Exploration of CAD Virtual Reality Interactive Interface Design based on Deep Convolution Neural Networks

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Abstract. Aiming at the shortcomings of traditional CAD (computer-aided design) interfaces in intuition and efficiency, this article proposes a VR interactive interface design scheme combining AI (Artificial intelligence) algorithms. This method uses the powerful feature extraction and decision-making ability of DCNN (Deep Convolution Neural Network) to intelligently identify and optimize the user's operation in the process of CAD design and, at the same time, provide a natural and intuitive interactive way in the VR environment. The experimental results show that compared with RNN (Recurrent Neural Network) and BPNN (Back Propagation Neural Network), the DCNN proposed in this article takes 0.541 unit time to complete the task, and the error rate is lower, only 2.41%. In addition, the accuracy of the interactive interface in identifying user operations and presenting design results is over 97.01%, and the comprehensive score of the user satisfaction survey is about 95%. Therefore, this article draws a conclusion that the VR interactive interface design scheme combined with DCNN can significantly improve the efficiency and user experience of CAD design and provide a more efficient, accurate, and natural interactive way for future CAD design. This research achievement is of great significance for promoting the deep integration of CAD design and VR technology.

Keywords: Deep convolutional neural networks (DCNNs); Computer-Aided Design; Deep Convolution Neural Network; Virtual Reality; Interactive Interface Design
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1 INTRODUCTION

CAD is a technology that uses computer technology to assist designers in their design work. It can help designers complete design tasks more efficiently and accurately and improve design quality and efficiency. CAD intelligent manufacturing technology also provides strong support for the implementation of product design. Through precise CAD modelling and simulation analysis, designers can ensure that the structure, function, and performance of products reach their optimal state. The application of intelligent manufacturing technology makes the product manufacturing process more efficient, precise, and controllable, greatly shortening the product design to market cycle. When the hybrid reality tools of interactive virtual prototyping are combined with CAD intelligent manufacturing technology, the user empowerment of product design is further enhanced. Arrighi and Mougenot [1] collect real-time feedback from users through virtual prototyping and input this feedback directly into the CAD system for quick modification and optimization. Meanwhile, intelligent manufacturing technology can quickly respond to these modifications, generating new virtual or physical prototypes for users to further experience and evaluate. This closed-loop design feedback optimization process makes product design more closely aligned with user needs, truly achieving user empowerment. CAD technology is widely used in the design of machinery, architecture and electronics. In augmented reality interaction, converter-based language models play a crucial role. Firstly, it can help achieve more natural and smooth voice interaction. By recognizing the user's voice input, the model can convert it into text and conduct in-depth understanding and analysis. Then, the model can generate corresponding responses or perform corresponding operations based on the user's intention and contextual information, thereby achieving intelligent dialogue with the user. By combining computer vision technology, models can recognize objects and scene information in AR scenes and generate corresponding text descriptions or operation instructions based on user needs and intentions. In this way, users can achieve precise operation and interaction of AR scenes through simple voice or gesture control [2]. CAD systems usually include graphic processing, data management, analysis and calculation and other functional modules, which can meet the design needs of designers at different stages. The human-computer interaction in traditional CAD systems often relies on complex command inputs and parameter settings, which not only increases user learning costs but also limits the improvement of design efficiency. Intelligent recommendation and prediction technology also provides strong support for the automation of CAD human-computer interaction. By analyzing user design habits and preferences, the system can automatically recommend suitable tools, materials, and design solutions, reducing user confusion and time consumption in the selection process. Dubey et al. [3] utilized deep learning algorithms to learn and analyze a large number of excellent CAD interfaces, extracting commonalities and patterns in interface design. Then, based on these patterns and personalized user needs, the system automatically generates interface layouts, colour combinations, and element arrangements that meet the requirements. This can not only reduce the workload of designers but also ensure the consistency and usability of the interface. With the continuous development of science and technology, CAD technology is also improving and perfecting, which brings more convenience and innovation to the field of modern design. Traditional CAD input techniques often rely on peripherals such as mice and keyboards, making this input method inefficient and insufficiently intuitive for complex 3D designs. Erdolu [4] designed a more intelligent input technology. By introducing gesture recognition and speech recognition technology, users can directly perform CAD operations through gestures or speech commands. This approach is more natural and intuitive and can greatly improve design efficiency. Secondly, using deep learning algorithms, it trains models to automatically recognize and parse two-dimensional drawings or three-dimensional models. In this way, users only need to input simple sketches or descriptions, and the CAD system can automatically generate complex 3D models. This intelligent input method will greatly simplify the design process and reduce the threshold for use. However, the traditional CAD system has some limitations in interactivity and intuition.

In recent years, the rise of VR technology has provided a new interactive way for CAD systems, which enables designers to design and modify more intuitively. Engineering image space research focuses on utilizing computer graphics, image processing and other technologies to efficiently and accurately visualize spatial data. This study not only focuses on the acquisition and processing of image data but also on how to utilize this data for spatial analysis and decision support. Fu et al. [5] utilized the achievements of Kansas Engineering Image Space Research to conduct in-depth analysis and processing of spatial data, extracting key information and features. Based on these data and features, design interface layouts and interaction methods that are more in line with user cognition and data characteristics. Explore new interaction methods based on the characteristics of virtual reality technology, such as gesture recognition and speech control. These new interaction methods can not only improve user operational efficiency but also increase user immersion and experience. By collecting and analyzing user interaction data and behavioural habits, provide personalized and customized visual interface options for users. VR technology is a technology to simulates the real world through a computer-generated three-dimensional virtual environment. Users can interact with the virtual environment by wearing devices such as helmet-mounted displays and handheld controllers and get an immersive experience. Fukuda et al. [6] explored a virtual reality rendering method for training deep learning, analyzing landscapes, and preventing virtual reality. In the training process of deep learning, a large amount of high-quality data is indispensable. Traditional data acquisition methods are often time-consuming and labor-intensive, and data quality is difficult to ensure. The virtual reality rendering method can simulate various complex scenes, generate a large amount of high-quality data, and provide strong support for the training of deep learning models. By adjusting the parameters and conditions in the virtual environment, it can generate datasets with different features, thereby training more accurate and robust deep learning models. VR technology is highly interactive, immersive and imaginative, and is widely used in games and entertainment, education and training, medical rehabilitation and other fields. Introducing VR technology into CAD systems can provide users with a more intuitive and natural interaction mode and improve design efficiency and user experience.

