Retraction

Retracted: An Empirical Study on the Artificial Intelligence-Aided Quantitative Design of Art Images

Wireless Communications and Mobile Computing

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] W. Zhang and S. Tsai, "An Empirical Study on the Artificial Intelligence-Aided Quantitative Design of Art Images," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 8036323, 11 pages, 2021.

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Research Article

An Empirical Study on the Artificial Intelligence-Aided Quantitative Design of Art Images

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This paper presents an indepth analysis and research on the quantitative design of fine art images through artificial intelligence algorithms. A CycleGAN-based network model for automatic generation of sketches of fine art images is constructed to extract the edge and contour features of fine art images. The network uses 512×1024 high-resolution art images as input and Pitchman as a discriminator. To further enhance the sketch generation effect, a bilateral filtering algorithm is added to the generator model for noise reduction, and then a K-means algorithm is used for color quantization to solve the problem of cluttered lines in the generated sketches. The experimental results show that the network model can effectively realize the automatic generation of art image sketches and can retain the detailed part of the costume information well. A rendering platform is built to realize the application of art image generation algorithms and coloring algorithms. The platform integrates the functions of image preprocessing, sketch generation, and sketch coloring, demonstrates the results of the main research content of this paper, and finally increases the interest of the system through the rendering function of the art image grid, which further improves the practicality of the platform.

1. Introduction

With the development of image processing technology, various types of image processing have become a necessary part of production and life. The image processing process relies on high-quality raw images, and if the acquired images themselves are of low quality, it will affect the effect of the processing and will not be able to play the value of the images themselves. However, in the actual technical application, the image acquisition is easily disturbed by a series of factors such as weather conditions (e.g., fog and rain), the poor performance of the acquisition equipment, and insufficient lighting conditions [1]. As a result, the quality of directly acquired images is difficult to meet the usage standards and problems such as inconspicuous details, color distortion, and excessive noise occur, which affect the process of image feature extraction and target recognition and ultimately reduce the efficiency of image processing [2]. Different filters activate different content, showing different activation values, and finally visualized as different images. From the perspective of different convolutional layers, the shallow convolutional layer has a function like edge detection and can basically extract the texture information of the image. To address these problems, image enhancement technology can play an important role in improving the display of images and making them more accurate in conveying information. Image enhancement refers to a series of processing according to certain specific requirements for the captured image with poor quality, and the algorithm is used to enhance the information expressed by the image subject and suppress the disturbing information in the image to improve the image quality and provide a better data source for the later image processing [3]. Therefore, image enhancement plays a key role in the image data preprocessing stage and occupies an irreplaceable position in the digital image processing process.

In recent years, along with the gradual improvement of hardware computing power, the application scenarios of image enhancement algorithms have been further expanded,

the human measurement of image enhancement algorithms has been improved, and such algorithms have been applied to medical care, transportation, education, and agricultural production. In the field of face recognition, image enhancement provides higher quality recognition images for later recognition algorithms, which facilitates the recognition algorithms to play their best role; in the smart city application scenario, video surveillance images processed by image enhancement algorithms can provide the important information needed by observers more intuitively; in the direction of medical imaging, image enhancement algorithms can increase the accuracy of medical equipment [4]. In the direction of medical imaging, image enhancement algorithms can increase the accuracy of medical equipment to reflect the patient's condition and facilitate medical workers to make more accurate judgments about the patient's condition. For the inheritance and protection of art images, on the one hand, we need to try to rescue the existing representative art images; on the other hand, we also need to actively guide the reform of art images, based on trying to maintain their national traditions and cultural characteristics, integrate some modern colors so that they can adapt to the needs of society so that more people can accept and like art images, and provide a new opportunity for the development of art images [5]. The sketches of art images are the basis to produce art images, and the various sketches of art images provide more choices for national costumes so that you can select the art images that meet your needs. As the art image production starts from the art image sketch, then it goes through a series of complicated processing and finally the coloring. This process is very time-consuming and labor-intensive, which is why there are only a few art images in circulation, and this brings great inconvenience to the inheritance and development of art images.

With the continuous development of artificial intelligence, there are increased collections and collations about art image sketches, which are a visual expression form composed of a few lines and can be executed quickly. For example, a certain filter may capture the vertical texture existing in the image, and a certain filter in the same layer may capture a certain color area, for example, a certain filter in the first convolutional layer may capture the eye feature is activated to highlight it. Using modern technology, the art image sketches are rendered stably and efficiently, and the art image's style is combined with modern people's aesthetics to innovate and apply it to art image design, and this kind of art image with the modernized clothing with ethnic characteristics will contain the beautiful symbolic meaning of minority elements and at the same time meet the aesthetics of most people, which provides a new direction for the inheritance and development of art image culture. Most of the traditional coloring methods require manual interaction and professional equipment processing, which is very difficult and requires manual correction if the coloring effect is not good; because of the manual interaction, the coloring of each image requires human participation, which makes it difficult to apply to the mass production industry [6]. Recently, there are many coloring algorithms based on deep learning, especially automatic sketch coloring, which can be roughly divided into guided user coloring and unsupervised coloring.

2. Current Status of Research

Image style migration methods based on image iteration can generate excellent stylized images, but the problems of slow speed and high resource usage of the whole style migration process make this type of method still have limitations. The generative neural methods based on model iteration (fast neural style migration) solve the above problems to some extent by improving the inference speed and reducing the computational cost [7]. The key idea of model iteration-based methods is to optimize the network model by iteratively updating the model instead of iteratively updating the image pixels using the gradient descent method [6]. Depending on the model iteration method, the main approaches based on model iteration can be grouped into generative model-based and image-reconfiguration decoder-based approaches. Wang et al. were the first to propose an iterative optimization of the generative model for image style migration, and their related work provides a good idea for improving the efficiency of image style migration, which builds on the algorithm [8]. Gündüz et al. by using a perceptual loss function is used to train a generative model for a particular style [9]. In addition, the work of Schaller et al. conducted using a similar network architecture and experimentally showed that the use of instance normalization during the training of the generative model can significantly improve the quality of the generated images [10]. Schaller et al. proposed a multimodal convolutional neural network that considers the feature representation of the color and luminance channels to perform stylization in a multiscale hierarchical manner, effectively solving the texture scale adaptation problem and produced considerable image generation results on high-resolution images [11].

