Trends in Social Sciences and Humanities Research
Print ISSN: 2959-992X
Online ISSN: 2959-9938
DOI: https://doi.org/10.61784/tsshr3212

SATISFACTION PREDICTION OF URBAN WATERFRONT SPACE LANDSCAPES USING CNNS

XiaoYao Liu
Shandong Normal University Academy of Fine Arts, Shandong Normal University, Jinan 250014, Shandong, China.

Abstract: Urban waterfront spaces, as core carriers integrating the natural and human environment, possess both ecological regulation and public activity functions. Their quality directly impacts user satisfaction. However, current construction suffers from problems such as incoordination with the urban environment and insufficient ecological protection. Traditional satisfaction evaluation methods based on questionnaires and expert ratings are highly subjective and inefficient. This study aims to construct an efficient and accurate prediction model for urban waterfront space landscape satisfaction, providing technical support for spatial planning optimization. Through a multi-source data fusion strategy, landscape images, environmental parameters, user questionnaires, and behavioral data were collected to construct a comprehensive dataset. A prediction model was designed based on a convolutional neural network (CNN), optimizing key parameters such as kernel size and learning rate. Performance was compared with support vector machine (SVM) and random forest (RF) models. The results show that the constructed CNN model achieves a prediction accuracy of 87.3%, a coefficient of determination R^2 of 0.891, and a root mean square error (RMSE) of 0.324, significantly outperforming traditional machine learning models. This study introduces deep learning technology into the field of urban waterfront space evaluation, improving the efficiency and objectivity of satisfaction assessment and providing new technical paths and decision-making basis for the sustainable development of urban waterfront spaces and urban renewal.
Keywords: Waterfront space; Satisfaction prediction; Convolutional neural network; Urban planning; Ecological environment

1 INTRODUCTION

1.1 Research Background and Significance

Urban waterfront space, as a specific spatial area in a city, refers to land or buildings adjacent to rivers, lakes, and seas, consisting of three parts: water area, waterfront, and land area[1]. This type of space occupies an important position in urban development, serving not only as an important carrier for the integration of natural and human environments in the city[2], but also as a material carrier for urban ecological environment conservation and public activities[3]. With the accelerated pace of urbanization, waterfront space has gradually become a window showcasing the unique charm of a city and an important development indicator for measuring urban acceptance.
Under the guidance of the concept of ecological civilization construction, the planning and construction of urban waterfront space faces new development directions. Waterfront space can regulate microclimate, improve environmental quality, provide special activity spaces for urban residents, and meet people's needs for the natural environment[4]. As the most vibrant and welcoming human-water interaction space in the city[5], waterfront areas connect the city's aquatic and terrestrial ecosystems, forming the richest ecological landscape area in the city[6]. However, the construction of urban waterfront spaces still faces many problems, such as a lack of coordination with the urban environment and neglect of ecological protection[7]. These problems directly affect user satisfaction and spatial quality.
Satisfaction evaluation of urban waterfront public spaces can fully reflect the advantages and disadvantages of the region's ecological environment, infrastructure construction, public security management and services, and is an important foundation for improving space quality, promoting urban renewal, and assisting planning and design. Traditional satisfaction evaluation methods mostly rely on questionnaires and expert ratings, which have limitations such as strong subjectivity and low efficiency. Convolutional neural networks, as an important technology in the field of deep learning, have shown powerful capabilities in image recognition and pattern classification. Applying CNN technology to the study on satisfaction prediction of urban waterfront space landscapes can quickly and accurately assess user satisfaction through intelligent analysis of waterfront space landscape images, providing a scientific basis for planning and design. This not only helps to promote the sustainable development of urban waterfront spaces, but also provides a new technical path and research perspective for improving space quality in the context of urban renewal.

1.2 Review of Relevant Research

Urban waterfront spaces, as important venues for urban image and citizens' leisure and entertainment, occupy an irreplaceable position in urban development. Waterfront spaces not only provide cities with multiple functions such as ecology, landscape, leisure, and culture[8], but also effectively enhance citizens' physical and mental health and social cohesion, while also contributing to improving the city's landscape image and transportation convenience. From a psychological perspective, people generally have a affinity for water; the process of getting close to, playing in, and observing water can bring people physical and mental pleasure. Waterfront landscapes, situated at the junction of water and land, serve functions such as ecological protection, wetland conservation, and climate improvement, while also providing recreational, sightseeing, and water-related activities[9].

