Evaluating Aesthetic Preferences for Indoor Landscapes From a Cybersecurity Perspective Using Machine

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Abstract:

Introduction: With the acceleration of modern urbanization, indoor landscape design has not only become an important element to improve the quality of life, but also closely related to network security. However, how to scientifically evaluate the aesthetic preferences of indoor landscapes while ensuring network security has become a question worth exploring.

Objectives: In response to the subjectivity and low efficiency of traditional aesthetic evaluation methods, this study proposes a deep learning based indoor landscape aesthetic quality evaluation method.

Methods: This method combines convolutional neural networks and graph neural networks to extract and analyze global and local aesthetic features of indoor images, taking into account the impact of indoor layout on network security.

Results: The results showed that the aesthetic evaluation accuracy of this method on indoor landscape datasets reached 97.74%, an increase of 7.54 percentage points compared to traditional methods. Compared with other aesthetic evaluation schemes, this method achieved a 14.21% higher aesthetic score and a 10.6 point improvement in functional evaluation.

Conclusions: The conclusion indicates that this method can effectively improve the objectivity and efficiency of indoor landscape aesthetic evaluation, providing a novel evaluation tool for indoor landscape design under the premise of ensuring network security.

Keywords: indoor landscape; aesthetic evaluation; deep learning; convolutional neural network; graph neural network; network security.

INTRODUCTION

The advancement of urbanization has led to an increasing demand for aesthetic living and working environments among people. Interior landscape design, as an important means to enhance spatial quality and improve living experience, has become a hot topic in the field of design in terms of evaluating and optimizing its aesthetic value [1]. However, traditional Indoor Landscape Aesthetic (ILA) evaluation methods often rely on subjective judgments from experts, which is not only inefficient but also difficult to meet diverse and personalized aesthetic needs [2]. Therefore, exploring a scientific and objective evaluation method for ILA preferences has become a problem to be solved in the field of interior landscape design [3].

In recent years, deep learning (DL) technology has made significant progress in fields such as image recognition and pattern recognition. Its powerful feature extraction ability and high automation potential provide new ideas for ILA evaluation [4]. Especially the application of Convolutional Neural Network (CNN) and Graph Neural Network (GNN) provides effective technical means for the analysis of ILA features [5]. In addition, the importance of cybersecurity in the evaluation of indoor landscape aesthetic preferences is increasingly prominent. Unreasonable indoor layout may affect the coverage area of surveillance cameras, increase security blind spots, and thus reduce overall network security.

CNN is widely used in aesthetic evaluation due to its outstanding performance in image recognition and classification tasks. Takimoto H et al. proposed an image aesthetic evaluation method based on multi task CNN and saliency features. This method extracted global and salient features from the input image to provide higher-level visual information. The proposed method could effectively improve the performance of aesthetic evaluation [6]. Kim SE et al. developed a hybrid aesthetic evaluation model for quantifying image cognitive features. This model extracted local features of aesthetic images through CNN, reflected global features using visual transformers, and analyzed the aesthetic value of images. The Pearson correlation coefficient of this model has increased by 2%-4% compared to traditional models [7]. Ke Y et al. proposed a dual stream image aesthetic evaluation model that combines transformer and CNN features. This model extracted local aesthetic features of images through CNN and learned global aesthetic features using transformer networks. The proposed model achieved a green occupancy rate of 84.5% during the classification task [8]. Bougourzi et al. proposed an aesthetic analysis method based on CNN for dynamic robust loss and set regression. This method improved the performance of the model by introducing a parabolic dynamic law based approach to control the parameters of robust loss. The evaluation effect of this method was superior to existing advanced methods [9]. Dai Y proposed an image aesthetic evaluation and prediction model based on the CNN framework to address poor aesthetic performance in existing images. This model improved prediction performance by extracting the attention areas of the model on the image and analyzing the consistency between the model and the image subject. The F1 score of this model has increased by 5.4% and 33.1% compared to models A and B [10].

GNN, as a DL model for processing graph structured data, has attracted widespread attention in the field of ILA evaluation in recent years due to its ability to efficiently capture the complex relationships and spatial structures between elements in indoor landscapes. Wang X et al. proposed a DL framework based on CNN and GNN in China. This method generated layouts by compromising between multiple preset aesthetics and proposed two adaptive training strategies that dynamically adjust the weight factors of each aesthetic during the training process. The proposed method could flexibly adapt to different aesthetic standards [11]. Miao H et al. proposed an image aesthetic analysis model based on multi-modal GNN. This model stacked GNNs and introduced a common attention module to achieve the learning of aesthetic features. This model had excellent generalization ability on the AVA and ArtPhoto datasets [12]. Li L et al. proposed an image aesthetic evaluation method based on visual attribute inference. This method trained GNN by simulating the human perception process in aesthetic images, extracted aesthetic attribute features, and could effectively evaluate image aesthetics [13]. Li L et al. proposed an attribute assisted GNN-based image aesthetics method to address the highly abstract nature of image aesthetics. It captured the attribute perception information most relevant to images and related comments to obtain more discriminative aesthetic representations. Compared to other aesthetic methods, this method had superior performance [14].

