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Research on Identification Method and Improvement of Various Crop Diseases based on Resnet18

Yihe Ma[1], Tan Chen[2], Jiayi Zheng[1], Wanqi Wang[1], Shanyang Gao[*]

[1] Henan Engineering Research Center for Artificial Intelligence Theory and Algorithms, School of Mathematics and Statistics, Henan University, Kaifeng 475000, P. R. China

[2] School of Computer and Information Engineering, Henan University, Kaifeng, China, 475000, P. R.China

[*]Correspondence author: 2696026763@qq.com

Abstract

With the rapid development of high-quality agriculture, the identification of crop diseases has become a hot research topic. Aiming at the research task of identifying various crop diseases, in this paper, ResNet18, channel attention mechanism and transfer learning are combined to achieve the goal of accurately identifying various diseases of various crops. The images of four crop diseases, corn, tomato, apple and grape, in PlantVillage of Tensorflow data set are used as training sets. The original ResNet18 is used for training and the identification effect is obtained; the combination of ResNet18 original model and transfer learning model is used for training and the identification effect is obtained; ResNet18 is proposed to combine with transfer learning model and channel attention mechanism for training. Finally, through the method of class activation map, the disease results are visualized, and the function of channel attention mechanism is further analyzed. The experimental results show that ResNet18 combined with channel attention mechanism and transfer learning model solves the problems of gradient explosion or disappearance, degradation and over-fitting, moreover achieves better extraction of feature information on pictures, which improves the identification accuracy of various crop diseases and the efficiency of training model. This method is suitable for crop disease identification tasks with complicated picture information and many situations. In this paper, many diseases of various crops are accurately identified, and identification methods suitable for complex crop diseases are put forward, which provides technical support for high-yield and high-quality agricultural development.

Keywords

Crop Diseases; ResNet18; Transfer Learning Model; Attention Mechanism; Class Activation Map.

1. Introduction

“Food is the heaven for the people”, agriculture is related to people’s livelihood and plays a fundamental role in the national economy, the problem of crop diseases has also be- come the focus of agricultural research. Crop diseases are characterized by complex species and great influence, their occurrence range and severity often cause significant losses to China’s national economy and agricultural production, solving the problem of crop diseases is the starting point on increasing crop yield[1]. Researches can obtain the main diseases of corn include rust[2], gray spot disease and leaf spot; the main diseases of tomato include spot blight, yellow leafcurl virus and leaf mould; the main diseases of apple in- clude black rot, black star disease and cedar rust; the main diseases of grape include black rot[3], black measles and leaf blight,these important crop diseases need to be discovered and resolved in time. At present, solving the problems of crop diseases mainly relies on the manual identification of agricultural experts, which is slow and not suitable for simul- taneous identification of various crop diseases. Therefore, it is of great significance for China's agricultural development to realize smart agriculture and use neural network to com- plete the identification work.

With the continuous in-depth research on the application of computer intelligence, the technology that combines deep learning and image identification is now more and more widely used in crop diseases identification, and better results have been achieved. L. Xu, X. Xu, M. Hu, et al[4] propose an adaptive multi-classifier method combined with cluster analysis to identify corn leaf diseases and improve the ac- curacy of corn leaf disease identification. J. Xu, M. Shao,Y. Wang, and W. Han[5] uses deep learning technology to study the method of identifying corn spot disease and rustdisease, and achieve high identification accuracy. Z. Zhang, H. Xue, G. Fan, et al[6] established an automatic identifica- tion method of jujube defects based on improved convolu- tional neural network, which optimized the structure of con- volutional neural network and improved the detection accu- racy, network learning speed and convergence speed. W. Hu, J. Fan, Y. Du, et al[7] dentified 14 fine-grained diseases of tomato, and optimized the depth residual network by means of data enhancement and change optimizer, which could ac- curately locate the severity of diseases. D. Wang, and J. Wang[8] improve again the model of deep residual neural network SE-ResNeXt-101, he propose an image classifica- tion method of crop diseases TL-SE-ResNeXt-101 based on transfer learning, which was used for disease detection and classification of unspecified crop species and complete the model training and experiment on the reconstructed AI Chal- lenger 2018 crop disease data set. Y. Zhang, Z. Zhao, X. Wang, et al[9] chose the ResNet-18 structure and SGD op- timization algorithm to establish a deep learning model to distinguish eight kinds of green tea, which provided a foun- dation for constructing a visual identification model of tea and applying it to the mobile terminal. H. Wang and J. Li[10] proposed a ResNeXt model based on attention mech- anism to solve the problems of insufficient feature extraction in ResNeXt network (residual network) and interference of background information in data set, which can effectively extract key features and make full use of different levels of feature information to obtain better accuracy.

