RESEARCH ARTICLE

Visual communication design of ecological garden landscape based on image processing algorithm

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In recent years, the integration of ecological principles into urban landscape design has gained increasing attention, particularly in the context of rising environmental awareness and sustainable development goals. However, effectively conveying ecological values through visual design remains a significant challenge in ecological garden landscape planning. This study addressed this gap by introducing a novel image processing algorithm tailored for visual communication in ecological garden landscapes. The proposed model incorporated advanced modules including image feature extraction, adaptive enhancement, region segmentation, and ecological element fusion to optimize landscape imagery both structurally and ecologically. A comprehensive dataset comprising 80,000 annotated images from diverse categories of natural scenery, urban greenspace, and built environments was employed to evaluate the model's performance. By comparing with four state-of-the-art models including U-Net, VGG16, CycleGAN, and Deep Image Prior (DIP), the results demonstrated that the proposed model achieved superior performance with a structural similarity (SSIM) score of 0.91, a peak signal-to-noise ratio (PSNR) of 32.5 dB, a color fidelity score of 0.95, and a user satisfaction rating of 4.8 out of 5. These results clearly indicated an improvement over baseline models. This study presented a new methodology for enhancing the ecological communication function of garden landscape design, bridged aesthetics with environmental education, and supported the goals of sustainable urban development.

Keywords: image processing algorithm; ecological garden landscape; visual communication design; structural similarity; peak signal-to-noise ratio.

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Introduction

Ecological garden landscape design plays a pivotal role not only in urban beautification but also in promoting the concept of harmonious coexistence between humans and nature. With the intensification of global climate change and environmental degradation, the integration of ecological awareness into urban green space design has become a critical part of sustainable urban development [1]. According to the United Nations Environment Programme (UNEP), 80% of the world's population will reside in urban areas by 2050, placing increased pressure on cities to create green environments that support both ecological functionality and human well-being. Research has shown that even a 10% increase in urban green coverage can lead to a 20% improvement in the overall health of urban residents.

The development of ecological gardens has evolved from simple ornamental landscaping to complex systems that embody educational, ecological, and environmental values [2, 3]. Image processing technology has increasingly been applied in landscape architecture to enhance visual effects *via* tools such as color correction, shadow simulation, and textural refinement [4]. Advanced models including deep convolutional networks and generative adversarial networks are increasingly integrated into garden design workflows to optimize presentation quality and accelerate design iterations [5]. These technologies have demonstrated effectiveness in improving clarity, layering, and perceptual detail of landscape images. Despite these advances, significant gaps remain. Existing studies often focus on surface level aesthetic improvements without fully integrating ecological information into the visual outputs [6, 7]. Moreover, while technologies such as image enhancement or light simulation can improve image fidelity, they do not inherently support the communication of ecological functions. Researchers have noted a general lack of systematic approaches to align image processing algorithms with the goals of ecological education and environmental communication [8, 9]. The core question of how visual design can not only provide beautiful landscapes but also effectively convey ecological meaning to the public persists.

This study aimed to bridge the gap between visual aesthetic optimization and ecological value delivery by developing an image processing model suitable for the needs of ecological garden landscape design, and to explore how image optimization algorithms can be used not only to enhance visual impact but also to promote ecological awareness and education through landscape images. The study proposed an integrated image processing framework incorporating four core components including feature extraction, adaptive image enhancement, region segmentation, and ecological element fusion. By embedding ecological theory into the algorithmic logic of image optimization, the framework facilitated both visual refinement and concept communication. The model was validated using a large-scale dataset of 80,000 annotated images and benchmarked against four leading image optimization models of U-Net, VGG16, CycleGAN, and DIP. This research systematically combined ecological design principles with cutting-edge image processing technology, filling a critical gap in existing landscape design. By advancing ecological communication through landscape visualization, this study provided a scalable solution for enhancing public environmental consciousness and guiding sustainable urban development.

