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Construction and Application of Classification Model of Art Design Patterns based on Random Matrix

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Abstract: With the continuous enhancement of computer technology, digital technology brings people more convenience with its powerful functions, and the classification accuracy of art design patterns is getting higher and higher, which greatly expands the creative space of art design. This paper improves the traditional model based on a random matrix, mainly to improve the pattern recognition efficiency and pattern classification accuracy, focusing on the construction and application of the art design pattern classification model, using the random matrix model proposed in this paper can better classify the art design pattern classification, art design pattern classification accuracy is higher, can better promote the combination of art and technology to promote the development of the industry This paper presents a random matrix model to classify art design patterns with higher accuracy, which can better promote the development of art and technology combination. Traditional machine learning methods are used to classify art and design patterns by changing the weights and focusing on the desired target. However, updating the model weights is on the architecture of the original model, which only involves the iterative update of the weights, and the accuracy of the art design pattern classification cannot be significantly improved, still, there is a problem of poor classification accuracy for art pattern classification, and this problem exists, the recognition model based on the random matrix is improved. Based on 73388 art design samples, this paper extracts art design patterns, and improves the accuracy by using the improvement of the random matrix algorithm model.

Keywords: random matrix; art design pattern score; model construction; technology integration

1. INTRODUCTION

In practical applications, it is usually difficult to obtain so much high-quality training data in art design patterns, because much of the data contains noise, even data with label noise. So the trained classification models can easily over-fit the noisy data, resulting in poor classification results. As can be seen, how improving the generalization ability to exist image classification models on data containing noise is still a challenging problem to be solved in the field of image classification. Based on the nature of reference matrices such as Sudoku matrices and chaotic systems, we design a new reference matrix, the random matrix (RM), embed the secret information into the original image through the guidelines of the reference matrix, and make the image with secret information better concealment and higher security. The classical problem in computer vision is to determine whether the image data contains some specific object, feature, or activity [1].

Based on the image classification scheme based on the random matrix, this paper proposes a construction scheme of an extended random matrix, which maintains the advantages of the random matrix in image quality and steganographic efficiency while making it possible to generate different constructions of extended random matrix adaptively based on different artistic design pattern requirements to generate steganographic images with different capacities of steganographic secret information. Through the analysis of experimental results, the quality of steganographic images is improved under different steganographic capacities in this paper, combined with the theoretical analysis of the extended random matrix image classification as an important research problem in the field of computer vision, and also as a basis for solving other computer vision problems. The methods of image classification have numerous uses in life, and with the development of image classification techniques, their applications are expanding and their impact on the way of social life is increasing. The goal of image classification research is to design an image classification model and make the classification model able to accurately determine the class of a new input image by learning from different images on the input. To achieve this goal, traditional machine learning image classification methods divide the entire classification algorithm into several stages: input of image information [2], pre-processing of the image, extraction of features from the image, selection of the extracted features, and construction of the classifier. However, traditional machine learning methods require manual extraction of feature information to do classification based on the features, which has great limitations in practical use. It takes a lot of time to process a large dataset, and if there is noise in the training set, such as label noise, the model often has poor generalization ability and it is difficult to get satisfactory classification results. The random matrix-based art design pattern classification model is beneficial to improve the accuracy and perform better art image design classification.

2. RELATED DISCUSSIONS

In recent years, the random matrix-based classification model for art and design patterns has become a major approach to solving image classification tasks. The technique of image classification has been used in many applications in various industries. However, it has been found that the image classification accuracy is greatly reduced when the training data contains noisy data, and it is very difficult to always obtain a large amount of clean data in real applications. Therefore, it is very important to improve the generalization ability of classification models. Couillet R [3] improved the generalization ability of network models is currently considered by academics mainly from two aspects: network and loss. Image classification has been developed so far, and gradually changed from the traditional feature extraction and then classification method to an end-to-end model based on deep neural networks, and has continuously improved and improved its network model, and the accuracy and detection speed of classification have been greatly improved. However, in recent years, researchers are no longer satisfied with the proposed methods to improve classification accuracy on noise-free or low-noise data, because many image classification tasks, in reality, do not have access to such high-quality data sets for training.

In terms of loss, Corazzo J [4] addressed the effect of noisy data by weighting the samples to achieve the minimization of the effect of noisy samples during training. Since in deep neural network methods, samples with greater losses are usually considered more likely to be noisy, the literatureassigns self-paced learning (SPL) to sample losses based on training losses. This method can dynamically assign weights to samples during training, by assigning smaller weights to samples with large training losses and larger weights to samples with small training losses, thereby attenuating the effect of noisy data with typically larger losses on training. Scholars proposed the symmetric cross-entropy loss function, which is inspired by the KL scatter to combine the inverse cross-entropy function and the cross-entropy function to obtain the symmetric cross-entropy loss function, which can not only promote the learning of difficult samples but also improve the robustness of deep neural networks to noise.

