Exploration of the Indoor Layout Optimization Model in Computer-Aided Visual Analysis

Yang Liu[1] and Guanjie Wang[2]

[1]Admissions and Employment Office, ChengDe College of Applied Technology, Chengde 067000, China, hebiacer2002@163.com
[2]Department of Jin Cheng Art and Design, ChengDe College of Applied Technology, Chengde 067000, China, nightowl@126.com

Corresponding author: Guanjie Wang, nightowl@126.com

Abstract. At present, the functional software of computers can effectively help us understand the layout of functional spaces in designing buildings. Computer technology has become an indispensable factor in the perception analysis process of indoor environment design. In order to more efficiently evaluate the accuracy of computer layout optimization and conduct an investigation and analysis of advanced design tools for indoor space layout optimization, this article used visual analysis tools for interior design in the process of computer model design analysis to accurately design the plan. A deep learning-based indoor user space enhancement experience optimization model has been proposed.

Keywords: Indoor Layout; Optimize The Model; Computer-Aided Design; Visual Analysis
DOI: https://doi.org/10.14733/cadaps.2025.S4.167-180

1 INTRODUCTION

Accurate interior design art is of great significance for the study of interior design history, the protection of interior design heritage, and urban construction. By aggregating the neighborhood features of nodes to update the feature vectors of each node, a classifier related to semantic data is generated [1]. Therefore, in order to create image label data for interior design. At present, there are two main shortcomings in interior design art: firstly, due to the uniqueness of interior design styles, most feature extraction methods make it difficult to extract key features of interior design styles effectively. However, due to the similarities between different interior design styles and the differences within the same interior design style, the dataset lacks labeled interior design categories [2]. Channel spatial attention can focus on important regions in the image that are relevant to the task and ignore unimportant elements. Graph convolutional networks can use knowledge graphs to express relationships between categories [3]. Therefore, using zero-sample classification techniques to classify interior design images with missing label data has become a worthwhile research topic. In the absence of information, it is possible to effectively extract the main body and detailed features of interior design, and explore the strong semantic labels between different styles. The emerging interior design retains early interior design elements, with similar relationships between semantic labels of different categories, making it difficult to learn classifiers with high fitness. Channel attention network learns different channel weights to locate interior design objects in images; The spatial attention network embeds location information into the channel attention map to capture detailed features in the target, obtaining feature representations with dual dimensions of channel and space. Firstly, two models, channel attention and spatial attention, are introduced to enhance the representation of specific regions in the image. To effectively locate interior design elements related to classification tasks in interior design images, a zero-sample interior design image classification method based on a dual attention mechanism is proposed. This article studies zero sample indoor design image classification based on a dual attention mechanism and weighted graph convolutional network [4].

Secondly, to reduce information loss during spatial mapping, a generator is used to reconstruct visual features. Firstly, utilize feature extraction networks to extract interior design features and expand them into vector representations. The experiment verified the effectiveness of the method. Considering the strong correlation between semantic labels of interior design styles, we use explicit knowledge graphs to mine the relationships between categories. Finally, design a zero sample interior design image classification model embedded in public spaces, align visual and semantic features in subspaces, and achieve classification tasks through nearest neighbour matching. Improve the clustering of interior designs within the same category, enhance the differentiation between different categories, and train classifiers for all interior design categories. Calculate the distance between semantic features and weigh the relationships between nodes. Use a weighted graph convolutional network to train and update the features of nodes, in order to alleviate the problem of over-smoothing caused by too many network layers. Propose a zero sample indoor design image classification method based on a weighted graph convolutional network. Construct a graph structure using the hierarchical distance relationship between all style labels as prior knowledge [5]. The experimental results show that the proposed method improves the average classification accuracy by 0.6 percentage points on the interior design style dataset compared to the current zero-sample learning method. Perform dot product operation between visual features and classifier, and use the classifier to classify unknown styles during the prediction process, further enhancing the transferability of the model. To determine the optimal direction of the IRS mirror array, we face a complex optimization problem. This problem is non-convex, and traditional methods are difficult to solve directly. Through simulation experiments, we have verified the effectiveness of the proposed IRS-assisted VLC system design and optimization algorithm in overcoming LoS blocking problems. A partially proposed IRS-assisted VLC system model takes into account the uncertainty of user behaviour and the complexity of indoor environments [6].

