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Creativity and Sustainable Design of Wickerwork Handicraft Patterns Based on Artificial Intelligence

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Abstract: Protecting and inheriting local traditional handicrafts and developing them into characteristic handicraft industries plays a certain role in maintaining social harmony and stability. This study proposes an innovative design method for wickerwork patterns to achieve the sustainable development of wickerwork handicraft culture. In order to accurately grasp the emotional perception law of wickerwork handicraft patterns and creatively generate wickerwork pattern design schemes in accordance with the user's emotional preference, a wickerwork pattern design method based on deep learning is proposed. Firstly, the image recognition model of the Funan wickerwork patterns is established by using the ResNet. The experimental results show that the best recognition rate of ResNet34 for the whole pattern design image dataset is 94.36%, the recognition rate of modern patterns is 95.92%, and the recognition rate of traditional wickerwork patterns is 93.45%. Secondly, based on deep convolution generative adversarial network (DCGAN), a design scheme generation model of Funan wickerwork patterns is built. DCGAN can automatically and creatively generate pattern design schemes that can effectively stimulate consumers' emotional feelings. Finally, the designer uses creative pictures as a source of inspiration, innovates the design of the generated images, and designs wickerwork patterns with exquisite personality. This proposed method will increase the diversity of patterns and promote the sustainable development of traditional wickerwork techniques. Moreover, this proposed method can help design companies identify customers' psychological needs and support designers in innovatively and efficiently creating new cultural innovation design solutions.

Keywords: sustainable design; deep convolutional neural network; DCGAN; wickerwork handicraft patterns

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1. Introduction

At present, environmental sustainability has become the driving force of economic development, and sustainable design has received widespread attention. The development of new products pays more and more attention to the use of environmentally friendly materials. Traditional handicraft is the important part of my country's intangible cultural heritage. As one of the traditional Chinese folk handicrafts, the wickerwork handicraft exudes strong cultural connotations and local cultural characteristics. It has been widely used in daily life, highlighting natural elegance and beauty. After years of development, the Funan wickerwork handicraft has transformed from traditional wickerwork to covering traditional home furnishing, decoration, art and other cultural industries. At present, Funan county has built an 83,000 mu willow planting base, with an annual output of 280,000 tons of willows; about 130,000 people in 14 towns are engaged in willow production and management; and farmers' income has increased by nearly 500 million yuan.

The sustainable development of intangible cultural heritage is a hot topic, and among these categories of intangible cultural heritage, traditional crafts are one of the most important categories. The current academic research on handicrafts is mainly focused on an anthropological perspective, that is, discussing handicraft features [1,2], discussing handicraft problems and suggestions, formulation of new policies [3], mechanism of inheritance of traditional Chinese crafts [4], and workshops [5] promoting the sustainable development of traditional crafts. In recent years, with the rapid development of research and application of network technology, 3D printing, virtual reality, augmented reality and other technologies, digital technology is playing an increasingly important role in the field of cultural heritage protection and inheritance, and it also contributes to the sustainable development of traditional folk crafts.

The digital technology can effectively solve many problems in the archiving, research and inheritance of cultural heritage information, which is an important means to realizing the immortality and value promotion of intangible cultural heritage. How to use the digital technology to let the culture contained in cultural heritage play a greater role in the present is an important issue to be solved in the protection and sustainable development of the handicraft cultural heritage task. In the digital age, a variety of digital intelligence technologies can be effectively used to design solutions that meet the various needs of users. At the same time, consumers have high expectations for new handicraft expression. They care about some emotional aspects, such as elegant appearance, comfortable touch and attractive elements that can meet their emotional needs [6]. Some emotional design methods explore the user's emotional image information and converts it into product design elements. Kansei engineering (KE) is the most reliable and useful in dealing with the user's emotional needs [7], and many scholars have applied this method in industrial fields such as automobiles [8], clothing, furniture [9], mobile phones [10], computers [11] and electric bicycles [12]. Scholars have been using the KE method to study the relationship between physical attributes and emotions [13]; the current research of KE mainly focuses on the aspects of constructing relevant research theories and methods with the help of various smart tools to solve the emotional reactions between individuals and products. There are three steps in the design process [14]: 1. obtain and quantify the user's emotional image information; 2. explore the complex relationship between the user's emotional image and the design factor of products [15,16] and establish a mapping model; 3. convert the model into an objective function [12], and use the intelligent algorithm [17,18] to optimize the design, so that designers can quickly generate design schemes.

KE provides research methods and intelligent tools for the product's emotional design and research, which effectively improves the quality of product design [12,16,19]. However, there are still some limitations in solving strategies. On the one hand, parameter coding of morphological design characteristics is required during the research process, so the combination of a few defined local style features is limited to representative styles, which cannot generate new creative design schemes, and the limited results also restrict the creativity of designers. Some researchers used QFD [15], artificial neural networks [18] and genetic algorithm [20] models to map the nonlinear relationship between consumer emotional responses and product form design variables. It has been proven that artificial neural networks and SVM technologies [21] are suitable for modeling the relationship between product form design variables and user emotional responses, and the disadvantage is that the datasets of user perception characteristics of these prediction models are built manually. The user's perceptional image of the product is subjective [22], so it is difficult to establish a precise relationship model between the product form design variables and the user's emotional response. On the other hand, the quality of the scheme depends entirely on the precision of the established model [23], and it is difficult to learn the implicit design law directly from the samples, which greatly weakens the diversity and innovation of product design schemes. Doubtless, this brings more challenges during design development process.

In recent years, the technology of deep learning has developed rapidly, and has achieved remarkable results in many fields including language recognition and image classification processing. For example, the deep convolution neural network (DCNN) [24] has been widely used, and great breakthroughs have been made in production development and achieving creative tasks. Lixiong et al. [25] have proposed a framework for the product concept generation method based on deep learning and Kansei engineering. Through KE and DCNN, an emotion recognition model was established, and a product design GAN model (PD-GAN) was proposed to generate product concept images with emotional preferences. Ding et al. [26] described a method for product color emotional design based on DCNN and search neural networks. The above research proves the advantages of deep learning methods in product identification classification and design. In view of the fact that the DCNN model can generate vivid image samples in a unsupervised way, thereby generating creative and vivid images design in the art design process.

However, as a traditional intangible cultural heritage, wickerwork is homogenized and fragmented due to the intervention of digital technology that has shaded the unique history and culture of wickerwork and the life experience of the craftsmen. In fact, wickerwork craftsmen have accumulated a lot of knowledge and experience that is difficult to comprehend, and this knowledge is inseparable from the personal emotions and meaning assigned by the craftsmen. However, digital technology only passively accepts data and cannot perceive the influence of subjective and objective factors such as history, culture and social awareness. To this end, an effective way is to involve the designer in the design process with fully combined creativity and emotional expression and creatively integrate the experience, craftsmanship and emotion contained in the tacit knowledge in handicrafts, so as to interpret the connotation and characteristics of intangible cultural heritage.