Similarly, another "pre-processing" method to eliminate moiré is to implement pixel merging. The pixel merging technique combines several pixels into a single pixel. Combining a group of 2×2 pixels into a single pixel is equivalent to enlarging the RGB array on the sensor, which allows for signal dispersion and suppresses moiré. Similar to OLPF, the reduction in the number of pixels leads to a significant loss of image information, and although moiré suppression and noise reduction are achieved, this is at the cost of image sharpness. Second, another approach from pixels is to achieve a pixel density increase [12]. An increase in pixel density means that the sensor holds more information, and when the pixel density is increased to a level much greater than the density of the scene being captured, there is no high-frequency interference, thus suppressing moiré. However, the limitation of increasing pixel density is that it is technically difficult to achieve: when the size of the imaging components remains the same, the pixel density increases, the area occupied by each pixel decreases, and the resolution increases but the sensitivity and error tolerance decreases; in addition, when the number of pixels increases, the requirements for the processor also increase greatly, and the processor has great difficulty in processing in the face of the huge amount of data read, so by increasing pixel density [13]. This

technique is too expensive to achieve moiré suppression. Soleymanian et al. proposed a method for moiré suppression in 3D stereo imaging based on tilted lens arrays [14]. By changing the tilt angle between the lens array and the display panel, the best angle to reduce the appearance of moiré is selected. However, this method is time-consuming and may not achieve the desired results; so, the elimination of moiré by "post-processing" becomes the best choice [15].

An artificial feature extraction method for image classification is to design features artificially for image classification by observing the scene and analyzing the data, depending on the image data and for a specific scene. The image size perspective, which is changed by stretching and rotating, is not sensitive to the color feature and is easy to obtain by simple computation and is often used in applications such as image classification retrieval and search. The color feature color allows for an efficient and simple description of the color in an image and can reduce the loss in the image quantization process. A nine-dimensional feature vector is finally generated by calculating the mean and standard deviation of the three-color channels and the skewness. The color histogram describes the proportion of different colors in the same image, which has the disadvantage that it is easy to ignore the color information in the context of the image. Color correlation map features not only count the probability of occurrence of different colors in a single image but also reflect the correlation between pairs of these colors in space. Image texture features are portrayed by quantifying the pixels of an image to describe the distribution of grayscale and luminance of regions of interest in the image. Cascading local binary pattern texture features by structural analysis and gradient histogram texture features by statistical analysis can effectively improve image classification.

3. Artificial Intelligence-Aided Quantitative Design of Art Images

3.1. Artificial Intelligence-Aided Design. There are various colorful colors in nature, and how to display them to electronic devices requires a mathematical modeling method to achieve this, which is called color space or color pattern within the industry. Edge detection and contour extraction are a very tricky job. The texture itself is a very weak edge distribution pattern, and poorly handled detail parts are easily masked by overly strong image lines; so, edge detection has a very important position in digital image technology, and the main role of edge detection is to distinguish the detection target from the background. The sketches are highly abstract, sparse, and other characteristics, which leads to different people when describing the same art image, and the clothing sketches produced are often different. Therefore, there are many difficulties in the current collection and arrangement of art image sketches. It also greatly influences the research related to the understanding and analysis of fine art images. There are three main categories of commonly used image edge extraction methods: classical edge extraction methods, which are based on fixed mathematical operations in the image localization, such as differentiation and fitting method. Global extraction methods are based

on the principle of energy minimization and use rigorous mathematical methods to analyze the edge extraction problem, based on a one-dimensional value function to extract and remove the image edges from a global optimization perspective, e.g., relaxation method and neural network analysis. The newly developed image edge extraction methods in recent years are represented by wavelet transform and mathematical morphology, especially the wavelet transform method makes full use of the multiscale features of the image to achieve the extraction of image edge contours, which is widely used in many research topics [16]. With the further development and research of deep learning technology, the commonly used image edge extraction algorithms today are holistic nested edge detection (HED), accurate edge detector with convolutional features (RCF), and bidirectional cascade network structure (BDCN).

In multiscale feature learning, the commonly used methods are the image pyramid method and the deep neural network method, but both methods have many drawbacks, such as repeated operations in feature learning and many parameters, which can lead to long inference time. The BDCN method is designed with a lightweight network structure for edge detection based on the convolution part of VGG and achieves good results; each layer in the BDCN corresponds to a scale of features, which solves the problem that the shallow layers can only focus on local patterns because of the perceptual field, while the higher layers can notice the target level information; so, it is unreasonable to use the same label for the last layer and the middle layers for supervision. To better achieve edge feature extraction, a module more like ASPP also propose, which uses a novel bidirectional loss supervision approach to let each intermediate layer learn its appropriate scale, is shown in Figure 1.

Convolutional neural networks were first successful in the field of image recognition. Machine recognition of images is not able to recognize complex images at once, but the complete image is partitioned into several small parts; then, the features of each small part are extracted separately (recognizing each small part), then the features of several small parts are aggregated together, and machine recognition of images can be achieved. The principle of image recognition is that the input layer reads in the image that has been preprocessed image, the convolution layer initially extracts features, the pooling layer extracts the main features, and the fully connected layer aggregates the features of each part and finally generates a classifier for predictive recognition. The principle of image style migration is to input features and then output images with corresponding features. Therefore, the powerful feature extraction capability of convolutional neural networks can be used to perform research work related to image style migration. This allows the cloud to largely solve the computing requirements of applications, but in some application scenarios, computing must be performed locally.

