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Innovation of Apparel Design Based on Deep Generative Modeling and Its Practice of CAD Collaborative Design

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Abstract. Consumers are no longer satisfied with the practicality of traditional clothing design but pay more attention to the innovative and personalized needs of clothing design. The traditional clothing design model has limitations on designers' design and is very dependent on their experience, which makes it difficult to meet consumers' changing needs. The apparel design innovation model based on the depth generation model and CAD co-design (CAD Collaborative Design) can provide new ideas for apparel innovation design. Therefore, this paper discusses the method of apparel design innovation based on the depth generation model and analyzes its synergy with computer-aided design (CAD). Through the application of the depth generation model, the automatic generation and optimization of apparel styles are realized, which improves the design efficiency and innovativeness, and the effectiveness and practicality of the method are verified through experiments. The experimental results show that compared with the other four models, the model performance of this paper has better stability, which can effectively reduce function loss, improve the quality of innovative clothing design, and gain more recognition from designers and consumers.

Keywords: Generative Adversarial Modeling; Apparel Design; CAD Collaboration; Convolutional Neural Networks; Apparel Style Migration
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1 INTRODUCTION

Consumers' demand for innovation in apparel design is growing, and they not only pursue fashion and beauty but also value personalization and differentiation. Modern consumers are concerned about the comfort and practicality of clothing but also eager to show their own style through clothing, so their demand for innovation in apparel design is both diversified and comprehensive; designers need to follow the trend of the times and constantly push forward to provide unique and creative design solutions to meet the expectations of consumers. The application of fibre-reinforced polymer composites in the field of clothing design is becoming increasingly widespread. As an important means of modern design, computer-aided design (CAD) has played an important role in the collaborative application of fibre-reinforced polymer composite clothing design, not only improving design efficiency but also optimizing performance. Showcasing enormous potential in clothing design. Especially in the design of special functional clothing such as sportswear and protective clothing, the application of this material can significantly improve the performance and comfort of clothing. Boon et al. [1] transformed creativity into concrete design solutions through digital means. In the clothing design of fibre-reinforced polymer composites, CAD technology can accurately simulate the mechanical and thermal properties of materials, helping designers to have a deep understanding of material properties in the early stages of design. At the same time, CAD technology can also achieve rapid comparison and optimization of multiple schemes, ensuring that design schemes meet performance requirements and have excellent aesthetics. In the traditional fashion design mode, designers have the problem of relying too much on traditional design concepts and techniques, lacking innovative thinking and breakthroughs. They may pay too much attention to the inheritance and retention of classic elements and neglect the combination with modern fashion trends, resulting in the lack of novelty and uniqueness of the designed clothing works.

Chen and Cheng [2] proposed a clothing product pattern design system based on the Kansei engineering and BP neural network, aiming to improve the accuracy and efficiency of pattern design by introducing emotional engineering and machine learning techniques. Ding et al. [3] analyzed the design and development process of knitted clothing based on the theory of sustainable clothing design, combined with the characteristics of knitted clothing design and production and digital visualization. It utilized literature research, brand case analysis, and the Analytic Hierarchy Process to establish a sustainable design and development model and strategy list for the entire lifecycle of knitted clothing, including the target layer, criterion layer, and scheme layer. Based on this, construct a sustainable evaluation model for knitted clothing that relies on products and processes. Finally, the availability and effectiveness of sustainable development models and evaluation models for knitted clothing were verified through research and case analysis. To provide a preliminary reference for enriching the theory of sustainable design of knitted clothing and promoting the practice and evaluation of sustainable knitted clothing design and development. It compared and analyzed the digital visualization of knitted clothing design and development mode compared to traditional development mode. The advantages of promoting sustainable design and development of knitted clothing include process optimization, cost reduction and efficiency improvement, and promoting efficient collaboration in the industry. Based on the characteristics of the design and development process of knitted clothing, a list of sustainable design and development models and strategies for knitted clothing covering the entire lifecycle was constructed, based on the United Nations Sustainable Development Goals and Sustainable Design and Development Guidelines for Clothing. On this basis, an evaluation model for sustainable design and development of knitted clothing was established, providing a reference for sustainable analysis and optimization of knitted clothing products and their development process. The feasibility of this model in enterprises was verified through on-site research and sustainable strategy analysis of three different types of enterprises in the industrial chain. Then, based on the constructed sustainable design and development model and evaluation model, the design and development practice of knitted sweaters and the sustainable evaluation of products and processes were carried out. The carbon footprint of knitted clothing with different weaving processes was calculated. They pay too much attention to their own aesthetics and creativity and ignore the actual needs of the market and consumers.