Therefore, a collaborative design mode combining designers with artificial intelligence is established to promote the sustainable development of wickerwork handicraft, thus rejuvenating the Funan wickerwork handicraft. In this paper, we apply digital technology to explore the creative design and sustainable development of traditional crafts. The main significance of this paper is in building a new design path in which artificial intelligence and designers work together in harmony and promote each other. By applying AI technology to provide designers with enough rich design stimuli and constructive opinions and inspiration, and by designers to devoting themselves more to creative design activities, this path can produce design solutions and create design values faster and better. Specifically, due to its powerful self-learning ability, DCNN can independently learn the expression of image features from a massive amount of data to realize automatic semantic cognition and creative design, which effectively overcomes the shortcomings the of time-consuming, labor-intensive and more cumbersome design process caused by the traditional manual method of extracting design features, so as to realize the personalized creative design of pictures in an autonomous and innovative way. Furthermore, the computer takes the initiative to provide the designer with constructive creative design solutions, and the designer completes the improvement and creative design on this basis, thus providing new ideas and methods for the study of the sustainable development of nonheritage-based cultural wickerwork. Based on this, this framework further improves design efficiency and achieves the purpose of quickly generating innovative wickerwork pattern designs, realized by the digital survival and sustainable development of wickerwork handicraft culture. The main contributions of this study can be considered as follows:

Firstly, the wickerwork pattern emotional image recognition model is established by using the ResNet model based on DCNN. With this model, the identification and evaluation of massive wickerwork pattern samples can be completed quickly, and the recognition of wickerwork patterns can be completed automatically, which can save labor and time and maximize design efficiency.

Secondly, the wickerwork pattern creative design scheme generation model is constructed based on a big dataset and deep convolutional generative adversarial networks (DCGANs) so as to innovate the pattern design scheme by learning the data distribution characteristics of traditional wickerwork pattern samples, which effectively reduces the number of research steps and improves the diversity and innovation of the design scheme.

Finally, the designers involved complete the innovative design and development of the wickerwork patterns. The designer takes the creative wickerwork pattern sample as the inspiration to develop creative wickerwork pattern designs, so as to produce an innovative wickerwork pattern design scheme that realizes the digital sustainable development of wickerwork culture.

To sum up, this proposed method can creatively generate wickerwork design schemes in accordance with the user's emotional images, improve the innovation and diversity of wickerwork design schemes, effectively provide new ideas for the design optimization of wickerwork patterns and textures. In addition, a short comparison is provided in Table 1 to explain the differences between the research in this paper and the previous studies.

Table 1. A brief comparison between this study and the previous study.

References	Kansei Evaluation	Functional Characteristics	Design Innovation	Product Configuration
This paper	ResNet		Designers design	DCGAN
Wang [27]	KE	RST		CA, GRA
Wang [28]	KE	RST	TRIZ	FCRP
Wang and Zhou [12]	Kano			IGA
Hsiao et al. [29]	AHP			QT-I, GA,
Wang [19]	NLP, GRA			Fuzzy TOPSIS
Wang and Zhou [14]	CFKM	RST		FWARM
Gan et al. [30]				DCGAN
Ji et al. [31]	Kano			QFD
Su et al. [32]	CNN			
Quan et al. [33]	FA			NST

QFD: quality function deployment, CA: conjoint analysis, FA: factor analysis, KE: Kansei engineering, EGM: evaluation grid method, NLP: natural language processing, NN: neural network, RST: rough set theory, FWARM: fuzzy weight association rule mining, GA: genetic algorithm, TRIZ: the theory of inventive problem solving, MLR: multiple linear regression, AHP: analytic hierarchy process, NST: neural style transfer.

2. Review

2.1. Sustainable Development of Wickerwork Based on Digital Technology

As a sport on the fingers, weaving is one of the oldest handicrafts in human history [34]. The time-honored Funan style of wickerwork is an artistic accumulation of work, and it conveys people's pursuit of a beautiful life. Through the close combination of modern design methods and traditional handicraft, it can effectively promote its dynamic and sustainable evolution and development. With the rapid development of computer technology in recent years, the research on innovative design based on modern design and the integration of digital technology is conducive to accelerating the transformation from traditional wickerwork to digital wickerwork, and realizing the sustainable and rapid development of wickerwork craftsmanship, for example, developing a three-dimensional simulation system for wickerwork handicrafts and adopting parametric methods to digitize the texture of wickerwork. Such digital technology not only activates the endangered artform and preserves its "authentic" spiritual culture, but also injects the vitality of the new era into a solidified artform, innovates the expression's forms, and shapes multiple characteristics of intangible traditional cultural heritage. As a result, digital technology has stimulated the vitality potential of an intangible cultural heritage to elevate it to an activated state, while also greatly enhancing the plasticity of said intangible cultural heritage.

Therefore, digital technology is used to transform information from wickerwork patterns into measurable digital models, and for the recognition and innovation of weaving patterns and textures to design more innovative wickerwork patterns. Some scholars carried out research and had a discussion in reference [35] about the application of 3D scanning, 3D modeling, motion capture and other technologies in the reconstruction and digital protection of virtual, intangible cultural heritage activities. You Lisi et al. [36] used digital technology to carry out parametric researches on bamboo weaving techniques, and put forward new ideas for bamboo weaving product design under digitalization. Yu Rengui et al. [37] studied and developed the wickerwork handicraft 3D simulation system to enable designers to quickly and conveniently produce various design schemes, which is helpful for wickerwork product innovation design research. However, the disadvantages are, on one hand, a large number of mathematical calculations in this system may discourage product designers; on the other hand, relating to the author's profession, these studies are only the application of computer technology, which is not as free and flexible as manual weaving.

In fact, due to the progress of modern wickerwork techniques and tools, new wickerwork patterns have emerged, and different knitting techniques are integrated and innovated to show a complex and completely different texture. With the participation of digital technology, the main values of innovation and development of traditional wickerwork are as follows: 1. the texture of traditional wickerwork is transformed into parametric methods to realize the reproduction and reconstruction, and put forward new method guidelines for the innovative development of wickerwork techniques; 2. digitalization and the parametric method are combined to effectively promote the digital inheritance of traditional wickerwork to realize sustainable development; 3. massive results can be quickly generated based on digital technology, thereby saving time and cost and improving design efficiency.

2.2. Deep Learning

Deep learning forms more abstract high-level representations (attribute classes or characteristics) by combining low-level characteristics to discover distributed characteristic representations of data [38]. The essence of deep learning is a multilayer perceptron (MLP) with multiple hidden layers, which is an artificial neural network with deeper levels used to simulate the biological nervous system to make computers highly intelligent. The deep learning model realizes complex function approximation by learning a deep nonlinear network structure, characterizes the distributed representation of input data, and shows a strong ability to learn the essential characteristics of datasets from a small number of sample sets.

In recent years, various deep learning models have been proposed. In 1980, Fukushima [39] first proposed a theoretical model based on receptive field, neocognitron, which is a self-organizing multilayer neural network model. LeCun et al. [24] proposed a backpropagation algorithm based on gradient to train convolutional neural network model LeNet-5. When the convolution kernel in the convolutional layer completes the function of receptive field, the local area information of lower level can be excited to a higher level through the convolution kernel. Since 2010, more deep learning models have emerged. For example, Krizhevsky et al. [40] introduced the AlexNet model based on LeNet-5. Subsequently, the VGGNet [41] with a depth of 16 to 19 layers was presented. Then, in 2014, the Google team proposed an improved the convolutional neural network model, the GoogLeNet model [42]. The core idea is to optimize the performance of the convolutional neural network model by increasing the depth and width of the network model, and two loss functions are added to avoid gradient diffusion [43]. He et al. [44] from Microsoft proposed a residual learning network. This ResNet can form a very deep network after stacking, and the problem of gradient explosion and gradient disappearance caused by the deepening of the network is effectively solved based on the residual mapping function of the network. At the same time, it also simplifies the learning objective and reduces learning difficulty.