By convolutional neural network for feature extraction of content image and style image and visualization of the convolutional layers of the network, it can be found that the activation state of each layer of neurons in the convolutional neural network corresponds to a specific kind of
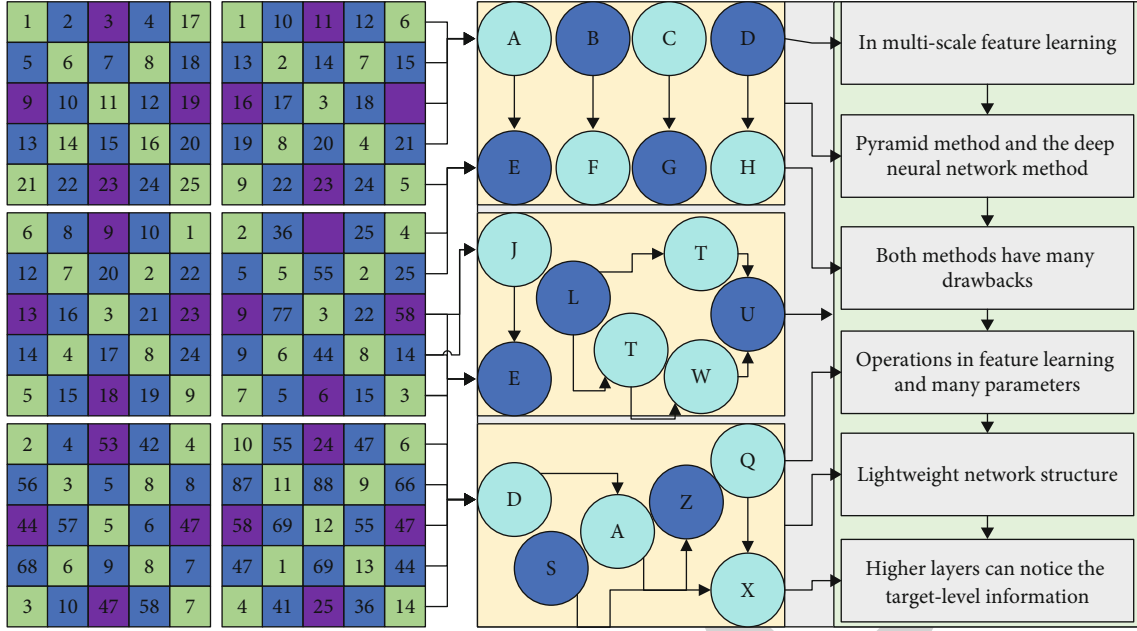
FIGURE 1: Artificial intelligence-assisted algorithm.

information, and different filters are activated for different contents, which exhibit different activation values and finally visualized as different images. From the perspective of different convolutional layers, the shallow convolutional layer plays a similar function to edge detection and can extract the texture information of the image [17]. The shape of the kitten's eyes can be observed; the deep convolutional layer can extract the actual content and spatial information (complex structure, object class) and can only observe the object class in the image as a kitten, and some detailed features of the kitten are completely lost, mainly due to the deepening with the number of convolutional layers. Certain convolutional kernels do not extract the features they want in the input image; so, the deeper convolutional layers extract progressively less detailed information about the image, which leads to increasingly abstract features for the visualization display. For the same convolutional layer, different filters of the convolutional layer will capture different features, e.g., a certain filter may capture the vertical texture present in the image, while a certain filter of the same layer may capture a certain color region, e.g., a certain filter of the first convolutional layer will activate the eye feature in the image and thus highlight it.

The expression of the exponential transformation function is shown below.

$$g(x, y) = af(x, y)^{\lambda}, \qquad (1)$$

where a and λ are used as parameters to adjust the shape of the curve of the exponential transform function, respectively, to achieve different image enhancement effects. This nonlinear transform can be used to extend the high gray areas of the image and have a better compression effect on the low gray areas. The spatial domain filtering method

essentially utilizes a template method for processing, which can remove noise or redundant details from digital images. Spatial domain filtering acts the specified neighborhood pixel values with the corresponding neighborhood subimage pixel values having the same dimension, and the resulting new pixel values replace the original pixel values.

$$g(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s, t) f(x - s, y - t), \qquad (2)$$

where $w(s, t)$ is the filter coefficient representing the weight of the template at the pixel point, and $f(x - s, y - t)$ is the pixel value of the input image. The simplified form of the spatial domain filtering is

$$R = w_1 z_1 - w_2 z_2 - \cdots - w_m z_m. \qquad (3)$$

In the above equation, w is the filter coefficient, z is the image gray value corresponding to this filter coefficient, and Mn is the total number of pixel points contained in the filter. The image pixels processed by the geometric mean filter are obtained mainly based on the inner product power of the pixels in the template window. The geometric mean filter can better filter the Gaussian noise and at the same time has a better effect on preserving the edge information of the image. However, due to the special composition of the algorithm, this filter is more sensitive to 0 pixels. When a pixel in the filter window has a gray value of 0, then the output of the corresponding geometric filter is 0, which will have a significant impact on the image denoising effect.

