





Application of Graph Neural Network and Virtual Reality Based on the Concept of Sustainable Design

Nana Li^{1,3}  and Hui Ma^{2,4} 

¹College of Art and Design, Hefei University of Economics, Hefei 230000, China, linanaart@gmail.com

²School of Intelligent Manufacturing, Anhui Wenda University of Information Engineering, Hefei 230000, China, 202009060020@student-city.edu.my

^{3,4} City Graduate School, City University Malaysia, Kuala Lumpur 46100, Malaysia, ³linanaart@gmail.com, ⁴202009060020@student-city.edu.my

Corresponding author: Hui Ma, 202009060020@student-city.edu.my

Abstract. With the rapid development of science and technology, sustainable design has gradually become the core concept in the field of design. The purpose of this study is to explore the application of a graphical neural network (GNN) model combined with CAD in order to support the practice of sustainable design. By integrating the latest research progress at home and abroad, we show the innovative potential of the combination of CAD and VR in the design field. At the technical and methodological level, we propose a new model based on a graph neural network, which integrates CAD design data with VR experience data to achieve real-time and immersive feedback and interaction of designers. The experimental design selects the actual design case and compares the traditional design process with the design process based on the GNN model. The results show that the model has significantly improved the design efficiency and quality, which helps designers better understand the feasibility of the design scheme. The research provides new ideas and tools for the integration of sustainable design concepts and technology in the design field and further promotes the development of the design industry.

Keywords: Sustainable Design; Core Concepts; Computer-Aided Design; Virtual Reality

DOI: <https://doi.org/10.14733/cadaps.2024.S28.15-27>

1 INTRODUCTION

Computer-aided design (CAD) and virtual reality (VR) are two important technologies in the field of modern design. CAD is a tool for computer-aided design and drawing, and it is widely used in architecture, engineering, industrial design, and so on. The successful application of neural networks has brought significant progress to related fields. Angrish et al. [1] analyzed the multi-view convolutional network algorithm for 3D model applications. They explored the engineering convolutional network model under metadata. the classification accuracy of MVCNN++ has improved

by 5.8%, proving its effectiveness in engineering model classification. These technologies help us more accurately capture the structural features of 3D CAD models, thereby improving the accuracy of classification and retrieval. By utilizing pre-trained model parameters in relevant fields, we can accelerate the training process of new models while maintaining high classification accuracy. When dealing with the training data capture problem unique to 3D CAD models, it adopts relaxation classification technology and original angle cameras to capture feature details. It can improve the design efficiency, accuracy and designer's work efficiency, and provide strong support for the production and modification of design schemes. Bian et al. [2] ingeniously proposed a machine learning architecture called HG-CAD, which is based on the intelligence of Graph Neural Networks (GNNs). Research has shown that using optimization algorithms embedded in virtual networks can improve the efficiency of network resource utilization. By embedding algorithms in virtual networks, relatively flexible, reliable, secure, and efficient web services can be provided for virtual network requests, providing better network support for new applications such as cloud computing, the Internet of Things, and 5G. Secondly, through algorithms, the virtual network is assigned to multiple physical networks, thereby improving the reliability of the network and avoiding errors. Avoiding the chaotic use of physical networks also enhances the network's related capabilities. The virtual network embedding algorithm can also support dynamic adjustment of the size and position of the virtual network, improving the agility and adaptability of virtualization technology. By allocating physical resources to users, the computing, storage, and network resources in the physical network are utilized reasonably by the users in need. This type of algorithm is still a direction pursued by researchers in the field of network technology, involving multiple directions such as algorithm optimization, network topology, network security, etc. It is of great significance for promoting the development and application of network technology. At the same time, Deng and his team also brought us a visual and cultural feast. They cleverly integrated cultural experience backgrounds into the design of virtual tourism products, solving the dilemma of homogenization of tourism products. By leveraging the magic of computer-aided design (CAD) and graphical neural networks (GNN), they have created a unique virtual 3D modelling system and VR interactive tourism products [3].

Driven by the digital wave, the digital twin industrial system environment of virtual reality is gradually becoming the core of user interaction statistics. This technology is not only highly anticipated in the entertainment and gaming fields, but also demonstrates enormous potential in industrial design. Currently, the development of 6G network hardware networks is slow, and it is necessary to study network virtualization technology to achieve resource sharing, among which the problem of virtual network embedding is a key challenge [4]. In order to meet and balance the needs of network service providers and users, the designed virtual network embedding algorithm needs to maximize the revenue of network service providers and user experience. The optimization objectives for existing solutions usually focus on a single indicator or a simple combination of multiple indicators, making it difficult to embed virtual network requests reasonably, and the experimental results are also unsatisfactory. Li et al. [5] proposed a virtual network embedding algorithm GAT-VNE based on a graph attention mechanism. Through simulation experiments, we have verified the performance of the GAT-VNE algorithm at different network scales. In the node embedding stage, a node resource capability quantification method was proposed to quantify the node embedding potential. Not only does it consider the resource capacity of nodes, but also the resource capacity of the entire network. By introducing an attention mechanism to determine the weights between nodes, the relationship between nodes can be measured. Through simulation experiments, it has been proven that the VGAE-VNE algorithm performs well in the evaluation indicators of acceptance rate, long-term average revenue, and long-term average CPU resource utilization, and its overall performance is superior to other comparative algorithms. These representations aggregate the characteristics of the nodes themselves and the network structure, and then we use the K-means clustering method to distinguish the embedded representations obtained. Simple embedding representations can be learned through variational graph autoencoders. Although graph convolutional neural networks can encode representations of nodes, they ignore the relationship between nodes during encoding, which may result in suboptimal embedding results.

