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Computer-Aided Design AND APPLICATIONS

A Scene Rendering Algorithm for the Fusion of CAD Data and Neural Networks in Environmental Art Design

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Abstract. The traditional computer-aided design (CAD) software is often not realistic in rendering scenes, such as light, materials, shadows, and other details, which leads designers to spend a lot of energy on manual adjustment. The rendering algorithm based on deep learning (DL) can automatically learn the complex output, and the effect is usually better than traditional methods. In this article, a convolutional neural network (GA-CNN) based on genetic algorithm (GA) optimization is proposed, and it is combined with CAD data and applied to the rendering of environmental art design scenes. This method uses GA to optimize the parameters of CNN to improve its learning effect and generalization ability. From the overall trend, the response speed of GA-CNN algorithm and support vector machine (SVM). The response speed of the traditional CNN method is relatively slow, and the fluctuation range is large. This is because traditional CNN needs a lot of convolution operations and feature extraction when dealing with artistic scenes in complex environments, which leads to a long calculation time. In practical application, it is necessary to select appropriate algorithms and parameter settings according to specific task requirements to achieve the best results.

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1 INTRODUCTION

The field of environmental design is experiencing a technological revolution. Traditional environmental art design mainly relies on hand drawing and static image rendering. In order to better show and predict the actual effect of the design, designers began to use computer-generated 3D dynamic image rendering technology. Among them, human tracking is an important function of indoor mobile robots, which can help robots better adapt to human life and work. Indoor mobile robot human tracking technology based on environmental colour features utilizes deep learning algorithms to extract and analyze environmental colour features, achieving accurate human tracking. Algabri and Choi [1] provided a detailed introduction to human-following technology for indoor mobile robots based on deep learning. The extraction of environmental colour features is a key step in human following technology for indoor mobile robots. By extracting colour features from the environment, information about the human position and movement status can be obtained. In deep learning, Convolutional Neural Networks (CNN) is a commonly used method for extracting colour features. Color features are extracted from the image, and these features are used for subsequent analysis and processing. Deep learning-based indoor mobile robot human tracking technology based on environmental colour features is an effective technical means to achieve accurate tracking of target characters. This technology has good robustness and adaptability and can achieve stable human tracking in different environments. CAD data plays a fundamental role in environmental design. Designers use CAD software to model and build a virtual 3D scene. When traditional CAD software renders scenes, the details such as light, materials, and shadows are often not true enough, which leads designers to spend a lot of energy on manual adjustment.

With the continuous progress and innovation of technology, the way landscape architecture design and education are also undergoing changes. The traditional landscape architecture education model mainly combines theory and practice, but in the era of information explosion, how can we more effectively impart knowledge and skills? Ge et al. [2] aim to explore an intelligent. The landscape architecture technology network model is a computer technology-based landscape architecture design tool that can digitize various landscape architecture elements and share and collaborate information through network technology. The quality of landscape architecture design also provides educators with richer and more vivid teaching resources. In order to verify the effectiveness of the landscape architecture intelligent education framework based on the landscape architecture technology network model, we conducted practical application and effectiveness evaluation. The results show that this framework can significantly improve students' learning outcomes and interests, promote communication and cooperation among students, reduce educational costs, and improve educational quality. At the same time, this framework also provides educators with richer and more vivid teaching resources, improving teaching effectiveness and satisfaction. NN has strong learning and optimization ability and can adjust its parameters by training itself so as to realize deep understanding and efficient processing of complex data. Topographic maps are important tools for describing the characteristics of the Earth's surface and are widely used in fields such as urban planning, land resource management, and environmental protection. Traditional terrain mapping often relies on manual or semi-automatic methods, which are not only inefficient but also prone to errors. Terrain map drawing has gradually shifted towards digitization and automation. However, existing terrain mapping methods often require expensive hardware equipment and professional technicians, which limits their application in some low-cost environments. Habib and Pradhan [3] proposed a method that utilizes computer graphics and geographic information system (GIS) technology to convert CAD topographic maps into high-precision and efficient spatial rendering data. This method can be implemented on low-cost hardware devices, reducing the cost of terrain map drawing and improving efficiency. We conducted experimental tests. They convert CAD-based terrain maps into high-quality spatial rendering data and can be implemented on low-cost hardware devices. Compared with traditional terrain map drawing methods, this method has higher efficiency and lower cost. The powerful computing power of NN is expected to develop a new algorithm that can automatically, quickly and accurately render complex scenes.

In landscape design, terrain modelling and digital landscape architecture are two key links. Hurkxkens and Bernhard [4] discussed the application of distance function CAD calculation in terrain modelling and digital landscape architecture in large-scale landscape design. The distance function refers to a function that describes the distance relationship between two points in space. In large-scale landscape design, the distance function can be used to calculate the distance between a point on the terrain surface and a certain benchmark or baseline. Through CAD software, we can use distance functions for terrain modelling. Firstly, establish a terrain surface model in CAD software, and then use a distance function to the reference points or lines by defining them. In this way, we can obtain the elevation information of the terrain surface, providing basic data for subsequent digital landscape architectural design. Digital landscape architecture. Digital landscape architecture can achieve digital modelling and optimization of spatial layout, structural form, material selection, and other aspects of landscape architecture. The combination of art and technology is aimed at creating comfortable, beautiful, and functional indoor and outdoor spaces. With the advancement of technology, CAD data and neural network technology have provided new methods and perspectives for environmental art and design teaching. Jin et al. [5] explored data and neural network fusion in environmental art and design teaching. CAD data is an important tool for environmental art design; by training neural network models, students can predict the effects of different design styles, thereby better understanding the characteristics and application scenarios of different styles. Students can use neural networks to optimize design schemes. By analyzing the emotional reactions of users to design solutions, neural networks can help students understand their needs and preferences, thereby better meeting their needs. Combining CAD data with neural network technology can provide more comprehensive and in-depth applications for environmental art and design teaching. For example, students can use CAD data and neural network technology for comprehensive design and evaluation in order to principles and methods of environmental art design. Teachers can also use these technologies for teaching assistance and evaluation, improving teaching quality and effectiveness.

