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EfficientNet based recognition of maize diseases by leaf image classification

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EfficientNet based recognition of maize diseases by leaf image classification

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Abstract. For the research on the recognition and classification of maize leaf disease pictures, this paper proposes a method of fine-tuning model parameters based on transfer learning EfficientNet, which can improve the accuracy and speed of network recognition for a small sample of maize disease dataset. First of all, perform data cleaning and data augmentation on the dataset to obtain richer image data; then, transfer the pre-trained model obtained by EfficientNet training on ImageNet to this model method; finally, the last layer of EfficientNet classifier replace with 8 classes of softmax classifier, and train the entire network to obtain a training model for maize disease prediction. In order to verify the robustness and accuracy of the method proposed in this paper, test verification was carried out in the test dataset with VGG-16, Inception-v3 and Resnet-50, respectively. The experimental results show that the training speed of the network model proposed in this paper has been significantly improved, and its recognition accuracy is far better than other networks with a maximum of 98.52%, which can realize agricultural production applications.

1. Introduction

Maize is an important raw material for food crops and feed processing in China[1], and its annual planting and consumption ranks among the top in the world. However, the income of farmers has not been improved due to the increase in yield. The most important reason is that the poor quality of maize caused by disease affects the selling price. There are many reasons leading to the frequent occurrence of maize diseases[2]. Currently, the breeding of viruses and bacteria cannot be effectively prevented. Therefore, preventive measures in advance and early diagnosis and treatment of diseases become effective means to curb the spread of diseases. Although many diseases of maize are concentrated in the leaves[3], due to the very similar characteristic forms of many diseases, diseases can be easily misdiagnosed and mistreated through naked eye observation and identification, and thus cannot be effectively treated, resulting in the abuse of pesticides and fertilizers and low production efficiency.

Due to the application of deep learning in image processing, object detection[4] and semantic segmentation[5] in various environments have made good progress. Many researchers have combined image recognition technology with agricultural production, which has greatly promoted the development of intelligent agriculture in China. Zhang Naifu [6] analyzed the characteristics of five common diseases of maize and potato, constructed a 13-layer convolutional neural network and carried out comparative tests with different pooling methods and optimizers respectively, and obtained the final model recognition accuracy of 93.95%. Chen Guifen [7] conducted trainsfer learning and training for Inception-v3, and used four data augmentation methods to expand the dataset. The average identification accuracy of five common corn diseases reached 96.6%. Xu Jinghui [8] improved the full connection layer module of VGG-16, adopted transfer learning to accelerate the training, and conducted experimental comparison between the two transfer learning methods of training only full connection and training all network layers. The experiment showed that the recognition accuracy of all network layers of training reached the highest of 95.33% in three kinds of maize diseases. Waheed A[9] proposed an optimized and improved maize leaf disease recognition model based on DenseNet, and performed data enhancement techniques such as scaling, translation and rotation on the dataset. The accuracy of the leveling recognition of the three diseases reached 98.06%.

To sum up, many deep learning algorithms have been applied to maize disease image recognition. The network using transfer learning has a faster recognition speed and higher accuracy than the network not using transfer learning. The deeper the network is, the wider the network parameters will increase accordingly. In view of this situation, this paper proposes a transfer learning network based on EffiientNet. EfficientNet has fewer network parameters than DenseNet, Inception, using transfer learning can significantly improve the performance.

2. Materials and Methods

2.1. The experimental materials

In the process of learning and processing image data, the most important thing is to do the preparatory work, so a large enough dataset should be done before the experiment. The larger dataset, the richer the learning features of the neural network, the better the recognition and classification effect of the obtained model for turtle images, and the better the generalization ability of the model. The experimental data in this paper are from AI Challenge dataset, and some disease data are collected on the Internet, and the data are first cleaned and screened to get the maize diseases dataset. Due to the small number of sample data of maize diseases, data enhancement and other operations were needed for the disease pictures. After random scaling, translation and rotation, the dataset was expanded to 9279 pictures, and the dataset was divided according to 7:3, among which 6496 were training dataset and 2783 were test dataset. Fig.1 is a schematic diagram of maize disease samples, from left to right: healthy, cercospora zeaemaydis tehon and daniels general, cercospora zeaemaydis tehon and daniels serious, puccinia polysora general, puccinia polysora serious, corn curvularia leaf spot fungus general, corn curvularia leaf spot fungus serious, maize dwarf mosaic virus.