In summary, numerous scholars have conducted extensive research on aesthetic evaluation methods and achieved excellent results. However, existing methods can only extract global aesthetic features and ignore local aesthetic features, resulting in a decrease in the accuracy of ILA evaluation [15]. Therefore, this study proposes a method that combines CNN and GNN aesthetic feature evaluation, aiming to extract global and local aesthetic features, efficiently evaluate aesthetics, and improve evaluation accuracy.

OBJECTIVES

This study proposes an ILA evaluation system based on CNN and GNN, which achieves feature extraction and analysis of ILA through the collaborative work of CNN and GNN, to achieve more efficient and objective aesthetic evaluation effects. This method not only focuses on the extraction and analysis of aesthetic features, but also considers the potential impact of indoor layout on network security.

The innovation of this study lies in: (1) By utilizing the advantages of CNN in image feature extraction and the ability of GNN to process graph structure data and capture complex relationships between elements, efficient extraction and analysis of global and local aesthetic features have been achieved; (2) A dual dimensional attention feature extraction module that integrates space and channels has been introduced to accurately capture key features that have a significant impact on image aesthetics, enhancing the DL model's ability to recognize aesthetic features. (3) For the first time, incorporating cybersecurity factors into the evaluation of indoor landscape aesthetic preferences provides a novel evaluation tool for indoor landscape design that considers both aesthetics and security.

METHODS

CONSTRUCTION OF INDOOR LANDSCAPE AESTHETICS AND NETWORK SECURITY EVALUATION SYSTEM BASED ON CNN AND GNN

This section constructs an ILA evaluation system model based on CNN and GNN. This model extracts global aesthetic features through CNN and uses GNN to extract local aesthetic features to improve the performance of the ILA evaluation system.

GLOBAL AESTHETIC FEATURE EXTRACTION AND SYSTEM ARCHITECTURE DESIGN BASED ON CNN

In ILA evaluation, CNN can automatically extract global features of images, including color, texture, shape, etc., which are crucial for evaluating overall aesthetic perception [16]. To improve the efficiency and accuracy of aesthetic evaluation, this study proposes a CNN-based global aesthetic feature extraction method and designs the overall architecture of the aesthetic evaluation system. This study constructs an end-to-end framework that includes data preprocessing module, feature extraction module, feature fusion module, and aesthetic evaluation model. For the data preprocessing module, to enhance the generalization ability of the aesthetic evaluation model, this study introduces a data augmentation strategy with a fixed sample size to enrich the diversity of the samples and avoid overfitting of the model. The preprocessing process of aesthetic image data is shown in Fig.1.

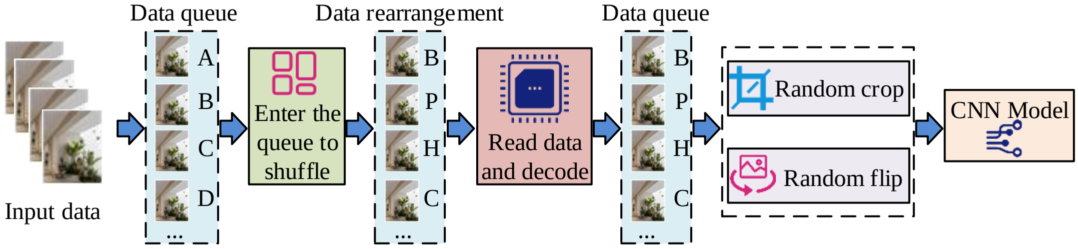


Fig.1 Pre-processing process of aesthetic image data

Due to the limitations of CNN in capturing the global structure and information of aesthetic images, such as low efficiency, this study will integrate a highly efficient Transformer model into CNN to improve its ability to extract global aesthetic features [17]. This method solves the problem of slow convergence speed of the model through batch normalization, and uses L2 normalization to prevent overfitting and improve the robustness of the model [18]. The expression for the mean and variance of batch normalization feature extraction is shown in equation (1).

$$\begin{cases} Ave_b = \dfrac{1}{m}\sum_{i=1}^{m} f_i \\ \sigma_b^2 = \dfrac{1}{m}\sum_{i=1}^{m}\left(f_i - Ave_b\right)^2 \end{cases} \qquad (1)$$

In equation (1), Ave_b is the feature mean. σ_b^2 is the characteristic variance. f_i is the input feature. Among them, $i=1,2,\ldots,m$. m is the size of the batch. The response values of the regularization process and the final normalized features obtained are shown in equation (2).

$$\begin{cases} f_i' = \dfrac{f_i - Ave_b}{\sqrt{\sigma_b^2 + e}} \\ g_i = \gamma\, f_i' + \beta \end{cases} \qquad (2)$$

In equation (2), f_i' is the normalized eigenvalue. e is a decimal close to 0 to prevent splitting into 0. g_i is the response value of the normalized feature. β is the offset coefficient. γ is the scale coefficient. In order to avoid overfitting, this study adopts the L2 normalization strategy to extract features, and its expression is shown in equation (3).

$$\begin{cases} f_i'' = \dfrac{f_i}{\max\left(\|f\|_2, e\right)} \\ \|f\|_2 = \sqrt{\sum_{i=1}^{n} |f_i|^2} \end{cases} \quad (3)$$

In equation (3), f_i'' is the feature value normalized by L2. $\|f\|_2$ is the L2 norm of the eigenvector f . n is the number of features. Then, this study introduces a dual dimensional attention feature extraction module that integrates space and channels to accurately capture key features that have a significant impact on image aesthetics, and assigns higher weights to these features to achieve DL [19]. The feature extraction diagram of this module is shown in Fig.2.

