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Intentional Characteristics and Public Perceived Preferences of Lake Parks Based on Machine Learning Models

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Abstract: This research aimed to analyze and understand the perceived landscape preferences of lake parks (LPs) and how the public perceives and prefers these elements within the context of lake parks. The objective was to provide insights beneficial for landscape design, urban planning, and the creation of more appealing and sustainable lake parks. To achieve this, two primary methods were employed in this study: the Automated Machine Learning (Auto ML) model and the DeepLab v3+ model. To gather data for the research, 46,444 images were collected from 20 different lake parks from 2019 to 2022. Social media platforms such as Instagram, Flickr, and specific lake park community groups were tapped to source photographs from both professional photographers and the general public. According to the experimental findings, the perceived frequency of natural landscapes was 69.27%, which was higher than that of humanistic landscapes by 30.73%. The perceived intensity was also maintained between 0.09 and 0.25. The perceived frequency of water body landscapes was much greater on a macro-scale, at 73.02%, and the public had various plant preferences throughout the year. Aquatic plant landscapes with low-to-medium green visibility were preferred by the public, according to the landscape share characterization, while amusement rides with medium-to-high openness were preferred. The sky visibility of amusement rides was between 0 and 0.1 and between 0.3 and 0.5, indicating that the public preferred amusement rides with medium-to-high openness. In lake parks, the populace chose settings with less obvious architectural features. When combined, the two models used in this study are useful for identifying and analyzing the intended traits and preferences of lake parks among the general public. They also have theoretical and practical application value for directing the development of lake parks and urban landscapes.

Keywords: auto ML modeling; lake parks; imagery features; public perceived preferences

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1. Introduction

As an important component of the urban ecological environment and public space, lake parks (LPs) play a decisive role in the quality of the water environment and the urban landscape. They are pivotal in enhancing the urban recreational environment and people's well-being [1]. However, urban lakes face the pressures of shrinkage, loss, pollution, and degradation due to the tension between urban water resources and rapid urbanization [2]. Furthermore, as the economy develops, people's demand for high-quality landscape environments is rapidly increasing, and public landscape preferences are critical in determining the improvement of landscape spatial quality [3]. The emergence of big data technology and machine learning models offers great convenience and technical support for data mining, analysis, and urban LP research [4]. However, current research on landscape preferences mostly adopts traditional questionnaire surveys, relying on manual coding with small sample sizes and rarely applying network big data and machine learning models. Based on this, in this study, an Automated Machine Learning (Auto ML) model was constructed based on the Google Cloud Vision algorithm for image classification and content recognition and DeepLab v3+ for semantic image segmentation. The primary

objective of this approach was to address the challenges associated with the sustainable development of urban habitats and to offer valuable theoretical and methodological insights for research aimed at subjectively evaluating cities through the analysis of extensive image-based big data.

This research is divided into three parts: The first part summarizes and discusses current research related to perceived landscape preferences both domestically and internationally. The second part analyzes the imagery features (IFs) and public perceived preferences (PPPs) of LPs, including the proposed Auto ML model and DeepLab v3+ model. The third part applies these two models to analyze the IFs and PPPs of LPs to verify the models' validity.

2. Related Work

A landscape is an area perceivable by the public, a place where humans and nature interact that is dominated by visual perception [5]. A visual landscape refers to entities in a specific area that evoke visual perception and impression, an important part of the landscape under people's intuitive perception. Analyzing and evaluating the visual connotation and quality of a landscape is crucial, forming an important aspect of landscape construction and management [6]. A study focusing on public landscape preferences in Norway used ordered logistic regression and machine learning to construct a structural subject-modeling analysis method, providing supporting data for landscape construction policy proposals while analyzing public landscape preferences [7]. In response to public perceptual preferences for forest landscapes, some researchers have modeled the aesthetic quality of forested areas using machine learning models, including support vector machines and multilayer perceptrons, thus offering guidance for ecological technology planting in woodland landscapes [8]. The authors of [9] proposed a new method of user preference classification, integrating a machine learning model with a geographic information system (GIS), to address issues related to the public perceptual preferences for the landscape in a geopark project in the United States, effectively guiding the construction of the geopark project. Researchers have also tackled the problems associated with landscape character assessment by proposing an evaluation method for users' visual perception of a landscape based on artificial intelligence, providing supporting data for a deeper understanding of human–nature interactions and the sustainable management of the environment [10].

In addition, researchers have addressed the management of urban parks by collecting data from six high-rise area parks in India through a questionnaire survey. This survey aimed to analyze the public's landscape preferences and their willingness to pay for urban parks, thus providing assistance in managing urban green spaces in a multidimensional manner [11]. Researchers in the Netherlands have analyzed the landscape preferences of residents in suburban areas through questionnaire interviews. This approach helped address the diversity of residents' perceived landscape preferences, enhancing the management and multifunctionality of suburban landscapes [12]. For issues associated with the visual perception of the urban landscape, researchers proposed an active perception method to measure visual preference. This method, based on an analysis of window views, provides supporting data for landscape planners to improve the visual quality of the built environment [13]. Evaluating the public's subjective preferences in urban landscapes involved a comprehensive discussion and a comparison of natural and urban landscapes, providing appropriate guidance for urban landscape construction [14].

Domestic and international studies reveal that the current research on perceived landscape preferences is comprehensive. However, most studies still rely on questionnaires to obtain the public's aesthetic preferences or use methods like beauty degree evaluation and hierarchical analysis to analyze key influencing factors of landscape preferences. These methods, dependent on manual coding and qualitative analyses of small samples, are susceptible to researchers' bias and subjectivity. Additionally, the content and algorithms for landscape perceptual preference analysis are currently limited, making the use of the Auto ML model and the DeepLab v3+ model for the IF and PPP analysis of LPs innovative.

In this study, machine learning models were employed to analyze and gain insights into the relationships between various landscape elements and the public's perceptions and preferences within the context of lake parks. Essentially, this research aimed to provide a comprehensive understanding of the features and preferences in lake park landscapes, offering valuable insights for landscape design, urban planning, and the creation of more appealing and sustainable lake parks.

3. Research Method

The research methodology employed in this study involved building an Automated Machine Learning (Auto ML) model based on the Google Cloud Vision algorithm for image classification and content recognition. Additionally, the DeepLab v3+ model was utilized for semantic image segmentation. These methods were applied to analyze perceived landscape preferences in lake parks (LPs) at two levels.

The Auto ML model was primarily used to analyze the compositional features within perceived LP preferences. Conversely, the DeepLab v3+ model analyzed the proportional features within these preferences. This segmentation model employed the DeepLab v3+ algorithm to extract data regarding the proportions of elements such as vegetation, sky, and buildings from images, yielding three key indicators: green visibility, sky visibility, and building visibility. These are essential visual evaluation criteria for outdoor urban environments.

Understanding that public preferences significantly influence the development of lake parks, in this study, both models were applied to analyze the perceived landscape preferences and public preferences for LPs. This not only served to validate the effectiveness of the two models but also provided valuable supporting data to guide the development of lake parks.

