Classification of Painting Style Based on Image Feature Extraction

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***Abstract*—The classification of painting style can help viewers find the works they want to appreciate more conveniently, which has a very important role. This paper realized image feature extraction and classification of paintings based on ResNet50. On the basis of ResNet50, squeeze-and-excitation, and convolutional block attention module (CBAM) attention mechanisms were introduced, and different activation functions were selected for improvement. Then, the effect of this method on painting style classification was studied using the Pandora dataset. It was found that ResNet50 obtained the best classification accuracy under a learning rate of 0.0001, a batch size of 32, and 50 iterations. After combining the CBAM attention mechanism, the accuracy rate was 65.64%, which was 6.77% higher than the original ResNet50 and 2.52% higher than ResNet50+SE. Under different activation functions, ResNet50+CBAM (CeLU) had the most excellent performance, with an accuracy rate of 67.13%, and was also superior to the other classification approaches such as Visual Geometry Group (VGG) 16. The findings prove that the proposed approach is applicable to the style classification of painting works and can be applied in practice.**

Keywords*—*Feature extraction; painting; style classification; ResNet50; attention

I. Introduction

A. Research Background

Under the influence of the continuous development and progress of various technologies, more and more resources are stored in the format of data, which provides a way for people to get the resources they want more conveniently and quickly. Painting, as an art form, has accumulated many excellent works after a long development. An increasing number of approaches have been applied in the research and analysis of paintings as the machine vision technology gradually develops [1]. Painting style refers to the artistic characteristics and expression techniques shown by artists in their works, which can reflect the emotions, personalities, and aesthetics during the creation of artists [2]. The classification of painting styles can help people gain a better understanding of different painting styles, which is an important content in the research of paintings. The traditional style classification of paintings is carried out by professional appreciation experts, which requires experts to have excellent professional knowledge and appreciation ability [3]. However, the manual method requires a lot of workload and has a low efficiency. With the development of machine vision, there is a growing trend of preserving paintings in digital format. As an image classification task, painting style classification can also be realized based on image classification technology.

B. Literature Review

In the current classification of painting works, most methods used to achieve classification based on the extraction and quantification of image color, texture, and other features [4]. Liu [5] decomposed paintings into sparse components and other components based on sparse decomposition and then realized style classification using naive Bayes. It was found through experiments that this method achieved 98.63% accuracy and consumed the shortest classification time. Li et al. [6] extracted the main details and edge information from Dongba paintings for the classification of Naxi Dongba paintings, realized the classification based on a multi-layer graph neural network (GNN), and proved the advantages of this method through experiments on small sample datasets. Bianconi [7] evaluated the effects of color stability and enhancement in paintings and found that neither feature showed significant advantages. Deep learning methods have shown strong capabilities in image feature extraction. Considering the shortcomings of traditional methods in feature extraction, deep learning-based approaches have been increasingly applied in image processing [8]. Liong et al. [9] compared the effectiveness of several deep learning approaches for the automatic classification of Chinese paintings and found that the improved pre-trained neural network achieved 99.66% accuracy when classifying more than 1,000 Chinese paintings belonging to six categories. Qing and Ce [10] proposed a multi-scale convolutional neural network (CNN) framework for classifying painting images, which can integrate global and local information into a single image. They achieved accuracies of 74.12% and 75.88% for the WikiArt dataset and Web Gallery of Art dataset respectively. Zhao et al. [11] constructed an artistic comment graph based on co-occurrence relations and document word relations, enabling through analysis of art comments, they used a graph convolutional network technology to realize the classification of painting types, genres, etc. Extensive experiments verified the performance of this method. Zhong et al. [12] proposed a dual-channel dual-path network for art painting classification. Experiments on two datasets demonstrated that this method achieved good classification accuracy.

C. Research Content

This paper conducted research on the classification of painting styles based on image feature extraction. In Section II, it introduces a method for image feature extraction and classification based on ResNet50, and the improvement to ResNet50 was proposed. In Section III, the designed method was experimentally validated, and the experimental dataset and results were described, demonstrating the effectiveness of the proposed improvement to ResNet50. Compared with current research, this paper achieved optimization of ResNet50 performance in terms of the attention mechanism and activation function. This article provides a novel and useful method for the classification of painting styles in practice and provides strong support for subsequent painting retrieval and artist identification. Finally, the paper is concluded in Section IV.

