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Research Article

Autonomous Classification of Digital Painting Images Based on Wireless Network

Lu Liu

College of Communication, Xijing University, Xi'an, 710123 Shaanxi, China

Correspondence should be addressed to Lu Liu; 20150090@xijing.edu.cn

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With the advancement of digital technology, the precise classification and rapid search of digital painting is important to the creation of digital painting image digitization. In order to deeply study the construction of a self-service classification system based on wireless network, this paper uses the parameter sample insertion method, comparative analysis method, and deconstruction column method, analyzes the independent classification algorithm, and simplifies the algorithm. And finally, we realize and create an efficient system that can independently classify digital images. When studying the best points of the classification efficiency of classification systems, the number of training sets is 2000 and the number of test sets is 120. The input data is classified as 3 layers, and the learning rate of each layer is 1.5, 0.06, and the sparsity is 0.04. The results show that when the sparsity value of both layers of CRBM is taken as 0.02, the classification results reach the best, indicating that here is the best result of this experiment. Further studying the classification system stability, the image from the F1 training set is labeled as 0 and the network data is labeled as 1, thus providing a training two-way model, and the ratio between the training and test sets is 3 : 1. The classification accuracy is quite stable. With the addition of more training data, the classification accuracy remains at around 50%. This shows that the system stability is guaranteed. Based on wireless network technology, a complete system is designed to classify digital images.

1. Introduction

Having seen all kinds of outside societies, most young people today have great curiosity about colorful images. Today's fast-developing society is already an information society. Not only is more and more information recorded in computers. Moreover, all aspects of society have been gradually infiltrated by various computer technologies, and computer technology can be said to be pervasive. In the early stage of technological development, the sources of information for people are mainly text. With the development of various computer technologies, images have gradually become and have become an important source of information for people. As an important way to understand the objective world of matter, the amount of information contained in images is increasing rapidly with the progress of the times. Therefore, how to effectively process images has also become a hot topic of research in computer technology.

With the continuous development of digital image information, a large amount of digital image information will be generated at any moment. If the previous manual calibration method is used, a large amount of manpower and material resources are required, which is extremely time-consuming and cannot satisfy people in the information age. Therefore, in scientific research, it is of great significance to propose efficient and accurate image classification algorithms. In addition, the research of image classification helps to promote the research of related fields in the field of computer vision, such as inspection and evaluation, military field, artificial intelligence, Internet browsing, CT, and MRI. It can be seen that computer image classification has a huge application space in people's lives, and the study of classification algorithms with good classification characteristics is of great significance in many fields and will bring huge social and economic benefits.

The significance of being able to independently classify so many images is naturally self-evident. With the support of technology, many scholars at home and abroad have done a lot of research. In 2019, Garea et al.'s deep learning technology based on convolutional neural networks (CNN) was widely used in the classification of hyperspectral images. They propose the implementation of GPU (graphic processing units based on spatial spectral supervision classification schemes based on CNN and applied to remote sensing data sets). They obtain a high acceleration ratio and a competitive classification accuracy. Even though the classification results are encouraging, it is too inefficient [1]. In 2019, Fatih et al. introduced a heart disease test based on heart tone. The proposed method employs three continuous stages, such as spectral graph generation, deep feature extraction, and classification. The proposed approach is evaluated on two data sets from the classification heart tone challenge. The obtained results are compared with some existing methods. The comparison shows that their proposed method outperforms others. However, the comparison here is less extensive and cannot support big data [2]. In 2019, Villain studied the development of connected devices and its large-scale practical applications for the current prevalence of Wi-Fi wireless networks. The first goal of his research is to propose a monitoring solution independent of communication networks. The second goal is to develop a signal capable to perform these analyses, and they recommend monitoring and analyzing electromagnetic (EM) signals received by the receiver monitoring the antenna and collecting the electromagnetic spectrum. But the signal here is weak and cannot be spread out [3]. In 2018, Matsumoto et al. established an experiment to classify AA pictures using character features and image features. They tried to clarify which feature is more effective for the method of classifying AA pictures. They proposed five methods. They train the neural network by using these five features. In the experimental results, the feed-forward neural network using character image features obtains the best classification accuracy. However, the classification accuracy here is very problematic, and there is no scientific support [4]. In 2017, Kumar said that digital images are common today. The use of digital images is divided into natural images and computer graphic images. Due to the high fidelity of CG images, it is difficult for users to distinguish them from natural images with the naked eye. This article describes a comparative study of existing schemes for classifying digital images. The research here has errors and the data is unreasonable [5]. In 2021, Sokipriala and Orike proposed a comparison between an 8-layer convolutional neural network (CNN) and certain states, such as arts models such as VGG16 and Resnet50. The design shows that by applying various enhancements to CNN, their 8-layer model can surpass the most advanced model with higher test accuracy, 50 times the training parameters and faster training speed. Their 8-layer model can reach 96% test accuracy rate. The training model is good enough, but there are problems with the training method [6]. In 2020, Alhussainy and Jasim proposed a deep learning classification system by using different layers of convolution, rectifier, and pooling operations, which can be used to increase the feature extraction of ECG signals. Train the model to improve the accuracy of the model by performing geometric transformations (such as rotation and shearing) on the original input image. The results show that the proposed model improves the classification efficiency in the two systems. The classification efficiency is the highest, but the accuracy needs to be considered [7].

The innovations of this article are as follows: (1) Image processing technology is the basis of image pattern recognition technology, so the focus is on the image processing technology generally included in the pattern recognition system and the operations to be performed in the enhancement of image features and sample segmentation. (2) Rigorous argumentation can propose high-efficiency eigenvalues for samples and use them for discriminative classification. And it can well reduce the work of calculating these features to a lower level. (3) When choosing a classifier, the neural network technology was tried, with the advantages of simple principle, easy program implementation, and fast learning. After training with some samples, the classifier can quickly make classification discrimination, and the accuracy is guaranteed. Through the above work, the integrity and efficient identification process of the independent classification system based on wireless network technology are ensured.

2. Method of the Research on Autonomous Classification of Digital Painting Images Based on Wireless Network

2.1. Wireless Network. In today's society and life, wireless networks relying on wireless communication technology have not only become more and more important, but they have also developed rapidly around the world [8]. A wireless network is a network implemented using wireless (also called cellular) technology, which uses wireless technology to send and receive data. Wireless network cognition can use environmental cognition to obtain environmental information, analyze and learn the information, make intelligent decisions, and then restructure the network to achieve dynamic adaptation to changes in the wireless environment. Its working principle is shown in Figure 1 [9].

