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Computer-Aided Design and Applications

Research and Practice of Interior Design Based on Deep Convolutional Generative Adversarial Networks Algorithms

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Abstract. This article aims to explore the application of Deep Learning (DL) algorithms in computer-assisted instruction (CAI) for interior design to enhance the efficiency and quality of interior design education. The study constructs a DL-based auxiliary system for interior design to achieve this objective and employs a series of experimental methods to evaluate it comprehensively. The research tests the time required to generate interior design schemes under different numbers of images and nodes, compares the modelling accuracy of different algorithms, analyzes the error variation of the test set during the training process, and invites users to experience the system personally, rating its interactivity. The findings suggest that the proposed system is capable of enhancing the efficiency of generating interior design schemes while maintaining modelling accuracy. Compared with traditional algorithms, the Deep Convolutional Generative Adversarial Networks (DCGAN) model proposed in this article achieves an improvement of up to 25.46% in modelling accuracy. Furthermore, as the training progresses, the performance of the Convolutional Neural Network (CNN) classifier continuously improves, and the test set error continues to decrease. User experience assessments also reveal that the system has received high recognition from users in terms of interactivity.

Keywords: Deep Learning; Interior Design; Computer-Assisted Instruction; User Experience
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1 INTRODUCTION

Image segmentation plays an important role in tasks such as 3D reconstruction in the field of architecture. The existing segmentation algorithms are difficult to perform well in the face of diverse segmentation objects and, therefore, cannot meet the needs of users [1]. In addition, classifying pixels solely based on the Euclidean distance between pixel coordinate positions cannot fully describe the distribution characteristics of pixels, which can easily lead to misclassification of pixels. The algorithm first establishes vertical and horizontal scans of the colour histogram to obtain peak points with high density and a certain distance apart [2]. Due to the utilization of the overall colour

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distribution characteristics of the image, a more reasonable number of classifications and initial centre points were obtained. Use the peak point count and corresponding K pixel blocks as the classification number and initial centre point, respectively. Based on this, this article proposes a color-building image segmentation algorithm based on improved K-means. Further, analyze the characteristics of colour-building images, use multidimensional feature constraints to calculate the similarity between pixel blocks, avoid misclassification of pixel blocks, and improve image segmentation performance [3]. A K-means parameter adaptive algorithm based on the colour histogram is proposed to address the sensitivity of the K-means-based colour image segmentation algorithm to initial parameters. Then, a reasonable number of classifications and representative initial centre points are obtained. Firstly, through preprocessing, the clustering objects of the algorithm are converted into pixel blocks, effectively reducing the computational complexity of the algorithm. This algorithm analyzes the characteristics of colour-building images and proposes to separately calculate the similarity of pixel blocks in colour, texture, and spatial position features, and combine the three as the final similarity to divide pixel blocks [4]. It proposes a multi-dimensional feature similarity calculation algorithm, making it suitable for the segmentation of colour-building images. The use of multi-feature constraints can comprehensively describe the local and global distribution of pixel blocks in an image, improve the classification accuracy of pixel blocks, and effectively segment buildings into meaningful regions [5].

Deep learning algorithms can significantly improve the user experience and visualization quality of SAR in interior design. In addition, deep learning can also achieve advanced visual effects such as dynamic shadow generation and lighting simulation, further enhancing the sense of reality. Combining style transfer techniques in deep learning. Users only need to perform simple operations to preview multiple design schemes on the physical model, greatly accelerating the design iteration process. The SAR system can automatically adjust the colour, texture, and layout of interior decoration elements based on user preferences or specific design styles, providing personalized design recommendations. In a SAR environment, these algorithms can evaluate the rationality of users placing furniture, lighting fixtures and other elements in real-time, provide layout optimization suggestions, ensure maximum space utilization and comply with ergonomic principles [6]. To adapt to the reflection characteristics of different environmental lighting and material surfaces, ensuring clear, realistic projection content and harmonious coexistence with the environment. The BIM-based SAR operation framework proposed in this article can further enhance its automation and intelligence level by integrating deep learning algorithms [7]. For example, using deep learning to accurately match BIM models with physical models reduces the workload of manual adjustments; Alternatively, by training models to predict visual effects under different projection conditions, projection parameters can be optimized in advance [8]. This feature makes the DL algorithm have great application potential in the design field. By introducing the DL algorithm into the interior design process, the automatic extraction of design elements, intelligent identification of design style and independent optimization of design schemes can be realized, thus greatly improving the personalized level of interior design.