CAD data is the core information in the process of architectural design and manufacturing, while a computational model connection, with strong learning and reasoning abilities. Combining CAD data with neural network technology can achieve automation and intelligence in architectural design. For example, analyze CAD data, thereby achieving optimized design of building structures and automated control of manufacturing processes. Combining CAD data with neural network technology in architectural scene applications to achieve integrated design and manufacturing of biomimetic folding mechanisms has become a challenging problem. Krner et al. [6] explored the integrated design and manufacturing method of biomimetic folding mechanisms in architectural scene applications that integrate CAD data and neural networks. The biomimetic folding mechanism is a mechanism that mimics the folding behaviour of natural organisms, with characteristics such as lightweight, high strength, and foldability. In the application of architectural scenarios, biomimetic folding mechanisms can be used to achieve adaptive deformation and scalability of buildings, thereby improving their adaptability and Sustainability. In the design process of biomimetic folding mechanisms, CAD data is used to analyze and simulate the folding behaviour of the mechanism, thereby achieving optimization of the mechanism design. Automate the manufacturing process. Intelligent environmental scenarios have become an important component of our daily life and work. The intelligent environment scene not only provides convenient life services but also provides people with a more comfortable and intelligent experience. In order to better understand and describe intelligent environment scenarios, Lee et al. [7] described them. The interactive platform in intelligent environment scenarios refers to the use of human-machine interaction technology to achieve interaction between humans and the environment. This interaction method not only includes traditional input devices such as mice and keyboards but also new interaction methods such as speech recognition and gesture recognition. Through interactive platforms, people can interact more intuitively with intelligent environmental scenes, thereby obtaining more convenient and intelligent services. The collective platform in intelligent environment scenarios refers to the collaborative work between multiple intelligent devices or systems. These devices or systems can communicate with each other and share data and resources, thus forming a collective intelligent environment. This collective platform can provide users with more comprehensive and personalized services while also improving the efficiency and stability of the entire system. In intelligent environment scenarios, multiple devices or systems need to work together. A responsive architecture needs to support distributed collaboration so that these devices or systems can communicate with each other, share data and resources, and form a collaborative collective. This provides users with more comprehensive and personalized services.

The rendering algorithm based on DL can automatically render, and the effect is usually better than the traditional method. CNN is one of the most representative DL models and has achieved remarkable success in many fields, such as image recognition and natural language processing. How to effectively fuse CAD data and NN to achieve high-quality real-time rendering is an urgent problem. In this article, a GA-CNN based on GA optimization is proposed, combined with CAD data, and applied to the rendering of environmental art design scenes. This method uses GA to optimize the parameters of CNN to improve its learning effect and generalization ability. In this study, a data fusion strategy is designed to fuse the optimized network with CAD data effectively.

Highlight points:

(1) This article proposes a GA-CNN based on GA optimization. By combining the global searching ability of GA with the DL characteristics of CNN, this method can automatically find the best network parameters.

(2) According to the characteristics of the field of environmental design, this article designs a fusion strategy of CAD data and NN. This strategy can make full use of the precise geometric information of CAD data and combine the powerful learning ability of NN to achieve high-quality scene rendering.

(3) The GA-CNN method has strong expansibility and flexibility and can be combined with other advanced rendering technologies to achieve higher-quality scene rendering.

Firstly, this article introduces the background and purpose of CAD and NN research. Then, a CNN based on GA optimization is proposed, which is combined with CAD data and applied to the rendering of environmental art design scenes. Then, the application effects of the GA-CNN algorithm, traditional CNN, and SVM in environmental art design are analyzed in detail. Finally, the research results and practical significance are summarized.

2 THEORETICAL BASIS

The architectural design and manufacturing. The development environment of the algorithm framework for integrating CAD data. Lin [8] explores the topology structure of CAD data and neural network fusion application algorithm framework in architectural conceptual design. In order to improve their accuracy and generalization ability. By analyzing the topological structure of neural network models, key features and patterns in architectural conceptual design can be revealed. In architectural conceptual design, topological structure refers to the characteristics of a building's spatial layout, structural form, and material selection. Through the fusion application algorithm framework of CAD data and neural networks, in-depth analysis and research can be conducted on the topological structure of architectural conceptual design. For example, neural network models can be used to predict and optimize the spatial layout of buildings in order to obtain more reasonable and beautiful architectural design schemes.

The global feature can provide the overall structure and detail information of the image, while the local feature can provide the local detail information of the image. By combining these two features, we can more comprehensively describe the characteristics of the image and improve the accuracy and reliability of matching. In addition, we can also consider using deep learning technology to extract image features. Deep learning technology can automatically learn the feature representation of images, avoiding the tedious process of manually designing features. At the same time, deep learning technology can also process high-dimensional data to describe the characteristics of images better. In the matching process, we can consider using a similarity measurement method to measure the similarity between two images. Common similarity measurement methods include Euclidean distance, cosine similarity, etc. These methods can measure the distance or similarity between two images in the feature space to determine whether they match. Nie et al. [9] extract global and local features of images through grid partitioning and multi-density analysis, achieving more accurate and efficient image matching. Divide the ancient architectural environment art, each representing a local area of the image. Extract the texture, colour, shape, and other features of the image in each grid.

