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Computer-Aided Design AND APPLICATIONS

Construction and Implementation of Soft Interior Design System Based on Deep Learning Aided CAD Modeling

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Abstract. The gradual popularization of computer multimedia technology has brought great convenience to people. The birth of CAD design software effectively combined computer technology with interior design, so more and more interior design began to use CAD for design. Based on DL (Deep learning) technology, this article discusses the related problems of soft interior design. This article introduces the main design idea, technical route and main functional characteristics of the soft interior design CAD system, and discusses the advantages of adopting object-oriented design idea and DL in the CAD system. Based on this, DL is effectively used to assist CAD modeling, thus a new soft interior design system is constructed. The soft interior design system constructed by using DL aided with CAD modeling successfully unified the process of soft interior design and fully met the needs of designers. At present, CAD reflect significant significance in the interior design of soft clothes. It is hoped that this research can further expand the application scope of DL and promote the positive growth of interior design.

Keywords: Deep Learning; Deep Neural Network; CAD Modeling; Soft-Mounted Interior Design
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1 INTRODUCTION

Nowadays, driven by economic growth, people have higher and higher requirements for their living space, which also makes many people pay attention to indoor soft decoration design. Soft-fitting design in architectural interior design is put forward relative to the hard structure of the building itself. Soft-fitting means that after the building is hard-fitting, people match the overall style of the building according to their own preferences, and rust or transform the building space through decorations to improve the warmth or modernity. Its main consideration is the owner's requirements for the atmosphere, connotation, culture and spirit of the environment, and the overall layout and unified planning are carried out. It mainly includes green plants, furniture, bedding, decorations, daily necessities, curtains and carpets. As a necessary environment for residents to get along with most of the time, the indoor environment puts forward high requirements in terms of ornamental, so as to meet people's spiritual needs. Therefore, more and more people attach importance to and recognize the soft interior design. Soft-fitting design can well decorate and improve the design taste of space and make up for the defects and deficiencies of the original space, which plays a decisive role in creating space atmosphere and creating space style. This requires designers to comprehensively consider all aspects, reasonably use soft-fitting collocation, and appropriately use design elements for embellishment. At present, soft decoration has become the key research direction of interior designers in the decoration industry. Moreover, thanks to the growth of technology, CAD modeling also plays a more important role in soft interior design.

Deep learning assisted CAD modeling for interior soft design analysis is a promising field. In interior design, soft design is an important part, including furniture, decoration, curtains, carpets, etc. Interior soft design analysis based on deep learning can help designers complete design tasks faster and more accurately. Firstly, deep learning can be used for automatic layout of indoor soft design. Through deep learning algorithms, the optimal furniture layout scheme can be automatically generated based on user needs and room size. This can greatly reduce the workload of designers and improve design efficiency. Secondly, deep learning can be used for automatic style matching in indoor soft design. Through deep learning algorithms, suitable furniture and decorations can be automatically recommended based on the decoration style of the room. This can ensure consistency between soft design and hard design styles, improving the overall effect of the design. Finally, deep learning can be used for automatic color matching in indoor soft design. Through deep learning algorithms, the optimal color scheme can be automatically generated based on the lighting conditions of the room and user preferences. This can ensure that the soft design meets the aesthetic needs of users and improve design satisfaction. In summary, the analysis of interior soft design based on deep learning is a very promising field. It can help designers complete design tasks faster and more accurately, improving the efficiency and quality of design. DL started from cybernetics, and the earliest concept of DL drew lessons from the system structure of biological NN (Neural network) system and built a simple artificial NN model. Its principle is to transfer the underlying features layer by layer like the NN of the brain, and transform the input underlying features into more abstract and advanced features, thus discovering the inherent distributed features of the data. DL is a brand-new branch of traditional machine learning. Its main content is a deeper expansion of the original NN structure, so it has a more complex structure. At present, DL has good experimental results in many research fields such as image processing, natural language processing and computer vision, and has great potential for research and development. Compared with the traditional methods, DL network automatically obtains the weight parameters through multiple trainings, and it is easy to get the optimal segmentation result, so the algorithm has better generalization. With the improvement of hardware, especially the capacity and access speed of graphics computing unit, it provides hardware support for 3D data storage and parallel computing, and the quality of DL modeling is also improved due to the improvement of computer performance.

The methods of 3D voxel model generation based on DL can be divided into the following categories: 3D voxel model generation based on feature representation learning; 3D voxel model generation based on spatial mapping; 3D voxel model generation based on collaborative learning. At present, most DL algorithms acting on voxels mostly adopt 3D convolution NN similar to 2D convolution NN. In this article, the main design idea, technical route and main functional characteristics of the soft interior design CAD system are introduced, and the advantages of adopting object-oriented design idea and DL in the CAD system are discussed. Moreover, DL is effectively used to assist CAD modeling, thus constructing a new soft interior design system. Its innovations are as follows:

(1) In the past, there were some problems in 3D model generation, such as low accuracy, large network parameters, slow prediction speed, etc. This article considered applying DL to CAD modeling, and effectively used DL to assist CAD modeling, thus constructing a new soft interior design system.

(2) In order to improve the problem of uneven edges of objects in scene segmentation, an edge convolution reuse method is proposed to capture edge feature information. Moreover, a lot of compression has been carried out on the model size and the calculation amount of the model, which makes the model have fast operation speed, low calculation overhead and good accuracy. And the operation efficiency is improved.

