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Research on Tea Disease Detection System Based on Improved YOLOv8

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Abstract: Aiming at the problems of low efficiency and poor accuracy of traditional tea pest and disease detection, this study constructs an improved detection system based on YOLOv8.By integrating FasterBlock, EMA multi-scale attention mechanism and BiFPN module, we combine migration learning and multi-scale training to improve the detection accuracy and robustness. The performance of the improved model is excellent, with mAP50 reaching 75.0% and mAP50-95 51.6%, with a small number of parameters and low computational complexity. Finally, the detection results are fed into DeepSeek to generate prevention and control recommendations. The improved model has excellent performance, and the detection results are connected to the DeepSeek large model knowledge base to automatically analyse and generate control recommendations, which provides powerful support for the management of tea plantations and promotes the intelligent development of the tea industry.

1. Introduction

China is the world's largest tea producer, with a wide area of tea cultivation and an annual output of about 280 million kg, and the tea industry has a pivotal position as one of the important agricultural pillar industries [1]. However, the problem of tea pests and diseases is still serious, and diseases such as anthracnose, white star disease, and tea cake disease occur frequently, which seriously affect the yield and quality of tea. Traditional pest and disease detection relies on manual observation, which is inefficient and inaccurate, and is easily interfered by factors such as ambient light and the lack of obvious early symptoms of diseases, resulting in frequent omissions and misdetections [2][3]. According to the Technical Regulations for Tea Production issued by the Ministry of Agriculture, improving the accuracy and real-time performance of pest and disease detection is crucial for safeguarding the quality of tea and improving yield [4]. Traditional methods are not only time-consuming and labour-intensive, but also costly, which cannot meet the needs of modern tea garden management.

In response to the national policy of modernisation and intelligent development of agriculture, this project is based on the improved YOLOv8 target detection algorithm, combined with FasterBlock, EMA multi-scale attention mechanism and BiFPN feature fusion module, to improve the accuracy and speed of tea disease detection. The model can accurately identify disease areas in complex backgrounds and optimise the amount of computation to meet the demand of real-time monitoring. By constructing an intelligent tea disease detection platform and accessing DeepSeek to automatically parse the detection results, it improves the management efficiency of tea gardens, reduces economic losses, promotes the intelligent development of the tea industry, and assists tea farmers in precise planting and disease control.

2. Related Work

In the field of plant pest and disease detection and diagnosis, traditional methods have achieved some research results. These methods usually use a combination of feature engineering and machine learning algorithms [5] for pest and disease detection and identification. In such methods, features such as colour, texture, shape, etc., are first extracted from plant pest and disease images, and then traditional machine learning algorithms (e.g., support vector machines, random forests, K-nearest neighbours, etc.) are used for classification and recognition. These methods improve the accuracy and efficiency of plant pest and disease detection to a certain extent and provide a scientific basis for pest and disease control.

In recent years, a large number of studies have confirmed the effectiveness of deep learning methods in plant disease and pest detection. Many researchers have utilised deep learning methods for target detection of plant diseases, usually based on one-stage target detection algorithms and two-stage target detection algorithms with improvements. One-stage target detection methods detect and identify objects in an image through a single forward propagation network, such as YOLO [6] and SSD [7], etc. In 2021, Fang L [8] et al. used MobileNetV2 as the backbone network for ginger seedling orientation detection based on the YOLOv4-Lite model, replacing some of the traditional convolutions with Do-Conv convolutions, and the detection In 2022, Yin Xianbo et al [9] used YOLOX-Nano as the base network to improve citrus new shoot detection and shoot stage identification. By using multiple attention mechanisms to optimise the Focus module, SPP module and PAFPN module, the model recognition classification accuracy is improved. At the same time, a multivariate orchard pre-training dataset was constructed for migration learning to achieve an average AP value of 88.07% for each category.2022 In 2022, Hu K. et al [10] proposed an improved SSD algorithm for the detection of pests and diseases of wide Buddha's hand, which used ResNet50 to replace VGG16 as the backbone network, and added a lightweight and efficient feature fusion module in front of the predictive feature layer. The experimental results show that the improved algorithm has an average accuracy of 92.86%, which is 6.61% higher than the original SSD. These studies show that the application of deep learning technology in the field of plant pest and disease detection has great potential. By continuously improving and optimising deep learning algorithms, this paper can look forward to achieving more efficient and intelligent solutions in plant pest and disease detection and treatment in the future.