These features can reflect the local information of the image and provide basic data for subsequent matching. The experimental results show accuracy and efficiency in matching ancient architectural environment art images. Compared with traditional feature matching methods, this method can better handle the detailed information and overall structure of images, improving the accuracy of matching. The integration of CAD data and neural networks provides more efficient and intelligent design tools for environmental art design. Through CAD data, designers can accurately express design intentions and achieve precise calculations and simulation of design solutions. Neural networks, on the other hand, can provide valuable feedback and suggestions to designers through learning and reasoning. This fusion approach can improve design efficiency and reduce design costs. The integration of CAD data and neural networks in environmental art design has brought unprecedented opportunities for digital building environments, but at the same time, it has also brought corresponding network threats. Parn and Edwards [10] discussed the network threats faced by the integration of CAD data and neural networks in digital architectural environments in environmental art design and proposed corresponding response strategies. In the process of integrating CAD data with neural networks, a large amount of sensitive data is involved, such as design drawings, user information, etc. If these data are illegally obtained or leaked, it will cause serious damage to personal privacy and corporate interests. Hackers may exploit vulnerabilities in CAD data and neural networks for attacks, such as tampering with design schemes, disrupting system stability, etc., which can cause significant inconvenience to users and designers. Computer viruses may spread through CAD data and neural networks, leading to system crashes, data loss, and other issues, seriously affecting the normal operation of the digital building environment.

Tai and Sung [11] simulate the spatial layout of buildings, thereby better understanding and evaluating their spatial effects. Through CAD data, the structure of a building can be analyzed and evaluated to ensure its safety and stability. By utilizing CAD data, suitable materials can be selected according to the needs of the building, thereby improving its performance and cost-effectiveness. Combining CAD data with neural network technology can provide a more comprehensive and in-depth application. For example, using CAD data and neural network technology can intelligently analyze and evaluate the spatial layout, structure, materials, and other information of buildings, thereby providing valuable feedback and suggestions for designers. Meanwhile, through the emotional analysis and user experience prediction functions of neural networks, designers can be provided with more accurate and personalized design solutions, thereby improving the performance and user experience of buildings. Virtual reality technology, with its unique immersive experience, allows us to delve deeper into the interior of coastal scenes and experience every detail. Designers can use VR technology to simulate real coastal scenes in a virtual environment, including elements such as beaches, lighthouses, ships, and waves. Through this simulation, designers can discover and solve potential problems at an early stage, greatly improving design efficiency and quality. Intelligent algorithms, especially machine learning and deep learning algorithms, can help designers automate many tedious tasks, such as lighting adjustment and texture mapping. These algorithms can automatically find the optimal solution by learning a large amount of data, greatly improving design efficiency. Meanwhile, intelligent algorithms can also create more realistic natural phenomena, such as the surging waves and changes in the sky, which undoubtedly brings greater possibilities for coastal scene rendering design. Wang [12] utilized the immersive environment provided by virtual reality technology for real-time observation and design modification. Intelligent algorithms can automatically optimize and adjust based on the designer's intentions and feedback.

Environmental spatial modulation full polarization CAD computational imaging super-resolution technology is a method that utilizes scene conversion and full polarization information to improve imaging resolution. It achieves high-resolution image reconstruction by modulating the environmental space and processing full polarization information. Environmental spatial modulation is a technique that affects image imaging by changing the physical properties of the environmental space. In environmental spatial modulation, different physical parameters (such as lighting, reflection, etc.) can be used to control the imaging quality of the image. By precisely modulating the environmental space, clearer and more accurate image information can be obtained. Full polarization information refers to image information that contains both horizontal and vertical polarization information. Full polarization information can provide more image details and depth information, which helps improve the resolution and clarity of images. CAD computational imaging super-resolution technology based on scene conversion is a method that combines scene conversion with CAD computational imaging technology. Xu et al. [13] utilized advanced scene conversion techniques and CAD computational imaging algorithms to achieve high-resolution image reconstruction. During the scene conversion process, environmental spatial modulation technology can be used to accurately modulate the scene, thereby obtaining clearer and more accurate image information. In the CAD imaging process, full polarization information processing technology can be used to reconstruct images, further improving their resolution and clarity finely. Neural network technology has been widely applied in various fields, including environmental landscape art design. Yu et al. [14], by training neural network models, it is possible to automatically generate landscape element layouts that comply with design rules, improving design efficiency and quality. Integrating CAD data with neural networks can achieve dynamic, nonlinear, parameterized environmental landscape art design. Specifically, designers can use CAD software to draw initial landscape design plans and then optimize them using neural network models. Neural network models can automatically adjust various elements in the design scheme based on input CAD data and learned rules to achieve the optimal landscape effect. Meanwhile, this fusion method can also achieve dynamic design, which automatically adjusts the elements and parameters in the design scheme according to different time and space conditions to adapt to different environments and needs.

Which is of great significance in creating a landscape atmosphere and enhancing visual effects. In landscape architecture design, such as cultural background, regional characteristics, material texture, etc. Through reasonable colour matching, a comfortable and pleasant landscape environment can be created, improving people's aesthetic experience. Colour, as an important element in landscape architecture design, is of great significance in creating a landscape atmosphere and enhancing visual effects. Zhang and Deng [15] explored the computer-aided collaborative design system that can easily achieve the combination and combination of multiple colours, providing designers with more choices. By adjusting parameters such as brightness, saturation, and contrast of colours, a rich and colourful landscape effect can be created. In landscape architecture design, the selection of colours needs to consider the factors of the surrounding environment. Through computer-aided collaborative design systems, colour effects in different environments can be simulated to select colour-matching schemes that are coordinated with the environment. Zhao [16] discussed the application of 3D CAD in landscape design and how to improve design quality and efficiency through hierarchical detail optimization. 3D CAD technology can quickly create 3D models of landscape design. Designers can construct landscape elements such as terrain, architecture, vegetation, etc., by inputting parameters or manually drawing. This 3D model can intuitively display the spatial relationships and forms of the design, providing designers. 3D CAD can simulate the lighting effect of natural light, providing a realistic light-shadow relationship for landscape design. Designers can achieve lighting effects at different times and angles by adjusting lighting parameters, enhancing the visual impact of the design. 3D CAD can also achieve animation and rendering functions. Designers can make landscape design more dynamic and vibrant by simulating motion trajectories and animation effects. Meanwhile, high-quality rendering effects can improve the visual quality of the design and provide a more intuitive design display for Party A. By adjusting the size, height, and positional relationship of landscape elements, a rich sense of hierarchy can be created. In 3D CAD, designers can optimize the hierarchical relationships of landscape elements and spatial layout by adjusting parameters or performing Boolean operations. The handling of details in landscape design is crucial. Through the detail editing tools of 3D CAD, designers can make precise adjustments and embellishments to the model, such as adding vegetation, adjusting terrain slopes, etc. The refinement of these details can enhance the precision and overall quality of the design.