Literature random matrix combined with traditional feature convergence, the classification accuracy increases gradually with the increase of network depth in the experiment. Although several methods have been proposed to try to solve various noise problems, they all have great limitations and are still very demanding for the training set itself. However, more and more computer vision researchers have started to pay attention to the application of meta-learning in the field of image classification because of the good performance of [5], which requires only a small number of high-quality training samples for training. The literature [6] presents an algorithm for classifying artistic design patterns based on random matrices. Liang W automatically assigns weights to training samples based on the gradient direction without adding additional hyperparameters. This method can improve the robustness of image classification tasks and is effective in solving problems such as class imbalance and label noise. Of course, the application of the random matrix-based art design pattern classification model in the image field is still in its infancy, and there are still some problems in the application [7].

Chorilli M [8] proposed a combination of random matrices and traditional feature convergence, and the classification accuracy increases gradually with the increase of network depth in the experiments. The literature [9] et al. proposed a gradient random convolutional network (GBRCN) classification framework in 2016, which combines multiple deep neural networks. The literature [10] literature proposes a deep feature combined with the Root SIFT random matrix framework, which achieves a matching rate of 76.12% on the CUHK05 dataset. The literature [11] implements SIFT on a single GPU of the NVIDIA S1070 device, which provides a significant performance advantage over CPU-based implementations in terms of execution performance. The literature [12] proposes an efficient FPGA-based hardware architecture for the SIFT algorithm, which improves the frequency of the SIFT algorithm by nearly two orders of magnitude compared to running it on an Intel Core i7 CPU-4790 (3.60Hz). The literature [13] completed the design implementation of an image-based 3D reconstruction system in the 1990s.

3.ART DESIGN PATTERN CLASSIFICATION MODEL

3.1Artistic design pattern realization

Art patterns are culturally based to achieve the purpose of decorating and expressing people's abstract thinking concepts based on the function of the object or space. Humans try to achieve a perfect combination of visual, cultural, aesthetic, and functional with the help of art patterns. People use art patterns to express their thoughts, aesthetics, and emotions; therefore, the ideological content and form of art patterns depend on both the economic base of the society at that time and are also a reflection of the politics, economy, morality, and ethics of the society at that time [14].

Artistic patterns are abstract symbols with a sense of formal beauty, following certain laws and regulations of formal beauty, for decoration, which can be used for the appearance of microscopic single product decoration, but also as a macro area planning and landscape design form design language [15]. Artistic patterns are the visual expression of people's abstract concepts and ideas, including style, color, texture, proportional relationships, and other techniques to create a different spatial atmosphere, thus reflecting the designer's view of life, nature, and the world [16][17].

Human beings have a long history of using graphics [18]. The paintings and totems of our ancestors in the primitive period and the pictographs are the beginning of early graphics, which were used to record people's thoughts and feelings and to communicate with each other. With the development of human civilization [19], people's aesthetics are no longer satisfied with simple graphic decoration. The pattern is a derivative of the development of graphics [20], which consists of one or more graphics, and these graphics are organized according to the laws of formal beauty. Pattern and composition are inextricably linked, and the laws of composition, formal beauty and regularity of both them are similar. From the point of view of service function, both are also used to produce services and decorate products. In terms of the nature of the class, graphics, patterns, composition, and art patterns are all visual symbols. The earliest time of their production is graphics, then patterns, followed by composition, and finally art patterns. Artistic patterns are the synthesis of visual art symbols such as graphics, patterns, and composition. They penetrate each other, influence each other, and are opposed to each other and unified. Art design pattern composition is shown in Figure 1.