The outstanding contribution of Madni et al. [6] lies in their vision and concept of perfectly integrating digital twin technology with graph neural networks (GNN) and model-based systems engineering (MBSE). VR, with its unique real-time feedback and immersive experience, has brought unprecedented design effects to designers. Designers seem to be immersed in a real three-dimensional world, able to intuitively feel every detail and change of the design. This integration not only demonstrates the power of technology but also reflects the thoughtful consideration and humanistic care for future industrial design. The immersive experience enables designers to comprehensively evaluate the impact of design solutions on the environment and society, ensuring that the design is more in line with practical needs. Virtual reality technology has entered a stage of rapid development. Virtual reality technology generates realistic images through computer graphics methods and provides users with an immersive experience through various interactive means. McDonald et al. provided a way for users to communicate face-to-face through facial expressions in virtual reality environments. The recognition and classification of facial expressions utilize the emerging framework of convolutional neural networks. This system effectively combines the advantages of both and achieves good results. The system is mainly divided into two main parts: an algorithm for automatic recognition, tracking, and segmentation of user faces, and a facial expression recognition part based on convolutional neural networks. The experimental data shows that this system performs well in both computational performance and recognition rate. The system is mainly aimed at the field of mobile virtual reality and has broad application prospects in multiplayer applications and games. This system proposes a unique and innovative facial expression recognition process algorithm under the interactive topic of virtual reality. The user facial recognition, tracking, and segmentation algorithms mainly use traditional digital image processing techniques, which analyze image feature information and colour histograms. In current virtual reality applications and games, users often can only interact with each other through voice (microphone) and gestures (controller). This makes face-to-face communication between users not smooth and intuitive enough [7]. The reduction in experimental frequency and cost will bring more time and energy for researchers to focus on more valuable explorations. Imagine when scientists no longer need to spend a lot of time and resources blindly experimenting, but can quickly target molecules through GNN technology, what kind of changes will this bring to fields such as material synthesis and drug discovery? On the stage of computer-aided material design (CAMD), the introduction of GNN is like a wise man proficient in music, chess, calligraphy, and painting, helping scientists quickly explore countless possible molecular combinations. It means less energy consumption, less waste generation, and shorter product development cycles, which undoubtedly makes a huge contribution to the environment. The wave of industrial digitization is sweeping through, with the core goal of cleverly integrating artificial intelligence (AI) into manufacturing systems. However, it is not easy to make GNN shine in the industry, lower its technological threshold, and promote widespread application. In the integration of CAD and VR, GNN is like an invisible conductor, silently handling the relationship between design data and virtual reality data, providing designers with richer and more accurate feedback. Mourtzis et al. [8] ingeniously proposed a framework based on augmented reality (AR), which is not only a technical tool but also a bridge connecting technology and human understanding. This intuitive understanding framework will undoubtedly greatly simplify the construction and training process of GNN, enabling engineers to more easily and efficiently create high-performance GNN models. Not only dedicated to promoting engineers to have a deeper understanding and construction of GNN but also committed to spreading the power of knowledge widely through diverse communication channels. Especially by utilizing cutting-edge technologies such as Graph Neural Networks (GNN), intelligent machinery and optimized production processes are brought to the manufacturing industry. In the vast field of design, CAD and VR technologies each shine with unique characteristics.

It breaks the boundaries of traditional design, allowing designers to intuitively feel every detail and change in the design. Designers can use VR technology for real-time preview and modification under the precise guidance of CAD, making the entire design process more efficient and smooth. When delving into innovative technologies in the field of design, it is not difficult to discover the unique charm and potential of CAD (computer-aided design) and VR (virtual reality). However, as we

look further into the future, we realize that the combination of CAD and VR is not just a simple technological overlay. VR, on the other hand, brings designers into seemingly real three-dimensional space with its immersive experience, allowing them to intuitively feel, evaluate, and even modify design proposals, undoubtedly injecting new vitality into the design process. Their interaction and integration are quietly leading the design field into a new era. CAD, with its precise and digital characteristics, provides unparalleled auxiliary tools for designers, enabling every design detail to be accurately presented, greatly improving the accuracy and efficiency of design.

