# Computer-Aided Design and Simulation of Clothing Style Based on Big Data Analysis

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**Abstract.** Because of the long design cycle, low efficiency, and high dependence on the designer's experience, the traditional clothing style design increases the probability that the clothing style design is not competitive in the market and cannot meet the diverse needs of consumers. Therefore, this paper combines big data technology to build a clothing style design model through a deep learning algorithm and a clothing style outline recognition model through the generative adversarial network (GAN), effectively improving the accuracy of model recognition. It also constructs a clothing style transfer module through GA, which improves the model detail retention performance and image authenticity. The experimental results show that the model in this paper can analyze the fashion trend of clothing styles according to the market sales data and consumer preference data and provide designers with decision-making data information. Designers can calculate the probability of different designs being selected by consumers according to the model and choose better designs for design refinement. The model effectively combines the needs of consumers to realize the style transfer of clothing styles and improves the overall clothing design effect through the change of local details.

**Keywords:** Clothing Style; Big Data; Computer-Aided Design; GAN
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## 1 INTRODUCTION

The clothing design technological wave not only profoundly changes the design process and production efficiency but also greatly broadens the source and realization of design inspiration, making the problems faced by traditional fashion design methods more prominent [1]. The first problem of the traditional manual design mode is the mismatch between design efficiency and market demand. In today's prevalence of fast fashion and personalized customization [2]. The design cycle is long, and it is difficult to capture and transform the market signal quickly, resulting in a slow product market speed and difficulty meeting the immediate needs of the market [3]. The second problem is limited design innovation; that is, in the traditional design process, designers' creativity is often limited by personal knowledge base, experience accumulation, and limited industry exchanges, and it is difficult to break through the existing framework to achieve true cross-border integration and innovation [4]. The third problem is that it is difficult to carry out cost control and quality control in traditional design mode. Manual design is often accompanied by high labour costs and time costs, and errors and waste are prone to occur in the transformation process from design to production [5]. Finally, the traditional design method can provide less space for consumers to participate in clothing design, and it is difficult to meet consumers' desire to participate in clothing design and express their own personalized needs [6].

Traditional weaving techniques, with their unique weaving techniques and totem patterns, carry rich cultural information and aesthetic value by collecting and analyzing massive market data, consumer behaviour data, and fashion trend data [7]. However, with the changing times, these precious skills are facing the risk of extinction. Designers can more accurately grasp the pulse of the market, predict future trends, and design clothing styles that better meet market demand and consumer preferences. To save this cultural heritage, we not only need to record and preserve it but also need to revitalize it through innovative ways so that it can be revitalized in modern society. In the modernization transformation of weaving technology, we can use parametric design methods to control the form, structure, and function of design objects by setting a series of parameters, making the design process more flexible and efficient [8]. Subsequently, these models were transformed into physical prototypes through 3D printing technology, achieving a leap from virtual to reality. This combination not only demonstrates the perfect integration of traditional craftsmanship and modern technology but also provides new ideas and directions for the development of cultural and creative industries [9].

It is gradually solving the problems of efficiency, innovation, cost and consumer participation in the traditional fashion design model, and promoting the development of the fashion design field in a more intelligent, efficient and personalized direction. In the early stage of fashion design, through big data analysis and machine learning technology, artificial intelligence can learn and analyze massive fashion images, consumer behaviour and sales data, etc., and identify market trends and consumer preferences [10]. This helps designers quickly catch market changes, and adjust the design direction. Artificial intelligence technology can also automate the design process, such as automatically adjusting design elements, colours, patterns, etc., thereby saving designers time and energy and improving design efficiency. At the same time, big data and artificial intelligence technology can gather global design resources, fashion trends and other information, providing designers with cross-border inspiration sources. This helps designers break through the shackles of traditional design thinking and realize design innovation.

First of all, the model in this paper analyzes the relevant data of clothing styles from multiple dimensions such as market, consumers and clothing stores by combining big data technology, and provides corresponding prediction information according to the analysis results.

Secondly, clothing style design often contains rich structural information and spatial relationships, such as the relative position and shape changes between components such as collars, cuffs, and skirts. These complex spatial features are difficult to effectively capture through traditional convolutional neural networks (CNNs), as CNNs are better at handling regular grid data (such as images) and may struggle to handle graphic data with complex topological structures. In contrast, GAN is designed specifically for graph-structured data and can naturally handle the connection relationships between nodes, thereby more accurately capturing the structural features and spatial layout in clothing styles.

