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Computer-Aided Design AND APPLICATIONS

Intelligent Analysis and Optimization of Computer Aided Furniture Design by Deep Learning

Yun Wang[1] and Feng Chen[2]

[1,2] China Academy of Art, Design Innovation Center of CAA, Hangzhou, Zhejiang 310000, China,
[1]wy@caa.edu.cn, [2]20191086@caa.edu.cn

Corresponding author: Feng Chen, 20191086@caa.edu.cn

Abstract. Furniture design is an indispensable part of interior design; furniture design not only needs to meet the needs of consumers for basic functions but also to meet the aesthetic needs of consumers' personalized design. Traditional furniture design is centered on the designer. Furniture design is completed based on market demand, but the personalized needs of consumers are ignored, which easily produces the problem of homogenization of design. Therefore, this paper builds an intelligent furniture design analysis and optimization model based on deep learning, combines CNN and KNN to recognize and classify furniture design styles, and optimizes furniture design through the Pix2pix model. The experimental results show that the model has good and stable performance in furniture design style recognition and classification. Design optimization can be realized based on designer design results combined with consumer feedback information, and the efficiency is faster. In addition, the furniture design output of the model, according to the design labels provided by designers and consumers, can meet the needs of most consumers for personalized and comfortable furniture design.

Keywords: Deep Learning; Computer Aided; Furniture Design; Convolutional Neural Network; Pix2pix Model
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1 INTRODUCTION

Traditional visual elements are not only treasures of Chinese culture but also key elements in showcasing artistic charm and cultural connotations in furniture design. These elements may come from traditional Chinese patterns, colours, materials, or shapes, combined with intelligent technology to create furniture products that have both traditional charm and a modern technological sense [1]. In the early stages of intelligent furniture design, designers not only focus on the appearance and visual effects of products but also incorporate traditional visual elements. With the rapid development of society, especially the rise of intelligent technology, furniture design is also facing a transformation from traditional to intelligent [2]. Traditional materials and craftsmanship have unique textures and aesthetics, and designers can combine them with modern technology to create smart furniture that is both comfortable and practical. Traditional colours and patterns have unique cultural connotations and aesthetic values, and designers can integrate them into the design of smart furniture, making the furniture not only have traditional charm but also conform to modern aesthetics [3]. The importance of design thinking is becoming increasingly prominent in innovation management. Designers need to constantly expand their design knowledge and skills to adapt to rapidly changing market and user demands. Designers can introduce technologies such as intelligent control systems and sensors to enable the furniture to have more intelligent functions, such as automatic adjustment of temperature, humidity, light, etc. while achieving interaction and communication with users [4].

In this process, the combination of traditional visual elements and intelligent design not only satisfies people's pursuit of material life but also provides users with a brand-new experience at the spiritual level. In the design process of smart furniture, designers will pay more attention to user experience and market demand [5]. Designers will apply aesthetics and design principles, combined with modern technology such as intelligent control systems, sensors, etc., to make furniture not only attractive in appearance, but also intelligent and convenient in functionality. At the same time, designers will also pay attention to the interactivity and scalability of furniture, and by introducing innovative technologies and strategies, make furniture more intelligent and personalized [6]. They combine user needs, market trends, and intelligent technology through product thinking to ensure that furniture products are both practical and meet user aesthetic needs. By introducing innovative management concepts, designers can better apply design thinking, combine traditional visual elements with intelligent technology, and create more competitive and innovative furniture products. In the design process, designers should pay attention to environmental and sustainable development issues, adopt environmentally friendly materials and processes, and reduce energy consumption and pollution in furniture production. Furniture is an inseparable part of people's lives [7]. Its importance is not only reflected in its practicality and functionality but also in the creation of space atmosphere, emotional connection, social interaction, aesthetic decoration, health and safety, cultural inheritance and other aspects, which create a comfortable, beautiful, practical and meaningful living environment for us. With the development of the economy and the improvement of people's living standards, people's attention to furniture is also gradually increasing, especially in home design and style more pursuit of aesthetic diversification, unique design and personalized. Traditional furniture design is based on market research data analysis combined with the experience of designers to achieve furniture design. Due to the excessive dependence on the experience and level of designers, this mode has great limitations in innovation and diversification, and the flexibility of furniture design is poor. In addition, market research has a certain lag and change, it is difficult for designers to grasp the trend of furniture design style the first time, and the design results lack adaptability, which makes it difficult to obtain the recognition of the market and consumers to a large extent. While pursuing the aesthetics and style of furniture design, people also pay attention to the humanized design of furniture design, whether it meets the ergonomic requirements and satisfies people's higher comfort needs [8]. However, traditional furniture design often attaches more importance to the integrity of design, ignoring the details and functional design needs. Moreover, after the design is determined, the design cost, time cost and economic cost are taken into account, and the degree of homogeneity of furniture design will increase, making it difficult to meet the dual needs of consumers for personalization and comfort.