With the continuous integration with some traditional algorithms, and the introduction of migration learning methods, the application field of convolutional neural networks is expanding rapidly. In the field of product design, Ding et al. [26] described a method for product color emotional design based on DCNNs and search neural networks. Wu and Zhang [45] use deep learning for innovative design of umbrellas. With the development of deep learning, researchers applied deep learning for the automatic generation of artistic style images [46], but in the field of pattern and innovative design of traditional intangible cultural heritages, there are few studies on product image recognition and classification based on a DCNN. In light of the strong self-learning feature extraction and content recognition capability, DCNN is suitable for the evaluation and judgment of the pattern and image recognition of intangible cultural heritages.

2.3. GAN

A generative adversarial network (GAN) is a generation network model for learning data distribution through confrontation mechanism. Goodfellow et al. [47] presented a GAN model that essentially trains two networks, a generative network and a discriminator network. The generator is designed to deceive the discriminator by generating an image that is indistinguishable from the real one. The discriminator attempts to categorize the "true" and "false" images. The generator and discriminator are trained jointly by solving the following minimum and maximum values. Generator model G can improve its ability to generate real samples by discriminating between true and false through discriminator D, and discriminator D can improve its ability to judge the authenticity of generated samples through continuous learning of real samples, and the two networks can continuously improve their respective performance through mutual gaming. When the generating model and the discriminating model cannot improve themselves, the generating model becomes a comparatively perfect model [48]. The emergence of the GAN provides new technology and means for computer vision applications and provides a powerful algorithm framework for creating an unsupervised learning model. It subverts the traditional AI algorithm and does not use human thinking to limit the machine. Through its own continuous countermeasure game and sufficient data training, it can learn the inherent laws of the real world.

Subsequently, various derivative models based on GAN have been proposed, such as multiscale gradients for generative adversarial networks (MSG-GAN) [49], conditional generative adversarial networks [50], deep convolutional generative adversarial networks (DCGAN) [51] and so on. These studies have all made substantial improvements to model generation results, where the DCGAN could significantly improve the stability of GAN and the quality of the generated results. The DCGAN is the effective combination of CNN and the original GAN, and it performs well in the field of computer vision and sets a series of restrictions for the network topology of CNN, so that it can train stably. By using the learned feature representations for image classification, obtaining good results in verifying the model's feature expression ability, the DCGAN achieves very good results in engineering and design applications [52].

Several scholars have improved the performance of DCGANs, and have used a unified generation and discriminative network. To handle the small amount problem of data in person re-identification (re-ID), Zheng et al. [53] proposed unclassed labeled samples generated by the DCGAN. A DCGAN is used to solve the problem of low data volume in re-ID. Meanwhile, regarding how the labels of the generated fake images are defined, the authors proposed the method of label smoothing; the generated fake image labels are defined between (0,1), and thus the labels are assigned. The method consists of two parts: an adversarial model for unsupervised learning and a convolutional neural network for semi-supervised learning. The main significance of this method is that it can be supplemented with GAN when there is not enough data. Ashish Shrivastava et al. [54] proposed the simulated and unsupervised learning approach. Specifically, the realism of the simulator-generated images is improved by using real images without labels, while keeping the annotation information of the original synthetic images unchanged. The structure of the entire network is designed using a network with unsupervised data to discriminate whether it is a generated image or not. Moreover, the authors also devised a mechanism to divide the image into different patches. Zheng et al. [55] proposed a joint learning framework that consists of a generation module that could encode each person as an appearance and structure code, respectively. The generation module could generate high-quality cross-id synthetic images by switching between the appearance code or the structure code. This algorithm is argued to have better performance by exploiting the variation of poses within the existing dataset as well as other diversity beyond the poses to produce more diverse results.

To review these studies, using GANs and a DCGAN for design has two advantages. Firstly, they can generate diversified design images in a short period of time, saving development time and lowering costs. Second, GANs and DCGAN can create innovative designs to meet customers' needs. Based on the above analysis, this paper puts forward an emotion design method based on DCGAN training, and innovatively applies it to the innovative sustainable design process of Funan wickerwork handicraft. The DCGAN generates creative image samples when dealing with a large amount of image information, and it learns favorable real-time features from many unannotated images, so as to generate a new wickerwork pattern design solutions.

2.4. Research Gap

Reviewing the previous literature, we have identified the following gaps. First, the existing literature shows that some scholars have explored the digital development of wickerwork techniques from the perspective of 3D simulation system development and parametric design, while other scholars have paid attention to the sustainable development of traditional cultural craftsmanship [51] and discussed the relationship between traditional cultural elements and customer satisfaction. However, they mainly focus on the traditional quantitative methods [52], including expert interviews and traditional questionnaires [18]. As the users' perceptions and evaluations are subjective, the evaluation results have a certain degree of errors, these previous research methods leave gaps in the direction of design accuracy and automation. Thus, in this study, in order to fill this gaps, the DCNN and DCGAN models are introduced into the innovative design of wickerwork patterns, and the automatic recognition and classification of images is carried out by imitating human emotional cognitions, which not only helps to accurately and efficiently identify the real wickerwork pattern schemes in large datasets, but also ensures that the diversified design schemes are generated in a timely and effective manner. Obviously, the previous literature shows that this method combination has never been applied to the creative design of wickerwork patterns. Therefore, it is crucial to comprehensively address these barriers and gaps based on the human–machine collaborative innovation method proposed in this paper by providing inspiration to designers through computer generated creative design solutions, and designers implementing creative designs to produce valuable design solutions in a more efficient manner, thus realizing the sustainable development of the wickerwork handicraft in the digital era.

3. Method

This study constructed a digital design method for the sustainable development of wickerwork patterns, and the specific technical steps and flow are shown in Figure 1. The purpose of this study is to develop a smart recognition and design method for wickerwork images. Firstly, it was necessary to establish a Funan wickerwork pattern database, build a wickerwork pattern image cognition model based on ResNet-34 and use this model to automatically filter traditional wickerwork patterns from the large wickerwork pattern database, so as to obtain massive wickerwork pattern image datasets. Secondly, the traditional Funan wickerwork pattern database was used as an input for network training of the generator model of the DCGAN. Through learning the sample probability distribution mapping relation of traditional wickerwork patterns, DCGAN intelligently generated new wickerwork patterns, and finally provided rich inspiration for designers. Finally, designers took the generated wickerwork patterns as a new design inspiration, expressed the creativity on the generated image with ideas and experience, and completed the creative wickerwork design pattern to the trend. Moreover, this proposed method generates new wickerwork patterns and provides digital design services, thereby promoting the sustainable development of the wickerwork handicraft.