Finally, to meet consumers' demand for clothing and provide designers with more design inspiration, this paper constructs a fashion style transfer model through GAN, and designers can display the design effect of clothing style through CAD in a short time according to consumers' needs, to improve consumers' sense of participation.

## 2 RELATED WORK

Clothing design was originally designed by designers to improve clothing based on lifestyle behaviours, in order to ensure that consumers wear comfortable and convenient clothing in their daily lives. With the improvement of consumers' living standards and aesthetic taste, Maghraby [11] gradually attaches importance to aesthetic style in the process of clothing design. However, clothing design at this time is still based on the designer's experience and vision, with low innovation. The flourishing development of 3D technology has pushed clothing design to a whole new level. Poggi et al. [12] used high-precision 3D modelling and rendering techniques to create clothing models that are almost indistinguishable from reality. These models can accurately simulate the wearing effect of clothing under different body types and postures, as well as the visual perception under different lighting conditions and material expressions. This technology not only enhances the realism and immersion of design but also provides designers with unprecedented creative space, allowing them to freely explore and implement various unprecedented design concepts. In addition, the designer has implemented the classification of clothing styles and fabrics through big data and K-means and established a very practical clothing style material database. In addition, designers have optimized clothing styles and colours through computer-aided technology to enhance the visual effect of colour matching. With the increasing demand for personalized clothing from consumers, personalized algorithms have been widely applied in clothing design. Sajja et al. [13] combined CAD with personalized algorithms to construct a personalized clothing recommendation model that recommends clothing styles that better meet consumer needs. Other designers analyze big data such as popular topics, consumer reviews, and purchase records on social media to predict future fashion trends and meet the personalized needs of consumers. At present, clothing style design is developing towards technological integration and innovation.

Utaibi et al. [14] extended and analyzed how big data analysis can provide support for the computer-aided design process of clothing styles. In this context, computer-aided design systems can utilize the results of big data analysis to automatically generate clothing style design schemes that conform to current trends, including popular colours, style preferences, material selection, etc., providing designers with comprehensive and in-depth insights. In the clothing industry, big data analysis is not limited to predicting market trends and analyzing consumer behaviour but is also widely used to optimize and innovate clothing style design. By integrating deep learning algorithms, these systems can further analyze historical design data and learn and predict future design trends, thereby improving design efficiency and market response speed while maintaining designer creativity. Specifically, big data analysis technology can integrate a large amount of data from various channels such as social media, e-commerce platforms, and fashion magazines. The combination of advanced fabric defect detection and classification technology with big data analysis-driven clothing style design not only improves the level of product quality control but also promotes the acceleration of design innovation. Efficient defect detection in the fabric production process can reduce the incidence of defective products and improve production efficiency. In the design process, big data analysis and computer-aided design jointly promote the diversification and personalized development of clothing styles, meeting consumers' dual pursuit of fashion and quality.

This data-driven design approach makes clothing style design more in line with consumer needs, reduces market forecasting uncertainty, and improves product market acceptance and competitiveness. Furthermore, Won and Lee [15] conducted an in-depth analysis of the dynamic changes in investment behaviour in the fashion industry by introducing differential equations and delayed dynamics models. This innovative attempt not only reveals the complex relationship between investment frequency, market volatility, and changes in consumer behaviour but also reveals the underlying mechanisms and driving factors behind these changes. This analytical method provides investors and decision-makers with a more scientific and systematic theoretical basis, helping them better grasp market dynamics, optimize investment strategies, and reduce investment risks. This predictive ability based on big data provides strong data support for investment decisions, enabling investors to evaluate investment prospects more rationally and avoid risks. In dynamic analysis, some scholars pay special attention to the stability and instability criteria of the system, as well as the conditions under which bifurcation phenomena occur. In addition, by utilizing robust optimization tools such as genetic algorithms, we can efficiently and accurately estimate the parameters of such differential equations, improving the prediction accuracy and applicability of the model. Especially the Hopf fork, which reveals the critical point at which the system transitions from a stable state to an unstable state, means investors need to remain vigilant and avoid entering these high-risk areas. By analyzing massive market data, including social media trends, sales records, customer feedback, etc., designers and decision-makers can more accurately grasp the pulse of fashion trends and predict future fashion trends [16]. This not only helps us better understand the dynamic characteristics of investment trends but also provides a scientific basis for formulating investment strategies. By constructing a differential equation model that includes delay effects, we can simulate time delay phenomena in the investment process, such as market reaction delays, supply chain adjustment times, etc., thus more accurately reflecting the operating laws of the investment market.