2 RELATED WORK

Nagarajan et al. [9] adopted an innovative approach by utilizing machine learning techniques to model multiple key process variables in AM. Moreover, its model design also emphasizes interpretability, enabling engineers and technicians to clearly understand the working principle and prediction basis of the model. A 3D model retrieval algorithm based on paired view weighted graph neural network. Non-local modules are used for mining multi-view relationships. The weighted view aggregation layer is used for weighing different views and aggregating view features. The information contained in views from different perspectives is different. Mining high discriminative views to reduce the impact of easily confused views is the key to improving retrieval performance. This paper designs a Paired View Weighted Graph Neural Network (PVWGN). Original feature capture is used to capture features at different levels. It includes three modules: original feature capture, multi-view relationship mining, and multi-view feature aggregation. Finally, the paired discrimination loss function was used to further improve feature discrimination. Experiments on public datasets have shown that PVWGN achieves advanced performance in 3D model retrieval tasks [10]. More and more 3D models are being applied in various fields such as industrial product design, virtual reality, etc., and 3D model retrieval is becoming increasingly important in these fields. With the development of deep learning, some researchers have applied it to 3D model retrieval, but currently, there is a lack of comprehensive evaluation of the performance of deep learning in 3D model retrieval. The 3D model retrieval algorithm based on multiple perspectives has achieved superior performance, but there is still room for improvement in mining potential associations from multiple perspectives. Some researchers have also applied it to 3D model retrieval, but currently, there is a lack of comprehensive evaluation of the performance of deep learning in 3D model retrieval. Based on the above issues, Parker et al. [11] conducted a comprehensive evaluation of the performance of deep learning algorithms in multi-view 3D model retrieval. Exploration of Deep Learning in 3D Model Retrieval. Although deep learning has achieved tremendous results in fields such as speech recognition and image recognition. The performance of deep learning in 3D model retrieval was systematically evaluated through the following methods. At the same time, potential correlation information from multiple perspectives was analyzed and discussed, and non-local graph neural networks and paired view weighted graph neural networks were designed. The results of large-scale experiments show that in 3D model retrieval, the performance of deep learning features is significantly better than that of manually designed features, and deep learning features have better robustness. This method utilizes residual networks as the base network and embeds non-local graph neural networks into the base network to learn potential correlations between multiple perspectives. Finally, high-response 3D shape descriptors are obtained through maximum pooling. The experimental results on public datasets show that non-local graph neural networks have excellent performance in mining potential associations from multiple perspectives. In addition, multi-perspective deep learning features have lower computational complexity and better performance, making them more practical.

Virtual network embedding algorithms can promote innovation and development of networks in multiple directions, which is of great significance for promoting the development and application of network technology. By embedding algorithms in virtual networks, relatively flexible, reliable, secure, and efficient web services can be provided for virtual network requests, providing better network support for new applications such as cloud computing, the Internet of Things, and 5G. Virtual network embedding algorithms can help 5G networks achieve virtual network slicing and resource allocation, making 5G networks more stable and efficient. The virtual network embedding algorithm

can help data centres manage and allocate virtual network resources, and the efficiency and reliability of data centre networks will be improved. Algorithms play a certain role in the rational allocation and dynamic scheduling of network resources, thereby making network services more reliable and improving efficiency [12]. Multi-tenant cloud service management: In multi-tenant environments such as cloud computing, virtual network embedding algorithms can help cloud service providers achieve resource sharing and virtual network segmentation, improving the agility and scalability of cloud services. The network embedding algorithm can help software define the virtual network flow table in the network to achieve dynamic adjustment and mapping and achieve the flexibility and programmability of network functions. Virtual network embedding algorithms can help IoT devices connect and manage virtual networks, improving the communication efficiency and reliability of IoT devices. The research of Shan and Sun [13] shows that using optimization algorithms embedded in virtual networks can improve the efficiency of network resource utilization. By using algorithms, virtual networks are assigned to multiple physical networks to improve their reliability and avoid errors. Avoiding the chaotic use of physical networks also enhances the network's related capabilities. In addition, the virtual network embedding algorithm can also support dynamic adjustment of the size and position of the virtual network, improving the agility and adaptability of virtualization technology.

Traditional facial detection and recognition based on digital image processing mostly rely directly on pixels and some simple feature values when classifying images. How to track and recognize occluded faces in the process of multi-user interaction is also one of the problems that needs to be solved in the new environment. Therefore, traditional facial recognition based on digital image processing is difficult to play a role in virtual reality environments. The system described by Vernica et al. [14] provides users with an intuitive face-to-face interaction by recognizing their facial expressions in a virtual reality environment. They demonstrated an innovative system with simple and fully functional hardware devices. It proposes an automatic facial expression recognition processing pipeline that can effectively apply traditional digital image processing techniques to modern virtual reality environments. This framework is suitable for recognizing facial expressions when users wear headsets. This framework is based on convolutional neural network models, allowing users to experience real-time and intuitive interaction with other users in virtual reality environments, and is suitable for various application scenarios. This method only requires an additional RGB colour camera on top of existing head-mounted display devices. The required hardware components are easy to obtain and assemble. This interaction method can be applied in multiplayer virtual reality applications. Exploration of Deep Learning in 3D Model Retrieval. Yin et al. [15] evaluated deep learning features from multiple perspectives by comparing different deep learning features with manual features. In order to fully utilize the spatial relationships between different perspectives, this paper proposes a 3D model retrieval method based on a local Graph Neural Network (NGNN). After capturing advanced features from multiple perspectives, the weighted view aggregation layer is used to weigh different views and aggregate view features. On the basis of non-local graph neural networks, they designed a pairwise view weighted graph neural network to obtain high discrimination model features through the following three modules. This method utilizes residual networks as the base network and embeds non-local graph neural networks into the base network for learning potential correlations between multiple perspectives.

