

Rural Landscape Image Processing: Improved DeepLab v3+ Segmentation and K-means Color Quantification

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Abstract: To improve the accuracy and effectiveness of digital optimization of rural landscapes, a method combining improved Deep Laboratory v3+ (DeepLab v3+) and optimized K-Means Clustering (KMC) quantification is proposed. In the landscape image segmentation process, the Deep Laboratory v3+ model is improved by introducing cross-stripe pooling, a convolutional attention mechanism, and a residual feature fusion module. The experiment verified that the average segmentation accuracy of the model reached 99.1%, the average Dice coefficient was 0.906, the average intersection to union ratio was 0.881, and the average segmentation speed was increased to 0.22 seconds per image. All indicators were better than the comparison model. The ablation experiment showed that the residual feature fusion module could improve the intersection to union ratio by 1.7%, with the most significant improvement in segmentation performance. In the color quantization optimization stage, the node index method, elbow rule, and average error vector optimization K-means algorithm were used. Validation results showed that the weighted average peak signal-to-noise ratios for natural, semi-natural, and cultural rural landscapes were 32.4 dB, 34.5 dB, and 36.6 dB, respectively. The average quantization speed was 1.6 seconds per image, and the average quantization error was only 0.781, outperforming other comparison methods. Through precise segmentation of landscape elements and efficient color quantification, the study has enriched color levels and enhanced aesthetic value in rural landscapes. This provides operational technical support for digital design, ecological livability planning, and other management decisions in rural landscapes.

Keywords: Rural landscape, DeepLab v3+, k-means, cross stripe pooling, residual feature fusion.

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1. Introduction

As a concentrated carrier of rural regional culture, ecological environment, production and life, rural landscape quality not only directly affects residents' sense of well-being but is also a key element in promoting the realization of the "ecological livability" goal in the rural revitalization strategy. In recent years, with the rapid development of the rural tourism industry and the in-depth advancement of human settlements improvement work, the traditional landscape optimization model that relies on manual survey and subjective evaluation has been unable to meet the needs for precision and efficiency. Manual assessment is susceptible to experience bias and cannot objectively quantify the spatial distribution characteristics of multiple types of landscape elements, such as natural vegetation, humanistic buildings, and artificial facilities. Moreover, the optimization of visual attributes such as the rationality of color matching and the richness of landscape levels lacks data support. These will lead to problems such as serious homogeneity, separation of ecological and cultural characteristics, and insufficient ornamental value in some rural landscapes (Xia and Chen, 2025; Cai, 2025). Meanwhile, breakthroughs in computer vision technology provide new paths for digital analysis of rural landscapes. The semantic segmentation model can realize automatic identification and extraction of landscape elements, and the color quantification algorithm can provide a quantitative basis for landscape visual optimization (Qin and Jian, 2025). However, existing technologies still have limitations in rural scene applications. The mainstream Deep Laboratory v3+ (DeepLab v3+) model is not adaptable enough to multi-scale targets in rural landscapes (such as tall trees, low shrubs and small humanistic markers) and is prone to problems such as loss of boundary details and low segmentation accuracy. The traditional K-Means Clustering (KMC) algorithm often falls into local optima due to random initialization of the centroids. Moreover, in large sample landscape images, its convergence speed is slow, and it is difficult to efficiently support color optimization requirements (Xie et al., 2023). Therefore, it is necessary to develop a model that can accurately extract rural landscape elements and efficiently quantify colors.

DeepLab v3+ is a Deep Learning (DL) framework that is widely utilized in many different fields and offers the benefits of excellent segmentation accuracy and quick reasoning speed. Given the challenge of identifying underwater cracks in concrete dams, Wang et al. (2024) proposed a semantic segmentation model based on MobileNetV2-DeepLabv3+. This model introduced the lightweight network MobileNetV2 and reduced the depth feature downsampling multiple times by a factor of 8 to improve recognition accuracy and inference speed under small data sets. Cheng et al. (2024) proposed a navigation line extraction method for combine harvesters based on sunlight robustness, DeepLabV3+, to address the problem of insufficient visual navigation line recognition accuracy for intelligent combine harvesters under different sunlight conditions. By creating a fresh dataset and forecasting the boundaries of cut and uncut regions, this approach generated navigation lines, with the MobileNetV2 module added for enhancement. To address the challenge of extracting road information from intricate high-resolution remote sensing imagery, Dong et al. (2024) proposed a road feature enhancement network based on the DeepLabV3+ architecture. The findings demonstrated that the network's intersection over union (IoU) and F1-score were better than those of the baseline.

The KMC algorithm is a widely used unsupervised learning algorithm for discovering natural groups or clusters in data sets. It has the advantages of strong scalability and good interpretability. Qun et al. (2024) proposed a hierarchical space reduction method to solve the problems of high dimensionality, high computational cost, and "black box" characteristics in hull shape optimization. To facilitate hull shape optimization, the proposed method clustered the visualization results of self-organizing mapping through KMC, selected regions of interest, and used data mining to extract the knowledge inherent in the sample simulation data. The outcomes demonstrated that this strategy produced a higher quality optimization solution by reducing the total resistance of the ideal ship type by 2.266%. A color analysis technique based on KMC was presented by Rong et al. (2024) based on the interaction of color selection in posters created by artificial intelligence with posters created by humans. Through quantitative analysis, the approach examined the color preferences of a sample of 120 examples in each category and demonstrated the general similarity of color choices. The results showed that although artificial intelligence was still less concentrated than humans in terms of color diversity, it showed that there was a gap with human expertise in color proportions and distribution. Bin et al. (2025) presented a novel, all-encompassing strategy based on KMC for typical solar radiation years to address the problem of maximizing solar radiation absorption by optimizing energy use and solar panel efficiency. The findings demonstrated that this approach might enhance energy harvesting more successfully than conventional techniques.

