# Application of CAD and Big Data Technology in Fabric Matching and Selection

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**Abstract.** With the increase in fabric types, consumers' demand for fabrics is more personalized and unique, which requires designers to choose the right fabric match. However, the traditional fabric matching method mainly relies on manual completion. This method is not only low efficiency and has a large error, but it is difficult to meet the needs of designers in a short time. Therefore, this paper combines CAD and big data technology to build a fabric matching and selection model through the combination of several algorithm models. The model improves fabric identification performance by using complex networks and SVM, as well as fabric matching and selection demand prediction performance by using the Apriori algorithm and LSTM. Performance test results show that compared with other models, the proposed model exhibits higher fabric identification and classification accuracy, lower error rate, and better stability in fabric matching. The experimental results show that in practical application, the matching degree of material, pattern, and colour of the fabric is better than that of other models, and the demand prediction of fabric selection is more in line with the actual demand, which can provide designers with more reliable decision support.

**Keywords:** CAD; Big Data Technology; Clothing Fabric; Complex Network; SVM; Apriori Algorithm; LSTM
**DOI:** https://doi.org/10.14733/cadaps.2025.S9.279-293

## 1 INTRODUCTION

With the continuous rise of consumers' demand for personalized and diversified clothing, the choice and exquisite matching of clothing fabrics has become a key bottleneck to promoting the innovation and development of the clothing industry. In this diversified era, there are many kinds of fabrics, from natural fibres such as cotton, hemp, silk, and wool, to synthetic fibres such as polyester fibre, nylon, and rayon, and then to high-tech functional fabrics such as waterproof breathable film, intelligent temperature control fibre, environmental protection, and renewable materials, each fabric carries a unique texture, colour, breathability, and functionality. It provides designers with unprecedented creative space [1]. However, in the face of such a wide range of fabric choices, the traditional design and production process seems inadequate. Traditional methods often rely heavily on the designer's personal experience and intuitive judgment of the market, and the best fabric combination is found through manual samples and repeated adjustment. This process is not only time-consuming and inefficient but also may lead to high costs and deviations between the final product and market demand [2]. In addition, the limitations of manual operation also limit the precision of fabric matching, and it is difficult to ensure that each design can accurately touch the individual needs of consumers. To break through this dilemma, the apparel industry is actively exploring the road of digital transformation, using advanced technology to optimize the fabric selection and matching process. Some designers have introduced CAD and fabric simulation technology to quickly preview the effects of different fabric combinations in a virtual environment, greatly shortening the design cycle and reducing the cost of trial and error [3]. In addition, designers can simulate the texture, gloss, and texture details of various fabrics through the CAD system combined with advanced texture mapping algorithms, which greatly improves the realism of the design and reduces the production requirements of physical samples [4].

Some designers adjust the color, pattern, density, and other parameters of fabrics through CAD and parametric design methods, and the system automatically generates corresponding design effects to achieve rapid iteration and optimization. This technology not only speeds up the design speed but also makes the design scheme more flexible [5]. To improve the accuracy of fabric matching, some researchers use big data analysis technology to analyze consumers' purchase history, browsing history, social media interaction, and other data, providing accurate market guidance for fabric selection [6]. Other researchers built a fabric classification model based on the BP neural network to help designers improve the efficiency and accuracy of selecting from a large number of fabric types through accurate identification and classification [7]. In terms of fabric cutting and sewing, some designers have pointed out that different properties and characteristics of fabrics have different ways of applying fabrics, and they realize high-precision cutting and stitching of fabrics by integrating sensors, machine vision, and control systems [8]. These devices can automatically adjust parameters according to preset patterns and sizes, reducing manual intervention and errors and improving production efficiency and product quality. In terms of fabric management, some researchers believe that good fabric management can improve the efficiency of fabric selection and matching, and through the integration of Internet of Things (IoT) technology, fabric inventory management, and supply chain coordination are more efficient and transparent, providing a strong guarantee for rapid response to market demand [9]. According to the existing research literature, the current model research on fabrics mainly focuses on image retrieval, classification, and performance evaluation of fabrics and lacks systematic research on fabric matching and selection [10]. The results of fabric matching and selection research mainly use a single model to achieve the purpose; with the rapid increase of fabric scale, the performance of the model cannot fully meet the needs of designers. Therefore, according to the fabric selection principle and matching demand analysis results, this paper combined CAD and big data technology to build a clothing fabric matching and selection model. Through the model, the identification of different fabrics, and according to the market and consumer data analysis, the fashion trend of fabrics is predicted to achieve accurate matching and selection of fabrics.