In order to improve the efficiency and effectiveness of building signage system design, some scholars have innovatively developed AUTOSIGN - an advanced tool integrated into a computer-aided design (CAD) environment, which is specifically designed for cyclic and multi-standard optimization of signage layout in complex buildings. By utilizing the powerful search capability of evolutionary algorithms and combining it with the designer's experience weighted cognitive heuristic objective function, a comprehensive exploration and optimization of possible navigation path combinations can be carried out. This process aims to maximize the information coverage area of the signage, ensuring clear and effective navigation guidance at key decision points, high-traffic areas, and easily lost areas while reducing unnecessary visual interference and path overlap. To cope with competing goals such as minimizing the total distance travelled, reducing the number of turns, optimizing the centrality of decision points, avoiding path overlap, and streamlining the number of decisions, while ensuring compliance with user-set signage position and direction constraints. AUTOSIGN not only transforms the problem of signage placement into a complex multi-objective optimization challenge but also cleverly integrates indoor layout optimization models [7]. The introduction of indoor layout optimization models enables AUTOSIGN to automatically adapt to the unique spatial characteristics of different buildings, quickly generate signage layout schemes that meet requirements, and greatly shorten the design cycle. Subsequently, a particle swarm optimization algorithm was used to finely adjust the specific position and orientation of the signage for each optimized navigation path. Image segmentation is a crucial step in image processing. Image segmentation plays an important role in tasks such as 3D reconstruction in interior design. Then, a reasonable number of classifications and representative initial centre points are obtained through the colour histogram of the image. The K-means algorithm for interior design has the characteristics of strong adaptability and high efficiency, but it relies on user input parameters. In addition, classifying pixels based solely on the Euclidean distance between pixel coordinate positions cannot fully describe the distribution characteristics of pixels, which can easily lead to misclassification of pixels. However, existing segmentation algorithms are difficult to perform well in the face of diverse segmentation objects, and therefore cannot meet the needs of users [8]. Therefore, it is necessary to propose an efficient interior design image segmentation algorithm. Some scholars believe that the essence of image segmentation is the clustering of pixels as the basis for analysis, and combine specific segmentation methods with segmentation objects to analyze and study the K-means algorithm. Some scholars have proposed an interior design image segmentation algorithm based on improved K-means. Firstly, through preprocessing, the clustering objects of the algorithm are converted into pixel blocks, effectively reducing the computational complexity of the algorithm. Re-analyze the characteristics of interior design images, use multidimensional feature constraints to calculate the similarity between pixel blocks, avoid misclassification of pixel blocks, and improve image segmentation performance [9]. At the same time, this process will also stimulate their innovative thinking and creativity, enabling them to better cope with complex and ever-changing design challenges in their future careers, and become high-quality talents with innovative abilities and practical skills. This article is based on this background, deeply exploring the application of interior layout optimization models, and proposing a DL based interior layout optimization model, in order to provide new ideas and methods for interior design education and practice [10].

On the basis of existing research, this article further explores and proposes a DL-based indoor layout optimization model. This innovation not only improves design efficiency but also makes the layout optimization process more intelligent and automated, providing new technological support for the future development of interior design. This study spans multiple disciplines such as computer science, interior design, and education, achieving an organic integration of interdisciplinary knowledge.

The beginning of this article provides an in-depth analysis of the macro background and profound significance of the research. Subsequently, the article focuses on the innovative application of indoor layout optimization models and conducts a comprehensive and detailed exploration. On this basis, we elaborated in detail the construction process and algorithm logic of the indoor layout optimization model driven by DL technology, demonstrating the enormous potential of technology integration in improving design efficiency and accuracy. To verify the actual effectiveness and feasibility of the model, we carefully designed and implemented a series of rigorous experiments. Finally, in the summary and outlook section, this article highly summarizes the core findings and innovative highlights of the DL-driven indoor layout optimization model.

2 RELATED WORK

Constructing advanced structured 3D models of real-world indoor scenes from captured data is a core task at the intersection of computer graphics and computer vision. Shen et al. [11] studied various input sources, including but not limited to laser scanning, RGB-D camera data, photo collections, and user inputs, each with its unique characteristics and challenges. In the integration of indoor layout optimization models and computer-aided design, we have noticed that building an efficient and user-friendly indoor scene reconstruction system requires not only high-precision 3D reconstruction technology but also the layout optimization capabilities of CAD systems. Meanwhile, in order to bridge the gap between imperfect inputs and ideal outputs, Turgut and Kakisim [12] introduced rich prior knowledge, such as common patterns of indoor spatial layout, correspondence between furniture dimensions and functions, etc. Given the complexity and variability of indoor environments, as well as the common noise and incompleteness in data capture processes, despite significant technological advancements, there are still many open research questions that urgently need to be addressed in the face of these challenges. At the output end, it defines the standards for advanced structured 3D models, emphasizing the need for the model to accurately reflect key elements such as geometry, materials, lighting, and furniture layout of indoor spaces. Its importance in various fields, such as architectural design, virtual reality, augmented reality, and smart homes, is becoming increasingly prominent. This survey not only summarizes the latest developments in the field but also delves into the complementary advantages of computer graphics and computer vision technology. CAD systems are adept at handling complex interior layout designs, automatically adjusting furniture positions, optimizing space utilization, and considering personalized factors such as pedestrian flow and visibility. Based on the reconstructed 3D model, automatically detect and adjust unreasonable furniture layouts to improve the rationality and comfort of space use.

