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Research on Recognition Model of Crop Diseases and Insect Pests Based on Deep Learning in Harsh Environments

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ABSTRACT Agricultural diseases and insect pests are one of the most important factors that seriously threaten agricultural production. Early detection and identification of pests can effectively reduce the economic losses caused by pests. In this paper, convolution neural network is used to automatically identify crop diseases. The data set comes from the public data set of the AI Challenger Competition in 2018, with 27 disease images of 10 crops. In this paper, the Inception-ResNet-v2 model is used for training. The cross-layer direct edge and multi-layer convolution in the residual network unit to the model. After the combined convolution operation is completed, it is activated by the connection into the ReLu function. The experimental results show that the overall recognition accuracy is 86.1% in this model, which verifies the effectiveness. After the training of this model, we designed and implemented the Wechat applet of crop diseases and insect pests recognition. Then we carried out the actual test. The results show that the system can accurately identify crop diseases, and give the corresponding guidance.

INDEX TERMS Recognition of pests and diseases, deep learning, convolutional neural network, harsh environment.

I. INTRODUCTION

As a superpower with more than 20% of the world's total population, China has been facing the problem of insufficient arable land resources. According to the survey data of the Ministry of Agriculture, the proportion of cultivated land in China is even less than 10% of China's land area.

According to statistics data, the mountainous area accounts for about two-thirds of the total land area in China, while the plain area accounts for only one-third. About one third of the country's agricultural population and arable land are in mountainous areas. This situation has resulted in the relatively poor production conditions of agriculture, forestry and animal husbandry in China. According to the statistics of the Food and Agriculture Organization of the United Nations, the per capita cultivated land area in China is less than half of the world average level, and shows a decreasing trend year by year. Once the natural disasters cause agricultural production reduction, it will seriously affect the output of agricultural products and agricultural development. So how to develop agriculture stably, especially in the complex environment, is extremely important for China.

Although with the development of science and technology, agricultural production is progressing. But due to various natural factors and non-natural factors, the yield of crops has not been greatly improved. Among the various factors, the largest proportion is the problem of crop diseases and insect pests. According to statistics, the area of crops affected by pests and diseases in China is as high as 280 million km^2 every year, and the direct yield loss is at least 25 billion kg [1]. In recent years, this problem is on the rise and seriously threatens the development of planting industry. Timely diagnosis and prevention of crop diseases has become particularly important. At present, agricultural workers often use books and network, contact local experts and use other methods to protect and manage crop diseases. But for various reasons, misjudgments and other problems often occur, resulting in agricultural production is deeply affected.

At present, the research on crop diseases is mainly divided into two directions. The first one is the traditional physical

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method, which is mainly based on spectral detection to identify different diseases. Different types of diseases and insect pests cause different leaf damage, which leads to different spectral absorption and reflection of leaves eroded by diseases and healthy crops. The other one is to use computer vision technology to identify images. That is to say, the characteristics of disease images are extracted by using computer related technology, and the recognition is carried out through the different characteristics of diseased plants and healthy plants.

In recent years, the rapid development of artificial intelligence has made life more convenient, and AI has become a well-known technology. For example, AlphaGo defeated the world champion of Go. Siri and Alexa as voice assistants of Apple and Amazon are all applications of artificial intelligence technology represented by deep learning in various fields. As the key research object of computer vision and artificial intelligence, image recognition has been greatly developed in recent years. In agricultural applications, the goal of image recognition is to identify and classify different types of pictures, and analyze the types of crops, disease types, severity and so on. Then we can formulate corresponding countermeasures to solve various problems in agricultural production in a timely and efficient manner. So as to further ensure and improve the yield of crops and help the better development of agriculture.