CAD technology provides powerful design tools for textile designers through digital means. In the process of fabric selection, CAD systems can simulate the combination effects of different fabrics' materials, colours, and textures, helping designers quickly preview and optimize design schemes. The introduction of big data technology enables textile enterprises to collect and analyze massive market data, consumer preferences, sales records, and other information. By deeply mining these data, enterprises can gain insights into market trends, predict consumer demand, and guide the decision-making process for fabric selection. This technology not only shortens the design cycle but also improves the accuracy and innovation of the design. Designers can easily adjust fabric parameters such as density, glossiness, stretchability, etc., based on CAD platforms to meet different application scenarios and customer needs. For example, big data analysis can reveal which types of fabric combinations are more popular in the market and which colors or patterns of fabrics have higher sales potential. These pieces of information provide a scientific decision-making basis for textile enterprises, helping them to accurately position the market, optimize product structure, and enhance market competitiveness. On the one hand, CAD systems can generate a large number of design solutions, while big data technology can quickly screen and evaluate these solutions to find the design that best meets market demand. Combining CAD technology with big data technology can further improve the efficiency and accuracy of fabric selection. On the other hand, big data technology can also provide real-time market feedback and consumer insights for CAD systems, helping designers continuously adjust and optimize their design ideas during the creative process. This two-way interactive mode not only accelerates the speed of design iteration but also ensures the market adaptability and competitiveness of the design scheme.

## 2 RELATED WORK

The fashion industry is actively adopting learning-based strategies, especially in e-commerce applications such as clothing recognition, clothing search, and clothing attribute detection, which greatly improves user experience and shopping efficiency. The introduction of Atmospheric Dark Light Adjustment (ADLA) technology significantly improved image quality in the preprocessing stage, thereby extracting richer feature information. Big data technology provides scientific decision support for fabric selection by collecting and analyzing market data, consumer preferences, and other information. Facing clothing with similar appearance but different labels, achieving efficient and accurate clothing recognition remains challenging. To address this challenge, Panneerselvam and Prakash [11] proposed an innovative clothing recognition framework that cleverly combines convolutional neural networks (CNN) with accelerated robust features. When these two technologies are combined, they can jointly promote the intelligent process of the fashion industry, achieving more precise and personalized fabric selection solutions. It is worth noting that the integration of CAD (computer-aided design) and big data technology also plays an important role in the field of fabric selection. This technology optimization is similar to the application of CAD and big data technology in fabric selection. CAD technology not only provides designers with powerful design tools but also accelerates the design process and improves design accuracy by simulating the effects of different fabric combinations. Specifically, CAD technology allows designers to try different fabric combinations in a virtual environment, while big data technology helps analyze which combinations are more popular in the market. Su [12] introduced ADLA technology into the clothing recognition framework, which not only improves image quality but also lays a solid foundation for subsequent feature extraction and classification tasks.

A major challenge in utilizing virtual fitting technology to promote clothing production and the online shopping experience is how to capture and convey the sensory characteristics of fabrics accurately. Especially in terms of drape and tactile experience, these features are often difficult to quantify directly through traditional digital means. The system uses drape and tactile features as quantitative indicators to explore the potential for collaborative application of CAD and big data technology in fabric selection, comprehensively enhancing the intelligence level of the textile industry. Given this situation, Tan et al. [13] not only focused on developing an innovative fabric sensory feature classification system. This process provides objective quantitative standards for the sensory characteristics of fabrics and verifies the classification system's effectiveness and practicality through subjective evaluation by experts. Next, the study further explored the application of artificial neural networks in predicting fabric classification groups. The experimental results show that the model has a prediction accuracy of 83.5% for 534 training samples and 243 validation samples, fully demonstrating the enormous potential of artificial intelligence technology in evaluating the sensory characteristics of fabrics. By embedding the classification system into CAD and big data platforms, Xiang et al. [14] can more effectively screen and match fabric materials that meet market demand, thereby accelerating product development cycles, improving product quality, and enhancing market competitiveness. This study introduces for the first time the fuzzy c-means clustering analysis technique to scientifically classify fabrics' drape and tactile sensation (such as softness). By training an artificial neural network model based on mechanical properties such as drape and tactile softness, the model successfully achieved high-precision classification and prediction of a large number of fabric samples. The establishment of this classification system provides more accurate data support for the subsequent fabric selection process.