From 2019 to 2022, a total of 46,444 images from 20 different lake parks were collected and used for training and to study public preferences.

Using social media platforms such as Instagram, Flickr, and specific lake park community groups to interact with photographers or the general public and share photographs of lake parks can be valuable for research. However, it is important to acknowledge that photographs shared on social media platforms often come from specific user groups, potentially leaning toward younger individuals or enthusiasts with particular interests. This can result in a lack of representativeness in a sample, potentially not fully reflecting the diverse landscape preferences of the general public. Consequently, research outcomes may be influenced by the preferences of these specific user groups. Additionally, the quality of photographs on social media platforms varies widely, ranging from professional photography to low-resolution smartphone snapshots. This variability in image quality can impact the accuracy of image analysis, particularly in cases where semantic segmentation or the extraction of fine features is required. To mitigate these potential issues, researchers can take the following measures:

- Clearly describe the sources of photographs used in research, including the social media platforms and the types of users involved.
- Strive to diversify the sources of a sample, including photographs from different social media platforms and various user demographics to obtain a more comprehensive representation of public preferences.
- Implement quality control measures to exclude low-quality or irrelevant photographs from a dataset.
- Consider comparing and analyzing social media data alongside data from other sources to ensure a more comprehensive and balanced research outcome.

In summary, when using photographs from social media platforms for research, it is essential to exercise caution and take steps to ensure the credibility and representativeness of the research results.

4. LP-Oriented IF and PPP Analysis

The imagery features (IFs) of lake parks (LPs) encompass both compositional and occupancy features. This section primarily analyzes the Automated Machine Learning (Auto ML) model for image classification and content recognition, as well as the DeepLab v3+ model for semantic segmentation. These models are employed to construct a framework for the quantitative measurement of landscape imagery.

4.1. Analysis of Auto ML Models for Image Classification and Content Recognition

Aiming to address the current issue of the sustainable development of urban habitats impacted by the destruction of lake parks (LPs), in this study, an Automated Machine Learning (Auto ML) model was developed for image classification and content recognition. This model was based on the Google Cloud Vision algorithm. Additionally, the DeepLab v3+ model was used for semantic image segmentation to analyze lake park imagery features (LPIFs) and public perceived preferences (PPPs) at two levels. The technical route for the construction of the image classification and content recognition model using the Auto ML model is depicted in Figure 1.

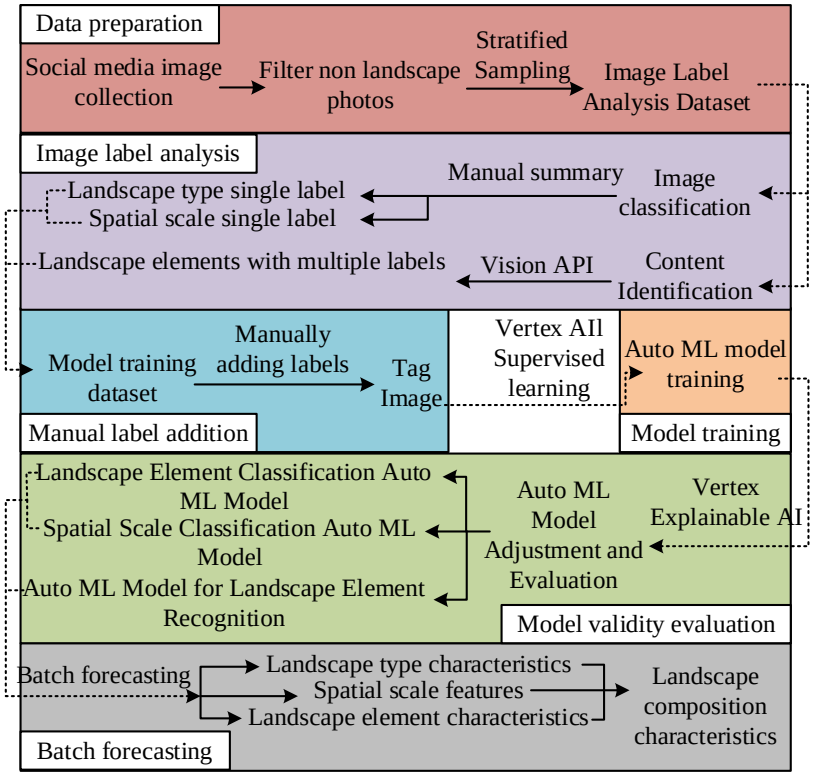


Figure 1. Model construction of image classification and content recognition using Auto ML model technology roadmap.

As can be seen in Figure 1, in this study, the Visual Application Programming Interface (Vision API), Auto ML Vision, and Vertex Artificial Intelligence (Vertex AI) platforms are mainly used to determine the landscape element, the spatial scale, and the classification of the landscape element identification. The platform consists of six main modules, namely data preparation, image label analysis, manual label addition, model training, model validity evaluation, and batch prediction. In the model validity assessment, the Auto ML model is adjusted to be classified into three Auto ML models, namely landscape elements, spatial scale, and landscape element identification, and the Auto ML model is trained through the conventional evaluation indices of machine learning models and the interpretability of machine learning models. The evaluation metrics include the precision

rate, recall rate, average precision rate, F1 value, and P-R curve. The computational expression of the precision rate is shown in Equation (1).

$$\gamma = \frac{\kappa}{\kappa + \alpha} \tag{1}$$

In Equation (1), γ denotes the precision rate, κ denotes the actual number of samples that were correctly classified as positive examples, and α denotes the actual number of samples that were incorrectly classified as positive examples. The recall rate expression is shown in Equation (2).

$$\nu = \frac{\kappa}{\kappa + \beta} \tag{2}$$

In Equation (2), ν denotes the recall rate and β denotes the actual number of samples misclassified as negative cases. The F1 value is expressed as shown in Equation (3).

$$F = \frac{2\gamma\nu}{\gamma + \nu} \tag{3}$$

In Equation (3), F represents the reconciled mean of precision and recall. Finally, the average precision rate is expressed as shown in Equation (4).

$$\rho = \sum_n (\nu_n - \nu_{n-1})\gamma_n \tag{4}$$

In Equation (4), ρ denotes the average accuracy. And in batch forecasting, the combination of these three features represents the constitutive features in LPIFs.

