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AI-driven design innovation: the integration of computational methods in the analysis of Shuangdun Carved Symbols and product design

Yipeng Fan[1], Yijing Chen[2,✉], Wenjing Liang[3], Sharul Azim Bin Sharudin[4]

[1] *College of Art and Design, Bengbu University, Bengbu, Anhui, 233000, China*
[2] *School of Humanities & Art, Bengbu College of Technology and Business, Bengbu, Anhui, 233000, China*
[3] *School of Art, Shanghai Zhongqiao Vocational and Technical University, Shanghai, 201514, China*
[4] *Faculty of Creative Arts, Universiti Malaysia, Kuala Lumpur, 50603, Malaysia*

ABSTRACT
Artificial intelligence technology can effectively improve the quality and efficiency of industrial design and manufacturing, so the study takes Shuangdun Carved Symbols of cultural products as an example, utilizes the generative adversarial neural network to carry out style migration processing in the design of Shuangdun Carved Symbols and their products, and constructs the DCGAN model to assist the design and generation of Shuangdun Carved Symbols of cultural products. After semantic analysis of the color symbols of Shuangdun Carved Symbols products generated with the aid of DCGAN model in this paper, quantitative and qualitative measurements are carried out. Users of Shuangdun Carved Symbols products rated the products after the style migration significantly higher than before the migration in terms of volumetricity, distance, emotion, character, and texture.CycleGAN and DCGAN models achieved the best overall results in terms of PSNR, SSIM, FID, and KID indicators. The DCGAN model with added spectral normalization and Res2Net outperformed the CycleGAN model in the ablation experiments. The overall user rating of the Shuangdun Carved Symbols product designed by the DCGAN model in this paper is 4.24, and the product has obtained more satisfactory evaluation results.

Keywords: artificial intelligence techniques, style migration, generative adversarial networks, Shuangdun Carved Symbols, product design

1. Introduction

Product design has always been in pursuit of innovation and development, and nowadays, in the context of the technological era, product innovation and design with the help of modern science and

✉ Corresponding author.
E-mail address: fbr0705@163.com (Y. Chen).
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technology, to obtain more high-end, more interesting new products. The development of the popular Artificial Intelligence (AI) technology has had a profound impact on various industries, and the field of product design is no exception. In the field of art design, generative AI, for example, specializes in art design image generation and processing, designers for design language and concept input, AI for the effect of the program map output, greatly shortening the design cycle, improve the design efficiency [1-2]. Until now, AI has been updated rapidly and is an important skill for designers in the future. The use of AI technology can help designers better understand user needs, provide innovative ideas, accelerate the design process, thereby improving the innovation of product design [3-4]. In addition, AI technology can also parse numbers, letters, images, symbols in audio, etc., especially in cultural relics. In the field of archaeology and cultural heritage protection, various AI technologies can reveal the historical background of cultural relics, prove the existence of dynasties, and protect cultural relics by recognizing and analyzing the patterns or traces of tribal totems, costumes, porcelains, murals, stelae, and unearthed vessels, which facilitates the better transmission of cultural heritage [5-6]. As the cultural relics with special symbols in the excavated artifacts of Shuangdun site in Bengbu, Anhui Province, China, the incised symbols are not only early in age and large in number, but also rich in incised symbols, with high research value and good prospects for inheritance and application. However, the symbols need to be analyzed and put into application, and AI technology is a good choice.

The use of AI technology can help designers better understand user needs, provide innovative ideas, and accelerate the design process, thus improving the innovation of product design. Literature [7] mentions that the use of AI technology can predict user needs and market trends, and assist enterprises in retail, manufacturing and other fields in the innovative design of product positioning, appearance, utility and so on. Literature [8] uses AI technology to identify the emotions and behaviors of customers in business to better understand customer needs and thus achieve precision marketing services. Literature [9] fuses variational autoencoder and reinforcement learning to create an AI-assisted design model, which also incorporates AI-driven decision support to achieve user satisfaction for cultural and creative products while improving design efficiency. Literature [10] applies generative adversarial network in AI technology to product innovation design, starting from the concept of innovative design to the generation of product creative patterns to complete the overall innovative design of the product. Literature [11] proposes a personalized intelligent design system, which is realized through AI technology and graph theory, mainly combining the user's personality characteristics and cultural elements to intelligently design personalized products. Literature [12] feature extracted traditional cultural symbols through the convolutional neural network algorithm in AI technology and applied these symbolic features to product design, expanding the market and traditional cultural characteristics while innovating products. Literature [13] combines statistical analysis, feature collection, image conversion and other technical methods in AI technology to complete the innovative design of ethnic clothing from body shape formulation, fabric selection to innovative design pattern generation.

After the theoretical analysis of Shuangdun Carved Symbols, the article applies artificial intelligence technology to the product design related to Shuangdun Carved Symbols, and selects generative adversarial neural network to carry out the research on the style migration of cultural products of Shuangdun Carved Symbols. Construct DCGAN model product design generating model to assist the design of Shuangdun Carved Symbols cultural products. Take color as an example of symbolic features for semantic analysis, to explore the use of DCGAN model effect. After that, PSNR, SSIM, FID and KID indicators are selected for quantitative analysis. The hierarchical analysis method is used to construct the evaluation index system of Shuangdun engraved symbol products, and qualitative analysis is carried out to explore the user subjective evaluation of Shuangdun Carved Symbols cultural products generated based on DCGAN design.

2. Research on product design based on AI technology

2.1. Application of AI technology in cultural products

2.1.1. Characteristics of the content of the Shuangdun engraved symbols. In the middle reaches of the Huai River there is the Shuangdun site in Bengbu, Anhui Province, known as the Houjiazhai culture, and the Shuangdun site and the Houjiazhai site have been found with chevron-inscribed symbols on the bottoms of rim-footed pottery. Shuangdun Carved Symbols refer to the more than 630 incised symbols unearthed at the Shuangdun site in Bengbu, Anhui Province, which are colorful, numerous and concentrated, and are by far the largest and richest batch of materials related to the origin of writing unearthed from the Neolithic sites, and have an important position in the history of Chinese writing and the origin of Chinese characters. Most of the pottery vessels from Shuangdun site have symbols on the mouth rims, bellies, inner walls, and the ground of the footrims, while the number of vessels with chevron symbols on the bottom reaches 287, and there are 59 major individuals. Among them, 146 pieces were identified by ware type. The symbols are mainly engraved on the bottom of the inner circle of the bowl and bowl rim.