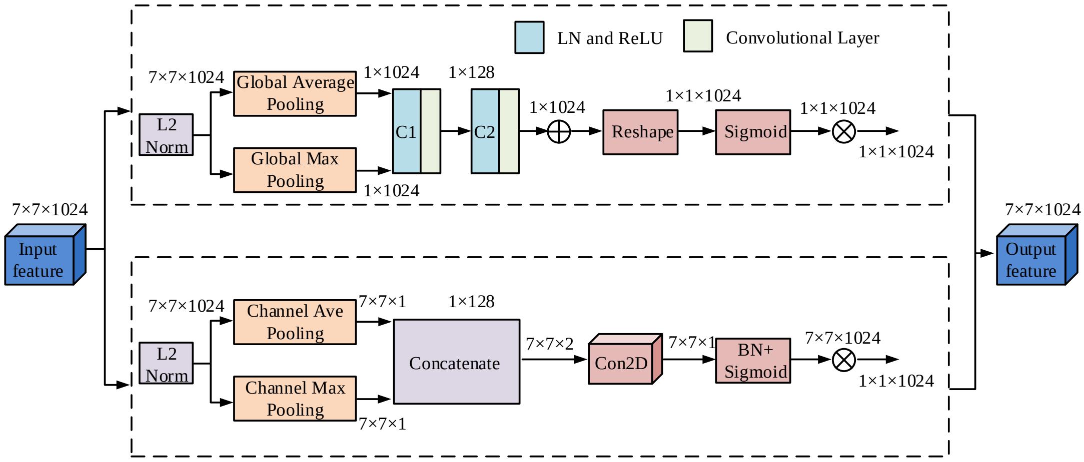


Fig.2 Dual dimensional attention feature extraction module structure diagram of fusion space and channel

This module performs dimensionality reduction on the input aesthetic image features through Global Average Pooling (GAP) and Global Max Pooling (GMP), and converts the two-dimensional feature map into a single real value [20]. The calculation of GAP is shown in equation (4).

$$F_{avg} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} f(i, j) \quad (4)$$

In equation (4), F_{avg} is the output feature obtained after GAP operation. H and W are the height and width of the aesthetic feature map. $f(i, j)$ is the pixel value at position (i, j) on the feature map. The calculation of GMP is shown in equation (5).

$$F_{\max} = \max_{1 \le i \le H, 1 \le j \le W} f(i, j) \quad (5)$$

In equation (5), $F_{\max}$ is the output feature obtained after GMP operation. This study uses the activation function Sigmoid to fuse the output features and obtain the weight coefficients of the channels, as shown in equation (6).

$$W = \sigma\left(MLP\left(F_{avg}\right) + MLP\left(F_{\max}\right)\right) \quad (6)$$

In equation (6), W is the weight coefficient, where $W \in R^{1\times1\times d}$ and d are the number of channels. MLP is the shared network layer. σ is the Sigmoid function. To enable the network to automatically adjust the weights of each feature channel, this study introduces the Squeeze and Excitation (SE) module based on different attribute features [21]. The schematic diagram of the structure of this module is shown in Fig.3.

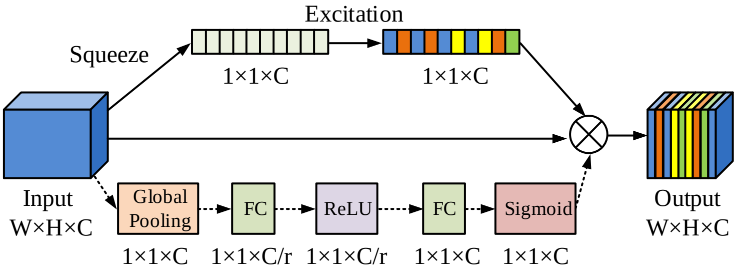


Fig.3 Structure diagram of SE module

For the overall design of the system, this study trains the MobieNet network on an indoor landscape dataset. This network can evaluate the aesthetic features of images and provide corresponding scores, and then use the sliding window method to segment the images into regions of different sizes. Each region needs to be trained using the MobieNet network to generate aesthetic attribute ratings. Finally, the aesthetic attribute data of the image are filtered using Non-Maximum Suppression (NMS) algorithm to obtain the final aesthetic evaluation result.

LOCAL AESTHETICS AND NETWORK SECURITY ANALYSIS BASED ON GNN

The extraction of global aesthetic features and the design of the overall system architecture can provide a framework and features for overall aesthetics from a macro perspective. However, to further deepen the understanding of aesthetic elements, it is necessary to examine aesthetic features from a more nuanced perspective [22]. Compared to CNN, GNN is better at capturing local features and structural information, which is crucial for understanding the complex relationships and spatial structures between elements in indoor landscapes. Therefore, this study proposes a local aesthetic evaluation method based on GNN. This method provides a more detailed aesthetic evaluation by analyzing the interactions between indoor landscape elements, and simultaneously analyzes the potential impact of these features on network security. To achieve local region analysis of aesthetic images, this study introduces Region Proposal Network (RPN) to enhance the local aesthetic analysis effect of GNN [23]. This method utilizes sliding window technology to extract information from image regions of different scales. These regions are combined with the precise candidate regions obtained through the Selective Search algorithm, as shown in equation (7).