4.2. DeepLab v3+ Model Analysis and Quantitative Measurement Framework for Landscape Imagery

The Auto ML model mainly analyzes the compositional features in the intentional LP features, while the DeepLab v3+ model used for semantic image segmentation analyzes the occupancy features in the intentional LP features. In this study, the DeepLab v3+ algorithm is used for semantic segmentation to extract the proportions of vegetation, sky, and architectural elements in the image data to obtain the three indicators of an LP's green visibility, sky visibility, and architectural visibility, which are three important visual evaluation indicators of the urban outdoor environment. Among them, green visibility mainly refers to the actual proportion of green vegetation perceived by human vision, which characterizes human activity space rather than urban surface space and focuses more on the restoration of the actual vitality space of the landscape. Higher green visibility can relax people physically and mentally and enhance life satisfaction [15–18]. The corresponding expression is shown in Equation (5).

$$G = \frac{Area_g}{Area_t} \times 100\% \tag{5}$$

In Equation (5), G denotes the green visibility, $Area_g$ denotes the actual area of green vegetation in the picture, and $Area_t$ denotes the actual total area of the picture. Sky visibility can be geometrically quantified using the sky visibility index, i.e., the proportion of visible sky area within the field of view, which can be used to quantify the spatial openness of a landscape [19]. The computational expression of sky visibility is shown in Equation (6).

$$S = \frac{Area_{sk}}{Area_t} \times 100\% \tag{6}$$

In Equation (6), S denotes the sky visibility and $Area_{sk}$ denotes the actual area of the sky in the picture. In addition, the building visibility is geometrically quantified accordingly using the building visibility index, which is the ratio of the buildings in the actual field of

view to the area of the field of view. The computational expression of building visibility is shown in Equation (7).

$$B = \frac{Area_{bu}}{Area_t} \times 100\% \quad (7)$$

In Equation (7), B denotes the sky visibility and $Area_{bu}$ denotes the area of the sky in the picture. Through the classification and content recognition of image data (semantic image segmentation), the relevant landscape feature information in a picture is mined, and based on it, the two dimensions of landscape imagery are proposed, namely the landscape composition and the landscape proportion and color. The landscape composition can be decomposed into the landscape type, spatial scale, and landscape elements; the landscape ratio includes the green visibility, sky visibility, and building visibility. The two are used to construct a multidimensional landscape imagery measurement framework using public perception, the content of which is shown in Figure 2.

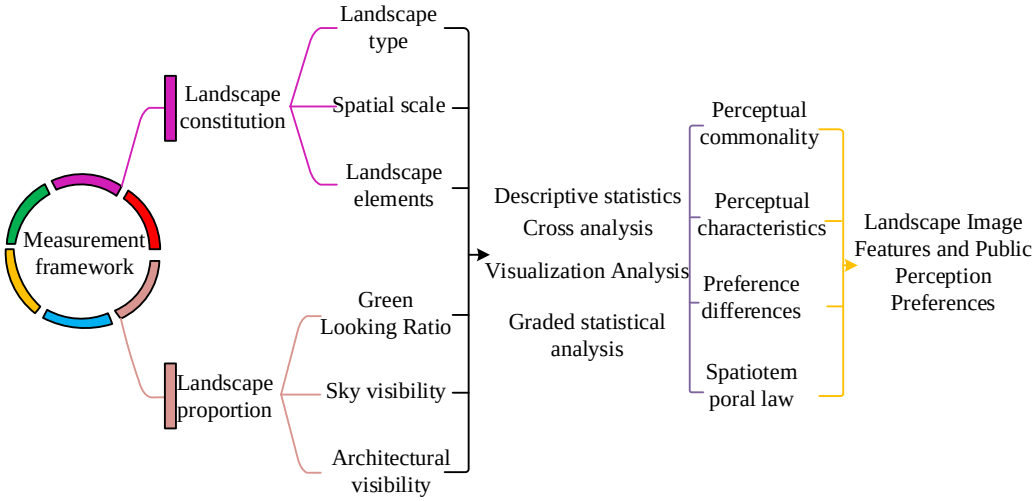


Figure 2. A multidimensional landscape image measurement framework for public perception.

As can be seen in Figure 2, after the classification under the two landscape IFs, the corresponding descriptive statistics were obtained, and cross-tabulation, visualization, and hierarchical statistical analyses were performed to obtain the perceptual commonalities and characteristics, the preference differences and spatiotemporal patterns, and finally, the landscape IFs and PPPs.

5. LP Landscape IF and PPP Analysis

PPPs influence the construction of LPs, so this section focuses on applying the two models to the analysis of LP landscape IFs and PPPs to validate the two models while also providing supporting data to guide the construction of LPs.

5.1. Landscape Composition Characterization and PPP Analysis

In order to verify the effectiveness of the two models in LPIF and PPP analysis, in this study, 20 LPs in a downtown urban area in central China were taken as the research object, with data from social media platforms such as Volkswagen Dianping.com spanning from 2019 to 2022, and a total of 46,444 images from the 20 LPs were acquired. Due to the complexity of the image data sources, their data were cleaned accordingly, and finally, 35631 valid landscape images were retained. Profiles of the 20 LPs in the region are shown in Table 1.

Table 1. Overview of 20 lake parks in the central urban area of a city in central China.

-	1	2	3	4	5	6	7	8	9	10
Grade	Scenic area level	Scenic area level	Urban level	City level	City level	County level	City level	Urban level	Urban level	County level
Lake area	3280 ha	3280 ha	276 ha	14 ha	8 ha	6 ha	767 ha	31 ha	5 ha	4 ha
Park area	607 ha	1325 ha	377 ha	30 ha	20 ha	10 ha	31 ha	81 ha	63 ha	13 ha
-	11	12	13	14	15	16	17	18	19	20
Grade	County level	City level	Community level	County level	County level	Urban level	Urban level	Urban level	Urban level	County level
Lake area	9 ha	5 ha	3 ha	10 ha	9 ha	19 ha	48 ha	71 ha	364 ha	8 ha
Park area	14 ha	24 ha	7 ha	13 ha	15 ha	79 ha	103 ha	106 ha	107 ha	12 ha

In Table 2, A~D denote natural landscapes, which are water bodies, forests, flowers, and aquatic plants, respectively; E~H denote humanistic landscapes, which are history and culture, landscape facilities, amusement facilities, and road environments, respectively. From Table 2, it can be seen that the average accuracy values of G, C, and D are 1.000, 0.955, and 0.946, respectively, which indicate better recognition ability, while the average accuracy values of B and H are 0.911 and 0.905, which indicate slightly worse recognition ability. The results show that the model can classify single landscape type labels better, and overall, the Auto ML model for landscape element classification has high accuracy and can be subsequently applied to identify the types of landscape elements. In addition, the average accuracies of micro- and macro-landscapes are 0.982 and 0.963, with better recognition ability, while the average accuracy of mesoscopic landscapes is 0.807, with slightly worse recognition ability. Overall, the trained Auto ML model for spatial-scale classification has higher accuracy and can be subsequently used to identify spatial-scale types. The landscape element recognition model is mainly used to verify the classification ability of the Auto ML model with multiple labels, and the results are shown in Figure 3.

Table 2. Landscape element Auto ML model and spatial-scale Auto ML model evaluation indicator results.