The content of the symbols is rooted in the basic categories of life, such as plants and animals, fishing nets and spinning tools, as well as geometric symbols. In addition to single symbols, there are also combinations of symbols. Among these symbols, there are many symbols related to spinning, which is a major feature. The function of Shuangdun Carved Symbols can be divided into three categories: ideograms, stamps, and counts, which are the inevitable products of the development of social economy and culture to a certain stage, and are in the stage of the development of the origin of words and phrases, and have already had the nature of the primitive characters.

The round foot and rounded bottom can be recognized as analogous to the cosmic sphere. The circle unites the earth in a celestial tire. The symbols on the bottom of the footrim of the pottery placed in the sacrificial arena are in the tire in the dark part of the universe. The fact that the symbols are engraved on the bottom of the circle means that human beings exist in that place. By means of the symbols, we placed ourselves in the celestial womb in the darkness of the universe. Subsequently, it dialogues with heaven from the celestial body in the dark place where the earth has merged. The Shuangdun man is by no means an intuitive outside the circle. They are conscious of their existence in the heavenly body, which is the fetus within the circle, and are rooted in the "things" (symbols) that are the basic categories of life, and they also express the technical processes of life in symbols. Through sacrifices, one reports and prays to the heavens. Talking to the heavens means asserting aspirational qualities and contributing to the development of narratives of language formation.

2.1.2. Use of AI in cultural products. Artificial intelligence has great potential for application in cultural product design, such as recognizing and analyzing cultural patterns and images (symbols), style generation and innovative design, analyzing user behavior and feedback data, providing optimization solutions for the interaction design and user experience of cultural products, and helping designers of cultural products with artistic creation and trend prediction.

Currently, many studies use artificial intelligence technology to identify, analyze and utilize image elements such as patterns and motifs in culture. Collect and organize relevant image samples, pattern elements and cultural information and preprocess the images to form a material library. Select appropriate neural network algorithms to construct a generative model for cultural product design. Then use the collected image samples to train the generative model in a large number of iterations, so that the model can learn and capture the characteristics and styles of culture, and improve the quality and diversity of the images generated by the model. Using the trained generative model, by inputting different conditions such as colors, shapes, patterns, etc., we can generate patterns of cultural and creative products that meet the requirements or allow designers to get inspiration from them. By continuously optimizing the generation algorithm model and absorbing enough non-heritage cultural samples and features, the generated cultural products can be made to have obvious cultural styles and characteristics. This method can promote the integration of traditional culture and modern design to create more innovative and unique cultural products.

2.2. Research on Style Migration and Generation

2.2.1. Fundamentals of Style Migration. While academic research has a long historical background in exploring stylistic features of images, the use of neural networks for image style migration is innovative work. Prior to the popularity of neural network technology, research on image style migration focused on analyzing the features of a particular style and creating a dedicated mathematical model for that particular style. Through this model, the target image can be migrated to a new image containing the specific style, which is effective but inefficient and has limited application.

By using VGG-Net to extract information from an image, it is found that the feature maps obtained from different convolutional layers in the network structure contain deep information about the image. Some of this information can be intuitively understood as the content features of the image, i.e., the main content of the image, while others include the stylistic features of the image, i.e., the style or texture of the image, which can be viewed as a statistical model of the local features of the image. Before 2015, most of the research on image texture was done through manual modeling. Texture features of an image were extracted using VGG19 and defined as style features after simple processing. Although this definition is based more on the subjective judgment of the authors and is not a strict definition in academia, it is generally accepted by the industry. The style migration method for images mainly consists of three steps: content reconstruction, style reconstruction and style migration.

1) Content reconstruction. When an image is input into the VGG19 model, the hidden layer inside VGG19 contains several convolutional layers, and each convolutional layer outputs several feature maps. In this process, if an image containing white noise is introduced and a loss function for measuring the content difference between this white noise image and the original input image is defined, the content of the original image can be reconstructed on the white noise image through the optimization method of backpropagation. The specific loss function settings are shown below:

$$\mathrm{L}_{content}(\vec{p},\vec{x},l)=\frac{1}{2}\sum_{i,j}(F_{ij}^{l}-P_{ij}^{l})^{2} \tag{1}$$

where, p and x represent the original image and white noise image respectively. l represents a convolutional layer. And F_{ij}^{l} and P_{ij}^{l} represent the activation responses for the original image and the white noise image through the ith filter at position j on the lth convolutional layer, respectively. The resulting image can be viewed as a visual representation of the feature information contained in the feature vectors of that layer.

2) Style Reconstruction. In neural network style migration techniques, the style loss function is usually defined by means of a Gram matrix.The Gram matrix shares similarities with the covariance matrix, and is realized by calculating the inner products of the feature maps of the different channels within the convolutional layer, a computational process that reveals the correlations between the different feature map channels. Specifically, the feature maps of each channel are flattened into one-dimensional vectors, and then the inner product between these vectors is computed to construct the Gram matrix.Each element in the Gram matrix represents the similarity between the two vectors, and thus it reflects the correlation of the eigenvalues between different channels.

The elements on the diagonal of the Gram matrix, on the other hand, are the inner product of the vectors with themselves, reflecting the proportion of the distribution of each feature in the whole

image. Therefore, the difference between the original image and the corresponding Gram matrix of the white noise image is considered as a loss in image style.
where l represents a particular convolutional layer. The stylized features of the image are computed and represented by the inner product of the ird and jth feature maps in layer l, generating a stylized feature of G_{ij}^{l} for the image:

$$G_{ij}^{l} = \sum_{k} F_{ik}^{l} F_{jk}^{l} \tag{2}$$

In further discussion, the style loss function E_l between the original image and the white noise image in the lst convolutional layer will be defined in detail as follows:

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^{l} - A_{ij}^{l})^2 \tag{3}$$

where N_l is the number of feature maps in the lnd network layer and M_l is the size of the feature maps in the lth layer. Finally, we weight and sum the style loss of each layer to obtain a total style loss function of $\mathrm{L}_{style}(\vec{a},\vec{x})$, and w_l is the weight of each layer:

$$\mathrm{L}_{style}(\vec{a},\vec{x}) = \sum_{l=0}^{L} w_l E_l \tag{4}$$

3) Style Migration. The fundamental purpose of style migration is to create a picture that contains both the stylistic characteristics of image a and incorporates the content characteristics of image p [14]. Defined by a white noise image x, the content loss and style loss functions between it and the original image are set, and continuously optimized by back propagation techniques, with the aim of making the total loss value close to zero, thus producing an ideal image for style migration. Obtained by weighted merging of the content loss function and style loss function, the total loss function expression is:

$$\mathrm{L}_{total}(\vec{p},\vec{a},\vec{x}) = \alpha \mathrm{L}_{content}(\vec{p},\vec{x}) + \beta \mathrm{L}_{styde}(\vec{a},\vec{x}) \tag{5}$$

where, α and β are the weights of content loss function and style loss function respectively.