In order to put forward a more suitable method for iden- tifying various diseases of various crops, based on previ- ous studies, this paper first analyzes the differences between convolutional neural network and ResNets residual network. Then through training the data sets of four crops diseases of corn, tomato, apple and grape, according to the experimental results, we compare the difference of identification effect be- tween the original model of ResNet18 with or without trans- fer learning, the difference of identification effect between with or without combination of transfer learning and channel attention mechanism. Finally we choose the class activation map to visualize the results of diseases. So as to achieve the goal of achieving the best identification effect of various crop diseases by combining the ResNet18 with channel attention mechanism and transfer learning model.

2. Method

2.1 Introduction of Data Set

This paper selects PlantVillage[11] of Tensorflow as the experimental data set, this data set collates many images of crop diseases and it is the most widely used data set in this field. In our experiment, 16 types of diseases of four crops are selected as follows: corn health, corn rust, corn gray spot disease and corn leaf spot; tomato health, tomato spot blight, tomato yellow leafcurl virus and tomato leaf mould; apple health, apple black rot, apple black star disease and apple cedar rust; grape health, grape black rot, grape black measles and grape leaf blight. There are 16 categories of data sets. the image size is 224 pixels by 224 pixels. Fig.1 is detailed.

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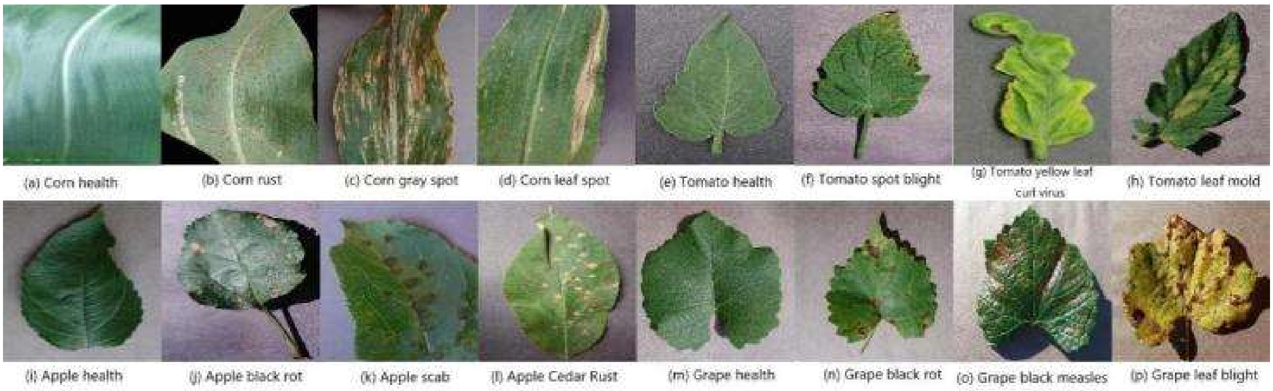

Fig. 1 Picture of 16 crop diseases

2.2 The Superiority of ResNets

The convolutional neural network[12] has a mature sys- tem and has a wide range of applications in the field of crop image processing and identification[13]. Convolutional neu- ral network is mainly composed of convolutional layer, acti- vation layer and pooling layer[14] with additional fully con- nected layer appear[15] alternately. Image features are ex- tracted by superimposing convolution layers, weight sharing is realized by downsampling technology of pooling layer re- duces dimensions, the learning of intelligent filter can get better identification effect faster. Theoretically, with the increase of the depth of the network structure, the train- ing effect will be better, however, increasing the depth will lead to the vanishing gradient or exploding gradient and degradation[16], so the error rate of the training results will not decrease but increase, the expected effect cannot be achieved.