In the traditional fashion design process, designers often rely on hand-drawn or two-dimensional design software for creation, which is not only inefficient but also difficult to present the three-dimensional effects of clothing visually. The digital twin system based on 3D reconstruction technology, Doungtap et al. [4] quickly generates 3D clothing models according to the designer's intentions, and performs real-time rendering and display on the mobile end. Designers can modify and adjust models anytime and anywhere until satisfactory results are achieved. By collecting and analyzing consumer body data, the system can generate three-dimensional clothing models that conform to the characteristics of the consumer's body shape, providing consumers with more fitting clothing choices. At the same time, consumers can also view and adjust models in real-time on mobile devices, achieving personalized design and customization. This leads to the design of clothing works disconnected from the market demand, and it is difficult to obtain the recognition and love of consumers. The traditional apparel design process often relies on the designer's manual drawing and repeated modification, the process is cumbersome and inefficient, and it is difficult to adapt to the rapidly changing market demand. Traditional pressure estimation methods often rely on empirical formulas or simple physical models, making it difficult to accurately reflect the performance of highly elastic materials under complex stress conditions. Horiba et al. [5] proposed a clothing pressure estimation proposal based on a hybrid method of clothing CAD and finite element analysis software, aiming to improve the accuracy and reliability of the estimation. Build a 3D model of tight-fitting clothing using clothing CAD software. By inputting information such as clothing style, size, and fabric parameters, CAD software can generate accurate 3D models, providing basic data for subsequent pressure analysis. In addition, CAD software can also perform virtual fitting, simulating the deformation of clothing in different postures and movements of the human body, thereby more comprehensively considering the factors affecting clothing pressure. The introduction of deep generative modelling has revolutionized the innovation of apparel design.

Deep generative models are able to automatically learn the rules and features of apparel design through powerful learning and processing capabilities to generate diverse design solutions. The intelligent clothing modelling CAD system based on components has emerged, which can not only improve design efficiency but also achieve intelligent and personalized design, bringing revolutionary changes to the clothing industry. Hu [6] analyzed the component-based intelligent clothing modelling CAD system adopting a modular design. Divide each function into independent components and achieve the functionality of the entire system through collaborative work between components. The system mainly includes a user interaction module, shape generation module, database management module, and intelligent optimization module. Users can input design requirements through the interaction module, and the system automatically generates preliminary styling schemes based on these requirements. Through intelligent optimization modules, the scheme is optimized and adjusted, ultimately outputting clothing styles that meet the designer's requirements. These models can not only mimic the style of existing designs but also create new and creative design elements. Designers can obtain a constant stream of inspiration by interacting with the in-depth generated models, breaking the limitations of traditional design and promoting the innovation and development of apparel design. In addition, CAD technology, as an important tool in the apparel industry, plays a key role in the application of depth-generated models, which can realize the precise expression and rapid transformation of design solutions, and rapidly transform the design solutions generated by depth-generated models into practical and feasible apparel samples. This not only greatly improves the efficiency of design to production, but also ensures the accuracy and implementability of the design scheme. Therefore, this paper combines the convolutional neural network and generative adversarial network to construct a style migration model based on the deep generative model for apparel innovation design, which achieves the purpose of enhancing the innovation and efficiency of apparel design under CAD co-design, to satisfy the market and consumer demand for personalized, diversified, and innovative apparel.

2 RELATED WORK

With the rapid development of the clothing industry, the demand for fabric quality is also increasing. Traditional fabric defect detection methods often rely on manual visual inspection, which is not only inefficient but also susceptible to human factors, leading to missed or false detections. Therefore, it is particularly important to develop a technology that can quickly and accurately automatically detect and classify defects in clothing fabrics. Jankoska [7] analyzed 3D clothing modelling and animation generation as important issues in the field of computer graphics. It has a wide range of applications in the film and television industry, gaming and entertainment, virtual fitting, and other fields. In the process of 3D clothing modelling, most clothing is designed and modelled with different proportions based on the standard body shape as a reference. However, for body shapes with distinct local characteristics, the dressing effect of standard clothing cannot retain the style of the sample clothing. In addition, for the generation of 3D clothing animations, in order to construct a continuous and collision-free clothing animation, the traditional workflow requires solving fabric deformation frame by frame based on human motion through physical simulation. However, high-quality physical simulation requires a large amount of computing resources, is difficult to implement, and requires complex parameters for control. Jeyaraj and Nadar [8] locked the target audience through 3D modelling of clothing images. Most existing work focuses on how to fit a given style of clothing onto the target body shape or posture while neglecting whether the style of the clothing can be preserved. A small amount of work has been conducted on the issue of style transfer, but there are issues such as time consumption, reliance on parameter settings between the human body and clothing, and inability to handle distinctive body types. For clothing animation generation, researchers use instance data-based methods to simulate clothing deformation animations more efficiently by reusing existing data.

