

Retraction

Retracted: Icon Art Design with Generative Adversarial Network under Deep Learning

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

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- [1] N. Meng, J. Yang, and H. Wang, "Icon Art Design with Generative Adversarial Network under Deep Learning," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 3499570, 9 pages, 2022.

Research Article

Icon Art Design with Generative Adversarial Network under Deep Learning

Nan Meng, Jia Yang, and Haibo Wang 

College of Arts and Design, Nanchang Jiaotong Institute, Nanchang, 330100 Jiangxi, China

Correspondence should be addressed to Haibo Wang; whbcu@ncjti.edu.cn

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With the rapid development of the Internet, application interface design has undergone rapid changes. Numerous new design styles and resources have appeared; thus, a large number of interface icon design needs have been generated. Icons are quite different from ordinary photographed images, because they are all drawn by designers and have certain schematic and artistic features. Moreover, artistic icons can convey their drawn characteristics and meanings faster and better than captured images. The ideation process in icon design is time-consuming, and its design style and method of drawing are influenced by the device and the environment in which it is used. To simplify the process of icon design and enrich the creativity of icon conception, this study proposes to use the generative adversarial network technology in deep learning to train computers to generate artistic icons. This paper completes the construction of the icon generation model with generative adversarial network (GAN) model combined with the actual icon design process. For the problem of automatic icon generation, this paper does the following research work: (1) based on the conditional classification generative adversarial network, a multifeature icon generation model (MFIGM) is proposed. In the discriminator, a multifeature identification module is added to optimize the structure of the conditional feature to ensure that the icon generated by the model meets the given conditional feature. (2) Experiments on the icon dataset show that the MFIGM-based icon generation model proposed in this paper has better performance in designing various feature expressions of icons.

1. Introduction

With the steady improvement of computer hardware and software and the emergence of information big data mining technology, deep learning and generative adversarial networks have become the most concerned research fields. It has attracted the attention and exploration of major universities and science and technology companies at home and abroad. Deep learning technology can improve image recognition performance and reduce the cost of image feature extraction, thereby optimizing computational efficiency and obtaining high-quality output. In the field of image recognition, applications that have a direct impact on daily life include face recognition, license plate detection, and skin diagnosis. The introduction of deep learning in image recognition has become a hot spot in the research and application of the Internet technology innovation industry in the future, and the design and proposal of generative adversarial net-

works have aroused strong repercussions. Compared with recurrent convolutional networks used for image recognition and classification, generative adversarial networks are characterized by the ability to train computers to generate new data based on the existing sample data. By identifying and memorizing the sample data in the training set, the generative adversarial network analyzes and grasps the distribution of the data and judges and adjusts different inputs. This neural network model brings new creative space and possibilities to many artists and designers [1–5].

Generative adversarial network makes the generator's forgery ability and the discriminator's judgment ability continuously improve by letting the generator and the discriminator play a zero-sum game until the generator and the discriminator reach the Nash equilibrium. In this way, the generative adversarial network can learn the probability distribution of training samples and improve the generator's ability to fit the data distribution through continuous

iteration. This makes the probability distribution of the generated image and the probability distribution of the real image continue to approach until the gap between the generated image and the real image narrows to exceed the judgment ability of the discriminator, and the generator and discriminator reach Nash equilibrium. Since GAN was proposed, it has been widely used in the direction of image generation due to its unsupervised learning characteristics. The powerful learning ability of GAN is not only applicable to image generation. In recent years, GANs have continuously made breakthroughs in the fields of image synthesis, text-to-image translation, style transfer, superresolution, and text generation in natural language processing [6–10].

Icons, as a branch of images, are mostly artificially drawn and have semantics, acting as an interaction medium and an indication channel for people and objects in life. In the 1970s, the graphical operation mode entered the desktop of the personal computer, and at the same time, new design fields such as interface design, graphic design, and icon design were derived. With the efforts of many designers, interface and icon design has developed rapidly and various styles have been formed in line with the needs of the times and aesthetic changes. From a single linear icon to a colorful three-dimensional icon, from a skeuomorphic icon to a flat style icon, it reflects the progress of design and the development of aesthetics. Icons are not only an important component of a graphical interface but also serve as a direct medium for users to communicate and collaborate with various devices. Although different styles of interface icons can be quickly retrieved on the Internet, how to design and draw a beautiful and reasonable icon is still a problem that designers often consider. Entering the era of mobile Internet, the time people face icons every day is increasing, and the significance of icon design is becoming more and more important. Therefore, the starting point of this research is to simplify the process of icon design, enrich icon design, and combine this emotional and aesthetic behavior with logical deep learning technology [11–15].