$$\begin{cases} R_1 = \{r_1, r_2, \ldots, r_k\} \\ R_{all} = (R_1 \cap R_2) \cup R_2 \end{cases} \quad (7)$$

In equation (7), R_1 is the set of candidate regions obtained in the first round. k is the number of candidate boxes obtained through sliding window technology. R_2 is a set of candidate regions obtained through the Selective Search algorithm. R_{all} is the merged set of candidate regions. In order to analyze the aesthetic image features of each region in more detail, this study uses the Sobel operator of the image region partitioning algorithm for edge detection, as shown in equation (8).

$$g(i,j) = \sqrt{(DX)^2 + (DY)^2} \quad (8)$$

In equation (8), $g(i,j)$ is the grayscale value of the image. DX and DY are gradients in the horizontal and vertical directions. Due to the fact that traditional NMS algorithms can only evaluate a single aesthetic feature, their efficiency is low [24]. Therefore, this study proposes a Multi-Attribute NMS (MA-NMS) method to improve the quality of candidate regions. This method can comprehensively score and rank candidate regions based on aesthetic attributes to determine the key aesthetic regions of the image, improving the accuracy and efficiency of local aesthetic analysis, as shown in equation (9).

$$IoU(R_i, R_j) = \frac{Area(R_i \cap R_j)}{Area(R_i \cup R_j)} \quad (9)$$

In equation (9), R_i and R_j are two different bounding boxes. $Area(R_i \cap R_j)$ and $Area(R_i \cup R_j)$ are the intersection and union areas of the bounding boxes. IoU is the intersection ratio of two bounding boxes. To fully utilize the advantages of CNN and GNN, this study proposes an aesthetic evaluation method that combines CNN and GNN, as shown in Fig.4.

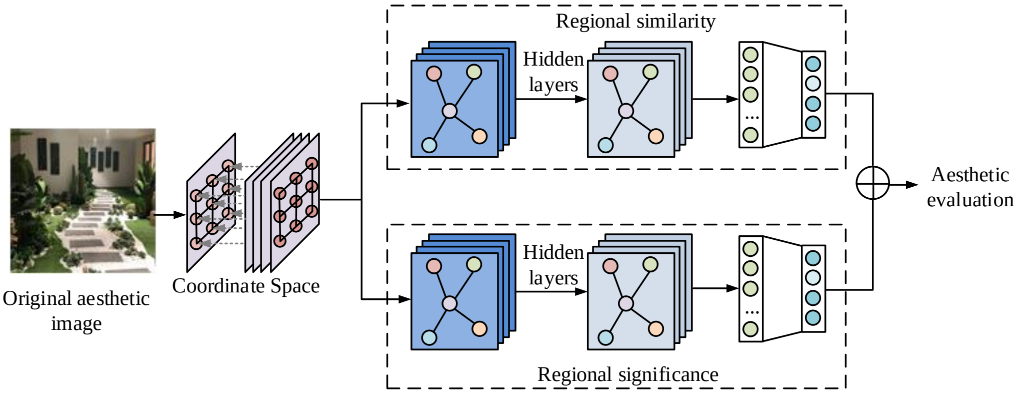


Fig.4 Structural diagram of aesthetic evaluation model combining CNN and GNN

This study integrates the global features extracted by CNN with the local features analyzed by GNN through a feature fusion module. A CNN-GNN algorithm has been proposed to improve the accuracy of ILA evaluation, enhance the model's generalization ability to different types of indoor landscapes. At the same time, this method also considers the impact of indoor layout on network security, achieving a comprehensive aesthetic and security assessment. This method analyzes aesthetic images in both coordinate and attribute dimensions to construct a model that captures the hierarchical structure and visual focus of the image. For any specific aesthetic image, this study first uses the ResNet model to extract a Full Convolutional Network (FCN) feature map with dimension $W \times H \times C$ [25]. To capture the interrelationships between local regions in aesthetic images, this study constructs a region similarity GNN. This network convolves the aesthetic graph to facilitate information exchange of node attributes in the graph, enhance the refinement of feature maps, and create a visual expression with spatial perception. The schematic diagram of the local area of the GNN preserved aesthetic image is shown in Fig.5.

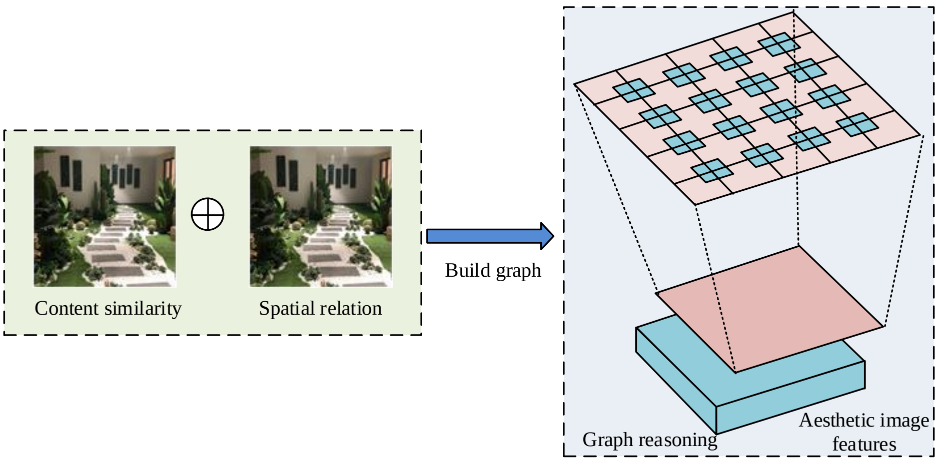


Fig.5 GNN for preserving local regions of aesthetic images

Due to the fact that most existing image saliency assessment methods are based on human visual attention, their accuracy is poor. Therefore, this study proposes a region saliency GNN and combines it with region similarity GNN to improve the accuracy of aesthetic image evaluation. The image saliency ratio calculated by the network is shown in equation (10).