The core idea of the research area is to use convolutional neural network to extract the high-level features of the image and define the content loss function and style loss function between the original image and the target image, and iteratively optimize the target image by back propagation technique in order to achieve the style migration.

2.2.2. Self-Encoder and Variational Self-Encoder Models:

1) Style Generation Learning Based on Self-Encoder Modeling. Self-encoder (AE) as a basic neural network composition structure, its main structure is shown in Fig. 1, which contains the following three parts: input layer, output layer and intermediate layer. The model structure can be divided into two parts: encoder structure and decoder structure. The working principle of the self-encoder model is to minimize the mean square error between the output and the input through the nonlinear transformations of the encoder and the decoder, and then learn an effective encoder mapping function to characterize the information in the input layer during the training process. It can be obtained that AE, as an unsupervised learning, does not require feature labeling information during the training process, and the features extracted during the learning process can be used for the implementation of tasks such as classification regression.

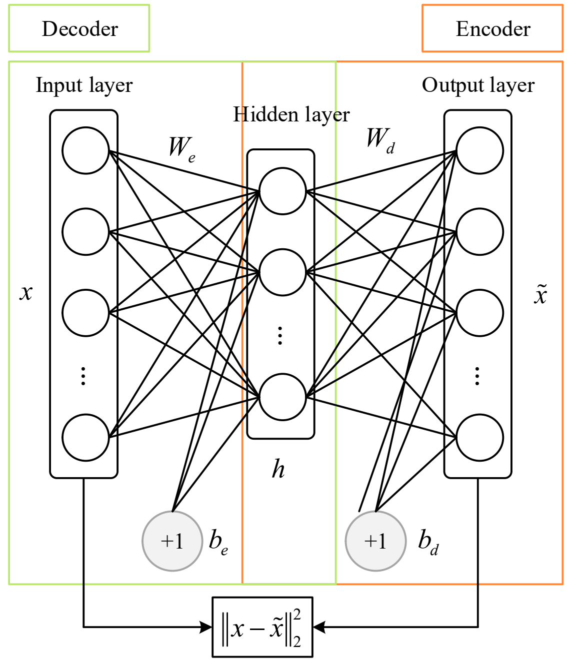


Fig. 1. AutoEncoder structure

In the encoder, the input sample $x \in \Re^n$ (n is the number of neurons in the input layer) is mapped to the hidden layer under the function $f(x,\theta_e)$, and the hidden layer is then characterized by the feature representation $h \in \Re^m$ (m is the number of neurons in the hidden layer):

$$h = f(x,\theta_e) = s_e(W_e x + b_e) \tag{6}$$

In Eq. $W_e \in \Re^{m\times n}$ is the weight matrix, $b_e \in \Re^m$ is the bias vector. θ_e is the encoder parameter set, and $s_e(\cdot)$ is the activation function for encoding.

Similarly, in the decoder structure, the decoding function is denoted as $g(h,\theta_d)$, and the hidden layer features $h \in \Re^m$ are mapped to the reconstruction of the output layer $\tilde{x}$ through the nonlinear transformation function $g(h,\theta_d)$:

$$\tilde{x} = g(h,\theta_d) = s_d(W_d h + b_d) \tag{7}$$

where θ_d and $s_d(\cdot)$ are the parameter set of the decoder and and the decoding activation function, respectively. $W_d \in \Re^{n\times m}$ is the weight matrix and $b_d \in \Re^n$ is the bias vector.

In the decoding process, the output $\tilde{x}$ is obtained by reconstructing the input x, and the output $\tilde{x}$ can approximate the input x. The reconstruction errors of output $\tilde{x}$ and input x are calculated and the optimal solution (minimum value) is found through iterative training, and the AE finally obtains the optimal parameter sets θ_e and θ_d. Therefore, for any input, the corresponding feature information is extracted by the AE network, which can be used to realize the completion of the subsequent regression tasks.

With the rapid development of generative modeling in recent years, the study of self-encoder models has also re-entered the limelight. In addition to existing tasks such as data dimensionality reduction or image denoising, self-encoder models have also been applied to the study of image generation, style generation and other problems.

In the learning of style generation, the self-encoder uses a coding network to learn the common features of two images of different styles with similar attributes, and then uses two decoding networks to generate the corresponding style images respectively.

Take the table lamp style generation as an example. The overall structure of the model consists of one input (encoder), and two outputs (decoders). The inputs are two different styles of table lamp images, the network learns the common features of the two source images in the hidden layer, and generates different styles of style generation images at the two outputs (decoders), and the generated images use the L1 loss function for style reconstruction loss calculation.

The two decoders are A and B. The decoder generation process is as follows:

$$A' = D_{A-\text{decoder}}(E_{\text{encoder}}(A)) \tag{8}$$

$$B' = D_{B-\text{decoder}}(E_{\text{encoder}}(B)) \tag{9}$$

However, despite the fact that the self-encoder is able to accomplish the work of generating style images, the self-encoder is not able to generate style images arbitrarily and still has shortcomings.

2) Style generation learning based on the variational autoencoder model. Variational Auto-Encoder (VAE): its composition contains an encoder and a decoder, and its structure is shown in Fig. 2.

