Optimization of Clothing Pattern Design Combining Deep Learning and CAD

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Abstract. Current consumption is relatively broad in the design of clothing graphics. Traditional graphic learning models have relatively narrow applications in market consumer demand. At present, clothing graphics based on deep learning have become mainstream. This article conducts model research and analysis on clothing graphic data based on deep learning models. Cracked the original technical design framework, conducted extensive iterative analysis on the application design principles of clothing graphics, and created a relatively detailed clothing graphics scene model. In the display of research application results, the deep learning optimization model proposed in this article has achieved groundbreaking seamless technological integration in terms of graphics quality. The clothing patterns based on CAD technology demonstrate a relatively novel value in creative applications. Compared with traditional methods, the deep learning clothing pattern design method proposed in this article has significant advantages in design efficiency.

Keywords: Deep Learning; CAD Technology; Clothing Pattern Design; Design Optimization; Automated Design
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1 INTRODUCTION

Deep learning algorithms have achieved significant results in clothing pattern recognition and design, providing designers and consumers with diverse choices and personalized experiences. Agarwal et al. [1] proposed a novel non-deep learning method aimed at enhancing the robustness of clothing pattern recognition and design systems. The existing defense methods based on deep networks often appear inadequate in the face of complex adversarial attacks. In the field of clothing patterns, this means that our method can more effectively resist attacks that attempt to mislead algorithms by adding subtle perturbations or noise. Specifically, in clothing pattern design, designers often need to handle patterns of various styles, sizes, and textures. This method extracts pattern features by searching and applying a set of classic image transformation techniques. The solution is based on image transformation due to its non-differential nature, multi-scale analysis, and directional filtering characteristics, which demonstrate strong defense capabilities. In addition, due to its excellent defense against stealth attacks (i.e., small disturbances that are difficult to detect with the naked eye), this method can play an important role in protecting design intellectual property and preventing piracy. With the rapid development of computer technology, its application in various industries has become increasingly widespread, especially in the field of clothing pattern design. The introduction of computer technology has greatly promoted the innovation and efficiency of design. Chai [2] elaborated on the construction and implementation process of this computer-aided design system for clothing patterns. This system adopts advanced computer technology and can support the full process of design from sketch drawing to finished product preview. In terms of functional structure, according to the actual needs of clothing pattern design, multiple functional modules have been designed, including pattern drawing, colour management, texture editing, size adjustment, simulation display, etc. In terms of system functionality, it utilizes computer graphics processing technology to achieve high-precision drawing and editing of clothing patterns. In terms of system architecture, we have adopted a modular design, making the entire system easy to expand and maintain. This not only helps to improve the overall quality of clothing pattern design but also helps designers better capture market dynamics and consumer needs, thereby designing clothing patterns that are more in line with market demand.

Chen et al. [3] developed an upper loop fashion design method based on discarded denim materials, aiming to explore and study the original upper loop design concept in depth. The expression method of upper loop fashion design involves multiple key steps, including disassembly, collage, transplantation, weaving, and tearing, all of which are centred around unique design methods, transforming discarded denim fabric into fashionable design elements. This design approach allows designers to flexibly apply five or more pieces of work to the same fabric and accurately implement them through digital production technology. Not only has it achieved the recycling and utilization of existing resources, providing effective solutions to environmental pollution problems, but it has also brought broader opportunities for the design process of sustainable fashion products. These patterns can be derived from the textures and patterns of discarded denim fabric itself, or they can be newly created through digital design techniques. These processes not only focus on functionality but also emphasize creating various stunning 3D modelling effects through creative operations in flat form. By using embroidery or printing techniques on denim, traditional Chinese patterns or modern popular geometric patterns are integrated, making fashionable items not only environmentally friendly but also rich in cultural heritage. When the differences in clothing patterns are not significant, Chen and Dong [4] studied a fast clothing pattern recognition method based on deep learning and dual-tree complex wavelet transform. Firstly, it utilizes the Dual-Tree Complex Wavelet Transform (DT-CWT) to preprocess the obtained clothing pattern images. These layers have been defined based on new image classification tasks to meet the recognition needs of clothing patterns. Clothing appearance design is one of the core links in clothing design, which makes an important contribution to the overall beauty and sales of clothing. The overall style design method of clothing based on DCGAN also has the problem of blurred transfer effect. It mainly includes three aspects: clothing partial attribute design, clothing partial decoration design, and clothing overall style design. The pattern design methods in clothing partial decoration design heavily rely on designers and lack end-to-end intelligent design solutions. However, the current WGAN-based clothing local attribute design method has poor attribute generation performance. Deng et al. [5] proposed a clothing local attribute editing algorithm based on improved WGAN. In response to the problem of poor attribute editing performance caused by insufficient feature extraction network representation ability in the original WGAN algorithm, residual structure optimization is adopted to enhance feature extraction ability. At the same time, the perceptual loss function was used to optimize the attribute learning process, significantly improving the effectiveness of attribute generation. Based on the clothing dataset design experiment, it was verified that the algorithm proposed in this paper can generate and edit various local clothing attributes. In terms of fabric selection, we use artificial intelligence to analyze the performance of fabrics, such as texture, colour, and pattern adaptability, in order to optimize material selection. This not only demonstrates the powerful application of machine learning in pattern recognition but also provides accurate body shape data for subsequent pattern design. This algorithm not only generates diverse new patterns based on the style and characteristics of traditional Miao patterns but also integrates modern design elements, enriching and updating the uniqueness of ethnic clothing. In addition, it particularly emphasizes the collaborative integration of traditional process methods and modern technological applications. Hu [6] proposed a design framework for an intelligent clothing styling CAD system based on components and patterns. Based on the analysis of the current development status of clothing CAD software at home and abroad, we found that although the software functions are increasingly improving, there are still shortcomings in supporting intelligent pattern design, automated style matching, and other aspects. The core idea of this framework is to decompose clothing into multiple relatively independent but interrelated components and pattern design units. Especially in the context of meeting consumer demands for personalized and unique clothing, developing intelligent clothing CAD systems to support innovative designs of patterns and styles has become a new research hotspot and trend. In order to break through this bottleneck, it utilizes the structural characteristics and pattern design principles of clothing to divide the clothing style into a combination of multiple components and patterns. At the same time, they can be intelligently matched and combined through preset rules and algorithms to generate a rich and diverse range of clothing styles and patterns. When analyzing the design process and functions of an intelligent style design system, we particularly emphasize the importance of pattern design.