AI algorithm refers to a kind of algorithm that simulates human intelligent behaviour through computer programs. Gordieev [7] explored a quality model and evaluation method for the usability of CAD human-computer interaction software interfaces that combine artificial intelligence algorithms. It utilizes technologies such as natural language processing and speech recognition to achieve natural language interaction between users and CAD systems, reducing learning costs and improving operational efficiency. By analyzing user habits and preferences, a personalized recommendation system is constructed to provide users with design tools and material recommendations that meet their needs. Based on user behaviour data and device characteristics, it utilizes machine learning algorithms for adaptive adjustment of interface layout. Ensure that users can have a good interactive experience across different devices and scenarios. It can solve complex tasks and problems through learning, reasoning and decision-making. AI algorithm includes machine learning, deep learning, neural network and other types, and is widely used in image recognition, speech recognition, natural language processing and other fields. Guo and Ma [8] discussed the application and development of human-machine interaction systems for product design in virtual reality environments based on computer-aided technology. It analyzed its potential and challenges in improving design efficiency and optimizing user experience. Virtual reality technology allows users to immerse themselves in a three-dimensional virtual environment and interact with virtual objects in real time. In the field of product design, virtual reality technology provides designers with a brand-new creative space. In a virtual reality environment, computer-aided technology can achieve precise control of the virtual environment and precise operation of virtual objects. By combining virtual reality technology and computer-aided technology, an efficient and intuitive human-machine interaction system for product design can be constructed. Introducing AI algorithms into CAD systems can realize intelligent design decisions, automatic optimization and other functions and improve design quality and efficiency.

This research mainly focuses on the design of VR interactive interfaces combined with AI algorithms. Firstly, the interaction mode and existing problems of existing CAD systems are analyzed. Secondly, the application methods and advantages of VR technology in CAD systems are studied. Thirdly, the implementation and application scenarios of AI algorithms in CAD systems are discussed. Finally, a VR interactive interface prototype combined with an AI algorithm is designed and implemented, and its effectiveness and feasibility are verified by simulation experiments.

The innovation of this study is mainly reflected in the following aspects: (1) A design method of VR interactive interface combined with AI algorithm is proposed; Realize intelligent interactive experience by introducing DCNN; Efficient CAD interactive operation is realized in VR environment; It provides a new CAD interactive mode and intelligent design idea for the modern design field.

This article is divided into six sections. The first section mainly introduces the research background and significance, research content and innovation. The second section summarizes the research status and development trend. The second to fifth sections are the main parts of this article, which respectively introduce the requirements analysis, design and implementation, simulation experiment design and implementation, and experimental results analysis and discussion of the VR interactive interface. The sixth section summarizes the main achievements and contributions of this study and points out the future research direction and challenges.

2 RELATED WORK

In this era, augmented reality (AR) and virtual reality (VR) technologies will become key bridges for our interaction with the digital world. Hazarika and Rahmati [9] explored the application of 5G and its ultra-low latency communication in augmented reality and virtual reality and how they collectively drive the evolution of immersive interactive experiences. Virtual reality technology creates a completely virtual environment for users, allowing them to immerse themselves and interact with it. The ultra-low latency communication of 5G technology provides VR applications with more stable and high-quality network connections, allowing users to enjoy a smoother and more realistic virtual experience. In VR games, players can experience more realistic scenes and more precise interactive feedback. In VR tourism, users can immerse themselves in visiting scenic spots and historical sites around the world. Deep learning has made significant progress in areas such as image recognition and motion capture, providing strong support for innovation in VR hand interfaces. Kang et al. [10] explored the advantages, applications, and future development trends of using deep learning hand interfaces in immersive virtual reality. Deep learning techniques can recognize hand movements through training models without the need for additional hardware equipment, greatly improving the naturalness and accuracy of hand interfaces. Deep learning technology can process a large amount of image and video data and learn the features and patterns of hand movements through training models. In VR environments, user hand movements can be captured in real time and converted into digital signals, which are then recognized and analyzed through deep learning models. This enables the hand interface to more accurately recognize user gestures and actions, thereby achieving a more precise and natural interactive experience. The visual information enhancement method for multimedia human-computer interaction interface based on virtual reality technology mainly optimizes interface design, enhances visual elements, and improves interaction experience, enabling users to obtain information more conveniently and efficiently in the virtual environment and complete interaction tasks. Li [11] analyzed the enhancement of visual information in multimedia human-computer interaction interfaces. In terms of interface design, utilizing the 3D modelling capabilities of VR technology can create more three-dimensional and realistic interface scenes. Through reasonable layout and colour matching, important information can be highlighted, and user cognitive load can be reduced. Meanwhile, utilizing light and shadow effects and material textures can create a more realistic visual experience and enhance user immersion. In terms of enhancing visual elements, the dynamic rendering and interactive characteristics of VR technology can be utilized to optimize visual elements such as text, icons, and buttons in the interface.