Materials and methods

Theoretical basis of the model

The model constructed in this study was mainly based on two core theoretical systems including the basic theory of image processing and the special needs of visual presentation and ecological information communication in ecological garden design. In the field of image processing, the model focused on multi-level feature extraction and optimization to make the image more expressive in the visual communication of ecological garden landscape through precise regulation of multi-dimensional visual features [10]. From the theoretical framework, the model introduced an adaptive visual feature enhancement mechanism, which could not only highlight the key information of the image, but also ensure that the ecological characteristics contained in the ecological garden design could be accurately expressed, which met the requirements of visual communication design. Specifically, when processing images, the image was regarded as a complex high-dimensional data set. The information carried by each pixel not only included color, but also covered multi-level features such as shape, texture, and spatial structure, which was crucial for the visual communication design of ecological garden landscapes. Different features carried different design element information such as the texture characteristics of plants could reflect their types and growth status, and the color characteristics could reflect seasonal changes [11]. Therefore, the image processing goal was to use complex mathematical methods to comprehensively optimize the multi-feature dimensions of the image to ensure that each design element could accurately convey the design intention of the ecological garden landscape. This theory was expressed below.

$$I_{opt}(x,y) = f(I(x,y), W_{feature}(x,y), P_{adjust}) \quad (1)$$

where $I(x,y)$ was the pixel value of original image at coordinates (x,y). $I_{opt}(x,y)$ was the pixel value of the optimized image at the same coordinate. $W_{feature}(x,y)$ was the feature weighting coefficient, which was used to measure the importance of different features in the optimization process. For ecological garden landscapes, the weight of plant color features might be set higher when highlighting the seasonal theme. P_{adjust} covered many aspects of global and local adjustment parameters including brightness adjustment parameters ($P_{brightness}$), contrast adjustment parameters ($P_{contrast}$), color saturation adjustment parameters ($P_{saturation}$), *etc.* and was expressed as $P_{adjust} = \{P_{brightness}, P_{contrast}, P_{saturation}, \text{L}\}$. By reasonably setting and coordinating these parameters, accurate optimization of the multi-dimensional features of the image could be achieved to meet the needs of visual communication design of ecological garden landscapes [12].

Core components of the model

The image optimization model designed in this study contained multiple core components that worked together and performed their respective functions. Each component had a unique key function and interacted closely with other components. Ultimately, through the coordinated operation of these components, an all-round and comprehensive optimization of ecological garden landscape image was achieved to enhance the visual communication effect [13].

(1) Feature extraction

The feature extraction component was crucial in the entire model. Its core task was to accurately extract visual information with ecological garden landscape design value and ecological communication significance from the image. Ecological garden design images had the characteristics of rich colors, diverse forms, and changeable light and shadow effects. These characteristics were key elements of visual communication design. This research adopted a joint method based on gradient and color space conversion. By converting the image to the CIE-LAB color space, the visual perception effect of the image was enhanced, and the local detail information of the image was obtained by combining gradient calculation [14], which could efficiently capture the subtle features in garden design, make the design elements in the image clearly stand out, and help visual communication. The classic Sobel operator was used in the gradient calculation as follows.

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \otimes I(x,y) \quad (2)$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \otimes I(x,y) \quad (3)$$

$$\nabla I(x,y) = \sqrt{G_x^2 + G_y^2} \quad (4)$$

where G_x and G_y were the images in x and y directions. The gradient approximation in the direction, $\otimes$, was the convolution operation. Through the above calculation, the gradient value of the image at each position was obtained as $\nabla I(x,y)$. This operation enhanced the edge information of the image, helped capture the local structure and shape characteristics in the garden landscape, and provided basic data for the visual communication design of the ecological garden landscape. In the feature extraction process, each area of the image was deeply analyzed based on its unique visual features such as color distribution uniformity, texture complexity, *etc*. By rationally weighting different features, it was ensured that the extracted information was both targeted and had good differentiation, providing a solid data foundation for subsequent image processing steps and serving the visual communication design of ecological garden landscapes [15].