## 3 COMPUTER-AIDED CLOTHING STYLE DESIGN MODEL BASED ON BIG DATA ANALYSIS

### 3.1 Clothing Style Demand Analysis Module Based on Big Data

The traditional fashion style design model is often rooted in the keen capture and interpretation of the instant dynamics of the fashion industry, which is highly dependent on the designer's personal aesthetic preference, industry insight and the speculation of consumer psychology. Designers will carefully analyze the current fashion elements, such as colour, fabric, cut style, etc., and then predict the clothing trend that may rise in the future period. However, this prediction model inevitably has a strong subjective colour, which is limited by the designer's personal experience, intuition and the breadth and depth of receiving external information, and it is difficult to ensure the comprehensiveness and accuracy of the analysis results. At the same time, the lack of systematic data support and quantifiable evaluation criteria makes the design decision-making process seem more arbitrary and difficult to back verify, that is, the lack of so-called "reversibility". In contrast, the big data-driven market analysis model builds a complex but coherent network structure that can fully and deeply mine the massive data related to clothing style design, as shown in Figure 1. The data covers consumer behaviour (such as purchase history, and browsing preferences), social media trends (such as trending topics, and celebrity wear), historical sales data, seasonal climate change, and even global economic indicators. By applying advanced data analysis techniques such as machine learning, data mining, and predictive analytics, big data models can reveal complex associations and dynamic balances between different influencing factors to accurately predict fashion trends. This kind of analysis based on big data not only improves the objectivity and system of prediction results but also gives designers unprecedented decision support. Designers can make more targeted style designs based on quantitative information such as specific demand distribution, style preferences, and colour trends obtained from big data analysis to reduce blindly following trends and waste of resources. At the same time, the traceability and verifiability of big data make the design decision-making process more transparent, facilitate subsequent evaluation and adjustment, and enhance the flexibility and adaptability of the design.

The comparison results of the two fashion design modes are shown in Table 1. It can be seen from the table that the fashion trend information in the big data analysis mode is more accurate, comprehensive, dynamic, and objective, and there is a high correlation and cooperation between the information, which can complete the prediction and analysis of the historical data of fashion styles and fashion trends in a very short time. At the same time, it can also obtain more comprehensive consumer demand for clothing style design and timely feedback. It can be seen that big data technology and computer-aided technology can provide reliable data support and technical support for clothing style design.