-	A	B	C	D	E	F	G	H
ρ	0.943	0.911	0.955	0.946	0.970	0.982	1.000	0.905
γ	82.351%	95.001%	88.241%	83.331%	95.461%	94.442%	100.00%	69.231%
ν	96.551%	65.522%	93.753%	100.000%	84.001%	80.952%	90.912%	81.819%
F	0.890	0.777	0.910	0.910	0.895	0.873	0.953	0.751
Spatial-Scale Auto ML Model Evaluation Indicator Results								
-	Macro-distance		Macroscopic		Microscopic		Intermediate perspective	
ρ	0.982		0.963		0.914		0.807	
γ	95.832%		87.501%		88.101%		73.813%	
ν	92.001%		85.372%		84.091%		73.811%	
F	0.940		0.865		0.861		0.739	

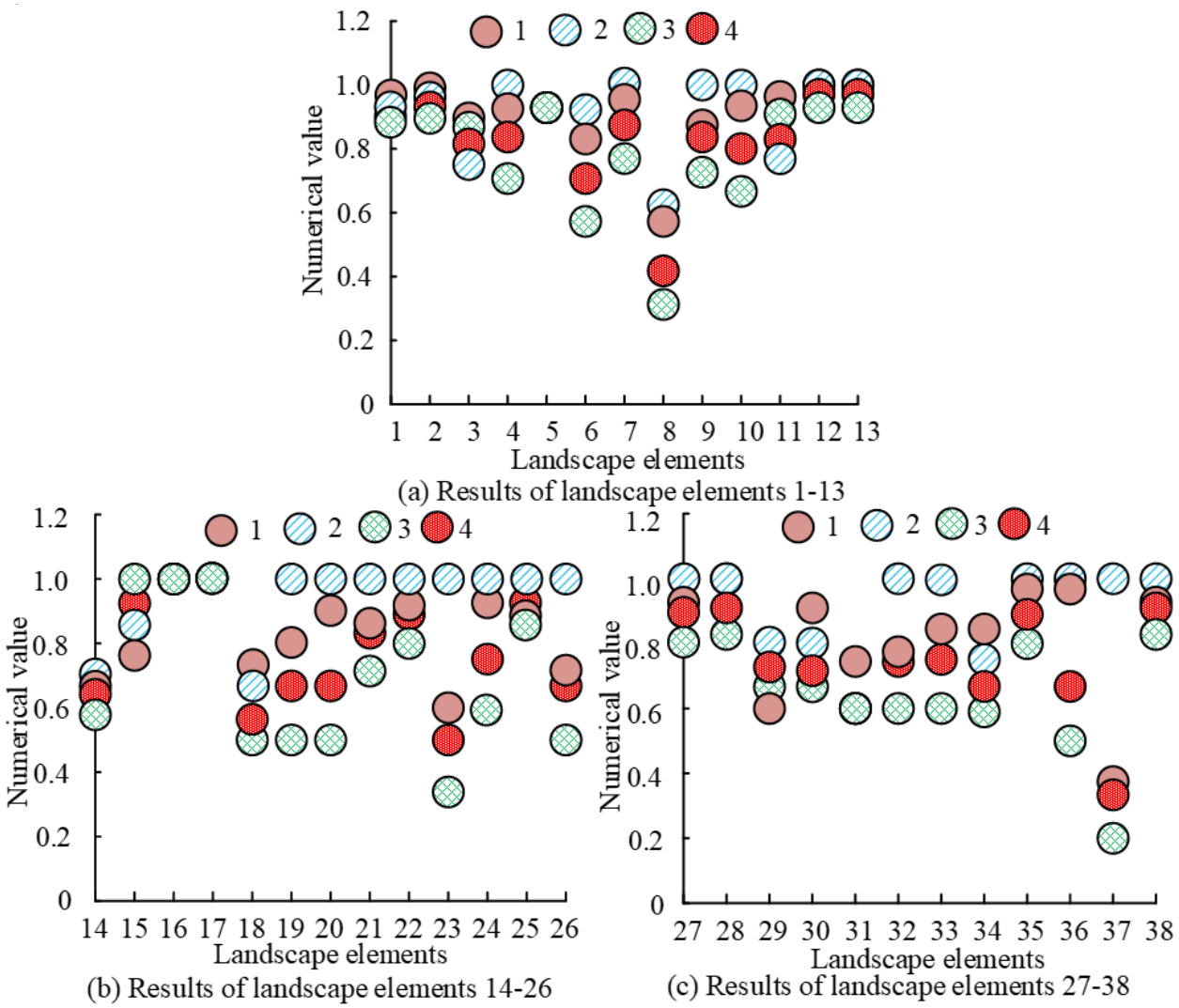


Figure 3. Evaluation index results of landscape element recognition model.

In Figure 3, values 1~38 indicate 38 landscape elements, including cable cars, lights, evergreen trees, and reflections. Comprehensively, Figure 3 shows that the average accuracy values of cable cars, forests, lights, night scenery, evergreen trees, and reflections are greater than 0.9, indicating that the model has the best ability to identify these six labels and is more likely to identify the labels with more explicit landscape features. This result is consistent with the process of manual identification. The model error is easily affected by the limitations of the sample images and the deviation of manual recognition, but it is within the normal range, so it can be applied in the content recognition of image data.

In the analysis of LP landscape composition characteristics and perception preferences, the batch prediction of 35,631 landscape images of 20 LPs was initiated based on the Auto ML model to obtain the prediction results of image classification and content recognition for each image, and sample data with confidence values lower than 0.5 were deleted from the predicted data. Thus, a total of 32,348 images of relevant data were retained for the subsequent analyses. Among the landscape types perceived by the Auto ML model, the statistical results of the perceived frequency of each landscape type using the landscape element classification model are shown in Figure 4.

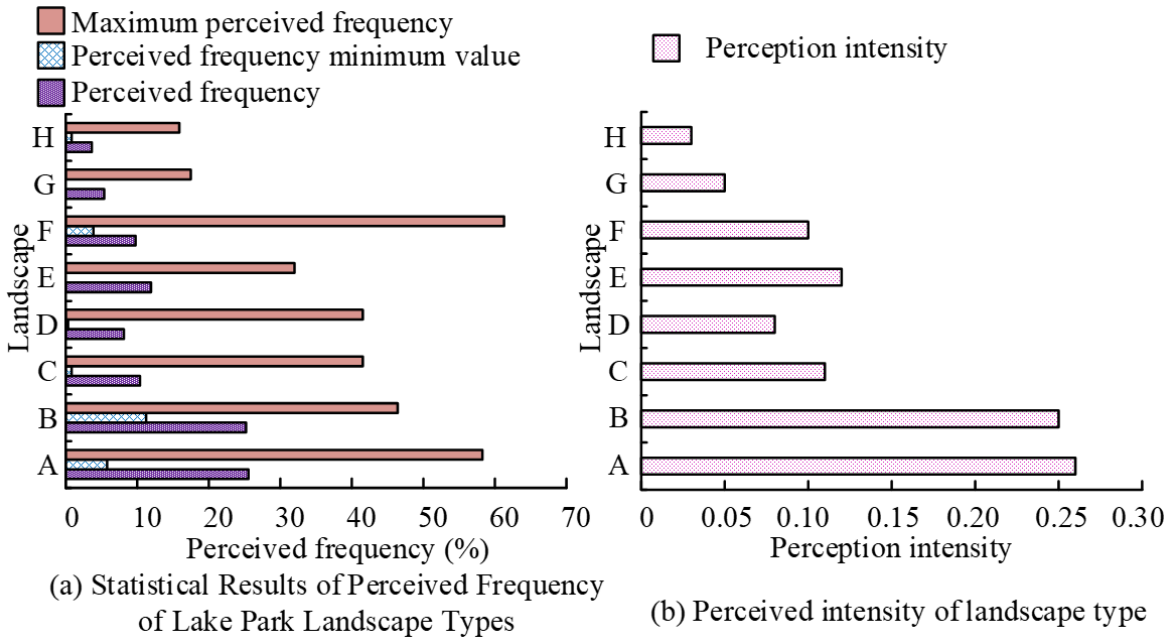


Figure 4. Statistical results of perceived frequency of different landscape types in lake parks based on landscape element classification model.