The neural network-assisted optimization system for CAD virtual reality interactive simulation design space exploration is mainly based on CAD technology to construct a virtual design environment, and real-time interaction between designers and the virtual environment is achieved through VR technology. As the core of the system, neural networks provide intelligent design suggestions and optimization solutions for designers by learning and analyzing a large amount of design data. Specifically, the system first utilizes CAD technology to establish accurate 3D models and presents these models to designers through VR technology. Li et al. [12] engage in interactive operations in virtual environments, such as modifying design parameters and observing design effects. At the same time, the system captures the designer's operational data through sensors and tracking devices and inputs this data into the neural network. In the vast ocean of deep learning, large neural networks are like a mysterious black box, with complex connections and computational processes that are difficult for humans to understand intuitively. However, with the continuous development of virtual reality (VR) technology, Linse et al. [13] have adopted a more intuitive approach to explore this black box - through 3D visualization technology, the complex structure and operational process of neural networks are presented in virtual space. Traditional neural network visualization methods are often limited to two-dimensional planes, making it difficult to fully display the three-dimensional structure and dynamic changes of neural networks. However, virtual reality technology breaks this limitation by being able to construct the real form of neural networks in three-dimensional space, allowing users to delve into it from a first-person perspective and experience its complex and beautiful structure. Mourtzis and Angelopoulos [14] discussed the integration and development of artificial neural network modelling based on augmented reality and virtual reality interaction and analyzed its potential applications in improving user experience and promoting innovative design. Augmented reality technology brings users an immersive experience by overlaying virtual information onto the real world. Artificial neural networks, on the other hand, are adept at handling complex data patterns and possess powerful learning and reasoning abilities. By combining the two, artificial neural networks can be used to gain a deeper understanding and analysis of the real world. Through augmented reality technology, these analysis results are presented to users intuitively and vividly. A virtual reality interaction system based on artificial neural networks can intelligently learn and adapt to user behaviour and habits, providing users with a more natural and smooth interaction experience.

Traditional CAD systems still face many challenges in handling complex materials and achieving human-computer interaction. Materials science is a field that involves numerous variables and complex interactions. Traditional CAD systems often struggle to accurately simulate the true performance and behavior of materials. These algorithms can be applied to CAD systems to achieve accurate prediction and optimization of material properties. Qamar et al. [15] utilized these prediction results to select materials more accurately and improve the reliability and performance of the design. Augmented reality technology provides intuitive and vivid operational guidance for manufacturing personnel by overlaying virtual information onto the real world. In complex manufacturing processes, AR technology can help workers quickly and accurately locate components, understand assembly sequences, and master operational skills. This not only reduces the difficulty of operation and error rate but also greatly improves work efficiency. Artificial intelligence achieves intelligent monitoring and optimization of manufacturing processes through machine learning and big data analysis. AI technology can conduct real-time analysis of manufacturing data, predict potential problems, and provide solutions in advance. At the same time, AI can also fine-tune the manufacturing process through optimization algorithms, further improving manufacturing efficiency and quality [16]. Virtual reality technology creates highly realistic virtual environments, allowing users to immerse themselves and interact with virtual objects in real time. In welding operations, VR technology can be used to simulate various welding scenarios, including welding of different materials and simulation of different welding positions. By modelling the operation of welders, Wang et al. [17] collected and analyzed the operational data of welders in a virtual environment, thereby optimizing welding processes and improving welding quality. Motion capture technology can accurately record the movement trajectory of welders in a virtual environment, providing a foundation for subsequent data analysis. Force feedback technology can simulate the force sensation during the welding process, allowing welders to feel the real welding force in a virtual environment, thus more accurately simulating actual operations.

The future CAD system will be more humanized and intelligent and can be adjusted adaptively according to the needs and habits of designers. At the same time, with the development of new technologies such as 5G and cloud computing, the remote collaboration and real-time rendering capabilities of CAD systems will be further improved, enabling designers to collaborate more efficiently across regions.

3 DEMAND ANALYSIS OF VR INTERACTIVE INTERFACE

Interactive interface design refers to designing a user-friendly interface through a reasonable layout, beautiful visual effects, and good interactivity. Good interactive interface design can improve users' experience and satisfaction. When designing an interactive interface, we need to follow some basic principles and methods, such as the user-centered principle, consistency principle, feedback principle and so on. At the same time, it is necessary to consider the cognitive characteristics and usage habits of users to ensure that the designed interface meets the needs and expectations of users. In the design of a VR interactive interface, we also need to follow these principles and methods and combine the characteristics of VR technology and AI algorithms for targeted design.

In the user demand analysis of VR interactive interface, this article first defines the user groups and their characteristics. These users may be professional designers, engineers, design students or ordinary users interested in design. Their common demand is that with the help of VR technology, CAD design can be more intuitive and efficient. Specifically, users may expect to realize the following functions through the VR interactive interface: freely browse and modify the design model in three-dimensional space; Operate by natural interaction such as gesture recognition; Real-time view of the modified design effect; Remote collaboration with design team members, etc. In addition, users also hope that the system can provide rich design resources and material libraries, as well as intelligent design suggestions and optimization schemes. In order to meet these needs, it is necessary to deeply analyze the user's operating habits, cognitive characteristics, and usage scenarios to ensure that the designed VR interactive interface meets the user's expectations and usage habits.

In terms of functional requirements analysis, the VR interactive interface needs to realize the core functions in Table 1.

Functional category	*Specific description*
3D model browsing and editing Natural interaction mode support	Users can freely browse and edit 3D CAD models in a VR environment, including basic operations such as model rotation, scaling and translation, as well as more advanced editing functions such as cutting, merging and mirroring. The system needs to support gesture recognition, voice control and other natural interaction methods to reduce the learning cost of users and improve the operation efficiency.
Real-time rendering and feedback	When users modify the design, the system needs to render and show the modified effect in real-time so that users can adjust and optimize the design scheme in time. At the same time, the system also needs to provide real-time feedback and prompt information to help users successfully complete the design task.
Collaboration and sharing functions	In order to meet the needs of teamwork, the system needs to provide remote collaboration and sharing functions, allowing multiple users to participate in a design project at the same time and communicate in real-time.

Table 1: VR interactive interface core function requirements table.

