Color Matching and Light and Shadow Processing in Intelligent Interior Environment Art Design Analysis and Application Based on Neural Network

Ji Yang[1]*, Meifen Song[2]
Yancheng Institute of Technology, Yancheng 224000, China[1]
Yancheng Hongxin Decoration Co., Ltd, Yancheng 224001, China[2]

***Abstract*—In recent years, the application of Virtual Reality (VR) technology in the field of interior environmental design has expanded significantly, offering designers innovative methods to present complex design concepts within virtual spaces. However, the current color matching and light and shadow processing in reality are not mature enough, and the deep learning algorithms applied in VR are relatively basic with low running efficiency. The consistency and authenticity of virtual reality are not stable enough. This paper explores the integration of color matching and light-shadow processing in interior environmental design within VR technology, with a particular emphasis on leveraging neural network models to achieve automated design optimization. By incorporating deep learning algorithms, this study proposes a neural network-based approach to enhance color matching and light-shadow processing, aiming to improve the realism and aesthetic appeal of virtual environments. Experimental results demonstrate that this method offers substantial advantages in terms of color matching accuracy, naturalness of light-shadow effects, and computational efficiency, highlighting its broad potential for application in virtual reality.**

Keywords*—*Interior environment design; color matching; virtual reality; neural network; light and shadow processing

I. Introduction

In recent years, the application of Virtual Reality (VR) technology in the field of interior environmental design has seen substantial growth, offering designers novel means to present complex design solutions within virtual spaces. This technological advancement surpasses the limitations of traditional design methods, providing a more intuitive and immersive user experience. Within a VR environment, users can freely explore virtual spaces and perceive design outcomes with heightened realism, significantly enhancing interactivity and visualization throughout the design process.

In the realm of interior environmental art design, color coordination and light-shadow processing are two critical elements. The choice and combination of colors directly influence the atmosphere and visual perception of a space, while the treatment of light and shadows adds depth and dynamic effects, creating a sense of dimensionality. The integration of these two aspects largely determines users' emotional responses and overall impressions of the space. However, traditional design methods often rely heavily on the designer's experience and subjective judgment, making it challenging to address the complex and variable demands of design. Moreover, achieving automated and personalized design optimization remains particularly difficult. Consequently, the exploration of intelligent design methods has become a crucial topic in the current field of interior environmental art design.

With the rapid advancement of intelligent technologies, breakthroughs in neural networks within the domains of image processing and visual perception have introduced new possibilities for the intelligent development of interior environmental design. By leveraging neural networks, designers can automate the learning and optimization of color coordination and light-shadow processing, thereby reducing the need for human intervention and enhancing both design efficiency and effectiveness.

There are still several challenges in the current field of indoor environmental art design, including:

1) High quality, high-resolution, and efficient color and lighting processing methods are required. Color coordination and light and shadow processing play a crucial role in environmental design. Color not only determines the visual effect of space, but also affects people's emotions and psychological states. Light and shadow processing enhances spatial depth and realism by accurately simulating light sources, shadows, and reflections. In virtual reality, achieving high-quality color and lighting processing while maintaining computational efficiency remains an urgent technological challenge.

2) Currently, neural networks are rarely used for virtual reality implementation in indoor environments, and the methods used are relatively basic. The running efficiency, consistency, and authenticity of virtual reality are not stable enough. In recent years, neural networks, especially convolutional neural networks (CNNs), have made significant progress in image processing and computer vision, opening up new possibilities for automated design. The application of Generative Adversarial Networks (GANs) in image generation and style conversion provides new methods for color coordination and light and shadow processing. However, effectively applying these technologies to environmental design in virtual reality requires further targeted optimization.

*Corresponding Author.

To address this issue, we propose a neural network-based method for color coordination and light and shadow processing in indoor environment design, aimed at improving design efficiency. We explore how to use neural network technology to optimize color matching and lighting processing in indoor environment design, in order to further enhance the design quality and user experience in virtual reality. We propose a neural network algorithm based on deep learning models that can automatically identify and optimize color and light elements in space. This algorithm has demonstrated significant innovation and effectiveness in practical applications, providing a new intelligent solution for color matching and light and shadow processing in indoor environmental art design.

Specifically, by studying the visual characteristics of color in spatial perception and the perception patterns of indoor environment color by spatial users, we proposed the influencing factors of indoor environment color matching and constructed a regression model for evaluating indoor environment color matching based on these factors. This model learns color matching rules from large-scale data through deep learning, forming a systematic indoor environment color matching design method, and successfully applying it to practical design projects. Through this intelligent design approach, we can better meet personalized design needs and enhance users' immersive experience in virtual reality.

