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Flower Classification and Recognition Based on Significance Test and Transfer Learning

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***Abstract*—Aiming at the problem that traditional flower classification methods and ordinary convolutional neural networks are difficult to reduce the effect of flower background, the classification effect is not ideal. This paper designs a flower classification model that combines saliency detection and VGG-16 convolutional neural network, and adopts stochastic gradient descent algorithm and prevents over-fitting technology to improve the model. Experiments on the international public flower recognition data set Oxford flower-102 show that the model proposed in this paper is better than other traditional network models and has high recognition accuracy , robustness and generalization ability, which can classify flowers and have higher practical value accurately and quickly.**

Keywords-Deep Learning; Transfer Learning; Significance Detection; Flower Recognition.

I. INTRODUCTION

Flower classification is a fundamental work in the field of botany. It is difficult for traditional flower classification methods to reduce the influence of flower background, which leads to the problem of unsatisfactory classification effect. With the advent of the era of big data and the rapid development of Internet technology, deep learning method has become a research hot-spot in image classification tasks. As one of the most widely used methods in deep learning technology, convolutional neural network has powerful feature extraction capabilities and nonlinear data fitting capabilities. Many researchers have carried out a lot of research on convolutional neural networks and image classification.

Zhou Wei [1] proposed a new image classification algorithm based on the saliency map, which integrates the saliency map into the image feature extraction process, thus avoiding image segmentation and enhancing the adaptability and reliability of the algorithm. Pei Xiaofang [2] proposed a method based on ResNet-18, which is now classified by the Softmax layer, and an attention-based residual structure improvement method. Compared with previous flower image classification methods, this method can remove the key characteristics of the information more effectively, suppress the information of the interference area and suitable for fine-grained image classification. Yin Hong [3] used the deep convolutional neural network VGG-16 model pre-trained by Image Net to perform feature learning on the pre-processed flower image, and selected effective deep convolution features according to the response value distribution of the feature map, and combined Multi-layer deep convolution features. Finally, softmax classification layer is used for classification. Wu Di [4] proposed an improved InceptionV3 network for the classification of flower images. Using the transfer learning method, the InceptionV3 network trained on a large-scale data set was only used for the classification of flower image data sets. The activation function has been improved. Wu Yong [5] proposed a deep network migration method of flower image classification for the problems of deep model structure, huge parameters, too long training time, easy network over-fitting, weak generalization ability and need to improve recognition accuracy. Gao Xiang [6] proposed a fine-grained image based on a deep model transfer learning to the difficulty of feature description operator design, weak feature extraction ability, complex structure of deep model, large parameter scale, and difficulty in fitting small data sets. However, the accuracy of the above algorithm for flower classification needs yet to be improved.

This paper establishes a flower classification model based on the traditional VGG-16 network, and optimizes the gradient descent algorithm to resolve the model over-fitting problem. The saliency detection is used to preprocess the image, which improves the classification accuracy of the model on the basis of reducing the parameters of the convolutional neural network. This model can quickly and accurately give the flower type to which it belongs based on the flower image, which has higher practical value.

II. THE FLOWER IMAGE CLASSIFICATION MODEL

This section is mainly composed of three parts: salient region extraction, transfer learning and model optimization.

A. Salient Area Extraction

Hou Xiaodi [7] proposed a simple model for calculating visual saliency maps based on the spectral residual method. From the perspective of information theory, the information of an image consists of a novel part (the salient part of the image) and a priori knowledge part (the residual information of the image). Natural images are not random, but in a highly predictable distribution state, that is the expectation of the amplitude spectrum is inversely proportional to the frequency. By removing the statistical residual part of the image to obtain the innovative part, the salient area of the image will be highlighted. After statistically comparing the logarithmic spectra of a large number of images, the following conclusions are drawn: the fluctuating part of the logarithmic spectrum of an image is the significant part, and the smooth linear area is the redundant part. Therefore, the saliency map can be

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calculated by subtracting the logarithmic spectrum after the area mean filtering from the logarithmic spectrum of an image. The specific calculation steps are as followings:

First, calculate the two-dimensional Fourier transform of an image, transform it from the spatial domain to the frequency domain, and obtain the amplitude spectrum at the same time. Then take the logarithm of the amplitude spectrum to obtain the logarithmic spectrum. The process is shown in (1)-(3).

$$A(f) = \partial(F(\mathrm{Im}\, g)) \tag{1}$$

$$P(f) = \Phi(F(\mathrm{Im}\, g)) \tag{2}$$

$$L(f) = \log(A(f)) \tag{3}$$

In the formula: F represents two-dimensional Fourier transform; ∂ and Φ represent amplitude and phase respectively; P(f) and L(f) represent the phase spectrum and logarithmic amplitude spectrum (hereinafter referred to as "logarithmic spectrum"). Then a 3×3 mean filter hn(f) is used to smooth the logarithmic spectrum, as shown in (4). Then the logarithmic spectrum and the smoothed logarithmic spectrum are differenced to obtain the spectral residual R(f) in equation (5).

$$V(f) = L(f) * h_n(f) \tag{4}$$

$$R(f) = L(f) - V(f) \tag{5}$$

In order to extract the salient regions, take R(f) as the real part and the original phase spectrum P(f) as the imaginary part to perform a two-dimensional inverse Fourier transform. The result is squared, and finally processed by Gaussian blur filter g(x)to get the significant area, the calculation is shown as (6).

$$S(x) = g(x) * F^{-1}[\exp(V(f) + P(f))]^2 \tag{6}$$

B. VGG-16 Model

The VGG[8] network is a deep convolutional network jointly developed by the Computer Vision Group of Oxford University and Google DeepMind.

This model is highly efficient and concise, so it quickly became the most common convolutional neural network model at the time. It showed very good results in image classification tasks, and its deformed structure VGG-16 performed more prominently, so the VGG-16 convolutional neural network is used as the classifier model of flowers in this paper. VGG-16 is a network model with excellent classification performance in convolutional neural networks. It uses convolutional blocks to make the network model have a wider receptive field and fewer network parameters. At the same time, VGG-16 can achieve more linear transformations and enhance the learning ability of the model by using the ReLU activation function multiple times. The VGG-16 network model contains 13 convolutional layers, 5 maximum pooling layers, and 3 fully connected layers and 1 output layer, the network model structure is shown in Figure 1.

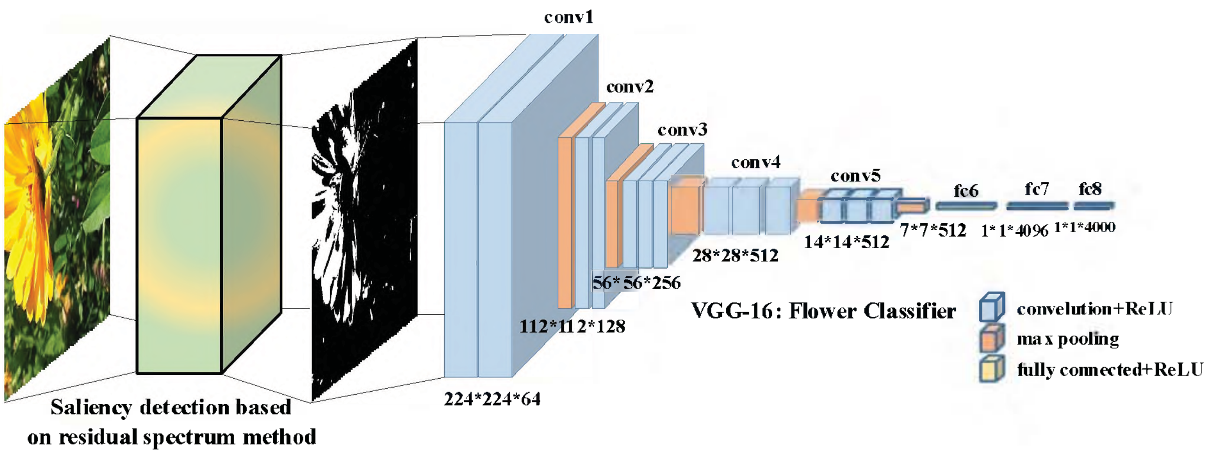

Figure 1. The framework of the proposed model.

