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Computer-Aided Design AND APPLICATIONS

Exploration of Feature Detection and Fusion for Cultural and Creative Product Based on Deep Learning

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Abstract. The aim of this article is to investigate the incorporation of deep learning attributes into CAD design methodologies for Cultural and creative (Cultural Creativity) product development. Leveraging a deep learning-driven feature detection and integration framework integrated with CAD design tools, we facilitate an effective transformation from image data to high-precision 3D models. Our findings indicate that CAD design methodologies augmented with deep learning capabilities significantly excel in design speed, novelty, and user satisfaction. This approach not only elevates design efficiency but also fosters the birth and expression of creativity. By introducing deep learning into the CAD design realm, we successfully demonstrate its applicability in Cultural and creative product design, thereby offering a novel solution and a fresh perspective for the advancement of CAD design systems. Future iterations of CAD design systems will undergo continual enhancement to accommodate the evolving complexities of design needs.

Keywords: Deep Learning; CAD Design; Cultural and creative Product Design; Feature Detection; Feature Fusion
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1 INTRODUCTION

The application of topology optimization methods in industrial engineering is not limited to designing lightweight and efficient industrial components, but it also shows great potential. However, traditional surface smoothing algorithms may encounter some challenges when dealing with culture, such as the loss of details caused by excessive mesh shrinkage or the problem of key geometric features being smoothed out. As carriers of culture and creativity, have extremely high requirements for design details, appearance, and user experience. Bacciaglia et al. [1] proposed and optimized it specifically for the characteristics that often emphasize their uniqueness and artistry; therefore, surface smoothing technology has become particularly important here. In addition, the algorithm also includes some subroutines for automatically recognizing and preserving these features during the smoothing process, thereby reducing the need for user intervention. In response to the high homogenization of tourism products across the country, some scholars have proposed designing a virtual tourism cultural and creative product that integrates cultural experience backgrounds, aiming to allow tourists to deeply experience the local cultural characteristics when visiting different scenic spots. By combining computer-aided design (CAD) technology, Deng et al. [2] constructed a multifunctional virtual 3D modelling system. It collected 157 high-quality images. This system not only provides precise digital reproduction for scenic spots but also allows for customized unique travel experiences based on the cultural background of each scenic spot. This system not only showcases the natural scenery of the scenic area, but also incorporates rich cultural background introductions and interactive elements, allowing tourists to gain a deeper understanding of the local history, culture, and customs during their travels. In this cultural and creative product, we have introduced VR real-life interactive tourism products. Through 360 ° VR panoramic display technology, tourists can experience the magnificent natural scenery such as Elephant Nose Mountain Park firsthand.

In the new globalized cultural environment, people living, studying, and working abroad not only face language and career challenges but also need to bear more cultural adaptation pressure. Gao et al. [3] designed a virtual reality application that focuses on typical Western holiday culture - Christmas culture and incorporates relevant cultural and creative product elements. As a bridge for cultural exchange, cultural and creative products have unique value and significance. Combining VR technology and cultural and creative products can create a brand-new immersive experience, allowing users to experience and learn foreign cultures firsthand and for example, decorating Christmas trees, attending Christmas parties, and interacting with various cultural and creative products, such as trying on traditional Christmas costumes and appreciating Christmas-themed artworks. Although the results of ANCOVA and mixed analysis of variance showed that virtual reality methods do not show significant advantages in knowledge learning, behaviour learning, and attitude learning, we note that the majority of participants show a strong interest and love for virtual reality methods. This learning approach that combines cultural and creative products not only makes the learning process more vivid and interesting but also deepens learners' understanding and respect for culture. View-based 3D model retrieval is gradually demonstrating its unique value and innovation. Deep learning features have stronger robustness and can cope with complex changes and diversity. With the rapid development of computer vision and machine learning technology, how to efficiently and accurately retrieve and match 3D models has become the key to promoting innovation in cultural and creative product design. With the rapid development of Internet technology, a comprehensive digital era has arrived. The trend of integration of culture and technology industries has become prominent. A large number of cultural and creative products have been born and spread rapidly through the Internet. The issue of intellectual property protection for such digital cultural and creative works is currently a serious issue facing the cultural and creative industry. The current digital form of copyright confirmation for cultural and creative products faces problems such as long certification cycles, difficulties in providing evidence for rights protection, low efficiency in product sharing, and limited means of protection and supervision, which are also pain points of traditional copyright confirmation methods. Gao et al. [4] used text-mining methods to study user evaluations in the Forbidden City. Crawling comment data on four popular categories from Taobao in the Forbidden City through a web crawler.

Han et al. [5] extracted important features involved in comment texts from a more comprehensive perspective of coarse granularity, and obtained the factors that users are concerned about and the relationships between each factor. After data cleaning, normalization, and construction of feature word lists, word cloud maps, semantic networks, etc. are used The LDA topic model performs text feature analysis on comment texts. On this basis, establish an emotional lexicon calculate emotional values, and conduct emotional analysis from a more specific perspective of "fine-grained". Further, summarizes and analyzes the key features that affect user emotional tendencies based on sentiment values through decision tree algorithms and logistic regression. And functional semantics of cultural and creative products, we established a structure-function relationship model based on multi-color sets. In addition, a more comprehensive and in-depth analysis of the structure-function correlation was achieved.