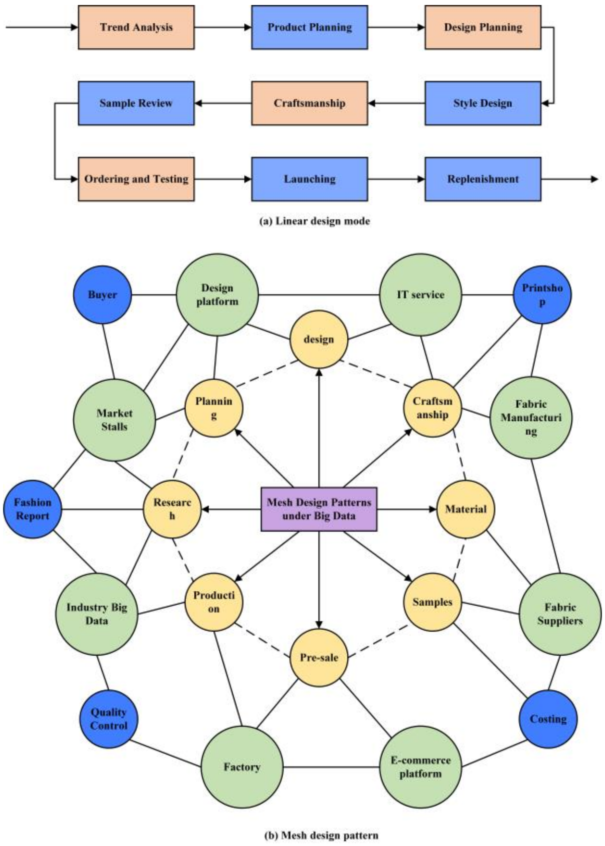


**Figure 1**: Traditional linear design model and big data network analysis model.

| *Comparative dimension* | *Traditional clothing design* | *Big data analysis* |
|---|---|---|
| Fashion trend survey | Information discretization | Accurate information |
| Information acquisition channel | Brand internal, offline, independent research | Network data, all-channel, big data research |
| Design and plan-making. | Subjective, uncertain | Objective and accurate |
| Design thinking mode | Subjective thinking | Data Thinking |
| Development information collaboration | Low, discrete information | High, collaborative cooperation |
| Data participation degree | Short-term, conceptual planning phase | Continuous participation in all stages |
| Style development cost | The price is volatile and uncertain | The price is transparent and controllable |
| Design and development cycle | Long, ready inventory | Short, quick response |
| Consumer relevance | Requirements, tests, consumption information | Demand, feedback, technology, trends, etc. |
| Consumer satisfaction | low | high |

**Table 1**: Comparison between traditional fashion design mode and big data analysis.

### 3.2 Clothing Style Contour Recognition Module Based on Graph Convolutional Neural Network

The outline recognition of clothing style is the starting point and basis of clothing design, and also the key factor in determining the overall style and visual effect of clothing. In this paper, the image convolutional neural network (GAN) is used to construct the garment-style contour recognition module. Compared with classical convolutional neural networks, GAN can model complex relationships in clothing styles, such as connections, layers, and dependencies between different parts. These relationships are difficult to capture directly in traditional image processing methods. Through the image convolution operation, GAN can integrate the feature information of each part of the clothing style to form a deep understanding of the overall outline. Compared with CNN, GAN is better at capturing the subtle differences and changes in clothing styles, such as the position of folds and ornaments, and can extract more feature data. In the graph structure, GAN reduces the number of parameters in the model through the parameter-sharing mechanism, thus speeding up the learning process. The parallelization capability of GAN allows it to remain efficient when processing large-scale graph-structured data. In the field of personalized clothing design, GAN can recommend suitable clothing styles according to the user's preferences and body characteristics. Therefore, GAN has a unique advantage in the processing of graph structure data in the recognition of clothing style contour.

Let the topology data adjacency matrix be described as $G$, the node features are expressed as $H$ the adjacency matrix after adding the connected edges is described as $\hat{G}$ node characteristics are represented as shown in (1):

$$H^{(l+1)} = \sigma(J^{-\frac{1}{2}} G \hat{J}^{-\frac{1}{2}} H^l W^l) \tag{1}$$

Where the balance ratio after matrix normalization is described as $J^{-\frac{1}{2}} G \hat{J}^{-\frac{1}{2}}$, $\hat{J}$ be matrix $\hat{G}$ the degree matrix of the weight matrix is expressed as $W$.

$$Y = f(H,G) = soft\max(G \cdot \mathrm{Re}LU(\hat{G}HW^0)W^1) \tag{2}$$

Where the normalized self-joining adjacency matrix is described as $\hat{G}$, GANThe learnable weight parameters with sequence numbers one and two are represented as $W^0,W^1$, the activation function is expressed as $\mathrm{Re}LU(\cdot)$, the final output is the probability that each node belongs to a class.

The nonlinear activation function is described in (3):

$$Leaky\,\mathrm{Re}LU(x) = \begin{cases} x, if x \geq 0 \\ \alpha x, if x < 0 \end{cases} \tag{3}$$

Among them, $\alpha \in [0,1]$.

