RESEARCH ARTICLE

# Urban Park environmental art design and ecological benefit analysis combined with deep learning

Shan Wang*

College of Arts, Jiaozuo University, Jiaozuo, Henan, China.

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**With the acceleration of urbanization, the planning and design of urban parks have a significant impact on urban ecosystems and the quality of residents' life. Traditional Park design methods lack the systematicness and innovation of environmental art and is difficult to fully realize ecological benefits. This research constructed an urban park environmental art design and ecological benefit analysis model combined with deep learning to improve the ecological benefits of parks. Convolutional neural network (CNN) was used to extract spatial features, while deep neural network (DNN) was used to predict ecological benefits, and multi-objective optimization algorithm was used to optimize the scheme. The study selected various types of urban park design images as data sets. The results showed that the average accuracy of the model in spatial feature extraction was more than 92%. After optimization, the comprehensive ecological benefit score of each park design scheme increased by 8.1 - 9.3%, and various ecological indicators including biodiversity and carbon absorption capacity were significantly improved. The model effectively improved the ecological benefits and landscape quality of urban parks and provided a scientific basis and innovative methods for the sustainable design of urban parks.**

**Keywords:** urban park; deep learning; environmental art design; ecological benefit; optimization model.

***Corresponding author:** Shan Wang, College of Arts, Jiaozuo University, Jiaozuo 454000, Henan, China. Email: wangshan188@outlook.com.

## Introduction

Urban parks, as a critical component of modern urban ecosystems, not only serve as essential public spaces for recreation and social interaction but also play a pivotal role in improving environmental quality and promoting sustainable urban development [1]. With the rapid pace of urbanization, cities increasingly face ecological degradation, microclimatic imbalances, and declining biodiversity. Urban parks are thus expected to provide multifunctional ecological services such as carbon sequestration, habitat support, air purification, and urban heat island mitigation [2]. In recent years, the discipline of environmental art design in urban parks has received growing attention for its potential to integrate aesthetic value with ecological functionality. Studies indicate that, through thoughtful spatial planning including native plant selection, green space patterning, and water body distribution, parks can significantly contribute to biodiversity enhancement and urban ecological resilience [3, 4]. However, most traditional design approaches remain limited to visual aesthetics and intuitive planning, often lacking the systematic frameworks and scientific metrics necessary for comprehensive ecological evaluation and optimization [5, 6]. Additionally, the synergistic relationship between ecological processes and design elements such as cultural symbolism, social interaction, and spatial dynamics remains underexplored in current methodologies [7, 8].

Deep learning has emerged as a transformative tool in urban planning and environmental modeling due to its strong capacity for data-driven analysis, spatial pattern recognition, and predictive modeling [9, 10]. Recent applications in urban studies include landscape classification, vegetation analysis, and ecological pattern prediction using convolutional neural networks (CNNs), generative adversarial networks (GANs), and deep neural networks (DNNs) [11, 12]. While these technologies have demonstrated potential in extracting complex features from park design images and forecasting ecological metrics, their integration into comprehensive park design frameworks remains in its infancy [13]. Furthermore, existing deep learning models are often confined to narrow tasks such as visual analysis or design image generation without forming a holistic solution that links design elements to tangible ecological benefits [14, 15]. The current research gap lies in the absence of an interdisciplinary, data-informed model that not only quantifies ecological benefits but also guides real-time decision-making in park design. There is an urgent need for methods that can evaluate multiple ecological indicators such as carbon absorption, biodiversity, air quality improvement dynamically and suggest optimized design alternatives accordingly [16, 17]. Moreover, the limited availability and heterogeneity of ecological data across urban contexts pose challenges for model generalization and scalability [18-20].

To address these limitations, the present study aimed to construct a comprehensive environmental art design and ecological benefit assessment model for urban parks by integrating deep learning techniques. Specifically, the research proposed a three-module system that included spatial feature extraction using CNNs, ecological benefit prediction using DNNs, and design scheme optimization using multi-objective algorithms. This framework allowed for the intelligent interpretation of urban park design images, prediction of associated ecological outcomes, and iterative refinement of design schemes to maximize ecological value. This research bridged the gap between environmental art and artificial intelligence by establishing a data-driven paradigm for ecological design and practically offered a robust decision-support system for urban planners, landscape architects, and policymakers to quantitatively evaluate and optimize park layouts. By enhancing biodiversity, mitigating climate effects, and elevating public satisfaction, this model provided a scalable strategy for fostering resilient and ecologically functional urban green spaces [21-23].