$$\begin{cases} A_r = e_{ij} \times A^{\mathrm{sal}} \\ A_{kl}^{sal} = \bar{v}_k / \bar{v}_l \end{cases} \quad (10)$$

In equation (10), A_r is the adjacent matrix in the region saliency network. A_{kl}^{sal} is the significance ratio. k and l are node numbers in the network. A^{sal} is the similarity measure between node k and node l. e_{ij} is the original weight between adjacent vectors. The aesthetic image evaluation method based on CNN-GNN algorithm first needs to calculate the original attention weights of two adjacent nodes and normalize them to obtain the final complete weight coefficients, as shown in equation (11).

$$\begin{cases} e_{ij}^{(l)} = Leaky\mathrm{Re}LU\left(\vec{a}^{(l)}\left(X_i^{(l)} \middle\| X_j^{(l)}\right)\right)^T \\ a_{ij} = soft\max_j\left(e_{ij}\right) \end{cases} \quad (11)$$

In equation (11), $e_{ij}^{(l)}$ is the original attention weight. a_{ij} is the complete weight coefficient. $LeakyLU$ is a nonlinear activation function. (l) is the feature vector related to nodes. X is the output feature matrix. $soft\max$ is the normalization function. Finally, the aesthetic images are evaluated using the CNN-GNN algorithm.

RESULTS

PERFORMANCE TESTING AND NETWORK SECURITY EVALUATION OF INDOOR LANDSCAPE AESTHETIC PREFERENCE EVALUATION SYSTEM

This section tests the performance of the indoor landscape aesthetic evaluation system based on the CNN-GNN algorithm, and analyzes the applicability results of the system considering network security factors to verify the effectiveness of the proposed aesthetic evaluation method in assessing indoor landscape aesthetic preferences while ensuring network security.

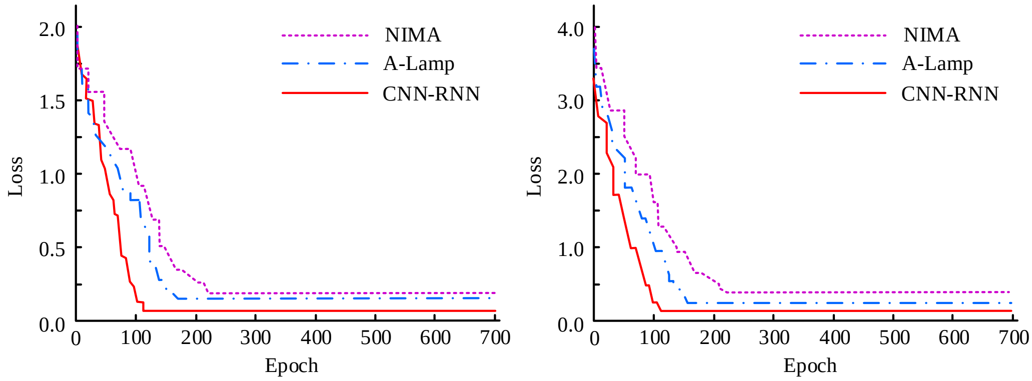
PERFORMANCE TESTING OF CNN-GNN ALGORITHM

To verify the effectiveness of the ILA evaluation system based on the CNN-GNN algorithm, this study tests the performance of the CNN-GNN algorithm. This study mainly uses the large-scale indoor landscape datasets Taskomy and S3DIS as experimental datasets. Table 1 shows the hardware and software configurations and parameters of the experiment.

Table 1 Experimental configuration and parameters

Hardware and software name	Type	Hardware and software name		Type
DL framework	Jittor	Function library	Pandas	0.23.0
Operating system	Ubuntu16.04.5 LTS		Cuda	10.0
Graphics card	Tesla V100-DGXS		Numpy	1.14.3
Central processing unit	Intel(R)core ™ CPU		Pillow	5.1.0
Image processor	Nvidia GeForce GTX		Matolotlib	2.2.2
Mini-batch	200	learning rate of epoch		0.001

This study tests the loss function of the CNN-GNN algorithm on two datasets and compares it with popular aesthetic evaluation methods, including Neural Image Assessment (NIMA) and Adaptive Layout Aware Multi Patch Deep CNN (A-Lamp). The results are shown in Fig.6. In Fig.6 (a), in the Taskonomy dataset, at 100 iterations, the loss functions of NIMA and A-Lamp algorithms are 1.23 and 1.12, while the loss function of CNN-GNN is 0.27. When the iteration reaches 115, the loss function of CNN-GNN reaches its lowest point and tends to stabilize at 0.06. When the iteration reaches 180, A-Lamp tends to stabilize at 0.12. At 227 iterations, the loss function of NIMA reaches its minimum of 0.22. In Fig.6 (b), in the S3DIS dataset, at 100 iterations, the loss functions of the three algorithms are 0.48, 1.13, and 2.02. When iterating 300, the loss functions of the three algorithms tend to stabilize at 0.11, 0.25, and 0.47. This indicates that the research algorithm has superior robustness.