In summary, DeepLab v3+ and K-means algorithms (KMAs) are widely used in various fields, and after improvements in existing research, the performance of the above algorithms has been significantly improved. However, it is challenging to satisfy the requirements of landscape color optimization in the field of rural landscape optimization due to issues like low segmentation accuracy and loss of boundary features. In summary, the current optimization of rural landscapes faces the following problems. (1) How to improve the segmentation accuracy and efficiency of natural vegetation, cultural landmarks, and other landscape elements by improving the DeepLab v3+ model structure to address the issues of low accuracy in multi-scale object segmentation and loss of boundary details in rural landscapes, and provide high-precision basic data for subsequent color quantification? (2) The traditional KMA has several shortcomings when it comes to quantifying rural landscape colors. These include random initial centroids, slow convergence with large samples, and susceptibility to local optima. How to optimize the algorithm process through heuristic methods to achieve efficient and accurate quantification of landscape colors? (3) How to build a technical chain of "accurate image segmentation, color quantification optimization, landscape visual enhancement," establish a quantitative correlation between algorithm performance and the enhancement of rural landscape viewing value, and provide actionable technical solutions for digital optimization of rural landscapes? In view of this, the study proposes a rural landscape optimization method that integrates improved DeepLab v3+ and KMC, along with quantification, to achieve accurate extraction of rural landscape elements and efficient color quantification. The innovation of the research is that this research first introduces cross stripe pooling, Convolutional Block Attention Module (CBAM), and residual feature fusion module to improve DeepLab v3+ to improve its segmentation performance of landscape images. Second, this study uses the node index method, the elbow rule and the average error vector to improve the KMA to avoid it falling into local optimality. The research has established a complete technical chain of "high-precision semantic segmentation, efficient color quantification, landscape visual optimization," directly linking computer vision algorithms with rural landscape planning requirements. Quantifying indicators such as color richness and landscape contrast establishes a quantitative relationship between algorithm performance and the enhancement of landscape appreciation value. This provides a replicable and quantifiable technological paradigm for the digital optimization of rural landscapes. It fills the gap in traditional landscape optimization, which relies on subjective evaluation and lacks data support.

2. Methods and Materials

Aiming at the limitations of traditional rural landscape planning relying on subjective human judgment, a digital optimization theoretical framework of "precise segmentation, quantitative analysis, decision support" is proposed. This theory is based on the high-precision semantic segmentation of landscape elements and establishes a system for evaluating the visual quality of landscapes. This system uses color quantification indicators, such as color richness, hierarchical contrast, and visual comfort, to convert the quantified data output by image algorithms into actionable planning and design parameters. This method uses DeepLab v3+ to segment landscape images and uses KMC to quantify colors to optimize rural landscapes. The research aims to improve the visual coordination of the landscape, enhance the recognition of regional culture, and improve the experience of tourists and residents, in accordance with the landscape style control requirements in the "Rural Landscape Planning and Design Specification." At the same time, two key decision variables are established: the spatial configuration of landscape elements and the visual proportion of cultural landmarks and natural vegetation

coverage. Additionally, the color contrast of road corridors is considered. The second is the color quantification parameter variable, which covers color richness, seasonal change frequency, and the degree of matching between the main color tone and local culture.

2.1. Landscape Image Segmentation Method Based on Improved Deeplab v3+

Because rural landscape optimization involves many aspects such as nature, humanities, economy, and technology, it is highly complex. Therefore, to accurately analyze and evaluate the landscape, optimize the design plan, and improve the quality and efficiency of the landscape, it is first necessary to segment the landscape image. Before parametrically processing landscape images, many rural landscape images need to be collected first. As an important way for the public to express their perceived preferences and emotional evaluations, social media platforms contain a large quantity of rural landscape images and can be used as a source of image data. Taking into account the diversity of data, the study selects review pictures from the social media platforms of three domestic mainstream travel websites: Dianping.com, Ctrip.com, and Mafengwo.com as data sources. The study collects 27546 real-life photos of rural landscapes from three major platforms: Dianping, Ctrip, and Mafengwo. This data source can intuitively reflect the landscape features from the perspective of tourists. However, there is a selection bias: the images often display advantageous areas, making it difficult to cover the entire landscape. The differences in shooting equipment and lighting conditions affect the consistency of image quality. The study aims to reduce bias through strict filtering (removing duplicate, blurry, and excessively edited samples) and stratified sampling (balancing natural, semi-natural, and cultural landscapes). In the future, the comprehensiveness of the dataset can be further enhanced by combining residents' daily captured images with aerial data. This study employs a ground truth marking process that combines manual annotation with semi-automatic validation. The category definition covers six core objectives: natural vegetation, cultural architecture, road facilities, water bodies, farmland, and background. The labeling process is independently completed by three landscape planning background annotators using the LabelMe tool, following a unified boundary standard. Consistency validation uses the Kappa coefficient (≥ 0.85) on the data. It also uses semi-automatic algorithms to recheck and correct issues such as boundary blurring and category confusion. Ultimately, these steps form a high-quality annotated dataset. For the collected images, the study uses DeepLab v3+ for semantic segmentation. A DL model for semantic segmentation is called DeepLab v3+. To balance accuracy and running time, it uses an Encoder-Decoder structure and uses Atrous Convolution to regulate the resolution of the output Feature Map (FM). However, due to the insufficient processing of object scale diversity in the Encoder stage, and the insufficient use of feature semantic information at the Encoder-Decoder connection, the segmentation accuracy is poor (Mokayed et al., 2023; Pal et al., 2025; Pei et al., 2025). In view of this, the study introduces cross stripe pooling, boundary enhancement, and residual feature fusion to improve DeepLab v3+. Fig. 1 depicts the enhanced DeepLab v3+ architecture.