It can be seen from Figure 1 that the wireless network adopts the identification method and the process is immediately at hand, and it is also necessary to understand that the realization of this process requires sensor connection. A wireless sensor network is a wireless network composed of a large number of sensors in a self-organizing and multihop manner. These sensor devices are also regarded as segments of the wireless sensor network. They can cooperate with each other to use radio signals to perceive and process the sensed objects in the network coverage area and feedback the information to the control terminal [10]. The specific network structure is shown in Figure 2:

As shown in Figure 2, it is a typical wireless sensor network, which is mainly composed of sensor segment points, collection segment points, Internet, and user interface elements [11]. The network system is mainly formed by countless sensor segment points distributed in the coverage area.

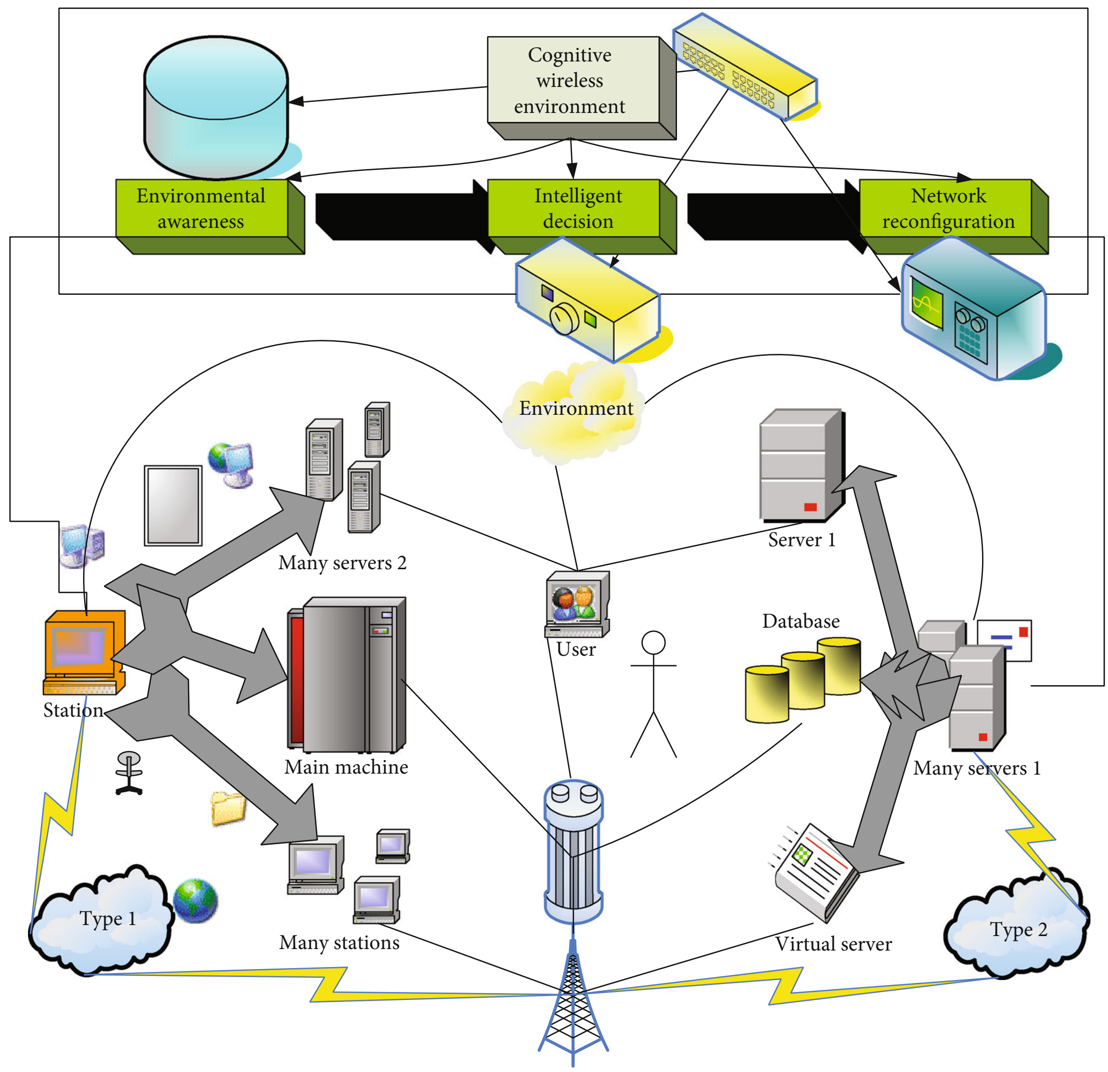

Figure 1: The working principle of cognitive wireless network.

It has the characteristics of multihop and self-organization. Through wireless communication, it uses the information collected by itself to exchange information between the segments and then pass it to converge points.

2.2. Digital Painting Technology. Digital painting, which can also be called coded painting or digital painting, refers to the use of special craftsmanship to make and process the work into lines and marked with digital symbols. The painter only needs to mark the number with the number. If the color is smeared in the colored area marked with the corresponding number, it can be counted as a hand-painted work [12]. In the field of digital image processing, there are many technologies involved, but the main key technologies are image sampling and quantization, image coding, image enhancement, image restoration, image segmentation, and image analysis [13].

The images we obtain are natural images that cannot be understood by computers. Therefore, computers cannot directly process such images and then let the computer process these digital image data. And digital image processing is a process of transforming one image into another image, during which the computer modifies the image [14], as it is shown in Table 1.

2.3. Image Classification and Recognition Technology. Image classification is a technology that uses classification technology to classify the extracted features of the target. Therefore, image classification belongs to pattern recognition, and the process of classification is the process of pattern recognition, which is a continuous and developed visual interpretation. Figure 3 is the image flow. The quality of the image is improved by the incoming inspection in advance, then the image is divided to extract the favorite nodes, and finally the purpose is taken out, and the appropriate method is selected for classification. Now, give a brief explanation of each detail as follows [15].

It can be seen from Figure 3 that the method of research is to indicate in the form of squares or directions after collecting and comparing the initial values. It is to extract the favorite part from the target, such as detail integration. The detailed description of the image cognition process is