## Materials and methods

### Model framework and design concept

The proposed model combined deep learning with ecological benefit evaluation in urban park environmental art design to form a systematic framework. The core idea of the model was to combine the deep neural network (DNN) and the convolutional neural network (CNN) based on the spatial design image data of urban parks, and comprehensively considered the spatial characteristics, ecological factors, and their interrelationships. The model framework consisted of spatial feature extraction module, ecological benefit prediction module, and comprehensive evaluation and optimization module. Each module processed the input data through efficient calculation and provided an optimized design solution in the final stage. The spatial feature extraction module was responsible for extracting spatial layout information from the design image, which was crucial for ecological benefit prediction. The ecological benefit prediction module predicted the ecological benefit scores of different design schemes based on spatial features through a DNN model. The comprehensive evaluation and optimization module used an optimization algorithm to evaluate different design schemes based on the results of the first two modules and ultimately output the optimal design scheme. During the overall design process, the flexibility and scalability of the model were emphasized, so that different urban park design schemes could be effectively evaluated and optimized within this framework.

**Spatial feature extraction module**

The spatial feature extraction module extracted features that could represent the spatial layout, green space distribution, building layout, *etc*. from the design images of urban parks. CNN was chosen to automatically identify spatial features such as the shape, position, and size of objects when processing image data. Assuming that the input design image was $I$, whose size was $m \times n$, the value of each pixel was $I_{ij}$. The convolution operation used a convolution kernel (filter) to perform sliding window calculations on the image to extract features of the local area. Assuming that the convolution kernel was $W$, the bias term was $b$, then the convolution operation was calculated as below.

$$F_{ij} = (IW)_{ij} + b = \sum_{p=-k}^{k} \sum_{q=-k}^{q} I_{i+p,j+q} W_{p,q} + b \tag{1}$$

where $F_{ij}$ was the element of the feature map obtained after convolution. $k$ was the half-width of the convolution kernel. The convolution operation could capture local features in the image such as buildings, green spaces, roads, *etc*., which played an important role in the subsequent ecological benefit prediction. The convolution feature map was down sampled through the pooling layer. The pooling operation could effectively reduce the amount of calculation while retaining the main information of the feature. Assuming that the maximum pooling was used, the pooling operation was calculated as follows.

$$F_p = \max\{F_{ij} \mid i \in [p, p+2], j \in [q, q+2]\} \tag{2}$$

The pooling operation reduced the size of the feature map by selecting the maximum value in the local area, thereby improving computational efficiency. After flattening, a one-dimensional spatial feature vector $F_s$ that contained the spatial layout information about the urban park design in the image was obtained.

$$F_s = \text{Flatten}(F_p) \tag{3}$$

This spatial feature vector $F_s$ served as the input of the subsequent ecological benefit prediction module to provide the model with spatial information of park design.

**Ecological benefit prediction and optimization module**

The ecological benefit prediction module predicted the ecological benefits of different urban park design schemes based on spatial feature vectors $F_s$. Ecological benefit evaluation indicators usually included biodiversity, air quality improvement, carbon absorption capacity, *etc*., which were modeled through neural network regression. DNN was used to predict these indicators. The network input was the spatial feature vector $F_s$ and the output was multiple ecological benefit indicators $E = (E_1, E_2, \ldots, E_n)$, where $E_n$ indicated *n* ecological indicators. DNN used multiple fully connected layers to achieve nonlinear mapping from input to output. The output of the layer $H_l$ was calculated as below.

$$H_l = \sigma(W_l H_{l-1} + b_l) \tag{4}$$

where $W_l$ and $b_l$ were the weight matrix and bias of the first layer $l$. $\sigma$ was the activation function such as ReLU or Sigmoid. $H_{l-1}$ was the output of the previous layer. The ecological benefit score of the output layer was $E$. The output of the last layer $H_L$ was calculated below.

$$E = W_L H_L + b_L \tag{5}$$

To optimize the performance of the model, the mean square error (MSE) loss function was used to measure the difference between predicted and true values and was calculated as follows.