Section II of this article introduces the relevant technologies and development status of neural networks, color matching, and light and shadow processing. Section III presents our proposed method, including a detailed neural network model and loss function. Section IV introduces the experimental setup, experimental design, and comparative results. Finally, a summary of the entire text was provided in Section V.

II. Literature Review

In this chapter, we introduce the development of neural networks, color matching and light and shadow processing in interior design, and summarize the research gaps.

A. Neural Network

In recent years, neural network technology has increasingly been applied to intelligent home systems and smart cities, suggesting its potential utility in interior environment design as well. HVAC (Heating, Ventilation, and Air Conditioning) systems are critical for maintaining comfortable indoor environments in buildings and vehicles. To detect HVAC malfunctions, Kim [1] proposed a hybrid model based on transformers, leveraging both temporal and spatial features. Fu [2] introduced an improved version of YOLOv5, specifically designed to enhance the efficiency and accuracy of defect detection in the decorative coverings of car interiors. Zhang [3] developed a color correction method for interior decoration projects, based on a dense convolutional neural network. This method detects color deviation and sets color correction goals such as color matching coordination, harmony, and visual comfort, with a calibrated objective function. Zhang [4] employed the Proximal Policy Optimization (PPO) algorithm to improve the self-planning path capabilities of renovation robots. Liang [5] proposed a pattern recognition method for artificial identification in environments to increase the success rate of target recognition and determine target position and posture in complex settings. Gao [6] introduced a krill swarm algorithm based on a long short-term memory network for interpretable artistic emotion analysis in interior decoration environments. Additionally, Jiang [7] proposed measures to enhance the ecological sustainability of urban waterfront landscapes, including the sponge city construction concept, sewage coupling treatment systems, and information flow monitoring systems. Shan [8] explored the application of traditional Chinese decorative colors in interior design and proposed a model for this application using an improved AlexNet network, optimized with Adam, BN, dropout, and data augmentation algorithms. Lastly, Zhu [9] proposed a system that integrates Mixed Reality (MR), Diminished Reality (DR), and Generative Adversarial Networks (GAN) to provide technological support for designers and other professionals.

In summary, neural network technology can be effectively applied to the artistic design of interior environments, enabling precise control and optimization of color schemes within these spaces.

B. Color Matching and Light Processing

In virtual reality environments, interaction design serves as a crucial source of user engagement [10]. Achieving a highly immersive experience relies heavily on the strategic use of light, which plays an indispensable role in virtual reality interaction design. In the virtual world, the function of light extends beyond mere illumination; it directly influences the realism and authenticity of the scene, thereby affecting various aspects of user engagement and emotional response. From the soft glow of dawn to the intense rays of afternoon sunlight, the dynamic changes in lighting breathe life into virtual interactive scenarios, imbuing virtual reality interaction design with a sense of vitality.

In virtual reality, common types of light sources include ambient light, directional light, point light, and spotlights. Each type of light source possesses distinct illumination characteristics and plays a role in simulating real-world lighting during the rendering process, thus bestowing visual properties upon objects within the scene. By simulating the interaction between light and object surfaces, various visual effects such as shading, shadows, highlights, and reflections can be achieved. The application of light directly impacts the realism and authenticity of rendered images.

Regarding color configuration, Dong [11] developed a green and red color conversion medium (CCM) film for VR/AR micro displays, enhancing color rendering. Wang [12] applied the photometric stereo algorithm to derive surface gradients, which were then used to reconstruct the 3D contours of a scene, significantly improving the dynamic performance of single-pixel 3D reconstruction systems. Stampfl [13] proposed a method for shadow processing that separates shadows from test images by segmenting them into umbra and penumbra regions using a thresholding approach.

In summary, convolutional neural network-based recognition methods have been applied across various fields. Therefore, with the continued development of technology, it is feasible to design more personalized learning recommendation services based on deep learning techniques.

III. Proposed Method

A. Neural Network Model

1) Overall model architecture: In the domain of Virtual Reality (VR) interior environment design, the effective handling and realistic representation of color schemes and lighting effects are crucial for achieving a high-quality immersive experience. Neural networks, particularly those utilizing convolutional structures, have demonstrated significant potential in processing complex visual data, making them well-suited for these tasks. This paper presents a comprehensive neural network architecture specifically designed for VR-based interior environment design, with a focus on color matching and light-shadow processing. The architecture integrates an encoder-decoder framework with a discriminator module, enabling detailed feature extraction, generation, and evaluation of visual elements.