Jo et al. [9] studied a clothing modelling technique that preserves the style and supports distinctive body shapes, which can efficiently transfer clothing styles between different body types. The core idea of this method is to learn a shared body shape feature space, thereby decoupling clothing deformation, retaining common clothing deformation caused by human body shape, and removing non-common clothing deformation caused by clothing style. The decoupled clothing deformation only includes body shape-related deformation components, which can be used for style transfer of any style or topology clothing model. Even if there is a significant change in the target body shape compared to the source body shape, the sample garment has rich wrinkle information. The clothing model generated by this method can still adapt to the target human body shape and maintain the style of the sample clothing. This method can efficiently generate three-dimensional clothing that retains the style of the sample clothing for the target body shape, thereby reducing the time and knowledge cost required for clothing modelling. Lee et al. [10] studied a continuous clothing animation generation method that adapts to loose clothing styles in both time and space. It can generate real-time clothing deformation sequences corresponding to the posture based on human motion representations. The method is based on a Transformer to construct a dynamic mapping relationship between human motion and clothing deformation. Its core lies in learning the contextual rules between animation frames through the attention mechanism so as to make the predicted clothing deformation have temporal consistency. The advantage of this method is that it allows clothing deformation to be controlled through high-level human motion parameters, making it suitable for various interactive application scenarios. In addition, this method has significant advantages in time efficiency compared to traditional physical simulation techniques and can be integrated into existing bone animation pipelines, thereby improving the efficiency and quality of clothing animation generation. Through experimental verification, the method supports clothing types that are inconsistent with the human body topology, and compared with other alternative methods, the clothing animation generated by this method is more realistic and stable. Therefore, Shi et al. [11] introduced multi-feature fusion technology to further improve the accuracy and stability of workpiece detection. Multi-feature fusion technology refers to the integration and fusion of feature information from different sources and types, in order to fully utilize the advantages of various features and improve the performance of object detection. In the fast workpiece detection method for clothing design based on multi-feature fusion SSD, we first extract various features of the workpiece, including colour, texture, shape, etc., through image preprocessing technology.

Intelligent clothing has become an important development direction for the future clothing industry. Among them, the wearable all-fibre intelligent clothing multifunctional sensor based on silk fibroin is gradually becoming a research hotspot due to its unique material properties and multi-functionality. Applying it to smart clothing not only provides a comfortable and soft wearing experience but also effectively integrates and functionalizes sensors. By integrating humidity sensors and sweat analysis modules, Wen et al. [12] monitor users' sweating and electrolyte balance in real-time, providing personalized exercise guidance for athletes and fitness enthusiasts. Meanwhile, utilizing the optical properties of silk fibroin can also achieve functions such as UV protection and intelligent colour change, providing users with more comprehensive protection. The difference in fit between virtual clothing and actual clothing has always been a focus of attention for consumers and designers. Therefore, it is of great significance to conduct research on the similarity of fit between actual clothing and virtual clothing based on the comparison of pants contours. Won and Lee [13] evaluated the fit performance of the virtual clothing fitting system by comparing the differences in silhouette between actual pants and virtual pants. It collected samples of pants of different sizes and used 3D scanning technology to obtain accurate contour data. At the same time, corresponding pants models were created in the virtual environment and adjusted parameters to match the actual sample size. The research results indicate that there are certain differences in the contour between virtual pants and actual pants. Some of these differences may be due to the simplification of material properties and physical properties in virtual environments. However, in most cases, the contour of virtual pants maintains a high degree of similarity with actual pants in key dimensions and overall shape.

In the field of intelligent clothing fashion design, texture and shape are the two core elements that constitute the visual effect of clothing. However, traditional generative models often find it difficult to effectively distinguish and handle the relationship between the two, resulting in intertwined textures and shapes in generated clothing images, making it difficult to achieve ideal design results. Yan et al. [14] verified the feasibility of generating adversarial networks through field research and sustainable strategy analysis on three different types of enterprises in the industrial chain. Then, based on the constructed sustainable design and development model and evaluation model, the design and development practice of knitted sweaters and the sustainable evaluation of products and processes were carried out. The carbon footprint of knitted clothing with different weaving processes was calculated. Analysis shows that overall formed knitted clothing has a smaller carbon footprint compared to sheet forming. Utilizing digital visualization technology can greatly improve product design and development efficiency and resource waste. The sustainable evaluation model for knitted clothing constructed in this article can be used to evaluate and analyze the sustainability of clothing products and their development processes. This provides tools and references for exploring more sustainable design and development strategies, and further promoting sustainable design, production, and consumption of knitted clothing. At the level of brand and product development, most practitioners and brands start from the sustainable design and development of textile and clothing products to promote sustainable fashion. Initially, people's understanding of sustainable design was more inclined towards the concept of environmental protection, mainly focusing on materials, processes, and other aspects to express the environmental attributes of clothing. For example, using natural organic materials and environmentally friendly dyeing processes. Later, with the continuous deepening of research on sustainable clothing design concepts, practitioners began to advocate the use of more diverse design methods. Not only focusing on materials and processes but also extending to the entire life cycle of clothing, comprehensively considering material processes, energy conditions, new technologies, etc. at each stage to reflect the environmental sustainability of clothing products. This also requires effective collaboration among various industry chain roles in clothing design and development [15].