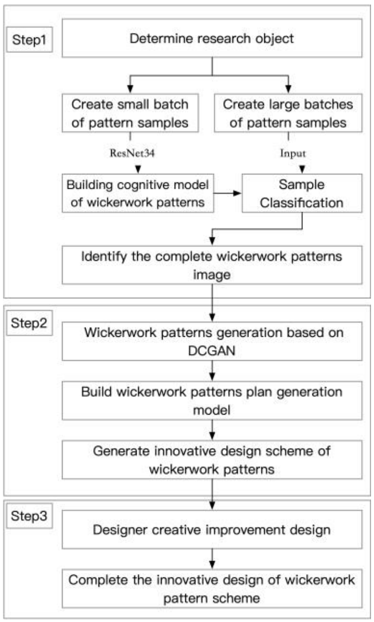

Figure 1. The design process of wickerwork patterns based on deep learning.

3.1. Establishment of Pattern Image Recognition Model of Wickerwork Patterns Based on ResNet

The image recognition on wickerwork patterns is constructed based on the deep convolutional neural network of ResNet, and the technical route is shown in Figure 2.

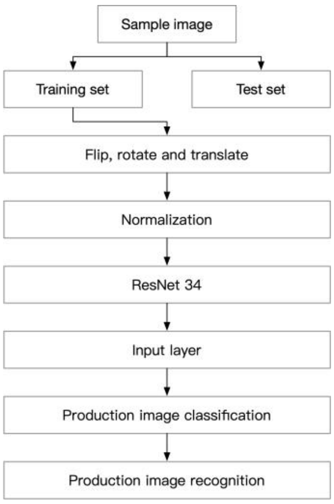

Figure 2. Wickerwork pattern image recognition based on ResNet34.

3.1.1. Constructing Wickerwork Pattern Dataset

This study established a wickerwork pattern database by collecting 9673 samples of traditional Funan wickerwork patterns and modern design patterns using thorough online data collection and field research. Each sample in the pattern dataset was different in size. Sample processing must ensure that the size and resolution of each sample picture are completely consistent, so as to construct the Funan wickerwork pattern database. As all samples cannot be displayed, some samples were selected from the dataset, as shown in Figure 3 below.

Figure 3. Some sample of wickerwork pattern and modern design patterns.

In general, DCNNs require input sample data of equal length and width, so the sample image was scaled to 224 × 224 by bilinear interpolation. In order to reduce the risk of overfitting in DCNN training, data augmentation is used to expand sample diversity, and traditional flipping, rotation and operations are utilized to expand the diversity of the dataset; thereby, the generalization ability of DCNN is enhanced.

3.1.2. Product Image Recognition Establishment with ResNet

ResNet (deep residual network): its core is to solve the problem of the decreasing accuracy rate after network deepening. Regarding improvement of the performance of the convolutional neural network, when the network depth is continuously increased, it is found that with the increase in the network's depth, a gradient descent of the network occurs. The gradient descent and explosion problems in the deep network are serious. In this case, in order to solve this problem, He et al. [44] proposed ResNet, which further deepens the network and improves the performance of image classification tasks.

ResNet consists of stacked residual blocks. In addition to the weight layer, the residual block also directly connects the input x to the output through a cross-layer connection. F(x) is the residual map, H(x) is the original map, and the residual network makes the stacked weight layer fit the residual map F(x) instead of the original map H(x), then F(x) = H(x) − x. The residual map is simpler than learning the original map. In addition, the cross-layer connection enables the characteristics of different layers to be transferred to each other, which alleviates the problem of gradient disappearance to a certain extent.

The ResNet has achieved great success in image classification tasks by stacking residual blocks to make the network depth reach 152 layers. In this paper, ResNet34 is used for fine-tuning training of wickerwork pattern recognition. The network structure is shown in Figure 4.

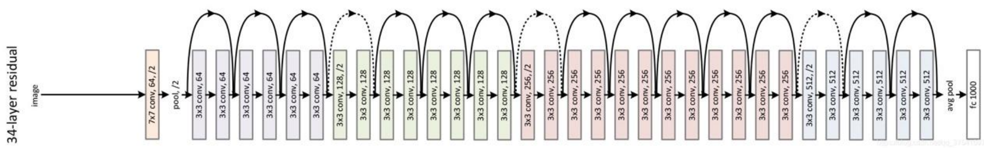

Figure 4. The overall structure of ResNet34 network model.

The network structure is shown in Figure 4. The ResNet34 contains 33 convolutional layers and 1 fully connected layer that can consist of 5 stages and a fully connected classification layer, and the network input is the sample image of the wicker pattern. After the image input of the convolution layer, the features of the sample are extracted. Stage 1 is the convolutional block of the common CONV + BN + ReLU + MAXPOOL, and stages 2 to 5 are residual convolutional blocks. There is a ReLU activation function behind each convolutional layer, which is a piecewise linear function that has the advantages of being simple and less costly to calculate. Its formula is as follows:

$$f(x) = \max(0, x) \tag{1}$$

The output formula of the neuron is as follows:

$$h_{i,j} = ReLU\left(\sum_{k=1}^{n} W_{i-1,k} X_{i-1,k} + b_{i-1}\right) \tag{2}$$

where $W_{i-1,k}$ represents the weight k in the $i-1$ layer and b_{i-1} represents the bias of the i-1th layer. Next, it is necessary to further calculate the cross-entropy loss function of a single sample:

$$L = -[y \log \hat{y} + (1-y)\log(1-\hat{y})] \tag{3}$$

The training process of the entire network is the process of finding the minimum parameter of the loss function. Then, the loss function (L) is calculated by forward propagation. Then, use the stochastic gradient descent algorithm of backpropagation to calculate the loss function derivative of each layer weight.

3.1.3. Algorithm Parameter Settings

In view of ResNet34, the training model used the Adam optimizer, setting the maximum learning rate to 0.0001 and the batch size to 512, and training for 100 epochs. Finally, the best parameters of the 100 epochs were retained. Then, ResNet34 was used to build a pattern image recognition model to identify the remaining pattern samples in the sample library [56], so as to quickly obtain the wickerwork pattern image dataset.

3.2. Generating Wickerwork Pattern Design Image Based on DCGAN

The DCGAN was used to build a creative design solution generation model to innovatively generate creative design solutions for Funan wickerwork pattern. The goal of this model is to generate the emotional design plan, thereby reducing the number of research steps while enhancing the innovation and diversity of design solutions. The structure of the wicker pattern generation design model is shown in Figure 5.

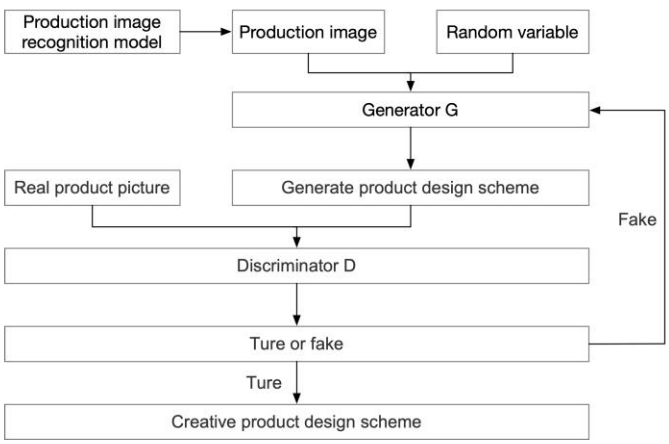

Figure 5. The overall structure of DCGAN.