The development and application of information technology and computer technology have broadened the development path of furniture design. The combination of deep learning algorithms and computer-aided technology can provide designers with powerful tools and methods to improve the design process, improve the design quality and efficiency, and promote the development speed of furniture design [9]. Computer-aided technology can efficiently collect and process a large amount of data required for furniture design, including customer needs, market trends, material properties, etc. Deep learning technology can conduct in-depth analysis of these data and extract key information. By learning historical design data, the deep learning model can predict the style, size and functional requirements of furniture that may be popular in the future, predict design trends and customer needs, and provide decision support for designers. At the same time, the combination of the two can quickly generate design schemes, display design results to consumers in diversified and intuitive forms, improve consumer participation and interaction, and provide more feedback information for the optimization of furniture design. Compared with traditional furniture design mode, furniture design mode combined with deep learning and computer-aided technology has more obvious advantages in design efficiency, optimization performance, and design quality [10]. Therefore, this paper will be driven by deep learning combined with computer assistance to build an intelligent home design analysis and optimization model. In the model, based on convolutional neural network (CNN), this paper introduces the K nearest neighbor (KNN) algorithm to improve the feature extraction, recognition, and classification of furniture design style, requirements, and features and builds a corresponding furniture installation database. Combined with consumer demand, ergonomics, and other information through the Pix2pix model to achieve the optimization of furniture design and improve the design aesthetics and functionality.

2 RELATED WORK

Machine learning algorithms play an important role in evaluating the visual elements of smart furniture design. Through these technologies, artificial intelligence can help designers more effectively generate and optimize visual elements of furniture, ensuring that they are not only aesthetically pleasing but also in line with user expectations and market trends. Lydekaityte and Tambo [11] combined user needs and market trends; artificial intelligence technology can play a role in multiple stages of furniture intelligent design. In addition, artificial intelligence technology can also predict market trends and provide designers with forward-looking design inspiration. In the innovation process of smart furniture design, artificial intelligence technology can help designers capture and integrate user needs, such as functional requirements, aesthetic preferences, and usage habits. By intelligently analyzing this data, designers can generate more personalized and market-oriented furniture design solutions. In the detailed design stage, artificial intelligence can help designers optimize the visual elements of furniture, such as colour, texture, shape, etc., to ensure they are consistent with the overall design style. This can be achieved through various methods, such as user feedback analysis, image quality evaluation, and style consistency check. In the preliminary design stage, artificial intelligence can help designers quickly generate multiple design solutions and select the best solution through evaluation. Designers can combine traditional visual elements with modern design through artificial intelligence technology to create furniture products that have both traditional charm and meet modern aesthetic and practical needs. Against the backdrop of cultural confidence, smart furniture design should also focus on inheriting and innovating the excellent traditional Chinese culture. This not only helps to enhance the cultural value of the product but also helps to establish a unique brand image in global competition. With the continuous development of artificial intelligence technology, the field of furniture intelligent design will also usher in more innovation and change. Through interdisciplinary collaboration and user engagement, Marion and Fixson [12] have gained a wider range of knowledge and skills, as well as deeper levels of user feedback and needs. This will help designers more accurately grasp market trends and user psychology, and achieve more efficient and personalized design. At the same time, this will also promote the rapid development and competitiveness enhancement of the furniture intelligent design industry. Furniture design has always been an important branch in the field of design, which is related to all aspects of people's lives. Furniture design is closely related to the development of social productivity and science and technology. In the early days, furniture design was mainly practical, concise, and with a single style, and the level of manual design and craftsmanship had a key impact on it. With the development of production technology, furniture design has become increasingly mature in terms of craftsmanship, shape, structure, decoration, etc., forming a unique style with strong regional and ethnic characteristics. In the industrial era, mechanized furniture production has gradually become the main mode of production. At this stage, furniture design still revolves around designers. With the diversification of materials and streamlined processes, furniture efficiency from design to production is higher, and the style of furniture design has changed from single to diverse, from regional to international. However, in the subsequent development, furniture design was limited by streamlined production, resulting in severe homogenization of design. Materials, decoration, style, and other aspects often relied more on market demand, gradually ignoring consumer needs.