Clothing, as an important component of the clothing industry, is increasingly favoured by more and more people due to its soft texture, comfortable wearing, and diverse categories. Its market demand is increasing year by year and gradually tending towards functionalization, personalization, and environmental protection. Compared to woven clothing, knitted clothing has a shorter industry chain and a wider range of yarn categories, and with the continuous upgrading and improvement of computer flat knitting technology. The design and development of knitted clothing is more efficient and convenient. Therefore, studying the sustainable design and development of knitted clothing products has natural advantages. In addition, with the continuous development of technology, digital visualization technologies such as clothing virtual design displays can further optimize the design and development process of knitted clothing. Effectively promoting the sustainable design of knitted clothing. In recent years, knitting-related enterprise brands have also attached increasing importance to the development of sustainable knitting products. However, different industry roles have different understandings and focus on the concept of sustainability, and the evaluation criteria are not unique. Moreover, some enterprises still need to improve their overall and systematic strategies and evaluation methods for sustainable clothing design and development.

3 CONSTRUCTION OF CLOTHING DESIGN INNOVATION MODEL BASED ON DEEP GENERATIVE MODELING

3.1 Combining Convolutional Neural Networks to Generate Adversarial Networks

Generative Adversarial Network (GAN) is a deep learning model whose main idea is to learn the distribution of data and generate new data samples through the mutual antagonism of two neural networks, a generator and a discriminator. The input to the generator in its network structure is a random noise vector (or potential vector) and the output is fake data similar to the real data. The goal of the generator is to generate high-quality fake data by getting as close as possible to the distribution of the real data and, in the case of apparel design, by learning real apparel design images to generate compliant images. The goal of the discriminator in the network structure is to binary classify the input data, i.e., to determine whether the input data is from a real data set or generated by the generator. The discriminator receives a data sample as input and then outputs a probability value indicating the likelihood that this sample belongs to the real data. The relationship between the discriminator and the generator is a mutual game, which ultimately makes the discriminator unable to judge the authenticity of the images generated by the generator. The target formulation of GAN is shown in (1):

$$\min_G \max_D V(G,D) = E_{x\sim pdata(x)}[\log D(x)] + E_{i\sim p_i(i)}[\log(1-D(G(i)))] \tag{1}$$

Where the real data is denoted as x and its distribution is denoted as $pdata(x)$, the distribution of the noisy data is denoted as $p_i(i)$, the data generated by the generator based on the noise is denoted as $G(i)$, the input noise is denoted as i, and the discriminator output probability is denoted as $D(\cdot)$. Based on the above formulas, it can be seen that there is a game between the discriminator and the generator's purpose, i.e., the discriminator wants to discriminate the real data as true, and the generated data as false, and the generator wants to let the discriminator architecture generate data to discriminate the data as true, so the former wants to maximize $V(G,D)$ and the latter wants to minimize it.

A convolutional neural network (CNN) is a type of neural network specialized in processing data with a grid-like structure, which extracts the features of the input image layer by layer by means of structures such as convolutional layers and pooling layers and ultimately forms a high-level feature representation. CNNs can be used in the generator part of a GAN to generate images with specific structures and textures. By combining the convolutional and inverse convolutional layers of the CNN with the generator of the GAN, image data can be better processed, and higher-quality images can be generated. The deep convolutional generative adversarial network structure is shown in Figure 1.

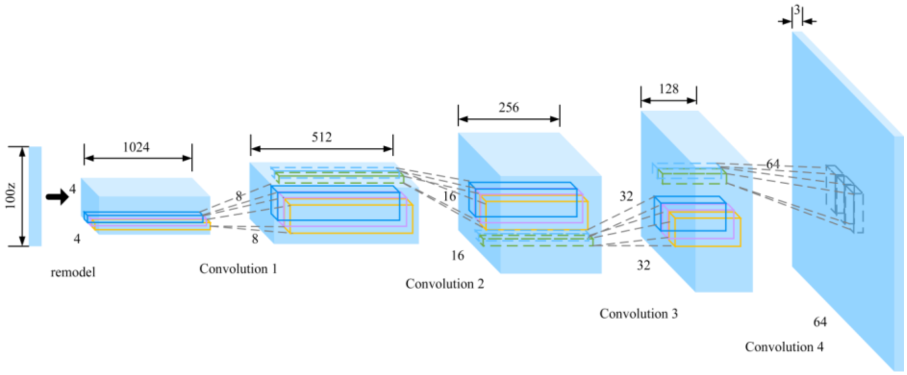

Figure 1: Deep convolutional generative adversarial network architecture.