3 DESIGN OF NEURAL NETWORK MODEL FOR SUSTAINABILITY MAP

3.1 Graph Neural Network

Domestic research has also begun to explore sustainable design methods based on CAD and VR, such as optimizing design schemes by simulating building energy consumption and environmental impact. Research at home and abroad has made progress in VR interaction, such as enhancing designers' interaction in VR environments through gesture recognition, eye tracking and other technologies. In addition, some studies focus on providing design feedback through VR to help designers more quickly identify potential problems and make adjustments.

In general, the relevant work at home and abroad focuses on the combination of CAD and VR, promoting the innovation of the design process through graph neural networks and other advanced technologies, improving design efficiency and quality, and promoting the practice of sustainable design. With the continuous development of technology, these fields will continue to attract researchers' attention and bring more opportunities to the design field. A neural network is a computational model based on a biological neural network, which simulates the learning and decision-making process of the human brain through a series of connected artificial neurons.

In the vast field of design and engineering, neural network algorithms also play a crucial role, providing innovative solutions for problems such as automatic design, structural optimization, and complex system modelling. During the design process, designers need to constantly adjust and optimize the design plan. By convolving and aggregating the features of nodes and edges through GNN, designers can gain a deeper understanding of the relationships between various parts of the design, thereby making more scientific and reasonable decisions. In graph theory, graphs are composed of nodes and edges, and graph neural networks extract and learn the relationships and features between data through these nodes and edges. In the fields of design and engineering, the advantages of graph neural networks are particularly evident. In the real world, a lot of data exists in the form of graph structures, such as social networks, transportation networks, circuit design, etc. Traditional neural networks often focus more on two-dimensional data when processing data. This enables GNN to be applicable to various complex design scenarios, whether it is architectural design, circuit design, or mechanical design, GNN can provide strong support for them. Secondly, GNN excels in extracting and analyzing the relationships and correlations between data. In design, the correlation and mutual influence between different parts are crucial.

3.2 Image Recognition Based on GNN

By optimizing and merging visual marker sequences, GNN can achieve more efficient performance in image recognition and analysis. Figure 1 highlights the complete autoregressive architecture ultimately used in CAD in this study.

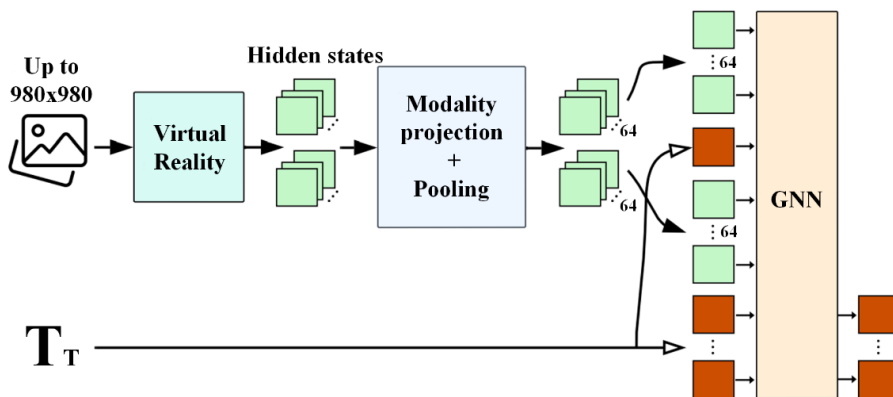


Figure 1: Complete autoregressive architecture diagram of GNN for CAD.

The complete autoregressive architecture in Figure 1 is that the VR input image is processed by the visual encoder. The generated visual features are mapped and optionally aggregated into the GNN input space to obtain visual markers, which is 64 in the standard configuration of this study. They are connected to the input sequence (green and red columns) embedded in the text and maybe interleaved. The connected sequence is input to the CAD model, which is output in the form of text tags.

The highest layer in Figure 1 will output a real number, and the lowest layer is the FM layer. The recognition probability is expressed by the following formula.

$$\hat{y} = \text{sigmoid}(W_3 l_2 + b_3) \quad (1)$$

l_2 in the formula is the input characteristic of its layer, which can be calculated by the formula.

$$l_2 = \tanh(W_2 l_1 + b_2) \quad (2)$$

Tanh is the activation function selected in this study. l_1 in the function is the original characteristic input value. The calculation formula is:

$$l_1 = \tanh(W_1 z + b_1), z = (w_0, z_1, z_2, \dots, z_i, \dots, z_n) \quad (3)$$

The number of domains is represented by n in the above formula and z_i is the vector parameter in the i domain. The calculation method is:

$$z_i = W_0^i \times x[\text{start}_i : \text{end}_i] = (w_i, v_i^1, v_i^2, \dots, v_i^K) \quad (4)$$

Initialize the vector FM of the first layer to get:

$$y_{FM} = \text{sigmoid}(w_0 + \sum_{i=1}^N w_i x_i + \sum_{i=1}^N \sum_{j=i+1}^N x_i x_j) \quad (5)$$

Through the above calculation steps, the GNN algorithm can improve the model's learning ability and generate more potential data relationships. Continue to add the weight of the hidden layer to the algorithm model for calculation. First, the cross-loss function is used to initialize all four layers.

$$L(y, \hat{y}) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y}) \quad (6)$$

Because the input element has only one positive value, backpropagation can be used to update the weight value, making the GNN algorithm model more effective.

