International Journal for Housing Science and Its Applications
Publish March 30, 2025. Volume 46, Issue 1 Pages 26-33

https://doi.org/10.70517/ijhsa46104

Research on soft decoration matching and design elements in architectural interior design based on deep learning

Xia Wang[1*] and Bin Shan[1]

[1]College of Urban Construction, Hainan Vocational University of Science and Technology, Haikou 571126, China
Corresponding authors: (e-mail:13398923400@163.com)

Abstract With the development of the information society, the importance of data in the field of interior design is increasingly prominent. From collecting and analyzing design requirements, to understanding the behavior patterns of space users, to evaluating design effects, data support is indispensable. Machine learning, as a powerful tool, demonstrates enormous potential in interior design by learning and improving from data.This article explores the application of machine learning in interior design, especially in the research of soft decoration matching and design elements, and analyzes the changes and challenges it brings. This article focuses on exploring data-driven soft decoration matching and design practices. By analyzing residential space design cases, it demonstrates how machine learning can understand residents' behavior patterns and preferences, predict design effects, optimize design decisions, and more.This article demonstrates the application of modern interior soft decoration, integrating traditional cultural elements into the soft decoration of modern living spaces through modern design techniques, achieving the integration of tradition and modernity, and meeting the aesthetic and spiritual needs of residents.

Index Terms interior design, machine learning, soft outfit matching, style transfer, image segmentation, sustainability

I. Introduction

In today's highly developed society of informatization and intelligence, the widespread application of data has become the core driving force for the progress of various industries, and the field of interior design is no exception [1]. With the improvement of people's living standards and the continuous increase in requirements for living environment quality, interior design not only needs to meet the basic needs of functionality and aesthetics, but also needs to be comprehensively designed based on various factors such as personalized needs of residents, health considerations, and intelligent applications [2]. This complex and ever-changing design requirement poses a huge challenge to traditional design methods, and artificial intelligence technology represented by machine learning, with its powerful data processing and analysis capabilities, is gradually becoming a key means to solve this problem [3].

Interior design involves multiple aspects such as space planning, material selection, lighting design, color matching, etc. Each stage requires designers to possess extensive professional knowledge and skills [4]. In the design process, designers need to quickly understand and respond to clients' needs and expectations, while also considering issues such as environmental sustainability and energy efficiency.Traditional design methods mainly rely on the experience and intuition of designers, making it difficult to process and analyze large amounts of complex data in a short period of time, and thus unable to fully meet the diverse needs of modern interior design [5]. The introduction of machine learning technology provides a new research perspective and technical means for the field of interior design, which is expected to significantly improve design efficiency and effectiveness [6].

Although machine learning has shown great potential in interior design, its application still faces many challenges. Firstly, the collection and processing of data is a crucial issue. In the early stages of the project, designers need to collect various data, including spatial dimensions, user requirements, environmental factors, etc [7]. These data sources are diverse and of varying quality, and the workload of data cleaning and preprocessing is heavy, directly affecting the performance of machine learning models. How to efficiently collect, process, and manage this data is one of the main challenges in current research. Secondly, how designers can extract useful features from a large amount of unstructured data is also a major challenge.For example, traditional methods for extracting spatial layout, color, and material information from design drawings often rely on manual annotation, which is inefficient and prone to errors [8]. By using machine learning technology to automatically extract these features, not only can efficiency be improved, but data consistency and accuracy can also be ensured [9]. However, current feature extraction techniques still have shortcomings in complex design scenarios and require further research and optimization.

In addition, current research mostly focuses on the analysis and optimization of single design elements, lacking comprehensive evaluation and prediction models for overall design effects. Interior design is a systematic project, and optimizing a single element may not necessarily guarantee an overall improvement in effect.How to build a comprehensive design evaluation system that comprehensively considers the mutual influence and synergistic effects between various design elements is an urgent problem to be solved.

