Identification of maize disease based on transfer learning

Xiaolin Sun, Jiangshu Wei*

College of Information Engineering, Sichuan Agricultural University, Ya’an, Sichuan, 625014, China

*Corresponding author’s e-mail: weijiangshu66@163.com

Abstract. To reduce the time and energy needed by agricultural experts to evaluate maize diseases and improve the accuracy of image recognition of maize diseases, considering that the maize disease dataset is a small sample dataset, a method of image recognition of maize disease based on transfer learning is proposed, which is to fine tune the pre-trained convolutional neural network model. This paper compares and analyzes the experimental results of training only the last layer of Inception-v3 / Inception-v4 model and training all parameters of Inception-v3 / Inception-v4 model, and compares the results with the initial training VGG16, AlexNet and other models. The experimental results show that the method of transfer learning can reduce the training time of network, and the trained deep convolutional neural network can recognize maize diseases.

1. Introduction

Maize is an important raw material for food and feed processing, but the occurrence of maize diseases will seriously affect the yield and quality of maize. Traditional identification methods of maize disease are mainly manual identification by plant protection experts or experienced agricultural producers, which have great drawbacks. Maize diseases mainly occur in four main parts: leaves, ears, rhizomes, and the whole plant. This paper mainly focuses on the identification of corn leaf diseases. Although the traditional methods of crop disease image recognition have achieved good results, it is necessary to pre-process and segment the image, and extract the color, texture, shape and other features of the image, and then classify it using artificial neural network, support vector machine and other methods.

In recent years, the convolutional neural network [1] has been widely used in the field of image recognition because it does not depend on specific features and has been applied to the recognition of plant diseases. Mohanty et al. [2] used AlexNet and GoogleNet models to classify and recognize 26 diseases of 14 plants in PlantVillage. The recognition accuracy can reach 97.82% and 99.35%. Sladojevic et al. [3] used convolutional neural networks for plant leaf disease identification, and improved CaffeNet model with fine-tuning method, achieving good recognition results.

However, only when the network structure is complex and the number of training samples is large enough can CNN show superior performance [4]. When the training samples are missing, the phenomenon of over-fitting and falling into local optimum solution is easy to appear [5]. The addition of transfer learning can well solve the above problems caused by the lack of training samples and is widely used in the field of image recognition.

In this paper, a convolutional neural network method based on transfer learning is proposed for maize disease image recognition. This method uses the parameters of Inception-v3 and Inception-v4 models that have been trained on ImageNet as the initial values of training, which not only saves a lot of training time, but also helps to improve the performance of classifiers.
2. Transfer learning

2.1. Transfer learning
In recent years, transfer learning has attracted more and more scholars' attention and research. The DARPA Robotics Competition Document Series of the US Department of Defense defines the basic concept of transfer learning: the ability to identify new tasks by using prior learning knowledge and skills. Wikipedia defines it as: transfer learning focuses on the use of knowledge stored when solving a problem, applying it to a different but related problem. In other words, transfer learning is a machine learning method that uses existing knowledge to solve different but related domain problems. Its goal is to complete the transfer of knowledge between related fields. For convolutional neural networks, transfer learning is to successfully apply the "knowledge" trained on specific datasets to new fields [6]. Donahue et al. [7] used the deep CNN model trained on the ImageNet dataset to extract common visual features, and used this feature to achieve good classification results in new tasks such as scene recognition and bird recognition.

2.2. Fine-Tuning
As a method of transfer learning, fine-tuning refers to using existing parameter files to initialize new network parameters, transferring part of the pre-trained model to other tasks, combining with freeze and other parameter-tuning methods, which can save training time and make up for some shortcomings caused by small data sets [8].

3. Dataset description
The data in this paper are derived from the dataset of crop diseases provided by AI Challenger. Firstly, the acquired data is pre-processed, and the redundant data in the dataset is deleted and stored in categories. Screening out all the pictures of maize diseases contained in the dataset to compose a new dataset for experiment. The dataset of maize diseases contains 8 categories and 3503 pictures, of which 3068 pictures are in training set and 435 pictures are in testing set.
Figure 1. Maize disease images. (a) Corn healthy (b) Cercospora zeamaydis tehon and daniels general (c) Cercospora zeamaydis tehon and daniels serious (d) Puccinia polysora general (e) Puccinia polysora serious (f) Corn curvularia leaf spot fungus general (g) Corn curvularia leaf spot fungus serious (h) Maize dwarf mosaic virus.

