Identification of Anoectochilus roxburghii based on transfer learning

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Abstract: Different varieties of Anoectochilus roxburghii (A. roxburghii) have different medicinal values. However, the identification and the clinical efficacy of A. roxburghii was seriously affected by the phenomena of doping and adulteration. Thus, accurate identification of different varieties of A. roxburghii is important. However, traditional identification methods for A. roxburghii identification are usually time-consuming, laborious or have low accuracy. Thus, an A. roxburghii leaf image recognition method based on transfer learning is proposed. The model use convolution neural network to extract leaf features of A. roxburghii automatically. Then, the knowledge, learned by a model from a large-scale image data set ImageNet, is transferred to realize the task of A. roxburghii image recognition with the help of transfer learning. Low training cost and high precision classification of leaf strains is realized in this way. Finally, 368 leaf images of 6 species of A. roxburghii are collected for recognition, including dayuanye, xiaoyuanye, and etc.. To test the transfer effect, the Resnet50 transfer learning model is compared with the other four models. The comparison results show that the accuracy of Resnet50 transfer learning model reaches 100% in a quicker speed, which illustrates that the model has good robustness and better performance of realizing the accurate recognition and classification of the leaves of A. roxburghii. Moreover, data augmentation helps to reduce the over-fit phenomenon of the transfer learning model.

1. Introduction

Different strains of A. roxburghii which have different medicinal and commercial values[1]. The adulteration of A. roxburghii seriously affected clinical efficacy of A. roxburghii. Thus, it is important to realize strain identification for A. roxburghii. Distinguishing different strains of A. roxburghii from the leaves is the most commonly used method. The shape, color and texture features of A. roxburghii leaves from different strains are extremely similar, so it is hard to tell them apart by our eyes. Thus artificial identification models based on different leaf information collection methods are constructed. In [2], the chemical composition and biological activity analysis were used to analyze the components of A. roxburghii at the molecular level. These methods require special instruments to carry out leaf information collection experiments at a high cost. In particular, they lack on-site identifications. Considering these drawbacks, artificial identification models based on leaf images are proposed, which play an important role in plant identification [3,4]. Studies show that the use of a convolution neural network (CNN) [5] based...
deep learning model is better than traditional machine learning methods, because it reduces the complex image preprocessing and automatically extract key feature extraction in the convolutional layers. However, the performance of CNN model depends on the complexity of the model and a large number of marked data sets. In practical, it is difficult to obtain a large numbers of datasets. In addition, general computer hardware conditions are limited, and training of complex models causes a huge computation burden. Therefore, the accuracy and generalization of the model is hard to be guaranteed. Transfer learning [6] can learn the relevant target domain knowledge with the help of the knowledge of the source domain, which provide a new way to construct CNN models [7,8]. Thus, in view of application limitations, in this paper, a strain recognition method based on CNN transfer learning will be studied.

2. Materials and Methods

2.1. Image datasets

Polysaccharides and flavones contained in A.roxburghii are the effective components of its efficacy. Contents of different species of A.roxburghii are significantly different, which affects its selling price. At present, the main varieties sold in the market are divided into Xiaoyuan, Dayuan, Jianye, anoectochilusformosanus (A.formosanus) and hybrid A.roxburghii (Hongxia, Yizhuyuan). Therefore, these 6 species widely sold in the market were collected as research objects in this study.

![Fig.1 Comparison of the characteristics of Anoectochilusroxburghii leaves with 6 species](image_url)

Leaf images from A.roxburghii planting industrial base in Nanjing, Fujian were used in the research. The six categories are shown in Fig. 1. A total of 368 images in six categories were collected to form the database. There were 55 Dayuan leaves, 50 Xiaoyuan leaves, 70 Hongxia leaves, 58 Jianye leaves, 69 A. formosanus and 66 Yizhuyuan leaves. The background of the image is a single scanned image, and the size of the image is uniformly modified to 224×224. Due to the complexity of its model, CNN requires a large number of training datasets with labels. In order to reduce the over-fitting phenomenon caused by a small amount of data, Python scripts are used to perform data augmentation operations on leaf images, including random rotation, flip horizontally, and flip vertically. The total number of enhanced data sets is 10110. After that, the data set was divided into training set and test set by 4:1.

2.2. Resnet50 model

CNN is a basic algorithm of deep learning, which has feedforward neural network structure and generally composed of convolutional layer, activation layer, pooling layer and full connection layer. It has been reported that deep networks can fit features better and learn more complex expressions. However, in increasing the number of layers after the conventional deep CNN network reaches a certain depth will lead to the degradation of classification performance and even the phenomenon of overfitting. Thus improved CNNs are needed. Resnet50 [9] model is a series of concrete implementations of CNN. Its model structure is shown in Fig.2. Resnet50 uses residual structure that reduces the burden of network training and maintains accuracy even as depth increases. It contains 49 convolutional layers and 1 full connection layer. Among them, ID Block in stages 2 to 5 represent residual blocks that do not change dime
nsions. Conv blocks represent residual blocks that add dimensions. Each residual block contains three convolutional layers, so $1+3 \times (3+4+6+3) = 49$ convolutional layers.

2.3. Strain identification based on transfer learning strategy

Under the limitations of our computer power and sample data, it is difficult to guarantee the accuracy and generalization of deep CNN model. As CNN, it applies the parameter transfer obtained by training on a specific dataset to a new field. For this reason, reusing the parameters and weights of complex structures can greatly reduce the threshold for further learning.