Jankoska [7] is not limited to the basic modelling process for 2D patterns and 3D simulations of men's shirts, but will also conduct more in-depth discussions in conjunction with the expansion analysis of clothing patterns. Enrich the visual effect and cultural connotation of shirts by introducing popular elements, cultural symbols, or brand characteristics. Then, through physical simulation, multiple iterations and adjustments are carried out until the expected visual effect and wearing experience are achieved. Secondly, in the process of converting 2D patterns into 3D clothing, in addition to ensuring accurate matching and stitching of the patterns, attention should also be paid to the three-dimensional effect and wearing experience of 3D clothing. In the 2D pattern design of men's shirts, in addition to considering the basic size and style, attention should also be paid to the creativity and combination of pattern elements. Through precise 3D simulation technology, the wearing effect and dynamic beauty of shirts can be more realistically displayed. This includes the simulation of physical characteristics such as wrinkles, drapes, and stretching of clothing, as well as the influence of human movement on clothing morphology. At the same time, the layout, colour matching, and detailed handling of patterns are also crucial, as they can affect the overall style and wearing effect of the shirt. At the same time, it is also possible to explore the performance effects of patterns in different materials and processes, as well as how to use advanced printing and embroidery techniques to enhance the texture and layering of patterns. By analyzing the expansion of clothing patterns, we can further explore innovative paths in shirt design. Jeyaraj and Samuel [8] use advanced learning algorithms to design and develop computer-aided fabric defect detection and classification. By adopting deep learning algorithms, the accuracy of defect classification has been improved. It forms a deep convolutional neural network to learn from the training stages of various defect datasets. During the testing phase, the author used a learning function for defect classification. The quantitative values of performance indicators indicate the effectiveness of the developed classification algorithm. In addition, calculation times for different fabric treatments were provided to verify the computational range of the proposed algorithm compared to traditional fabric treatment techniques. The method was evaluated using 20 different datasets collected from different raw fabrics. The algorithm was tested on the standard dataset provided by the Ministry of Textile.

The objective of this investigation is to integrate DL and CAD technology in order to develop an intelligent clothing pattern design optimization framework. This model aims to autonomously learn and create patterns that align with design specifications while also leveraging CAD technology for precise drafting and effect visualization. Through this model, designers can quickly generate diversified pattern design schemes and improve design efficiency and innovation.

This study needs to solve the following problems:

How do we use the DL model to learn and generate patterns that meet the design requirements automatically?

How to combine the DL model with CAD technology to realize accurate drawing of patterns and preview of effects?

How to assess and optimize the performance of the design optimization model to meet the practical application requirements?

The study confronts several key limitations:

Data set constraints: The training of DL models necessitates a significant amount of labelled data. Obtaining or creating a high-quality dataset for clothing patterns can pose a challenge.

Difficulty in technical realization: Combining the DL model with CAD technology needs to solve a series of technical problems, such as model interface design and data format conversion.

Limitation of experimental conditions: experimental environment, equipment configuration and time may have some influence on the research results.

The key innovations of this study stand out in the following distinct areas:

(1) We introduce a novel optimization model for clothing pattern design, integrating DL and CAD technology to foster intelligent and personalized design solutions.

(2) An efficient DL model architecture is crafted, capable of autonomously learning and generating patterns tailored to design specifications.

(3) A seamless amalgamation of the DL model and CAD technology is achieved, facilitating precise pattern drafting and effect previews.

The organizational framework of this article is structured as follows:

The introductory section outlines the research backdrop, objectives, scope, and innovative contributions. The subsequent section reviews pertinent advancements in related research domains. The third section delves into the detailed construction of the proposed research model. The fourth section elucidates the specific experimental implementation process. The fifth section provides an in-depth analysis and discussion of the experimental outcomes. Finally, the concluding section summarizes the key findings and directs future research avenues.

