Application of Product Form Recognition Combined with Deep Learning Algorithm

Xia Wu[1] and Leiming Zhu[2]

[1]Creative Arts School, Jinhua Polytechnic, Jinhua 321017, China, 20101049@jhc.edu.cn
[2]College of Design, Wenzhou Technology, Wenzhou 325035, China, 2016080129@wzpt.edu.cn

Corresponding author: Xia Wu, 20101049@jhc.edu.cn

Abstract. CAD plays an important role in current product form recognition. How to accurately identify the product form and improve the design efficiency has become an urgent demand for garment CAD design. This article aims to explore the application of deep learning (DL) technology in clothing product form recognition and design. This article constructs a clothing product shape recognition and classification model based on ACNN and machine vision technology, which adopts the ACNN approach. After experimental verification, the model exhibits superior performance in processing time and efficiency. Compared to traditional CNN and LSTM models, ACNN has higher classification accuracy and shorter processing time when processing clothing product images. These results provide intelligent methods and tools for clothing CAD design and demonstrate the potential of DL technology. In the future, further optimization of models, exploration of multimodal data fusion, cross-domain applications, and real-time interactive design can bring more innovation and breakthroughs to the field of product design.

Keywords: Deep Learning; Clothing Design; Product Form; CAD; Machine Vision
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1 INTRODUCTION

Based on the growing demand of consumers for personalized and customized products, the clothing industry is facing more diversified market demands and design challenges. Clothing enterprises need to be able to respond quickly and meet these needs. This means that they need to be able to complete diversified designs. The traditional design method obviously cannot meet this demand, so it is necessary to find a new technical solution. With the widespread application of computer-aided design (CAD), the demand for model shape classification and retrieval is increasing. Traditional model shape classification and retrieval methods mainly rely on manual operations or simple machine learning algorithms and cannot handle complex 3D model shapes. Anguish and Bharadwaj [1] introduce a model shape classification and retrieval method. It can learn feature representations from different perspectives and fuse them into global feature representations. When processing the shape of a 3D model, a multi view convolutional neural network can project the 3D model from different angles. Obtain multiple 2D images and learn feature representations of 3D models from these images. As an important tool of product design, It can not only help designers complete the design faster, but also ensure the accuracy and consistency of the design. Industrial robots is becoming increasingly widespread. Binocular vision, as a common machine vision technology, has higher spatial positioning accuracy and a wider range of applications. Ben and Cengiz [2] explored the research of industrial robot visual orientation guidance based on CAD models under binocular vision. Binocular vision involves simultaneously obtaining images from different angles using two cameras and then calculating the three-dimensional coordinates and shape of the target object through a series of algorithms. Binocular vision has high spatial positioning accuracy and field of view breadth, making it suitable for navigation and positioning of industrial robots. A CAD model is a digital product model that contains information such as geometric shapes, dimensions, and features of the product. In the visual orientation guidance of industrial robots, CAD models can provide geometric constraints and feature information of target objects, providing a basis for path planning and precise control of robots. However, traditional CAD design tools often require designers to have superb skills and experience when dealing with complex clothing forms and styles [3]. Therefore, accurately identifying the product form and improving the design efficiency have become urgent demands for garment CAD design. This strongly supports researchers in applying the DL algorithm in CAD design.

CAD technology has brought revolutionary changes to the traditional manufacturing industry. Especially in the field of casting manufacturing, the application of CAD technology makes the design process more precise and efficient. Favi et al. [4] explore how to use CAD technology to design casting manufacturing methods. A mechanical manufacturing enterprise utilizes CAD technology to design casting manufacturing methods. Firstly, designers use CAD software for structural design and 3D modeling of castings. Then, by simulating the pouring and cooling processes, some issues in the design were identified and corrected. Finally, the use of CAD software for digital management of production plans enables real-time monitoring and adjustment of production progress. The optimized casting manufacturing method has greatly improved production efficiency and quality. The design of casting manufacturing methods based on CAD is an important trend in modern manufacturing industry. Through the application of CAD technology, the structural design, process planning, and production management of castings can be optimized, improving production efficiency and quality. However, the application of CAD technology in casting manufacturing still faces some challenges, such as data security, technical training, and other issues. Therefore, enterprises and designers need to continuously learn and explore to improve the application level and management ability of CAD technology. In the research field of garment product shape recognition combined with DL algorithm, many scholars have achieved rich research results. AutoCAD is a widely used CAD software that provides powerful 3D modeling capabilities and great convenience for industrial design. Hu [5] explores a wireframe model is a simple three-dimensional model composed of line segments and vertices. Designers can construct the basic shape and structure of products by creating and modifying wireframe models. A surface model is a model composed of multiple surfaces. Designers can construct the appearance and details of products by creating and modifying surface models. A solid model is a model with physical attributes such as mass, volume, and center of gravity. Designers can construct the complete form of a product by creating and modifying physical models. In mold manufacturing, AutoCAD can help designers create and modify the shape and structure of molds. By using 3D modeling tools, designers can quickly build prototypes of molds and conduct simulations and tests to verify the manufacturing process and accuracy of molds.