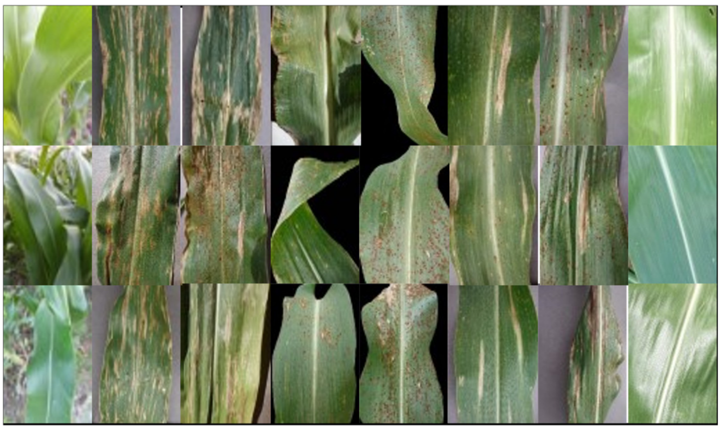

Fig.1 Schematic diagram of maize disease samples

2.2. EfficientNet neural network model

The birth of convolutional neural network promotes the development of deep learning, from the original convolutional layer, pooling layer and full connection layer, which consist of simple network LeNet, AlexNet and VGG-16[10], to ResNet, Inception and GoogleNet. By deepening the network depth and widening the network channel size to get more complex network, improving the resolution of image data can also make more rich fine-grained characteristics. These operations not only improve the recognition accuracy of the network, but also bring the problem that the calculation cost of gradient explosion parameters is too high. ResNet[11] proposed that skip connection could avoid gradient explosion skillfully; MobileNet[12] used pointwise convolution and depthwise convolution to reduce network parameters and improve training efficiency; SENet[13] set weights of various features differently according to loss of network training, so as to achieve better results in model training. The EfficientNet integrated the characteristics of the above network, through setting the appropriate composite ratio coefficient to balance the width, depth and resolution of the network, so you can get a better model performance when expanding the three dimensions of the network. The formula for calculating the composite proportion coefficient is as follows:

$$\begin{cases} depth: d = \alpha^{\phi} \\ width: w = \beta^{\phi} \quad s.t.\ \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \\ resolution: r = \gamma^{\phi} \end{cases}$$

Where $\alpha \geq 1, \beta \geq 1, \gamma \geq 1$. w, d, r can be used for scaling network width, depth and resolution coefficient, given value ϕ can be used to determine the amount of effective resources extension model, constant α, β, γ is used to allocate these resources to the network depth, width and resolution of three dimensions. According to the research of Tan[14] in his paper, the network parameter of Efficientnet-B0 is shown in table.1 below, and the optimal coefficient of the network is: $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$.

Table 1. Efficientnet-B0 network parameter table

Stage i	**Operator** $\hat{f}_i$	**Resolution** $\hat{H}_i \times \hat{W}_i$	**#Channels** $\hat{C}_i$	**#Layers** $\hat{L}_i$
1	Conv3 × 3	224 × 224	32	1
2	MBConv1, k3 × 3	112 × 112	16	1
3	MBConv6, k3 × 3	112 × 112	24	2
4	MBConv6, k5 × 5	56 × 56	40	2
5	MBConv6, k3 × 3	28 × 28	80	3
6	MBConv6, k5 × 5	28 ×28	112	3
7	MBConv6, k5 × 5	14 × 14	192	4
8	MBConv6, k3 × 3	7 ×7	320	1
9	Conv1 × 1&Pooling&FC	7 × 7	1280	1

2.3. Transfer learning

In both machine learning and deep learning applications, a large amount of data and labels are needed, but it is difficult to sort out a large dataset for some reasons, and it is time-consuming and laborious to collect data. Because the parameters in the network model are not trained from beginning to end, training the model is usually faster than training a new network model. Transfer learning[15] belongs to semi-supervised learning, which can reduce the dependence on tag data when the dataset is small. It is also because of its good generalization ability that makes it robust. Fig.2 is the schematic diagram of transfer learning principle.

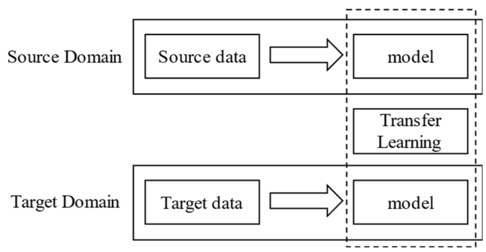

Fig.2 Schematic Diagram of Transfer Learning

In this paper, the method adopted in the experiment is to freeze the parameters of the previous convolutional layer and pooling layer, specifically, the model parameter file loaded on the ImageNet data set is pre-trained to initialize the new network. The migration pre-training model was carried out on the new task, and the parameters of the full connection layer and the Softmax layer were optimized in combination with the parameter tuning method, so that the network structure could adapt to the new classification task, thus accelerating and optimizing the learning efficiency of the model and enhancing the generalization ability. The transfer learning model of this paper is shown in Fig.3, which uses the model trained by the ImageNet dataset with 1000 category objects and then transfer to the task of maize disease recognition and classification.

