

Graph Neural Networks-Based Virtual Reality Data Fusion Display for New Media Art

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Abstract. New media art is a specific manifestation of the integration of artistic expression and data technology. Its combination with virtual reality technology can enrich the forms of artistic expression and enhance the interactivity and immersion of artistic display. At the same time, the integration of CAD and virtual reality data poses challenges in terms of compatibility, interactivity, and stability for new media art displays. Therefore, this paper constructs a CAD and virtual reality data fusion model based on graph neural networks and LSTM and constructs an interactive scene recognition model combined with GRU. The experimental results show that the model in this paper exhibits good data fusion performance and stability, which can improve the rendering effect of virtual reality scenes and enhance the immersion of the scenes. Meanwhile, the scene recognition accuracy in two different datasets and can effectively recognize complex and confusing dynamic scenes and make corresponding judgments, providing good virtual reality interactive technical support for new media art displays.

Keywords: Graph Neural Network; New Media Art; Virtual Reality; Data Fusion; Scene Recognition **DOI:** https://doi.org/10.14733/cadaps.2024.S28.97-109

1. INTRODUCTION

With the rapid development of new media art, the forms of artistic expression and interactive experiences are becoming increasingly diversified. The integration of CAD (Computer-Aided Design) and VR (Virtual Reality) technology has gradually become a research hotspot. New media art, with its unique innovation and interactivity, has brought unprecedented artistic experiences to the audience. In the context of new media art, Akilan et al. [1] utilized this technology to create dynamic artworks. In addition, by artistically processing and recombining these features, we can create unique visual effects, such as the deformation, reconstruction, or fusion with other visual elements of FG objects. By perfectly combining digital media technology with art, new media interactive installation art has become a new form of art. Bansal et al. [2] will start from an artistic perspective and use new media

interactive installation art as a prerequisite. Define the concepts of new media interactive installation art, virtual and real, and immersive, and analyze the development of new media interactive installation art. By using literature research and case analysis methods, this emerging art is studied for its diverse and diverse forms of expression, as well as its unique aesthetic characteristics. At the same time, its media, the relationship between authors and readers, and the way it experiences texts have undergone unprecedented changes. This gives new media interactive installation art unique aesthetic features. Due to the fact that most of the existing theoretical achievements are based on a technical perspective. New media interactive installation art is different from traditional art forms. Due to the use of multiple media, it brings infinite possibilities for the creative and expressive forms of new media interactive installation art. New media interactive installation art integrates digital technology, interactive concepts, and interactive art on the basis of traditional installation art.

Cedillo et al. [3] studied three contemporary art exhibitions based on different types in Shanghai. Contemporary art exhibitions need to improve their media communication strategies and modes, shifting from mass media communication to a unique mode of art communication. Different types of contemporary art exhibitions have different communication effects based on different communication contents, channels and input costs. Taking different types of art audiences as research objects, this paper elaborates on the current acceptance effect of online media on audiences, as well as the overall impact of art exhibition media dissemination. The audience attention of internet celebrity new media art exhibitions is relatively high, while academic exhibitions have weaker dissemination effects on ordinary audiences. There are differences in the cognitive, emotional, and attitudinal evaluations of contemporary art exhibition media communication among different types of audiences. The media dissemination of exhibitions has different impacts on ordinary audiences, enthusiasts, and professionals. On the other hand, in-depth interviews were conducted with 23 different types of exhibition audiences to explore the differences in the cognition, attitude, emotion, and behaviour of art audiences towards exhibition media communication. Play greater value in audience interaction, artistic criticism, and shaping public cultural spaces [4]. This fusion display method undoubtedly injects new vitality and creativity into the development of new media art.