Problems in adversarial generative networks, such as gradient fading, can be solved by the Wasserstein distance, which is defined as shown in Equation 2:

$$W(pdata, p_h) = \inf_{\gamma \in \prod(pdata, p_h)} E_{(x,y)\sim\gamma}[\|x - y\|] \tag{2}$$

where the set of joint distributions for all possible combinations of $pdata$ and p_h exist is denoted as $\prod(pdata, p_h)$, and each joint distribution γ that exists in the set can be sampled from $(x,y) \sim \gamma$ and obtains the true sample and the generated sample, and the distance between the two samples is denoted as $\|x - y\|$.

The generator loss function representation of the corresponding generative adversarial network is shown in (3):

$$E_{x\sim p_h}[f_w(x)] - E_{x\sim pdata}[f_w(x)] \tag{3}$$

In the above case, the total objective function of the generative adversarial network with the addition of the penalty term is shown in Equation (4):

$$L = E_{\tilde{x}\sim p_h}[D(\tilde{x})] - E_{x\sim pdata}[D(x)] - \lambda_{hp} E_{\tilde{x}\sim p_{\tilde{x}}}[(\|\nabla_{\tilde{x}} D(\tilde{x})\|_2 - 1)^2] \tag{4}$$

where the gradient penalty is denoted as λ_{hp}, the random sample is denoted as $\tilde{x} \sim p_h$, and $\tilde{x}$ is the data in the range between the real and generated data.

The quality of image generation can be improved by generative adversarial network improved by least squares loss function with discriminator loss function as shown in (5):

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x\sim pdata(x)}[(D(x) - \beta)^2] + \frac{1}{2} E_{i\sim p_i(i)}[(D(G(i)) - \alpha)^2] \tag{5}$$

The corresponding generator loss function is shown in (6):

$$\min_G V_{LSGAN}(G) = \frac{1}{2} E_{i\sim p_i(i)}[(D(G(i)) - \delta)^2] \tag{6}$$

In the formula, $\beta - \delta = 1, \beta - \alpha = 2$.

3.2 Generative Adversarial Network-based Style Migration Model for Creative Clothing Designs

The style migration algorithm model can provide rich creative inspirations for clothing designers; by combining different art styles with clothing design, designers can break the traditional design boundaries and create unique clothing works. At the same time, style migration makes the creation of personalized art products possible. In clothing design, designers can skillfully integrate various art styles, such as Impressionism, Cubism, Pop Art, and so on, into clothing design. In this way, clothing is no longer a simple tool for wearing but an important carrier for displaying artistic style and personality expression. Consumers can choose clothing with unique artistic styles according to their own preferences and aesthetic needs, thus meeting the demand for personalized art products. In addition, style migration also provides new design methods and means for clothing designers. Traditional clothing design often relies on the designer's personal experience and intuition, while style migration technology provides a more scientific and systematic design method. Designers can apply artistic styles to apparel design through in-depth research and analysis, thus realizing a more accurate and efficient design process.

In this paper, a supervised image style migration model is used, whose main goal is to realize the task of style migration between images from two different regions, that is, the model presents two sets of images from two different regions with significant differences in the style level while maintaining a high degree of consistency in the content level. For example, one set is a sketch of the same clothing design and the other is a color image that has been colorized. Images generated from such paired datasets by a supervised image style migration algorithm tend to be more visually realistic and natural with more prominent details compared to those generated by an unsupervised style migration model. This is because the supervised learning algorithm is able to learn the mapping relationship between style and content directly from the paired data, thus retaining the content information of the original image more accurately during the migration process while incorporating the target style effectively.

In this paper, a cross-domain self-coding generative adversarial network is used to realize the style migration, and its loss function contains the loss of the generative adversarial network, the reconstruction loss and the loss generated between the image style migration process and the target domain. The discriminator D_y generator loss of one-way mapping $x \rightarrow y$ is shown in (7):

$$\min_{G} L_{LSGAN}(G) = \frac{1}{2} E_{x\sim pdata(x)}[(D_y(\widehat{x}) - 1)^2] \tag{7}$$

where the input image is denoted as x, the encoder and decoder are denoted as E_x and F_y, respectively, and x The false image in the y-domain generated by the encoder and decoder is denoted as $\widehat{x}$. The probability that the output image of the discriminator is real data is denoted as $D(\cdot)$.

The discriminator D_y loss function is shown in (8):

$$\min_{G} L_{LSGAN}(G) = \frac{1}{2} E_{x\sim pdata(x)}[(D_y(\widehat{x}) - 1)^2] \tag{8}$$

The discriminator generator loss for the one-way mapping $y \rightarrow x$ is shown in (9):

$$\min_{G} L_{LSGAN}(G) = \frac{1}{2} E_{x\sim pdata(y)}[(D_x(\widehat{y}) - 1)^2] \tag{9}$$

where the input image is denoted as y, the encoder and decoder are denoted as E_y and F_x , respectively, and x The false image in the y-domain generated by the encoder and decoder is denoted as $\widehat{x}$. The probability that the output image of the discriminator is real data is denoted as.