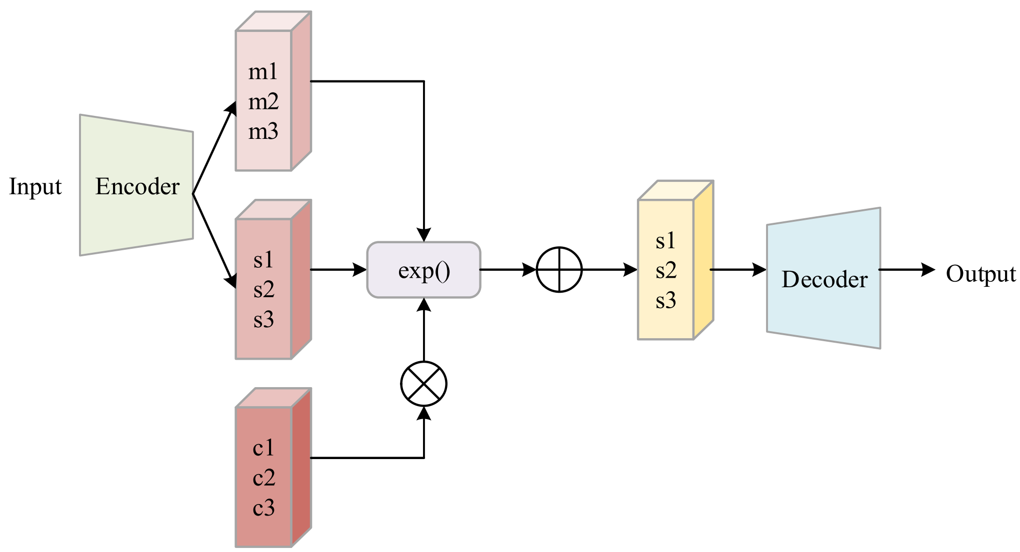


Fig. 2. VAE model

Unlike the autocoder which produces only the corresponding single code after the source image sample, the variational autocoder produces two codes after the input image sample, respectively:

$$\vec{m} = (m_0, m_1, \ldots m_n)\vec{s} = (s_0, s_1, \ldots s_n) \tag{10}$$

$\vec{m} = (m_0, m_1, \ldots m_n)$ is the original encoding of the input samples, and $\vec{\vec{s}} = (s_0, s_1, \ldots s_n)$ is used to control the noise vector $\vec{e} = (e_0, e_1, \ldots e_n)$ weight encoding.

In order to restrict the weights to be constantly positive, an exponent of e (the natural base) is taken for $\vec{s} = (s_0, s_1, \ldots s_n)$ to obtain the output of the encoder:

$$\vec{c} = \exp(\vec{s}\,) \times \vec{e} + \vec{m} \tag{11}$$

In the process of generating images, in order to ensure the quality of image generation, the encoder training process will make the noise weight vector tends to take the value close to negative infinity, so as to reduce the influence of the noise vector, but this restriction will make the variational self-encoder lose its meaning and thus become a self-encoder, so the variational self-encoder to avoid this situation by adding an additional loss function:

$$L=\sum_{i=1}^{n}(\exp(s_i)-(1+s_i)+(m_i)^2) \tag{12}$$

However, the improved VAE still has the drawbacks of generating fuzzy images and poor representation of complex models.

2.2.3. Generating Adversarial Neural Networks. Generative Adversarial Neural Network (GAN) consists of two parts: discriminative network and generative network [15-16]. They are called discriminator D and generator G respectively.The workflow of generative adversarial neural network is shown in Fig. 3. Generator G expects that the data distribution $P_G(x)$ of the generated image can converge to the data distribution $P_{data}(x)$ of the real image as much as possible through several iterations, i.e., the generated image $x=G(z)$ is as similar as possible to the real image $P_x \sim data(x)$ in appearance, so that the discriminator incorrectly identifies the input generated image $G(z)$ as the real image. The discriminator D then expects to improve its ability to discriminate whether the input image is a real image x or a generated image $G(z)$ during the iteration process, and gives $D(x)=1, D(G(z))=0$ a score.

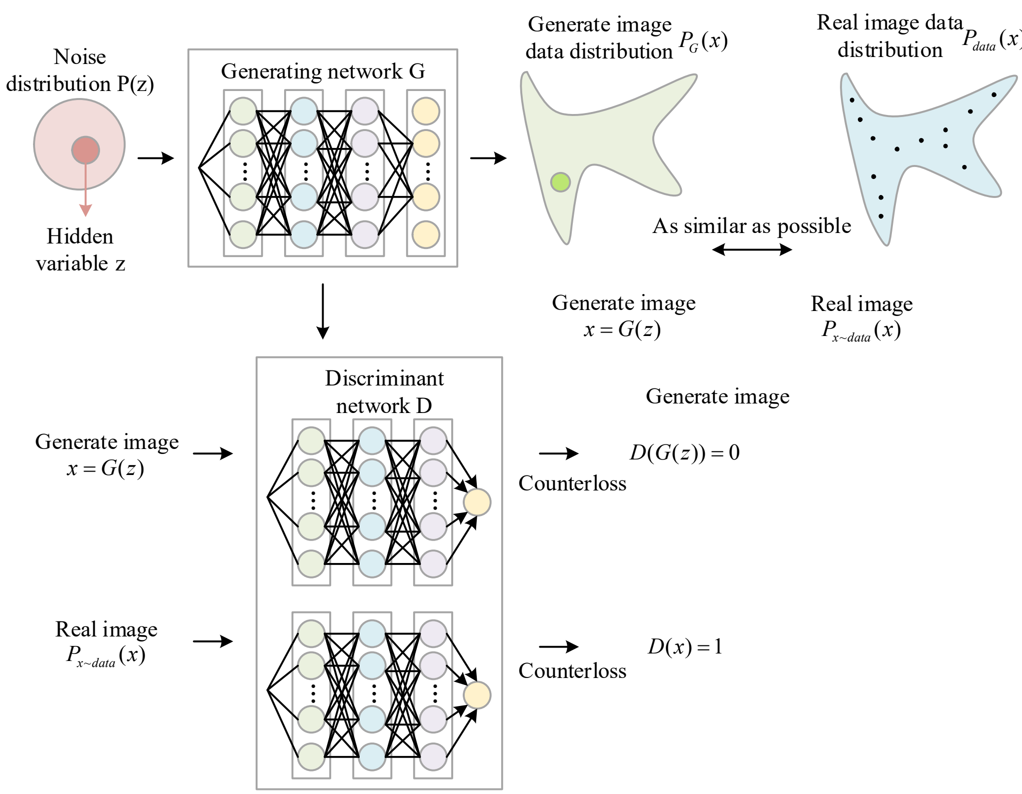


Fig. 3. Workflow diagram of generative adversarial network

For the initial generative adversarial network, a noise distribution P_z (random noise) is set, the hidden variable z is obtained from the noise distribution P_z, $P_{data}(x)$ represents the real image data distribution, and $P_G(x)$ represents the generated image data distribution of the generator G.

$G(x)$ follows the learned x distribution defined by G and $D(x)$ the probability of x since $P_{data}(x)$ instead of $P_G(x)$.