With the rapid development of deep learning [2], especially in image recognition [3], speech analysis, natural language processing and other fields, it shows the uniqueness and efficiency of deep learning. Compared with the traditional methods, deep learning is more efficient in the diagnosis of crop diseases in the field of agricultural production. The deep learning model can monitor, diagnose and prevent the growth of crops in time. Image recognition of crop diseases and insect pests can reduce the dependence on plant protection technicians in agricultural production, so that farmers can solve the problem in time. Compared with artificial identification, the speed of intelligent network identification is much faster than that of manual detection. And the recognition accuracy is getting higher and higher in the continuous development. The establishment of a sound agricultural network and the combination of Internet and agricultural industry can not only solve the problems related to crop yield affected by diseases and insect pests, but also be conducive to the development of agricultural informatization [4].

However, due to the rugged terrain of the mountain environment, the surrounding interference factors are greater. Therefore, the image acquisition is more difficult than the general environment. In addition, the camera and network transmission needed for image recognition and processing will also have a certain impact. Therefore, it is more difficult to carry out intelligent recognition in mountainous areas. This paper tries to build the Internet of Things platform in the complex environment of mountainous areas, and carry out the research on the identification model of crop diseases and insect pests. The purpose of this model is to improve agricultural informatization, deal with the harm of pests and diseases to crops, and improve crop yield.

II. RELATED WORKS

The identification and prevention of crop diseases and insect pests is a continuous research topic. With the development of technology, many sensor networks and automatic monitoring systems have been proposed.

A method of detection of specific disease in grapes is proposed in [5]. Downy mildew pest/disease can be detected by the real time system with weather data. The central sever provide forecast service of weather condition and disease. Another kind of solution related of monitoring traps which are used to capture pest is with the help of image sensors [6]. In [6], he authors designed and implemented a low power consumed system which is based on wireless image sensors and powered by battery. The frequency of capturing and transferring trap images of sensors can be set and remote adjusted by trapping application.

Acoustic sensors are also used in monitoring system. In [7], the authors give a solution to detect red palm weevil (abbr. RPW) with them. With the help of acoustic device sensor, the pest's noise can be captured automatically. When the noise level of pest increases to some threshold, the system will notify the client that the infestation is occurring in the specific area. It helped farmers to be economical of time and energy to check every part of cropland by themselves and increase the labor efficiency. All acoustic sensors will be connected to base stations and each one will report the noise level if the predefined threshold value is surpassed [7].

Machine learning also had been applied in the agricultural field, such as investigation of plant disease and pests and so on. Plenty of techniques of machine learning had been widely used to solve the problem of plant disease diagnosis. In [8], a Neural Network based method of estimating the health of potato with leaf image datasets is proposed.

Additionally, the experimental research in [9] was carried out, which aimed to implement a system of recognizing plant disease with images. In order to distinguish wheat stripe rust from wheat leaf rust and grape downy mildew from powdery mildew, four different types of neural networks were trained based on color, shape and texture features extracted from disease image dataset. The work showed that neural network based on image processing can increase the effectivity of diagnosing plant disease [9].

What's more, scab disease of potato could be also detected by the image processing methods [10]. Firstly, the images from various potato fields were collected in [10]. After image enhancement, image segmentation was carried out to acquire target region. At last, a histogram-based approach to analyses the target region was applied, so that the phase of the disease could be found [10].

III. CONVOLUTIONAL NEURAL NETWORKS

Deep neural network is gradually applied to the identification of crop diseases and insect pests. Deep neural network is designed by imitating the structure of biological neural

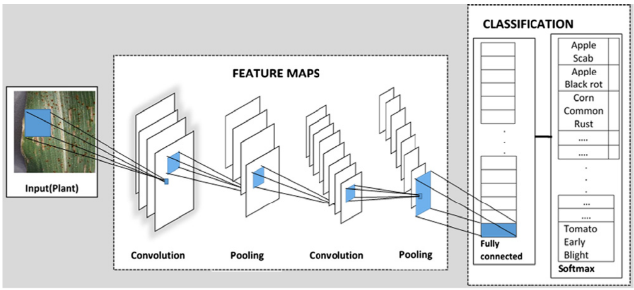


FIGURE 1. **A typical Convolution Neural Network architecture [13].**

network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons [3]. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward neural network [4]. The appearance of the deeper AlexNet network [11] in 2012 is the beginning of the modern convolutional neural network. The success of AlexNet network model also confirms the importance of convolutional neural network model. Since then, convolutional neural networks have developed vigorously and have been widely used in financial supervision, text and speech recognition, smart home, medical diagnosis and other fields.