The discriminator loss function is shown in (10):

$$\min_{D} L_{LSGAN}(D) = \frac{1}{2} E_{x\sim pdata(x)}[(D_x(x) - 1)^2] + \frac{1}{2} E_{x\sim pdata(y)}[(D_x(\hat{y}))^2] \tag{10}$$

The x-domain and y-domain reconstruction loss functions are shown in (11) and (12), respectively:

$$L_{l1}(x) = E_{x\sim pdata(x)}[\|x - \hat{x}\|_1] \tag{11}$$

$$L_{l1}(y) = E_{y\sim pdata(x)}[\|y - \hat{y}\|_1] \tag{12}$$

Where the input images x and y go through the encoder and decoder to generate reconstructed images of the corresponding regions denoted as $\hat{x}$ and $\hat{y}$ respectively.

The total reconstruction loss function is shown in (13):

$$L_{l1}(x,y) = L_{l1}(x) + L_{l1}(y) \tag{13}$$

The loss generated between the image style migration process and the target domain is denoted as l_1 , and the existence of a partial loss function in its x-domain is shown in (14):

$$L_{lossx}(x) = E_{x\sim pdata(x)}[\|x - \hat{y}\|_1] \tag{14}$$

The partial loss function present in the Y domain is shown in (15):

$$L_{lossy}(y) = E_{x\sim pdata(x)}[\|y-\hat{x}\|_1] \quad (15)$$

The total loss is shown in (16):

$$L_{loss}(x,y) = L_{lossx}(x) + L_{lossy}(y) \quad (16)$$

In summary, the objective loss function of the whole network is shown in (17):

$$L(x,y) = \alpha L_{LSGAN}(x,y) + \beta L_{l1}(x,y) + \gamma \quad (17)$$

where the equilibrium hyperparameters of the partial loss functions are α, β, γ .

As shown in Figure 2 is a schematic diagram of the style migration model of apparel creative design based on a generative adversarial network.

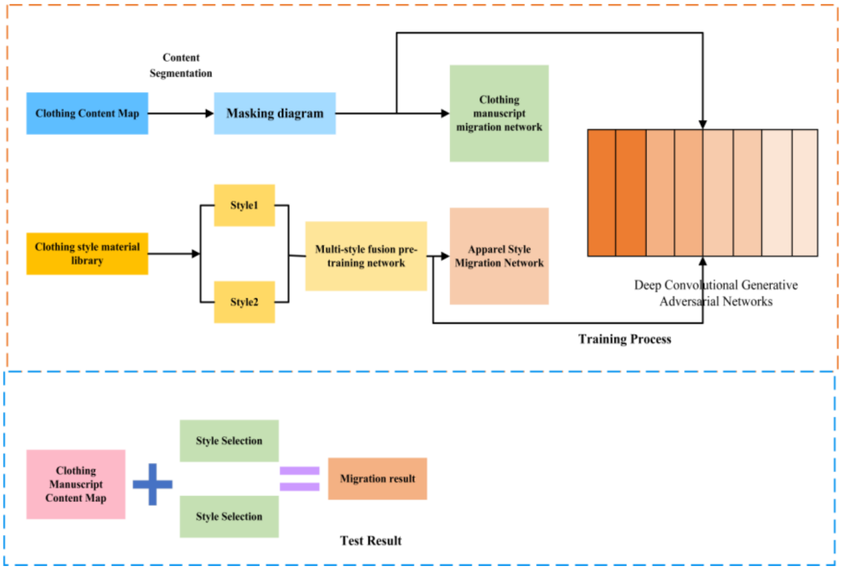

Figure 2: Schematic diagram of the style migration model of clothing creative design based on a generative adversarial network.

4 A DEEP GENERATIVE MODELING-BASED INNOVATION MODEL FOR APPAREL DESIGN AND ITS INTEGRATION TEST WITH CAD CO-DESIGN

In order to compare the performance of the apparel design innovation model based on the deep generative model, it is trained and compared with the GAN model in the apparel innovation design sketches and multi-grain apparel design drawings dataset with the total loss function. Taking full account of the fact that clothing design innovation is characterized by artistry, abstraction, jumping, etc., and it is easy to have an accidental error in training and testing in relatively small-scale data, this paper trains the model for about 300000 iterations so that it can meet the basic requirements of designers. As shown in Figures 3 and 4, the results of the total loss function for the two models are shown for design sketches and multi-grain design drawings, respectively. Fig. 3 The data shows that the loss curve of this paper's model converges faster and has a lower value than that of GAN in terms of garment design sketches. Fig. 4 The results show that the loss curve of this paper's model performs better in multi-texture garment design, and the gap between the two loss curves increases compared to the results in Fig. 3. This shows that the model in this paper can effectively reduce the loss generated in the process of clothing design, and the higher the difficulty, the more obvious the loss reduction efficiency.