Section 1: introduces and analyzes the research significance, and puts forward the research methods of this article. Section 2: Related work. The research status of related fields is summarized. Section 3: Discussed the related problems of DL application. Section 4: Using DL to assist CAD modeling, a soft interior design system is constructed. Section 5: Conduct simulation experiments and analyze the experimental results. Section 6: Summarizes the methods and contributions of this article.

2 RELATED WORK

With the improvement of people's living standards, the demand for indoor space layout is becoming increasingly diverse and personalized. Therefore, the future Computer-aided design system needs the ability to generate personalized layout design schemes according to user needs and preferences. Today, with the concept of sustainable development increasingly ingrained in people's hearts, green and environmentally friendly design has become an inevitable trend in indoor space layout design. Future research should focus on how to use computer Assistive technology to achieve green design in energy conservation, environmental protection, health and other aspects. The cross integration with other disciplines will bring new development opportunities for computer-aided indoor space layout design. For example, combining disciplines such as psychology and anthropology with design to study the impact of human behavior and psychological characteristics on indoor spatial layout will help improve the practicality and comfort of design schemes. The application of virtual reality (VR) and augmented reality (AR) technology will greatly enhance the immersion and realism of computer-aided indoor space layout design. Designers and users can experience and adjust layout design solutions in real-time through VR or AR devices, thereby improving communication efficiency and user satisfaction. In short, computer-aided indoor space layout design is developing towards intelligence, automation, networking, and green environmental protection. With the continuous progress of technology and the expansion of application scope, we have reason to believe that future computer-aided indoor space layout design will create a more comfortable, beautiful, and livable living environment for people.

Alanezi et al. [1] conducted an intelligent building construction using the Internet of Things wireless network. The optimal location for intelligent buildings has been determined through the development of progressive basic measures for CAD networks. The acquired experience talent can automatically obtain the development and construction of intervention modes and router numbers. Ghazouly and Antably [2] designed the interior 3D model of the Mannequin. It constructs a customized quantitative indoor ergonomic model closed-loop analysis framework. Evaluate the ergonomic comfort of interior layout and furniture design by using digital Mannequin. Hoang et al. [3] conducted a solution test for localization neural networks. It constructs measurement correlation analysis under signal strength indicators. By analyzing the data of the weighted average filter, different types of structural algorithms were used, and the errors under different structural probability algorithms were given. Huang et al. [4] analyzed interactive computational design experiments in interior design. By visualizing and analyzing the collected data, a clustering method based on color intervals was constructed to capture the design. The results indicate that the recommendation application of visualization systems brings enormous potential to experimental clustering in data analysis. Kurkela et al. [5] conducted environmental model comparison standards for space physics cameras. By analyzing the geometric structure of a three-dimensional building model. It constructs the measurement process of indoor measurement objects in buildings. Perez et al. [6] analyzed the traditional working method of Convolutional neural network analysis image construction. It conducts asset security assessment through object localization and is used for automatic image detection. By objectively describing building defects, the defects and degradation effects of automatic building equipment under steady-state building conditions were analyzed. Qin et al. [7] analyzed the automatic coding Convolutional neural network for indoor transmission. By extracting key features from the online stage dataset, a validation technology for indoor fingerprint localization based on CNN output position was constructed. Improved the accuracy and robustness of indoor positioning technology. Runge and Zmeureanu [8] conducted feature extraction for data-driven analysis of overall energy in buildings. It enhances the basic ability of nonlinear phenomena through the application of deep learning technology. By extracting model features from deep learning, it summarizes the current driving models for deep learning. Shahriari et al. [9] used a linear regression model to provide spatial design feedback on the layout of store space. After adopting the model layout of the standard board, it constructed the statistical film collection data behavior of the basic store in terms of structure. After emphasizing the design of layout factors. It optimized the flight attendant structure prediction for the scene. The Committed step of intelligent indoor service awareness is topology-based tracking. Tamas and Toth [10] have defined the classification of buildings for indoor symbol positioning. A dataset comparison was conducted on the gravitational error of symbol positions in room corridors. The results indicate that buildings based on topological structure exhibit more detailed performance in indoor language labeling. Tarihmen et al. [11] carried out route analysis of Indoor positioning system. It introduces the digital concept of CAD signal technology models into the environment to build the first step of intelligent 3D indoor design. Thakur and Han [12] conducted spatial environment assistance design for indoor positioning. It verifies the location of the active area through the interactive Big data driving method, and constructs the spatial coordinate analysis of the user's indoor location of acceleration. When testing the dataset, this method performs system positioning and error analysis. Wang et al. [13] proposed a synthesis planning encoding method based on internal scenes, which constructs a deep learning image semantic relationship encoding graph. By analyzing the flexibility of the spatial model of the scene and the quality of the scene, it generates graphics to support scene synthesis using the program. Yu et al. [14] conducted technical management and control optimization of traditional building energy. There are many model defects in current buildings. When building energy models have significant parameter management requirements, they have different control optimization features in different feature extraction and parameter design. Through optimization analysis of energy management, the technical issues of system parameters were constructed. Zhang et al. [15] developed a computer technology for fusion materials. A CAD based support structure analysis framework was constructed by designing the parts of the automatic structure generation module. Evaluate the analyzable features of graphics using dynamic computer geometry algorithm parameters.