The unique contribution of the proposed approach includes the following:

- (i) A multifeature icon generation model (MFIGM) is proposed on the basis of conditional classification-based generative adversarial network
- (ii) A multifeature identification module is implemented to optimize the structure of the conditional feature and ensure that the icon generated by the model meets the given conditional feature

The organization of the paper is as follows: Section 2 presents the related studies. Section 3 discusses the method followed by the results in Section 4. Section 5 presents and consolidates the concluding points of the research.

2. Related Work

Reference [16] pointed out that GAN uses the deep neural network as the basic unit of the model and constructs two

subnetworks, namely, the generator and the discriminator. The generator is used to generate fake samples, and the discriminator is used to determine whether the samples are real or fake. GAN adopts the idea of adversarial game in training. The generator needs to continuously update its own parameters to generate more real data to deceive the discriminator, while the discriminator needs to accurately judge whether the sample comes from the real dataset or the generated sample. Reference [17] pointed out that in the training process of GAN, the training instability often occurs, which can easily cause mode collapse. GANs caught in mode collapse will only generate a single sample, greatly limiting the intrinsic learning ability. In reference [18], considering the significant role of convolutional neural networks in the image field, a deep convolutional generative adversarial network (DCGAN) was constructed by combining convolutional neural networks and GANs. DCGAN utilizes the powerful feature extraction capability of convolutional networks to reduce the data complexity introduced by images. In addition, DCGAN cancels all pooling layers and uses transposed convolution operations for upsampling. Reference [19] proposed WGAN to try to solve the training instability problem of GAN. The researchers believe that the original GAN had various problems in training because the distance metric used to measure the distribution had certain shortcomings. In the original GAN, optimizing the objective loss function is equivalent to optimizing the Jensen-Shannon distance and Kullback-Leibler divergence. However, when the two distributions do not intersect or the overlap is negligible, the objective loss function will be close to a constant, resulting in the lack of model gradients during training. The researchers propose to use the Wasserstein distance to replace the distance metric in the original GAN. The Wasserstein distance is a smoother measure of distance, so it can alleviate the disappearance of gradient and so on.

Reference [20] pointed out that in order to strengthen the influence of label information on the generator, InfoGAN chose to only concatenate the label information in the input of the generator and at the same time added a classifier to judge the sample category of the input discriminator. In the literature [21], the discriminator is given more capabilities in sGAN, which not only needs to judge the authenticity of the input samples but also needs to judge the specific categories of the training samples. sGAN allows the discriminator to have the ability to judge categories through the training set and indirectly affects the generator through the discriminator, so that the generator can generate samples with category differences under the guidance of the discriminator. In reference [22], in order to generate corresponding samples for a certain category, a multigenerator network structure MAD-GAN is proposed. MAD-GAN sets a generator for each category, and the discriminator is also given the ability of category judgment. Since only some parameters are shared between generators, it is equivalent to invisibly forcing the outputs of each generator to have class differences as much as possible. Reference [23] designed MGAN, a similar multigenerator structure used, but with an additional network as the classifier. The benefit of this

is that the sensitivity of the generator to class differences can be tuned via hyperparameters