Based on this problem, in order to obtain higher accu- racy, the deep residual neural network ResNets[17] are pro- posed. Compared with the convolutional neural network, the ResNets add multi-layer residual blocks[18] to solve the degradation problem in convolutional neural network. At the same time, we also use the Batch Normalization[19, 20] Principle to standardize the image, which can not only real- ize that with the increase of the number of network layers, the identification accuracy is also increasing, but also solve the vanishing gradient or exploding gradient of the convolu- tional neural network, get higher identification accuracy and accelerate the convergence rate of the network.

2.3 ResNet18

Considering that the data set of crop diseases images is not large, to prevent over-fitting, we adopt ResNet18 based on convolutional neural network. ResNet18 consists of 17 con- volutional layers, 1 maximum pooling down-sampling layer, 4 series of stacked residual blocks, 1 average pooling layer and 1 fully connected layer.Fig.2 is detailed.

Take a residual block of ResNet18 as an example, as shown in Fig.3. Firstly, the input feature matrix gets the output matrix through two 3×3 convolution layers. Sec- ondly, that the shape of the main branch and the shortcut branch’s output feature matrix are the same, the operation is performed by ”⊕” that is H(x) = F (x) + x[21], the feature matrix obtained by the main branch and the matrix obtained by the identity mapping performed of the shortcut branch are added. Finally, the result is optimized through the ReLU[22] activation function.So ResNet18 solves the problem of net- work degradation.

Use the principle of Batch Normalization to standardize the image, solve the problem of the vanishing gradient or exploding gradient and improve the convergence speed. Its principle is to adjust the data distribution of each layer of the feature map of the input image data to meet the distribution rule that the mean value is 1 and the variance is 0.

