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Intelligent interior design based on deep learning and CF algorithm

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Abstract: The application of recommendation algorithms in interior design helps users quickly determine their preferred design style and improve the efficiency. In response to the low personalisation and low recommendation accuracy in current home matching and style recommendation systems, research has been conducted on modelling interior design on the foundation of deep learning and collaborative filtering algorithms. Firstly, the collaborative filtering algorithm was optimised by combining content-based recommendation methods and principal component analysis. Meanwhile, a home matching recommendation model based on improved collaborative filtering algorithm was constructed. Then, a neural collaborative filtering style recommendation model based on channel attention was constructed by combining attention mechanism, convolutional neural network, and generalised matrix decomposition. These results confirmed that the improved home matching recommendation model had a higher accuracy of 88.4%. In the collected dataset of bedroom home matching schemes, the accuracy of the home matching recommendation model in home recommendations can reach 92.14%. The neural collaborative filtering style recommendation model on the foundation of channel attention had a hit rate of 0.8865. In summary, the constructed model has good application effects in interior design, which helps to promote the development of interior design.

Keywords: collaborative filtering; CF; neural network; NN; interior design; attention mechanism; recommendation algorithm.

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Biographical notes: Yuan Ren is a member of the Communist Party of China, he holds a Master's degree and is an Associate Professor. He graduated with a Bachelor's degree in Art and Design from the School of Fine Arts of Henan Normal University in 2006, and a Master's degree in Fine Arts from the School of Fine Arts of Henan Normal University in 2012. His research direction is environmental art design. He has been teaching at the School of Art and Media of Shangqiu College since July 2006.

1 Introduction

The massive amounts of information data have exacerbated the information overload. Recommendation algorithms have a powerful role in alleviating information overload (Khaleel et al., 2020). The interior design is to create an indoor environment that meets people's material and spiritual needs, including spatial elements, colour elements, decorative elements, and light and shadow elements. As the economy develops, people's demand and requirements for interior design also increase (Shen et al., 2020; Sitanggang et al., 2020). Collaborative filtering (CF) uses the preferences of groups with similar interests and shared experience to recommend information that users are interested in. CF-based recommendation algorithms play a powerful role in recommendation systems, mainly divided into two categories: item-based CF and user-based CF (Cui et al., 2020; Wang et al., 2021). Deep learning (DL) has become increasingly popular in recommendation systems, where nonlinear feature representations of users and projects are learned in deep neural network (NN). Interior design involves multiple aspects such as furniture matching, style selection, and spatial layout. Traditional home matching and style recommendation systems often only consider some of these factors, which only recommend based on the user's historical behaviour and preferences, lacking personalisation and accuracy. In this context, an intelligent interior design model on the foundation of DL and CF algorithms is developed to better understand user preferences and interests, which improves the accuracy of recommendations. The main contribution of the research lies in the ability to more accurately understand user preferences and interests, thereby providing users with more accurate home matching and style recommendations. At the same time, this research can provide more scientific, accurate, and personalised home matching and style recommendation technologies for interior design. The innovation of this study mainly includes two points. The first point is to address the issue of the compatibility model built based on the CF algorithm relying on historical matching data. The content-based (CB) recommendation algorithm is combined to optimise the model. VGG-16 and PCA are used to extract and reduce the dimensionality of the 2D rendering image feature vectors of the home model. The second point is to add efficient channel attention for deep convolutional neural network (ECA-Net) on top of convolutional neural network (CNN) to capture the interaction information between users and items across channels. This study consists of four parts. The first step is to analyse the current research status. Secondly, a home matching recommendation model based on improved CF and a neural CF style recommendation model based on channel attention are constructed. The third part is to analyse the model's application effect. Finally, there is a summary of the entire study.

2 Related works

DL is a new research direction in machine learning, aimed at learning the inherent patterns and representation levels of sample data. DL has achieved many results in natural language processing, search technology, recommendation, and personalised technology. There are substantial differences in the various DL techniques for image denoising, but there is little research to summarise the different DL techniques used for image denoising. Regarding this, Tian et al. (2020) conducted comparative research on deep level techniques for image denoising. They analysed the motivations and principles

of different types of DL and pointed out some potential challenges and future research directions. Chen et al. (2024) proposed a hybrid DL method that recommended similar textures to address the lack of intelligent design methods for interior designers, which helped improve the accuracy and efficiency of interior design texture retrieval. The results showed that the recommended image accuracy of the proposed method was 91.41%, which promoted the intelligent development of the design industry. The integration of DL had achieved collaborative improvements in model accuracy, stability, and reproducibility, triggering a new wave of research and application. Therefore, Cao et al. (2020) shared the latest key developments in integrated DL to promote future research and development and to inspire new bioinformatics applications that traditional methods could not achieve. In the optimisation and decision-making, uncertainty quantification methods played a crucial role in reducing the impact of uncertainty. However, Bayesian approximation and ensemble learning techniques were two widely used uncertainty quantification methods. Therefore, Abdar et al. (2021) reviewed the latest developments in uncertainty quantification methods used in DL and investigated their applications in reinforcement learning. Ma et al. (2021) stated that DL was a machine learning subset that used hierarchical structural layers to learn multi-level abstractions of data, providing an effective means for designing photonic structures. Meanwhile, they reviewed the latest progress in DL-based photon design by providing historical background, algorithm foundation, and key applications, with a focus on introducing various model architectures for specific photon tasks.

Based on the environment, nature of use, and corresponding standards of the building, interior design utilises architectural design principles and material technology to create an indoor environment that is functionally reasonable and can meet the needs of residents. Wu conducted research on interactive genetic algorithm-based interior design recommendation for architectural interior design, combined with practical optimisation problems. This helped people to understand interior design more simply and effectively. People could experience interior design more intuitively. Meanwhile, interior design was better carried out (Wu, 2022). To determine effective interior design strategies and corresponding design solutions, Colenberg and Jylhä (2021) collected examples of workplace design features that had a positive impact on employee well-being and identified four main workplace design strategies. They encouraged designers, managers, and researchers to adopt interdisciplinary and evidence-based approaches to achieve a healthy workplace by proposing complementary perspectives. Kim and Lee (2020) proposed a method for randomly identifying and attaching interior design style information using reference images and DL models. They addressed the issue of how to define interior design style categories in previous studies. The results showed that the proposed method effectively identified the design style of interior images, which helped promote the management and utilisation of interior design reference databases. Sarkar and Bardhan (2020) aimed to optimise the interior design layout of low-income resettlement apartment units, improve the indoor environmental experience, and utilise the high cooling and energy-saving potential by maximising natural ventilation. They adopted a mixed mode research framework to determine the optimal design layout that enhanced the quality of experiential environment under natural ventilation conditions. Simultaneously, verification was conducted through environmental sensor data and a questionnaire survey on residents' behaviour. Huang et al. introduced data-driven research based on interior design experiments to address the data analysis in design experiments. They also introduced an interactive evolutionary computation design

