# Traditional Chinese Clothing Style Recognition and Design Based on Deep Learning

Yilin Fan[1] and Meixin Li[2]

[1,2] School of Fashion, Dalian University of Art, Jinzhou 116600, China,
[1]fanyilin@dac.edu.cn, [2]limeixin@dac.edu.cn

Corresponding author: Yilin Fan, fanyilin@dac.edu.cn

**Abstract.** With the rapid growth of the Internet and e-commerce, the number of Chinese Clothing Styles on the Internet is growing exponentially. The demand for intelligent recognition of a large number of Chinese Clothing Styles is increasingly urgent. Especially on e-commerce platforms, quickly and accurately identifying Chinese Clothing Styles can not only improve search efficiency but also help users find products that better meet their needs and preferences. In response to the above issues, this article proposes a new method for traditional Chinese Clothing Style recognition and CAD based on deep learning (DL). This method utilizes DL models to train on a large dataset of annotated clothing images, enabling the model to learn feature representations of Chinese Clothing Styles and achieve fast and accurate recognition of Chinese Clothing Styles. At the same time, combined with CAD software, we have designed a CAD system that integrates DL models. The system can automatically generate preliminary design sketches based on user input Chinese Clothing Style requirements, providing designers with efficient auxiliary design tools. The experimental results show that the method proposed in this article has high accuracy and efficiency in Chinese Clothing Style recognition and can handle complex and variable Chinese Clothing Styles.

**Keywords:** Deep Learning; Traditional Clothing; Style Recognition; CAD Assisted Design
**DOI:** https://doi.org/10.14733/cadaps.2025.S1.326-341

## 1 INTRODUCTION

In the current era of the 21st century, economic prosperity and the augmentation of people's quality of life have led to a mounting demand for personalized attire and dressing styles. 3D printing technology has now penetrated into multiple industries, with the fashion industry being particularly prominent. As a cutting-edge technology, 3D printing not only changes the production methods of products but also provides new creative design tools for fashion and textile designers. In this process, designers not only utilized advanced 3D printing technology but also delved into traditional Chinese Clothing Style recognition elements. Especially in integrating traditional Chinese Clothing Style recognition elements, 3D printing technology has demonstrated its unique advantages. Fashion designers can create fashion items with multi-colour surface textures in unprecedented ways through 3D printing technology, such as clothing, fabrics, or fashion accessories. Chan et al. [1] are committed to developing a theoretical design process model specifically designed for creating 3D printed fashion prototypes with multi-colour surface textures. Combining the theory, practical concepts, and physical prototype technology of 3D printing technology, this paper deeply analyzes the expression and application of various design elements in traditional Chinese Clothing Styles. In the development process of the model, we pay special attention to the integration of traditional Chinese Clothing Style recognition elements. The cutting of Chinese cheongsam, patterns of Japanese kimono, and colours of Indian sari are cleverly integrated into the design of 3D printed fashion prototypes. Parallel to this, the emergence and growth of e-commerce have introduced sweeping changes to the clothing industry. Customers now have access to a vast array of Chinese Clothing Styles, which they can browse, search, and purchase on various online platforms, significantly broadening their options.

Chang [2] proposed an innovative design concept. Combining traditional Chinese Clothing Style recognition elements with weaving art not only enriches the expression techniques of weaving art but also injects new vitality into traditional clothing culture. By utilizing parametric design methods and combining traditional Chinese Clothing Style recognition elements, a 3D model with knitted characteristics is constructed, and a physical prototype is printed using 3D printing technology. Weaving art, as an ancient and charming technique, its unique textures and patterns not only have aesthetic value but also carry profound cultural connotations. These elements not only reflect the aesthetic concepts of different regions, ethnic groups, and eras but also carry rich historical and cultural information. This design process aims to combine traditional weaving techniques with modern manufacturing technology, showcasing the aesthetic and cultural value of weaving art in a new perspective and way. With the rapid development of computer-aided design technology, especially the rise of parametric design methods, it provides unlimited possibilities for the innovative application of traditional weaving art. In today's booming cultural and creative industry, it is necessary for us to re-examine and inherit this precious traditional craft. The textile and clothing industry is an important pillar of China's economic development. However, the textile manufacturing industry still adopts the traditional production mode of "mass production", with low automation levels, serious problems such as information silos, production capacity bottlenecks, and rigid production. In response to the above challenges, Deng et al. [3] conducted research on clothing production workflow modelling, production process and resource knowledge modelling, as well as dynamic bottleneck detection and spatiotemporal prediction methods. To meet the automation needs of textile and clothing enterprises and achieve fast and efficient clothing production, enterprises need to accurately identify and predict process bottlenecks in clothing production. This solves the process bottleneck in clothing production, which affects the efficiency and quality of clothing production. Export standard event log data from the enterprise information system, and generate a real clothing production workflow model based on an inductive process discovery mining algorithm. Design an ontology knowledge model for clothing production processes and resources, and classify and correlate production process data. Realize unified management and query of production process knowledge, providing data sources for subsequent bottleneck detection and prediction. It studied the dynamic bottleneck detection and prediction method of the clothing production process and proposed a clothing production dynamic detection method based on the turning point method for the layout structure analysis of clothing production lines. Conduct spatiotemporal analysis on the bottleneck characteristics of clothing production and analyze the reasons that lead to production bottlenecks. Elboq et al. [4] proposed an automatic clothing pattern generation method based on an improved deep convolutional generative adversarial network (DCGAN) model. Build a fast style transfer model for the style transfer section, and conduct comparative experiments with three different content loss and style loss parameters. Adding attention mechanism CA to the generative network enhances the overall beauty of floral and animal patterns. Introduce a combination of objective and subjective methods to evaluate the generated patterns. Replace the ReLU activation function in the generative network with the PReLU activation function to obtain rich features and increase the local details and patterns of texture-like patterns. The research results indicate that compared to traditional DCGAN, both improved models proposed in the paper have better comprehensive performance. The previous research found that the pattern generated by generative methods for concrete cat-like patterns had poor results. Therefore, concrete cat-like patterns were introduced as the research object, and three styles, namely ink wash style, oil painting style, and pixel style, were selected as the style standards. Given that clothing patterns have different constituent elements, a DeepLabV3+semantic segmentation model is constructed to segment the target pattern and background, and comparative experiments are conducted with different feature extraction networks. Personnel in the textile and clothing industry have also given positive feedback on the quality, diversity, attractiveness, and inspiration of the improved model in generating patterns, which has high practical reference and application value.