(1) This study first breaks through the limitations of traditional interior design data processing, integrating heterogeneous data from multiple sources including spatial dimensions, furniture layout, colour matching, material selection, light and shadow effects, and user preferences. Through advanced feature extraction and fusion techniques, the model can comprehensively capture the intrinsic connections and mutual influences between design elements.

(2) A computer-aided interior design system integrating the DL algorithm is developed, which can provide users with intelligent design assistance and real-time feedback, thus breaking the shackles of traditional mode.

(3) The intelligent design feedback and assessment mechanism is realized in the system so that users can know their design level and existing problems in time and conduct targeted learning.

The structure of this article is summarized as follows: Firstly, the present situation of the interior design industry and the influence of the development of CAD and DL technology on the design field are expounded, and the purpose and significance of the research are clarified. Then, the present

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situation of interior design theory and practice, the research progress, and the shortcomings of existing research and the improvement of this study are pointed out. Then, the application of the DL algorithm in interior design is discussed, including the algorithm foundation, key problems in interior design and DL solutions, as well as the construction process of the DL algorithm model. Next, it introduces the design and implementation of computer-aided interior design systems, including system demand analysis, architecture design, function realization and so on. In the part of experimental design and result analysis, the experimental environment, methods and results are displayed, and the results are analyzed and discussed.

2 LITERATURE REVIEW

Interior design, as a comprehensive subject that combines art and science, is constantly seeking development in practice. With the rise of technologies such as CAD and virtual reality (VR), the research and practice of interior design has gradually reached a new height.

To deeply integrate augmented reality (AR) technology with interior design based on deep learning algorithms, and effectively promote the participation and experience of end-users in design collaboration, Safikhani et al. [10] comprehensively evaluated and optimized the application of AR systems in interior design review from the perspective of end-users. The protection of architectural heritage, and urban construction. By aggregating the neighbourhood features of nodes to update the feature vectors of each node, a classifier related to semantic data is generated. Triatmodjo [11] conducted research on zero sample building image classification based on a dual attention mechanism and weighted graph convolutional network. Among them, the channel attention network learns different channel weights to locate buildings in the image. Therefore, to effectively extract the main body and its detailed features of buildings and my semantic labels between different styles in the absence of architectural image label data. Multiple emerging building elements in the early stage of confidentiality have similar relationships between semantic labels of different categories, making it difficult to learn classifiers with high adaptability. Secondly, to reduce information loss during spatial mapping, a generator is used to reconstruct visual features. Secondly, the hierarchical distance relationship between all style labels is used as prior knowledge to construct the graph structure. A zero-sample building image classification method based on a dual attention mechanism is proposed to effectively locate building elements related to classification tasks in building images. Considering the strong correlation between semantic labels of architectural styles, a zero-sample architectural image classification method based on a weighted graph convolutional network is proposed by using an explicit knowledge graph to mine the relationships between categories. Channel spatial attention can focus on important regions in the image that are relevant to the task and ignore unimportant elements. Introduce two models, channel attention and spatial attention, to enhance the representation of specific regions in the image. Design a zero sample building image classification model embedded in public spaces, align visual and semantic features in subspaces, and achieve classification tasks through nearest neighbour matching. Graph convolutional networks can use knowledge graphs to express relationships between categories. In addition, AR has a much higher rating in terms of acceptance and user experience compared to other systems, mainly due to its innovative interaction methods and instant feedback mechanism. For example, ensuring the stability and reliability of AR systems to cope with complex and constantly changing indoor environments.