The error generated by calculating the GNN neural network for each iteration is:

$$\delta_j = \frac{\partial L}{\partial z_j} = \frac{\partial L}{\partial a_j} \times \frac{\partial a_j}{\partial z_j} = \nabla a_j \times \sigma(z_j) \quad (7)$$

Then vectorization is carried out to obtain:

$$\delta^L = \nabla a^L \odot \sigma(z^L) \quad (8)$$

Where \odot is the product of the corresponding weight value? The error of each layer can be recursively calculated as follows:

$$\delta_j = \frac{\partial C}{\partial z_j} = \sum_k \frac{\partial C}{\partial z_k} \times \frac{\partial z_k}{\partial a_j} \quad (9)$$

$$\sum_k \delta_k w_{kj} \sigma(z_j) = \sum_k \delta_k \times \frac{\partial(w_k a_i + b_i)}{\partial a_j} \quad (10)$$

The offset gradient of each layer in the model structure is:

$$\nabla b_j = \frac{\partial C}{\partial b_j} = \delta_j \frac{\partial(w_j a_i + b_i)}{\partial w_{ji}} \quad (11)$$

Within the range of this gradient, and taking into account the error obtained, the aided design model of sustainable graph neural network algorithm is finally obtained.

4 APPLICATION OF NEURAL NETWORK MODEL OF SUSTAINABILITY MAP

The neural network model of sustainability maps has a wide application potential in the field of design and computer vision. The main experiment of this study includes two studies. Firstly, the moving people or objects in the video are extracted by a graph neural network model, and then they are replaced with different backgrounds. This method can be used in video production, film special effects, virtual reality and other fields to help creators flexibly change the background and create different scenes without changing the subject. Through feature extraction and fusion of the model, it can recognize others or objects more accurately, and maintain their original features and actions in the new background.

Secondly, this study also scores and ranks the order of short videos. This paper analyzes the time series data in a short video by graphing the neural network model, extracting the characteristics and structure of video content, and making a comprehensive evaluation. The model can give the score of video order according to the theme coherence, content richness, and editing fluency of the video and sort the short video. This method can be used for content recommendation and ranking on short video platforms to improve user experience and content quality.

4.1 Extracting Moving People or Objects in Video for Background Replacement

Video scene replacement is a complex and challenging task that involves accurate recognition and replacement of moving objects in video. The experiment based on a graph neural network model regards the motion of the head, legs, and feet as the baseline to ensure the continuity and consistency of motion in the process of video replacement. Dynamic Gaussian splash is used to represent the motion flow line, and the motion trajectory of the object is presented by the flow line graph generated in the video. This method can help the model better understand the motion features in video.

In the experiment, the image recognized by VR is replaced with the frame generated by the video model to achieve the reference frame in the video. This method can ensure that the displacement of the video scene is more accurate and realistic so as to retain the action and characteristics of the original object in the new scene. Since baseline mainly deals with single-object video, it is also compared with its variants, which combine the technology of motion baseline and video scene decomposition. By regrouping these Gaussian objects, the quality and effect of video displacement can be further improved. The effect is shown in Figure 2 below.

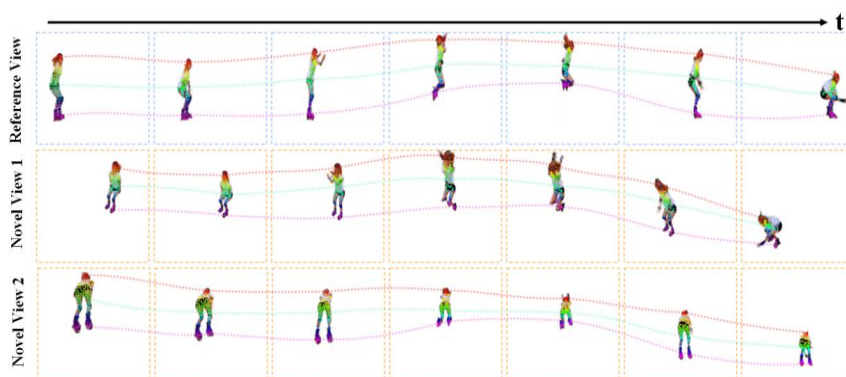


Figure 2: The model uses VR technology to extract human action.

Ablation experiments were also carried out to eliminate the flow rendering loss and physical-based motion loss. These ablation experiments can help researchers better understand the contribution of different model components to the overall effect and the interaction between them. The ablation

experiment can optimize the performance of the model and improve the quality of video scene replacement. The result of replacing the extracted moving character with a graffiti background wall is shown in Figure 3 below.

