The Research on Detection of Crop Diseases Ranking Based on Transfer Learning

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***Abstract*—Crop diseases are a major global threat to food security. Because the lack of agriculture experts or necessary facilities, it is difficult to determine the type of disease, as well as the degree of disease in time, which became the major factor affecting in crop production. In recent years, with the development of the transfer learning in deep learning domain, the experience of experts can be simulated to detect crop diseases in time. In this paper, we have proposed an improved transfer learning method based on ResNet 50 in crop disease diagnosis. The AI Challenger 2018 dataset has been deeper analyzed, the degree of crops diseases are detected. Comparing with non-transfer learning, the proposed transfer learning method achieved better results, which can significantly improve accuracy results by 5.1%~1.87% with reducing half of the running time.**

Keywords-crop disease; deep learning; transfer learning; ResNet 50

I. Introduction

Modern science and technologies have given human society to produce enough food to meet the requirements of more than 7 billion people. However, the yield of crops depends on the factors of climate change, crops diseases, and others[1]. Crops diseases[2] are considered as significant issues for smallholder farmers, which are also recognized as serious global problem[3]. In developed countries, agricultural modernization degree is higher than developing countries. Developed countries have adopted many strategies to control the crop loss which caused by various factors. However, in developing countries, more than 80 percent of the agricultural production is generated by smallholder farmers and meanwhile more than 50 percent of crops loss is associated with diseases[3]. For example, in China, the largest developing country in world, the grain output is 600 million to 650 million tons each year, and the grain loss caused by diseases up to 30 percent of the total loss. The economic losses are more than 2 billion dollars. Diseases have not only caused grain reduction and food contamination, but also caused viral transmission indirectly which will seriously affect people's health.

Historically, most diseases control methods use biological or chemical agents. Accordingly, ***how to judge the type of diseases correctly as well as the disease level has become an important step to control diseases effectively and reduce economic losses.***

In the past, the detection of diseases had to require the experts or agricultural organizations frequently. In recent years, with the development of the Internet, people can also consult experts online. Formerly, the detection of crops diseases often used visual inspection. Visual inspection tends to require inspectors have rich experience in crop diseases detection domain, which have the drawbacks of cannot get the information of diseases and are not able to adopt the efficacious means of prevention and treatment in time. In particular, the symptoms of some crops in the early stage are very similar so that the experts are very difficult to distinguish the differences.

The disease distinguish is a typical application of image recognition. The most popular method is convolutional neural network (CNN) in image recognition. By using CNN, the disease area' edge and contour of each part can be figured out in pixel's level easily. This advantage make CNN achieves good performance in disease detection[4, 5].

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Many researchers[6, 7] employed CNN in crop disease detection already. However, using CNN to do image detection and conduct model training for all stages is quite time-consuming and not suitable to use in practice. In order to save running time and improve the accuracy of disease detection, we has proposed an improved transfer learning method called CDCNN based on ResNet 50[8] (original model pre-trained from ImageNet[9]) to classify the degree of disease (such as healthy, general serious or even serious).

In this paper, on the basis of studying ResNet 50, we have proposed an improved transfer learning method. The crop pest dataset named ‘AI Challenger 2018’ has been deeper analyzed and adopted to conduct the experiments. The running mechanism of the proposed method is concluded as follows. The weights are pre-trained based on ImageNet, fine-tuning approach is used, and then part of the convolution of ResNet 50 is frozen. According to the dataset of crop pests and diseases, adds '0' to fill picture's margin when the picture is entered. Finally, an average pooling and two fully connected layers are added after the convolution layer. The experiments performance have shown that the accuracy of the proposed improved transfer learning method outperforms current excellent algorithms by 5.1%~1.87% with reducing half of the running time.

The paper is organized as follows. Section II illustrates current leading research works in crop diseases detection. Section III demonstrates the details of ResNet 50 and then the theory and the running mechanism of the proposed improved transfer learning method are given. Extensive experiments results are conduct and analyzed in section IV. Finally, the contribution of the proposed method is discussed and the future work is proposed in section V.

