layer and triple attention mechanism (Triplet Attention), strengthening the perception ability for subtle differences; at the same time, it combines transfer learning and pre-training on public datasets to alleviate data insufficiency. Experiments show that super-resolution preprocessing increases the detection accuracy of YOLOv8 for early blight to 95.4%, compared to the original image by 4%; G-YOLOv8 achieves an average accuracy of 97.8% after transfer learning, 3.2% higher than that of the original YOLOv8, effectively improving the ability to identify small targets and distinguish multiple diseases [11].

4 Current Limitations and Future Prospects

4.1 Current Limitations

The current crop disease and pest detection technologies still face several key challenges: Firstly, the models have insufficient adaptability in complex scenarios, especially showing significant degradation in stability under conditions of varying light, foliage obstruction, and extremely low illumination; Secondly, in multi-target recognition tasks, such as when multiple disease spots accumulate on tomatoes or concurrent pest infestations occur in rice populations, there are often cases of missed detections and false detections, resulting in bottlenecks in recognition efficiency; Moreover, it is difficult to balance lightweight design and detection accuracy. While meeting the low-resource deployment requirements of embedded devices, this often leads to a decline in model performance and high migration costs across platforms.

4.2 Future Outlook

Although current research has achieved remarkable results, the implementation of smart agriculture still faces three major challenges. In the future, key breakthroughs are needed: enhancing the generalization ability in extreme environments. Existing models show significant performance degradation in low-light conditions (below 10 lux), heavy rainfall or high-density obstruction scenarios. It is necessary to develop multimodal fusion perception technology (such as infrared-visible light collaboration), combine physically enhanced synthetic data training, and construct a weather-resistant robust model. Lightweight deep innovation: Explore the joint optimization of neural architecture search (NAS) and hardware perception to achieve QMDF-YOLO at the 11th level of accuracy running in edge devices with less than 1W power consumption (such as solar pest monitoring stations); Develop cross-model distillation technology to transfer the knowledge of YOLOv8sCBAM to the YOLOv11s micro-architecture. Embedding agricultural prior knowledge: Transform the disease and pest pathogen expansion mode into geometric constraints (such as the equation of disease spot morphology evolution, the trajectory of pests movement), design physically guided attention mechanisms, reduce the reliance on labeled data, and enhance the model's generalization ability across crops and regions. Construction of ecological-level intelligent systems: Promote the upgrade of single-point detection technology to a "monitoring-warn-decision" closed loop, integrate unmanned aerial vehicle remote sensing, Internet of Things sensors and blockchain traceability, establish a spatiotemporal transmission prediction model for pests and diseases, and ultimately form a "precision perception-intelligent diagnosis-autonomous control" smart agriculture ecosystem.

This review reveals that the detection of crop diseases and pests is moving from algorithm optimization to in-depth scene exploration. The breakthrough points in the future lie in three dimensions: environmental adaptability, energy consumption limit compression, and agricultural knowledge integration. Only by breaking through the "innovation technology-agricultural laws-industrial demand" closed loop can deep learning truly take root in the fields and inject core momentum into global food security and agricultural sustainable development.

5 Conclusions

At the forefront of smart agriculture development, deep learning technology is leading the paradigm shift in the field of crop disease and pest detection. By simulating the diagnostic thinking of human experts, it builds a high-precision and high-efficiency intelligent protection system for important crops such as rice and tomatoes. Facing challenges such as small target volume, complex background, and group aggregation in rice pest detection, several advanced models have been proposed: QMDF-YOLO11 enhances multi-scale feature fusion through the QS-RepGFPN structure and improves detection robustness in complex environments using DySample dynamic upsampling; YOLOv8-Rice combines Context Guided Block with depthwise separable convolution to achieve efficient feature extraction and lightweight design, suitable for deployment on mobile terminals; YOLOv8-DiDL enhances small target recognition and geometric deformation adaptation capabilities by leveraging the inverted residual mobile module (iRMB) and deformable convolution (DCNv2). In the identification of tomato leaf diseases, QMDF-YOLO11 demonstrates excellent cross-scenario generalization ability and can accurately distinguish various diseases such as early blight and late blight; G-YOLOv8 integrates super-resolution generative adversarial networks (SRGAN) and a triple attention mechanism (Triplet Attention) to enhance the ability to identify subtle symptoms and adapt to geometric deformations through image enhancement and multi-dimensional feature focusing. These models not only significantly improve the accuracy of disease and pest detection but also provide key technical support for intelligent agricultural management and precise control. The significance of this research lies in systematically reviewing the disease and pest detection technologies for smart agriculture, providing feasible paths to solve core problems such as small target detection, complex background adaptation, and lightweight deployment, promoting algorithm performance improvement at the technical level, supporting precise pesticide application and crop management at the application level, and helping to reduce pesticide use and enhance the sustainability of agricultural production. With the continuous integration of deep learning and agricultural scenarios, crop disease and pest detection is continuously evolving towards practicality, intelligence, and systematization, providing important technical impetus for ensuring food security and promoting agricultural sustainable development.

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