II. Image Feature Extraction and Classification Based on ResNet50

A. ResNet50

In the study of image classification, the frequently used method is to extract image features such as color and texture [13] and then classify images based on decision trees, neural networks, and other classifiers. However, compared with ordinary images, paintings contain more details and artistry. Therefore, the traditional image classification methods have poor performance in the classification of painting styles. Deep learning can extract image features through a deep network and realize automatic classification [14]; therefore, feature learning is deeper and more comprehensive. Therefore, this paper chooses the deep learning method to classify painting styles.

ResNet50 is a kind of deep CNN [15]. Generally speaking, as the quantity of layers in the network increases, gradient explosion and disappearance may occur when the feature extraction ability of the network is improved. However, the ResNet series network uses skip connection, that is, in the forward propagation, the input of a layer is directly transmitted to the following layers, so that the feature information of different layers can be transmitted to each other. It has been extensively used in image classification and other scenarios [16]. ResNet50 consists of 49 convolutional layers and one fully connected layer, and Table I presents its structure.

TABLE I. ResNet50 Structure

Layer name	50-Layer
Conv1	7×7, 64, S=2 3×3 maxpool, S=2
Conv2_x	$\begin{bmatrix} 1\times 1,64 \\ 3\times 3,64 \\ 1\times 1,256 \end{bmatrix}\times 3$
Conv3_x	$\begin{bmatrix} 1\times 1,128 \\ 3\times 3,128 \\ 1\times 1,512 \end{bmatrix}\times 4$
Conv4_x	$\begin{bmatrix} 1\times 1,256 \\ 3\times 3,256 \\ 1\times 1,1024 \end{bmatrix}\times 6$
Conv5_x	$\begin{bmatrix} 1\times 1,512 \\ 3\times 3,512 \\ 1\times 1,2048 \end{bmatrix}\times 3$
	Mean pool, fully connected layer, Softmax

As shown in Table I, ResNet50 first carries out a convolution and maximum pooling and then carried out feature extraction through four modules with 3, 4, 6, and 3 repetitions. Each block contains three convolutions, and the size of the convolution kernel is 1, 3, and 1, respectively. Finally, the obtained features are passed through mean pooling and the fully connected layer. Softmax outputs classification results.

B. Improvements to ResNet50

In order to enhance ResNet50's focus on the important information related to style distinction in paintings, this paper introduces the attention mechanism to improve the traditional ResNet50. For the modules from Conv2_x to Conv5_x in ResNet50, an attention module is added at the end of each module to improve ResNet50's ability to learn important features. The following two types of attention modules are added.

1) Squeeze-and-excitation (SE) attention mechanism [17]: its principle is to realize the attention of the channel with a high weight by adding a weight to each channel in the feature graph, and there are three main steps.

a) Squeeze: Before squeeze, the importance of each channel is the same. For a $H \times W \times C$ feature graph ($H \times W$ represents the height and width of the feature graph, C is the quantity of channels), the feature value of each channel is computed:

$$z_j = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{k=1}^{W} X_{ijk} \tag{1}$$

where X_{ijk} refers to the pixel value of the j-th channel in the i-th row and k-th column of the feature map.

b) Excitation: The weight for each channel is learned based on the fully connected neural network. The weight of the j-th channel is written as:

$$s_j = \sigma\left[W_2 f\left(W_1 z_j\right)\right], \tag{2}$$

where W_1 and W_2 are the weights of the two fully connected layers.

c) Scale: The feature graph is weighted based on the channel weight. The weighted feature graph is written as:

$$\tilde{X}_{ijk} = s_j \times X_{ijk}. \tag{3}$$

2) Convolutional block attention module (CBAM) attention mechanism [18]: its principle is to weight both channel and spatial dimensions. The features of the two dimensions are described as follows.

a) Channel attention: The feature descriptions of different dimensions are obtained through pooling operation and then stacked on the channel dimension:

$$M_c(X) = \sigma\left[MLP\left(AvgPool(X)\right) + MLP\left(MaxPool(X)\right)\right], \tag{4}$$

where σ is the Sigmoid activation function and MLP is the fully connected layer.