More and more products are being produced using 3D printing technology. However, surface fault detection of 3D printed products remains a challenge. Traditional detection methods usually require manual operation, which is inefficient and prone to errors. To address this issue, we propose using machine learning technology to enhance surface fault detection of 3D printed products. Kadam et al. [6] introduced the basic principles, methods, and experimental results of innovation in this application system. We conducted experiments using a commercial 3D printer and successfully printed a batch of 3D printing products. By comparing with our proposed method, it was found that our method can effectively detect surface faults of products, with an accuracy rate of over 90%. At the same time, our method also has high efficiency a short time. A method for enhancing surface fault detection of 3D printed products using machine learning technology has been proposed. Through experimental verification, it was found that this method can effectively detect surface faults of products, with high accuracy and efficiency. This method provides a new approach for quality control of 3D printing products. Compared with the complicated feature engineering of traditional machine learning algorithm, DL can automatically extract features from original data for modeling by manual feature extraction and selection based on domain knowledge. Artificial neural networks (ANNs), as a powerful tool, can effectively solve complex process planning problems. Krishnan and Gokulachandran [7] reviewed the application of artificial neural network technology in computer-aided process planning. Artificial neural network is a computational model that simulates the structure of neural networks in the human brain. It can learn and simulate human cognitive and decision-making processes through a large number of interconnected neurons. Artificial neural networks have powerful nonlinear mapping capabilities and can handle complex and uncertain problems. A certain automobile manufacturing enterprise utilizes artificial neural network technology to optimize the engine manufacturing process. By training the neural network, the optimal combination of processing parameters was found, which improved engine performance and production efficiency. In addition, the enterprise also established a process fault prediction model using artificial neural networks, successfully predicting multiple potential process faults and avoiding production losses. The core idea of ACNN is to introduce a new parameter called "expansion rate" into the standard convolution layer. Additive manufacturing (AM) is a manufacturing method based on 3D model data, which constructs objects by adding materials layer by layer. Driving innovation in design, process, and production control. Kumar et al. [8] introduced the latest progress in machine learning technology in additive manufacturing, including research on design optimization, process control, and production efficiency improvement. Machine learning algorithms can help designers predict and optimize designs in the early stages. Providing designers with the best design solution by simulating and analyzing a large number of structures. In the additive manufacturing process, machine learning can help us better control process parameters, thereby improving product quality and production efficiency. Thereby automatically adjusting process parameters and optimizing the manufacturing process. This article will discuss the application of product shape recognition combined with DL algorithm in CAD design. Taking garment product design as an example, a garment product shape recognition and classification model based on ACNN is constructed, and an effective feature representation is extracted by analyzing the characteristics of the garment product shape. After extracting enough rich features, the shape of clothing products can be identified and classified through classifiers or other decision-making mechanisms. By training and optimizing the model parameters, the accurate identification of clothing product shape is realized, which provides new ideas and methods for improving the intelligence level and design efficiency of clothing design.

The innovation points of this study are mainly reflected in:

(1) This article applies DL algorithms to clothing CAD design, achieving automatic recognition and classification of clothing product morphology.

(2) This study proposes a recognition model based on ACNN and machine vision, which effectively improves recognition efficiency.

(3) The research methods and achievements of this article can provide new ideas and methodological references for CAD technology in other product design fields.

The structure of this article is arranged as follows:

Section 1: Introduction

This section introduces the research background and significance, elaborates on the importance of clothing product form recognition and classification in product design, and introduces the research purpose and issues of this article.

Section 2: Overview of Product Form Theory

This section provides an overview of product form theory, including the introduction and classification of product form design concepts and clothing product factors.

Section 3: Product Image Recognition and Classification Based on DL

This section provides a detailed introduction to the design and implementation process of a clothing product form recognition and classification model based on ACNN.

Section 4: Experimental Results and Analysis

This section first describes the experimental data, and then presents the experimental results of clothing product shape recognition and classification, and conducts a detailed analysis of them. By comparing with other methods, the effectiveness and superiority of this method are verified.

Section 5: Conclusion and Prospects

This section summarizes the research work of this article and points out the shortcomings in current research and possible future research directions.

2 OVERVIEW OF PRODUCT MORPHOLOGY THEORY

Accurate 3D models are crucial for the processing and performance of parts. However, traditional 3D model reconstruction methods typically require a large amount of manual intervention and cannot fully consider complex factors such as machining features. Deep learning technology has shown great potential in 3D model reconstruction. Lee et al. [9] introduce a dataset and method for reconstructing based on deep learning. Collect a large number of 3D CAD models through web crawlers or directly exporting from CAD software. Organize professional technical personnel to annotate the machining features of the collected 3D models, including cutting marks, tool marks, etc. Import the annotated 3D model into the dataset and add corresponding labels. Perform preprocessing operations such as data cleaning and deduplication. Applying the trained deep learning model to actual 3D CAD model reconstruction can greatly reduce manual intervention and improve reconstruction efficiency. At the same time, the effectiveness and superiority of deep learning models can be evaluated by comparing the model accuracy and feature extraction effects before and after reconstruction. The form design of a product is a crucial part of product design, which is related to the appearance, beauty, user experience, and market acceptance of the product. As a typical representative of form design, the design process of clothing products involves rich form theories. In clothing product design, form design mainly focuses on the contour, structure, color, material, and other elements of clothing. The traditional product development process often relies on the experience and intuition of designers, lacking systematic, innovative methods. In recent years, the development of deep learning and perceptual engineering has provided new avenues for the generation of product innovation concepts. Li et al. [10] explored how to apply deep learning and perceptual engineering to the generation of product innovation concepts, improving the innovation and efficiency of design. Deep learning is a branch of machine learning that simulates the workings of human brain neural networks for learning and reasoning. In product innovation, deep learning can be used to learn a large amount of historical data, discover hidden patterns and trends, and guide the generation of new product concepts. Take a smart home company as an example; it uses deep learning and perceptual engineering methods to generate product innovation concepts. Firstly, they collected a large amount of historical product and market data, analyzed them using deep learning techniques, and discovered hidden patterns and trends in the data.