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU [12]. A typical architecture of CNN model for pattern recognition is shown in Fig. 1.

The leftmost image is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

Convolutional neural network mainly solves the following two problems.

1) **Problem of too many parameters:** It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters, and does not need to optimize learning for each parameter of each position.
2) **Image stability:** Image stability is the local invariant feature, which means that the natural image will not be affected by the scaling, translation and rotation of the image size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the image. This problem can be solved by convolution operation in convolutional neural network.

Authors of [14] developed a mobile software of plant hospital, which could assist users to diagnose lots kinds plant disease through deep learning technical. An image dataset consisting of 54,306 pictures of healthy or infected plant leaves is used to train a CNN model, in order to identify 14 kinds of crop species and 26 types of diseases. Authors of [15] did the similar work. They change CNN model to Deep CNN, in order to increase the ability of plant disease diagnosis and extend the ability of distinguishing plants from their surroundings.

Plants species classification was also attempted to solve by deep learning method. In [16], authors tried to recognize weeds and plant species by CNN model trained with colorful images. A dataset consisting of 10,413 images with 22 weeds and crop species was tested, and the network failed to classify some plant species due to absence of training sample of corresponding species.

A system called DeepFruits was developed to detecting fruit in [17]. The authors use imagery data to detect fruit by CNN approach. In order to build an accurate, fast and reliable fruit detection system, they choose the faster-RNN model and made some adjustment [18]. The trained model was able to achieve an improvement of 0.838 precision and recall rate in sweet pepper detection task. They claimed they could complete the entire process of training an annotating a new model per fruit in four hours [17].

At present, the typical convolutional neural networks widely used are as follows.

1) LeNet-5 [19], [20]: Although proposed very early, but LeNet-5 is a complete and successful neural network, especially in handwritten numeral recognition system applications. The LeNet-5 network has seven layers, including two convolution layers, two convergence layers (also called pooling layers), and three full connection layers. The input image size is $32 * 32$, and the output corresponds to 10 categories.

2) ALexNet [21]: AlexNet consists of five convolution layers, three convergence layers and three full connection layers. ALexNet absorbs the idea and principle of LeNet-5

network, and also makes many innovations. These include using the ReLU function instead of the Sigmoid function to solve the gradient dispersion problem. Dropout is used at the fully connected level to avoid overfitting.

3) Inception Network [22]: Inception is different from the general convolution neural network in that it contains multiple convolution kernels of different sizes in its convolution layer, and the output of Inception is the depth stitching of the feature map. GoogLeNet, the winner of the 2014 ImageNet Image Classification Competition, is the earliest version of Inception v1 used.

4) Residual network [23]: The core idea of residual network is to make a non-linear element composed of neural networks infinitely approximate the original objective function or residual function by using the general approximation theorem. Many nonlinear elements form a very deep network, which is called residual network.

IV. CROP DISEASE RECOGNITION MODEL

In this paper, a complex Internet of Things environment of crop diseases and insect pests identification model is established. Through the deployment of sensors and cameras in complex mountainous environment, the environmental information and image information of the scene are collected, and the basic database of crop pest identification is established. Through the deep learning network model, the image information is learned and recognized, which is used to identify and collect leaf images, and then identify pests and diseases.