Clothing image recognition, especially clothing attribute recognition, has received widespread attention in commercial and social applications due to its enormous potential. Therefore, Xiang et al. [15] proposed an innovative recognition framework based on Region Convolutional Neural Network (RCNN) architecture and combined the concepts of CAD and big data technology to optimize the image recognition process in fabric selection. In this framework, it first adopts an improved selective search algorithm to more accurately extract potential clothing regions in the image as candidate suggestions. To comprehensively evaluate the performance of the framework, we specifically constructed a large dataset containing approximately 100000 shirt images, covering various styles, colours, and materials to simulate complex situations in the real world. Faced with the diversity of clothing appearances and styles, as well as the complexity of image capture environments, research in this field faces many challenges. Subsequently, the Inception ResNet V1 model, which integrates the L-Softmax loss function, was used for in-depth feature representation and category recognition of these regions. After obtaining preliminary region detection results, we adopted a softened non-maximum suppression (soft NMS) strategy to optimize the detection results and reduce false positives in overlapping regions. The introduction of L-Softmax enhances the model's ability to distinguish subtle differences and helps improve recognition accuracy. Although traditional deep convolutional neural networks (CNNs) are powerful, they often struggle to achieve ideal results when processing highly variable clothing images. Finally, use a simple neural network to fine-tune the boundaries of the bounding boxes to ensure accurate recognition. The experimental results show that the overall annotation rate, accuracy, and recall rate of the framework are 87.77%, 73.59%, and 83.84%, respectively, which are significantly better than traditional methods, proving their effectiveness and superiority.

## 3 CLOTHING FABRIC MATCHING AND SELECTION MODEL BASED ON BIG DATA TECHNOLOGY

Fabric is not only an important basis for presenting clothing design but also related to consumers' feelings of use. Its selection principles and basis involve many aspects to ensure that the final effect of clothing or products meets the requirements of design, function, comfort and cost-effectiveness. In terms of selection principles, fabrics should be coordinated with the style and design style of clothing or products to ensure overall aesthetics and functionality. The fabric should have good air permeability and moisture absorption to ensure that the wearer remains dry and comfortable during wear. Under the premise of meeting the design requirements and wearing comfort, cost-effective fabrics should be selected as far as possible. This will help control product costs and improve market competitiveness. Fabrics should meet specific functional requirements, such as waterproofing, antifouling, sun protection, etc. At the same time, the fabric should also be durable enough to withstand wear and aging during daily use and washing. In terms of fabric selection, different fabrics have different characteristics, such as air permeability, moisture absorption, warmth retention, elasticity, etc. These characteristics will directly affect the product's use effect and wearing comfort. Therefore, when choosing fabrics, we should fully understand their characteristics and choose according to actual needs. Design requirements are one of the important bases for fabric selection. Designers usually choose the right fabric based on the overall style and design concept of the product. Market demand is also an important consideration in fabric selection. Manufacturers should choose the right fabric according to the needs of the target market and consumer preferences. The process properties of fabrics are also an important basis for selection. Different fabrics may exhibit different properties and effects during sewing, ironing, bonding, and other processes. Therefore, the selection of fabrics in this paper will be based on the results of the 5W1H analysis tool. The detailed contents of the 5W1H analysis tool are shown in Table 1.

| *Index* | *Specific content* |
|---|---|
| Who | It should be clear who the target consumers of the fabric are |
| Why | Be clear about the purpose of the fabric, whether it is for warmth, shading, fashion, functionality, or something else. |
| Where | Consider the region where the fabric will be used, the climate, and the occasion. |
| When | Consider which season the fabric will be used in. Different seasons have different needs for fabric thickness, air permeability, heat preservation, etc. |
| What | Based on the previous analysis, determine the type of fabric that needs to be selected, such as cotton, linen, silk, wool, chemical fibre, etc. |
| How | Determine how to obtain the required fabric, including cooperation with suppliers, procurement channels, price negotiations, etc.<br>Consider the method of use and maintenance of the fabric to ensure that the performance of the fabric is fully developed and extends the service life. |

**Table 1**: 5W1H analysis tool details.

In addition, the functional requirements of different parts of the human body are different; that is, the fabrics selected for clothing design should be able to meet the basic needs of different parts of the human body, as shown in Table 2, the directional functional requirements of different parts of the human body and the corresponding clothing components. Through this table, the corresponding parts and functions of clothing design can be clarified when selecting fabrics. There are more requirements for fabric functionality, which is an important basis for fabric matching and selection.

| *Body part* | *Directed functional requirements* | *Clothing and its parts* |
|---|---|---|
| Head/ears | Keep warm and avoid the cold | Hats, turbans, ear warmers, ear caps, etc. |
| Oral part | Antibacterial, antiviral, warm | Face mask |
| * Neck | Keep warm and avoid the cold | Scarf, collar, hat, etc. |
| * Shoulders | Keep warm and avoid the cold | Over the shoulder, shoulder pads, shoulder pads, sleeve hill, etc. |
| * Chest | antibiosis | Bras, chest shields, etc. |
| * Waist/abdomen | Warm and cold, antibacterial | Waist support, high waist head, hem, underlit, etc. |
| Hand/wrist/elbow | Warm and cold, antibacterial | Gloves, wrist guards, cuff elbows, cuff cuff, cuff cuff, etc. |
| * Crotch | Antibacterial and antiviral | Underwear, separable antibacterial inner crotch, etc. |
| * Buttocks | antibiosis | Three-dimensional pocket, pocket, etc. |
| * Legs/knees | Keep warm and avoid the cold | Knee pads, hemlines, etc. |
| * Foot/ankle | Warm, antibacterial, and deodorant | Bottoms, socks, soles, etc. |

**Table 2**: Directional functional requirements of different parts of the human body and corresponding clothing components.