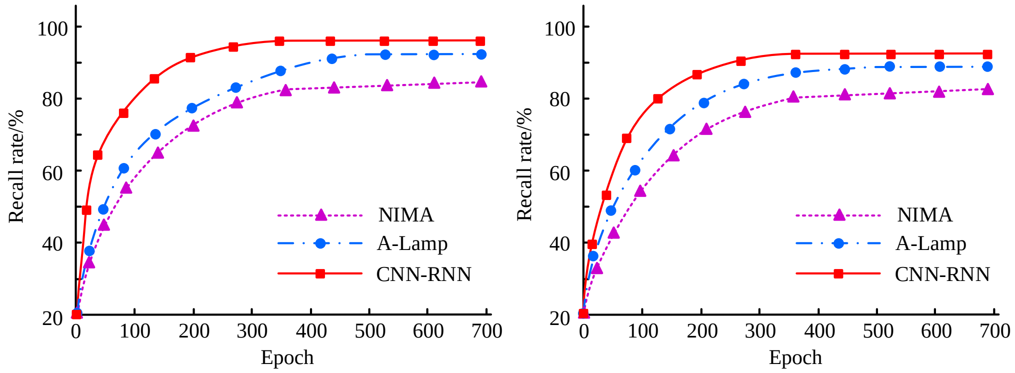


(a) Loss functions of different models in the Taskonomy dataset

(b) Loss functions of different models in the S3DIS dataset

Fig.6 Loss functions of different models under two data sets

To further verify the reliability of CNN-GNN, this study compares and analyzes the recall rates of the algorithm with NIMA and A-Lamp on two datasets, as shown in Fig.7. In Fig.7 (a), when iterating for 100, the recall rates of NIMA, A-Lamp, and CNN-GNN on Taskomy are 54.72%, 62.17%, and 77.85%. When iterated to 400, the recall rates of the three algorithms are 80.04%, 88.69%, and 93.24%. Compared with NIMA and A-Lamp algorithms, the recall rate of the research algorithm has increased by 13.2% and 4.55%. In Fig.7 (b), at iteration 100, the recall rates of the three algorithms on the S3DIS dataset are 54.21%, 60.25%, and 76.48%. When iterating to 400, the recall rates of NIMA and A-Lamp are 78.58% and 87.69%. Compared with them, the recall rates of the research algorithm increase by 11.96% and 2.85%. This indicates that the recall rate of CNN-GNN is better than the comparison algorithm in both datasets, proving the effectiveness of the algorithm.

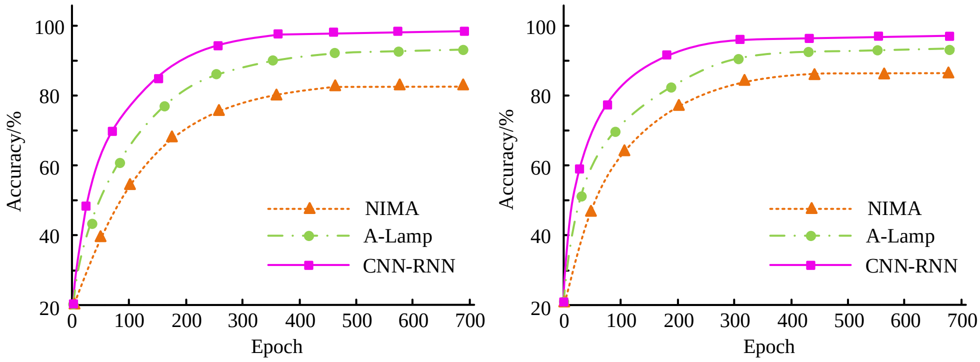


(a) Comparison of recall rate of different models in the Taskonomy dataset

(b) Comparison of recall rate of different models in the S3DIS dataset

Fig.7 Comparison of recall rates of different models under two data sets

The accuracy of the research algorithm is compared with NIMA and A-Lamp on two datasets, Taskonomy and S3DIS, to verify its superiority, as shown in Fig.8. In Fig.8 (a), in Taskonomy, at iteration 100, the accuracies of NIMA, A-Lamp, and CNN-GNN are 54.22%, 68.15%, and 75.62%. When the number of iterations reaches 400, the accuracy of NIMA and A-Lamp is 78.62% and 89.17%. Compared with it, the accuracy of the research algorithm is as high as 98.69%, which has increased by 20.07% and 9.52%. In Fig.8 (b), in S3DIS, the accuracy of the three algorithms at iteration 100 is 60.25%, 70.03%, and 85.67%. When iterates to 400, the accuracy of the three algorithms is 82.66%, 91.24%, and 96.78%. In both datasets, the ILA evaluation method based on CNN-GNN algorithm has high accuracy.