$$g(x, y) = \frac{\mathrm{nm}^2}{\sum_{(x,y) \in S_{xy}} (1/f(x, y))}. \qquad (4)$$
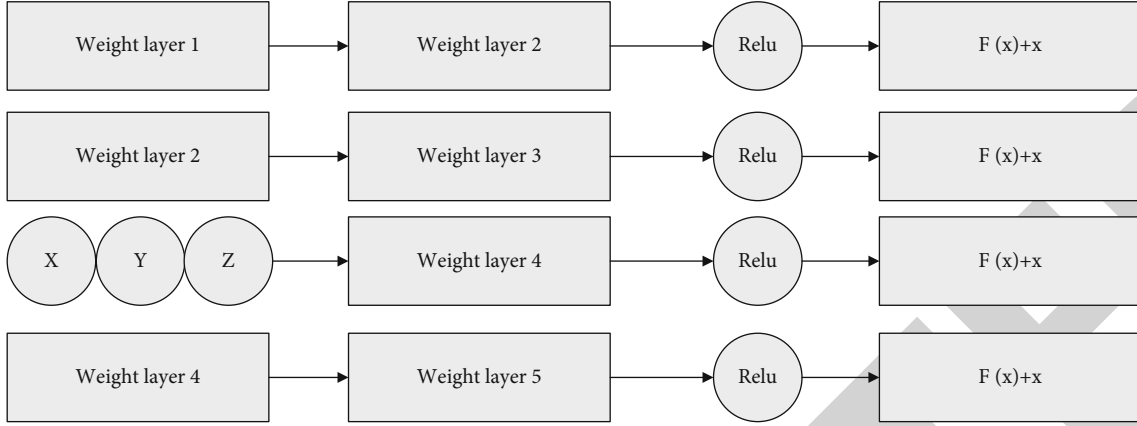
Figure 2: Resnet block.

The filter is more effective in processing salt grain noise and can be applied to the processing of Gaussian noise as well, but it is difficult to achieve the expected results in pepper noise processing.

$$g(x, y) = \frac{\sum_{(x,y) \in S_{xy}} \left(f(x,y)^Q / f(x,y) \right)}{\sum_{(x,y) \in S_{xy}} (1/f(x,y))}. \tag{5}$$

The first method, also known as the direct method, has the main idea of optimizing the objective function while considering all data categories. According to the traditional support vector machine binary classification model, multiple classification planes constructed for multiple categories, and then the objective function is optimized by the parameters of each classification plane, which is transformed into a quadratic programming problem that can solve multiple classification problems at once. To a certain extent, the improved method overcomes the problem of high storage and calculation cost of image style transfer model and huge computing resource consumption. It can only be used on a limited platform and cannot be transplanted to the mobile terminal at all. Although this algorithm seems to be simple and convenient, the complexity of its objective function is high, and because its computational process involves many variables, it makes the computational cost and complexity not only high but also difficult to implement the process. For linearly divisible samples, only a linear function needs to be designed as a segmentation hyperplane, and the familiar linearly divisible support vector machine can divide the data correctly and with maximum interval. In the sample space, the partitioning hyperplane can be done by equation (6).

$$W^T x - b = 0. \tag{6}$$

We know that GAN networks extract features by coding and decoding; however, for neural networks, as the number of layers increases, more features are extracted from each layer. Ideally, the network would need to add more layers to achieve good results, but in practice, as the number of

layers increases, the neural network model goes backward, as shown in Figure 2.

Where x is the input information, the input has been extracting features in the process of convolution, and after linear changes into $F(x)$; as the network continues to deepen, to ensure that the process of extracting features will not lead to information loss due to problems such as gradient disappearance in the process of increasing the network, the input x can be added to the output, and the learned features $F(x)$ together as the next layer of calculation input; so, the final output $y = F(x) - x$, and then the residual $y = F(x) + x$; when the residual is 0, the output result y = x, by the way of residual at least can ensure that the overall of the network will not decline.

Cause distortion and degradation of image quality: the quality of the image directly affects the effect of the image application field. For example, in face recognition, the image quality directly affects the accuracy of the recognition result. Sketches of art images, which consist of clean white backgrounds and black lines, contain many patterns and motifs and are an important basis to produce ethnic costumes, as well as an important reference in the field of fashion design when producing works with ethnic characteristics. However, due to the diversity and richness of art image styles and the high abstraction and sparseness of sketches, the sketches produced by different people when describing the same art image are often different; so, there are many difficulties in collecting and organizing art image sketches, which also greatly affect the research related to art image understanding and analysis. How to generate high-quality art image sketches efficiently has become the focus of research. Currently, deep learning based on the generation of cartoon and caricature images has achieved good results, but there are still many problems in the application of art image sketch generation direction, such as the generation of clothing sketch texture is not clear, the generation of sketch appears messy lines, and in the process of generating clothing sketch detail information is lost.

3.2. Quantitative Design of Fine Art Images. The trend of deep learning development is that the network structure is getting deeper and deeper; thus, causing deep learning
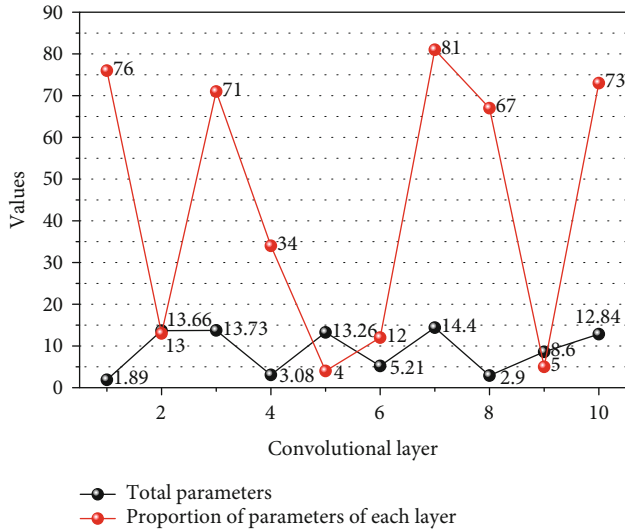
Figure 3: Number of parameters in each layer.