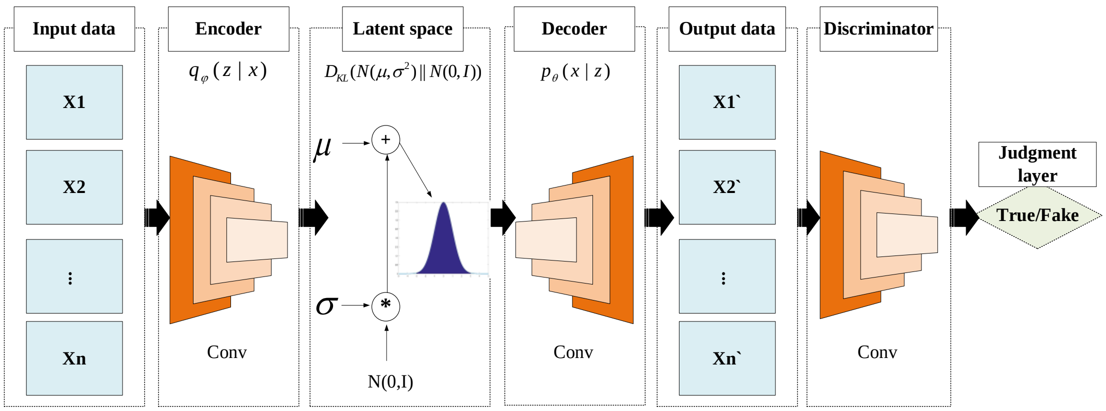

Fig. 1. Overall model architecture.

The neural network model proposed in this study is composed of the following key components:

a) Overall architecture: The architecture consists of three primary components: the encoder, the decoder, and the discriminator, all of which are enhanced by a scalable network. Fig. 1 illustrates this architecture.

b) Input data: The input data comprises a set of images, each depicting a distinct indoor design scenario (X_1, X_2, ..., Xn).

c) Encoder: The encoder employs Convolutional Neural Networks (CNNs) to extract features from the input images. These extracted features are mapped to a latent space, where they are represented by a mean vector (μ) and a standard deviation vector (σ). This latent space is crucial for generating new design samples, such as color schemes or lighting effects. The generator processes a noise vector to produce design outputs.

d) Latent space: The latent space is where the distribution of encoded features is regularized to follow a normal distribution, denoted as $N(0, I)$. This regularization is essential for the decoder to generate consistent and plausible outputs.

e) Decoder: The decoder reconstructs the original images from the latent space, producing outputs (X_1', X_2', ..., Xn') that are similar to the input data.

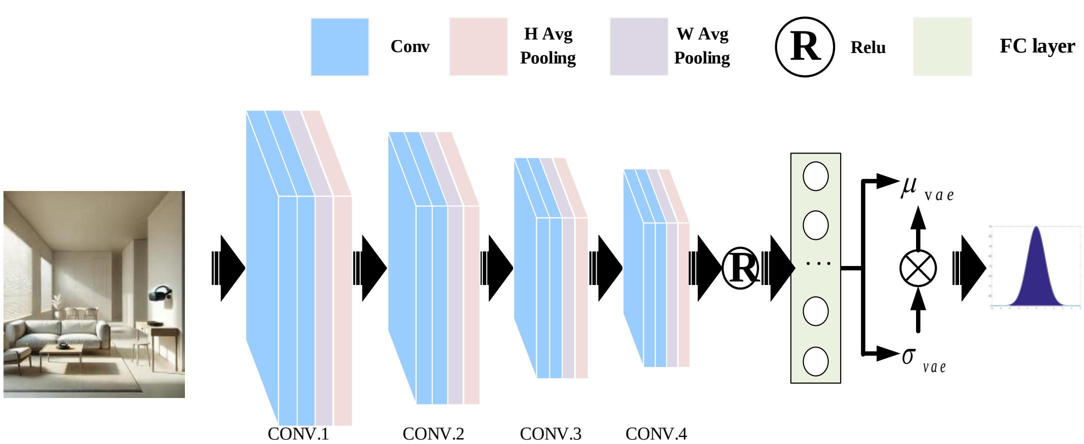

Fig. 2. Encoder structure.

f) Discriminator: The discriminator differentiates between real and generated images, providing feedback to the encoder-decoder system to enhance the quality of the generated images. This setup mirrors the architecture used in Generative Adversarial Networks (GANs), where the output (real/fake) guides the optimization process. The discriminator evaluates the realism of the generator's outputs by comparing generated samples with real samples, thereby providing feedback that drives the generator to refine its outputs continually.