experiment aimed at revealing the categories and processes of design through data analysis, visualisation, and recommendation. The experimental results demonstrated the enormous potential of various data-driven methods in design research (Huang et al., 2020). Nishikawa et al. proposed a novel search engine that recommended furniture combinations that users like based on image features. This could solve the lack of research on the internal combination of furniture in existing search engines. This method analysed the images selected by users and recommended items that matched the selected items based on furniture combination rules and personal preferences (Nishikawa et al., 2019). Aljunid et al. (2020) stated that the importance of hospital interior design quality as a trigger factor for patient satisfaction was becoming a significant topic. They conducted a self-management questionnaire survey on inpatients to determine the factors that affected the satisfaction of inpatients with interior design quality in Malaysian public hospitals. They applied structural equation modelling techniques to test causal relationships and test patients' hypothesis of satisfaction with interior design quality.

In summary, although many scholars have conducted extensive research on interior design in the past, the above interior design methods require obtaining actual 3D home models, 3D layout scenes, and other information, making the feature extraction process difficult and computationally challenging. Therefore, in order to further improve the efficiency of intelligent interior design, this research builds a CF-based home matching recommendation model and a neural CF style recommendation model based on channel attention. Its contribution lies in the ability to effectively extract features of home combinations and design styles using CF algorithm and channel attention mechanism, achieving efficient recommendation of actual 3D home models and layout scenes, thereby improving the efficiency of intelligent interior design, enabling users to quickly and accurately obtain home combinations and design style recommendations that meet their preferences and needs.

3 Building an intelligent recommendation model for interior design based on improved CF and NN

The interior space design industry has strong professionalism and high costs. Artificial intelligence has created favourable conditions for reducing design costs. To promote the intelligent development of interior design, improve the efficiency and user satisfaction of interior design, the research will build a home matching recommendation model based on improved CF and a neural CF style recommendation model based on channel attention.

3.1 Building a home matching recommendation model based on improved CF

To make the intelligent interior designing more efficient, a project-based CF recommendation algorithm is used to construct a basic compatibility model for home matching issues in interior design. Jaccard similarity is a statistical measure used to compare the similarity and diversity between limited sample sets. It evaluates the similarity between two sets based on the ratio of the intersection size to the union size. Jaccard similarity has the advantages of simple calculation process, easy comparison and interpretation. Therefore, research uses Jaccard similarity to evaluate the degree of collocation between items. CF does not require strict modelling of the research object, which does not require the attribute description of the research object to be machine

understandable. CF is easy to implement, has low computational difficulty, and does not need to consider the inherent attributes of 3D home projects. This recommendation mechanism is independent of the research object's field and can be applied to most scenarios. Common CF includes model-based CF, project-based CF, and user-based CF. Figure 1 shows the principle of the CF recommendation algorithm.

The calculation of similarity is the foundation of recommendation algorithms. Common methods for calculating similarity include Euclidean distance, Pearson correlation coefficient, Hamming distance, cosine similarity, and Jaccard similarity. Pairability refers to the degree of compatibility between home items. Jaccard similarity is used to compare the difference between samples in a limited sample, and is applicable to binary data in equation (1).

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

In equation (1), A and B represent the target object. $J(A, B)$ refers to the proportion of the intersection of A and B to the union of A and B , with a value in the $[0, 1]$ range. A large proportion indicates high similarity. However, the compatibility model constructed solely based on CF relies on historical compatibility data. When two projects lack historical compatibility data, the compatibility degree may reach a value of 0, which affects the recommending accuracy. Therefore, this study optimises the home matching recommendation model by mixing CB recommendation algorithms. CB relies on the internal attribute features of the research object and recommends users through the similarity between feature vectors. It only relies on the content of 3D home model to achieve recommendations, so the interpretability of recommendation results is high (Afsar et al., 2022). CB needs to use image feature extraction algorithms to extract effective information from image content and build an offline image feature vector library. The study selects VGG-16, which has good performance in object detection and image classification to extract features from two-dimensional rendered images of home models (Nimrah and Saifullah, 2022). The softmax layer of VGG is used to classify images, while research based on image content requires the extraction of image features. Therefore, the study selects the penultimate fully connected layer in VGG-16 that can reflect the high-level features of the image as the feature extraction layer for the image. Figure 2 shows the network structure of VGG-16.

After normalising the image, the extracted image features are a 4096-dimensional vector through the structure and weights of the transferred VGG-16. The high computational complexity of obtaining similarity seriously affects the operational speed of recommendation algorithms. PCA and singular value decomposition (SVD) are two commonly used dimensionality reduction techniques, but compared to SVD, PCA can directly manipulate the covariance matrix and performs better in data processing and dimensionality reduction. To this end, the study utilises PCA to make the extracted feature vectors' dimensionality reduced. PCA is a commonly used dimensionality reduction algorithm that reduces a set of potentially linearly correlated data into the linearly independent data between different dimensions by linear transforming. PCA can extract the main feature components of the data (Uddin et al., 2021). If the n dimensional image feature target vector should be reduced to k dimension, k unit orthogonal bases need to be selected to project the original image feature data into a new coordinate system. To cover as much information as possible in each dimension, the pairwise

covariance between each dimension is 0, indicating that there is no correlation between the two dimensions.

Figure 1 Schematic diagram of CF recommendation algorithm (see online version for colours)