Based on DL, this article discusses the related problems of soft interior design. Based on this, DL is effectively used to assist CAD modeling, thus a new soft interior design system is constructed. The soft interior design system constructed by using DL aided with CAD modeling successfully unified the process of soft interior design and fully met the needs of designers.

3 APPLICATION OF DL

Deep learning algorithms can automatically generate the optimal furniture layout plan based on the room size and requirements provided by users, helping designers complete layout design tasks faster and more accurately. Deep learning algorithms can automatically recommend suitable furniture and decorations based on the decoration style of a room, ensuring consistency between soft and hard design styles, and improving the overall design effect. Deep learning algorithms can automatically generate the best color scheme based on the lighting conditions of the room and user preferences, helping designers quickly and accurately complete color design tasks. In addition, this algorithm can automatically segment different objects and regions based on the pixel information in the image, thereby helping designers draw and design indoor scenes more accurately. Deep learning algorithms can automatically search and recommend suitable furniture products based on the furniture styles and sizes provided by users, helping designers more accurately select the right furniture for their rooms. In short, the application of deep learning in the field of interior design can help designers complete design tasks faster and more accurately, improving the efficiency and quality of design. The brain adopts a layered mechanism for processing external information. When the brain receives information from sensory organs, it will hand it over to multi-layer progressive neurons for processing, and extract the features representing things in each layer, and form a cognition of things through layer-by-layer transmission. To a great extent, the construction of deep NN is based on this cognitive process, which abstracts information for many times. For NN, depth refers to the quantity of nonlinear operation combinations in the function automatically learned by the network model through neuron parameters and the neuron hierarchy of NN. The sparseness of the connection between the layers of DL network and the parameter sharing mechanism of convolution kernel in the hidden layer make it possible to learn audio, images, texts, etc. with a small amount of calculation, and to mine its high-dimensional implicit features. Moreover, there is no need for additional conversion of input data. The corresponding calculation formula of single neuron connection structure is as follows:

$$h(x,w,b) = f\left(w^T x\right) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{1}$$

Where w_i represents a trainable weight parameter multiplied by the input x_i; b stands for bias, which ensures that the nonlinear function does not pass through the zero origin; f represents a nonlinear function mapping relationship that can be learned by a certain network.

Because NN adopts distributed storage structure, it has strong fault tolerance. Moreover, it has a good generalization function, can handle all kinds of noise interference well, and has good stability. NN can extract different regional features from different levels from shallow to deep, and its abstract ability will be enhanced with the deepening of the level. Different from the shallow network structure, DNN (Deep neural network) needs to design the input nodes, network layers and hidden nodes in detail according to specific tasks, so as to achieve better prediction results. The NN neuron conversion function can use a sigmoid function, and the function form is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The loss function used in this article is the square loss function, as shown in the following formula:

$$J(\theta) = \min_{\theta} \frac{1}{2} \sum_{i=1}^{m} \left(h_\theta\left(x^{(i)} - y^{(i)}\right)\right)^2 \tag{3}$$

Among them, $J(\theta)$ represents the function that minimizes the variance about θ, which is actually the value of the loss function, representing the coincidence degree between the model and the training data.

$$\theta_i = \theta_i - \alpha \frac{\partial}{\partial \theta_i} J(\theta) \tag{4}$$

Where θ_i represents the value of the loss function; α represents the value of learning rate; The learning rate to the right indicates the downward direction. Gradient descent method is an algorithm to solve the minimum value of cost function. By calculating the gradient value of the function and using the constructed cost function, the minimum value is obtained, and finally the optimal weight parameters and offset are obtained. The formula is as follows:

$$w = w - \alpha \frac{\partial J(w,b)}{\partial w} \tag{5}$$

$$b = b - \alpha \frac{\partial J(w,b)}{\partial b} \tag{6}$$

The gradient descent method is to make the cost function approach the lowest point and find its optimal solution.

The weight sharing of DNN (Deep Neural Network) framework graphs is an important technique that can help us reduce the number of parameters that need to be learned, thereby improving the generalization performance of the model and avoiding overfitting. Weight sharing can significantly reduce the number of parameters that need to be learned, thereby reducing computational complexity and storage requirements. This is because it allows us to use the same weight parameters throughout the entire network without the need to learn a new weight parameter for each neuron. This can significantly reduce the complexity of the model, especially when the network layers are deep. Weight sharing can also promote the reuse of features, thereby improving the efficiency of the model. Due to the fact that the same weight parameters can be reused in different positions, we can more effectively utilize the learned features without the need to relearn them. This helps to improve the training speed and generalization performance of the model. However, weight sharing may also introduce some limitations. It may limit the expressive power of the model as it cannot make specific weight adjustments for each position. This may lead to poor performance of the model in certain situations. In addition, if weight sharing is abused or improperly used, it may also lead to information redundancy and waste. Therefore, when using weight sharing, it is necessary to weigh its advantages and disadvantages and make adjustments according to the specific situation. For example, different weight sharing strategies such as local connections, convolution operations, etc. can be used to balance the complexity and expressive power of the model. In addition, the risk of over fitting and under fitting of the model can be controlled through Learning rate, regularization and other technologies. In summary, weight sharing in DNN framework graphs is an important technique that can help us reduce the number of parameters that need to be learned, improve the efficiency and generalization performance of the model. However, when using it, it is necessary to pay attention to its advantages and disadvantages and make adjustments according to the specific situation. The framework of DNN is shown in Figure 1.