This model framework facilitates the generation of high-quality design samples by integrating these components into a cohesive system that enhances both the quality and diversity of the generated outputs.

Residual mapping is utilized to enhance the model's ability to capture long-range dependencies. In the context of color matching and light-shadow processing, self-attention mechanisms play a critical role. By computing the correlations between different color regions in the input image, the model gains an understanding of the interactions between colors, leading to more harmonious color schemes. Additionally, self-attention facilitates the identification of long-range dependencies between light sources and shadows, ensuring that the generated light-shadow effects are natural and fluid.

The integration of residual mapping with self-attention mechanisms allows the model to address both the intricate color relationships and the complex spatial dependencies associated with light and shadow. This dual approach improves the overall coherence and quality of the generated design outputs, making the model more effective in producing aesthetically pleasing and contextually appropriate results.

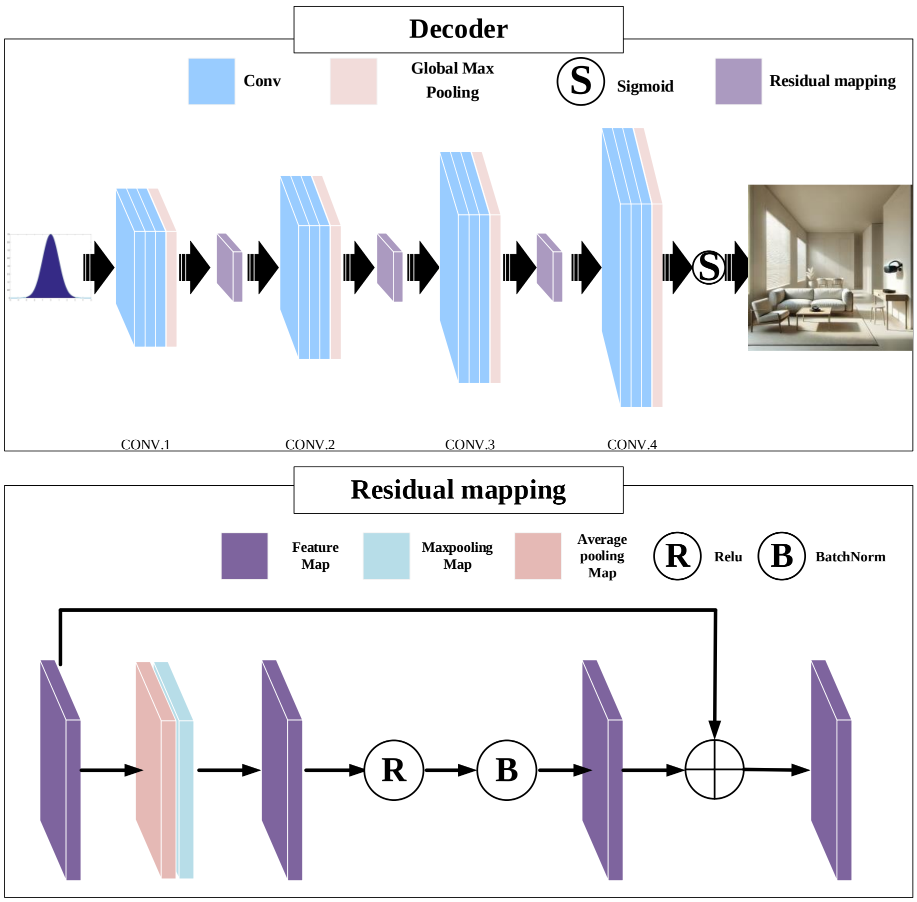

Fig. 3. Decoder structure.

2) Encoder module: As depicted in Fig. 2, the encoder architecture is meticulously crafted to efficiently extract and preserve both spatial and color information from the input images by employing a series of convolutional layers. The encoder comprises four convolutional layers (CONV 1-4), each strategically paired with horizontal (H) and vertical (W) average pooling layers. This design not only reduces the dimensionality of the feature maps but also ensures that critical spatial and color information is retained, facilitating the model's ability to capture the nuanced details of the input images.

Following the convolutional layers, the feature maps undergo a transformation through a fully connected (FC) layer, preceded by the application of the ReLU activation function. This phase is vital for generating the mean vector (μ) and standard deviation vector (σ), which characterize the feature distribution within the latent space. The precision in defining these vectors is paramount as they directly influence the quality of the latent space representation.