3 METHODOLOGY

In environmental art and design scene rendering, CNN can effectively learn and extract complex scene features from a large amount of training data, thereby generating high-quality rendered images. GA has global search capability and can find better solutions in a short amount of time. This article uses GA to optimize CNN's parameters. In the study, the parameters of CNN were encoded as chromosomes, and the performance of each chromosome was evaluated through a fitness function. Then, selection, crossover, and mutation operations were used to generate new chromosomes, i.e. new network parameters. This process is repeated until the optimal network parameters are found. In order to achieve effective integration of CAD data and NNs, this article proposes a strategy based on data conversion and network embedding. This strategy first converts CAD data into a format that can be processed by NNs, such as point cloud data or voxel data. Then, a network embedding method was designed to embed the geometric and texture information of CAD data into the input layer of the NN. Through this fusion strategy, the accuracy of CAD data and the generalization ability of NNs can be fully utilized to achieve high-quality scene rendering. Real-time rendering refers to generating high-quality rendered images in a short period of time to meet the real-time requirements in practical applications. In order to achieve real-time rendering, this article adopts various technical means, such as network structure optimization, parallel computing, and hardware acceleration. In the study, a lightweight CNN structure was designed based on the characteristics of environmental art design scenes to reduce computational complexity and memory usage. Parallel computing and hardware acceleration technologies such as GPU acceleration and distributed computing are also used to improve rendering speed.

Environmental art image fusion refers to the fusion of multiple environmental art images into a new image to create a richer and more diverse scene. CNN can play an important role in this process. Semantic segmentation is a DL-based image segmentation technique that can classify each pixel in an image into different semantic categories, such as sky, grassland, buildings, etc. In environmental art image fusion, semantic segmentation processes different elements in the image, thereby achieving more accurate image fusion. Train a simple image classification CNN by inputting pixel blocks representing pixels and using the classification of the central pixel as the label for the input image. The semantic segmentation process is shown in Figure 1.

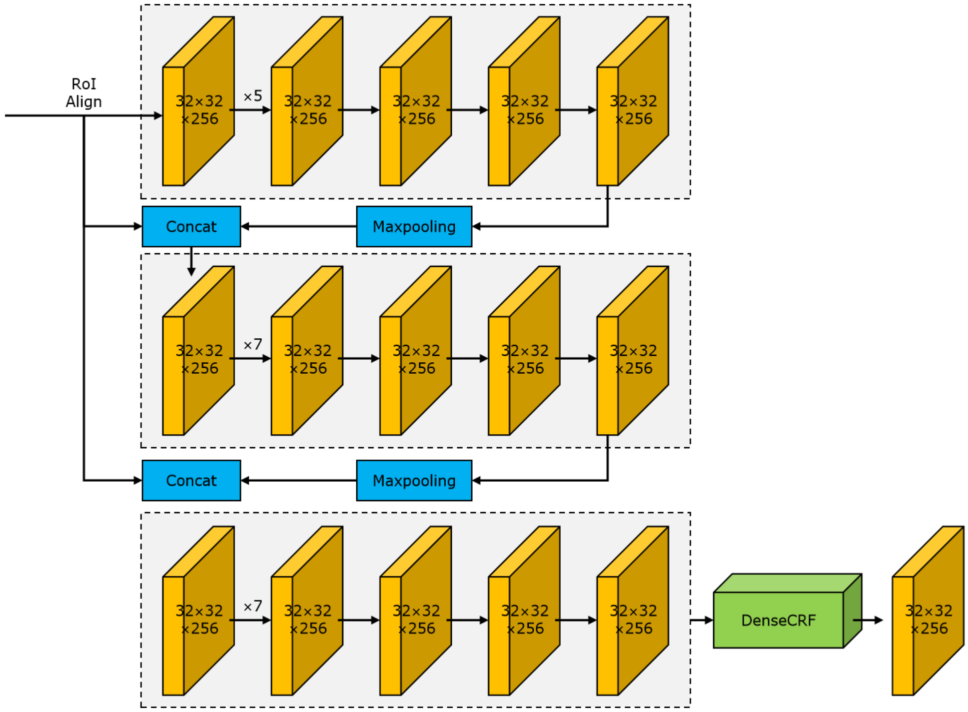


Figure 1: CNN semantic segmentation.

Pooling operation is an important technique in CNN, used to reduce feature dimensions and enhance the translation invariance of features. In environmental art image fusion, the pooling operation can extract more important feature information, ignore some unimportant details, and achieve more efficient image fusion. Pooling operations can map each region in an image to a feature value, resulting in a more compact and important set of feature information. Then, use this feature information for subsequent image fusion operations. By combining semantic segmentation and pooling techniques, more precise and efficient image fusion operations can be achieved, providing richer materials and inspiration for environmental design. The pooling operation of this model is shown in Figure 2.