Balancing multiple factors such as aesthetics, functionality, and user psychological needs is a highly challenging task in colour design for 3D indoor scenes. In this process, the constraints of colour design are cleverly extended from the two-dimensional image domain to the three-dimensional space (R3), enabling a more comprehensive and accurate evaluation and optimization of colour schemes in 3D indoor environments. Traditionally, colour-matching strategies learned from images perform well in natural scenes, but their limitations are highlighted when faced with indoor spaces filled with various artificial elements. Wu and Han [12] analyzed a large number of interior design cases and user feedback data through deep learning models. A zero sample-building image classification method based on a dual attention mechanism first introduces two models, channel attention and spatial attention, to enhance the representation of specific regions in the image. The effectiveness of

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this method was validated on zero sample datasets and architectural style datasets, and a zero sample architectural image classification based on weighted graph convolutional neural networks was proposed. The spatial attention network embeds location information into channel attention maps to capture detailed features in the building body, obtaining feature representations with dual dimensions of channels and space. Among them, the channel attention network learns different channel weights to locate buildings in the image. Secondly, to reduce information loss during spatial mapping, a generator is used to reconstruct visual features. Yang [13] used a feature extraction network composed of a dual attention mechanism to extract discriminative features of building images. Finally, design a zero sample building image classification model embedded in public subspaces, align visual and semantic features in subspaces, and achieve classification tasks through nearest neighbour matching. Encode semantic attributes into feature vectors as nodes in the graph, and use the hierarchical relationships between all semantic categories as prior knowledge to construct an adjacency matrix. Calculate the distance between semantic features to weight the original adjacency matrix, improve the clustering of samples of the same class, enhance the differentiation between different classes, and train classifiers related to building categories. Finally, in the prediction process, a classifier is used to classify unknown class samples, further improving the accuracy of the model and enhancing its transferability.

These learning outcomes were applied in VR demonstrations, where Zhang et al. [14] demonstrated realistic and creative interior design effects through high-precision 3D modelling and real-time rendering techniques. According to different application scenarios and user needs, VR interior design displays can be divided into various types, such as personalized customization displays, scene simulation experiences, and design scheme comparisons. In terms of 3D production technology, innovative applications of deep learning algorithms, such as automatic modelling, intelligent lighting adjustment, and material mapping optimization, have greatly improved production efficiency and quality. Each type fully utilizes the intelligent analysis capabilities of deep learning algorithms to provide users with tailored display experiences. From residential to commercial spaces, from public buildings to exhibition displays, VR interior design exhibitions based on deep learning algorithms cover almost all areas of interior design. For example, deep learning models can automatically generate complex indoor space models based on a small amount of input data, greatly saving modelling time. Meanwhile, Zhang [15] can intelligently adjust the lighting effect by analyzing the reflection and refraction laws of light on different materials, making the virtual scene more realistic.

In summary, notable progress has been made in interior design research and practice, particularly in CAD and VR technology applications. Despite these achievements, challenges persist. This study aims to explore the feasibility and practical pathway of interior design CAI based on DL algorithms, aiming to contribute novel ideas to this field. It seeks to address issues of inefficiency and lack of innovation in traditional interior design processes, fostering further industry development.

3 THE APPLICATION OF THE DL ALGORITHM IN INTERIOR DESIGN

The rapid development of artificial intelligence technology has highlighted the significant potential and value of its core branch, DL, across multiple domains. In interior design, the implementation of DL algorithms is progressively transforming traditional design methodologies, offering designers more efficient, intelligent, and personalized tools.

The core purpose of target detection is to accurately locate the objects in the image and assign the correct category labels to them. It can help the system understand the content of pictures uploaded by users, thus providing more accurate suggestions and design schemes. However, in the actual implementation of the inspection task, there will be many challenges: there are many types of objects in interior design, from furniture to decorations, each with its own unique size, posture and placement position. In addition, when users upload pictures, the positions of these objects in the pictures are also extremely uncertain. These factors together constitute the complexity of object detection in the field of interior design. In contrast, although the main task of image recognition, as

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shown in Figure 1, also involves the understanding and classification of image content, it does not require accurate positioning of specific objects in the image and detailed category labelling like target detection.