2 LITERATURE REVIEW

In cutting-edge fields such as SocialVR, performance capture, and virtual fitting, the pursuit of realistic reproduction of real clothing in virtual environments has become a core task. Traditional 3D clothing deep learning methods often establish specific models for a single clothing or clothing type. Although this method is highly targeted, it is difficult to generalize to new clothing types. Using clothing sewing patterns as an efficient and realistic clothing descriptor to better estimate the inherent shape of clothing. To achieve this goal, Korosteleva and Lee [9] proposed an innovative approach. This task not only requires faithful replication of the inherent shape of clothing, but also considers the unique characteristics of the fabric, physical forces, and complex deformations that occur when the clothing comes into contact with the body. NeuroTailor is not only able to effectively reconstruct 2D clothing sewing patterns from 3D point cloud clothing models, but more importantly, it can also extend this ability to clothing types with pattern topologies that have not been encountered in training. This helps designers to make flexible design adjustments while maintaining the original pattern style. Lee et al. [10] focus on developing an innovative process that automatically extracts vector format planar sketch elements from clothing images, with a particular focus on the fine processing of clothing patterns. The research team utilized a carefully prepared fashion image dataset, particularly one containing a variety of clothing patterns, to train an edge detection model based on convolutional neural networks.

The original DCGAN algorithm found it difficult to learn the inter-class differences of various styles using the cross entropy loss function. Liu et al. [11] proposed a clothing local pattern design algorithm based on an improved style transfer network. It specifically improves the normalization method and loss function of the real-time style transfer network, making the generated local patterns more realistic. To this end, it is proposed that real-time style transfer networks be used to intelligently generate new fashion patterns. Traditional clothing pattern design heavily relies on designer experience and inspiration for design, lacking intelligent generation solutions. And seamlessly fit it onto stylish clothing, achieving the end-to-end intelligent design of local clothing patterns. The problem of ambiguous style transfer effects is caused by the use of conditional contrastive loss functions to fully guide the network in learning the differences between styles. Finally, it was verified through experiments that the algorithm proposed in this article can effectively achieve intelligent design of local clothing patterns. Developed intelligent auxiliary design software for clothing appearance [12]. A requirement analysis and system design were conducted on the intelligent auxiliary design software for clothing appearance. Comparative experiments have verified that the algorithm proposed in this paper can achieve better clothing style transfer effects. Verified that the three algorithms proposed in this article can help users conveniently carry out intelligent auxiliary design of clothing appearance.

The realistic clothing style and effect design system is one of the important contents of current clothing CAD research. In computer-aided design, designers always hope to see what their preliminary design looks like and have a sufficiently realistic image. By using computer graphics display technology, it is easy to display realistic images of the product on the screen, and the product's appearance can be observed from various angles. In the past, manual drawing or making of physical models was often used to verify the design effect, and as the plan was modified, repeated drawing or making of models required a lot of manpower and material resources. Papachristou et al. [13] studied the dressing effect of three-dimensional clothing styles based on texture mapping. It adheres to the design concept of an intelligent design system for clothing styles and has researched and designed a display module for three-dimensional clothing styles based on it. To this end, a three-dimensional controllable human platform was generated, and corresponding three-dimensional clothing styles were generated based on the two-dimensional clothing style plan of the intelligent design system for clothing styles. Further research was conducted on the texture mapping algorithm and implementation of 3D clothing styles, enabling users to transition from 2D to 3D. You can always see the display effect of your designed style, making the style design operation simple and practical. The intelligent design system for clothing styles is developed for the domestic clothing production market. Salama et al. [14] aimed to achieve a foolproof clothing style software design. On the basis of a certain clothing style, users only need to input simple commands, and through internal expert reasoning mechanisms, they can obtain a satisfactory clothing style planar structure diagram. On this basis, intelligently complete the functions of fabric colour filling and style serialization. Enable users to instantly see the design results and make interactive or proactive style modifications. Therefore, if a three-dimensional clothing style CAD is developed based on the clothing style drawings provided by the existing style design system, it can directly achieve three-dimensional effects from the style drawings. Allowing designers to see the three-dimensional dressing effect during style design not only makes it intuitive but also improves work efficiency. After a series of optimizations and tests, our framework has achieved significant results in optimizing clothing pattern layout tasks.