Pelliccia et al. [13] analyzed furniture intelligent design: defining, modelling, and serving as a bridge between digital and physical product management. Furniture intelligent design is a new method that integrates intelligent technology into furniture design, achieving intelligent management and interaction of furniture by integrating advanced technologies such as sensors, communication technology, and data processing. By embedding sensors, furniture can perceive the environment and user behaviour, such as temperature, humidity, human posture, etc., and automatically adjust the state of furniture based on this information, such as adjusting light brightness, heating or cooling. These digital models can be customized according to the characteristics of furniture and user needs, helping designers optimize the structure, function, and appearance of furniture. In terms of modelling, furniture intelligent design establishes digital models to simulate and predict the performance and user experience of furniture in actual use. Intelligent furniture design also provides personalized customization services. Salahuddin et al. [14] customized unique smart furniture solutions for users based on their personal preferences and needs. By simulating different usage scenarios, designers can identify potential problems in advance and make improvements, thereby improving the quality and reliability of furniture. In addition, smart furniture design also achieves interconnection with other smart devices through communication technology, forming a smart home ecosystem. These solutions not only meet the basic needs of users but also provide personalized interaction methods and intelligent functions, such as voice control, remote control, etc., bringing users a more convenient and comfortable life experience. Smart furniture design not only focuses on the appearance and comfort of furniture but also emphasizes its intelligent functions and user experience. By utilizing advanced manufacturing equipment and production lines, intelligent furniture products that meet design requirements can be quickly and accurately produced. In terms of intelligent manufacturing, furniture intelligent design achieves efficient production and manufacturing through automation technology. This efficient production method can greatly shorten the production cycle of products, reduce production costs, and improve market competitiveness. Since entering the information age, people have attached increasing importance to furniture design, and the concept of green environmental protection has emerged, becoming an important trend in furniture design. Saleh et al. [15] began to focus on using sustainable, non-toxic, and low-volatility decorative materials, such as bamboo flooring instead of traditional wood flooring, and water-based coatings instead of solvent-based coatings. These materials are not only environmentally friendly but also help improve indoor air quality and protect the health of residents. At the Milan International Furniture Exhibition, many brands proposed sustainable use and ecological design of wood, such as Arco Works such as Dew coffee tables reflect the importance of environmental protection. Some designers have proposed flexible and multifunctional design concepts based on the functionality of furniture. Designers focus on the various uses of furniture, such as foldable dining tables and sofa beds, to meet different living needs. The development of smart homes has also promoted innovation in furniture design. For example, smart lockers can automatically sort, store, and retrieve items, improving the convenience of daily life. In terms of intelligent furniture design, Zhou et al. [16] tend to add intelligent services and functions to existing designs and achieve intelligent control of some furniture through AI intelligence. Some designers optimize the layout of furniture spaces through intelligent algorithms. It can be seen that the optimization application of furniture design through computers and intelligent algorithms is still in the early stage of development. Therefore, this study has certain practical significance and can provide technical support for the development of furniture design.