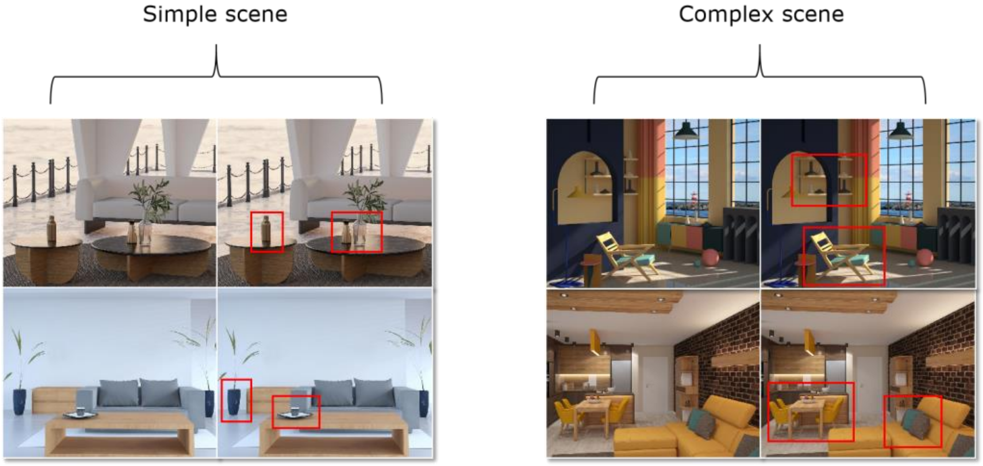

Figure 1: Image recognition display.

During indoor image processing, the original image undergoes resizing through the generation of new pixels. In the implementation, $\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}$ represents four neighbouring pixels, P landing on one of these four points. Assuming the top-left corner of the area as its origin, and Δ_{col} denoting the horizontal distance from the target pixel to this origin, the formula for calculating the colour value R_1, R_2 in the x direction is provided below:

$$\delta\ R_1 = Color\ M_{21} - Color\ M_{11}\ \cdot\Delta_{col} + Color\ M_{11}\ \cdot 256 \tag{1}$$

$$\delta\ R_2 = Color\ M_{22} - Color\ M_{12}\ \cdot\Delta_{col} + Color\ M_{12}\ \cdot 256 \tag{2}$$

In this context, $Color\ X$ signifies the color value of the point X, utilizing the 24-bit true colour format for specific calculations. A segment of the image is converted into HSV, HIS, and YUV colour spaces, and the first-order moments of these three components are weighted and merged to derive the first-order moments $F_{MIX-L}\ \mu$ of the brightness component within the mixed colour space:

$$F_{MIX-L}\ \mu = \frac{W_{HSV} \times F_{HSV-V}\ \mu + W_{HIS} \times F_{HIS-I}\ \mu + W_{YUV} \times F_{YUV-Y}\ \mu}{W_{HSV} + W_{HIS} + W_{YUV}} \tag{3}$$

$W_{HSV}, W_{HIS}, W_{YUV}$ represent the weights assigned to the respective colour spaces.

DL algorithm realizes the intelligent processing of interior design through the following steps:

(1) Data preprocessing: The original data related to interior design are cleaned, normalized and segmented to facilitate model training. These data may include space size, furniture layout, colour samples, etc.

(2) Model training: use the marked design data to train the DL model. Through optimization techniques such as the backpropagation algorithm and gradient descent algorithm, the weight and

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bias of the model are constantly adjusted to minimize the loss function and improve the prediction and generation ability of the model.

(3) Design generation and optimization: Based on the trained DL model, various interior design schemes can be automatically generated and optimized according to user needs and environmental conditions. Designers can make further modifications according to the scheme generated by the model.

In the image processing of interior design CAI, the application of mixed colour space brings new possibilities for colour feature extraction. Through the block processing of mixed colour space, we can finally get a detailed description of nine colour feature vectors in a block. This process not only helps to capture the colour information in interior design images more accurately but also can effectively deal with complex scenes such as lighting changes, which provides strong support for colour matching and style analysis of interior design. By combining the advantages of different colour spaces, such as the intuition of RGB colour space and the separation of hue, saturation and brightness of HSV colour space, the mixed colour space realizes the comprehensive and efficient extraction of colour features of interior design images.