To improve the ability of the model to process graph structure data, improve the accuracy of feature extraction, and enhance the robustness of the model, this paper introduces a mixed attention mechanism. Hybrid attention mechanisms can simultaneously focus on different aspects of input data, such as the correlation between channels, the importance of spatial regions, and the context in sequence data, to capture key features more comprehensively. The channel attention mechanism is shown in formula (4):

$$\begin{aligned} M_c(F) &= \sigma\{MLP[AvgPool(F)] + MLP[MaxPool(F)]\} \\ &= \sigma\{MLP[\frac{1}{H+W}\sum_{n_0=1}^{H}\sum_{m_0=1}^{W} f_{x_0}(n_0,m_0)] + MLP[\max_{n\in H, m\in W} f_{x_0}(n,m)]\} \end{aligned} \tag{4}$$

Where the activation function is Sigmoid. It is expressed as $\sigma$, the height and width of the input feature map are expressed as $H$ and $W$, input eigenvalues in sequence number $x_0$ the coordinates in the channel are $(n_0, m_0)$ the point corresponding to the pixel value is expressed as $f_{x_0}(n_0, m_0)$.

The spatial attention module expression is shown in (5):

$$M_s(F) = \sigma\{f^{k\times k}[AvgPool(F'); MaxPool(F')]\} \tag{5}$$

Where the size of the convolution kernel is $k \times k$ the convolution layer is represented by $f^{k\times k}$.

To test the performance of the garment style contour recognition module based on the graph convolutional neural network, this paper compares the performance of CNN with that of CNN, and the results are shown in Figure 2. In the performance experiment, the test data were randomly divided into ten groups, each containing the same number but different styles of clothing. Results The results showed that in terms of the accuracy of clothing style contour recognition, the accuracy of GAN's clothing style was above 85%, and the highest recognition accuracy reached 97%. The accuracy of CNN is relatively low; the lowest can reach more than 73%, and the highest accuracy is 87%. The ten groups of test result curves of the two models have relatively large changes, which is because there are clothing style data with high similarity in the test data, and there are differences only in subtle features, which requires high recognition performance of the model. In terms of recall rate, the recall rate of GAN is higher than that of CNN. Combined with the accuracy results, it can be seen that the GAN model has better clothing style contour recognition performance than the CNN model.

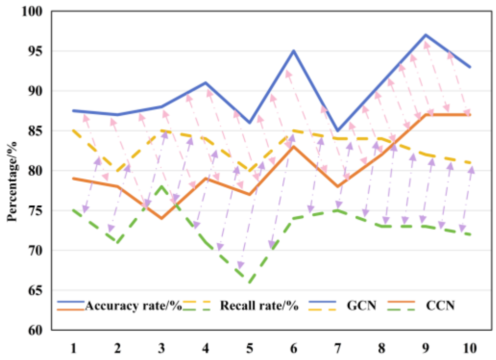


Figure 2: GAN and CNN clothing style contour recognition accuracy rate and recall rate.

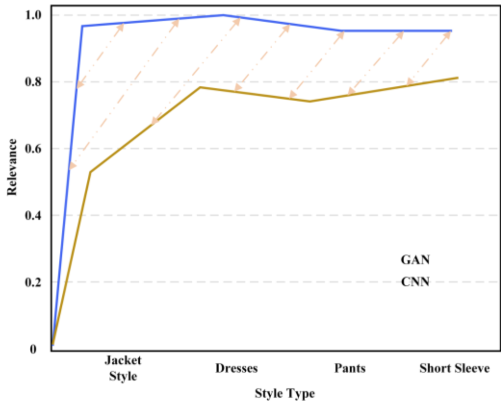


Figure 3: Correlation effect of GAN and CNN on contour recognition of different clothing styles.

Based on the above experimental tests, this paper further tested the application effect of the model in the contour recognition of different clothing styles. The test took the recognition correlation degree as the index, and the value was positively correlated with the recognition effect, there should be no identification errors in the recognition results of the model, as shown in Figure 3. The results in the figure show that the correlation degree of GAN is significantly higher than that of the CNN model, and the value is close to 1. This shows that, compared with CNN, GAN has stronger detail recognition and feature extraction capabilities, which can reduce or avoid the loss of clothing style details, more completely express the outline features of clothing styles, and provide a more reliable data basis for future applications.

### 3.3 Clothing Style Transfer Design Module Based on Generative Adversarial Network

The style transfer module can integrate elements from different styles and different eras, providing fashion designers with unprecedented creative inspiration. By drawing on the style characteristics of different art schools, cultural backgrounds, or historical periods, designers can break the shackles of traditional design thinking and create new and unique clothing styles. Through the style transfer module, designers can quickly integrate different style elements into clothing styles according to the individual needs of consumers and make several modifications and adjustments. This enables designers to turn ideas into actual products more quickly.