In recent years, academic research on urban waterfront spaces has remained consistently strong, with research perspectives gradually shifting from single-dimensional morphological design to multi-dimensional comprehensive evaluation[10]. Satisfaction evaluation, as an important means of reflecting the advantages and disadvantages of various aspects such as the ecological environment, infrastructure construction, public security management, and services within a region, is a crucial foundation for improving spatial quality, promoting urban renewal, and assisting planning and design. Current quantitative research on urban waterfront public spaces mainly focuses on spatial creation and vitality evaluation, but lacks in-depth evaluation research on post-use space satisfaction. Creating a good waterfront urban space based on the wandering experience and perception of the people themselves plays a positive role in balancing the relationship between waterfront spaces and public demands.

In the practice of waterfront landscape design, the main problems include a lack of coordination with the urban environment. In the design process, only the effect and iconicity of individual buildings are often considered, while the coordination with the surrounding environment, ecology and landscape is ignored. Early urban development and construction led to a disordered urban interface along the waterfront, squeezing public spaces and impacting the public's experience. Optimizing the ecological vitality and ecological nature of waterfront public spaces, establishing natural rivers while activating and optimizing the interaction between people and flora and fauna in the waterfront area and its surrounding environment, and enhancing urban vitality with minimal intervention and behavioral means, truly achieving symbiosis between humans and nature[11]. These studies provide a theoretical foundation and practical reference for constructing a CNN-based urban waterfront landscape satisfaction prediction model in this paper.

2 RESEARCH METHODS AND DESIGN

2.1 Data Collection Methods

The foundation of urban waterfront landscape satisfaction prediction research lies in obtaining high-quality, multi-dimensional data samples. This study adopts a multi-source data fusion strategy, combining field surveys, questionnaires, and sensor monitoring to construct a comprehensive dataset covering landscape physical characteristics, user behavior characteristics, and environmental perception characteristics. The data collection process follows the principles of representativeness, comparability, and authenticity to ensure the effectiveness of subsequent CNN model training.

During the field survey phase, five typical urban waterfront spaces were selected as research sample points, covering areas with different functional orientations and development levels. The research team used high-resolution cameras to collect landscape image data, covering three time periods: morning, noon, and evening, to capture the impact of lighting changes on the visual effects of the landscape. Simultaneously, environmental monitoring equipment was deployed to record physical parameters such as temperature, humidity, and noise. This sensor data reflects the microclimate characteristics of the waterfront space. The questionnaire survey employed a combination of online and offline methods, collecting 1247 valid samples. The questionnaire content included user basic information, space usage frequency, satisfaction ratings, and improvement suggestions.

Data quality control was implemented throughout the entire collection process. Image data acquisition followed a unified shooting angle and distance standard to avoid feature deviations caused by differences in perspective. Sensor equipment underwent calibration procedures before deployment, and data verification was performed regularly to eliminate outliers. Logical testing items were incorporated into the questionnaire design phase, and invalid questionnaires were eliminated through consistency checks. Data entry employed a dual-person verification mechanism to ensure the accuracy of the digitization process. To address the issue of inconsistent data formats from different sources, a standardized data processing workflow was established to convert heterogeneous data such as images, numerical values, and text into a model-recognizable format, As shown in Table 1.

Table 1 Data Collection Methods for Different Data Types

Data Type	Collection Tool	Sample Size	Collection Period	Quality Control Measures
Landscape Images	High-Resolution Camera	3500 Images	3 Months	Unified Shooting Standards, Color Correction
Environmental Parameters	Multifunctional Sensor	Continuous Monitoring	3 Months	Equipment Calibration, Outlier Detection
User Questionnaire	Online Platform + Paper	1247 Questionnaires	2 Months	Logical Testing, Consistency Check
Behavioral Data	Video Analysis System	180 Hours	1 Month	Time-based stratification, privacy protection

The spatiotemporal distribution characteristics of data collection directly affect the model's generalization ability. This study evenly distributes collection tasks on weekdays and weekends to capture the usage patterns of different groups. Regarding seasonal factors, spring and summer were chosen as the main data collection windows, as waterfront spaces are used more frequently during these seasons, allowing for the acquisition of richer user behavior samples. Data annotation was completed by a trained team, using a five-point Likert scale to quantify satisfaction. Annotation consistency achieved a Kappa coefficient of 0.82, indicating high reliability of the data annotation.