3. Model Theory

This project proposes an intelligent detection system for tea pests and diseases based on improved YOLOv8, aiming to improve the recognition accuracy and efficiency of tea pests and diseases by combining multi-scale feature extraction, real-time detection techniques and optimisation of the deep learning model YOLO. The core module includes YOLOv8-based target detection algorithm, FasterBlock structure, EMA multi-scale attention mechanism and BiFPN feature fusion module to optimise the computational performance and real-time performance of the tea pest and disease detection model. Through the training of large-scale tea pest and disease image data, we solve the problem of pest and disease recognition in complex environments, so as to achieve fast, accurate and low-cost automatic detection of tea pest and disease. Ultimately, a set of intelligent tea pest and disease monitoring platform is constructed to improve the intelligent level of tea garden management, help the development of precision agriculture, reduce pest and disease losses in tea production, and promote the process of agricultural modernisation.

3.1 Data Acquisition and Pre-processing

The system constructs diverse datasets by collecting image data of tea pests and diseases, including images of different kinds of pests and diseases and healthy tea. The preprocessing process includes steps such as denoising, image enhancement, size unification, data normalisation, and background removal to ensure that the image quality is suitable for deep learning model training. Meanwhile, image annotation tools were used to manually mark the pest areas to provide accurate labelled data for training the YOLOv8 model. Data enhancement techniques, such as rotation, scaling, and flipping, were used to increase the diversity of the data and improve the robustness and generalisation of the model.

3.2 Model Construction and Training

3.2.1 YOLOv8 Network Model

YOLOv8 is the smallest network model in the latest YOLO v8 series of models, which is divided into five different model versions based on the depth and width of the network structure: *n*, *s*, *m*, *l*, and *x*. The structure of YOLOv8 consists of four main parts: the input side, the backbone network, the neck, and the output side, as shown in Fig. 1. The input side performs data preprocessing, including operations such as data enhancement, adaptive anchor frames and image scaling. The backbone network, compared to YOLOv5, replaces the C3 module with the C2f module, which enhances the feature fusion ability of the convolutional neural network through a dense residual structure, and adjusts the number of channels through the splitting and splicing operations, thus making the backbone network more lightweight and improving the inference speed. The tail uses SPPF (Spatial Pyramid Pooling Layer) to enhance the sensory field of the backbone network while fusing features at different scales. The neck structure uses PANet and C2f modules for feature aggregation to efficiently transfer shallow information to deeper layers. The output uses a decoupled head structure for detection and classification of objects at different scales through three decoupled heads, p3, p4 and p5.

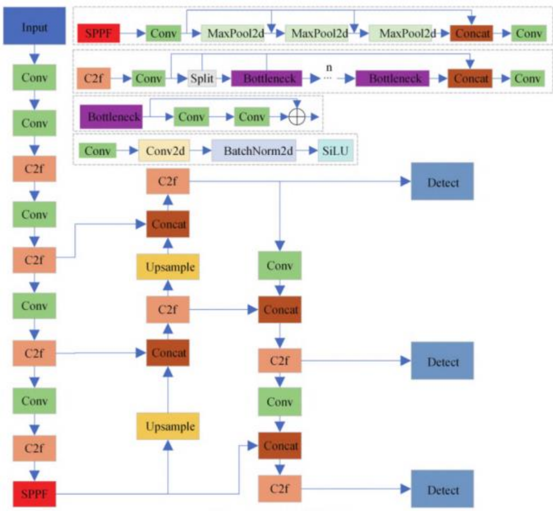

Figure 1: YOLO v8 Network Architecture

This project is improved based on YOLO v8, as shown in Figure 2. Firstly, the FasterBlock and EMA are integrated into the Faster_EMA module, which replaces the BottleNeck module in C2f to form the C2f_Faster_EMA module, thus replacing all the C2f modules in the original network. Next, the neck network was replaced with the improved neck network of this project and the Fusion parameter was set to the BiFPN structure adopted in this project. With these improvements, the performance of the model in terms of feature extraction and segmentation accuracy was enhanced.

