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Scenic Beauty of Plant Communities in Hefei Botanical Garden Based on Semantic Segmentation Method

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Abstract Taking the plant community of Hefei Botanical Garden as the research object, semantic segmentation method is used to evaluate the scenic beauty of the plant community. It points out the importance of scenic beauty estimation of plant communities and the problems with existing methods. Subsequently, a review of the current research status both domestically and internationally is conducted, and existing research methods and achievements are summarized. Next, it explains the content and technical route of this study, including data sources and processing, landscape image segmentation of plant community, color feature extraction, texture feature extraction, and establishment of scenic beauty estimation models. Finally, the effectiveness and feasibility of the proposed scenic beauty estimation model are verified through experiments. This paper has guiding significance for improving the landscape design and management level of botanical gardens, and can also provide reference and guidance for research in other related fields.

Keywords Plant community, Scenic beauty estimation, Semantic segmentation, Color characteristics, Texture features
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With the acceleration of urbanization, people's demand for green spaces has shifted from a single shade to a comprehensive experience that emphasizes both ecological benefits and landscape aesthetics. As an important green infrastructure in cities, botanical gardens are not only important places for species conservation and scientific research, but also the core carrier for citizens' leisure and recreation. However, traditional plant arrangements often focus on dust retention ability or a single visual aesthetic, lacking in-depth analysis of the quantitative relationship between plant community structure and public perception[1].

Currently, scenic beauty estimation (SBE) mainly relies on manual questionnaire surveys or expert ratings. Although this method is widely recognized, it has obvious limitations such as strong subjectivity, low efficiency, and lack of spatial information. Traditional methods are difficult to handle massive image data and are prone to recall bias, making them difficult to accurately identify specific landscape factors that affect aesthetics.

In recent years, the rapid development of image semantic segmentation technology has provided a new path for objectively quantifying landscapes. This technology can perform pixel-level classification on images, thereby extracting quantitative landscape element indicators such as green vision rate, vegetation coverage, building proportion, and visual complexity. By combining geotagged photos, researchers can construct large-scale and high-precision landscape databases to analyze the correspondence between public aesthetic preferences and landscape elements in specific locations.

The botanical gardens have a high diversity of plant species and a complex community structure. Existing research has shown that the proportion of trees, shrubs, and grasses, color richness, and structural hierarchy richness are significantly positively correlated with scenic beauty. However, how to scientifically quantify the specific contributions of these complex structures to public psychological perception still requires deep exploration through automated image processing technology.

In summary, the research on the scenic beauty of plant communities based on semantic segmentation not only solves the problem of "black box" operation in traditional evaluation methods and achieves a leap from "qualitative description" to "quantitative analysis", but also provides scientific data support for building stable, ecological, beautiful and sustainable plant communities. In addition, this paper is of great significance in guiding the scientific planning and design of botanical gardens, improving the quality of recreational services, and supporting ecosystem management decisions[2].

As a cutting-edge research in the intersection of landscape architecture and computer vision, the scenic beauty estimation of plant community has made significant progress in recent years. Early research abroad mainly used image processing technology for basic classification and recognition of landscapes. With the development of deep learning, especially semantic segmentation technology, research is advancing towards higher accuracy and deeper levels. The research teams from the United States and Europe have achieved high-precision recognition and quantitative analysis of landscape elements such as vegetation and sky by training models such as DeepLab V3$^+$ and PSPNet. With the development of big data and artificial intelligence technology in China, research on the scenic beauty estimation of plant community based on semantic segmentation is gradually emerging. Scholars have conducted a large number of experimental verifications based on algorithm innovation combined with localized datasets. The application research in urban green spaces, parks, and nature reserves provides scientific basis for urban planning and ecological restoration.