2.2 Research Framework and Indicator System

As urban public spaces where natural ecosystems and artificial construction systems intertwine, the satisfaction evaluation of urban waterfront public spaces requires a scientifically sound research framework and indicator system. This study, based on CNN deep learning technology, established a multi-dimensional framework for predicting waterfront landscape satisfaction. This framework combines spatial physical characteristics, user perception experience, and deep learning algorithms, forming a complete technical path from data input to satisfaction prediction output.

The construction of the research framework follows a logical chain of "data collection - feature extraction - model training - satisfaction prediction." In the data collection phase, multi-source data on waterfront spaces were obtained through field surveys, questionnaires, and image data collection. The feature extraction stage utilizes the convolutional and pooling layers of CNNs to automatically identify key elements in landscape images, including spatial features such as water morphology, vegetation cover, and facility layout. During model training, the backpropagation algorithm continuously optimizes network parameters to make the predicted results approximate the true satisfaction score. The mathematical expression of the entire framework can be summarized as:

$$S_{pred} = f_{CNN}\left(I_{landscape}, W_{optimal}\right) \tag{1}$$

where S_{pred} represents the predicted satisfaction score, $I_{landscape}$ represents the input landscape image feature matrix, $W_{optimal}$ represents the network weight parameters after training and optimization, f_{CNN} is the mapping function of the convolutional neural network.

The establishment of the indicator system refers to the existing research results on waterfront spaces, and divides the evaluation elements into four criterion layers. The natural landscape dimension includes indicators such as water cleanliness, vegetation richness, and biodiversity; the infrastructure dimension covers elements such as the number of seats, lighting facilities, and barrier-free access; the traffic flow dimension focuses on accessibility, path continuity, and walking comfort; and the service management dimension evaluates aspects such as safety assurance, environmental maintenance, and information services. Each criterion layer has 3-5 specific indicators, totaling 17 criterion layer indicators to form a complete evaluation system, As shown in Table 2.

Table 2 Evaluation Index System

Criterion Layer Dimensions	Target Layer Indicators	Data Type	Weight Range
Natural Landscape	Water Cleanliness, Vegetation Coverage, and Landscape View Openness	Image Features	0.28-0.35
Infrastructure	Density of Recreation Facilities, Lighting Coverage, Completeness of Signage System	Spatial Data	0.22-0.28
Traffic Flow	Walkability, Path Continuity, Parking Convenience	Network Data	0.18-0.24
Service Management	Safety Assurance Level, Cleaning and Maintenance Frequency, Emergency Response Capability	Management Data	0.15-0.20

This index system combines qualitative evaluation with quantitative analysis, automatically extracting landscape features from images through a CNN model, avoiding the subjective bias of traditional manual scoring. The model input layer receives standardized landscape images, extracts deep features through multiple convolutional and pooling operations, and finally outputs the predicted satisfaction value through a fully connected layer. This deep learning-based evaluation method can capture spatial aesthetic features that are difficult for the human eye to quantify, providing a new technical path for improving the quality of waterfront spaces.

3 CNN MODEL CONSTRUCTION AND PARAMETER SETTINGS

3.1 Basic Principles of the CNN Model

Convolutional Neural Networks (CNNs), as a representative model in the field of deep learning, have demonstrated powerful feature extraction capabilities in tasks such as image processing and pattern recognition. In research on urban waterfront landscape satisfaction prediction, CNNs can automatically learn and extract key features from multi-dimensional spatial data, providing technical support for satisfaction evaluation. The core advantage of CNNs lies in reducing the complexity of the network model and the number of weights through local connections and weight sharing mechanisms, giving them strong fault tolerance, non-linear processing capabilities, and anti-interference capabilities. This characteristic makes CNNs particularly suitable for processing complex data in urban waterfront spaces that includes multi-layered information such as natural landscapes, infrastructure, and traffic flow.