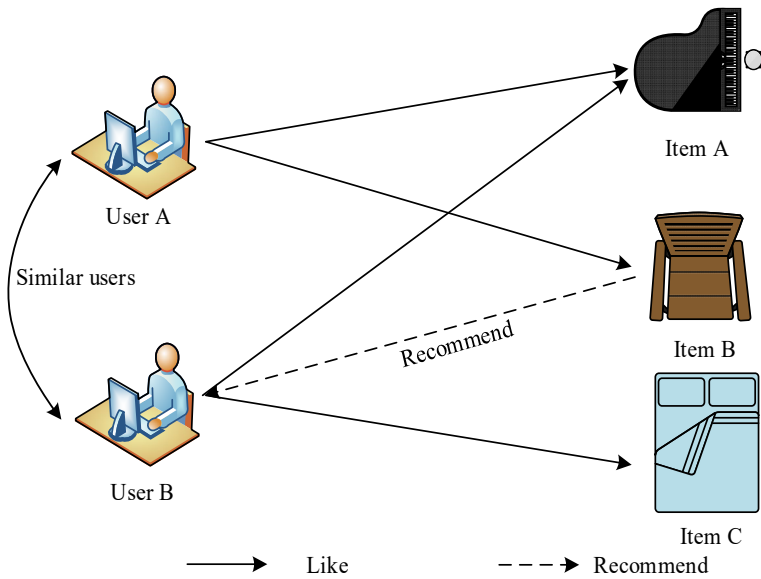
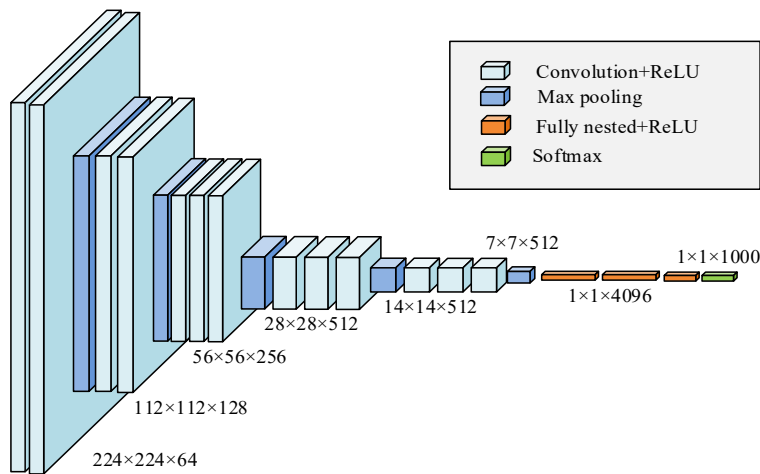


Figure 2 Network structure diagram of VGG-16 (see online version for colours)



After the original image feature data are transformed into a new coordinate system, the variance value is maximised, so that the information corresponding to the dimensionality reduction feature data are more representative. The core of PCA is to retain irrelevant parts based on the correlation between vectors in the feature matrix, which can better represent the image’s effective features and simplify the similarity calculation. The image feature vector matrix is constructed using VGG-16, with each row representing a feature

dimension. The elements of each row are subtracted from the mean feature to perform zero averaging and simplify the calculation of covariance. The averaged matrix is $A = [X_1, X_2, X_3, \dots, X_i, \dots, X_{1000}]^T$. Then, the covariance matrix A_{cov} of X is calculated. The eigenvectors and eigenvalues of A_{cov} are calculated to standardise the eigenvectors in equation (2).

$$A_{cov} X = \alpha x \quad (2)$$

In equation (2), x represents the feature vector. α represents the characteristic value. The eigenvalues are arranged in descending order. The projection matrix $P = [x_1, x_2, x_3, \dots, x_k]^T$ is formed by taking the eigenvectors corresponding to the first k eigenvalues. Finally, the matrix X is multiplied by the standardised data P to obtain the feature vector matrix data reduced to the k dimension. To densify the CF-based matchability recommendation matrix, the similarity between images is used to measure the visual similarity between 3D home projects. Similar home projects are used to predict the matching data between adjacent projects. The study applies Euclidean distance to calculate home projects' similarity in equation (3).

$$sim(type_m, type_n) = \frac{1}{1 + \sqrt{\sum (type_{m_i} - type_{n_i})^2}} \quad (3)$$

In equation (3), $type_m$ and $type_n$ represent two items. $\sqrt{\sum (type_{m_i} - type_{n_i})^2}$ represents the distance between two projects. Equation (4) is the predicted compatibility.

$$D[row, col] = Dm_{new} = \begin{cases} \frac{1}{2 \cdot i} \sum_i (Dm1 \cdot sim_1 + Dm2 \cdot sim_2), & 0 < i \leq simNum \\ 0, & i = 0 \end{cases} \quad (4)$$

In equation (4), sim_1 represents the similarity between similar home items sim_{type1} and $type1$. sim_2 represents the similarity between similar home items sim_{type2} and $type2$. $Dm1$ represents the compatibility between sim_{type1} and $type1$, and $Dm2$ represents the compatibility between sim_{type2} and $type2$. Among the top $simMum$ household items in the similarity ranking, items with matching data are counted to predict and calculate missing matching data, and new matching data is obtained. For all the first $simMum$ projects without matching data, the study adopts an iterative update method. The study fills in a sparse matrix on the basis of the original matching recommendation model to obtain a new recommendation model and cover the old recommendation model according to equation (5).

$$Dm = Dm(type1, type2)_{new} \quad (5)$$

The pseudocode of the home matching recommendation model based on the CF algorithm is shown in Figure 3.

3.2 Building a neural CF style recommendation model based on channel attention

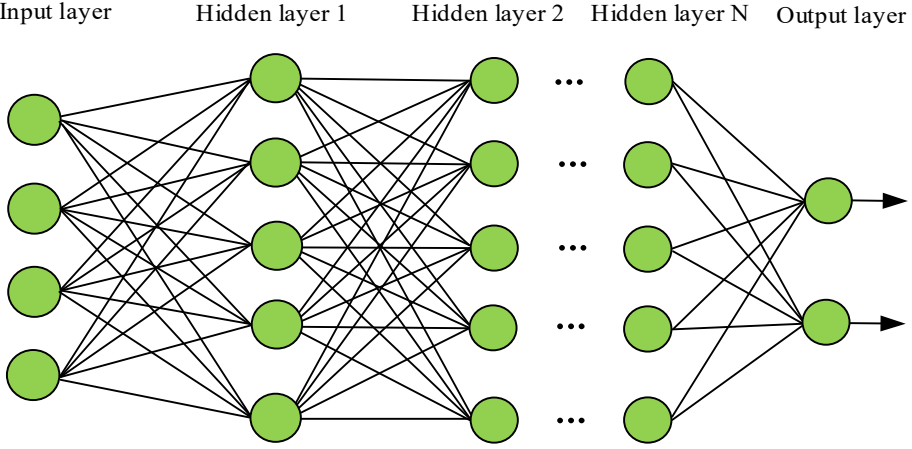
To ensure the efficiency of intelligent indoor space design and further improve user satisfaction, it is necessary for designers to have sufficient communication with customers to understand their preferences and needs. Therefore, a neural CF style recommendation model based on channel attention is constructed for this study. In practical recommendation scenarios, the historical feedback information of users purchasing items may not necessarily represent their true interests. To strengthen the correlation between users and items, CNN is used to learn the high-order correlation between their embedding dimensions and reduce the parameters between the embedding layer and hidden layer in the network. Channel attention mechanism is added to CNN to enhance the semantic information of users and items. Figure 4 shows the NN.