A. THE STRUCTURE OF CROP DISEASE RECOGNITION MODEL

In this paper, Inception-ResNet-v2 network is used as the basic model of crop disease recognition. This hybrid network not only has the depth advantage of residual network, but also retains the unique characteristics of multi-convolution core of inception network. After adding the residual unit in the inception network, although there is no significant improvement in accuracy, but it effectively solves the problems of gradient disappearance and gradient explosion. In addition, the convergence speed of the model is accelerated. Also, the training efficiency and the small-range promotion performance are improved. [24]. The structure of this model is shown in Fig. 2.

As shown in Fig. 3, the original inception module takes parallel structure for feature extraction, and then stack. In this paper, we add the cross-layer direct edge and multi-way convolution layer in the residual network unit to the model. After the combined convolution operation is completed, it is activated by the connection into the ReLu function.

As shown in Fig. 4, the 7×7 convolution structure in the original inception structure is replaced by 1×7 and 7×1 convolution in the inception layer B.

And the 3×3 structure in the residual layer C is replaced by successive 3×1 and 1×3 in Fig. 5. This model can effectively reduce the computational complexity of a single convolution layer by replacing the original large convolution kernel with multi-layer small convolution kernel. And it does not change the performance of the system. Because of the

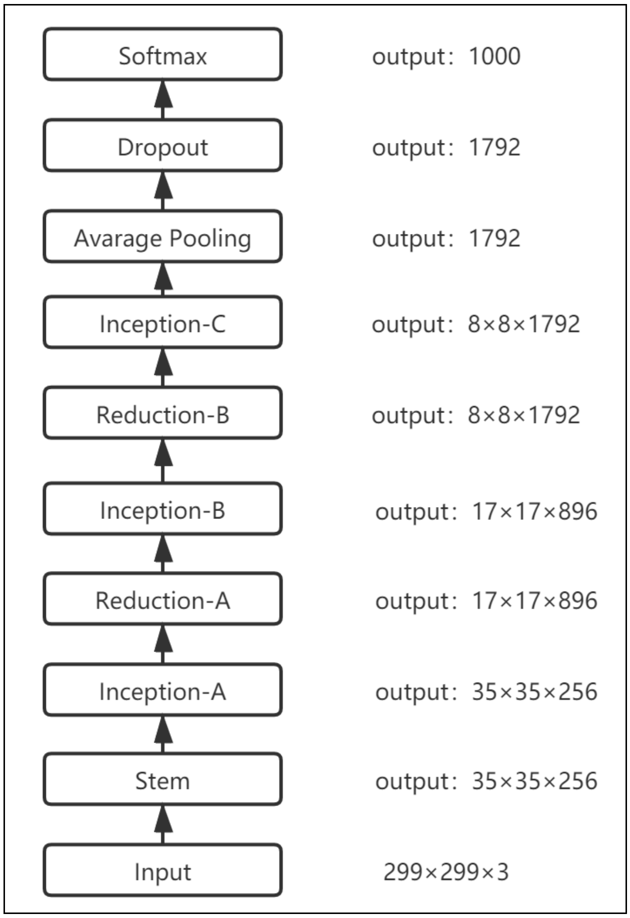


FIGURE 2. The structure of Inception-ResNet-v2.

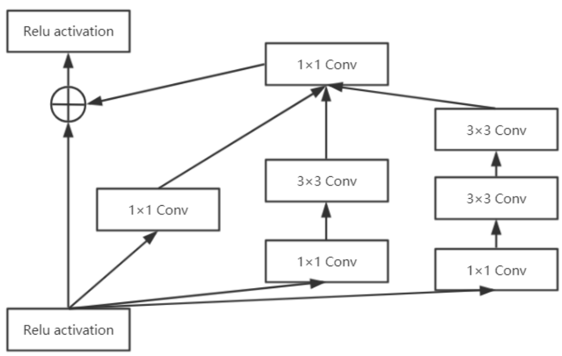


FIGURE 3. The structures of Inception-A in Inception-ResNet-v2.

increase of convolution layer and the deepening of network depth, the performance of this network is more excellent than before.

