International Journal of Applied Science and Engineering

WeChat mini program for wheat diseases recognition based on VGG-16 convolutional neural network

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ABSTRACT

To solve the problem of pesticide misuse in judging common wheat diseases, we propose a wheat disease identification scheme combining the VGG convolutional neural network model with WeChat mini program technology. In the model training process, we continuously adjust the structure of the convolutional neural network VGG-16 to realize the real-time and accurate identification model of wheat disease. Specifically, the model parameters are optimized by locally adjusting the convolution layer of the VGG-16 network to achieve accurate maximization. Through the verification, the best accuracy rate of the wheat disease identification model is 85.1%. The mini program is compiled by the WeChat developer tool, which is developed based on WXML, WXSS and JavaScript. After building the wheat disease identification model, it is deployed on a cloud server that works continuously for working 24 h a day. In addition, the mini program posts HTTPS requests as the function of wheat disease identification. The implementation of this scheme can help users identify different types of wheat diseases and provide corresponding solutions according to the results, which is of great significance in underdeveloped agricultural areas.

Keywords: Wheat disease detection, Image identification, WeChat mini program, VGG-16, Convolutional neural network.

OPEN ACCESS

Received: April 16, 2023
Revised: May 12, 2023
Accepted: June 8, 2023

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Publisher:
Chaoyang University of Technology
ISSN: 1727-2394 (Print)
ISSN: 1727-7841 (Online)

1. INTRODUCTION

Wheat is one of the most important grain crops in China. Based on the strategic consideration of food security and constant changes in the international situation, it is necessary to put forward higher requirements for the stability of domestic grain production. Wheat disease is a distracting thing in agriculture because it affects the quantity and quality of crops. Usually, to overcome disease problems in wheat plants, farmers subconsciously spray pesticides on plants to eradicate pests, weeds, insects and other factors (Shahid et al., 2017; Andrianto et al., 2020; Yin et al., 2020). However, direct spraying of pesticides without a diagnosis of crop disease may not reduce the severity of crop disease. Pesticide sprays will not be efficient in controlling plant disease if they are not done through appropriate methods (Shah et al., 2016; Laghari et al., 2018; Karim et al., 2022). Understanding plant appearance, symptoms, and the life cycle is key to successful control process. Besides, if the pesticide spraying is excessive (Wang et al., 2020), it will pollute the environment and be harmful to the health of humans. Farmers protect their crops from disease through direct observation or consulting agricultural experts (Durmuşet al., 2017). However, these behaviors are time-consuming, laborious, and sometimes less accurate (Shruthi et al., 2019). In this case, AI technology is very important in sustainable agriculture to increase agricultural yields. Technological continuous breakthroughs in artificial intelligence ensure low-diseased agriculture is possible (Ai et al., 2020; Yin and Li, 2020; Zhong et al., 2020; Khakimov et al., 2022; Vallabhajosyula et al., 2022). However, the above methods have some disadvantages such as low effectiveness, time-consuming. So we propose a wheat disease identification scheme combining the VGG convolutional neural network model with WeChat mini program technology. In the model training process, we continuously adjust the structure of the convolutional neural network VGG-16 to realize the real-time and accurate identification model of wheat disease. Specifically, the model parameters are optimized by locally adjusting the convolution layer of the VGG-16 network to achieve accurate maximization.

This paper is organized as follows. In Section 2, we give the related works. Section 3 introduces the proposed method in detail. Experiments are conducted in Section 4. There is a conclusion in Section 5.

2. RELATED RESEARCH

In recent years, CNN (Convolutional Neural Network) has been widely used in various sectors, such as face recognition, image classification, voice recognition, and smart agriculture etc. With the development of machine learning and deep learning technology, plant disease detection can be done automatically by a deep learning methodology (Singh et al., 2022). Several studies regarding the use of machine learning to detect diseases in rice have been conducted (Burhan et al., 2020; Khan et al., 2022; Subramanian et al., 2022).