Guan et al. [5] developed an advanced Chinese Clothing Style learning and recommendation system. In order to build such a system, a new type of Chinese Clothing Style training data containing rich design elements was created from the perspective of costume designing design. The model combines convolutional neural networks (CNN) to capture visual features of clothing images and combines them with baseline classifiers such as support vector machines (SVM) for preliminary classification prediction. This system can not only recognize the deep design-related features of clothing, but also insight into the connotations related to style, body, and costume designing design elements contained in these features, thus providing high-quality recommendations like skilled human experts. Then, based on these predicted attributes, combined with costume designing design elements, further predict the meaning and style of clothing. This strategy not only improves the model's ability to capture deep design features of clothing (for example, from 73.5% of Model B to 86% of Model C). Body shape is not only related to proportion but also complements fashion style. Through appropriate matching, these proportions can be transformed into unique charms. Hidayati et al. [6] developed a framework that can learn and recommend compatibility between body shape and Chinese Clothing Style. It proposes an innovative fashion style recommender that combines user body attributes with costume designing design elements. For many people, finding a fashion style that highlights their body shape advantage is a challenging task. With the rich knowledge of fashion styling in social big data, we aim to provide users with personalized fashion advice. Although fashion designers and stylists have been delving into the intrinsic connection between human body shape and fashion style, there is still insufficient research on the integration of this topic in the fields of multimedia science and costume designing design. These elements not only affect the aesthetic appearance of clothing but also directly relate to whether the fashion style can highlight the user's body shape advantage. By analyzing the semantic features in Chinese Clothing Styles and body types, potential correlations between them are discovered. This step not only considers the physical characteristics of body shape, but also incorporates considerations for costume design elements such as clothing cutting, lines, and colours.

Hong [7] selected representative individuals from different age groups, such as 49-year-old males, 22-year-old males, and 50-year-old females, as the study subjects for the simulation experiment to ensure the universality and applicability of the research results. The average accuracy of human frontal and lateral recognition is as high as 93%, which not only achieves effective recognition of human features but also provides valuable reference data for fashion designers. The experimental results show that the trained network can effectively recognize typical lines of the human neck, chest, shoulders, and waist. By introducing costume design elements, we can incorporate more creativity and inspiration into 3D clothing design, making the design more attractive and recognizable. Moreover, by combining costume design elements, these key features can be further highlighted, and the personalization and attractiveness of clothing design can be enhanced. In this study, we not only utilized CNN for training but also delved into the integration of 3D clothing models and costume design elements. The innovative application of hierarchical perception technology in three-dimensional (3D) clothing design was studied based on convolutional neural networks (CNN), with special attention paid to the important role of costume design elements. Intended to address the increasingly prominent issues in modern life, such as the fast-paced lifestyle requiring higher efficiency, the growing demand for personalized products from consumers, and the fierce brand competition and severe product homogenization faced by the clothing industry. These elements can include colours, patterns, materials, textures, etc., which together constitute the visual language of clothing design, conveying the creativity of designers and the individual needs of consumers. Statistical learning of human body shape has broad application potential in the fashion and clothing industry, not only for reconstructing or estimating body shape based on incomplete data, but also for integrating traditional Chinese Clothing Style recognition elements into semantic parameter design, modifying images and videos, and simulation processes. Huang et al. [8] proposed a hierarchical method for human statistical learning based on deep neural networks (DNN), which uses feature wireframes as key layers to connect semantic parameters and human mesh. Considering that the geometric properties of the human body are non-Euclidean, applying deep learning techniques directly to this non-Euclidean domain is challenging. In the representation of digital human bodies, the large number of grid vertices in high-dimensional space makes it difficult for traditional principal component analysis (PCA) methods to accurately capture the true changes in human body shape, especially when combined with traditional Chinese Clothing Styles. Specifically, we first identify and extract feature wireframes related to specific Chinese Clothing Styles, and then associate these wireframes with semantic parameters.

This method not only improves the accuracy of recognition but also greatly shortens the recognition time, providing efficient and accurate clothing search and recommendation services for e-commerce platforms. However, simply recognizing and classifying Chinese Clothing Styles is not enough to meet the needs of fashion designers.

In clothing design, plate-making design is an important link, which involves three-dimensional cutting and pattern design of clothing. The traditional plate-making design method mainly relies on the experience and skills of designers, requiring a lot of time and effort to design and modify. With the growth and progress of clothing CAD technology, the current clothing CAD drawing technology has initially possessed the characteristics of standardization, intelligence, parameterization, and integration. However, how to combine these advanced CAD technologies with DL technology to provide designers with efficient auxiliary design tools is still a problem worth exploring. Therefore, this article proposes a new method for traditional Chinese Clothing Style recognition and CAD based on DL. This method utilizes DL models to train on a large dataset of annotated clothing images, enabling the model to learn feature representations of Chinese Clothing Styles and achieve fast and accurate recognition of Chinese Clothing Styles. At the same time, combined with CAD software, we have designed a CAD system that integrates DL models. The system can automatically generate preliminary design sketches based on user input Chinese Clothing Style requirements, providing designers with efficient auxiliary design tools.

The innovation points of this article are as follows:

(1) This article applies DL technology for the first time to the recognition of traditional Chinese Clothing Styles and achieves fast and accurate recognition of Chinese Clothing Styles by constructing a DL model.

(2) This article combines DL and CAD technology to design a CAD system that integrates DL models. This innovation breaks the limitations of traditional CAD software that relies on designer experience and skills and achieves intelligence and automation of the design process by introducing DL models.

(3) The method proposed in this article not only achieves fast and accurate recognition of Chinese Clothing Styles but also provides strong support for personalized clothing customization services. By analyzing a large amount of user data through the DL model, we can understand their preferences and needs and recommend Chinese Clothing Styles that match their personal style.