For example, they found that users increasingly value the intelligent functions of their products while also preferring simple and fashionable product designs. These elements together constitute the overall form of clothing products, determining the style and characteristics of clothing. For example, contour design can showcase the elegance, straightness, or softness of clothing. Structural design is related to the comfort and practicality of clothing. In today's engineering field, a large amount of design information is communicated and stored in the form of two-dimensional drawings. However, the analysis and understanding of these drawings still rely on manpower, which is inefficient and prone to errors. To solve this problem, we can use deep learning technology to establish a system for automatically recognizing and understanding two-dimensional engineering drawings. Lin et al. [11] explored how to integrate deep learning into automatic recognition of two-dimensional engineering drawings. Deep learning is a branch of machine learning that simulates the workings of human brain neural networks for learning and reasoning. In the field of image recognition, deep learning has achieved significant results. Convolutional neural network (CNN) is a commonly used model in deep learning, which can learn complex feature representations from a large amount of image data. For automatic recognition of two-dimensional engineering drawings, we can convert the drawings into image format and then use deep learning technology for recognition and understanding. Specifically, we can use CNN to train and classify drawing images for automatic recognition. Experiments were conducted using a large engineering drawing database, and the results showed that the two-dimensional engineering drawing automatic recognition system based on deep learning has high accuracy and efficiency. Compared to traditional methods, this method can better handle complex drawing images and improve recognition accuracy. The rapid design method for industrial products based on 3D CAD systems mainly utilizes the characteristics of 3D CAD systems and combines modern design theories to achieve rapid product design. This method emphasizes the iteration and optimization of design, and designers can continuously adjust and optimize the design scheme during the design process. Liu [12] utilized an engineering improvement technique based on CAD three-dimensional numerical model data to analyze product design. By analyzing the functions of different parameterized modules, a digital series of reverse engineering techniques was obtained, which helped designers predict product design in finite element space. Thereby avoiding potential problems that may arise in the later stages. The choice of color and material directly affects the visual effect and texture of clothing. When designing clothing product form, designers usually need to follow some basic form principles, including balance, contrast and harmony, rhythm and rhythm, etc. By studying the shape and proportion of the human body, designers can design clothing that is more suitable for the human body and comfortable to wear. The application of principles of form aesthetics, such as balance, contrast, and harmony, can help designers create clothing forms with aesthetic and visual appeal.

Additive manufacturing (AM) is a revolutionary manufacturing technology that uses 3D model data to add materials layer by layer to construct objects. Although AM has many advantages, there are still some challenges, the most prominent of which is manufacturing errors. These errors can be attributed to various factors, such as equipment limitations, material characteristics, or process instability. To address this issue, researchers have begun exploring the application of machine learning (ML) to error compensation. Omairi and Ismail [13] introduce the applied sciences in this new field and discuss the latest developments in it. In additive manufacturing, error compensation is a crucial step that ensures that final product match the design model. Traditional error compensation methods are usually based on experience or trial and error, while machine learning provides a more efficient and accurate method. By learning the relationship between historical data and process parameters and errors, machine learning algorithms can predict and correct future manufacturing errors. Saleh et al. [14] Through CAD technology, designers can conduct detailed modeling and simulation during the product design phase. In addition, CAD technology can also support precise parameter optimization and structural design, improving product performance and reliability. CAD technology can greatly shorten the product development cycle. Designers can quickly create and modify product design models through CAD software, achieving rapid prototyping and testing of products. Reducing development time and costs, and improve product maintainability and scalability. High quality product design can increase market competitiveness. In the increasingly fierce market competition, product quality and innovation have become key factors determining consumer choices. Through CAD technology, designers can create more innovative and attractive products, improve their market competitiveness, and thus gain more market share. A brand is the "behind the scenes controller" that shapes and promotes the product form, but the product itself is the "front stage performer" that determines the product form. Consumers, as "off-stage viewers," are responsible for interpreting the information conveyed by the product, and only through an in-depth understanding of the product can the true product form be formed. The key to accurately shaping the planned product form for consumers lies in the control of product factors for consumers; the three different factors of product technology, appearance, and market work together to construct the product form they perceive (see Figure 1).

Technical factors	Appearance factors	Market factors
Fabric, tailoring, design and sewing	Color, pattern, style, texture, accessories	Target consumer group, price strategy, brand image, advertising and promotion