Structure of DCGAN Model

The structure of the DCGAN consists of two parts: a generative model and a discriminative model. The input of the generative model consists of a random variable and a classical wickerwork pattern, and the output is a real classical wickerwork pattern design based on automated generation. For the discriminant model, the input is the generated design picture and a real picture, and the output is a probability value to determine whether the generated picture is "real" or not. This model training process is actually a gaming process, and the ability of *G* and *D* could gradually improve during the training process. In fact, previous practice has proven that DCGAN has certain stability. Thus, the design plan was generated, which is completely automatic and does not require any human intervention process. Specifically, the generative model structure is shown in Figure 6.

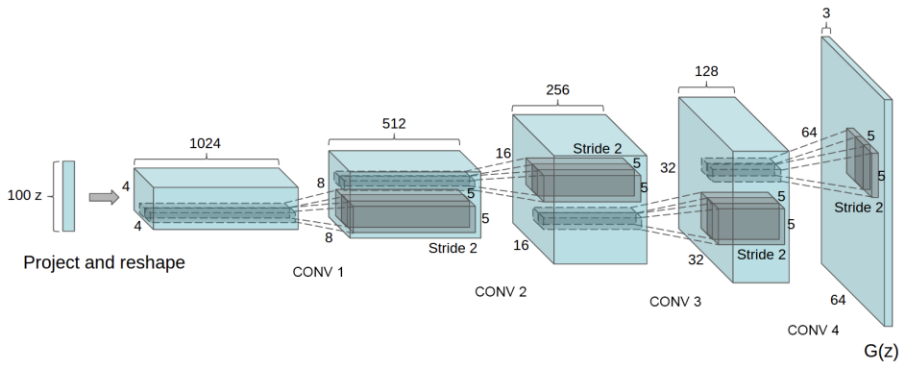

Figure 6. Overall structure of DCGAN generator [51].

The output sizes of the deconvolution layers of conv1, conv2, conv3, and conv4 are $8 \times 8 \times 512$, $16 \times 16 \times 256$, $32 \times 32 \times 128$, and $64 \times 64 \times 3$, respectively. The output of the deconvolution layer conv4 is the output of the generative model. This layer can obtain the generated pattern of the wickerwork pattern design scheme. The final output is the probability of whether the image is real or not.

The structure of the discriminator model is shown in Figure 7. From the perspective of the discriminator *D*, it hopes that it can distinguish real samples and fake samples as much as possible, so it hopes that $D(x)$ is as large as possible, and $D(G(z))$ is as small as possible, that is, $V(D,G)$ is as large as possible. From the perspective of the generator *G*, it hopes to deceive *D* as much as possible, that is, it hopes that $D(G(z))$ is as large as possible so that the $V(D,G)$ is as small as possible. Therefore, two models confront each other and finally reach the global optimum. Its mathematical objective function formula is as follows:

$$\min_G \max_D V(D,G) = E_{x\sim p_{\text{data}}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1 - D(G(z)))] \tag{4}$$

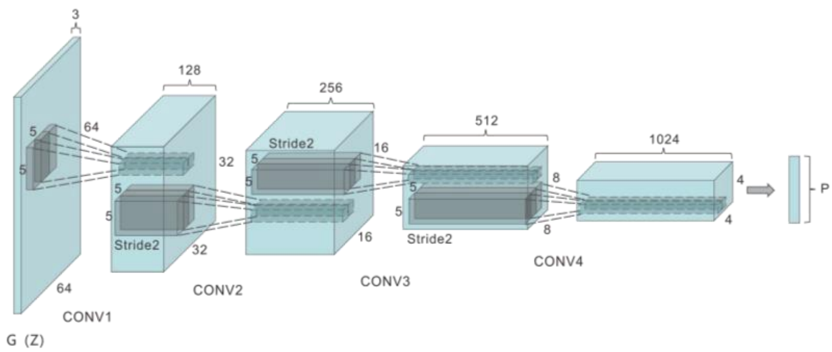

Figure 7. Overall structure of DCGAN discrimination [51].

The DCGAN loss function could be expressed as follows:

$$G(X) = -\frac{1}{N}\sum_{i=1}^{N} y_n \log p(x_n), \tag{5}$$

$$\begin{aligned} D(X) &= -\tfrac{1}{N}\sum_{i=1}^{N}[y_n \log p(x_n) + (1-y_n)\log(1-p(x_n))] \\ &= -\tfrac{1}{N}\sum_{i=1}^{N}[\log p(x_n) + \log(1-p(x_n))], \end{aligned} \tag{6}$$

where X is all the samples inside a batch, $x_n \in X$; N is the number of samples inside the batch size; $p(x_n)$ is the probability that the n sample is true; y_n is the label of the n sample.

The entire model was optimized using the stochastic gradient descent algorithm. The model batch size was set to 32, and the learning rate α was 0.0002. A round of experiments requires 1200 iterations to complete. The entire training process was completed on the Python and pytorch platforms. During the training process, the generator and the discriminator were updated alternately. For each iteration, we first fed real samples into the discriminator to train and enable the discriminator to judge whether a certain sample was generated or real. After 1200 iterations of training, the model gradually narrowed the gap of the model's predicted measurement value between real images and generated images, for which the performance of the generator tended to be stable. Finally, the DCGAN-based wicker pattern design scheme generation model was obtained.

4. Results

4.1. Experimental Results of Wickerwork Image Recognition Model

To construct an image dataset related to wickerwork, patterns are the first and most important step in the cognitive model training process. In this experiment, we collected 9673 wicker pattern and modern pattern images from books and websites. We asked 39 participants to choose images of patterns that brought them pleasure and comfort, and whose attributes such as texture, pattern or color could increase participants' aesthetic attention. Finally, 6790 wickerwork patterns samples with rich feature changes were selected to build a large dataset, and then 1561 wickerwork patterns and modern patterns from the large database could be selected randomly to build a small dataset, and training on traditional wickerwork patterns through ResNet34, the image recognition models could then be obtained and product images classified. The ResNet structure was implemented by calling the Pytorch environment, and the model was trained using a small-volume wicker pattern image dataset. The pattern image sample was input in .jpg image format, and the input size was 224 px $\times$ 224 px. The number of epochs was set to 100 and the base learning rate α was set to 0.001; the accuracy curve and the loss curve of experimental results is shown in Figures 8 and 9. Obviously, we can see that as the training time deepens, the network converges more and more, and the loss values of the training set and test set get closer to 0, and basically the convergence completes in the 40th epoch. ResNet34 has the best recognition rate of 94.36% for the entire dataset of wicker pattern design images. The recognition rate of modern patterns is 95.92%, while that of traditional wicker patterns is 93.45%. The experimental results show that the ResNet34 model has strong effectiveness in image recognition tasks for classic wickerwork patterns and modern patterns.