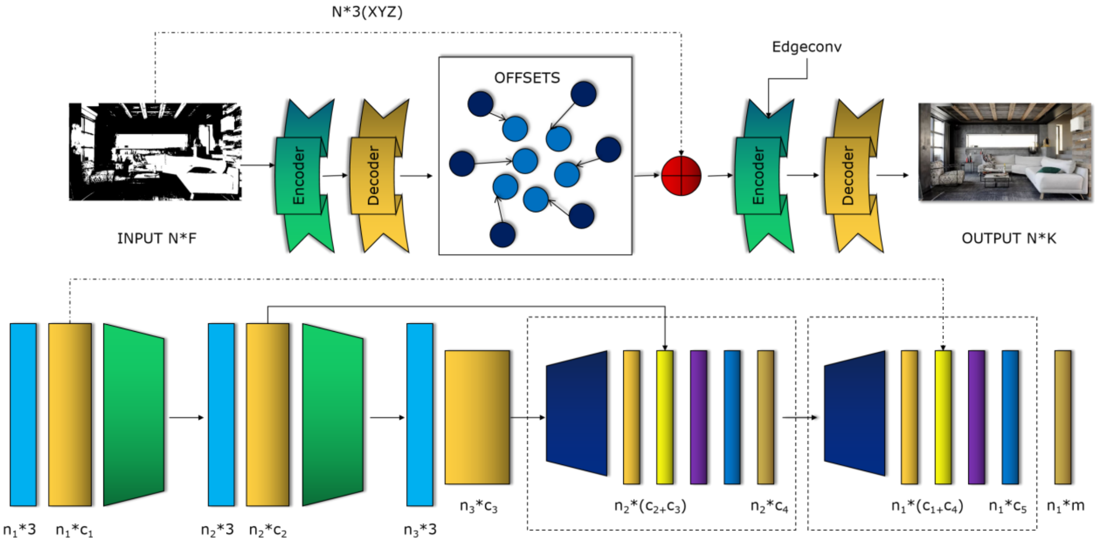

Figure 1: DNN frame diagram.

Weight sharing makes convolution layer have translation invariance to image features, that is, both network input and output have the same translation change.

4 DL AIDED CAD MODELING TO BUILD SOFT INTERIOR DESIGN SYSTEM

With the continuous progress of science and technology, Computer-aided design (CAD) has become an important tool for indoor space layout design. This article will explore the methods and techniques of computer-aided indoor space layout design, and analyze its future development direction. Firstly, it is crucial to understand the basic ideas of indoor spatial layout. During the design process, clarifying the design objectives, conducting Spatial analysis and implementing layout optimization are the Committed step to ensure that the final layout scheme meets the expectations. Design objectives need to be formulated according to specific needs and site conditions. Spatial analysis needs to analyze the size, shape, orientation and other elements of the site, while layout optimization needs to consider functionality, aesthetics, comfort and other factors. Secondly, mastering computer Assistive technology is the key to realize efficient design. At present, computer-aided indoor space layout design mainly relies on technical means such as image processing, model construction, and scene simulation. Image processing can help designers edit, analyze, and process original images, making layout design more accurate and efficient. Model construction can transform spatial information into three-dimensional models, making it easier for designers to examine design effects from different perspectives. Scene simulation can help designers evaluate the feasibility and actual effectiveness of layout plans by simulating actual usage scenarios. When evaluating layout plans, user feedback and data analysis are important indicators. Designers need to obtain user feedback through user surveys, Focus group and other means in order to optimize the design scheme. At the same time, using data analysis tools to conduct data mining on layout plans, such as spatial utilization rate, pedestrian flow distribution, comfort evaluation, etc., can provide more objective basis for decision-making. Finally, looking forward to the future development direction of computer-aided indoor space layout design, intelligence, automation, and networking are the main trends. With the development of artificial intelligence technology, the future Computer-aided design system will have more intelligent layout design scheme recommendation and optimization capabilities. Meanwhile, automation technology will enable designers to more efficiently implement design solutions and reduce the impact of human factors on design results. Networking will enable designers to collaborate remotely and jointly complete complex layout design tasks.

In order to ensure the accuracy of detection, the interface of closed operation is called by the morphologyE* function, which connects the large white areas in the background difference results, removes the small white noise and enhances the image characteristics. Finally, the minimum bounding rectangle is obtained from the result image of closed operation by minAreaRet function. According to the coordinates of the rectangle, the region of interest is set in the original image, and the target is cut out for the subsequent DL. DL network has fast data processing speed and high accuracy, and can accommodate new samples and adjust model parameters accordingly, so that the error can be greatly reduced. At present, the more successful DL network structures are Alex Net, Mobile Net, GoogLeNet, ResNet and so on. Back propagation is to transmit the output result in NN and the error of real label back to NN. From the output layer, along each layer of NN, the error generated in NN is transmitted back to each neuron, which is used as the basis for correcting the weights and deviations in neurons and adjusting the parameters in NN. Using DNN with multiple hidden layers to directly process image data will require a huge amount of parameters in the network, which requires strong hardware computing power to process, greatly increasing the network training cost and practical application difficulty. Therefore, in order to apply DL to image processing and analysis, it is need to reduce the amount of network parameters. The MobileNet structural model draws lessons from depth separation convolution, which can classify 3D images accurately and quickly. The core idea of depth separation convolution is to solve the traditional convolution into a depth convolution and a 1*1 convolution. Because of the multi-hidden layer structure of the network, it is difficult to achieve global optimization, so the greedy algorithm of layer-by-layer optimization is adopted in its learning process. Using unsupervised learning method, only two adjacent layers of Boltzmann machines in the network are learned at a time; When learning, the restricted Boltzmann machine of each layer obtains the hidden node value and connection weight parameters of this layer through maximum likelihood learning method according to the input information. The convolution calculation process is shown in Figure 2.