However, there are some problems that need to be studied. On the one hand, most of the studies aim at rice diseases, wheat also is an important food crop and plays an irreplaceable role in the food family. There are just a few cases involving wheat diseases (Lu et al., 2017; Figueroa et al., 2018). On the other hand, mini-programs that rely on mobile operating systems or mobile applications have the characteristics of rapid development and convenient use. It can be well combined with machine learning (Hao et al., 2018). But previous studies have not been concerned with the development of smartphone mini-programs as plant disease detection devices on the client side and machine-learning applications on the server side. In this research, we have developed a WeChat mini program and a wheat disease recognition model for the wheat plant disease. It is believed that this new method can effectively help farmers provide a new inspiration for the implementation of machine-learning technology.

3. RESEARCH METHOD

The development framework of the WeChat mini program is based on the MINA framework. MINA is a network communication application framework based on Java technology. Compared with the traditional mobile client App, the WeChat mini program has simpler system architecture and simpler page code (Li, 2017). The execution for developing a WeChat mini program for the detection of wheat plant disease based on deep learning consists of three steps, namely, uploading an image from the phone's camera or album, posting images to a remote model, and modeling sent results. Fig. 1 shows the proposed scheme in this study.

3.1 The Wheat Disease Detection System Architecture

The wheat disease detection system architecture consists of extracting wheat plant image features, modeling on the cloud server, and a plant disease detection WeChat mini program on smartphones. The training result model in the cloud server is used to process wheat disease feature information images. The wheat plant disease detection application on a smartphone will take wheat images through the camera or album on the smartphone, then send the image to the platform on the cloud server. The platform will process images and send classification results of wheat plant disease types to the WeChat mini program. It will receive the information and display it.

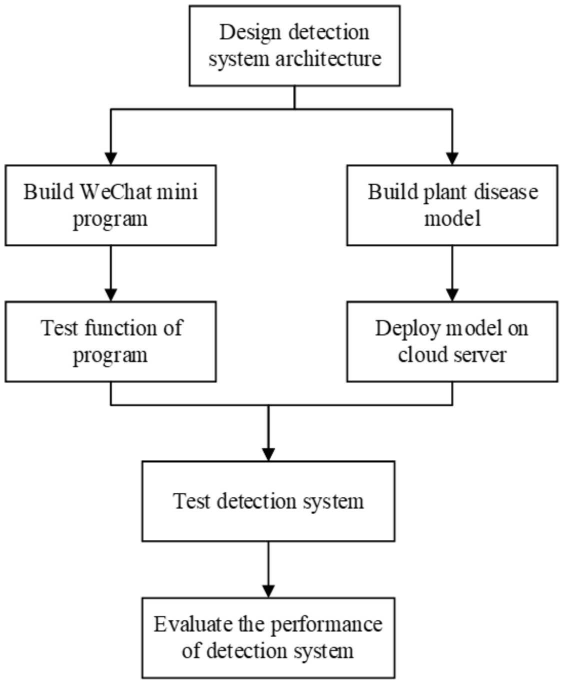

Fig. 1. The design of disease identification system

3.2 Application on Cloud Server and WeChat Mini Program

Application to detect diseases in wheat plants is divided into two parts, cloud server application running the model and WeChat mini program sending the image to the server. The cloud server application is built by Flask and Nginx. Flask, a Python framework, is useful for running plant disease identification models. Nginx is a highly reliable Web and reverses proxy server that can run almost 24 h one day. In this experiment, Nginx is the medium between WeChat applets and the Flask framework. It receives requests from applets and forwards information to the model of identification service built by the Flask framework, and vice versa. Meanwhile, the mobile terminal is built using the WeChat mini program that is used as a tool to get crop image input using the camera or photo in the phone which will be sent to the cloud server application in the form of Base64. Then the cloud server performs plant disease predictions on the input image and sends the results to the WeChat mini program. It describes the specific process in Fig. 2 and Fig. 3.