As digital natives, students have demonstrated unique learning methods and needs when exposed to and learning new technologies, especially courses related to computer graphic design. Siti et al. [15] delved into the characteristics of students and combined them with clothing pattern design to identify future-oriented learning and teaching standards. Research has found that students have little difficulty accessing and using complex technological tools, which fully aligns with their characteristics as digital natives. In the clothing pattern design course, they are not only able to quickly master the operation of graphic design software in technology but also able to exert creativity in design practice and create unique pattern works. They adopted qualitative research methods, conducting case studies through interviews, focus group discussions, and empathy mapping tools, while using qualitative descriptive analysis techniques to organize and analyze data. By thinking from the perspective of students, we can more accurately grasp their learning needs and tailor more effective teaching plans for them. Wang et al. [16] proposed a 3D reverse clothing design method that integrates machine learning technology. The clothing industry is representative of traditional industries with the large-scale flow, division of labour, and mass production. However, each clothing industry can only produce clothing categories with its own style, which leads to clothing design technology being limited to the clothing brands of the enterprise. Wu et al. [17] started with technology projects and established a database of children's net size and sample size for children's clothing. It adopts machine learning technology to establish a neural network model system for the intelligent design of children's clothing. With the flow of clothing designers, our company's clothing style design technology will also be lost, so the intelligent design of the clothing industry has received great attention with the development of machine learning. On the way, super-resolution reconstruction is performed on low-resolution children's clothing images to obtain high-resolution images of children's clothing and improve the transfer effect of children's clothing styles. Automatically generate a size model for children's clothing, and then transfer the style of children's clothing. Xu et al. [18] designed an intelligent clothing size design system, which collects children's net body size data and clothing sample size data based on actual project requirements. Analyze, learn, and train the net body size data and clothing sample size data in the database to establish a prediction model. Input the net body data to be customized and obtain detailed specification data for clothing pattern design based on the prediction model. Meet the customization needs of tailored clothing for different heights and body types, and achieve rapid and efficient batch design of personalized individual customized clothing. Store the collected clothing net body size data and clothing sample size data in the database. Input the detailed specification data into a CAD-made pattern model to obtain customized children's clothing patterns, breaking the traditional practice of mainly printing patterns based on fixed height standards.

3 OPTIMIZATION MODEL OF GARMENT PATTERN DESIGN

3.1 Selection and Construction of DL Model

In our research, we opt for a countermeasure network as the fundamental structure for a DL model. This GAN is comprised of two distinct components: a generator and a discriminator. Through a dynamic interplay of confrontation and iterative refinement, the GAN is capable of producing high-quality and varied imagery. Specifically for clothing pattern design, the GAN can discern and replicate the inherent patterns and features, generating designs that adhere to specific requirements.

The GAN framework inherently contains a generator and discriminator. The generator is tasked with learning the fundamental rules and attributes of clothing patterns, ultimately crafting designs that align with specified criteria. Meanwhile, the discriminator serves as a critic, determining whether an input pattern is genuine or a synthetic creation of the generator. This constant adversarial process stimulates the generator to yield more authentic and varied designs.

During the development of the GAN model, we first establish the architecture of both the generator and discriminator. The generator utilizes a deconvolutional network, gradually enhancing the spatial clarity of the image to generate patterns that fulfil design specifications. The discriminator, on the other hand, employs a convolutional neural network to extract the defining features of an input pattern through a series of convolutions and pooling operations, subsequently assessing its authenticity. To further enhance the performance of the convolutional neural networks, we introduce a nonlinear activation function:

$$f\ x\ = \begin{cases} 1 & x \geq x_0 \\ ax + b & x_1 \leq x \leq x_0 \\ 0 & x \leq x_0 \end{cases} \tag{1}$$

The Sigmoid function is a continuously differentiable, monotone function whose output ranges within the interval of (0,1) or (-1,1), depending on its specific formulation. It is often expressed by a kind of mathematical expression with an S-shaped curve, such as a logarithm or tangent. Taking the logarithmic S curve as an example, this function has a specific mathematical form and can smoothly map the input value into the output range (0,1) or (-1,1). This characteristic makes the S-type transfer function play an important role in many application scenarios such as neural networks and logistic regression. The formula is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

S-type functions have unique mathematical characteristics, including smoothness, asymptotic behaviour, and monotonicity in the whole definition domain. This function can smoothly map the input value to the output range, and with the increase or decrease of the input value, its output value will gradually approach its upper and lower limits. The error function of the GAN model and the discriminant error function of the generator are respectively:

$$L_{GAN}(G,D) = E_{y}\left[\log D(y)\right] + E_{x,z}\left[\log(1-D(G(x,z)))\right] \tag{3}$$

$$L_{1}(G) = E_{x,y,z}\left[\left\| y - G(x,z) \right\|_{1}\right] \tag{4}$$

Where y stands for guidance information, z stands for condition information and x stands for generation information.

It is worth mentioning that in the design of the generator, this article introduces the principle of sub-pixel convolution, as shown in Figure 1. Sub-pixel convolution effectively improves the resolution and clarity of generated patterns by rearranging low-resolution feature maps into high-resolution images.

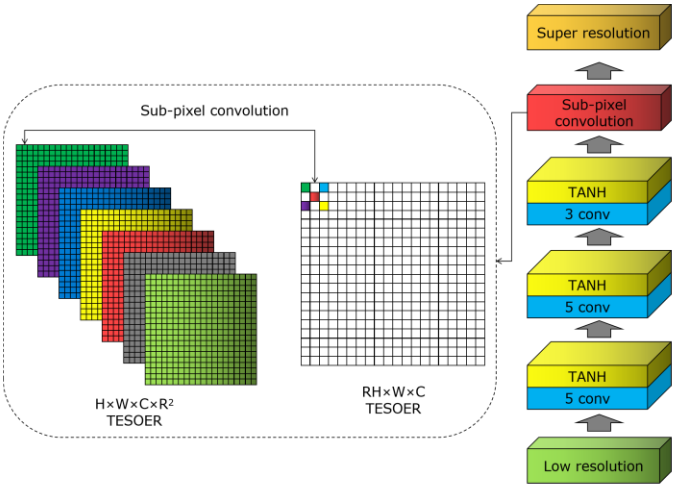

Figure 1: Sub-pixel convolution principle diagram.