All companies are interested in how products can accurately meet the unique tastes and cultural needs of their target customer groups. Indrie et al. [6] utilized automation technologies such as computer pattern design, to design and produce cultural and creative products with unique cultural elements. By introducing 3D technology, cultural and creative product manufacturers can significantly reduce the cost and time of sample production, while improving product quality and reducing scrap rates. It pays special attention to two different types of fabrics - woven and knitted, each with unique textures and expressive power. A three-dimensional visualization model of cultural and creative products was created using fabric patterns and material data in a three-dimensional simulation software. Through official and internal standards, material properties that must be accurately mastered through 3D simulation, such as fabric softness, elasticity, glossiness, etc., have been determined. These models not only help us understand the appearance and texture of the product more intuitively but also provide accurate data support for the subsequent production process. Using traditional neutral formats (such as product model data exchange standards or initial graphic exchange specifications) to exchange parameterized assembly models also faces challenges. In order to preserve design intent while exchanging parameter information, Kim et al. [7] proposed a macro parameter method based on design history and optimized it for the characteristics. To overcome the issue of editable assembly models after exchange, we introduced a set of neutral assembly commands. It usually involves the combination and connection of multiple components, which form a whole through complex constraint relationships. In traditional design formats, models often only support the transmission of boundary representation information. This breakthrough progress is that we are not only able to exchange complex assembly models composed of coaxial constraints and event constraints. However, with our efforts, we have successfully achieved a seamless exchange of assembly models for cultural and creative products between CATIA and NX, two industry-leading computer-aided design systems. This greatly limits the designer's ability to reassess design parameters after model exchange, invisibly putting shackles on the design and innovation of cultural and creative products. And ensure that the exchanged assembly model still maintains the original design parameters. This means that designers can continue to parameterize and evaluate models in the new design environment, greatly enhancing the flexibility and innovation of cultural and creative product design.

As design concepts evolve and technology advances, the approach to Cultural and creative product design is evolving as well. The traditional design approach, heavily reliant on a designer's experience and intuition, often struggles with complex and fluctuating design demands. Subsequently, it delves into the theoretical underpinnings of deep learning and provides a comprehensive account of the development of a CAD design system tailored for Cultural and creative products. The discussion then progresses to a detailed exploration of the CAD design approach that integrates deep learning features. Concludingly, the article substantiates the efficacy of the proposed methodology through simulation experiments while analyzing and discussing the outcomes attained.

2 RELATED WORK

When exploring the potential of the Unity3D cultural game engine, significant progress has been made not only in visualizing large-scale terrain data. Especially those products that emphasize cultural inheritance and experience. In order to provide these models with geographical references, some scholars have adopted the Mapbox for Unity plugin, which not only provides accurate geographic location information for 3D models. Laksono and Aditya [8] successfully created highly detailed Unity3D from a mixed source of ground laser scanner models and topographic map data. In the expansion of cultural and creative products, these 3D models are combined with rich cultural elements to create a series of educational and interactive cultural and creative products. These models not only showcase the appearance of the building but also retain rich, detailed information through FBX format conversion. When customers plan to customize cultural and creative products, such as limited edition notebooks, art decorations, or customized cultural T-shirts, cultural and creative product providers will first ask them to provide design drafts or ideas. Based on preliminary market research, Liow et al. [9] found that the majority of respondents indicated that they have a clear understanding of their ideas for cultural and creative products, but often find it difficult to accurately convey them to designers through language or text. In the interview, it was learned that customers are eager to have more choices to participate in the design process, rather than simply relying on the designer's creativity. Customers often feel disappointed because the designer's work fails to fully capture their ideas and cultural vision. This communication barrier not only increases the complexity and time consumption of the design process but may also result in the final cultural and creative product not fully meeting customer expectations. This online editor allows customers to express their ideas and cultural vision in an intuitive and interactive way. Through this approach, customers can better control the design process, ensuring that the final product accurately reflects their personality and cultural taste. A designer matching platform that not only helps clients accurately match designers skilled in specific cultural fields but also provides users with an online editor.

The study of social networks plays an important role in multiple fields, but traditional social network analysis often focuses on structural changes at the node and relationship levels, with limited perspectives. In order to better understand and optimize the collaboration mode in cultural and creative product teams, Lu et al. [10] proposed a team collaboration network visualization analysis method that combines task classification. Through the needs of team collaboration in cultural and creative products, we have established a task classification method suitable for team collaboration analysis in cultural and creative products. Next, we designed a series of related visual views to visually and vividly display the characteristics and evolution patterns of collaborative relationships between and within cultural and creative product teams. These views not only present the overall structure of the collaboration network but also highlight key nodes, important relationships, and collaboration bottlenecks, helping team members better understand the collaboration process and identify potential issues. The experimental results show that this visualization view can clearly demonstrate the complexity and dynamics of team collaboration in cultural and creative products, which helps team members better understand the collaboration process and improve collaboration efficiency. In the field of cultural and creative product design, Lu and his team [11] conducted an innovative exploration and proposed a data-driven optimization design method. Through an in-depth analysis of online comments, Lu et al. conducted a clustering analysis on user comments using the K-means algorithm. Their research method is based on rich textual data from online reviews of cultural and creative products, utilizing the feedback of these real users to gain insights into market demand and consumer sentiment. This method can not only help designers more accurately grasp the cultural preferences of users but also gain a deeper understanding of their aesthetic needs and expectations for product functionality. They are intended to address the common issues of time-consuming, labour-intensive, and inefficient traditional design processes. This data-driven design method not only improves the efficiency and accuracy of design but also provides strong support for the innovation and development of cultural and creative products. Based on the clustering results, the optimization objectives of product design were clarified, which not only include functional improvement but also include the integration of cultural elements and the enhancement of aesthetic value. Considering that cultural and creative products are deeply influenced by user emotions and cultural resonance, online comments are used as the data source for user needs, and web crawler tools such as Scrapy are used for crawling. Taking a cultural and creative tea set that incorporates traditional Chinese elements as an example, we applied the above method for design optimization. The results showed that the optimized tea set not only improved in functionality but more importantly, achieved significant results in the integration of cultural elements and the enhancement of aesthetic value.