3.3 Research of VGG

Simonyan and Zisserman (2014) proposed the VGG model to improve its feature extraction capability by increasing the model depth and stacking small kernel convolutions. Many researches are based on the VGG model to explore the influence of neural network depth on its accuracy. Badrinarayana et al. (2015) proposed SegNet base on the VGG model, which was a deep evolutionary encoder-decoder architecture for image segmentation. It has played an important role in solving image semantic segmentation of automatic driving or intelligent robots. Girshick (2015) proposed Fast Region-based Convolutional Network (Fast R-CNN) method for object detection. It could efficiently classify object proposals using deep convolutional networks.

VGG-16 has 13 convolutional layers, 4 maximum pooling layers, and 3 fully connected layers, and the parameter amount is approximately 14728266. Compared with the latest network, VGG-16 has many features such as simple bottleneck structure, regular design, and stackable convolution blocks. Fig. 4 reflects the specific structure and identification process of VGG-16.

3.4 Data Set Preparation

The data source of the experiment is the Agricultural Disease and Insect Pest Research Library which is an agricultural disease and insect image sample resource constructed by the Chinese Academy of Sciences in conjunction with multiple departments. Each disease or insect has thousands of high-quality images, which can provide the samples needed for machine learning modeling for crop disease image recognition and research (Nagasubramanian et al., 2021). We select a wheat disease data set from IDADP that contains five common diseases of wheat. They are leaf rust, powdery mildew, scab, leaf blight, and stripe rust. The sample images are shown in Fig. 5. In order to ensure the accuracy of the experiment, we also select some images from Kaggle. The image number of wheat disease used for the test set and training set is shown in Table 1.

3.5 Experiment of Training Strategy

The network weight parameters trained by a large number of data sets are transferred to our tiny-tuned VGG-16 network for training. To reduce interference with image quality, we preprocess them to eliminate the useless information in the data set.

1. Loading the pre-training model. We keep the convolutional layer parameters in the original model and set the pooling layer 2 × 2 window size as the initial parameters.
2. Setting the parameters. Learning rate = 0.0001 and batch_size = 16. The workout count is set to 5 epochs to find the best value.
3. The preprocessed train set and verification set are randomly sent to train the network.
4. After the model training, recognition and classification are completed on the test set. A summary of the performance metrics is recorded for the data set.

