Retraction Notice

The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

HY and ZL either did not respond directly or could not be reached.

Image recognition technology of crop diseases based on neural network model fusion

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Abstract. The neural network is an important model of machine learning that utilizes a hierarchical structure composed of multiple neurons to fit complex nonlinear classification surfaces. Deep learning is a new direction in the field of machine learning. Learning the inherent laws and representation levels of sample data, the information obtained during the learning process plays a great role in interpreting data such as images and speech. The crop disease image recognition technology based on the neural network model is studied to develop a system with an improved accuracy. First, we analyze the background and significance of image recognition technology applied to crops; then, on the basis of understanding the general background, the pattern recognition method based on the image is deeply studied; and, finally, the experimental design of crop disease image recognition based on convolutional neural network (CNN) is tested. The experimental results show that, in the problem of disease identification, compared with a single CNN model, the proposed model further improves the highest verification accuracy. The integration of DenseNet and the visual geometry group model has the best effect on cucumber and rice disease identification, and the verification accuracy can reach 96.24%. *© 2022 SPIE and IS&T*
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1 Introduction

Crops are important agricultural products, and agriculture is an important industry for the construction and development of the national economy. It can be seen that the development of crops has become particularly important. But every year, crop yields are greatly reduced due to diseases, insect pests, and various natural factors, which brings huge economic losses to farmers. So far, there are various methods for dealing with crop diseases, and the most prominent one is the method of manual diagnosis. There are many factors in the diagnosis and treatment of disease, which lead to many problems. It is precisely because of this problem that diagnostic methods based on image recognition of crop diseases are developing rapidly.

The extensive development and application of various new technologies are well applied in the field of crops. Using crop image datasets to identify crop disease images for monitoring is a new method that is more effective and faster than traditional crop disease diagnosis. The application of image recognition technology to the diagnosis and recognition of crop diseases not only is superior to the traditional methods of diagnosis and recognition but also can greatly improve its output and bring greater economic benefits to a certain extent.

The innovative of this paper are as follows: (1) The image recognition method is the basis of the analysis of this paper. It focuses on the identification method of a standard artificial neural network and conducts in-depth research on the algorithm. (2) It combines an artificial neural network algorithm and a convolutional neural network (CNN) and proposes an image recognition method combining artificial neural network (ANNs) pattern recognition and CNNs. It first uses the knowledge obtained from the large dataset of four independent CNN network

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frameworks for training and parameter adjustment to alleviate the over-fitting problem, and by training multiple neural network models, the accuracy of crop disease identification is further improved.

2 Related Work

At present, neural networks exist in various fields. Zhao and Nan[1] discussed stochastic Cohen–Grossberg neural networks with time delays and gave some sufficient criteria to ensure almost certain exponential stability of the network. The obtained results contributed to the stability of the network when random noise was considered, but the network speed was not fast enough. The network proposed by Havaei et al.[2] is tailored for glioblastomas (low and high grade) depicted in MR images; it is a fully automatic brain tumor segmentation method based on a deep neural network. Actively exploring a machine learning solution, the authors discovered different model choices that were necessary to obtain competitive performance and explored different architectures based on CNN, but they did not conduct a comparative analysis. Perna and Rocca[3] proposed a strategy for choosing the hidden layer size in a feedforward neural network model. The method was based on a comparison of different models for a given loss function in terms of out-of-sample predictive power. To overcome the problem of data snooping, they extended the scheme using reality checks and modified it to compare nested models. However, the data accuracy was lacking. Ghafoorian et al.[4] proposed an automated two-stage approach using deep CNNs. They first used it to detect initial candidates and then used a 3D CNN as a tool to reduce false positives. They trained, validated, and tested the network on a large dataset of 1075 cases from two different studies. However, the network data stability was not enough. Xue and Liu[5] investigated the feasibility of using NNs to simulate complex relationships between seismic and soil parameters and liquefaction potential. The NNs were trained using actual field recordings, and as more input variables were provided, the performance of the neural network model improved. However, there were multiple data in the experiment that affect the experimental results. Gong et al.[6] proposed a deep learning-based synthetic aperture radar image change detection method. They designed a deep neural network to detect changed and unchanged regions, which could avoid the influence of DI on the change detection results. However, the performance needed to be improved. Chen et al.[7] proposed an adaptive neural network consensus control method. The approximation properties of radial basis function neural networks were used to neutralize uncertain nonlinear dynamics in agents. However, they did not consider realistic factors. Zhang et al.[8] studied the delay-dependent stability of generalized continuous neural networks with time-varying delays and developed a novel Lyapunov–Krasovskii functional. It considered more information about activation functions and delay ceilings for delayed neural networks while reviewing and comparing the most common techniques for dealing with Lakefield derivatives. By introducing relaxation matrices, the obtained criterion was extended to a system with a single time-varying delay; its effectiveness was experimentally verified, but its feasibility was low.

3 Image-Based Pattern Recognition Method

3.1 *Template Matching Method*

The most original recognition method is template matching, which determines where the feature under study is located in the image and then identifies the object, which is a matching problem. Because it is the most primitive matching method, it has the limitations of time. It can only move in parallel; if the corresponding object in the original image is rotated or resized, the algorithm is invalid, making it not very suitable for this new era of technological development.[9,10]

Let $f(m,n)$ indicate an acquired input image that matches a known pattern image and $F(m,n)$ indicate the default standard sequence. $Q(m,n)$ is the pattern matching method shown in Fig. 1 after comparing the correlators and their outputs.