3 FURNITURE DESIGN OPTIMIZATION BASED ON DEEP LEARNING

3.1 Furniture Design Style Identification and Classification

Furniture style is one of the important manifestations of the connotation of furniture design. Different furniture styles have unique visual characteristics and design elements, which constitute the uniqueness and identification of furniture design, and also show the cultural characteristics of different regions and different times. Furniture style is the basis of furniture design innovation and development, which not only affects the appearance of furniture but also affects the emotional experience of users. Therefore, this paper will build the furniture design style recognition and classification module by combining CNN and KNN, and build the corresponding data set to provide data support for future furniture design optimization. In the process of furniture development, a variety of furniture styles have been formed and derived, and different furniture styles have certain differences in the choice of design elements, performance, colour texture and other aspects. The combination of multiple style labels, can better show the meaning of furniture design and provide elastic imagination space for design. At the same time, the model constructed in this paper can also better enter into the in-depth analysis according to different furniture style labels and obtain the corresponding data characteristics.

As a deep structure and feedforward neural network, CNN has a strong performance in image data processing, which meets the requirements of furniture design data processing. The CNN structure is composed of multiple layers of different networks stacked together in a specific order and way to realize the processing of input data and feature extraction. Figure 1 shows the CNN network structure diagram and convolutional operation process.

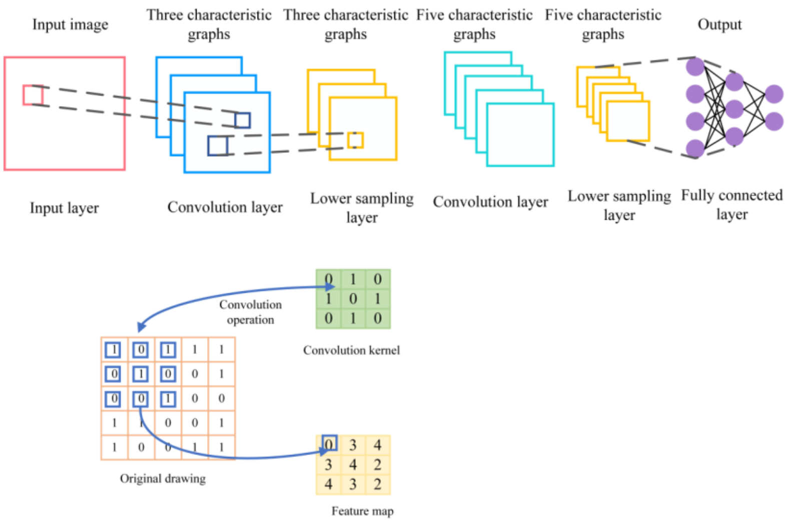

Figure 1: Schematic diagram of CNN network structure and convolution operation process.

The input layer of a CNN usually receives raw images or pre-processed image data, which is usually represented as a multidimensional array (such as a 3D array of RGB images). As the core part of CNN, the convolutional layer is responsible for the feature extraction of input data through a set of learnable convolutional checks. These convolution cores slide over the input data and perform dot product operations at each position to generate feature maps (otherwise known as feature maps). Through the mechanism of local connection and weight sharing, the convolutional layer significantly reduces the number of parameters in the model and improves the generalization ability and computational efficiency of the model. This structure enables CNNS to process image data efficiently and has achieved remarkable results in computer vision tasks. Formula (1) is shown as follows h Layer feature extraction output:

$$t_n^h = f(\sum_{m=1}^{M} t_m^{h-1} * w_{mn}^h + b_n^h) \tag{1}$$

among $n = 1,2,...,N$ The output characteristics of this layer are described as t_n^h The input data features are described as t_m^{h-1} the weight of the convolution kernel is expressed as w_{mn}^h the offset is written as b_n^h $f(\cdot)$ Indicates that the activation function is nonlinear.

The activation function of the convolution operation is shown in (2):

$$relu(x) = \max(0, x) \tag{2}$$

Pooling operations usually include maximum pooling and average pooling, where maximum pooling selects the maximum value within each pooling window as the output, while average pooling computes the average value within each pooling window as the output. In mid-layer control j The output feature map is represented t_j^{L-1} After passing through the pooling layer, as shown in formula (3):

$$t_j^L = f(down(t_j^{L-1}) + c_j^L \tag{3}$$

The amount of bias in the formula is expressed as c_j^L a pooling function $down(\cdot)$.