Next, the interior design image in the mixed-colour space is divided into several small areas by using the block processing strategy. Colour feature extraction is carried out independently in each small area, which helps capture the local colour distribution characteristics of the image and reduces the global calculation. In each block, the first moment (average), the second moment (variance) and the third moment (skewness) of each colour channel can be obtained by calculating the colour moment, which is an effective colour feature descriptor, totalling 9 colour feature vectors. These colour feature vectors can well describe the statistical distribution characteristics of colours in interior design images, and provide a basis for subsequent colour analysis and style recognition.

The steps of the block colour feature extraction algorithm in mixed colour space are shown in Figure 2. It enhances the accuracy and robustness of colour feature extraction and provides rich colour information support for tasks such as the automatic generation of interior design schemes, colour-matching suggestions and style classification.

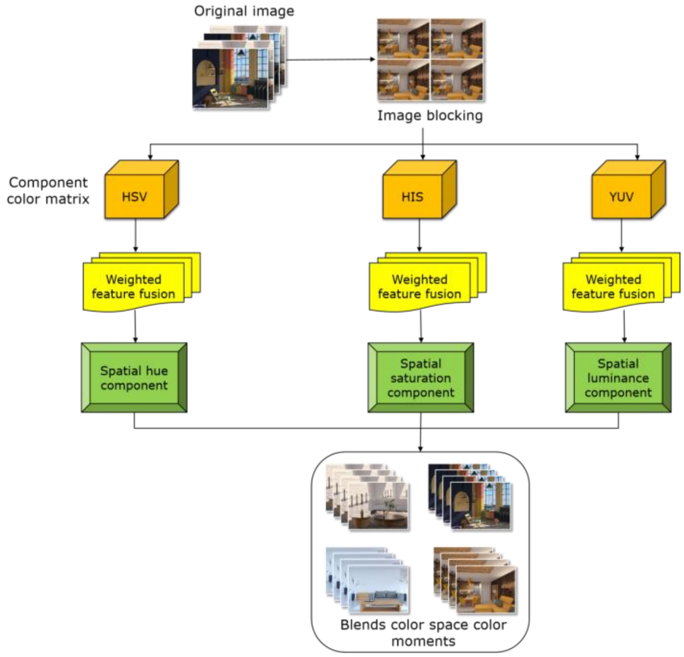

Figure 2: Color moments of mixed colour space.

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Measuring the similarity between the reference pattern P^R and the transformed candidate pattern $P_k\ i$ requires calculating the distance between the i candidate pattern and the reference pattern, specifically:

$$d=\frac{1}{k+1}\sum_{j=0}^{k-1}\sqrt{\sum_{r=1}^{m}\ x_{r,i+j}-x_{r,N-k+j+1}\ {}^{2}} \tag{4}$$

Thus, observing the similarity $s_i = 1/d_i$ between the two patterns, it's evident that similarity and distance exhibit an inverse relationship; a larger distance value corresponds to lesser pattern similarity. Considering g_j as the equal weight and g_j as the weight coefficient of the combined model:

$$y_{N+1}=\sum_{j=1}^{F} g_j y_{j+k+i-l} \tag{5}$$

Within the context, $\tau, i=1,2,\cdots,\tau$ represents the forecast range; $y_{N+1}, y_{j+k+i-l}$ denotes the extension of variables to be predicted in both reference and similar modes. Subsequently, the prediction is derived from combining F similar patterns.