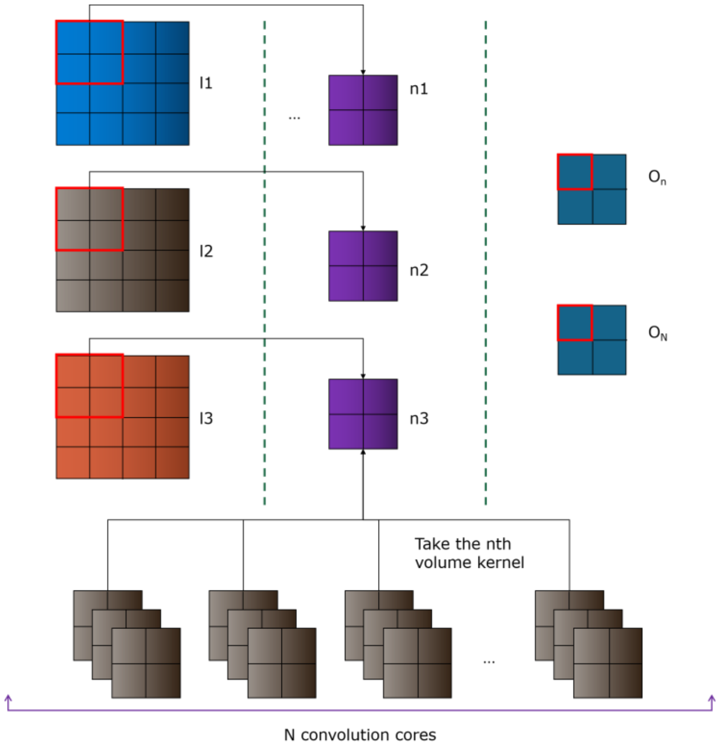

Figure 2: Convolution calculation process.

Assume that there are N layer point cloud data sets, and each layer point cloud data set has M frames, so each layer point cloud data set of the space scene can be expressed as:

$$\left(P_1^1;P_1^1;P_3^1;\ldots;P_M^1\right),\left(P_1^2;P_1^2;P_3^2;\ldots;P_M^2\right)\ldots,\left(P_1^N;P_2^N;P_3^N;\ldots;P_M^N\right) \tag{7}$$

Where N represents the quantity of layers collected in the scene; M stands for the quantity of frames per layer. Assuming that the predicted scene object is represented by symbol $\hat{V}_n$ and the true voxel is represented by symbol V_n, the loss function can be expressed as:

$$L_V = \frac{1}{N}\sum\nolimits_n V_n \log\hat{V}_n + \left(1-V_n\right)\log\left(1-\hat{V}_n\right) \tag{8}$$

The rotation degree of the target object is represented by unit regularization quaternion. For the convenience of training, this process is compared with the classification task, the rotation vectors are divided into 24 categories and the probability of each category k_d is predicted. Assuming that

k represents the true value of the container and the loss function is set as a negative likelihood function, the loss function can be expressed as:

$$L_q^c = -\log\left(k_d^k\right) \tag{9}$$

The translation and scaling loss function of the target object can be expressed as follows:

$$L_t = \left\|t - \hat{t}\right\|_2^2 \tag{10}$$

$$L_c = \left\|\log\left(c\right) - \log\left(\hat{c}\right)\right\|_2^2 \tag{11}$$

Among them, t and c represent the selection translation coefficient of truth value respectively. $\hat{t}$ and $\hat{c}$ represent the structure of the forecast. In order to improve the accuracy of matching, the rotation and translation matrix obtained based on feature matching pairs is taken as the initial value of the algorithm, and P_2^1 is used to match P_1^1. The ultimate goal is to calculate the rigid transformation between point sets P_1^1 and P_2^1, and find the corresponding relationship between them. Therefore, the minimum mean square error function can be obtained as follows:

$$\min_{\mathrm{R,t,j}\in\{1,2,\ldots,N_m\}} \sum_{i=1}^{N_n} \left\|Rb_i + t - a_j\right\|_2^2 \tag{12}$$

$$s.t. \quad R^T R = I_m, \det\left(R\right) = 1 \tag{13}$$

Where $R \in R^{m\times n}$ is the rotation matrix; t is a translation matrix.

The mini-batch gradient descent algorithm used in this article is an optimization of the batch gradient descent algorithm and the random gradient descent algorithm. Each iteration randomly selects samples from the total sample for gradient descent, so that the solution can converge to the optimal solution and save time. Firstly, the input feature map is convolved by depth separable convolution one by one; Then use 1*1 convolution check to convolve the results of the first step one by one. The deeply separable convolution operation reduces the network complexity and improves the model performance without increasing the quantity of parameters. The computation of deep separable convolution is reduced to about 1/9 of that of traditional convolution. The training steps of DL network are shown in Figure 3.