$$L = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{j=1}^{n}(E_{ij}^{\text{pred}} - E_{ij}^{\text{true}})^2\right) \quad (6)$$

where $E_{ij}^{\text{pred}}$ and $E_{ij}^{\text{true}}$ were the predicted and true values of the eco-benefit sub-scores of samples $i$ and $j$, respectively. $N$ was the number of samples. By minimizing this loss function, the parameters of the neural network could be optimized to make the prediction results more accurate. During the training process, the backpropagation algorithm was used to calculate the gradient of the loss function for the weights of each layer, while optimization algorithms such as Adam or SGD were used to update the parameters to optimize the performance of the model. After the completion of eco-benefit evaluation, different design schemes were optimized through multi-objective optimization algorithms such as genetic algorithms (GA) or particle swarm optimization (PSO) and calculated below.

$$E_{\text{total}} = \sum_{i=1}^{n} w_i E_i \quad (7)$$

where $E_{\text{total}}$ was the comprehensive eco-benefit score. $w_i$ was the weight of the $i$. Optimization process adjusted the design parameters through the optimal design solution that could maximize the comprehensive ecological benefit score as follows.

$$\mathbf{S}^\wedge = \arg\max_{\mathbf{S}} E_{\text{total}}(\mathbf{S}) \quad (8)$$

where $\mathbf{S}^\wedge$ was the optimal design solution. $\boldsymbol{S}$ was the set of all candidate solutions. Through the iterative process of the optimization algorithm, the park design solution with the best ecological benefit was finally obtained.

**Experimental design**

The research systematically evaluated the proposed model through multiple actual urban park design cases, mainly examining its ability in spatial feature extraction, ecological benefit prediction, and optimization using multiple links of testing to ensure that the model could accurately predict and optimize ecological benefits in complex park design scenarios. To ensure the representativeness and scientificity, several urban park design images with different characteristics were selected from ArchDaily (https://www.archdaily.com/), Landscape Performance Series (https://www.landscape performance.org/), and local government planning portals including the Shanghai Green Space Administration (Shanghai, China) and Shenzhen Urban Planning and Design Institute (Shenzhen, Guangdong, China), which included urban, suburban, and ecological parks covering different design styles and geographical environments between 2018 and 2023. Each design image was at least 1,920 × 1,080 pixels and some architectural renderings reaching up to 3,840 × 2,160 pixels, which showed the spatial layout, green space distribution, and building location of the design in detail. The dataset consisted of 150 urban park design images including 30 ecological parks, 30 wetland parks, 30 multifunctional urban parks, 30 community parks, 30 and urban green corridors. The ecological benefits of each design image were manually annotated by professional ecological planners and environmental engineers and included indicators of biodiversity indices, air purification potential, carbon sequestration estimates, and water management parameters. The ecological benefit scores were assigned based on a composite indicator system adapted from the "Urban Green Space Ecological Evaluation Guidelines" issued by China's Ministry of Ecology and Environment supplemented by reference to the i-Tree Eco model developed by the U.S. Forest Service. An independent test dataset was used to evaluate the proposed model through the prediction accuracy using MSE, mean absolute error (MAE), and $R^2$ value as core indicators, the changes of eco-efficiency scores before and after optimization, and the effectiveness in practical applications. The operational efficiency of the proposed model was also considered, especially the computing time when processing large-scale datasets. By measuring the time required for training, prediction, and optimization, the feasibility of the proposed model in practical applications was evaluated. The proposed model was validated and tested by comparing with existing traditional design optimization methods to examine the accuracy and flexibility of the models in dealing with complex design tasks. The different ecological benefit scores of different park design schemes were quantified and further examined for the contribution of the optimization module to the improvement of ecological benefits. The total dataset of 150 images was split into three parts as 90 images (60%) for training, 30 images (20%) for validation, and 30 images (20%) for testing. Stratified sampling was applied to ensure each design category was proportionally represented in all three subsets.

## Results and discussion

### Spatial feature extraction accuracy

The performance of different design image samples in spatial feature extraction showed that, the model demonstrated stable time and accuracy with an average extraction accuracy of more than 92% and a high NMI value (Figure 1), indicating that the model could effectively extract spatial features and had good information preservation capabilities, which might be due to the advanced algorithm used in the model to accurately capture the key features in the image and suitable for feature analysis of various park design drawings, providing a solid data foundation for subsequent design evaluation and optimization.