DL algorithm can automatically generate a variety of spatial layout schemes according to information such as room size, furniture size, and user demand. Through the study and analysis of a large number of spatial layout data, the algorithm can master the laws between different layouts, thus generating a layout scheme that meets the functional requirements and is beautiful and practical. Colour matching is a crucial part of interior design. DL algorithm can automatically generate a colour-matching scheme that conforms to users' preferences and room styles by learning a large number of colour samples and matching rules. The algorithm can comprehensively consider factors such as light, material, and furniture in the room and generate a harmonious, unified, and layered color-matching scheme. The selection of materials and the simulation of texture are very important for the overall effect of interior design. Designers can preview the performance of different materials in the room in the virtual environment to choose the appropriate materials more intuitively. In addition, the algorithm can also recommend the appropriate material collocation scheme according to the overall style of the room and the user's needs. In the process of interior design, designers often need to make a lot of decision-making, such as furniture selection and decoration placement. DL algorithm can assist designers in making these decisions and provide suggestions and solutions based on big data and intelligent analysis. The algorithm can recommend suitable furniture and decorations according to the needs and preferences of users and the actual situation of the room and give suggestions on placement.

Given the H,S,V value, the corresponding three primary colours R,G,B are as follows:

$$R,G,B\ =\ R'+\lambda, G'+\lambda, B'+\lambda \tag{6}$$

Where $\lambda = V - C$.

During homomorphic filtering calculation, the accuracy of the final transformation is directly influenced by the value of the homomorphic filtering function $H\ u,t$. By incorporating the characteristics of the homomorphic filter function, a Butterworth homomorphic filter is designed, with its expression given as:

$$H\ u,t\ =\ \gamma_H-\gamma_L\left[\frac{1}{1+\left[D_0/D\ u,t\ \right]^{2\pi}}\right]+\gamma_L \tag{7}$$

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Here, L denotes the smoothing order of the filter; D_0 represents the cutoff frequency for filtering; $D(u,t)$ and signifies the distance from a point (u,t) to the starting point of the discrete cosine transform. Multi-scale refers to utilizing multiple distinct Gaussian function parameters c, and the output of the multi-scale Retinex algorithm is derived by weighting the sum of reflected brightness across different scales:

$$R_{MSR,i} = \sum_{n=1}^{N} w_n R_{n,i} \tag{8}$$

Where N denotes the scale number, typically set to $N = 3$. $R_{n,i}$ signifies the reflection brightness of the n scale within the i channel, while $R_{MSR,i}$ represents the reflection brightness derived from multi-scale weighting of the i channel. w_n is the weight of the n scale, usually $w_n = 1/N$.

Assuming n represents the number of indoor images involved in indoor space modelling, and C_i denotes the internal and external parameters of the i th image, m 3D spatial points were reconstructed. The coordinates of the j th 3D spatial point are X_j. The objective function for beam adjustment optimization is given as:

$$g(C,X) = \sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} \left\| q_{ij} - P(C_i, X_j) \right\|^2 \tag{9}$$

In the formula, w_{ij} serves as an indicator variable, indicating whether a point j is present in the image N_{new} i. If a point j exists in the image i, w_{ij} is assigned a value of 1; otherwise, it is 0. $P(C_i, X_j)$ represents the coordinate of the point j on the image i after projection transformation, while q_{ij} denoting the actual image coordinate of the point j on the image i.

As an effective parameter regularization technology, the core mechanism of Dropout lies in randomly selecting some nodes in the network for temporary "discarding" according to the preset discarding ratio in the process of model training. This operation aims to reduce the feature dimension, effectively curb the over-fitting phenomenon, and then improve the robustness and generalization ability of the model. In the first iteration of training, some neurons in a fully connected layer are randomly selected for temporary discarding according to the preset discarding ratio, and then the model is trained and optimized based on this adjusted network structure. When entering the second iteration, another part of the neurons will be selected for discarding. The specific structure and working principle of Dropout are shown in Figure 3. By randomly discarding neurons in this way, Dropout not only simplifies the structure of the model but also promotes the model to learn more robust feature representation.

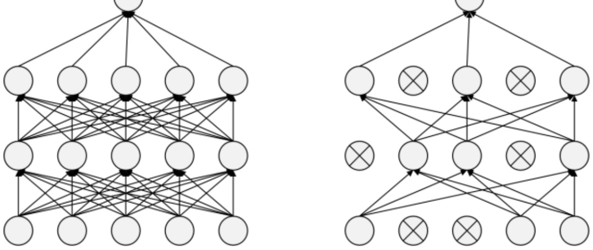

Figure 3: Dropout structure.