In terms of performance requirements analysis, the VR interactive interface needs to meet the requirements in Table 2:

Performance requirement category	*Specific description*
High frame rate rendering	In order to ensure the smooth experience of users in the process of use, the system needs to render at a high frame rate to avoid jamming or delay.
Low latency interaction	The system needs to respond to the user's interactive operation quickly, ensure that users can get feedback and results in time, and provide an instant interactive experience.
Stability and reliability	The system needs to ensure the stability and reliability of long-term operation, avoid problems such as crash, flashback, or data loss,

	and ensure the safety of user data.
Good compatibility	The system needs to be compatible with all kinds of mainstream VR devices and operating systems, including different hardware platforms, VR headsets, controllers, etc., to ensure wide user coverage and convenient use experience.

Table 2: VR interactive interface performance requirements table.

In terms of usability requirements analysis, the VR interactive interface needs to pay attention to the following points in Table 3.

Availability requirement category	*Specific description*
Easy to learn and use	The system should provide an intuitive and easy-to-use operation interface and simple operation flow that conforms to the user's habit of interaction so as to reduce the learning cost and use difficulty and enable users to get started quickly and complete the design efficiently.
The information is clear and clear.	The system should clearly display the design model information, status, and operation tips, and the interface layout is reasonable, and the information is intuitive and easy to understand, so as to help users quickly understand and complete the operation.
Error prevention and recovery	The system should design effective error prevention and recovery mechanisms, such as undo/redo, automatic saving and error prompt, to prevent data loss or design errors caused by user misoperation and provide timely help when encountering problems.
User experience optimization	The system should continue to pay attention to the user experience, collect feedback and analyze usage data, and make timely improvements and upgrades according to problems and needs so as to improve functions, improve performance, optimize interaction and improve user satisfaction and loyalty.

Table 3: VR interactive interface usability requirement table.

4 DESIGN OF VR INTERACTIVE INTERFACE COMBINING DEEP CONVOLUTIONAL NEURAL NETWORKS

4.1 Design Ideas and Overall Architecture

When designing a VR interactive interface with an AI algorithm, the core idea of this article is to combine the decision-making optimization ability of AI with the intuitive interactive characteristics of VR to improve the efficiency of CAD design and user experience. The overall architecture is divided into four main parts: data input and processing, deep convolutional neural network decision-making, VR interactive presentation, and user feedback collection.

The data input and processing module is responsible for receiving and analyzing CAD model data, user interaction data and external resource data. After preprocessing, these data are sent to the decision module of the AI algorithm. In this module, this article uses a neural network algorithm to optimize the design scheme and intelligently identify and respond to the user's operation. The VR interactive presentation module is responsible for presenting the optimized design scheme to the user in an intuitive way and responding to the user's interactive operation. The user feedback collection module is responsible for collecting the feedback data of users in the process of use so as to improve and optimize the system in the future.

4.2 Application of Deep Convolutional Neural Network Algorithm in Interactive Interface

In the interactive interface, the application of the AI algorithm is mainly reflected in the modelling and implementation of neural networks. In this article, a neural network model is constructed, which is used for intelligent processing of various tasks in the CAD design process. These tasks include, but are not limited to, design optimization, operation identification, error prediction, etc.

When building a neural network model for a VR interactive interface, it needs to go through several stages, such as model design, data collection and processing, model training, verification and tuning. Model design is the first step of neural network modelling, which determines the key elements such as network structure, layer number and activation function, and directly affects the final performance of the model. For VR interactive tasks, this article designs a Deep convolutional neural network (DCNN) to recognize the user's interactive gestures. If the input layer x_p is a m dimensional vector and the output layer is a n dimensional y_p vector. The hidden layer is:

$$Z_i, i = 1,2,\cdots,j \tag{1}$$

Then, the output of the k hidden layer neuron is:

$$H\ p,q\ = -\sum_x p\ x\ \log q\ x\ y_k = \sum_{i=1}^{j} w_{ik} \cdot \exp\left(-\frac{1}{2\sigma^2}\left\|x_p, Z_j\right\|\right) \tag{2}$$

In this article, it is set that if the number of a convolution layer is l, the number of the pool layer that follows it is $l+1$. In order to obtain the sensitivity of the Z layer, it is necessary to perform an up-sampling operation on the sensitivity of the corresponding pool layer to ensure that the sensitivity matches the output dimension of the corresponding convolution layer. Therefore, for the convolution layer numbered l, the calculation process of the j th sensitivity is as follows:

$$\delta_j^l = \beta_j^{l+1}\ f'\ u_j^l\ \circ up\ \delta_j^{l+1} \tag{3}$$

Where β_j^{l+1} represents the weight corresponding to the pool layer; $up\ \cdot$ stands for up-sampling operation. The number of hidden layer nodes is selected according to the following empirical formula:

$$N = \sqrt{m+n} + \alpha \tag{4}$$

Where N is the number of neurons in the hidden layer, m is the number of input neurons, and n is the number of neurons.

A neural network model needs a lot of data to train, so data collection and processing is a very critical step in the modelling process. For the VR interactive interface, the data to be collected includes CAD model data, user interaction data (such as gestures, voice commands, etc.), and user feedback information (such as operation success or failure, user satisfaction, etc.). The collected raw data often contains noise and redundant information, which needs preprocessing before it can be used for model training. The preprocessing steps include removing outliers and noises, scaling the data to the same scale, and extracting features useful for model training from the original data. Figure 1 shows the DCNN model.

Model training is the core of neural network modelling. It constantly adjusts the network parameters through an iterative optimization algorithm so that the performance of the model on training data is gradually improved. In the training process, it is necessary to choose the appropriate loss function and optimizer. The loss function is used to measure the difference between the predicted results of the model and the actual results, while the optimizer is responsible for updating the network parameters according to the gradient of the loss function.