In order to integrate real-time Internet of Things (IoT) technology with cultural and creative product design and overcome potential obstacles in cultural and creative product display and interaction, Mahajan et al. [12] proposed an innovative framework that combines computer vision and deep learning technology. Cultural and creative products, such as art exhibitions, interactive installations, and virtual exhibitions, often require real-time collection of user interaction data, exhibition status information, and environmental data. For example, in an exhibition in a virtual museum, robots can recognize the exhibits that users are viewing through visual sensors and provide real-time feedback on user interests and behaviour data, in order to provide personalized navigation or interactive experiences for users. Through our framework, this data can be collected in real-time through mobile robots and used to enhance the user experience and interaction effects of cultural and creative products. It can not only automatically detect and predict the movement of robots based on the initial video frame sequence features, but also predict the display effect and user interaction trend of cultural and creative products. Unlike traditional geolocation-based navigation strategies, we focus on utilizing real-time video/image data and geographic information captured by sensors to drive the development of Internet of Things (IoT) technology in cultural and creative products.

Self-shaping machine woven textiles, as a unique type of textile, are unique in their ability to exhibit shape transformation and three-dimensional behaviour through the interaction between fabric structure and active yarns. Meiklejohn et al. [13] proposed a design iteration workflow for self-shaping woven textiles. However, this complex interaction and change process poses challenges for designers in predicting and planning the final product form. The shrinkage, twisting, or other forms of movement of active yarns during the finishing process (such as steam treatment) endow these textiles with a unique dynamic aesthetic. This characteristic makes them a valuable resource, providing designers with unlimited possibilities to achieve innovative design. The application of this workflow is not limited to the design of textiles themselves, but we also apply it to the design of cultural and creative products. Through this approach, we can create cultural and creative furniture products that are both practical and artistic, such as unique chairs, sofas, or decorative tapestries. This process starts with simulation-assisted drawing, and through advanced simulation techniques, designers can foresee the shape changes and three-dimensional behaviour of textiles during the design phase. Industry 4.0 is not only reshaping the way manufacturing and design processes are conceived but also bringing revolutionary changes to the field. Pellicia et al. [14] conducted in-depth research on how to cleverly utilize cutting-edge 3D simulation software in the design and development process of cultural and creative products, in order to enhance the practicality and efficiency of computer-aided participatory design meetings. In the vast world of cultural and creative industries, such attempts not only demonstrate the innovative power of technology, but also build a communication bridge between designers, developers, and users. These technologies have not fully met the requirements of participatory design, which limits the effective implementation of computer-aided participatory design workshops. The unique charm of cultural and creative products stems from their profound cultural heritage, outstanding artistic value, and the deep emotional bond established with users. Therefore, when designing these products, we must pay extra attention to user participation and genuine feedback. By deeply understanding the cultural background, aesthetic preferences, and lifestyle habits of users, designers can better grasp their psychological needs. This is not only to reflect the uniqueness and cultural connotation of the product but also to generate deeper emotional resonance with consumers. Taking cultural and creative products as an example, incorporating cultural elements into the design process is crucial. Thus creating cultural and creative products that are both aesthetically pleasing and rich in cultural connotations. Artistic style and user experience, rather than just functionality and efficiency. Therefore, we need to develop software tools with higher flexibility and customizability to meet the special requirements of cultural and creative product design.