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DL algorithm can automatically process and analyze a large amount of design data, generate a variety of design schemes, and optimize them. By studying and analyzing a large number of excellent design cases and laws, the DL algorithm can generate high-quality design schemes. DL algorithm can generate personalized designs and optimize adjustments according to users' needs and preferences, and it can provide a design scheme that is more in line with users' expectations.

4 EXPERIMENTAL DESIGN AND RESULT ANALYSIS

4.1 Generation Time Test

Initially, the time needed to generate an interior design scheme was tested across varying numbers of pictures and nodes, with the experimental outcomes presented in Figure 4.

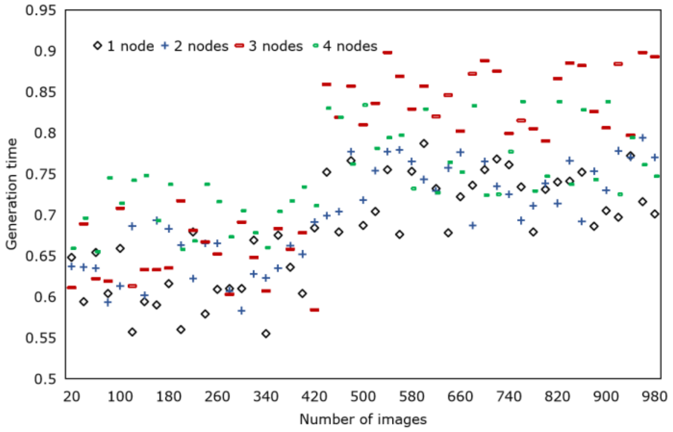

Figure 4: Image generation consumes time.

Figure 4 illustrates the variation of generation time concerning the number of pictures and nodes. When the image count is low, augmenting the node count results in a prolonged generation time, potentially due to the relatively high number of model parameters on small-scale datasets, which enhances computational complexity. Conversely, as the image count increases, the benefits of multiple nodes become evident. Distributed computing efficiently distributes the computational load, notably enhancing generation efficiency.

4.2 Comparison of Modeling Accuracy

To verify the advantages of the DC-GAN model proposed in this article in modelling accuracy, it is compared with the traditional GAN algorithm. The experimental results are shown in Figure 5.

Figure 5 shows the modelling accuracy results of different algorithms. Compared with the traditional GAN algorithm, the DCGAN model proposed in this article has significantly improved the modelling accuracy. The highest increase rate reached 25.46%. This shows that the DCGAN model can better capture the characteristics of interior design data and generate more realistic and satisfying interior design schemes.

4.3 Training Process Analysis

To deeply understand the performance changes of the CNN classifier in the training process, the error changes of the test set are recorded with the increase of training rounds. The results are shown in Figure 6.

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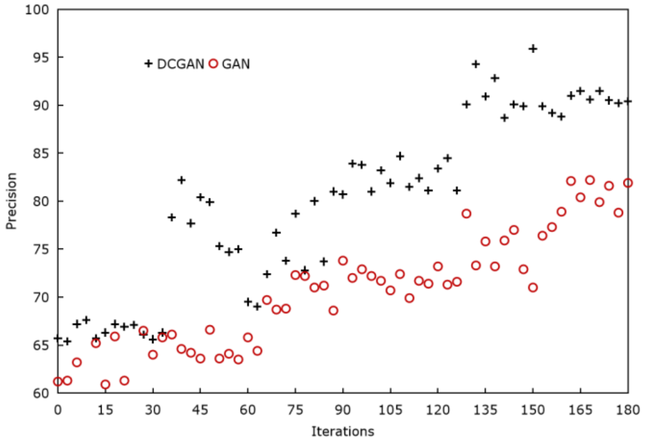

Figure 5: Accuracy results of different algorithms.