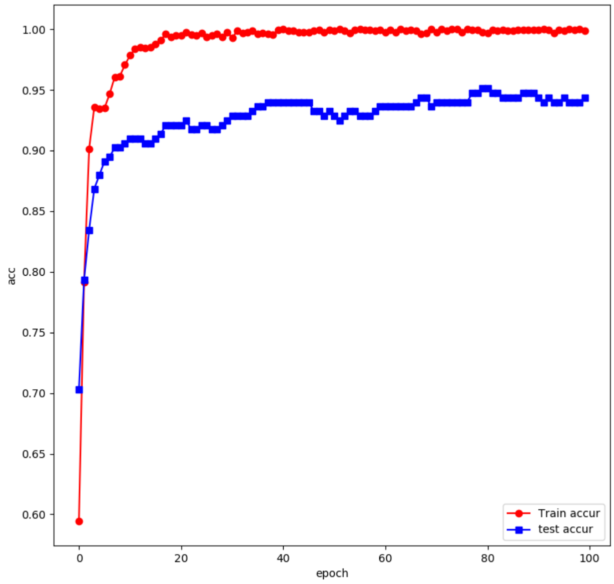

Figure 8. The accuracy curves.

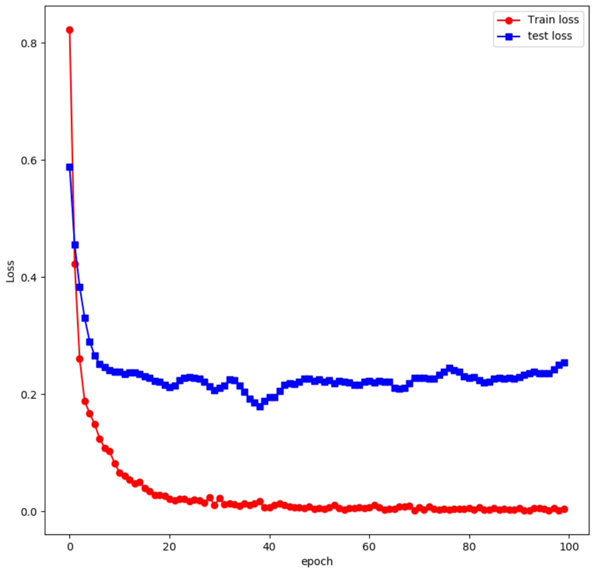

Figure 9. The loss curves.

4.2. Identification the Wickerwork Image for Large Batches Samples

In order to generate a pattern design scheme with high clarity and accuracy, the construction of the wickerwork pattern design generative model needs to be supported by sufficient samples, so the small-volume wicker dataset established only through manual classification is not enough to meet the requirements of model building. Therefore, under the goal of saving labor costs and time costs, the pattern evaluation model built by ResNet was used to classify the remaining 5229 pattern samples of the sample database so as to quickly obtain 1907 real wickerwork patterns images from the large-scale pattern image dataset, and the partial results are shown in Figure 10.

Figure 10. Funan wickerwork pattern dataset (partial).

4.3. Integrating Wickerwork Patterns

The large-volume image dataset containing 1907 pattern design samples and the small-batch wicker pattern image dataset containing 912 samples were summarized, and finally, the dataset containing 2819 wicker pattern image datasets were obtained for the subsequent pattern design scheme generation model training.

4.4. Analysis of the Design Result

The experimental conditions were the python3.10+pytorch1.12 platform, the feature categories were adjusted, and the program was run. After 1200 rounds of iterative training, the pattern generation model output 512 final pattern design schemes, the partial result is as shown in Figure 11. The output result of the model is the overall image of the wicker weave pattern. Compared with the traditional method, which only outputs the numerical information of the design parameters, the overall pattern performance can be felt more directly and quickly so as to improve the work efficiency of designers.

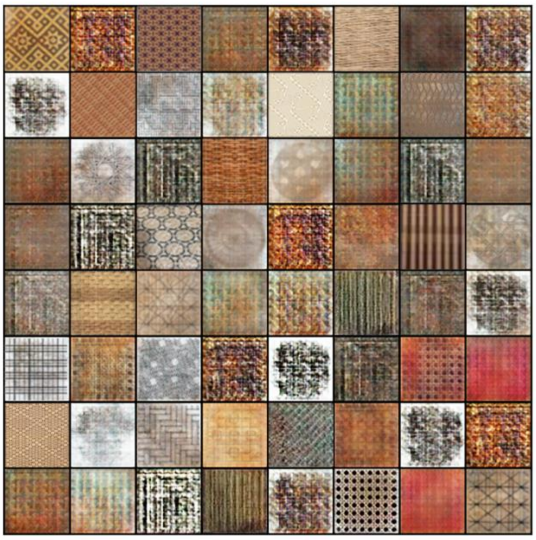

Figure 11. Generator model wickerwork pattern design scheme output.

After 1200 iterations, the DCGAN model finally converged. It produced some shallow classic wickerwork patterns, and it can be seen that these generated classic wickerwork patterns are similar to real ones. The contours and patterns of the elements are relatively clear on the whole and conform to the characteristics of traditional wickerwork weaving cultural elements. It not only integrates element innovation, but also can see the style of Funan wickerwork weaving's traditional cultural elements. However, compared with the real and traditional wicker pattern design, the definition of the generated image is relatively low, and the quality of the picture needs to be further improved. The reasons may be as follows: (1) The traditional wickerwork pattern is more complicated, it usually has a variety of pattern textures, but due to technical instability, DCGAN can only learn and make blurred images, so it could not present the specific details of the patterns. (2) The size of the network can only generate a rough image of 64×64, so we cannot see more details. Fortunately, the lack of design details provides designers with free space and imagination through the presentation of blurred pictures.

In order to judge the effectiveness of this DCGAN model, as well as screen and eliminate low-quality pattern pictures that do not meet the requirements, 16 creative wicker design schemes were selected from Figure 11, as shown in Figure 12.

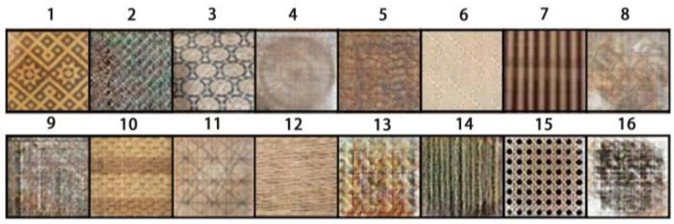

Figure 12. Sixteen selected creative wicker design schemes.

By using the semantic difference method to conduct the questionnaire survey on user perception, 292 subjects were invited to evaluate and verify the wickerwork pattern generation scheme. It can be seen from Table 2 that the quantitative characteristics of demographic variables can reflect the distribution of respondents in this survey. From the results of the frequency analysis of the sex and age of the respondents, it can be seen that the distribution basically meets the needs of the survey. Among them, in the gender survey results, men accounted for 46.23%, women accounted for 53.77%; in the age survey, the effect can be observed mainly in the 18–22 age group, a total of 182 people, accounting for 62.33%, followed by the 23–38 age group, a total of 110 people, accounting for 37.67%; the group with three years of design experience accounted for 10.27%, the group with five years of design experience accounted for 6.85%, and the group with three years or less of design experience accounted for 82.88%. The current questionnaire survey mainly focuses on the evaluation of Chinese urban youth groups.