At present, both domestic and foreign studies have shown that semantic segmentation technology can effectively improve the accuracy and efficiency of scenic beauty estimation of plant communities. By using deep learning algorithms for pixel-level classification of landscape images, key landscape elements such as "vegetation", "sky", and "architecture" can be accurately extracted, and their relationship with public aesthetic evaluation can be further quantified and analyzed. In addition, researchers are exploring the application of emerging technologies such as generative AI and panoramic image fusion in scenic beauty estimation, to obtain more comprehensive and in-depth

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analysis results.

Overall, research on the scenic beauty estimation of plant community based on semantic segmentation has made positive progress both domestically and internationally. But it still faces challenges such as geographic and habitat deviations, dynamic succession monitoring, and deep integration of generative design. Future research needs to further strengthen interdisciplinary cooperation and deepen the integration of theory and practice, to promote the development of this field[3].

1 Research content and technical route

This paper aims to quantitatively evaluate the scenic beauty of plant communities through semantic segmentation techniques, including data collection, image preprocessing, construction and training of deep learning model, landscape element extraction, and correlation analysis of scenic beauty. The technical roadmap follows a "bottom-up" logic and is divided into four core stages: data collection and preprocessing, construction and training of deep learning model, quantitative extraction of landscape elements, and correlation analysis of scenic beauty.

During the data collection and preprocessing stage, representative urban plant community areas are selected for image capture to ensure data consistency and diversity. Professional annotation tools are used for pixel-level annotation, and it is converted into a format suitable for model training, to improve generalization ability and accuracy. In response to the complex boundaries and large scale differences of plant communities, U-Net and its variants are selected as baseline models, and optimization strategies such as lightweight backbone networks and channel attention mechanisms are introduced. To address the issue of class imbalance, Dice Loss or Focal Loss combined with cross entropy loss function are used to enhance the segmentation accuracy of small vegetation areas[4].

In the stage of quantitative extraction of landscape elements, not only is the green view index calculated, but also the richness of plant communities is evaluated through methods such as Shannon diversity index, and indicators such as vertical stratification and spatial structure are analyzed to comprehensively reflect spatial distribution characteristics. In the stage of scenic beauty estimation and correlation analysis, a large number of subjects' ratings of the same group of images are collected. Pearson or Spearman correlation coefficients and multiple linear regression or machine learning models are used to predict scores of scenic beauty and identify key factors that affect aesthetics.

Overall, the technical roadmap of this paper aims to use advanced computer vision technology and deep learning algorithms to automatically identify and quantify complex plant community structures, and further evaluate their scenic beauty, thereby providing scientific basis for urban planning and landscape design, and technical support and theoretical guidance for optimizing the design of urban green space systems and improving residents' quality of life[5].

2 Data source and processing

2.1 Data source

The diversity and accuracy of data sources are key to ensuring the quality of research when studying the scenic beauty of plant communities in Hefei Botanical Garden. The data for this paper mainly comes from the following aspects[6]:

(1) Official database of Hefei Botanical Garden. This database contains detailed information about all plants in the botanical garden, including species names, growth environments, maintenance records, etc. These data provide fundamental information for studying the scenic beauty of plant community.

(2) Annual biodiversity monitoring reports of Hefei Botanical Garden. These reports provide detailed records of plant species, quantities, and their changes in different seasons and years within the botanical garden, which is of great significance for analyzing the dynamic changes of plant communities.

(3) Geographic Information System (GIS) data. Through GIS technology, geographic information such as terrain, soil types, and climate conditions within the botanical garden can be obtained, which is crucial for understanding the distribution and growth conditions of plant communities.

(4) Expert interviews and field investigations. By interviewing with horticulturists, ecologists, and experts in related fields at the botanical garden, their professional insights on the scenic beauty of plant communities can be obtained. At the same time, first-hand plant community data such as plant species and growth status can be collected through field investigations.

(5) Literature materials. Referring to relevant academic papers, books, and reports, the research progress and methods on the scenic beauty estimation of plant community at home and abroad can be understood, thereby providing theoretical support and technical references for this paper.