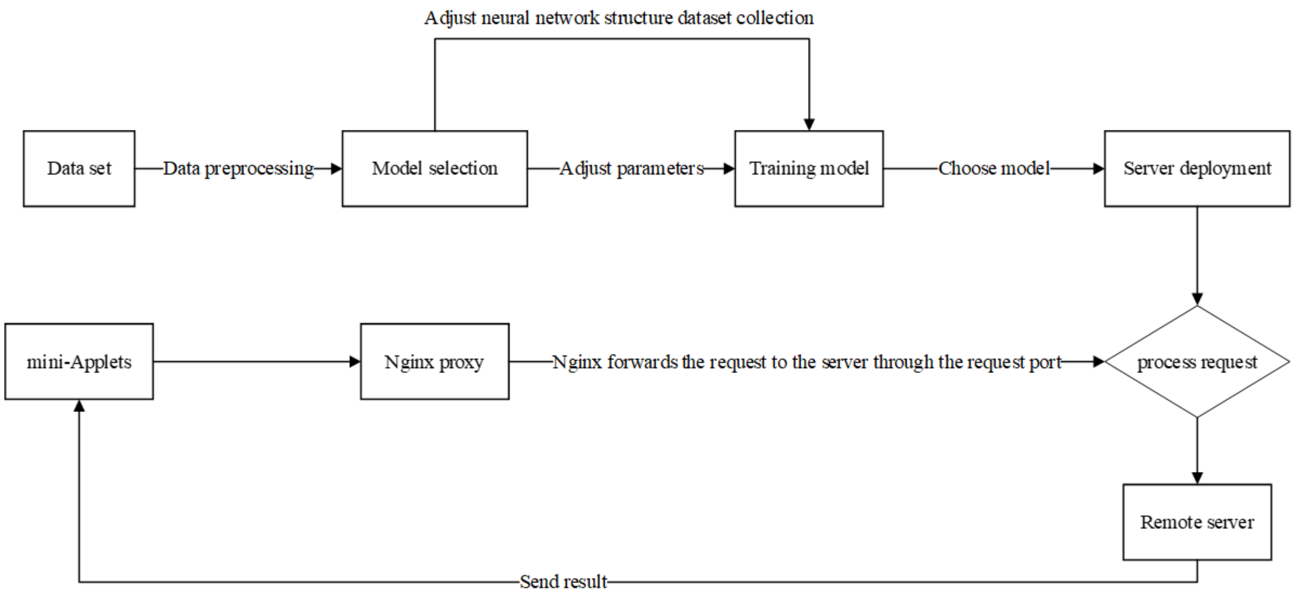

Fig. 2. System execution flow chart

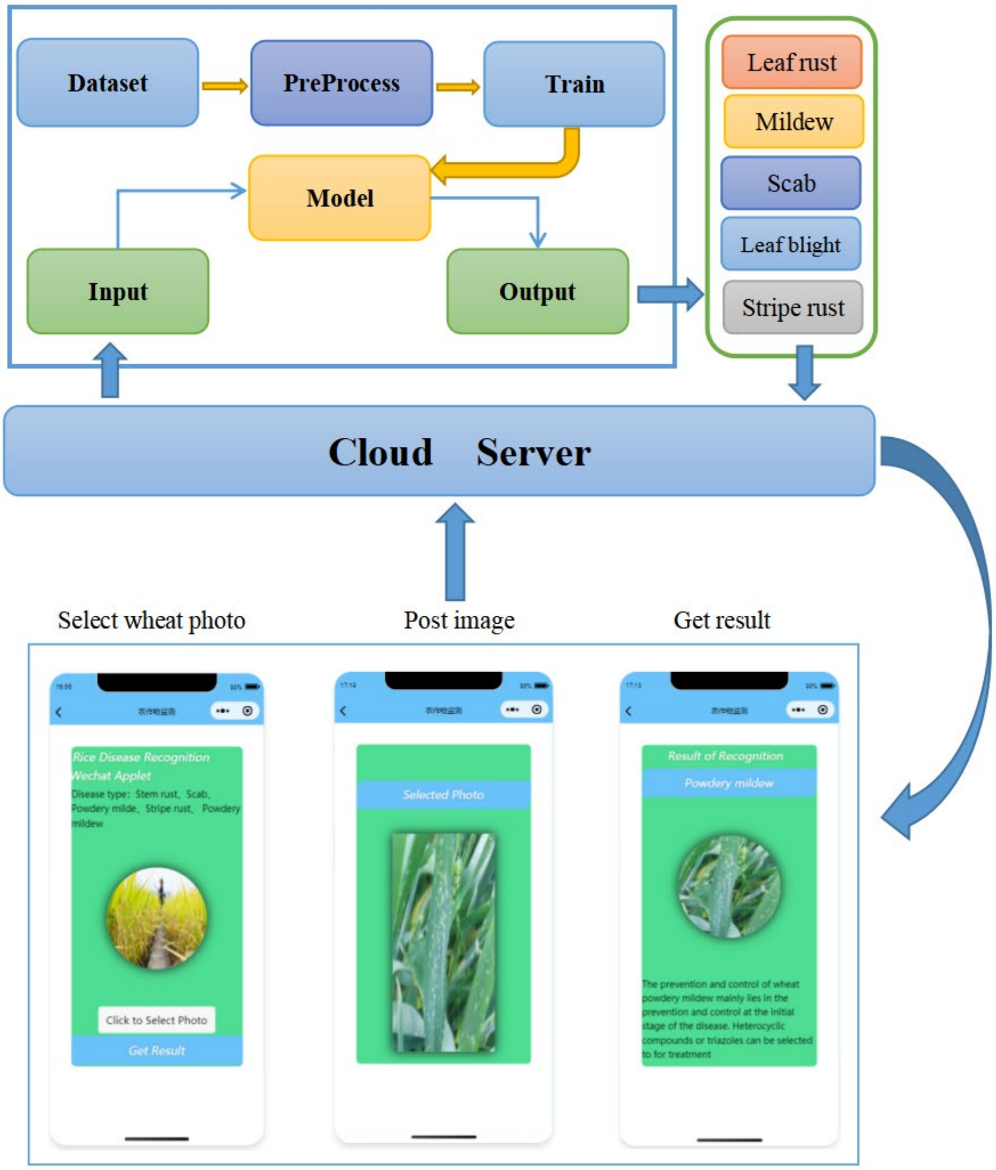

Fig. 3. The simulation process of system

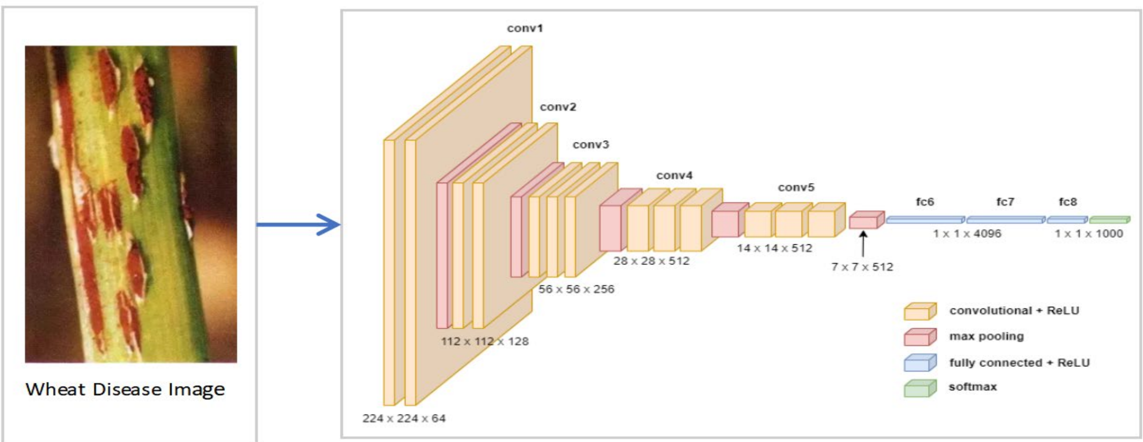

Fig. 4. VGG-16 convolutional neural network architecture

Powdery mildew Leaf rust Leaf blight

Scab Stripe rust Normal wheat

Fig. 5. Experiment samples

Table 1. Sample numbers of researched subjects

Item	Stripe rust	Powdery mildew	Scab	Leap rust	Leaf blight
Training DataSet	288	278	335	227	291
Test DataSet	35	35	35	35	35
Total	323	313	370	262	326

The experimental environment for wheat disease image recognition is deployed on a computer that is equipped with the Ubuntu 20.04 LTS operating system and Pytorch 1.12.0 framework.

3.6 Optimization Algorithm of Experiment

The stochastic gradient descent (SGD) algorithm comes from the Taylor polynomial at Equation (1). If the function satisfies certain conditions, the Taylor polynomial can use the derivative values of the function at a certain point as coefficients to construct a polynomial to approximate the function and use a polynomial function to approximate the original function.

$$f(x) = \sum_{n=0}^{N} \frac{f^{(n)}(a)}{n!}(x-a)^n + R_n(x) \tag{1}$$

The first-order expansion of the Taylor series (Equation 2) can approximate any function, and it is not difficult to obtain the corresponding gradient representation (Equation 3, W is the updated weight parameter, and the gradient of the loss function with respect to W is recorded as $\partial L/\partial W$, η is the learning rate). The SGD algorithm finds an optimal solution by finding the minimum value of the approximate function and using the minimum value as the element for the next iteration. The simple and efficient optimized algorithm has been widely used in machine learning.