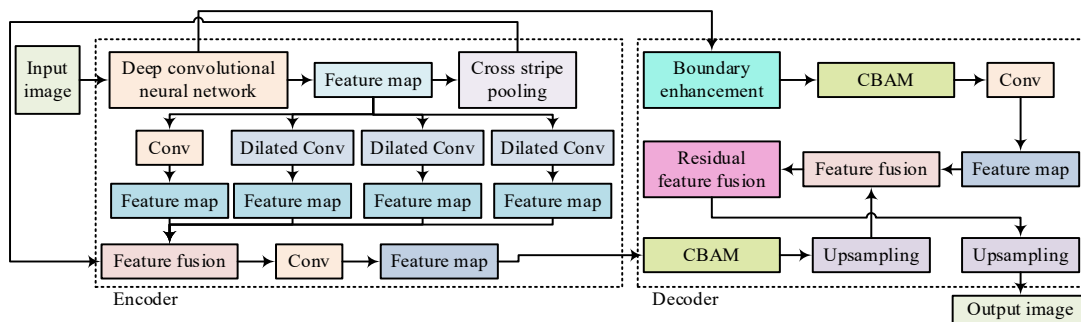


Fig. 1. Architecture of improved DeepLab v3+

In Fig. 1, unlike the traditional DeepLab v3+Encoder, which relies solely on dilated convolutions to extract multi-scale features and the decoder, which only performs simple feature upsampling and fusion, the improved model incorporates a cross-stripe pooling module in the Encoder section. This module captures long-range dependencies through narrow pooling windows in both the horizontal and vertical directions, reducing information interference. It reduces information interference and strengthens associations between contextual features. At the same time, the improved model's Decoder also integrates a three-layer structure of a boundary enhancement module, Convolutional Block Attention Module (CBAM), attention mechanism, and a residual feature fusion module. First, edge features are extracted and fused through the boundary enhancement module. Then CBAM is used to enhance key features from the channel and spatial dimensions. Finally, efficient reuse of deep and shallow features is achieved through residual feature fusion. In the Encoder part, this module extracts features through a deep convolutional neural network by improving DeepLab v3+ and obtains a deep Feature Map (FM) of 1/16 size. Then, cross stripe pooling is used to extract the feature information of the deep FM. Then, the features are spliced through batch processing, batch normalization and ReLU activation function, and the encoding

stage output is obtained after 1×1 convolution processing. The Decoder part consists of a boundary enhancement module, a CBAM module, and a residual feature fusion module. It first outputs shallow features and enhances boundary information. Then it strengthens deep and shallow features, fuses them, refines the fused features, and obtains the final segmentation result. Fig. 2 depicts the cross-stripe pooling module's structure.

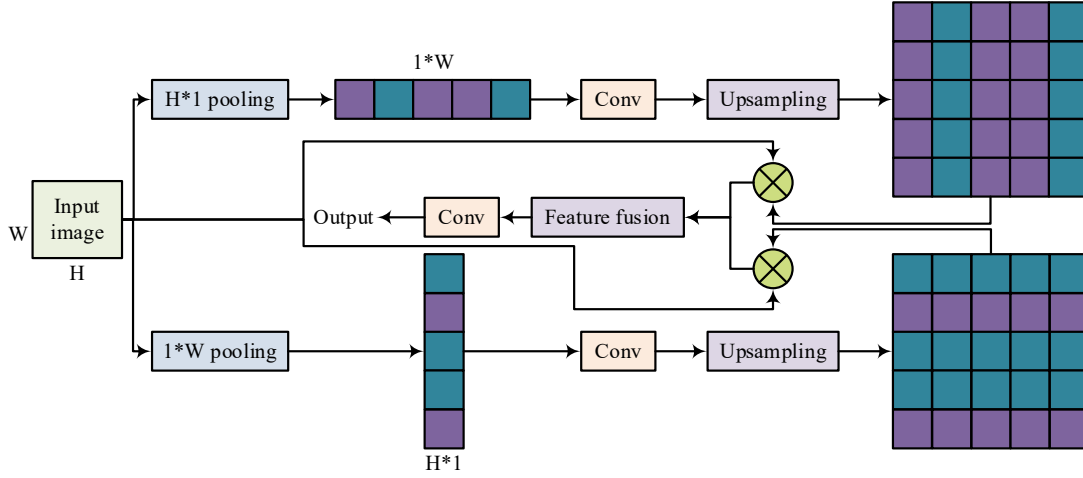


Fig. 2. Structure of cross stripe pooling module

In Fig. 2, unlike ordinary pooling, cross-stripe pooling captures long-distance dependencies of images accurately through a rectangular pooling window, while reducing information interference from non-target areas. This module offers several advantages. It can enhance the local contextual correlation of multi-scale targets, such as high and low vegetation and small cultural landmarks, in rural landscapes. It can also improve the specificity of feature extraction. The pooling result is shown in Eq. (1).

$$\begin{cases} p_j^v = \frac{1}{H} \sum_{i=0}^{H-1} P_{i,j} \\ p_i^h = \frac{1}{W} \sum_{j=0}^{W-1} P_{i,j} \end{cases} \quad (1)$$

In Eq. (1), p_j^v and p_i^h represent the pooling results in the vertical and horizontal dimensions, respectively. H and W display the height and width of the input FM, respectively. $P_{i,j}$ represents the pixel value of row i and column j of the input FM. Since DeepLabv3+ has the problem of losing boundary details, the study introduces a boundary enhancement module to improve the model's sensitivity to object boundary features. This module obtains edge features by subtracting image edge blur from the image and fuses the edge FM with the original image to enhance the boundary. The edge feature calculation formula is shown in Eq. (2).