At present, the application of machine learning in interior design mainly focuses on the following aspects: by analyzing a large amount of design case data, machine learning models help designers understand the impact of different design elements on spatial functionality and comfort; By learning from user behavior data, reveal their actual usage and needs for space to guide design optimization [10]. In specific applications, designers use clustering analysis methods to divide customers into different groups and analyze the impact of different design elements on residents' satisfaction through decision tree models, in order to propose personalized design solutions [11]. However, existing research tends to focus more on theoretical exploration and lacks verification through practical application cases. At the same time, the prediction and evaluation models for design effects are not yet perfect, making it difficult to comprehensively reflect the advantages and disadvantages of design schemes.

Some studies have begun to explore how to use deep learning techniques for automatic generation and optimization of interior design elements [12]. For example, generating design solutions that meet specific styles and requirements through Generative Adversarial Networks (GANs), or extracting feature information from design images through Convolutional Neural Networks (CNNs).However, most of these studies are still in the experimental stage and have a certain distance from practical applications. Especially when dealing with complex and diverse practical design requirements, the generalization ability and robustness of existing models still need to be further improved [13].

This article aims to address the shortcomings of current research by exploring in detail the application of machine learning in interior design. Firstly, this article systematically elaborates on the main problems and challenges faced by interior design, and deeply analyzes the specific application of machine learning in solving these problems through practical cases. Secondly, this article provides a detailed discussion on data-driven soft decoration matching and design practices, demonstrating how to use machine learning to understand residents' behavior patterns and preferences, predict design effects, and optimize design decisions. Through case studies, this article demonstrates how designers can use machine learning techniques to extract valuable information from large amounts of data and provide design solutions that better meet customer needs [14].

In terms of technical implementation, this article explores the implementation process of modern home image style transfer technology, including image segmentation, content loss, and style loss calculation methods, as well as the application of Poisson image editing to constrain image gradients [15]. The combination of these technological means can not only generate clear and accurate stylized images, but also effectively integrate different style elements in practical design [16].

II. Data collection and processing

In the practice of data-driven interior design, data collection and processing are key steps. In the early stages of the project, designers need to collect various data, including spatial dimensions, user requirements, environmental factors, etc. [17]. These data can be obtained from various sources, such as on-site measurements, customer interviews, questionnaire surveys, etc.Modern technologies, such as sensors and IoT devices, can also provide richer and more accurate data, such as space usage, environmental noise, lighting conditions, etc. After data collection, data cleaning and preprocessing are required for subsequent analysis and modeling [18]. This may include steps such as removing outliers, handling missing data, and standardizing data. This is an important but often overlooked step, as data quality directly affects the performance of machine learning models.In addition, feature extraction is also required for unstructured data such as text and images. For example, when analyzing design drawings, it may be necessary to use computer vision technology to extract features such as spatial layout, color, and materials [19]. These features can be used by machine learning models to understand the style and effect of the design (see Figure 1).

III. Method implementation

Due to the complexity and authenticity of the semantic content in modern home image style transfer, it is required that the generated images should be as similar as possible to the content images in terms of content and details, without distortion or errors in image content transfer. The style should be as similar as possible to the style images, and strive for clear and realistic effects. The implementation process of style transfer is shown in Figure 2.

III. A. Image segmentation

Due to the differences in design content between different types of modern home styles, directly calculating the style loss of the entire image does not take into account semantic content. During the transfer process, the texture is mapped to areas that do not correspond to the texture semantics, and ignoring the differences in content can lead to the overflow of object styles to other parts of the image. This may result in the content of objects on the home style content image not matching the content of objects on the style image, leading to mismatched transfer transformations.This article uses image semantic segmentation to limit style transfer to regions with the same semantic content. Firstly, the input content image and style image are segmented separately, and the segmented images of the same category are labeled with the same mask color. Images of different categories are labeled with different colors, which can construct separate style losses for each semantic category. Then, the content image, style image, and segmented images marked by both are input as input images to a trained VGG-19 network without fully connected layers to extract feature information at different levels of the image, in order to transfer between semantically equivalent subregions and ensure consistent mapping within each subregion. We use the quick selection tool of Photoshop software to perform image segmentation. Objects such as cabinets, tables, chairs, etc. in home images are roughly divided into frames and marked with mask colors. Different object contents are marked with different colors, as shown in the marked segmentation image in Figure 3.