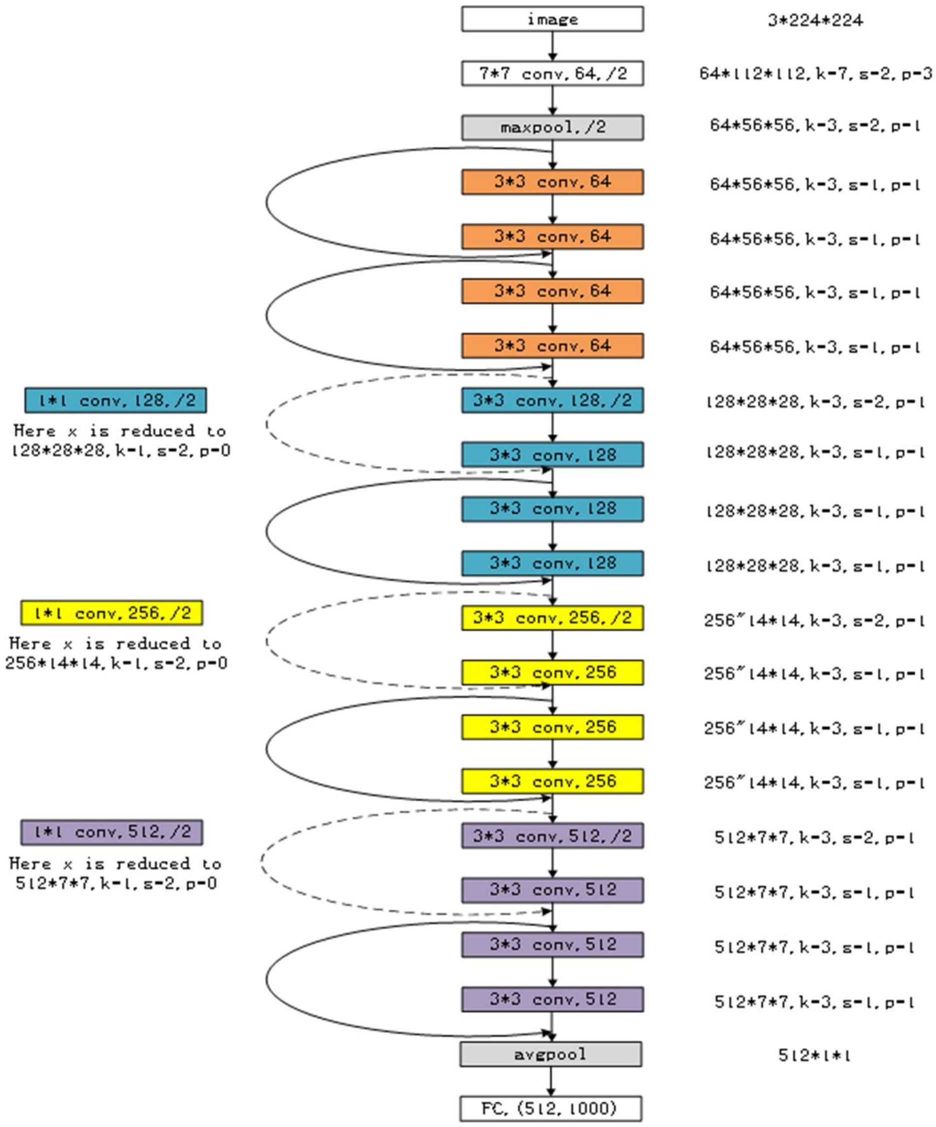

Fig. 2 ResNet18 framework

2.4 Transfer Learning Model

Since it is necessary to identify images of diseases of various crops, in order to improve the accuracy and speed of identification, avoid over-fitting problem, we consider the transfer learning model[23]. Transfer the pre-training

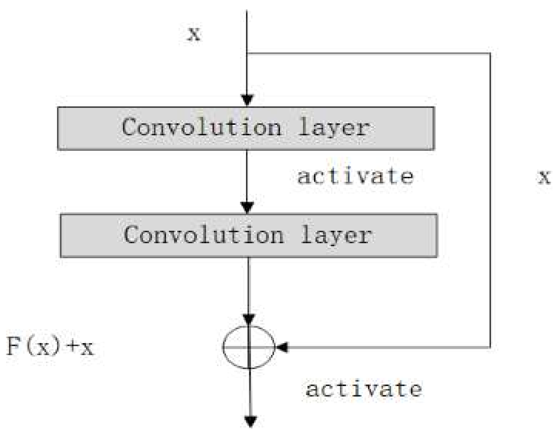

Fig. 3 Residual block

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ResNet18 model trained on the ImageNet to this applica- tion, we transfer the general features of the bottom of the network to this model, so that it has the identification abil- ity to identify the general features of the bottom layer. In addition, a new ResNet18 is formed by adding the full con- nection layer suitable for new tasks. A new classification and identification task can be realized by training the new model with PlantVillage of Tensorflow crop diseases data set, which greatly improves the training speed. Through this method, we can identify the diseases of apple, corn, grape and tomato.

2.5 Channel Attention Mechanism

Based on the problem that the feature channels in the orig- inal ResNet18 have a certain correlation and the importance of each feature channel is different, we add channel atten- tion mechanism[24] between the first convolution layer and maxpool layer, between the last convolution layer and av- gool layer in the original ResNet18 model. The channel attention mechanism consists of two operations, Sequeeze and Excitation[25]. The Sequeeze operation completes the spatial dimension feature compression without changing the number of channels; the Excitation operation obtains the weight of each feature channel, which can be used to get the different feature channel weight based on different iden- tification tasks, so as to realize the ResNet18 which is more suitable for the identification of various crops. Fig.4 is de- tailed.

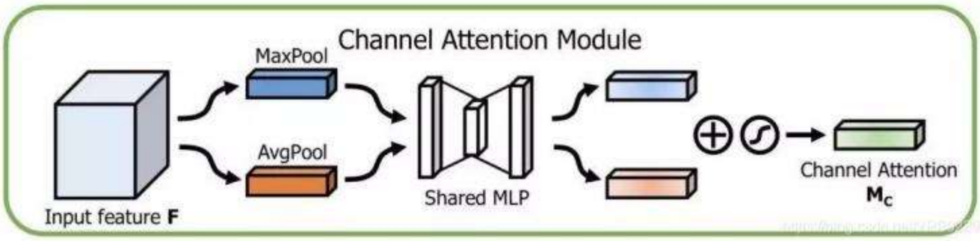

Fig. 4 Principle of channel attention module

3. Experiment

3.1 Experimental Environment

The experiment is completed in the software environment of python3.6 and pyTorch. The hardware environment CPU used Intel(R) Core(TM) i7-9750, clocked at 2.6GHz, and GPU used NVIDIA Intel(R)UHD Graphics 630 4G video memory.