$$B_j = F_j - \frac{1}{M_j} \sum_{i \in M_j} F_j \quad (2)$$

In Eq. (2), F_j represents the edge feature. F_j represents the original FM. M_j represents the average filter area. The boundary enhanced FM is shown in Eq. (3).

$$E = 2F_j - \frac{1}{M_j} \sum_{i \in M_j} F_j \quad (3)$$

The boundary information can be enhanced through the above boundary enhancement module. In addition, to improve the model's attention to deep features, the study also introduces CBAM. CBAM consists of channel attention (CA) and spatial attention (SA), which enhances the model's attention to key features by learning weights on space and channels. The CA FM and SA FM are shown in Eq. (4).

$$\begin{cases} F_c = \sigma(\omega_1 \times \tau(\omega_0 \times F_{avg}^c) + \omega_1 \times \tau(\omega_0 \times F_{max}^c)) \\ F_s = \sigma(Conv_{7 \times 7}([F_{avg}^s, F_{max}^s])) \end{cases} \quad (4)$$

In Eq. (4), F_c and F_s represent the CA FM and the SA FM. σ displays sigmoid function. τ represents the ReLU function. ω_0 and ω_1 represent the weights of the hidden layer and output layer of the multi-layer perceptron. F_{avg}^c and F_{max}^c display the FMs after average pooling and maximum pooling in the channel dimension. $Conv_{7 \times 7}$ stands for 7*7 convolution. F_{avg}^s and F_{max}^s respectively display the FMs after average pooling and maximum pooling in the spatial dimension. Finally, the study also presents a residual feature fusion module to accomplish the fusion of deep and shallow features. Fig. 3 depicts its structure.

In Fig. 3, the residual feature fusion module implements feature fusion through the channel segmentation strategy. Each layer contains two convolution operations. One part through the channel for feature preservation, and the other part through the channel for feature extraction. The channel segmentation operation is divided into three layers, first decomposing the input FM to extract key information. Each layer retains and extracts features separately to ensure complete information. Then, the three feature layers are spliced, and the features are enhanced using the CBAM module. Finally, the residual connection is performed with the original FM to obtain a refined feature result, which provides information for subsequent tasks (Tao et al., 2025; Li et al., 2024). The loss function of the model consists of the Cross-Entropy Loss Function (CELF) and the Dice Loss Function (DLF). The CELF is shown in Eq. (5).

$$L_{CE} = - \sum_{c=1}^N (l_c \log(g_c)) \quad (5)$$

In Eq. (5), L_{CE} represents the CELF. N represents the number of categories. l_c represents the label vector of the c th class object. g_c represents the probability value of predicting the c class. Considering that the proportion of object pixels is much smaller than that of the background, the Cross-Entropy Loss Function (CELF) will cause the model to be biased towards the background. Therefore, to solve the above problems, the study introduced the DLF to balance them. The DLF is shown in Eq. (6).

$$L_{Dice} = 1 - \frac{2 \sum_{pixels} l_{true} p_{pred}}{\sum_{pixels} (l_{true}^2 + l_{pred}^2)} \quad (6)$$

In Eq. (6), l_{true} represents the label matrix. p_{pred} represents the prediction matrix. Through the above method, a landscape image segmentation method based on improved DeepLab v3+ is constructed. Six types of landscape elements, including natural vegetation, cultural architecture, and road facilities, will be segmented according to the core tasks of ecological foundation construction, cultural node creation, and transportation corridor optimization in the planning.

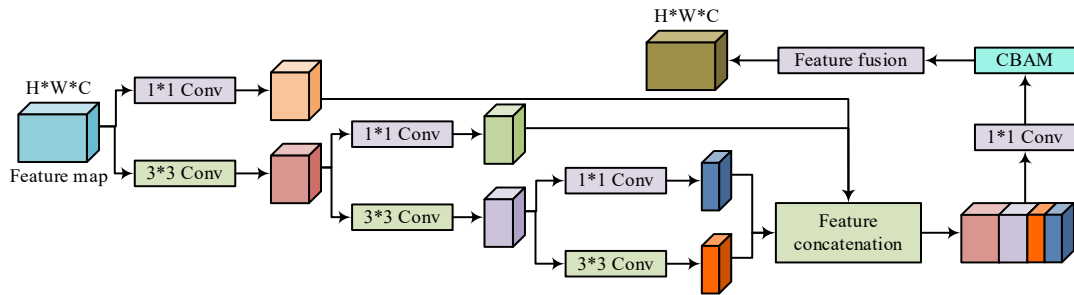


Fig. 3. Structure of residual feature fusion module

2.2. Landscape Image Color Quantification Method Based on Improved K-Means

After segmenting the landscape image by improving DeepLab v3+, the color of the image can then be quantified to enhance the color contrast and saturation of the landscape, making the landscape more vivid and attractive, and improving the attractiveness of the landscape. K-means is a clustering algorithm that achieves color quantification by grouping similar

pixel colors into K clusters and replacing the color of each pixel with the centroid color of its cluster (Khullar, 2024). Fig. 4 illustrates the KMA principle.