$$f(x) \approx f(x_0) + (x - x_0)f'(x_0) \tag{2}$$

$$W = W - \eta \frac{\partial L}{\partial W} \tag{3}$$

In the application of plant disease identification, the experiment uses the Nesterov Momentum method to ensure that the model has good identification ability. The real gradient is replaced by simulating the concept and accumulating momentum (Equation 4 and Equation 5, x_t represents independent variable of the time step, η represents the learning rate, γ is the momentum hyperparameter, $0 \le \gamma < 1$). The moving range of the independent variable in each direction depends not only on the current gradient but also on whether past gradients are consistent in different directions. This optimization method can dynamically adjust the learning rate so that the model can obtain a higher convergence rate to avoid local optimal solutions.

$$v_t = \gamma v_{t-1} + \eta_t g_t \tag{4}$$

$$x_t = x_{t-1} - v_t \tag{5}$$

4. RESULTS AND DISCUSSION

4.1 Evaluation of Wheat Disease Model

Identification of wheat disease is essentially a binary classification problem. We define diseased wheat as positive and non-disease wheat as negative. Usually, the performance evaluation of the machine learning result is done by measuring the accuracy, precision, F1-score, recall and confusion matrix.

Precision is the ratio of the number of relevant samples in the recognition or retrieval results to the total number of samples in the results. Its value is positively correlated with the experimental training results.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

Accuracy is an indicator that can intuitively measure the quality of the model. Accuracy is usually presented as a percentage and calculated by:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

Recall is used to measure positive pattern fractions that are classified correctly, Recall is calculated using:

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

The F1-Score indicator combines the output results of Precision and Recall. F1 is calculated using:

$$F1 = \frac{TP}{TP+(FN+FP)/2} \tag{9}$$

According to experimental results, Fig. 6 and Fig. 7 show model accuracy and model losses. When the epoch is between 20–30, the loss value changes significantly and then decreases in a fluctuating manner. Table 2 shows the performance evaluation of the training result.

In order to illustrate the experimental results more intuitively, we construct a confusion matrix. In Fig. 8, it can be found that the difference in the recognition rate of other diseases is not too obvious except for leaf blight. The reason for this phenomenon is that the features of leaf blight are not significantly different from other diseases, leading to it being recognized as another disease.