3.2 Image Preprocessing

In this experiment, the pre-training model on ImageNet is used as the transfer learning model. The mean value of ImageNet data set on R, G and B channels is (0.485, 0.456, 0.406) and the standard deviation is (0.229, 0.224, 0.225). Therefore, the standardized operation of the data set used in this experiment should be consistent with the standardized operation on ImageNet. At the same time, adjust the size of the pictures in the experimental data set to 224 pixels * 224 pixels to ensure consistency with the input of ImageNet pre-training model.

In order to improve the generalization ability of the model, this experiment randomly flips. We rotates the image during training, and randomly changes the brightness, contrast, sat- uration and hue of the image to increase the training samples.

3.3 Parameter Setting

Considering the hardware performance and training ef- fect, 80% of the data set is used as training set and 20% as test set. We use SGD optimizer; the loss function adopts cross entropy loss function CrossEntropyLoss; set batchsize is 32, that is load 32 pictures in each batch; set the learn- ing rate to 0.0001, the momentum to 0.9 and the number of iterations to 100 rounds.

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3.4 Experiment and Analysis

3.4.1 Transfer Learning Model Comparison

By build that experiment in the above way, the perfor- mance of the model is measured by two indicators: the ac- curacy of crop disease identification and the stability of the model. The ResNet18 original model without pre-training model is compared with the ResNet18 model with pre- training model, with 100 training rounds each. The results are shown in Table1.

Table 1. Comparison of disease identification accuracy with and without transfer learning

Crop species	No transfer learning	transfer learning
corn	73.75%	94.74%
tomato	71.74%	95.00%
apple	72.49%	97.30%
grape	72.24%	99.21%

It can be seen from Table 1 that using transfer learning model can greatly improve the accuracy of disease identifi- cation by the model. After using transfer learning, the ac- curacy of diseases identification by the model has increased by about 20%, the identification accuracy of different dis- eases of each crop has reached more than 90%. Fig.5 shows the training process of corn, tomato, apple and grape use ResNet18 with or without transfer learning model. From the Fig.5, it can be seen that there are problems of unstable per- formance and low identification accuracy in the training pro- cess of non-transfer learning. However, in the training pro- cess, the image fluctuation of transfer learning is small and the r accuracy is high, which proves that transfer learning can greatly improve the identification accuracy and stabil- ity of the model. Therefore, in this experiment, the neural network model after transfer learning is used for subsequent experiments of adding channel attention mechanism.