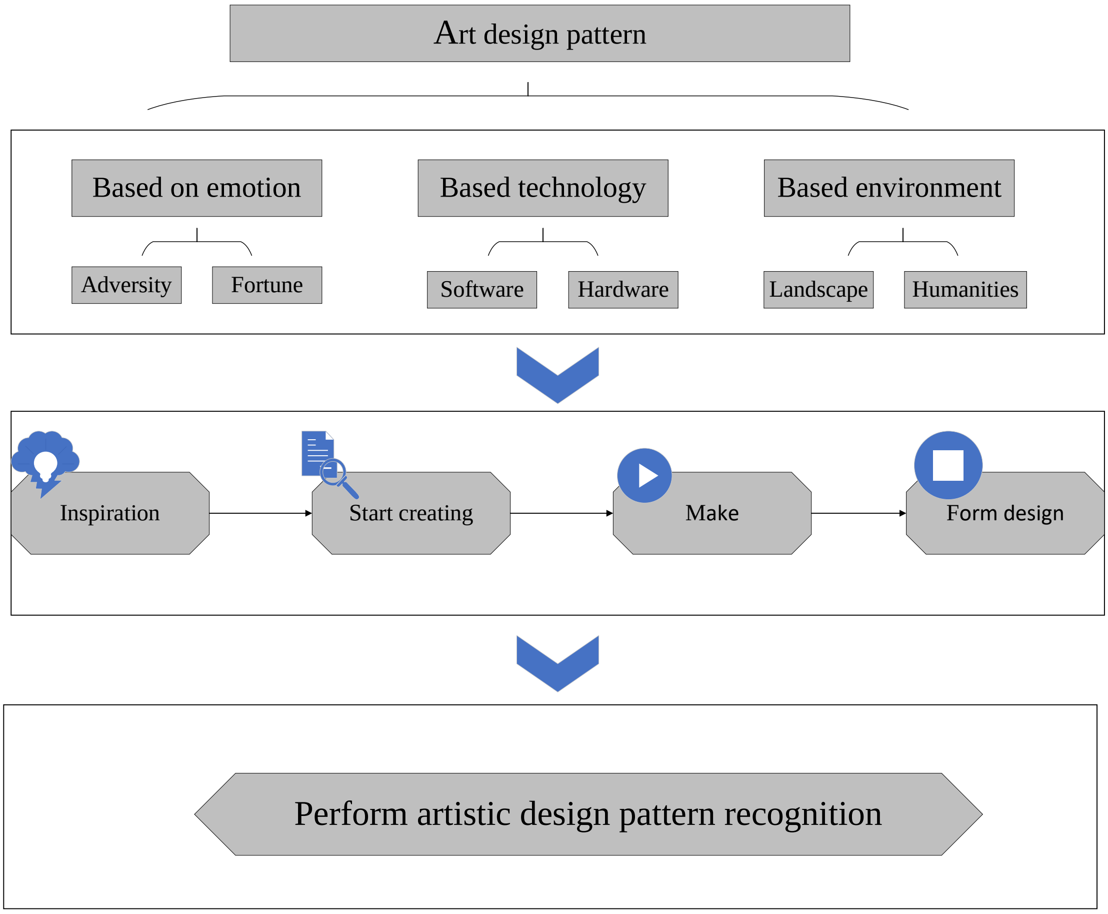

Figure 1. Art design pattern composition

Pictograms are geometric diagrams represented by points, lines, surfaces, and three-dimensional space. The paintings, totems, and pictographs of our ancestors in the primitive period were the beginning of early graphics, which were used to record people's thoughts and feelings and to communicate with each other. People used graphics to create civilizations in different fields such as visual, linguistic and cultural, aesthetic and recreational, and economic. The study of human graphics can be traced back to the earliest time in the West in ancient Egypt and ancient Greece [21]. According to the time-division, patterns can be divided into two categories: traditional patterns and modern patterns. The traditional pattern subject matter, style, and color have obvious regional and national characteristics, according to the geographical division can be divided into Eastern traditional patterns and Western traditional patterns. Eastern traditional patterns are mainly divided into the patterns of Southeast Asian countries represented by China, Japan, and Vietnam, and the patterns of Eastern European countries such as Russia, Greece, and Romania, which belief in Orthodox Christianity.

3.2 Art and design image classification methods

Whether in the East, the Middle East, or the West, the traditional pattern style is based on natural forms, using the figurative expression, these patterns have strong regional cultural characteristics and a handcrafted atmosphere. The patterns at the end of the century and the beginning of the century belong to the category of modern patterns, due to the improvement of productivity and science and technology, the expression of patterns is no longer mainly handmade, but the form of industrial processing mass production; the birth of abstract art in the century, so that the pattern style also from the traditional figurative form into abstract form. Therefore, the two distinctive features of modern patterns that are different from traditional patterns are industrial and abstractness. Whether in the East, the Middle East, or the West, traditional patterns are based on natural forms, and the use of the figurative expression, these patterns have strong regional cultural characteristics and a handmade atmosphere [22]. The patterns at the end of the century and the beginning of the century belong to the category of modern patterns, due to the level of productivity and science and technology, the expression of patterns is no longer mainly handmade, but the use of industrial processing forms of mass production; the birth of abstract art in the century, so that the pattern style also from the traditional figurative form into abstract form. Therefore, the modern pattern is different from the traditional pattern of the two distinctive features are industrial and abstract.