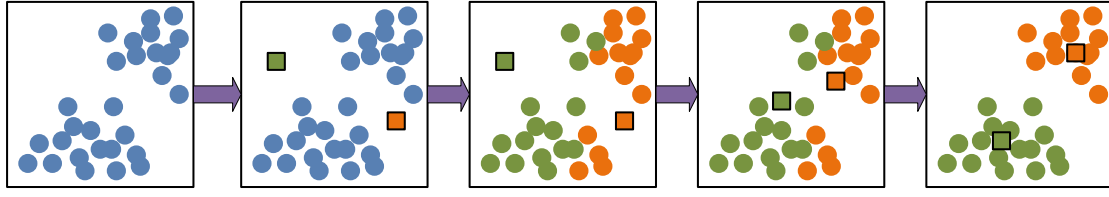


Fig. 4. Principle of K-means algorithm

In Fig. 4, the KMA will first choose two centroids at random, determine the centroid's distance from the sample point, and then categorize them. Then the centroid position is updated, and the classification and update process is repeated until the centroid position is stable, and the final classification result can be obtained (Yan, 2023; Liu et al., 2025). The calculation formula of the center of mass is shown in Eq. (7).

$$\mu_k = \frac{1}{|S_k|} \sum_{x \in S_k} x \quad (7)$$

In Eq. (7), μ_k represents the center of mass. S_k represents the set of all points in cluster k . x represents the sample point. The Euclidean distance is typically used to calculate the separation between the sample location and the centroid. The Euclidean distance calculation formula is shown in Eq. (8).

$$d(x, \mu_k) = \sqrt{\sum_{i=1}^n (x_i - \mu_{k,i})^2} \quad (8)$$

In Eq. (8), $d(x, \mu_k)$ represents the distance between the sample point and the center of mass. x_i represents the coordinates of the sample point in the i th dimension. $\mu_{k,i}$ represents the coordinates of the center of mass in the i th dimension. It is simple to enter local optimality because the KMA's initial clustering center is chosen at random. In view of this, the study introduces the node index method and the elbow rule to improve K-means. The node index method calculates the distance between each node and other nodes and selects specific nodes as high-index nodes after sorting. Among high-index nodes, the first cluster center is selected according to the dispersion principle, and the remaining cluster centers are selected among the remaining nodes, away from the existing cluster centers (Buchdadi, 2024; Hai-Wang et al., 2024). The formula for calculating the elbow rule division index is given in Eq. (9).

$$f(S) = \min \sum_{e=1}^C \sum_{f=1}^{|S_k|} d_{j\epsilon_i}^2 \quad (9)$$

In Eq. (9), $f(S)$ represents the division index. C represents the number of clusters. $d_{j\epsilon_i}$ represents the distance between the node and the cluster center. The improved KMA flow is shown in Fig. 5.

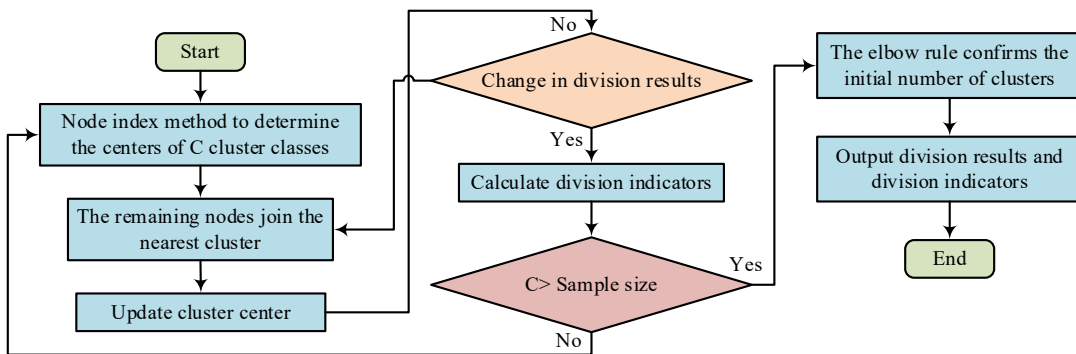


Fig. 5. Improved K-means algorithm flow

In Fig. 5, the node index method is first used to determine the centroid, and the remaining nodes are assigned to corresponding clusters based on distance. Next, update the centroid. Meanwhile, if the clustering results change, the nodes will be reassigned. Otherwise, the partition index is calculated. The elbow approach is used to calculate the initial number of clusters, and the division results and division indicators are output if the number of clusters exceeds the number of samples. Otherwise, it is returned to step one. Although the local optimal problem of K-means is solved after the introduction of the node index method and the elbow rule, it still has the problem of slow convergence when the cluster value is large (Zhang, 2025; Li et al., 2025; Guamón and Herrera, 2025). To solve the above problems, the study introduces the average error vector to optimize and accelerate it. Now it is assumed that there is a quantified landscape image. Its absolute quantization error is shown in Eq. (10).

$$Q(a,b) = \sum_{l=1}^L \sum_{w=1}^W \| a(l,w) - b(l,w) \| \quad (10)$$

In Eq. (10), $Q(a,b)$ represents the absolute quantization error between image a and quantized image b . L and W represent the length and width of the image. Table (l,w) represents the pixel area. For image color quantization, the quantization quality is determined by the color palette. The K-Means color quantization process includes initializing the color palette, quantizing, and updating the color palette. Since finding the optimal color palette is slow, this study updates the color palette through the average error vector method to speed up quantization. The quantization error of any color in the palette is shown in Eq. (11).

$$V(col) = \sum_{(l,w) \in \Omega(b=col)} [a(l,w) - b(l,w)] \quad (11)$$

In Eq. (11), $V(col)$ represents the quantization error vector of the colors in the palette. According to the quantization error vector of the color, a better color vector can be calculated, as displayed in Eq. (12).

$$col' = col + \frac{V(col)}{\Omega(b=col)} \quad (12)$$

In Eq. (12), col' represents the optimized color vector. col represents the current color vector. Ω represents the rectangular area occupied by the image. Through the above method, a color quantization method based on improved K-means is constructed. The process is shown in Fig. 6.