Figure 3 Calculation process of home matching recommendation model based on CF algorithm (see online version for colours)

Algorithm: A Home Matching Recommendation Model Based on CF Algorithm
Input: Home project type, compatibility D_m between home projects
Output: Top N recommended home projects
Step 1: Use the CF recommendation algorithm to construct the basic compatibility matrix D
Step 2: Use the second to last fully connected layer of VGG-16 as the extractor for image features, and construct a feature vector library for home project images separately
Step 3: Use PCA algorithm to reduce the dimensionality of the image feature matrix for each household item category
Step 4: Build a similarity table for each category of home furnishings projects
Step 5: Use the matching data of the first two similar home items to predict the zero values in the matching recommendation model, and fill in the sparse matrix
Step 6: Iterative update
 6.1 Iterative update of the matching recommendation model once.
 6.2 Repeat step 5.
Step 7: Determine model parameters and complete the construction of the matching recommendation model
Step 8: Based on the recommended home item category type, search for all items under the type home category, calculate the sum of their compatibility with other home items in the plan, and perform a TopN recommendation ranking.

The research aims to improve the representation ability of deep NN by incorporating attention-based matching function learning (A-MLP). The impact of different feature attributes of the project on user purchasing behaviour is calculated using the attention function in equation (6).

$$f(p_u, q_i) = \text{ReLU}(W(p_u \odot q_i) + b_0) \quad (6)$$

Figure 4 The structure of NN (see online version for colours)

In equation (6), p_u and q_i represent the potential embeddings of user u and style i . W represents the weight matrix from the inputting layer to the hidden layer. b_0 represents a bias vector. ReLU represents an activation function. SoftMax function is used to convert the obtained attention weights into a probability distribution, and equation (7) is its attention coefficient.

$$\alpha(u, i) = \frac{\exp(f(p_u, q_i))}{\sum_{i \in R_u} \exp(f(p_u, q_i))} \quad (7)$$

In equation (7), $\alpha(u, i)$ represents the attention weights of user u and project i . R_u represents the interaction history set between user u and project i . ECA-Net can perform dimensionality reduction operations on feature dimensions in CNN and enhance information exchange between channels (Zhang et al., 2023). To capture the interaction information between users and projects in cross channels, ECA-Net is added to CNN to form the E-CNN module. Firstly, the outer product of user embedding and project embedding is calculated as their interaction in equation (8).

$$FW = p_u \otimes q_i = p_u q_i^T \quad (8)$$

The two-dimensional matrix is obtained through the outer product operation, and then pulled into a vector with dimension K^2 through the Flatten operation. E-CNN consists of two parts. Firstly, the user and style interaction representations are input into the CNN for training. When the training reaches the final layer, the ECA-Net attention network is added between convolutional blocks (Waghumbare et al., 2024). Equation (9) represents the interaction of user and style information between channels.

$$\begin{cases} y = \frac{1}{WH} \sum_{u=1, i=1}^{W, H} \chi_{ui} \\ w = \text{Sigmoid}(\text{CID}(y)) \end{cases} \quad (9)$$

In equation (9), y represents the global average channel pooling. w represents the interaction weight in the convolutional attention. CID represents one-dimensional

convolution. Equation (10) is the final prediction score $\hat{y}_{ui}^{E-CNN} \in R^{K \times 1}$ in the prediction layer.

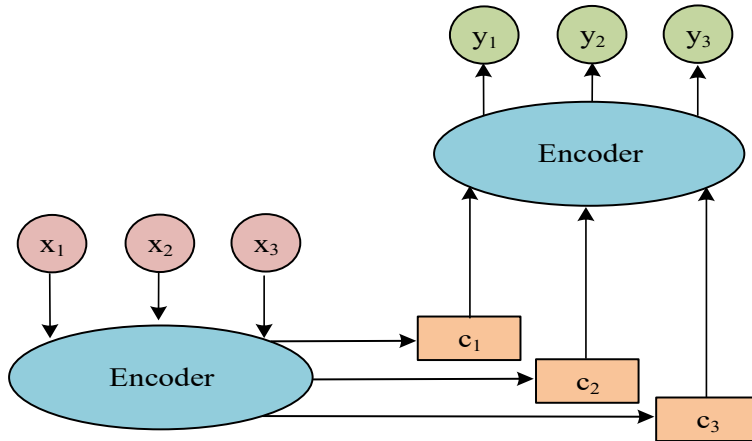
$$\hat{y}_{ui}^{E-CNN} = G(FM)W_G^T \quad (10)$$

In equation (10), $G(FM)$ represents the output vector of the model in multiple intermediate layers. W_G^T represents the reweighting of user and item weights in the output vector. Figure 5 shows the attention mechanism.

Generalised matrix factorisation (GMF) uses linear embedding functions as the representation function and dot products as the matching function (Kidzinski et al., 2022). Therefore, the study uses GMF to alleviate the problem of data sparsity caused by user project interactions. In the experiment, the embedding vectors of users and styles are directly used for point multiplication operations. Equation (11) is the prediction vector.

$$z(p_u, q_i) = p_u \odot q_i \quad (11)$$

Figure 5 Attention mechanism (see online version for colours)



In equation (11), $\odot$ represents the element by element product of user's embedding vector p_u and the style's embedding vector q_i . The prediction vector is mapped to the prediction layer in equation (12).

$$\hat{y}_{ui}^{MF} \in R^{K \times 1} \quad (12)$$

In equation (12), σ_o represents the activation function. W_o represents the connection weight matrix. Finally, A-MLP, E-CNN, and GMF are fused. The learned representations are concatenated to obtain their joint representation. The vector is treated as a user-project feature, and then input into a fully connecting layer, allowing this model to assign different weights to the features of different parts in the joint representation. Sigmoid is used as the activation function of the fully connected layer. The three sub-modules are merged using equation (13).