Yang [13] deployed multiple virtual cameras in the virtual space of a three-dimensional indoor environment, capturing detailed views of the environment from different angles by simulating camera rotation and movement and generating a series of high-quality 2D images. A K-means parameter adaptive algorithm based on a colour histogram is proposed to address the sensitivity of a K-means-based colour image segmentation algorithm to initial parameters. Yang et al. [14] proposed a multidimensional feature similarity calculation algorithm, which is suitable for the segmentation of colour-building images. This algorithm analyzes the characteristics of color-building images and proposes to separately calculate the similarity of pixel blocks in color, texture, and spatial position features and combine the three as the final similarity to divide pixel blocks. Use the peak point count and corresponding K pixel blocks as the classification number and initial centre point, respectively. The algorithm first establishes a colour histogram of the image in the HSI colour space, and vertically and horizontally scans the colour histogram to obtain peak points with high density and a certain distance apart. Due to the utilization of the overall colour distribution characteristics of the image, a more reasonable number of classifications and initial centre points were obtained. 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. Traditional methods focus on analyzing the complex structure of indoor environments through spatial layout, semantic understanding, and functional relationships between objects, providing a basic framework for scene generation. This combination enables the algorithm to generate aesthetically pleasing and practical interior design solutions, greatly improving the intelligence level of the design. CVAE maps input scene information to a latent Gaussian distribution space through an encoder, and a generator samples noise from this distribution and decodes it into a new scene layout. However, with the advent of the big data era and the improvement of computing power, we have proposed an innovative approach. In order to further meet the diversity requirements of furniture layout, Zhang et al. [15] innovatively combined conditional variational autoencoder (CVAE) with a graph neural network. In the context of computer-aided design (CAD), the introduction of interior layout optimization models has added new dimensions to furniture layout. Embedding unstructured furniture data into graphical structures and utilizing the powerful capabilities of Graph Neural Networks (GNNs) to iteratively learn and capture the intrinsic distribution patterns of scene layouts.

The research in the field of interior layout optimization is undergoing rapid deepening and expansion, from the profound exposition of classical layout theory to the rapid rise of modern DL algorithms. The rapid advancement of technological means continues to open up unprecedented possibilities and innovative dimensions for the field of interior design.

3 APPLICATION OF INDOOR LAYOUT OPTIMIZATION MODEL

3.1 Indoor Layout Optimization Model

The interior layout optimization model, as a core tool in the field of modern interior design, is ingenious in using advanced computer algorithms to finely and scientifically plan indoor spaces. This model not only understands the essence of space utilization but also takes into account key factors such as lighting, ventilation, and dynamic layout and strives to maximize the function and experience in every inch of space. Through complex and precise computational logic, indoor layout optimization models can quickly generate diverse layout schemes, each of which is a deep exploration and clever reconstruction of the spatial potential. These plans not only consider the physical properties of the space, such as area, shape, height, etc., but also incorporate the concept of humanized design to ensure that the spatial layout meets both functional requirements and the psychological feelings of residents.

After generating the plan, the model will further apply simulation analysis techniques to evaluate and compare each plan comprehensively. Every detail, from maximizing space utilization to optimizing lighting and ventilation effects to ensuring a smooth layout, has been rigorously considered and finely adjusted. In the end, the model will select the optimal solution, which is the perfect layout scheme that can meet the diverse needs of users and achieve efficient utilization of spatial resources. In short, the interior layout optimization model has brought unprecedented changes to the interior design industry with its powerful computing power and scientific planning concepts. It not only improves design efficiency and quality but also promotes the development of indoor space planning towards a more intelligent, personalized, and efficient direction.

3.2 CAD

The application of indoor layout optimization models in CAD teaching has injected new vitality and depth into the curriculum. CAD software is not only an important tool for interior designers to express their creativity and draw drawings but also a key platform for implementing interior layout optimization strategies. In teaching, teachers first explain the core concepts and algorithmic logic of indoor layout optimization in a clear and concise manner, helping students construct theoretical frameworks and understand how to improve space utilization efficiency and living experience through scientific methods. Subsequently, by selecting typical interior design cases and combining them with practical demonstrations of CAD software, students were allowed to operate by hand, incorporating layout optimization thinking into every step, from precise drawing of 2D planes to simulated construction of three-dimensional spaces. In the process of 3D modeling, students not only need to master the creation of object shapes but also need to learn how to use CAD tools to analyze light and wind directions, optimize flow design, and ensure that the design is both beautiful and practical.

In addition, the teaching of rendering and material mapping not only cultivates students' visual expression but also enables them to deeply understand how to use technical means to present the optimized spatial effects of layout, making the design more closely related to real-life scenes. The CAD application case shown in Figure 1 is a direct reflection of the results of this process, which clearly demonstrates how indoor layout optimization can be achieved with the assistance of CAD software, giving students confidence in how to use CAD for efficient design in future work. In short, incorporating the application of interior layout optimization models into CAD teaching not only enriches the course content and improves students' practical skills, but also stimulates their enthusiasm for exploring new design fields, laying a solid foundation for cultivating interior design talents with innovative thinking and practical abilities.

4 INDOOR LAYOUT OPTIMIZATION MODEL

4.1 Model Building

DL, as a shining pearl in the field of machine learning (ML), is leading the innovation and leap of AI technology. In the complex and refined field of indoor layout optimization, the introduction of DL, especially CNN, provides strong technical support for designing intelligent and personalized indoor spaces. The indoor layout optimization model based on multi-task supervised learning proposed in this article not only integrates the latest developments in DL but also achieves efficient and accurate optimization of indoor spatial layout through innovative module design.