DNN has sparse weight, because the image input nodes will reuse the weight parameters of each convolution kernel in the convolution layer, which will not reduce the time complexity, but will make DNN have the characteristics of weight sharing between convolution layers. Compared with the traditional NN, this has played a role in reducing the scale of weight parameters. Deep convolution combined with 1*1 convolution replaces traditional convolution. Because 1*1 convolution is widely used, highly optimized matrix multiplication can be directly used to complete the operation, and 1*1 convolution does not need im2colP pretreatment operation, which improves the operation efficiency. When there is enough data, the deeper the hierarchy of NN, the better its performance. However, in the training process, because the numerical value needs to go through the process of derivative transfer many times, it is easy to have the problems of gradient disappearance and gradient diffusion. Aiming at the problem of gradient disappearance and gradient diffusion, this article uses depth residual NN to complete the feature extraction of the image, thus extracting more representative image information. The system adopts the object-oriented analysis and design method, and uses the open structure of AutoCAD core database and the inheritance and derivation mechanism of base classes and classes provided by ObjectARX to define all kinds of main professional objects of soft packaging by class.

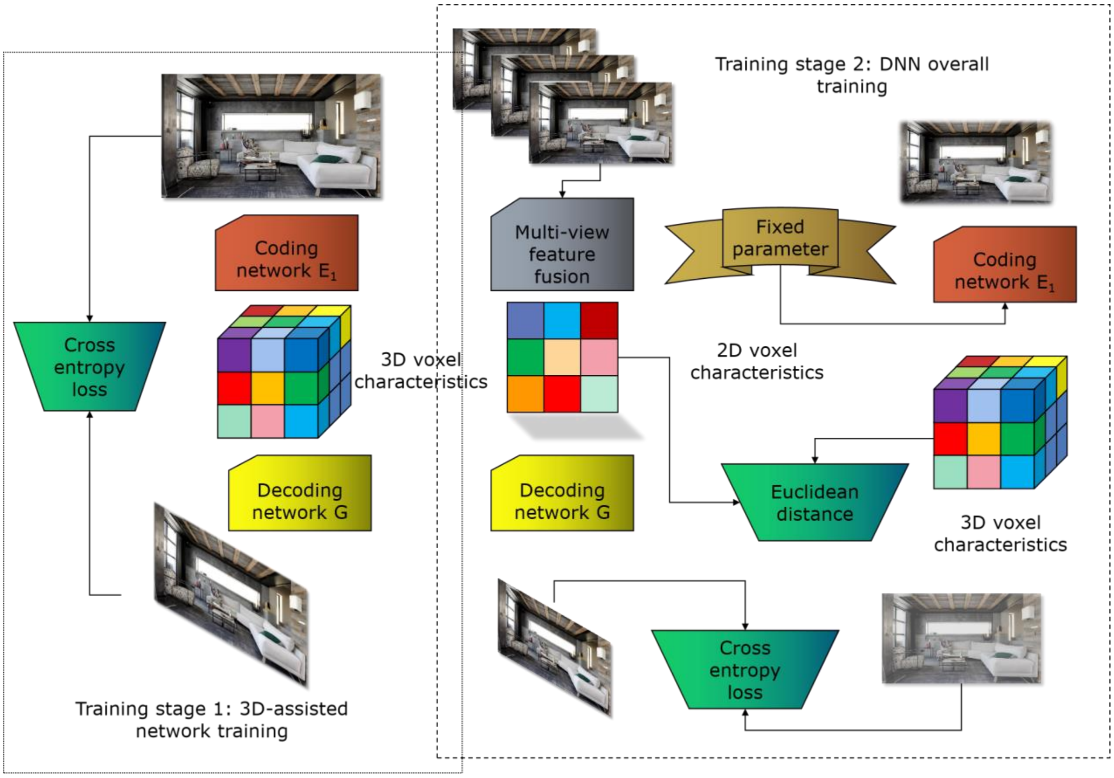

Figure 3: DL network training step diagram.

This enables the structure and style of the generated entity to be dynamically generated and changed according to the attributes and parameters specified by the user. This can better meet the needs of users and effectively improve the flexibility of the system.

5 TRAINING OF DNN PARAMETERS AND ANALYSIS OF TEST DATA

In order to train a high-performance NN, two conditions are needed, one is to have a large-scale NN structure, and the other is to have enough data for large-scale networks to train. In this article, DL framework and MobileNet model are installed first, and then the target sample pictures are trained to train the corresponding NN. When training a single network, all the parameters of the previous layer network will be frozen, that is, the weight parameters will not be updated by back propagation, but only the weight parameters of some networks will be trained and updated. The optimization algorithm for training is Adam. The setting of learning rate is an important link in network construction, which is related to the balance between convergence speed and stability. Improper learning rate will lead to slow convergence speed, low efficiency and unstable system. Therefore, it is need to set the value of the learning rate in an appropriate range. The way to find the optimal solution is to keep trying. At the beginning, you can set it a little bigger and find the optimal learning rate through experimental attempts. Generally speaking, the learning rate is usually set between 0.0001 and 0.1, and this article sets the learning rate to 0.001.