At the beginning of this article, we provide a detailed explanation of the background and profound significance of the research. Subsequently, we delve into the enormous potential of DL and CAD technologies in the field of traditional Chinese Clothing Style recognition and design. Subsequently, we constructed a method for traditional Chinese Clothing Style recognition and CAD based on DL technology in detail and explained its algorithm flow and implementation details in detail. In order to comprehensively verify the effectiveness and practicality of this method, we conducted a series of carefully designed experiments. In the conclusion section, this article systematically summarizes the main research achievements and innovative points of traditional Chinese Clothing Style recognition and CAD methods based on DL technology. At the same time, it also points out the direction for future research and puts forward constructive suggestions.

## 2 RELATED WORK

The body shape is indeed closely related to the proportion of the body, and the art of fashion style lies in how to emphasize and optimize these proportions cleverly. Joukovsky et al. [9] used deep multimodal representation learning techniques to construct a joint embedding model that integrates Chinese Clothing Style and human body measurements on a carefully selected reference dataset according to fashion rules. For many people, finding a fashion style that highlights their body shape advantage is not an easy task. It proposes a new fashion style recommender that integrates costume designing design elements, aiming to recommend suitable fashion styles for users based on their body attributes. Fashion designers and stylists have been deeply exploring the inherent connection between the shape of the human body and fashion style. Therefore, developing a framework that can intelligently match body shape and Chinese Clothing Style compatibility has become particularly crucial. These features not only involve the proportion and form of body shape but also cover costume design elements such as clothing cutting, line flow, color matching, and pattern layout. It integrates costume design elements such as colours, patterns, lines, materials, etc., which play a crucial role in shaping fashion styles.

Kulsum [10] enhances students' understanding and grading of women's fashion patterns by introducing costume designing design elements and utilizing CAD pattern systems to learn media, thereby improving the quality of learning. In the research process, we particularly focus on incorporating costume design elements into teaching content and methods. In the implementation phase, we use CAD pattern systems to learn media and guide students in using these tools to draw, edit, and evaluate women's fashion patterns. During the observation phase, we collected student work, test scores, and feedback to evaluate their progress in understanding and applying costume design elements. In addition, we also observed the interaction and discussion among students in the classroom to understand their interest and understanding of the learning content. In the reflection stage, we analyzed the collected data and summarized the teaching effectiveness of using CAD pattern systems to learn media combined with costume designing design elements. This study adopted the design method of classroom action research and was divided into two cycles, each cycle consisting of four stages: planning, implementation, observation, and reflection. The changes in clothing and carrying status not only affect the performance of gait recognition but also are indispensable elements in fashion and costume designing design. In order to accurately capture and compare these gait characteristics that vary due to changes in clothing and carrying status, Li et al. [11] proposed a novel gait recognition method - the Unified Joint Strength Transformer Network. In gait recognition technology, these factors, as covariates, significantly affect the intensity distribution and feature extraction in traditional gait representation methods (such as gait energy images). This is because visual design elements such as intensity distribution, colour contrast, and patterns are equally important in gait images, as they can reveal the uniqueness and variability of gait. The joint strength transformation module utilizes the metrics learned from the joint strength measurement estimation network to transform the spatial dissimilarity of two gait energy images. The joint strength measurement estimation network accurately estimates the sample-related joint strength of the input gait energy image through a carefully designed encoder-decoder structure. In daily walking, people wear various types of clothing and carry various items. These changes not only reflect personal style and preferences but also directly affect the characteristics of gait. This method not only focuses on spatial measurement of gait but also introduces intensity measurement closely related to costume designing design. Due to the fact that the network has fully considered the influence of clothing and carrying status, its recognition performance is more robust and accurate.

With the advent of the information age, consumer clothing needs are gradually shifting towards fashion, personalization, novelty, sample-oriented, high-quality, and high-end directions. Liu [12] explored the application of computer-aided technology in clothing design driven by emotional factors and specifically expanded the analysis by combining traditional Chinese Clothing Style recognition elements. This feature information is crucial for identifying specific fabrics, patterns, and textures in traditional clothing. Due to the different features exhibited by texture images under illumination in different directions, using texture images under multi-directional illumination can extract richer 3D texture feature information. Under this trend, clothing computer-aided design software plays an increasingly important role in promoting product sales and enterprise development. Traditional Chinese Clothing Styles often carry rich cultural, historical, and artistic connotations, and their unique cutting, fabric, and pattern elements constitute their unique visual characteristics. Considering the characteristics of images and the practical needs of clothing design, we can compare new ideas and applications with the latest models to find the most suitable technical path for traditional Chinese Clothing Style recognition. Through the training and classification of machine learning algorithms, it can accurately identify the texture features of different traditional Chinese Clothing Styles, providing strong support for designers. The study applies deep learning techniques to traditional Chinese clothing style recognition and trains models to accurately recognize different style features through a large amount of image data.

Geometric understanding plays a crucial role in computer-aided design and engineering (CAD/CAE). In this work, Vidanes et al. [13] re-examined a point-based graph neural network, which is a universal and relatively simple 3D deep learning method. Deep neural networks, as effective tools for processing complex data and implementing high-level abstract tasks, bring new opportunities to the fields of CAD/CAE and costume designing design. It can combine costume design elements to provide designers with richer and more flexible design tools. Through in-depth research and development of best practices and modifications, we aim to overcome their traditional shortcomings and explore their potential applications in CAD tasks and costume designing design. By utilizing the flexibility of this network, we have studied how to more effectively utilize boundary representation data, which is crucial in both CAD and costume designing design. Through a series of experiments and additive studies, we have successfully improved the prediction accuracy of the PointNet++network on multiple CAD model segmentation datasets and achieved state-of-the-art performance on the MFCAD++machining feature dataset. As an important component of costume designing, the diversity of Chinese Clothing Styles and individual differences in understanding pose unique challenges for image recognition in the fashion field. StyleNet adopts a multitasking learning framework aimed at representing clothing images in a more fine-grained manner by integrating multiple types of label information. Yan et al. [14] proposed a style representation learning model based on deep neural networks called StyleNet. Although deep learning methods have made significant progress in the field of image processing, we still face many challenges in accurately classifying Chinese Clothing Style labels. In order to further improve the accuracy of StyleNet, an innovative loss function optimization method is proposed, which combines distance confusion loss and traditional cross-entropy loss. StyleNet not only focuses on the overall style of images but also deeply analyzes costume design elements such as colour, material, pattern, cutting, etc., which together constitute the unique style of clothing. Through this method, StyleNet can more accurately capture costume design elements in clothing images, thereby improving the accuracy of the classification of style labels. This optimization method not only considers the discrimination between categories but also focuses on the subtle differences between different styles within the same category.