Specifically, literature materials are mainly used in the following three aspects. Firstly, it is used to construct a category system and annotation specification for semantic segmentation models. Referring to existing research, classification standards for trees, shrubs, herbaceous plants, grasslands, water bodies, etc. are determined. Secondly, it is used to screen color and texture feature indicators, such as Shannon entropy, gray level co-occurrence matrix, etc., to ensure the scientificity and comparability of feature extraction methods. Thirdly, it is used to provide theoretical basis for the selection of independent variables in the scenic beauty estimation model. For example, the selection of the factors (proportion of tree area, color richness, boundary complexity, etc.) is based on the significant correlations verified in the literature. Therefore, although literature does not directly participate in the construction of image data, it plays a key theoretical supporting role in the method system and indicator selection.

To present the structure of data sources more intuitively, Fig.1 is used to represent the proportion of each data source in this paper.

25% of the data comes from annual biodiversity monitoring reports, 20% comes from expert interviews and field investigations, 15% comes from GIS data, 15% comes from the official database of Hefei Botanical Garden, and 10% comes from literature materials from CNKI. The comprehensive application of the above information could provide comprehensive and in-depth data support for studying the scenic beauty of plant communities in Hefei Botanical Garden, and help accurately evaluate and improve the landscape beauty quality of the botanical garden[7].

2.2 Data preprocessing

Data preprocessing is a crucial step in image analysis and machine learning, as it directly affects the training effectiveness and final prediction accuracy of subsequent models. In this paper, it mainly deals with the landscape image data of plant communities in Hefei Botanical Garden to ensure the quality and consistency of the data, and provide a reliable basis for the scenic beauty estimation[8]. From April 2025 to October 2025, a Canon EOS 5D Mark IV digital camera (lens focal length of 24–70 mm, aperture f/8, ISO 100) was used for shooting. The shooting time was selected during 09:00–15:00 on clear weather to avoid the impact of strong shadows and backlighting on image quality. The filming locations cover representative areas such as the tree area, shrub area, herbaceous plant area, aquatic plant area, and mixed community area

within the Hefei Botanical Garden. A total of 360 image samples were collected, and 300 valid images were retained after screening for subsequent preprocessing and model training (Fig.2, Table 1).

Data preprocessing mainly includes the following steps:

(1) Image denoising. Due to limitations in the shooting environment and equipment, the original image may contain noise. Gaussian filter is used for smooth processing of images, to reduce the impact of noise. The mathematical expression for Gaussian filtering is:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{\frac{x^2+y^2}{2\sigma^2}}$$

where x and y are pixel coordinates; σ is standard deviation. In this paper, comparative experiments are conducted with σ values of 0.5, 1.0, and 1.5. Ultimately, σ=1.0 is chosen because it achieves the best balance between removing noise and preserving plant edge details, effectively suppressing high-frequency noise while avoiding texture information loss caused by excessive smoothing.

(2) Image normalization. To eliminate differences in brightness and contrast between different images, all images are normalized. The specific method is to scale each pixel value between 0 and 1.

(3) Image cropping. Considering that the landscape images of plant communities in the botanical garden may have incomplete edges, the images are cropped to only retain the central area to ensure data consistency and integrity.

(4) Image enhancement. In order to improve the visual effect of the image and the accuracy of subsequent processing, histogram equalization technology is used to enhance the contrast of the image.

(5) Data annotation. For each processed image, different plant species and regions are manually annotated for subsequent semantic segmentation and feature extraction.

Through the above steps, not only has the quality of the image been improved, but a solid data foundation has also been provided for subsequent semantic segmentation and scenic beauty estimation. These preprocessing steps ensure the consistency and reliability of the data, laying a solid foundation for subsequent research work.

