Virtual Reality Practice and Learning Platform Based on Generative Adversarial Networks Algorithm

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Abstract. Educational reforms have not only raised the requirements for students' ability to apply theoretical knowledge but also emphasized the importance of practical skills. Therefore, this paper constructs a CAD-aided teaching and virtual reality practice platform based on deep learning algorithms. To optimize the performance of the platform, this paper constructs an image recognition and classification module based on convolutional neural networks (CNNs) and a virtual teaching scene construction module based on generative adversarial networks (GANs). The experimental results show that the application of CNNs can effectively improve the accuracy of CAD model recognition and classification of the entire system, providing effective basic data for the virtual reality practice environment. Meanwhile, the application of GANs effectively improves the average import rate of the virtual reality practice environment and reduces the error of image positioning calibration. The application experimental results show that this model can provide students with a virtual reality practice environment that better meets their actual needs, helping them to learn CAD models and effectively improve their comprehensive practical abilities.

Keywords: Generative Adversarial Networks; Convolutional Neural Networks; CAD-aided Teaching; Virtual Reality
DOI: https://doi.org/10.14733/cadaps.2024.S28.266-279

1 INTRODUCTION

Teaching reform has become the key driving force for promoting educational progress and improving teaching quality in today's educational field. The combination of CAD (Computer-Aided Design) assisted teaching and virtual reality (VR) practice is particularly important in this process. The development and widespread application of virtual reality technology in education and teaching meet the practical needs of educational development and the requirements of educational informatization construction. People gradually realize that the usefulness of technology does not play a decisive role but rather the teacher's grasp of instructional design. Through reviewing the research background and current research status both domestically and internationally, Apostolopoulos et al. [1] found that instructional design incorporating generative learning strategies has a potential promoting effect on immersive teaching. Through virtual reality technology, any imagined educational and teaching environment can be achieved, and its immersion, interactivity, and conceptualization enable students to immerse themselves in learning objects and teaching processes. After analyzing the applicability of generative learning strategies, it was decided to use generative summarization and painting strategies for teaching. Integrate appropriate strategies into the instructional design of immersive virtual reality. At the same time, new educational and teaching models and methods have emerged, but virtual reality technology has not had a clear promoting effect on teaching effectiveness. It tested the application effect of generative learning strategies in immersive teaching in secondary schools. Promote the deep integration of immersive virtual reality and secondary education. However, due to high equipment costs and complex technology, it is not conducive to the popularization of equipment in schools and the development of teacher resources, making it difficult to verify the effectiveness of immersive virtual reality teaching. This study examines the learning effectiveness of generative learning strategies in immersive virtual reality teaching through the analysis of experimental data from other groups, in order to promote the deep integration of immersive virtual reality and secondary education. Through reasonable teaching design, enhance students' learning experience and effectiveness in various subjects, explore learning methods and strategies that adapt to new technologies, and promote students' acquisition of abstract subject knowledge points. It explores the impact mechanism and path of generative learning strategies on immersive virtual reality learning and provides a reference for immersive teaching design by analyzing the mechanism of learning experience and learning effectiveness.

The integration of virtual reality technology and teaching is not yet deep enough, and there are also problems such as a lack of effective teaching strategy guidance. Further exploration is needed to design and use effective teaching strategies for the application of virtual technology. Its interactive and imaginative characteristics are conducive to stimulating the learning interest of vocational college students, enhancing the learning experience and improving learning effectiveness, as well as overcoming the high cost and difficulty of constructing real work scenarios. Bruzzone et al. [2] conducted a study on the virtual learning effects of 198 vocational college students in Guangdong Province using experimental research and questionnaire survey methods. The results showed that scaffolding-based teaching strategies such as leading organizers, teaching explanations, and teaching demonstrations can improve the effectiveness of virtual learning, specifically by improving academic performance and satisfaction and reducing cognitive load. The specific presentation form of teaching strategies needs to adapt to the characteristics of vivid and perceptual learning styles, visual thinking, unstable attention, and limited working memory capacity in higher vocational education. Through three series of experiments, explore the impact of pre-organizers and teaching demonstrations on the virtual learning effectiveness of vocational college students in a desktop virtual reality learning environment. There are differences in the effects of different types of teaching strategies on transfer and retention of grades, with learning cognitive load and satisfaction as observation variables for virtual learning outcomes. Teaching strategies and their different presentation forms have varying degrees of impact on the effectiveness of virtual learning. Teaching strategies with scaffolding effects, such as pre-organizers, teaching explanations, and teaching demonstrations, can promote student learning [3]. The complexity of the 3D design process, as well as the creation and editing of VR training courses, require a significant amount of time and resource investment, which makes the development cost of VR training systems high and the cycle long. This method first creates a virtual model of the workstation through 3D reconstruction technology. This step utilizes advanced scanning and modelling techniques to accurately reproduce the layout and equipment of a real workstation. These simulation operation processes can not only be used for teaching demonstrations but also as materials for operators to practice.