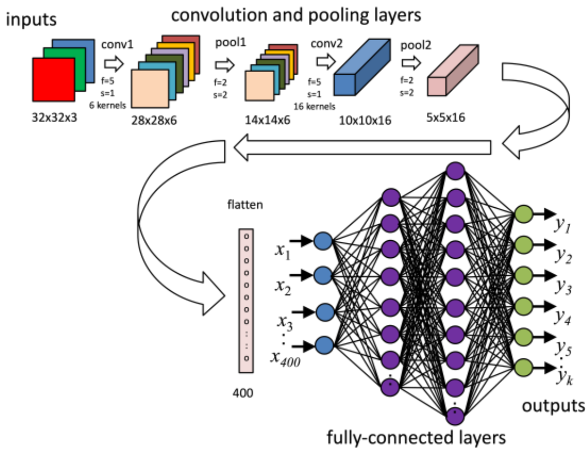

Figure 1: Main process of machine learning algorithm

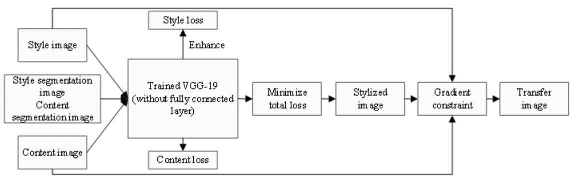

Figure 2: Implementation process of style transfer

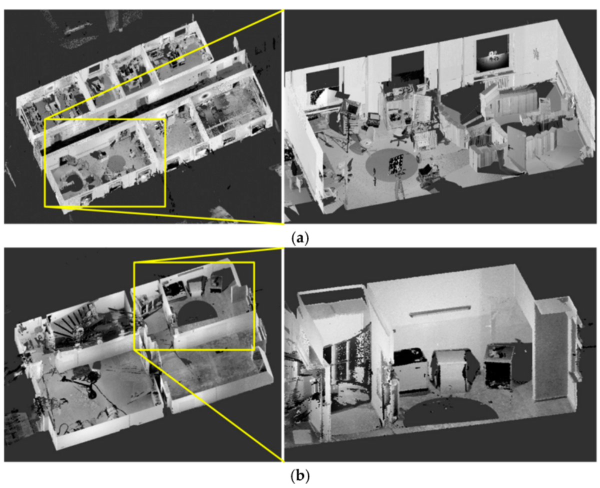

Figure 3: Home style segmentation diagram

III. B. Content loss

Given a home style content image c, a style image s, and a random white noise image, they are input into the VGG-19 network. Low level responses are used to extract the style of the image, while high-level responses extract the content of the image. The random white noise image is used as the initial input.Then calculate the content loss between the content feature map and the white noise feature map, and obtain many feature maps through convolutional layers. Choose conv3-2 and conv4-2 layers as the representations of the content image. Finally, image g is generated, which is similar in content to image c. The average loss function is used to calculate the content loss of both the content image and the generated image as follows:

$$L_{\text{content}}\left(c, g, l\right)=\frac{1}{2} \sum\left\|K_{l}(g)-K_{1}(c)\right\|^{2}, \tag{1}$$

where, L represents the l-th convolutional layer of the convolutional neural network, with N_1 features per layer. The features are vectorized to obtain a vector of size D_1; K_1 is the feature matrix representation of the image in the VGG-19 network:

$$K_{1} \in R^{N_{1} \times D_{1}}. \tag{2}$$

In addition, the gradient of the generated image g can be calculated through error backpropagation, and the generated image g can be updated as the input image, continuously changing the initial random image until the same response as the content image is generated in the convolutional neural network layer.

III. C. Enhanced Style Loss

The style of an image, that is, texture information, can be represented by the correlation between features. Using the Gram matrix to calculate the correlation between features and capture the texture information of the image, select conv1-1, conv2-1, conv3-1, conv4-1, and conv5-1 as the style representations of the image, and construct an image that matches the style representation of the given image by using gradient descent of white noise images.In addition, adding the segmented images with good coloring to the input image as another channel can construct separate style losses for each semantic category. By connecting the segmentation channels, the convolutional neural network algorithm can be enhanced, and the style loss between the output image g and the style image s can be calculated using the following function:

$$L_{style}(s, g, 1, c)=\sum_{c=1}^{c} \frac{1}{2} \sum\left\|G_{c, 1}(g)-G_{c, 1}(s)\right\|^{2}, \tag{3}$$

where, $G_{1,c}(\cdot)=K_{1,c}(\cdot)K_{1,c}(\cdot)^{T}$ is the Gram matrix operation, which is the inner product between vector feature maps, and c is the number of categories in the semantic segmentation mask.