II. RELATED WORK

In the past research, Anyela Camargo et al. used traditional digital image processing to predict banana leaf infected with Black Sigatoka at various stages of infection[10]. Some other researchers used machine learning to diagnose whether a crop was diseased. J. E. Yuen et al. used Bayesian analysis to prediction plant disease[11]. Amanda Ramcharan et al. used deep learning to detection cassava disease[12]. Compared with the research mentioned before, Sharada P. Mohanth et al. used a relatively large dataset-PlantVillage project[13] to detection various plants that had various diseases[14].

Their algorithms have advantages and disadvantages. Traditional digital image processing has high precision and wide applicability, but the processing cannot be conducted without experts guiding. Meanwhile, since the expert normally only familiar with several plants, they cannot classify plants diseases more than 61[15]. Machine learning methods can automatically distinguish the crop disease. However, it still need experts to label out the feature of diseases on the original image manually[16, 17]. Deep learning methods makes thing easily, it only needs experts label out whether an image has disease or not. On the base of these simple labels, it can automatic do the classification.

Since the traditional digital image processing method and machine learning method heavily depend on expert experience and complex way to label out the features of disease, they cannot build a dataset which has massive images. Thanks for deep learning method, experts can build a large dataset which includes more than 10 thousands images.

On the bases of the big dataset, deep learning method can do the classification automatically. However, only use deep learning method to do the classification is time-consuming and need huge calculation resource. In order to solve this issue, this paper proposes to conduct a transfer learning method that using fine-tuning strategy into the crops disease detection. The more detail information of our method will be described in the section three.

III. METHOD

In this part, we show the network structure which we used and how we implement it.

In order to achieve crop diseases ranking, we need a dataset (target dataset) which has the knowledge of crop diseases degree. However, if we use deep learning method to do the ranking directly, it will time-consuming and need huge calculation resource. Therefore, we try to use the parameters which already trained on another similar and larger dataset (source dataset). By transferring the existing parameters of source dataset into the target dataset, the training time can be saved and the accuracy can be improved.

In this paper, we use ImageNet as the source dataset which has 14 million images and contains more than 20,000 categories. However, the ImageNet has no knowledge of crop disease. In order to distinguish the crop disease degree, we need a dataset which has knowledge of crop disease as target dataset. On the basis of pre-trained model by ImageNet, we can get common low-level features of various images. Then, we can use a strategy which called fine-tuning to transfer the parameters of pre-trained model on ImageNet dataset into the target dataset. Thanks for the common low-level features from pre-trained model and the knowledge of crop diseases in target dataset, we can finally do the ranking job.

The process of fine-tuning is to adjust the one or more layers before used the parameters from the pre-trained model, and goes on training based on AI Challenger 2018 crop disease detection in China (CDImage) to suit our task. Then, in this paper, we use ResNet 50 as the based model, pre-trained for object detection task on the ImageNet dataset. Adopted the fine-tuning strategy and add some layers to meet our task of crop disease rank detection.

The proposed method called CDCNN consists of the following basic steps:

1) When the images input the network, we add a zero padding and padding window is 3×3. Filling the edges of the crop images with a value of '0', we can extract the edges information of input images better.

2) Using ResNet 50 as the based model, pre-trained for object detection task on the ImageNet dataset, we transferred the first 49 layers of ResNet 50 which are frozen, and forbidden training update.

3) After the frozen convolutional layers, we add an average pooling layer and the pooling window is 2×2. We need to get the mean value of 2*2 picture matrix area to retain more image information.

4) After the average pooling layer, we use flatten function to add a flatten layer which let multidimensional input into one-dimensional.

5) The next, we add two fully connected layers. The first fully connected layer that outputs dimensions of 2,048 and uses 'Relu' function as the activation function. In order to classify 61 degree of crop diseases, the second fully connected layer is designed as 61 output dimensions and the activation function is 'Softmax'.

