# National Cultural Symbols Recognition Based on Convolutional Neural Network

Huang Zhixiong
School of art and design
Guilin University of Electronic Technology
Guilin, China
E-mail: 845142224@qq.com

Shi Zhuo
Artificial intelligence Cross Institute
Guilin University of Electronic Technology
Guilin, China
E-mail: shzh@guet.edu.cn

Kong Qian
School of art and design
Guilin University of Electronic Technology
Guilin, China
E-mail: 847893236@qq.com

Li Rongbin
School of art and design
Guilin University of Electronic Technology
Guilin, China
E-mail: 272130977@qq.com

Yang Ming
School of art and design
Guilin University of Electronic Technology
Guilin, China
E-mail: 747608245@qq.com

Zhang Mengxue
School of art and design
Guilin University of Electronic Technology
Guilin, China
E-mail: 1032163360@qq.com

Yu Ke
Dean's Office
Guilin University of Electronic Technology
Guilin, China
E-mail: 61763023@guet.edu.cn

***Abstract*—In order to solve the problem that the process of manually identifying national symbols is extremely tedious and the recognition effect is not satisfactory, the paper uses the TensorFlow framework to build a convolutional neural network to identify domestic symbols simply and efficiently. In this paper, the classified Zhuang ethnic symbol pictures are labeled and normalized to make a data set, and then during the training process, the loss value between the prediction result and the correct answer is continuously reduced to train a convolution layer, pool The convolutional neural network of the visualization layer, the fully connected layer, and the SoftMax layer. Finally, the images are classified by the SoftMax layer. The experimental results show that after a lot of training, the model has been more robust, and the recognition rate of 15 symbol types can reach 89%, which is faster and more accurate than the manual recognition process.**

***Keywords—Convolution Neural Network, National Symbol, Decorative Pattern, Image Recognition, Deep Learning***

## I. Introduction

In the long history of the Chinese nation, many national cultural symbols with distinct cultural characteristics have been bred. They condense the nation's unique way of thinking, aesthetic taste and spiritual beliefs, and highlight the characteristics and characteristics of a nation. In recent years, modern Chinese design works, in order to break through the thinking concepts that were limited by western values in the past, pay more and more attention to the organic combination of traditional Chinese culture and modern product design, explore original designs from traditional national culture, and take modern characteristics with national characteristics. The Road [1-2]. However, in the status qua of the application of national cultural symbols, due to the cumbersome and unclear classification process of national cultural symbols, there is a phenomenon of misuse of national cultural symbols, which hinders the process of describing national characteristics and showing regional customs [3].

Convolutional Neural Network (CNN) is a neural network with obvious learning effect and excellent recognition efficiency. Numerous recent studies have shown that CNN features are effective input for various classifiers [4]. CNN combines feature extraction and classification in the process of training neural network models, and has achieved notable success in the field of image classification. Its accuracy rate is clearly superior to traditional recognition methods [5]. In order to make full use of its advantages in image classification, this paper applies a method for training CNN models based on the TensorFlow open source framework, collecting the classified Zhuang ethnic symbol pictures as a data set, and making the convolutional neural network layer to extract Zhuang The increasingly complex traits in national symbols have trained a network model dedicated to identifying the national symbols of the Zhuang nationality, which provides a feasible way to solve the problems of complicated process and symbol misuse in the artificial identification of national cultural symbols.

## II. Production of Data Sets

The original data of this experiment was mainly collected through field shooting and network. The picture data set used for training was based on the Zhuang ethnic symbols, including 17 patterns such as diamond pattern, cloud thunder pattern, flower pattern, etc., a total of 789 pictures. In order to reduce the interference of the redundant information on the model during training and enhance the detectability of the pertinent information, the original data needs to be preprocessed, and these assorted sizes of magnificent decorative pattern pictures are trimmed to unique regions. As following.