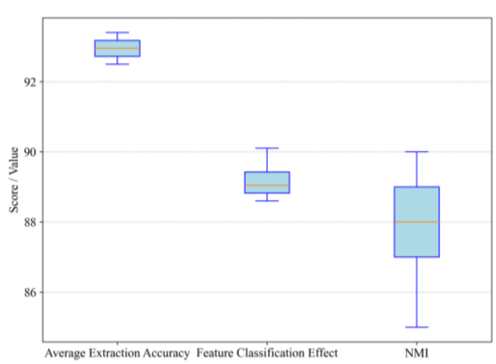


**Figure 1.** Effect of spatial feature extraction.

### Ecological benefit prediction and optimization outcomes

The ecological benefit prediction results of different park design schemes before optimization demonstrated that the initial ecological status of each scheme could be intuitively understood through various scores. The model conducted a multi-dimensional evaluation of the park design scheme based on the relevant principles and parameters of the ecosystem, providing a clear direction for subsequent optimization. The results reflected the systematic and scientific nature of the model in comprehensively evaluating the ecological benefits of the park, which could help designers quickly grasp the ecological shortcomings of the scheme. The ecological benefit scores of each park design scheme after optimization showed that, compared with before optimization, the scores of each item had been significantly improved, indicating that the optimization module of the model could accurately improve the ecological benefit indicators (Figure 2). The model effectively improved the ecological benefits by adjusting the ecological layout, vegetation configuration, and other factors of the park, fully proving the effectiveness and practicality of the model in improving the ecological quality of the park, and providing strong support for creating a park with greater ecological value. The changes in carbon absorption capacity before and after optimization of different park design schemes showed that the model enhanced the photosynthesis of the park by optimizing the vegetation types and distribution, thereby effectively improving the carbon absorption capacity. The score of the urban ecological park design increased from 0.80 to 0.88 after optimization with an increase of 10%, while the air quality was improved by 5%, and carbon emissions was reduced by 3% (Table 1). The results reflected the significant advantages of the model in responding to climate change and improving the carbon sink function of the park, indicating that the model was applicable to various park designs to enhance their positive impact on the environment.

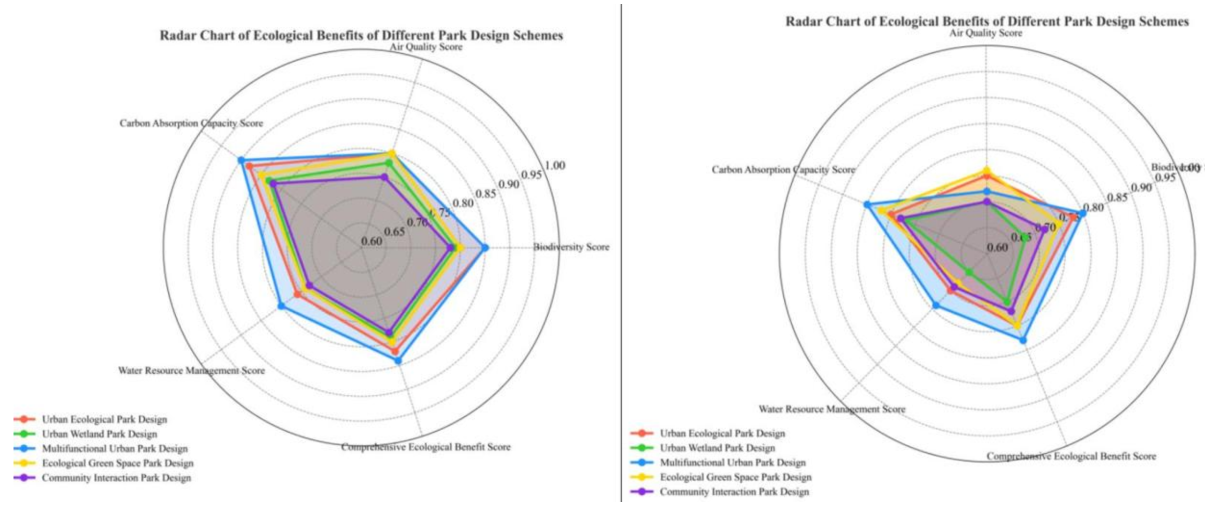


**Figure 2.** Ecological benefit prediction results.

**Table 1.** Carbon absorption capacity evaluation.

| Design | Carbon absorption capacity score | | Increase | Improved air quality | Carbon emissions reduction |
|---|---|---|---|---|---|
| | Before optimization | After optimization | | | |
| Urban ecological park | 0.80 | 0.88 | 10% | 5% | 3% |
| Urban wetland park | 0.77 | 0.83 | 8% | 4% | 2% |
| Multifunctional urban park | 0.85 | 0.90 | 6% | 3% | 4% |
| Ecological green park | 0.82 | 0.85 | 3% | 2% | 1% |
| Community interactive park | 0.78 | 0.82 | 5% | 2% | 2% |