b) Spatial attention: The feature representations of different dimensions are obtained through pooling operation. After splicing, it passes through a 7×7 convolution layer and then through the Sigmoid function to get the weight coefficient. After multiplying the coefficient with the features, the final feature map is obtained:

$$M_s(X) = \sigma\left[f^{7\times7}\left(AvgPool(X); MaxPool(X)\right)\right], \quad (5)$$

where $f^{7\times7}$ is a 7×7 convolution kernel

In addition to adding the attention mechanism, the ReLU activation function used in ResNet50 is also improved, and the following activation functions are selected:

- PReLU [19]: $PReLU = max(0,x) + t * min(0,x)$, t takes the default value of 0.25;
- LeakyReLU [20]: $LeakyReLU = \begin{cases} x, x \geq 0 \\ ax, x < 0 \end{cases}$, a takes the default value of 0.01;
- CeLU [21]: $CeLU = max(0,x) + min\left(0, a * \left(exp\left(\frac{x}{a}\right) - 1\right)\right)$, a takes the default value of 1.

III. Experiment and Results

A. Experimental Setup

The experiment was carried out on a Windows 64-bit system, with Inter(R)Core(TM)i5-12500 and 32 G memory. The algorithm was implemented based on the TensorFlow2.4.0 framework. Python programming language was used.

At present, in the investigation of categorizing painting styles, the commonly used datasets include Pandora dataset [22], Wikipaintings dataset [23], etc. As the latter contains more than 80,000 works, it is impossible to achieve adequate training under the limited computing resources. Therefore, only a few images were selected from the Wikipaintings dataset for study. The experimental datasets used are as follows.

1) Pandora dataset: There are a few types of painting styles in it, but they include different styles from 17th ancient Greece to the present. Table II presents different styles and the corresponding number of paintings. During the experiment, an 80% portion was allocated for training purposes while the remaining 20% was designated as the test set.

TABLE II. Distribution of the Pandora Dataset1

Style	Number
Pottery of ancient Greece	350
Movement to destroy religious statues	665
Renaissance	812
Baroque	960
Rococo style	844
Romanticism	874
Realism	307
Impressionism	984
Brutalism	426
Cubism	920
Surrealism	242
Abstract expressionism	340

2) Wikipaintings dataset: It includes more than 80,000 painting works belonging to 25 styles. This paper selected images from ten of these styles for research. The selected styles and corresponding number are shown in Table III. They were also divided into a training set and a test set in a ratio of 8:2.

TABLE III. The Distribution of the Wikipaintings Dataset

Style	Number
Rococo	1,007
Baroque	1,056
Neoclasscism	1,345
Impressionism	1,541
Expressionism	1,112
Early Renaissance	1,512
High Renaissance	1,864
Post-Impressionism	1,825
Surrealism	1,854
Symbolism	1,021

The evaluation of the classification performance was based on the following indicators.

a) Accuracy (A): The proportion of the correctly classified samples to total samples is:

$$A = \frac{n_{TP}+n_{TN}}{n_{TP}+n_{TN}+n_{FP}+n_{FN}},$$

where n_{TP} refers to the true positive sample, n_{TN} refers to the true negative sample, n_{FP} refers to the false positive sample, and n_{FN} refers to the false negative sample.

b) Precision (P): The proportion of positive samples classified as positive is:

$$P = \frac{n_{TP}}{n_{TP}+n_{FP}}.$$

c) Recall rate (R): The proportion of positive samples classified as positive is:

$$R = \frac{n_{TP}}{n_{TP}+n_{FN}}.$$

d) F1 value: The comprehensive evaluation of P and R is:

$$F_1 = \frac{2\times P\times R}{P+R}.$$

B. Analysis of Results

In the follow-up experiment, the parameters of ResNet50 were adjusted to obtain better classification performance. Parameter experiments were performed on the Pandora dataset. First, for the learning rate, the batch size was set at 32, and the total count of iterations was 50. The changes in accuracy under different learning rates are presented in Fig. 1.

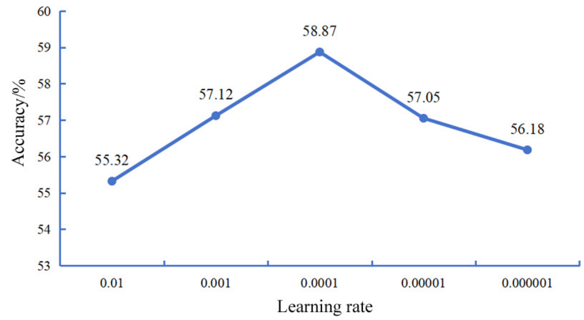

Fig. 1. Changes in accuracy under different learning rates.