However, in practical applications, there are still many problems and challenges in the integration of CAD-aided teaching and virtual reality practice platforms. Among them, the integration of teaching content and the improvement of learning experience are important research topics. CAD and VR technologies involve multiple disciplines, such as computer science, graphics, and mechanical engineering. In terms of teaching content, how to effectively integrate this interdisciplinary knowledge to enable students to fully understand and master relevant skills is a problem that needs to be addressed. Chen et al. [4] investigated the performance differences between sequence-based (traditional) and context-based instructional design. The efficiency and interactivity of landscape architecture teaching interactive classrooms have been successfully improved through the systematic design of virtual reality (VR) technology. It hopes to operate in a self-developed virtual reality computer numerical control (VRCNC) training environment. Based on the proposed teaching and experimental design, conduct corresponding pre-tests, teaching activities, and post-tests. This not only provides new ideas and methods for the teaching of landscape architecture but also provides useful reference and inspiration for the teaching reform of other disciplines. On average, situational teaching design has shown excellent performance in most learning outcomes. The survey results also showed that students gained more satisfaction and confidence after situational teaching.

The virtual environment constructed by VR technology has relatively low realism, and the operation of students in the virtual environment has significant positioning errors and poor interactive performance, which also reduces the teaching effect of the integration of the two. Multi-view Stereoscopic (MVS) technology plays a crucial role in the fields of 3D modelling and computer-aided design (CAD). Chen et al. [5] proposed MVSNet++, an end-to-end trainable network specifically designed for dense depth estimation. Due to the complexity and abstraction of 3D models, students often find it difficult to intuitively understand their structure and characteristics. It can reconstruct accurate 3D point cloud models from multiple 2D views. Students can observe and understand the shape and changes of 3D models from different perspectives by manipulating and adjusting different views, thereby better mastering the core concepts and techniques of 3D design. MVSNet++ not only has significant advantages in the field of MVS but also has a potential application in CAD-assisted teaching that cannot be ignored. In the design of MVSNet++, they adopted a feature pyramid structure for feature extraction and cost volume regularization. This is particularly important for CAD-assisted teaching, as accurate 3D models can help students better understand the details and accuracy of 3D design. MVSNet++ can provide students with a more intuitive and realistic learning experience by reconstructing 3D models from multiple 2D views. For the above problems, deep learning algorithms can provide new solutions. The application of deep learning algorithms in the integration of CAD-aided teaching and virtual reality practice platforms can improve the processing efficiency and effectiveness of data images. Identifying and classifying CAD models and virtual reality scenes can help students improve their understanding of CAD models and enhance the realism and immersion of the virtual environment. Therefore, based on deep learning algorithms, this paper constructs a CAD-aided teaching and virtual reality practice integration system. It optimizes image recognition and classification through a convolutional neural network (CNN), and on this basis, it combines a Generative Adversarial Network (GAN) to enhance the realism and interactivity of the virtual environment, thereby improving teaching effectiveness.

2 RELEVANT WORK

The teaching mode of landscape architecture urgently needs to go beyond the framework of traditional teaching methods due to its unique disciplinary characteristics and content. Adhering to the embodied cognitive theory of "cognition rooted in the body," Deng and Zhou [6] provided a theoretical basis for promoting the optimization and upgrading of teaching situations. It has many successful application cases in disciplines such as medicine, sports, art, and English, providing a broader development space for embodied learning. Firstly, sort out and analyze the theoretical basis for creating virtual teaching scenarios. By reviewing existing literature and analyzing the structural elements of virtual teaching scenarios, we can identify the elements and their relationships that should be considered in the design process. These technologies have greatly enriched the means to support the creation of teaching contexts, especially in the field of somatosensory VR, which can highlight the interaction between users and contexts. And analyze the relationship between embodied cognition theory, situational cognition theory, and flow experience theory. These two aspects lay the foundation for the design of virtual teaching scenarios. It starts with the construction of abstract design models, gradually realizes the specific design of virtual teaching scenarios, and verifies its effectiveness in teaching practice. Therefore, creating virtual teaching situations through sensory interaction can provide a solution for achieving embodied teaching situations. Integrating the framework of the user experience element model with the SECI knowledge transformation process and the design principles and strategy elements mentioned above, a virtual teaching scenario design model is constructed [7]. By reconstructing three-dimensional models from two-dimensional images, students can gain a more intuitive and realistic learning experience. Especially with the rapid development of Convolutional Neural Networks (CNN), image-based 3D reconstruction methods have gradually emerged, and their application in CAD-assisted teaching has also aroused great interest. Secondly, 3D reconstruction technology can also provide rich materials and cases for CAD teaching.