Reference [24] uses artificial intelligence design software, which is mainly responsible for drawing promotional posters for products instead of visual designers to meet the browsing preferences of different users. During the half-month shopping festival, according to user browsing records and duration, combined with product attributes and characteristics, it has a large number of design templates in memory and generates promotional posters that are comparable to the works of junior visual designers. Reference [25, 26] launched a trademark intelligent design service, so that users without design foundation can independently and quickly obtain beautifully designed logos. Its operation steps are very simple, only need to provide the brand name, and choose the preferred color and design style, and then, the logo can be quickly synthesized by the computer. Reference [27] introduced an online icon customization platform based on deep learning. It uses techniques of convolutional networks, text embedding, and generative adversarial networks to deal with elements such as the subject, text, and shape in the icon. The platform uses the icon library provided by Noun Project, a famous foreign design resource website, to identify and analyze the icons in the library and classify the icons with similar meanings but different visual expressions. Reference [28] established large-scale icon datasets of LLD-icon and LLD-logo by themselves after comparing with the existing icon datasets. This dataset contains more than 600,000 logos and icons collected from the Internet. Based on the generative adversarial network, the researchers added cluster analysis and synthetic labels and proposed a training network model to obtain high-quality generated icons.

3. Method

This work proposes a multifeature icon generation model (MFIGM). In the discriminator, a multifeature identification module is added to optimize the structure of the conditional feature to ensure that the icon generated by the model meets the given conditional feature.

3.1. GAN. As a generative model, GAN hopes to gain the ability to generate fake samples through learning. Taking image generation as an example, GAN uses a generative network to convert noise into images of the same size as real samples and then mix these images into real images. They are input to the discriminative network together, and the result of the discriminant network is used to modify the generative network. Until the generation network and the discrimination network reach the Nash equilibrium, that is, the discriminator cannot judge the source of each sample through calculation and can only use random guessing to discriminate the samples. At this time, it is considered that the quality of the generated image has reached the standard of falsehood. In this case, the generator has learned a mapping from the noise distribution to the real distribution of the sample.

Figure 1 shows the basic structure of a GAN; the generator is generally composed of a multilayer neural network.

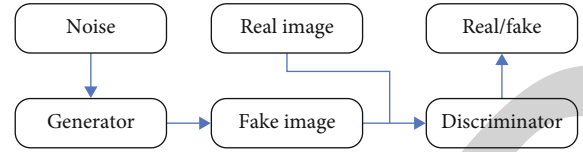


FIGURE 1: The pipeline of GAN.

When it is necessary to limit the characteristics of the generated image, a control vector is added to the noise. Then, the fake image and the real image are mixed and input into the discriminator, and the network is updated with the result of the authenticity determination of each fake image.

Due to the neural network structure, generative adversarial networks have many advantages that previous models did not have. Compared with the previous models, GAN can generate sufficiently complex models and avoid the problem that the mixture of Gaussian models has insufficient parameters to accurately describe the model. There is also no need to use Markov chains to resample samples, avoiding complex probability approximations. Using deconvolutional neural networks, GANs are also faster to generate than VAEs. The biggest advantage of GAN over the previous model is that GAN does not require a manually specified loss calculation function but directly uses the discriminator's discrimination results. This makes the generation space of GAN almost infinite in theory, so GAN can be trained to get any generative network. Instead of selecting the corresponding generative model according to the characteristics of the dataset, other generative models need to make some assumptions and restrictions on the dataset.

The special structure makes GAN different from the general neural network when training. During training, the entire network is updated with the loss of the discriminator. The objective function of the discriminator is to maximize the distance between the generated data and the real data and accurately identify the authenticity of the input. The goal of the generator is to minimize the distance between the generated data and the real data. It can be found that the training objectives of the generator and the discriminator are completely opposite, and they confront each other during the training process, and the learning degree is kept balanced by the confrontation [29, 30].

$$\text{Loss} = E_{p(x)}[\log D(x)] + E_{p(z)}[\log (1 - D(G(z)))],$$

$$V = \int [P(x) \log D(x) + P_g(x) \log (1 - D(x))], \quad (1)$$

$$\text{Loss} = -2 \log 2 + 2JS.$$

The loss function should be updated in the direction that minimizes the JS divergence. This objective function reaches a minimum value when the generated data distribution is consistent with the real data distribution. In practical applications, when the gap between the generated data of the generator and the real data is small enough, the GAN can be considered to have reached the optimal solution. The training of generative adversarial network is generally divided

into two steps: training the generative network and training the discriminant network. When training the generator, the goal of the network is to make the generated samples and real samples as consistent as possible, so that the discriminator cannot distinguish the authenticity of the samples. Therefore, when training the generator, a fixed discriminator is used.