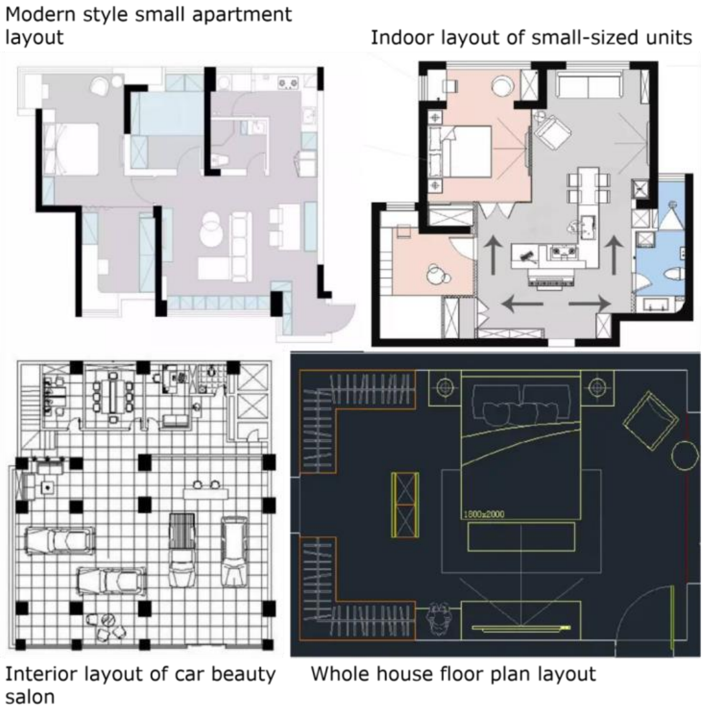

Figure 1: CAD application case.

Figure 2 shows the network framework of the model proposed in this article. The core of this model lies in its carefully designed encoder-decoder architecture. Improving the encoder structure enhances the network's ability to capture complex features of indoor environments, effectively expands the receptive field of convolution operations, and enables the model to understand and parse the structural information of indoor spaces more comprehensively.

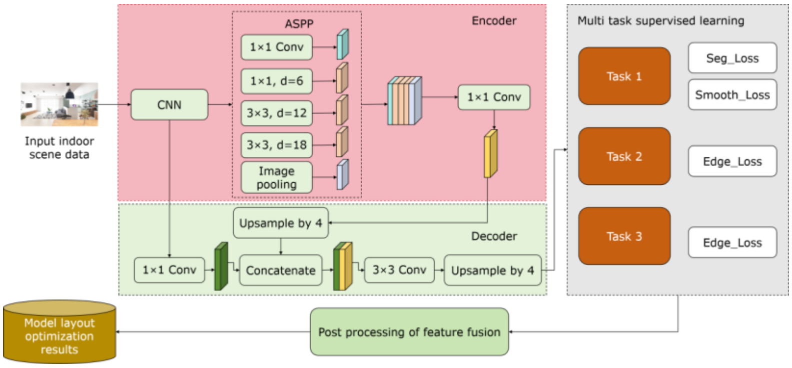

Figure 2: Indoor layout optimization model based on multi-task supervised learning.

Meanwhile, the introduction of a multi-task supervised learning module is a significant breakthrough over the traditional single-task learning model. This module refines the indoor layout optimization task into multiple sub-tasks for parallel processing, including preliminary segmentation of spatial layout, complete extraction of edge features, and semantic edge recognition of various spatial regions. This parallel processing mechanism not only improves the learning efficiency of the model but also promotes the sharing and complementarity of information between different tasks, which helps the model to more comprehensively understand the semantic and geometric relationships of indoor space. The feature fusion post-processing module serves as the finishing touch of the model, cleverly fusing edge features with preliminary semantic segmentation results, and further improving the accuracy and detail of the segmentation map through local refinement processing. This step not only corrects possible segmentation errors but also enhances the segmentation map's ability to describe indoor spatial details, making the optimized indoor layout more in line with practical usage needs.

Finally, the application of the joint loss function ensures that the model can optimize multiple tasks simultaneously during training, achieving overall performance optimization by balancing the loss contributions between different tasks. This training strategy not only improves the model's generalization ability but also enables the model to maintain stable performance when facing complex and changing indoor environments. In summary, the DL-based indoor layout optimization model proposed in this article achieves efficient and precise optimization of indoor spatial layouts through innovative module design and optimization strategies. This model not only brings intelligent solutions to the field of interior design but also provides new ideas and directions for the application of DL in complex scene understanding.

4.2 Algorithm Principle

Indoor layout can be regarded as a special case of constraint satisfaction problem, and the core lies in selecting the best solution from limited layout schemes. This is actually a combinatorial optimization problem aimed at selecting the optimal solution or solution set from a massive number of combinations under established constraints. To simplify the discussion, we abstract it as a general combinatorial optimization problem for analysis.

$$\begin{aligned} \min \quad & f\ x \\ s.t. \quad & g\ x\ \geq 0 \\ & x \in D \end{aligned} \tag{1}$$

Among them, x are the configuration variable in indoor layout, $f\ x$ the objective function, $g\ x$ the constraint equation, and D the domain of the configuration variable.

In CNN, the parameters of the convolutional kernel are automatically learned and determined through the training process, making its design more flexible and versatile compared to fixed convolutional kernels in traditional image processing. For single-channel images, we use a $M * N$ convolution kernel for convolution operation. This process involves systematically sliding the convolution kernel on the image, and performing a convolution calculation of element-wise multiplication and summation every time it slides to a new position. This series of operations ultimately generates an output single-channel image, and the formula for convolution calculation is defined as follows:

$$y_{i,j} = \sum_{m=1}^{M} \sum_{n=1}^{N} w_{m,n} x_{i+m,j+n} \tag{2}$$

Among them, $y_{i,j}$ represents the elements in the i row and j column of the output image, $w_{m,n}$ represents the elements in the m row and n column of the convolution kernel, and $x_{i,j}$ represents the elements in the i row and j column of the input image.