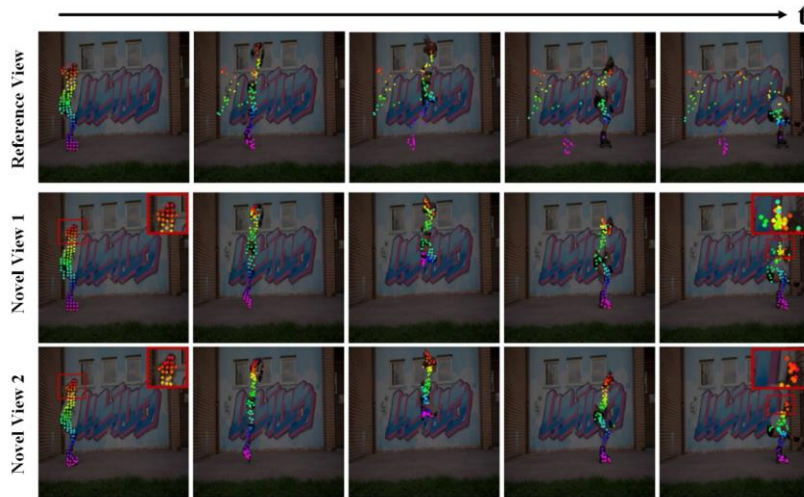


Figure 3: Background result of model replacement.

In Figure 3 the moving characters were accurately replaced in front of the graffiti wall, and appropriate light and shadow effects were added to the scene. The multi-colour origin in the red box is generated by extracting the colour features of the head of a moving person through the VR device. This shows that the results of background replacement using this study are very reliable. The effect shown in Figure 3 reflects the model's ability to accurately recognize moving objects and replace backgrounds in complex video environments. Through the accurate extraction of character motion and colour features, as well as the seamless integration with the background, this study successfully realized the replacement of characters in the video scene and enhanced the authenticity and viewing of the scene.

In order to verify the importance of VR technology in the system, the background replacement accuracy experiment is carried out in this paper. First of all, the benchmark group was set up, with the non-use of VR technology as the control group and the use of VR technology as the experimental group for verification. In order to ensure the scientificity of the experiment, five videos were selected as the object, and the three groups were used for action extraction and background replacement. The accuracy was visually analyzed, as shown in Figure 4.

By comparing the results of the control group and the experimental group, we can intuitively observe the influence of VR technology on the accuracy of background replacement in the system. In the experimental group, we deeply explored the application effect of VR technology in background replacement tasks, especially in maintaining motion continuity and ensuring the accuracy of background replacement. This experimental result fully demonstrates the crucial role that virtual reality technology plays in the entire system. The introduction of VR technology not only enhances its practicality but also brings unprecedented innovation to the field of video production. With short videos becoming the mainstream form of media today, the uneven quality of their content has brought significant challenges to video platforms. We believe that this research will provide a solid theoretical foundation and technical support for future video processing research and applications. Through this experiment, we were able to gain a deeper understanding of the indispensable role of VR technology in video processing and background replacement.

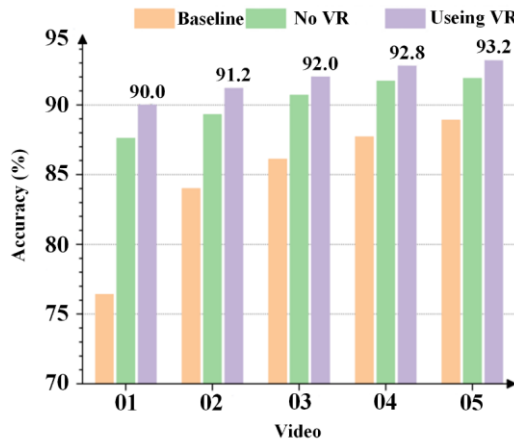


Figure 4: Experimental results of video background replacement accuracy.

4.2 The Model Scores the Order of Short Videos

By analyzing the ranking of short videos, we can more accurately evaluate their quality and provide valuable references for video platforms. Short videos with high order often attract the audience's attention and provide a smooth and interesting viewing experience. This not only helps to improve the content quality of video platforms but also brings a better viewing experience to the audience. In order to effectively evaluate the quality of short videos, video platforms need a scientific method to sort and rate videos. The core indicator we focus on here is the order of the video, which includes the continuity, richness, and smoothness of the video content. Therefore, the study of short video ranking and rating has important practical significance and far-reaching application prospects.