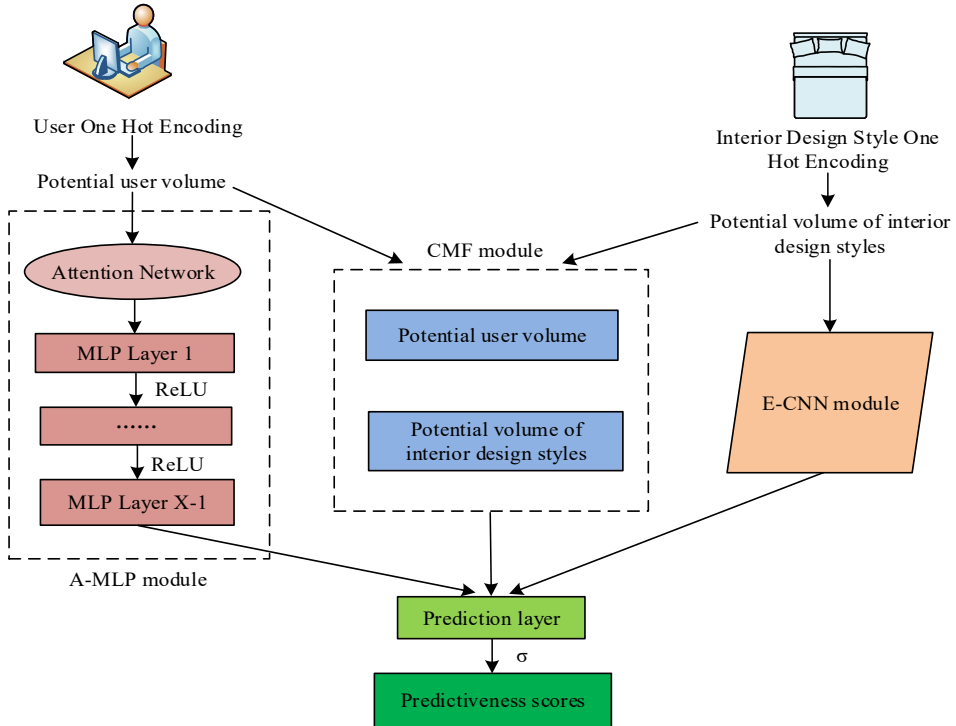
$$\begin{cases} C_1 = W_0^T(x_n, z(p_u, q_i)) \\ C_2 = \text{concat}(C_1, W_G^T(FM)) \\ \hat{y}_{ui} = \text{Si gmoid}(C_2) \end{cases} \quad (13)$$

After the modules are merged, the prediction score of the model is obtained through learning. The point wise objective function is used to transform the user style interaction prediction problem into a score prediction problem. Equation (14) is a loss function.

$$L = - \sum_{(u,i) \in \gamma^+ \cup \gamma^-} y_{ui} \log \hat{y}_{ui} - (1 - y_{ui}) \log(1 - \hat{y}_{ui}) \quad (14)$$

In equation (14), y^+ and y^- represent positive and negative instances of sampled samples in the user project interaction matrix, respectively. y_{ui} represents the true value. In summary, Figure 6 shows a neural CF model based on channel attention.

Figure 6 Architecture of neural CF model based on channel attention (see online version for colours)



4 Analysis of the effectiveness of an interior design intelligent recommendation model based on improved CF and NN

A home matching recommendation model based on improved CF and a neural CF style recommendation model based on channel attention were studied and built to improve the

intelligent interior designing efficiency. However, the effectiveness needed further verification. The research mainly analysed from two aspects. Firstly, the analysis of the effectiveness of the home matching recommendation model on the foundation of improved CF. Secondly, the effectiveness of the neural CF style recommendation model based on channel attention was verified.

4.1 Analysis of the effectiveness of home matching recommendation model on the foundation of improved CF

The study selected 832 bedroom home matching schemes by professional designers on an interior space design software platform for experiments, including 5 categories of home items, a total of 1,183 items. 600 pieces of matching data were randomly selected as a training set. A matching recommendation model was established. 300 pieces of testing data were randomly selected from the remaining 232 pieces of data to be expanded and constructed as a test set. The accuracy of the recommendation model was tested. The CPU processor was Intel (R) Core (TM) i7-10710U. The GPU processor was NVIDIA GeForce MX350. To verify this home matching recommendation model's effectiveness, this study compared its recommendation accuracy with that of a single CF. $pcaNum = 409651256128,64$ was selected, where $pcaNum = 4096$ represented dimensionality reduction without PCA algorithm. Figure 7 shows the results. Compared to a single CF, the improved home matching recommendation model had higher accuracy, with the highest accuracy of 88.4% at $TopN = 30$, $pcaNum$, and 128. Meanwhile, when $TopN = 30$, the recommendation accuracy of the improved CF algorithm was significantly higher than when $TopN = 20$ ($P < 0.05$). In addition, the recommendation accuracy was the lowest when $pcaNum = 4096$, indicating that using PCA algorithm to reduce image feature matrix's dimensionality could effectively improve the accuracy, which had certain feasibility and effectiveness.

To verify the superiority of the home matching recommendation model based on improved CF, the study set $iterNum$ to 2, $pcaNum$ to 128, and $simNum$ to 4, and compared the accuracy with neural collaborative filtering (NCF) and deep matrix factorisation (DMF) models. The NCF model is a recommendation algorithm based on NNs, mainly composed of GMF and MLP. It aims to enhance the nonlinear modelling ability through multi-layer perceptrons, thereby improving traditional CF methods. The DMF model is a model that combines matrix factorisation and MLP, based on the traditional matrix factorisation model. By introducing the structure of NNs, the expression ability and flexibility of the model are improved. Figure 8 shows the results. Among these three algorithms, the research model had the highest accuracy, reaching 92.14%, significantly higher than the NCF model and DMF model ($P < 0.05$). These results demonstrated the superiority of the home matching recommendation model based on improved CF.

Figure 7 Comparison results of recommendation accuracy between two algorithms, (a) single CF algorithm (b) improved furniture matching recommendation model (see online version for colours)

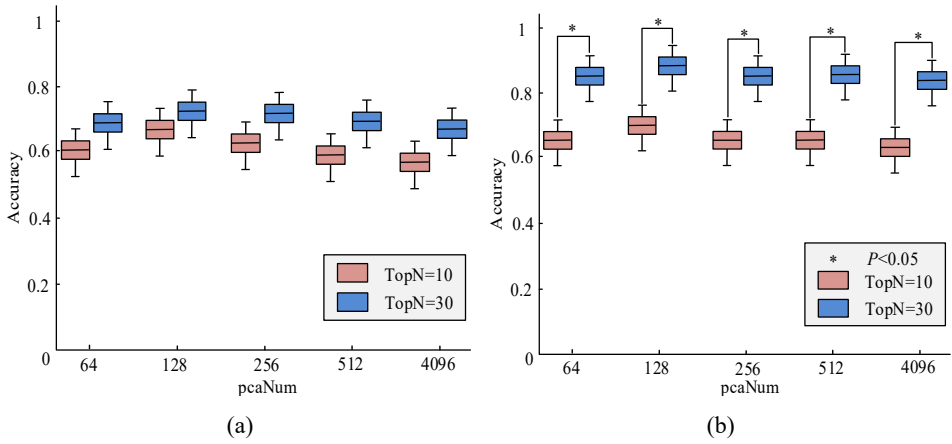
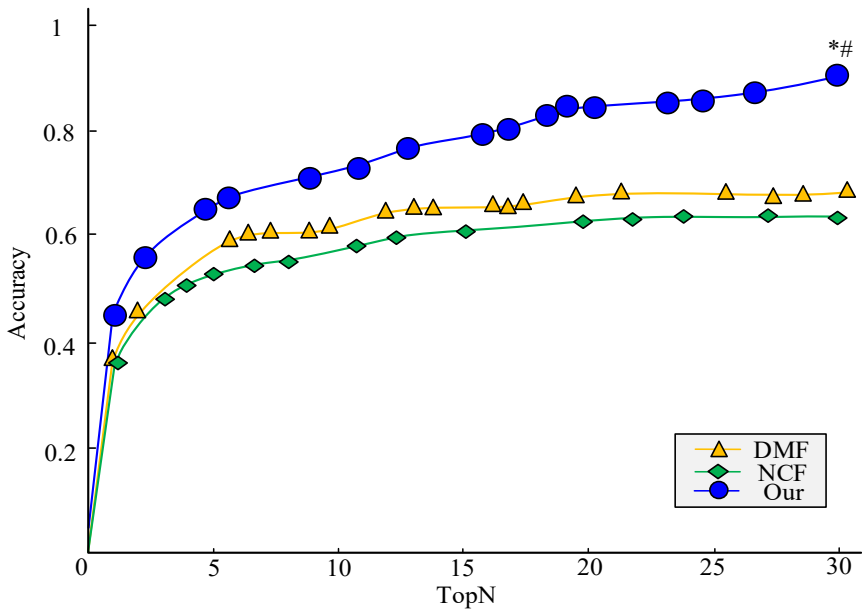