The total loss function for training D and G is:

$$\min_G \max_D V(D,G) = \mathrm{E}_{x\sim p_{dan}(z)}[\log D(x)] + \mathrm{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{13}$$

The training of the GAN is done in two iterative stages, firstly the discriminator is trained and the discriminator D is expected to improve its ability to identify the input image as real image x or generated image $G(z)$ during the iteration process. Therefore, for the part of the above equation that extracts the optimization objective as $\max V$, since this item is the maximization term, its optimization loss function during optimization using gradient descent method should be:

$$\mathrm{L}_D = -\mathrm{E}_{x\sim p_{dan}(x)}[\log D(x)] - \mathrm{E}_{z\sim N(x|0,1)}[\log(1-D(G(z))] \tag{14}$$

In the ideal discriminator, the real image x discriminator $D(x)=1$ and the generated image $G(z)$ discriminator $D(G(z))=0$. Therefore, the loss function is $\mathrm{L}_D=0$ when the input is the real image x. The loss function is $\mathrm{L}_D=\infty$ when the input is the generated image.

Retrain the generator G with optimization objective $\min V$. Notice that only the second term of the total loss function contains G, so the loss function should be:

$$\mathrm{L}_G = \mathrm{E}_{z\sim N(z|0,1)}[\log(1-D(G(z))] \tag{15}$$

2.3. Cultural product design method based on generative adversarial neural network

2.3.1. Product Design Process. The content of this subsection uses generative adversarial network for product design, which reduces the refinement steps in the optimization of the design process, through which highly referential design image results can be generated directly, better assisting designers to generate more design inspiration and design solutions. The product design process and creative design optimization process is shown in Figure 4.

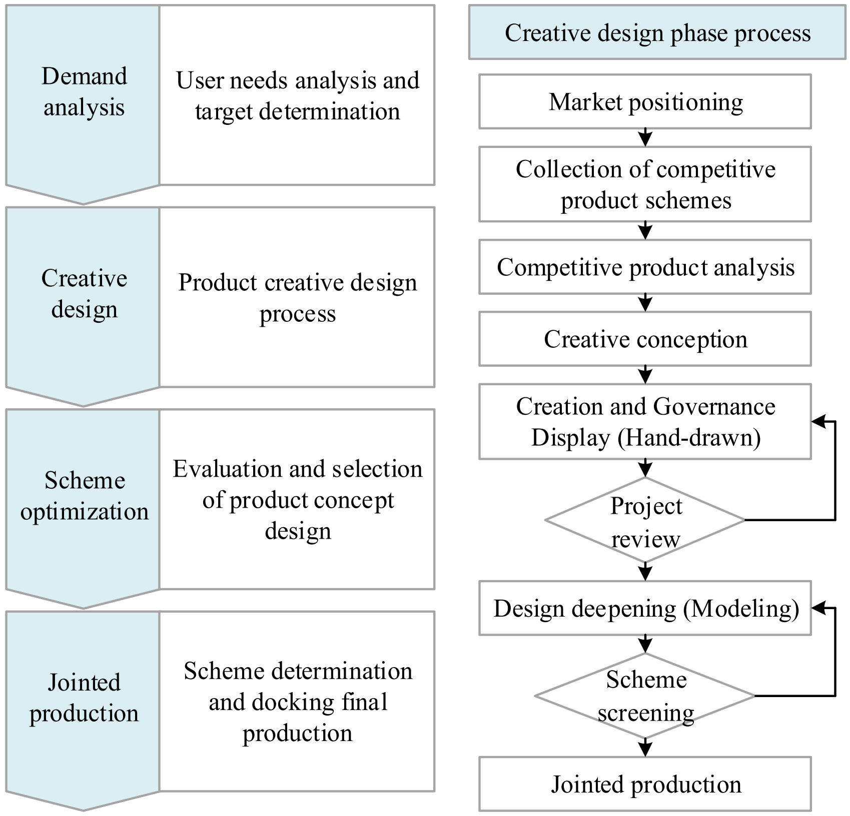


Fig. 4. Product design flowchart and creative design refining process

Products are constantly being updated and their iterative design is gradually accelerating. Product design itself is an iterative process, and a product tends to be perfected as it continues to refine its design. How to quickly carry out product styling design is the focus of designers. For product designers, the rapid output of product design styling design program, you can accelerate the speed of the product from design to market sales, but also in the product competition in a more favorable position. However, the existing design process constrains the ability of designers to produce a large number of programs. Designers spend weeks or even months researching, hand-drawing, and modeling new product development. A slow product design process will put the company at a disadvantage in the fierce product competition.

2.3.2. Product design assistance based on generative adversarial networks. This subsection takes the product design of table lamp with Shuangdun Carved Symbols as an example, and proposes a method to quickly generate product design solutions. Now there have been researchers through the generative adversarial network for generative design experiments, but the existing generative adversarial network design research more than a single material to generate the product, such as clothing, shoes, chairs, etc., this subsection to the table lamp as an example to verify that the generative adversarial network of complex product design learning results, the table lamp material for a rich variety of materials, including metals, plastics, wood, etc., the color is very The color is also very rich. This section takes the table lamp as an example to verify the ability of the generative adversarial network to learn the combination of multiple materials and shapes.

The generative adversarial network must be trained by the corresponding data sets, first collect the data sets of product modeling design, unify the data sets to remove the features that interfere with modeling learning. The dataset is imported into the generative adversarial network to generate the product styling design, and the computer-generated design scheme is hand-drawn by the designer for refinement, the hand-drawn design drawings are colored using the Style2paints network, and the design scheme is finally modeled and rendered and docked for production. The advantage of this method is to use deep learning to reduce the designer in the collection of materials, innovation and design of the time and effort required to quickly generate product modeling program. The generated product design can be used as a reference for designers in the design process.

2.3.3. Data collection and pre-processing of datasets. In order to obtain a variety of table lamp design images, firstly, we select Pinterest, which is a common platform for designers to collect inspirations and image collections, to collect reference images of table lamp styling and design, and use the PinterestScraper crawler to crawl the images from the website, using the BeautifulSoup module to parse the html, and the Time module to control the timeout control of whether or not the results are returned during the crawling process. The Time module is used to control the timeout of the crawling process, Selenium module is used for retrieval, Urlretrieve completes the work of downloading pictures from the URL, OS and Threads are used to throughput the data and multi-threaded operation, because Pinterest is an English website, and most of the names and annotations of the pictures are in English, so we use Headphones as the keyword of the crawler to retrieve and download pictures in bulk. Because Pinterest is an English website and most of its images have English names and labels, Headphones is used as the crawler to retrieve and download the keywords in batch, and a large number of product design images of desk lamps are collected according to the requirements.