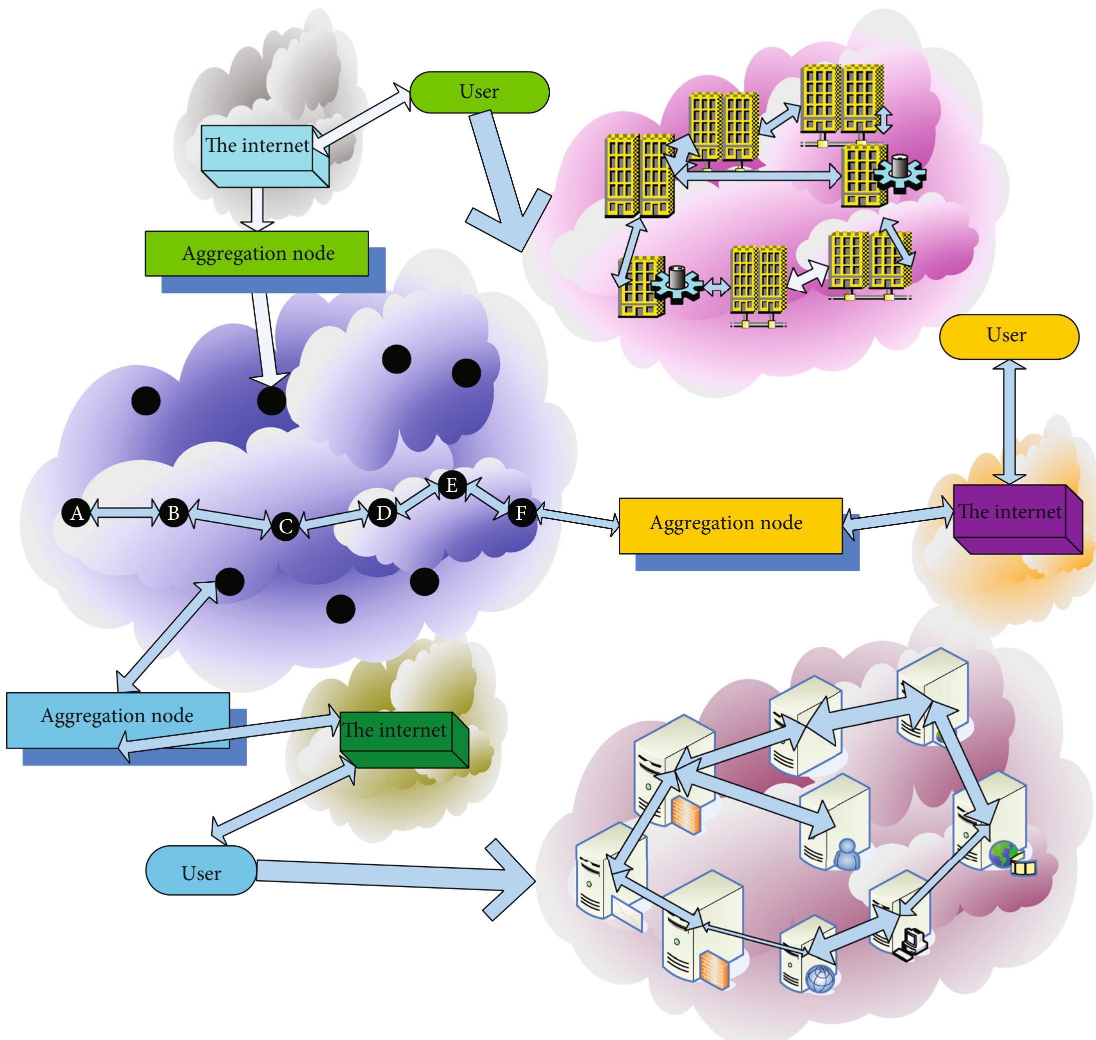

Figure 2: Wireless sensor networks.

Table 1: Some application areas of digital painting image processing.

Subject	Application area	Number of people affected	Satisfaction (%)
Physical chemistry	Spectrum analysis	1258	95%
Geology	Resource exploration	1548	96%
Law	Fingerprint recognition	1265	92%
Water conservancy	Distribution of rivers	6285	91%
Agriculture and forestry	Vegetation distribution survey	486	93.2%
Meteorological	Cloud image analysis	698	95.5%
Ocean	Fish finder	1125	91.5%

realized through various methods, such as icon description [16]. In view of the dispersion of this technology, the following descriptions are made separately [17].

2.3.1. Image Feature Extraction. Good coordinate values are the decisive factor for image classification to achieve high efficiency, so the selection of features is very important for image classification. Feature extraction can be compared to a process of continuously splitting and combining small and weak shapes, which can ultimately maximize its performance. First, calculate the eigenvalues of each category.

$$\widehat{\pi}_{ak} = \frac{1}{o_k}\sum_{u=0}^{o_k} a_{uk},$$
$$\widehat{\pi}_{bk} = \frac{1}{o_k}\sum_{u=1}^{o_u} b_{uk}. \tag{1}$$

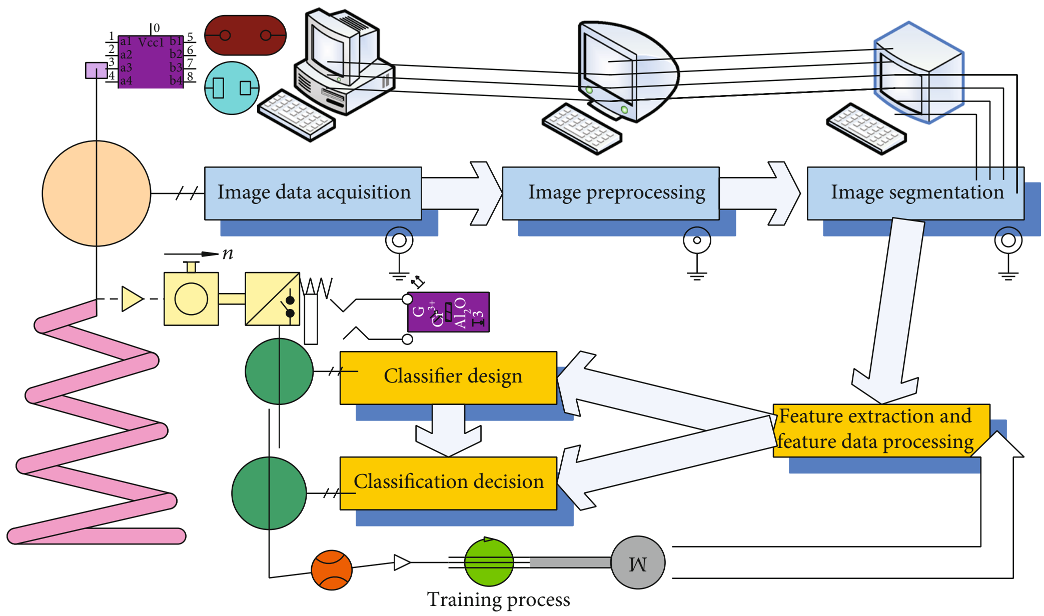

FIGURE 3: Image recognition process.

In equation (1), the results of the two equations are approximate parameters based on the basic value, o_k refers to the k type database, and a_{uk} and b_{uk} are the two value ranges of the u sample in the k type.