After the data feature values are processed by the pooling layer, new feature points are obtained, and the feature points are mapped in the sample label space by the fully connected layer to achieve the purpose of data classification. After the fusion features, the output of the previous layer is transformed from the classifier into a probability vector, and the result represents the probability of the current sample belonging to the classification item, as shown in formula (4):

$$l_n = \frac{e^{b_n}}{\sum_{k=1}^{N} e^{b_k}} \tag{4}$$

Where the sample classification item type is denoted as N the fully connected layer output vector is described as b_k.

The loss function is shown in formula (5):

$$loss(Y, \hat{Y}) = \frac{1}{N}\sum_{i=1}^{N}(\overset{\wedge}{y_i} - y_i)^2 \tag{5}$$

KNN is a classification algorithm based on the measurement of the distance between different features, that is, the target sample is classified into the category with the greatest probability among the k samples closest to it. Let the space dimension be a, and there are two points in this space, respectively $e(x_{11}, x_{12}, ..., x_{1a})$, $f(x_{21}, x_{22}, ..., x_{2a})$ The Euclidean distance calculation formula after the two-point tibia normalization treatment is shown in (6):

$$d = \sqrt{\sum_{i=1}^{a}(x_{1a} - x_{2a})^2} \tag{6}$$

If the spatial dimension is high, it can be calculated from the Manhattan distance, as shown in (7):

$$l = \sum_{i=1}^{a}\left|x_{1a} - x_{2a}\right| \tag{7}$$

In order to test the performance of the furniture design style recognition and classification model combined with CNN and KNN algorithm, this paper adopts two indicators of accuracy and recall rate for evaluation, as shown in formulas (8) and (9):

$$AC = \frac{m}{m+n} \tag{8}$$

$$RE = \frac{m}{m+c} \tag{9}$$

Where the accuracy is described as The recall rate is described as RE The data to be determined divided into positive cases and negative cases. The number of positive cases that are correctly classified is m, the number of positive examples of classification errors is n, and the number of positive cases classified with negative cases is c.

Considering the diversity of furniture design styles, this paper obtains the classification results of furniture design styles based on the relevant classification information provided by 20 designers, as shown in Table 1. As can be seen from Table 1, the classification labels of furniture design style are divided into two levels, and the key classification words of the first level are new technology style, modern style, Eastern style and Western style. Each level keyword contains several secondary style labels to refine the furniture design style further.

Furniture style	*Style vocabulary*
New technology style	Streamlined, parametric, industrial style
Modern style	Modern, net red, minimalist, simple European, classic Nordic
Oriental style	Japanese, New Chinese, Traditional Chinese
Western style	European, American, and Italian light luxury

Table 1: Furniture design style classification results.

Based on the above classification results of furniture design styles, this paper randomly selected the corresponding data of ten different furniture styles that were not classified to test the performance of model recognition and classification. The classification results are shown in Figure 2. The results in the figure show that the classification accuracy of ten furniture design styles can reach more than 80% and maintain a high recall rate. At the same time, in terms of recognition time, most recognition time is between 200 and 250s, and the recognition time of a few styles is less than 200s. This shows that the model has good and stable performance of furniture style recognition and classification, the recognition time is relatively short, and different styles can be recognized within a certain time range, which proves that the model has high application feasibility.

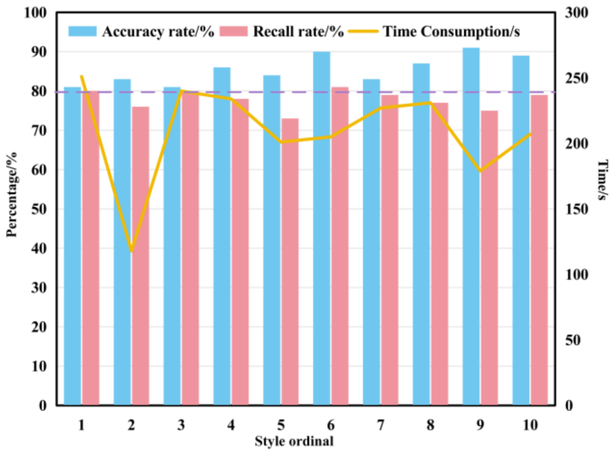

Figure 2: Classification results of furniture style recognition and classification model based on convolutional neural network and KNN.