(2) Image enhancement

The image enhancement process aimed to significantly improve the image quality and detail expression by fine-tuning the basic visual attributes of the image including brightness, contrast, and saturation to optimize the visual communication effect of the ecological garden landscape image. This study adopted an adaptive enhancement algorithm, which made personalized adaptive adjustments to each area based on the specific characteristics of the local area of the image to ensure that each area obtained the best enhancement effect according to its own characteristics [16]. The specific implementation method was based on the local brightness of the image ($L(x,y)$) and contrast ($C(x,y)$). The image was transformed nonlinearly based on features to enhance details while avoiding visual distortion caused by over-processing. This was crucial for accurately presenting the details of ecological garden landscapes and improving the visual communication effect. The enhancement process was calculated as below.

$$I_{enh}(x,y) = \alpha(x,y) \cdot I(x,y) + \beta(x,y) \quad (5)$$

where $I_{enh}(x,y)$ was the pixel value after enhancement. $\alpha(x,y)$ and $\beta(x,y)$ were parameters that controlled the enhancement effect dynamically and were adjusted according to the local features of the image. $\alpha(x,y)$ was calculated as follows.

$$\alpha(x,y) = k_1 \cdot \frac{C(x,y)}{\bar{C}} + k_2 \quad (6)$$

where k_1 and k_2 were constants. $\bar{C}$ was the average contrast of the global image. $\beta(x,y)$ was calculated as below.

$$\beta(x,y) = k_3 \cdot (L(x,y) - \bar{L}) \quad (7)$$

where k_3 was a constant. $\bar{L}$ was the average brightness of the whole image. By adaptively adjusting each pixel value, the image contrast and detail clarity were significantly improved, making the ecological garden landscape design elements more visually prominent and enhancing the overall visual communication effect of the image.

(3) Region segmentation

Region segmentation was a key step in image processing to accurately segment different ecological garden elements such as plant communities, waterscape areas, building structures, *etc*. in the image into independent regions, so that each element could be processed separately and carefully, which was of great significance to the visual communication design of ecological garden landscapes [17]. Different landscape elements had different roles in visual communication and needed to be optimized independently. A threshold-based method was adopted in this study to divide the image into regions and accurately identify different regions by analyzing the changes in image grayscale values using the classic Otsu threshold algorithm. The core of this algorithm was to find the optimal threshold T, so that the variance between the two categories after image segmentation was maximized and calculated as follows.

$$\mathrm{Var}(T) = \omega_1(T) \cdot (\mu_1(T) - \mu_T)^2 + \omega_2(T) \cdot (\mu_2(T) - \mu_T)^2 \quad (8)$$

where $\mathrm{Var}(T)$ was the variance of threshold segmentation. $\omega_1(T)$ and $\omega_2(T)$ were the thresholds. T was the ratio of the number of pixels in the two categories after segmentation to the total number of pixels and was the inter-class weight. $\mu_1(T)$ and $\mu_2(T)$ were the means of the two categories. μ_T was the global mean. By traversing different thresholds T, the corresponding $\mathrm{Var}(T)$ was calculated. The largest T was selected as the optimal threshold. The image was divided into multiple areas, each of which represented a specific element in the garden landscape such as plant area, waterscape area, *etc*., which facilitated the subsequent targeted processing of different elements and improved the accuracy of the visual communication design of the ecological garden landscape [18].

(4) Integration of ecological elements

The fusion of ecological elements deeply and cleverly integrated ecological theory with image processing technology and was committed to ensure that, in the ecological garden design image, various ecological elements including rich and diverse plant species, flexible and changeable water forms, and distinctive soil textures achieved a high degree of harmony and unity in visual presentation, thereby greatly enhancing the ecological characteristics in the visual communication design of ecological garden landscapes [19]. This fusion process was mainly achieved by weighted fusion of information from different regions. For each ecological element, a specific weight coefficient was assigned based on multiple factors such as its actual importance in the ecosystem and the degree of prominence expected in the overall design. In this way, it could ensure that the unique ecological characteristics contained in each ecological element could be reasonably and fully displayed in the visual communication process [20]. The fusion of ecological elements was calculated as below.

$$I_{eco}(x,y)=\sum_{i=1}^{n}W_i\cdot f(I_i(x,y)) \tag{9}$$

where $I_{eco}(x,y)$ was the pixel value at the coordinates (x,y) of the fused image. W_i was the weight coefficients of the ecological elements that had a rigorous basis for their selection. $f(I_i(x,y))$ was the function that had strong flexibility and could further adjust or optimize the characteristics of ecological elements according to specific design requirements. Through this weighted processing method, the expressiveness of each ecological element could be effectively highlighted in the image to ensure that they achieved a visually harmonious and unified effect with other design elements to better convey the rich ecological concepts contained in the ecological garden landscape design to the audience and significantly improve the connotation and quality of the visual communication design.