Figure 8 Accuracy comparison results of three models (see online version for colours)



Notes: * Indicates that the recommendation accuracy of the model in this study is significantly higher than that of the DMF model ($P < 0.05$). # indicates that the recommendation accuracy of this research model is significantly higher than that of the NCF model ($P < 0.05$).

4.2 Analysis of the effectiveness of a neural CF style recommendation model on the foundation of channel attention

To verify the superiority of the neural CF style recommendation model on the foundation of channel attention, the study used the COCO dataset and ADE20K dataset. The COCO dataset is a large-scale dataset that can be used for image detection, covering over 330K images, and each image contains five sentence descriptions (Ma et al., 2022). The ADE20K dataset is a large dataset released by the Massachusetts Institute of Technology, containing over 25,000 images of complex everyday scenes that can be used for scene perception, parsing, segmentation, multi object recognition, and semantic understanding (Song et al., 2022). These two datasets contain indoor design images of various styles, layouts, and decorative styles. Meanwhile, set the batch size to 256, the learning rate to 0.0001, and the embedding dimension of each model to 6. Experiments on the proposed model were conducted under the PyTorch framework and programmed using Python 3.7. It was compared with hit rate (HR) and normalised discount cumulative gain (NDCG) of DMF, MLP, and DeepCF. HR measures the accuracy of recommendations based on recall, which can effectively indicate whether the top K items in the list contain testing items. NDCG is an indicator that measures the quality of a project's ranking, considering the impact of the ranking position of search results on user satisfaction, and assigning different weights to search results at different positions, reflecting a non binary evaluation of relevance. Both of these evaluation indicators have higher values indicating better performance. The MLP model is a feedforward artificial neural network model that can include one or more hidden layers, enabling it to learn and process more complex patterns. The DeepCF model models the interaction between users and items based on matching representation learning, enabling the model to improve the representation ability of the matching function while maintaining effective learning. Table 1 shows the results. Among these four methods, the proposed model achieved better performance in terms of indicators. In the COCO dataset, both indicators were higher, with HR of 0.8865 and NDCG of 0.6002. Next was the DeepCF model, with HR and NDCG indicators of 0.8796 and 0.5939, respectively. In addition, the running time of DMF and MLP was relatively short. The proposed style recommendation model had a longer running time, but it was still within an acceptable range. These results demonstrated the superiority of the neural CF style recommendation model based on channel attention.

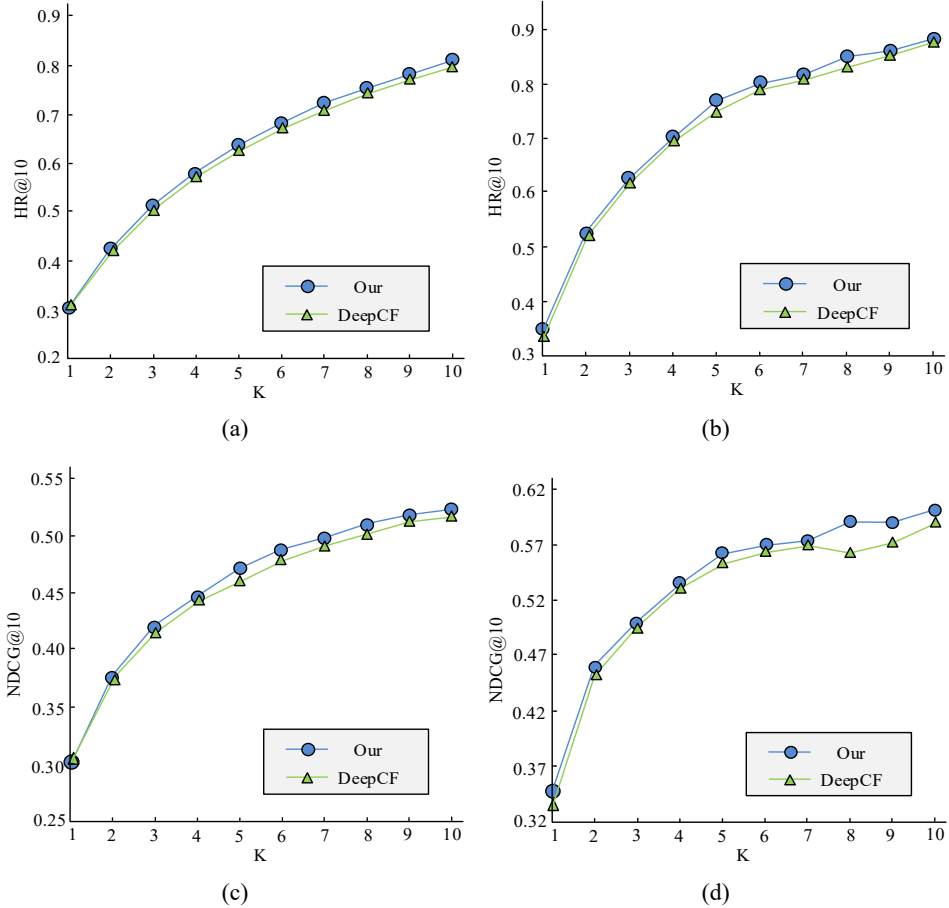
Table 1 Comparison of indicator results of four models in two datasets

Model	COCO			ADE20K		
	HR	NDCG	Time/s	HR	NDCG	Time/s
DMF	0.8629	0.5811	976	0.8147	0.5714	988
MLP	0.8722	0.5871	977	0.8269	0.5769	983
DeepCF	0.8796	0.5939	1,254	0.8403	0.5815	1,689
Our	0.8865	0.6002	1,865	0.8762	0.5962	2,157

To verify the impact of top-K on the model's performance, the study compared the HR and NDCG of the proposed model with DeepCF in Figure 9. As the K value increased, the indicators of both models gradually increased, but the performance of the model in this study was better. When K was equal to 10, the research model had improved HR by about 2.52% compared to DeepCF, and NDCG by about 2.64%. These results confirmed

that the neural CF style recommendation model on the foundation of channel attention could more accurately capture interactive feature representations, which had certain feasibility and effectiveness.