With the rapid development of digital technology, model-based 3D design has not only achieved significant results in the field of engineering but also gradually demonstrated enormous potential. Ramnath et al. [15] implemented a copyright confirmation system based on consortium blockchain technology. It can complete copyright authentication and generate reliable copyright authentication information. The copyright confirmation system for cultural and creative products based on blockchain can meet the availability of the system. Design a storage mechanism for offline work source files, utilizing OBS private storage to store the data information of cultural and creative product source files that require copyright confirmation to ensure the security of offline data storage. We have studied the key technologies in intellectual property protection that can ensure the originality of works and introduced an image perception hashing algorithm in this system. The blockchain network and OBS storage on the server can operate normally and reliably store the source files of cultural and creative products. Avoiding similar images for copyright confirmation again reduces the possibility of plagiarism and tampering in the work. Realize copyright confirmation of image type cultural and creative products and query corresponding copyright information of cultural and creative products after completing similarity detection. Cultural and creative products provide unique aesthetic experiences and spiritual enjoyment beyond their functions through the visual expression of cultural elements, spirits, symbols, etc. At present, there are problems in the design of cultural and creative products, such as a large workload for modifying schemes, a single scheme, and high costs for personalized customization. Saleh et al. [16] proposed a parameterized modelling method that utilizes algorithms to generate product patterns and meets the requirements of selective laser melting (SLM) technology for metal 3D printing. Metal 3D printing not only provides free modelling possibilities and customized technical channels but also has material textures that non-metallic materials do not possess, making it very suitable for combined applications with cultural and creative products. In response to the existing limitations and support issues of SLM technology, this paper also develops a function to add support to the generated model based on the Grasshopper platform. Through finite element analysis and simulation verification of the structure, it can be concluded that the support structure generated by this method meets the usage requirements. Shandong et al. [17] integrated this feature into modelling tools to better connect product solution output with 3D printing production, to entity process. The results indicate that the parameterized design research of metal SLM technology in this article can provide richer design forms. In the design practice, the paper introduces three representative metal 3D printing cultural and creative products designed by the author using parametric modelling, some of which have been released on online platforms. It has higher efficiency and adaptability to metal 3D printing production, reducing design workload, and design cases have been recognized by customers and the market. Firstly, the issue of data exchange is a major challenge at present. Yun and Leng [18] have developed a more unified data exchange standard to achieve seamless integration between different systems. At present, the data exchange between virtual design systems and CAD systems is not smooth, which greatly affects the coherence and efficiency of the design process. In addition, the transmission speed and data processing ability of the network also affect the practical application effect of virtual design. In order to overcome these limitations, we need to promote innovation and upgrading of hardware technology continuously. Combining VR technology with CAD software for packaging design optimization can not only achieve complete digitization of products.

3 CONSTRUCTION OF CAD DESIGN SYSTEM FOR CULTURAL AND CREATIVE PRODUCTS

3.1 The Architecture of the Cultural and Creative Product CAD Design System

Cultural and creative product CAD design system adopts a modular design idea and divides the whole system into several relatively independent modules. Each module is responsible for completing specific functions and interacting with other modules through interfaces (Figure 1). The overall architecture of the system includes the following parts: ⊖ User interaction layer: providing an interactive interface between users and the system, receiving user input, and displaying system output. ⊜ Business logic layer: responsible for handling user requests and business logic and calling corresponding modules to complete design tasks. ⊛ Data storage layer: responsible for storing design data, model data, and user data and providing data access interface. ④ Deep learning module: responsible for the training and reasoning of deep learning model and providing intelligent design support for the system.

The functions of each module are as follows: the user interaction module provides user-friendly interactive interfaces and tools and supports designers in drawing sketches, building models, and map materials. The design module is responsible for sketch recognition, 3D modeling, feature detection, and fusion. The deep learning module is responsible for the training and reasoning of the deep learning model and provides intelligent design support for the design module. This module can interact with other modules, obtain design data, and output design suggestions. The data storage module is responsible for storing design data, model data, and user data and providing data access interfaces. This module can interact with other modules and provide them with data support.

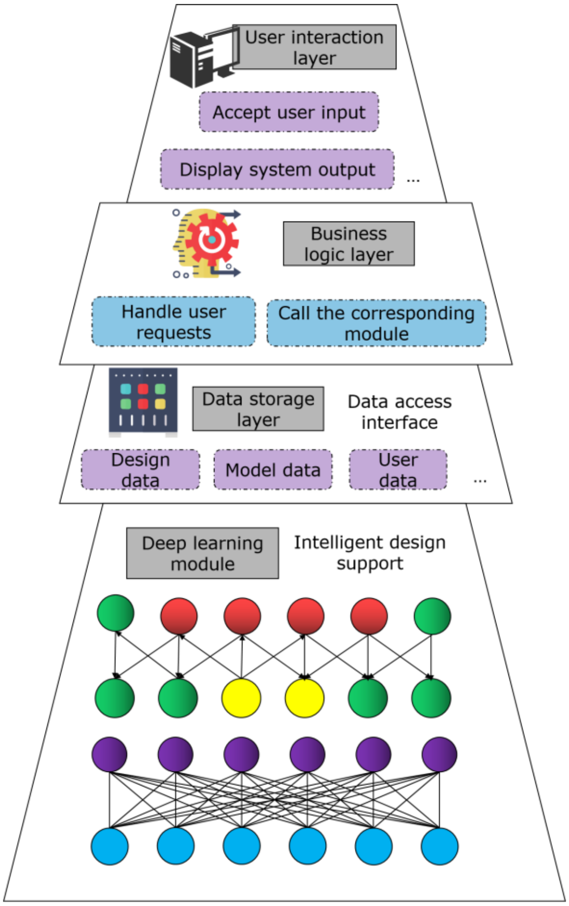

Figure 1: System architecture diagram.