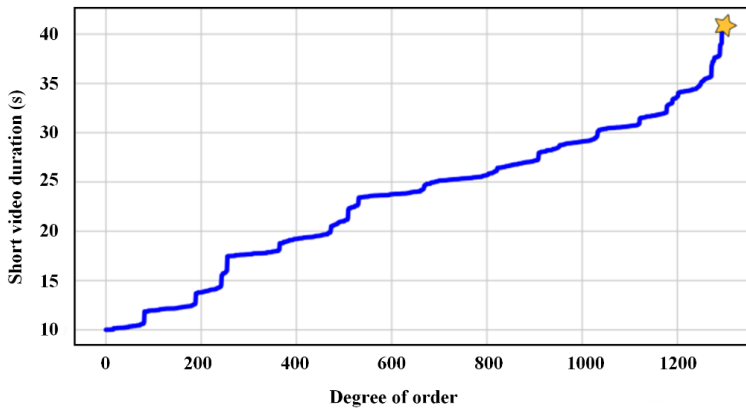


Figure 5: Diagram of order test results of the model on short video.

Figure 5 clearly depicts the order score curve, which intuitively displays the performance differences and arrangement order between different short videos. This difference is not accidental, they may stem from multiple aspects such as video production skills, creative ideas, and content quality. In order to gain a deeper understanding of the characteristics and differences of these short videos, we utilized a sustainable graph neural network model. Specifically, the model reveals key indicators such

as important plot transitions, thematic expression, content richness, and coherence in short videos by extracting the "threshold kernel" of the video. By observing this curve, it is not difficult to find significant differences in the scores and rankings of various short videos. These threshold kernels not only help us comprehensively evaluate the content creativity and production quality of short videos but also provide a reliable basis for video platforms to evaluate and recommend high-quality short videos accurately. Figure 6 shows the threshold kernel results of these short videos, and through comparison, we can clearly see the advantages of high-order short videos in content creativity, production skills, and overall quality. This model has powerful data analysis and feature extraction capabilities and can accurately capture key features and core elements in short videos.

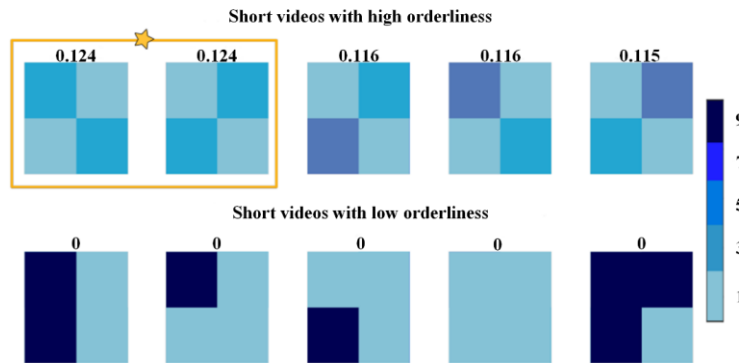


Figure 6: Model analysis short video threshold kernel.

Observing Figure 6 in-depth, it is not difficult to find that short videos with high order also exhibit more diverse threshold kernels. Especially for short videos with star logos, their scores still rank first, fully demonstrating their outstanding quality in the field of short videos. The platform can more accurately recommend high-quality short videos to users, improving user experience and the platform's reputation. In order to further reveal the threshold kernel distribution pattern of short video content, this software was used to conduct an in-depth analysis of a large number of works on short video platforms. By carefully analyzing these threshold kernels, the highlights and shortcomings of short videos can be clearly identified. This provides valuable feedback for video platforms and creators. The distribution results of threshold kernels for these works are shown in Figure 7. These short videos not only have rich and colourful content but also have excellent performance in various key indicators. This distribution chart intuitively reflects the overall performance of short videos in terms of key features and content quality. Including the compactness of plot structure, clarity of thematic expression, and coherence of content.

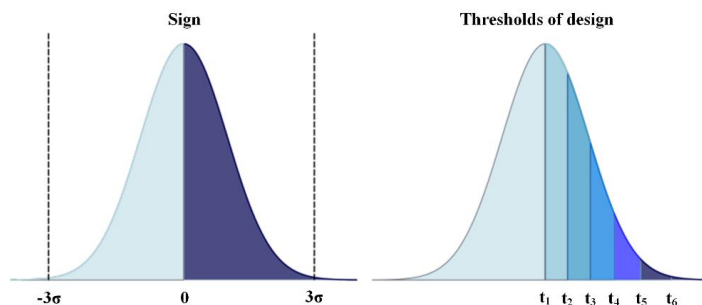


Figure 7: Short video threshold kernel distribution.

5 CONCLUSIONS

After a series of carefully designed experiments, this study fully validated the outstanding performance and widespread application of the Graph Neural Network (GNN) model in the fields of design and computer vision. This new design pattern brings designers an unprecedented immersive experience, making the design process more intuitive, efficient, and creative. With the help of GNN-based models, this article seamlessly integrates CAD data and VR technology into the design process, achieving real-time visualization and interaction. It can accurately identify and replace moving characters while ensuring that the replaced background perfectly blends with the action details and features of the original characters. This technology not only greatly enriches the means of video production but also demonstrates enormous potential for application in the fields of movie special effects and virtual reality. Firstly, in the video replacement experiment, the GNN-based model demonstrated extraordinary talent. By conducting an in-depth analysis of the time series data of short videos, this model can accurately extract the features and structure of video content and scientifically grade and rank short videos. This article provides an intuitive view of CAD models in a virtual reality environment and quickly adjusts and optimizes design solutions based on real-time feedback and in-depth analysis provided by GNN. This not only helps video platforms recommend higher-quality short video content to users but also provides valuable feedback and suggestions for creators.