Subsequently, latent vectors are sampled from a normal distribution, modulated by the parameters μ and σ. These latent vectors serve as a condensed and informative representation of the input image within the latent space, encapsulating the core information necessary for the decoder to accurately reconstruct the original image. This process not only optimizes the efficiency of the model but also enhances its capability to generate high-fidelity reconstructions, thereby demonstrating the robustness of the encoder's design in capturing complex image features.

3) Decoder module: As depicted in Fig. 3, the decoder plays a crucial role in reconstructing images from latent vectors by employing a structure that mirrors the encoder. This symmetry is vital for ensuring that the reconstruction is as accurate as possible. The decoder's architecture includes a series of convolutional layers (CONV 1-4), which systematically upscale the latent vectors back into full-sized images. To maintain the integrity of high-level features and prevent information loss, each convolutional layer is followed by global max pooling and residual mapping. The incorporation of residual mapping is particularly important as it addresses the vanishing gradient problem, thereby enhancing the flow of gradients during backpropagation. This process involves passing feature maps through a series of transformations, such as average pooling and ReLU activation, before reintegrating them into the main feature stream.

The decoder's final output is generated through a Sigmoid activation function, which produces pixel values for the reconstructed image. These pixel values are then directly compared with the original image to calculate the reconstruction loss, a critical measure of the model's performance.

The encoder-decoder architecture, which includes an integrated encoder, is meticulously designed to handle the complexities of indoor environment design within virtual reality (VR). It effectively captures and reconstructs intricate color schemes and lighting effects, ensuring that the spatial hierarchies are preserved throughout the process. Additionally, latent space regularization is employed to ensure the production of high-quality, consistent outputs. The framework also integrates an adversarial training mechanism, which compels the generator to create outputs that are virtually indistinguishable from real images, thereby significantly enhancing the realism of the final visual content.

This neural network architecture offers a powerful framework for VR-based indoor environment design, with a particular focus on the precise representation of color matching and light-shadow effects. By leveraging state-of-the-art techniques such as latent space regularization, residual mapping, and adversarial training, the architecture provides designers with advanced tools to create highly immersive and realistic VR environments.

B. Loss function

We utilize loss functions to optimize the performance of both the generator and the discriminator. For color matching, the loss function is designed based on color harmony and aesthetic standards, ensuring that the generated color schemes are visually pleasing and coherent. In the context of light-shadow processing, the loss function focuses on the naturalness and realism of the light and shadow effects, aiming to achieve visually accurate and contextually appropriate results.

In the neural network model, the loss function measures the discrepancy between the model's outputs and the ground truth values. Different tasks and objectives necessitate the use of specific loss functions tailored to their respective requirements. The choice of loss function directly influences the model's ability to generate high-quality and realistic outputs, thus playing a crucial role in the overall effectiveness of the model.

1) Color matching loss function: The color harmony loss function is employed to evaluate whether the generated color schemes adhere to aesthetic standards. The color harmony loss is computed using the following formula:

$$L_{color} = \frac{1}{N}\sum_{i=1}^{N} ||c_i^{gen} - c_i^{true}||_2 \quad (1)$$

Let c_i^{gen} denote the RGB value of the i-th generated color, and c_i^{true} represent the RGB value of the i-th true color. Here, N is the total number of colors. The term $||\cdot||_2$ denotes the Euclidean distance. This loss function quantifies the discrepancy between the generated colors and the true colors, with a smaller distance indicating better color harmony.

Color Contrast Loss: To ensure that the generated colors exhibit sufficient contrast, the following loss function can be employed:

$$L_{contrast} = \frac{1}{N}\sum_{i=1}^{N} ||contrast(c_i^{gen}) - contrast(c_i^{true})||_2 \quad (2)$$

$$L_{color\_total} = \alpha \cdot L_{color} + \beta \cdot L_{contrast} \quad (3)$$

$contrast(\cdot)$ represents a function that calculates color contrast. Total loss of coordination with contrast color loses. Where: α and β are weight coefficients, used to balance the impact of the loss of each part.

2) Light processing loss function: The light-shadow realism loss is used to assess how closely the generated light and shadow effects resemble those in real scenes. The light-shadow smoothness loss is designed to ensure that the generated light-shadow transitions are natural, avoiding abrupt shadows or reflections. The combined light-shadow loss integrates both the realism loss and the smoothness loss to achieve a more comprehensive evaluation of the generated effects.

$$L_{shadow} = \frac{1}{M}\sum_{j=1}^{M} ||l_j^{gen} - l_j^{true}||_2 \quad (4)$$

$$L_{smooth} = \frac{1}{P}\sum_{p=1}^{P} ||smooth(l_j^{gen}) - smooth(l_j^{true})||_2 \quad (5)$$

$$L_{shadow\_total} = \gamma \cdot L_{shadow} + \delta \cdot L_{smooth} \quad (6)$$

Among them: l_j^{gen} first j is to generate a light characteristic. l_j^{true} is the first j a real light and shadow. M is the total number of light and shadow features. $smooth(\cdot)$

represents a function for calculating the smoothness of light and shadow. Gamma and δ are the weight coefficients.