In order to further verify the recognition and classification effectiveness of this model, this paper selected two other commonly used classification models for performance comparison, and the results are shown in Figure 3. As can be seen from the figure, the classification accuracy of the LFD model is the lowest among the three models, while the model presented in this paper is the highest. Moreover, in different style classifications, the classification accuracy of the LFD model shows great volatility, while the accuracy of the other two style classification models can fluctuate within a certain range, showing good stability. In summary, the model presented in this paper has the best comprehensive performance of recognition and classification among the three models and can provide good classification data support for future applications.

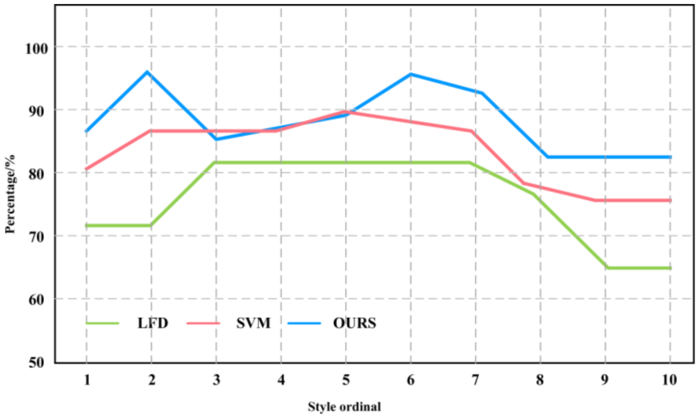

Figure 3: Classification accuracy results of three furniture design style classification models.

3.2 Furniture Design Optimization Module Based on Pix2pix Model

Generative adversarial network is a kind of deep learning model, its main idea is to learn the distribution of data and generate new data samples through two neural networks - generator and discriminator against each other. Its application in the field of image recognition strengthens the correlation between image recognition technology and image generation technology. However, the generative adversarial network has some limitations, such as weak correlation between user control and output image and low quality of generated image. Therefore, this paper selects the Pix2pix model of the production countermeasure network to construct a furniture design optimization module. The Pix2pix model is a kind of image-to-image conversion model based on a condition generation adversarial network, which has better performance in image conversion and improves image clarity. Pix2pix model in home design optimization can help designers quickly change the design style, enhance the effect of the design sketch, and greatly improve the efficiency of the design. At the same time, it can also optimize the furniture design according to the description provided by the consumer or the designer.

The basic structure of the Pix2pix model is similar to that of the generative adversarial network, both of which have a generator and a discriminator. In order to improve the control of generative images, conditional information is added to achieve the purpose. The generator is a U-Net network structure and can improve the decoder's learning ability to encoder feature parameters by means of a jump connection. At the same time, PatchGAN was added to the discriminator, which could change the judgment of the output results on the whole image, that is, from a single numerical judgment to a matrix for different regions, so as to improve the optimization of diversified feedback information. Figure. 4 shows the schematic diagram of the simple process of generating an adversarial network and Pix2pix model.

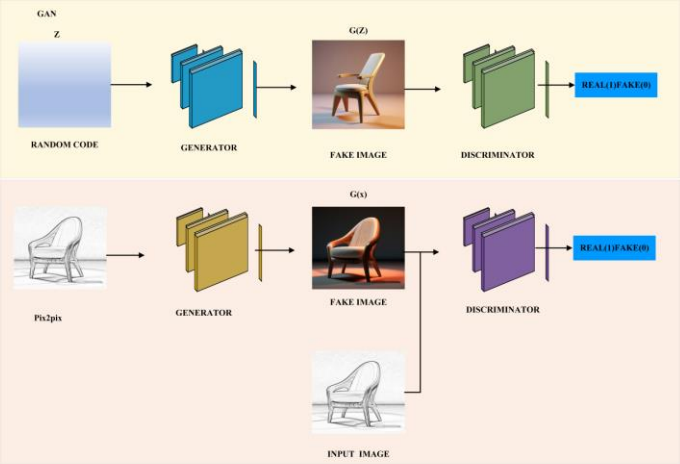

Figure 4: Schematic diagram of a simple process for generating adversarial networks and Pix2pix models.