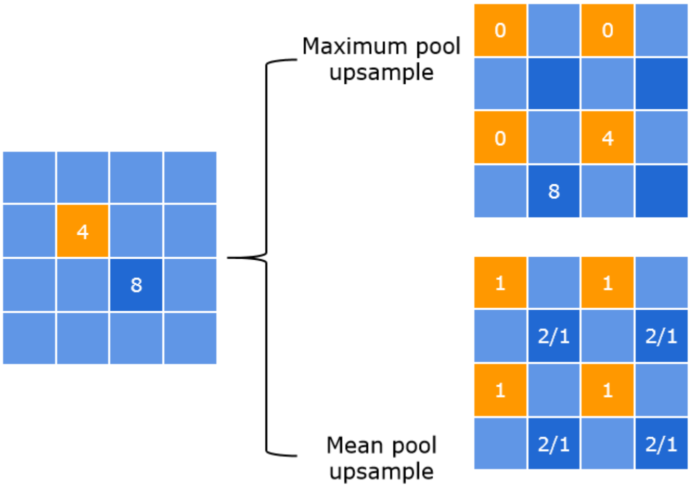


Figure 2: Pool operation.

In the field of environmental design, CAD technology has become an indispensable tool for designers. Through CAD software, designers can easily create, edit, and modify various complex scene models. Traditional CAD software often has low efficiency in processing large amounts of data and cannot meet the needs of real-time rendering and high-quality image fusion. These data may come from models created by designers themselves, as well as from open-source datasets or commercial databases. When obtaining data, it is needed to ensure the integrity of the data for subsequent processing. Due to the possibility of errors or inconsistencies in CAD data, such as excess line segments, missing faces, or overlapping entities, it is necessary to use professional CAD software or algorithms to clean these data. Texture information is added to the CAD model to enhance the rendering effect. This can be achieved through texture mapping technology.

Through persistent learning and training processes, the BPNN is able to discern patterns and regularities within an extensive dataset comprising diverse, unknown patterns—this applies to all types of data. Typically, certain prerequisites must be fulfilled, including:

$$m = \sqrt{x + y} + R(10) \tag{1}$$

$$R^{-}(X) = \ U_2, U_3, U_4, U_5, U_7 \tag{2}$$

$$R_{-}(X) = \ U_2, U_4, U_5 \ \neq \phi \tag{3}$$

Therefore:

$$\rho(X) = 1 - \frac{\left|POS_C(X)\right|}{\left|R^-(X)\right|} = 0.6 \tag{4}$$

If $X = U_2, U_3$ it is not definable because:

$$R^-(X) == U_2, U_3, U_5, U_7 \tag{5}$$

$$R\_(X) = x \in U \left| R(x) \cap X \neq \phi \right. \neq \phi \tag{6}$$

In order to overcome the limitations of traditional CNN in rendering environmental art design scenes, this section proposes a CNN method based on GA optimization. This method uses GA to search the optimal network parameters and improve the learning effect of CNN. Firstly, the parameters of CNN are encoded into chromosomes for GA operation. Using binary coding, each parameter is represented as a string of binary numbers. That is the performance of its corresponding CNN in the rendering task of the environmental art design scene. In the selection stage, according to the fitness value of each chromosome, the chromosome with the higher fitness is selected as the parent. Then, a crossover operation is used to generate new offspring chromosomes. The optimization principle based on GA-CNN is shown in Figure 3.

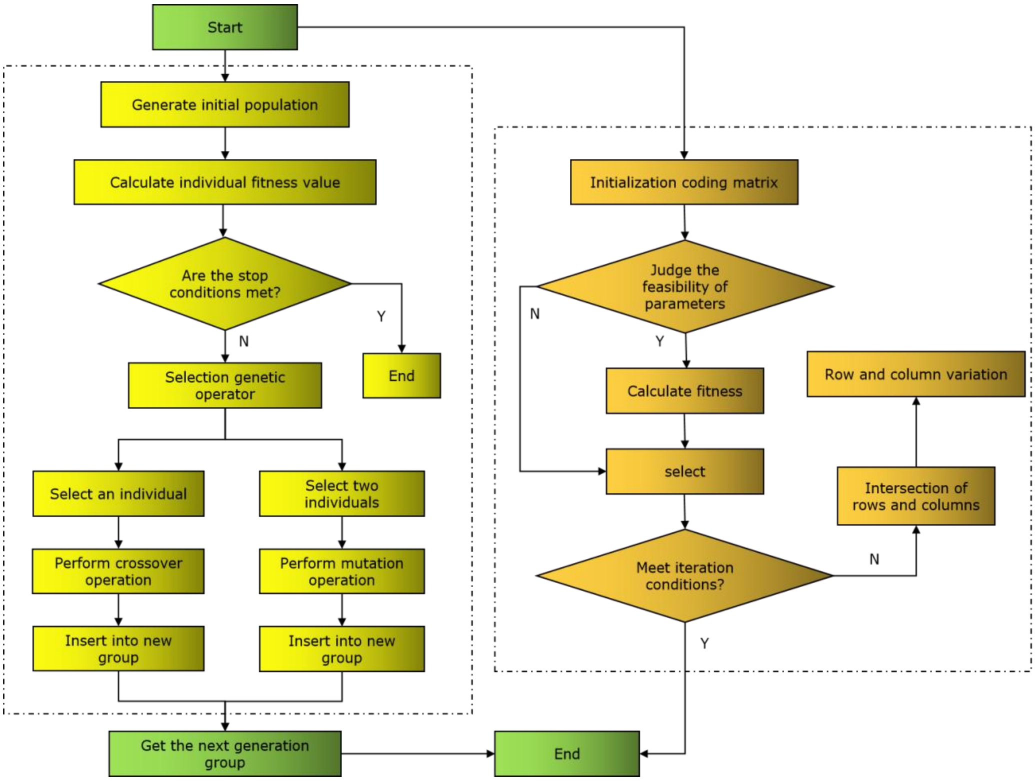


Figure 3: CNN optimization principle.