When training the discriminator, the goal of the discriminant network is to distinguish the real samples. The samples are samples which are generated by the generator in majority of the instances. Hence, it can be safely assumed that the parameter difference in the objective function would be large enough. Since the learning difficulty of the generator is more difficult than that of the discriminator, the training methods of the generator and the discriminator are not consistent during training. In general, a fixed discriminator is used to update the generator for n rounds of training and a fixed generator to update the trainer for one round of training to maintain the balance between the generator and the discriminator. If the difference between the learning degree of the generator and the discriminator is too large, it will lead to the problem that the discriminator cannot distinguish between genuine and fake samples or completely and accurately distinguish between genuine and fake samples. As a result, the overall network loses the update direction and degenerates to random updates.

The GAN model is one of the most predominant deep generative modeling techniques. The primary difference between GAN and other VAEs is that GAN helps in matching the pixel level distribution in comparison to the data distribution and it also optimizes the model distribution to the genuine distribution using a different method. In contrast to VAEs, GAN does not explicitly learn the likelihood distribution. Various studies have implemented GAN in different verticals. As an example, the study in [29] highlighted the capability of GAN to perform data generation without modelling the probability density function explicitly. Hence, this model has been extremely popular for researchers in the medical imaging field for reconstruction, segmentation, detection, classification, and cross-modality synthesis. The study in [30] proposed an automatic steganographic distortion learning framework using GAN. This model was developed incorporating generative subnetwork and steganalytic discriminative subnetwork. The results of the framework yielded promising results and also steadily improved the security performance of the framework when the training iterations were increased.

3.2. MFIGM for Icon Art Design. One of the most important features of an icon is its shape. People see the shape of an icon and approximate the meaning of the icon by matching it with the actual affairs. The second important feature of icons is color. The real world is colorful, and people are also accepting various colors. Color has an important impact on the psychology of users, so color is also an important feature in the design of icons. For the icon generation model, various characteristics of the icon are also very important metrics. Whether the icon meets the needs of the user can be judged from whether the various characteristics of the icon

are satisfied. Therefore, the icon generation model needs to fit various characteristics of the icon to meet the needs of users. In this study, we discuss and design the model based on the two main characteristics of icons (shape and color) and build a multifeature-based icon generation model, so that the model can be generated according to the main characteristics of various icons.

The improvement of MFIGM over conditional generative adversarial networks is that for the generator, the conditional features are still input into the generator for data generation. On the discriminator side, conditional features are not input into the discriminator. Instead, a conditional feature recognition module is added to the output, and the discriminator identifies whether the input image satisfies the conditional feature input in the generator. In this way, the roles of the discriminator and the generator are more obvious, the generator generates images according to the conditions, and the discriminator identifies whether the images meet the conditions. The MFIGM model is shown in Figure 2. The model is more able to fit important conditional features such as the color and shape of the real image, making the image more realistic.

Based on the conditional generative adversarial network, MFIGM not only uses the label information in the generator, but the discriminator not only needs to identify the authenticity of the image data but also needs to identify the label of the image. After the generator not only inputs the noise vector but also needs to input the class label, the discriminator discriminates both the source distribution and the class label distribution; the loss function is divided into the following two parts.

$$\begin{aligned} L_s &= E[\log P(S = r|X_r)] + E[\log P(S = f|X_f)], \\ L_c &= E[\log P(C = c|X_r)] + E[\log P(C = c|X_f)]. \end{aligned} \quad (2)$$

MFIGM is a new type of neural network model based on conditional generative adversarial network improvement. Since the conditional generative adversarial network still cannot control the important characteristics such as the color and shape of the image, it is necessary to build a more detailed neural network model. Thereby, the generated icon can better meet the given condition requirements. Studies have been conducted for icon generation using GAN in the past. As an example, the study in [11, 31] constructed an icon dataset which included 8 different icon categories, wherein training techniques such as attention mechanism and spectral normalization based on StyleGAN was implemented. The results of the model generated icons which were extremely useful for the designers and reflected superior design quality.