The recognition of fashion style in clothing images is crucial for clothing retrieval and personalized recommendations on e-commerce platforms. The existing fashion style recognition methods mainly rely on deep neural networks to classify pixel-level or region-level features of clothing images. Even clothing with the same style may present a completely different visual appearance due to differences in costume design elements such as design elements, color matching, and material selection. Design problem maps (DIGs) not only include the basic attributes of clothing, such as style, colour, material, etc. but also incorporate costume design elements. Yue et al. [15] introduced an innovative approach to capture the global and semantic representation of fashion styles by constructing design problem graphs (DIGs) with clothing attributes. These methods are often limited to feature extraction in local areas and lack a deep semantic understanding of fashion styles, making them susceptible to minor changes in clothing appearance. Based on this idea, it proposes a joint fashion style recognition model consisting of two convolutional neural networks. One of the networks is used to process clothing images and extract visual features from the images. In today's rapidly developing information technology, the quantity and variety of clothing products are becoming increasingly large, and consumers can easily access a large amount of clothing information. Clothing, as a special type of commodity, has the characteristics of being soft, deformable, and diverse in variety. Zhao et al. [16] have improved the efficiency of clothing retrieval and added new businesses such as personalized clothing recommendations, which have become important links in improving the online clothing shopping experience of consumers. These new businesses rely on rich and accurate clothing attribute information. It proposes a clothing recognition method based on a multi-model fusion network and conducts research on clothing multi-attribute recognition. Preliminary implementation and verification of clothing personalized recommendation application based on recognition results. It leads to objective factors such as clothing wrinkles and deformation, partial occlusion, etc. that affect the recognition effect and result in a single recognition result during the recognition process. By using EfficientNet and ResNet-18 models to extract global and local features of clothing, multiple features are fused to improve recognition accuracy under complex influence conditions. We mainly conduct in-depth research on the characteristics of clothing colours, styles, and categories, and propose an objective hierarchical label classification method for clothing datasets.

## 3 CHINESE CLOTHING STYLE RECOGNITION BASED ON DL AND CAD

### 3.1 Convolutional Neural Networks

The introduction of DL technology has brought strong potential and broad application prospects for Chinese Clothing Style recognition, which is undoubtedly a revolutionary leap for the fashion industry and e-commerce field. With the help of deep learning technology, Convolutional Neural Networks (CNN) have become the core force in Chinese Clothing Style recognition. Figure 1 shows the R-FCN structure diagram.

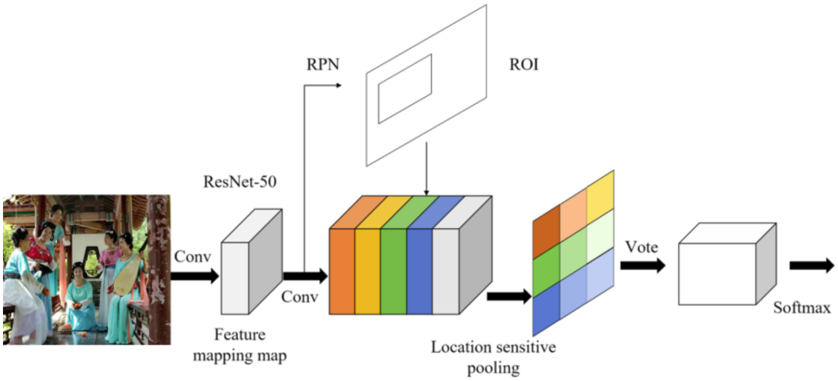


**Figure 1**: R-FCN structure diagram.

### 3.2 CAD

Through the software's built-in rich texture library or custom textures, designers can easily apply the appearance and texture of various fabrics to 3D models, allowing the design to present the visual effect of finished clothing in the early stages. Figure 2 shows the application of CAD in clothing design.

**Figure 2**: Application of CAD in clothing design.

## 4 CAD SYSTEM INTEGRATING DL MODEL

### 4.1 Algorithm Principle

Assuming that the data sample set of the entire training set is $X = \; X_1, X_2, \cdots, X_n$ , where each $X_i$ represents a data sample, and its corresponding dataset sample label set is $Y = \; y_1, y_2, \cdots, y_n$ , where each $y_i$ corresponds to the label of $X_i$. In scenarios where it is necessary to calculate the distance between data samples or between data samples and specific points, we can use appropriate distance calculation formulas. A common distance calculation formula can be expressed as:

$$sim \; X_i, X_j \; = \sqrt{\sum_{t=1}^{n} \; X_{it} - X_{jt} \; ^2} \tag{1}$$

In the formula $X_i$ represents the current predicted sample; $X_j$ is the $j$ th clothing sample in the training set data sample $X$ ; $X_{it}$ and $X_{jt}$ are the $t$ th dimensional vectors of the current prediction sample and the $j$ th clothing, respectively; $n$ is the dimension of the sample.

When evaluating the similarity between predicted clothing and the entire clothing dataset, we used the Euclidean distance calculation formula. Through this calculation, we successfully identified the top $K$ similar clothing sets closest to the predicted clothing in the entire dataset, denoted as $X_1, X_2, \cdots, X_K$ . Meanwhile, we also obtained the label sets corresponding to these similar clothing sets, namely $y_1, y_2, \cdots, y_k$ . These labels provide us with important information about the classification of similar clothing. By using equations (2) and (3), we can accurately select the $K$ samples that are most similar to the predicted clothing, providing strong support for subsequent recommendations, classification, or analysis.

$$S_i = sim \; X, X_i \tag{2}$$

$$S = \; S_1, S_2, \cdots, S_K \tag{3}$$

In the formula $i \in 1,2,\cdots,K$ ; $S_i$ is the similarity score obtained through similarity calculation; $S$ is the attention weight of the first $K$ sequences in the dataset, and $S$ is used to weight the output labels and output vectors of the first $K$ similar clothing sequences in the obtained clothing dataset.