Subsequently, the article delves into the definition of the model's loss function. Specifically, the GAN's loss function comprises two distinct components: the generator's loss and the discriminator's loss. To minimize the discrepancy between the synthesized and genuine patterns, the generator's loss employs a cross-entropy loss formulation. This is expressed mathematically as:

$$H(p,q) = -\sum_{x} p(x)\log q(x) \tag{5}$$

When it is used as the loss function of GAN, p stands for the correct answer and q stands for the predicted value. When the value of cross entropy tends to be smaller, it means that the similarity between the two probability distributions increases, which shows that the performance of the constructed GAN model is better because it predicts the probability distribution in the data more accurately.

The loss of discriminator adopts binary cross entropy loss to maximize the discrimination accuracy of real data and generated data. The formula of the binary cross entropy loss function is:

$$L=-\frac{1}{N}\sum_{i=1}^{N}\left[y_i\log\ p_i\ +\ 1-y_i\ \log\ 1-p_i\ \right] \tag{6}$$

Where L is the loss function value; N is the total number of samples; y_i is the real label of the i sample, for real data $y_i=1$, for generated data $y_i=0$. p_i is the output probability of the discriminator for the i th sample, indicating the probability that the sample is true data.

This article focuses on context cohesion in the process of image conversion, the style transfer effect of clothing styles and the realism of the limbs of the background of the characters in the generated images. To this end, the loss of background optimization is added:

$$L_{back}=\left\|\omega_2 f\ \ a,b'\ \Theta\ \ x-y'\ \right\|_1+\frac{\omega_3}{N}\sum\nolimits_{n=1}^{N}\sum\nolimits_{c=1}^{3}\left\|\ G\ \ x\ \ -x\ \ -\ \ y-F\ \ y\ \ \right\|_1 \tag{7}$$

Where x stands for content domain image; a represents the selected area of the content domain mask; y' represents the image after image conversion in the content domain; b' represents the mask overlapping area after the content domain is converted; ω_2 and ω_3 are used as weights to adjust content retention and skin colour display respectively; N represents the number of pixels in the conversion area; c is the number of channels.

During the training procedure, this model employs an alternating training approach. Initially, the discriminator's parameters are held constant while exclusively training the generator. Here, the generator's objective is to craft increasingly realistic patterns that can deceive the discriminator. This optimization of the generator's parameters is achieved through the backpropagation algorithm and gradient descent method, aiming to produce patterns that align more closely with the design specifications. Subsequently, the generator's parameters are fixed, and the discriminator undergoes training. In this phase, the discriminator strives to precisely discern genuine data from the synthetic patterns produced by the generator. Similarly, the discriminator's parameters are refined using the backpropagation algorithm and gradient descent method, enhancing its capability to distinguish between authentic and generated data. The mathematical expression for the gradient descent algorithm is:

$$\theta_{G/D}\leftarrow\theta_{G/D}-\alpha\nabla_{\theta_{G/D}}L_{G/D} \tag{8}$$

Where $\theta_{G/D}$ is the parameter of the generator/discriminator and a is the learning rate?

By training the generator and discriminator alternately, the antagonistic relationship between them is gradually strengthened. The generator gradually learned how to generate more realistic patterns to deceive the discriminator, and the discriminator gradually improved its discriminating ability, which can identify real data and generate data more accurately. This alternating training method makes the whole GAN model progress continuously in iterative optimization; the generator can generate patterns that meet the design requirements better, and the discriminator can better assist the training of the generator.

3.2 Application of CAD Technology in Design Optimization

In order to combine the DL model with CAD technology, this article chooses a powerful and easy-to-integrate CAD software -BoKe Cloud. The software has the functions of accurate drawing, size adjustment, effect preview and so on, which can meet various needs of clothing pattern design. Furthermore, we also developed the corresponding interface program to realize the data interaction and function call between the DL model and CAD software.

In the model training stage, CAD software is mainly used to generate training data sets. In this article, a large number of clothing patterns are drawn as real data by using the accurate drawing function of CAD software. Furthermore, the parametric design function of CAD software is used to generate some false data that meet the design requirements as the input of the generator. By inputting these data into the DL model for training, the model can learn the inherent laws and characteristics of patterns.

In the pattern design stage, CAD software is used to realize the accurate drawing of patterns and preview the effect. When the DL model generates a new pattern, the generated pattern data is imported into the CAD software, and it is drawn by using the drawing function of the CAD software, as shown in Figure 2.

Figure 2: Preview of drawing renderings.