3.2.1 Art image classification model

A random matrix is a feedforward neural network incorporating convolutional operations, often used for visual image-like problems, and is one of the most well-known underlying network architectures for deep neural networks. Convolutional neural networks are artificial neural networks containing human-like neuron nodes inspired by human visual cognition [23]. Convolutional neural networks take the input data through multiple hidden layers and perform convolutional operations and nonlinear transformations to extract the features of the input data, then obtain higher-level local features by fusing the features, and finally classify the images by the obtained features. Unlike other feedforward neural networks, the convolutional operations in convolutional neural networks are weight-sharing, which makes the network require fewer parameters, and the neural network structure becomes simpler and more generalizable [24]. The so-called weight sharing is when the convolutional neural network shares a set of weights for all feature values under the same channel on the feature map. The product layer is the most important part of the convolutional neural network, and the feature extraction in the image is done by the convolutional layer. Each convolutional layer has multiple convolutional kernels, and different features can be extracted by doing convolutional operations with 2D images through different convolutional kernels. In addition, the activation function is introduced in the convolutional neural network to increase the nonlinear factor, which facilitates the approximation of arbitrary functions by the convolutional neural network and enhances the feature expression capability of the network model. Its formula is expressed as.

$$Z^{l} = W^{l} * Z^{\mathrm{l\text{-}1}} + \frac{x-\mu}{\sigma}$$
$$A^{l} = f(Z^{l}) \quad (1)$$

where Z^{l-1} is the input of the lth layer, Z^{l} is the output of the lth layer after convolution, A^{l} denotes the output after activation, and f is the activation function. In convolutional neural networks, the pooling layer is usually inserted between successive convolutional layers, and its role is mainly to downsample the feature map after the convolutional layer outputs the feature map. The pooling layer removes redundant feature information and reduces the size of the feature map by downsampling, which can reduce the overall number of parameters in the network and also alleviate the overfitting of the network model. The common processing methods of the pooling layer are Max Pooling and Average Pooling, and Max Pooling is the most used in convolutional neural networks. Max pooling is to keep only the maximum value in the target region, and a larger value means a stronger response. Focusing on such feature information and ignoring other information can help reduce the effect of noise and improve the robustness of the model [25].

3.2.2 Pattern classification model flow

Classification for art design patterns requires input to the art design patterns, some degree of machine learning of the patterns, recognition of the patterns, and then output for classification. The art design pattern recognition process is shown in Figure 2.

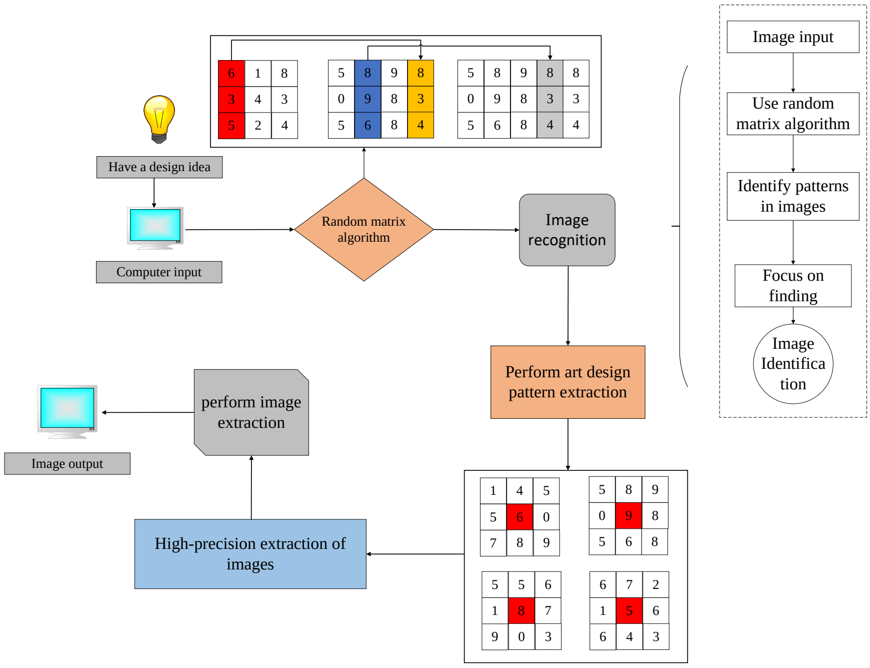

Figure 2. Art design pattern recognition process

Channel attention considers the feature map as a combination of individual channel features, and simply blending all channel information equally and performing learning is problematic. In the random matrix, the original image is convolved through different convolution layers to produce multiple. The formula looks like this:

$$Z = \sum_{i=1}^{n} X_i Y_i + \frac{1}{n}\sigma_X^2 \quad (2)$$

The resulting channel features are necessarily different for the representation of the original image, and the individual channel features are different for the contribution to the original image is necessarily different. Therefore, the channel attention mechanism expects the model to learn each channel. The importance of the attention to achieve the effect of a deeper identification of the art design for classification, the complex process of which is shown in Figure 3.