IV. Experiment and Verification

In this chapter, we verify the reliability and validity of the proposed method through experiments.

A. Experimental Environment

This study validated the algorithm's effectiveness using an environment comprising an 11th Gen Intel(R) Core (TM) i7-11700K @ 3.60GHz CPU with 32.0 GB of RAM.

B. Data Preparation and Preprocessing

We sourced authentic interior design images and design schemes from various interior design projects, design galleries, and architectural design websites. Each image was annotated with the primary colors, recording their RGB values or coordinates in the color space. Additionally, the position and intensity of light sources, as well as shadow regions, were annotated. The images were further classified by style (e.g., modern, classical, minimalist) and by light-shadow effects (e.g., natural light, artificial lighting, shadow types). The dataset underwent noise reduction and consistency checks to ensure data quality. Finally, the dataset was split into training, validation, and test sets with a ratio of 8:1:1.

C. Evaluation Parameter

The CIEDE2000 metric is employed for the precise calculation of color differences, based on the human eye's perceptual characteristics. The Structural Similarity Index (SSIM) is used to evaluate the structural similarity of images, aligning more closely with human visual perception. The Peak Signal-to-Noise Ratio (PSNR) measures the image quality by focusing on brightness differences. Together, these three metrics provide a comprehensive evaluation of both color and image quality, aiding in the optimization of design effects in virtual reality [14]-[17].

For evaluating color harmony, we assess the aesthetic quality of color schemes through user ratings and expert evaluations. User satisfaction scores are derived from survey results. Additionally, we calculate the color difference between generated and real colors using the CIEDE2000 metric, which is based on the CIELAB color space. CIEDE2000 improves upon the CIE76 and CIE94 formulas to offer a more perceptually accurate measure of color difference, better reflecting human visual perception.

In the CIEDE2000 formula, $\Delta L^{`}$ represents the lightness difference, $\Delta C^{`}$ denotes the chroma difference, and $\Delta H^{`}$ indicates the hue difference. The parameter k is a weighting factor set to 1, and S represents a scaling factor dependent on the color's properties. R_T is a rotation term that accounts for variations in color differences across different hues. CIEDE2000 aligns more closely with human perception of color differences, and a smaller ΔE_{00} value indicates that the colors are visually closer.

For evaluating light and shadow effects, we assess the realism of the generated effects by comparing them to real scenes, using SSIM and PSNR metrics. The Peak Signal-to-Noise Ratio (PSNR) is a metric used to measure image quality and similarity, typically taking paired images as input. Since PSNR is rooted in signal processing and defined using Mean Squared Error (MSE), it is often expressed in decibels (dB). A lower MSE value results in a higher PSNR, indicating better image quality or greater similarity to the source image. Generally, a higher PSNR suggests higher similarity between paired images or better performance in image reconstruction experiments.

Structural Similarity Index (SSIM) is a critical method for assessing the similarity between paired images. It evaluates image similarity by extracting three features—luminance, contrast, and structure—from the test image and comparing these features to human visual perception of pixel structure. SSIM is commonly used as an evaluation metric for paired images and as a loss function improvement in image reconstruction tasks, with l(x,y), c(x,y), and s(x,y) representing the similarity in luminance, contrast, and structure information between images x and y.

$$\Delta E_{00} = \sqrt{(\frac{\Delta L^{`}}{k_L \cdot S_L})^2 + (\frac{\Delta C^{`}}{k_C \cdot S_C})^2 + (\frac{\Delta H^{`}}{k_H \cdot S_H})^2 + R_T \cdot \Delta C} \quad (7)$$

$$PSNR = 10 \cdot log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot log_{10}(\frac{MAX_I}{\sqrt{MSE}}) \quad (8)$$

$$SSIM = l(x,y)^{\alpha} * c(x,y)^{\beta} * s(x,y)^{\gamma} \quad (9)$$

To evaluate the real-time rendering performance of the model within virtual reality environments, the rendering speed can be assessed by measuring the frame rendering time, typically expressed in frames per second (FPS). This metric provides a quantitative measure of how efficiently the model handles rendering tasks in real-time scenarios, ensuring a smooth and responsive user experience.