2.3 Experimental Design

To evaluate the effectiveness of the proposed model, the model was benchmarked against four widely recognized image optimization architectures including U-Net (https://github.com/zhixuhao/unet) that was known for medical image segmentation and restoration accuracy [21], VGG16 (https://www.robots.ox.ac.uk/~vgg/research/very_deep/) that was effective in feature-based denoising and detail enhancement, CycleGAN (https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix) that was capable of unpaired domain translation using generative adversarial learning, and Deep Image Prior (DIP) (https://github.com/DmitryUlyanov/deep-image-prior) that relied on internal network for unsupervised image restoration. The Landscape Visual Data Collection (LVDC) (https://www.greenvisiondata. org/lvdc), a large-scale open access dataset of 80,000 annotated images was employed for this study, which covered natural ecological scenes, architectural features, urban park landscapes, and time-variant seasonal garden views. Each image included metadata on scene category, dominant object types, plant and water feature descriptors, color and texture statistics, and spatial layout information with the average image resolution of 1,080 × 1,920 pixels. This data supported both training and evaluation of multi-dimensional feature extraction, enhancement, and ecological segmentation performance. Four key performance metrics

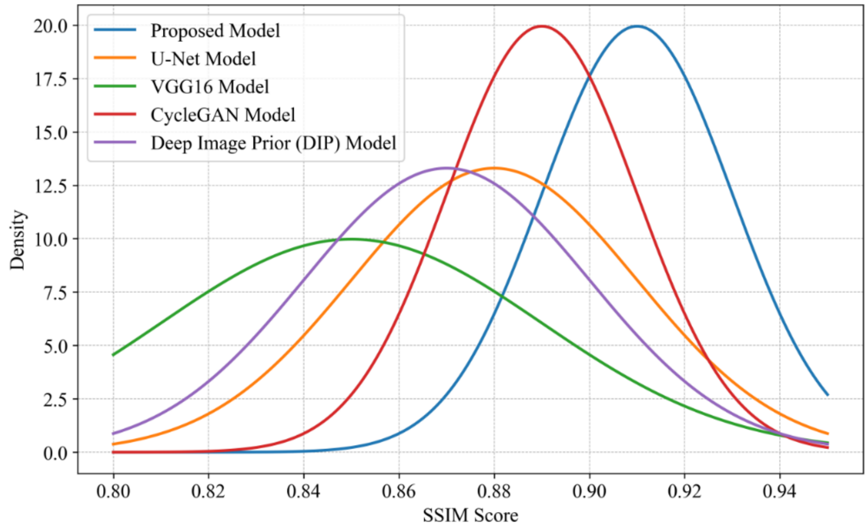

Figure 1. Comparison of image structural similarity (SSIM) scores of different models.

were selected for comparison including structural similarity index (SSIM) to measure structural fidelity, peak signal-to-noise ratio (PSNR) to assess image clarity and distortion, color fidelity score to evaluate color accuracy, and user rating derived from evaluations by both expert analysts and non-specialist viewers to reflect subjective quality. All models were applied to the same dataset, and results were recorded across all metrics to ensure a fair, quantitative evaluation of model performance in ecological design optimization.

Results and discussion

Comparison of SSIM scores of different image optimization models

The results of image optimization using different models showed that the proposed model performed the best in SSIM with a score of 0.91, which was due to its unique architecture that combined convolutional neural networks (CNN) with generative adversarial networks. CNN could efficiently extract the multi-level structural features of the image, while the generative adversarial network used an adversarial training mechanism to make the generated image approach the real image in structure. When processing images, the model could accurately capture and retain the contours, textures, and other structural details of various objects in the image. In a landscape image, the undulating contours of the mountains and the textures of the branches of the trees were well preserved and restored by the model, making the optimized image highly similar to the original image at the structural level. In contrast, the SSIM score of the VGG16 model was relatively low because the VGG16 network was mainly designed for image classification tasks. Its network structure focused on extracting features that were helpful for classification. When optimizing images, it paid insufficient attention to and retains the details of the image structure, resulting in poor performance of the optimized image in terms of structural similarity (Figure 1).