Calculate the variance of the feature, the estimated value of the variance of the two features of the k-th category:

$$\begin{aligned} \hat{\tau}_{ak}^2 &= \frac{1}{o_k}\sum_{u=1}^{o_k}\left(a_{uk}-\hat{\pi}_{ak}\right)a^2, \\ \hat{\tau}_{bk}^2 &= \frac{1}{o_k}\sum_{u=1}^{o_k} a_{bk}. \end{aligned} \tag{2}$$

In the wireless field, the corresponding amount of all objects of the same type is generally very left-close, and the eigen difference in (2) is very small in the wireless field. Calculate the feature range:

$$\hat{\tau}_{abk} = \frac{\left[1/o_k \sum_{u=1}^{o_k}\left(a_{uk}-\hat{\pi}_{ak}\right)\left(b_{uk}-\hat{\pi}_{bk}\right)\right]a^2}{\hat{\tau}_{ak}^2\,\hat{\tau}_{bk}^2}. \tag{3}$$

The above formula $\hat{\tau}_{abk}$ is the measured quantity between the k category a and b, and the range is [-0.5, 0.5]. If the value is 0, it means that there is no connection between the two, which can be defined as two independent feature components; if it is close to 0.5, it indicates that the correlation between the two is extremely strong, and one of them can be merged or deleted [18]. If it is close to -0.5, it means that one characteristic component is inversely proportional to the inverse value of the other, just marking the difference [19].

Calculate the distance between classes [20]. For the measurement constant a, it is different (u and k), and the distance between classes is

$$\hat{\omega}_{auk} = \frac{\left|\hat{\pi}_{au}-\hat{\pi}_{ak}\right|}{\sqrt{\hat{\tau}_{au}^2+\hat{\tau}_{ak}^2}}. \tag{4}$$

Similar special b has the same budget. Obviously, the larger the distance is the better the quality of the feature.

Using a straight dimension $c = xa + yb$ can combine two features a and b into a new constant c. The coefficients x and y determined the proportion of each of the two features in the aggregation. Just a little restriction on the characteristic coefficient, $x^2 + y^2 = \sin^2\sigma + \cos^2\sigma = 1$, then there is

$$\mathrm{c} = a\sin\sigma + b\cos\sigma + \tan\sigma \times \frac{\sin\sigma}{\cos\sigma}. \tag{5}$$

In this way, c is the original two coefficients x, and y becomes a variable σ. At the same time, the feature that maximizes the distance should be selected for integration.

2.3.2. Classifier. Figure 4 is the basic structure of the classifier. First, the constant is calculated, and then, the degree of similarity is transported to the second step. The second stage of the classifier reacts to the first stage and uses some algorithms to explore the corresponding mean value. mean value until the step of obtaining the final value [21].

As shown in Figure 4, in the network structure, the input data of the current layer comes from the output of the previous layer, and the output of the current layer is calculated by the activation function on the input data, which is passed backwards in turn until the last layer [22]. The output method of the current layer is shown.

$$a^i = l\left(d^i a^{i-1} + y^i\right) + \mathrm{u}\left(d^u a^{u-1} + y^u\right). \tag{6}$$

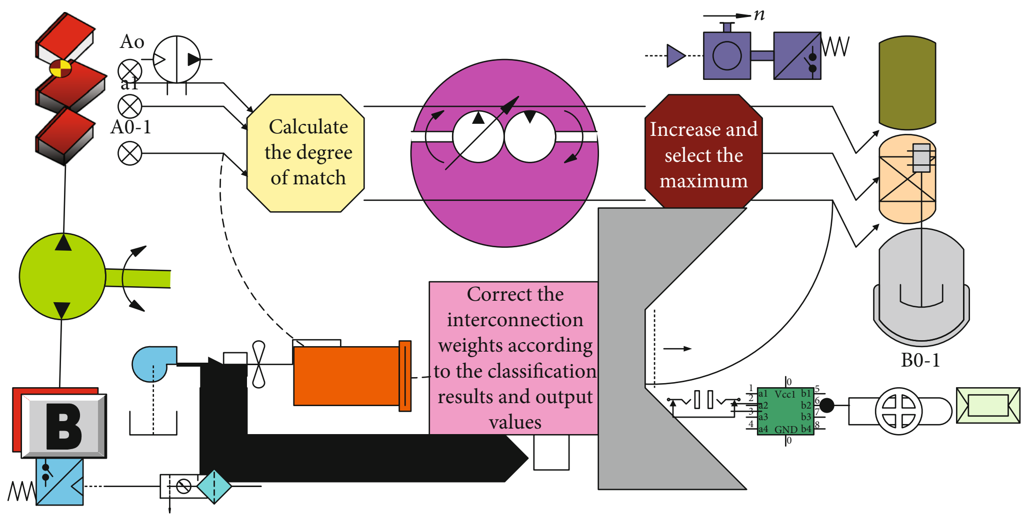

Figure 4: Neural network classifier diagram.

The above formula a is the current output layer, i represents the number of layers, l represents the selected activation function of the current layer, d is the weight of the current layer, and y is a bias of the current layer.

The output result of this layer is generated by convolution and function activation of the output feature map of the previous layer. The formula is shown.

$$a_k^i = l\left(\sum_{u\in n_k} a_u^{i-1} * g_{uk}^i + y_k^i\right). \tag{7}$$

a_k^i represent the output result. Each convolutional layer is followed by a subsampling layer t to achieve local averaging and subsampling. The output of the convolutional layer is used as the input data of the layer, and then, the layer is obtained by formula (8) the output of [23].

$$a_k^i = 1\left(\gamma_k^i \text{upgrade}\left(a_k^{i-1}\right) + y_k^i\right), \tag{8}$$

where upgrade(a_k^{i-1}) is the downsampling function and γ and y are the multiplicative bias and the additive bias, respectively. This layer generally sums the area of the input $o \times o$ map and reduces the output result by o times in two dimensions.

When adjusting parameters in back propagation, the square error cost function is often used. In the z categories of o training samples, the square error cost function is shown [24].

$$r^o = \frac{1}{2}\sum_{o=1}^{o}\sum_{g=1}^{z}\left(s_g^o - b_g^o\right)q^2. \tag{9}$$

where r is the output error, s_g^o refers to the g dimension label corresponding to the o sample, and b_g^o refers to the g output corresponding to the o sample.

Clustering coefficient is an important statistical parameter for the study of network topology properties. There are two types of definitions, namely, global clustering coefficient and local clustering coefficient.

In the weightless network, the local clustering coefficient is used to characterize the topological characteristics of each segment. Assuming that the segment point u has g_u neighbor segment points, the local clustering coefficient is defined as

$$z_u(u) = \frac{2r_u}{g_u(g_u-1)} + \frac{3r_u}{h_u(h_{u-1})}. \tag{10}$$

In the formula, $g_u(g_u-1)/2$ represents the maximum possible number of edges between neighboring segment points; r_u represents the actual number of edges in the unweighted network.

Similarly, in the weighted network, in order to solve this problem, the weighted clustering coefficient of segment u is defined as

$$z_{id}(u) = \frac{1}{t_u(g_u-1)}\sum_{k,g}\frac{d_{uk}+d_{kg}}{2}x_{uk}x_{kg}x_{gu}. \tag{11}$$

In the formula, x_{uk}, x_{kg}, and x_{gu} represent the connection between the three segment points; t_u represents the strength of the segment point u; d_{uk} and d_{kg} represent the weight of the corresponding segment point.