Given that natural light mainly enters indoor spaces through windows, the windows in a room can be likened to a unique set of LED light sources that only emit scattered noise power without generating direct signal power. It is worth noting that the intensity distribution of this granular noise is negatively correlated with the spacing between windows, that is, the larger the window spacing, the relatively lower the noise level. This phenomenon can be mathematically expressed as:

$$P_w = \frac{\sigma_{sh}^2}{d^2} \tag{3}$$

Among them, d are the distance from the transmitting end to the receiving end, P_w the power of natural light noise, and σ_{sh} the variance of shot noise.

The size perception energy term E_s of the entire indoor environment is the sum of the size perception energy (covering both width and length) of all objects in the room. By accumulating this energy term for each object, the size perception characteristics of the indoor environment are comprehensively reflected.

$$E_s = \sum_{s_i} E_{l,s_i} + E_{w,s_i} \tag{4}$$

Among them, E_{l,s_i}, E_{w,s_i} refers to the size-aware energy terms of each object in the length and width directions.

This article constructs three parallel task modules to analyze indoor environments: the complete edge task extracts the overall semantic boundary and outputs a deep feature map; Refine the single plane boundary in the local edge task and outputs a 5-depth feature map, with each dimension corresponding to a plane; The segmentation task generates a semantic segmentation map of the plane, outputs a 5-depth feature map, and predicts the probabilities of different categories of planes in each dimension. In the data processing flow, X_{input}^{low} serves as the low-resolution output of the encoder's final upsampling layer and becomes the basis for subsequent operations. By carefully designing Conv2d (2D convolution operation), combined with specific convolution kernel size k, stride $stride$, and output depth o, feature extraction and transformation are achieved. The key upsampling step uses Upsampleby4 technology to achieve a 4x resolution improvement through bilinear interpolation, ensuring precise information recovery. In the end, X_{seg}^{high}, $X_{t\_edge}^{high}$, and $X_{a\_edge}^{high}$ were used as high-resolution outputs for segmentation tasks, complete edge tasks, and local edge tasks, respectively, perfectly matching the original size of the input image and achieving comprehensive analysis from low resolution to high resolution. The entire calculation process is detailed in expressions (5) to (7), which f represent convolution operation and I upsampling operation, jointly weaving a technical framework for a profound understanding of indoor environments.

$$X_{seg}^{high} = I\left[f_{1\times1}^{stride=1,o=5} \quad X_{input}^{low}\right] \tag{5}$$

$$X_{t\_edge}^{high} = I\left[f_{1\times1}^{stride=1,o=1} \quad X_{input}^{low}\right] \tag{6}$$

$$X_{a\_seg}^{high} = I\left[f_{1\times1}^{stride=1,o=5} \quad X_{input}^{low}\right] \tag{7}$$

In this article, the construction of the loss function covers three key components: segmentation loss, smoothing loss, and edge loss. Specifically, segmentation loss, as the primary performance indicator of the model, quantifies the multi-class cross-entropy difference between the predicted results and the actual labels. Its precise definition is shown in formula (8).

$$L_{seg} = -\log \; soft\max \; x_{label} \quad = -\log \frac{\exp \; x_{label}}{\sum_i \exp \; x_i} \tag{8}$$

x_{label} is the actual value of the layout estimation label, and x_i is the predicted value of the model for the network nodes corresponding to each planar region category.

5 RESULT ANALYSIS AND DISCUSSION

To verify the performance of the indoor layout optimization model based on multi-task supervised learning in this paper, a comparative experiment will be conducted with traditional ML-based optimization models.

Figure 3 compares the processing time performance of the proposed model and the traditional model in indoor layout optimization tasks. From the figure, it can be clearly observed that compared to traditional models, the model constructed in this paper exhibits significant advantages in processing time. Specifically, traditional ML models often require a long time to analyze each design element one by one when dealing with complex indoor layout optimization tasks, and gradually approach the optimal solution through iterative calculations. In contrast, the model proposed in this article achieves parallel processing and collaborative optimization of indoor layout optimization tasks by introducing a multi-task supervised learning mechanism. This parallel processing method greatly improves the computational efficiency of the model, making the entire optimization process faster and more effective.

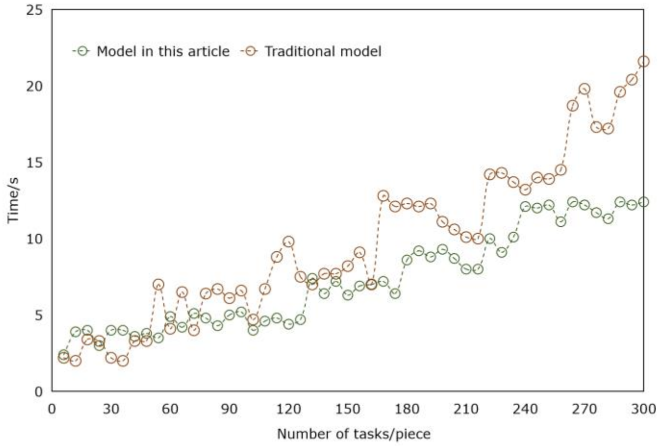

Figure 3: Comparison of task processing time.