This study proposes an icon generative adversarial network model that integrates multiple conditional features. According to the existing various conditional feature information, the feature information can be fused and passed into the conditional generative adversarial network model to generate eligible icons. The model redefines its class labels according to the MFIGM model, extending it from single-

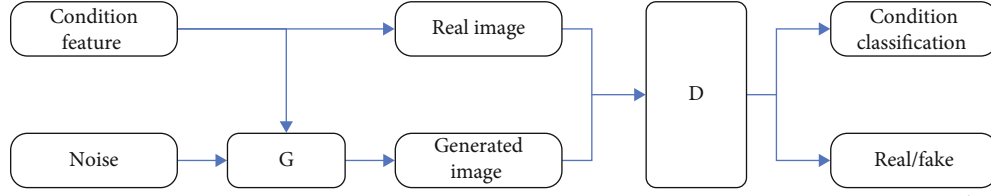


FIGURE 2: The pipeline of MFIGM.

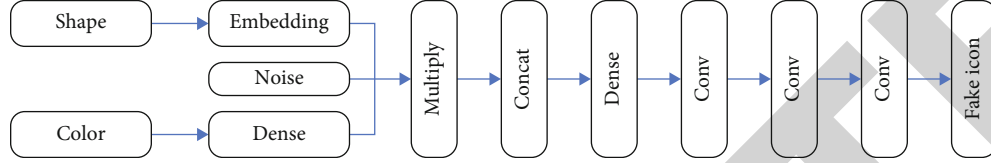


FIGURE 3: The generator model of MFIGM.

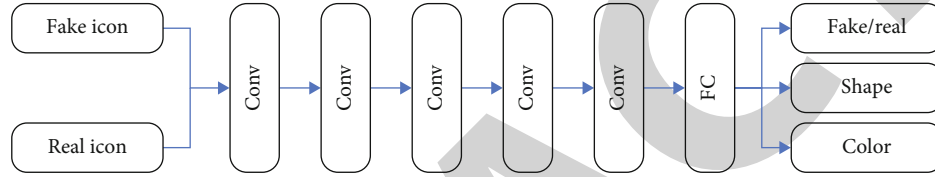


FIGURE 4: The discriminator model of MFIGM.

TABLE 1: The detailed information of two dataset.

Dataset	Number	Class	Size
IconA	25354	70	$32 \times 32 \times 3$
IconB	34531	60	$120 \times 120 \times 3$

TABLE 2: Experiment environment information.

Item	Detail
Operating system	Ubuntu 16.04
CPU	i7-6700
Memory	32GB
Deep framework	PyTorch 1.6

class labels to multiclass labels.

$$L_c = E[\log P(C = c_1, c_2, \dots | X_r)] + E[\log P(C = c_1, c_2, \dots | X_f)]. \quad (3)$$

The generator fuses the input multicategory label features with a noise vector that obeys a normal distribution and feeds it into the generation network as input. The generated image and the real image are sent to the discriminator at the same time, and the true and false information of the image is obtained as well as the various category labels to which the image belongs, indicating the category features identified by the discriminator. The generator updates the weight parameters of the neural network according to the data fed back by the discriminator, and the two are cyclically

trained, and finally, the two reach a balance. The discriminator cannot tell the authenticity of the image.

The generator in the MFIGM icon generation model proposed in this chapter is shown in Figure 3. The user inputs the shape feature and color feature of the icon, and then, the shape feature is embedded and then expanded to match the size of the noise parameter, and the color feature is enlarged to the dimension of the noise parameter through the fully connected layer. The two are then multiplied by the noise parameter and concatenated together to form the input of the generator. It is then reorganized into a multidimensional tensor and enlarged to the size of the icon through a multilayer deconvolution layer, and batch normalization is used in the deconvolution layer to prevent the model from overfitting.

After the generator generates the icons, the generated icons are fed into the discriminator along with the ground-truth icons collected from the dataset. Features are extracted using a multilayer convolutional network. Finally, the extracted features are expanded and passed to three conditional discriminative layers. The first is the output layer that is used to identify the true and false icons in the generative adversarial network, followed by the shape classification layer that identifies the icon shape category, and finally, the color classification layer that identifies the icon color. The discriminator model is shown in Figure 4.