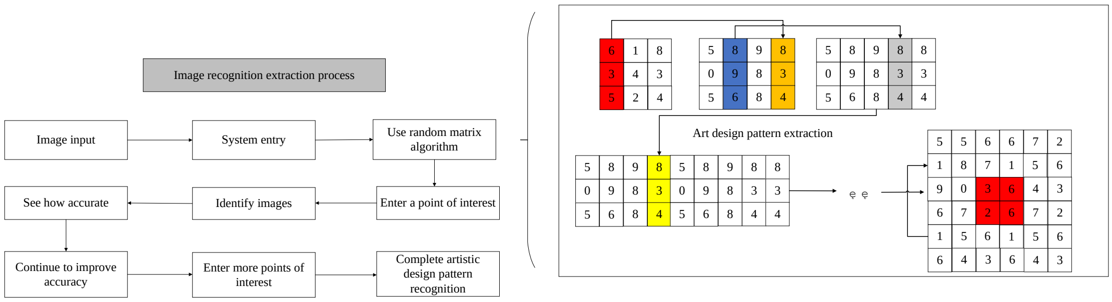

Figure 3. Art design pattern classification model flow

There have been many related types of research for label noise learning. A random matrix-based classification model for art design patterns extracts noise-free information from the dataset by ignoring or not weighting the information from noisy samples. To avoid the risk of removing too much data, sample selection is performed by continuously monitoring the basic classifier to select the samples to be used in the next training iteration. Sample importance weighting allows for more effective training by assigning weights to samples based on their estimated noise level. This has the effect of emphasizing cleaner samples to better update model weights, as in Curriculum Learning (CL) and Self-paced Learning (SPL), The formula looks like this:

$$Y = \frac{1}{n}\mu_X + (X_1, \dots, X_n) \quad (3)$$

They perform well when a priori information about the structure is available, but most of the time the a priori information is difficult to understand. The advantage of noise-model-based approaches is the decoupling of label noise estimation and classification, which helps them to be used together with classification algorithms. The formula looks like this:

$$M = \frac{x-\mu}{\sigma} + \frac{1}{n}\sigma_X^2 \quad (4)$$

Noise-free model-based approaches aim to propose inherently noise-robust methods without explicit modeling of the noise structure and without requiring a priori information about the noise structure. The formula looks like this:

$$Y = \frac{x-\mu}{\sigma} + \frac{1}{n}\sigma_X^2 + \sum_{i=1}^{n} X_i Y_i \quad (5)$$

Thus, they are easier to implement if the noise is random and overfitting is the cause of performance degradation. Secondly, inspired by the development of meta-learning, some methods for learning adaptive weighting schemes from data have been proposed recently, enabling learning to please manual design and be more reliable.

3.3 Art design pattern classification theory

The main task of random matrix theory is to study the limit properties in the random and order-tending-to-infinity case. Random matrices often require a large amount of data for learning, and the more reliable the input data, obviously the better the learned model will be. However, in reality, the data are often mixed with noisy and confusing data, which makes the learned model not strong enough to generalize. Self-paced learning (SPL) is a typical robust learning method that has received more and more attention in the field of machine learning and pattern recognition. incorporating complex information into the learning.

SPL is based on the model dynamically selecting simple samples by weighting them during iteration, while CL requires a predefined strategy and then adding the samples to the learning gradually in order of the difficulty of the strategy. Although both help to accelerate convergence and obtain better generalization, SPL has broader applicability. Its artistic design pattern classification random matrix theory originated from the study of the energy levels of a large number of particles in quantum mechanics. Many of the laws in mathematical physics were discovered through the study of numerical values. In the late 1950s, the study of the semicircular law of Gaussian matrices began when scholars elaborated on the problem based on the empirical distribution of random matrices. Since then, the theory of random matrices has formed an active branch in modern probability theory. The effect of art and design pattern classification is shown in Figure 4.