3.2 Deep Learning Model Integration

When selecting a deep learning approach, the key considerations are its precision, adaptability to new data, and computational performance. Specifically, for the feature detection and integration process in Cultural and creative product design, this article opts for a CNN model. CNN is prevalent in image recognition and feature extraction within the deep learning realm. Fundamentally, CNN utilizes convolution kernels to conduct sliding convolutions on input images, capturing local image features. These captured features undergo multi-layer convolution processing and are eventually transformed into a hierarchical feature representation. Furthermore, CNN incorporates pooling layers to diminish dimensionality, compress features, enhance computational efficiency, and bolster model robustness. The final stage, the fully connected layer, bridges the extracted features to the output, enabling tasks such as classification or regression.

In CNN, the convolution layer is the core of constructing feature representation. With the deepening of the network, each convolution layer will learn more abstract and complex features based on the features extracted from the previous layer. This hierarchical structure enables CNN to gradually abstract high-level semantic information from the original image, which is very important for completing complex image recognition tasks. The convolution operation can be expressed as:

$$y = /\partial ice_{c} onv \ \ x, W, b \ \ = \sigma \ \ Wx + b \tag{1}$$

In this context, x serves as the input dataset, while W representing the convolutional kernel. b designates a specific offset, and σ functions as the activation mechanism. The resulting computation in the concealed layer node, labelled h, and the ultimate output from the output layer node, designated s, are derived as follows:

$$y_h^k = f\left(\sum_{i=1}^{N1} w_{ih} x_i^k + \theta_h\right) \tag{2}$$

$$o_s^k = g\left(\sum_{h=1}^{N2} w_{hs} y_h^k + \theta_s\right) \tag{3}$$

Within the given sample set, k represents a specific k instance. Additionally, θ_h and θ_s represent the respective threshold values for the hidden layer node and the output node, while f and g serve as the corresponding transformation functions.

In Cultural and creative product design, feature detection and fusion are key steps, which directly determine the innovation and uniqueness of product design. CNN model, with its powerful feature detection ability and hierarchical structure, provides an effective solution for such tasks. The CNN model structure is shown in Figure 2.

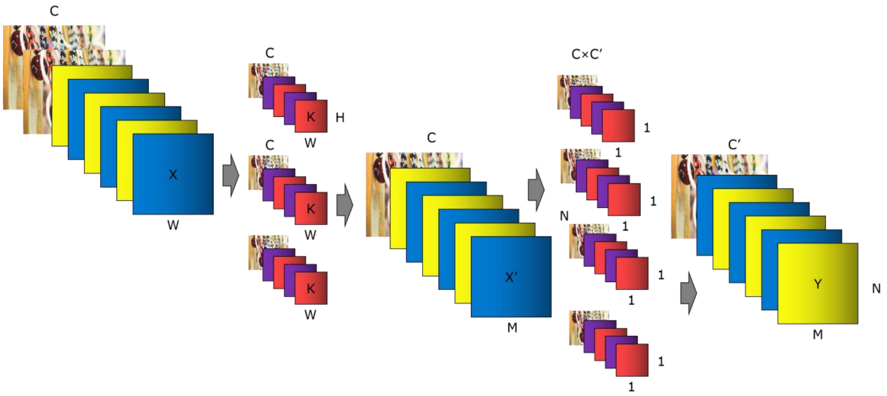

Figure 2: CNN model structure diagram.

During the model's training phase, a substantial amount of design data is required as input. This data is then utilized to refine the model's parameters via the backpropagation algorithm and gradient descent, enabling the model to align with the true data distribution progressively. Initially, the model forwards the input data, subsequently extracting pertinent features from the design data through layers such as convolution, pooling, and full connection. Subsequently, the model assesses the disparity between its output and the actual label, serving as the foundation for the backward propagation process. In the process of backpropagation, the model calculates the gradient of each layer parameter according to the error value, and these gradients indicate the degree of influence of parameters on the error.

Let the input vector of the training network be:

$$X = \left[x_1, x_2, x_3, \ldots, x_n\right] \tag{4}$$

The radial quantity of the training network is:

$$H = \left[y_1, y_2, y_3, \ldots, y_j\right] \tag{5}$$

Then the formula of the Gauss function is:

$$y_j = \exp\left(-\frac{\left\|X - C_j\right\|^2}{2b_j^2}\right) \tag{6}$$

$$C_j = \left[c_{1j}, c_{2j}, \ldots, c_{ij}, \ldots, c_{nj}\right] \tag{7}$$

In the neural training network, C_j denotes the centroid vector of the j node. $B = \left[b_1, b_2, b_3, \ldots, b_m\right]$ represents the base width vector, while b_j specifying the base width parameter for nodes j and $b_j > 0$. $W = \left[w_1, w_2, w_3, \ldots, w_m\right]$ serves as the weight vector of the entire network. During the training process, the model leverages the gradient descent algorithm to adjust the parameters in a direction opposite to the gradient's flow, thereby ensuring that the model's output increasingly aligns with the genuine label. This process will be repeated until the performance of the model reaches the preset standard or the maximum number of iterations. Through training, the CNN model can learn the key features of design data, and fuse these features to form useful information for Cultural and creative product design. These features include design elements such as lines, colours, shapes and textures, as well as their combination and layout. By extracting and fusing these features, the model can generate an innovative and unique product design scheme for culture and creativity.

There are many ways to integrate deep learning models in CAD systems. The way adopted in this article is to take the deep learning model as a plug-in or extension module of the CAD system and interact with the CAD system through the interface. In this way, designers can directly call the functions of deep learning models in CAD systems, such as feature detection and design suggestions.