The loss function of the Pix2pix model also adds the L1 loss function on the basis of the generated adduction network loss function, and its calculation formula is shown as (10) - (12):

$$L_{cGAN}(G,D)=E_{x,y}\left[\log D(x,y)\right]+E_{x,y}\left[\log(1-D(x,G(x,z)\right] \tag{10}$$

$$L_{L1}(G)=E_{x,y,z}\left[\left\|y-G(x,z)\right\|_1\right] \tag{11}$$

$$G^* \arg\min_G \max_D L_{cGAN}(G,D)+\alpha L_{L1}(G) \tag{12}$$

Where, the Pix2pix model generator network and discriminator network are respectively expressed as G , D , The real input image and output image are respectively represented as x,y the generator forms an image described as $G(x,z)$ The input random noise is denoted as z The weight value is denoted as a .

In order to improve the performance of the Pix2pix model, the Adam learning efficiency adaptive algorithm is selected as the optimization algorithm in this paper, whose performance is directly affected by the initial learning rate to a large extent. Therefore, this paper will observe the relationship between the loss function of the Pix2pix model generator and the number of iterations under different learning efficiency parameters without changing the hyperparameters. Before the experiment, this paper smoothed the loss function values of each group by formula (13) to achieve the purpose of increasing the intuitiveness of the results:

$$S_n=i_0\times w+i_n\times(1-w) \tag{13}$$

Where, the value obtained after smoothing is expressed as S_n The first sequence number in the data to be processed is expressed i_0 The raw data for processing is described as i_n , and the weight is expressed as w .

Figure 5 shows the relationship between the loss function of the Pix2pix model generator and the number of iterations under different learning efficiency parameters. The results in Figure 5(a) show that when the learning rate is very different, the performance of the loss function is the best when the learning rate is 0.0002. The premature convergence time of the loss function after a tenfold increase in the learning rate leads to a significant increase in the probability of the loss function falling into the local optimal, and the training time required by the loss function after a tenfold decrease in the learning rate increases significantly. When the learning rate is increased a hundred times, the loss function shows an increasing state. In order to further observe the influence of the learning rate,

Figure 5(b) takes 0.0002 as the centre to further observe the changing trend of the loss function. When the learning rate is doubled, there is a certain improvement in the performance of the loss function, but there is no significant change between the performance and the performance before the change. When the learning efficiency is increased by 50%, the performance of the loss function is worse than before the change. Therefore, in full consideration of the actual demand, the learning rate of the Pix2pix model in this paper is determined to be 0.0002.

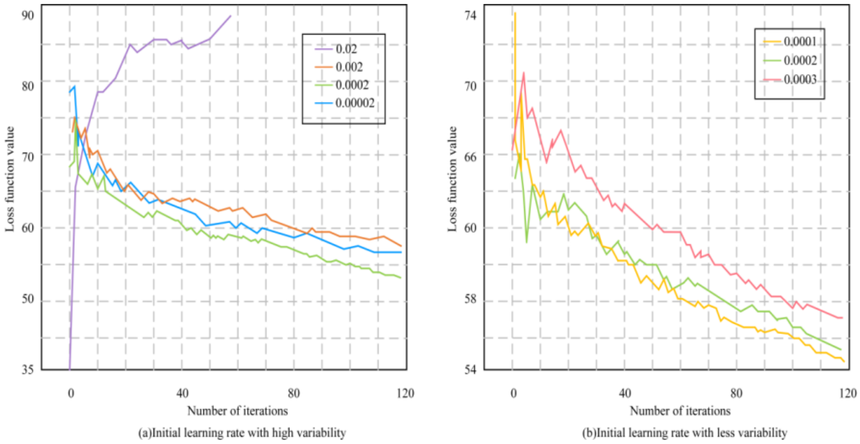

Figure 5: The relationship between the loss function of the Pix2pix model generator and the number of iterations under different learning efficiency parameters.

4 EXPERIMENT RESULTS

In order to test the application effect of intelligent analysis and optimization models of furniture design based on deep learning, this paper examines the optimization and design innovation of model furniture design.