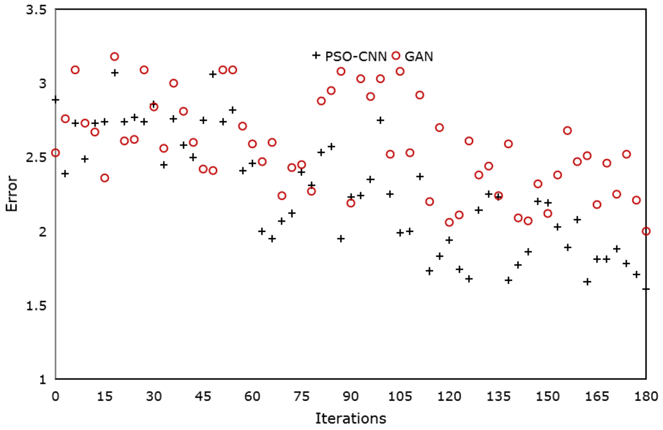

Figure 6: Error changes in the training process.

Figure 6 shows the change in test set error during training. With the progress of training, the error of the test set is decreasing. This shows that the performance of the CNN classifier is constantly improving, and the inherent laws and characteristics of interior design data are gradually learned. This also verifies the feasibility of the DL algorithm in the field of interior design.

4.4 User Experience Assessment

To evaluate the user experience of the interior design CAI system proposed in this article, a group of users were invited to experience the system personally, and the interactivity of the system was rated. The experimental results are shown in Figure 7.

Figure 7 depicts the user rating outcomes for system interactivity, revealing that the system introduced in this article has garnered high user ratings, signifying its notable advantages in enhancing user experience. Users generally perceive the system as having a user-friendly interface, ease of operation, and prompt feedback, which can effectively elevate the efficiency and quality of interior design learning.

In conclusion, a series of experimental tests and analyses have verified the feasibility and effectiveness of the DL algorithm-based interior design CAI. The system has exhibited exceptional performance in terms of generation time, modelling accuracy, training process, and user experience, ushering in novel transformations within the interior design industry and education field. Looking ahead, we aim to continually optimize and refine the system, exploring further possibilities for the application of DL algorithms in interior design.

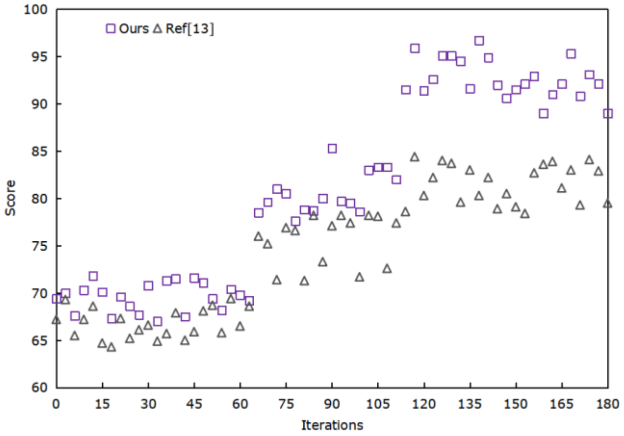

Figure 7: System interactivity score.

5 CONCLUSIONS

In interior design, CAD technology facilitates designers by enabling rapid construction of 3D models, spatial layout execution, and material rendering, significantly enhancing design efficiency and accuracy. This study introduces the automatic generation and classification of interior design schemes through the development of DL models, notably DCGAN and CNN classifiers, introducing innovative transformations to the interior design industry and education sector. With varying image and node counts, the system efficiently generates interior design solutions that meet requirements. Compared to traditional GAN algorithms, the DCGAN model exhibits a substantial improvement in modelling accuracy, with a maximum increase of 25.46%, further confirming the robust potential of DL algorithms in interior design.

Moreover, as training epochs increase, the CNN classifier's performance consistently improves, while the test set error decreases, indicating the DL model's ability to learn the inherent rules and characteristics of interior design data, providing substantial support for automatic scheme generation. Regarding user experience, the system has received high ratings, with users praising its user-friendly interface, ease of operation, and timely feedback, effectively enhancing the efficiency of interior design learning. This serves as compelling evidence for the practical application of CAI in interior design.

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