In Fig. 6, an initial color palette is first randomly generated for the input image, and the image is quantized using this color palette to obtain the initial quantized image. Next, the quantization error between the color palette and the input image is calculated. Then, the colors in the palette are updated based on the quantization error. Meanwhile, if the number of colors meets the requirements, the original image is quantified using the updated color palette to obtain a new quantized image. Otherwise, colors are randomly selected from the original image to supplement, and then the image is quantified and updated. At this time, if the absolute average error of the two quantized images is less than the set threshold, the quantized image will be output. Otherwise, the quantization error for each color is recalculated. The above methods can be used to quantify landscape colors, and color richness, hierarchical contrast, and visual comfort can be used as quantitative indicators to guide landscape plant planting schemes.

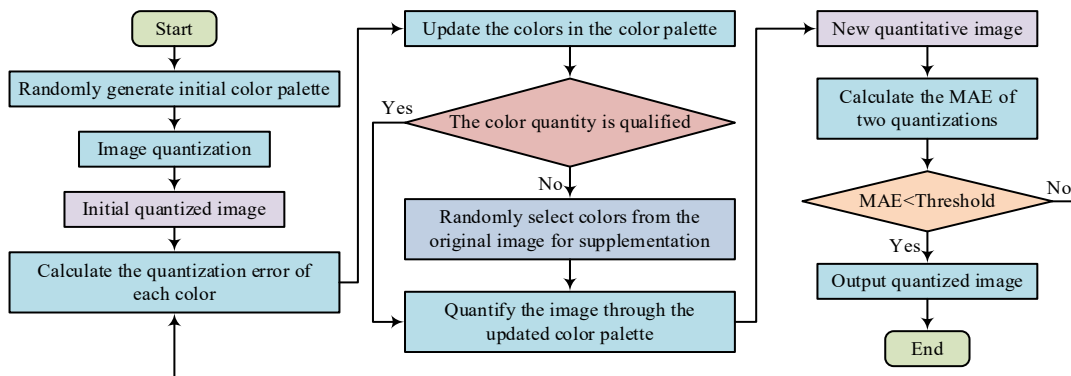


Fig. 6. Color quantization process based on improved K-means

3. Results

3.1. Rural Landscape Image Segmentation Test Results

To verify the image segmentation performance of the improved DeepLab v3+ proposed in the study, the study tests it and compares it with dual attention guided U-Net++ (DAGU-Net++) and proportional pooling mixed attention pyramid scene parsing network (PMA-PSPNet). The dataset used in the experiment is the self-collected dataset in Section 2.1, which contains 27546 rural landscape images. In the experiment, the initial learning rate and minimum learning rate of the model are 0.007 and 0.00007, respectively, and the batch size is 16. The optimizer is stochastic gradient descent, with momentum and weight decay rates of 0.9 and 0.0001, respectively. The segmentation accuracy and Dice coefficient of different methods are shown in Fig. 7.

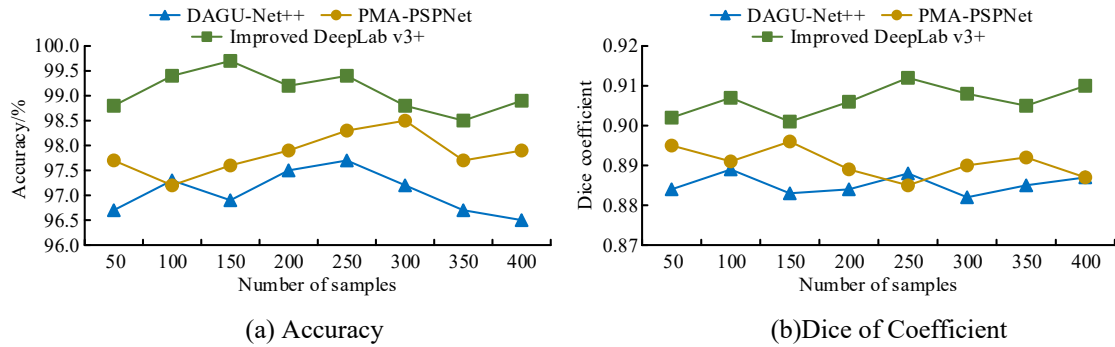


Fig.7. Segmentation accuracy and Dice coefficient of different methods

In Fig. 7(a), the highest segmentation accuracies of DAGU-Net++ and PMA-PSPNet are 97.7% and 98.5%, respectively, and their average accuracies are 97.1% and 97.9%, respectively. The improved DeepLab v3+ has a maximum accuracy of 99.7% and an average accuracy of 99.1%, both of which are higher than those of other methods. In Fig. 7(b), the highest Dice coefficients of DAGU-Net++ and PMA-PSPNet are 0.889 and 0.896, and the average Dice coefficients are 0.885 and 0.891. The enhanced DeepLab v3+ has an average Dice coefficient of 0.906 and a maximum Dice coefficient of 0.912, both of which are greater than those of other techniques. The above outcomes show that improved DeepLab v3+ can achieve accurate segmentation of rural landscapes. The IoU and segmentation speed of different methods are shown in Fig. 8.