In the field of new media art, the data fusion between CAD (Computer-Aided Design) and VR (Virtual Reality) technologies is confronted with a series of issues, such as data format and compatibility, performance optimization, interactive design, user adaptability, security and stability, etc. Art images play a crucial role in new media art, whether as the foundational material for creation or as a medium for showcasing artistic works. However, these artistic images are often influenced by the Hughes effect, which records information about individual scenes in different spectral bands, resulting in excessively high data dimensions and increasing the difficulty of processing and analysis. In the preprocessing stage, artists can optimize the quality and details of images by adjusting parameters, laying a solid foundation for subsequent creations. In the multi-agent optimization stage, artists can use advanced optimization algorithms to find the optimal frequency band combination and parameter settings to achieve the best visual and creative effects. By selecting and combining different frequency bands, artists can explore the hidden colours, textures, and details in images, further enriching and expanding their creative techniques. In the adjacent band clustering stage, artists can select appropriate frequency bands for clustering and combination based on the characteristics and needs of the image, in order to emphasize or weaken certain features in the image [4]. These issues limit the creation, display, and interactive experience of new media artworks. However, the application of Graph Neural Networks (GNNs) on graph-structured data can capture the complex relationships between nodes and edges, and learn deep feature representation of data. In the field of virtual painting, virtual brush modelling undoubtedly occupies a core position. Looking back at the development process of virtual brush modelling, Huang et al. [5] found that typical modelling methods mainly include empirical methods and physical methods. This not only realistically simulates the characteristics of traditional brushes, but also brings unprecedented creative experiences and possibilities to artists. In virtual brush modelling, brushes, paper and ink, and human-computer interaction devices all play crucial roles. The accuracy, response speed, and operation mode of human-computer interaction devices determine the creative experience and efficiency of artists in virtual painting. Empirical methods rely on the artist's intuitive perception and long-term practice, optimizing the brush model through continuous experimentation and adjustment to better meet the needs of artistic creation. Secondly, how to combine different paper and ink materials and human-computer interaction devices to achieve richer and more diverse painting effects is also one of the current hotspots in virtual painting research. In the data fusion of CAD and VR technologies in new media art, the application of GNNs can serve as an intermediate layer to convert CAD models into graph-structured data that VR systems can recognize. Traditional artistic creation methods appear single and limited in the context of the new era, making it difficult to meet the growing aesthetic needs of the audience. Liang and Kim [6] aim to delve into the characteristics of various elements in new media art, such as ink, projection, interaction, and forced distance, and their clever combination in creation. The simple accumulation of technology is no longer the core value of artistic creation but needs to be combined with technology, and integrated with profound and creative content, in order to generate true artistic influence. Ink and wash elements, as treasures of traditional Chinese art, have given rise to new vitality in new media art. These elements not only possess unique artistic charm but also can stimulate richer and more diverse artistic effects through their fusion and collision with each other. Human activities are already closely linked to digital media, and the public can use digital media to express, create, and communicate freely anytime, anywhere. Digital media art relies on digital media technology to showcase creativity, which has a profound and crucial impact on the development and growth of the cultural and creative industry. Countries around the world focus on the economic benefits brought by the cultural and creative industry. Therefore, Liang et al. [7] clarified the concepts of digital media and digital media art through academic research by domestic and foreign scholars and understood the relationship between digital media technology and artificial intelligence. From the perspective of technology, communication, and art, observe the current performance of digital media art at an increasingly intelligent level. Have a clear concept of digital media technology and a general understanding of the application scenarios of digital media technology in the era of intelligence. It conducts relevant talent cultivation thinking on the new talent demand brought about by the development and growth of the digital media industry. Think about digital media art education in Chinese universities and understand the relevant policies of the country to support the development of digital media art. Therefore, relevant promotion policies have been introduced one after another, and the cultivation of talents in digital media art has been given greater attention. To understand the digital transformation brought about by digital media art in the era of artificial intelligence, and to explore the characteristics and future development of digital media art. Think about innovative development strategies for digital media art and analyze the digital media industry. GNNs can also assist in designing more natural and intuitive interaction mechanisms. By analyzing the interaction data between users and CAD models in VR environments, GNNs can learn user interaction habits and preferences, optimizing interaction methods accordingly. Meanwhile, GNNs can help improve users' adaptability to new media artworks. By analyzing users' personal information, historical behaviour, and feedback data, GNNs can learn users' interests and preferences, recommending artworks and interaction methods suitable for them. Therefore, this paper constructs a new media art CAD and VR data fusion display model based on GNNs. It achieves the fusion of heterogeneous data through GCN (Graph Convolutional Networks) and CNN (Convolutional Neural Networks), and on this basis realizes scene recognition in the art interaction mechanism to increase the participation and immersion of new media art.