The classification network of R-FCN cleverly utilizes ResNet-50 as its basic feature extractor to generate detailed feature maps. During this process, R-FCN utilizes convolution operations to create $k \times k$ position-sensitive score maps for each category on the entire image, which effectively describe the spatial grid information of corresponding positions in the image. Each position-sensitive map has an output of $C$ channels, which $C$ represents $C-1$ objects of different categories plus an additional channel for distinguishing the background. When R-FCN encounters a candidate target box of $w \times h$ size generated by the RPN network, it cleverly divides it into $k \times k$ equally sized sub-regions, each with a size of $w \times h / k^2$. For any subregion $bin\ i,j$ , where $0 < i,j < k-1$, R-FCN implements a specific location-sensitive pooling operation. Through this refined processing method, R-FCN can achieve more accurate detection and classification of target objects.

$$r_c\ i,j \mid \Theta\ = \sum_{x,y\ \in bin\ i,j} \frac{1}{n} z_{i,j,C}\ \ x+x_0, y+y_0 \mid \Theta \tag{4}$$

The formula $r$ signifies the aggregated response of the sub-region $bin\ i,j$ towards the categorization of $C$ . $z$ designates the spatially-sensitive scoring map that aligns with the specified sub-region $bin\ i,j$ . $x,y$ denotes the x, and y coordinates indicating the top-left vertex of the prospective bounding box. $n$ represents the total pixel count within the sub-region $bin\ i,j$ , while $\Theta$ encapsulating all the parameters that have been learned and optimized by the neural network.

In R-FCN, to effectively reduce the risk of overfitting, we adopted the Label Smoothing Regularization (LSR) method. This method adopts a variant form of unique hot encoding for labels $q\ k / x$ during the model training process. Specifically, we no longer set the labels of real categories to strict 1, but set the labels of non-real categories to a smaller positive number (such as 0.1), and correspondingly reduce the labels of real categories (such as 0.9), thus forming a smooth probability distribution $p\ k / x$ .

$$p\left(\frac{k}{x}\right) = \frac{\exp\ z_k}{\sum_{i}^{i=k} \exp\ z_i} \tag{5}$$

The loss function is:

$$H\ q,p\ = \sum_{k=1}^{K} \log\ p\ k\ q\ k \tag{6}$$

It is a common practice in CAD to use the chamfer distance (CD) of 3D space to measure the quality of reconstruction results. The smaller the CD score, the better the reconstruction effect is usually indicated. The definition of CD in 3D space involves two sets of 3D point clouds $S_1, S_2$. The calculation of this distance consists of two parts: one is the sum of distances from any point $x$ in $S_1$ to the nearest point in $S_2$, and the other is the sum of distances from any point $y$ in $S_2$ to the nearest point in $S_1$. By calculating and accumulating the distance values between these two parts, a comprehensive CD value can be obtained. During the reconstruction process, if the CD score is small, it indicates that the shape difference between the reference point cloud and the target point cloud is small, which means that the reconstruction effect is better. On the contrary, if the CD score is high, it indicates a significant difference in shape between the two sets of point clouds, and further optimization or adjustment may be needed to improve the reconstruction effect. The calculation formula is:

$$d_{CD}\left(S_1,S_2\right)=\frac{1}{S_1}\sum_{x\in S_1}\min_{y\in S_2}\left\|x-y\right\|_2^2+\frac{1}{S_2}\sum_{x\in S_2}\min_{y\in S_1}\left\|y-x\right\|_2^2 \tag{7}$$

When facing multi-classification problems, The SoftMax function plays a crucial role. It generates an output vector with the same dimension as the number of categories based on their quantity. In this vector, the values of each element are between 0 and 1, which actually represent the probability estimation of each category as the true label of the input data. It is worth noting that, The SoftMax function ensures that the sum of these probability values is strictly equal to 1, thereby ensuring that the elements of the output vector have probability distribution characteristics, enabling accurate and intuitive representation of the possibilities of each category in multi-classification scenarios. The SoftMax function is defined in the formula:

$$S_i=\frac{e^{V_i}}{\sum_i^C e^{V_i}} \tag{8}$$

In this context, $V_i$ signifies the outcome stemming from the preceding output unit of the classifier. $i$ denotes the categorical identifier, while $C$ stands for the aggregate count of all categories. Lastly, $S_i$ portrays the proportion of the present element's index in relation to the summation of indices across all elements.

## 5 RESULT ANALYSIS AND DISCUSSION

To validate the effectiveness of the proposed method, we will proceed with experimental evaluations. Figure 3 offers a visual comparison of Chinese Clothing Style recognition, contrasting the conventional DL-based approach (particularly the R-FCN model) with the traditional support vector machine (SVM) method employed in this study. The graph clearly depicts that the R-FCN-backed DL model excels in Chinese Clothing Style recognition accuracy. By integrating DL and feature extraction mechanisms, the R-FCN model can autonomously learn and extract intricate features from numerous clothing images. This enables it to capture Chinese Clothing Style nuances more comprehensively and precisely, thus boosting recognition accuracy. Conversely, while SVMs are effective classifiers, their performance in complex Chinese Clothing Style recognition scenarios is often constrained by their feature extraction methodologies, resulting in suboptimal SVM recognition accuracy.