Figure 4 shows that the frequency of perception values of the four landscapes in the natural landscape are 25.54%, 25.22%, 10.38%, and 18.13%, with an overall value of 69.27%, while the frequency of perception values of the four landscapes in the humanistic landscape are 11.93%, 9.77%, 5.38%, and 3.65%, with an overall value of 30.73%. In addition, the value of the natural landscape in the comparison of perceived intensity is maintained at 0.09 to 0.25, while the humanistic landscape is maintained between 0.04 and 0.11. Natural landscapes are higher than humanistic landscapes in both the frequency and intensity of perception, and their perceptual changes are more diverse than those of humanistic landscapes. In the spatial-scale perceptual characterization analysis, the spatial-scale classification model in the Auto ML model was used in this study, and the resultant outcomes related to the perceptual frequency and perceptual intensity of landscape types at different spatial scales are shown in Figure 5.

In Figure 5, the four classifications of spatial scales, i.e., macro-, meso-, micro-, and macro-scales, are represented from the inner ring to the outer ring. There are three pillars for the analysis and recording of cities, namely heritage analysis, urban and environmental analysis, and sensory mapping analysis [20]. Comprehensively, Figure 4 shows that in the natural landscape, the perception frequency of water landscape is higher at the macro-scale, at 73.02%; the perception frequency of forest landscape is higher at the meso- and micro-scales, at 41.77% and 38.96%, respectively; and the perception frequency of floral landscape is higher at the macro-scale, at 61.23%. In the humanistic landscape, the perception frequency of amusement facilities is higher at the macro-scale, at 9.82%; the perception frequency of history and culture is higher at the meso- and micro-scales, at 16.37% and 25.57%; and the perception frequency of landscape facilities is higher at the macro-scale, at 0.64%. The values of the perception intensity comparison between macro- and macro-scales are 1.0 and 0.9, respectively. On the whole, the public perception of the natural landscape is significantly higher than that of the humanistic landscape on the macro- and micro-scales, and overall, the spatial perception level of an LP landscape is more preferred by tourists for spatially expansive and far-reaching natural landscapes on large scales and for humanistic landscapes on small scales with refined designs.

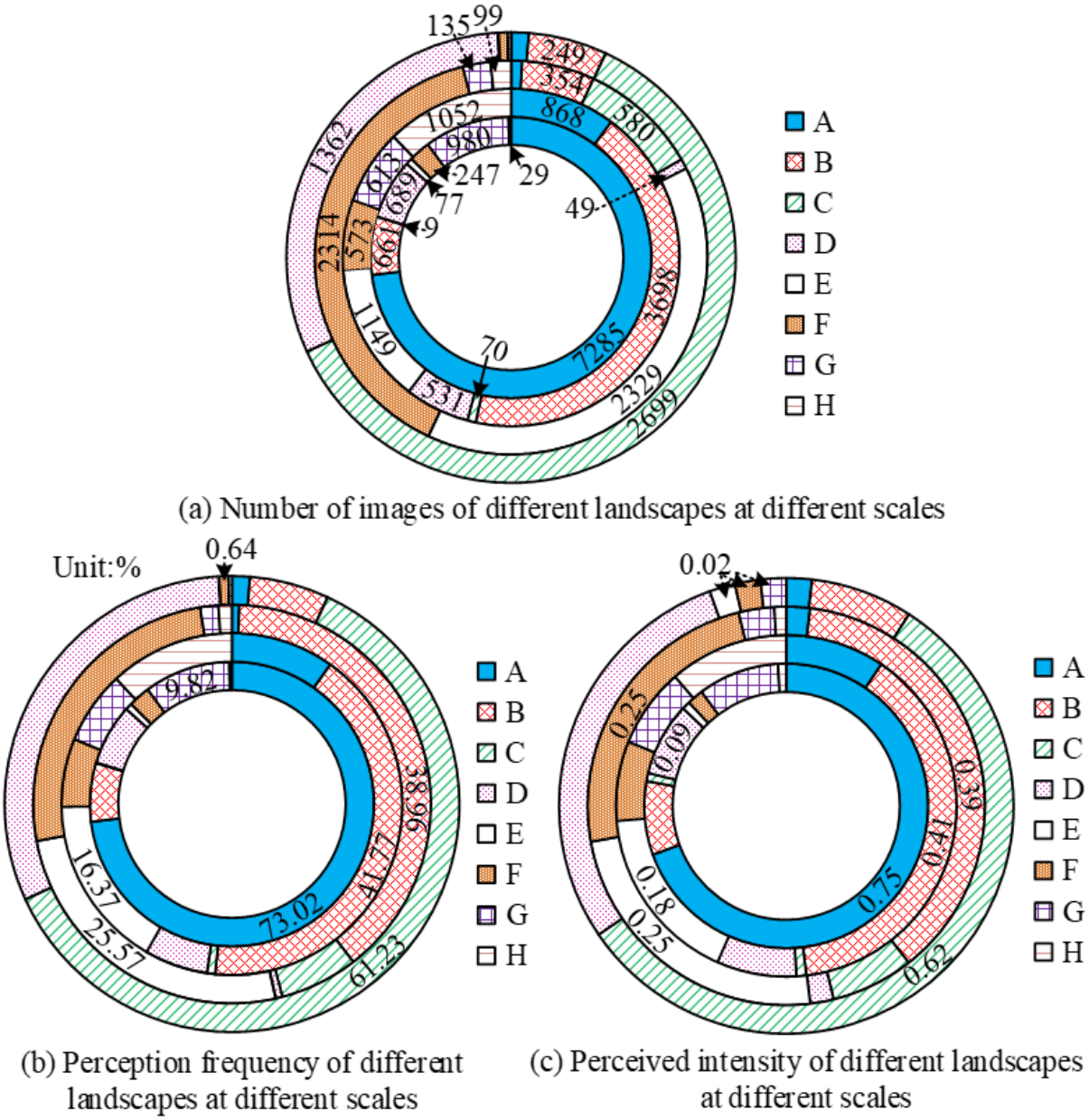


Figure 5. Perception frequency and intensity results of landscape types at different spatial scales.