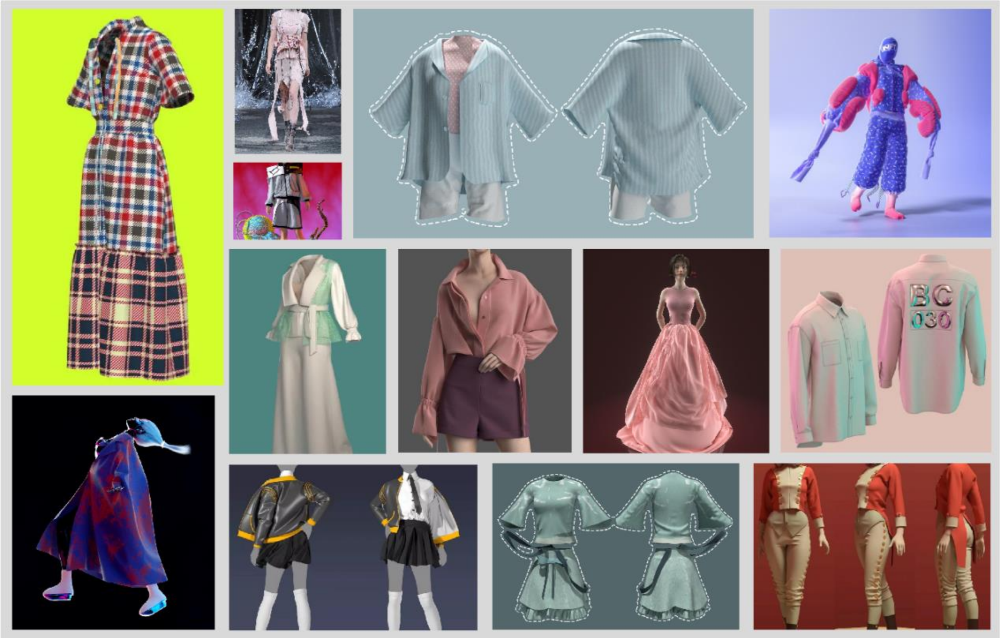

Figure 1: Product factors of clothing products.

With the increasing complexity of products, traditional design and assembly processes are no longer able manufacturing. Intelligent assembly modeling, especially, provides an effective means to solve this problem. Mo et al. [15] explored the specific goals and intentions assigned by designers in product design, including requirements for product functionality, performance, aesthetics, and human-computer interaction. By establishing a parameterized product design model, the designer's design intent can be accurately expressed. Parametric design can change the shape and size of the model by adjusting parameters, thereby achieving rapid design changes. Constraints are constraints on the shape and position of a product model, which can express the designer's specific requirements for the product. Constraint modeling can clarify the designer's design intent and ensure the accuracy of the model. Material properties include physical properties such as elastic modulus, Poisson's ratio, density, and processing properties such as processing performance and surface treatment of the material. These attributes have a significant impact on the performance and manufacturing process of the product. The assembly relationship describes the connection and fit relationship between various components in a product. It includes constraints such as positioning, fit, and insertion, as well as assembly tolerance, and sequence information. Technology is the core of a product, which determines its functionality and practicality. Advanced technology can make products more intelligent and user-friendly, meeting various consumer needs. Brands need to continuously invest in technological research and innovation to ensure product technology leadership, stability, and reliability. Moreover, brands also need to effectively convey technological achievements to consumers, allowing them to understand the technological advantages of the product, thereby forming an accurate understanding of the product form. Computer-aided process planning (CAPP) is an important technology in the manufacturing industry that utilizes computers for automated design and management of process planning. The application scope and demand of CAPP are also constantly expanding. Soori and Asmael [16] explored the research and application classification of computer-aided process planning in manufacturing systems. In batch production manufacturing, the CAPP system can be used to automatically generate process flows, improve production efficiency and quality. It achieves refined management of the production process by optimizing process parameters, managing process resources, and monitoring the process. In customized manufacturing, the CAPP system can be used to support multiple varieties and small batch production modes. It meets the personalized needs of customers by quickly adjusting process parameters, flexibly configuring process resources, optimizing process flow, and other means. In intelligent manufacturing, CAPP systems can be integrated and collaborated with other intelligent technologies, such as industrial IoT and big data analysis. It achieves adaptive and intelligent production processes through real-time monitoring of production data, optimization of process flow, prediction of equipment failures, and other means. Appearance is the first impression of a product, which determines its visual appeal and emotional connection. A product appearance with a unique aesthetic and design sense can quickly catch consumers' attention and stimulate their purchasing desire. Brands need to focus on product appearance design, pursue uniqueness and innovation, while maintaining consistency with brand image and target consumer aesthetics. The market is the ultimate destination of a product, which determines its competitiveness and vitality. Brands need to conduct in-depth market research, understand consumer needs, preferences, and purchasing habits, and develop and design products accordingly. Moreover, brands also need to pay attention to the dynamics of competitors, analyze market trends, and ensure that products maintain a leading position in the market.

Wang and Arora [17] explored the continuous trajectory planning method and its application for industrial welding robots based on CAD technology. Continuous trajectory planning is an important part of motion planning for industrial welding robots. By continuously planning the trajectory of the robot, it can maintain stability during movement, improve welding accuracy and efficiency. The spline curve method is an algorithm that calculates a continuous smooth curve based on a given set of control points. In the trajectory planning of industrial welding robots, the spline curve method can calculate a continuous and smooth welding path by giving a starting point, target point, and intermediate point. A certain automobile manufacturing enterprise utilizes CAD technology and continuous trajectory planning method to plan the motion of welding robots. The designer first uses CAD technology to design the structure of the car body, and then plans the welding path based on the body structure and welding requirements. Through continuous trajectory planning methods such as interpolation, spline curve, and Bezier curve, the designer calculates a continuous and smooth welding path. Finally, using the simulation function of CAD technology, the designer simulates the welding process to check whether the welding quality and efficiency meet the requirements.