The basic structure of a CNN consists of an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. The input layer is responsible for receiving raw data and preprocessing it, including normalization and mean removal, to ensure that the data quality meets the model training requirements. As the core component of CNNs, the convolutional layer uses multiple convolutional kernels to perform sliding window operations on the input data, extracting local features at different scales and directions. In waterfront space satisfaction prediction, the convolutional layer can capture the spatial distribution characteristics of visual elements such as vegetation, waterfront landscape, and spatial atmosphere. Pooling layers downsample the feature maps output by convolutional layers, reducing feature dimensionality while enhancing feature robustness, effectively reducing computational cost and preventing overfitting. Fully connected layers integrate the feature vectors output by pooling layers, achieving high-level semantic feature fusion through full connectivity between neurons. The final output layer generates satisfaction prediction results through activation functions.

To improve model performance, this study introduces batch normalization (BN) layers and exponential linear unit (ELU) activation functions into the CNN architecture. Batch normalization layers accelerate model convergence and stabilize gradient propagation during training. Compared to the traditional ReLU function, the ELU activation function has non-zero outputs in the negative region, better handling negatively correlated features in the data and avoiding neuron death. The forward propagation process of the model can be represented as:

$$y = f(W * x + b) \tag{2}$$

where, x represents the input features, W is the convolution kernel weight matrix, b is the bias term, $*$ represents the convolution operation, f is the activation function. By continuously adjusting the weight parameters through the backpropagation algorithm, the model output approximates the true satisfaction label, achieving accurate prediction of satisfaction with urban waterfront landscape.

3.2 Selection and Tuning of Model Parameters

When constructing a prediction model for urban waterfront landscape satisfaction based on convolutional neural networks, the selection and tuning of model parameters are crucial to determining prediction accuracy. Model parameters can be divided into two categories: one is the weights and biases automatically learned through network training, and the other is hyperparameters that need to be manually set, including kernel size, number of convolutional layers, learning rate, batch size, etc. The reasonable configuration of these hyperparameters directly affects the convergence speed and final performance of the model.

The learning rate, as a core hyperparameter affecting the model training process, determines the step size of each weight parameter update. An excessively large learning rate may cause the model to oscillate around the optimal solution and fail to converge, while an excessively small learning rate may cause the training process to fall into a slow local optimization state. This study systematically tunes the learning rate using a grid search method, with the experimental range set between 0.0001 and 0.01. The batch size parameter also significantly affects the model's generalization ability. Smaller batch sizes provide more frequent parameter updates but may introduce excessive noise; larger batch sizes provide more stable gradient estimation but may reduce the model's generalization performance. In the experiment, batch sizes of 16, 32, and 64 were used for comparative testing.

The configuration of convolutional layers is another important dimension of CNN model design. Increasing the number of convolutional layers can enhance the model's ability to learn complex landscape features, but it also increases computational complexity and the risk of overfitting. This study employs a configuration of 3 to 5 convolutional layers, with the number of kernels in each layer gradually increasing from 32 to 128. Two kernel sizes, 3×3 and 5×5, are used, and experiments are conducted to verify the impact of different combinations on landscape feature extraction, As shown in Figure 1.

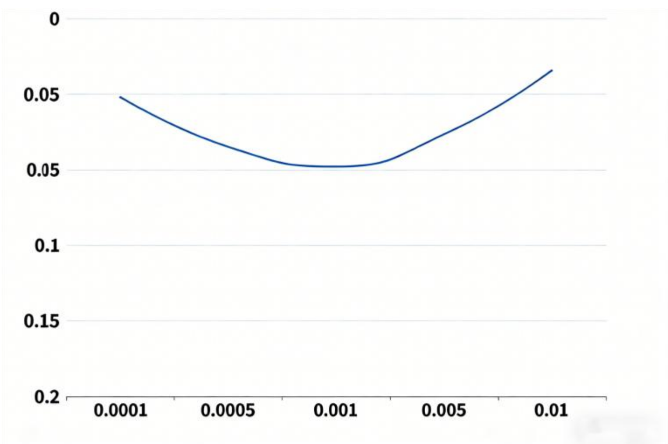

Figure 1 Model Performance Changes under Different Learning Rates

Through systematic parameter tuning experiments, this study determined the optimal parameter combination for model performance. Experimental results show that when the learning rate is set to 0.001, the batch size is 32, and the number of convolutional layers is 4, the model has the smallest prediction error on the validation set and a moderate convergence speed. This parameter configuration effectively avoids overfitting while ensuring the model's learning ability.