Table 2. The basic information about questionnaire survey.

Basic Information of Subjects			
Project Name	**Content**	**Frequency**	**Percentage(%)**
Gender	Male	135	46.23
	Female	157	53.77
Age group	18–22 years old	182	62.33
	23–38 years old	110	37.67
Design experience	Three years	30	10.27
	Five years	20	6.85
	Three years and below	242	82.88
Education level	Undergraduate	188	64.38
	Master and above	104	35.62

Cronbach's Alpha is a reliability test performed in SPSS to measure the interior consistency and reliability of questionnaires. According to the Cronbach's *a* reliability analysis results, the reliability value was at one point 0.835, thus indicating that the research results indicate a very satisfactory reliability of this study [57]. The results of this experiment are shown in Table 3. The average score of this obtained classic wickerwork pattern is

3.12, and the highest score is 3.93, which fully verifies the validity of the model proposed by this research. It can be seen that the pattern generation model based on DCGAN can innovatively generate pattern design schemes, and the generation schemes can effectively stimulate the emotional needs of users while ensuring diversity. Therefore, this result could show that the method proposed in this study can effectively improve the accuracy and reliability of the emotional design of wickerwork patterns and realize the sustainable development of innovation for wickerwork handicraft.

Table 3. The evaluation values of the design scheme.

No.	1	2	3	4	5	6	7	8
Average Value	3.73	2.09	3.32	3.22	2.13	3.11	2.89	3.93
Number	9	10	11	12	13	14	15	16
Average Value	2.12	3.54	3.72	3.12	3.43	3.24	3.89	1.76

4.5. Design Innovation of Wickerwork Pattern

Judging from the new image generated by DCGAN, the generated image was clear in shape, but the pixels were still blurred. Hence, it was necessary to carry out the design with a designer's social awareness and modern aesthetic experience. In order to achieve this goal, we invited six professional designers and three graduate students to refine the creative design. Then, starting from the generated pattern results, the wickerwork pattern was innovatively designed.

4.5.1. Detailed Design for Wickerwork Pattern

When designers participated in the wickerwork weaving design process, each designer first randomly selected an image as a prototype, and then designed under the following guidance: the main features of the selected image should be preserved, and interesting shape design, pattern design or pleasant color design must be used as design examples. Designers used PS/AI design software for visual drawing and design work. In the end, eight wickerwork patterns with a clear appearance were created, as shown in Figure 13. In this in-depth detailed design process, the designers combined their subjective judgments and effectively guided the design based on aesthetics and emotion; this process is considered a human computer interaction design process [30]. Specifically, the DCGAN model was used to generate the creative wickerwork prototype, and the designer was responsible for visualizing the detailed design for an overall final design that will appeal to the client. Based on DCGAN feature extraction of wickerwork samples, it could inherit the general aesthetic and preference qualities of wickerwork samples and generate some initial innovative images. This image generation process can be regarded as the basis for subsequent designer creations, designers extend their innovations through in-depth creative thinking. Thence, this collaborative design method, integrating computer intelligence and human intelligence, reduces the risk of uncertainty and improves the efficiency of emotional design.

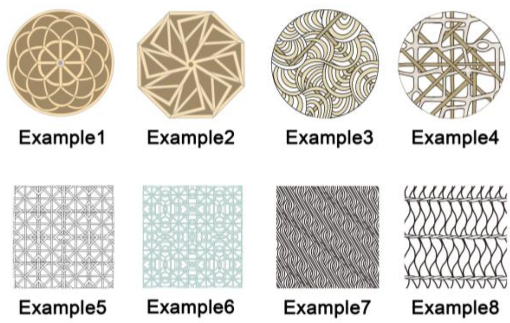

Figure 13. Eight wicker pattern designs based on designers.

4.5.2. Aesthetic Evaluation and Verification for New Designs Plan

In this section, we tested the customers' perception of aesthetics and preferences for eight new wickerwork pattern designs based on the shape, color and texture of the proposal. The study was conducted in the means of questionnaire, and a total of 151 participants, 57 men and 94 women answered questionnaires online and offline between 13 September and 28 October 2022. The Cronbach's alpha was 0.890, indicating that the questionnaire has high credibility.

The final score of the statistics is shown in Figure 14. Wickerwork pattern No. 3 scored the highest, followed by wickerwork pattern No. 4, wickerwork pattern No. 2 and wickerwork pattern No. 5. We compared the eight new wickerwork pattern designs with the eight wickerwork patterns with the highest scores in Table 3, and the results are shown in Figure 15. The red part represents the top eight scoring schemes in the generated wickerwork pattern designs, and the blue part represents eight newly designed wickerwork design patterns. It can be seen that six of the wickerwork pattern schemes have higher scores than the original wickerwork pattern schemes generated by DCGAN. Thence, this result shows that the proposed design method of combining DCGAN training and professional design can create beautiful and stylish wickerwork pattern design schemes, which indicates that the mode of combining AI and human cognition can effectively reduce the complexity and ambiguity in the design process.

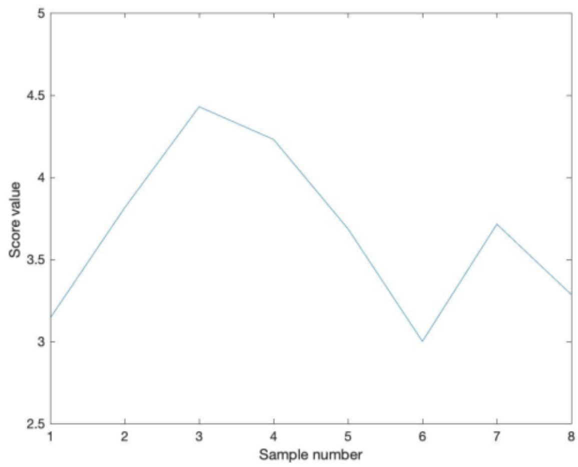

Figure 14. Aesthetic evaluation ranking.

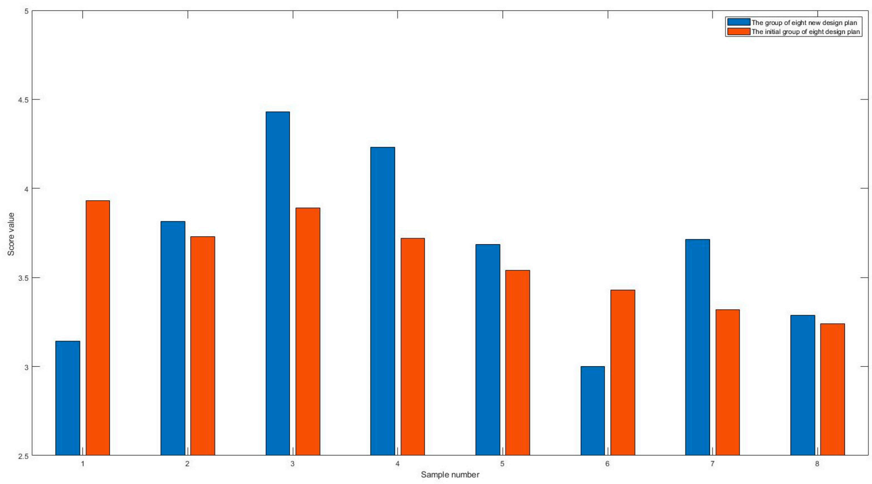

Figure 15. Aesthetic comparison between the initial design and new design.