**Table 2.** Evaluation of water resources management effectiveness.

| Design | Water resource management score | | Increase | Water saving effect | Improved water quality |
|---|---|---|---|---|---|
| | Before optimization | After optimization | | | |
| Urban ecological park | 0.75 | 0.82 | 9% | 4% | 3% |
| Urban wetland park | 0.74 | 0.80 | 8% | 5% | 3% |
| Multifunctional urban park | 0.76 | 0.83 | 7% | 4% | 2% |
| Ecological green park | 0.70 | 0.75 | 7% | 3% | 2% |
| Community interactive park | 0.72 | 0.78 | 6% | 2% | 2% |

**Carbon absorption and water management**

The optimization results of park design in water resource management showed that the model rationally planed the water system circulation and rainwater collection and utilization system according to the park's terrain and water demand and improved the level of water resource management. The score of the urban ecological park design increased from 0.75 to 0.82 after optimization, while the water saving effect reached 4%, and the water quality improved by 3% (Table 2). The results showed that the model had outstanding advantages in improving the efficiency of park water resource utilization and protecting water resources and was suitable for different types of parks to achieve sustainable use of water resources.

**Biodiversity and heat island mitigation**

The optimization results of different park design schemes in terms of biodiversity demonstrated that, based on the principle of ecosystem, the

**Table 3.** Biodiversity optimization assessment.

| Design | Biodiversity score | | Increase | Species diversity | Ecological stability |
|---|---|---|---|---|---|
| | Before optimization | After optimization | | | |
| Urban ecological park | 0.78 | 0.85 | 9% | 5% | 4% |
| Urban wetland park | 0.70 | 0.76 | 8% | 4% | 3% |
| Multifunctional urban park | 0.80 | 0.88 | 10% | 6% | 5% |
| Ecological green park | 0.75 | 0.80 | 7% | 3% | 4% |
| Community interactive park | 0.72 | 0.78 | 8% | 4% | 3% |

**Table 4.** Comprehensive ecological benefit evaluation.

| Design | Comprehensive ecological benefit score | | Increase | Ecological Benefit Rating | Ecosystem service value |
|---|---|---|---|---|---|
| | Before optimization | After optimization | | | |
| Urban ecological park | 0.75 | 0.82 | 9.3% | 4% | 6% |
| Urban wetland park | 0.70 | 0.76 | 8.6% | 3% | 5% |
| Multifunctional urban park | 0.78 | 0.85 | 9.0% | 5% | 7% |
| Ecological green park | 0.72 | 0.78 | 8.3% | 3% | 5% |
| Community interactive park | 0.74 | 0.80 | 8.1% | 4% | 5% |

model effectively improved biodiversity by increasing plant species and building diverse ecological habitats. Taking the multifunctional urban park design as an example, the biodiversity score after optimization increased from 0.80 to 0.88, while the species diversity increased by 6%, and the ecological stability increased by 5% (Table 3). The results showed that the model had a strong advantage in enhancing the stability and biodiversity of the park ecosystem and was suitable for all types of park designs to promote ecological health development. The changes in the comprehensive ecological benefits of all design schemes before and after optimization showed that the optimized schemes had significantly improved the ecological benefit scores and ecosystem service values, further proving the effectiveness of the model optimization module (Table 4). Starting from the perspective of the overall ecosystem, the model comprehensively considered various ecological factors, comprehensively optimized the park design, improved the comprehensive ecological value of the park, and provided a scientific method and powerful tool for urban ecological construction.