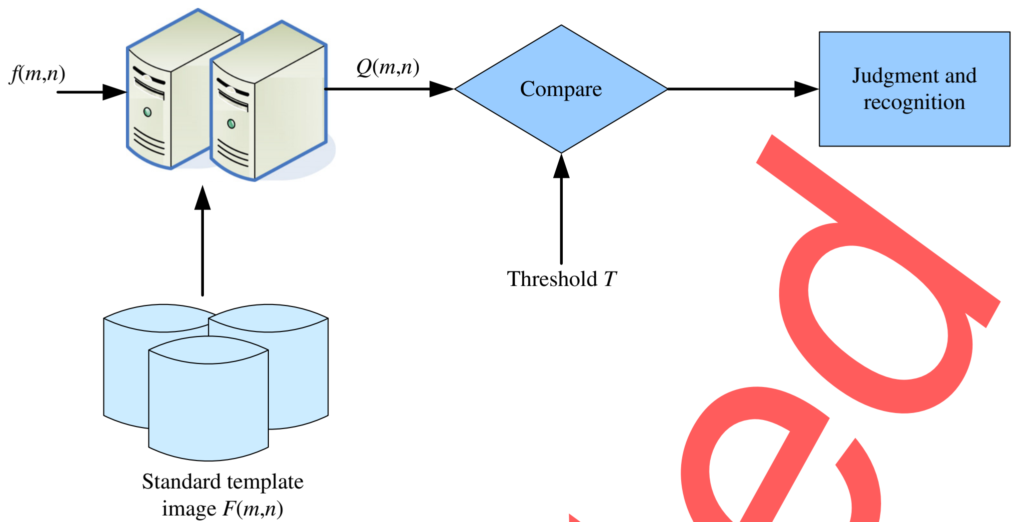

Fig. 1 Pattern recognition system diagram of the template matching method.

Assuming 1, 2, 3, and 4 are random variables, the classifier output is

$$\varphi(m_1 - m_2, n_1 - n_2) \quad = \iint f(m,n)F[(m + (m_1 - m_2), n + (n_1 - n_2)]\mathrm{d}m\mathrm{d}n. \tag{1}$$

When and m_2 are equal and n_1 and n_2 are equal,

$$\varphi(0,0) = \iint f(m,n)F(m,n)\mathrm{d}m\mathrm{d}n. \tag{2}$$

When $f(m,n)$ and $F(m,n)$ are equal,

$$\varphi(0,0) = \iint f(m,n)f(m,n)\mathrm{d}m\mathrm{d}n. \tag{3}$$

Among them, $\varphi(0,0) \geq \varphi(m,n)$; it can be seen that $\varphi(m,n)$ has a main peak at $\varphi(0,0)$ and other points may appear as secondary peaks. Since these are not equivalent, they can be identified by appropriate limits. In this standard, the matching method can be performed in the time domain or frequency domain; it not only fits the whole image but also finds the image with the same orientation and shape as the small pattern in the large image, paying attention to the position of the target in the big picture. The advantage of this method is that, under certain conditions, the possibility of error and the drop rate are minimal. It is suitable for low-noise parts such as standard matching and text matching. Also, it is sensitive to noise, so it would not work with text images.

3.2 *Statistical Pattern Recognition Method*

The statistical pattern recognition process is shown in Fig. 2. The image information that it inputs is a digital symbol that the computer can recognize, which is similar to the bitmap image. To characteristically extract images from the original, it uses filtering and restores the acquired image processing, which is also the main goal of image processing. The latter is the result of recognition and classification results.[11] When determining the recognition discriminant function, it is necessary to use a large number of different images to adjust the recognition parameters by calculating the statistical data of the sample features. The content described above is the statistical learning process.

Among them, there are two main methods in the recognition of model images: one is the feature extraction method and feature selection method; the other is the feature selection discrete

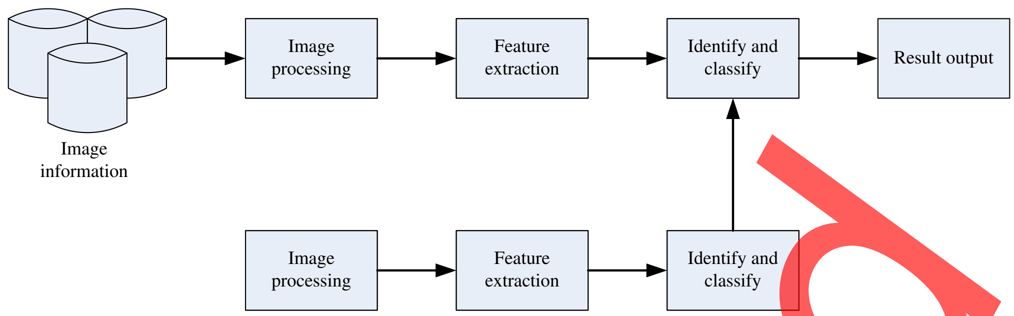

Fig. 2 Statistical pattern recognition system diagram.