In the perceptual feature analysis of landscape elements, one to nine labels were retained for each image through confidence filtering; thus, 89,089 label data were obtained. In addition, in the perceptual intensity analysis, the five elements that best represented the commonality of LP landscape imagery, namely evergreen trees, lakes, grass, background buildings, and reflections, were excluded, and only the strongest perceptual landscape elements were counted for each park. Therefore, the frequency and intensity of each landscape element are shown in Figure 6.

In Figure 6d, values 1 to 20 on the horizontal axis indicate the 20 lakes. Figure 6 shows that the five common elements have the largest values in the perceptual frequency analysis, at 27.40%, 13.21%, 10.02%, 8.65%, and 5.68% [21]. The perceived intensity values of parks 2, 4, and 15 for traditional architecture are the largest, at 0.11, 0.21, and 0.31, respectively. Comprehensively, the public prefers a natural landscape with green trees and blue waves, and the perceptual intensity results show that the landscape qualities of an urban LP fit the current situation of the green environment and are also in line with the actual situation in the study area. Based on this, PPP was further analyzed, and due to space constraints, this

study only explored the differences in perceived preferences for landscape components in different seasons. The results depicting seasonal preference differences for various landscape types and elements are presented in Figure 7.

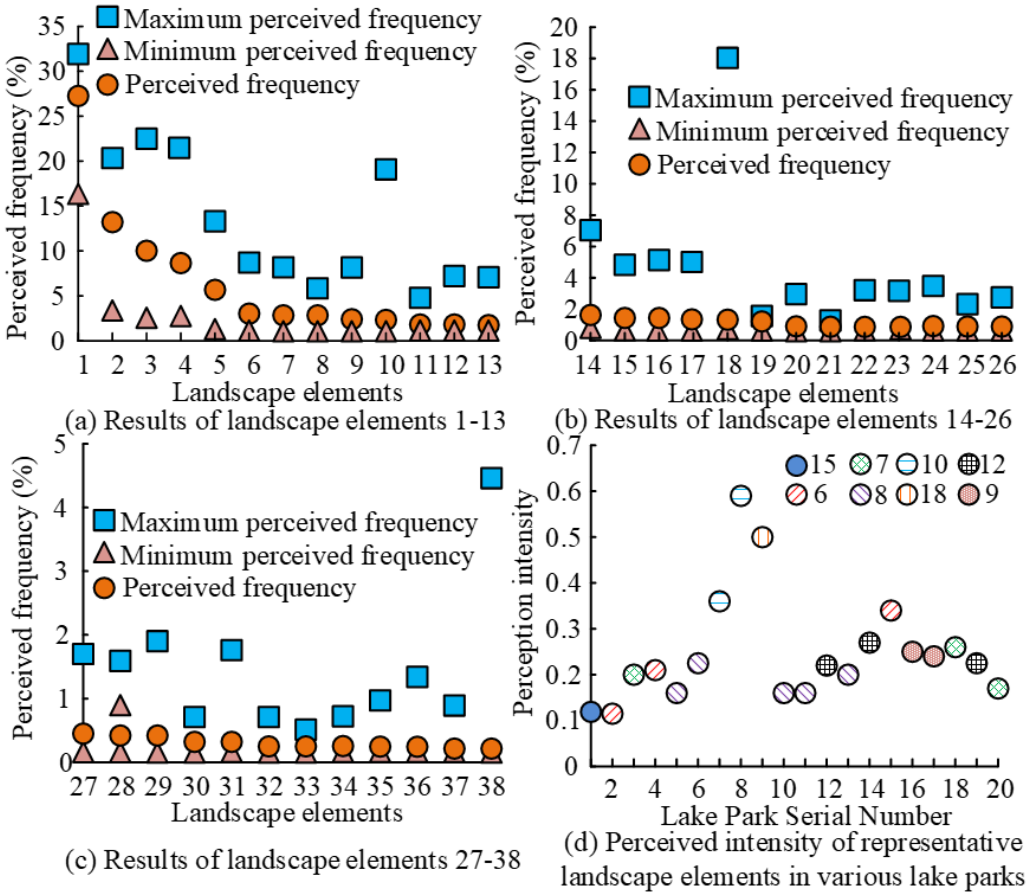


Figure 6. Perception frequency and intensity of various landscape elements.

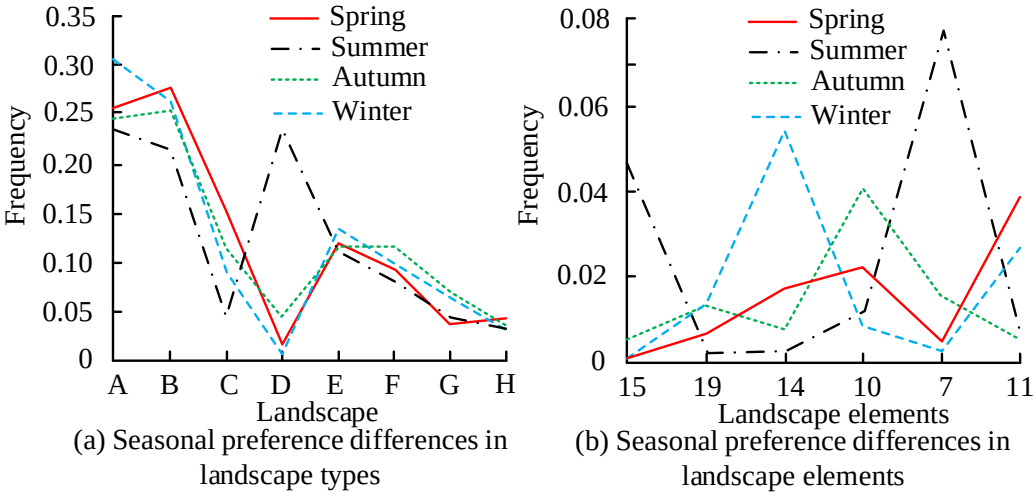


Figure 7. Seasonal preference differences among different landscape types and elements.

Figure 7 shows that the seasonal preference for humanistic landscapes is not significant due to the fact that there is no significant seasonal difference in the characteristics of humanistic landscapes, while the preference for natural landscapes is more obvious. Among them, there is a water body landscape preference in winter, when the frequency is 0.31;

there is a forest landscape and flower landscape preference in spring; and there is an aquatic landscape preference in summer. In addition, the landscape element analysis showed the most significant differences in seasonal preferences for aquatic flowers, plants with colored foliage, deciduous trees, herbaceous flowers, lotus leaves, and woody flowers. Taken together, plant landscapes had the most significant effect on the public's preferences for LP seasons, especially for the various types of floral elements, and this result is generally consistent with the actual results. Overall, the Auto ML model is effective in determining LP landscape composition characteristics and in PPP analysis.

5.2. Landscape Share Characterization and PPP Analysis

The LP landscape share characterization in this study is based on three indicators in the DeepLab v3+ model. In particular, in this study, the green visibility was classified using three criteria: low (ranks 1–3, with value intervals of 0–0.05, 0.05–0.15, and 0.15–0.30, respectively), medium (ranks 4–5, with value intervals of 0.30–0.50 and 0.50–0.65, respectively), and high (rank 6, with a value interval of 0.65–1). The green visibility results of different landscape types and different spatial scales for the DeepLab v3+ model analysis are shown in Figure 8.