The field of visual communication design is undergoing a revolutionary transformation, which not only reshapes the methods, means, and expressions of design but also has a profound impact on educational concepts, methods, and means. AI can assist teachers in analyzing and evaluating student work and providing personalized learning advice. The traditional education model is shifting towards a student-centered, practical, and innovative educational philosophy. Liu and Yao [8] took the integration of AI and CAD technology in contemporary visual communication design as a starting point and analyzed in depth how CAD-assisted teaching can play a role in this field. And explore the possibility of teaching modes based on their characteristics in order to promote the transformation and upgrading of visual communication design education to intelligent teaching. With the continuous development of technology, the younger generation's acceptance and dependence on digital technology are increasing. The mobile augmented reality (AR) application developed by Marinakis et al. [9] not only brings revolutionary changes to the learning of mechanical drawing courses for engineering students but also significantly enhances traditional textbooks and teaching methods. This feature greatly enriches the learning experience of students, allowing them to have a more intuitive understanding of the correspondence between mechanical drawings and 3D models. Through the graphical user interface, students can import projection models and use advanced 3D conversion tools for interactive operations.

Generative learning strategies, instructional design strategies, and instructional design techniques have potential advantages for immersive virtual reality learning and have a promoting effect on learning outcomes. Park et al. [10] analyzed the characteristics and applicability of immersive virtual reality teaching strategies and proposed the use of generative summarization strategies and painting strategies to conduct experimental research on immersive teaching. At present, the impact path of generative learning strategies on immersive virtual reality learning is not clear, and in disciplinary research, most studies are focused on biology and medicine. For immersive teaching under strategies, there is relatively abundant research abroad, while there is a relative lack of such research in China. In addition, most studies focus on higher education, with less involvement in basic research. Through AMOS, confirmatory factor analysis and path analysis were conducted on the structural equation model, exploring the causal relationship between academic performance and various dimensional factors. The effectiveness of the equation model and the immersion evaluation model of the two strategies in teaching were verified through comparative analysis of equal sets of data. In higher vocational education, virtual reality learning has its advantages and disadvantages. Due to the emphasis on skill-based practical teaching in vocational education, it is based on the three major characteristics of immersion, interactivity, and imagination of virtual reality technology. It is entirely possible to determine the practicality, effectiveness, urgency, and scalability of the application of virtual reality in higher vocational education teaching. This is of great significance for improving the effectiveness of virtual reality technology in teaching applications, promoting virtual learning for vocational college students, and solving the problem of insufficient integration of virtual reality technology in teaching applications. At the same time, it was also found that teaching strategies, knowledge types, and knowledge complexity are key factors affecting the differences in virtual learning outcomes. Therefore, this study analyzes through experiments under what conditions vocational college students have the best learning effect in virtual learning. In a series of experimental studies on virtual learning, it was also found that there is no unified view on whether virtual reality technology can improve learning effectiveness [11].

These technologies can help students understand the sources, meanings, and applications of SHM data, and explore and analyze this data through interactive visualization tools. In the field of SHM, the application of BIM, VR, and AR technologies makes complex data management and visualization easier and more intuitive.

Augmented reality (AR), as a cutting-edge interactive medium, has not only brought revolutionary changes to the field of industrial manufacturing but also demonstrated enormous potential in the field of education. In manufacturing environments, AR technology enables technicians to understand and execute related tasks more intuitively by displaying complex assembly processes, mechanical internal structures, and maintenance steps in real-time. Especially when facing diverse learning content and complex learning scenarios, traditional AR techniques often struggle to provide accurate and rich information. Sahu et al. [12] provide information closely related to learning tasks, effectively reducing the cognitive load on students, thereby enhancing the learning experience and improving learning outcomes. This technology can help build more complex learning scenarios and achieve seamless integration between virtual objects and the real environment. Similar to manufacturing environments, the current strategies used in AR systems for key technologies such as camera calibration, detection, tracking, and attitude estimation mainly rely on traditional non-artificial intelligence methods, which limits the adaptability and flexibility of AR in educational scenarios. The university surveying and mapping experimental centre encounters problems such as chaotic recording, data loss, and difficulties in instrument usage statistics in the process of surveying and mapping equipment management. Wei and Han [13] proposed establishing a surveying and mapping equipment management information system based on a CAD framework and implemented it using MVC mode. Each module has been carefully designed to meet the various needs of the experimental centre for surveying and mapping equipment management. This information system consists of multiple functional modules, including device information management, device reservation management, usage statistics, and data analysis. This provides students with a convenient query platform, allowing them to stay informed about the required equipment at any time, thereby improving experimental efficiency. Students can book the required surveying equipment through the system, and the system will automatically allocate equipment to students based on the availability of the equipment. At the same time, teachers can also quickly understand the usage of equipment through the system, making full preparations for experimental teaching. This system not only optimizes the process of equipment management but also provides new possibilities for auxiliary teaching through its powerful data processing and visualization capabilities.