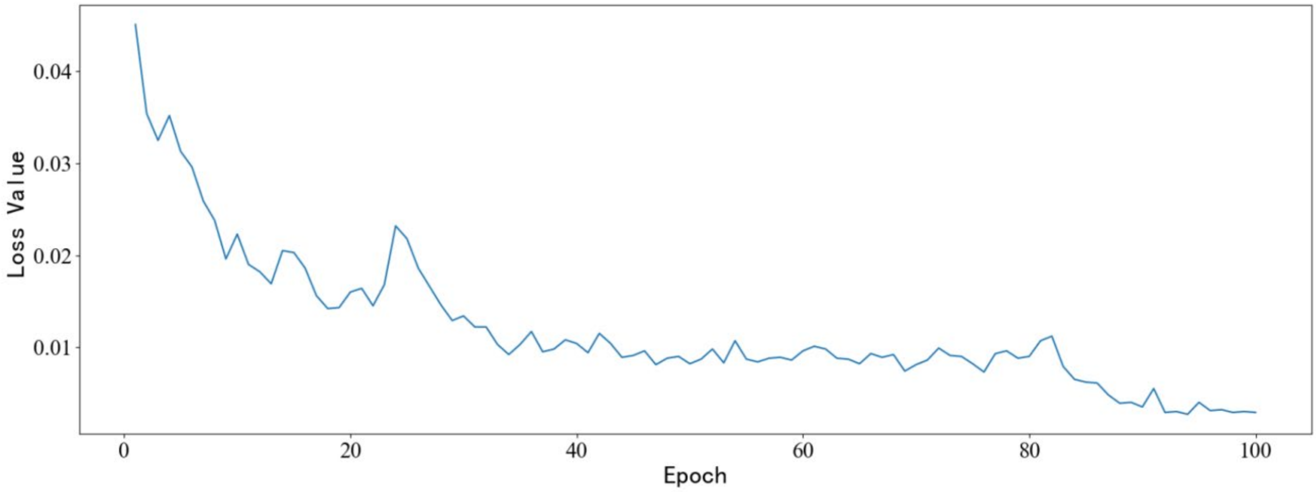

Fig. 6. Loss value curve chart

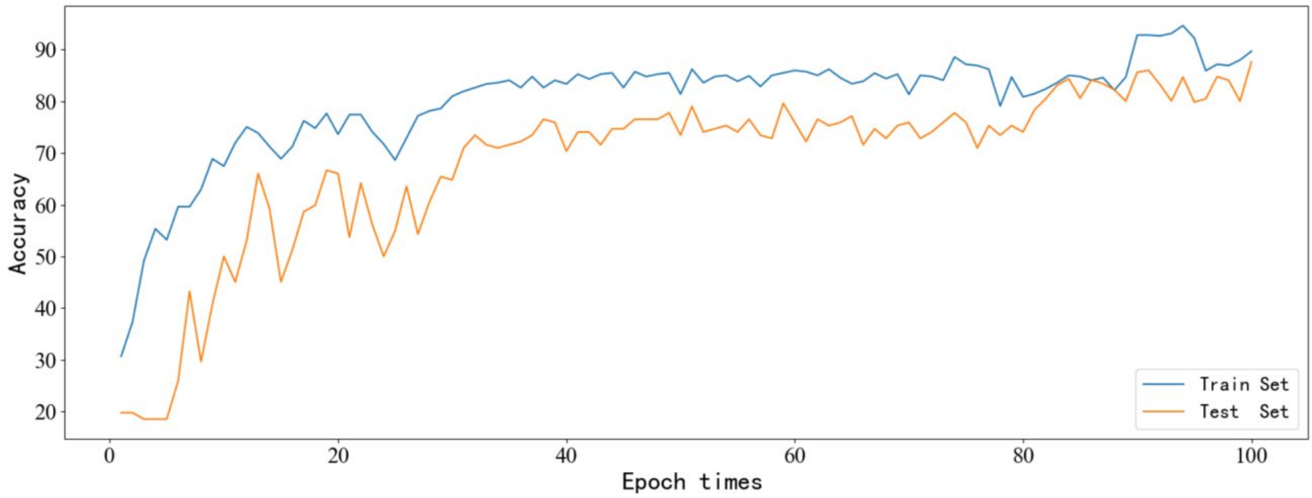

Fig. 7. Recognition accuracy comparison

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Table 2. Performance evaluation of training result

Disease	Performance evaluation			
	Precision/%	Recall/%	F1-score/%	Test samples
Stripe rust	85.7	76.9	81.3	35
Powdery mildew	91.4	86.5	88.9	35
Scab	88.6	96.9	92.5	35
Leap rust	82.9	78.4	80.4	35
Leaf blight	77.1	90.0	83.1	35
Macro avg	85.0	85.7	85.2	175