Comparison of PSNR of different models

The results showed that the proposed model performed outstandingly in terms of the PSNR indicator, reaching 32.5 dB, which was mainly due to the model's excellent ability in denoising and detail enhancement. The model could accurately identify and remove various types of noise through in-depth learning of image noise characteristics. Meanwhile, in the process of detail enhancement, it used advanced algorithms to restore and enhance the high-frequency details of the image. The model could effectively

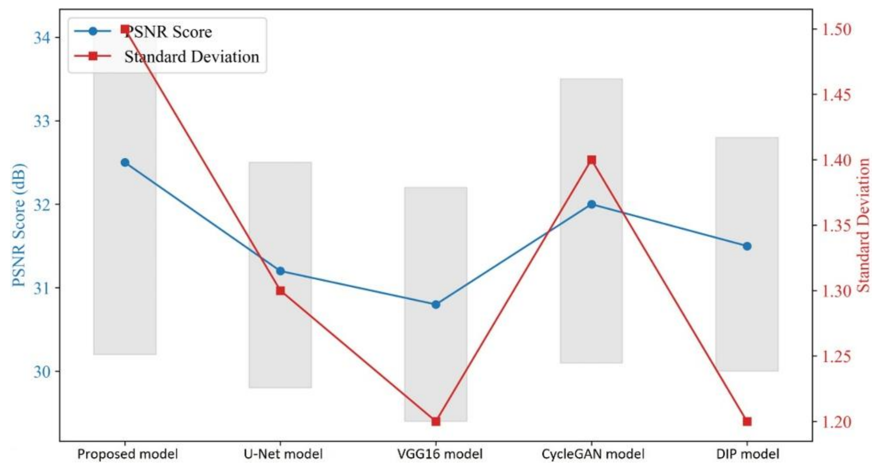

Figure 2. Peak signal-to-noise ratio (PSNR) comparison across different models.

remove noise such as scratches and stains on the old photo, while clearly restoring details such as facial expressions and clothing textures of the characters in the photo to improve image clarity and minimizing image distortion, thereby obtaining a higher PSNR value. The PSNR score of the CycleGAN model was 32.0 dB, which was close to the proposed model, indicating that CycleGAN also had certain strengths in image reconstruction and optimization, but there was still a gap in the sophistication of noise processing and detail optimization compared to the proposed model (Figure 2).

Comparison of color fidelity of different nodels

The proposed model performed the best in terms of color fidelity with a score of 0.95, while the other models achieved scores of 0.92, 0.89, 0.93, 0.91 for U-Net, VGG16, CycleGAN, DIP, respectively. During the training process, the model conducted in-depth learning of the color data of a large number of images and could accurately grasp the changing rules of different colors in different scenes and the relationship between colors. When optimizing the image, the model not only accurately restored the true colors of various objects in the image through fine adjustment of the color space, but also reasonably adjusted the brightness, saturation, and contrast of the color according to the overall atmosphere and lighting conditions of the image. The VGG16 model scored low in color fidelity because its network structure did not learn the color features deeply enough during the design, and color deviation or distortion was prone to occur during the image optimization process.

User rating comparison of different models

The proposed model received a high user score of 4.8 points, while the other models received scores of 4.6, 4.3, 4.7, 4.5 for U-Net, VGG16, CycleGAN, DIP, respectively, which showed that the optimized images were well-liked by users in terms of visual effects. During the optimization process, the model fully considered the user's visual needs for images, not only improving the quality of the images, but also focusing on maintaining the naturalness and beauty of the images. Whether in terms of image clarity, color coordination or overall visual comfort, it could meet user expectations. The user score of the VGG16 model was relatively low, which might be due to the fact that it failed to fully balance the relationship between image quality improvement and user visual experience during the image optimization process, resulting in the optimized images failing to meet user needs in some aspects.