4. Experiment and Analysis
Three experiments are carried out in this paper. Experiment 1 compares the results of identification of maize diseases by initial training of three models: LeNet, AlexNet and VGG16. Experiment 2 fine-tunes the pre-trained Inception-v3, compares and analyzes the test results of training only the logits layer and training all layers, and finally uses the trained model to identify a single picture. Experiment 3 compares and analyzes the experimental results of initial training and transfer training of maize disease dataset using Inception-v4 model. Both experiment 2 and experiment 3 used a fixed learning rate of 0.001, the RMSprop optimizer, the maximum number of execution steps was 100000, and the quadratic regularization hyper-parameter weight decay of all parameters in the model was 0.00004. The RMSprop parameter optimization algorithm can balance the large difference of gradient values of different variables and ensure that the derivatives of each dimension are in one order of magnitude.

4.1. Experiment 1
Initialization training of maize disease datasets was carried out using three models: LeNet, AlexNet and VGG16. The results of the experiment are shown in table 1.

| Models      | loss     | acc /%   | val_loss  | val_acc /% |
|-------------|----------|----------|-----------|------------|
| LeNet       | 0.2855   | 88.15    | 0.4929    | 79.76      |
| AlexNet     | 0.0501   | 98.24    | 0.9078    | 85.06      |
| VGG16       | 0.0226   | 99.12    | 0.9109    | 85.54      |

4.2. Experiment 2
Transfer learning was used to identify maize disease dataset, and the pre-trained ImageNet model, Inception-v3, was fine-tuned to train its logits layer and train all layers, respectively. The results of the experiment are shown in table 2.

| Training type | Accuracy /% | Recall_2 /% | Recall_5 /% |
|---------------|-------------|-------------|-------------|
| The end layer | 77.6        | 97.0        | 100         |
| Training all layers | 82.8        | 94.6        | 98.8        |
Accuracy represents the classification accuracy of the model, while Recall_5 represents the accuracy of Top5. The dataset contains few categories, and the degree of disease in dataset can be divided into general and serious, using Top2 is more in line with the actual situation of the dataset.

Finally, the trained two models are used to identify the single picture respectively, and the prediction results are shown in table 3. Score is the logit corresponding to each category. The test picture is shown in figure 1 (e).

| Model | score1     | score2     | score3     | score4     | score5     | score6     | score7     | score8     |
|-------|------------|------------|------------|------------|------------|------------|------------|------------|
| 1     | -0.98792   | -2.78690   | -2.37979   | 8.17422    | 9.38291    | -4.24996   | -3.25196   | -4.85924   |
| 2     | 0.67963    | -3.72221   | -5.33312   | 6.71195    | 15.20184   | -3.69813   | -8.29828   | -0.82725   |

*Notes: score1~score8 in the table are the predicted scores of 8 categories in (a) ~ (h) in figure 1.*

It can be seen from the table 3 that the first three most likely categories predicted by model 1 and model 2 are the same, and the probability from high to low is that puccinia polysora serious, puccinia polysora general, corn healthy. It can also be seen from the prediction results that the model recognition accuracy obtained by training all layers is higher.

4.3. Experiment 3
The Inception-v4 model was used for maize disease dataset, and the initial training and transfer training were used for the training methods. The experimental results are shown in table 4.

| Training method               | Accuracy /% | Recall_2 /% | Recall_5 /% |
|-------------------------------|-------------|-------------|-------------|
| Training from scratch         | 81.8        | 97.6        | 100         |
| The end layer                 | 77.0        | 95.2        | 99.8        |
| All layers                    | 81.0        | 94.4        | 99.2        |

Figure 2. Compare the losses of the three types of training.

From the experimental results, it is found that the results of initial training and training of all layers using Inception-v4 and Inception-v3 are similar. The reason is that the number of samples in the dataset is small and the categories are few, resulting in low recognition rate of the model, which do not reflect
the advantages of the model. It can be seen from the results of experiment 2 and 3 that the classification accuracy of all layers in training is more accurate and better than that of the training only the end layer.

5. Conclusion
In this paper, a transfer learning method based on Inception-v3 / Inception-v4 model is proposed to identify maize diseases, and the pre-trained model is fine-tuned, which provides a new idea for the identification of maize diseases. In crop disease image recognition, we can choose the appropriate model for our own dataset, considering the size of the model file, training time and accuracy. From the above results, it can be seen that no matter what training method is used, the results of using Inception-v3 and Inception-v4 models with the same parameters on maize disease data sets are similar. In terms of the model itself, the size of Inception-v3 model is 108.8MB, and that of Inception-v4 model is 184.4MB. When the experimental results are similar, Inception-v3 is more likely to be used for identification.

Compared with other non-agricultural data sets, crop disease data sets have higher requirements for collection and labeling, requiring not only professional knowledge and technical personnel, but also being affected by the growth cycle of crops. In addition, crop pests and diseases are of varying degrees. Using deep learning methods to identify crop pests and diseases, the data set is undoubtedly crucial.

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