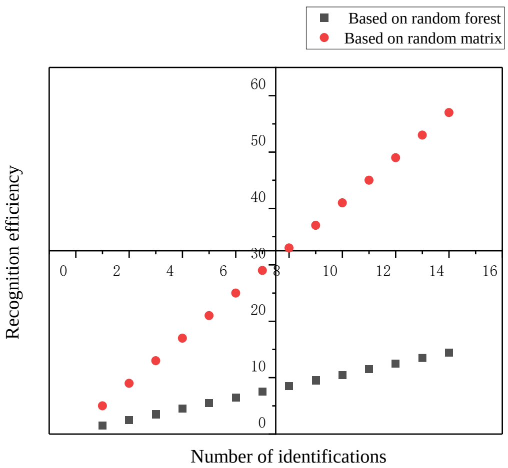

Figure 4. Art design pattern classification effect

4. EXPERIMENTAL DESIGN.

To validate and evaluate the effectiveness of the proposed random matrix-based classification model for art design patterns, experiments were conducted on multiple datasets with random label noise. The random label noise set in the experiments, as the name implies, is that each sample in the dataset is independently and randomly changed to any class in the total class with a probability of p. To conduct adequate experiments on the algorithm, two commonly used benchmark datasets, CIFAR-10 and CIFAR-100, which are widely used to evaluate the label noise problem, are chosen in this paper. Among them, the two publicly available datasets do not have validation set data, so after obtaining the datasets, 1000 randomly selected image samples with correct labels from the training set are firstly used as the validation set and also as the required metadata set in the HMSW algorithm. The details of the datasets used in the experiments are shown in Table 1 below.

Table 1. Experimental dataset

Data set	Category	size of the picture	Training set	Test set
random forest	102	44*32*4	34895	5000
random matrix	293	32*45*4	38493	5000

5. ANALYSIS OF RESULTS

Great progress has been made in the research of random matrix-based image classification algorithms. The study of robustness for classification network models has also been visited by more and more researchers.

5.1 Analysis of art design pattern data collection

It is still difficult for learning a better classification network model on data containing noise. Although some researchers have given their solutions for improving the robustness of classification models, most random matrix models for image classification still have significant limitations, such as the cross-entropy loss still used in the loss function part of the model can be too biased toward the noise, too many hyperparameters in the model and the contribution of each feature to the network is not fully considered when the feature map is extracted, etc. These problems still These problems are to be solved by the random matrix-based image classification algorithm. In this paper, the traditional cross-entropy loss function used in the random matrix for image classification is improved to alleviate the overfitting of noisy samples, and the degree of contribution of different features to improve the performance of the model is taken into account, and thus the generalization ability of the model for noisy samples is improved from two aspects. Its experimental efficiency is shown in Figure 5.

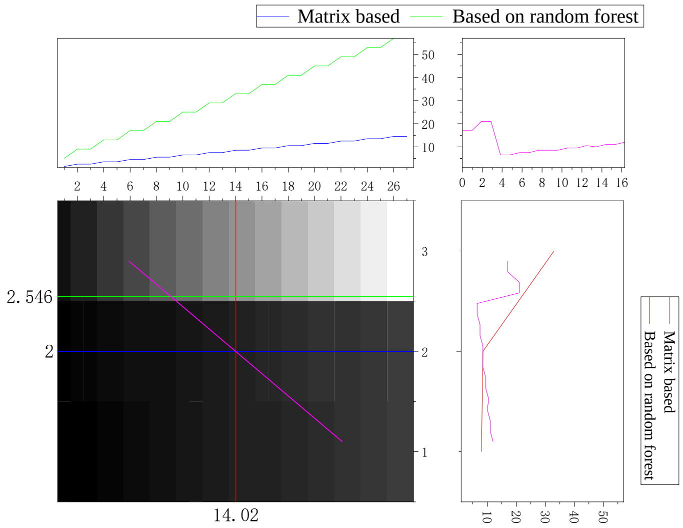

Figure 5. Experimental efficiency change of image data acquisition

The basic structure of the WRN-28-10 network is still used in the classification network of the random matrix algorithm, and the SE module is added to the wide residual module in the network to improve the expressiveness of the network model with the help of the channel attention mechanism of the SE module. To further verify the effectiveness of the channel attention mechanism in the network, the HB_loss in the random matrix algorithm is replaced with the previous cross-entropy loss function in the experiments of this section, and then the main network of the HMSW algorithm is SWN-28-10 with the addition of the SE module compared with the conventional wide residual network WRN-28-10, and the improvement in classification accuracy is achieved.

5.2 Art design pattern recognition analysis

To improve the generalization ability of the classification model under the label noise problem, an HMSW model based on a meta-weighting network and attention mechanism are proposed in this paper. In the proposed HMSW model, firstly, the cross-entropy loss function used in the original meta-weighting network weighting method is improved by using the HB_loss loss function, which is more robust to the noisy labels, to reduce the model's ability to generalize to the noisy labels. Overfitting of acoustic samples and improving the generalization ability of the model. Second, by adding the SE module to the classification network the network. The channel attention mechanism is introduced in the model to induce the model to learn more useful features, which in turn gives more accurate label predictions. In terms of the whole. For the first model, HB_loss helps to improve the generalization ability, adding HB_loss to the meta-weighting network and adding correlated sources to the network in this simulation, where the correlation coefficient between the first source and the second source is 0.6 and the third source is independent of the first two sources, the spatial-spectral function plots of MUSIC, WSF and RMT_E are obtained under the condition that the number of snapshots is 10 and the SNR is -8dB. The spatial-spectral function plots of the three algorithms of RMT_E with the efficiency of image recognition is shown in Figure 6.