Figure 4 compares the trend of loss function changes between the proposed model and the traditional model in indoor layout optimization tasks. It can be clearly seen from the figure that compared to traditional models, the loss function curve presented in this paper's model has a faster convergence speed, which significantly improves the efficiency and effectiveness of the optimization process. In traditional ML models, the convergence of the loss function often relies on complex iterative algorithms and extensive data training, which may encounter problems such as slow convergence speed and susceptibility to local optima. This not only prolongs the training time of the model but may also affect the accuracy of the final optimization results. The model presented in this article achieves parallel processing and collaborative optimization of multiple optimization tasks by introducing a multi-task supervised learning framework. During the training process, information sharing and complementarity between various task modules promote a rapid decrease in the loss function value, thereby achieving faster convergence speed.

Figure 5 shows the difference in design precision between our model and traditional models in indoor layout optimization tasks. From the figure, it can be clearly seen that compared to traditional models, the model presented in this paper demonstrates significant advantages in design precision. Traditional ML models are often limited by the learning ability of a single task and the limitations of data representation when optimizing indoor layouts, making it difficult to fully capture the complex features of indoor environments, resulting in certain deviations in design results.

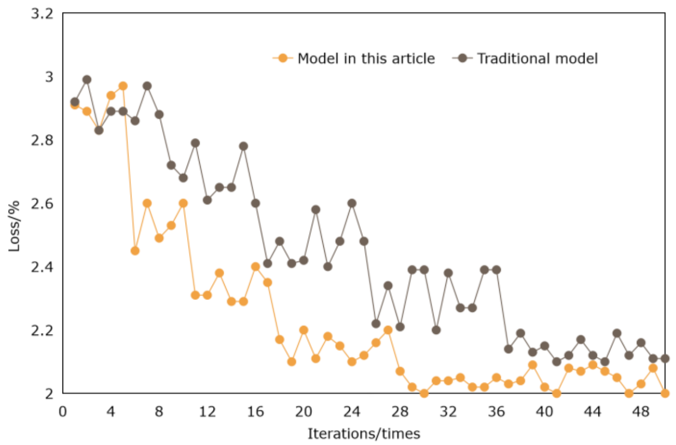

Figure 4: Comparison of loss functions.

This article's model achieves multidimensional and deep-level analysis of indoor layout optimization problems by constructing a multi-task supervised learning framework. This multi-task parallel learning method not only improves the learning efficiency and generalization ability of the model but also significantly enhances the design precision, making the optimized indoor layout more in line with actual needs and design expectations.

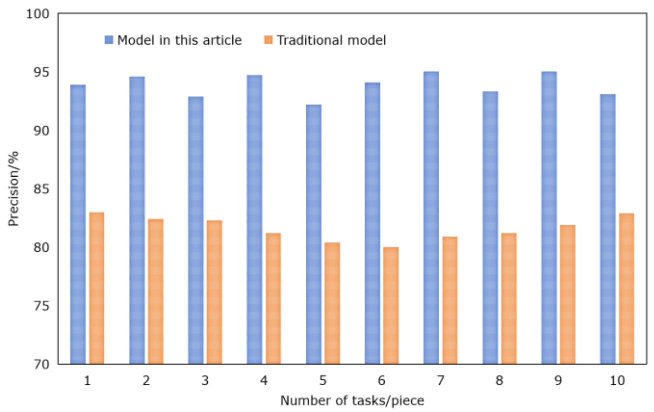

Figure 5: Comparison of design precision.

Figure 6 compares the actual performance of the proposed model and the traditional model in indoor layout optimization tasks, with user satisfaction ratings as the core. From the feedback data in the figure, it can be clearly seen that compared to traditional models, our model has achieved higher evaluations in terms of user satisfaction. Although traditional models can optimize indoor layout to a certain extent, their single-task learning approach and limited optimization capabilities often make it difficult to meet the diverse needs and expectations of users, resulting in limited improvement in user satisfaction. By introducing a multi-task supervised learning mechanism, this model not only achieves comprehensive coverage and accurate processing of indoor layout optimization tasks but also fully considers subjective factors such as user habits and aesthetic preferences. During the optimization process, the model can automatically adjust design parameters to better match users' personalized needs, thereby improving their user experience and satisfaction.

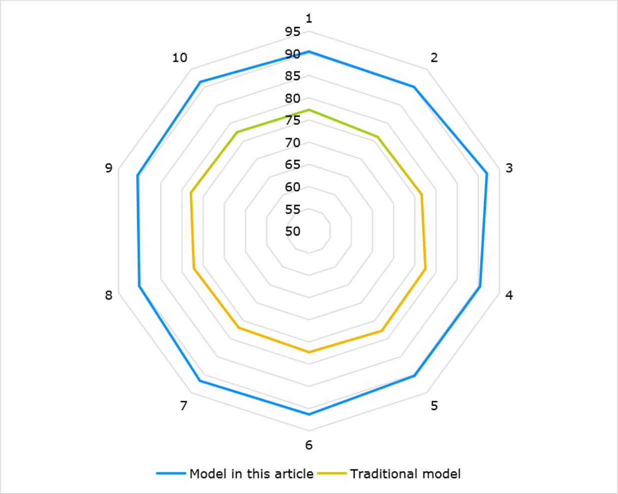

Figure 6: Comparison of user satisfaction.