With the flourishing development of corpus linguistics, the concept of DDL (Data-Driven Learning) has emerged, with its core concept of utilizing network and corpus resources to bring revolutionary changes to English teaching. Based on the concept of DDL, Yan [14] designed a data-driven college English teaching model in the practice of English teaching reform and explored its specific implementation plan in the teaching process in depth. Using online learning platforms, the DDL model can promote collaborative learning and interaction among learners. In addition, they also explored the practical application of the multi-agent deep RL (reinforcement learning) algorithm in DDL teaching mode and compared it with other RL algorithms. This teaching model not only utilizes corpus resources but also combines modern technological means such as intelligent learning platforms and virtual reality technology, providing learners with a rich and diverse learning experience. Research has shown that the algorithm proposed in this article improves the utilization of learning resources by 10.55% by optimizing the learning experience, significantly enhancing learning performance. The creation of teaching scenarios is not only the main means and methods of implementing school curricula but also a key part of educational theory research. The research on interactive teaching scenarios related to body sensation is beneficial for deepening the educational concept of "student-centered" and strengthening the teaching concept of "close connection between mind, body, and environment." In addition, the interactive virtual teaching scenario with body sensation meets the requirements of the new curriculum standard and also conforms to the teaching form advocated by the primary school science curriculum standard. In the context of educational informatization, creating principles and strategies for designing virtual teaching contexts and constructing principles for designing virtual teaching contexts are supplements to educational theory research. Židek et al. [15] enriched the research of relevant workers on the application theory of virtual reality education. The emerging information technology represented by VR is helping to achieve modernization in education, and its relationship with education is becoming increasingly close. Design teaching scenarios supported by Leap Motion, a typical device that supports VR implementation. No matter how technology evolves and innovates, the effectiveness it can achieve in the field of education depends on the transformation of teaching resources from design to practice that educators have made by utilizing this technology. This is a new exploration of the application of information technology teaching in primary school science subjects from the perspective of virtual teaching scenarios while enriching the theoretical research of VR education applications from the perspective of design processes. In intelligent tutoring, researchers use an intelligent tutoring system based on deep learning algorithms to analyze students' learning data and generate personalized tutoring plans based on their learning progress and difficulty. They automatically recommend relevant learning resources and practice questions to help students better grasp knowledge points. In intelligent management, researchers use deep learning algorithms to analyze and predict students' learning progress and grades based on their learning and behavioural data, providing management suggestions for teachers.

It can be seen that deep learning algorithms have good potential for application in the field of education. Its powerful performance and advantages can improve the integration performance of CAD-assisted teaching and virtual reality practice platforms, promoting their continuous development. By providing a more intelligent and personalized teaching system, as well as a more realistic and natural virtual environment, students will have a richer and deeper learning experience. Therefore, this article has certain practical significance for the research of CAD-assisted teaching and virtual reality practice platforms based on deep learning algorithms.

3 CAD-AIDED TEACHING AND VIRTUAL REALITY PRACTICE SYSTEM BASED ON DEEP LEARNING ALGORITHM

3.1 Image Recognition and Classification Module Based on Convolutional Neural Network

One of the prominent representative algorithms in the field of deep learning. The design of CNN is inspired by the biological visual perception mechanism. By simulating the image processing process of the biological visual system, CNN endows the network with powerful representation learning ability. This network can efficiently and accurately classify input information according to its unique hierarchical structure, so it is often vividly called a "translation-invariant artificial neural network". CNN uses convolutional layers and pooling layers to abstract and extract features layer by layer from input data, ultimately achieving accurate recognition and understanding of complex image information. CNN has advantages such as local connection and weight sharing, feature learning, translation, scaling, rotation invariance, efficient computational performance, and flexibility. These advantages have made CNN widely used in computer vision, natural language processing, speech recognition, and other fields. Figure 1 shows the structure of a convolutional neural network.

From the figure, it can be seen that the input layer of CNN is usually the original image or preprocessed image data, which is usually represented in the form of a multidimensional array. The convolution layer is the core part of CNN, which uses a set of learnable convolution kernels to perform convolution operations on the input data to extract features. These convolution kernels slide on the input data and perform point-product operations to generate feature maps. The convolution layer reduces the number of parameters and improves the model's generalization ability through local connection and weight sharing. As shown in formula (1), the output of layer feature extraction is:

$$i_n^h = f(\sum_{m=1}^{M} i_m^{h-1} * k_{mn}^h + a_n^h) \tag{1}$$

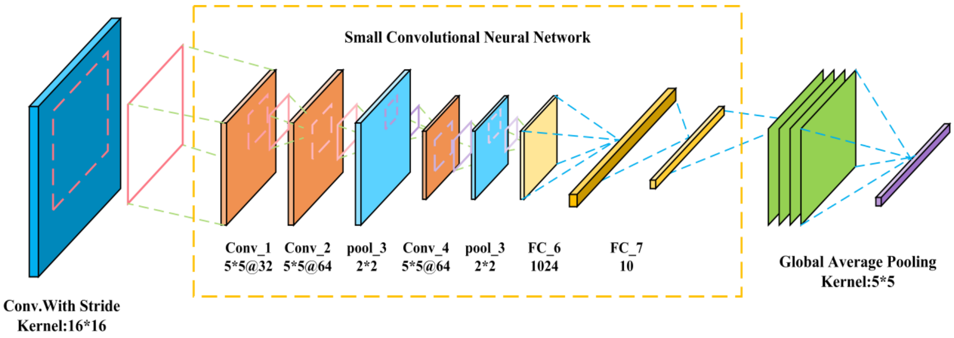

Figure 1: Schematic diagram of convolutional neural network structure.