2. DEVELOPMENT AND RESEARCH STATUS OF NEURAL NETWORK TECHNOLOGY

In the vast field of new media art, visual perception is often regarded as the core element of creation. For ordinary artists, their creative practices showcase the infinite possibilities of artistic expression. However, ordinary people lack visual perception, so further assistance is needed for artistic perception. McSwan [8] delves into how animation and virtual reality can serve as media, providing a new platform for artists to engage in creative practice. Through the construction of a virtual world, its project aims to provide users with a window to gain a deeper understanding and experience of the perceptual world of art. This method provides a new perspective to understand the diversity of artistic creation by deeply exploring the artist's creative process and methods.

With the rapid development of digital technology, traditional museum and art museum visiting experiences are undergoing unprecedented changes. Meinecke et al. [9] proposed a novel virtual museum experience that contextualizes digital artworks in galleries with related works in large image archives. For museums and art galleries seeking to expand their influence in the digital world, creating an interactive experience that is both interesting and educational is crucial. Utilizing large art datasets such as WikiArt, these datasets not only contain hundreds of thousands of high-quality images but also provide rich metadata. This allows us to conduct more detailed and diverse visual explorations. They applied advanced machine learning algorithms to analyze these images and extract multifaceted information about the objects detected in the artwork. Based on this information, calculate the similarity between artworks. Tourists can interactively explore artworks based on their interests and preferences, using various search filters such as artists, styles, or categories of objects detected in images. In the field of new media art, 3D display technology has always been regarded as a cutting-edge and promising medium that can bring users an immersive visual experience. In order to overcome this technological bottleneck, Mori and Bao [10] proposed an innovative 3D display device with LCD. Due to the low and fixed pixel density of LCD, its practical application and creative potential are significantly limited. This method not only improves the clarity of the image but also enables high image quality and parallax to be maintained when displaying 3D images. Due to the device's ability to display high-guality 3D images, it also allows viewers to immerse themselves more deeply in artistic works and gain a richer visual experience.

New media interactive installation art is a new form of art, but like the development path of other art forms in history, it is full of twists and challenges. New media interactive installation art originated abroad and has developed more rapidly than in China. However, interviews with some famous installation artists abroad also show their concerns about the future of this art form. Therefore, Pallasena et al. [11] took new media interactive installation art as the research object, further studied its diverse forms of expression and unique aesthetic characteristics, and explored its future development possibilities and directions. Although the new media interactive installation art conforms to the overall background of the information age and started relatively smoothly, its development still faces many obstacles. For example, excessive reliance on high technology leads to a lack of connotation in works, low artistic literacy among the public, and the dilemma of artists being unable to convey their creative ideas, resulting in works not being recognized by collectors, and so on. The healthy and sustainable development of an art form comes from the joint efforts of multiple parties, and any backwardness in any aspect will affect its overall development. We need to conduct a calm analysis of this emerging art form and comprehensively consider its future development direction. In terms of visual canvas/clues, AR technology brings realistic 3D models, visual and audio clues, and unique aesthetic experiences to new media art. Viewers can immerse themselves in the charm of artistic works through AR devices, and gain a richer artistic experience. Through interactive design, artists can create artworks that users can directly participate in and provide real-time feedback on. This interactivity not only enriches the forms of artistic expression but also brings the audience closer to the artwork, making them a part of artistic creation. In the creation and display of new media art, the depth synthesis of image textures is often overlooked, which limits the richness and depth of visual expression in works. Shan and Wang [12] proposed a film and television animation design method based on three-dimensional visual communication technology. This method effectively collects and integrates film and television animation video materials through three main steps: 3D visual communication content production, server processing, and client processing. In addition, to ensure the continuous variation of the scale factor between adjacent triangles in animation and video images. The introduction of this technology enables it to learn more refined and accurate image features from a large amount of data, thereby achieving higher-quality animation design. It innovatively constructs a scale factor field, which significantly improves the coherence and naturalness of the image. Not only does it provide new creative tools for new media artists, but it also greatly enriches the audience's visual experience. Under grayscale projection, we further identified and extracted frame features of video images, which not only contain basic information about the image but also contain rich artistic elements.