**Resident satisfaction and noise reduction**

The mitigation effect of different design schemes on the urban heat island effect showed that the model increased the vegetation coverage rate and adjusted the air humidity by optimizing the vegetation layout and water body settings of the park, thereby effectively reduced the urban heat island effect. After the optimization of the urban ecological park design, the heat island effect score increased from 0.72 to 0.80 with an increase of 11.1%. The cooling effect was 4%, the improvement of air humidity was 5%, and the vegetation coverage increased by 6% (Table 5). The results showed that the model had significant advantages in mitigating the urban heat island effect and was suitable for all types of park designs to provide an effective way to improve the urban microclimate. The results of residents' satisfaction evaluation before and after optimization of different design schemes showed that the model fully considered the residents' use needs, optimized the layout of public facilities, and improved safety and green space accessibility, thereby improving residents' satisfaction. In urban ecological parks, the residents' satisfaction score increased from 0.76 to 0.85 with an increase of 11.8% after optimization, while the convenience of public facilities increased by 6%, safety increased by 4%, and green space accessibility increased by 5%

**Table 5.** Evaluation of heat island effect mitigation effect.

| Design | Heat island effect score | | Increase | Cooling effect | Improved air humidity | Vegetation coverage |
|---|---|---|---|---|---|---|
| | Before optimization | After optimization | | | | |
| Urban ecological park | 0.72 | 0.80 | 11.1% | 4% | 5% | 6% |
| Urban wetland park | 0.70 | 0.78 | 11.4% | 3% | 4% | 5% |
| Multifunctional urban park | 0.75 | 0.82 | 9.3% | 5% | 6% | 7% |
| Ecological green park | 0.68 | 0.75 | 10.3% | 3% | 4% | 5% |
| Community interactive park | 0.71 | 0.77 | 8.5% | 3% | 4% | 6% |

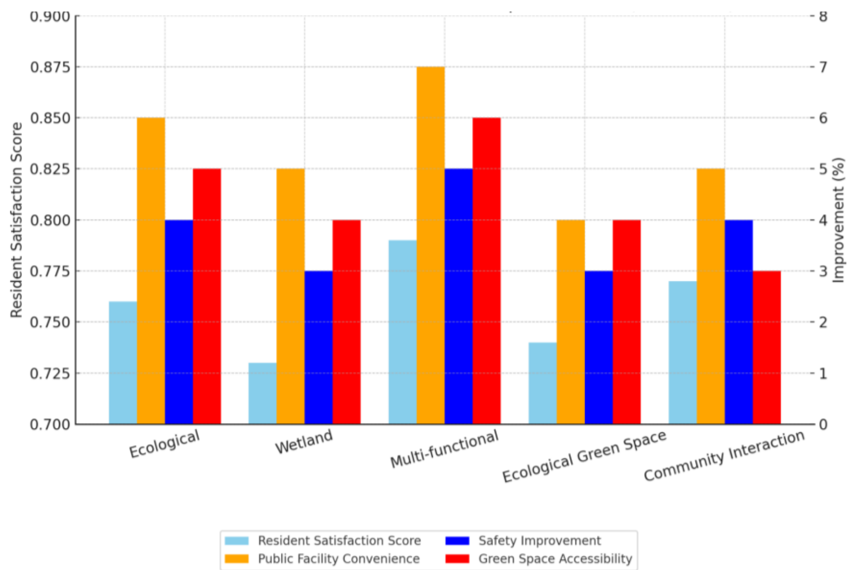


**Figure 3.** Residents' satisfaction evaluation.

(Figure 3). The results suggested that the model had significant advantages in meeting residents' needs for park use and was suitable for various park designs to improve the use value and social benefits of parks.

**Landscape aesthetics and model efficiency**

The optimization results of the park design in reducing noise pollution demonstrated that the model effectively reduced noise pollution by scientifically planning the park layout, reasonably setting up sound insulation facilities, and cleverly utilizing the noise reduction function of vegetation. In the design of urban ecological parks, the noise pollution score increased from 0.70 to 0.80 after optimization, which was a reduction of 14.3%. The effectiveness of noise reduction measures reached 70%, and the contribution of vegetation noise reduction was 30% (Table 6). The results might be that the model set up sound insulation barriers at key locations according to the distribution of noise sources around the park and planted multi-level noise reduction vegetation. The results proved that the model had outstanding advantages in solving urban noise pollution problems and was suitable for various park designs to create a quiet and comfortable leisure environment for residents. The optimization effect of the park design scheme in terms of landscape aesthetics showed that, based on aesthetic principles and public aesthetic needs, the model optimized the park landscape in all aspects. Taking the urban ecological park design as an example, the landscape aesthetics score after optimization increased from 0.75 to 0.85 with an increase of 13.3%. Among them, the landscape coordination increased by 40%, while the characteristic