$$\left\{\begin{array}{l} K_{1, c}(g)=K_{1}(g) P_{1, c}(c), \\ K_{1, c}(s)=K_{1}(s) P_{1, c}(s), \end{array}\right. \tag{4}$$

where, $P_{1,c}(c)$ is the segmentation mask of the content image and $P_{1,c}(s)$ is the segmentation mask for the style image. The total loss function is:

$$L_{total}=\alpha L_{content}=\beta L_{style}. \tag{5}$$

III. D. Poisson image editing constrains image gradient

In order to generate clear and accurate transfer effect images, using the stylized image $C_s(x,y)$ as the input image, the gradient field of the given content image c is:

$$g(x, y)=\nabla(x, y). \tag{6}$$

The constraint space gradient ensures that the objective function $F(x,y)$ that needs to be satisfied is:

$$L^{*}=\min \iint_{\Omega}\|\nabla F-g\|^{2}+\left(F, C_{s}\right)^{2}. \tag{7}$$

Thus, the Poisson equation for optimizing the objective function is derived as follows:

$$F\left(1-\lambda \nabla^{2}\right)=C_{s}-\lambda \nabla g, \tag{8}$$

where, λ is the relative weight between the two control terms. This equation can be solved using the least squares method.

IV. Case effects

IV. A. Residential space design

In residential space design, the application of machine learning is mainly reflected in understanding residents' behavior patterns and preferences, predicting design effects, and optimizing design decisions. The following case will specifically demonstrate how to apply machine learning to an apartment interior design project.In this case, the designer is responsible for the interior decoration design of an apartment, including the layout of living rooms, kitchens, bedrooms, furniture selection, and the design of decorative elements. The designer collected a large amount of data through reviewing and analyzing past projects, as well as interviews and surveys with clients, including room size, shape, lighting, client age, lifestyle habits, preferences, etc.Then, the designer used clustering analysis to divide the clients into several different groups, such as young singles, families with children, retired elderly people, etc. For each group, the designer used a decision tree model to analyze the impact of different design elements (such as furniture type and layout, color and material selection, etc.) on residents' satisfaction.This allows designers to propose design solutions that better meet the needs and preferences of different customer groups. Finally, the designer made a design decision based on the analysis results of the model. For example, model analysis shows that for young singles, modern and minimalist design styles, ample storage space, and social friendly public area designs can significantly improve their satisfaction.Therefore, the designer considered these factors in the design proposal. After the implementation of the design, the designer further optimized and adjusted the design scheme by collecting and analyzing customer feedback (see Figure 4 and Figure 5).