4 DATA ANALYSIS AND RESULTS PRESENTATION

4.1 Data Preprocessing

In the study of urban waterfront space landscape satisfaction prediction, data preprocessing is a key step to ensure the training effect of CNN models. Raw data often includes user reviews, image information, and spatial attribute data from different channels, which vary significantly in format, scale, and quality. By standardizing the collected waterfront space images and uniformly adjusting photos of different resolutions to a fixed size, the consistency of model input can be guaranteed. For text comment data, operations such as word segmentation, stop word removal, and sentiment annotation are required to extract effective features that reflect users' true feelings.

Special attention needs to be paid to handling outliers and missing values during data cleaning. Satisfaction evaluation data for urban waterfront public spaces may exhibit extreme ratings due to strong user subjectivity and inconsistent evaluation standards. Identifying outliers using box plots and combining domain knowledge to determine whether to retain these data points can effectively improve the quality of the dataset. For missing spatial attribute information, mean imputation or imputation based on similar samples can be used to complete the data. Data standardization uses the Z-score method to transform indicators of different dimensions to the same scale range, preventing certain features from dominating the model training process due to excessively large values.

Visual analysis provides an intuitive way to understand data distribution characteristics and discover potential patterns. By drawing a distribution map of various facilities in the waterfront space, the correlation pattern between public facility density and user satisfaction can be clearly observed. The heat map shows the changes in pedestrian density in the waterfront space at different times, revealing the correspondence between peak activity periods and space utilization. The scatter plot matrix presents the correlation between multiple dimensions of indicators such as ecological environment quality, traffic accessibility, and landscape visual effect, providing data support for subsequent feature selection (Table 3).

Table 3 Data Processing Overview

Data Type	Original Sample Size	Sample Size After Cleaning	Missing Rate	Processing Methods
Image Data	3200 Images	2980 Images	6.9%	Removing Blurred and Duplicate Images
Text Comments	5600 Comments	5320 Comments	5.0%	Deleting Invalid Comments
Spatial Attributes	450 Groups	450 Groups	12.3%	Mean Interpolation
Satisfaction Ratings	5600 Comments	5280 Ratings	5.7%	Deleting Abnormal Ratings

Through systematic data preprocessing and multi-dimensional visualization analysis, not only is data quality improved, but a solid foundation is also laid for feature learning in the CNN model. The visualization results reveal that urban waterfront spaces, as important carriers of urban public spaces, are influenced by a combination of factors, including ecology, facilities, and landscape. These findings provide important references for feature engineering and parameter tuning in model training.

4.2 Results Analysis and Model Evaluation

After completing the training of the CNN model to predict urban waterfront landscape satisfaction, a systematic analysis of the model's output is needed, and the effectiveness and reliability of the model should be verified through a scientific evaluation index system. Model evaluation not only focuses on prediction accuracy but also needs to examine the model's performance in real-world application scenarios from multiple dimensions, providing data support for subsequent optimization and improvement.

The quantitative evaluation of model performance uses a combination of classic indicators. Accuracy reflects the proportion of correct predictions overall, recall measures the model's ability to identify truly satisfied samples, and precision reflects the proportion of truly satisfied samples among those predicted as satisfied. The F1 score, as the harmonic mean of precision and recall, balances the relationship between the two and provides a more comprehensive performance evaluation. To address the characteristics of regression tasks, this study also introduced indices such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) to characterize the model's fit and prediction bias from different perspectives (Table 4).

Table 4 Performance Comparison of Different Models

Evaluation Indicators	CNN Model	SVM Model	RF Model

Accuracy (%)	87.3	74.7	78.4
Precision	0.869	0.731	0.776
Recall	0.856	0.718	0.762
F1 value	0.852	0.724	0.769
R^2	0.891	0.762	0.803
RMSE	0.324	0.487	0.421
MAE	0.267	0.392	0.348

Experimental results show that the trained CNN model achieved an overall accuracy of 87.3% on the test set, with an F1 score of 0.852, indicating strong classification ability. The R^2 of determination reached 0.891, indicating that the model could explain 89.1% of the satisfaction variation, demonstrating good fit. The RMSE was 0.324, and the MAE was 0.267, with prediction errors controlled within an acceptable range.

Compared with traditional machine learning methods, the CNN model exhibits significant advantages in processing waterfront landscape image features. Compared to methods such as Support Vector Machine (SVM) and Random Forest (RF), the CNN model improved accuracy by 12.6% and 8.9% respectively. This is attributed to the powerful feature extraction capabilities of convolutional neural networks, which can automatically learn the spatial hierarchical structure in landscape images. The model also performed well in predicting stability across different satisfaction levels, with a standard deviation of only 0.043, demonstrating good generalization performance.