17.6% of the parameters of the whole network model structure, the parameters of the five-layer residual network account for 88% of the parameters of the whole network model structure, and the calculation method of the original residual layer cell structure (convolutional method) causes the huge parameters of the residual layer. The large parameters not only affect the speed of inference but also occupy the storage resources of the mobile terminal. See Figure 3.

To solve the above problems, this paper improves the cell structure of the original residual network by designing more efficient network computation. It is shown that the improved method can overcome the problem that the image style migration model is expensive to store and compute, consumes huge computational resources, can only be used in limited platforms, and cannot be ported too mobile at all.

Image is a kind of media to express information, is the main source of human to obtain and exchange information, compared with other information is more intuitive, concrete, and vivid, contains rich information, and is widely used in many fields. In the process of image acquisition, processing, and transmission, it is easy to cause distortion and degradation of image quality due to unscientific processing methods, noise pollution, transmission media, and imperfect hardware equipment [19]. Image enhancement refers to a series of processing for the collected images of poor quality in accordance with certain specific needs. The algorithm is used to enhance the information expressed by the main body of the image, suppress the interference information in the image, improve the image quality at the same time, and provide a better data source for later image processing. For example, in face recognition, image quality directly affects the accuracy of recognition results; in traffic monitoring, high-quality images will play a good role in the analysis of traffic accidents; therefore, the evaluation of image quality is very important. In this paper, we successfully achieve the compression goal of the style migration model, and the evaluation of the image quality of the compressed model is a very important index to measure the performance of the compressed model. The main content of this section is to use an objective and accurate image quality evaluation method to evaluate the image quality of the migrated images after compressing the model to verify the loss of the performance of the compressed model.

In the field of digital image processing research, the gradient of an image can calculate to obtain the edge information of an image. The process of solving the gradient information of an image is generally a derivative operation of the image, and the result of the operation reflects the degree and direction of grayscale change of the image pixel points so that the edge of the image can be judged more accurately. When the gradient of an image is calculated by the first-order difference method, the pixel point with a larger gradient value is in the edge region of the image, and the pixel point with a smaller gradient value is in the smooth region of the image, as shown in Figure 4.

Based on keeping its own national traditions and cultural characteristics as much as possible, it incorporates some modern colors so that it can adapt to the needs of society. Noise reduction processing is an important preprocessing

models to become larger and larger, and the resources used for computation are also getting larger and larger. Even though most applications are placed in the cloud and use GPUs for computation, which makes the cloud largely solve the computational needs of applications, in some application scenarios, the computation must rely on local, for example, the hottest driverless, for example, the hottest driverless applications require a timely response to the external environment, including pedestrians outside the car and traffic lights. If the quality of the collected image itself is low, it will inevitably affect the processing effect, and the value of the image itself cannot be used. However, in actual technical applications, image collection is susceptible to interference from a series of factors, such as weather conditions (such as fog and rain), poor performance of the collection equipment, and insufficient lighting conditions. If the network is delayed or fails, it will have an incalculable impact [18]. For the image style migration system studied in this paper, from the demand of real-time response, it is possible to protect the privacy of users by running the processing style model locally without transferring related images and model parameters to the server.

Although we have used the fast image style migration method to improve the performance of the network and achieved amazing migration results, the problem of the network parameters of the style model ensues. The size of a single style model trained by the fast image style migration algorithm will be about 20 M, which can only be deployed in small amounts on mobile, and as the number of style models deployed increases, it will pose a huge challenge to the power, storage capacity, and computing power of mobile devices. As the number of style models deployed increases, it will pose a huge challenge to the power, storage capacity, and computing power of mobile devices. As shown in Figure 3, by analyzing the corresponding style models trained, it is found that the parameters of the whole network model are mainly concentrated in the residual layer, the parameters of the single-layer residual layer account for
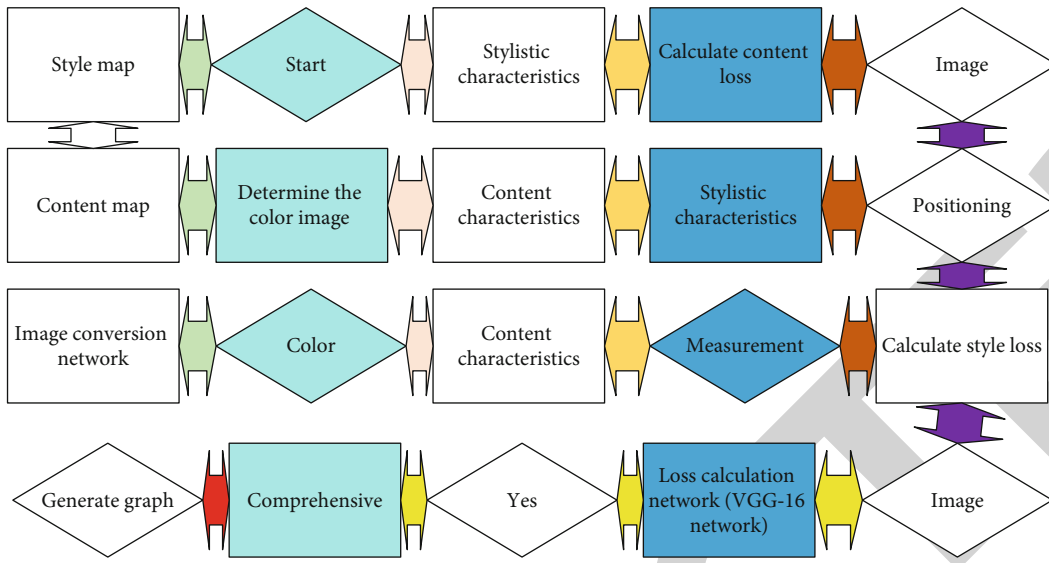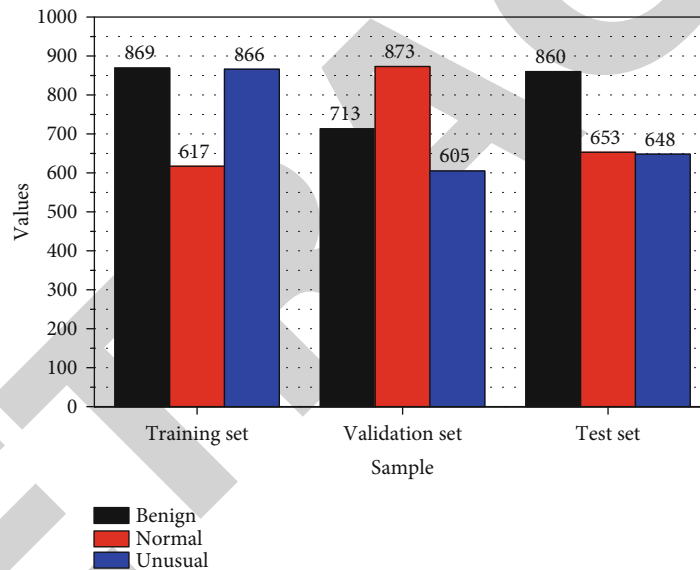
Figure 4: Image quantization design steps.