In the weightless network, the clustering coefficient of the segment points refers to the ratio of the number of edges between the actual neighbor segment points to the maximum possible number of edges between the neighbor segment points. The global aggregation coefficient of an unweighted network refers to the average of the aggregation coefficients of all segments in the network, which is defined as follows:

$$z_2 = \frac{\sum \rho_\nabla}{\sum \rho} + \frac{\sum u}{\sum w^e} \tag{12}$$

In the formula, $\sum \rho_{\nabla}$ is three times the number of closed triples in the network; $\sum \rho$ is the number of associated triples in the weightless network.

In a weighted network, the distance between two points is the sum of the weights of the edges on the shortest path connecting the two points. The average path length of the network refers to the average value of the distance between all points in the network, which is defined as follows:

$$i = \frac{1}{o(o+1)} \sum_{u=1}^{o} \sum_{k \geq u}^{o} d_{uk}. \tag{13}$$

In the formula, o represents the number of segment points in the network; d_{uk} represents the weight between the corresponding segment points. It shows the importance of certain points and edges in the network and reflects the global characteristics of the network.

2.3.3. Classification Algorithm. The energy function of CRBM is similar to that of RBM and can be defined as

$$r(w, g) = -\sum_{g=1}^{g} \sum_{k=1}^{o_k} \sum_{e,t=1}^{o_d} w_{u+e-1,k+t-1}, \tag{14}$$

where $r(w, g)$ is the mean value, which is further simplified to

$$r(w, g) = -\sum_{h-1}^{h} g^h \bullet \left(\tilde{d}^h \times w\right). \tag{15}$$

where $\sum_{h-1}^{h} g^h$ refers to the unit of the h sublayer in the hidden layer, g^h refers to the offset of the h sublayer, and x refers to the h convolution kernel. In the same way, the conditional probabilities of the hidden layer and the explicit layer of the model are similar to RBM, as shown in the following formulas:

$$q\left(g_{uk}^h = 1/w\right) = \rho\left(\left(\tilde{d}^h \times w\right)_{uk} + y_h\right), \tag{16}$$

$$q(w_{uk}^a = 1/g) = \rho\left(\left(\sum_h d^h \times g^h\right)_{uk} + z\right), \tag{17}$$

where ρ is a t-type function. The hidden layer is repeatedly inferred through Gibbs sampling and the visible layer is reconstructed. The training process of CRBM is the same as that of RBM [25].

At this time, the energy function of maximum pooling can be defined as

$$r(w, g) = -\sum_h \sum_{u,k} \left(g_{u,k}^h \left(d^h \times w\right) + y_h g_{u,k}^h\right), \tag{18}$$

where $g_{u,k}^h$ is the measured value and the input received by the h group of the detection layer g is the signal input from the bottom to the top of the visible layer v. The calculation formula is

$$u\left(g_{uk}^h\right) \triangleq y_h + \left(\check{d}^h \times w\right) + uk. \tag{19}$$

where $u(g_{uk}^h)$ is the measured value. In formula (19), the hidden layer activation probability is obtained from the visible layer, and the probability of formula (18) belongs to the corresponding pooling unit suppression probability. After passing through a unit of (17) with a probability of being activated in the whole pooled detection unit, the probability of at least one being activated is

$$\sum q = \sum_{(u,k)\in y_x} \frac{uzi\left(u\left(g_{u,k}^h\right)\right)}{1 + \sum_{(u,k)\in y} uzi\left(u\left(g_{u,k}^h\right)\right)}. \tag{20}$$

where x is the average and q is a constant. Since there are only two states, inhibition and activation, the sum of the probabilities of these two states is 1; that is, the sum of formulas (19) and (20) is 1.

3. Conclusions of the Design and Implementation Method of the Research on the Autonomous Classification of Digital Painting Images Based on Wireless Networks

3.1. Experimental Database. Because digital paintings are widely distributed, the classification is not clear, the number of each category is limited, and there is no professional digital painting system management organization on the Internet for people to appreciate and consult, so the realization of the classification of data painting is of great significance. This article divides paintings into three categories, animals, home appliances, and furniture, according to their different subjects. The division of the preliminary data is marked by several high-level graduate students, and then, the results of each annotator are summarized. Since the characteristics of animals, home appliances, and furniture are quite different, it is easier to identify manually, and the error rate will be relatively small. The final data classification results are basically the same. The sample representation is shown in Figure 5.

It can be seen from Figure 5 that because the objects analyzed by deep learning in the article are based on big data, and the distribution of digital paintings is not concentrated, the number is limited, etc., so the data in the experiment is obtained through a variety of ways, mainly from manual search of web pages. There are 2000 pieces of data animals, home appliances, and furniture in the experiment, 625 pieces of each category. The different types of division are manually classified and counted.

3.2. System Development Environment and Tool Design. The development environment of this system is carried out under Windows 7, mainly using Visual Studio 2005 development tools. Visual Studio 2005 is a development environment program issued by Microsoft, which has the effect of visualization. These development environments and development tools

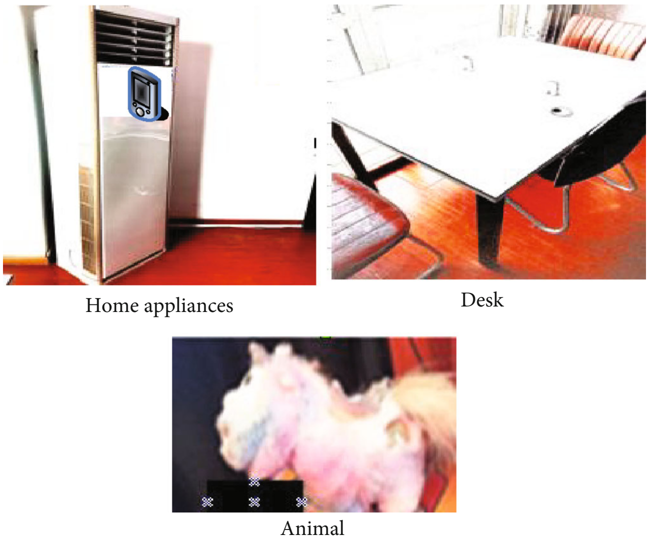

Figure 5: Schematic diagram of the sample.

provide a very stable and convenient platform for the development of this digital oil painting system.