6 ACKNOWLEDGEMENT

2022 Provincial Key Scientific Research Project of Higher Education Institutions (Philosophy and Social Sciences) "Research on Visualization Design of Public Health Popularization Information in the Post-Epidemic Era" (Project Number: 2022AH052617).

Nana Li, <https://orcid.org/0009-0007-2131-3857>

Hui Ma, <https://orcid.org/0009-0000-0179-6889>

REFERENCES

- [1] Angrish, A.; Bharadwaj, A.; Starly, B.: MVCNN++: computer-aided design model shape classification and retrieval using multi-view convolutional neural networks, *Journal of Computing and Information Science in Engineering*, 21(1), 2021, 011001. <https://doi.org/10.1115/1.4047486>
- [2] Bian, S.; Grandi, D.; Liu, T.; Jayaraman, P.-K.; Willis, K.; Sadler, E.; Li, B.: HG-CAD: hierarchical graph learning for material prediction and recommendation in computer-aided design, *Journal of Computing and Information Science in Engineering*, 24(1), 2024, 1-14. <https://doi.org/10.1115/1.4063226>
- [3] Deng, Y.; Han, S.-Y.; Li, J.; Rong, J.; Fan, W.; Sun, T.: The design of tourism product CAD three-dimensional modeling system using VR technology, *Plos One*, 15(12), 2020, e0244205. <https://doi.org/10.1371/journal.pone.0244205>
- [4] Jinzhi, L.; Zhaorui, Y.; Xiaochen, Z.; Jian, W.; Dimitris, K.: Exploring the concept of Cognitive Digital Twin from model-based systems engineering perspective, *The International Journal of Advanced Manufacturing Technology*, 121(9), 2022, 5835-5854. <https://doi.org/10.1007/s00170-022-09610-5>
- [5] Li, K.; Gan, V.-J.; Li, M.; Gao, M.-Y.; Tiong, R.-L.; Yang, Y.: Automated generative design and prefabrication of precast buildings using integrated BIM and graph convolutional neural network, *Developments in the Built Environment*, 18(1), 2024, 100418. <https://doi.org/10.1016/j.dibe.2024.100418>
- [6] Madni, A.-M.; Madni, C.-C.; Lucero, S.-D.: Leveraging digital twin technology in model-based systems engineering, *Systems*, 7(1), 2019, 7. <https://doi.org/10.3390/systems7010007>

- [7] McDonald, T.; Tsay, C.; Schweidtmann, A.-M.; Yorke, S.-N.: Mixed-integer optimisation of graph neural networks for computer-aided molecular design, *Computers & Chemical Engineering*, 185(1), 2024, 108660. <https://doi.org/10.1016/j.compchemeng.2024.108660>
- [8] 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>
- [9] Nagarajan, H.-P.; Mokhtarian, H.; Jafarian, H.; Dimassi, S.; Bakrani, B.-S.; Hamed, A.; Haapala, K.-R.: Knowledge-based design of artificial neural network topology for additive manufacturing process modeling: A new approach and case study for fused deposition modeling, *Journal of Mechanical Design*, 141(2), 2019, 021705. <https://doi.org/10.1115/1.4042084>
- [10] Ngoc, Q.-T.; Lee, S.; Song, B.-C.: Facial landmark-based emotion recognition via directed graph neural network, *Electronics*, 9(5), 2020, 764. <https://doi.org/10.3390/electronics9050764>
- [11] Parker, D.; Roudavski, S.; Jones, T.-M.; Bradsworth, N.; Isaac, B.; Lockett, M.-T.; Soanes, K.: A framework for computer-aided design and manufacturing of habitat structures for cavity-dependent animals, *Methods in Ecology and Evolution*, 13(4), 2022, 826-841. <https://doi.org/10.1111/2041-210X.13806>
- [12] Sadeghi, N.-A.; Choi, S.-M.: A survey of marker-less tracking and registration techniques for health & environmental applications to augmented reality and ubiquitous geospatial information systems, *Sensors*, 20(10), 2020, 2997. <https://doi.org/10.3390/s20102997>
- [13] Shan, P.; Sun, W.: Research on landscape design system based on 3D virtual reality and image processing technology, *Ecological Informatics*, 63(1), 2021, 101287. <https://doi.org/10.1016/j.ecoinf.2021.101287>
- [14] Vernica, T.; Lipman, R.; Kramer, T.; Kwon, S.; Bernstein, W.-Z.: Visualizing standardized model-based design and inspection data in augmented reality, *Journal of Computing and Information Science in Engineering*, 22(4), 2022, 041001. <https://doi.org/10.1115/1.4053154>
- [15] Yin, Y.; Zheng, P.; Li, C.; Wang, L.: A state-of-the-art survey on augmented reality-assisted digital twin for futuristic human-centric industry transformation, *Robotics and Computer-Integrated Manufacturing*, 81(1), 2023, 102515. <https://doi.org/10.1016/j.rcim.2022.102515>