With the rapid development of digital manufacturing technology, it has not only become more user-friendly and cost-effective but also demonstrated enormous potential in the field of education, especially in new media art and design education. Song [13] will introduce these technologies into K-12 art and design education. There is relatively little research in this field, and there is limited exploration of the quantitative evaluation of its potential benefits and how pre-service teachers can acquire relevant knowledge and skills to adapt to technical classrooms. Although the application of digital manufacturing technology in STEM education has been widely discussed, its application in K-12 art and design education is relatively lagging behind. We conducted an exploratory case study to gain a deeper understanding of the practical application of digital manufacturing technology in art and design education. It enables artists to cross the boundaries between tradition and numbers, creating unique visual and interactive experiences. Through classroom observation, work analysis, and questionnaire surveys, it collected data on the creative process of using digital manufacturing technology in the context of pre-service teacher programs and K-12 education. With the rise of new media art, environmental art design is presenting unprecedented diversity and innovation. The core of Wang and Hu [14] lies in exploring the integration of modern technology and traditional art. VR technology provides users with an immersive virtual environment by wearing glasses, and sound is transmitted through speakers or acoustics, providing users with a comprehensive sensory experience. This technology breaks through the limitations of traditional display modes and brings users a more realistic and vivid artistic experience. In the application of VR technology in environmental art design, three core principles need to be followed: the principle of content authenticity to ensure that the virtual environment can truly reflect the design concept and goals. Especially the application of VR technology in environmental art to achieve the modernization and upgrading of traditional environmental art. The principle of formal application requires designers to fully utilize the advantages of VR technology to create unique artistic forms and visual effects. In the field of new media art, ink-style rendering demonstrates the infinite possibility of perfect integration between digital technology and traditional art. The 3D ink style rendering method proposed by Yan et al. [15] utilizes texture synthesis and mapping techniques to make the contours and textures of mountain ranges more realistic and rich in the charm of ink painting. Not only did it focus on the entire rendering process of ink painting, but it also meticulously explored different winkle rendering techniques and canvas textures based on spatiotemporal consistency. In addition, it uses empirical models to simulate the diffusion effect of ink in the rendered image space, allowing the fluidity and layering of ink to be perfectly presented in three-dimensional space. By dividing the rendering process into feature line rendering and internal region stylization, it successfully achieved wrinkling rendering of 3D mountain models. This method uses a noise-based algorithm to generate canvas textures and maintains the 2D appearance of the canvas during camera motion.

3. NEW MEDIA ART CAD AND VIRTUAL REALITY DATA FUSION DISPLAY MODEL

3.1. Neural Network

Through iterative updates of node embeddings, graph convolution can achieve representation learning of graph structures. In addition to the two core parts mentioned above, GNN may also include other modules such as attention mechanisms, pooling layers, and classifiers better to handle the characteristics and complexity of graph data.

Graph neural networks can be divided into five categories, namely graph convolutional networks, graph attention networks, graph autoencoders, graph generative networks, and graph spatiotemporal networks. Among them, GCNs have significant advantages in processing graph-structured data. Considering that design elements and components often form a complex graph structure in new media CAD and that users, objects, and scenes also form a graph in VR environments, GCNs can be used to understand the interactions and relationships between these elements. In addition, GCNs can be combined with other types of neural networks (such as convolutional neural networks and recurrent neural networks) to achieve the fusion of cross-modal data and comprehend various types of data that show the integration of new media CAD and VR, such

as images, text, and 3D models. GCNs have good scalability and can handle large-scale graph-structured data. This makes them capable of dealing with complex scenarios and large-scale data that may arise in new media CAD and VR. In VR environments, GCNs can help the system better understand user intentions and behaviours, thereby providing display and interaction methods that better meet user needs. Therefore, this paper mainly uses GCNs for the construction of corresponding models.