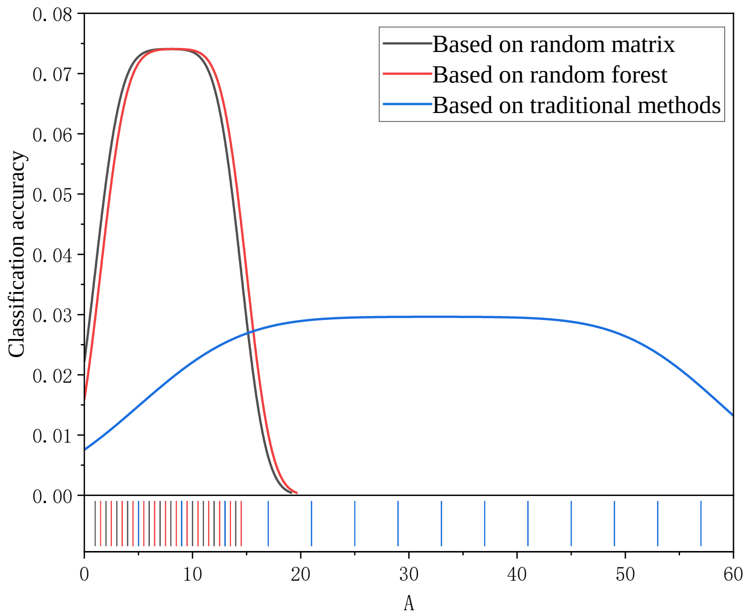

Figure 6. Image recognition efficiency

The results show that this subject image data acquisition technology in image detection recognition in many implementations there are missed and false detection, after using the algorithm of the random matrix but the detection accuracy of the image can reach more than90%. The color detection accuracy of multiple images decreases, but can also be maintained at more than 85%, highlighting the efficiency of the random matrix-based algorithm, for image recognition.

5.3 Analysis of art design pattern classification.

Image classification, as the name implies, is a pattern classification problem, and its goal is to classify different images into different categories precisely by some methods, and the smaller the error of this classification, the better. To achieve more accurate classification, it is especially important to obtain richer semantic information from images and to be able to extract relevant features. The traditional methods are very difficult to learn the underlying feature information, which makes it difficult to recognize complex images. Traditional image classification methods require extraction of the underlying features, then encoding and aggregation of features, and then classification by classifier. It can be seen that the traditional image classification algorithm is a complicated and heavy workload, and the learning of the underlying feature information is very difficult, and it is difficult to extract well by specific methods. In contrast, the random matrix-based image classification method can easily extract rich feature information and achieve better image classification results under its complex network and powerful feature representation capability. In short, the random matrix-based image classification method no longer needs humans to select the features, but the computer automatically learns the good features through the designed deep neural network. The efficiency of the traditional image classification method and the random matrix-based pattern classification method are shown in Figure 7.