D. Test and Evaluation

To validate the effectiveness of the proposed methodology, we carried out a series of rigorous experiments across a diverse range of virtual reality (VR) environments. Our experimental setup involved comparing the performance of our proposed algorithm with three state-of-the-art (SOTA) algorithms: the IRCGAN model [18], the LOHO model [19], and the FTGH model [20]. These algorithms were selected due to their prominence and relevance in the field of VR design and image processing.

As detailed in Table I, our proposed method demonstrates superior performance relative to these SOTA benchmarks across several key metrics. Specifically, in the domain of color matching, our approach consistently achieves higher accuracy in aligning generated colors with target colors, thus producing more aesthetically pleasing and coherent color schemes. The image quality results reveal that our algorithm excels in maintaining high fidelity and detail, surpassing the quality delivered by the IRCGAN, LOHO, and FTGH models.

Furthermore, our method significantly improves real-time performance, which is crucial for practical VR applications where timely and responsive rendering is essential. The enhanced efficiency and reduced computational overhead of our approach ensure that complex VR environments can be rendered smoothly without compromising on visual quality.

The superior performance of our proposed algorithm underscores its potential for advancing virtual reality interior environment design. By offering enhanced color accuracy, superior image quality, and efficient real-time rendering, our method provides a robust tool for designers and developers aiming to create immersive and realistic VR experiences. The results affirm the algorithm's capacity to address the current limitations of existing methods and to contribute effectively to the field of VR design.

TABLE I. ALGORITHM COMPARISON RESULTS

Metric	Proposed Algorithm	IRCGAN	LOHO	FTGH
CIEDE2000	1.23	2.15	1.89	1.56
SSIM	0.98	0.95	0.96	0.97
PSNR (dB)	32.8	30.5	31.1	31.8
FPS	60	45	50	55

The results demonstrate that the neural network-based approach to color matching and light-shadow processing offers significant advantages in the following areas. Compared to traditional methods, neural networks more accurately capture the relationships between colors, generating more harmonious color combinations. The light-shadow effects produced by the model closely resemble real-world scenes, with natural shadow transitions and realistic reflection effects. By optimizing the model structure, our method significantly reduces computation time while maintaining high-quality output, meeting the real-time rendering demands of virtual reality.

TABLE II. ALGORITHM COMPARISON RESULTS

	Satisfaction (%)
IRCGAN	89
LOHO	88
FTGH	93
Proposed Algorithm	100

In addition, we calculated and compared the satisfaction of 100 images generated using the above algorithm, and the comparison results are shown in Table 2. From the table, it can be seen that the satisfaction rate of the images generated using our proposed algorithm is 100%, far higher than other algorithms.

Fig. 4. Generated image.

As illustrated in Fig. 4, the results of our interior environment design demonstrate the effectiveness of the proposed methods in both color matching and light-shadow processing. The generated images exhibit high-quality outcomes, reflecting the model's capability to produce aesthetically pleasing and realistic visual effects.

V. CONCLUSION

The innovations presented in this study are reflected in several key areas:

1) Automated design optimization: By leveraging neural network models, this study achieves automation in color matching and light-shadow processing, significantly reducing the workload of designers.

2) Dynamic color adjustment: The model is capable of adjusting color schemes in real-time based on environmental changes, providing robust technical support for designing dynamic scenes in virtual reality.

3) Efficient light-shadow processing: The use of GANs to generate light-shadow effects not only enhances the realism of the design but also significantly improves computational efficiency, making it suitable for real-time rendering in virtual reality environments.

In terms of applications, the proposed method can be widely applied in various domains such as interior design in virtual reality, game scene development, and virtual exhibition platforms. As neural network technology continues to advance, this method is expected to play an increasingly important role in future virtual reality applications.

ACKNOWLEDGMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] Kim B, Kang JW, Kim CS, Kwon OK, Gwak J. “Hybrid Transformer for Anomaly Detection on Railway HVAC Systems Through Feature Ensemble of Spatial-Temporal with Multi-channel GADF Images.” JOURNAL OF ELECTRICAL ENGINEERING & TECHNOLOGY. 19 (4) , pp.2803-2815. 2024. https://doi.org/10.1007/s42835-024-01844-5

[2] Fu, YZ, Qiu, L, Kong, X, Xu, HF. “Deep Learning-Based Online Surface Defect Detection Method for Door Trim Panel.” ENGINEERING LETTERS. 32 (5) , pp.939-948. 2024.

[3] Chuan-qin Zhang and Hong-tao Xing. “Colour correction method of interior decoration engineering based on dense convolution neural network.” INTERNATIONAL JOURNAL OF ARTS AND TECHNOLOGY. 13 (2) , pp.108-122. 2021.