The output feature of this layer is described as the input data feature, the convolution kernel weight is represented, the bias is denoted, and the activation function is nonlinear.

After the convolution operation, an activation function is usually applied to increase the model's nonlinear capability. The activation function is shown in Figure 2

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

The pooling layer is located after the convolution layer and is used to reduce the spatial dimension of the feature map while retaining the main information. Pooling operations usually include maximum pooling and average pooling. Maximum pooling selects the maximum value within each pooling window as the output, while average pooling calculates the average value within each pooling window as the output. The output feature map in the layer is represented as and after passing through the pooling layer, it is shown as formula (3):

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

The offset in the equation is denoted as, and the pooling function is.

After being processed by the pooling layer, the eigenvalues of data features obtain new feature points, which are then mapped in the sample label space through the fully connected layer for data classification. Each neuron of the fully connected layer is connected to all neurons of the previous layer, which is used to integrate the extracted features and map them to the output layer. After fusing the features, the output of the previous layer is converted into a probability vector by the classifier, indicating the probability of the current sample belonging to the classification item, as shown in formula (4):

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

Among them, the type of sample classification item is noted, and the description of the fully connected layer output vector is given.

The loss function is shown in formula (5):

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

The structure of CNN can be flexibly adjusted to adapt to different tasks and datasets. For example, the structure of CNN can be adjusted by increasing or decreasing the number of convolutional layers and pooling layers, changing the size and number of filters, and using different activation functions. To improve the performance of CNN, this paper introduces a hybrid attention mechanism that integrates the channel attention mechanism and the spatial attention mechanism. The channel attention module focuses on different channels of the input features and assigns different weights to each channel. This helps the model understand which channel features are more important for the current task. It obtains a one-dimensional feature map of two feature maps compressed by spatial information through a shared multi-layer perceptron, and then calculates the channel weight values of the normalized feature map, as shown in formula (6):

$$\begin{aligned} M_c(F) &= \sigma\{MLP[AvgPool(F)] + MLP[MaxPool(F)]\} \\ &= \sigma\{MLP[\frac{1}{H+W}\sum_{n_0=1}^{H}\sum_{m_0=1}^{W} f_{x_0}(n_0, m_0)] + MLP[\max_{n\in H, m\in W} f_{x_0}(n, m)]\} \end{aligned} \tag{6}$$

In the formula, the activation function is Sigmoid, which is represented as, the height and width of the input feature map are represented as and respectively, and the pixel value corresponding to the point with coordinates in the channel with sequence number is represented as.

The spatial attention module allows the model to focus on different areas of the image in the spatial dimension. This is typically achieved by generating an attention map of the same size as the input image, where each value represents the importance of the corresponding location. The expression is shown in (7):

$$M_s(F) = \sigma\{f^{k\times k}[AvgPool(F^{'}); MaxPool(F^{'})]\} \tag{7}$$

In the formula, the convolution kernel size is denoted as the convolution layer.

The final expression of the mixed attention mechanism is shown in (8):

$$\begin{cases} F^{'} = M_c \otimes F \\ F^{"} = Ms \otimes F^{'} \end{cases} \tag{8}$$

In the formula, the corresponding elements of two matrices are multiplied and represented as. As shown in Figure 2, the schematic diagram of the structure of the channel attention module and spatial attention module in the hybrid attention mechanism.

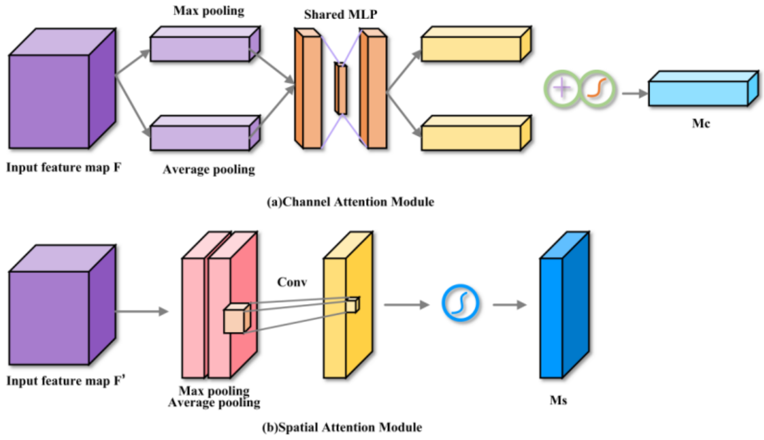

Figure 2: Schematic diagram of the structure of the channel attention module and spatial attention module in the hybrid attention mechanism.

