Identification of Tomato Pests and Diseases Based on Transfer Learning

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Abstract. There are numerous kinds of tomato diseases and insect pests. Their pathology is complex and different. It is hard to rely on manual identification purely and the error rate is high. After collecting a mass of leaf table pictures, our aim is to classify nine kinds of common tomato diseases in China. The idea of transfer learning is applied to achieve recognition and classification of tomato data set by the lightweight convolutional neural MobileNet. Finally, the model can obtain test classification accuracy of 97.19%. Experiments have proved that this method is not only simple to operate and easy to implement, but also can achieve high accuracy on plant diseases.

Keywords. MobileNet; tomato diseases; CNN; transfer learning.

1. Introduction

Deep Convolutional Neural Network (DCNN) is a kind of neural network with a special structure. It has been 22 years since LeCun \cite{1} put forward the first truly Convolutional Neural Network (CNN) in 1998. In 2012, the CNN has developed rapidly after the emergence of AlexNet. It has shown more excellent performance than traditional machine learning in many aspects such as image recognition, speech recognition, natural language processing and so on \cite{2}. Thus CNN has been applied to various fields.

Pattern recognition and machine learning have been developed continuously. Based on it, automatic identification on plant disease types has been achieved by using image processing technology \cite{3}. The more common is the identification and classification based on plant leaf surface images. However, training DCNN from scratch requires a mass of data and expensive computing resources \cite{4}. And it is time-consuming and laborious to obtain a large amount of operational data \cite{5}. Fortunately, transfer learning is a means to retrain pre-trained models and apply these models to other tasks in the field of deep learning. Generally, these pre-trained models have consumed huge time and computational resources during development. In this paper, CNN is used as the feature extractor. And adaptive layers are added to adjust the global parameters of the upper layer. Experimental results show that the method we proposed can learn rich characteristics of tomato diseases in the case of insufficient data \cite{6}. And then we can obtain a high accuracy.
2. Tomato Image Recognition Algorithm

2.1. CNN Model
MobileNet is one of the pretrained models on the TensorFlow. This structure is characterized by a small model, having fast computing speed and being suitable for deployment to mobile terminal or embedded system. Besides, it can also achieve ideal speed requirement on CPU. The most critical aspect of MobileNet is that traditional convolutions are replaced by depthwise separable convolutions (as shown in figure 1). It greatly reduces the amount of computation and parameters [7]. In addition, MobileNet also introduces width multiplier $\alpha$ and resolution multiplier $\beta$ to further shrink the model [8].

![Figure 1. Traditional convolution and depthwise separable convolution.](image)

2.2. Transfer Learning
The concept of transfer learning was proposed by professor Yang Qiang in 2005. Transfer learning is used to improve a learner from one domain by transferring information from a related domain [9]. Especially in the learning and working life with insufficient data or limited hardware conditions, it’s a very popular method in deep learning at present.

Transfer learning provides a new framework for digital image processing and prediction analysis. It can obtain higher accuracy. And it is a great potential in crop disease detection [10]. Traditional machine learning algorithms can only deal with isolated tasks. While transfer learning attempts to transfer knowledge learned in one or more original tasks and then uses it to improve learning in related target tasks. So the traditional machine learning algorithm can be enhanced [11]. In addition, transfer learning only needs to use a small amount of data to train the model and can achieve higher accuracy in a shorter training time compared with the traditional CNN [12]. Transfer learning shows its advantages when there is not sufficient data set and high test accuracy is needed [13].

2.3. Algorithm Design
The proposed algorithm mainly uses the MobileNet model as the source model of transfer learning. Then the algorithm classifies the data set with a customized full connection layer and classifier. Considering the differences between the source domain and the tomato disease domain, too many expansion layers will result in over-fitting [14] and decrease experimental performance. Therefore we adopt two extension layers namely Ex1 and Ex2. Ex1 is the fully connected layer containing 1024 neurons. Ex2 is the Softmax classification layer. Figure 2 is a roadmap of the model’s training and testing technology.

3. Experiment

3.1. Experiment Goal
Original data domain of transfer learning in this experiment is 1.26 million pieces of training data of ImageNet, and original model aims to classify 1000 kinds of pictures. Target data is 6480 pieces of tomato disease pictures and target model is supposed to classify the target data into 10 different species.
3.2. Data Set
Tomato data set in this paper consist of two parts. A part of it is taken from the AI Challenger (https://challenger.ai/). The other part is downloaded from Baidu and other websites.