The icon generation model learning rate is set to 0.00005, the batch parameter of the data is set to 32, the cut-off parameter of the neural network parameter update in the model is set to 0.01, the length of the noise parameter is set to 100, and the optimization function of the model is set to RMSprop. The loss function of the discriminator is set

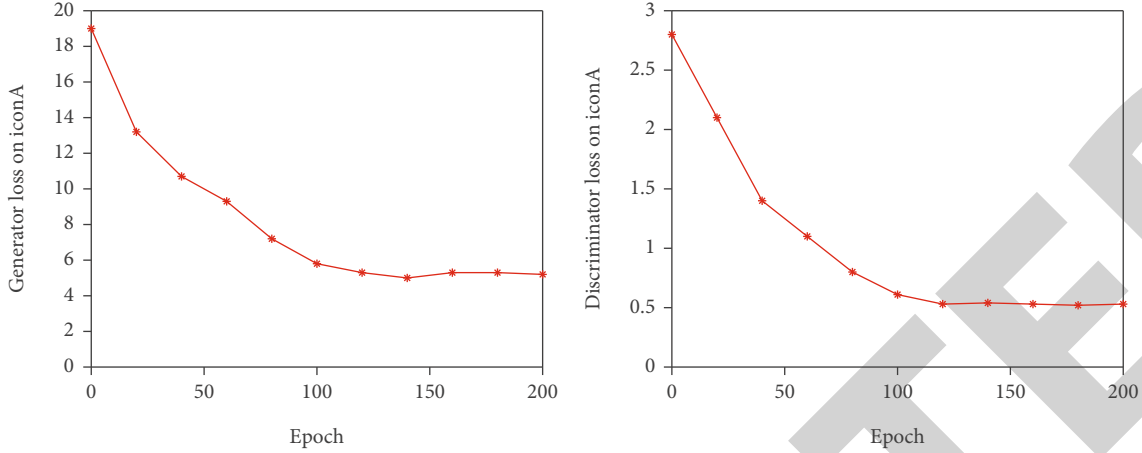


FIGURE 5: The training loss on IconA.

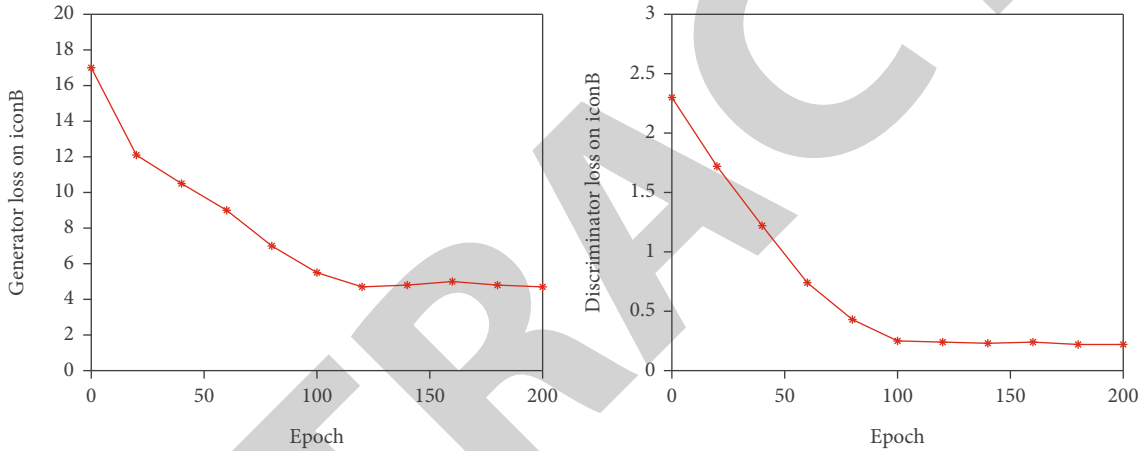


FIGURE 6: The training loss on IconB.

TABLE 3: Comparison with other methods.

Method	IconA		IconB	
	IS	FID	IS	FID
GAN	3.3	30.8	4.9	29.2
DCGAN	5.1	27.7	7.2	24.9
WGAN	7.3	25.3	8.5	23.7
MFIGM	8.7	22.6	9.5	20.8

according to its output as binary cross-entropy for discriminating true and false icons and multiclass logarithmic cross-entropy for discriminating icon color and shape loss function.