In the process of the learning rate decreasing from 0.01 to 0.0001, the accuracy of the improved ResNet50 gradually increased. It reached the highest (58.87%) when learning rate = 0.0001 and then declined. Therefore, the optimal learning rate was 0.0001.

For the batch size, the learning rate was fixed at 0.0001, and the count of iterations was 50. The variation in accuracy under different batch sizes is presented in Fig. 2.

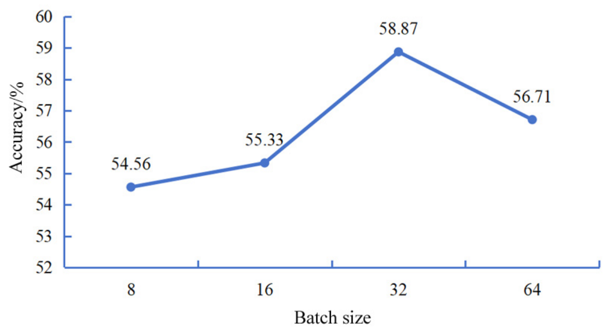

Fig. 2. Changes in accuracy under different batch sizes.

As the batch size increased, the improved ResNet50 also became more accurate. When the batch size was 8, the accuracy was 54.56% at the lowest level, and it was 32, the accuracy was 58.87% at the highest level. Therefore, the optimal batch size was 32.

For the number of iterations, the learning rate was fixed at 0.0001, and the batch size was 32. The changes in accuracy under different iteration numbers are displayed in Fig. 3.

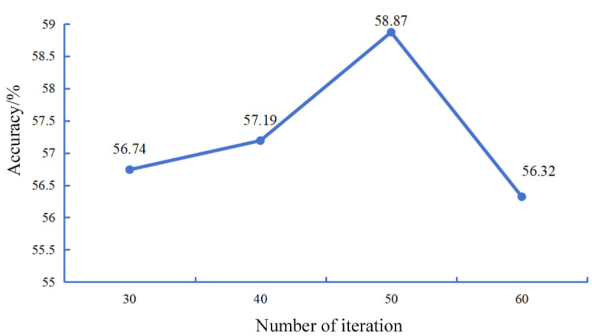

Fig. 3. Changes in accuracy rate under different iterations.

It can be found that when the number of iterations was 60, the accuracy of ResNet50 was the lowest, which was 56.32%; when the count of iterations was 50, the accuracy was the highest (58.87%). Therefore, the optimal number of iterations was 50.

Based on the above results, in the subsequent experiments, the learning rate of ResNet50 was set as 0.0001, the batch size was 32, and the count of iterations was 50. Moreover, ResNet50 was compared with other traditional residual network models. The floating point operations per seconds (FlOPs) and parameters of different algorithms are presented in Table IV.

TABLE IV. COMPARISONS WITH OTHER RESIDUAL NETWORK MODELS

	ResNet18 [24]	ResNet34 [25]	ResNet50	ResNet101 [26]
Accuracy/%	56.46	58.41	58.87	58.89
FLOPs/G	3.67	7.35	8.21	15.54
Parameter/M	11.71	21.83	25.55	44.56

It can be seen that with the increasing depth of the network, the accuracy of ResNet also gradually increased. Among them, ResNet101 achieved the highest accuracy at 58.89%, which indicated a slight improvement of 0.02% compared to ResNet50. However, there was a significant increase in FLOPs and parameter for ResNet101 compared to ResNet50, which not only increased the complexity of the model but also imposed higher requirements on hardware facilities. This was not conducive to practical applications. On the other hand, ResNet50 achieved a good balance between classification performance and complexity, verifying its reliability.

For the improvement of ResNet50, the original ResNet50 was combined with different attention mechanisms. The accuracy for different datasets is presented in Table V.