Figure 7 reveals the difference in scene throughput between our model and traditional models in indoor layout optimization tasks. This model achieves parallel processing and collaborative optimization of multiple optimization tasks through multi-task supervised learning. This mechanism enables the model to efficiently handle multiple spatial areas in indoor layouts while maintaining high accuracy and stability. Therefore, in terms of scene throughput, the model presented in this article demonstrates higher efficiency and stronger processing capabilities, which can better meet the high efficiency and wide applicability requirements for indoor layout optimization in practical applications.

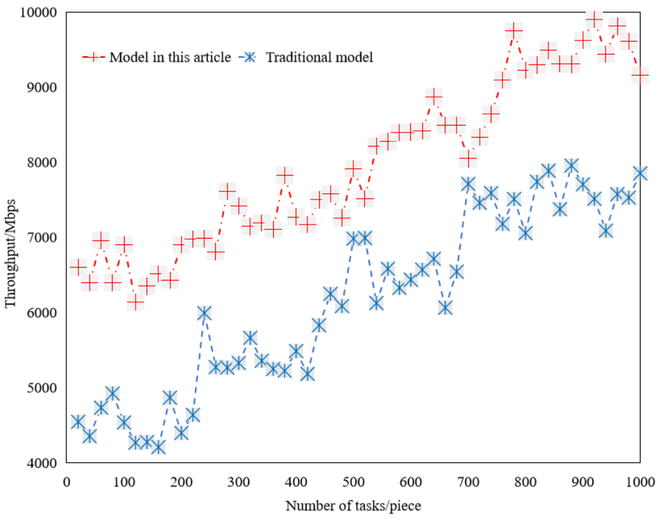

Figure 7: Comparison of throughput in different scenarios.

Figure 8 compares the CPU utilization of the proposed model and the traditional model during the execution of indoor layout optimization tasks. It can be clearly seen from the figure that compared to traditional models, the model presented in this paper shows a lower level of CPU utilization. Traditional models often require high CPU resources for indoor layout optimization due to increased algorithm complexity and data processing, resulting in a decrease in overall system efficiency. The model in this article effectively reduces the dependence of a single task on CPU resources and achieves efficient resource utilization by optimizing algorithm design and introducing a multi-task parallel processing mechanism.

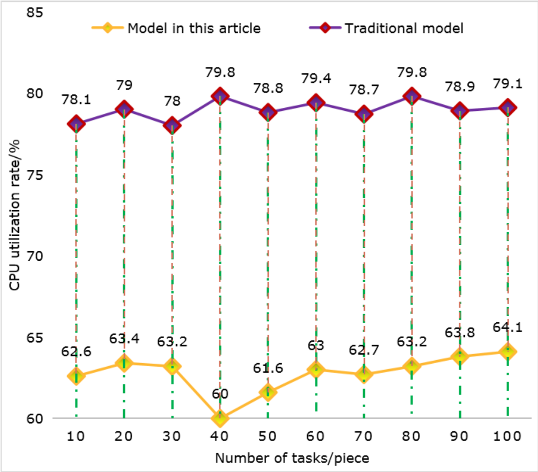

Figure 8: CPU utilization comparison.

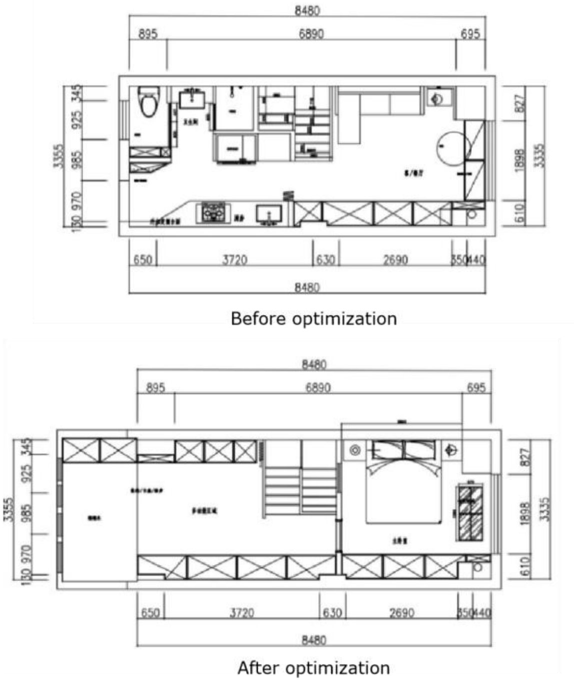

Figure 9: Layout design of apartment.

Figure 9 shows the comparison of a small apartment before and after the application of the proposed indoor layout optimization model. Before optimization, the spatial layout of the apartment is crowded and the functional areas are not clearly defined. After the optimization of the model, the space has been used more reasonably, and the overall layout is more in line with the living habits of residents.

Before optimization After optimization

Figure 10: Layout design of office space.

Figure 10 is an example of layout optimization of an open office space. Before optimization, the arrangement of workstations in the office space was chaotic and the passages were narrow, which affected the work efficiency and comfort of employees. After applying the indoor layout optimization model, the workstations are rearranged, forming a more spacious passage and a more reasonable cooperation area, and ensuring that every employee has sufficient working space and good sight.
Through these two design examples, we can clearly see the obvious advantages of the proposed indoor layout optimization model in practical application. It can not only help designers optimize the spatial layout more efficiently but also ensure that the optimized layout is more in line with the needs of users.

