Research on Plant Leaf Disease Identification Based on Transfer Learning Algorithm

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Abstract. Plant disease is one of the important threat factors that hinder the normal growth and development of plants. The intelligent identification of plant disease species has become increasingly important in the agricultural field. In this paper, the open-source data set including Black rot, bacterial spot, rust, and healthy leaves are used to train the ResNet model. And the transfer learning algorithm is applied on ResNet to establish a plant disease recognition model with good versatility and high training efficiency. The experiment results show that the disease identification accuracy of the transfer learning model is 83.75%, which is much higher than that of the traditional ResNet-101 model. Therefore, the plant disease recognition model based on transfer learning algorithm is highly feasible.

Key Words: Plant disease identification, Deep learning, Transfer learning, ResNet

1. Introduction
Plant diseases are closely related to human economic benefits. It is estimated that the annual global loss due to plant diseases is as high as US $220 billion[1]. Plant disease control helps crop growth and greatly reduces economic losses. The most basic prerequisite for preventing plant diseases is the accurate identification of plant disease types.

In recent years, convolutional neural networks have achieved great success in the field of image recognition. In generalized recognition, GoogLeNet[2] and ResNet[3] and other convolutional neural network models have also achieved good results. But deep learning training requires a large amount of data as a basis, and transfer learning algorithms can alleviate the problem of insufficient data to a certain extent [4].

This paper combines the transfer learning algorithm with the ResNet convolutional neural network structure, and proposes a plant leaf disease recognition model with good versatility and high training efficiency. The labeled plant images under complex background are input into a pre-trained transfer learning model. Compared with the recognition results of the traditional convolutional neural network ResNet model to verify the effectiveness of the proposed plant disease recognition model.

2. Literature Review
In recent years, with the increase of the amount of available data and the continuous improvement of the performance of computer hardware equipment, deep learning algorithms represented by
convolutional neural networks have played an important role in the field of plant disease image recognition. Mohanty SP[5] used CNN to train 54 306 images containing leaves of healthy and diseased plants to obtain a system that can automatically diagnose plant diseases. Amara[6] and others used LeNet as the neural network architecture to realize the identification of banana leaf diseases in complex environments. Wang[7] and others realized automatic assessment of the severity of apple black rot through training of convolutional neural networks. Mohammed Brahimi et al.[8] fine-tuned parameters on the Alexnet and Googlenet models, and used visualization methods to understand the location of tomato leaf disease areas.

Although the application of the convolutional neural network (CNN) in plant disease recognition has achieved good results, it usually requires a large number of samples for training. However, in real life, it is difficult and costly to collect a large amount of data required by the model.

As a result, The plant disease recognition model based on deep learning has higher requirements for the hardware equipment. The training process is longer and the training efficiency is lower, which is not conducive to the popularization of the model.

3. Model Building

3.1. Model Framework
The overall model framework for plant leaf disease recognition is shown in Figure 1. First, the disease images in complex environments are labeled by using a visual image labeling software called LabelImg. Then, the diseased leaf data set in a simple background is used to train the ResNet-101 convolutional neural network model. Finally, the labeled image of diseased leaves is input into the transfer learning model to achieve plant disease identification in complex environments.

![Figure 1. The model framework of plant disease recognition based on transfer learning algorithm](image)

3.2. Deep Residual Network
The deep residual neural network is a neural network model that can effectively alleviate the problem of network degradation[3]. Figure 2 shows the "bottleneck" structure designed for ResNet-50 / 101/152. The three-layer structure uses 1 * 1 convolution to reduce the input dimension first, and then performs 3 * 3 convolution before using 1 * 1 convolution to increase the dimension. The calculation amount of
the parameter amount is greatly reduced, and the depth and accuracy of the neural network are improved. In this study, the ResNet-101 model was selected as a pre-trained model for transfer learning.

![Figure 2. the "bottleneck" structure designed for ResNet-50/101/152](image)

3.3. Transfer Learning Algorithm
In order to solve the problem of long training time of the convolutional neural network model, this paper uses transfer learning algorithm based on ResNet to migrate the shallow network of the neural network for the source task to the neural network of the target task to improve the convergence speed.

Before introducing transfer learning, two concepts need to be explained first: domains and tasks. Let the domain be $D$, which includes two contents:

\[ D = X, P(X) \]  \hspace{1cm} (1)

$X$ represents the feature space and contains all possible feature values. $P(X)$ represents a specific feature sampling instance in the feature space.

Let task be $T$, which also includes two parts:

\[ T = Y, f(X) \]  \hspace{1cm} (2)

$Y$ is the label space, which is a vector space composed of all labels. $f(x)$ is a prediction function that is learned based on the characteristics and labels of the input data.

According to the above definition, transfer learning refers to an algorithm that uses the knowledge acquired in the source domain and the source task to solve the target task of the target domain given the source domain, source task, target domain, and target task. This paper initializes the last few layers of networks on the basis of the trained model, uses the data of the target domain and the target task to train it, and adjusts the model parameters to adapt to the target task[10].