In this paper, a generative adversarial network (GAN) is used to realize the style transfer of clothing styles. The model drives the learning process through a well-designed loss function to ensure that the effect of style transfer not only conforms to the competitive principle of generative adversarial network but also maintains the reconstruction quality of image content and accurately transfers the style of the source domain image to the target domain. Its loss function is mainly composed of the loss of three parts. The unidirectional mapping $x \to y$ discriminator of $D_y$ Generator losses are shown in (6):

$$\min_G L_{LSGAN}(G) = \frac{1}{2} E_{x\sim pdata(x)}[(D_y(\hat{x}) - 1)^2] \tag{6}$$

Arbiter $D_y$ the loss function is shown in (7):

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

Unidirectional mapping $y \to x$ the loss of the discriminator generator is shown in (8):

$$\min_G L_{LSGAN}(G) = \frac{1}{2} E_{x\sim pdata(y)}[(D_x(\hat{y}) - 1)^2] \tag{8}$$

The discriminator loss function is shown in (9):

$$\min_D L_{LSGAN}(D) = \frac{1}{2} E_{x\sim pdata(x)}[(D_x(x) - 1)^2] + \frac{1}{2} E_{x\sim pdata(y)}[(D_x(\hat{y}))^2] \tag{9}$$

X Field sum y the domain reconstruction loss function is shown in (10):

$$\begin{cases} L_{l1}(x) = E_{x\sim pdata(x)}[\|x - \hat{x}\|_1] \\ L_{l1}(y) = E_{y\sim pdata(x)}[\|y - \hat{y}\|_1] \end{cases} \tag{10}$$

Where the input image $x$ and $y$ the reconstructed images generated by the encoder and decoder in the corresponding regions are respectively expressed as $\hat{x}$ and $\hat{y}$.

The total reconstruction loss function is shown in (11):

$$L_{l1}(x, y) = L_{l1}(x) + L_{l1}(y) \tag{11}$$

Loss between image style transfer and target domain is denoted as $l_1$, some loss functions exist in the $x$ domain, as shown in (12):

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

The partial loss function existing in $Y$ the domain is shown in (13):

$$L_{lossy}(y) = E_{x\sim pdata(x)}[\|y - \hat{x}\|_1] \tag{13}$$

The total loss is shown in (14):

$$L_{loss}(x,y) = L_{lossx}(x) + L_{lossy}(y) \tag{14}$$

The target loss function of the whole network is shown in (15):

$$L(x,y) = \alpha L_{LSGAN}(x,y) + \beta L_{l1}(x,y) + \gamma \tag{15}$$

Where the equilibrium hyperparameter of each part of the loss function is $\alpha,\beta,\gamma$. Figure 4 shows the dynamic changes of the generator and discriminator during GAN training.