3 Scenic beauty estimation of plant communities

3.1 Landscape image segmentation of plant communities

Landscape image segmentation of plant community is a fundamental step in evaluating scenic beauty of plants, which involves accurately distinguishing different elements (such as plants, soil, water bodies, etc.) in the image at the pixel level. This process is crucial for subsequent color feature extraction and texture feature analysis[9].

When performing image segmentation, deep learning methods, especially semantic segmentation techniques, are commonly used. Semantic segmentation can assign a category label to each pixel, thereby achieving a refined understanding of image content. For example, trees, shrubs, herbaceous plants, and non vegetation areas (such as bare soil and water bodies) in the image can be marked separately.

The process of image segmentation can be represented as the following mathematical model:

$$L(x,y)=\arg_\{l\}\sum_{x,y}P(l|x,y)$$

where $L(x,y)$ shows pixel label at position (x,y); $P(l|x,y)$ is the probability of labeling l at a given pixel position (x,y).

In order to improve the accuracy and efficiency of segmentation, it is usually necessary to perform sufficient preprocessing on the dataset, including image normalization, application of enhancement strategies, and handling of class imbalance issues. In addition, it is also crucial by choosing the appropriate model architecture, and common models include U-Net, DeepLabV3$^+$, etc.

From Fig.3, it can be seen that in a typical landscape image of plant community, trees occupy a larger proportion, followed by shrubs and herbaceous plants. Although the areas of bare soil and water bodies are smaller, they are also important parts of the landscape[10]. In practical applications, image segmentation not only needs to consider the accuracy of classification, but also the consumption of computational resources and processing speed. Therefore, it is very important by choosing the appropriate model and optimizing the algorithm. For example, using lightweight models can significantly improve processing speed while ensuring a certain level of accuracy, making it suitable for real-time or large-scale data processing scenarios.

In summary, landscape image segmentation of plant community is a complex but crucial task that directly affects the accuracy and practicality of subsequent scenic beauty estimation. By continuously optimizing data preparation, model selection, and training processes, segmentation performance can be effectively improved, providing strong technical support for the study of plant scenic beauty.

3.2 Color feature extraction of landscape images

In the study of the scenic beauty of plant communities, the extraction of color features is an important step in evaluating the visual effects of landscapes. By analyzing the landscape images of Hefei Botanical Garden, color information can be effectively identified and quantified, providing scientific basis for the scenic beauty estimation[11].

Color feature extraction first involves image preprocessing, including denoising, enhancement, and lighting correction, to ensure the accuracy and reliability of subsequent processing. After completing these basic processes, the RGB image is converted to the HSV or CIELAB color space to better simulate the human eye's perception characteristics of color.

After color space conversion, color features are statistically calculated. For example, the proportion of dominant colors can be determined by calculating the proportion of the most frequently appearing color in the image. Color richness is measured by the Shannon entropy formula $H=-\sum p_i\log_2 p_i$, where p_i represents the probability distribution of each color.

The cool and warm color ratio is evaluated by comparing the area ratio of warm colors (such as red, orange, yellow) to cool colors (such as blue, purple, cyan) in an image. In addition, the hue index (H) reflects the overall color tone tendency, while the number of colors (XNC) represents the number of significant color types.

In order to demonstrate the process of color feature extraction more intuitively, the entire process from image acquisition to color feature calculation is described below through a flowchart (Fig.4).

Key color features are extracted from the landscape images of Hefei Botanical Garden, which lays a solid foundation for the establishment of subsequent evaluation models for scenic beauty. These color features

Table 1 Landscape image data of plant communities in Hefei Botanical Garden

Image No.	Original size//px	Processed size//px	Noise level
001	1,920×1,080	1,920×1,080	Low
002	2,560×1,440	2,560×1,440	Moderate
003	3,840×2,160	3,840×2,160	High

not only help to understand the visual beauty of plant communities, but also guide actual landscape design and management to enhance public aesthetic experience and environmental satisfaction[12].