2.3.4. Product Design Generation Model. The product design generation model is based on a generative adversarial network, which is trained by inputting a dataset of table lamp styling design images.The model structure of the DCGAN generative adversarial network used in this subsection is shown in Fig. 5.

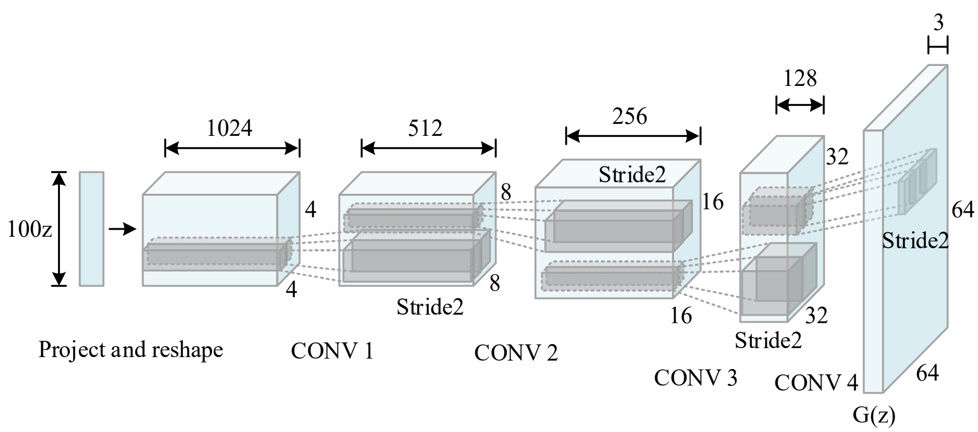


Fig. 5. DCGAN generator architecture

DCGAN makes the following improvements to traditional generative adversarial networks: the fully connected layer is removed to achieve a deeper architecture, a global pooling layer is used instead, batch normalization is added to both the generator and the discriminator, the output layer of the generator uses the Tanh activation function while the other layers use the ReLU function, and all the layers of the discriminator use the LeakyReLU activation function for all layers of the discriminator and step convolution is used in the discriminator and micro step convolution operation is used in the generator to replace the pooling layer in the network, the above modifications make the network more resilient and able to generate clearer images.

3. Analysis of the design of cultural products in Shuangdun

3.1. Semantic Analysis of Color Symbols

3.1.1. Color Semantic Analysis. Color sensation is the psychological perception produced by light through the crystal body stimulating the retina, and processed by the nerve fibers transmitted to the visual center of the brain, which reflects people's emotion and preference for color. In product design, color is also one of the most distinctive and attention-grabbing symbols. In this subsection, the color symbols of Shuangdun Carved Symbols cultural products are discussed in depth. Research shows that in the psychological reaction of people to objects, the influence of color accounts for 50~80% in the first 5min, and keeps 50% unchanged after 5min. This shows that color has a greater impact on human sensory characteristics.

This paper adopts a perceptual engineering approach to analyze the relationship between different wavelengths of color and the sense of volume ("shrunken - enlarged"), distance ("high cold - intimate"), softness ("soft – rigid"), lightness ("light - heavy"), warmth ("warm - cold"), mood ("relaxed – depressed"), personality ("flamboyant-understated"), and texture ("ornate-plain") correlations of the seven color semantic dimensions, as well as the relationship between sensory properties and stimulus response time, the color sensory hierarchy is shown in Table 1 shown. Taking the three semantic senses of volume, distance and texture as examples, the sensory properties of colors were visualized as shown in Figure 6. The results of Table 1 and Fig. 6 show that colors with long wavelengths give a strong sense of intimacy, flamboyance, and magnificence, while colors with short wavelengths are on the side of high coolness, low tone, and simplicity. In this section, the above findings are used to evaluate the semantics of the Shuangdun Carved Symbols style image. In the process of selecting style images, images composed of similar wavelength colors are consciously selected as style maps.

Table 1. Color sense level

	Volume sense	Distance sense	Hard sense	Weight sense	Warm-cold sense	Emotion	Character	Texture
	Small-large	Distant-close	Soft-hard	Light-heavy	Hot-cold	Relaxed-repressed	Flamboyant-silent	Ornate-plain
Red	2.125	1.771	1.126	-2.618	1.315	1.148	-2.575	-2.439
Orange	1.826	1.965	-1.017	-0.894	-2.041	-0.644	-2.078	-1.064
Yellow	2.019	2.015	-1.378	-1.525	-1.515	-0.213	-2.186	-1.026
Green	-1.185	-0.785	0.562	0.324	0.739	-1.511	0.895	0.267
Indigo	0.062	-0.745	-1.647	-2.211	0.462	-2.342	0.877	0.849
Blue	-1.036	-1.507	-0.846	-0.315	1.168	-1.398	-0.338	-0.158
Purple	-1.061	-1.396	1.206	1.066	0.073	1.065	-0.327	-2.021
Pink	0.873	2.288	-2.378	-2.069	-0.624	-1.087	-1.068	-0.037
White	1.737	0.537	-1.217	-2.559	0.953	-1.567	1.247	1.789
Black	-2.152	-2.349	2.783	2.895	2.284	2.629	2.852	2.488
Grey	-1.319	-1.425	0.479	0.876	2.039	1.063	2.212	1.817

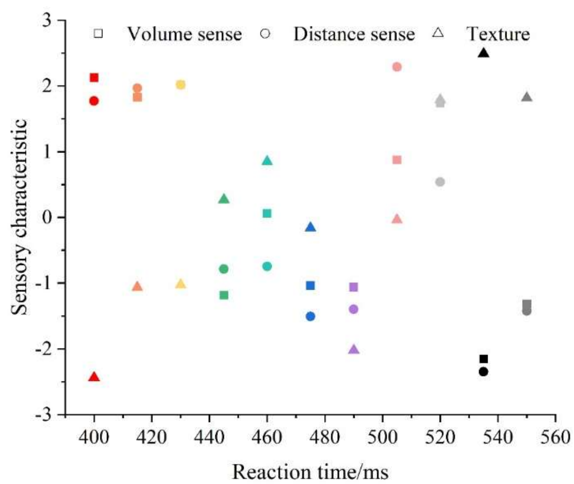
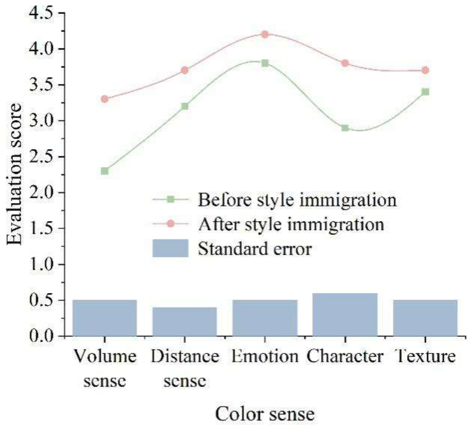