B. DATASET

The data set used in this paper is from the data set used in the Crop Disease Recognition Competition of the 2018 Artificial Intelligence Challenger Competition. The dataset includes 47363 images of 27 diseases related to 10 crops (mainly tomatoes, potatoes, corn, etc.). The data set is divided into three parts: 70% for training set, 10% for validation set and 20% for test set. Each picture contains only the

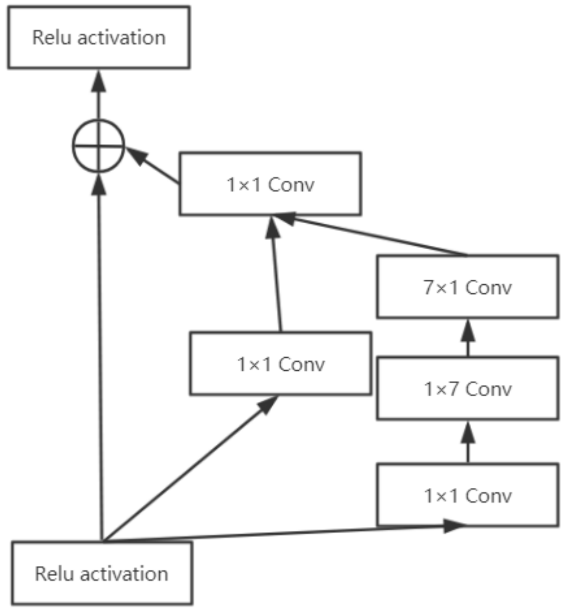


FIGURE 4. The structures of Inception-B in Inception-ResNet-v2.

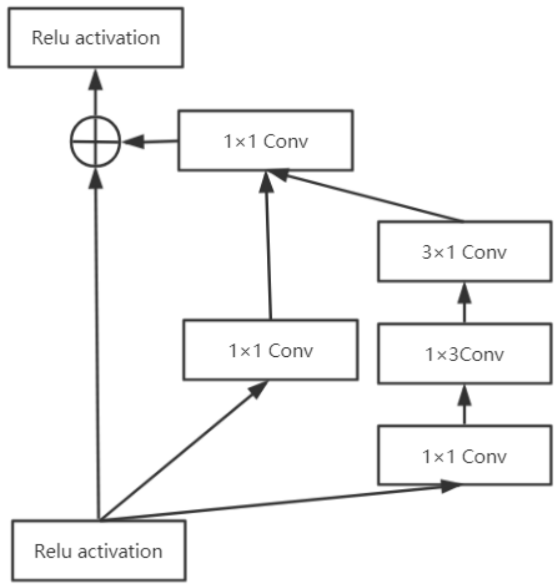
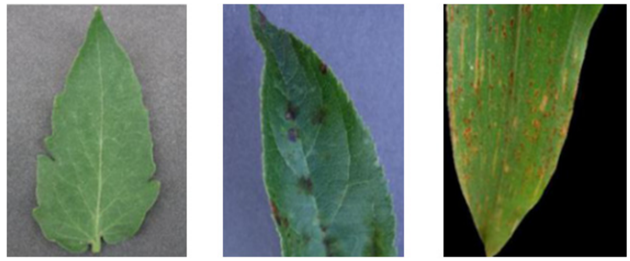


FIGURE 5. The structures of Inception-C in Inception-ResNet-v2.

leaves of a single crop. Some sample pictures are shown in Fig. 6.

C. IMAGE PREPROCESSING

The purpose of image preprocessing is to eliminate the interference of useless information in data set to model recognition, and to expand the data set to a certain extent. The neural network can achieve better training effect. In this way, the recognizability of the image can be effectively improved, so that the recognition accuracy of the model can be improved. At present, the commonly used preprocessing methods include geometric space transformation and pixel color transformation. The former includes flip, crop, rotate, zoom and so on. The latter includes changing contrast, adding Gaussian noise, color dithering and so on. Because of the uneven distribution of data sets, so in this paper, we mainly take the method of light transformation and random clipping. Enhance the feature information of the picture and the scale of the data set itself. The influence of the background factor and the data quantity problem on the model is weakened. It can make the model produce better learning effect and increase the stability of the model.