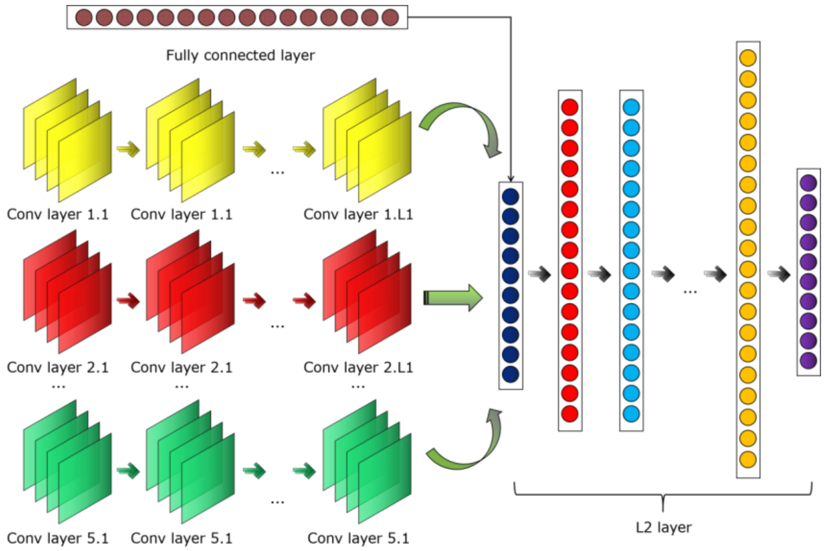

Figure 1: DCNN model.

For the VR interactive interface, the cross entropy loss function can be selected to deal with the classification task, and the mean square error loss function can be selected to deal with the regression task. Cross entropy is a common choice in the loss function, and this article also adopts cross entropy as the loss function to evaluate the performance of the model. Its mathematical expression is:

$$H(p,q) = -\sum_{x} p(x) \log q(x) \tag{5}$$

Where $p(x)$ represents the probability of true distribution and $q(x)$ represents the probability distribution predicted by the model. Cross entropy measures the difference between real distribution and predicted distribution, and is an important index to optimize the model performance in machine learning. The smaller the cross entropy is, the closer the two probability distributions are. After adding the penalty factor, the expression of the loss function is as follows:

$$L\left(y_n, \hat{y}_n\right) = -\left[\alpha y_n \log \hat{y}_n + \left(1 - \hat{y}_n\right) \log\left(1 - \hat{y}_n\right)\right] \tag{6}$$

Among them α is the penalty factor, n is the sample number, and $L(y_n, \hat{y}_n)$ is the loss function of the n sample about a user tag. When $\alpha = 1$ is the standard binary cross entropy when $\alpha > 1$, the loss function used is the binary cross entropy with the weight of misjudging one as 0, which is also the loss function finally determined by this method.

In order to prevent over-fitting and improve the generalization ability of the model, this article also introduces a verification set to verify the model in the training process and uses early stop and learning rate attenuation to adjust the training strategy. In order to prune the network more effectively and make the network weight quickly approach 0, it is necessary to add a penalty function term to the error function during training, which is as follows:

$$P = (w,v) = \frac{\varepsilon}{2}\left(\sum_{m=1}^{h}\sum_{l=1}^{n} w_{ml}^{2} + \sum_{m=1}^{h}\sum_{p=1}^{c} v_{pm}^{2}\right) \tag{7}$$

Where w_{ml} is the connection weight between the l node in the input layer and the m node in the hidden layer of the neural network; v_{pm} is the connection weight between the m th node of the hidden layer and the p th node of the fuzzy output layer; h is the total number of hidden layer nodes; ε is the parameter of the penalty function. In addition, this article adds the adjustment of learning efficiency to the algorithm to accelerate the convergence of the function:

$$\Delta w = \eta \xi_i n_i + \alpha \ \Delta w' \tag{8}$$

Where η is the learning efficiency and $\alpha \ \Delta w'$ is the momentum factor.

The processed CAD design data and user interaction data are used as training sets, and then the neural network model is trained by these data. After the training, the model can output the optimized design scheme or corresponding operation suggestions according to the input design parameters and user operation data. At the same time, the model can also predict the future operation intention of users according to their historical operation data so as to respond and prepare in advance.

After the model training is completed, its performance needs to be verified on an independent test set. If the performance of the model does not meet the requirements, it needs to be tuned. The method of tuning includes modifying super parameters such as learning rate and batch size. Learning rate is an important superparameter in machine learning algorithms, which determines the step size of model parameter updating in the training process. The learning rate setting experiment is shown in Figure 2.

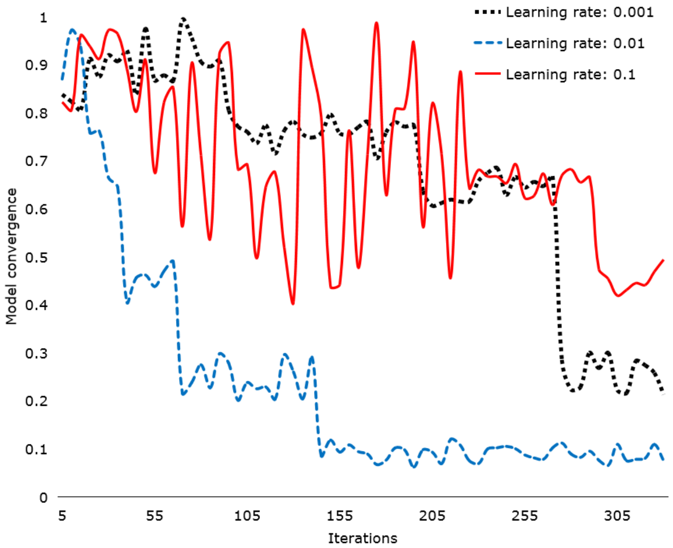

Figure 2: Experimental situation of learning rate setting.