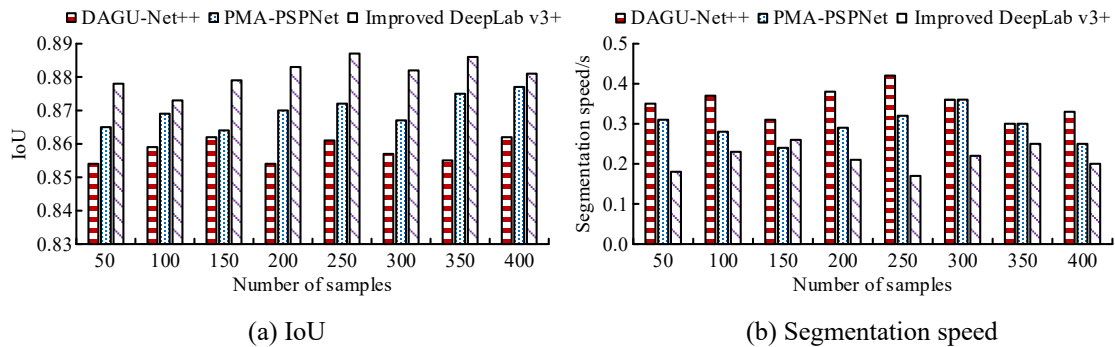


Fig. 8. IoU and segmentation speed of different methods

In Fig. 8(a), the maximum IoU of DAGU-Net++ and PMA-PSPNet are 0.862 and 0.877, and the average IoU are 0.858 and 0.870. The highest IoU for the improved DeepLab v3+ is 0.887, and the average IoU is 0.881, both of which are higher than those of other methods. In Fig. 8(b), the fastest segmentation speeds of DAGU-Net++ and PMA-PSPNet are 0.30s/picture and 0.24s/picture, respectively, and the average segmentation speeds are 0.35s/picture and 0.29s/picture, respectively. The fastest segmentation speed of improved DeepLab v3+ is 0.17s/image, and the average is 0.22s/image, both of which are faster than other methods. The aforementioned findings demonstrate that the enhanced DeepLab v3+ has superior segmentation performance and speed. To further explore and improve DeepLab v3+ performance, an ablation experiment is conducted. Table 1 displays the ablation experiment's findings.

In Table 1, compared with the original DeepLab v3+, after introducing cross-stripe pooling, CBAM, and residual feature fusion modules, the model's IoU increases by 0.881, a 4.1% increase. Among them, the model's performance is most significantly impacted by the residual feature fusion module. The IoU rises by 0.017 following the addition of this module. In conclusion, the study's suggested improvement plan can successfully raise the model's image semantic segmentation performance.

Table 1. Results of ablation experiment

Model	Cross-stripe pooling	CBAM	Residual feature fusion	IoU
1	×	×	×	0.846
2	√	×	×	0.854
3	×	√	×	0.857
4	×	×	√	0.863
5	√	√	×	0.869
6	√	×	√	0.873
7	×	√	√	0.876
8	√	√	√	0.881

3.2. Color Quantification and Landscape Optimization Results

To verify the performance of the color quantification method proposed in the study, the study tests it and compares it with UNet++-Relief and improved adaptive K-means (IDK-means). Table 2 displays the Peak Signal-To-Noise Ratio (PSNR) for several techniques.

Table 2. PSNR of different methods (dB)

Landscape type		UNet++-Relief	IDK-means	Ours
Natural landscape	Red component	28.7	31.3	35.2
	Green component	25.5	29.6	32.7
	Blue component	24.6	27.4	29.6
	Weighted average	26.1	28.3	32.4
Semi natural landscape	Red component	30.7	33.1	37.6
	Green component	28.2	30.8	35.4
	Blue component	25.9	28.6	31.8
	Weighted average	27.7	31.1	34.5
Humanistic landscape	Red component	32.6	35.9	39.8
	Green component	30.1	33.3	37.2
	Blue component	28.4	30.6	35.9
	Weighted average	30.6	33.8	36.6

In Table 2, compared with other methods, the color quantization method proposed in the study has a higher PSNR. Taking natural landscapes as an example, the weighted average PSNR of UNet++-Relief and IDK-means are 26.1dB and 28.3dB, respectively. The weighted average PSNR of the research method is 32.4dB, which is higher than that of other methods. In summary, the approach suggested in this work has superior color quantification quality. The quantization errors and quantization speeds of different methods are shown in Fig. 9.

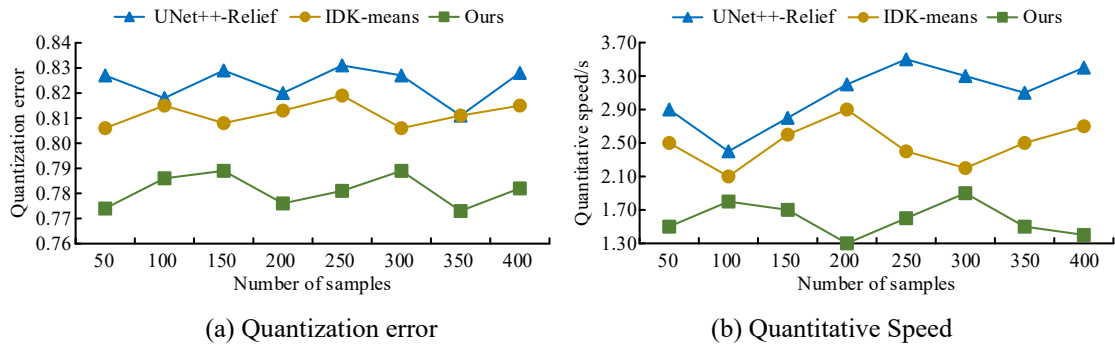


Fig. 9. Quantization error and quantization speed of different methods

In Fig. 9(a), the maximum quantization errors of UNet++-Relief and IDK-means are 0.831 and 0.81, and the average quantization errors are 0.824 and 0.812. The maximum quantization error of the proposed method is 0.789, and the average quantization error is 0.781, which is lower than that of other algorithms. In Fig. 9(b), the fastest quantization speeds of UNet++-Relief and IDK-means are 2.4s/photo and 2.1s/photo, respectively, and the average quantization speeds are 3.1s/photo and 2.5s/photo, respectively. The fastest quantization speed of the method proposed in the study is 1.3s/photo, and the average quantization speed is 1.6s/photo, which is faster than other methods. In summary, the method proposed in this study can achieve rapid and accurate quantification of rural landscape color. To explore the application effect of color quantification in rural landscape optimization, the study takes a rural landscape as an example to evaluate it. The rural landscape after color quantification and optimization is shown in Fig. 10.