These chromosomes need to be decoded into CNN parameters and trained on the network. During the training process, standard backpropagation algorithms are used to update network parameters and validation sets are used to monitor the training process to prevent overfitting. For a chromosome k with fitness f_k, its selection probability s_k is calculated as follows:

$$S_k = \frac{r_k}{\sum_{i=0}^{pop\_size} fi} \tag{7}$$

$$F = \sum_{i=1}^{pop\_size} fi \tag{8}$$

$$S_k = \frac{r_k}{F} \tag{9}$$

$$t_k = \sum_{i=1}^{pop\_size} S_i \tag{10}$$

In order to achieve effective integration of CAD data and NNs, this study embedded a special processing module in the input layer of the NN for processing the features of CAD data. This processing module can be customized according to specific task requirements. For example, in scene rendering tasks, a convolutional layer can be designed to process the texture information of CAD data and a fully connected layer can be used to process its geometric information. Let the measurement equation and state equation of the dynamic system be as follows:

$$T_k = H_k Y_k + L_k \tag{11}$$

$$Y_k = f_{k,k-1} Y_k + \eta_{k,k-1} W_{k-1} \tag{12}$$

In this formula, the system state at the k th time is represented by Y_k, the state transition matrices at the $k-1$th time and the k th time are respectively represented by $f_{k,k-1,}\eta_{k,k-1}$, the measured value at the k th time is represented by T_k, L_k, W_{k-1} represents the noise of measurement and process respectively, and the measured parameters are represented by H_k.

Every function (x,y) can be decomposed into several polynomial sums about (x,y), and each polynomial about (x,y) is an independent basis function filter:

$$f^{\theta}(x,y) = \sum_l \sum_j k_{ij}(\theta) x^l y^j \tag{13}$$

The coefficient $k_{ij}(\theta)$ can be regarded as an interpolation polynomial. Typically, these autonomous basis functions comprise a collection of functions that have the capability to establish a space capable of rotational adjustments to any desired angle.

$$f(R,t) = \sum_{i=1}^{N} \left\| Q_i - (RP_{i\_}T) \right\|^2 \tag{14}$$

$$\sum{}^2 = \sum_{i=1}^{N} \left\| q'_i - Rq_i \right\|^2 \tag{15}$$

The ultimate goal is to transform the point cloud into a comprehensive triangular mesh.

CAD data is usually stored in complex file formats, such as DWG or DXF. To convert it into a format that can be processed by NNs, first convert it into 3D point cloud data or voxel data. This conversion can be achieved through professional CAD software or open-source libraries. The converted data retains the geometric and texture information of the original CAD data and is easy for NNs to process. This study embedded a special processing module in the input layer of the NN for processing geometric and texture information of CAD data. This processing module can be customized and optimized according to specific task requirements. In scene rendering tasks, a convolutional layer can be designed to process the texture information of CAD data, and a fully connected layer can be used to process its geometric information. Through this embedding method, the accuracy of CAD data and the generalization ability of NNs can be fully utilized to achieve high-quality scene rendering.

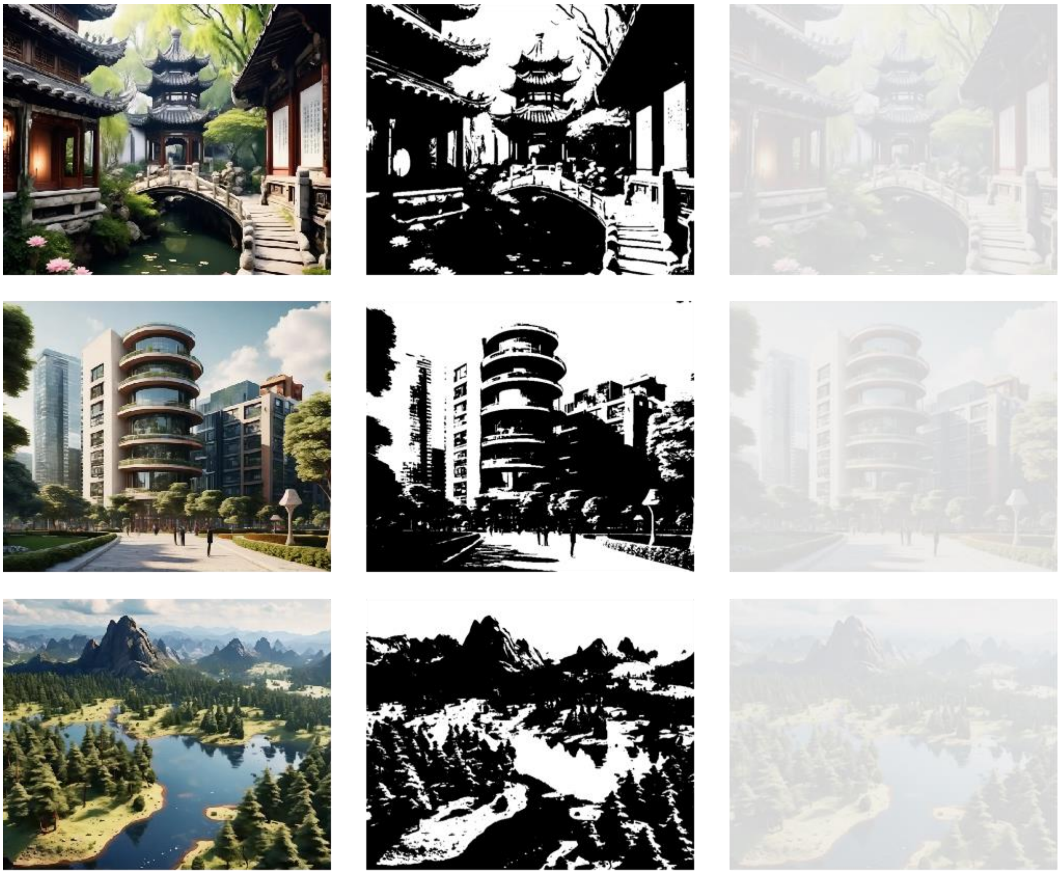
4 RESULT ANALYSIS AND DISCUSSION

4.1 Experimental Environment and Parameter Settings

In order to ensure the accuracy and repeatability of the experiment, this study used a high-performance computer as the experimental platform and configured appropriate hardware and software environments. In terms of parameter settings, detailed adjustments and optimizations have been made based on the requirements and characteristics of each algorithm to ensure that the algorithm runs at its optimal state. In addition, the study also used standard datasets for training and testing to ensure the reliability and generalization of the results. During the experiment, strictly control other variables that may affect the results to ensure the credibility of the experimental results.