The design principles of digital painting system have the following main features:

(1) Principles of reliability and safety: in the design and development of the system, we took the reliability and safety of the system into consideration to ensure the safe and reliable operation of the system, so that the system achieves the goals of safety, accuracy, practicality, and simplicity

(2) The principle of system interface friendliness: when designing the system, it has fully considered its practical value and commercial value, and at the same time, it allows users to understand the functions of the system at a glance when operating the system

(3) The maintainability principle of the system: in the development, the development cost should be considered as well as the future maintenance cost. In the daily maintenance, maintenance can be carried out simply and quickly, and new functions can be quickly added to improve the system

(4) The principle of easy scalability: when designing the system, it is urgent to consider the actual needs of current users and also the possibility of redevelopment in the future

3.3. Establishment of Network Image Data Set. In order to prove the effectiveness of this method, this article first collected four network data sets corresponding to four tasks of different nature. The four different tasks are skin disease recognition, dog breed recognition, plant species recognition, and indoor scene recognition. With reference to the data set collected by related work (as shown in Table 2), we grabbed images from three websites: Google, YouTube, and Twitter. The standard data set of each task and the situation of the images we collected are shown in Table 2 for the statistical information of the target and network data sets. "Training/testing" refers to the number of training and testing images in each target data set, and network data refers to images collected from the Internet. At the same time, the number of images from different network sources is plotted in Figure 6.

As shown in Figure 6, there is a large gap between the three sources of skin disease images, because people are generally unwilling to share more private images such as skin diseases on social networking sites, so the images obtained from YouTube and Twitter are less than Google Image Searching.

3.4. Experimental Design and Result Analysis. The number of training sets in the experiment is 2000, and the number of test sets is 120. The input data is normalized into 3 layers, the learning rate of each layer is 1.5, 0.06, the sparsity is 0.04, the size of the convolution kernel is 5×5, 10×10, and the feature map of the convolution layer is one and the numbers are 20 and 30, respectively, and the pooling size is 4×3.

3.4.1. Experiment 1. In this experiment, two layers of CRBM are used, so there will be a setting of sparsity value on each layer. After many experiments, it can be found that when the sparsity values of the two layers are both set to 0.02, the classification effect is the best. So here, we will set the sparsity value of one of the layers as a fixed value of 0.02 and the other as a variable to see the impact on the classification results when it takes different values. Among them, sparsity 1 represents the sparsity value of CRBM in the first layer and sparsity 2 in the second layer. The experimental effect is shown in Figure 7.

It can be seen from Figure 7 that on the one hand, the value of sparsity will affect the classification results of the experiment, which shows that the use of sparse regularization plays a certain role in the degradation of network data due to overcompleteness; on the other hand, in the selection of sparsity in the first layer, the value will affect the feature extraction of the second layer, which shows that the feature extraction of the first layer is very important. The quality of its training will affect the training of the subsequent network layers; it can also be seen that when the sparsity values of the two layers of CRBM are both taken at 0.02, the classification result is the best, indicating that this is the position where the experiment can take the best result.

Figure 8 shows the effect of the method in this paper on the experimental classification results when the size of the convolution kernel of one of the two layers of CRBM is unchanged, and the value of the other layer is different. Among them, kernel 1 and kernel 2 represent the size of the level convolution kernels, respectively. When they are used as invariants, their values are A and B, respectively. The experimental results are shown in Figure 8.

It can be seen from Figure 8 that the value of kernel d will affect the classification effect of kernel b. This is because kernel b performs feature extraction again on the basis of

TABLE 2: Statistics on the number of standard data sets and network data sets collected in this paper.

Data set name	Number of categories	Standard data set Total number of images	Training/testing (sheets)	Network data Number of images collected (photos)
SD	200	6258	3556 2656	79568
STD	118	20485	12583 9584	49582
F1	99	235965	69852 28475	236859
MIT	65	14587	4895 1526	69584

kernel d. When the value of kernel d is appropriate, the classification accuracy has been improved.

In Figure 9, epoch 1 and epoch 2, respectively, represent the number of iterations of CRBMs located in the two layers, where epoch 1 and epoch 2 are both 42 when used as invariants. Linear epoch 1 and epoch 2 represent the result change trend graph drawn with the change of the corresponding iteration number. Figure 9 shows the impact on the accuracy of the experimental results when the number of iterations of one layer is unchanged and the number of iterations of the other layer changes.

It can be seen from Figure 9 that as the number of iterations increases, the classification accuracy of the experiment will increase accordingly. When the number of iterations reaches a certain number, the increase in accuracy becomes smaller. This is because the network parameters will be continuously optimized as the number of iterations increases, resulting in the improvement of the classification accuracy. When a certain number of times are reached, the network parameters will be in a state of convergence, so that the parameters will not change too much, and the classification effect will be achieved optimal. The same as the mutual influence of the size of the two layers of convolution kernels, epoch 2 has better experimental results than epoch 1 on the basis that epoch 1 obtains an appropriate value.

3.4.2. Experiment 2. Table 3 shows the experimental results obtained by classifying the data when using traditional CNN, DBN, single-layer CRBM, and double-layer CRBM methods, respectively. The data used in these four experiments is the database in this article, and the training set and test set are 650 and 90, respectively.

It can be seen from the above table that the performance of the two-layer CRBM used in this article is better than the other three methods. The classification rate of the two-layer CRBM is higher than that of the single-layer, because the increase in depth can better characterize the data characteristics and improve the recognition rate, but the time spent on training will also increase.

3.5. Performance of Classification Results. After segmenting an image, you can use the formula to calculate the matrix of the image. The data in the appendix are the values of 80 training images selected from the above images. Just input the moment data of the selected image into the BP classifier, and set the error value at the end of the learning. After a period of learning, the wireless neural network completes the learning process, and then, the image can be recognized, as shown in Table 4.

Select a certain number of furniture images as samples to be classified (the sample images are provided by XD) and input them into the pattern recognition system. The classification results are as shown in Table 5:

Judging from the classification results, the correct rate of image classification is very high, indicating that the selection of image features is relatively correct. These features can well show the differences between different image samples in the system and can well quantify these differences. In turn, the computer can learn, understand these differences, and use them in the judgment. On the other hand, the amount of calculation of these features is not too large, indicating that the selected features have a high efficiency, so that the efficient and fast system classification and training can be guaranteed.

3.6. Stability Measurement. In order to analyze the effect of using an autonomous classification system on network data, we evaluated the performance of image training models from the following sources: F1 data set, FW images, and later network images were manually filtered and processed by pseudolabeling methods. The test set is F1's standard set, as shown in Figure 10.

As shown in Figure 10, we also use the mixed data (hybrid) of the network and Food-101 and the filtered network data (hybrid filter) to train the convolutional neural network. The images from the Food-101 training set are marked as 0 and the network data are marked as 1 to train the bidirectional model, and the ratio between the training and test sets is 3 : 1. For comparison, we also mark half of the sampled images as 0 and the rest as 1 to experiment with Food-101, and the classification accuracy is quite stable. After removal, the deviation of the relative data set becomes lower and is comparable to the standard data. In addition, with the addition of more training data, the classification accuracy remains at about 50%. On the contrary, the classification accuracy of "network data" and standard data sets tends to increase with the addition of more training data.