4 CAD DESIGN METHOD OF CULTURAL AND CREATIVE PRODUCTS

In the CAD design method integrating deep learning features, the design process is redefined as an innovative process based on data-driven and intelligent assistance. This process framework aims to integrate the powerful ability of deep learning into the traditional CAD design process to improve design efficiency, innovation and practicality.

The design flow framework mainly includes the following stages: data preparation, feature detection, feature fusion and creative design, CAD model generation and optimization. Each stage is closely connected to form a complete closed-loop design system. In the feature detection stage, firstly, we need to collect image data related to Cultural and creative product design. These data can come from the Internet, design libraries, user uploads and other channels. Prior to model training, the gathered image data undergoes comprehensive preprocessing to enhance both its quality and the efficacy of training. This involves procedures like denoising, scaling, and normalization. Among these, the Gaussian filter, a linear smoothing filter, is particularly adept at mitigating Gaussian noise. Its formula is expressed as follows:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{8}$$

Among them, $G(x,y)$ is the Gaussian kernel, $x^2 + y^2$ which is the coordinates of pixels within the kernel, and $2\pi\sigma^2$ is the standard deviation of the Gaussian function. Scaling (bilinear interpolation) is a method of performing linear interpolation in two directions separately. Assuming four points $Q_{11}, Q_{12}, Q_{21}, Q_{22}$ are known, interpolation to point $P(x,y)$ is required:

$$f(P) \approx \frac{f(Q_{11})(x_2 - x)(y_2 - y)\, f(Q_{21})(x - x_1)(y_2 - y) + f(Q_{12})(x_2 - x)(y - y_1)}{(x_2 - x_1)(y_2 - y_1)} \tag{9}$$

Normalization linearly transforms the original data into the range of [0,1]. The formula is as follows:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{10}$$

Here, X_{norm} represents the original dataset, whereas $X_{\min}$ and $X_{\max}$ denote the lowest and highest values within that dataset, respectively.

The deep learning model plays a core role in feature detection. In the feature fusion stage, features from different sources need to be fused to generate more comprehensive and accurate design features. On the basis of feature fusion, designers can use their own creativity and inspiration, and combine the results of feature fusion to generate diversified design schemes. In the stage of generating a CAD model, we need to use some advanced CAD model generation technologies. These technologies can transform the design scheme into a 3D model and support the editing and modification of the model.

5 SIMULATION EXPERIMENT ANALYSIS

5.1 Simulation Experiment Design

By annotating and pairing the captured user reviews, the evaluation data is preliminarily processed to calculate emotional scores and analyze emotional tendencies. The purpose of part-of-speech tagging is to classify the parts of speech of all words in a sentence. Namely, determine whether each word is a noun (/n), verb (/v), adjective (/a), adverb (/d), gerund (/vn), or other part of speech, in order to perform word pair matching. The Chinese word segmentation and part of the speech tagging method used in this article is the stuttering algorithm, which achieves high accuracy in word segmentation and part of speech tagging for high-frequency words. The graphical representation of the model's accuracy can be found in Figure 3.

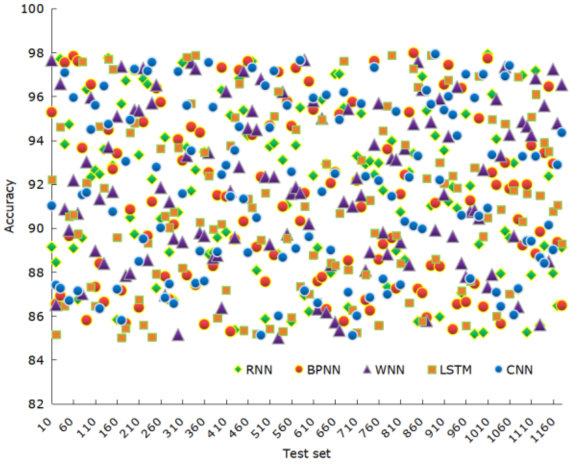

Figure 3: Accuracy of the model.

In Figure 3, we demonstrate the accuracy of five different deep learning models: RNN (Recurrent Neural Network), BPNN (Backpropagation Neural Network), WNN (Wavelet Neural Network), LSTM (Long Short Term Memory Network), and CNN (Convolutional Neural Network), in processing indoor layout optimization evaluation data. These models are used to analyze emotional tendencies in user comments, with Chinese word segmentation and part of speech tagging as preprocessing steps. Through algorithms, high-precision segmentation and part of speech tagging of high-frequency words have been achieved, laying a solid foundation for subsequent model training and analysis. It can be observed in Figure 3 that different models exhibit significant differences in accuracy. The recall rate of the model is shown in Figure 4.