(a) Potato healthy (b) Apple scab (c) Puccinia polysra

FIGURE 6. Sample pictures in data set.

Initially, this paper does not train the neural network by transfer learning method. In the end, although the training set has reached 90% accuracy. However, according to the loss trend and the final test set results, it can be clearly seen that there is an over-fitting phenomenon. After analysis, the most likely reason is that the data set is relatively small. Although data enhancement alleviates the problem of uneven distribution to some extent, it does not completely solve the problem of over-fitting. Thereafter, this paper uses transfer learning on this data set. It is to use the standard network for training, only need to modify the model slightly and train here can get very good training effect. To sum up, transfer learning can bring higher initial accuracy, faster convergence speed and more accurate approximation accuracy for the model.

D. NORMALIZED PROCESSING

After that above steps are complete, the picture of the data set will be normalized. Normalization can be considered to be an indispensable and important part of the convolutional neural network. It scales the characteristics of each dimension to the same range. On the one hand, it is convenient to calculate data and improve the efficiency of operation. On the other hand, the association between different features is eliminated. Therefore, the ideal model training result can be obtained.

$$x' = \frac{x\text{-}\mu}{\sigma} \quad \text{(Formula 1)}$$

In the formula 1, x and x' are the data before and after normalization. And μ means the average value while σ means the covariance.

V. EXPERIMENT

A. EXPERIMENTAL ENVIRONMENT

The operating system of this experiment is Windows. The programming language is Python and framework is TensorFlow deep learning framework. The specific equipment configuration is shown in Tab. 1.

TABLE 1. Experimental environment.

Configure	Param
CPU	Intel(R)Core (TM) i7-6200u
Anaconda	Anaconda 3.6
TensorFlow	1.2.1
Operating System	Windows 10
Hard disk	512GSSD
RAM	8G

B. TRAINING STRATEGY

In this paper, we use the Inception-ResNet-v2 model for migration. The network weight parameters trained by a large number of data sets are transferred to their own network for training, and the network is fine-tuned. The method comprises the following steps.

1) The pre-training model is loaded first. We keep the parameters of the convolution layer and the pooling layer in the original model as the initial parameters, and freeze the last fully connected layer. Set up a new full connection layer to achieve the classification problem of the target task.
2) Set the parameters. First set the learning rate to 0.001 and the batch_size to 32. The workout count is set to 5 epoch and the Dropout is set to 0.5.
3) The loss function of the loss layer uses a cross-entropy loss function. The optimizer chooses to update the weights and biases using the Adam optimization algorithm.
4) And that image in the preprocessed train set and the preprocessed verification set are randomly sent into an image with a batch size for training.
5) After the model training, the recognition and classification are completed on the test set. A summary of the performance metrics analyzed for the dataset.

C. RESULTS AND ANALYSIS

The evaluation index used in this paper is the commonly used Top1 accuracy in classification problems. It refers to the accuracy rate ACC of the class with the largest recognition probability of the model and the actual class. The formula is shown as Formula 2, where N is the number of samples and R is the number of correct predictions.

$$\text{acc} = \frac{R}{N} \qquad \text{(Formula 2)}$$

The images in the dataset are preprocessed and then trained. After each epoch iteration, a verification is performed. The image convergence process is shown in Fig. 7.

It can be seen from the graph that the curve of the convolution neural network training model used in this paper keeps stable after three epochs are trained, and its accuracy and loss keep a relatively stable state. The final accuracy is 86.1%, and the recognition effect reaches the expectation.

Although there is no great improvement in accuracy. However, the performance of this network model is better than other commonly used deep learning models. This also proves that this hybrid network model has better performance in the field of image recognition.