Fabric identification in the fabric matching and selection model is an important basis and premise of matching and selection, which can directly affect the final matching result. In the matching link, it is not only necessary to analyze the relevant data of consumers, but also to predict the future fabric selection trend in combination with market demand and consumer demand, on this basis, to achieve more accurate fabric matching and selection. Therefore, this paper will specifically describe the fabric identification and fabric matching methods.

### 3.1 Fabric Recognition Module Based on Complex Network and SVM

In fabric feature extraction, complex networks can capture and analyze multi-dimensional features in fabric images by utilizing the complexity and diversity of networks. Complex networks can construct multi-dimensional feature representations to describe complex properties such as color, texture, and structure of fabrics. These characteristics can be reflected by the nodes and edges of the network and the overall structure of the network. The complexity and regularity of the fabric's internal structure can be revealed by using a complex network model to model fabric images. Complex networks can reveal the structural relationships among pixels or regions in fabric images, such as clustering, hierarchy, etc. These structural features are important for understanding the overall layout and local details of the fabric. By analyzing the connections and interactions between nodes, complex networks can uncover hidden relationships and patterns in fabric images that may reflect the physical properties of the fabric or the production process. Figure 1 shows the schematic diagram of the fabric feature extraction process based on a complex network.

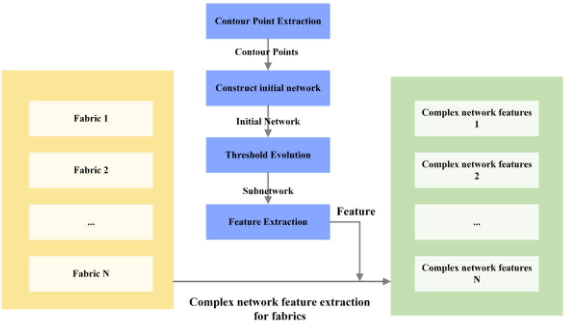


**Figure 1**: Schematic diagram of fabric feature extraction process based on complex network.

Let the number of connecting edges between any node and other nodes be expressed as $g(n)$ its calculation formula is shown in (1):

$$g_n = \sum_{m=1}^{M} a_{nm} \tag{1}$$

The number of nodes in the network is $g$ under the conditions, its proportion in all nodes is its distribution, as shown in formula (2):

$$p(g) = \frac{m_g}{M} \tag{2}$$

The middle degree of the node reaches $g$ the number of nodes is expressed as $m_g$ the total number of nodes is expressed as $M$ .

Suppose there are nodes in the complex network $v_n, v_m$ , the shortest path length between them is expressed as $l_{nm}$ the maximum distance between them is shown in formula (3):

$$\begin{cases} L = \max_{1 \le n,m \le i} l_{nm} \\ ave_L = \dfrac{1}{M^2} \sum_{m=1}^{M} \sum_{n=1}^{M} l_{nm} \end{cases} \tag{3}$$

The average path length of all nodes is shown in formula (4):

$$ave_L = \frac{1}{M^2} \sum_{m=1}^{M} \sum_{n=1}^{M} l_{nm} \tag{4}$$

Suppose any node exists $v_n$, the number of nodes connected to it is expressed as $g_n$, and the actual number of sides between these nodes is expressed as $I_n$, then the agglomeration coefficient of this node and the average value of all nodes in the network are shown in formula (5):

$$\begin{cases} C_n = \dfrac{2I_n}{g_n(g_n - 1)} \\ C = \dfrac{1}{M} \sum_{n=1}^{M} C_n = \dfrac{1}{M} \sum_{n=1}^{M} \dfrac{2I_n}{g_n(g_n - 1)} \end{cases} \tag{5}$$

The formula for calculating the number of nodes is shown in (6):

$$B_n = \sum_{m \ne l \ne n} \frac{M_{ml}^n}{M_{ml}} \tag{6}$$

Where node $v_m \to v_l$ the number of shortest paths between them is expressed as $M_{ml}$, which will pass through $v_n$ The number of shortest paths is expressed as $M_{ml}^n$.

According to the above formula, the static statistical characteristics of complex networks can be obtained, but there are also dynamic evolution characteristics, and different network dynamic evolution characteristics are different. At the same time, more information about network structure and dynamics can be obtained according to the dynamic evolution of the network. In this paper, K-nearest neighbours are adopted to realize the dynamic evolution of complex networks, and the process is shown in formula (7):

$$G_k = \delta(G_0, k) = \begin{cases} w_{nm} = 1, if \;\; m \in KNN(n) \\ w_{nm} = 0, otherwise \end{cases} \tag{7}$$

Formula $k = 1, 2, \ldots, |V| - 1$, the initial network is represented as $G_0$ the network vertex set is described as $V$ the directed edge between a node and its neighbours is expressed as $KNN(n)$.