3.2 Virtual Teaching Scenario Construction Module Based on Generative Adversarial Networks

GAN can be integrated with CAD-aided teaching and virtual reality practice platforms to help students better understand and learn by generating a large amount of CAD-related designs. Additionally, GAN can generate realistic virtual scenes and objects by learning from real-world datasets. This not only saves a lot of time and costs but also enhances the realism and immersion of the virtual environment.

GAN, as a cutting-edge deep learning model, is unique in that it simulates and learns the distribution of complex data by the mutual confrontation and competition of two neural networks, the generator, and the discriminator, to generate new data samples. The generator starts from random noise and aims to continuously train and optimize to generate fake data that is extremely similar to real data. The discriminator is responsible for distinguishing between real and fake data. It receives data samples and outputs a probability value, indicating the likelihood of the sample being real data. During the training process of GAN, a continuous game between the generator and the discriminator takes place: the generator strives to deceive the discriminator and generate more realistic fake data, while the discriminator strives to improve its discriminating ability and accurately differentiate between real and fake data. This continuous confrontation and evolution process ultimately makes it difficult for the discriminator to distinguish between fake data generated by the generator and real data, thus achieving the goal of generating high-quality, indistinguishable fake data. The target formula of GAN is shown in (9):

$$\min_G \max_D V(G,D) = E_{x\sim pdata(x)}[\log D(x)] + E_{m\sim p_m(m)}[\log(1-D(G(m)))] \tag{9}$$

In the formula, the true data is denoted as and its distribution is represented as, the distribution of noise data is represented as, the data generated by the generator based on noise is denoted as, the input noise is denoted as, and the probability output by the discriminator is denoted as. Based on the above formula, it can be seen that there is a game between the discriminator and the generator. That is, the discriminator aims to classify true data as true and generated data as false, while the generator aims to make the discriminator classify generated data as true. Therefore, the former wants to maximize this value, while the latter wants to minimize it.

The performance of the generator and discriminator of GAN gradually achieves the expected effect during the continuous training process. As shown in Figure 3, the dynamic change process of the generator and discriminator during the GAN training process is illustrated. The blue line in the figure represents the distribution state of the real data, the orange dashed line represents the distribution state of the data generated by the generator, and the purple line represents the performance state of the discriminator.

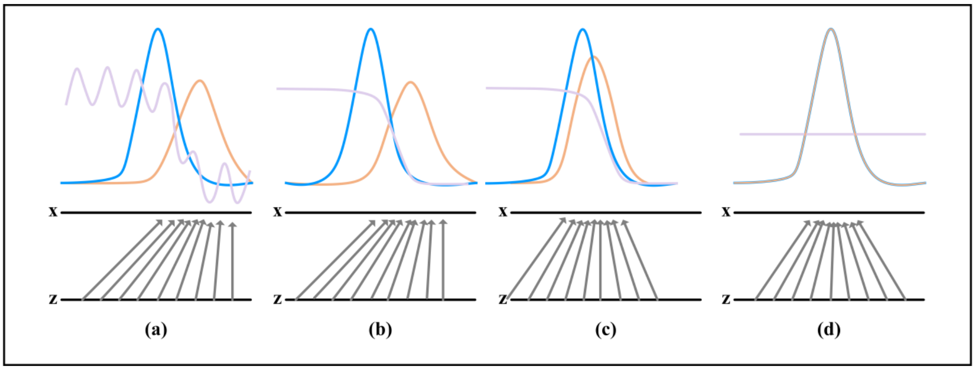

Figure 3: Dynamic change process of generator and discriminator during GAN training.

From the figure, it can be observed that in the initial stage of training, the discriminator's performance is relatively weak despite its ability to differentiate between real data and generated data. As the number of training samples increases, the discriminator's performance gradually improves, and its ability to differentiate between generated data and real data also increases. This is reflected in the downward trend of the corresponding line. This indicates that the generated data exhibits a decreasing probability, but its purpose is to increase the probability. Therefore, the orange line starts to move in the direction of the actual data distribution. The generator's performance also gradually improves during continuous training, which affects the discriminator's distribution. The two gradually reach a state of equilibrium during training. If the network is fixed, the optimal training result is shown in (10):

$$D_g^*(x) = p_{data}(x) / \left[p_{data}(x) + p_g(x) \right] \tag{10}$$

4 PERFORMANCE AND APPLICATION ANALYSIS OF CAD-AIDED TEACHING AND VIRTUAL REALITY SYSTEM BASED ON DEEP LEARNING ALGORITHM

4.1 Performance Experiment Results of CAD-Aided Teaching And Virtual Reality System Based on Deep Learning Algorithm

To verify the performance of CAD-assisted teaching and virtual reality systems based on deep learning algorithms, this paper selects three other common image recognition and classification models for comparative experiments. In the experiment, this paper selects CAD models of different complexity and types as the target of recognition and classification and annotates them in order from simple to complex. The results are shown in Figures 4 and 5. Figure 4 shows the relationship between the recognition accuracy of the four models and the number of iterations. The results in the figure show that the data amount required for the BP and RNN models during the model recognition training process is less than that of the other two models, mainly because they gradually enter a stable state after about 350 iterations. However, the final recognition rates are not ideal, all below 50%. The iteration times for reaching a stable state of this paper's model and LSTM model are significantly higher than those of the former two models, so the training time required is relatively long, and the final recognition rates are significantly improved. The recognition rate of this paper's model can reach over 92%, showing good recognition performance and stability.