It can be seen that when the learning rate is low (0.001), the model training is stable, but the convergence speed is slow, and more iterations are needed to achieve better performance. With the increase in learning rate (0.01), the convergence speed of the model is accelerated, and the performance improvement is more significant. However, when the learning rate further increases (0.1), the performance of the model begins to decline because the excessive learning rate leads to the unstable convergence of the model in the training process. Therefore, this article sets the learning rate as 0.01.

The batch size determines the number of samples used to update model parameters in each iteration. The experiment of batch size setting is shown in Figure 3.

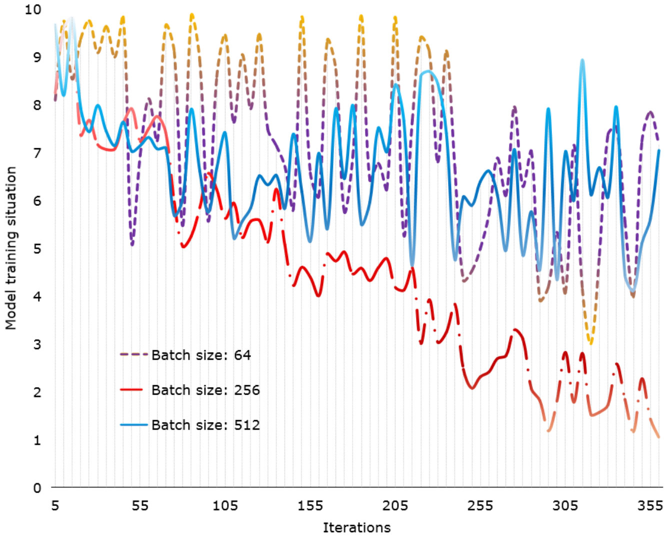

Figure 3: Experimental situation of batch size setting.

It can be observed that when the batch size is small (64), the model training fluctuates, but it can finally achieve better performance. With the increase of batch number (256), the training process of the model becomes more stable, and the convergence speed is accelerated. However, when the batch number is further increased (512), the performance of the model begins to decline due to the memory limitation and the instability of the gradient update. Therefore, this article sets the batch size as 256.

In the process of tuning, this article continues to experiment and compare until the optimal model configuration is found. The final neural network model will be deployed in the VR interactive interface to provide users with a more intelligent and efficient design experience. In implementation, this article uses TensorFlow to construct and train the neural network model. By constantly adjusting the model parameters and optimizing the network structure, a neural network model with excellent performance and suitable for a VR interactive interface can be obtained.

4.3 Interactive Design in VR Environment

When designing interaction in a VR environment, this article mainly focuses on two aspects: first, how to make users interact with the virtual environment more naturally, and second, how to effectively present the design information and feedback on the user's operation results.

In order to realize natural interaction, this article adopts gesture recognition, voice control and other interactive methods. Users can operate CAD models, query design information, or call system functions through simple gestures or voice commands. At the same time, the system can also make adaptive adjustments according to the user's operating habits and scene requirements to provide a more personalized interactive experience. In the aspect of presenting design information and feeding back the user's operation results, this article presents the CAD model in an intuitive way by using the three-dimensional rendering and dynamic simulation capabilities of VR technology. Users can view different perspectives, sections and details of the model at any time and view the modified effect in real-time. In addition, the system can provide users with operation feedback and prompt information through animation, sound and other ways to help users successfully complete the design task.

4.4 Design and Implementation of Interface Prototype

According to the above design ideas and interactive design principles, the interface prototype is designed and implemented. First, determine the overall layout and style of the interface to ensure that it conforms to the user's aesthetic habits and usage habits. Then, the specific interface elements and interaction processes of each functional module are designed to ensure that users can easily find the required functions and complete the operation. In implementation, this article uses the UnityVR development platform to build and develop the interface prototype. Through continuous debugging and optimization, a prototype of a VR interactive interface with perfect functions, excellent performance and ease of use is finally obtained, as shown in Figure 4, which shows an example of the user's interactive scene.

Figure 4: Example of interactive scenario.

5 DESIGN OF SIMULATION EXPERIMENT AND DISCUSSION OF RESULT ANALYSIS

The purpose of the simulation experiment is to verify the effectiveness, efficiency and user satisfaction of a VR interactive interface combined with an AI algorithm. The experiment in this section requires to ensure the authenticity of the experimental environment, the accuracy of the data and the repeatability of the results. At the same time, the experimental design is required to comprehensively evaluate the performance indicators of the interactive interface. The experimental environment includes high-performance computers, VR helmets, gesture recognition equipment and so on. The computer configuration has powerful graphics processing ability and enough memory to support the smooth operation of a VR environment. VR helmet has a high resolution, low delay and accurate positioning ability to provide an immersive user experience. Gesture recognition equipment can accurately capture the user's hand movements and convert them into interactive instructions.

The experimental scheme is divided into two parts: one is a benchmark test, which is used to evaluate the performance of the interactive interface under standard tasks; The second is user testing, which is used to collect the feedback data of real users when using the interactive interface. Benchmarking includes designing a series of typical CAD design tasks, such as model rotation, scaling and editing, and recording the time and error rate required to complete the tasks. In the user test, a certain number of users are invited to participate in the experiment so that they can use the interactive interface in the VR environment to complete the actual design tasks and fill in the satisfaction questionnaire. The collation of experimental data includes cleaning, classifying and summarizing the collected original data for subsequent analysis. Analysis methods include descriptive statistics, variance analysis, correlation analysis, etc. Descriptive statistics are used to describe the basic characteristics of data, such as mean and standard deviation. Analysis of variance is used to compare the differences between different groups; Correlation analysis is used to explore the relationship between variables. See Table 4 for details.