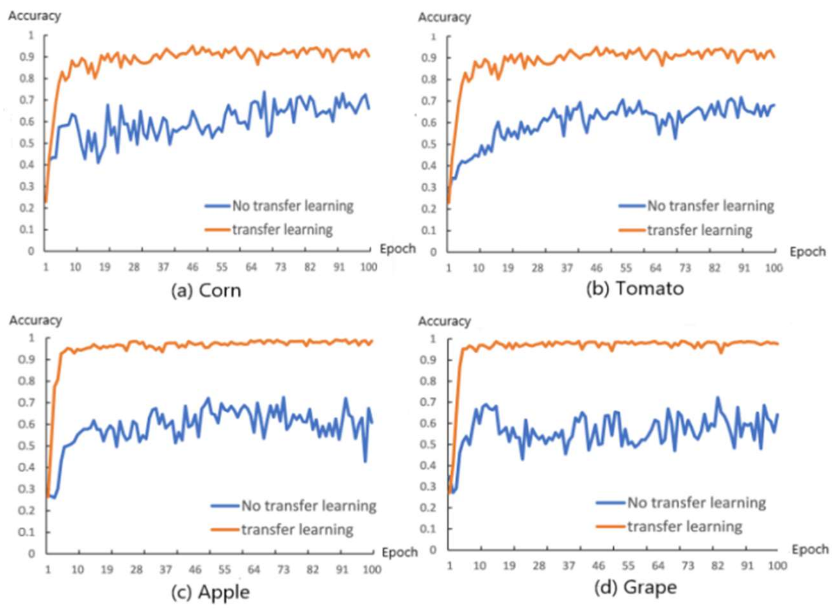

Fig. 5 Comparison of test set accuracy with and without transfer learning

3.4.2 Channel Attention Mechanism Comparison

In order to further improve the identification accuracy and stability of the model, we add channel attention mechanism after the first convolution layer and the last convolution layer of rsenet18 using

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the pre-training model. The transfer learn- ing model with channel attention module is compared with the transfer learning model without channel attention mech- anism. The results are shown in Table 2.

Table 2. Comparison of disease identification accuracy with and without channel attention mechanism

crop species	No channel attention mechanism	channel attention mechanism
corn	94.74%	96.12%
tomato	95.00%	96.75%
apple	97.30%	97.80%
grape	99.21%	99.75%

It can be seen from Table 2 that the identification accuracy of the transfer learning model can be improved by 1.38%, 1.75%, 0.50% and 0.54% respectively after adding the chan- nel attention mechanism. Fig.6 shows the training process of corn, tomato, apple and grape with or without channel attention mechanism in the transfer learning model.

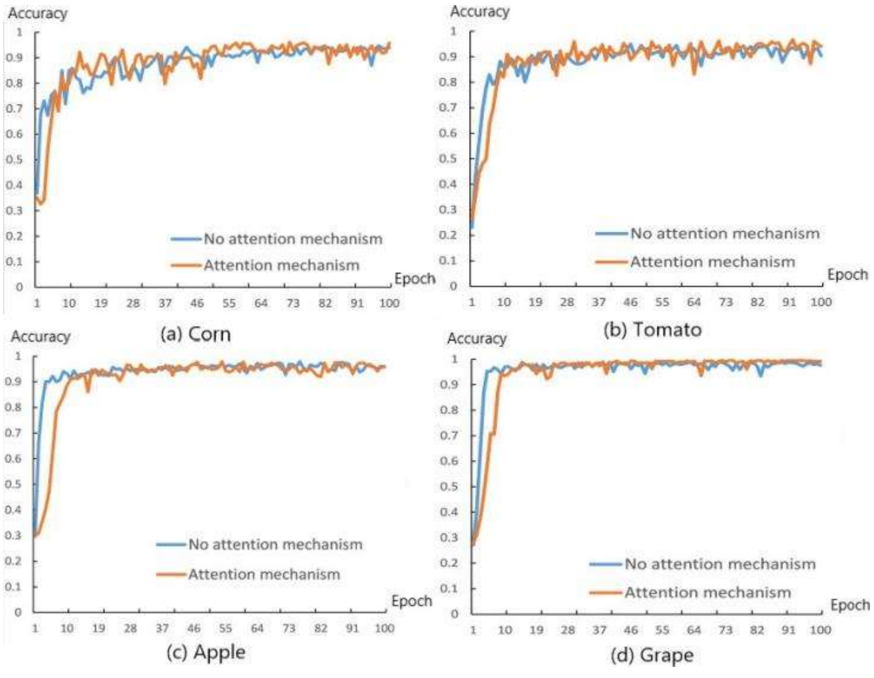

Fig. 6 Comparison of test set accuracy with and without channel attention mechanism

Through experiments, we find that the identification accu- racy of the model with channel attention mechanism is im- proved compared with the model without channel attention mechanism, but the improvement effect is not obvious. In order to further analyze the reasons why the identification accuracy is not improved obviously, we choose the class ac- tivation map to visualize the classification results of some crop diseases by the transfer learning model. From Fig.7, we can observe that the original transfer learning model has been able to identify and locate the location of crop diseases well, it is not excessively influenced by the background in- formation of the pictures. Therefore, this paper holds that the original transfer learning model can basically locate the dis- ease information because the picture background of the data set is single, so after adding the channel attention mecha- nism to the transfer learning model, the identification accu- racy of the model does

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not improve obviously. Therefore, the method of combining ResNet18 with channel attention mechanism and transfer learning is suitable for identifying various crop diseases with complicated situation, abundant picture information. Considering the complex characteris- tics of crop diseases in real farmland, this method is more suitable as the main method for identifying various crop dis- eases.