Imagenet has over 14 million images and over 20,000 categories, which contains a large number of leaf images, so the pretrained Resnet50 model parameters can be used for transfer learning. Combined with the convolutional neural network and transfer learning method, a Resnet50 model-based identification and classification method for A.roxburghi was proposed. The pretrained Resnet50 model was trained on the Imagenet datasets, and then its feature extraction layer parameters and structure were transferred to the A.roxburghi datasets for fine-tune training operation. It is necessary to fine-tune the FC layer and replace it with 10 classification categories. During this process, we will train the last FC layer and freeze the other layers. The model structure is shown in Fig.3. The number of the epochs is set to 100, batch_size is 64, the optimizer is SGD in which the learning rate is 0.001, momentum is 0.9 and l2_decay is $5 \times 10^{-4}$. Four models were used for comparison, which are Lenet5, Alexnet, Vgg16 and Densenet 121. The Lenet5 model does not use pre-trained model for fine-tuning among them.

3. Results and Discussion

The experiment software is python3.7 and the operating system uses windows10. Tensorflow, an open source deep learning framework, is used as the development environment. All the test data in the test results were obtained by using an Nvidia Gtx1050Gpu, with 2GB of video memory and 128 bit width of video card.

By the comparison of the experiment, the performance of the model related to image recognition of A.roxburghi was analyzed. Two groups of the five kinds model experiment were compared, which are the original datasets without data augmentation experiment and the experiment with data augmentation. The influence of the datasets for transfer learning was concluded by the comparisonal experient. The accuracy of the testsets used in the experiment is the evaluation index, whose formula is $P =$
\[ \frac{R}{N} \times 100\% \], where \( R \) is the correct number of test images and \( N \) is the number of the test images. The experimental comparison results are shown in the Fig.4 and Fig.5.

![Fig.4 Training process without data augmentation](image1)

It is seen from the results shown in Fig.4 that the Vgg and Resnet pretrained model perform better in acc and loss, in which Resnet can achieve convergence and stability within a short number of epochs. While the curve of Densenet is relatively shaken, and its acc performance is only higher than Lenet5, and the loss is also the worst.

![Fig.5 Training process with data augmentation](image2)

After the training of data augmentation datasets, the five model perform better than that training without data augmentation. This indicates that data augmentation is helpful to increase the diversity of data and avoid the phenomenon of overfitting. It is seen from the results shown in Fig.5 that the Resnet pretrained model performs best in the five models, in which its curves can achieve faster convergence and highest acc. While the curve of Densenet is still relatively shaken with a loss curve of oscillation. Using a large number of datasets can significantly improve the model training, which enables the model to learn more accurate image features. As Resnet uses the residual network structure, it ensures faster convergence and better stability during training while the number of model layers is deeper. Compared with other models, Densenet needs a larger datasets to learn the features of the image. Moreover, due to densenet's larger network weight, the training time is longer. The experimental results are evaluated by P-value. Table 1 and Table 2 show the number and P-value of test sets correctly identified by the model in each category. While, in Table 1 the total number of sample images for each categories are 11, 14, 14, 11, 10 and 13 respectively. In Table 2, the total number of sample images for each categories are 304, 378, 381, 319, 278 and 360 respectively. It can be seen from the two table that Resnet50 has the highest correct rate of image recognition.

Table 1. Comparision of the five models without data augemention
| Models | Dayuanye | Xiaoyuanye | Yizhuyuanye | Hongxia | Jianye | A.formosanus | P-value |
|--------|-----------|------------|-------------|---------|--------|--------------|---------|
| Lenet5 | 7         | 12         | 13          | 7       | 3      | 8            | 64.1%   |
| Alexnet| 10        | 14         | 14          | 11      | 9      | 11           | 88.5%   |
| Vgg16  | 11        | 14         | 14          | 11      | 10     | 10           | 89.7%   |
| Resnet50| 11       | 14         | 14          | 11      | 10     | 12           | 92.3%   |
| Denset121 | 10     | 14         | 13          | 6       | 10     | 5            | 74.4%   |

Table 2. Comparision of the five models with data augemtion

| Models | Dayuanye | Xiaoyuanye | Yizhuyuanye | Hongxia | Jianye | A.formosanus | P-value |
|--------|-----------|------------|-------------|---------|--------|--------------|---------|
| Lenet5 | 263       | 367        | 381         | 155     | 276    | 277          | 85.1%   |
| Alexnet| 302       | 377        | 381         | 306     | 278    | 340          | 98.2%   |
| Vgg16  | 302       | 378        | 381         | 318     | 278    | 339          | 98.8%   |
| Resnet50| 304      | 378        | 381         | 316     | 278    | 360          | 100%    |
| Denset121 | 304    | 378        | 381         | 306     | 278    | 297          | 94.5%   |

4. Conclusion
In this work, a transfer learning-based method for strain recognition of A. roxburghii is proposed. The pre-trained Resnet50 model is used for transfer learning, and the accuracy of the test set on the original data set and the augmentation data set can reach 92.3% and 100% respectively. By comparing with the other models, the Resnet50 model has a better effect of feature extraction and can achieve a faster convergence rate without overfitting appearance. The method provides a simple and fast method for the identification of A. roxburghii. The method can lay a foundation for the rapid identification of spot monitoring and spot transaction varieties in the future.

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