3.3 Texture feature extraction of landscape images

The texture feature extraction of landscape images is a key step in the scenic beauty estimation of plant communities, involving the extraction of features from images that can describe the spatial structure and distribution patterns of vegetation. Gray level co-occurrence matrix (GLCM) is a widely used technique in texture analysis, which describes texture characteristics by calculating the co-occurrence relationship between different gray levels in an image.

When applying GLCM for texture feature extraction, the primary task is to convert the original image into a grayscale image. This step typically involves grayscale degradation of multispectral or high-resolution images to reduce computational complexity and improve processing efficiency. Next, the appropriate window size and orientation are selected to construct the co-occurrence matrix. The window size is usually set to 3 × 3 to 7 × 7 px, with directions including 0°, 45°, 90°, 135°, etc.

The construction of co-occurrence matrix is based on the statistical analysis on the grayscale distribution relationship of pixel pairs at specific distances and directions. For example, for a given window size and orientation, the frequency at which all pairs of pixels (i, j) separated by d within the window appear together is calculated, forming an $N \times N$ matrix, where N is the number of gray levels.

Multiple texture operators can be extracted from the co-occurrence matrix, which reflect specific attributes of the image such as contrast, homogeneity, angular second moment, entropy, correlation, and variance. The specific calculation formulas for these features are as follows:

$$\text{Contrast}=\frac{1}{(N^2-1)}\sum_{i,j}(i-j)^2P(i,j)$$

$$\text{Homogeneity}=\frac{1}{1-\rho}\sum_{i,j}\frac{P(i,j)}{1+\rho^{|i-j|}}$$

where ρ is the proportion of grayscale levels.

$$\text{ASM/Energy}=\sum_{i,j}P(i,j)^2$$

$$\text{Entropy}=-\sum_{i,j}P(i,j)\log P(i,j)$$

Through the above steps, rich texture features can be extracted from landscape images, which can not only describe the spatial distribution and structure of vegetation, but also reflect its aesthetic value (Fig.5). In the establishment of subsequent evaluation models for scenic beauty, these texture features serve as important input parameters to help more accurately assess the aesthetic level of plant communities[13].

Table 2 Scenic beauty estimation by image segmentation

Element	Area proportion//%	Boundary complexity	Color richness
Tree	30	0.75	0.85
Shrub	20	0.65	0.70
Herbaceous plants	40	0.55	0.65
Water body	10	0.90	0.95

3.4 Establishment of a model for the scenic beauty estimation of plant communities

In the process of establishing an evaluation model for scenic beauty of plant community, multiple technical methods are used to ensure the accuracy and practicality of the model (Table 2). The establishment of the model is based on the following key steps:

(1) Data collection and preprocessing. The high-definition landscape images of Hefei Botanical Garden are collected, including shots taken in different seasons and at different time points, to ensure data diversity and representativeness.

(2) Semantic segmentation. Deep learning models are used to perform pixel-level classification on images, extracting detailed information about features such as plants, water bodies, and roads. This step is the foundation for the model to conduct subsequent analysis.

(3) Feature extraction. The features such as area ratio, boundary complexity, and color distribution are extracted from the segmented image, which serve as important parameters for the model input.

(4) Scenic beauty estimation. A 0−100 of scenic beauty rating is assigned to each image through expert review or public voting as the target variable for the model output.

(5) Regression modeling. Using the extracted features and scenic beauty ratings, a multiple linear regression model is established to analyze the contribution weights of each element to scenic beauty.

The mathematical expression of the model can be expressed as:

$$\text{SBE}=\beta_0+\sum_{j=1}^{n}\beta_jX_j+\varepsilon$$

where SBE shows scenic beauty estimation; X_j shows quantitative indicator of the j^{th} landscape element; β_j is corresponding regression coefficient; ε is error term.