4. Experiment and Discussion

4.1. Dataset and Evaluation Metric. The datasets used in this work are two self-made icon datasets, IconA and IconB. IconA is a large-scale icon dataset collected from crawlers on the web, and the dataset contains 25354 icons. Since the classification of datasets collected from the Internet is diffi-

cult, the categories of this dataset are clusters formed by clusters. The IconB dataset consists of 34531 icon images, which are collected from the Internet and contain 60 categories of icon image data. The specific dataset information is shown in Table 1. The experimental environment is illustrated in Table 2.

The evaluation metrics are inception score (IS) and Fréchet inception distance (FID). IS uses the output of the Inception Net classification network to obtain the image quality of the sample by calculating the classification probability of the sample in different categories. Since Inception Net has been sufficiently pretrained, it can be considered that the classification of the network approximates the true classification of the sample, so the IS indicator measures the quality of the sample through the following two aspects: for a certain input of the sample, the classification probability distribution obtained by Inception should be concentrated in a certain category. In this case, the entropy of the probability distribution is negatively correlated with the image samples, and the smaller the entropy of the classification probability distribution obtained by the image, the higher the image quality. For the sample as a whole, images

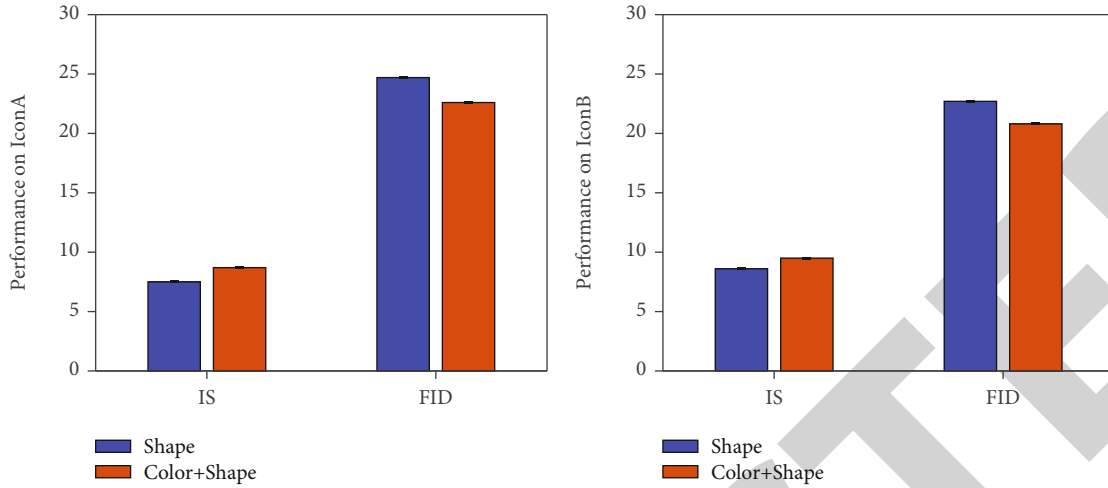


FIGURE 7: Comparison of single shape feature and multiple features.