Figure 3 visually compares the recognition of Chinese clothing styles. This graph compares traditional deep learning (DL) based methods, especially the Regional Fully Convolutional Network (R-FCN) model, with the traditional Support Vector Machine (SVM) method used in this study. Firstly, it is clear from the graph that the R-FCN-backed DL model has significant advantages in terms of accuracy in recognizing Chinese clothing styles. This is mainly due to the progressiveness of the R-FCN model in feature extraction and recognition mechanisms. R-FCN, through the structure of deep convolutional neural networks, can autonomously learn and extract complex features from a large number of clothing images, which include not only the overall shape and color of the clothing but also subtle differences such as textures and patterns. This comprehensive feature extraction capability enables R-FCN to capture the uniqueness and diversity of Chinese clothing styles more accurately. From Figure 4, it can be seen that the R-FCN model usually has a longer recognition time than SVM. This is mainly because R-FCN, as a deep learning model, requires a large amount of computation to extract complex features from images. Although this process is time-consuming, it ensures that the model can capture more detailed and comprehensive information, thereby improving the accuracy of recognition.

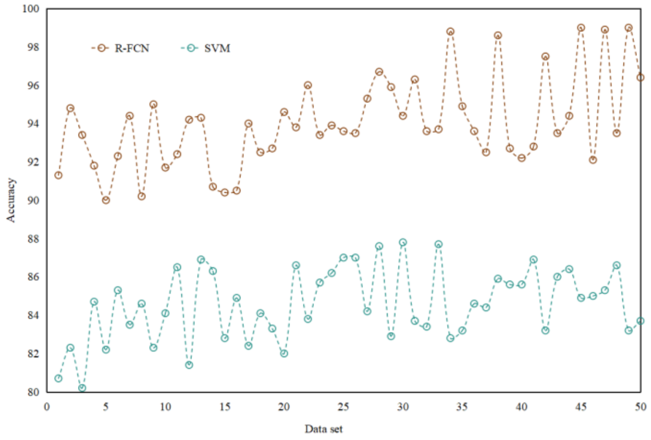


**Figure 3**: Comparison of recognition accuracy.

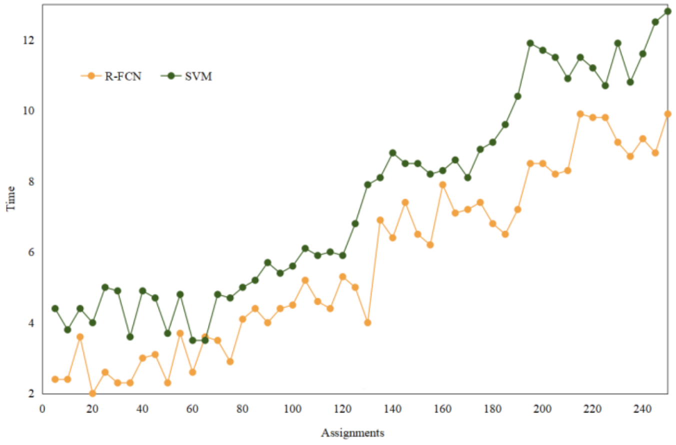


**Figure 4**: Comparison of recognition time.

However, this does not mean that R-FCN is completely behind SVM in efficiency. In fact, with the improvement of computing power and the optimization of deep learning frameworks, the recognition speed of R-FCN has been significantly improved. In addition, the recognition accuracy of R-FCN is much higher than SVM, which makes it an irreplaceable advantage in many applications that require high-precision recognition.

Figure 5 provides a comparison of recall rates between the R-FCN model and traditional support vector machine (SVM) methods in the field of Chinese clothing style recognition. Through this comparison, we can gain a more comprehensive understanding of the differences in recognition performance between the two methods, especially in terms of their ability to capture all relevant instances. From Figure 5, we can see that the R-FCN model significantly outperforms SVM in terms of recall. This is mainly due to the R-FCN model's ability to autonomously learn and extract complex features from a large number of clothing images by integrating deep learning and feature extraction mechanisms. These features not only cover the overall shape, colour, and texture of clothing but also include more subtle patterns and style elements.

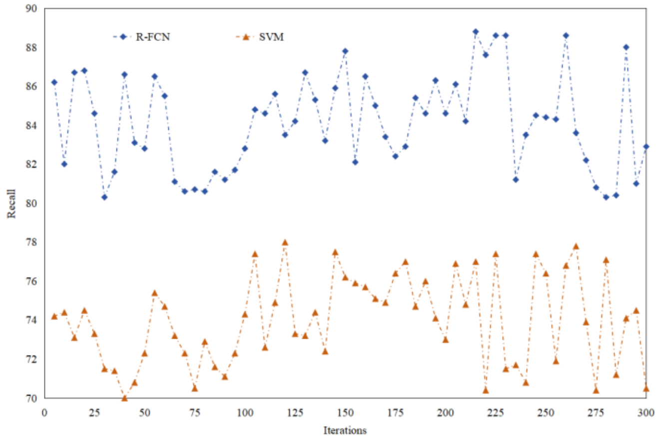


**Figure 5**: Comparison of recall rates.

Therefore, the R-FCN model can more comprehensively and accurately capture the subtle differences in Chinese clothing styles, thereby improving its recognition accuracy and recall rate. This article extracts complex features of model images in Figure 6. By evaluating the complex style autonomous learning of the RFCN model, the accurate recognition value of the model in complex images was extracted and constructed. It has applied value extraction in the feature extraction process of deep learning. From the results, it can be seen that the model proposed in this article has significant technical value in the style design of structural clothing.