It should be noted that Fig.6 shows the relative contribution weights of each landscape element in the regression model of scenic beauty, rather than the area proportion in the image. Specifically, the contribution weight of trees is 40%, shrubs are 20%, herbaceous plants are 30%, and grasslands are 10%. This data is not contradictory to the area proportion in Table 2 (30% for trees, 20% for shrubs, 40% for herbs, and 10% for water bodies), as Table 2 reflects the actual area proportion after image segmentation, while Fig.6 reflects the standardized regression coefficient proportion of each element for the scenic beauty rating. The two dimensions are different, with the former being the physical coverage ratio and the latter being the aesthetic contribution weight. The main text clearly distinguishes between these two concepts to avoid confusion.

To verify the effectiveness of the established evaluation model for scenic beauty, this paper uses the reservation method to divide the dataset into a training set and a testing set in a ratio of 7 ∶ 3. After establishing a multiple linear regression model using the training set, the predictive performance of the model is evaluated on the test set. The coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) are used as evaluation indicators. The results show that the R^2 of the model on the test set reaches 0.82, the RMSE is 4.36, and the MAE is 3.21, indicating that the model has good predictive ability for scenic beauty rating. The stability of the model is further tested through five-fold cross validation. The results show that the fluctuation range of R^2 for each fold is between 0.78 and 0.85, indicating that the model does not exhibit significant overfitting. In addition, significance tests are conducted on the regression coefficients, and the P values for the proportion of tree area, color richness, and boundary complexity are all lower than 0.05, verifying that these landscape elements have a significant impact on the scenic beauty. Through the above steps, not only can the scenic beauty of plant communities be objectively evaluated, but also the impact of different landscape elements on overall aesthetics can be deeply understood.