6 CONCLUSIONS

This article aims to explore the potential application of indoor layout optimization models, and innovatively propose a DL based indoor layout optimization model. Through a series of carefully designed experiments and comparative analysis, this model has demonstrated remarkable performance in multiple key indicators. Specifically, this model not only significantly improves design efficiency, but also enables designers to complete high-quality interior layout designs in a shorter amount of time; At the same time, it also optimizes spatial layout through intelligent algorithms, achieving maximum space utilization and meeting users' dual needs for functionality and aesthetics. In addition, the improvement in user satisfaction further validates the effectiveness of our model in enhancing user experience.

However, it is worth noting that although the model in this article has made significant progress in multiple aspects, there are still certain limitations. Firstly, the training of DL models relies on a large amount of annotated data, and the diversity and complexity of indoor layout design make obtaining high-quality datasets a major challenge. Secondly, the model may exhibit certain limitations when dealing with extremely complex or special indoor layouts, requiring further algorithm optimization and adaptive adjustments. Finally, the application scenarios and generalization ability of the model still need to be further expanded and validated to ensure its effectiveness and stability in different fields and scenarios.

Yang Liu, https://orcid.org/0009-0004-3717-9494
Guanjie Wang, https://orcid.org/0009-0008-1849-149X

REFERENCES

[1] Aboagye, S.; Ngatched, T.-M.-N.; Dobre, O.-A.: Intelligent reflecting surface-aided indoor visible light communication systems, IEEE Communications Letters, 25(12), 2021, 3913-3917. https://doi.org/10.1109/LCOMM.2021.3114594

[2] Africa, A.-D.-M.: Design and implementation of smart home system using packet tracer, International Journal of Advanced Trends in Computer Science and Engineering, 9(4), 2020, 5710-5715. https://doi.org/10.30534/ijatcse/2020/223942020

[3] Alizadeh, N.-A.; Ahmad, A.; Sheikholeslami, M.-M.; Claudio, P.; Sohn, G.: An unsupervised registration of 3D point clouds to 2D CAD model: a case study of the floor plan, ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2(1), 2020, 9-13. https://doi.org/10.5194/isprs-annals-V-2-2020-9-2020

[4] Alzoubi, A.: Machine learning for intelligent energy consumption in smart homes, International Journal of Computations, Information and Manufacturing (IJCIM), 2(1), 2022, 62-73. https://doi.org/10.54489/ijcim.v2i1.75

[5] Dubey, R.-K.; Khoo, W.-P.; Morad, M.-G.: AUTOSIGN: A multi-criteria optimization approach to computer-aided design of signage layouts in complex buildings, Computers & Graphics, 88(1), 2020, 13-23. https://doi.org/10.1016/j.cag.2020.02.007

[6] Fu, Q.; Yan, H.; Fu, H.: Interactive design and preview of colored snapshots of indoor scenes, Computer Graphics Forum, 39(7), 2020, 543-552. https://doi.org/10.1111/cgf.14166

[7] Li, Y.; Wang, Y.; Li, Y.: An artificial neural network assisted optimization system for analog design space exploration, IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 39(10), 2019, 2640-2653. https://doi.org/10.1109/TCAD.2019.2961322

[8] Liu, M.; Pan, X.; Gao, S.: Segmentation for indoor scenes based on DBSCAN clustering, Journal of Computer-Aided Design & Computer Graphics, 71(7), 2019, 1183-1193. https://doi.org/10.3724/SP.J.1089.2019.17519

[9] Maiti, P.; Mitra, D.: Three-dimensional measuring points locating algorithm based texture-patched matrix completion for indoor 3D REM design, Wireless Personal Communications, 126(2), 2022, 1075-1099. https://doi.org/10.1007/s11277-022-09783-y

[10] Pintore, G.; Mura, C.; Ganovelli, F.: State-of-the-art in Automatic 3D Reconstruction of Structured Indoor Environments, Computer Graphics Forum, 39(2), 2023, 667-699. https://doi.org/10.1111/cgf.14021

[11] Shen, L.; Li, G.; Xian, C.: Door and window detection in 3D point cloud of indoor scenes, Journal of Computer-Aided Design & Computer Graphics, 31(9), 2019, 1494-1501. https://doi.org/10.3724/SP.J.1089.2019.17575

[12] Turgut, Z.; Kakisim, A.-G.: An explainable hybrid deep learning architecture for WiFi-based indoor localization in the Internet of Things environment, Future Generation Computer Systems, 151(1), 2024, 196-213. https://doi.org/10.1016/j.future.2023.10.003

[13] Yang, J.: Teaching optimization of interior design based on three-dimensional computer-aided simulation, Computer-Aided Design and Applications, 18(S4), 2021, 72-83. https://doi.org/10.14733/cadaps.2021.S4.72-83

[14] Yang, M.; Fan, Q.; Wang, Y.: Graph neural network for generative furniture arrangement, Journal of Computer-Aided Design & Computer Graphics, 33(3), 2021, 457-464. https://doi.org/10.3724/SP.J.1089.2021.18457

[15] Zhang, C.; Zhu, A.-X.; Zhou, L.: Constraints for improving information integrity in information conversion from CAD building drawings to BIM model, IEEE Access, 8(1), 2020, 81190-81208. https://doi.org/10.1109/ACCESS.2020.2991200