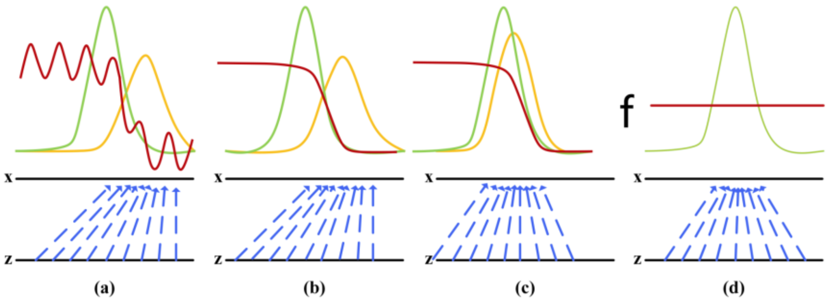


**Figure 4**: Dynamic changes of generator and discriminator during GAN training.

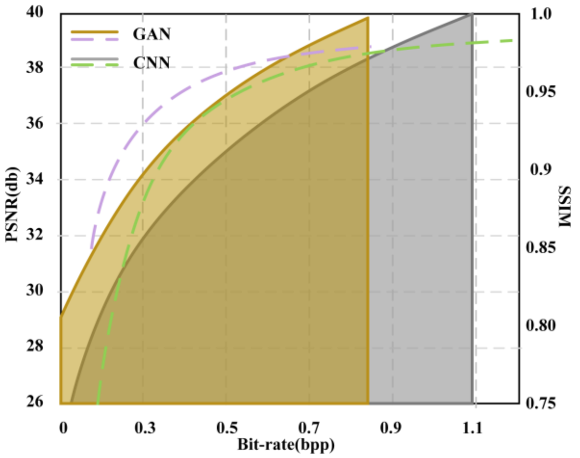


**Figure 5**: Performance index results of clothing style transfer module.

Figure 5 shows the detection results of the performance indicators of the clothing style transfer module. In the results, the index structure similarity (SSIM) can reflect the content retention ability of the model, and the index peak signal-to-noise ratio (PSNR) is used to evaluate the quality of the image. A high PSNR value usually indicates less distortion. The results show that the garment style SSIM value and PSNR value after style transfer of this module maintain a higher state, which indicates that it can retain more details within the scope specified by the designer in the style transfer process and is closer to the real design effect.

## 4 EXPERIMENTAL RESULTS OF COMPUTER-AIDED CLOTHING STYLE DESIGN MODEL BASED ON BIG DATA ANALYSIS

To test the application performance of a computer-aided clothing style design model based on big data analysis, this experiment will simulate the clothing design process in a certain year and start with the analysis of fashion market trends. Taking into account actual clothing sales, the experiment was aimed at women's clothing. Figure 6 shows the annual proportion of women's clothing categories and the analysis results of consumers' style preferences. The results show that this year, the proportion of wool knitwear in women's clothing was the highest, followed by dresses and shirts. In terms of clothing style, lady style, and vintage style are more favored by consumers.

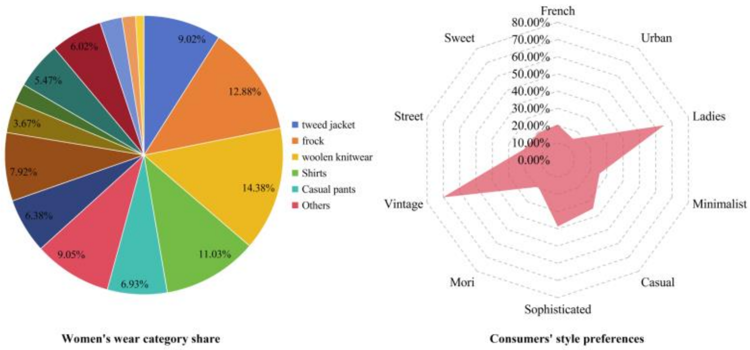


**Figure 6**: Analysis results of women's clothing category proportion and consumers' style preference in the whole year.

Figure 7 shows the sales volume of each category and the trend keywords of women's wear in competitive stores. The results show that woolly knitwear, dresses and shirts are still the three categories with the highest sales volume in competitive stores, which is consistent with the results in Figure 6. But the difference is that sales of dresses are much higher than sales of wool knitwear and shirts. As can be seen from the keyword analysis results of women's clothing trends, the colour of women's clothing has the highest impact, followed by silhouette, detail and fabric. To sum up, combined with the analysis results of Figure 6 and Figure 7, it can be seen that ladylike and retro dresses will have a strong fashion trend in the next year, and the influence of color, detail, and fabric is strong.

Based on the above analysis of market demand, the model designs dresses of lady style and vintage style according to the analysis results, and each series contains four different sub-series. To further improve the effectiveness and accuracy of clothing style design, the model calculates the proportion of dresses selected by consumers for each sub-series according to the needs of consumers, and the results are shown in Figure 8. As shown in the figure, among the lady style sub-series, sub-series 3 is selected by the highest proportion of consumers, while retro style sub-series 2 is selected by the highest proportion of consumers. Therefore, the two are the main objects of subsequent clothing design. To improve the competitiveness of fashion design in the market, the Lady style sub-series 4 and the retro style sub-series 3 will be the design objects of the second level.