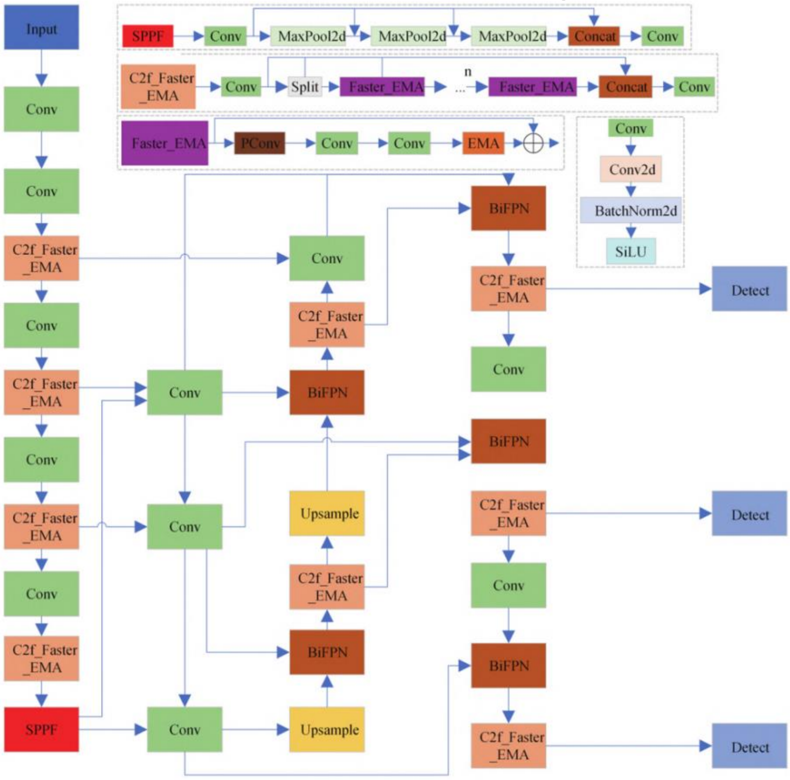

Figure 2: YOLO v8-Tea Network Architecture

The YOLO v8-Tea network architecture model has the following three innovations in network architecture:

3.2.2 Introducing the FasterBlock Module

The structure of the FasterBlock module is shown in Fig. 3, where spatial feature extraction is first performed by a Ponv convolutional layer. Unlike conventional convolution, the Ponv convolutional layer performs conventional convolutional operations on only a portion of the input channel, thus effectively reducing the computation and memory access of subsequent convolutional layers.

Next, the FasterBlock module includes two 1×1 convolutional layers. The first 1×1 convolutional layer serves to reduce the number of feature channels, which in turn reduces the computational cost and the number of parameters, while the second 1×1 convolutional layer is used to adjust the number of feature channels to ensure that the input and output dimensions are the same, facilitating the subsequent residual join operations. The module also performs normalisation and activation function operations to introduce non-linear properties, enabling the model to learn more complex feature transformations.

By introducing the FasterBlock module, this project significantly reduces the number of parameters and computation of the model, while improving the detection accuracy. The experimental results verify the effectiveness of the module in improving the performance of the model and effectively increase the computational efficiency of the model.

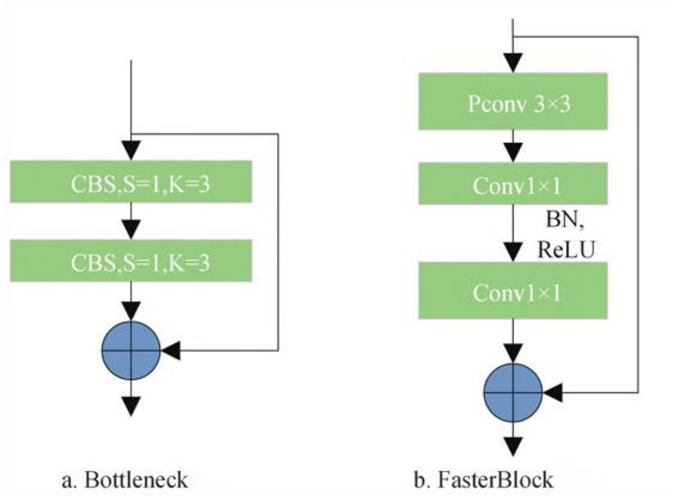

Figure 3: Bottleneck and FasterBlock structure

3.2.3 Introduction of the EMA Attention Mechanism

In model construction and training, in order to enhance the interaction between channels and spatial locations and to reduce the complexity, this project introduces the EMA attention module in YOLO v8, which is shown in Fig. 4 and contains three parts: feature grouping, parallel subnetting and cross-space learning.

a) Feature grouping: divide the input feature map channel into g sub-feature groups to extract richer semantic information and enhance feature expression.

b) Parallel sub-network: sub-features are processed through three parallel paths: two 1×1 convolutional branches perform global average pooling along the spatial direction, respectively, and then connect with atomic feature residuals to aggregate multi-scale spatial information through shared weights convolution and Sigmoid activation; and a 3×3 convolutional branch captures the local cross-channel interactions to expand the feature space and enable fast response.

c) Cross-space learning: aggregating the outputs of two 1×1 convolutional branches and one 3×3 convolutional branch, generating two spatial attention feature maps via group normalisation, global average pooling and Softmax function, and finally aggregating the weights via a Sigmoid function to capture the pixel-level relationships and emphasise the global contextual information.