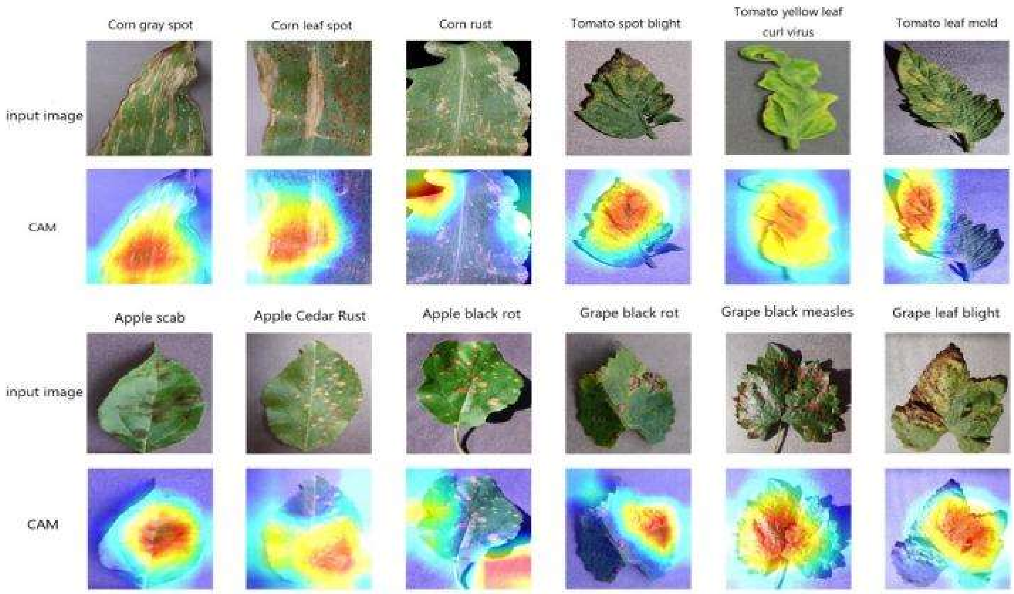

Fig. 7 Visual Result

3.4.3 Visualization of Crop Diseases Results

According to the difference analysis of identication effect of whether transfer learning model is added to ResNet18 original model and whether channel attention mechanism is added to transfer learning, we can conclude that adding transfer learning model and channel attention mechanism at the same time can improve the identification accuracy of im- ages of various diseases of four crops such as apple, corn, tomato and grape. Visualize the results of diseases through class activation map, we can draw a conclusion that the ad- vantages of channel attention mechanism will become more prominent with the complexity and diversification of data sets. Considering the characteristics of many kinds of crops and complex diseases, the combination of ResNet18 model, transfer learning model and channel attention channel can achieve the goal of more accurate identification of various crop diseases.

4. Conclusion

In this paper, we propose a method of combining ResNet18 with channel attention mechanism and transfer learning model, which can identify various diseases of corn, tomato, apple and grape. The experimental results show that the accuracy of model identification is improved by about 20% by using transfer learning, and the identification accu- racy of different diseases of each crop is over 90%. The combination of transfer learning model and channel atten- tion mechanism can improve the identification performance of the model by 1.38, 1.75, 0.50 and 0.54 percentage points respectively. By visualizing the results of disease identifica- tion through class activation map, it can be concluded that the use of channel attention mechanism is more suitable for identifying complex crop disease images. Therefore, adding transfer learning and channel attention mechanism based on ResNet18 model can greatly improve the accuracy of the model, and make it possible to identify various diseases of various crops as accurately as possible. This method can be used when the sample data set is complex and there are many kinds to be identified, which provides a new improvement idea for deep learning to complete image identification.

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