(a) Comparison of accuracy of different models in the Taskonomy dataset

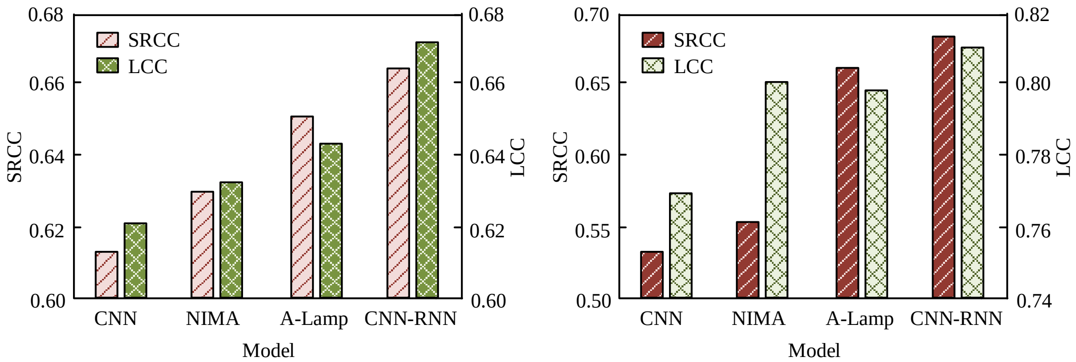
(b) Loss functions of different models in the S3DIS dataset

Fig.8 Comparison of the accuracy of different models under two data sets

APPLICABILITY AND NETWORK SECURITY ANALYSIS OF ILA PREFERENCE EVALUATION SYSTEM

The experiment uses Spearman's Rank Correlation Coefficient (SRCC) to evaluate the nonlinear correlation indicators of aesthetic images on Taskomy. The Linear Correlation Coefficient (LCC) is used to evaluate the correlation between subjective and objective evaluations. Earth Mover's Distance (EMD) is used to evaluate the similarity and difference between aesthetic images. Finally, statistical analysis is conducted on the Mean Square Error (MSE) to investigate the accuracy of the proposed ILA evaluation method.

To further investigate the evaluation effectiveness of the proposed method, the SRCC and LCC of four methods are compared under two datasets, as shown in Fig.9. In Fig.9 (a), for Taskomy, the SRCC of CNN, NIMA, and A-Lamp algorithms are 0.613, 0.628, and 0.650, and the LCC is 0.621, 0.634, and 0.643. Compared with these three methods, the SRCC of the research method increases by 7.54%, 5.28%, and 1.96%, and the LCC increases by 7.59%, 5.65%, and 4.32%. In Fig.9 (b), in S3DIS, the SRCC of the aesthetic evaluation method based on CNN and NIMA algorithms is 0.532 and 0.551, and the LCC is 0.769 and 0.800. The SRCC of the aesthetic evaluation method based on A-Lamp and CNN-GNN algorithm is 0.652 and 0.663, and the LCC is 0.795 and 0.812. Compared with the other three methods, the SRCC of the research method increases by 19.76%, 16.89%, and 1.66%, while the LCC increases by 5.30%, 1.48%, and 2.09%. The research method has the strongest correlation with human subjective evaluation in ILA assessment tasks, and its evaluation results are more reliable.



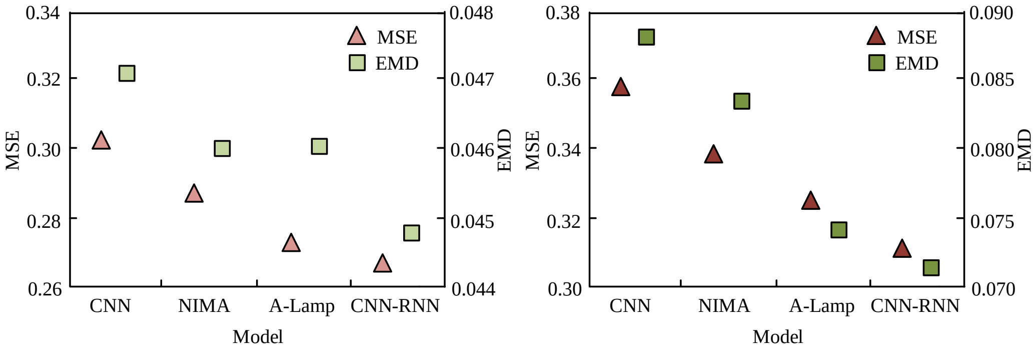
（a）Comparison of SRCC and LCC of different models in the Taskonomy dataset

（b）Comparison of SRCC and LCC of different models in the S3DIS dataset

Fig.9 Comparison of SRCC and LCC of different models in two data sets

To investigate the accuracy of the research method, the MSE and EMD of four methods are compared under two datasets, as shown in Fig.10. In Fig.10 (a), the MSE values of CNN, NIMA, A-Lamp, and CNN-GNN are 0.302, 0.287, 0.273, and 0.264, and the EMD values are 0.0472, 0.0460, 0.0461, and 0.0448, in the Taskomy. Compared with other methods, the MSE values of the research method decreased by 12.59%, 8.01%, and 3.30%, and the EMD decreased by 5.08%, 2.60%, and 2.82%. In Fig.10 (b), for S3DIS, the MSE values of CNN, NIMA, and A-Lamp algorithms are 0.358, 0.339, and 0.323, and the EMD values are 0.0882, 0.0840, and 0.0743. The MSE values and EMD of the research method are 0.307 and 0.071. Compared with this method, the

MSE values decreases by 14.25%, 9.44%, and 4.95%, and the EMD decreases by 18.48%, 14.40%, and 3.23%. This indicates that the research methods have high accuracy and are superior to other methods.