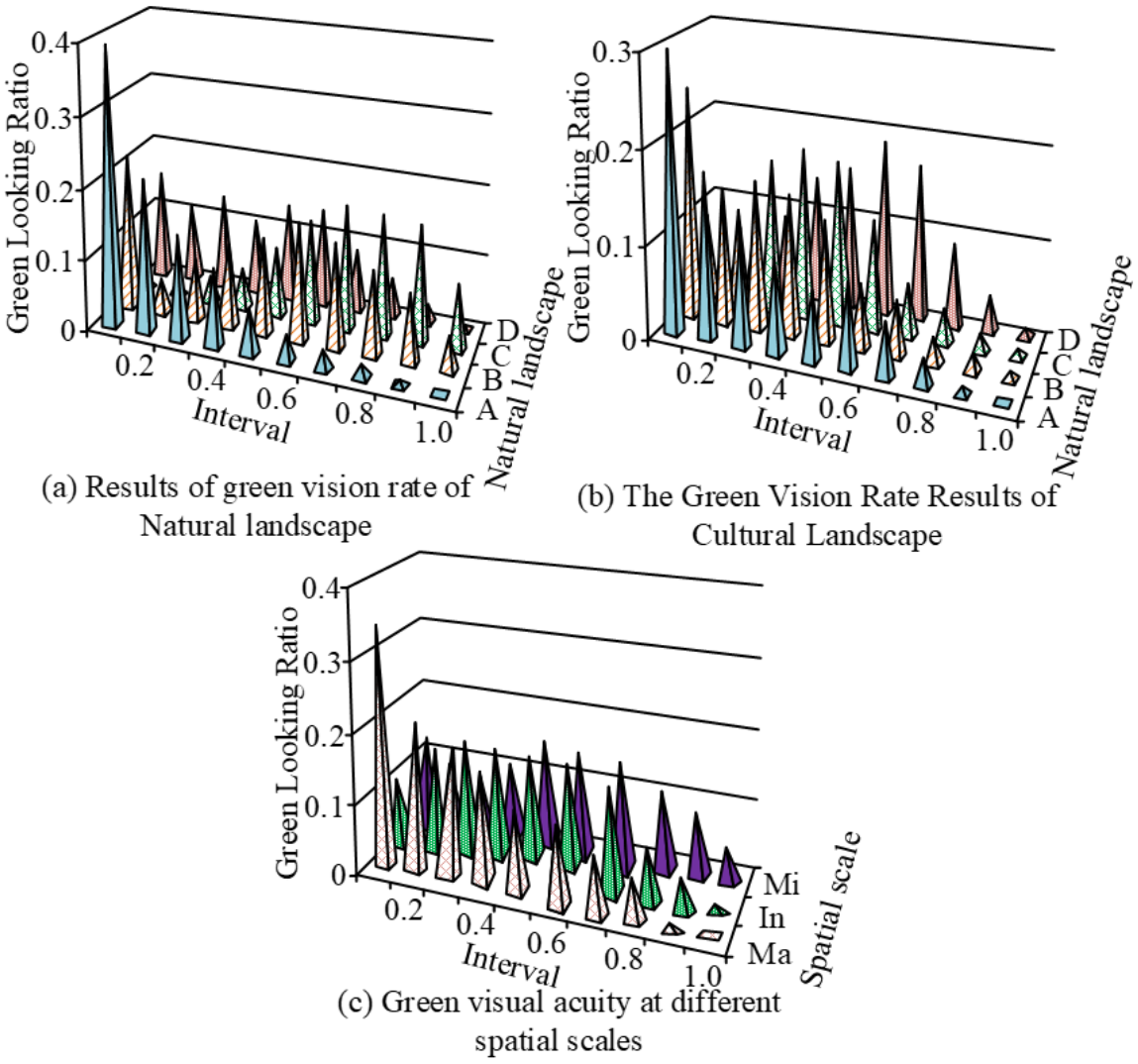
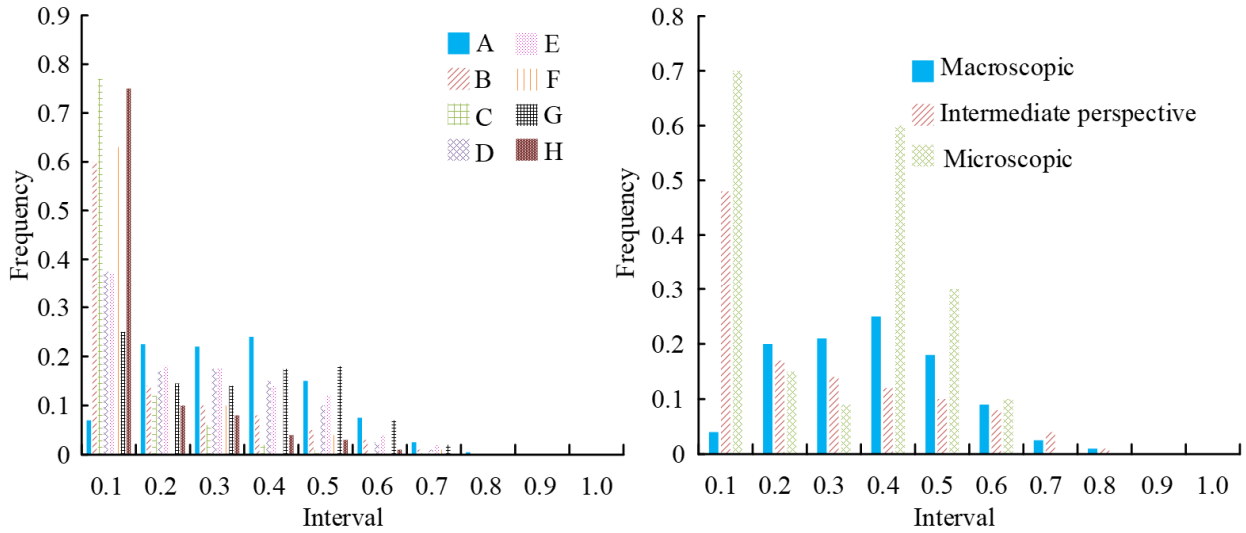


Figure 8. Green visual acuity of different landscape types and spatial scales.

In Figure 8c, Ma, In, and Mi represent macro-, meso-, and micro-scales, respectively. Figure 8 shows that the green visibility values of water landscapes, history and culture,

and landscape facilities are concentrated in the range of 0 to 0.2 and show a decreasing trend; the green visibility of aquatic plants is not much different in the range of 0 to 0.6, but when it is more than 0.6, the green visibility decreases significantly. The green visibility values of flower landscapes and amusement facilities are concentrated between 0.6 and 0.9 and between 0.2 and 0.5, and the green visibility values of forest landscapes and road environments are concentrated between 0.4 and 0.7. This shows that the public prefers water body landscapes, historical culture, and landscape facilities with low green visibility; aquatic plant landscapes with medium–low green visibility; road environments with medium–high green visibility; and flower landscapes with high green visibility. At the same time, the public prefers macro-landscapes with low green visibility, meso-landscapes with planted green visibility, and micro-landscapes with very low green visibility and medium–high green visibility.