[4] Zhang L, Qin AM. “Research on Key Technologies of Smart City Building Interior Decoration Construction based on In-Depth Learning.” INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS. 13 (12) , pp.1068-1076. 2022.

[5] Liang, TT, Liu, ZG, Wang, WZ. “Pattern recognition of decorative elements based on neural network.” JOURNAL OF INTELLIGENT &

FUZZY SYSTEMS. 39, 6, 8665-8673. 2020. https://doi.org/10.3233/JIFS-189262

[6] Gao ZQ. "A Novel Long and Short-Term Memory Network-Based Krill Herd Algorithm for Explainable Art Sentiment Analysis in Interior Decoration Environment." Journal of Cases on Information Technology.225(1). 2023. https://doi.org/10.4018/JCIT.324602

[7] Jiang G, Zuo L, Asutosh A T, Zhang J. "Environmental Sustainability Study of Urban Waterfront Landscapes Based on the LCA–Emergy–Carbon Footprint and Artificial Neural Network Method." Builings. 2024, 14, 386. 2024. https://doi.org/10.3390/buildings14020386

[8] Shan WL, Jin RM, Ding XY. "Chinese Decorative Color Based on Improved AlexNet in Interior Decoration Design." MATHEMATICAL PROBLEMS IN ENGINEERING. Sep 23 2022, 2358905. https://doi.org/10.1155/2022/2358905

[9] Zhu YH, Fukuda T, Yabuki N. "A Mixed Reality Design System for Interior Renovation: Inpainting with 360-Degree Live Streaming and Generative Adversarial Networks after Removal." TECHNOLOGIES. 12 (1). 2024. https://doi.org/10.3390/technologies12010009

[10] Jiashan Lu. "Research on influencing factors of virtual reality interaction design from the perspective of embodied cognition." China-arab States Science and Technology Forum,2023(04):111-115.

[11] Dong SC, Jiang YB,Tang CW. "Organic color-conversion media for full-color micro-LED displays." JOURNAL OF THE SOCIETY FOR INFORMATION DISPLAY. 29 (12) , pp.961-967. 2021. https://doi.org/10.1002/jsid.1072

[12] Wang M, Sun MJ, Huang C. "Single-pixel 3D reconstruction via a high-speed LED array." JOURNAL OF PHYSICS-PHOTONICS. 2 (2). 2020. https://doi.org/10.1088/2515-7647/ab83e5

[13] Stampfl V, Ahtik J. "Shadow Segmentation With Image Thresholding for Describing the Harshness of Light Sources." IEEE TRANSACTIONS ON IMAGE PROCESSING. 33, pp.3428-3440. 2024. https://doi.org/10.1109/TIP.2024.3403487

[14] Fu T, Li P, Liu S. "An imbalanced small sample slab defect recognition method based on image generation." Journal of Manufacturing Processes, 2024, 118: 376-388. https://doi.org/10.1016/j.jmapro.2024.03.028

[15] Fu T, Liu S, Li P. "Digital twin-driven smelting process management method for converter steelmaking." Journal of Intelligent Manufacturing, 2024: 1-17. https://doi.org/10.1007/s10845-024-02366-7

[16] Fu T, Li P, Liu S. "A method for quality inspection of continuous casting billet based on infrared flaw detection and two-dimensional image." IEEE Transactions on Instrumentation & Measurement. 2024. https://doi.org/10.1109/TIM.2024.3502874

[17] Fu T, Liu S, Li P. "Intelligent smelting process, management system: Efficient and intelligent management strategy by incorporating large language model." Frontiers of Engineering Management, 2024, 11(3): 396-412. https://doi.org/10.1007/s42524-024-4013-y

[18] Li, L., Wang, C., Zhang, H., & Zhang, B. "SAR Image Ship Object Generation and Classification with Improved Residual Conditional Generative Adversarial Network." IEEE Geoscience and Remote Sensing Letters, 19. 2022. https://doi.org/10.1109/LGRS.2020.3016692

[19] Saha, R.; Duke, B.; Shkurti, F.; Taylor, G.W.; Aarabi, P. "Loho: Latent Optimization of Hairstyles via Orthogonalization." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Nashville, TN, USA, 20–25 June 2021; pp. 1984–1993.

[20] Man, Q., Cho, Y. I., Jang, S. G., & Lee, H. J. "Transformer-Based GAN for New Hairstyle Generative Networks." Electronics (Switzerland), 11(13). 2022. https://doi.org/10.3390/electronics11132106.