SVM classifies fabrics in the fabric recognition module to improve the accuracy of fabric identification and matching. Considering the complexity of fabric classification, this paper uses a nonlinear kernel function to realize the classification. Commonly used nonlinear kernel functions include linear kernel functions, polynomial functions, Gaussian radial basis functions, and multilayer sensing functions, as shown in formula (8):

$$\begin{cases} Polynomial \quad : K(x_i, x_j) = (\gamma \left\langle x_i, x_j \right\rangle + r)^d \\ RBF : K(x_i, x_j) = exp(-\gamma \left\| x_i - x_j \right\|^2) \\ Sigmoid : K(x_i, x_j) = tanh(\gamma \left\langle x_i, x_j \right\rangle + r) \\ Linear \;\; Kernel : K(xi, xj) = \left\langle x_i, x_j \right\rangle \end{cases} \tag{8}$$

Where input data points are represented as $x_i, x_j$, the inner product of the two is expressed as $\langle x_i, x_j \rangle$, the corresponding Euclidean distance is expressed as $\|x_i - x_j\|$, the kernel function coefficient is expressed as $\gamma$, the parameter is expressed as $r$.

Because the key of SVM model training is to select the appropriate kernel function and parameters, the kernel function determines the mapping mode in the feature space. Therefore, this paper examines the performance of different kernel functions through fabric recognition training data sets. In the experiment, the training data were randomly divided into ten groups with different kernel function SVM models for classification, and the final average classification accuracy was shown in Figure 2. The results can be seen in the figure, except $Sigmoid$, the average classification accuracy of other kernel functions can reach more than 95%, among which the average accuracy of linear kernel function for fabric classification is the best, which can reach more than 97%. Therefore, the linear kernel function is chosen by SVM in this paper.

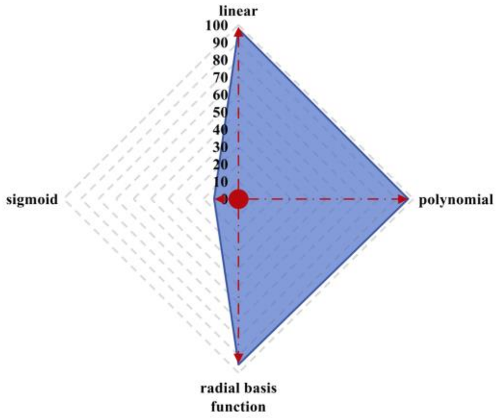


Figure 2: Comparison results of average classification accuracy of different kernel functions.

Figure 3 shows the comparison of fabric classification results of the three classification models. This experiment contains three categories of fabric. Logistic regression and decision tree classification models are selected for comparison. As can be seen from the results in the figure, some fabric classification results in the decision tree classification model are inaccurate, and the boundary between the three fabric data points is not obvious. The classification result of the logistic regression model is worse than that of the decision tree, and its classification effect on nonlinear problems is not ideal. The classification results of the model in this paper show obvious classification boundaries, and the data aggregation effect of the same fabric is better; that is, the classification of different fabrics can be better realized.

## 3.2 Fabric Matching Module Based on Apriori Algorithm and LSTM

In the process of fabric matching and selection, designers need to fully consider the needs of the market and consumers based on design needs and decide the choice of fabric according to the results of the two needs. Figure 4 shows the proportion of factors that consumers are affected by clothing fabrics. As can be seen from the results of the figure, under normal circumstances, consumers pay more attention to the thickness, elasticity, softness, and other factors of the fabric, and there is a certain mutual influence between different influencing factors, which will also have a certain impact on consumers. Therefore, this paper analyzes the correlation of relevant data using the Apriori algorithm.

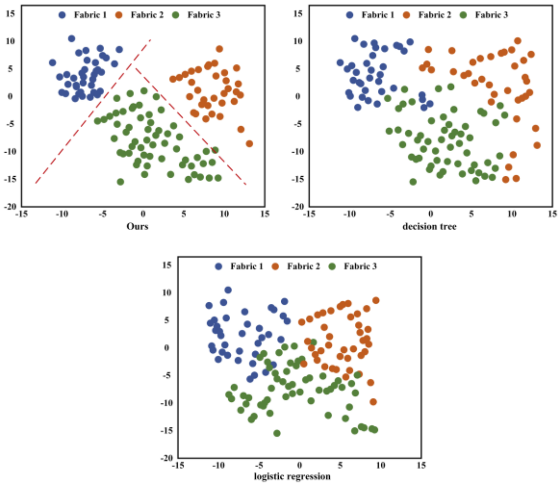


Figure 3: Fabric classification results of three classification models.