function. After the image processing is completed, a total of N features are extracted, and then all of the sample sets are divided into x types. Q in the N-bit vector space is a mode that performs identification operations, which is given as

$$Q = [q_1, q_2, q_3, \ldots, q_N]^T, \tag{4}$$

where $w_1, w_2, w_3, \ldots w_x$ are the category of the pattern and determining which part of w_x Q belongs to is what needs to be identified. $w_1, w_2, w_3, \ldots w_x$ mean that there are x categories in the pattern, and $D_1(Q), D_2(Q), D_3(Q) \ldots D_x(Q)$, means that there are a total of x discriminant functions. If Q belongs to class i, then

$$D_i(Q) > D_j(Q) \quad (j = 1, 2, 3, \ldots, x; j \neq i). \tag{5}$$

When $D_i(Q) = D_j(Q)$, Q belongs to both categories $D_i(Q) = D_j(Q)$ and w_j, and the distinguishing function fails, and other characteristics must be considered.

3.3 *Syntactic Pattern Recognition*

In this method, each pattern has a combined representation of its respective parts. There is a certain degree of similarity in structure and language syntax. Due to this factor, in general, recognition is carried out by means of comprehensive analysis.[12] The identification system is composed of two parts: identification and analysis. The recognition part includes preprocessing, primary extraction, and synthesis analysis, and the analysis part includes the primary selection and grammatical conclusion. The specific process is shown in Fig. 3.

3.4 *Artificial Neural Network Pattern Recognition*

The identification methods mentioned above all have their own advantages and disadvantages. They are suitable for recognition in different situations and need to be judged by themselves. To a certain extent, they each make a contribution to image recognition. However, most of these recognition methods have the problems of slow recognition, difficulty with function selection, and

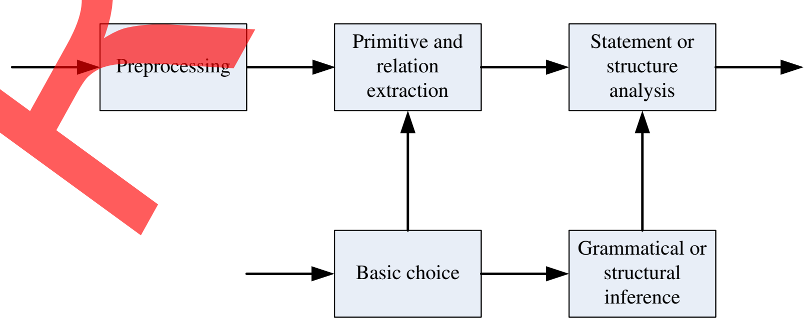

Fig. 3 Syntax pattern recognition system diagram.

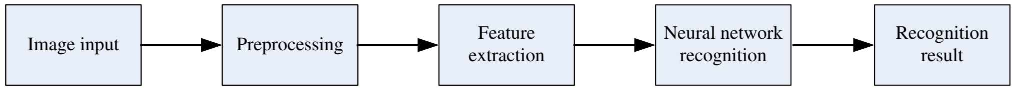

Fig. 4 General model of NNs applied to image recognition.

needing to be performed on a large number of data sets. These shortcomings are why they cannot be widely used in image recognition.[13,14] From this background, the model recognition method based on the artificial neural network emerged in the wave of artificial NNs development. In some ways, it is different from the recognition methods mentioned in the previous article.

With the development of artificial neural network technology, a new type of recognition method has emerged in pattern recognition technology: a model recognition method based on an artificial neural network. To a certain extent, the methods of identifying neural networks are different from those mentioned above, but to a certain extent, they have many similarities. A general model of a neural network for image recognition is shown in Fig. 4.

3.4.1 *Basic concepts of ANN*

ANN is an information processing system that has some characteristics of ordinary BNN. In short, the artificial neural network can be regarded as an integrated system of the mathematical model of the human brain, and the structure is shown in Fig. 5.

A large number of interconnected neurons constitute an ANN, and each neuron is interconnected with other neurons by having corresponding weights.[15] In this, the knowledge to solve the problem is represented by the weights. ANNs are composed of the feedforward network, feedback network, and mutual combination network. ANN applications can handle various problems such as storing and retrieving data, classifying criteria, matching input and output patterns, classifying similar patterns, solving constrained optimization problems, etc. Figure 6 is a simplified structure of a neuron.

It is a nonlinear element of multiple single-output inputs and is expressed as

$$I_i = \sum_{j=1}^{a} W_{ji} m_j - \theta_i, \tag{6}$$

$$n_i = f(I_i). \tag{7}$$

The input signal from other cells is represented by $m_j (j = 1, 2, \ldots, a)$, the bias of the neuron unit is represented by θ_i, the connection weight from cell j to cell i is denoted by w_{ji}, the number of input signals is denoted by a, and the exit of the nerve is denoted by n_i. $F(.)$ of the excitation function is also known as the transfer function. The excitation function belongs to both linear functions and nonlinear functions, such as a step function or S-shaped curve, but in general it belongs to the latter, which is expressed as follows:

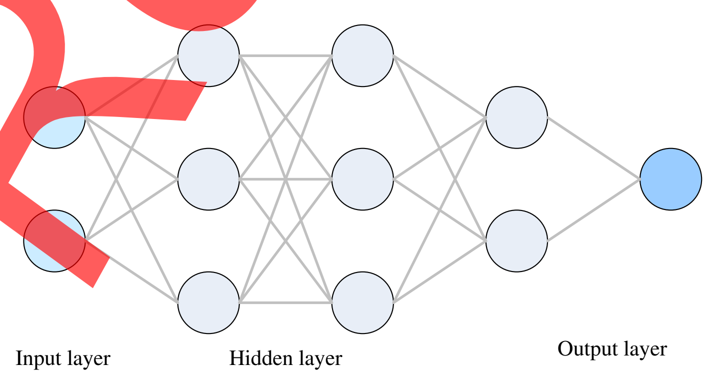

Fig. 5 The structure of the ANNs.