The sky visibility analysis, however, classified sky visibility into five levels, namely low openness (levels 1 and 2, with value intervals of 0~0.01 and 0.01~0.10, respectively), medium openness (levels 3 and 4, with value intervals of 0.10~0.25 and 0.25~0.40, respectively), and high openness (level 5, with a value interval of 0.40~0.84). The sky visibility results for different landscape types with different spatial scales for the DeepLab v3+ model analysis are shown in Figure 9.



(a) Sky visibility of different landscape types (b) Sky visibility at different spatial scales

Figure 9. Sky visibility for different landscape types and spatial scales.

Figure 9 shows that the sky visibility values of water landscapes are mainly concentrated between 0.1 and 0.5; the sky visibility values of forests, flowers, aquatic plants, history and culture, landscape facilities, and the actual road environment are all concentrated between 0 and 0.1. The sky visibility values of amusement facilities are in the ranges of 0–0.1 and 0.3–0.5. The average sky visibility values of macro-, meso-, and micro-landscapes are 0.315, 0.158, and 0.082, respectively. On the whole, the public prefers water body landscapes and amusement facilities with medium-to-high openness and other landscapes with low openness among different landscape types. For different scales of spatial openness, the public prefers macro-scale landscapes with medium–high openness and meso- and micro-scale landscapes with low openness.

For the building visibility analysis, based on the 20 LP classes in Table 1, the descriptive results of LP building visibility analyzed using the DeepLab v3+ model are shown in Table 3.

Table 3. Descriptive results of visibility of lake park buildings.

-	1	2	3	4	5	6	7	8	9	10
Average visibility of buildings	0.053	0.053	0.092	0.104	0.068	0.076	0.048	0.068	0.136	0.044
-	11	12	13	14	15	16	17	18	19	20
Average visibility of buildings	0.063	0.112	0.148	0.174	0.128	0.015	0.015	0.057	0.051	0.101
Standard for visibility classification of buildings										
-	Low building visibility				Medium building visibility			High building visibility		
	Level 1		Level 2		Level 3			Level 4		
Numerical range	(0, 0.01)		(0.01, 0.10)		(0.10, 0.30)			(0.30, 1.00)		
Perceived frequency	36.651%		37.032%		17.969%			8.349%		

As can be seen in Figure 3, the building visibility of most parks is maintained between 0.05 and 0.15, with LP14 having the highest building visibility of 0.174, which is attributed to the fact that the park is a fountain park, with the core landscape being the fountain landscape at night. The building visibility of the LP shows a gradually decreasing trend from the center to the outer ring, which is subject to the joint effects of urban building density, height, and landscape architecture. And after dividing the building visibility into four levels, it was found that the perceived frequency of level 2 was the highest; i.e., the public in the LP preferred a landscape with lower building visibility.

6. Discussion

Aiming to address the current problem of the sustainable development of urban habitats affected by the destruction of lake parks (LPs), this study proposes an Automated Machine Learning (Auto ML) model for image classification and content recognition, alongside the DeepLab v3+ model for the semantic segmentation of images. Experimental analyses of lake park imagery features (LPIFs) and public perceived preferences (PPPs) were conducted at two levels. The experimental results indicate that the Auto ML model had a commendable recognition performance, as evidenced by the average accuracy rates of 1.000 for amusement facilities, 0.955 for floral landscapes, and 0.946 for aquatic plant landscapes. Therefore, in the landscape composition characterization, the frequency of perception values of the four landscapes in the natural landscape category were 25.54%, 25.22%, 10.38%, and 18.13%, totaling 69.27%, which was higher than the value of the humanistic landscape. Additionally, the macroscopic water body landscape exhibited a higher frequency of perception of 73.02%. Plant landscapes, particularly various types of floral elements, significantly influenced the public's seasonal preferences for LPs.

Among the landscape elements, macroscopic water bodies exhibited a particularly high frequency of perception of 73.02%, highlighting their crucial role in shaping the public's landscape preferences and underscoring their importance in urban park design. The analysis of landscape proportion characteristics revealed that the public tends to prefer landscape elements with low green visibility, exemplified by water body landscapes, historical and cultural elements, and landscape facilities. This preference underscores the need to consider these elements in landscape design to enhance seasonal appeal and public satisfaction.

7. Conclusions

The application of the Automated Machine Learning (Auto ML) model for image classification and content recognition, along with the DeepLab v3+ model for semantic image segmentation, has demonstrated remarkable effectiveness. Notably high average accuracy rates for amusement facilities, floral landscapes, and aquatic plant landscapes showcase their superior recognition capabilities. Models of this kind offer a promising solution for analyzing perceived landscape preferences and hold practical utility in urban habitat development, guiding urban planning and design decisions to align with public preferences.

However, the main limitations of this study are as follows:

1. Data source bias: This study primarily relied on data from social media platforms, which may introduce a selection bias, as these platforms are more popular among younger demographics. This could impact the comprehensive understanding of the characteristics of lake parks and public preferences, as age, culture, and social background can lead to differences in landscape perception and preference.

2. Geographic limitations: This study focused on 20 lake parks in a specific city in central China. This geographic specificity could influence the research findings, as different regions with distinct cultures, climates, and natural conditions may have varying effects on the characteristics of lake parks and public preferences. Consequently, this study's results may not be universally applicable and require validation in different regions.

3. Model limitations: Despite the use of Automated Machine Learning (Auto ML) and deep learning models (DeepLab v3+) to analyze landscape features and public preferences, these models have limitations in terms of accuracy and interpretability. Their performance depends on the quality and quantity of training data, and they may not capture certain complex landscape features. Therefore, this study's results should be interpreted cautiously and may require further validation and improvement.

This study provides valuable insights into the landscape characteristics of lake parks and public preferences. However, the aforementioned limitations must be considered for an accurate interpretation and application of the research findings. Future research could address these limitations by diversifying the data sources, expanding the geographic coverage, and conducting in-depth qualitative studies. Nevertheless, this research on perceived lake park landscape preferences and the application of advanced image analysis models offers valuable insights for the sustainable development of urban habitats. These findings not only contribute to enhancing the quality of urban landscapes but also emphasize the importance of considering public preferences in landscape design and planning.

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Glossary

Parameter	Meaning
γ	The precision rate
κ	The actual number of samples that were correctly classified as positive examples
α	The actual number of samples that were incorrectly classified as positive examples
ν	The recall rate
β	The actual number of samples misclassified as negative cases

F	The reconciled mean of precision and recall
ρ	The average accuracy
G	The green visibility
$Area_g$	The actual area of green vegetation in the picture
$Area_t$	The actual total area of the picture
$Area_{sk}$	The actual area of the sky in the picture
$Area_{bu}$	The area of the sky in the picture

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