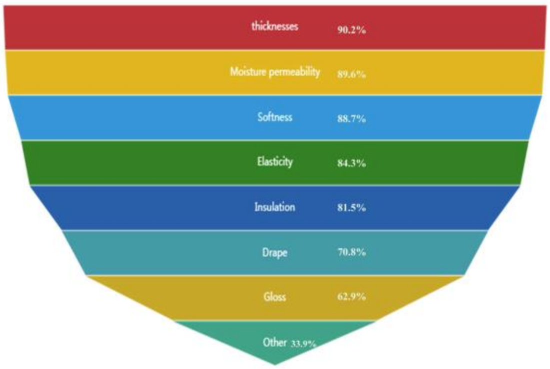


Figure 4: Proportion of factors affected by clothing fabrics.

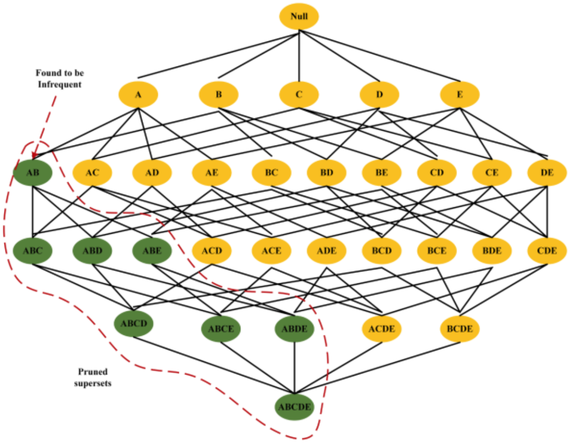


Figure 5: Apriori algorithm structure diagram.

The Apriori algorithm is mainly used to find frequent item sets and association rules in large-scale data sets. It finds out the relationship of item sets in the database through the iterative method of layer-by-layer search to form rules. The process consists of joining (and pruning). The algorithm is based on a priori property: if an item set is frequent, then all its subsets are frequent as well; Conversely, if an item set is infrequent, then all of its supersets are also infrequent. Figure 5 shows the structure diagram of the Apriori algorithm.

Let the two item sets be $X$ and $Y$ the strength of the association between the two is measured by approval rating and confidence rate, as shown in (9) and (10):

$$S(X,Y) = P(X,Y) = \frac{num(xy)}{num(allsamples)} \tag{9}$$

$$C(XY) = P(x|Y) = \frac{P(xy)}{P(y)} \tag{10}$$

Formula, $S$ and $C$ standing for approval rating and confidence rating, $num$ represents the aggregate.

The LSTM model is introduced in this paper to improve the performance of the model. In fabric matching analysis, LSTM can be used to learn complex relationships between fabric properties. With the LSTM model, feature vectors for a series of fabrics can be input, and the model can be trained to predict which fabrics are more likely to match each other visually or functionally. The LSTM model can capture the sequential relationship of different factors in fabric matching and selection and predict the appropriate choice for the next step based on the previous selection.

LSTM is a special recurrent neural network (RNN) that introduces a "gate" mechanism to solve the problem of gradient disappearance or gradient explosion, which is prone to occur when traditional RNN processes long sequences. When the time is set, the status of the forgetting door at the previous moment is $C_{t-1}$, its expression is shown in (11):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{11}$$

Where the activation function is expressed as $\sigma$, the weight matrix of the forgetting gate is described as $W_f$, the offset term is expressed as $b_f$ the output state of the migration sum is expressed as $h_{t-1}$ the current input is $x_t$ .

Let the currently existing candidate state be represented as $\tilde{C}_t$, the input gates are shown as (12) and (13):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{12}$$

$$tildeC_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{13}$$

Where the input gate output is expressed as $i_t$ , its weight matrix is expressed as $W_i$ , the weight matrix of candidate states is expressed as $W_C$ , the corresponding offset terms are $b_i, b_C$ .

Cell status updates are shown in (14):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{14}$$

The output gates are shown as (15) and (16):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{15}$$

$$h_t = o_t * tanh(C_t) \tag{16}$$

Where, the output gate output is expressed as $o_t$, the weight matrix is expressed as $W_o$, the offset term is $b_o$.

To test the performance of the fabric matching module, this paper selected two other models for comparison. Figure 6 shows the comparison results of the matching error rates of the three models. The results in the figure show that the error of the BP neural network and RNN neural network is significantly higher than that of the model in this paper, and the fluctuation of the error curves of the two is strong, which indicates that the stability of the two is relatively weak, and it is difficult to use different fabrics to match and select scenes in practical applications. The error curve of the model in this paper has a small fluctuation range, which indicates that it has good stability and can provide more reliable data support in fabric matching and selection.