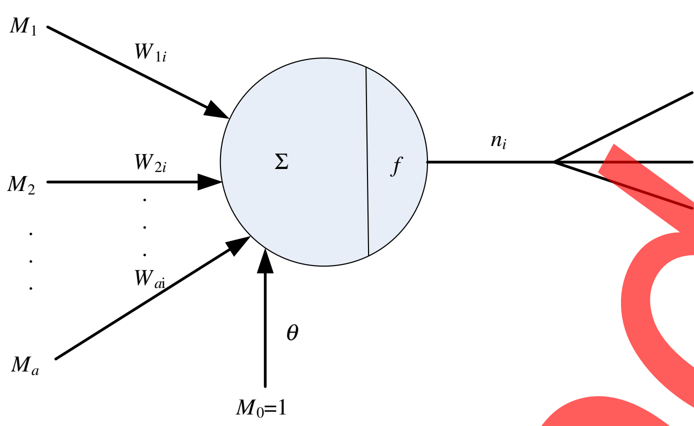

Fig. 6 Neuron structure model.

1. When n_i takes 0 or 1, $f(x)$ is a step function

$$f(m) = 1, (x \geq 0) \quad f(m) = 0, (x < 0). \tag{8}$$

2. The sigmoid curve is usually a monotone variable function with a constant value that is in the range of (0,1) or $(-1, 1)$, such as

$$f(m)\frac{1}{1 + \exp(-\beta m)}, \tag{9}$$

or

$$f(m) = \tanh(m). \tag{10}$$

As m tends to infinity, the sigmoid curve tends to a step function, and β is usually 1. Sometimes for convenience, a weight of θ_i input quantity m_0 is equal to 1 and is considered

$$I_i = \sum_{j=0}^{a} W_{ji} m_j. \tag{11}$$

where

$$W_{0i} = -\theta, \qquad m_0 = 1. \tag{12}$$

3.4.2 *Learning of artificial neural network*

$n_k(y)$ is the actual output of neuron k at time y when $m(y)$ is input, and the corresponding target output is represented by $d_k(y)$. Then, the error signal is

$$e_k = d_k(y) - n_k(y). \tag{13}$$

The ultimate goal of the delta learning rule is to minimize a certain objective function of $e_k(y)$, so the actual output of each output unit to the network is statistically closest to the target output. Once the form of the objective function is chosen, delta learning becomes a typical optimization problem. The most commonly used objective function is the mean square error block function, which is expressed as

$$J = Q\left(\frac{1}{2}\sum_{k} e_k^2(y)\right). \tag{14}$$

The expectation factor is denoted by Q, usually using the instantaneous value of J at time y, $\lambda(y)$, in place of J, and then

$$\lambda(y) = \frac{1}{2}\sum_{k} e_k^2(y). \tag{15}$$

The problem is to find the minimum value of $\lambda(y)$ for the weight w, which is obtained by the steepest gradient descent method

$$\Delta w_{kj}(y) = \eta e_k(y) m_j(y). \tag{16}$$

In the formula, η is the learning step size.

When the neuron activations at both ends of the synthesis are synchronized, the strength of the connection should be strengthened; otherwise, it should be weakened,[16] which is expressed as

$$\Delta w_{kj}(y) = F(n_k(y), n_j(y)), \tag{17}$$

where $n_k(y)$ and $m_j(y)$ are the states of neurons at both ends of w_{kj}. The most commonly used one is

$$\Delta w_{kj}(y) = \eta n_k(y) m_j(y), \tag{18}$$

where Δw_{kj} is proportional to the correlation of $n_k(y)$ and $m_j(y)$.

Assume that each output unit of the network competes with the others during competitive learning and only one of the strongest is activated; it is expressed as

$$\Delta w_{kj}(y) = \eta(m_j - w_{kj}). \tag{19}$$

Among them, neuron j competes to win.

$$\Delta w_{kj}(y) = 0. \tag{20}$$

Among them, neuron j failed to compete.

4 Experiment and Analysis of Crop Disease Image Recognition Based on CNN

In recent years, CNN models have been increasingly applied to some specialized fields, such as the medical and agricultural fields. The agricultural field is greatly affected by natural conditions and environmental factors, making it a very special case. For example, if the light in the farmland is different during the day and night, there will be problems with photo exposure and the light being too dark; the weather is different every day, and in airy weather, the leaves and weeds of crops are folded one into the other. The symptoms and manifestations of crop diseases are different. Most of them are in the form of lesions, and there are also powder diseases and granular diseases. The background of each plant is also different; some photos have simple backgrounds, and some weeds and crops have complex backgrounds.[17,18] Therefore, there are some limitations in identifying crop diseases and weeds using digital image processing techniques. The training process of the CNN model is an end-to-end learning process, in which there is no need for image segmentation and feature calculation, so the application is simple and convenient. In addition, the CNN model has strong feature learning ability for complex backgrounds and different types of pictures. Before CNN training, as long as different types of pictures are added to the training

Table 1 Hyperparameter settings for experiments.