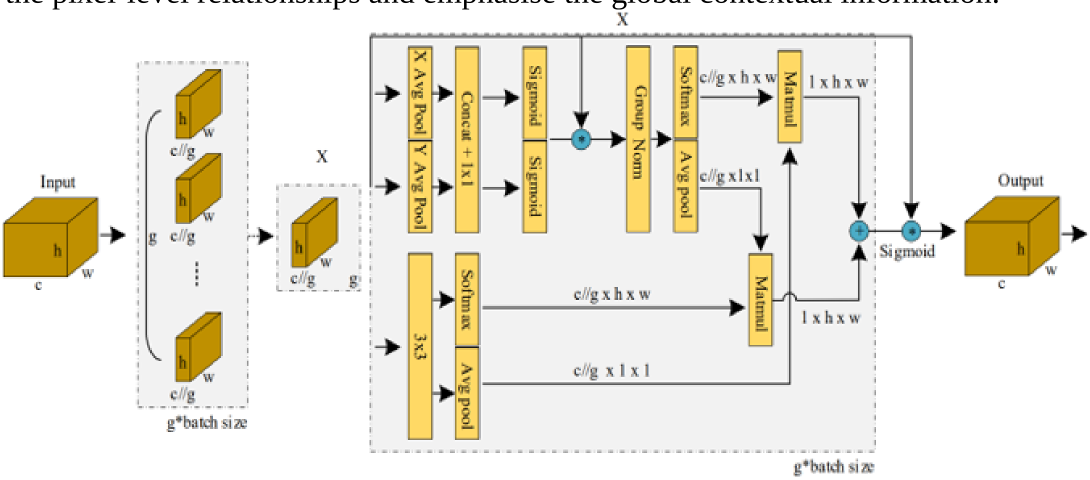

Figure 4: EMA structure

3.2.4 BiFPN Structure

This project innovatively introduces the BiFPN structure as an optimisation scheme to address the complexity of PA-Net in Feature Pyramid Networks (FPNs). Although PA-Net can theoretically improve the performance of FPNs, its multipath selection mechanism and path weighting component significantly increase the model complexity and computational overhead, especially in the scenario of limited hardware resources, the training efficiency and deployment feasibility are greatly limited. In particular, in scenarios with limited hardware resources, the training efficiency and deployment feasibility are greatly restricted. To solve this problem, BiFPN streamlines the design of the feature pyramid network through the adaptive connection weighting strategy, which not only effectively reduces the model complexity, but also simplifies the process of parameter tuning, and significantly improves the operation efficiency of the model in resource-constrained environments, as shown in Figure 5.

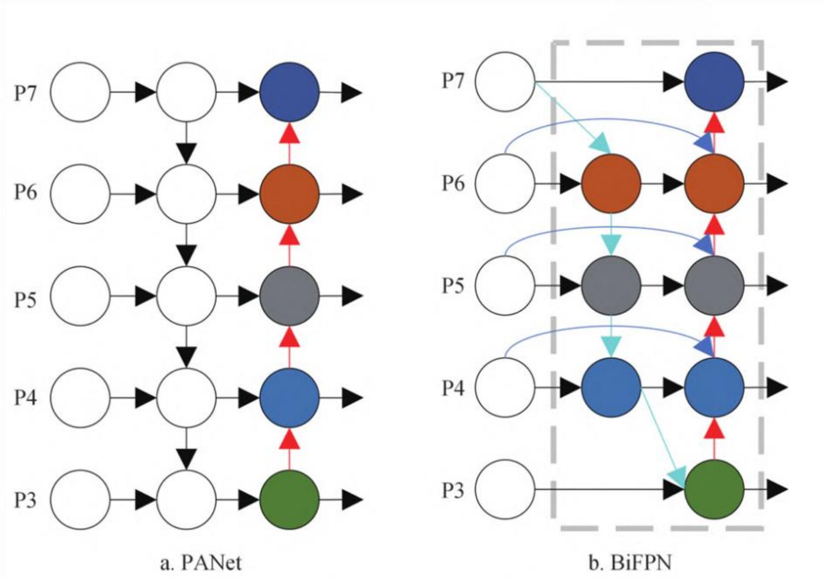

Figure 5: PANet and BiFPN structures

3.2.5 Improvement of Neck Network

In the model construction and training section, to address the limitations of the neck network in the original YOLO v8 network, this project improves it to enhance the model's flexibility and multi-scale sensing capability. The original neck network lacks effective processing for complex tasks and multi-scale features, resulting in performance degradation.