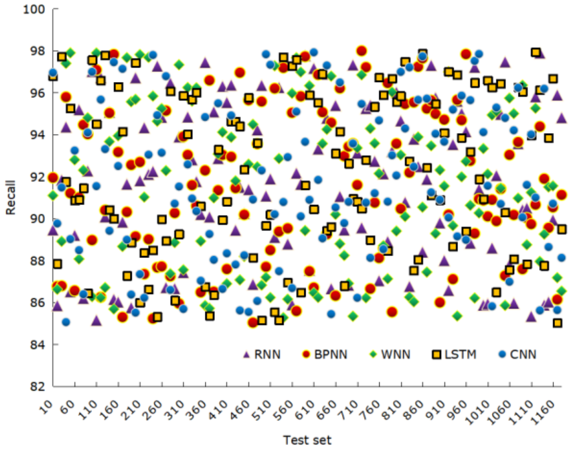

Figure 4: Recall rate of the model.

In Figure 4, we demonstrate the recall performance of five deep learning models, namely RNN (Recurrent Neural Network), BPNN (Backpropagation Neural Network), WNN (Wavelet Neural Network), LSTM (Long short-term memory Network), and CNN (Convolutional Neural Network), when processing indoor layout optimization evaluation data. Recall rate, as an important evaluation indicator, measures the model's ability to correctly identify instances that are actually positive samples. By comparing the recall rates of different models, we can more comprehensively evaluate the performance of these models in indoor layout optimization evaluation tasks. From the graph, it can be observed that the LSTM model performs excellently in terms of recall, significantly surpassing other models. This once again confirms the advantage of LSTM in processing sequential data, especially data with long-term dependencies. The memory unit of LSTM enables it to capture contextual information in textual data, thereby more accurately identifying positive or negative emotions in user comments. The F1 value of the model is shown in Figure 5.

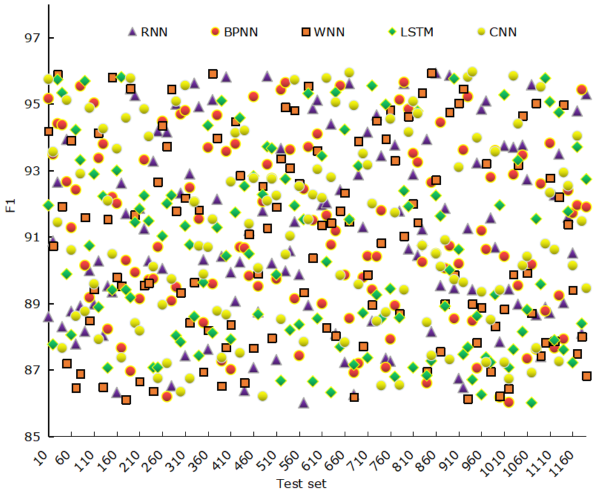

Figure 5: F1 value of the model.

In Figure 5, we clearly present the F1 model values of five deep learning models, namely RNN (Recurrent Neural Network), BPNN (Backpropagation Neural Network), WNN (Wavelet Neural Network), LSTM (Long short-term memory Network), and CNN (Convolutional Neural Network), when processing indoor layout optimization evaluation datasets. The F1 value, as a comprehensive indicator for evaluating model performance, considers two key factors: accuracy and recall, which can more comprehensively reflect the actual effectiveness of the model. From the graph, it can be seen that the CNN model performs outstandingly in F1 value, reaching over 96%, indicating that the CNN model has achieved excellent results in both accuracy and recall. This result not only demonstrates the effectiveness of CNN in handling text classification tasks but also demonstrates the applicability of CNN models in indoor layout optimization evaluation tasks. CNN can effectively extract local features from text through convolution operations and reduce data dimensions through pooling operations, thereby achieving a deep understanding of the text.

On the basis of evaluating the performance of the deep learning model, we further demonstrate the effect of the CAD design system. By comparing the design schemes with and without deep learning features, we can see the role of deep learning features in improving design efficiency (Figure 6).

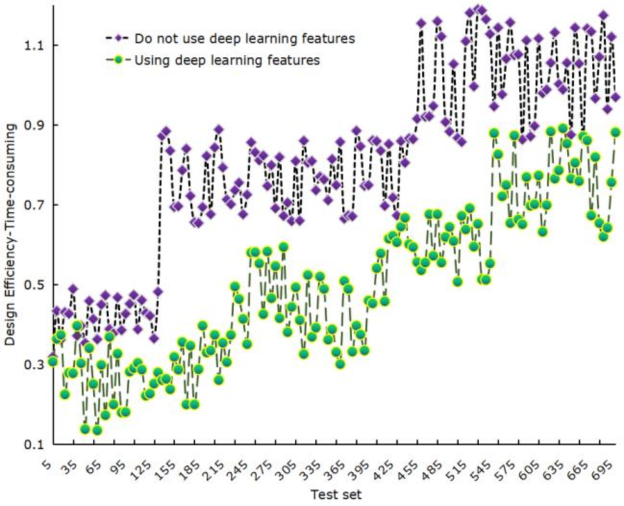

Figure 6: Improvement of design efficiency.

From Figure 6, it can be seen that the design system using deep learning function shows significant advantages in improving design efficiency. Specifically, the design time has been significantly reduced. This improvement is mainly attributed to the powerful learning and prediction capabilities of deep learning algorithms. By training a large amount of design data, deep learning models can quickly and accurately generate design solutions, thereby reducing the time for designers to adjust and optimize manually. The results show that deep learning features play a positive role in improving design efficiency. After adopting the deep learning feature, the design efficiency has been obviously improved.