In the experiments in this section, offline evaluation is basically used, which mainly includes algorithm error, accuracy and efficiency. Firstly, the training situation of the algorithm is given, as shown in Figure 4.

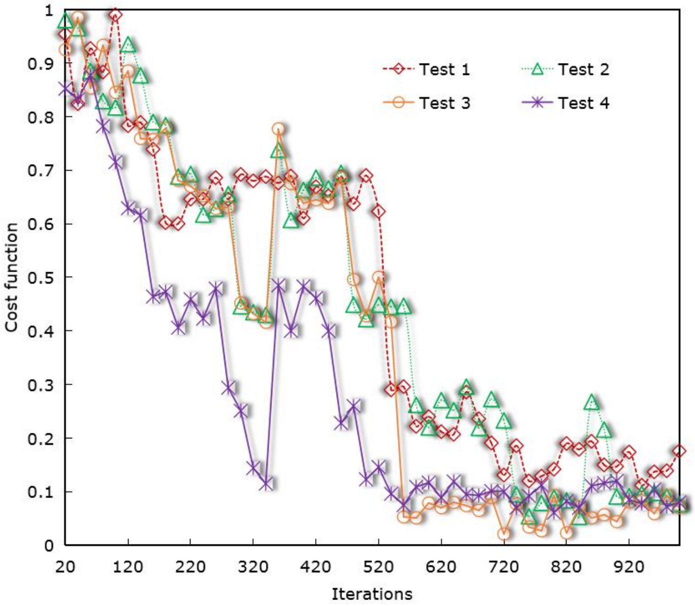

Figure 4: Algorithm training situation.

As shown in the figure, in this experiment, the quantity of training iterations is 1000. When the quantity of training reaches about 560, the cost function basically converges.

This system is designed and developed by using AutoCAD development platform and ObjectARX development system, so it has the basic functions of CAD, soft interior design and gallery navigation. All kinds of unfavorable factors will be encountered in the original data collection, so it is very important to finish the preprocessing operation of the picture reasonably. The sample data set trains the corresponding NN model which can be used for identification through the MobileNet structural model of the system, and the test data set is used to test the accuracy of the NN model. If the trained NN model achieves the expected accuracy, it can be used to achieve the final design goal. Table 1 shows the accuracy of different methods.

Model	*Training accuracy*	*Test accuracy*
Decision tree	0.921	0.631
Random forest	0.954	0.552
Traditional NN	0.807	0.416
DNN	0.892	0.902

Table 1: Accuracy of the algorithm.

Through the above simulation results, it can be seen that compared with NN method, this method has more advantages. DNN reduces the quantity of parameters and extracts salient features by sharing the weights of convolution kernel. The accuracy of the model is greatly improved by changing the parameters of gradient descent algorithm.

For the 3D model of the model database, the placement position of the model is arbitrary. In order to make the extracted two-dimensional views have unified regulations, the 3D model is often preprocessed before the view extraction of the model. The proposed method needs to place the model along the center of mass axis, so this article will do translation normalization. According to the method of PointNet, the room is divided into 1m*1m small squares on the ground, each block contains 4126 points, and there is an overlap of 0.5m between each block. In case segmentation, the features of each point are represented by 10-dimensional vectors. Moreover, the quantity of convolution layers of the encoder is increased to extract more advanced 3D voxel model features. In order to prevent the degradation of feature information caused by too many convolution layers, the encoder is designed to add jump connections between convolution layers, so that the features of high-level convolution layers and low-level convolution layers are integrated with each other.The error experiment of this algorithm is shown in Figure 5. In order to further reflect the superior performance of the algorithm in this paper, Figure 6 shows the comparison of error experiments of several different algorithms.

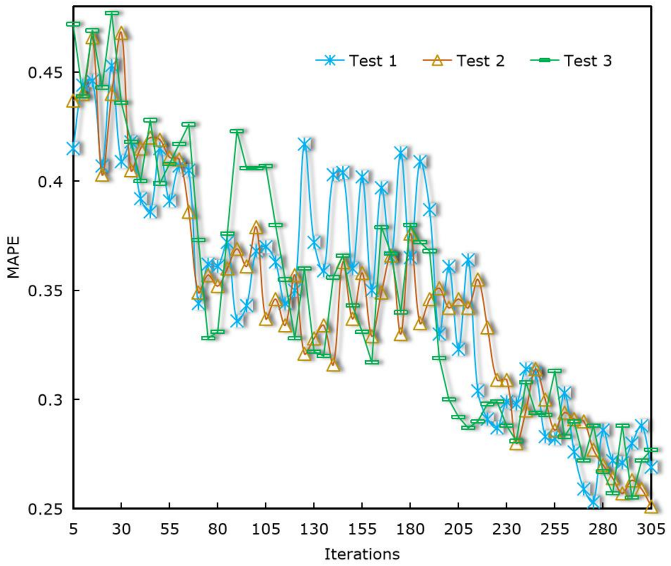

Figure 5: Error experiment of the algorithm in this paper.