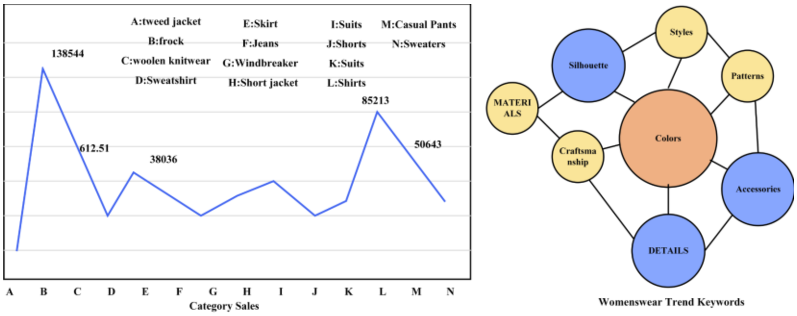


Figure 7: Sales of each category and keywords of women's fashion trends in competitive stores.

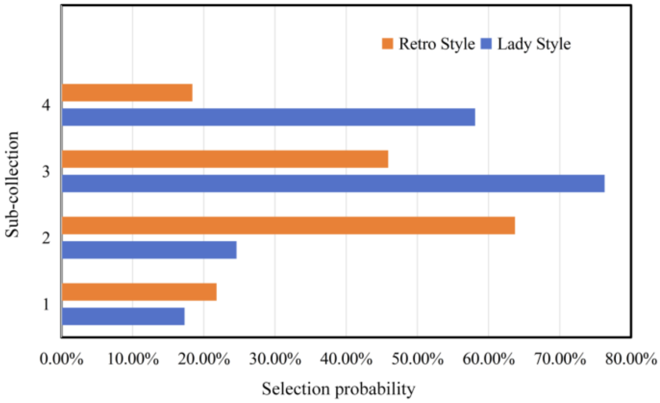


Figure 8: Probability and statistics of the selection of dress designs of lady style and vintage style series.

After selecting the style and basic style, the model will refine the clothing style design according to the needs of consumers, and the result is shown in Figure 9. Figure 9(A) shows the dress design of a ladylike style. The designer's original design is mainly based on a single colour, the neckline is a large V, the shoulder strap is slightly thin, and the overall skirt length is medium. After combining consumer preferences and style transfer, based on the basic outline of the dress, the neckline is transformed into a small V and the shoulder strap is widened, which highlights the waist and modifies the shoulder line. At the hemline, the hemline increases the level and length, making the hemline narrow, but also modifies the bottom line and elongates the bottom proportion. Figure 9(B) is the result of the transition of retro dress design style. The designer's original design is mainly dark colour, and the style is closer to the previous style. After the first style transfer, the colour of the clothing is mainly bright, the shoulder design is changed to achieve the visual effect through accessories, the sleeves are loose, which can modify the shoulder line, skirt hemline increases the sense of layer and achieves the design effect through colour conflict. After the second style transfer, the clothing style design is more in line with the current behaviour habits and aesthetics, the cuff is changed from narrow to wide, increasing the sense of elegance, the overall skirt length is slightly shortened, and the visual sense of level is improved by obvious contrast of length and length, the colour is more comfortable, the visual impact is reduced, and the use of skirt scenes is improved. It can be seen that the model in this paper can effectively extract the needs of consumers and the characteristics of clothing, realize the transfer of clothing style design style according to relevant data, achieve rapid design optimization, and make the design more in line with the current consumer aesthetic and market demand.

(A)

(B)

Figure 9: Effect of style transfer of dresses of two styles.

## 5 CONCLUSIONS

With the change of life pace and consumption concept, consumers have more and more diversified requirements for clothing styles, hoping to complete the transformation of different styles in a short time. Traditional clothing style design is highly dependent on manual experience, with long design cycles and low efficiency, it is difficult to complete the clothing design that meets the needs of consumers and the market in a short time. In the clothing style transfer module this model builds a clothing style transfer module based on GAN, which can ensure the authenticity of images while retaining more details of clothing styles to improve the quality of style transfer. The experimental results show that the model in this paper can analyze the relevant results of clothing styles in the current year according to the market sales and consumer behavior data and analyze the next fashion trend according to the results. According to the results of big data analysis, the designer can determine the clothing design of different series and calculate the probability of the design style being selected by consumers through the model, from which the better design is selected for the next design refinement. In the process of design refinement, the model can effectively combine the needs and preferences of consumers to carry out style transfer of clothing style design so that the design is more in line with the needs of consumers and the market.

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