Optimization	Adam optimization	Number of training rounds	20
Learning rate	0.001	L2 regularization	0.0001
Batch sample size	100	Dropout	0.5
Hyperparameters			Value

database to participate in feature learning and training, the resulting training model can recognize all data types.[19–21]

4.1 *Materials and Experimental Preparation*

The purpose of the experiment is to better compare the impact of network depth and training mechanisms on the recognition results. This paper unifies the hyperparameters of all experimental groups. This chapter conducts experiments using the same hyperparameters described in Table 1.

For the crop disease dataset, the purpose is to solve the overfitting problem caused by training the CNN model on a small-scale dataset. We use two training mechanisms to compare and explore the optimal results based on the above network structure. One idea is to train from scratch. We directly put the dataset into networks with different depths for training and then evaluate the results on the validation set. Another idea is to use transfer learning strategies. We can make full use of the pre-trained models trained on datasets in related fields, reuse them in the field of crop diseases, and alleviate the problem of overfitting caused by the small amount of disease data. Some researchers have achieved good results using transfer learning on trained ImageNet models. However, the PlantVillage dataset is more similar to our disease database than the ImageNet database. First, it uses the above network structure to obtain a pretrained model by training eight plant diseases in the PlantVillage dataset and saving it.[22] This pretrained model is then loaded into the same deep network to continue training on our eight cucumber and rice disease datasets. By training and tuning at this stage, the network parameters were able to adapt to the cucumber and rice disease datasets. Our data set plays the role of tuning parameters, and finally, the experimental results are evaluated on the tuned CNN model. The process of this transfer learning is shown in Fig. 7.

To test the method, we obtain a pretrained model using eight different types of diseases from the public dataset PlantVillage. Some image samples from the PlantVillage dataset are shown in Fig. 8. They are apple scab, corn rust, corn scab, grape black rot, grape black measles, grape leaf blight, pumpkin powdery mildew, and tomato leaf blight. Because the leaves of these plant diseases are collected and photographed from the field, the background is relatively simple. A total of 5026 images were used in this paper, and disease types with relatively uniform sample distribution were selected. This article will first use these images to obtain a pretrained model, and then experiments were carried out on the basis of pretraining the model using cucumber and rice disease data sets.

The dataset includes a total of 1215 images from eight diseases, which have been assigned to eight class labels. Figure 9 shows image samples for each crop disease in our dataset, namely

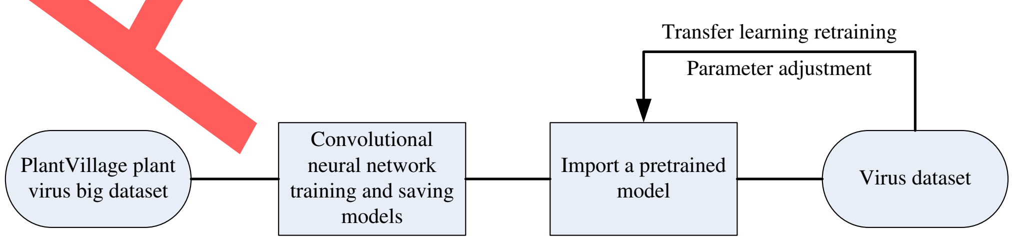

Fig. 7 The process of transfer learning using the PlantVillage dataset.

Fig. 8 Sample images from the public dataset PlantVillage.

Fig. 9 Sample images from the crop disease dataset.

cucumber target spot, cucumber powdery mildew, cucumber downy mildew, rice bacterial blight, rice false smut, rice blast, rice flax spot, and rice sheath blight. These raw images are all sourced from the natural environment, and their shooting is unlimited; they have different sizes, shooting angles, poses, backgrounds and lighting. In this work, we resize all images to 256×256 pixels before feeding them into the network for training. Figure 10 lists the number of samples for each crop disease, where 1 replaces cucumber target spot and so on.[23] As can be seen, the sample size of our cucumber and rice disease datasets is small. In the experiments, 80% of crop disease images are used for training, and the remaining 20% images are used for validation.