Deep learning technology is gradually being introduced into CAD/CAE systems. Yoo et al. [18] explored how to integrate deep learning technology into CAD/CAE systems, and introduced its application and effectiveness using the generation, design, and evaluation of 3D concept wheels as an example. Through deep learning techniques, one can learn the structural features and laws of concept wheels. Then, utilizing these features and laws, structural optimization can be automatically carried out to improve the performance and stability of the concept wheel. In conceptual wheel design, knowledge and requirements from multiple disciplinary fields are often involved. Deep learning can assist designers in multidisciplinary optimization, comprehensively considering the needs and constraints of each discipline, and arriving at the optimal design solution. Integrating deep learning into CAD/CAE systems. Taking the generation, design, and evaluation of 3D concept wheels as an example, deep learning can help designers automatically generate design solutions and conduct evaluation and screening, thereby improving the quality and efficiency of design. Deep learning can also assist designers in structural optimization and multidisciplinary optimization, comprehensively considering various needs and constraints, and arriving at the optimal design solution. In today's design field, computer-aided design (CAD) has become a mainstream tool. However, despite the powerful capabilities of CAD tools in design and modeling, there are still some challenges in product form recognition and optimization. Product form recognition involves identifying designs with similar features and attributes from a large number of designs, and the application of deep learning algorithms in this field provides new possibilities for solving this problem. Zhou et al. [19] explored the application of combining product shape recognition with deep learning algorithms in CAD design. Product form recognition is a technology that classifies and identifies a large number of product forms during the design process. Through this technology, designers can quickly find forms that are similar or related to the product they are designing. The traditional method of product form recognition mainly relies on the intuition and experience of designers, but this method often has subjectivity and low efficiency. Therefore, we need a more objective, accurate, and efficient method, and deep learning algorithms are the ideal tool to solve this problem.

3 PRODUCT IMAGE RECOGNITION AND CLASSIFICATION BASED ON DL

With the improvement of DL technology, its application in image recognition and processing is becoming increasingly widespread. This section will focus on DL-based product image recognition and classification methods, with a special focus on the recognition and classification of clothing product morphology. In terms of feature extraction, utilize the powerful capabilities of DL, especially CNN. CNN can automatically learn low-level to high-level features in images and extract effective features of clothing products at different levels of abstraction. After extracting sufficiently rich features, further, construct a clothing product shape recognition and classification model based on ACNN. The network structure of the product image recognition model is shown in Figure 2.

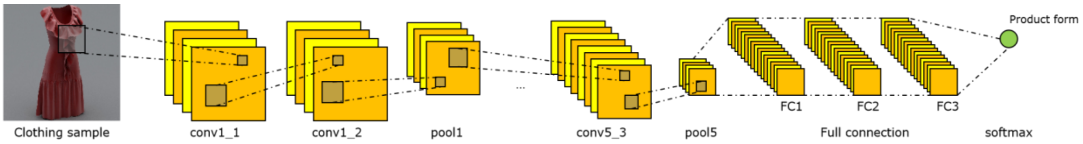

Figure 2: Network structure of product image recognition model.

Input the extracted features into ACNN and gradually abstract and represent the form of clothing products through the stacking of multiple atmosphere convolution layers. This enables the model to more effectively handle the diversity and complexity of clothing product forms. At the end of the model, connect a classifier or other decision-making mechanism to identify and classify the form of clothing products. By training and optimizing model parameters, accurate recognition of clothing product form can be achieved. In this process, a large number of clothing product images are used as training data, and the parameters of the model are optimized through backpropagation algorithm to minimize recognition errors.

Compared to traditional activation functions sigmoid and tanh, have advantages:

$$f\ x\ = \max\ 0,\chi \tag{1}$$

The formula for calculating the output of j neuron in i layer is:

$$h_{i,j} = \mathrm{Re}LU\left(\sum_{k=1}^{n} W_{i-1,k} X_{i-1,k} + b_{i-1}\right) \tag{2}$$

$$\Pr oduct \operatorname{Im} age_p \ \frac{1}{1+\exp\ -h_{FC3}} \tag{3}$$

Where $\Pr oduct \operatorname{Im} age_p$ represents the probability output of product image, and h_{FC3} represents the output of the last fully connected layer $FC3$. The loss function formula of the whole network is:

$$J\ W\ = -\frac{1}{m}\left[\sum_{1}^{m} y^{\ i} \log h_w\left(x^{\ i}\right) + \left(1-y^{\ i}\right)\log\left(1-h_w\left(x^{\ i}\right)\right)\right] \tag{4}$$

Where $\left(x^{i}, y^{i}\right)$ stands for the i sample, m stands for the number of training samples, and $h_w\ x$ stands for the hypothesis function. The whole process of network training is the parameter solving process of finding the minimum value of softmax loss function $J\ W$.

The experimental samples in the data set are used as input, and the loss function $J\ W$ is calculated by forward propagation through the network. The derivative $\frac{\partial J\ W}{\partial W_i}$ of the loss function to the weight of each layer is calculated by using the random gradient descent algorithm. Where i represents the number of layers of the network, and the weight of each layer is updated, and the updating formula is:

$$W_{i+1} = W_i - \alpha \frac{\partial J\ W}{\partial W_i} \tag{5}$$

Where a is the super-parametric learning rate, so as to continuously reduce the loss function $J\ W$, and minimize the difference in product image recognition.