**Table 6.** Evaluation of noise pollution reduction effect.

| Design | Noise pollution score | | Reduction | Effectiveness of noise reduction measures | Contribution of vegetation noise reduction |
|---|---|---|---|---|---|
| | Before optimization | After optimization | | | |
| Urban ecological park | 0.70 | 0.80 | 14.3% | 70% | 30% |
| Urban wetland park | 0.68 | 0.78 | 14.7% | 65% | 35% |
| Multifunctional urban park | 0.72 | 0.82 | 13.9% | 75% | 25% |
| Ecological green park | 0.66 | 0.76 | 15.2% | 60% | 40% |
| Community interactive park | 0.69 | 0.79 | 14.5% | 70% | 30% |

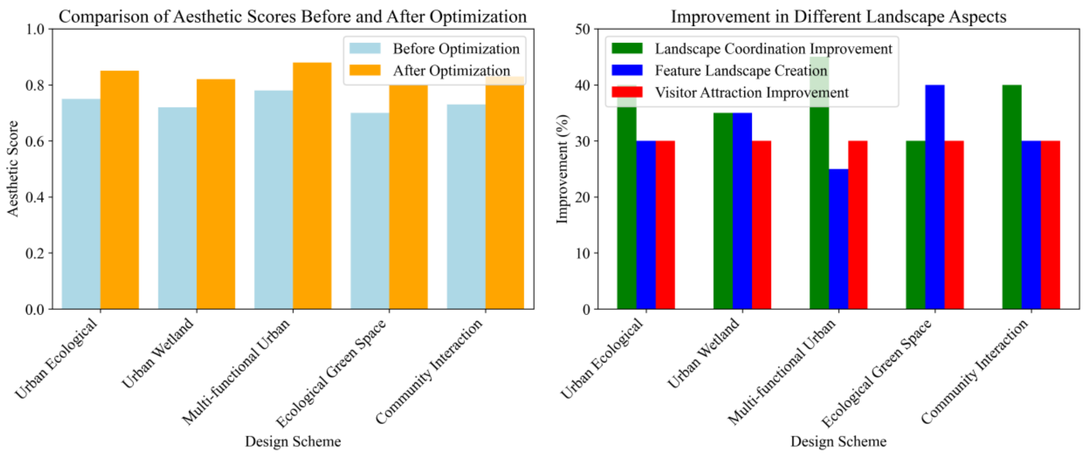


**Figure 4.** Landscape aesthetics improvement assessment.

landscape creation accounted for 30%, and the tourist attraction increased by 30% (Figure 4). The results were because the model focused on the matching and integration of landscape elements, created unique landscape nodes, and satisfied people's pursuit of beauty, which showed that the model had significant advantages in improving the aesthetic value of park landscapes and enhancing tourist attraction and was suitable for all types of park designs and improved the overall quality of parks.

## Conclusion

This research found that the proposed model based on deep learning could effectively improve the ecological benefits of urban parks to achieve ecological design. The results showed that the model performed well in spatial feature extraction, ecological benefit prediction, and scheme optimization. Compared with the previous research, the results of this study further deepened the application of deep learning in the field of urban park design, supplemented the shortcomings of traditional research in using emerging technologies to improve ecological benefits, and supported the theory of improving the ecological function of urban parks through technical means. This study provided new insights for the sustainable design of urban parks and had important practical significance in urban ecological construction and green space planning. Through the collaborative work of three key modules including spatial feature extraction, ecological benefit prediction, and optimization, the convolutional neural network and deep neural network were used to analyze and process the urban park design image data. After optimization, the comprehensive ecological benefit scores of each park design scheme were significantly improved. There were significant improvements in biodiversity, carbon absorption capacity, water resource management, which effectively improved the ecological value of the park and residents' satisfaction. However, this study also had certain limitations, which included that the data quality and quantity were limited that might affect the universality and accuracy of the model because data bias could lead to instability in model training. Future research may expand the sample size and improve data quality by collecting data through multiple channels and improving data processing methods, while exploring more complex ecological models to deeply understand the interaction between ecosystems. In addition, future research may focus on in-depth study of the internal mechanism of the ecosystem and further optimize the model for more accurately applications to urban park design and promote the sustainable development of the urban ecological environment.

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