4. Experiment

4.1. Data Sources

4.1.1. Plant leaf acquisition in simple background. PlantVillage is an agricultural database open to all users and contains a variety of plant diseases and healthy plant picture data. In this paper, 4174 images collected by the PlantVillage project are used as training data for the transfer learning model, of which 537 are black rot, 1032 are bacterial spot, 293 are rust, and 2852 are healthy leaves. The images are shown in Figure 3.
4.1.2. Plant leaf acquisition in complex background. China Plant Image Library is one of the world's largest plant classification picture libraries. In this paper, 1,000 leaf photos are initially collected from the Chinese plant image library. 189 pictures are selected as leaf photos in complex environments. The leaves are obscured without watermarks, the leaves are obvious, and it is easy to label.

4.1.3. Plant leaf data set production in complex background. LabelImg is a visual image labeling software. With this tool, you can quickly label images and generate XML files that meet the PASCAL VOC format. You can directly input target detection neural networks as training data. The labeled image is shown in Figure 4:

![Figure 4. Labeled Pictures](image)

4.2. Model parameter settings

4.2.1. ResNet-101 pre-trained model parameter settings. In this paper, ResNet-101 is used as a pre-training model, and the network is trained using a disease leaf data set in simple background. The ResNet-101 model fits the network according to the residuals during the model training process. It has achieved good classification results in the ImageNet image recognition competition, and has achieved a good optimization effect on the accuracy and speed of the deep learning network. ResNet-101 includes a 34-layer network, and its network parameters are shown in Table 1.

| Network layer       | Number of nuclei | Nuclear size | Output shape     | Number of parameters |
|---------------------|------------------|--------------|------------------|---------------------|
| Convolution         | 64               | (7,7)        | (112,112,64)    | 9408                |
| Maxpooling          | /                | (2,2)        | (56,56,64)      | 0                   |
| 5*Convolution       | 64               | (3,3)        | (56,56,64)      | 36864               |
| Convolution         | 128              | (3,3)        | (28,28,128)     | 73728               |
| 7*Convolution       | 128              | (3,3)        | (56,56,128)     | 147456              |
4.2.2. Transfer learning model parameter settings. This article modified the last output layer of ResNet-101, initialized all its parameters, and changed the classification number from 1000 to 4, corresponding to the four-leaf disease type recognition results in this paper.

The transfer learning model parameters include gradient descent, optimization parameters and training parameters. The specific parameter settings are shown in Table 2.

| Parameter categories          | Argument Name       | Parameter Settings |
|------------------------------|---------------------|--------------------|
| Gradient descent optimization parameters | Weight Decay       | 0.0005             |
|                              | Learning rate       | 0.001              |
|                              | Learning impulses   | 0.9                |
|                              | Learning rate decay | 0.1                |
| Training parameters          | Picture size        | (224, 224)         |
|                              | Batch size          | 256                |
|                              | Number of iterations| 4000               |

After 4000 iterations of training, the loss value of the transfer learning model and the traditional model and the accuracy of the training set are shown in Figure 5 and Figure 6.

**Figure 5.** Comparison of Migration Learning vs. Loss Value from The New Learning Training

**Figure 6.** Comparison of Migration Learning with Accuracy of Training Process from New Learning

According to Figure 5, it can be found that after the same 4000 iterations of training, the transfer learning model has a faster convergence speed than the traditional model, and has a lower model loss value after convergence.

According to Figure 6, during the model training process, the accuracy of transfer learning is higher, the variance is lower, and the recognition effect is better than that of re-learning.

Therefore, compared with re-learning, transfer learning in this paper can converge faster and achieve better model recognition results. It can meet the requirements of smart agriculture for low hardware resources, fast training time and high training efficiency.

4.3. Result Analysis
Input a simple data set into a transfer learning model. As a comparison, the images that have not been processed in this paper are input to the traditional ResNet-101 model for recognition. The recognition results are shown in Table 3.

**Table 3.** This article methodology compares to the results of the ResNet-101 model

| Disease category | Transfer Learning | ResNet-101 |
|------------------|------------------|------------|
|                  | Identification number | Recognition rate | Identification number | Recognition rate |
| Black rot        | 15                | 75.00%  | 8                    | 40.00%  |
| Bacterial Spot   | 16                | 80.00%  | 6                    | 30.00%  |
| Rust             | 18                | 90.00%  | 9                    | 45.00%  |
| Health           | 18                | 90.00%  | 11                   | 55.00%  |
| Summary          | 67                | 83.75%  | 34                   | 42.50%  |

The recognition results in Table 3 show that the average accuracy rate of the disease recognition model recognition based on the transfer learning algorithm is 83.75%, which is significantly better than that of the traditional ResNet-101 model. Comparing the method in this paper with the ResNet-101 model, it can be found that the method in this paper has higher correct recognition numbers and correct recognition rates in the four samples, and the recognition effect is better. Comparing the performance of the method in the four samples, it can be found that compared with black rot and bacterial spot, rust and healthy leaves can obtain better results, and the correct recognition rate is 90%.

5. Conclusions

Traditional deep learning models have high requirements for computer hardware, long training time, and low training efficiency. In this paper, an existing open-source dataset is used to build a plant disease identification model based on the transfer learning algorithm in a complex environment with unsupervised, high accuracy, good versatility, and high training efficiency. Experiments show that compared with traditional models, transfer learning models have faster convergence speed and lower model loss after convergence. The correct rate of recognition for black rot, bacterial spot, rust, and healthy leaves reached 83.75%, and the correct rate of rust and healthy leaves was 90%. The model effect is much better than that of the traditional ResNet-101 Correct rate. Therefore, transfer learning algorithms are highly feasible in plant disease recognition.

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