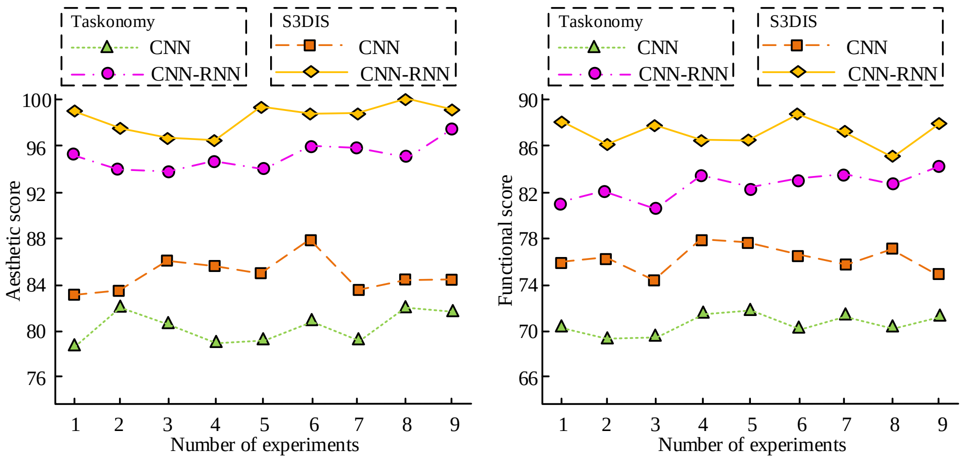


（a）Comparison of MSE and EMD of different models in the Taskonomy dataset

（b）Comparison of MSE and EMD of different models in the S3DIS dataset

Fig.10 Comparison of MSE and EMD of different models in two data sets

To verify the superiority of the research method, this study compares the aesthetic scores and functional evaluation results of different aesthetic evaluation methods in two datasets, as shown in Fig.11. In Fig.11 (a), the average aesthetic scores of CNN and research methods in Taskonomy are 81.2 and 95.5. For the S3DIS dataset, the average aesthetic scores of the two methods are 85.0 and 98.2. Compared with CNN, the aesthetic average score of the research method is 14.21% higher. In Fig.11 (b), for Taskomy, the functional evaluation scores of CNN and research methods are 71.6 and 82.4. In S3DIS, the functional evaluation scores of the two methods are 77.2 points and 87.6 points. Compared with CNN, the functional evaluation score of the research method has increased by an average of 10.6 points. This indicates that the research method has superior practical performance.



(a) Scores of aesthetic evaluation methods under two datasets

(b) Functional scores of aesthetic evaluation methods under two datasets

Fig.11 Aesthetic scores and functional scores of aesthetic evaluation methods under two datasets

To explore the effect of network security assessment, this study compares and analyzes the results of network security assessments under different algorithms. The results are shown in Table 2. In Table 2, the network attack frequency of the proposed method is low, and the repair efficiency of network vulnerabilities is high. The results show that the proposed method can effectively improve network security performance.

Table 2 Network Security Assessment Results of Different Algorithms

Network security index	CNN	NIMA	A-Lamp	CNN-GNN
Number of attacks	17	12	8	2
Average threat response time (s)	12.7	8.9	5.8	3.6
Average threat disposal time (s)	10.6	7.2	4.6	2.5

Vulnerability repair efficiency (%)	78.96	80.66	87.25%	98.74

DISCUSSION

This study proposed an ILA evaluation method that combines CNN and GNN, aiming to objectively evaluate the aesthetic preferences of indoor landscapes and improve the efficiency and accuracy of aesthetic evaluation methods. The CNN-GNN algorithm exhibited superior robustness, with the loss function reaching its lowest value and tending towards stability when the number of iterations was small. The aesthetic evaluation accuracy of this algorithm on indoor landscape datasets reached 97.74%, an improvement of 7.54% compared to traditional methods, demonstrating extremely high accuracy. The evaluation of SRCC and LCC showed that the research methods had the strongest correlation with human subjective evaluation, and their evaluation results were more reliable. In the comparison between MSE and EMD, the accuracy of this method was superior to other methods. In the Taskonomy dataset, MSE values decreased by 12.59%, 8.01%, and 3.30%, while EMD decreased by 5.08%, 2.60%, and 2.82%. Compared with traditional methods, the aesthetic score of the research method was 14.21% higher, and the functional evaluation was 10.6 points higher, indicating that this method has significantly improved efficiency and effectiveness. The network security analysis results show that the network vulnerability repair efficiency of the proposed method is as high as 98.74%. The results indicate that this not only performs well in aesthetic evaluation entropy, but also provides strong guarantees in ensuring network security.

In summary, the research method provides a new and effective tool for ILA evaluation, which has shown significant advantages in accuracy, efficiency, and relevance. The limitation of this study is that the proposed method used DL method, which may result in overfitting of the dataset. Therefore, future research still needs to learn models on large-scale datasets containing diversity to improve the generalization performance of the models.

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