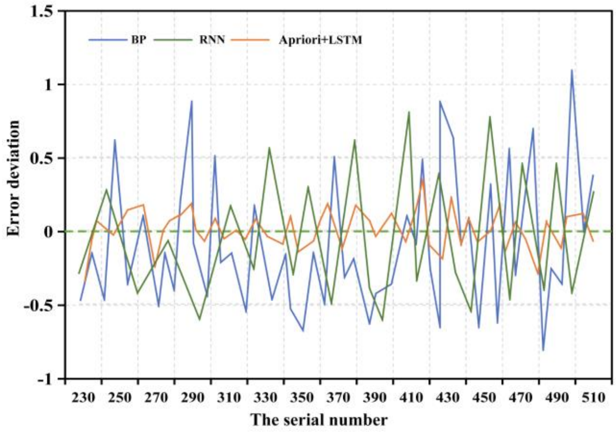


Figure 6: Comparison results of matching error rates of the three models.

## 4 EXPERIMENTAL RESULTS OF CLOTHING FABRIC MATCHING AND SELECTION MODEL APPLICATION BASED ON BIG DATA TECHNOLOGY

In the actual fabric matching and selection process, it is required that the fabric can meet the required standard in multiple dimensions. In this paper, two fabric-matching models will be selected to compare the matching degree of the fabric from three aspects: material, pattern, and color. To be closer to the actual application environment, 12082 fabric images were randomly selected as the training set and 1180 fabric images as the test set. Figure 7 shows the comparison results of the matching degree and matching time of the three models for different materials. From the matching results, the matching degree of the three models of fine cotton, canvas, and nylon is relatively low, mainly because the feature vector of the fabric of these three materials is similar to other fabrics, so it is difficult to identify and match. In terms of the matching degree of a single material fabric, the matching degree of this model is higher than that of the other two models. On the whole, the matching degree of the random forest model is above 80%, and the highest is 91.6%. The matching degree of data mining models is also above 80%, but the highest matching degree is relatively low, reaching 89.07%. The matching degree of the models in this paper is above 85%, and the maximum is 92.2%, which has certain advantages. In terms of matching time, the matching time of the other two models is significantly higher than the matching time of this paper, the fluctuation range of the time curve of the two models is larger, and the fluctuation of the time curve of the model in this paper is smaller. This shows that the fabric-matching efficiency and stability of the model in this paper are higher.

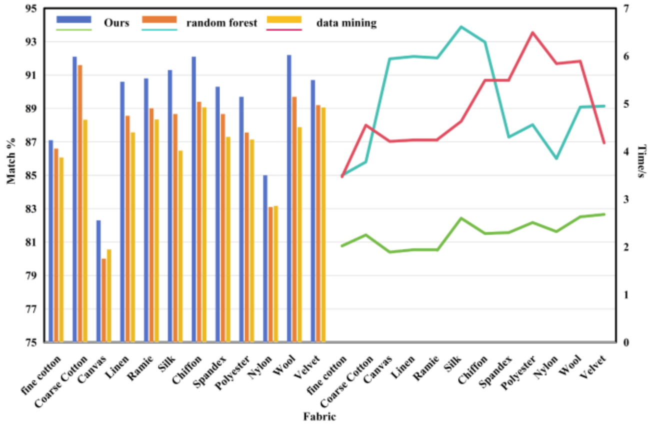


**Figure 7**: Matching degree and matching time of the three models for fabrics of different materials.

In fabric matching, the pattern of fabric has a direct impact on the final presentation effect of clothing. Figure 8 shows the matching degree and loss value of the three models for different pattern fabrics. The results show that the matching degree of the random forest and data mining models is relatively low at the initial stage of fabric matching. With the increase of times, the matching degree of the models increases to a certain extent, and the curves show a wavy upward trend and then tend to be stable. On this surface, the two models need to learn continuously to achieve the expected effect of matching degrees. The pattern-matching degree of the model in this paper is always in a high state, and the curve is stable. From the results of loss value, the loss value of random forest and data mining models decreased significantly in the initial stage and then stabilized. According to the loss value of the last few sets of data, the performance of the random forest model is better than that of the data mining model. Although the loss value of the proposed model changes little, the final loss value is significantly lower than that of the other two models, which indicates that the pattern-matching performance of the proposed model is better than that of the other two models and has good stability.