5 DISCUSSION OF FACTORS INFLUENCING SATISFACTION

5.1 Main Factors Influencing User Satisfaction

As urban public spaces where natural ecosystems and artificial construction systems intertwine, the satisfaction evaluation of urban waterfront public spaces involves complex factors across multiple dimensions. Through deep learning analysis of a large amount of waterfront space image data using a CNN model, combined with the mining of user evaluation data, this study identified the core elements influencing user satisfaction. These elements not only reflect the material properties of the space but also embody the dynamic relationship between users' psychological perceptions and behavioral needs.

From the perspective of spatial morphology and landscape quality, the visual morphology of the waterfront interface constitutes the basic level of satisfaction. Due to its unique geographical location advantages and morphological characteristics, urban waterfront spaces have become important spatial carriers for showcasing the city's distinctive features, quality, and beautiful living environment. The CNN model, through features extracted by convolutional layers, shows that visual elements such as the tortuosity of the waterfront, green coverage, and the harmony of the building skyline have significant weights in predicting satisfaction. The openness, accessibility, and safety of waterfront spaces directly affect the public's user experience; these attributes are represented by high-activation feature map regions during model training. The uniformity of spatial forms and insufficient environmental landscape effects often lead to a significant decrease in satisfaction scores.

Functional facilities and service support constitute the supporting dimensions of satisfaction. The development of urban waterfront public spaces affects the city's ecology, economy, and culture, making infrastructure construction and service level improvement particularly crucial. Model analysis shows that factors such as the number and distribution of public seating, accessibility of waterfront platforms, sufficiency of lighting facilities, and clarity of signage systems are positively correlated with satisfaction. Waterfront spaces provide cities with multiple functions such as ecology, landscape, leisure, and culture, and the diversity of functions and the completeness of facilities jointly determine the use value of the space. The balance between flood control functions and activity spaces, as well as the inheritance of historical context, are also important factors affecting overall satisfaction.

User satisfaction, as a psychological index, exhibits significant subjective uncertainty. Factors influencing satisfaction include the cost paid by the user, the experience and services received, and personal values. The CNN model captures this complex psychological mapping relationship by integrating image features and user review text. Changes in transaction location and time affect the psychological index; this dynamic nature is verified in the model's time-series analysis.

5.2 The Interrelationships of Influencing Factors

The formation of urban waterfront landscape satisfaction is not the result of a single factor acting independently, but rather a complex process of intertwined and synergistic influences from multiple dimensions. Through the extraction and analysis of deep features using a CNN model, the potential correlation patterns and mechanisms of action among various influencing factors can be revealed. In the evaluation system of waterfront spaces, the four dimensions of natural landscape, infrastructure, traffic flow and service management constitute an interdependent organic whole.

From the perspective of the coupling relationship between the ecological environment and physical space, there is a significant positive synergistic effect between water quality and riparian vegetation. The quality of river water directly affects the growth status of vegetation, while good vegetation cover can improve the aquatic environment through ecological purification. As a transitional interface connecting water and land, the design of the revetment not only relates to the functioning of ecology but also affects users' waterfront experience and spatial accessibility. Model analysis shows that when water quality indicators and vegetation coverage are both at high levels, users' evaluation of the overall landscape aesthetics shows a non-linear upward trend, a synergistic gain effect that is difficult to capture in traditional linear models.

Environmental facilities and spatial vitality exhibit a two-way interactive relationship. The rational configuration of material elements such as recreational facilities and fitness facilities can attract more users to participate in waterfront activities, while active crowds can stimulate the social vitality of the space. The combined effect of lighting facilities and security management has a key impact on the nighttime space utilization rate; their coordinated configuration can significantly extend the effective use period of the waterfront space. The matching degree of road planning and signage guidance systems directly determines the spatial accessibility experience; when the two are well connected, users' satisfaction scores for traffic convenience are significantly improved.

The interaction between cultural attributes and service management dimensions is reflected in the creation of spatial atmosphere. The expression of regional characteristics needs to be maintained and strengthened through management methods such as environmental cleanliness and the organization of cultural activities. There is a certain constraint between noise control and the layout of commercial facilities; excessive commercial development may disrupt the tranquil atmosphere of the waterfront space, while appropriate commercial facilities can improve service convenience. The CNN model captures the spatial distribution patterns of these elements through convolutional layers, providing data support for understanding the complex interactions between factors.