Image clarity comparison of different models

The proposed model performed well in image clarity with a score of 0.92, while the other models' scores were 0.89, 0.85, 0.91, 0.88 for U-Net, VGG16, CycleGAN, DIP, respectively, which

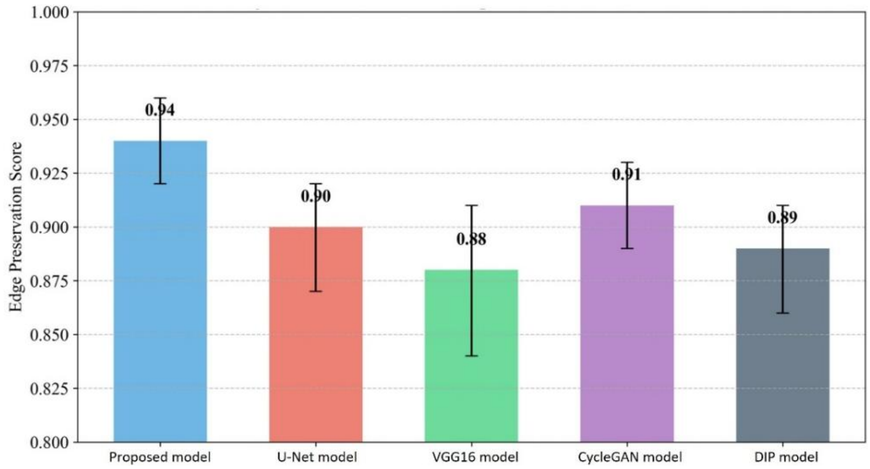

Figure 3. Comparison of edge preservation effects of different models.

was attributed to the model's advanced feature extraction and enhancement techniques. In the feature extraction stage, the model was able to deeply mine the subtle details in the image including the texture, edges, and other features of the object. In the subsequent enhancement process, these details were effectively enhanced through a unique algorithm, while avoiding image distortion caused by over-enhancement. The U-Net model also demonstrated well performance in image clarity, but compared with the proposed model, its ability to mine and enhance image details was relatively weak, so the clarity score was slightly lower.

Comparison of image denoising effects

The proposed model had outstanding performance in denoising with a score of 0.93, while the other models had denoising scores of 0.88, 0.85, 0.90, 0.89 for U-Net, VGG16, CycleGAN, DIP, respectively. The proposed model conducted in-depth learning and analysis of noise features by building a special denoising module. When processing images, it could accurately identify and remove various types of noise such as Gaussian noise, salt and pepper noise, *etc*., while retaining the original details of the image to the greatest extent. Its denoising algorithm could accurately separate noise and image signals in complex noise environments, avoiding damage to the useful information of the image during the denoising process. Although the U-Net model also demonstrated certain capabilities in denoising, its denoising algorithm had relatively weak adaptability and accuracy when facing complex noise, resulting in a lower denoising effect score than the proposed model.

Comparison of edge preservation effects

The proposed model performed well in edge preservation with a score of 0.94. The model used a special edge detection and protection mechanism in the image optimization process. In the feature extraction stage, it accurately captured the edge features of the object, and in the subsequent enhancement, denoising and other processing processes, the edge was targetedly protected by the algorithm to avoid blurring or distortion of the edge. The VGG16 model performed relatively poorly in edge preservation because its network structure was not designed to process edge information finely enough, which easily led to the loss of edge details during image optimization (Figure 3).

Comparison of color balance in different models

The proposed model performed the best in color balance with a score of 0.96, while the other models showed scores of 0.92, 0.89, 0.93, 0.91 for U-Net, VGG16, CycleGan, DIP, respectively. The proposed model could effectively balance the proportion and intensity of different colors in