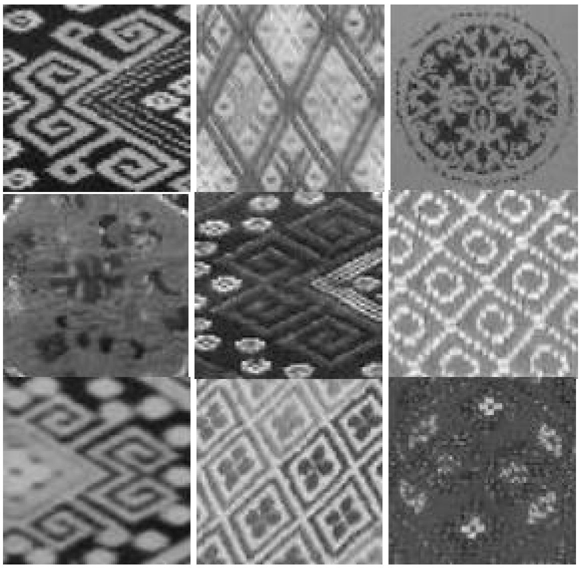


Fig.1 Sample of Zhuang brocade pattern data set

The preprocessed data set is given in figure 1.First, classified preprocessed data are extracted according to the preset path, and then the picture is adjusted to a uniform size ratio. The picture is converted into native bytes and produced the category. Into a serialized sample, when all the picture data is made into a symbolized sample, the algorithm will parse the image data and category data contained in each sample in turn, and then store these image data in a preset type in a preset Good path, category information will be named to the stored image data in digital form.

## III. CONSTRUCTION OF NEURAL NETWORK

The CNN network model generally consists of an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. Models generally include several convolutional layers and pooling layers, and the structure will be alternately matched with convolutional layers and pooling layers. Because each neuron in the output feature surface in the convolutional layer is locally connected to its input, and the corresponding connection weight is weighted and summed with the local input, plus the offset value,the neuron input value is obtained. For the convolution process,CNN also got its name [6].

The CNN network model used throughout this article consists of two convolutional layers, two pooling layers, two fully connected layers, and one SoftMax classification layer. The convolution kernel is a matrix representing the weight of various positions. For 2D images, a matrix of 3 * 3 or 5 * 5 sizes can be selected[7]. The convolution kernels used in this neural network are all in the 3 * 3 formats. The padding of each layer is placed at 'SAME' to keep the convolutional image consistent with the original image size [8].

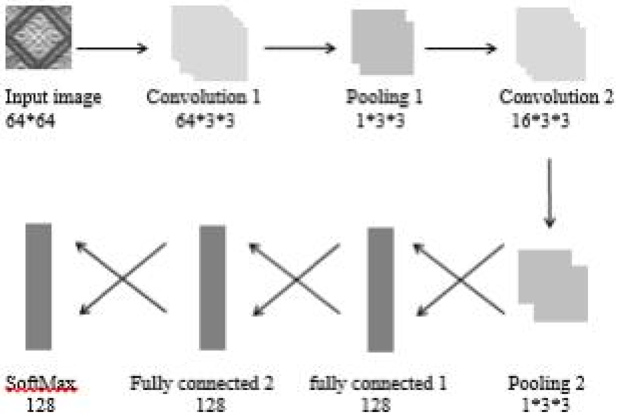



Fig.2 Convolutional neural network structure

### *A. Convolution layer and activationfunction Relu*

There are 64 convolution kernels in convolution layer 1 and 16 convolution kernels in convolution layer 2. By convolution operation of convolution layer, the original signal features can be enhanced and the noise can be reduced; for example, the image can be processed by convolution of enhanced edge,and the processed image edge features can be enhanced [9]. In the convolution layer, the weight and deviation values of each feature surface of image data will be extracted, and then the weight and deviation values will be put into the activation function relu function () to get an output value. The formula of relu is as follows [10]

$$F(x) = \max(x,0) \tag{1}$$

The Relu function can speed up the convergence speed, adjust the output of the convolution layer, add sparseness constraints to the CNN model, make the extracted features more consistent with human visual system observation requirements,and improve the model's recognition ability.

### *B. Pooling layer*

Pooling layer 1 is a single core. The step size is set to 2, pooling layer 2 is a single core, and the step size is set to 2 the average or maximum value of a particular feature. These summary statistical features not only have lower dimensions, but also reduce the risk of overfitting [11], which significantly reduces the computational load of the network model.