4.2 Result Analysis

Figure 4 shows decomposition examples of three sets of environmental art images, each containing the original image, structural part, and texture part. The original image of the first set of images presents a panoramic view of a classical garden. The original image of the second set of images displays a modern urban street view. The original image of the third group of images presents a natural landscape.



(a) original image (b) Structural part (c) Texture part

Figure 4: Example of artistic image decomposition.

The experiment mainly explored the performance of high-resolution environmental art image data on both uniform and real datasets when the learning rate was 0.001, and the learning rate was changed using a multistep method, with stepvalue set to 26000 and 54000, gamma set to 0.1, and maximum iteration count of 500. By comparing and analyzing the results, we can better understand the impact of learning rate changes on model performance.

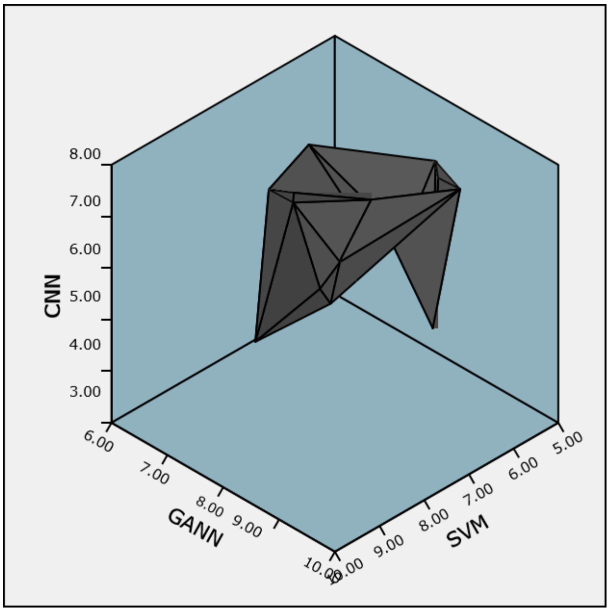


Figure 5: Effect of environmental art image data in uniform data set.

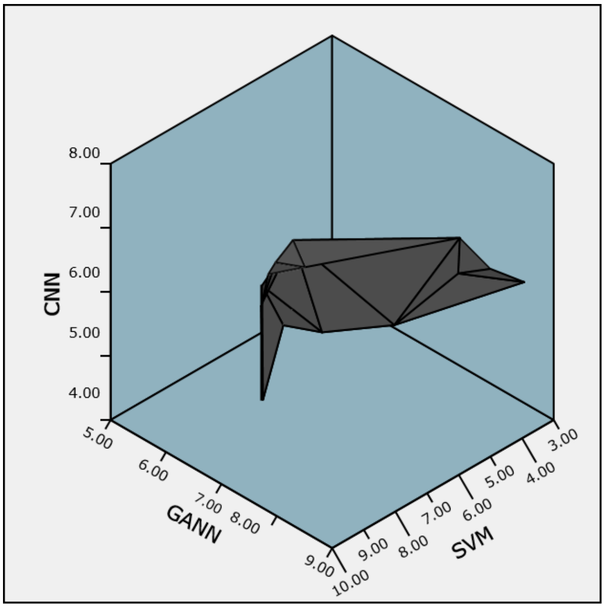


Figure 6: Effect of environmental art image data in real data set.

Figure 5 shows the performance of high-resolution environmental art image data on a uniform dataset. The model has a higher learning rate and a faster convergence speed in the early stages of training. As the quantity of iterations increases, the learning rate gradually decreases, and the convergence speed of the model also slows down accordingly. Figure 6 shows the performance of high-resolution environmental art image materials on real datasets. Compared to uniform datasets, real datasets are more challenging because they contain more noise and complex scenes. In the early stages of training, due to the high learning rate, the model converges faster, but it is also more likely to fall into local optima.

According to the results shown in Figure 7, the comparison of scene rendering accuracy between GA-CNN, CNN, and SVM algorithms can be analyzed. The method presented in this article performs well in terms of scene rendering accuracy, with a maximum accuracy rate of 95.24%. In contrast, CNN and SVM have lower accuracy.

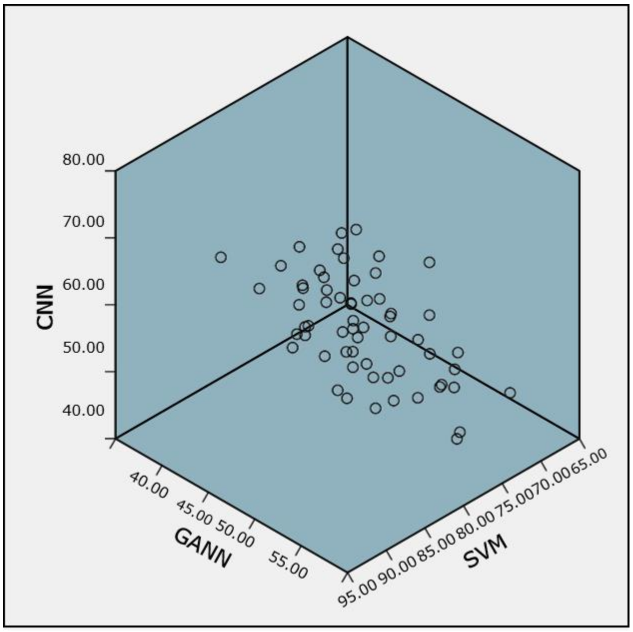


Figure 7: Accuracy of algorithm.