In Figure 1, we show the abbreviated network structure. In the next section, we will show the results of this network.

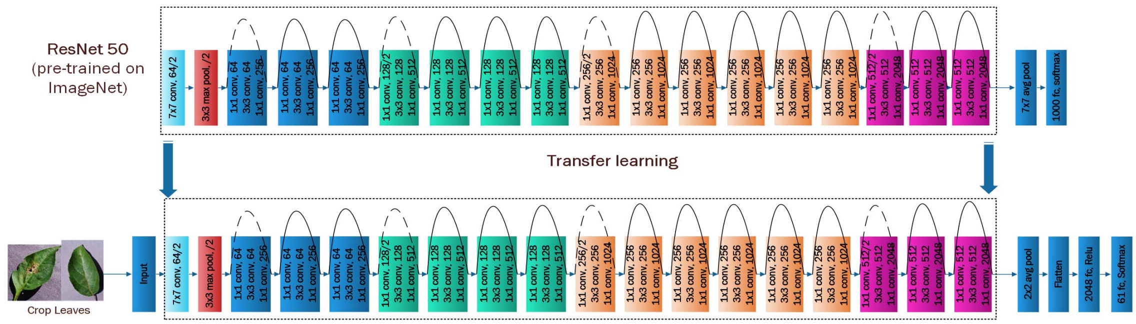


Figure 1. Overview of proposed method. ResNet 50 layers pre-trained on ImageNet are transferred to our CDCNN model. Frozen the parameters of the convolutional layers during the training process. Then add an average pooling layer, flatten layer and tow fully connected layers.

IV. Experiments and Results

A. Experiment Context

The proposed experiment has been run on CentOS 7 with Tesla P100 at 1,480MHz and 12GB of RAM base on Keras ResNet 50 transfer learning.

B. Dataset Description

In order to make our classifier more accurate, we needed a relatively large and verified dataset. Therefore, this experiment used an open dataset-AI Challenger 2018 crop disease detection in China. The dataset contains a variety of crop leaves. The training set has 31,721 tagged images and the verification set has 4,540 tagged images. This dataset includes a total of 27 diseases of 10 plants (such as apple, cherry, grape, orange, peach, strawberry, tomato, pepper, corn, potato). There are 61 classification (species-disease-degree) in total. For example, we showed one of the diseases of the apple in Figure 2.

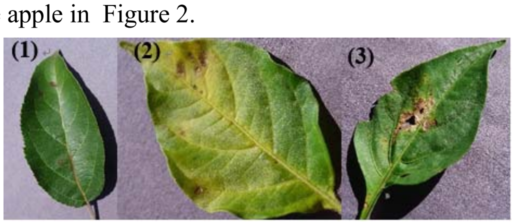


Figure 2. Example for apple leaves. (1) Healthy apple leaf (2)Venturia inaequalis-general (3)Venturia inaequalis-serious

C. Image Preprocessing

In the daily life of production, most of the time we cannot get the good sharpness and brightness pictures which proper for the future study. The actual pictures may be affected by brightness, angle, or even the camera so that we unable take the idealized image. Therefore, in order to improve the generalization ability of the model, in the preprocessing part, we randomly increase or decrease the brightness, rotate and flip the image of original dataset.

When we increase or decrease the brightness, the specific equations as follows:

$$f = g\times\alpha+\beta \tag{1}$$

The "g" is original image, "f" represents the changed image. "α" ∈ (0.9 , 1.1) , "β" ∈ (-10 , 10)and belongs to integer.

Then we normalized the image to (-1, 1). Afterwards, we set the center point and random rotation angle to generate rotation matrix. After that, affine the matrix and random mirror flip the image. Finally, scaled the image to a uniform size. In Figure 3, we will show the results of above-mentioned of each step.