The VGG-16 network combines 3×3 convolution kernels and 2×2 maximum pooling layers to extract a large number of detailed features in the input image. The stack combination of 3×3 convolution kernels can combine the same effect of the 5×5 or 7× 7 convolution kernel size. Compared with a single large-size convolution kernel, the combination of small-size convolution kernels can have better nonlinear characteristics.

C. Model Optimization

When using convolutional neural networks for flower image classification tasks, recognition accuracy, recognition speed, and memory consumption are the research goals. In order to further improve model recognition accuracy, reduce training time and resource consumption, this paper optimized the proposed model base on existing VGG-16 network. There are many ways to optimize the network model, which include adjusting the depth of the network, modifying the size of the convolution kernel, optimizing the loss function, balancing the data set, and using transfer learning. Among them, the gradient descent optimization algorithm is more commonly used in convolutional neural networks. This paper uses the optimization algorithm of stochastic gradient descent [9]-[11].

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Compared with other gradient descent algorithms, especially when the data is redundant, this algorithm can make more effective use of data information.

The stochastic gradient descent algorithm uses only one sample x(i) and its corresponding label y(i), the gradient calculation formula is shown in equation (7):

$$\theta = \theta - \alpha \cdot \nabla_{\theta} J\left(\theta; x^{(i)}; y^{(i)}\right) \quad (7)$$

The over-fitting phenomenon in convolutional neural networks is an important problem, which is that the model has a high recognition rate on the training set, but has a low accuracy rate on the validation set. This paper uses the Dropout method and the transfer learning method to reduce the overfitting of model.

The Dropout method [12]-[13] reduces the over-fitting phenomenon of the model by randomly discarding the training information. This method randomly samples the hidden nodes of the activation layer in a certain proportion when the model is backpropagated, so that the fully connected network has a certain sparseness, thereby reducing the synergistic effect of different characteristics. Since the hidden nodes appear randomly with a specified probability, the two neurons will not appear at the same time every time, thus reducing the co-adaptation relationship between neurons to improve the stability of the network by dropout method.

Transfer learning [14] can save training time and reduce the amount of training data required, which is to apply the trained model to new tasks. At the same time, due to the small number of images used in this research and the high cost of collection, the use of migration learning methods can solve the problem of insufficient image data. Using the pre-training model of VGG-16 on the ImageNet dataset to transfer relevant knowledge, optimize the parameters of each convolutional layer and pooling layer, and reduce the over-simulation, which also reduces the model training time.

III. Experiment and Analysis

The computer environment used in this experiment is Intel(R) Core(TM) i5-8300H CPU@2.30 GHz, GeForce GTX 1050 graphics card, 4GB video memory, 8GB memory, the programming environment is Python 3.6, and the deep learning tool used is Tensorflow.

A. Experimental Configuration and Data Set

This experiment uses the Oxfordflower-102 public data set, which comes from the flower image database created by the Oxford University Visual Geometry Group. It contains 102 categories of flowers, each category has between 40-258 pictures, a total of 8189 pictures. The database also takes into account all the difficulties in the field of image recognition, such as complex backgrounds, many flower types and complex color changes, and some different flowers are highly similar. Therefore, it is of great significance to the research on flower image classification. Part of the data set is shown in Figure 2.

B. Salient Area Extraction Result

The original image is processed using the visual saliency map model based on the spectral residual method. The experimental results are shown in Figure 3. It can be observed in the experimental results that this algorithm can more accurately extract the salient regions of flowers for different types of flowers in a complex background, which provides a basis for the classification of migration learning later.

Figure 2. Sample data set.

Figure 3. Salient area extraction.

C. Comparative Experiment Result

In order to prove the validity of the model proposed in this paper, relevant verification experiments are carried out. The number of iterations in the model training is set to 50, and the change in loss value and the change in classification accuracy are shown in Figure 4. It can be observed in the Figure 4 that the model loss value decreases rapidly during the training process. When the number of iterations is 20, the loss value is close to 0.5 and converges on the verification data set. When the number of training iterations of the model is about 25, the classification accuracy of flowers has reached a result of greater than 85%. The classification accuracy of different models is shown in Table 1. It can be observed in the table that the classification accuracy of the traditional model is low, and the model proposed in this paper has sufficient feature pre-extraction on the image and uses the transfer learning model to reduce In order to achieve the highest classification accuracy, the requirements for the amount of training data are achieved. In Figure 5, the classification results for Hard-leaved pocket

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orchid and Sunflower are given. It can be seen from the figure that the model can accurately classify different types of flowers.