Compared with comparative methods, GA-CNN shows better performance in scene rendering accuracy. The accuracy curve is relatively stable and shows an overall upward trend. This may be due to CNN's strong feature extraction ability, which can effectively identify and classify different elements in the scene. The method presented in this article performs well in terms of scene rendering accuracy, with a maximum accuracy rate of 95.24%. The performance of different algorithms in handling scene rendering tasks is influenced by various factors, such as the characteristics of the algorithms themselves, parameter settings, and dataset complexity.

The response speed comparison results of the GA-CNN algorithm, CNN and SVM algorithms are shown in Figure 8.

Figure 8 shows the comparison results of response speed between the GA-CNN algorithm, traditional CNN, and SVM algorithms. From the overall trend, the response speed of the GA-CNN algorithm is significantly better than traditional CNN and SVM methods. The response speed of traditional CNN methods is relatively slow and has a large fluctuation range. This is because traditional CNNs require a large amount of convolutional operations and feature extraction when dealing with complex environmental art scenes, resulting in longer computation time.

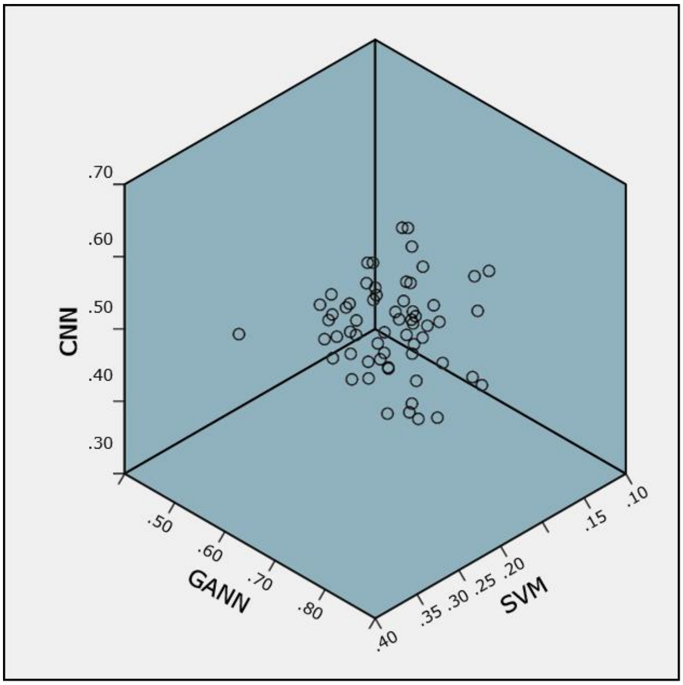


Figure 8: Comparison results of algorithm response speed.

The response time of the SVM algorithm is relatively short, but the fluctuation range is large, showing a certain degree of instability. Compared with traditional CNN and SVM methods, the GA-CNN algorithm shows significant advantages in response speed. Due to the combination of the advantages of GA and CNN, the GA-CNN algorithm improves the computational efficiency of the model by optimizing the network structure and parameter settings.

4.3 Discussion

The improved CNN model, namely the GA-CNN algorithm, has shown significant technical advantages in processing environmental art scenes. This advantage is not only in its computational stability but, more importantly, it provides practical technical support for the field of environmental design., From the perspective of response speed, the excellent performance of the GA-CNN algorithm means that in the actual environmental design stage, designers can quickly obtain the rendering effect of the scene, thereby accelerating the iterative process of design. For designers, this is undoubtedly a huge convenience, as it helps them try various design solutions more efficiently and achieve the desired results in a short period of time.

In environmental art design, designers must ensure that the rendering effect of the scene is both aesthetically pleasing and meets practical needs. The GA-CNN algorithm, by cleverly combining the characteristics of GA and CNN, ensures not only rendering speed but also rendering performance. Although the GA-CNN algorithm has significant technical advantages, designers still need to possess certain technical skills in order to fully utilize its functionality in practical operations. Therefore, attention should be paid to technical training for designers to help them become familiar with and master this cutting-edge algorithm tool. The efficient operation of the GA-CNN algorithm relies on strong hardware resource support. To ensure that the algorithm can perform at its optimal level in practical applications, we should consider optimizing the allocation of hardware resources. When using the GA-CNN algorithm for environmental art design, attention should also be paid to ethical and Sustainability issues.

5 CONCLUSION

High-quality scene rendering typically requires a significant amount of computational resources and time. In order to achieve effective integration of CAD data and NNs, this article proposes a strategy based on data conversion and network embedding. This strategy first converts CAD data into a format that can be processed by NNs, such as point cloud data or voxel data. Then, a network embedding method was designed to embed the geometric and texture information of CAD data into the input layer of the NN.

The application of the GA-CNN algorithm in environmental art design has shown significant advantages. Its fast response ability, high computational efficiency, and stability make it a powerful tool for designers when dealing with complex environmental art scenes. By combining the advantages of GA and CNN, the GA-CNN algorithm can ensure both rendering speed and quality. In order to fully tap into the potential of the GA-CNN algorithm in environmental art design, a series of corresponding measures should be taken. This includes strengthening technical training to familiarize designers with and master this advanced algorithm tool, Optimizing hardware resource allocation to ensure that algorithms can achieve optimal results in practical applications, Paying attention to ethical and Sustainability issues, and ensuring that the use of algorithms meets ethical and legal standards.

The development of technology needs to be combined with practical application scenarios, fully considering the needs and expectations of users. Only in this way can the GA-CNN algorithm maximize its value in environmental art design, bringing better experiences and benefits to designers and users.

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