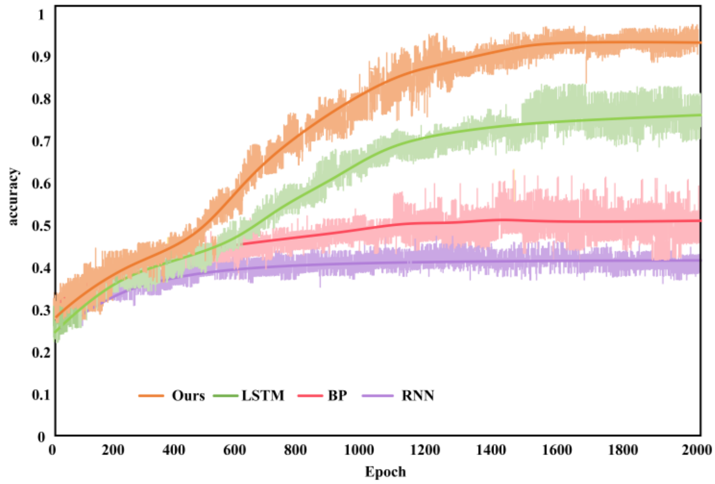

Figure 4: Relationship between recognition accuracy and iteration times of four models for different CAD models.

As shown in Figure 5, the classification rates of four models for different CAD models are presented. The type and model complexity will affect the classification performance of the model. The five CAD model types selected in this paper have certain similarities. The results show that the classification rates of the third and fifth CAD model types are relatively low, which is due to their highest similarity and great interference on classification performance. Overall, the classification rates of this paper's model for different CAD models are higher than those of the other three models, and all exceed 93%, which can provide a good data basis for future performance experiments and practical applications.

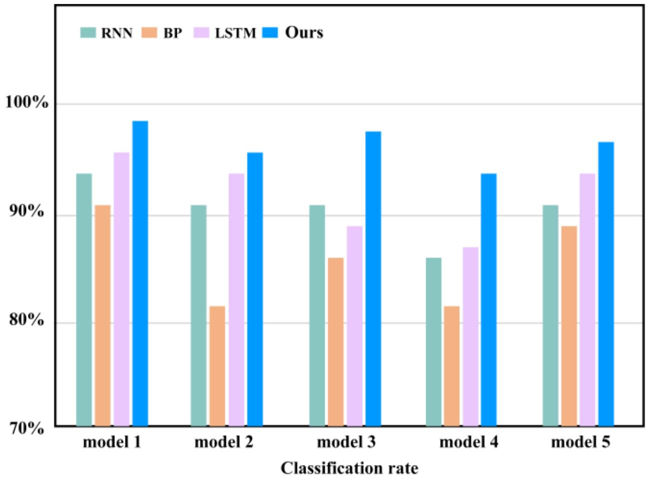

Figure 5: Classification rates of four models for different CAD models.

Based on the identification and classification results mentioned above, this study further tests the performance of the model in a virtual reality environment. Additionally, two other optimization models were selected for comparison. The results are shown in Figure 6. The figure indicates that in terms of model selection and average import rate in the virtual reality environment, the import rate of this study's model is significantly higher than that of the other two systems. Moreover, the rate variation range is minimal throughout the entire process, demonstrating good stability and accuracy. Additionally, in terms of image positioning calibration in the same virtual reality environment, this study's model has the lowest positioning error rate compared to the other two models. Furthermore, as the number of positioning increases, the error rate of this study's model changes minimally, maintaining a certain range. In contrast, the error rates of the other two models increase significantly.

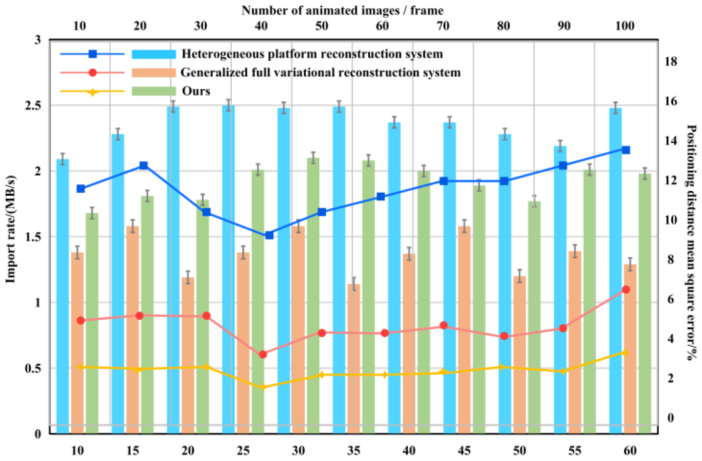

Figure 6: Comparison results of average import rate and positioning calibration error rate of virtual reality environments for three different systems.