In order to adapt to the task of tea disease detection, the neck network was optimised in this project as follows:

a) Fixed number of channels: fixes the number of channels in the neck network to 256 for all channels, ensuring uniformity and simplifying operations.

b) Adding Convolutional Layers: Add 3 convolutional layers to unify the number of channels of different output layers (p2, p3, p4, p5) in the backbone network to improve the feature fusion effect.

c) Multi-scale perception enhancement: further exploiting p2 features through convolutional layers to enhance the multi-scale perception capability of the model.

d) BiFPN fusion: BiFPN structure is used for feature fusion to improve the perception of targets at different scales.

4. Result and Discussion

Compared with other models, YOLOv8 excels in performance and efficiency. Its mAP50 and mAP50-95 reach 75.0% and 51.6%, respectively, with outstanding detection accuracy. Meanwhile, the number of model parameters is only 1.567 M, and the computational complexity is 5.8 G, which is 45.2% less than the weight of the original YOLOv8, which significantly improves the lightweight and deployment efficiency. YOLO v8 becomes an efficient and lightweight target detection algorithm, which is suitable for real-time monitoring scenarios. Figure 6 demonstrates its practical effect in tea pest detection, which verifies its high accuracy and practicality, and provides reliable support for intelligent monitoring. Figure 7 demonstrates the specific identification results of the tea pest detection system, which originated from an interface development in the preliminary work, and intuitively presents the performance of the system in practical applications.

Figure 6: Tea pest and disease detection results

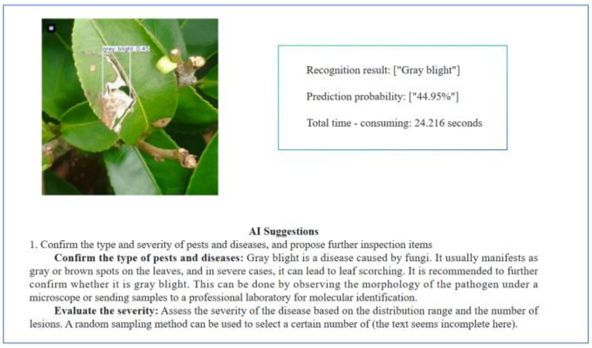

Figure 7: Green Leaf Escort Tea Pest and Disease Detection System

In this paper, YOLOv8 is used as the core detection model for pest and disease detection, with the aid of transfer learning technology for pest and disease detection tasks, while combining multi-scale training methods, so that the model can adapt to different sizes and angles of pest and disease targets, thus effectively improving the accuracy and robustness of detection. In the processing of detection results, this paper will process the results of real-time access to the large model knowledge base DeepSeek, the system automatically parses the detection information, generates detailed characteristics of pests and diseases, and combines with the knowledge base of agricultural experts to provide accurate prevention and control recommendations, and ultimately form an intelligent analysis report, which will help users to make decisions quickly.

5. Conclusion

In this study, the improved YOLOv8 algorithm is used to build a tea disease detection system with significant results. Through the integration of FasterBlock, EMA multi-scale attention mechanism and other technologies, the optimised model has high detection accuracy, small computational volume, and can accurately identify diseases in complex backgrounds, and also combines migration learning and multi-scale training to improve the model adaptability, and the results of the detection with the help of DeepSeek large model to generate intelligent reports, which can provide a strong support for prevention and control.

However, in the actual tea garden environment, factors such as light changes and differences in tea varieties will reduce the model's detection accuracy, and its generalisation ability still needs to be strengthened; in the face of the complexity of multiple concurrent diseases, the detection accuracy also needs to be improved. Subsequent research will focus on optimising the model structure, exploring new modules to enhance the model performance in complex environments; expanding and optimising the dataset to cover more images of tea pests and diseases under different conditions, so as to enhance the adaptability of the model; and researching the detection technology of concurrent multiple pests and diseases, combining with the multimodal data, so as to make the results of the detection more accurate and reliable, and to assist in the intelligent upgrading of the tea industry.

Acknowledgement

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