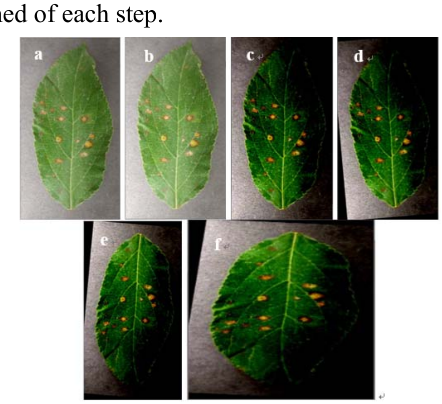


Figure 3. (a) original image, (b) increase or decrease the brightness, (c) normalization, (d) rotate, (e) mirror flip, (f) uniform size

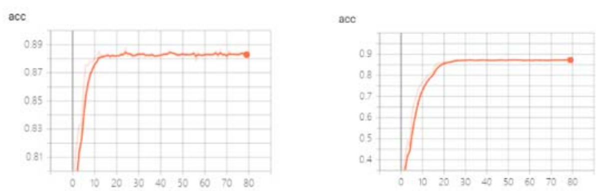
D. Results

In order to compare the effect of the transfer learning method we proposed, we did an experiment similarly used ResNet 50 without transfer learning. The TABLE I. shows the results of these two experiments.

TABLE I. THE RESULTS of EXPERIMENTS

Experiments	**Criteria**				
	Average Accuracy(%)	***Average converge time(h)***	***Batch Size***	***Epoch***	***Number of Experiments***
Without Transfer learning	87.52	9.78	64	80	10
Transfer learning	88.65	4.77	64	80	10

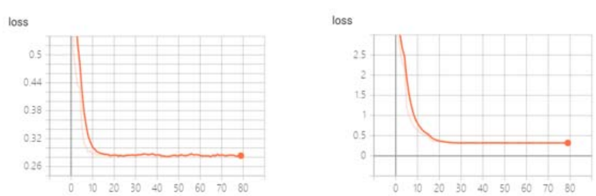
As we can see from the TABLE I, under the same experimental criteria, our experimental result is better than the other experiment. On average convergence time, the method with transfer learning costs 4.77 hours and without transfer learning costs 9.78 hours. We save the average convergence time more than 100%. And we get a higher accuracy.



(a) (b)

Figure 4. (a) ResNet 50 with transfer learning (b) ResNet 50 without transfer learning

As we can see from Figure 4, ResNet 50 with transfer learning converged at around 12th epoch. ResNet 50 without transfer learning converged at the 30th epoch. This shows that the ResNet 50 with transfer learning has faster convergence speed and higher accuracy.



(a) (b)

Figure 5. (a) ResNet 50 with transfer learning (b) ResNet 50 without transfer learning

Similarly, Figure 5 shows both types of experiments can get low losses. However, from the other side proved that our convergence speed is faster.

Therefore, our experiment can observe that transfer learning has faster convergence speed, and a better accuracy. Most important of all, we saved more than 100% time. Simultaneously, we reduced the cost of calculation resource.

V. DISCUSSION

The performance of CNN in object recognition and image classification made tremendous progress in the past few years. With the network layers become deeper and the amount of data growth, the huge cost of calculation and time are not able to afford directly. Transfer learning can solve the above problems. At the same time, insufficient data problem related to crop diseases detection has also been solved.

In large-scale agricultural disease detection, we have adopted transfer learning to deal with the issues in agricultural sciences. The results of this experiment show that the algorithm not only can determine the disease type quickly and effectively, but also can help detect the degree of disease. The proposed algorithm is beneficial for people to make different measures in different diseases and diverse stages of diseases. Nowadays, the experts who know plenty diseases are relatively few. Therefore, another merit is beneficial to precision medicine rapidly for smallholder farmers. In addition, this algorithm can also provide references to professional agricultural organizations.

In the future, we will do some follow-work. We will continue to improve the accuracy and generalization ability of the model. After that, we will realize online real-time detection.

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