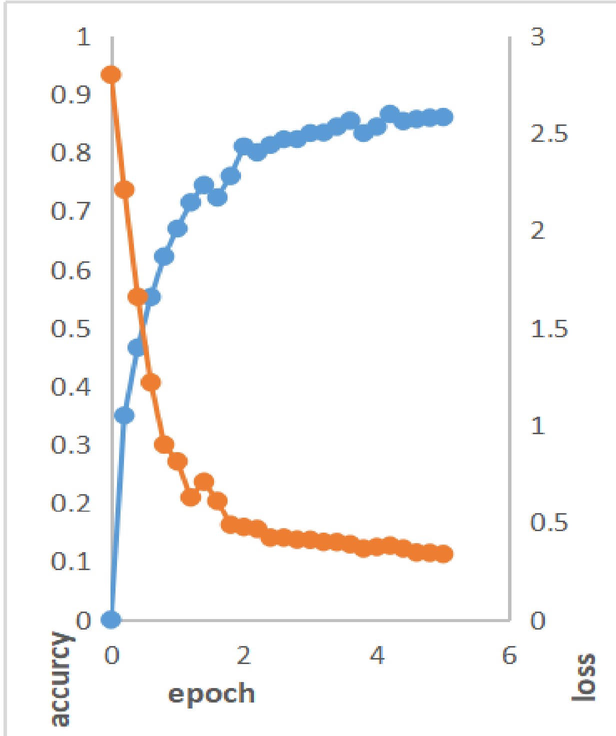


FIGURE 7. Accuracy and loss changes during model training.

D. IMPLEMENTATION

In order to enable farmers to identify and detect pests and diseases conveniently and quickly, this paper establishes a system based on Wechat applet. The program can identify the disease on the leaves of crops with diseases, which is convenient for farmers to understand the situation of diseases and insect pests and to obtain expert guidance. The system first uploads the image, and then transmits the image data to the back-end for processing through the network front-end. Image preprocessing is mainly to optimize the incoming image. First of all, the image is zoomed to meet the requirements of the model input, too large image will seriously affect the efficiency of recognition. Secondly, in order to achieve higher recognition efficiency, the image is cut randomly and the pixels are optimized. Finally, the name and status of the crop with the highest matching degree will be given after the recognition is completed. If the crop is in an unhealthy state, the corresponding guidance will be given and returned to the cell phone.

The detection result of the system is shown in Fig. 8, the identification result is peach scab, which is a common disease of peach trees, and the identification is accurate after verification.

Then we also identified healthy leaves. Fig. 9 shows that the recognition result is a healthy cherry leaf, and the recognition result is accurate.

FIGURE 8. Recognition result of peach scab.

FIGURE 9. Recognition result of healthy cherry leaf.

Finally, we recognize the corn leaves. Fig. 10 shows the results of identification of corn leaf rust. The occurrence of rust disease in maize will produce a pile of rust-colored powder on the leaves, which is harmful to maize crops. The recognition results show that the system can achieve the desired effect.

FIGURE 10. Recognition result of puccinia polysra.

VI. CONCLUSION

In this paper, 27 kinds of disease recognition of 10 kinds of crops were studied. The Inception-ResNet-v2 model is constructed by using deep learning theory and convolution neural network technology. Experiments show that the model can effectively identify the data set, and the overall recognition accuracy is as high as 86.1%. The results show that the recognition accuracy of this hybrid network model is relatively higher than the traditional model, and it can be effectively applied to the identification and detection of plant diseases and insect pests.

In the future work, there are two directions should be improved:

1) Extended data set. In this paper, only 27 diseases of 10 crop species were studied, and other species and diseases were not involved, such as rice and wheat, and their related diseases. Therefore, the next step is to obtain more crop species and disease images for research.
2) Optimize the model. Through the experiment of this paper, we can see that Inception-resnet-v2 this kind of mixed network has absorbed the corresponding advantage. This model has achieved good recognition accuracy, and is worthy of further study and optimization. At the same time, we should design a network model which can classify crop images with higher accuracy.

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