Imagery is a human association with a product, a perceptual behavior that expresses and interprets the personality and characteristics of the product. The essence of this behavior is that when observing a product, a person stimulates product information related to their cognition based on the existing perceptual cognition in their brain. The cognitive process of product imagery is obtained from three aspects: sensation, representation, and intuition. This process involves "logical textual language" and "perceptual morphological language", so product imagery can be expressed and interpreted through both textual and pictorial methods (see Figure 3).

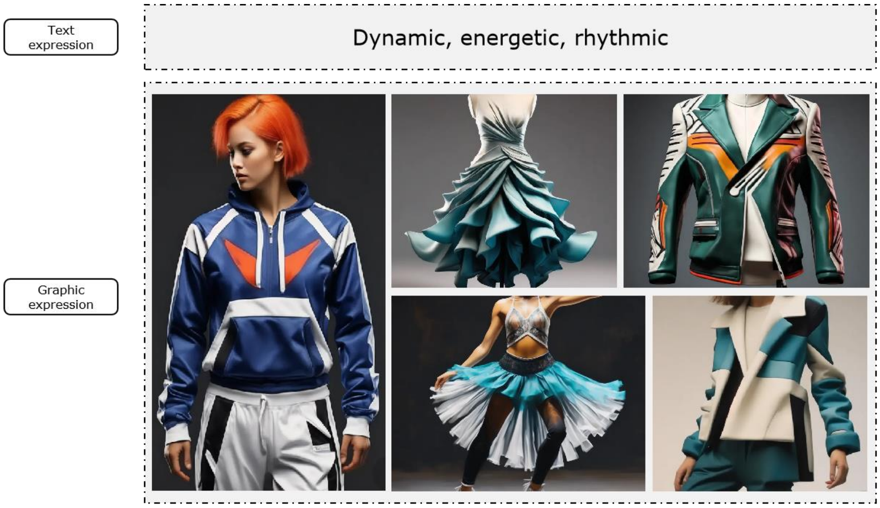

Figure 3: Expression and interpretation of product image.

$$m_{pq} = \sum_{x=1}^{m}\sum_{y=1}^{n} x^p y^q f\ x,y \tag{6}$$

Two first-order moments m_{10}, m_{01} represent the gray center of gravity of the image.

And the image processed by the neighborhood average method is $g(x,y)$, then:

$$g(x,y)=\frac{1}{M}\sum_{(m,n)\in S}f(m,n) \tag{7}$$

Image binarization is an important step in image processing. Its purpose is to simplify the complexity of images and make them easier to analyze and process. In the specific operation, a threshold value T is selected first. The binarization conversion rules of gray image are as follows:

$$g(x,y)=\begin{cases}1, & f(x,y)\geq T\\ 0, & f(x,y)<T\end{cases} \tag{8}$$

$f(x,y)$ is the value of the original pixel, $g(x,y)$ is the value of the binarized pixel, and T is the threshold.

The weighted code can be expressed as:

$$c_i=\sum_{j=0}^{T_x}a_{ij}f(x_j) \tag{9}$$

$$a_{ij}=\frac{\exp(e_{ij})}{\sum_{k=1}^{T_x}\exp(e_{ik})} \tag{10}$$

Utilize the trained ACNN based clothing product shape recognition and classification model to extract images from a large number of clothing products. This process can be automatically completed, and the model will extract effective features from the input image and recognize and classify product form based on these features. After image extraction, it needs to be parsed and transformed to enable its use in CAD design. This involves converting the extracted image features into CAD design parameters. Input the parsed and transformed image parameters into the clothing product CAD design system. These parameters will serve as design guidelines to assist designers in creating new clothing products in the CAD environment. In the CAD design process, designers can adjust and optimize image parameters based on actual situations. This adjustment can be based on the designer's experience and aesthetics, as well as consumer feedback. Through continuous iterative design and optimization, clothing product designs that meet both product imagery and market demand can be ultimately obtained.

4 VALIDATION EXPERIMENT

In order to train and test the proposed model, this study collected a large-scale clothing product image dataset. This dataset contains clothing product images from multiple categories such as men's formal, men's casual, women's formal, and women's leisure, with each category containing hundreds to thousands of images. These images cover clothing products from different angles, lighting conditions, and backgrounds to ensure data diversity and authenticity. The model underwent 100 rounds of iterative training, as shown in Figure 4. The results show the sample results of generative design schemes in the two image dimensions of "male female" and "casual formal". In addition, some design scheme samples with poor generative results are also displayed. Experiments have shown that conditional generative adversarial neural networks can generate product sample images under the guidance of product images, proving the feasibility of the model. And the samples have a certain degree of diversity. In "men's formal", the generated samples are all leather shoes in form, but have diversity in style. In the three dimensions of "men's texture", "women's formal", and "women's texture", there is not only diversity in style, but also diversity in the types of products generated. There are a small number of bad results in the generated samples. According to the statistics of the samples generated in the last two training rounds (2000 randomly selected samples), the proportion of bad results is about 3.8%. As shown in the last row of Figure 4, some have not successfully formed the shape of the product, some have some parts that are not connected to the main body of the product, and some have a lot of interference noise. For most generated samples, the effect is considerable, and users or designers can intuitively feel the positioning and shape of the product.