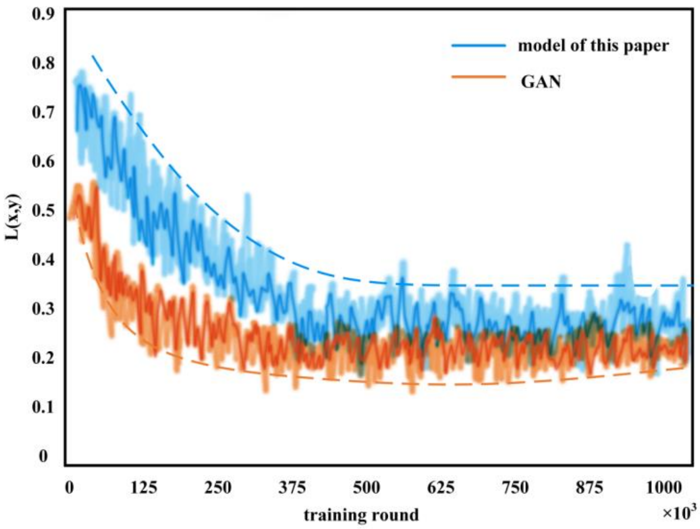

Figure 3: Total loss function results of two models in garment design sketches.

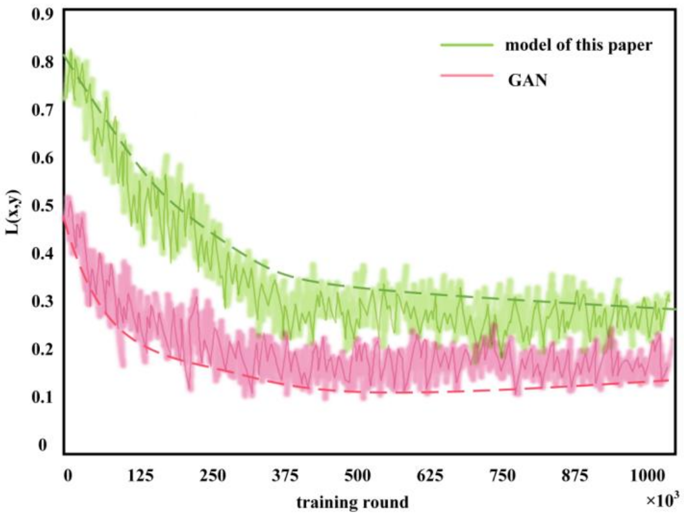

Figure 4: Total loss function results of the two models in multi-textured garment design charts.

In order to test the performance of the model further in this paper, four other models were selected for performance application comparison, and the results are shown in Figure 5. The results in the figure show that among the three evaluation indexes, the values of the three indexes of the EdfeGAN model are the highest, especially in the first index which is substantially higher than the other three models. While the model of this paper has the lowest values of the three indicators, and compared with the other three models its indicator values are significantly reduced. This indicates that, although all three models except the EdfeGAN model show better experimental performance, this paper's model performs better in terms of performance stability, information extraction and fusion.

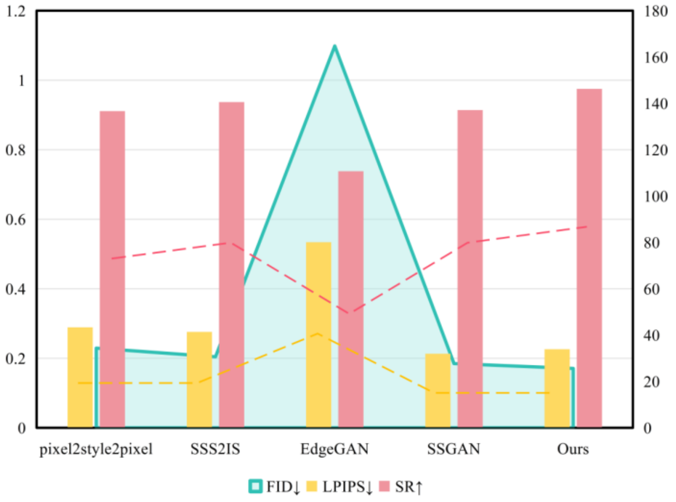

Figure 5: Baseline experimental results for the four models.