Figure 9 The effect of top k on model performance, (a) top k ranking based on ADE20K (b) top k ranking based on COCO (c) top k ranking based on ADE20K (d) top k ranking based on COCO (see online version for colours)



To verify the impact of different embedding dimensions on model performance, this study compared it with DeepCF under different embedding dimensions in Figure 10. In both datasets, the proposed model outperformed DeepCF in terms of indicators under different embedding dimensions, with the best performance at an embedding dimension of 64. When the embedding dimension was 128, the main reason for the performance degradation was the increase of network.

To further validate the effectiveness of this neural CF style recommendation model based on channel attention, ablation experiments were conducted on the model, and the HR of each module was compared in Figure 11. The performance of a complete model was superior to that of individual modules, with the GMF module performing the worst.

Figure 10 The impact of different embedding dimensions on model performance (a) under ADE20k HR@10index (b) under COCO HR@10index (c) under ADE20k NDCG@10index (d) under COCO NDCG@10index (see online version for colours)

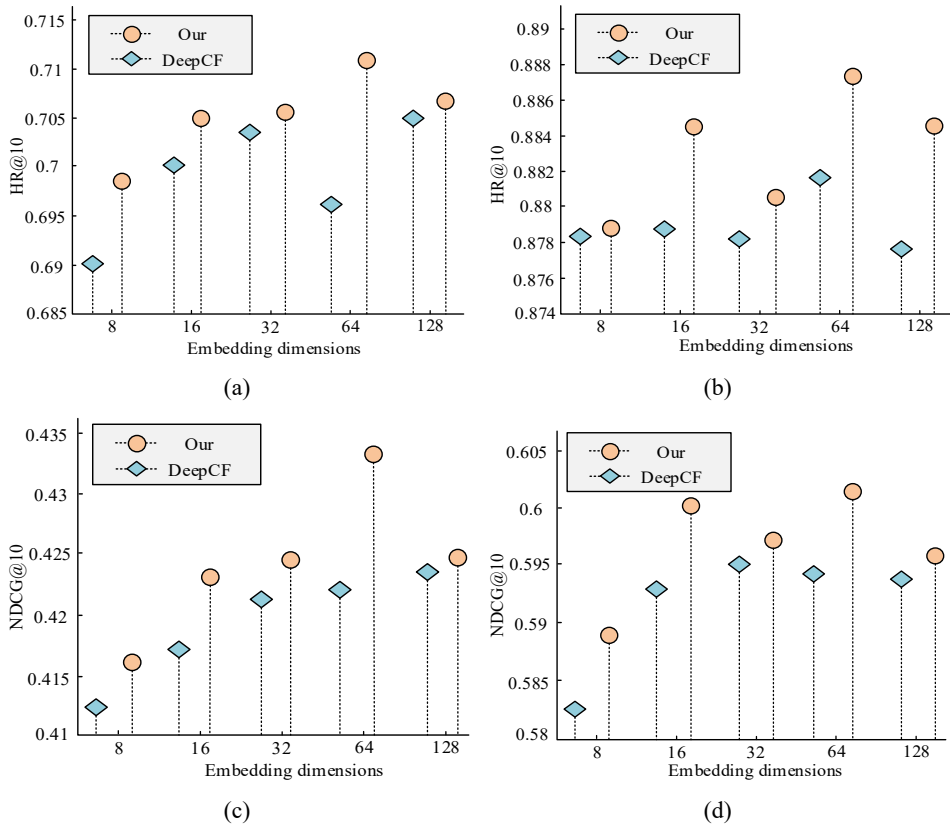
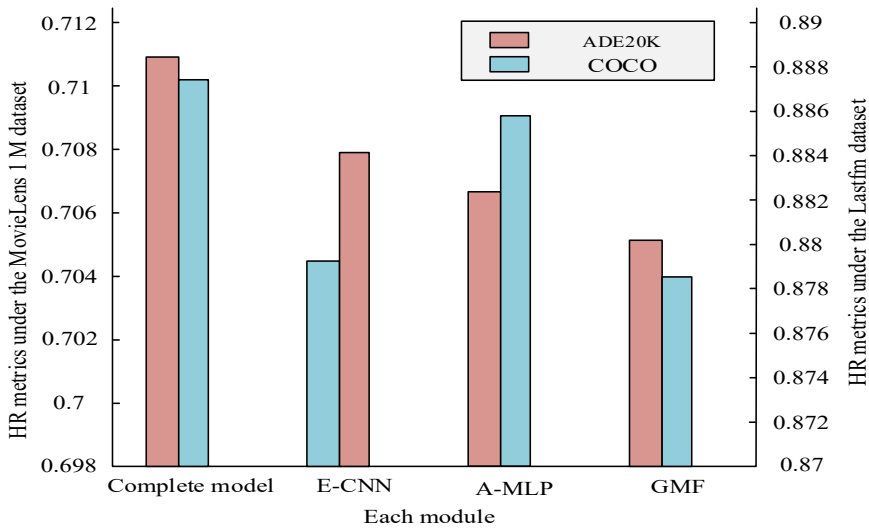


Figure 11 Results of ablation experiment (see online version for colours)



5 Conclusions

Various intelligent technologies have been applied to the interior design industry. In response to the time-consuming and high labour cost of interior design, a home matching recommendation model based on improved CF and a neural CF style recommendation model based on channel attention have been studied and built. These results confirmed that the improved home matching recommendation model had higher accuracy compared to a single CF, with the highest accuracy of 88.4% at TopN = 30, pcaNum, and 128. The home matching recommendation model based on improved CF had the highest accuracy, reaching 92.14%, which had certain advantages. The neural CF style recommendation model based on channel attention had higher values for both indicators in the COCO dataset, with HR of 0.8865 and NDCG of 0.6002, followed by DeepCF. When K was equal to 10, the model in this study improved HR by about 2.52% compared to DeepCF and NDCG by about 2.64%. The indicators of the proposed model were higher than DeepCF under different embedding dimensions, and the performance was best when the embedding dimension was 64. When the embedding dimension was 128, the main reason for the performance degradation was the increase of network. In summary, the research model had certain feasibility and effectiveness, which accurately recommended home decor and style to users. In addition, the proposed model had great potential in commercial applications, providing customers with more scientific and personalised recommendation services, improving customer satisfaction, and facilitating transaction completion. Meanwhile, the proposed model could promote the development of interior design companies and the entire industry. However, the study only considers the similarity between the project and users to simplify the calculation, ignoring factors such as popularity curves and forgetting curves, which may affect the practical application effect of the model. Therefore, factors such as decoration trends and forgetting curves should be further considered to build a model with better recommendation effects and further improve the efficiency of interior design scheme formulation.