TABLE V. RESNET50 COMBINING DIFFERENT ATTENTION MECHANISMS

	Pandora dataset	Wikipaintings dataset
ResNet50	58.87	51.37
ResNet50+SE	63.12	56.54
ResNet50+CBAM	65.64	58.79

As shown in Table V, when the Pandora dataset was used, after combining ResNet50 with the SE attention mechanism, the accuracy was 63.12%, which was 4.25% higher than the original ResNet50; when combined with the CBAM attention mechanism, the accuracy was 65.64%, which was 6.77% higher than the original ResNet50 and 2.52% higher than ResNet50+SE. When the Wikipaintings dataset was used, after combining ResNet50 with the SE attention mechanism, the accuracy achieved was 56.54%, which showed an improvement of 5.17% compared to the original ResNet50. When combined with the CBAM attention mechanism, the accuracy obtained was 58.79%, which showed an improvement of 7.42% compared to the original ResNet50 and an improvement of 2.25% compared to ResNet50+SE. These results showed that compared with SE, CBAM combined with ResNet50 could achieve better performance in the style classification of paintings and had stronger ability to extract image features.

Then, on the basis of ResNet50+CBAM, the improvement of the activation function was compared. The accuracy for different datasets is presented in Table VI.

TABLE VI. RESNET50 COMBINED WITH DIFFERENT ACTIVATION FUNCTIONS2

	Pandora dataset	Wikipaintings dataset
ResNet50+CBAM (ReLU)	65.64	58.79
ResNet50+CBAM (PReLU)	66.32	59.42
ResNet50+CBAM (LeakyReLU)	66.87	59.98
ResNet50+CBAM (CeLU)	67.13	60.37

The ReLU used in the original ResNet50 had the worst performance in classifying painting styles from the Pandora dataset, with an accuracy of only 66.32%. After replacing it with PReLU, the accuracy reached 66.32% (+0.68%). After replacing it with LeakyReLU, the accuracy reached 66.87% (+1.23%). After replacing it with CeLU, the accuracy reached 67.13% (+1.49%). It exhibited the same results for the Wikipaintings dataset. These results showed that CeLU could achieve the best effect in the style classification of paintings in ResNet50+CBAM.

Finally, the ResNet50+CBAM (CeLU) was compared with other methods (Table VII).

TABLE VII. COMPARISON BETWEEN DIFFERENT FEATURE EXTRACTION NETWORKS3

		Accuracy/ %	Precision/ %	Recall rate/ %	F1 value/ %
Pandora dataset	Pyramid local binary pattern (PLBP)+color structure descriptor (CSD)+support vector machine (SVM) [22]	54.70	52.13	50.77	51.44
	MobileNet [27]	54.87	52.31	51.22	51.76
	AlexNet [28]	55.36	53.64	52.11	52.86
	Visual Geometry Group (VGG) 16 [29]	56.52	54.77	55.07	54.92
	VGG 19 [30]	57.12	55.67	55.88	55.77
	InceptionV3 [31]	57.64	56.78	55.97	56.37
	ResNet50	58.87	57.32	56.42	56.87
	ResNet50+CBAM (CeLU)	67.13	65.45	64.59	65.02
Wikipaintings dataset	PLBP+CSD+SVM [22]	47.12	46.77	46.02	46.39
	MobileNet [27]	47.37	47.31	46.54	46.92
	AlexNet [28]	48.05	47.87	46.79	47.32
	VGG 16 [29]	49.35	48.61	47.56	48.08
	VGG 19 [30]	51.07	50.87	48.97	49.90
	InceptionV3 [31]	51.25	51.12	50.33	50.72
	ResNet50	51.37	51.07	50.98	51.02
	ResNet50+CBAM (CeLU)	60.37	59.84	58.49	59.16

It can be found that the traditional method PLBP+CSD+SVM based on feature extraction and classifier had poor performance in painting style classification, with the lowest accuracy of only 54.70% and 47.12%. Specifically, the ResNet50+CBAM (CeLU) exhibited the optimal performance for the two datasets, with F1 values of 65.02% and 59.16%, verifying the reliability of this method in classifying painting styles. Therefore, it can be used in practice to support the classification and retrieval of paintings in real life.

IV. CONCLUSION

This paper studied the classification of painting work styles. A ResNet50-based image feature extraction method was developed to obtain a higher-performance classification algorithm. ResNet50 was improved from aspects of attention mechanism and activation function to achieve image feature extraction and classification. Through experiments on the Pandora dataset, it was found that the classification accuracy achieved by ResNet50+CBAM (CeLU) was 67.13%, which was better than the other deep learning methods. This paper verifies the reliability of the proposed approach; thus, it can be applied in the actual classification of painting styles. The method can be applied in the field of painting work classification and painting information retrieval to promote the informatization and digitization of painting work management.

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