4. Discussion

4.1. Performance Improvement Analysis. In the past, the performance improvement obtained through network data label

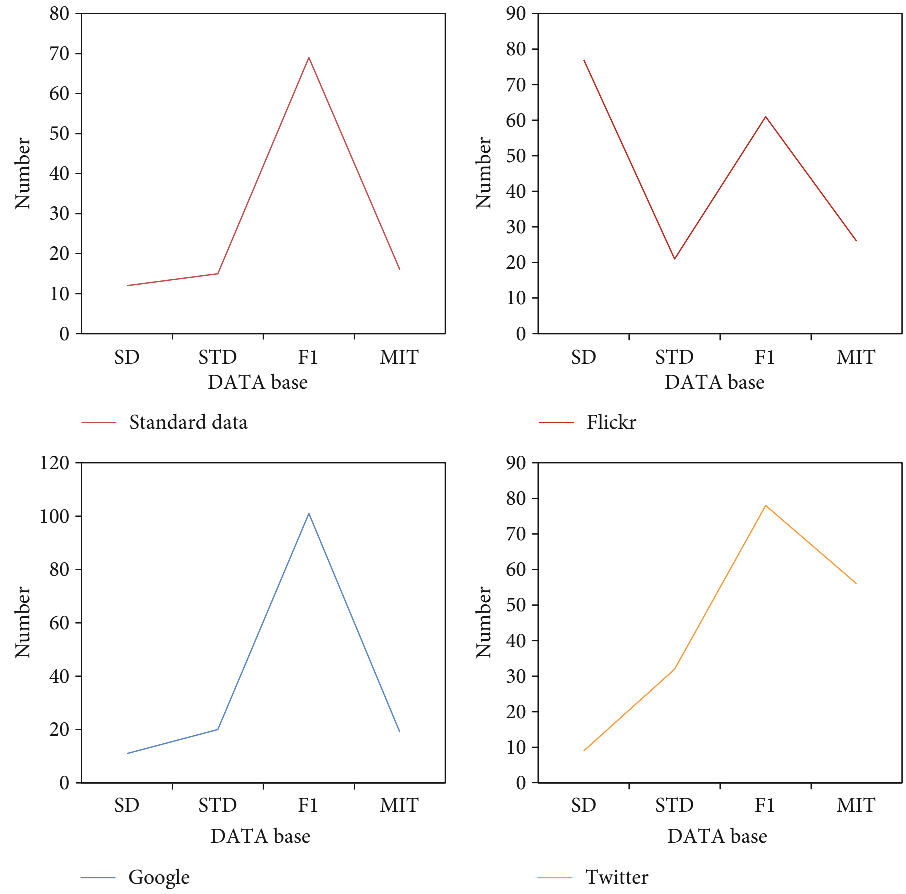

Figure 6: Distribution of the number of images from each network source.

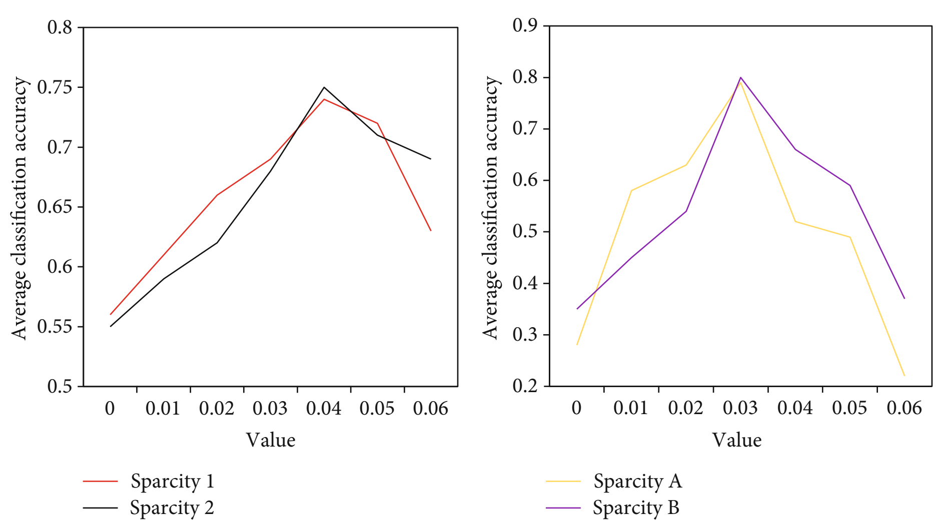

Figure 7: The influence of different sparsity values on the experimental results.

processing is usually not much. In this article, we put forward a completely different point of view, that is, dealing with data set deviations between standard data and network data. Through unsupervised object detection, the deviation of the data set is reduced, and the processing method is further encapsulated into a simple and extensible learning framework. Experiments show that the method effectively reduces the deviation of the data set and performs well on different data sets and different models, which proves the robustness of the method in this paper. By using unbiased network data, our method has shown good results on the latest technologies for a variety of classification tasks. Network

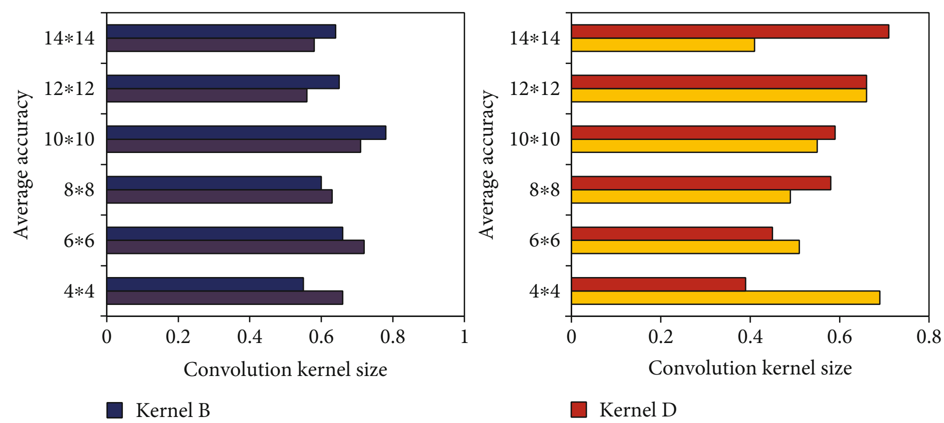

Figure 8: The influence of different convolution kernel sizes on the experimental results.