4 Conclusions

In this paper, the plant communities of

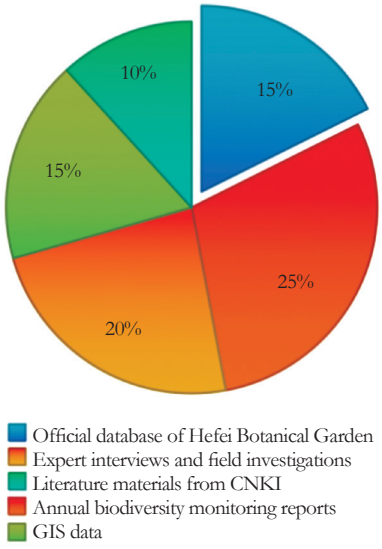


Fig.1 Distribution of data sources

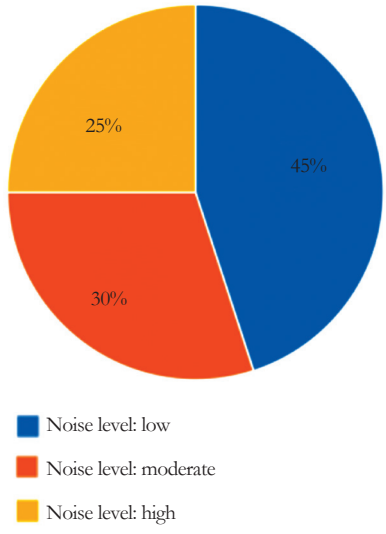


Fig.2 Distribution of image noise levels

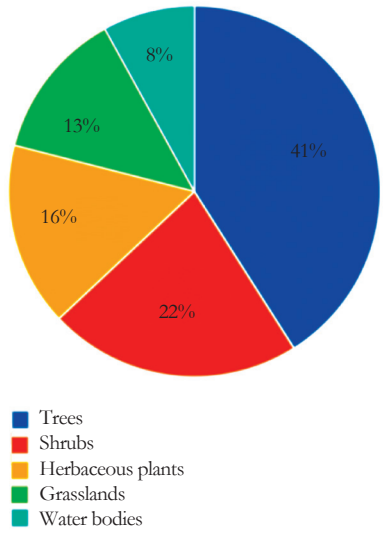


Fig.3 Proportion of various types in the landscape images of plant communities

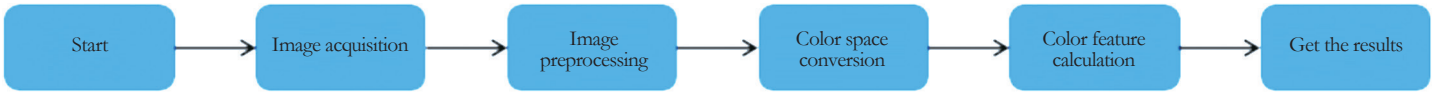


Fig.4 Flow of color feature extraction

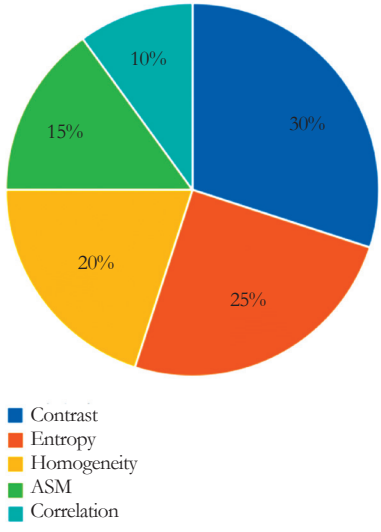


Fig.5 Importance of texture features in scenic beauty estimation

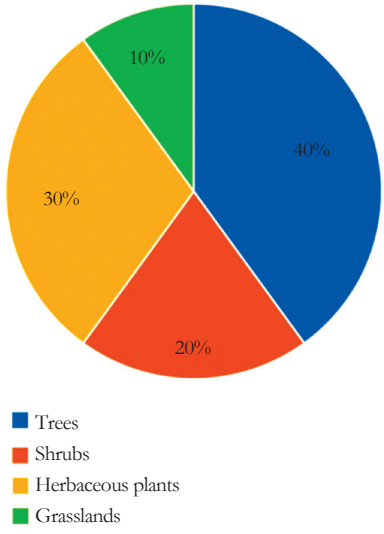


Fig.6 Distribution of elements in scenic beauty of plant communities

Hefei Botanical Garden are taken as the research objects. The semantic segmentation technology is introduced to construct a scenic beauty estimation model of plant community, which realizes the transformation from traditional subjective evaluation to objective quantitative analysis. The study uses U-Net and its variant models for pixel-level segmentation of landscape images, accurately extracting landscape elements such as trees, shrubs, herbaceous plants, grasslands, and water bodies. Combined with color and texture feature analysis, a multiple linear regression model is established to reveal the contribution weights of each landscape element to the scenic beauty. Research has shown that the area proportions of trees and shrubs, color richness, and boundary complexity are key factors affecting the scenic beauty of plant communities, with trees playing a particularly significant role in visual dominance.

The innovation of this paper lies in the application of semantic segmentation technology system in deep learning to evaluate the scenic beauty of plant communities, overcoming the limitations of traditional questionnaire survey methods such as strong subjectivity, low efficiency, and lack of spatial information, and providing a new paradigm for quantitative research on plant community landscapes. At the same time, the technology route constructed in this paper, covering data collection, image preprocessing, model construction, feature extraction, and scenic beauty correlation analysis, has good generalizability and can provide reference for landscape evaluation of urban green spaces, parks, and nature reserves.

However, this paper still has certain limitations. The sample data mainly comes from Hefei Botanical Garden, with limited geographical coverage; the model's consideration of seasonal dynamic changes is not yet sufficient; the scenic beauty rating still partially relies on the subjective judgment of experts. Future research can further expand the sample area, integrate multi temporal remote sensing images and panoramic images, explore the application of generative AI in landscape design optimization, and strengthen interdisciplinary cooperation to promote the development towards more intelligent and accurate direction in scenic beauty estimation of plant community.

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