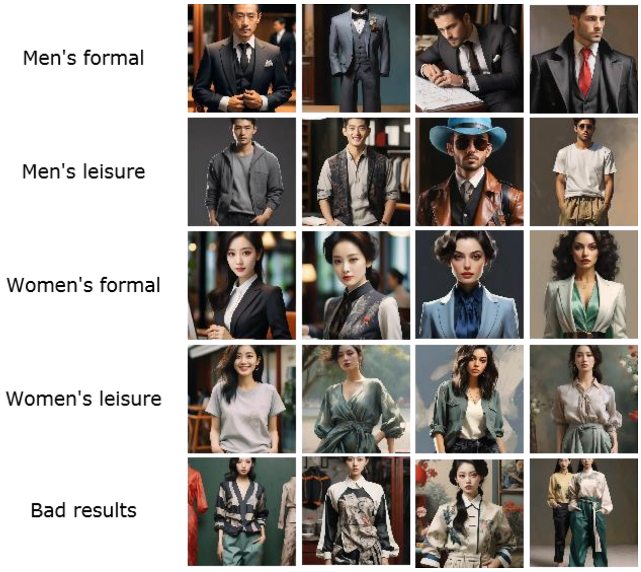

Figure 4: Sample generation example.

After collecting various types of clothing product images (including men's formal, men's texture, women's formal, and women's texture), three different types of DL models, ACNN, CNN, and LSTM, were tested to analyze their expressiveness and classification performance in clothing product image processing.

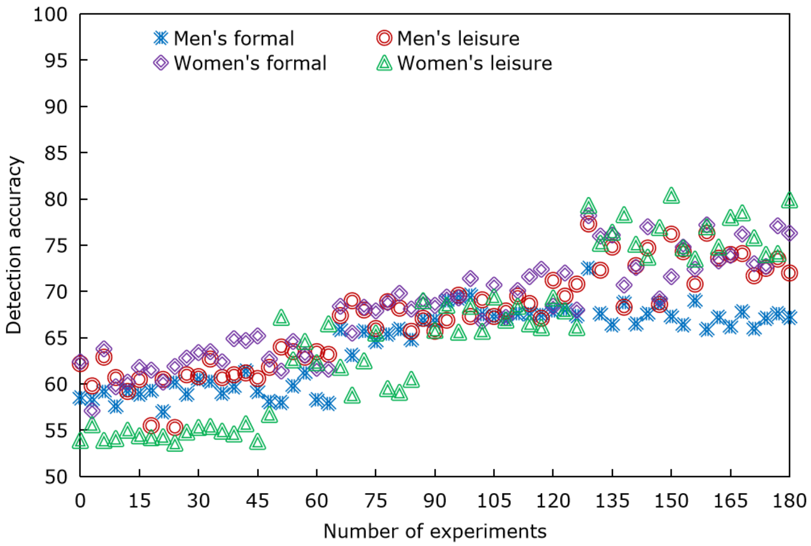

Figure 5: ACNN classification performance.

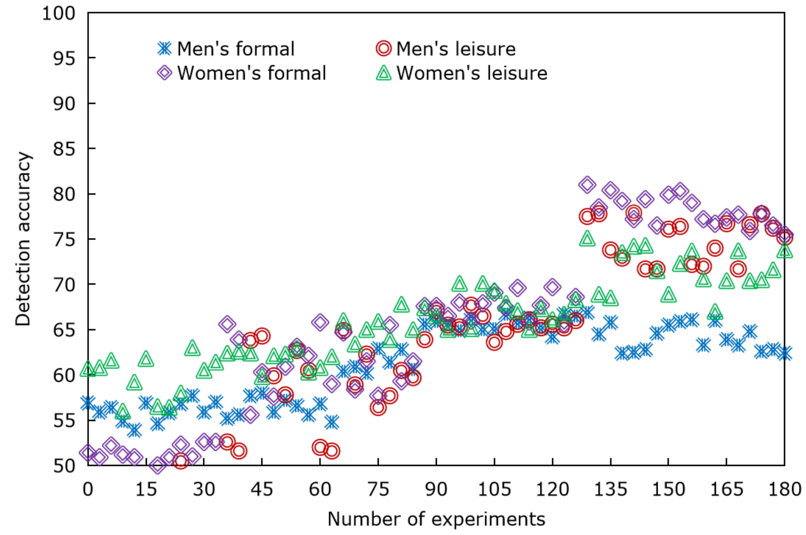

Figure 6: CNN classification performance.

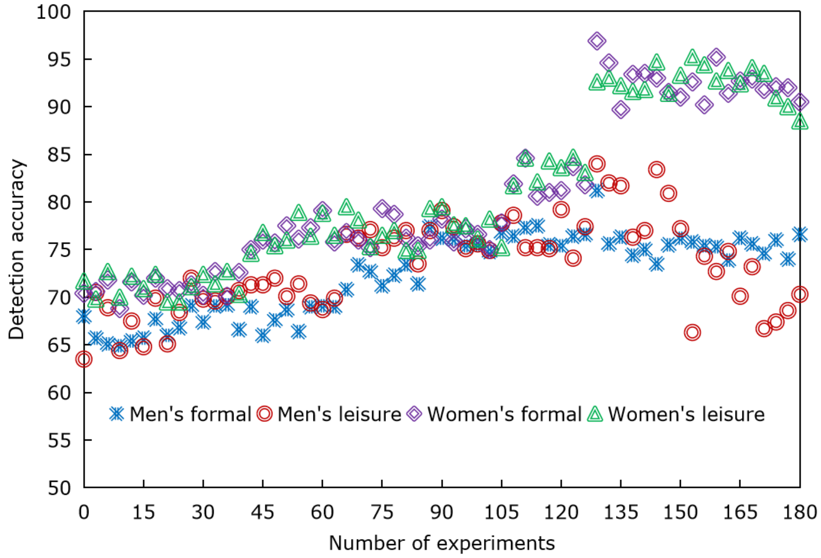

Figure 7: LSTM classification performance.