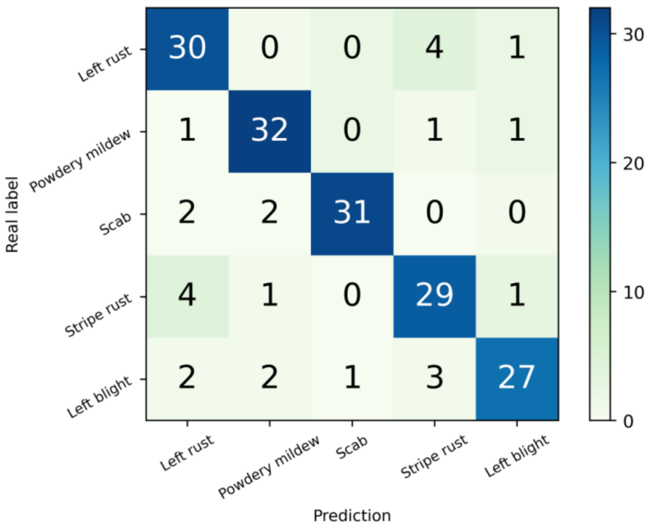

Fig. 8. Confusion matrix

4.2 Test on Real Practice

After the establishment of the wheat disease identification system, we further verified the work through the mobile phone installed with WeChat mini program. In process of wheat disease recognition model, we only judge the accuracy of the model through the test set, but in the validation process, we add images involving the non-disease state as the control group to ensure the effectiveness of the experimental results. The experimental results show that it can quickly and effectively identify various types of diseases without network obstacles. In Fig. 9, the actual experience result illustrates that the camera of a smartphone will be affected by the illumination and feature scale in the process of collecting disease photos.

The above experiment results prove a technology of mobile terminal rapid detection of common wheat diseases by combining WeChat mini program and remote identification model. In addition, if the uploaded image is affected by the natural environment, it will lead to inaccurate recognition results and errors. This phenomenon means that we need to consider external conditions to ensure the accuracy of detected results.

We also make comparison with other methods to show the effectiveness of proposed method. The result is shown in Table 3. Two methods including AFIG (Samson et al., 2022) and SMDE (Chiranjeevi et al., 2022) are used in this experiment. The average accuracy of proposed method is 93.3%, which is the best value in the testing process. And the error rate is the lowest with 9.6%.

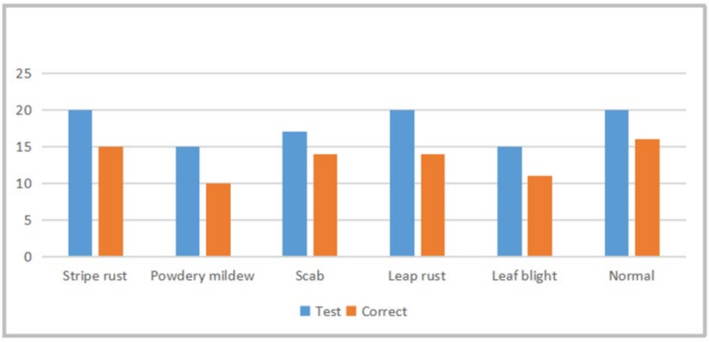

Fig. 9. Actual test on WeChat mini program

Table 3. Comparison with different methods

Method	AFIG	SMDE	Proposed
Average accuracy	79.6%	82.4%	93.3%
Error rate	21.7%	15.8%	9.60%

5. CONCLUSION

This paper mainly shows that the recognition accuracy of the proposed network can be effectively applied to the detection of plant diseases and provide a schema that can run models by a mobile terminal. In our future work, there are three directions that should be improved:

1. We hope to put image optimization methods such as image cutting on the applet side, so as to save the computing resources of the server side.
2. Extending data set. In this paper, only 5 diseases of the wheat crop are studied, and other species and diseases are not involved. Therefore, the next step is to obtain more disease species and disease images for research.
3. Optimizing the model. This experiment verifies the feasibility of the interaction between the mobile terminal and the remote recognition model but does not optimize the model too much. In the next step, we will try new methods such as transfer learning to increase the performance of the model.

ACKNOWLEDGMENT

This research was supported by the Scientific Research

Funds of Education Department of Liaoning Province in 2021 (General Project) (LJKZ1311).

CONFLICT OF INTERESTS

The authors would like to declare no conflict of interest in the publication of this manuscript.

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