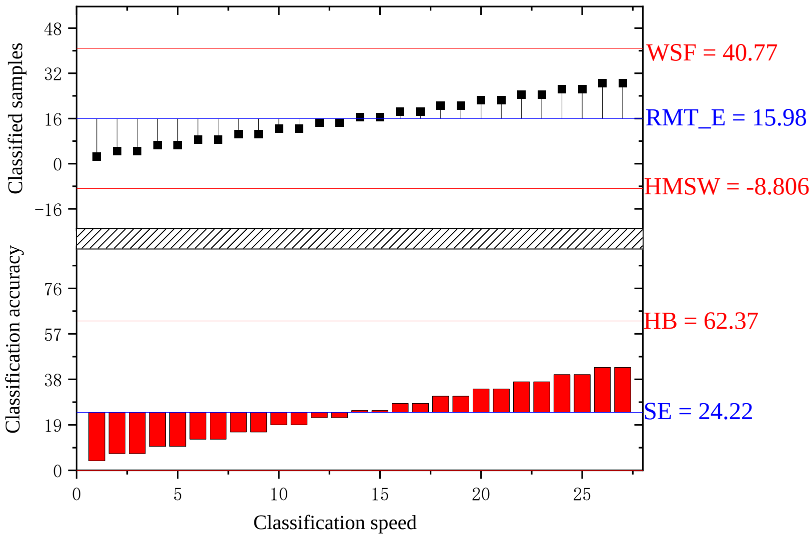

Figure 7. Comparison of the efficiency of art design pattern classification

5.4 Art design pattern classification model application

Variational Autoencoder is an important class of generative models whose core design motivation is the desire to propose a model that generates new data that is not available in the dataset but is highly similar to the samples in the dataset. The model makes strong assumptions about the distribution of the hidden variables and aids the representation learning process with the help of variational methods, which add loss terms compared to the traditional autoencoder design. Unlike the general self-encoder hidden layer that generates node representation vectors, the variational self-encoder generates a normal distribution of the data representation after encoding, with the key parameters inscribed in terms of mean and variance, and the variational self-encoder framework constrains the learned distribution to be as close as possible to the standard normal distribution. Since this process is not derivable, model training is often assisted in practice utilizing re-referencing. Contractive Autoencoder is designed with the motivation that for similar inputs, the compressed representation learned by the model should also be similar. Specifically, the model can be trained explicitly by constraining the derivatives of the hidden layer activation values to be small concerning the derivatives of the inputs, allowing it to achieve the original design intent of the comparative autoencoder. That is, the model should maintain a similar compressed representation for small changes in the input, which is similar to the idea of denoising self-encoders. The goal is that both want the model to be resistant to noisy input data. But the two are different in that denoising autoencoders constrain the reconstruction function (i.e., decoder) to be resistant to small and finite-size perturbations in the input, while systolic autoencoders constrain the feature extraction function (e.g., encoder) to be resistant to small perturbations in the input. This is because the framework constrains the model to learn how to shrink the neighborhood of the input to the neighborhood of the output, i.e., data points that are similar in the sample space are mapped to remain similar in the embedding space. Therefore, a constraint can be proposed to achieve this goal, which can penalize the hidden layer activation for larger gradient values of the input training samples. The framework of the art design pattern classification model scheme is shown in Figure 8.

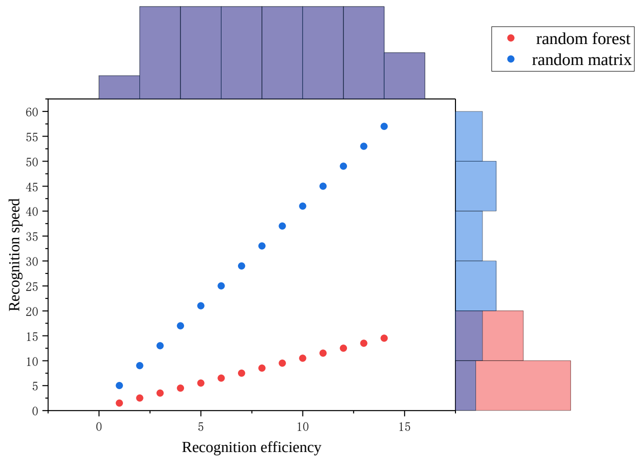

Figure 8.Comparison of Pattern Classification Efficiency Charts Based on Random Matrix

A key application of the self-encoder is the dimensionality reduction operation to do data compression. By encoding the input sample to a hidden layer representation, the information is compressed from the input into a low-dimensional vector, which is one of the main uses of the self-encoder used in this paper. In addition, the self-encoder is good at denoising the image. If there are some noise points in an image, we call it a noisy image, and to get the correct information in the sample, we can use the denoising self-encoder to denoise the sample. Self-encoders can also be used for feature extraction, and in the process of reducing reconstruction errors, encoders can help learn important implicit features in the input data. Finally, a key application of the self-encoder is as a generative model. For variational self-encoders, when the model training reaches convergence, new samples can be generated by sampling noise from the standard normal distribution and using the reparameterization technique to obtain the hidden variables, but the samples thus obtained are completely random and obey the training data distribution, and the algorithm based on the random matrix is capable of better classification of art and design images.

Although art design pattern classification, a fundamental task in computer vision, has developed rapidly and achieved many important results in recent years, there are still many problems that need to be solved. For noisy data, it is still a challenging problem to achieve accurate class recognition as a human can do by learning only a small amount of accurate data. In this paper, we have done some work on improving the generalization ability of image classification based on previous research, and to a certain extent, we have improved the robustness of classification network models for noisy data, but there is still a gap between achieving high accuracy and high efficiency in image classification tasks with high noise rate datasets, and the following are the research directions to be continued in further research.

(1) To address the problem that the classification accuracy of the classification model decreases too much in the case of a higher noise rate in the current stage method.Next, the noise labels are first distinguished as much as possible by the difference between the correct label distribution and the noise label distribution, and then the image classification problem with a high noise rate is solved by the semi-supervised learning method.

(2) For the problem of flipped label noise contained in the image. The flipped label noise is where the label of each sample is replaced with a certain probability of independently flipping to similar classes, the noise is considered to be more realistic because it destroys semantically similar classes. For example, in real life, datasets are often prone to errors between similar classes when labeled, so much noise is replaced by flipping label noise instead of reality. Therefore, we next proceed to solve the image classification problem under flipped label noise by using meta-learning to generate pseudo-labels. Thus, better art design pattern classification can be made more accurate.

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