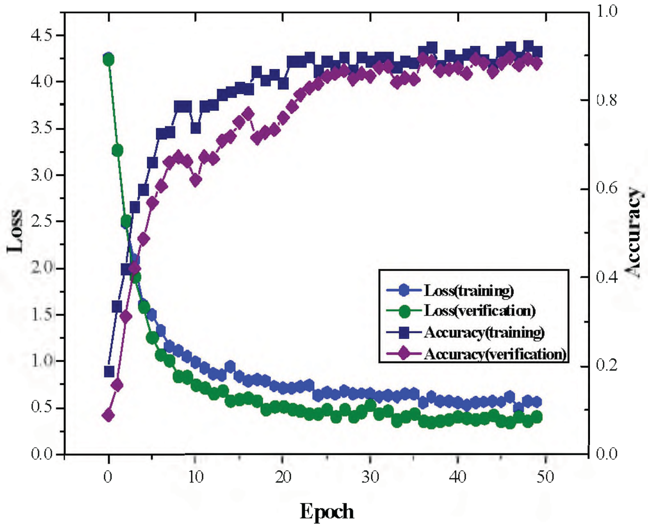

Figure 4. The training and verification process of the proposed model.

TABLE I. TARGET DETECTION RESULTS OF DIFFERENT MODELS

Model	CNN with ON/OFF ReLU	Improved CNN	Improved Alex network	The proposed in this paper
Accuracy-1	76.3%	83.6%	85.7%	91.5%
Accuracy-2	75.9%	84.9%	84.9%	92.6%
Accuracy-3	77.8%	82.4%	86.2%	91.7%
Average	76.7%	83.6%	85.6%	91.9%

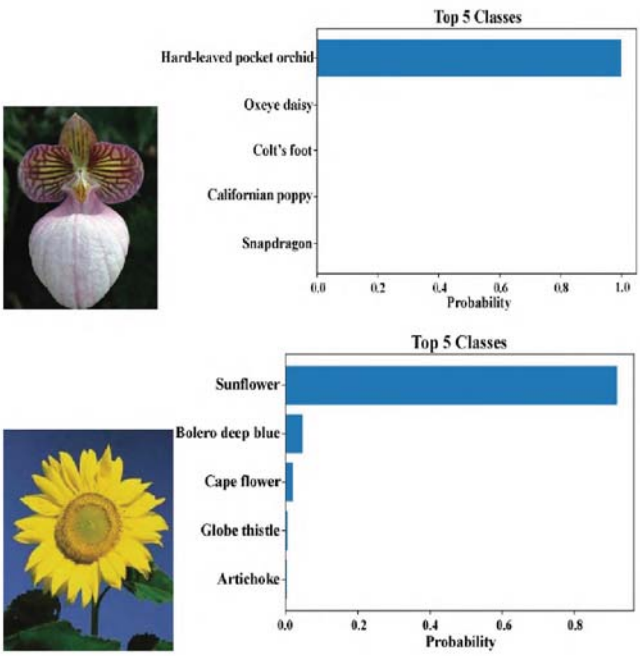

Figure 5. The classification label correctness.

IV. CONCLUSION

The complexity of the environment in which the flowers are located in the flower image, the diversity within the flower category and the similarity between the categories make the accuracy of flower classification unsatisfactory. Aiming at the complexity of the environment in which flowers are located, this paper constructs a flower classification model based on saliency detection and VGG-16 deep neural network model, uses stochastic gradient descent algorithm to update network weights, and uses Dropout method and transfer learning method to optimize the model. Experiments on the Oxford flower-102 data set show that the model has better classification results than traditional methods and other deep neural network architectures with a classification accuracy of 91.9%, which verifies the accuracy of this method for flower image classification tasks and the feasibility of flower identification.

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