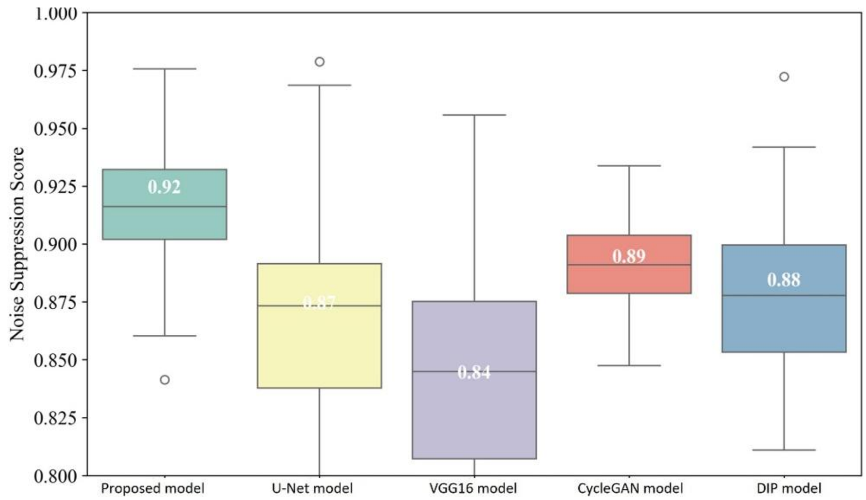

Figure 4. Noise suppression ability comparison.

the image through global analysis of image colors and local adjustment strategies. When processing images, the model considered the overall hue of the image, lighting conditions, and color distribution of various objects to optimize the color. The U-Net model performed well in color balance, but compared with the proposed model, there was a certain gap in the accuracy of subtle adjustments to colors and overall control.

Comparison of noise suppression of different models

The proposed model performed well in noise suppression with a score of 0.92. The proposed model built a multi-level noise suppression system that could effectively suppress noise of different types and intensities. The various modules in the system worked together, and there was corresponding algorithm support from noise feature recognition, separation to removal. When processing images, the model could quickly and accurately locate the noise position and use appropriate methods to remove the noise while keeping the details and structure of the image intact. The VGG16 model was relatively weak in noise suppression ability, mainly because its network structure focused mainly on image feature extraction, and the targeted design of noise suppression was insufficient (Figure 4).

Comparison of the comprehensive image quality scores of different models

The proposed model led to a comprehensive image quality score of 9.5 points. The comprehensive score comprehensively considered multiple key indicators including image clarity, structural similarity, color fidelity, denoising effect, edge preservation, and color balance, and fully reflected the comprehensive strength of the model in image optimization. The proposed model performed well in each optimization link. Its unique architecture and algorithm could work together to comprehensively optimize the image from multiple dimensions. The comprehensive score of the CycleGAN model was relatively high at 9.2 points, indicating that it also had strong capabilities in many aspects of image optimization, but there was still a certain gap compared with the proposed model in terms of some detail processing and comprehensive performance balance. The comprehensive score of the VGG16 model was relatively low, mainly because its performance in multiple key indicators was not as good as other models, resulting in limited overall comprehensive capabilities (Figure 5).

Conclusion

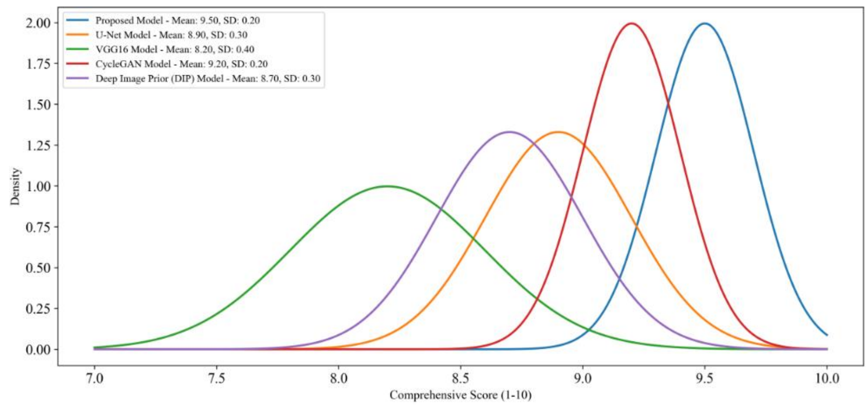

Figure 5. Image quality scores of different models.

The proposed model of this research represented a practical and theoretically grounded innovation in ecological landscape visualization. The results demonstrated that the proposed model outperformed several benchmark models across multiple key indicators, validating its effectiveness in the visual communication design of ecological garden landscapes. By integrating ecological semantics with technical image processing frameworks, it not only improved visual aesthetics but also strengthened the communication of ecological values. The research contributed a scalable, high-accuracy method that could support ecological education, enhance public environmental awareness, and promote the sustainable transformation of urban green space design. Its empirical performance and ecological relevance suggested strong potential for wider adoption in smart urban development and landscape architecture practice.

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