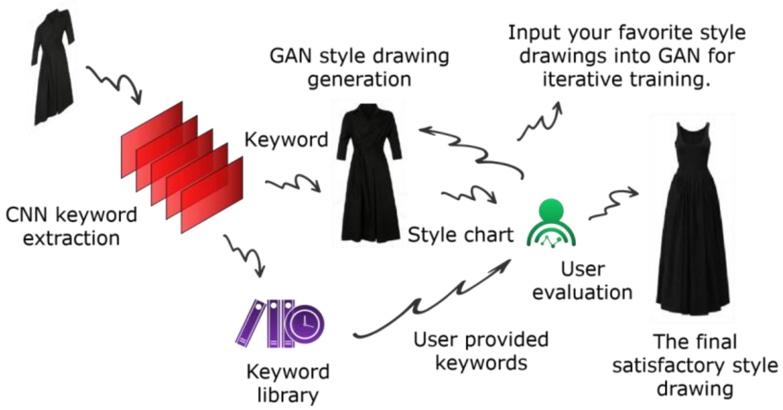

Figure 3: Framework of clothing pattern design optimization model.

Furthermore, the simulation function of CAD software can also be used to preview the effect and adjust and optimize the pattern. With the help of CAD software, we can observe the effect of the pattern more intuitively and adjust it to meet the actual needs.

3.3 Optimization Model Design of Clothing Pattern Design

In this research, the clothing pattern design optimization model integrates DL and CAD technology. The DL model is tasked with discovering the inherent patterns and characteristics to foster innovative pattern designs, while CAD technology ensures precise pattern drafting and effect previews. These two components collaborate and interact via a data interface, culminating in the optimization of the pattern design process. The architecture of this optimized clothing pattern design model is illustrated in Figure 3.

4 EXPERIMENTAL DESIGN AND IMPLEMENTATION

4.1 Data Set Construction

The training set fuels the model's learning process, the validation set aids in parameter adjustment and monitors performance during training, while the test set ultimately gauges the model's generalizability. Additionally, select datasets are annotated to support supervised learning within the DL model. The content of labelling includes the category, style and design elements of the pattern. See Table 1 for details.

Data set type	*Sample size*	*Pattern category*	*Pattern style*	*Design element*
Training set	10,000	1. Retro 2. Modern 3. Sporty ... 10. Fashionable	A. Bohemian B. Minimalism C. Streetwear ... P. Retro-Futurism	1. Floral 2. Geometric 3. Striped 4. Pattern Patchwork 5. Text
Verification set	2,000	1. Retro 2. Modern ... 10. Fashionable	A. Bohemian B. Minimalism ... P. Retro-Futurism	1. Floral 2. Geometric ... 5. Text
Test set	3,000	1. Retro 2. Modern ... 10. Fashionable	A. Bohemian B. Minimalism ... P. Retro-Futurism	1. Floral 2. Geometric ... 5. Text

Table 1: Dataset annotation content.

4.2 Experimental Setup

Concerning the experimental setup, a state-of-the-art computer cluster and DL framework are selected to facilitate the model's training and experimentation. Regarding parameter tuning, tailored hyperparameters are chosen based on the intricacies of the model and the dataset's peculiarities, such as network layer depth, neuron count, learning speed, and batch dimensions. Additionally, dropout techniques are implemented to mitigate overfitting. For a comprehensive overview, refer to Table 2.

Superparameter name	*Set value*
Network layer number	5
Number of neurons (per layer)	64, 128, 256, 128, 64

Learning rate	0.001
Batch size	32
Optimizer	Adam
Regularization intensity	0.0001
Epochs	100
Stop the rounds early	10

Table 2: Super parameter settings.

To extensively evaluate the model's performance, this article employs a diverse array of assessment metrics and methodologies. For generating the countermeasure network model, we use the quality, diversity and accuracy of the discriminator to assess its performance. For the application of CAD technology in pattern design, we assess its effect by comparing the similarity between CAD-drawn patterns and real patterns, user satisfaction and other indicators.

4.3 Experimental Process

In the training process of the DL model, this section adopts the strategy of phased training. Firstly, the unsupervised learning method is used to pre-train the generator and discriminator to get a preliminary understanding of the pattern data. Then, the supervised learning method is used to fine-tune the model, so that it can better fit the training data and generate high-quality patterns. During the training process, the performance of the model is constantly monitored and the hyperparameters are adjusted to achieve the optimal effect. The training process is shown in Figure 4.

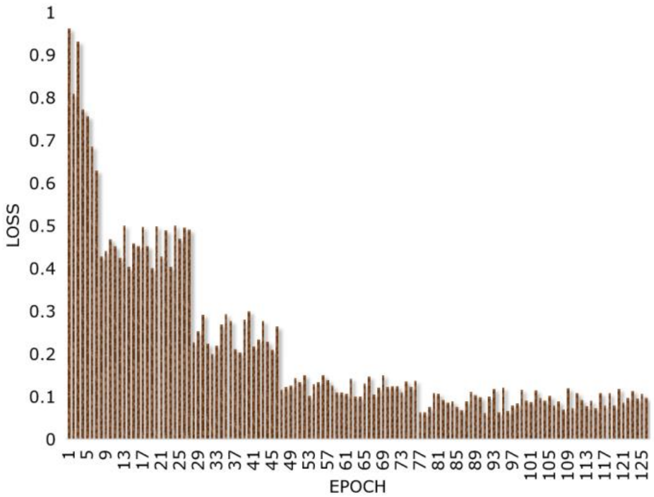

Figure 4: Training process diagram.