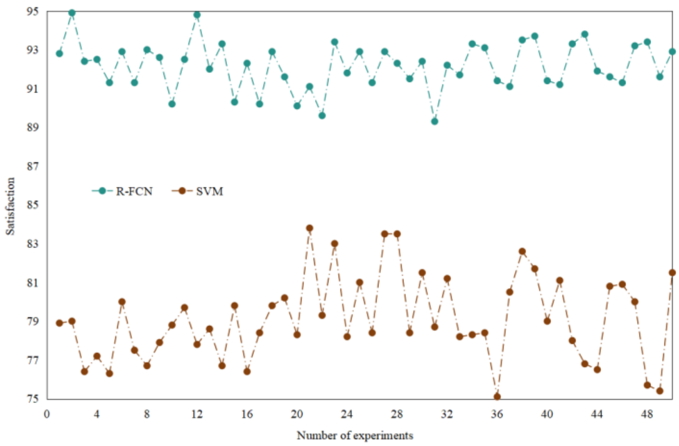


**Figure 6**: Satisfaction comparison.

In Figure 6, we compared the performance of different models in extracting complex image features and applying them to clothing style design satisfaction evaluation. By thoroughly evaluating the complex style self-learning ability of the R-FCN model, we have successfully extracted and constructed accurate recognition values of the model in complex images. The comparison curve between the RFCN model and SVM satisfaction shows that the RFCN model always outperforms the SVM model. In this process, we pay special attention to integrating value extraction (which can be understood as evaluating the importance of features) into the feature extraction process of deep learning, in order to further enhance the practical application value of the model in style design. The R-FCN model can automatically learn and extract complex features from images through its deep convolutional network structure. These features not only include the overall shape, colour, and texture of the clothing, but also encompass more subtle patterns, details, and stylistic elements. This comprehensive feature extraction capability enables the R-FCN model to more accurately capture the uniqueness and diversity of clothing styles.

Figure 7 shows the Loss function curve. To achieve a balance between recognition accuracy and inference speed in deep learning networks, the lightweight MobileNetv3 network is combined with the YOLOv5s deep learning network. Thus constructing a compact target recognition network. Although CSPDarkNet-53 can extract rich feature information, the backbone network has a large number of layers and complex inter-layer connections, resulting in a longer inference time for the network after inputting images. In order to make the deep learning network structure more compact, the backbone feature extraction network is optimized through modules such as deep separable convolution operation and inverted residual network structure used in the MobileNetv3 network. YOLOv5s uses CSPDarkNct-53 as the backbone network to extract features from input images, and outputs prediction results through prediction boxes at three scales: 76 × 76, 38x38, and 19x19. Provide a new solution to the difficulty of deploying deep learning networks due to factors such as insufficient computing power and memory resources in hardware devices. Realize lightweight network effects and further shorten the inference time of deep learning networks.

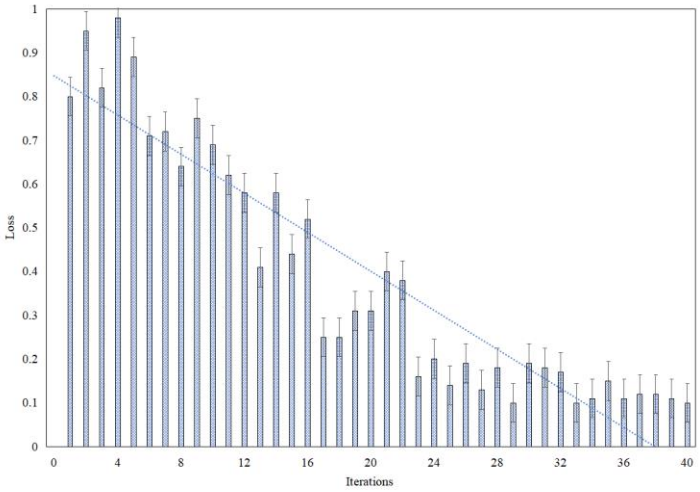


**Figure 7**: Loss function curve.

The downward trend of the loss function curve in Figure 7 indicates that as training progresses, the model gradually learns how to extract effective information from input data for accurate prediction. This learning ability is one of the core advantages of deep learning models, especially when dealing with complex image recognition tasks. Secondly, the introduction of the MobileNetv3 network has played a crucial role in optimizing the entire network structure. Through modules such as depthwise separable convolution and reverse residual network structure, MobileNetv3 can significantly reduce computational complexity and model parameter count while maintaining high recognition accuracy. This makes the deployment of networks on hardware devices easier, especially in scenarios with limited computing power and memory resources.

The YOLOv5s model is known for its fast and accurate characteristics. By using CSPDokNet-53 as the backbone network, YOLOv5s can extract rich feature information from input images and output prediction results through three different scale prediction boxes. This multi-scale prediction mechanism enables the model to simultaneously capture both large and small targets in the image, further improving the accuracy and robustness of recognition.

Figure 8 shows the comparison of design precision. Deep learning networks have become the core technology in the field of target recognition due to their powerful performance advantages, but there is still a huge gap between the current recognition performance and humanized performance. Although lightweight methods for target recognition deep learning networks have been studied from multiple perspectives, they are limited by memory resources and computational power. The application of large-scale deep learning networks on mobile and embedded hardware platforms still faces certain obstacles. The lightweight target recognition deep learning network also difficult to balance recognition accuracy and recognition efficiency. It is even more difficult to match the detection accuracy of large-scale target recognition deep learning networks. In terms of model lightweight and acceleration, the network lightweight algorithm based on global channel pruning prunes the R-FCN model after optimizing the loss function, resulting in varying degrees of loss in recognition accuracy of the generated lightweight network. In order to further improve the accuracy after fine-tuning, subsequent work can use methods such as knowledge distillation to restore the accuracy of the lightweight deep learning network generated after pruning.

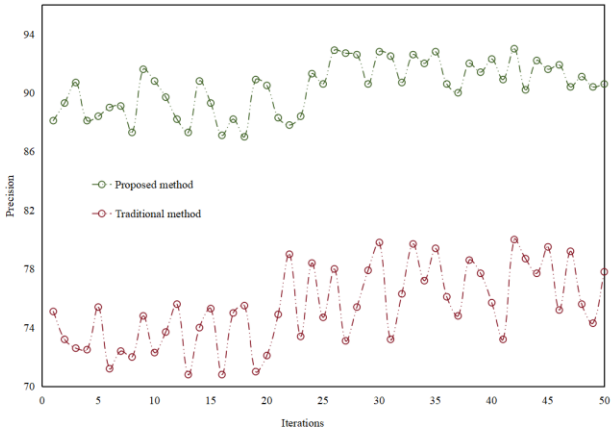


**Figure 8**: Comparison of design precision.

As shown in Figure 8, lightweight networks often sacrifice certain recognition accuracy while reducing computational costs. This is because these networks need to balance recognition accuracy and recognition efficiency in the design process. Therefore, how to further reduce the computational cost of the network while maintaining high recognition accuracy is a key issue in lightweight network design.