Fig. 6. Sensory characteristics of color

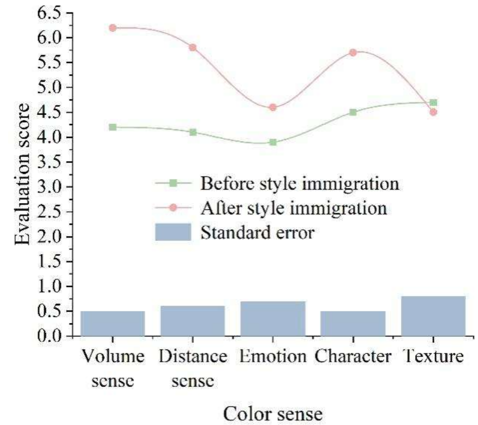
3.1.2. Stylistic analysis of migration results. Six table lamps are randomly selected as samples, and their attribute parameters are inputted into the trained generative adversarial network model (DCGAN) in Chapter 2 to obtain the style semantics of the six samples of the Shuangdun Carved Symbols. Based on the style semantics of the six samples, the corresponding style images are selected as style maps, and the six sample images and six style images constitute six groups of "content map - style map" map groups, and the "content map - style map" map groups are input into the previous section. The "content map - style map" map groups are input into the trained DCGAN style migration model in the previous section, and the migration results are obtained. A questionnaire was constructed and 50 users were randomly invited to evaluate the 6 groups of migration results. The comparison results of the semantics of the products before and after migration are shown in Fig. 7, and (a) ~ (f) are 6 samples.

The "pre-migration" score is obtained by inputting the product styling elements into the trained DCGAN network model. The mean and standard deviation of the "post-migration" scores are obtained from the evaluations of 50 users. The user ratings of the samples before the style migration are lower than the ratings after the migration, especially the overall ratings of Sample 1 and Sample 2 are more significantly improved after the style migration.

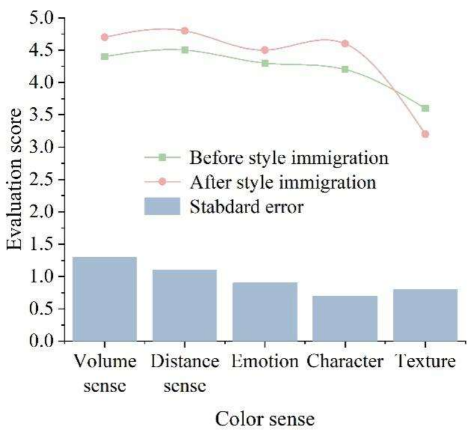
From the above results, it can be seen that migrating the color of the style image to the product design can strengthen the product semantics, i.e., the same style of product styling and the new product generated by the style map, the style intensity is enhanced, indicating that the style map has been successfully migrated to the product.



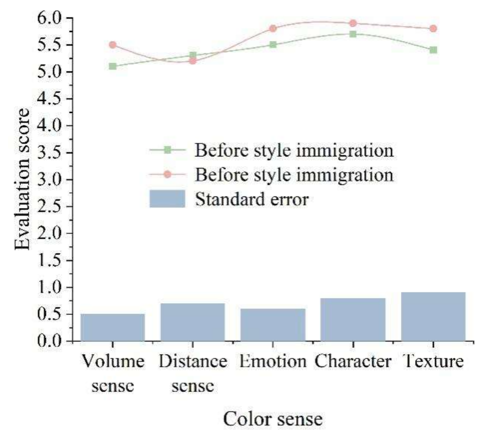
(a) Sample 1



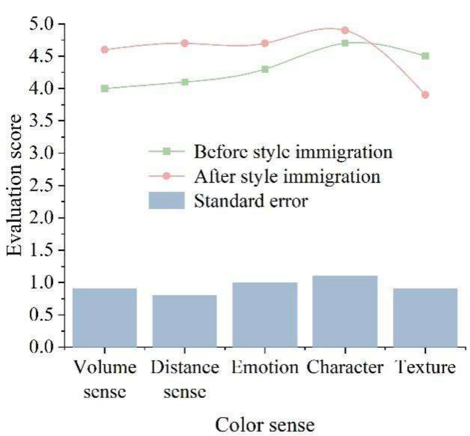
(b) Sample 2



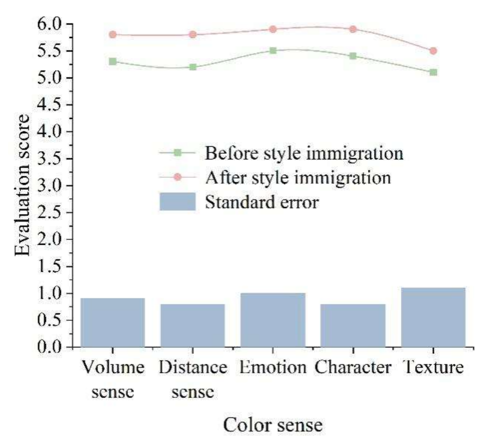
(c) Sample 3



(d) Sample 4



(e) Sample 5



(f) Sample 6

Fig. 7. New product style assessment

3.2. Quantitative analysis

In this experiment, four kinds of evaluation indexes PSNR, SSIM, FID and KID are used to quantitatively analyze the DCGAN Shuangdun Carved Symbols product style migration results. The values of the various evaluation indicators are shown in Table 2.

Based on the values of the four metrics PSNR, SSIM, FID and KID in Table 2, it can be seen that the overall performance of the two models based on generative adversarial networks (CycleGAN, DCGAN) significantly outperforms the other models on the four metrics.

Table 2. PSNR, SSIM, FID and KID contrast of the generated images

Method	PSNR		SSIM		FID		KID	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
CycleGAN	17.3673	18.7968	0.891	0.794	80.99	80.81	80.55	79.62
MUNIT	15.3335	16.0643	0.734	0.772	79.94	76.49	77.97	75.94
MAST	16.9456	17.3587	0.789	0.769	75.58	77.32	77.75	76.53
ArtFlow	16.8728	15.2836	0.824	0.753	77.65	76.76	77.16	76.03
CAST	17.0766	17.2979	0.869	0.761	78.04	77.85	79.32	77.85
DCGAN	17.3115	18.8635	0.909	0.817	80.81	80.92	80.46	80.04

Further ablation experiments are conducted on the best-performing CycleGAN among all the models and the DCGAN model in this paper, and two changes are made under the network structure of the original CycleGAN, firstly, a spectral paradigm normalization layer is added to the discriminator to replace the original batch normalization layer, which stabilizes the performance of the discriminator, and then strengthens the performance of the generator network to enhance the quality of the image conversion. Secondly, a new residual module (Res2Net) is added for downsampling feature extraction, which extracts richer features by group convolution to better realize the stylistic conversion and further promote the quality of the stylistically converted images.