3.2. Heterogeneous Data Fusion Module Based on Graph Convolutional Neural Network

Heterogeneous data refers to data of different types, versions, and structures. CAD (Computer-Aided Design) data is mainly used to describe and represent two-dimensional or three-dimensional object models, and it usually includes detailed geometric information, dimensions, material properties, etc. VR (Virtual Reality) data is mainly used to create and present immersive three-dimensional environments, and it may include scene models, texture maps, lighting information, sound effects, etc. Since CAD and VR data have differences in data structures, data types, and purposes, specific data conversion tools or middleware are needed to ensure the accuracy and consistency of data integration and exchange. In addition, the heterogeneity of CAD and VR data is also reflected in the software platforms and tools they rely on. The differences in data formats and interfaces between different software platforms and tools also increase the complexity of CAD and VR data as heterogeneous data. The integration of CAD and VR data in new media art can improve the display effect of new media art and effectively enhance the rendering effect of scenes in VR. In addition, new media art is generally presented in themed forms. GCN (Graph Convolutional Network) model can predict the theme trend of new media art while integrating data. As shown in the figure, it is a framework diagram of a heterogeneous data fusion module based on a graph convolutional neural network.



Figure 1: Framework of heterogeneous data fusion module based on graph convolutional neural network.

From Figure 1, it can be seen that the model framework includes an autoencoder structure, which is divided into two parts: encoder and decoder. The encoder is based on the forward propagation of a two-layer GCN module connection, as shown in (1) and (2):

$$H = \operatorname{Re} LU(\hat{J} - \frac{1}{2}\hat{G}\hat{J} - \frac{1}{2}TW_{(1)})$$
(1)

$$Z = \vec{J} - \frac{1}{2}\vec{G}\vec{J}\frac{1}{2}HW_{(2)}$$
(2)

$$\hat{G} = G + I \tag{3}$$

In the formula, the topic co-occurrence matrix and the identity matrix are represented as and respectively, the degree matrix is described as and, the topic multidimensional feature is denoted as the corresponding neural network weights are denoted as and, and the embedding vector is denoted as.

The output of the decoder is set to the node connection probability matrix, as shown in (4):

$$\tilde{G} = sig \mod(Z \ ZT) \tag{4}$$

Based on the results obtained from the above formula, the model will subsequently obtain vectors with representation information by minimizing the differences between matrices.

3.3. New Media Art Based on Graph Convolutional Neural Network

Scene interaction is one of the important ways of interactive display in many fields. The key aspect of scene interaction lies in scene recognition. However, classic scene recognition models often have errors in recognition performance, especially when scene similarity is high, which often makes it difficult to accurately distinguish and recognize, and thus cannot accurately convey the information that users want to express. Dynamic scene data has the characteristics of time series and long-range spatial correlation, which poses a challenge to the accuracy of scene recognition. To address this challenge, this paper combines Graph Convolutional Network (GCN) and Gated Recursive Unit (GRU) to construct a novel dynamic scene recognition model. This model can more effectively handle the time series and spatial correlation in dynamic scene data, thereby improving the accuracy and efficiency of scene recognition. Through this model, we expect to improve the performance of scene recognition and provide users with a smoother and more accurate interactive experience.

The joint scene poses information obtained through the graph convolutional neural network can avoid the problem of extracting non-Euclidean space data features. The addition of the adjacency matrix and the identity matrix can make the aggregated joint points form a self-loop. Meanwhile, the normalization of the matrix addition results can reduce the possibility of gradient disappearance or explosion caused by the difference in joint point degrees. When t is, the corresponding spatial feature extraction is shown as (5):

$$f_{s}^{t} = Leaky \operatorname{Re} LU(\Lambda^{-\frac{1}{2}}(G+I)\Lambda^{-\frac{1}{2}}FW)$$
(5)

In the formula, the weight matrix is described, the node pair angle matrix is described, and the result after normalization is represented.