Researchers have proposed various solutions to this problem. Among them, the lightweight network algorithm based on global channel pruning is an effective method. This algorithm prunes redundant channels in deep learning networks by optimizing the loss function, thereby generating a more compact network structure. However, this pruning process often leads to a decrease in recognition accuracy. In order to restore the accuracy of the trimmed network, researchers have proposed methods such as knowledge distillation. Knowledge distillation is a technique that transfers knowledge from large teacher networks to small student networks. By allowing the student network to mimic the output of the teacher network, the recognition accuracy of the student network can be restored to a certain extent.

## 6 CONCLUSIONS

In this article, we propose a novel approach aimed at tightly integrating traditional Chinese Clothing Style recognition with CAD. The system can automatically generate initial design drafts based on user-specified Chinese Clothing Style preferences. This method significantly improves the overall efficiency of clothing design while ensuring design accuracy. It adopts the R-FCN model and is trained on a large dataset of clothing images with detailed annotations. This method cleverly combines the excellent capabilities of deep learning (DL) in image recognition with the precision of CAD software in design, achieving unprecedented innovation. This model not only has excellent recognition ability of Chinese Clothing Style features but also can quickly and accurately complete the task of style recognition. In order to further meet the needs of designers, we have also developed a CAD system that integrates DL models. This feature provides designers with an efficient and user-friendly design support tool, greatly enhancing their work efficiency and creativity. However, although this method has achieved significant results, there are still some limitations. Firstly, the training of DL models requires a large amount of annotated data, and obtaining a large amount of high-quality annotated data is a challenge. Secondly, the generalization ability of the model needs to be further improved to meet more complex and ever-changing clothing design needs. In addition, how to better integrate DL technology with the creativity of designers is also a question worth further exploration. In the future, we will be committed to solving these problems and continuously improving and optimizing the methods proposed in this article to promote further growth of clothing design and CAD technology.

*Yilin Fan*, https://orcid.org/0009-0001-7414-2330
*Meixin Li*, https://orcid.org/0009-0008-0354-5811

## REFERENCES

[1] Chan, I.; Au, J.; Ho, C.; Lam, J.: Creation of 3D printed fashion prototype with multi-coloured texture: a practice-based approach, International Journal of Fashion Design, Technology and Education, 14(1), 2021, 78-90. https://doi.org/10.1080/17543266.2020.1861342
[2] Chang, H.-C.: Parametric design used in the creation of 3D models with weaving characteristics, Journal of Computer and Communications, 9(11), 2021, 112-127. https://doi.org/10.4236/jcc.2021.911008
[3] Deng, M.; Liu, Y.; Chen, L.: AI-driven innovation in ethnic clothing design: an intersection of machine learning and cultural heritage, Electronic Research Archive, 31(9), 2023, 5793-5814. https://doi.org/10.3934/era.2023295
[4] Elboq, R.; Fri, M.; Hlyal, M.: Modeling lean and six sigma integration using deep learning: applied to a clothing company, Autex Research Journal, 23(1), 2023, 1-10. https://doi.org/10.2478/aut-2021-0043
[5] Guan, C.; Qin, S.; Long, Y.: Apparel-based deep learning system design for apparel style recommendation, International Journal of Clothing Science and Technology, 31(3), 2019, 376-389. https://doi.org/10.1108/IJCST-02-2018-0019
[6] Hidayati, S.-C.; Goh, T.-W.; Chan, J.-S.-G.; Hsu, C.-C.; See, J.; Wong, L.-K.; Cheng, W.-H.: Dress with style: Learning style from joint deep embedding of Chinese Clothing Styles and body shapes, IEEE Transactions on Multimedia, 23(1), 2020, 365-377. https://doi.org/10.1109/TMM.2020.2980195
[7] Hong, Y.: Application of convolution neural networks-based hierarchical perception technology in 3D clothing designs, IET Networks, 11(6), 2022, 257-263. https://doi.org/10.1049/ntw2.12047
[8] Huang, J.; Kwok, T.-H.; Zhou, C.: Parametric design for human body modeling by wireframe-assisted deep learning, Computer-Aided Design, 108(1), 2019, 19-29. https://doi.org/10.1016/j.cad.2018.10.004
[9] Joukovsky, B.; Hu, P.; Munteanu, A.: Multi-modal deep network for RGB-D segmentation of clothes, Electronics Letters, 56(9), 2020, 432-435. https://doi.org/10.1049/el.2019.4150
[10] Kulsum, U.: Grading women's clothing patterns with the CAD pattern system to improve student learning outcomes and competencies, Journal of Education Technology, 4(2), 2020, 187-194. https://doi.org/10.23887/jet.v4i2.26205

[11] Li, X.; Makihara, Y.; Xu, C.: Joint intensity transformer network for gait recognition robust against clothing and carrying status, IEEE Transactions on Information Forensics and Security, 14(12), 2019, 3102-3115. https://doi.org/10.1109/TIFS.2019.2912577

[12] Liu, J.: Application and research of computer-aided technology in clothing design driven by emotional elements, International Journal of System Assurance Engineering and Management, 14(5), 2023, 1691-1702. https://doi.org/10.1007/s13198-023-01973-6

[13] Vidanes, G.; Toal, D.; Zhang, X.: Extending point-based deep learning approaches for better semantic segmentation in CAD, Computer-Aided Design, 166(1), 2024, 103629. https://doi.org/10.1016/j.cad.2023.103629

[14] Yan, C.; Zhou, L.; Wan, Y.: A multi-task learning model for better representation of clothing images, IEEE Access, 7(1), 2019, 34499-34507. https://doi.org/10.1109/ACCESS.2019.2904536

[15] Yue, X.; Zhang, C.; Fujita, H.: Clothing fashion style recognition with design issue graph, Applied Intelligence, 51(6), 2021, 3548-3560. https://doi.org/10.1007/s10489-020-01950-7

[16] Zhao, H.; Zhang, H.-X.; Cao, Q.-J.: Design and development of image recognition toolkit based on deep learning, International Journal of Pattern Recognition and Artificial Intelligence, 35(01), 2021, 2159002. https://doi.org/10.1142/S0218001421590023