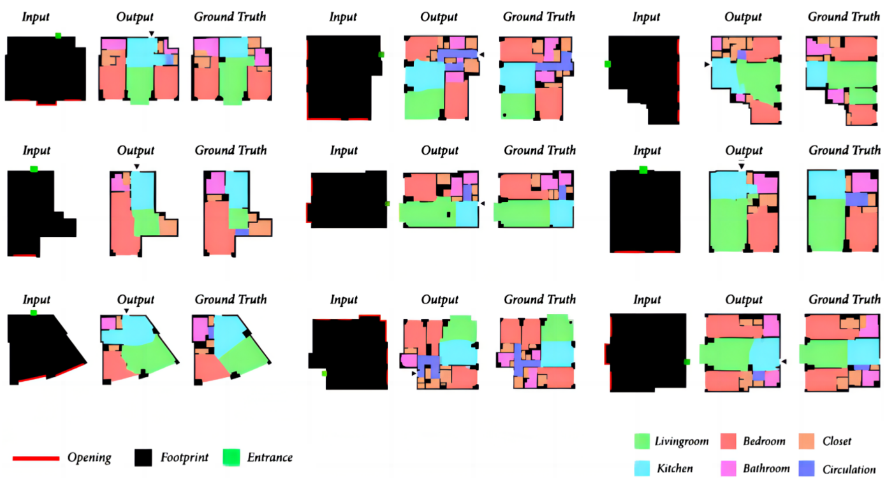

Figure 4: Plane planning network model

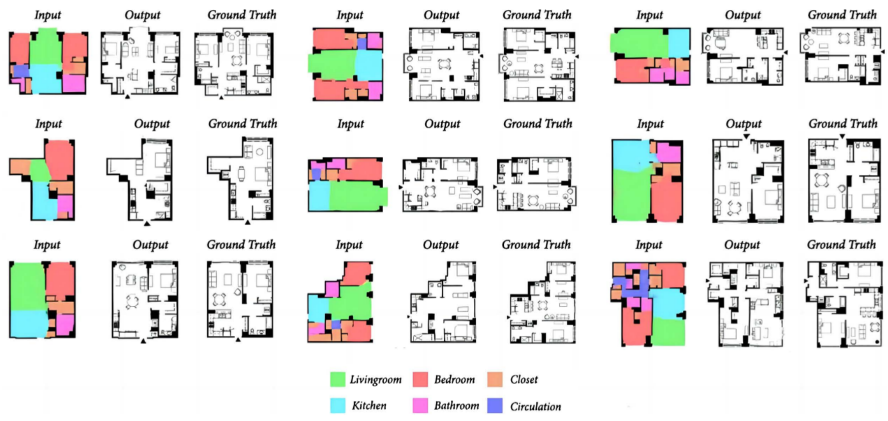

Figure 5: Network model for furniture generation

This case demonstrates how machine learning can be applied in residential space design to better understand and meet customer needs through data-driven approaches, achieving higher design satisfaction. This method can be widely applied in various fields and stages of interior design, providing designers with new design tools and ideas.

IV. B. Application display in modern interior soft decoration

Indoor soft decoration, as the soul of interior design and the carrier of culture, is a design that combines practicality and decorative function. The design scheme selects decorative murals, curtains, pillows, and bedding as carriers, and presents them for design application, as shown in Figure 6.

Figure 6: Application in decorative murals

Wall hanging or decorative paintings are often hung in public or residential spaces to embellish the space, among which decorative paintings have strong decorative functions and are one of the commonly used elements in indoor soft decoration design. Figure 7 shows a decorative mural display in the tea drinking space, which can be made of silk and mounted. This application not only decorates the space, but also brings joy and relaxation to visitors, allowing them to experience the unique charm of traditional Chinese culture.Soft decorations such as curtains, pillows or cushions, lighting fixtures, bedding, etc. are commonly seen in modern residential spaces, which can meet people's aesthetic demands and spiritual needs for the living environment.Therefore, the author uses modern design techniques to extract and simplify the forms, hairstyles, and clothing in modern images, combined with elements such as flowers and ancient architecture, and uses modern techniques to evolve and design patterns and colors that meet the aesthetic needs of modern people for color matching. Finally, they apply them to curtains, pillows, and bedding (see Figure 8 and Figure 9), so that residential soft decoration not only inherits traditional Chinese culture but also maintains fashion and modern style, meeting the dual aesthetic and spiritual needs of residents.

Figure 7: New Chinese style curtains

Figure 8: Application of modern pillows

Figure 9: Application of modern bedroom bedding

V. Conclusion

This article fills the gap in current research by exploring in detail the application of machine learning in interior design. We systematically elaborated on the main problems and challenges faced by interior design, and analyzed in depth the specific applications of machine learning in solving these problems through practical cases.We discussed in detail the data based soft decoration matching and design practices, demonstrating how to use machine learning to understand residents' behavior patterns and preferences, predict design effects, and optimize design decisions. Through case studies, this article demonstrates how designers can utilize machine learning techniques to extract valuable information from large amounts of data and provide design solutions that better meet customer needs.