4.2 *Identification Results and Discussion of Cucumber and Rice Diseases*

Figure 11 shows the effects of different training mechanisms on the classification results of the cucumber and rice disease datasets under the same depth of CNN; these include three convolutional layers + two fully connected layers, five convolutional layers + three fully connected layers, and eight convolutional layers + four fully connected layers. Among them, three convolutional layers + two fully connected layers indicate that the network contains three convolutional layers and two fully connected layers. By comparing the changes in

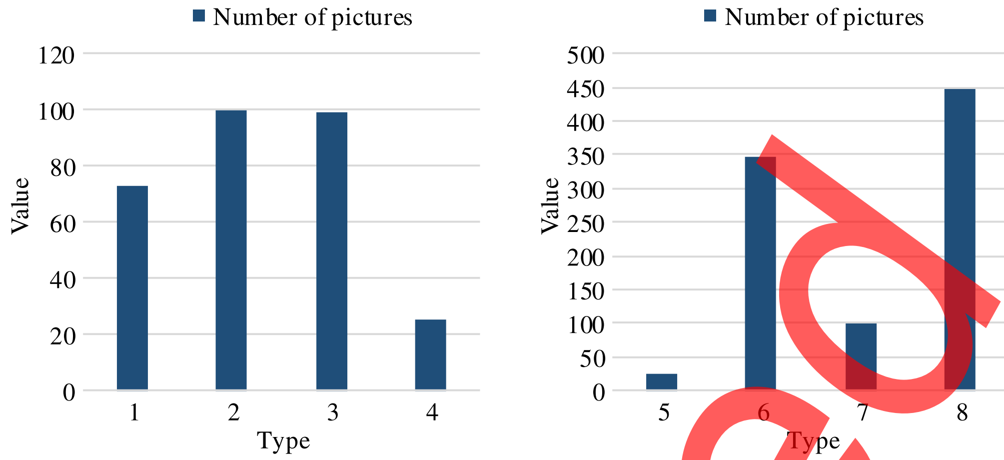

Fig. 10 Number of samples for each crop disease.

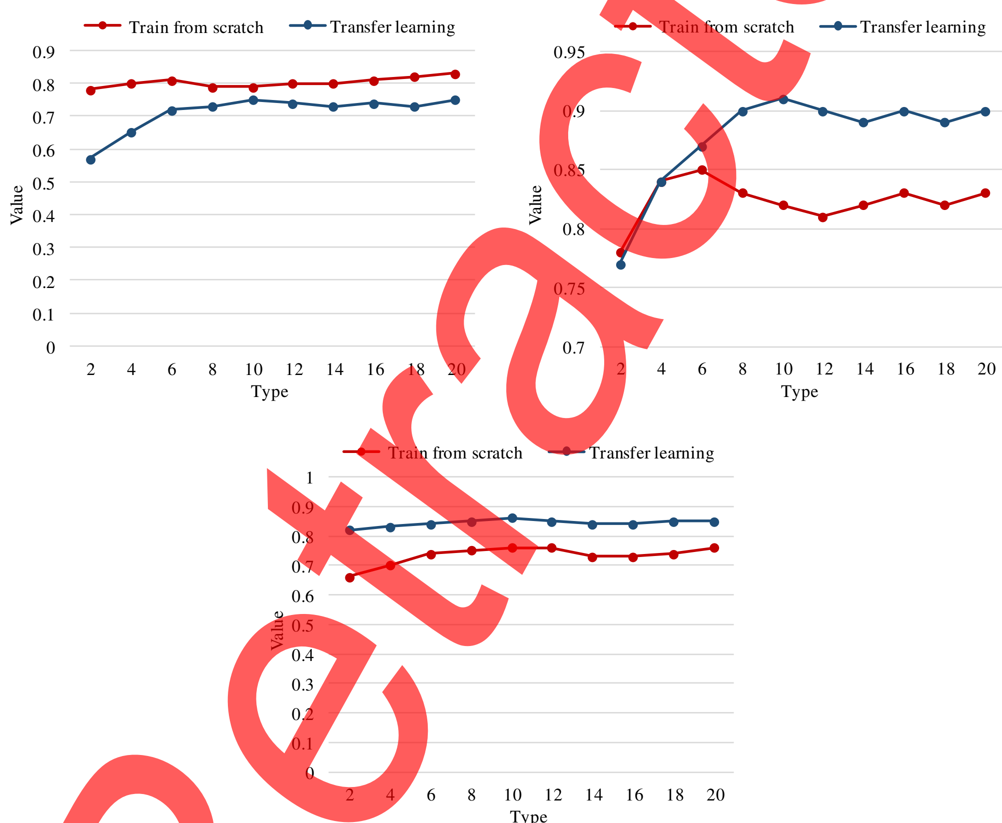

Fig. 11 Influence of the training mechanism in CNN of the same depth on classification results.

the graph, we find that, when the network depth is shallower, the accuracy obtained using the transfer learning strategy is lower than that obtained by training from scratch.[24] But as the depth of the network increases, using transfer learning on our small dataset gradually outperforms training from scratch. This is because the network with three or four convolutional layers can learn limited features and cannot learn more extensive visual features from the PlantVillage dataset to fit on the cucumber and rice disease datasets. This shows that the deep network can learn enough disease features, which can be reused on our dataset. It is obvious from the figure that using transfer learning on a network with five to eight convolutional layers is very effective, and the disease identification results are better than the mechanism trained from scratch.

Table 2 Validation accuracy of all experiments.