Data processing stage	*Processing method*	*Specific application*	*Examples of numerical indicators*
Data cleaning	Remove duplicate values	Delete exactly the same record	Number of duplicate records: 100- 0
	Missing value processing	Fill or delete records with missing data	Missing value ratio: 5%-0%
	Outlier detection	Identify and process extreme or unreasonable data	Number of outliers: 15- 2
Data classification	Grouping by characteristics	Classify data according to specific attributes	Number of classification groups: 4
	Coding conversion	Convert non-numeric data into numeric data	Coding conversion rate: 100%
Summarization of data	Computational statistics	Calculate the mean, median and mode of each group	Mean: 75, median: 70, mode: 70.
Descriptive statistic	Mean value	Describe the average level of data	Average value of all samples: 75
	Standard deviation	Describe the degree of dispersion of data	The standard deviation of all samples: 10
Variance analysis	Single-factor variance analysis	Compare the differences between different groups	F value: 5.67, significance: $p<0.05$.
Correlation analysis	Pearson correlation coefficients	Explore the linear relationship between two variables	Correlation coefficient: 0.85, significance: $p<0.01$.

Table 4: Overview of experimental data analysis methods and applications.

During the experiment, this article strictly follows the experimental scheme to ensure the consistency and repeatability of each test link. For benchmark testing, this section uses automated testing tools to record the time required to complete the task and the error rate. For the user test, this section observes and records the user's behaviour when using the interactive interface and collects the satisfaction questionnaire data filled out by the user. The comparison of the time required for the algorithm to complete the task is shown in Figure 5.

The experimental results show that DCNN is excellent in the time required to complete the task, and the time is only 0.541. In contrast, RNN and BPNN need a longer time to complete the same task. This advantage is attributed to the unique hierarchical structure and convolution operation of DCNN, which enables it to process input data more efficiently and extract useful features. The comparison of algorithm error rates is shown in Figure 6.

In terms of error rate, DCNN also shows excellent performance, and the error rate of the algorithm is only 2.41%. This means that DCNN can identify and execute users' operation instructions with high accuracy when dealing with CAD design tasks. In contrast, RNN and BPNN have higher error rates, which are 5.89% and 8.97% respectively. This is due to their limitations in dealing with complex or high-dimensional data. The accuracy of the interactive interface in identifying user operations and presenting design results is shown in Figure 7. The user satisfaction survey is shown in Figure 8.

In addition to the performance of the algorithm itself, the experimental results in Figure 7 also show that the accuracy of the interactive interface in identifying user operations and presenting design results is over 97.01%.

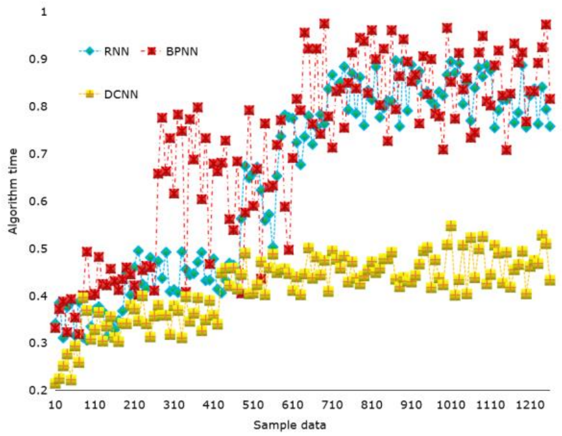

Figure 5: Comparison of the time required for algorithms to complete tasks.

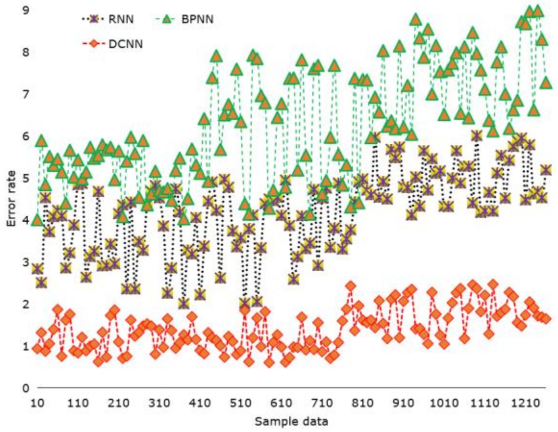

Figure 6: Algorithm error rate comparison.

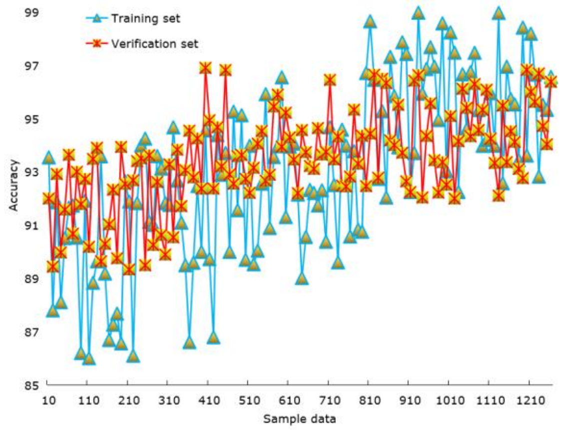

Figure 7: Identify the accuracy of user operations and present results.

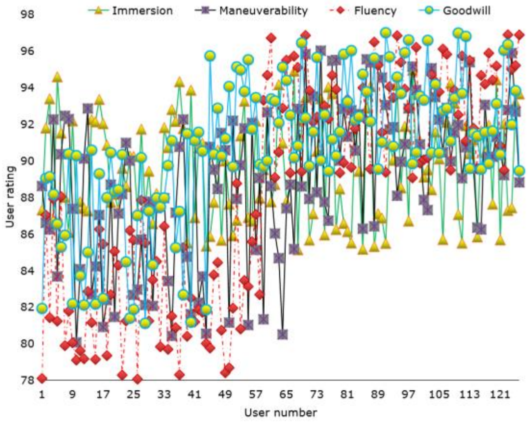

Figure 8: User satisfaction survey.