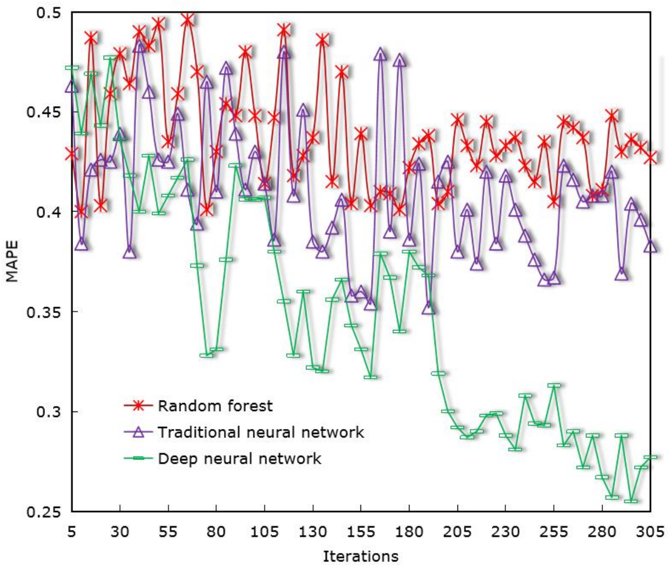

Figure 6: Comparison of error experiments of different algorithms.

The model can be directly embedded into the network to generate edge features describing the relationship between a point and its adjacent points. Therefore, the model can group points in Euclidean space and semantic space. In order to better analyze the results, this section draws the efficiency comparison diagram of several algorithms according to the data, and the specific results are shown in Figure 5.

Shared convolutional kernel is a technique to reduce the number of parameters in Convolutional neural network. Its basic idea is to use the same convolutional kernel on different feature maps at the same location. The advantage of doing so is that it can reduce the number of parameters that need to be learned, thereby reducing computational and storage requirements. Specifically, let's assume we have a k * k convolution kernel that performs convolution operations on the input feature map of m * n. If each feature map uses a different convolutional kernel, then the number of parameters we need to learn will be $(m - k+1) \times (n - k+1) \times K^2$. However, if we use a shared convolutional kernel, which means using the same convolutional kernel on all feature maps, then the number of parameters we need to learn will be reduced to $k^2 \times (m - k+1) \times (n - k+1)$.

This technique can significantly reduce the number of parameters, especially when using large convolutional kernels. For example, when using a 3 * 3 convolutional kernel, if each feature map uses a different convolutional kernel, the number of parameters to learn would be 81. However, if shared convolutional kernels are used, the number of parameters that need to be learned will be reduced to 27.

It should be noted that although shared convolutional kernels can reduce the number of parameters, they may also introduce some limitations. For example, it may lead to the reuse of information, which may introduce redundant information. In addition, shared convolutional kernels may also limit the model's expressive power as it cannot perform specific convolution operations on each feature map. Therefore, when using shared convolutional kernels, it is necessary to weigh their advantages and disadvantages and make adjustments according to the specific situation.

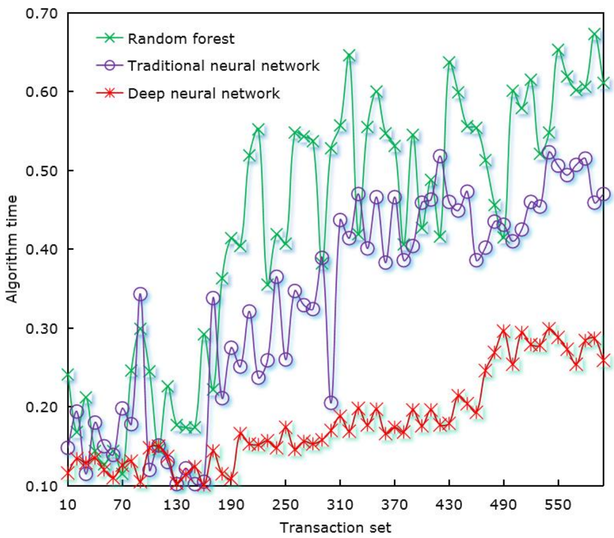

Figure 7: Efficiency of the algorithm.

The network transmits the preprocessed image at the input layer, and after convolution, activation function and pooling, a new feature map is obtained. Finally, it is classified by full connection operation. The data analysis (Figure 7) shows that DNN reduces the quantity of parameters by sharing the weights of convolution kernel, and also extracts salient features. By changing the parameters of gradient descent algorithm, the accuracy of the model is greatly improved. The method in this article can automatically intercept sample pictures from a large quantity of picture information in a short time, which simplifies the process of obtaining samples by DL.

6 CONCLUSIONS

We are in a period of rapid growth in economy, information, sci & tech, culture and other aspects, and people also put forward higher requirements for the quality of their production and living environment. Soft interior design gradually forms a new culture, and it will also become a new trend, which will gradually affect people's home life. Based on DL, this article discusses the related problems of soft interior design. This article introduces the main design idea, technical route and main functional characteristics of the soft interior design CAD system, and discusses the advantages of adopting object-oriented design idea and DL in the CAD system. Based on this, DL is effectively used to assist CAD modeling, thus a new soft interior design system is constructed. The simulation results show that this method has more advantages than the traditional NN method. DNN reduces the quantity of parameters and extracts salient features by sharing the weights of convolution kernel. The accuracy of the model is greatly improved by changing the parameters of gradient descent algorithm. Moreover, the soft interior design system based on DL aided by CAD modeling adopts object-oriented analysis and design method, so that the structure and style of the generated entity can be dynamically generated and changed according to the attributes and parameters specified by users. This can better meet the needs of users and effectively improve the flexibility of the system. I hope it can help the relevant soft interior design staff.

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