In order to verify the effectiveness of the changes to the network structure, this experiment conducts four sets of ablation experiments on the abstract dataset a and the figurative dataset b based on the improved network structure. The results of the four sets of ablation experiments and the evaluation indexes proposed above are quantitatively analyzed to verify whether the changes to the network are effective, and the results of the ablation experiments are shown in Table 3.

As can be seen from Table 3, the experimental results of CycleGAN and DCGAN models of discriminator networks with the addition of spectral normalization are better than the traditional network structure. This indicates that the use of spectral normalization can improve the performance of the network to some extent. The performance of Res2Net with the new residual module is even better than the original network structure model with only the addition of spectral normalization in terms of index performance, which indicates that the addition of Res2Net better preserves the color information and texture, structure and other features of the original image domain, and plays a certain optimization role in the network model. In addition to this, it can also be observed from Table 3 that the DCGAN model with the addition of spectral normalization and Res2Net outperforms the CycleGAN model in terms of PSNR, SSIM, FID and KID.

Table 3. Ablation experiment results

Method	PSNR		SSIM		FID		KID	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
CycleGAN	17.3673	18.7968	0.891	0.794	80.99	80.81	80.55	79.62
CycleGAN+SN	17.8563	19.456	0.915	0.852	81.64	81.07	80.86	80.53
CycleGAN+SN+Res2Net	18.2356	19.865	0.926	0.869	81.88	81.56	81.22	80.92
DCGAN	17.3115	18.8635	0.909	0.817	80.81	80.92	80.46	80.04
DCGAN+SN	18.0648	19.896	0.942	0.896	82.66	81.74	80.94	81.79
DCGAN +SN+Res2Net	18.7549	20.556	0.975	0.914	82.93	82.06	81.73	82.17

3.3. *Qualitative analysis*

Take the table lamp as an example, the DCGAN model of this paper is used to migrate the style of the product to design the Shuangdun Carved able lamp. In order to obtain the subjective opinion of the product, this paper constructs the evaluation index system of Shuangdun Carved table lamp products with the help of hierarchical analysis, and calculates the weight of each index in the evaluation index system, and the results are shown in Table 4.

Table 4. Product evaluation index system

	Primary index	Weight	Secondary index	Weight
Shuangdun Carved Symbols product evaluation	Model performance (A1)	0.1353	Model generation efficiency (A11)	0.2764
			Model stability (A12)	0.1957
			Model accuracy (A13)	0.2871
			Model extensibility (A14)	0.2408
	Image quality (A2)	0.3413	Image fidelity (A21)	0.0807
			Detail accuracy (A22)	0.1535
			Image diversity (A23)	0.1174
			Image expression (A24)	0.1534
			Image innovation (A25)	0.1085
			Image art (A26)	0.1403
			Image practicality (A27)	0.0816
			Image texture (A28)	0.1547
	Holistic perception (A3)	0.5234	Shape perception (A31)	0.2012
			Color perception (A32)	0.2393
			Material perception (A33)	0.1829
			Shadow perception (A34)	0.1757
			Detail texture (A35)	0.2009

Questionnaires are designed based on the evaluation index system and Likert five-level scale in Table 4 and distributed to 100 trial users. After collecting the questionnaire data, based on the calculation of the index weights, we get the qualitative evaluation results of the Shuangdun Carved Symbols product designed by the DCGAN model in this paper as shown in Table 5.

As seen in Table 5, the DCGAN model design of this paper's Shuangdun Carved Symbols product was rated 4.24 points overall, with more balanced scores on the three primary indicators of model performance, image quality and overall perception, and the scores of the secondary indicators were between 4.10 and 4.54. This paper DCGAN model design of Shuangdun Carved Symbols products in the trial users to obtain a more satisfactory effect.

Table 5. Qualitative evaluation results

	Primary index	Score	Secondary index	Score
Shuangdun Carved symbols product evaluation (4.24)	Model performance (A1)	4.23	Model generation efficiency (A11)	4.21
			Model stability (A12)	4.28
			Model accuracy (A13)	4.21
			Model extensibility (A14)	4.24
	Image quality (A2)	4.22	Image fidelity (A21)	4.54
			Detail accuracy (A22)	4.10
			Image diversity (A23)	4.47
			Image expression (A24)	4.16
			Image innovation (A25)	4.30
			Image art (A26)	4.27
			Image practicality (A27)	4.10
			Image texture (A28)	4.27
	Holistic perception (A3)	4.25	Shape perception (A31)	4.42
			Color perception (A32)	4.24
			Material perception (A33)	4.30
			Shadow perception (A34)	4.10
			Detail texture (A35)	4.19

4. Conclusion

In this paper, the style migration algorithm in artificial intelligence technology is applied to the product design of Shuangdun Carved Symbols, and the DCGAN model is constructed to assist the design of Shuangdun Carved Symbols cultural products. The semantic analysis of color symbols and quantitative and qualitative analysis of the products of Shuangdun Carved Symbols are carried out.

Examining the changes in the sense of volume, distance, emotion, character and texture of the Shuangdun engraved talisman products before and after the style migration, it is obvious that the audience's evaluation of the products before the style migration is lower than the rating after the migration. The cultural products of Shuangdun Carved Symbols after the style migration process received higher ratings. Migrating the color of image styles to product design is important for strengthening product semantics.

PSNR, SSIM, FID and KID values are selected as the measures for quantitative evaluation, and CycleGAN and DCGAN models have the best overall results among all models. In the ablation experiments, the DCGAN model with added spectral normalization and Res2Net has better PSNR, SSIM, FID and KID values than the CycleGAN model.

The overall score of the user's product of Shuangdun Carved Symbols designed based on the DCGAN model is 4.24, and the scores of the three first-level indexes of model performance, image quality, and overall perception are 4.23, 4.22, and 4.25, respectively, and the scores of the second-level indexes are not less than 4.10, and the overall results have been achieved better.

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