In the application of CAD technology in pattern design, firstly, CAD software is used to accurately draw the generated pattern. Then, through the simulation function of CAD software, the effect of the drawn pattern is previewed adjusted and optimized. In this process, we can modify the pattern in real-time and iteratively optimize it according to the user's needs and feedback. Finally, the optimized pattern is output as a file format that can be used in actual production. After the integration of the DL model and CAD technology, we conducted a comprehensive test and verification of the design optimization model. In the test process, this article selects different types of clothing patterns as input data and observes whether the model can generate patterns that meet the design requirements. The quality of the generated clothing pattern is shown in Figure 5.

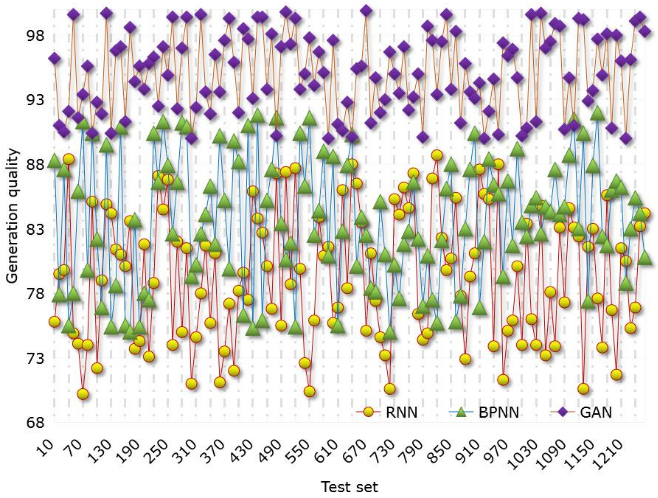

Figure 5: Quality of clothing pattern generated.

Figure 5 visually illustrates the quality comparison of three deep learning models, RNN (Recurrent Neural Network), BPNN (Backpropagation Neural Network), and GAN (Generative Adversarial Network), in generating clothing patterns. From the graph, it can be seen that the quality of clothing patterns generated by GAN is the highest, and the clarity, richness of details, and innovation of the patterns are superior to the other two models. The pattern quality generated by BPNN is secondary, although it can also produce some attractive designs, it may appear slightly rough in some details. In contrast, the quality of clothing patterns generated by RNN is the lowest, possibly due to its limitations in processing long sequence data, resulting in insufficient coherence and innovation in the generated patterns. The efficiency of clothing pattern generation is shown in Figure 6.

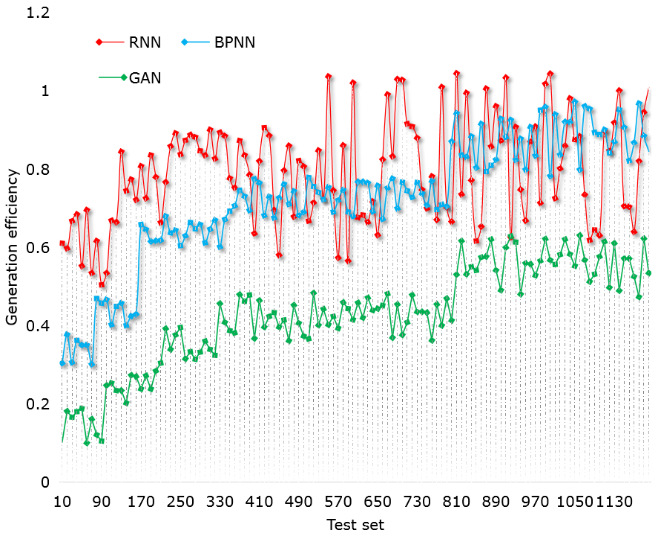

Figure 6: Efficiency of clothing pattern generation.

Figure 6 provides a detailed comparison of the efficiency of three deep learning models, namely RNN (Recurrent Neural Network), BPNN (Backpropagation Neural Network), and GAN (Generative Adversarial Network), in generating clothing patterns. The high efficiency of RNN in clothing pattern generation mainly stems from its processing characteristics of sequential data. RNN is particularly adept at handling data with time series properties because it can capture long-term dependencies in the data. In clothing pattern generation tasks, RNN can gradually generate various parts of the pattern through serialization, thereby achieving fast and coherent pattern generation. From the graph, it can be seen that RNN exhibits the highest efficiency in generating clothing patterns, followed closely by BPNN, while GAN has relatively lower efficiency. The accuracy of the discriminator is shown in Figure 7.