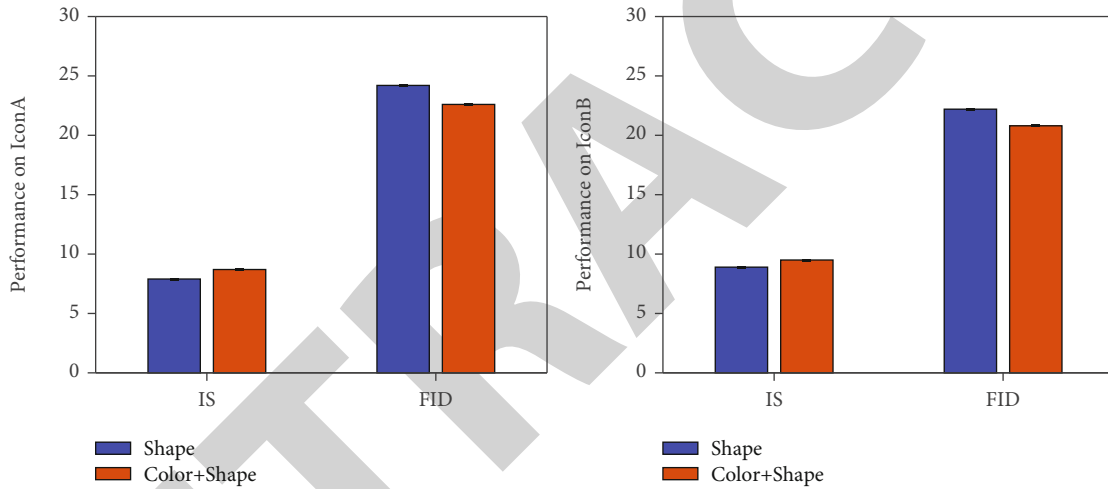


FIGURE 8: Comparison of color shape feature and multiple features.

should be distributed as evenly as possible across all classes. Therefore, the mean values of the distribution probabilities obtained by all samples should be close to each other, and the entropy of the mean value of the sample classification probability distribution is positively correlated with the classification quality of the samples. The stronger the sample diversity, the greater the entropy. The larger the IS value, the higher the quality of the resulting image. FID modified Inception Net to not use the original output of the network as a basis. Instead, the original output layer of the model is removed, and the samples are evaluated using the last pooling layer. FID assumes that the generated image and the real image follow a similar distribution and measures the similarity of the two distributions by comparing the mean and variance of the generated image distribution and the real image distribution. If their mean and variance are close enough, the quality of the generated image is higher and the generated image is more realistic. Since the covariance matrix of the real image and the generated image cannot be calculated, FID uses Inception Net to

convert the image into a high-dimensional feature vector. Then, the closeness of the generated image to the real image is obtained by comparing the mean value of the eigenvectors and the covariance matrix, and then, the quality of the generated image is measured. The FID is negatively correlated with the quality of image generation. The lower the FID, the closer the generated image is to the real image, and the higher the quality of the generated image, the stronger the diversity.

4.2. Evaluation on Network Training. In deep learning, network training is very important. This work first evaluates the training loss of MFIGM on two datasets, and the experimental results are illustrated in Figures 5 and 6.

With the deepening of training, on both datasets, the losses of both the generator and the discriminator gradually decrease and finally reach a state of convergence.

4.3. Comparison with Other Method. To further verify the effectiveness of the MFIGM method, it is compared with

other methods. The compared methods include GAN, DCGAN, and WGAN, and the experimental results are illustrated in Table 3.

Obviously, compared with other generative adversarial networks, the MFIGM method proposed in this work can achieve the highest IS and lowest FID on both datasets. This can prove the correctness and effectiveness of the MFIGM method.

4.4. Evaluation on Condition Feature. This work uses shape features and color features as conditional features. To verify the effectiveness of these two conditional features, this work conducts comparative experiments. This experiment compares the network performance when using a single feature and multiple features, respectively, and the experimental results are shown in Figures 7 and 8.

Obviously, the best performance is not obtained using a single shape or color condition feature. The best quality of icon art design can only be achieved when both conditional features are used together.

5. Conclusion

Various models of image generation continue to emerge, and various models of deep learning shine in this field. Generative adversarial network, as a very important member, has a very enlightening significance. The related application results of generative adversarial networks in the field of image generation are also quite rich, and the indicators of the generated images are also constantly improving. As a very special image that is often used in daily life, the icon is of great significance to the research on the artistic design model of the icon. Therefore, the combination of the generative adversarial network model and the actual design process of the icon is the research direction of this paper. This paper first summarizes the current development process of image generation and related models and organizes and introduces the basic theories and related applications of related models. Then, this paper gradually introduces a generative adversarial network model for icon art design tasks. The characteristics of icons are more complex, and a single conditional characteristic cannot summarize the characteristics of icons. This work combines the conditional classification generative adversarial network to propose a multifeature icon art design model, which can be oriented by combining the shape and color of the icon. The experimental results show that this model can meet the various characteristics set by the generated icon, so that the effect of the generated icon is better than that of other models. This provides a certain guiding significance for the follow-up research on icon art design that is more personalized, higher quality, and more efficient.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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