In terms of technical implementation, this article explores the implementation process of modern home image style transfer technology, including image segmentation, content loss, and style loss calculation methods, as well as the application of Poisson image editing to constrain image gradients. The combination of these technological means can not only generate clear and accurate stylized images, but also effectively integrate different style elements in practical design.In addition, this article also demonstrates the application of modern interior soft decoration, which integrates traditional cultural elements into the soft decoration of modern residential spaces through modern design techniques, achieving the fusion of tradition and modernity. This innovative design not only inherits traditional Chinese culture, but also meets the aesthetic and spiritual needs of modern people for living environments, and has important cultural and social value.

Funding statement

There is no funding support for this study.

References

[1] Gong M. Application and Practice of Artificial Intelligence Technology in Interior Design. Applied Mathematics and Nonlinear Sciences. 2023;8(1):3077-94.
[2] Zhang J. Graphic Design Optimization Method Based on Deep Reinforcement Learning Model. Applied Mathematics and Nonlinear Sciences. 2023;8(2):2053-60.
[3] Xu H, Mamat MJ. Display Tradition, Innovative Design——Regional Culture in the Interior Decoration of the Chinese Museum. International Journal of Religion. 2024;5(5):794-804.
[4] Zhou J. Visualization of green building landscape space environment design based on image processing and artificial intelligence algorithm. Soft Computing. 2023 Jul;27(14):10225-35.
[5] Pan J, Wang L. Analysis of the Application of Traditional Culture in Modern Design. Journal of Social Science Humanities and Literature. 2023 Dec 29;6(6):102-6.
[6] Wang D, Chang F. RETRACTED ARTICLE: Application of machine learning-based BIM in green public building design. Soft Computing. 2023 Jul;27(13):9031-40.
[7] Wu Y, Kyungsun K. Automatic generation of traditional patterns and aesthetic quality evaluation technology. Information Technology and Management. 2024 Jun;25(2):125-43.
[8] Min Q, Zhaoxian R, Jiang W. An integrated approach to design and evaluate Chinese-style stools. Journal of Intelligent & Fuzzy Systems. 2023 Jan 1;45(5):8297-316.
[9] Vinothkumar KR, Reka DM, Janani ES. Predictions Of Consumer Behaviour And Their Impact On Visual Merchandising Using Combined Machine Learning Concept. Educational Administration: Theory and Practice. 2024 Apr;30(4):2865-78.
[10] Wong IA, Wan YK, Sun D. Understanding hospitality service aesthetics through the lens of aesthetic theory. Journal of Hospitality Marketing & Management. 2023 Apr 3;32(3):410-44.
[11] Abdurrafi MF, Ningsih DH. Content-based filtering using cosine similarity algorithm for alternative selection on training programs. Journal of Soft Computing Exploration. 2023 Dec 11;4(4):204-12.
[12] Zhang C. Creation of a system for designing textile patterns using an iterative function system. International Journal of Innovative Research and Scientific Studies. 2024;7(1):115-26.
[13] Wang Y, Liu Q. A virtual evaluation system for product designing using virtual reality. Soft Computing. 2023 Oct;27(19):14285-303.
[14] Li K, Zhang J, Forsyth D. POVNet: Image-based virtual try-on through accurate warping and residual. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2023 Jun 9;45(10):12222-35.
[15] Zeng D, Miao J, Tang C, Long Y, He M. Hybrid gene regulatory network for product styling construction in interactive evolutionary design. Journal of Engineering Design. 2023 Dec 2;34(12):986-1012.
[16] Song H, Song Y. Analysis of the Inner Epidermis Design of Elderly Care Buildings. Journal of Civil Engineering and Urban Planning. 2023;5(5):64-72.
[17] Cui M, Li S. Design of a New Physical Bookstore with Intangible Cultural Heritage Paper Theme based on Cultural Experience. hiaad [Internet]. 2023 Jun. 26 [cited 2025 Mar. 25];3(2):60-7.
[18] Yum MS. New Museology Approaches in Cultural Heritage Centers. Journal of Interior Design and Academy. 2024 Jul 19;4(1):13-42.
[19] Gao ZB, Qiu W, Lee SM, Yang TC, Sun CX. On vertex Euclidean deficiency of one-point union and one-edge union of complete graphs. Journal of Combinatorial Mathematics and Combinatorial Computing. 2024;121(1):107-12.