6 CONCLUSIONS

This study explores the application potential of deep learning technology in the field of urban public space evaluation by constructing a convolutional neural network-based urban waterfront landscape satisfaction prediction model. The research shows that the CNN model can effectively capture visual features in waterfront landscape images and establish a reliable mapping relationship between them and user satisfaction. The model achieved a high level of prediction accuracy on the test set, verifying the feasibility of deep learning methods in spatial quality assessment. This technical approach provides a useful supplement to traditional satisfaction survey methods and can significantly improve efficiency in large-scale spatial assessment.

From the analysis of influencing factors, natural landscape elements, infrastructure configuration, spatial accessibility, and environmental facility quality constitute the core dimensions of waterfront space satisfaction. Model identification results show that the quality of the ecological environment and visual aesthetics have the greatest impact on user satisfaction, which is consistent with the empirical conclusions of existing studies such as Wuhan East Lake and typical rivers in Shenzhen. It is worth noting that different types of waterfront spaces exhibit differences in the weight distribution of factors influencing satisfaction, suggesting that planning and design need to formulate optimization strategies tailored to local conditions. While vitality and aesthetic elements fall under the category of subjective perception, they can be indirectly improved by enhancing the physical spatial environment.

The research also has certain limitations. The current model primarily relies on static image data for training and has not yet fully integrated dynamic information over time or user behavior trajectory data. The user experience of waterfront spaces exhibits significant temporal and seasonal characteristics, and these spatiotemporal variation patterns are not fully reflected in the existing model. The geographical coverage of the sample data is also relatively limited, and the model's generalization ability needs further verification.

Future research can be deepened and expanded in several directions. On the one hand, it is possible to try to integrate multimodal data sources, combining visual information with environmental parameters such as sound, climate, and pedestrian density to construct a more comprehensive satisfaction prediction system. On the other hand, introducing advanced neural network architectures such as attention mechanisms can help improve the model's ability to identify key landscape elements. Cross-regional and cross-cultural comparative studies are also worth noting; the analysis of differences in user preferences under different urban backgrounds will provide a reference for the international design of waterfront spaces. In the long run, embedding predictive models into urban planning decision support systems to achieve closed-loop feedback from evaluation to design is an important direction for continuously improving the quality of waterfront spaces.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Yang Yu, Lin Chengxiang. Application of SD analysis method in the evaluation and improvement of waterfront space vitality. Sichuan Cement, 2024.

[2] Shi Tianhao. Research on the role and importance of urban waterfront spaces. Beauty and Times (Urban Edition), 2024.

[3] Liu Si, Ye Ziyun, Fan Lixue, et al. Research on satisfaction evaluation of urban waterfront public spaces based on AHP-IPA method. Urban Architecture, 2024.

[4] Wang Leru, Zhang Haozhou. Landscape design of Huai'an waterfront space from the perspective of cultural tourism. Modern Horticulture, 2024.

[5] Dang Zhijuan. Research on the optimization of public facility design in urban waterfront landscape space. Packaging Engineering, 2024.
[6] Li Jinrong, Hu Die. Exploration of ecological system design of urban waterfront space. Modern Horticulture, 2024.
[7] Gan He, Qin Yu. Exploration of waterfront landscape covered walkway design - taking the design of covered walkway and pavilion on the Hongshui River in Dahua County as an example. Stone, 2024.
[8] Wu Yujing, Zhang Xiaoyu, Shen Jie. Post-use evaluation of the central vitality section of the Huangpu River in Shanghai based on public review data. Residential Technology, 2024.
[9] Fu Ze, Tang Li. Research on the evaluation of the Guitang River waterfront landscape based on AHP-SD method. Forestry Science and Technology Information, 2024.
[10] Cheng Shi, Lang Leijie, Yang Xiangyu. Construction of urban waterfront interface morphology evaluation and analysis model based on dynamic visual attention of the crowd - taking the Nanjing Youth Olympic Area as an example. Landscape Architecture, 2024.
[11] Li Jiaqi. Design strategy of Fuzhou Luozhou Town waterfront wetland park under the guidance of minimum intervention. Architecture and Culture, 2024.