Figure 6 shows the optimized result of this model according to the designer's furniture design effect and consumers' suggestions. As can be seen from the results of the figure, figures 6(a) and 6(c) are the renderings of the chair and wardrobe designed by the designer according to the needs of consumers. It can be seen that the designer focuses on the basic performance of the chair in the chair design, but according to the feedback information of consumers, it can be seen that consumers want to increase the design sense of the chair on the basis of the basic performance. There is a certain gap between the design effect of designers and consumers. In terms of wardrobe design, designers pay more attention to the overall design and ornamental sense of the wardrobe, while consumers are more inclined to practicality and convenience, there is also a certain gap between the two. Figures 6(b) and 6(d) respectively show the design effect diagram obtained from the design optimization of the model according to the feedback information of consumers. It can be seen from the results that the model in this paper can optimize the design based on the designer's furniture design effect combined with the feedback information of consumers, and the optimized design effect can better meet the needs of consumers and maintain the basic connotation of designers.

Considering that although there are many types of furniture, chairs rank high among the furniture that are most commonly used and consumers have higher design requirements. Therefore, in the design innovation application test, this paper takes the chair as the design object for experiments. Figure 7 shows the chair design results output by this model according to the prompts of designers and consumers.

Figure 6: The optimized results of the model based on the furniture design effect of the designer and consumer suggestions.

Figure 7: The model outputs the result of the chair design according to the prompt information of the designer and the consumer.

Based on the results of the chair innovation design in Figure 7, this paper invited 100 consumers to conduct a creative design satisfaction survey, and the results are shown in Figure 8. The survey mainly includes three aspects of chair design innovation, usability and overall satisfaction. The final result is the average of all consumer ratings, and the evaluation value is a percentage system. According to the data in the figure, in terms of design satisfaction, only design effects (b) and (d) did not reach more than 70 points, and the others all reached more than 70 points. In terms of usability, all designs have reached more than 70 points. The lowest average for overall satisfaction was 74. It can be seen that a small number of designs score low in creativity, but overall satisfaction is relatively high. This may be due to the low acceptability of different styles by different consumers, but combined with the label and demand, the design can reach the consumer's demand point. This shows that the model can effectively design furniture according to the designer and consumer label, and can meet the needs of most consumers for furniture design and usability.

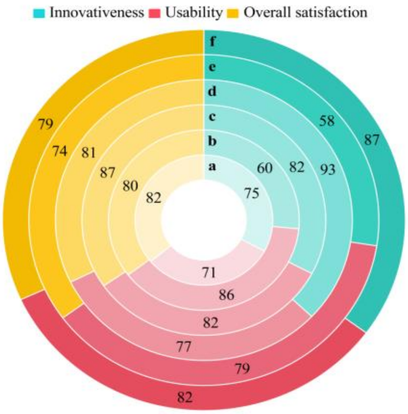

Figure 8: Results of consumer satisfaction survey on innovative chair design.

5 CONCLUSIONS

Furniture plays an important role in people's lives, which can not only provide basic practical functional services for people's home life but also meet people's aesthetic needs. Traditional furniture design is limited by the experience of designers and the influence of the market, the efficiency of furniture design is slow and there is a large probability of homogenization design, which can not meet the current consumers' pursuit of personalized and comfortable furniture design. Therefore, this paper builds an intelligent analysis and optimization model of furniture design driven by deep learning algorithms. Combined with a convolutional neural network and K nearest neighbour algorithm, the model improves the recognition and classification performance of different furniture design styles and provides basic support for the construction of furniture design data sets. In addition, the model also constructs the furniture design optimization module through the Pix2pix model, which realizes the purpose of optimizing the designer's furniture design effect. The experimental results show that the model has good and stable performance of furniture design style recognition and classification, and can provide good optimization technical support for application experiments. The model can realize the purpose of design optimization based on designer design drawing combined with consumer feedback information and can output corresponding design results according to different style labels, and the results can be recognized by most people. However, the model in this paper still has shortcomings in the rendering of design drawings. It is necessary to strengthen the optimization of deep learning algorithms in future studies, improve the style transfer effect and the rendering performance of design drawings, and help designers improve design efficiency and quality.

Yun Wang, https://orcid.org/0009-0004-4429-6605
Feng Chen, https://orcid.org/0009-0005-1271-8161

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