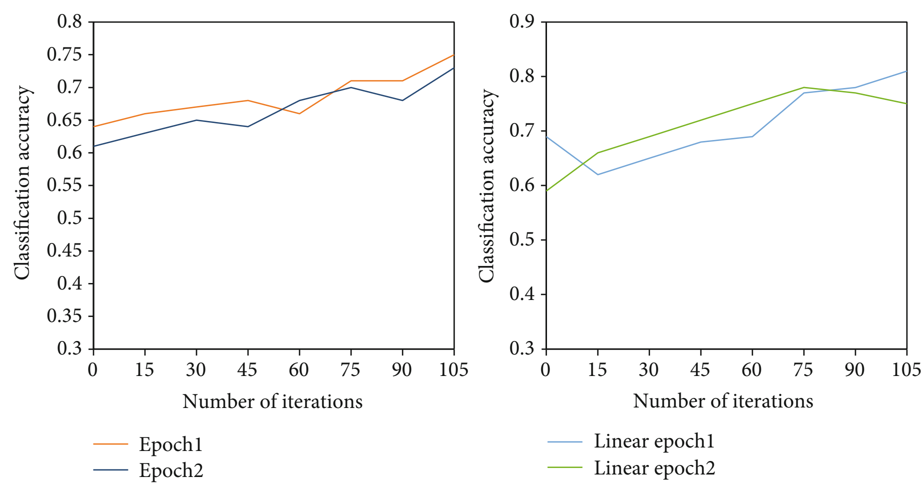

Figure 9: Experimental results of different iteration times.

Table 3: Classification results of different algorithms.

Adopt an algorithm	CNN	DBN	Single-layer CRBM	Two-tier CRBM
Test accuracy rate (%)	63.9	59.6	65.3	71.5
Convergence steps	188	188	80.9	59.9
Each iteration time (s)	859	25	24.5	29.5

Table 4: Gesture discrimination results.

Name	Testing amount	Correct number	Correct rate
Image 1	360	352	95%
Image 2	360	342	98%
Image 3	360	329	96%
Image 4	360	306	91%
Image 5	360	311	92%
Image 6	360	324	89%
Image 7	360	319	88%
Total	2520	2283	91.5%

Table 5: Furniture classification results.

Name	Testing amount	Correct number	Correct rate
Monocyte	250	244	92.1%
Lymphocytes	250	241	95.5%
Eosinophils	250	235	96.3%
Neutrophils	250	239	97.8%
Neutrophils	250	246	92.5%
Total	1250	1205	95.4%

images are easy to obtain and do not require fees. Although the elimination of deviations has not yet been completely resolved, this work shows that this direction has great prospects.

4.2. Summary of Classifier Performance. The article first introduces the image classification algorithm in the research of image classification. Commonly used are random forest, KNN, SVM, and other classifiers. Secondly, it introduces the classification principle and advantages of the support vector machine classifier used in this article. Finally, the algorithm used in this article is compared with the previous

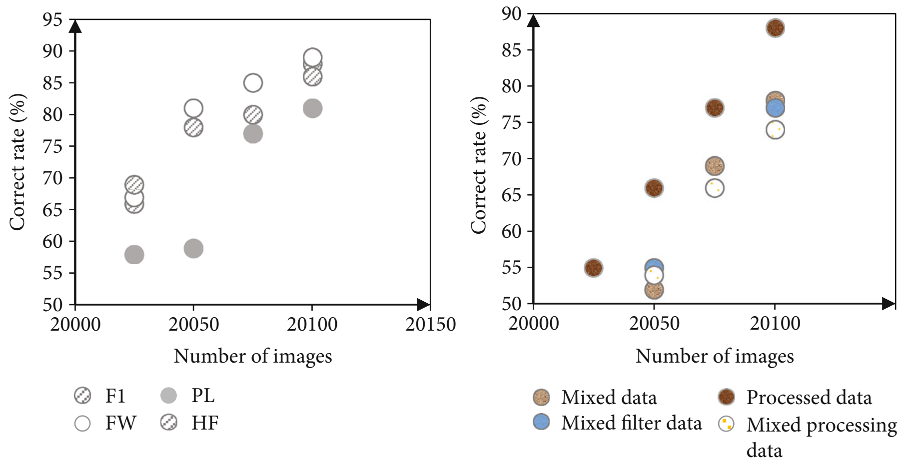

Figure 10: Schematic diagram of the impact of data increase on classification results.

algorithms on the image 15 data set, and the stability of the algorithm is analyzed on the data set of 6 types of images. In this paragraph, the effectiveness of the feature extraction method using SIFT feature points as segment points and the correlation coefficient of segment points as weights is analyzed. It is verified that within a certain range, the network parameter extraction based on image features improves the image accuracy of classification; at the same time, a comparative experiment was carried out on the two encoding methods, which showed that the nonnegativity of encoding reduces the volatility in the encoding process and improves the accuracy of classification.

4.3. Summary of Classification Methods. Aiming at the situation that the traditional DBN does not take the two-dimensional structure of the image into account, a CD BN-based classification method for painting images is proposed. At the same time, the maximum probability pool model is used in the structure for probabilistic reasoning, and sparse regularization is applied to resolve it. The model is too complete and the calculation becomes complicated. In the experiment, different algorithms are used to verify the feasibility of the algorithm proposed in this paper. Through different settings of parameters, it is proved that the settings of different parameters will affect the accuracy of the experimental results; a new classification method based on CNN was proposed. By comparing the experimental results of different amplification sets and the experimental results of different depth learning methods, it can be analyzed that the method in this paper has a better effect on the classification of painting images.

5. Conclusions

The establishment of digital images is not only a demand for the development of electronic informationization of contemporary products but also a basic requirement for people to retrieve, consult, and manage images. In order to further study the construction of an autonomous classification system for digital painting images based on wireless networks, the methods used in this paper include parameter sample insertion method, contrast analysis method, and deconstruction display method, collecting samples, analyzing the autonomous classification algorithm, and simplifying the algorithm. And finally, it realized and created an efficient system that can autonomously classify digital images. In the first study of the best point of classification efficiency of the classification system, the number of training sets is selected as 2000, and the number of test sets is 120. The input data is normalized into 3 layers, the learning rate of each layer is 1.5, 0.06, and the sparsity is 0.04. The results show that when the sparsity value of the two layers of CRBM is both 0.02, the classification result reaches best, indicating that this is where the best results of this experiment can be obtained. To further study the stability of the classification system, the images from the F1 training set are marked as 0 and the network data are marked as 1 to train the bidirectional model, and the ratio between the training and test sets is 3 : 1. With the addition of more training data, the classification accuracy remains at about 50%. The shortcomings of this article are as follows: first, although the application of convolution and sparse regularization has achieved the extraction of high-dimensional features of Chinese paintings and alleviated the overcomplete training, the training time is longer due to the large training data; secondly because of the background of the painting and the information that has nothing to do with the theme, such as the print section, the fusion of different categories, etc., it has a certain interference to the classification results, and this algorithm does not take them into consideration. In the next research plan, this article is expected to use other technologies to speed up the paragraph and make the classification theme more clear, so that this article can live up to expectations and achieve more accurate classification requirements in a wider field.

Data Availability

No data were used to support this study.

Conflicts of Interest

There is no potential conflict of interest in this study.

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