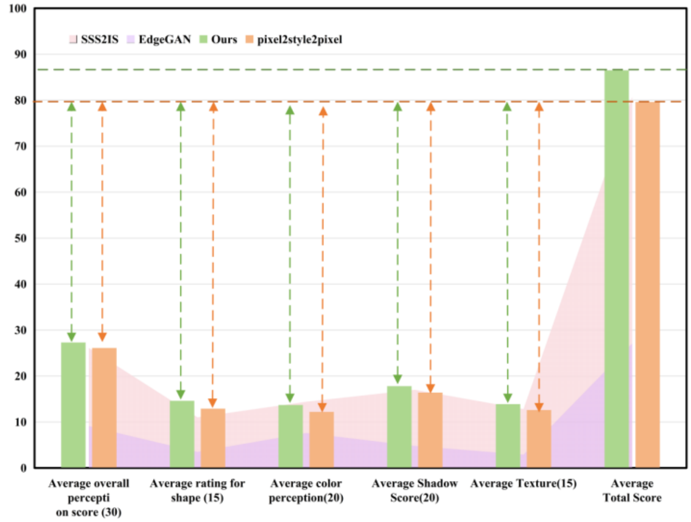

Figure 6: Comprehensive evaluation results of the four models of clothing innovation design map.

The application of the apparel design innovation model based on the depth generation model in apparel design is to improve the design innovativeness, quality, and efficiency, and the apparel innovativeness and quality, etc., can be comprehensively evaluated from the five senses of the design as a whole, shape, colour, detail texture, and shading. Therefore, in this paper, thirty randomly selected clothing designers and consumers were evaluated comprehensively on the four models of clothing innovation design charts respectively, and the results are shown in Figure 6. The results in the figure show that the designers and consumers have the lowest evaluation of the five aspects of the clothing creative design map generated by the EdfeGAN model, and there is a big gap between the comprehensive evaluation results of the other three models. Among the comprehensive evaluation results of the other three models, the model in this paper has the highest average score in terms of overall shape, shadow, and detail texture. In terms of colour sensation, the SSS2IS model has the highest average score. For the final average total score, this paper's model performed the best. This indicates that, compared with other models, this paper's model has the best overall performance and is able to generate innovative design drawings for clothing that meet the aesthetics and requirements of most designers and consumers.

From the above experimental results, it can be seen that the overall performance of this paper's model and the SSS2IS model is better, so this paper compares the design satisfaction of the two, and the results are shown in Figure 7. From the structure of the figure, it can be seen that although the difference between the results of the two models in the performance test is relatively small, in the actual application, the creative design of clothing generated by this paper's model can be recognized by more designers and consumers. This shows that the model can effectively generate creative clothing designs while maintaining the quality and personalization needs of the design drawings.

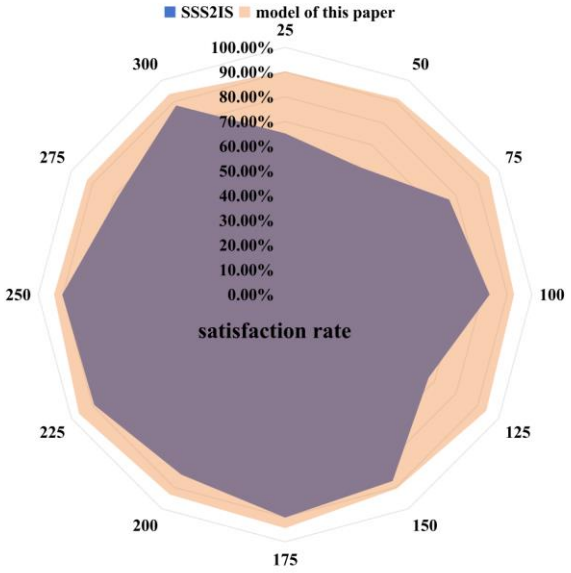

Figure 7: Satisfaction level of designers and consumers when different numbers of creative design drawings of garments are generated by the SSS2IS model and this paper's model.

5 CONCLUSIONS

Consumers and the market demand for apparel design is constantly changing, designers need to quickly complete the apparel innovation design and meet consumers' personalized needs in a shorter period of time, which is difficult to achieve in the traditional apparel design mode. The innovation of apparel design based on deep generative modeling and its co-design with CAD is an efficient and practical method, which can significantly improve the innovation and productivity of apparel design. Therefore, this paper combines a convolutional neural network and generative adversarial network to construct a garment design innovation model based on a deep generative model, which helps designers broaden their design thinking and improve design efficiency and quality. The experimental results show that the apparel design innovation model based on the deep generative model can effectively reduce function loss in different scenarios, show good stability, and perform better in information extraction and fusion. Compared with the other four models, the comprehensive evaluation results of the apparel innovation design diagrams of this model are the highest overall, and it has a high level of satisfaction while maintaining quality. This shows that it can effectively help designers obtain innovative elements and integrate them into clothing design, which can meet the personalized needs and requirements of most consumers.

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