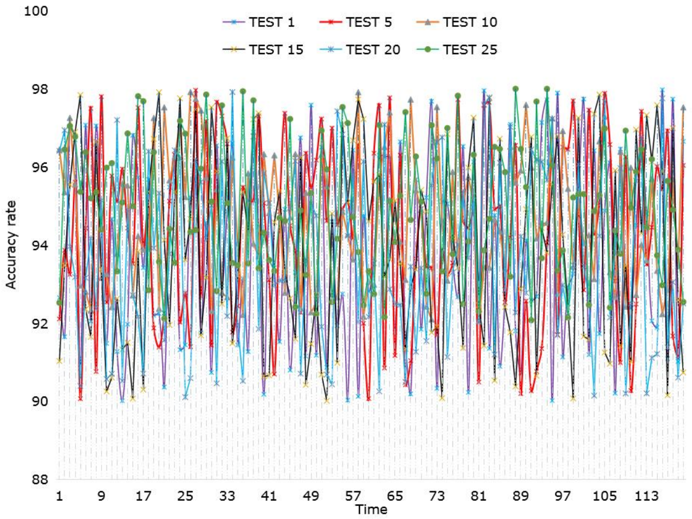

Figure 7: Accuracy of discriminator.

Figure 7 shows the accuracy of the discriminator on different test objects. The horizontal axis represents six different test objects (Test 1, Test 5, Test 10, Test 15, Test 20, and Test 25), while the vertical axis corresponds to the accuracy or precision of the discriminator on these test objects. All test results have an accuracy between 90% and 98%. Figure 7 provides us with intuitive information about the accuracy of the discriminator. By analyzing and interpreting these data in depth, we can gain a more comprehensive understanding of the performance of the discriminator and provide valuable references for its subsequent optimization and improvement. Furthermore, this article also invited professional designers and users to grade and feedback on the generated patterns to assess the practicality and user satisfaction of the model. Through continuous testing and verification, we constantly improve and optimize the model to achieve the best performance and effect. The selection rate of users who adopt different clothing pattern design methods is shown in Table 3. The scores of professional designers and users are shown in Figure 8.

Design method	*User selection rate*
Traditional hand-drawing method	21%
A method based on CNN	28%
A method based on RNN	36%
This method (before optimization)	42%
This method (after optimization)	53%

Table 3: User selection rate of different clothing pattern design methods.

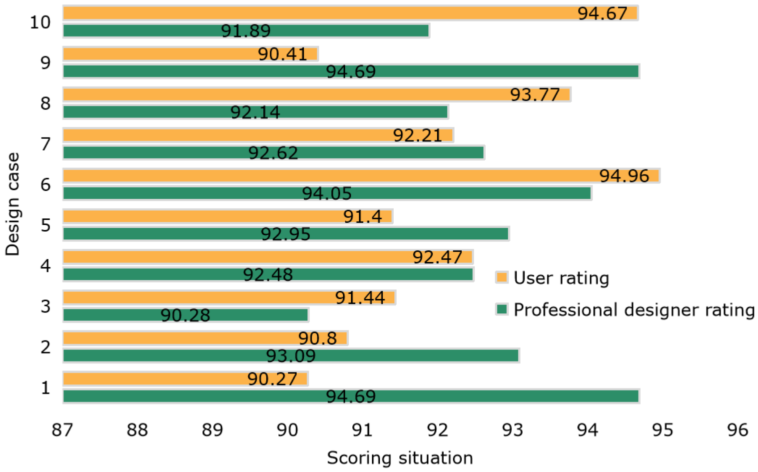

Figure 8: Professional designers and user ratings.

Figure 8 provides a detailed comparison of the ratings of professional designers and users on the same set of clothing patterns or design works. This chart provides us with evaluation results from two different perspectives: professional designer ratings and user ratings. By comparing these two dimensions, we can gain a more comprehensive understanding of the quality and market acceptance of design works. From the perspective of professional designers, they may place greater emphasis on design innovation, technical difficulty, and compliance with design principles and trends. The rating of professional designers is usually based on their deep understanding and professional knowledge of the design field, so their evaluation often has high authority and professionalism. After a series of experimental training and testing, this article assesses the performance of the DL model. Generating a countermeasure network shows excellent ability in generating clothing patterns, which can generate diversified, high-quality patterns that meet the design requirements. Anticipated are stellar outcomes for both the training and test sets, exhibiting superior pattern resolution, clarity, and intricate detailing. Additionally, CAD technology has yielded outstanding achievements in pattern design. Leveraging CAD software, we are able to precisely render patterns generated by the DL model, allowing for real-time preview and refinement of the design.

5 CONCLUSIONS

By combining the DL model and CAD technology, this study successfully constructed a model for clothing pattern design optimization. The results show that the model can automatically generate diversified and high-quality clothing patterns, and realize accurate drawing and effect preview through CAD software. In contrast to existing methodologies, the model introduced in this research stands out in terms of design efficiency, precision, and versatility. The principal value of this work lies in introducing a cutting-edge, automated, and intelligent design instrument for the realm of apparel pattern design, thereby broadening designers' creative horizons and options.

While this study has garnered noteworthy accomplishments, it is not without its limitations and shortcomings. Forthcoming investigations may delve into more sophisticated DL models to enhance the quality and diversity of pattern generation. Furthermore, the function and performance of CAD software can be further optimized to meet the needs of clothing pattern design. In addition, we can also study the collocation and fusion algorithm of patterns and clothing as a whole to provide a more comprehensive and systematic design scheme. In a word, the development prospect of the clothing pattern design optimization model is broad, which is worth further study and exploration.

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