Figure 5: Experimental data.

tool in the field of computer vision. Noise interference and other experimental external environments and the imaging qualities of the camera can sometimes seriously affect the digitization and transmission of images, resulting in serious degradation of image quality. Therefore, to obtain high-quality images that can maintain the complete original image information while removing useless information, image noise reduction processing is particularly important [20]. In recent years, how noise reduction algorithms can have both advantages has become the focus of research [21–23].

In this paper, we construct a CycleGAN network-based sketch generation model for ethnic costumes. In this paper, we construct a sketch generation model based on the Cycle-GAN network, which can realize the conversion from color images to sketches without large-scale high-resolution datasets. The model in this paper solves the requirement of pair-wise data sets for general deep learning methods and does not restrict pairwise data for the images of the input model; so, we choose high-resolution minority dress images and other images with high resolution for training, which can improve the training effect of CycleGAN network model and effectively realize the generation of minority dress sketches. See Figure 4.

4. Analysis of Results

4.1. Artificial Intelligence Algorithm Performance Results. To make the experimental configuration more realistic and challenging, we divided the region of interest data of mammography images into 60% training set, 20% validation set, and 20% test set, as shown in Figure 5, which consisted of 6971, 2323, and 2268 images as training data set, validation
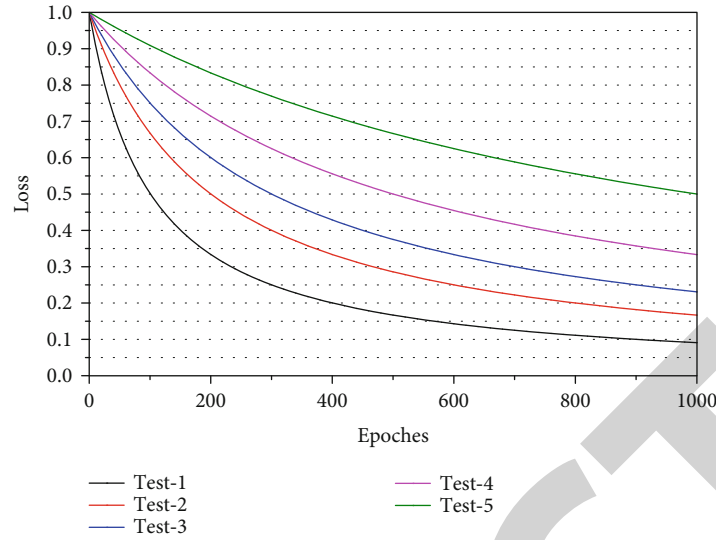
Figure 6: Algorithm loss results.

data set, and test data set, respectively. In these datasets, three categories of 1119 benign, 1266 malignant, and 9177 positives' normal regions of interest were included. A total of 677 benign, 764 malignant, and 5530 normal regions of interest randomly selected as the training dataset; 225 benign, 254 malignant, and 1844 normal regions of interest were selected as the validation dataset: the remaining 217 benign, 248 malignant, and 1803 normal regions of interest were used as the test dataset, making up a total of 11562 mammogram image data for this paper. Since the production of fine art image starts with the fine art image sketch, then it goes through a series of complicated processing and finally is the coloring. In this process, the coloring of the fine art image sketch is very time-consuming and labor-intensive. A total of 11562 mammogram images constitute the mammogram image database of this paper. The training set is used to train the model, then the validation set is used to validate the model, and the model is continuously adjusted according to the validation results of the validation set to select the best model. See Figure 5.

The horizontal and from coordinates in Figure 6 indicate the number of iterations of model training and the loss of model training, respectively, from which the change of classification loss with and without migration learning can be observed, and the classification loss of migration learning becomes smaller and smaller with the increase of the number of iterations. When the number of training is 100000, i.e., Figure 6, the classification loss converges around 0.4, while the classification loss converges around 1 and 0.6 when the number of training is 1000 and 10000, respectively, in Figure 6. If the coloring effect is not good, it needs to be corrected manually; because it is manual interaction, the coloring of each image requires human participation, which makes it difficult to apply to mass production industries. The red curve indicating the classification loss by migration learning is significantly smaller than the blue curve without migration learning, and the gap between them becomes larger as the number of training iterations increases. The dif-

ference between the loss at 1000 and 10000 iterations is not less than 0.4, showing that the performance of migration learning becomes better than that without migration learning as the number of training iterations increases. See Figure 6.