After its pooling, local response normalization (LRN) operation has to be carried out. The principle of local response normalization is to mimic the inhibition of neighboring neurons by biologically active neurons to create local neuron activities. The competition mechanism makes the larger response value relatively larger and suppresses other neurons with smaller feedback, which enhances the generalization ability of the model. The formula is indicated below[12].

$$b^i_{x,y} = a^i_{x,y} \Big/ \left(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a^j_{x,y})^2\right)^{\beta} \tag{2}$$

### *C. Fully connected layer*

After two layers of convolution layer and pooling layer,

there are full connection layer 1 and 2, and the number of neurons is 128. Different from full connection layer 2, full connection layer 1 will first convert the tensor matrix output by pooling layer 2 into one-dimensional list form through reshape to ensure that the dimension of input data is consistent. After that, the fully connected layers 1 and 2 will extract the weight and deviation values of each feature surface of the image data, which is somewhat similar to the convolution layer, but the neurons contained in the fully connected layer 1 will be fully connected with the previous layer. The local features are extracted by the previous convolution layer, pooling layer, and the activation function is combined and output to a neuron somewhere in the fully connected layer 2 to activate the neuron here. The activation function of the neurons in this layer still utilizes the Relu function.

*D. SoftMax classification layer*

The main function of this layer is tantamount to perform a linear regression on the output of the preceding fully connected layer. It calculates the score of the pictures belonging to each category. There are 17 categories in the article. So this layer will output 17 score.

The softmax function maps k $(-\infty, +\infty)$ real numbers to k (0,1) real numbers, while ensuring that their sum is 1, which represents the probability of belonging to each class. Details as following:

$$y = soft\max(z) = soft\max(W^T x + b) \quad (3)$$

Among them, x is the full connection layer input, $W^T x$ is the weight, b is the bias term, y is the probability of softmax output, and the calculation method of softmax is as follows [13]:

$$\text{soft}\max(z_j) = \frac{e^{z_j}}{\sum_K e^{z_j}} \quad (4)$$

## IV. CNN Model Training

The specific experimental environment is as follows: Linux16.04 operating system, TensorFlow deep learning framework, CPU is Inteli7-8700HQ, GPU model is GTX 1050Ti, and memory is 8G.

The training process of the convolutional neural network is alternately performed in two parts: forward propagation and back propagation. The calculation process of the model can be established by forward propagation. The calculation result is obtained by a set of input values, which make the model have inference ability. Pictured:

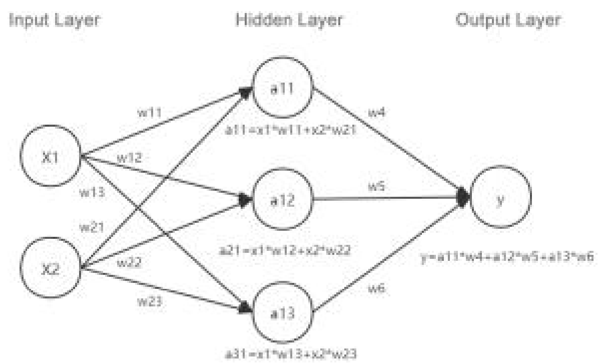



Fig.3 Forward propagation process

Back propagation can compare the data obtained by forward propagation with the actual picture label, and get the deviation between the actual output and the ideal output, that is, the loss value. The loss function uses the mean square error MSE, and the formula is as follows [14-15]:

$$MSE(\bar{y}, y) = \frac{\sum_{i=1}^{n} (y - \bar{y})^2}{n} \quad (5)$$

According to the obtained loss value, the parameters are continuously adjusted to decrease the loss value. When the loss value is decreased, the accuracy rate of model training is also continuously improved, which makes the trained model more robust to image classification.