The nonlinear activation function is described as shown in (6):

$$Leaky \operatorname{Re} LU(x) = \begin{cases} x, if x \ge 0\\ \alpha x, if x < 0 \end{cases}$$
(6)

The introduction of the gated recurrent unit is to control information such as input and memory, thereby simplifying the operation mechanism of long short-term memory units, improving recognition efficiency, and reducing recognition errors. Assuming that the spatial feature description of the scene data is and, the conversion process of different sampling spatial features in the same joint point is shown in (7):

$$\left\{f_{s}^{n}\right\}_{n=1}^{M} = H\left\{f_{s}^{n}\right\}_{t=1}^{T}$$
(7)

In the formula, the transformation matrix is described as.

In the gated recurrent unit, the time series feature is represented as the previous hidden state, and the two form the update gate and obtain an updated state. Therefore, the amount of information transmitted between the current time step and the previous time step is calculated as shown in (8):

$$z_t = \sigma(W_z f_t + U_z h_{t-1} + b_z) \tag{8}$$

In the equation, the feature in the update gate and the corresponding weight matrix of the previous hidden layer state are denoted as and respectively, and the bias is denoted as.

The amount of forgotten scene information of the previous moment by the reset gate at the current moment is shown in (9):

$$r_{t} = \sigma(W_{r}f_{t} + U_{r}h_{t-1} + b_{r})$$
(9)

In the equation, the feature in the reset gate and the corresponding weight matrix of the previous hidden layer state are denoted as and respectively, and the bias is denoted as.

The final information content of the new memory state and the current time step is shown in (10) and (11):

$$\tilde{h}_t = \tanh(r \otimes U_h h_{t-1} + W_h f + b_h) \tag{10}$$

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \tilde{h}_t$$
(11)

In the formula, the multiplication is represented as the features in the new memory state and the corresponding weight matrix of the previous hidden layer state are represented as and respectively, and the bias is denoted as.

4. APPLICATION OF NEW MEDIA ART CAD AND VIRTUAL REALITY DATA FUSION DISPLAY MODEL BASED ON GRAPH NEURAL NETWORK

4.1. Performance Test of Heterogeneous Data Fusion Based on Graph Convolutional Neural Network

In the aspect of heterogeneous data fusion, this paper's model is achieved by combining the graph convolutional neural network (GCNN) and LSTM. To test the performance of this model, several other commonly used models were selected for comparison. The performance test was mainly conducted from two aspects: whether data was fused and model structure performance. The test results are shown in Figure 2. In terms of whether data was fused, compared with other models, this paper's model achieved data fusion based on multi-dimensional features and co-occurrence relationships. Other models either adopted multi-dimensional features or shared relationship data, which made them relatively weak in predicting and analyzing the development trend of new media art. In addition, this paper's model can complement information during the data fusion process, providing an effective data foundation for analyzing and predicting new media art theme trends and improving the accuracy of analysis. In terms of model structure, the results of different models in terms of accuracy and AUC were not significantly different, indicating that they could be applied in the fusion of new media art theme data. However, in terms of model recall rate, this paper's model performed best, significantly higher than other models. This indicates that this model has better graph feature extraction ability, can effectively and accurately process graph data, and has good performance in selecting graph learning models. In addition, the LSTM model in this paper is significantly better than other model structures in classification accuracy and recall rate, making it more suitable for application in predicting new media art themes. Therefore, this paper's model has the best overall performance among all models, with lower error rates and better recall rates, which can accurately predict classification and better integrate CAD and virtual reality data.

An important purpose of combining new media art with virtual reality technology is to provide better presentation and visual effects for the audience and to enhance the audience's immersion. Therefore, many new media arts will use eye tracking to enhance the interactivity and experience of the work during the exhibition and improve the real-time rendering effect of the virtual reality scene.



Figure 2: Performance test results of different heterogeneous data fusion models.



Pre-fusion data



Figure 3: Application Effect of Data Fusion Model in the Virtual Reality Display Scenario of New Media Art.

Therefore, this paper tests the application effect of heterogeneous data fusion based on graph convolutional neural networks in virtual reality eye tracking, as shown in Figure 3. The results in Figure (a) show that the rendering effect of the scene after combining eye tracking and data fusion is significantly better than that before the combination, which can reduce the requirements for virtual reality hardware during new media art displays. The results in Figure (b) show that data fusion can help eye tracking improve the accuracy of tracking position, and the rendering effect of the virtual reality scene is more consistent with expected effects, which can enhance the immersion of the

virtual reality scene and better display the content of new media art. The results show that among six models, the accuracy of this model is the highest in two datasets. In addition, the accuracy of GRU and SVM models in the second dataset decreases to a certain extent, and the decrease is more obvious for the latter. The accuracy of other models in the second dataset increases to a certain extent, indicating that the model has good stability.