From the figure, different quantization results can be obtained after different processing of the incoming parameter values. The quantization result of the image is close to the linear transformation, and the dark area of the image gets a better enhancement effect, while the bright area of the image has a lower contrast, which is difficult to have a better visual effect. By increasing the value of parameter, a, the pixels in the middle region of the image are enhanced, and the enhancement effect is obvious in the region with higher brightness, while the detail information is missing more in the region with lower brightness. Poorly processed details are easily concealed by too strong image lines. Therefore, edge detection has a very important position in digital image technology. The main function of edge detection is to distinguish the detection target from the background. Therefore, this paper adopts the control parameter into the value to adjust the quantization effect of the reflection image, obtains the optimal solutions of the light and dark regions, distinguishes the light and dark regions of the reflection image with the help of the improved multi-threshold OTSU algorithm, and finally fuses the optimal solutions of the light and dark regions to obtain the resultant image.

In the evaluation of the experimental results, two main types of methods are used. The first type is the observation of the image enhancement result image by human eyes, which can get the subjective visual evaluation of the image enhancement effect; although this type of method has a certain subjectivity for the resulting image, one of the criteria to judge whether it can play its value is whether the necessary information can be obtained by human eyes. At the same time, image enhancement algorithms are mostly born to meet human visual observation, and subjective evaluation of images is one of the indispensable components of image
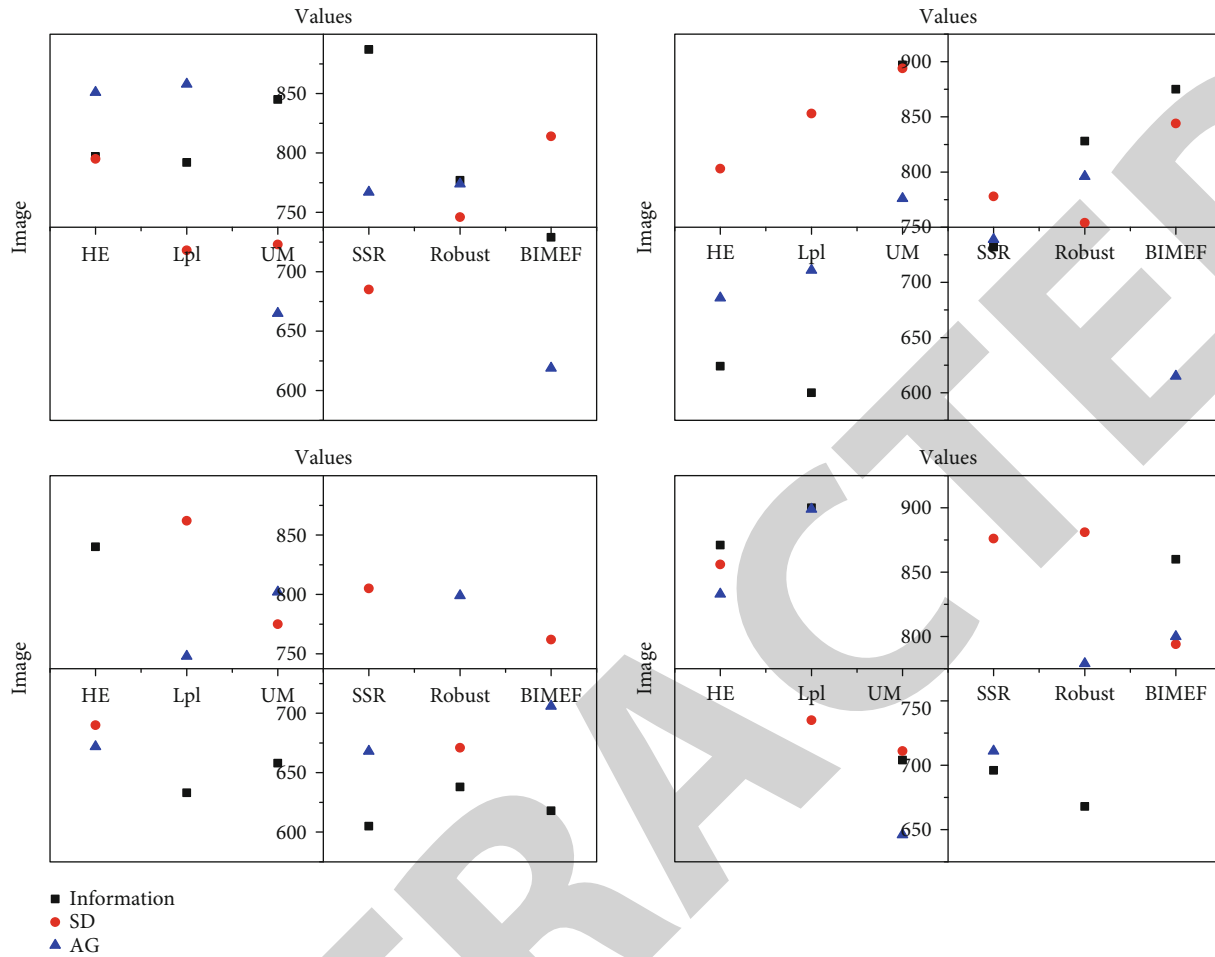
Figure 7: Comparison of image enhancement results.

evaluation criteria; the second category is to evaluate and judge the image enhancement results using objective values, i.e., calculate the relevant indexes by quantified methods, evaluate them according to the size of the index data, and complete the improvement of the algorithm according to the evaluation results.

4.2. Quantitative Design Results for Art Images. To objectively evaluate the application effect of various algorithms, several evaluation indexes were used for quantitative analysis, mainly the average gradient, information entropy, and standard deviation indexes, and the specific results are shown in Figure 7.