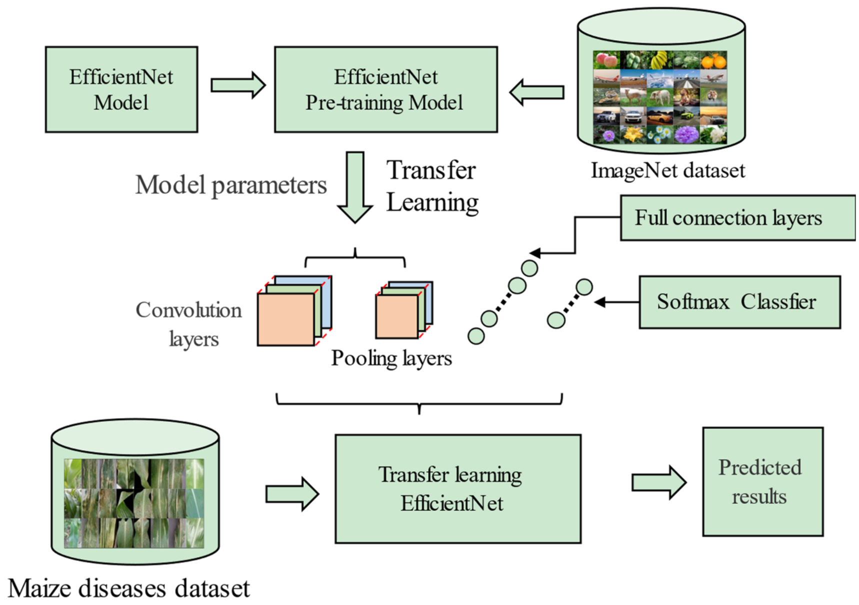

Fig.3 Transfer learning model of EfficientNet

3. Results and Analysis

3.1. Model Evaluation

In order to evaluate the performance of the model, according to the characteristics of network model and dataset, the average accuracy rate and loss rate are used as the evaluation criteria. The average accuracy of the model is defined as follows:

$$Acc = \frac{R_A}{R} \times 100\%$$

Where R represents the total number of verified images and R_A represents the number of correctly classified images.

3.2. Image analysis

In this experimental model, python drawing tool is used to draw data analysis curve, and the curve of accuracy rate and loss rate is drawn based on the data of 100 epoch experiments. As shown in Fig.4, the upper part of the figure shows that the accuracy of the model in this paper reaches 90% in the 9th epoch, and after 9 ~ 38 epochs, the model gradually rises to stability, and the final accuracy reaches 98.52%. Based on the comprehensive curve analysis, it can be found that in the curve changes of the accuracy rate and loss rate of the test dataset, the model has good generalization ability and no over-fitting or under-fitting occurs, which indicates that the model has a good performance in dealing with various classification and identification problems of maize diseases and achieves the expected effect.

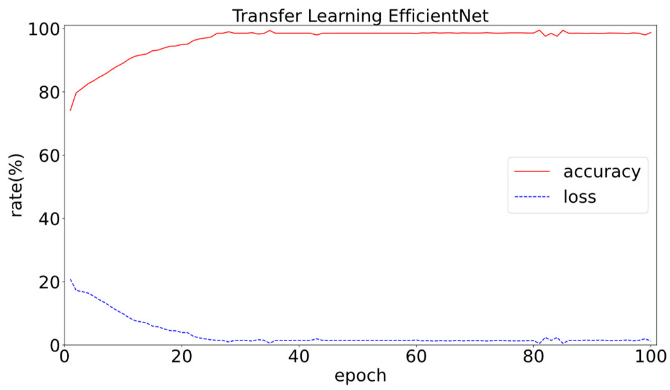

Fig.4 Curve graph for transfer learning model of EfficientNet

3.3. Experimental comparison

In order to verify the improving effect of the model proposed in this paper on maize leaf disease recognition, four network models were used as the experimental control group, the Inception-v3, VGG-16, Resnet-50 and the train from zero efficientnet-b0 respectively. The experimental comparison result of the model is shown in Table 2. The table shows that the efficient model using transfer learning is better than the other network, while the VGG-16 transfer learning model have lower accuracy than the one using zero training. This proves that transfer learning EfficientNet is helpful to improve the accuracy and speed.

Table 2. Experimental comparison results of verification set of the model

Model	*Acc(%)*	*Loss(%)*
Tain EfficientNet-b0 from scratch	94.37	5.63
Inception-v3 Transfer learning	96.35	3.65
VGG-16 Transfer learning	93.90	6.10
Resnet-50 Transfer learning	96.76	3.24
EfficientNet-b0 Transfer learning	98.52	1.48

4. Conclusion

In order to realize automatic recognition of maize disease images, this paper proposes the transfer learning method based on EfficientNet. The convolutional layer and pooling layer of fixed network, only trains the full connection layer, and the weight and learning rate of the model are fine adjusted. In order to evaluate the performance of the network model, the EfficientNet experiment was carried out with the original training, the control group also added Inexpon-V3, VGG-16, Resnet-50 as the experiment contrast. Whether the transfer learning method was adopted or not, the effect was generally better than that of VGG-16 by experiment, and the transfer learning method was better than the other network. In this paper, the experimental effect of the method is the highest, the recognition accuracy of the eight different categories of disease pictures reaches 98.52%, and the number of network parameters is the smallest.

To solve the problem of maize diseases recognition, the experimental results of the model can be further improved with the continuous expansion of the dataset and the continuous improvement of the image recognition algorithm. This experimental method can be deployed in mobile devices as a good assistant for the diagnosis and treatment of maize diseases, thus reducing the loss caused by diseases.

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