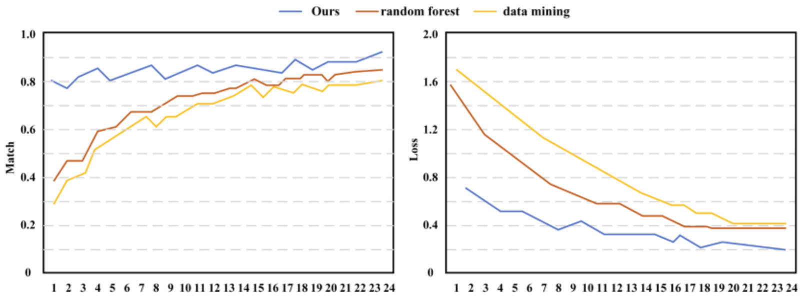


**Figure 8**: Matching degree and loss value of three models for fabrics of different patterns.

Figure 9 shows the matching degree and loss value of the three models for fabrics of different colours. The results in the figure show that the performance of fabric color matching degree and pattern matching by random forest and data mining models are consistent; that is, the matching degree increases with the increase of test times, while the loss value decreases to a certain extent. The matching degree of the model in this paper has been kept in a high range, and the change range of the loss value is small, but the value is the lowest. This shows that the fabric colour-matching performance of the model is better.

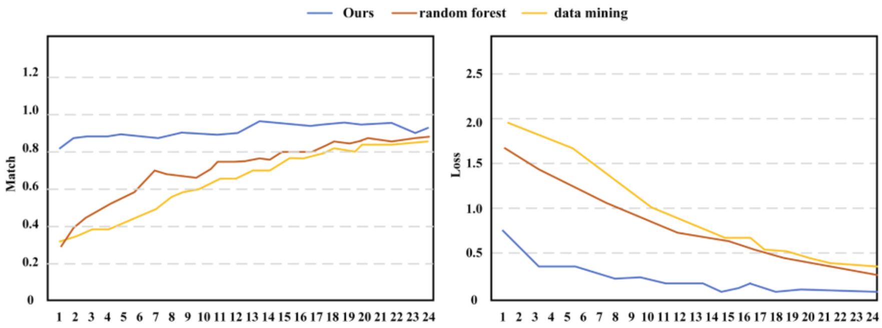


Figure 9: Matching degree and loss value of three models for fabrics of different colours.

The matching and selection of fabrics are meant to meet the needs of consumers and the market, so the development trend of fabrics should be predicted during the selection process. Therefore, this paper tested the fabric selection prediction results of the three models, as shown in Figure 10. The red curve in the figure is the actual fabric demand curve. The results show that although the data mining model has a relatively poor performance in fabric matching performance, it has a great advantage in mining the correlation between factors. Therefore, its fabric demand prediction result is slightly better than the random forest model, but there is still a big gap between it and the actual fabric demand. The gap between the predicted curve of fabric demand and the actual curve of this model is smaller. This shows that it has better predictive performance in practical applications, can accurately predict the change of fabric demand according to the analysis results of consumers and market historical data, and provides designers with more reliable information for fabric selection decisions.

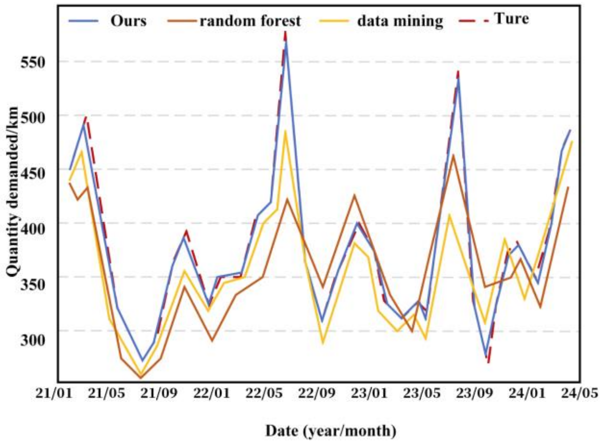


Figure 10: Comparison of the predicted results of fabric selection by three models.

## 5 CONCLUSIONS

The matching degree and selection of fabrics have a direct impact on the final presentation effect of clothing design. In the past, limited by conditions, the annual growth of the types of fabrics was limited, and the demand for matching and selection of clothing fabrics could be met by artificial means. However, with the improvement of production technology, the number of fabric types, patterns, colors, and other changes has increased sharply, and the error rate of traditional fabric selection is getting higher and higher, which can no longer meet the demand. Therefore, combining CAD and big data technology, this paper constructs a fabric matching and selection model by combining various algorithms. The model improves the accuracy of fabric identification by using complex networks and SVM. The test results show that the model is better than the other two models in fabric identification and classification. The model also improves the accuracy of fabric matching and selection by combining the Apriori algorithm and LSTM. The performance results show that the error rate of the module is significantly lower than other models, which can provide reliable basic data for practical applications. The experimental results show that compared with the random forest and data mining models, the proposed model is significantly higher in material matching, pattern matching and color matching, and shows good stability. At the same time, the combination of multiple algorithms effectively improves the prediction performance of the model for fabric selection demand, and the prediction results are more in line with the actual situation, which can provide designers with more accurate, effective and reliable decision data information.

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