TABLE I. Training main parameter setting

| Training set: Test set | Category | Image size | Batch | Capacity | Maximum steps | Learning rate |
|---|---|---|---|---|---|---|
| 9:1 | 17 | 64*64 | 20 | 200 | 3000 | 0.0001 |

The line chart of the loss value and training accuracy rate with the number of trainings during the training is shown below

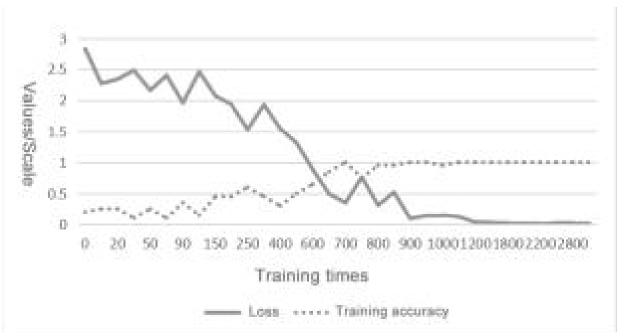


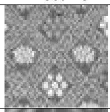
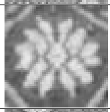
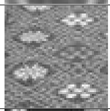
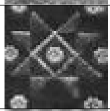
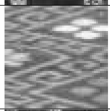

Fig.4 Training loss value and accuracy change

It can be seen from the image that when the number of training times reaches 1200, the loss value has reached 0, and the training accuracy rate is close to 100%, which indicates that the model's prediction accuracy for the sample is relatively ideal.

## V. Testing of CNN Models

When the number of training steps reaches the maximum number of steps, the model is saved in the specified path. The model will randomly select 33 samples from the remaining 79 test sets to test the model's recognition ability. The rate is shown in the following table

TABLE II. TEST TYPE IDENTIFICATION RATE

| Type | Picture | Recognition rate |
|---|---|---|
| Flower pattern |  | 93.18% |
| Chrysanthemum pattern |  | 99.92% |
| Diamond pattern |  | 98.11% |
| Octagon pattern |  | 87.12% |
| Cloud Thunder pattern |  | 66.63% |
| Phoenix pattern |  | 91.30% |
| Others | | 85.17% |
| Average | | 88.73% |

The table shows the recognition rate of several kinds with better training,and the results of cloud-ray patterns similar to diamond patterns. It can be seen from the test results that the recognition rate obtained for the more abundant types of training pictures is higher, and the individual types are almost close to zero error recognition, but for the less trained types, the maximum score is other types during testing Some types have a recognition rate of only about 70%. This is explained by the decline in the recognition ability of too many models for insufficiently trained species. Some species are insufficiently trained owing to their age and insufficient acquisition of image data. Another reason is perhaps that the similarity between some categories and other categories is too high.For example, the characteristics of the cloud pattern and diamond pattern are quite similar, but the cloud pattern has more roll decoration than the diamond pattern. Cloud-ray patterns were often mistaken for diamond-shaped patterns, but diamond-shaped patterns did do not seem to be considered cloud-type patterns.

## VI. SIGNIFICANCE

First of all, the clear classification of national cultural symbols can prevent designers from misuse in art design. Brocade of guangxi ethnic minorities has the same root, and has many common points in decorative patterns. Through artificial intelligence classification, this kind of generality will be obvious. After we have the Zhuang brocade decoration patterns with clear classification as a reference, we will not misuse the timing when it is applied to the national square with Zhuang characteristics.

Secondly, on the basis of avoiding misuse, clearly classified national cultural symbols can become the innovation and creative points of art design work and improve the level of art design of designers. On November 9, 2018, the first TV program produced by the Palace Museum, New · the Palace Museum, was broadcast on Beijing Satellite TV, breaking everyone's stereotype of the Palace Museum. On June 14, 2019, at the 25th Shanghai TV Festival, the program won the Magnolia Award for the best variety TV program. The most important reason for the hot discussion and love of the general audience is to take the traditional national cultural symbols as the creative and innovative points to get new inspiration. National cultural symbols become creative and innovative points, with new life and vitality, designers can also improve their own design level.

Fig.5 Architectural design of bronze drum elements of Zhuang Nationality

Finally, designers effectively and rationally use and innovate national cultural symbols in artistic design work, which is conducive to the inheritance and development of national cultural symbols. Leo Tolstoy said, "the right way is to take what your predecessors did and go on." It tells us the relationship between inheritance and development that national cultural symbols should be inherited and developed on the basis of inheritance. We use new technology and artificial intelligence to classify national cultural symbols clearly and clearly, so that designers can use them more effectively and reasonably in all kinds of art and design works, and combine the long ancient charm and vigorous vitality organically, so that more people can understand, like and pay attention to national cultural symbols, and make them reborn. This is an effective means for the inheritance and development of national cultural symbols.