This shows that the interactive interface can accurately understand the user's intention and transform it into the corresponding design operation. At the same time, the comprehensive score of the user satisfaction survey is about 95%, which further confirms the excellent performance and user experience of the interactive interface. In the VR environment, natural and intuitive interaction is very important to improve users' immersion and work efficiency. Therefore, the interactive interface design scheme of DCNN combined with VR technology proposed in this article has achieved remarkable results in improving user experience.

6 CONCLUSIONS

This article mainly explores the VR interactive interface design of deep convolutional neural networks Through in-depth theoretical analysis and practical verification, a series of meaningful research results have been achieved. In the research process, this article first combs the design idea and overall architecture of the VR interactive interface and makes clear the research goal and direction. Then, the focus was on the application of deep convolutional neural networks in interactive interfaces, especially the modeling and implementation of neural networks, which provided strong support for the intelligence of interactive interfaces. In addition, this article also discusses the interactive design in a VR environment and puts forward an interactive way that conforms to users' cognition and operating habits, finally, through the simulation experiment design and result analysis and discussion. The experimental results fully prove that the DCNN proposed in this article is excellent in the time required to complete the task, error rate and interactive interface performance. This provides new ideas and methods for the design of VR interactive interfaces, and is expected to bring more efficient, more accurate and more natural user experience for future CAD design.

In the future, we will explore how to integrate and incorporate the interactive interface proposed in this study with other CAD systems. This can be achieved by formulating a unified data exchange standard, developing a common interface module or building a cloud service platform. At the same time, we can also consider applying the research results to other related fields, such as architectural design and mechanical design, so as to promote the progress and development of the whole industry.

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REFERENCES

[1] Arrighi, P.-A.; Mougenot, C.: Towards user empowerment in product design: a mixed reality tool for interactive virtual prototyping, Journal of Intelligent Manufacturing, 30(2), 2019, 743-754. https://doi.org/10.1007/s10845-016-1276-0

[2] Bouschery, S.-G.; Blazevic, V.; Piller, F.-T.: Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models, Journal of Product Innovation Management, 40(2), 2023, 139-153. https://doi.org/10.1111/jpim.12656

[3] Dubey, A.-K.; Kolhe, M.-L.; Singh, V.-K.: Human-computer interactive future framework: automation of human interaction and interfaces, International Journal of Computational Vision and Robotics, 10(5), 2020, 426. https://doi.org/10.1504/IJCVR.2020.109392

[4] Erdolu, E.: Lines, triangles, and nets: A framework for designing input technologies and interaction techniques for computer-aided design, International Journal of Architectural Computing, 17(4), 2019, 357-381. https://doi.org/10.1177/1478077119887360

[5] Fu, Q.; Lv, J.; Tang, S.; Xie, Q.: Optimal design of virtual reality visualization interface based on kansei engineering image space research, Symmetry, 12(10), 2020, 1722. https://doi.org/10.3390/sym12101722

[6] Fukuda, T.; Novak, M.; Fujii, H.; Pencreach, Y.: Virtual reality rendering methods for training deep learning, analyzing landscapes, and preventing virtual reality sickness, International Journal of Architectural Computing, 19(2), 2021, 190-207. https://doi.org/10.1177/1478077120957544

[7] Gordieiev, O.: Quality models and assessment of software interface usability for human-computer interaction, Èlektronnoe Modelirovanie, 42(5), 2020, 24-37. https://doi.org/10.15407/emodel.42.05.024

[8] Guo, Q.-Q.; Ma, G.-F.: Exploration of human-computer interaction system for product design in virtual reality environment based on computer-aided technology, Computer-Aided Design & Applications 19(S5), 2022, 87-98. https://doi.org/10.14733/cadaps.2022.S5.87-98

[9] Hazarika, A.; Rahmati, M.: Towards an evolved immersive experience: Exploring 5G-and beyond-enabled ultra-low-latency communications for augmented and virtual reality, Sensors, 23(7), 2023, 3682. https://doi.org/10.3390/s23073682

[10] Kang, T.; Chae, M.; Seo, E.; Kim, M.; Kim, J.: DeepHandsVR: Hand interface using deep learning in immersive virtual reality, Electronics, 9(11), 2020, 1863. https://doi.org/10.3390/electronics9111863

[11] Li, N.-A.: Visual information enhancement method of multimedia human-computer interaction interface based on virtual reality technology, International Journal of Information and Communication Technology, 19(2), 2021, 127. https://doi.org/10.1504/IJICT.2021.117042

[12] Li, Y.; Wang, Y.; Li, Y.; Zhou, R.; Lin, Z.: An artificial neural network assisted optimization system for analog design space exploration, IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 39(10), 2019, 2640-2653. https://doi.org/10.1109/TCAD.2019.2961322

[13] Linse, C.; Alshazly, H.; Martinetz, T.: A walk in the black-box: 3D visualization of large neural networks in virtual reality, Neural Computing and Applications, 34(23), 2022, 21237-21252. https://doi.org/10.1007/s00521-022-07608-4

[14] Mourtzis, D.; Angelopoulos, J.: An intelligent framework for modelling and simulation of artificial neural networks (ANNs) based on augmented reality, The International Journal of Advanced Manufacturing Technology, 111(5), 2020, 1603-1616. https://doi.org/10.1007/s00170-020-06192-y

[15] Qamar, I.; Groh, R.; Holman, D.: Bridgingthe gap between material science and human-computer interaction, Interactions, 26(5), 2019, 64-69. https://doi.org/10.1145/3344943
[16] Sahu, C.-K.; Young, C.; Rai, R.: Artificial intelligence (AI) in augmented reality (AR)-assisted manufacturing applications: a review, International Journal of Production Research, 59(16), 2021, 4903-4959. https://doi.org/10.1080/00207543.2020.1859636
[17] Wang, Q.; Jiao, W.; Yu, R.; Johnson, M.-T.; Zhang, Y.: Modeling of human welders' operations in virtual reality human–robot interaction, IEEE Robotics and Automation Letters, 4(3), 2019, 2958-2964. https://doi.org/10.1109/LRA.2019.2921928