	Pretrained model (%)	Training from scratch (%)	Transfer learning (%)
Three convolutional layers	94.8	80.15	73.98
Four convolutional layers	94.66	85.73	84.45
Five convolutional layers	97.43	86.84	90.76
Six convolutional layers	96.83	86.17	88.85
Seven convolutional layers	94.56	80.81	85.73
Eight convolutional layers	93.85	76.35	84.04

Table 2 lists the validation accuracy of the disease dataset for all experiments. In this experiment, we performed each group of experiments nine times and took the median of the nine experiments as the final disease identification result. The pretrained model achieved high disease recognition accuracy because of the large scale of PlantVillage dataset, which means that the scale of the training data set plays an important role in the recognition results of the network. The larger the dataset size is, the more the network can capture the information and distribution of more samples. For our cucumber and rice disease datasets, when the network reaches a certain depth, using the pre training model obtained from the PlantVillage dataset for transportation is more accurate than training from the beginning.[25] The most obvious is that, on a CNN with eight convolutional layers, with the help of transfer learning, the identification accuracy of the disease data set is improved by 7.69% compared with the de novo training of the network. Using transfer learning to tune the parameters of the PlantVillage pretrained model on a network with five convolutional layers, the data set can achieve a classification of 90.76%. To some extent, compared with the data set of PlantVillage, it will be more cumbersome to be selected as the data set in the experiment. Furthermore, the experimental data set has samples for each disease, which are distributed unevenly. Better transfer results can be obtained if the complexity of the background is reduced and the number of samples per class is uniform.

Due to the overfitting problem caused by the crop disease datasets, the pretrained models were obtained using the relevant PlantVillage datasets, and new recognition models were obtained by adjusting parameters by continuing to train the cucumber and rice disease datasets. According to the experimental data, we see that, using the training mechanism of transfer learning, a disease classification accuracy of 90.76% is achieved in a CNN with five convolutional layers, which proves that the combination of CNN and transfer learning strategy is effective for the classification of crop diseases. The identification results of crop diseases prove that the use of convolutional neural networks to identify small datasets in the agricultural field is effective, and the training strategy of transfer learning can further improve the identification accuracy when the network depth is sufficient.

4.3 *Crop Disease Identification Based on CNN Model Integration*

4.3.1 *Identification results of cucumber and rice diseases under a single model*

Figures 12 and 13 show the training process of the cucumber and rice disease datasets under different deep CNN frameworks and transfer learning strategies. Observing the data in the following pictures, the training and verification starting point of visual geometry group (VGG) network framework is higher than that of the other three networks, i.e., the initial training accuracy and verification accuracy are higher. In DenseNet, the accuracy of the validation set fluctuated significantly in the middle, but the training and validation accuracy tended to stabilize at the end. In the other words, the features learned from large datasets can be better transferred to the identification of cucumber and rice disease datasets, provided that they are in the network. The training and verification process curves of the three networks of VGG, Inception-v3 and ResNet all converged smoothly. On the whole, due to the help of transfer learning, the training

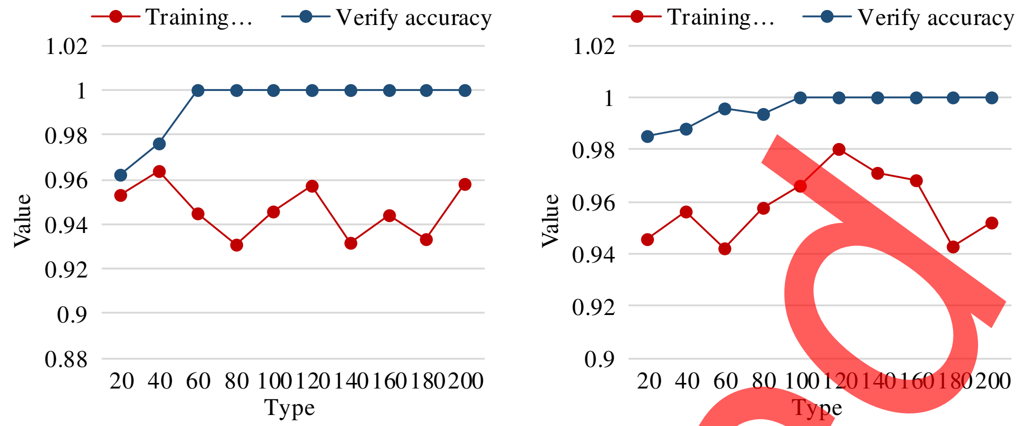

Fig. 12 Training process of the crop disease dataset based on VGG, Inceptionv3 CNN framework, and transfer learning.

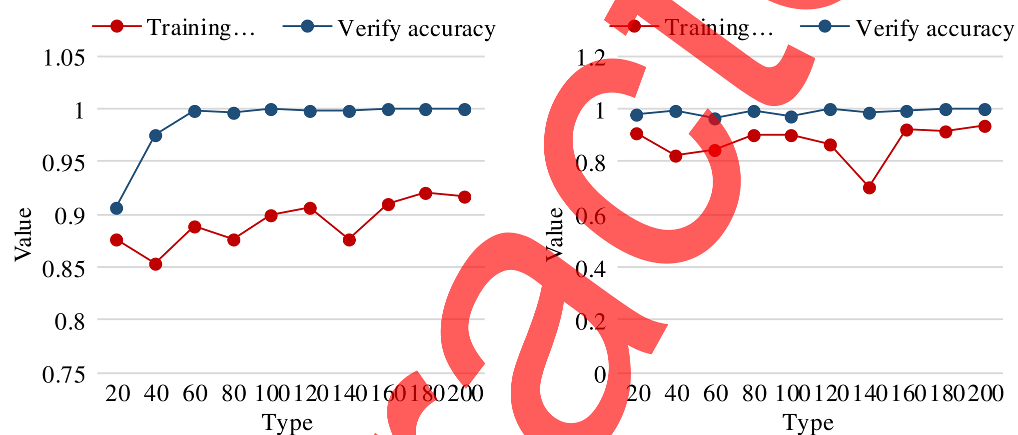

Fig. 13 Training process of crop disease dataset based on ResNet, DenseNet-based CNN framework, and transfer learning.

time of all deep network frameworks was relatively short, and the curve basically converged at 20Epochs.

