Lightweight Model for Wheat Disease Detection

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As technology evolves, mobile devices are becoming more sophisticated. Lightweight networks have great potential and advantages in agricultural disease detection. The lightweight network model has the characteristics of high precision, few parameters, and high computing cost, and can serve scenarios with limited computing resources such as mobile devices and embedded systems.

Keywords: Wheat disease detection ; Lightweight models

1. Introduction

Wheat disease detection is crucial for disease diagnosis, pesticide application optimization, disease control, and wheat yield and quality improvement. However, the detection of wheat diseases is difficult due to their various types. Detecting wheat diseases in complex fields is also challenging. Traditional models are difficult to apply to mobile devices because they have large parameters, and high computation and resource requirements.

2.The Significance of Wheat Disease Detection

According to statistics, China's wheat cultivation area in 2022 was about 22.962 million hectares, with a production of 135.76 million tons, accounting for about 18% of the world's total wheat production. Wheat has high nutritional value and contains abundant carbohydrates, fats, and proteins, and many other substances essential for human survival. Wheat yield and quality are largely affected by diseases. The decline in wheat yield not only causes economic losses but also jeopardizes human life. Nowadays, the world's population is still growing and human dietary demands are rising, so it is necessary to improve the quality and yield of wheat to meet human material needs [1][2][3][4].

Wheat powdery mildew, wheat rust, and wheat leaf blight are typical and severe wheat diseases [5]. Due to these diseases, the wheat yield has been reduced by nearly one-third, bringing huge damage to food security and the agricultural economy. Controlling crop diseases has become a serious challenge. Disease detection and identification have become a vital research field for improving the high yield and quality of the crop [6].

3.. Disease Identification in Wheat Based on Machine Learning and Deep Learning

In the early years, the detection of wheat diseases was mainly performed by manual inspection and identification, but manual identification had problems such as subjectivity, low efficiency, and low accuracy. With the development of technology, spectral analysis, machine learning, and deep learning are now widely used for wheat disease detection. Zhang et al. [7] used hyperspectral remote sensing to detect and distinguish yellow rust from nutrient stress. They detected yellow rust and mapped its spatial distribution based on the physiological reflex index PhRI. The proposed smart agriculture has motivated the use of various machine learning algorithms for the detection of wheat diseases. Using hyperspectral wheat images and classification regression trees to identify the severity of powdery mildew, Zhang et al. [8] achieved more than 87.8% identification of disease infection levels, but they had inaccurate identification of mildly infected wheat with a high probability of this being mistaken for healthy or moderately infected leaves. To enable early detection, prevention, and control of crop diseases, Khan et al. [9] proposed a least squares regression model to detect early wheat disease severity with an overall accuracy of more than 82.35%. However, the high cost of hyperspectral equipment makes it difficult for the average farmer to afford it. Wang et al. [10] used spectral data and established a combined model to detect and identify wheat stripe rust and wheat leaf rust, with an overall identification accuracy of 82% on a test set. However, the model's recognition accuracy is bound to decrease unless the influence of various factors such as weather, soil, and complex background on the spectral data is eliminated or attenuated. Bao et al. [11] proposed an algorithm for identifying leaf diseases and their severity. First, they segmented the wheat disease images to obtain disease spot features, and then they recognized the segmented diseases and their severity with a maximum recognition accuracy of 94.16%. This makes an important contribution to the intelligent recognition of wheat leaf diseases.

In recent years, computer vision and deep learning have been used to detect crop diseases. Aboneh et al. [12] collected and labeled wheat disease image data and used five deep learning models to identify wheat diseases, and they found that the VGG19 model had the highest classification accuracy after experimental comparison. Liu et al. [13] introduced a two-layer inception structure and cosine similarity convolution into a normal convolution block. The proposed model achieved 97.54% accuracy for buckwheat disease detection. However, the inclusion of the inception structure also increases the time consumption. Jin et al. [14] focused on the generalization capability of the model as the first consideration, shaped wheat head spectral data into two-dimensional data, and fed it into a hybrid neural network, which achieved an accuracy of 84.6% on the validation dataset. This pushed the development of large-scale crop disease detection. To address the low accuracy of traditional methods, Deng et al. [15] used the Segformer algorithm to segment the stripe rust disease images, and the performance of the model was greatly improved after the data were enhanced. Nevertheless, this method only applies to fall wheat diseases. Su et al. [16] proposed an integrated Mask-RCNN-based FHB severity assessment method for high-throughput wheat spike identification and the accurate segmentation of FHB infestation under complex field conditions, which can help in the selection of disease-resistant wheat varieties. To effectively prevent the damage of yellow rust, SHAFI et al. [17] conducted a classification study on the types of wheat yellow rust infection and deployed the ResNet-50 model on smart edge devices to detect the severity of yellow rust. Obtaining high-resolution, low-cost, and large-coverage remote sensing data through drones can improve the accuracy and efficiency of disease identification. Huang et al. [18], using UAV remote sensing technology to identify and detect wheat leaf spot, significantly improved the efficiency of disease monitoring. Considering the large amount of effort required for data annotation, Pan et al. [19] proposed a weakly supervised method for detecting yellow showers disease of wheat photographed by UAV with 98% accuracy. Some diseases are difficult to detect without prominent characteristics. To improve the recognition of disease features, Mi et al. [20] introduced the CBAM module based on DenseNet and achieved 97.99% test accuracy on the wheat stripe rust dataset. However, the above mentioned methods have complex models and large computational volumes that are difficult to port to mobile devices. To reduce the model parameters and computational effort, Bao et al. [21] proposed a lightweight SimpleNet model with an accuracy of 94.1%. Adding the CBAM attention mechanism to the inverted residual blocks of this model made the wheat ear disease information more significant. However, this method is not applicable to other crop images.

4. The Advantages of Lightweight Models in Wheat Disease Detection and the Work of This

With the development of technology, mobile devices are becoming more and more mature. Mobile devices can use computer vision technology to intelligently identify and diagnose crop diseases from the leaves, determine the type and severity of diseases, and provide farmers with timely suggestions for prevention and control. Therefore, lightweight networks have great potential and advantages in agricultural disease detection. Lightweight network models have the characteristics of high accuracy, low parameter numbers, and computational costs, and can serve scenarios with limited computing resources such as mobile devices and embedded systems. For example, without the need for professionals or laboratory equipment, smartphones or other portable devices can be used for testing, provide reasonable suggestions for prevention and control based on the test results, and interact with human experts or other data sources to improve control effectiveness and agricultural productivity. There is no doubt that the methods summarized above have achieved favorable results in wheat disease detection. However, these methods also have some limitations, such as hyperspectral remote sensing technology having high accuracy in disease detection but requiring very expensive equipment; large-scale network models being effective in disease detection but being difficult to run on mobile devices; environmental factors such as wind, temperature, and humidity that can affect the flight stability and safety of drones; the types of diseases studied being relatively limited, and the research on wheat disease detection under complex backgrounds being insufficient; and the coexistence of multiple different diseases and occluded diseases that are difficult to identify.

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