References

- Abdar, M., Pourpanah, F., Hussain, S., Rezazadegan, D., Liu, L., Ghavamzadeh, M., Feiguth, P., Cao, X., Khosravi, A., Acharya, U.R., Makarenkov, V. and Nahavandi, S. (2021) 'A review of uncertainty quantification in deep learning: Techniques, applications and challenges', *Information Fusion*, Vol. 76, No. 5, pp.243–297.
- Afsar, M.M., Crump, T. and Far, B. (2022) 'Reinforcement learning based recommender systems: a survey', *ACM Computing Surveys*, Vol. 55, No. 7, pp.1–38.
- Aljunid, S.S., Shukri, N.N.H.M., Taib, M.Z.M. and Samah, Z.A. (2020) 'Determinants of patient satisfaction on interior design quality of public hospitals in Malaysia', *Malaysian Journal of Public Health Medicine*, Vol. 20, No. 2, pp.233–241.
- Cao, Y., Geddes, T.A., Yang, J.Y.H. and Yang, P. (2020) 'Ensemble deep learning in bioinformatics', *Nature Machine Intelligence*, Vol. 2, No. 9, pp.500–508.
- Chen, J., Shao, Z., Cen, C. and Li, J. (2024) 'Hynet: a novel hybrid deep learning approach for efficient interior design texture retrieval', *Multimedia Tools and Applications*, Vol. 3, No. 9, pp.28125–28145.
- Colenberg, S. and Jylhä, T. (2021) 'Identifying interior design strategies for healthy workplaces—a literature review', *Journal of Corporate Real Estate*, Vol. 24, No. 3, pp.173–189.

- Cui, Z., Xu, X., Xue, F., Cai, X., Cao, Y., Zhang, W. and Chen, J. (2020) 'Personalized recommendation system based on collaborative filtering for IoT scenarios', *IEEE Transactions on Services Computing*, Vol. 13, No. 4, pp.685–695.
- Huang, W., Su, X., Wu, M. and Yang, L. (2020) 'Category, process, and recommendation of design in an interactive evolutionary computation interior design experiment: a data-driven study', *AI EDAM*, Vol. 34, No. 2, pp.233–247.
- Khaleel, I., Wimmer, B.C., Peterson, G.M., Zaidi, S.T.R., Roehrer, E., Cummings, E. and Lee, K. (2020) 'Health information overload among health consumers: a scoping review', *Patient Education and Counseling*, Vol. 103, No. 1, pp.15–32.
- Kidzinski, L., Hui, F.K., Warton, D.I. and Hastie, T.J. (2022) 'Generalized matrix factorization: efficient algorithms for fitting generalized linear latent variable models to large data arrays', *Journal of Machine Learning Research*, Vol. 23, No. 291, pp.1–29.
- Kim, J. and Lee, J.K. (2020) 'Stochastic detection of interior design styles using a deep-learning model for reference images', *Applied Sciences*, Vol. 10, No. 20, pp.7299–7299.
- Ma, J., Ushiku, Y. and Sagara, M. (2022) 'The effect of improving annotation quality on object detection datasets: a preliminary study', in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition 2022*, pp.4850–4859.
- Ma, W., Liu, Z., Kudyshev, Z.A., Boltasseva, A., Cai, W. and Liu, Y. (2021) 'Deep learning for the design of photonic structures', *Nature Photonics*, Vol. 15, No. 2, pp.77–90.
- Nimrah, S. and Saifullah, S. (2022) 'Context-free word importance scores for attacking neural networks', *Journal of Computational and Cognitive Engineering*, Vol. 1, No. 4, pp.187–192.
- Nishikawa, A., Ono, K. and Miki, M. (2019) 'User-friendly interior design recommendation', *InSIGGRAPH Asia 2019 Posters*, Vol. 2019, No. 17, pp.1–2.
- Sarkar, A. and Bardhan, R. (2020) 'Optimal interior design for naturally ventilated low-income housing: a design-route for environmental quality and cooling energy saving', *Advances in Building Energy Research*, Vol. 14, No. 4, pp.494–526.
- Shen, J., Zhang, X. and Lian, Z. (2020) 'Impact of wooden versus non-wooden interior designs on office workers' cognitive performance', *Perceptual and Motor Skills*, Vol. 127, No. 1, pp.36–51.
- Sitanggang, N., Luthan, P. and Dwiyanto, F. (2020) 'The effect of Google SketchUp and need for achievement on the students' learning achievement of building interior design', *International Journal of Emerging Technologies in Learning (iJET)*, Vol. 15, No. 15, pp.4–19.
- Song, Q., Li, J., Li, C., Guo, H. and Huang, R. (2022) 'Fully attentional network for semantic segmentation', in *Proceedings of the AAAI Conference on Artificial Intelligence 2022*, Vol. 36, No. 2, pp.2280–2288.
- Tian, C., Fei, L., Zheng, W., Xu, Y., Zuo, W., Lin, C., Khosravi, M.R. and Qi, L. (2020) 'Deep learning on image denoising: an overview', *Neural Networks*, Vol. 131, No. 7, pp.251–275.
- Uddin, M.P., Mamun, M.A. and Hossain, M.A. (2021) 'PCA-based feature reduction for hyperspectral remote sensing image classification', *IETE Technical Review*, Vol. 38, No. 4, pp.377–396.
- Waghumbare, A., Singh, U. and Kasera, S. (2024) 'DIAT-DSCNN-ECA-Net: separable convolutional neural network-based classification of galaxy morphology', *Astrophysics and Space Science*, Vol. 369, No. 4, pp.1–7.
- Wang, F., Zhu, H., Srivastava, G. and Li, S. (2021) 'Robust collaborative filtering recommendation with user-item-trust records', *IEEE Transactions on Computational Social Systems*, Vol. 9, No. 4, pp.986–996.
- Wu, B. (2022) 'Interior design recommendation technology based on interactive genetic algorithm', in *International Conference on Innovative Computing*, Vol. 935, pp.693–698, Springer Nature Singapore, Singapore.
- Zhang, P., Jiang, M., Li, Y., Xia, L., Wang, Z., Wu, Y., Wang, Y. and Zhang, H. (2023) 'An efficient ECG denoising method by fusing ECA-Net and CycleGAN', *Mathematical Biosciences and Engineering*, Vol. 20, No. 7, pp.3415–3433.