4.2. Experimental Results of New Media Art Application Based on Graph Convolutional Neural Network

Digital art recognition plays an important role in modern interactive systems, and its performance directly affects user experience. In order to evaluate the performance of the media recognition model based on Graph Convolutional Neural Network (GCN), this paper compared its performance with five other commonly used scene recognition modes. In order to ensure the fairness and accuracy of the experiment, a unified, standardized form was adopted while ensuring that the parameters of the sensors and other devices used remained consistent. In addition, this article selected two datasets for model training and testing, namely the composite dataset and the basic dynamic dataset. The ratio between the training dataset and the testing dataset is set to 7:3. In terms of model construction, the graph convolutional neural network in this article adopts a free-filling method to handle blank dimension values of different dimensions, and the learning rate is set to 0.005. Through training and optimization, we have obtained an excellent recognition model. As shown in Figure 4, this article presents the analysis results of scene recognition accuracy for six different models on two datasets. This comparison not only demonstrates the performance advantages of GCN-based recognition models but also provides valuable references for future research on art media recognition.



Figure 4: Scene recognition accuracy analysis results of six models on two datasets.

To further analyze the model's scene recognition accuracy, this paper analyzes the confusion matrix of the model during the scene recognition process on two datasets. The results are shown in Figure 5. The figure shows that the accuracy of the model in this paper is above 92% in different datasets, and it can effectively recognize dynamic scenes with high complexity, improving recognition efficiency and providing a good interactive experience for the audience of new media art.

Based on the results in Figure 6, we can observe that there are two types of graphical data that are particularly prone to confusion. This confusion may arise from the high similarity between these two images during execution, resulting in a narrow range of data changes, making it difficult for sensors to capture and distinguish the trajectories of these data from multiple perspectives.



Figure 5: Two datasets scene recognition confusion matrix.

Therefore, digital art recognition models often tend to misjudge these model data as the same, which affects the overall recognition accuracy. In order to test the performance of the model in handling such confusion, we conducted recognition experiments specifically for these two models. The experimental results indicate that although there is a certain overlap range between the trajectories of these two models, and the amplitude and frequency changes of the models also have certain similarities. However, the model can still accurately distinguish these two states and make correct judgments. In summary, the digital art recognition model not only demonstrates good accuracy in graphic recognition but also effectively identifies highly similar and easily confused dynamics. This feature makes it widely applicable in various interactive situations, such as human-computer interaction, virtual reality, and other fields.



Figure 6: Recognition results of two easily confused scene motion trajectories.

5. CONCLUSIONS

This paper constructs a new media CAD and virtual reality data fusion module and a scene recognition module based on graph convolutional neural networks combined with LSTM and GRU and verifies the model performance and application effects through a series of experiments. The experimental results show that the combination of graph convolutional neural networks and LSTM effectively improves the fusion performance of CAD and virtual reality data and enhances the model's prediction and analysis

effect on the development trend of new media art themes. In the application of virtual reality eye tracking, data fusion can improve the rendering effect of virtual reality scenes and is conducive to improving the accuracy of eye tracking position, enhancing the immersion of new media art virtual reality scenes. In scene recognition, the combination of graph convolutional neural networks and GRU effectively improves the accuracy of scene recognition and has the best recognition performance among the six models. In addition, in complex and ambiguous scene recognition, this paper's model has higher recognition performance, with recognition accuracy reaching over 92%, and can effectively identify ambiguous scenes and make corresponding judgments. Although this study has achieved some results, there are still many shortcomings, such as the non-standardization of audience interactive scenes in new media art displays, which needs further research to include non-standardized scene recognition optimization and verification. In addition, it can continue to explore the application and effect of graph neural networks in CAD and virtual reality data fusion.

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