From Figures 5, 6, and 7, it can be clearly observed that the ACNN model achieved the highest classification accuracy among all tested clothing product types. In contrast, CNN and LSTM perform relatively poorly. This result confirms the expectation of this study that ACNN has higher accuracy in handling complex and diverse forms of clothing products. ACNN increases the receptive field while keeping the number of parameters constant, thus being able to capture more contextual information. This enables the model to more effectively handle various types of clothing product forms and accurately classify them. On the other hand, CNN and LSTM models, although they can also complete the classification task of clothing products to a certain extent, have lower classification accuracy compared to ACNN. This may be because these two models lack effective feature extraction and representation capabilities when dealing with complex and diverse forms of clothing products.

The optimization processing time of clothing product features using different methods is shown in Figure 8. From the results, it can be seen that the clothing product image processing method studied in this study exhibits superior performance in terms of processing time and efficiency.

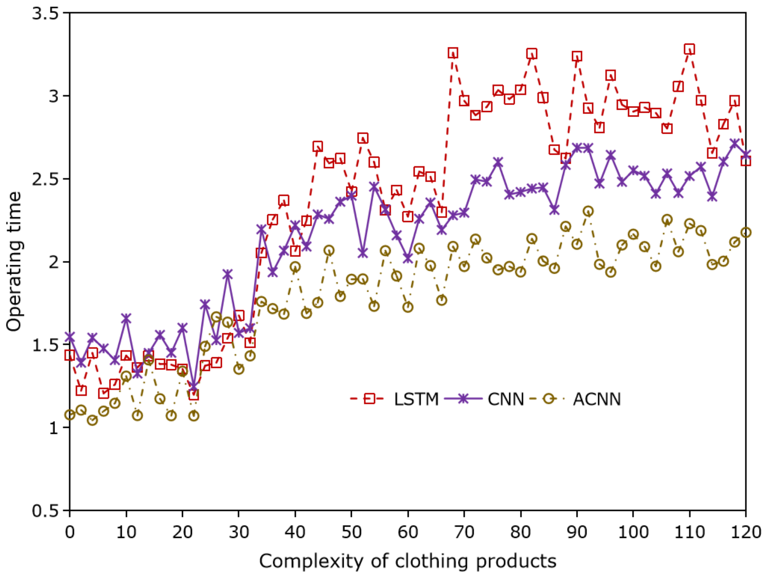

Figure 8: Time comparison of clothing product feature optimization.

For the results of optimizing the processing time of clothing product features, some important observations can be drawn from Figure 8. The ACNN model exhibits significant advantages in processing time. Compared to CNN and LSTM models, ACNN model has significantly shorter time consumption when processing clothing product images, which means it has higher performance in processing efficiency. In contrast, traditional CNN models often require more layers to achieve similar performance, thereby increasing computational time and model complexity. However, due to its recursive structure, the LSTM model usually takes a long processing time and is not suitable for image classification tasks. Due to the parallel computation of ACNN's convolution-based operations, the model can fully utilize computing resources and accelerate processing speed. In addition, the characteristics of atmosphere convolution enable the model to maintain high accuracy while reducing unnecessary computational complexity, further improving processing efficiency.

The excellent performance of ACNN model in clothing product shape recognition and classification tasks provides a more accurate and efficient tool for product design. In the process of product design, accurately identifying and classifying the form of products helps designers better understand and grasp market demands, position product styles, and carry out targeted design. The powerful feature extraction and classification capabilities of the ACNN model enable designers to quickly obtain information about product form and make more informed decisions during the design process. Technologies based on DL, such as the ACNN model, can play a greater role in the field of product design. By combining strong feature extraction capabilities and efficient classification performance, automated and intelligent product design methods and systems can be further explored, encouraging designers and developers to continuously explore innovative methods and technologies and promoting product design development to a higher level.

5 CONCLUSION

Traditional CAD design tools often require designers to possess exceptional skills and experience when dealing with complex clothing shapes and styles. This article explores the application of product form recognition combined with DL algorithms in CAD design, and constructs a clothing product form recognition and classification model based on ACNN. The results show that DL techniques, especially ACNN, have shown significant advantages in clothing product shape recognition and classification tasks. By processing and analyzing clothing product images, the ACNN model can accurately extract and represent effective features, and achieve high-precision classification. Compared to traditional CNN and LSTM models, ACNN also exhibits superior performance in processing time and efficiency, with higher computational efficiency and shorter processing time. These results provide intelligent methods and tools for clothing CAD design, and promote the development of the product design industry towards a more efficient and accurate direction. The results are not limited to the field of clothing product design, but also provide new ideas and methods for reference in other product design fields.

DL based technology can be widely applied in product design, helping designers better understand and grasp market demands through automatic learning and feature extraction, and improving the intelligence and efficiency of design. The current research mainly focuses on image data, but other types of data are also involved in the product design process, such as text descriptions and user feedback. Future research can explore how to effectively integrate multimodal data and provide more comprehensive decision support for product design.

Xia Wu, https://orcid.org/0009-0008-8821-5060
Leiming Zhu, https://orcid.org/0000-0002-5115-4566

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