In this paper, nine common tomato diseases and healthy tomato leaves are selected as the research objects. So the total classification tasks are subdivided into 10 classes. From left to right in screenshot are Healthy Tomato, Tomato Leaf Mould, Tomato Septorial Blight, Tomato Stemphylium Leaf Spot, Tomato Early Blight, Tomato Late Blight, Tomato Powdery Mildew, Tomato Red Spider Damage, Tomato Mosaic Disease and Tomato Yellow Leaf Curl Virus.

3.3. CNN Architecture
Considering that the detection of diseases will be implanted into the mobile platform, the MobileNet model is preferred. The traditional training process of CNN is roughly as follows: data reading and preprocessing; the generation, reading and parsing of TFRecord; construction of network model and training. In contrast, the application module of Keras we used provides deep learning models with training weight. These models can be directly utilized for prediction, feature extraction and fine-tuning.

3.4. Experiment Result
The experiment results are shown in table 1.

| Data set     | The training samples | The test samples |
|--------------|----------------------|------------------|
| Accuracy     | 99.71%               | 92.04%           |

Among it, the test sample results of every tomato diseases are shown in table 2. Besides, the accuracy curve obtained in the training process is shown in figure 3.

Figure 3 show accuracy curves of training set and testing set respectively. As can be seen from tables 1 and 2, figure 3, a high accuracy can be obtained by using the above algorithm to detect tomato diseases. This is mainly because the CNN can well extract the disease characteristics of tomato leaves. However, there is still a small gap between the accuracy of test samples and training samples. This is mainly because the CNN is easy to over-fitting. The over-fitting is still inevitable although some measures have been taken in the training [15].

The confusion matrix of the test results is shown in the following table 3.
Table 2. Test results of every tomato disease.

| Disease                        | Number of samples | Correct number | Accuracy |
|--------------------------------|-------------------|----------------|----------|
| Tomato Powdery Mildew          | 162               | 162            | 100%     |
| Tomato Stemphylium Leaf Spot   | 162               | 151            | 93.2%    |
| Tomato Septorial Blight        | 162               | 152            | 93.8%    |
| Tomato red Spider Damage       | 162               | 156            | 96.3%    |
| Tomato Yellow Leaf Curl Virus  | 162               | 156            | 96.3%    |
| Tomato Health                  | 162               | 152            | 93.8%    |
| Tomato lunban                  | 162               | 137            | 84.6%    |
| Tomato Late Blight             | 162               | 141            | 87%      |
| Tomato Leaf Mould              | 162               | 156            | 96.3%    |
| Tomato Early Blight            | 162               | 128            | 79%      |

Figure 3. Accuracy curve.

Table 3. Confusion matrix of test results.

| Species | a   | b   | c   | d   | e   | f   | g   | h   | i   | j   |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| a       | 162 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| b       | 0   | 151 | 5   | 0   | 1   | 0   | 2   | 1   | 0   | 2   |
| c       | 0   | 1   | 152 | 1   | 0   | 1   | 2   | 2   | 0   | 3   |
| d       | 0   | 0   | 0   | 156 | 0   | 0   | 4   | 0   | 2   | 0   |
| e       | 0   | 0   | 1   | 3   | 156 | 0   | 1   | 0   | 1   | 0   |
| f       | 0   | 0   | 0   | 1   | 0   | 152 | 8   | 0   | 1   | 0   |
| g       | 0   | 2   | 4   | 11  | 0   | 4   | 137 | 1   | 0   | 3   |
| h       | 0   | 0   | 1   | 1   | 0   | 0   | 3   | 141 | 8   | 8   |
| i       | 0   | 0   | 1   | 2   | 0   | 0   | 2   | 156 | 1   |     |
| j       | 1   | 2   | 9   | 3   | 1   | 2   | 3   | 8   | 5   | 128 |

It can be seen from table 2 that the classification accuracy of Tomato Powdery Mildew can obtain 100%. Meanwhile Tomato Early Blight gets 79% accuracy which is the lowest. According to table 3 of the confusion matrix, the probability of Tomato Early Blight to be mistakenly identified as Tomato Septorial Blight is the highest. And Tomato Septorial Blight is also the most easily misidentified as Tomato Early Blight. By comparing these two kinds of pictures, we find that there is a high degree of similarity between some features of the two diseases. So there are certain difficulties to always accurately distinguish them.
4. Conclusions
In the detection of tomato diseases, CNN is easy to over-fit due to its complex structure and many parameters. In order to improve the classification accuracy and ease the over-fitting, transfer learning based on MobileNet is proposed. The experiment shows that the method is not only simple and easy to implement, but also can obtain high accuracy. It is enough to meet the needs of daily life and work.

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