Furthermore, this section further shows the performance of the CAD design system in practical application, including the quality of generated 3D Cultural and creative products and user feedback, as shown in Figure 7 and Figure 8.

In addition to the excellent performance of deep learning models in feature extraction and fusion, Figure 8 also shows in depth the quality of 3D cultural and creative products generated by CAD design systems in practical applications, as well as user feedback. The user evaluation content covers multiple dimensions, including functionality, creativity, stability and reliability, availability, compatibility, customization and scalability, as well as performance and efficiency. These evaluations provide valuable references for us to comprehensively evaluate the effectiveness of CAD design systems. Through the simulation experiment, this article draws some experimental conclusions.

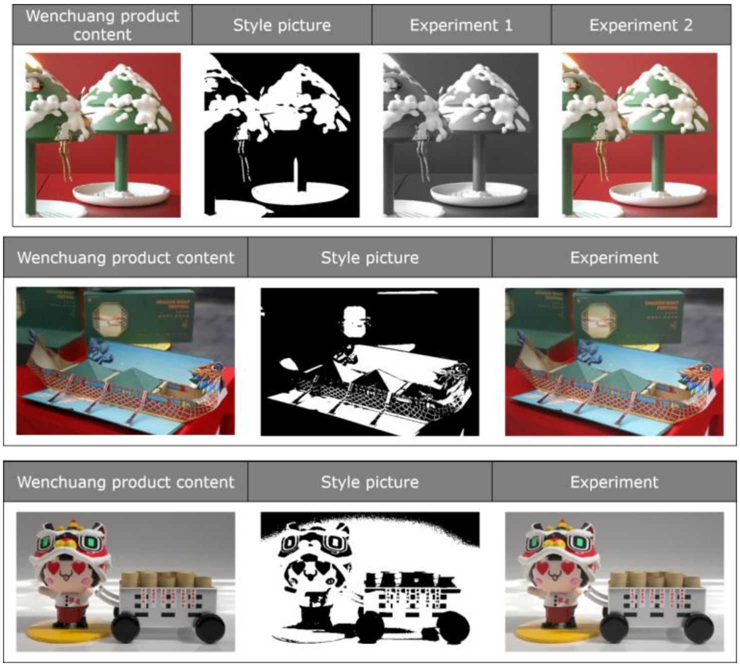

Figure 7: Model-generated Cultural and creative product example.

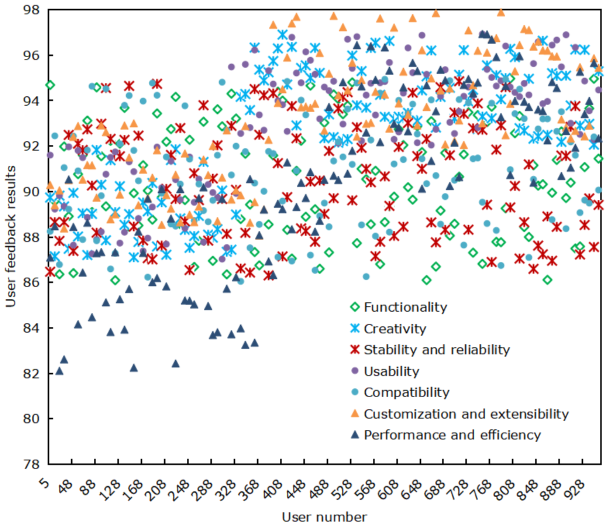

Figure 8: User feedback results.

First of all, the deep learning model performs well in feature detection and fusion, and can effectively extract the key features in Cultural and creative product design; Secondly, the CAD design system can transform these features into high-quality 3D models of Cultural and creative products, and support designers to carry out creative design and optimization; Finally, by comparing different design schemes and user feedback, we find that CAD design method with deep learning features has significant advantages and potential in Cultural and creative product design.

The experimental conclusion provides us with some inspirations for design: designers should make full use of advanced technologies such as deep learning to assist the design process and improve design efficiency and innovation; Designers should pay attention to data collection and processing to ensure that the deep learning model can learn accurate and useful features; Designers should constantly try new design methods and tools to explore more design possibilities and creative space.

6 CONCLUSIONS

This article demonstrates the successful integration of deep learning technology into the Cultural and creative product design process. By exploring CAD design methodologies tailored to the unique demands of Cultural and creative products, we have achieved significant improvements in design efficiency and creativity. Our simulation experiments validate the practicality and advantages of leveraging deep learning features in CAD design for Cultural and creative products. This approach not only facilitates swift and precise feature extraction from image data but also seamlessly integrates these insights into the design process, thus inspiring and enhancing the creativity of designers. Key findings include the profound capabilities of deep learning models in feature detection and fusion, as well as the CAD design system's proficiency in generating and optimizing 3D models. These advancements not only underscore the transformative potential of deep learning in Cultural and creative product design but also pave the way for novel advancements in CAD design systems.

As we look to the future, deep learning's significance in Cultural and creative product design is poised to grow even further. As technology evolves, we expect deep learning models to handle increasingly intricate and varied design data, leading to higher design quality and efficiency. Additionally, CAD design systems will undergo continuous optimization and enhancements to cater to the evolving complexity of design requirements. Future research will delve deeper into the application of deep learning in Cultural and creative product design, fostering further innovation and progress in the design landscape.

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