With the analysis of Figure 7, it can be seen that the four contrast algorithms have significant enhancement effects on haze images, among which, the enhancement effects of HE, SSR, and the algorithm in this paper are more significant for the direction of image contrast enhancement; for the direction of image edge information retention, the effects of Lpl, SSR, and the algorithm in this paper are more obvious; in terms of image contrast, HE algorithm and the algorithm in this paper perform better; in terms of image sharpness, HE, SSR, and the algorithm in this paper have the best results. In terms of image contrast, HE, SSR, and the algorithm in this paper have better performance; in

terms of image sharpness, HE, SSR, and the algorithm in this paper have significant effects. In the process of image acquisition, under some special acquisition conditions, due to the limitation of the acquisition equipment, the acquired images may have low contrast, which has a certain degree of impact on human eye observation and subsequent image processing. The specific manifestation is that the overall image is grayish, the distinction between dark and bright areas of the image is not obvious, and the edge information is weakened.

Firstly, the filtering methods, whether BF, LLF, or SF, all have a large amount of moiré structure, and neither the moiré of colored stripes nor the moiré of vertical stripes is well eliminated; although the SDGF algorithm uses guided filtering, the moiré of colored stripes still has a large amount of residual, and secondly, the hue of the image is changed, and there is an over smoothing phenomenon in the recovered image. In addition, the recovered image also has the ringing effect; the PS software smoothest out the image details and edge information, resulting in an oversmoothed image, while the moiré component remains; the recovered image of the proposed algorithm not only eliminates each type of moiré but also retains the image details. Compared with other algorithms, the recovered image of the proposed algorithm is optimal in terms of visual quality.
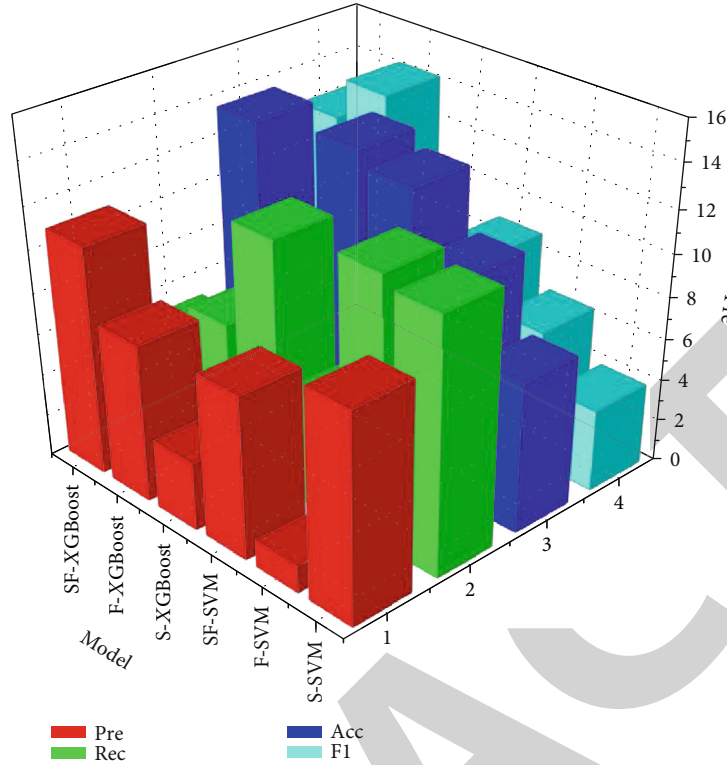
FIGURE 8: Comparison of tests with different feature combination strategies.

The same is true for the image similarity index SSIM. The higher the similarity, the closer the generated image is to the real image. The above results show that the output of the image generated by using Pix2Pix (generator using Unet128) is roughly close to the original image and has the effect of clear details, but its problem is that it adds a lot of extra unnecessary details, which is far from the original real image in terms of details. Since the residual blocks can better preserve the detail information of the image, the output result using Pix2Pix (Resnet_9 blocks) is more satisfactory, which not only improves the details but also makes the target image clearer, and the generated image is closer to the real image, achieving a good coloring effect, as shown in Figure 8.

It allows users to go for image edge contour extraction and sketching quickly and easily for coloring and adds some diversified functions in the design process, such as ethnic style rendering module, which allows users to realize various types of image stylization according to their needs, bringing more interesting experiences to users and making this platform realize end-to-end operation in a real sense. The convolutional layer initially extracts features, the pooling layer extracts main features, and the fully connected layer summarizes the features of each part and finally generates a classifier for predictive recognition. Various salient features of target objects in images are important representations of images; however, the diversity of target object types in images, the structure and texture of the same region of interest, and the ambiguity of target region boundaries not only increase the difficulty of special representations but also bring difficulties to image classification in identifying target

categories in images of various fields. Single classification techniques are often limited by the specificity of different data and classifier preferences. In this paper, multifeature fusion is applied to overcome the defects of image classification.

5. Conclusion

In this paper, based on deep learning, GAN and its related networks are used to achieve the effective rendering of sketches. The problem of insufficient sketch dataset in the rendering task is firstly solved by using CycleGAN network, and then Pix2Pix is used to add constraints to the generator to generate reasonably colored target images, and finally, an image rendering platform is built on this basis to further verify the effectiveness of the method in this paper. By improving the image data preprocessing part, the sketch generation model can efficiently extract the edge contour information of the minority dress image, enhance the sketch generation effect, and provide data support for the subsequent part of the coloring. The experimental results demonstrate that the structural similarity of the sketch generated by using this method reaches 0.854, and the correct detection rate is 0.793, which fully proves the effectiveness of the sketch generation method. Then, by comparing the methods of generators U-net 128 and U-net 256 and relock, it is proved that the model achieves a better coloring effect. It is demonstrated that the peak signal-to-noise ratio of sketch coloring for ethnic dresses using this model reaches 24.061, and the structural similarity reaches 0.820. Compared with other

methods, this model plays an effective result in the field of sketch coloring.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

No competing interests exist concerning this study.

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