4.3.2 *Identification results of cucumber and rice diseases under multimodel*

Tables 3 and 4 are the experimental results of single-model and multimodel combination integration on the cucumber rice disease dataset.

Since the validation accuracy of the disease dataset on the four single models is not much different, a random function is selected to assign the weights. A total of four sets of weights are given, and Table 4 takes the best set of weights and gives the results. A replaces the DenseNet model, B replaces the Inception-v3 model, C replaces the ResNet model, and D replaces the VGG model; (A, B) replaces the ensemble of DenseNet and Inception-v3 models, and other representations are similar. In the experiment, we take the weight parameter with the highest validation accuracy obtained during training. Observing the experimental data of only one model, the ResNet framework has the lowest classification accuracy for cucumber and rice diseases, which is 94.11%. The VGG framework is the most suitable data set for identifying our data set, up to 95.95%. In the direct average method, the DenseNet and VGG model ensemble had the best effect on cucumber and rice disease identification, with a verification accuracy of 96.24%. the model ensemble results of DenseNet and Inception-v3 followed, with a validation accuracy of 95.57%. In the multimodel ensemble network based on the weight method, the

Table 3 Experimental results of direct averaging method on the crop disease data set.

Model	Accuracy (%)	Model	Accuracy (%)	Model	Accuracy (%)
(A)	94.73	(A,C)	94.32	(A,B,C)	94.73
(B)	94.73	(A,D)	96.24	(A,B,D)	95.81
(C)	94.11	(B,C)	94.73	(A,C,D)	95.95
(D)	95.95	(B,D)	95.12	(B,C,D)	95.80
(A,B)	95.57	(C,D)	94.81	(A,B,C,D)	95.30

Table 4 Experimental results of weighted method on the crop disease data set.

Model	Accuracy (%)	Model	Accuracy (%)	Model	Accuracy (%)
(A)	94.73	(A,C)	93.48	(A,B,C)	94.96
(B)	97.73	(A,D)	95.89	(A,B,D)	95.77
(C)	94.11	(B,C)	94.83	(A,C,D)	95.76
(D)	95.95	(B,D)	95.71	(B,C,D)	95.97
(A,B)	93.80	(C,D)	94.72	(A,B,C,D)	95.68

DenseNet and VGG model ensemble had the highest verification accuracy of 95.89% for cucumber and rice disease identification. It can be seen that the highest validation accuracy of the multi-model ensemble exceeds the highest recognition accuracy of the single model. The results show that the method based on the CNN model set can further improve the verification accuracy of crop disease identification.[26]

5 Discussion

Through the study of relevant knowledge of the literature, this paper clarified the significance and necessity of image recognition of crop diseases and discussed the development of neural networks and image technology. Then, the image-based pattern recognition method was introduced, and the artificial neural network pattern recognition method was introduced, with its concept and algorithm expounded. This laid the foundation for the study of image recognition of crop diseases based on convolutional neural networks. Then, this paper conducted experiments and analyses on the case design of crop disease image recognition, pointed out the overfitting problem caused by crop disease datasets, and proposed a recognition method to deeply study crop diseases using four separate CNN models.[27]

Through experimental design and data analysis, the identification results of crop diseases proved that the use of convolutional neural networks to identify small datasets in the agricultural field was effective. And when the network depth was sufficient, the training strategy of transfer learning further improved the recognition accuracy. It also showed that deep CNN network combined with transfer learning played a significant role in helping the accuracy of initial training. In the problem of disease recognition, compared with only one CNN model, the method of a group of multiple CNN models further promoted the verification accuracy.

In this paper, the use and analysis of crop disease image recognition were carried out. First, transfer learning was performed using the similarity between the PlantVillage dataset and our crop disease dataset for classification. Then it passed the influence of different training mechanisms on the classification results of the cucumber and rice disease datasets under the same depth of CNN. Finally, it drew conclusions about the effectiveness of using convolutional networks.

6 Conclusions

The continuous development of the economy and society has brought all kinds of problems that have greatly impacted people's daily life and been harmful to people's health. The survival of microorganisms with different carriers has caused the incidence rate of crops and insects to increase rapidly, and the problem is becoming increasingly serious. In view of these problems, the prevention of crop diseases, disease diagnosis, and rehabilitation measures are particularly important.[28] Although the current image recognition technology has achieved good recognition results, it is still ineffective in the face of some problems. In future work, we will focus on the complex pest images in agricultural areas, which will help to improve development. Building on existing algorithms, it will leverage the strengths of deep learning to learn to recognize complex backgrounds and blurry images. The use of this technology is of great significance to ensure agricultural production and can promote rural economic development.

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