## VII. CONCLUSION

This paper uses Zhuang ethnic symbols as sample data to study a classification and recognition method of indigenous cultural symbols based on convolutional neural networks. After testing the trained CNN model, it is concluded that the accuracy rate of 17 types of recognition can reach 88.73%, and the recognition process is much faster than manual recognition, which can reduce the risk of misuse due to the unclear classification in the modern design using traditional national symbols. This article will continue to extend the type and number of nationalities in the training set of picture data, optimize the neural network structure, and make the trained model have a wider area and higher recognition efficiency.

## ACKNOWLEDGEMENTS

This work was supported jointly by the National Natural Science Foundation of China (No. 61862018), Guangxi Natural Science Foundation (No. 2018GXNSFAA138084), Guangxi Experiment Center of Information Science (No. YB1506), Project of Guangxi Key Laboratory of Intelligent Processing of Computer Image and Graphics (No. GIIP201404).

## REFERENCES


[1] Liu Yanfeng, “Research on the application of national symbols in the packaging of art articles,” Literary life, Midterm,pp.49,Feb. 2019.

[2] Pan Gangjian. “Research on the deep integration of national symbols and film and television art design,” Art literature,pp.114-115,Feb.2019.

[3] Han Shaoqing,“Rational application of national symbols in design,” Business culture,pp.198- 199,Dec. 2011.

[4] Van Keirsbilck M, Keller A, Yang X,“Rethinking Full Connectivity in Recurrent Neural Networks,”Statistics, 2019.

[5] Yufeng Zheng, Jun Huang, Tianwen Chen, Yang Ou, Wu Zhou,“CNN classification based on global and local features,”Proceedings of SPIE - The International Society for Optical Engineering,Vol.10996,May.2019.

[6] Zhou Feiyan, Jin Linpeng, Dong Jun,“Review of Convolutional Neural Network,” Chinese Journal of Computers,Vol.40, Jun.2017.

[7] Gao L, Chen P Y, Yu S,“Demonstration of Convolution Kernel Operation on Resistive Cross-point Array,” IEEE Electron Device Letters,Vol.37,pp.870-873, 2016.

[8] Liu Pengfei, Zhao Huaici, Liu Mingdi,“Image Super-Resolution Based on Convolutional Neural Network,”Computer Engineering and Applications,Vol.55,pp.197-202,2019.

[9] WANG Jun,ZHU He,LEI Peng,ZHENG Tong,GAO Fei,“CNN Based Classification of Rigid Targets in Space Using Radar Micro-Doppler Signatures,”Chinese Journal of Electronics,Vol.28,pp.856-862,2019.

[10] Chulhee Yun,Suvrit Sra,Ali Jadbabaie,“Efficiently testing local optimality and escaping saddles for ReLU networks,”Statistics,2018.

[11] Niu Yaxi, Ji Xiaoping,“Image Retrieval Algorithm Based on Convolutional Neural Network,”Computer Engineering and Applications, Vol.55,pp.201-206.2019.

[12] Krizhevsky A, Sutskever I, Hinton G,“ImageNet Classification with Deep Convolutional Neural Networks,”Advances in neural information processing systems, Vol.25,2012.

[13] Zhong Zhiquan, Yuan Jin, Tang Xiaoying,“Left-vs-Right Eye Discrimination Based on Convolutional Neural Network, Journal of Computer Research and Development, Vol.55,pp.73-79,Feb.2018.

[14] Zhang Kaikai, Guo Songlin, Bi ChenLin, “Application of RBF neural network classifier and CNN in cancer cell image classification,”Electronic Test, Vol.22,pp.66-67,2019.

[15] Feng Xingjie, Xu Yixiong, Zeng Yunze, “Dual channel CNN recommendation algorithm combining user and product reviews,”Modern Electronics Technique, Vol.42,pp.121-126,Jul.2019.