Through the aesthetic evaluation of scenarios by 151 participants, the analysis revealed that design scenarios 1 and 6 were rated lower than the original computer-generated design. In fact, there are individual differences in designers' knowledge base and experience, and different designers come up with different design solutions based on the design task. At the same time, designers incorporate their own inspiration, thinking and creativity into the design's process and results, and the resulting design solutions are somewhat subjective and cannot ensure that all designs are successful. Therefore, based on the experimental results, most of the design solutions can be successful, but it was found that the scores of solutions 1 and 6 were low, these two designs were still defective in terms of structure and form so need further improvement.

5. Discussion

5.1. Efficiency of DCNN in Creative Design for Traditional Handicraft

5.1.1. Comparative Analysis

In order to verify the superiority of ResNet for wickerwork image recognition, the same dataset was used for experiments in VGGNet and CaffeNet. The VGGNet16, which contains 16 layers with weights, including 13 convolutional layers and 3 fully connected layers. This model was used to train the wickerwork images. The initial learning rate of FC3 was set to 0.001, and the learning rate was divided by 10 for every 100 iterations. The Caffe was used to complete the whole training process, and the training was carried out on the wickerwork image dataset. Furthermore, Table 4 shows the final recognition accuracy of VGGNet16 and ResNet.

Table 4. Accuracy results of wickerwork pattern classification based on VGGNet.

Pattern Category	Recognition Accuracy %	
	VGGNet	**ResNet**
Whole pattern image	88.72	94.36
Traditional wickerwork patterns	87.76	93.45
Modern patterns	89.29	95.92

Then, the same dataset was applied to CaffeNet, which is a DCNN with eight weighted layers, including five convolutional layers and three fully connected layers. In order to compare with the experimental results of ResNet, the parameters of CaffeNet are designed in the same way as VGGNet, and the data are preprocessed in the same way. Finally, the accuracy of the experimental results of CaffeNet were obtained, as shown in Table 5.

Table 5. Accuracy results of wickerwork pattern classification based on CaffeNet.

Pattern Category	Recognition Accuracy %	
	CaffeNet	**ResNet**
Whole pattern image	84.59	94.36
Traditional wickerwork patterns	81.63	93.45
Modern patterns	86.31	95.92

Based on Tables 4 and 5, it can be seen that ResNet has a significant advantage over VGGNet and CaffeNet in the recognition rate of wickerwork pattern imagery. Obviously, it can also be seen that ResNet achieves a higher recognition accuracy of 94.36, which significantly validates the usability and superiority of this adopted model.

5.1.2. Efficiency of DCNN

The DCNN is one of the high-performance deep learning models for various image processing tasks, which can realize supervised learning and unsupervised learning. Current DCNN has entered a boom period because they are able to automatically extract features with multiple levels of abstraction from a large number of images. The sharing of internal convolution kernel parameters in the hidden layer and the sparsity of interlayer connections enable DCNN to produce stable effects on grid-like topological features with a small amount of calculation. In this study, we used ResNet to establish a correlation model between patterns and users' emotional cognition and realized the automatic recognition of wicker patterns under the imitation of human cognitive characteristics, which has the advantages of automation and systematization. Compared with traditional neural networks, the DCNN has better pattern classification ability. In addition, the traditional classification methods of pattern appearance rely on a series of questionnaires consisting of product image and perceptual attributes, which obtain high-quality results but have the disadvantages of small data size and one-time use, which undoubtedly consume a lot of time and money. Fortunately, DCNN can be quickly and easily applied to creative design based on its powerful deep learning capabilities, thereby improving research and development efficiency. This model has positive significance for the sustainable development of traditional handicrafts such as paper-cutting, wickerwork and embroidery.

5.2. Advantages of DCGAN in Pattern and Product Design

In the process of pattern creative design, the traditional design process and methods are relatively cumbersome. Whether it is Stanford's creative design thinking or user-driven design method [31,58,59], they can easily deviate from design practice during the implementation process. In contrast, in the process of generative design, DCGAN quantitatively evaluates the features extracted from the sample image through unsupervised learning and retains some implicit features of the sample data in the process of image generation. The middle stage of DCGAN training is to inherit the intangible aesthetic and emotional qualities of wicker cultural heritage samples through image generation based on the unsupervised learning. It can extract features from existing products or pattern images, and automatically generate new 3D renderings based on the features, which is in stark contrast to the parametric design generated by traditional methods in KE. Due to the reliable function of DCGAN in image generation, we chose it as the prototype of the initial design. On this basis, designers could obtain a lot of design materials and enrich their own design thinking.

The main situation where the DCGAN emotional design method proposed in this paper can be applied in the industrial field is when the product's appearance is relatively integrated and its physical properties are not diverse enough, which means that it is difficult to apply traditional design methods to design innovation. In this case, this emotional design method is recommended for products with rich appearance attributes.

Finally, professional designers retain the characteristics of images generated by DCGAN in the final design stage of detailed design but add the designer's subjective thinking on emotional design of traditional handicraft. As a result, the final new design preserves both the quality of the images generated by DCGAN and the designer's personal creations. Therefore, the method improves design efficiency, and potentially increases user satisfaction so as to realize the sustainable development of traditional handicrafts.

6. Conclusions

This study put forward a Funan wickerwork image recognition model using ResNet. After model training, it can realize the automatic evaluation of attribute in a large scale designs, while avoiding manual repetition and time-consuming operations. The experimental results show that both wickerwork patterns and modern pattern images achieved high emotional recognition rates, and the effectiveness and accuracy of the model improved significantly. In addition, DCGAN was used to construct the wickerwork pattern design generation model, and through rapid iterative learning, pictures with similar characteristics to known product pictures were generated, and 16 more creative pictures were selected from them, which directly assisted designers in redrawing and improving creative design schemes. Then, six designers and three graduate students sketched eight design schemes based on the generated schemes and completed the design's improvement using visual design to achieve the purpose of meeting customers' emotional needs. Finally, our results show that this method helps designers to further develop more popular and competitive Funan wickerwork patterns. The main contribution of this method is use DCGAN to support the design process and promotes the automatic design of innovative pattern images, based on these newly generated images, designers have many choices for emotional design expansion. It is hoped that it can be widely used in the sustainable development of intangible cultural heritage, so as to continuously innovate the connotation and value of intangible cultural heritage culture and realize sustainable development.

However, there is still room for improvement in the emotional design of wickerwork patterns by applying deep learning. Firstly, in the future, we will continue to use deep learning method theory to explore novel design methods, shorten the design process and increase design innovation; secondly, the wickerwork pattern database applied in this research is a small-scale dataset, which may limit the quality of DCGAN generation results; finally, pattern schemes with more complex structures may require models with better performance and the development of smart systems so as to automatically output the design schemes to meet users' expectations, thus realizing the creative display of wickerwork culture.

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