4.2 CAD-Assisted Instruction and Virtual Reality System Application Based on Deep Learning Algorithm

To verify the application effect of CAD-based teaching and virtual reality in the field of deep learning algorithms, this paper selects two students of the same grade and major for a teaching comparison experiment. Class A is the control group, which completes the teaching practice content through the traditional CAD-based teaching platform, while Class B is the experimental group, which completes the teaching practice content through the practical platform of this paper, with a duration of one month. As shown in Figure 7, the schematic diagram of the CAD teaching-assisted virtual reality practice environment for two classes is presented. It can be seen from the figure that the virtual reality practice environment for Class A is still the traditional classroom environment. Although this environment has a high similarity with the familiar environment and can bring a sense of reality and immersion to students' practice, neglecting the importance of the environment required for student practice reduces the convenience and authenticity of students' practical operations. The virtual reality practice environment for Class B is constructed on the basis of the original real classroom environment to provide a space environment required for student practice, allowing students to immerse in the process of practical operation in a highly realistic environment, thereby improving the possibility and convenience of operation.

(a)Schematic diagram of the virtual reality operating environment in class A

(b)Class B virtual reality operating environment diagram

Figure 7: Schematic diagram of the virtual reality practice environment for CAD teaching assistance in two classes.

As shown in Figure 8, the average scores of four practical operation exams for two classes are presented. Each of the four types of practical operation exams assesses the speed, accuracy, and correctness of the operation. The final determination of whether the operation is fully passed is based on the class average scores. The data in the figure shows that only two of the four practical operation scores for Class A were fully passed, with an average score of about 70. However, all four practical operation scores for Class B were passed, with an average score above 85. This indicates that the application of CAD-assisted teaching based on deep learning algorithms and virtual reality systems in practical teaching can provide students with a virtual reality practice environment that better meets their actual needs, effectively improving their practical operation ability and performance.

5 CONCLUSIONS

In the context of educational reform, the teaching content and objectives have placed more emphasis on the balance between theory and practice, and the practical operation ability of students is increasingly emphasized. The integration of CAD-aided teaching and virtual reality practice platforms has broadened the development path for educational reform.

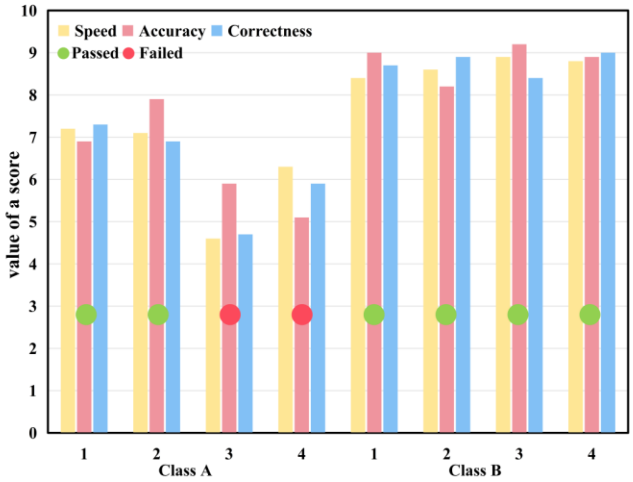

Figure 8: Comparison of average scores for four practical operation exams between two classes.

To enhance the integration of CAD-aided teaching and virtual reality practice platforms, this paper constructs an image recognition and classification module based on CNN in deep learning algorithms to improve the efficiency of CAD model recognition and classification, providing effective basic data for the construction of a virtual reality practice environment. Meanwhile, this paper also constructs a virtual teaching scene construction module based on GAN, which optimizes the virtual reality practice environment, improves image positioning performance, and reduces the time for selecting and importing a virtual environment. Experimental results show that compared with other models, this model exhibits higher CAD model recognition accuracy and good classification rate and performs well in CAD model recognition and classification of different difficulty levels, demonstrating high stability. Additionally, this model effectively improves the selection and import speed of the virtual reality practice environment, reducing the image positioning error rate. In application experiments, this model can provide students with a virtual reality practice environment that is more in line with actual situations and needs, increasing the possibility and convenience of students' practical operation in this environment and effectively improving their practical operation ability.

6 ACKNOWLEDGEMENT

Scientific Research Program Funded by Shaanxi Provincial Education Department "Construction and Empirical Research of College Students' Autonomous Learning Ability Model from the Perspective of Digital Transformation" (No.23JK0436).

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