Fig. 10. Rural landscape optimized by color quantization (Image source: <https://colorhub.me/photos/ovBrK>)

In Fig. 10, before optimization, due to the lack of ornamental trees and evergreen tree species, the scenery in other seasons has no obvious changes, and the colors are relatively monotonous without obvious layering. After optimization, seasonal ornamental tree species are introduced on both sides of the road to enrich the colors, with clear color changes both horizontally and vertically. Specifically, (1) Color richness: Improving the KMC method to count the number of color levels results in a 42% increase in optimization. (2) Landscape level contrast: It is calculated using a weighted contrast algorithm, optimized to increase by 35%. (3) Visual comfort rating: Based on 100 professional landscape designer ratings, the optimized average score has increased from 6.2 to 8.7. The aforementioned findings demonstrate how the approach suggested in the study might enhance the landscape’s color levels and raise awareness of rural areas. To verify the consistency between algorithm output and human perception and planning standards, this study adds subjective and objective collaborative verification experiments. Moreover, this study selects 30 landscape planning practitioners and 50 ordinary tourists to form an evaluation team. Using a 5-point Likert scale, subjectively evaluate the landscape images before and after optimization across three dimensions: color coordination, layer richness, and visual appeal.

Table 3. Verification results of human perception and planning standards

Verify dimensions	Evaluation metrics	Before optimization	Optimized	Increase margin
Human perception	Color coordination	2.9	4.5	55.2%
	Hierarchical richness	2.7	4.4	63.0%
	Visual attractiveness	3.1	4.6	48.4%
Planning standards	Color richness level	IV	II	Upgrade by 2 levels
	Seasonal variation degree	Single-season phase	Four distinct seasons	Realize multi-season adaptation

According to Table 3, after optimization, various indicators have significantly improved: color coordination (+55.2%), layer richness (+63.0%), and visual attractiveness (+48.4%). All of these indicators exceed 4.4 points, indicating a significant improvement in visual quality. The color richness has been optimized from level IV to level II, in compliance

with the Rural Landscape Regulations. The seasonal change has been upgraded from “single season” to “distinct four seasons”, meeting the ecological landscape planting standards. This algorithm achieves the unified verification of aesthetic quality improvement and professional planning standards.

4. Discussion

To improve the living environment of rural residents and promote the development of rural tourism, this study proposes a rural landscape optimization method that integrates improved DeepLab v3+ and KMC quantification. It effectively solves the problems of insufficient segmentation accuracy and low color quantification efficiency in traditional landscape analysis and provides a feasible technical path for digital optimization of rural landscapes.

At the level of landscape image segmentation, to address the shortcomings of the original DeepLab v3+ in insufficient processing of object scale diversity and loss of boundary details, this study introduces cross stripe pooling, CBAM attention mechanism, and a residual feature fusion module, which significantly improved the segmentation performance. The outcomes revealed that the average IoU of the improved DeepLab v3+ reached 0.881, which was 2.3% and 1.1% higher than DAGU-Net++ and PMA-PSPNet, respectively, and the average segmentation speed was increased to 0.22s/image. It was proven that multi-module collaborative improvement could ensure accuracy while taking into account efficiency. The ablation experiment further verified that the residual feature fusion module made the most significant contribution to performance improvement (IoU increased by 1.7%). It showed that the effective fusion of deep and shallow features was the key to improving the segmentation accuracy of complex scenes in rural landscapes. This was highly compatible with the coexistence of multi-scale targets such as natural vegetation, artificial buildings, and cultural facilities in rural landscapes.

In the color quantification process, the traditional KMA was optimized through the node index method, the elbow rule, and the average error vector. This method solved the local optimal problem caused by the random initial cluster center and the slow convergence of large clusters. Comparative experiments showed that this method had the highest weighted average PSNR (32.4dB, 34.5dB, 36.6dB) in three types of natural, semi-natural, and cultural landscapes, and the average quantization speed reached 1.6s/image, which was 48.4% higher than UNet++-Relief, and the quantization error was reduced by 5.2%. In actual landscape optimization cases, the color gradation of seasonal tree species on both sides of the road was more distinct after color quantification. The horizontal and vertical visual changes were richer, which verified the practical value of this method in improving the ornamental value of rural landscapes.

This technological process fills the theoretical gap in computer vision and rural landscape planning. By mapping quantitative indicators, such as IoU, PSNR, and color richness, planning objectives, a verifiable paradigm for the digital optimization of rural landscapes is provided, and the transformation of planning models from experience-driven to data-driven is promoted. The actual application process includes: (1) It uses improved DeepLab v3+ to segment landscape elements and obtain spatial distribution data. (2) It adopts the improved K-means algorithm for color quantization and determining the optimization threshold. (3) It develops optimization plans based on quantitative data, such as planting seasonal tree species and enhancing landmark recognition. (4) After implementation, it collects images again for verification, forming a closed loop of “collection design feedback”.

In summary, the rural landscape optimization method proposed in this study can effectively quantify the color of the landscape and improve its color richness and layering. However, this study has three limitations: (1) Data dimension limitations. The data only comes from tourists taking photos in areas with a pleasant view of the landscape. There is a lack of data on residents' daily activity areas, leading to an optimization plan that is poorly adapted to their needs. (2) Technical implementation limitations. The technology chain has not yet been integrated with the planning approval process or construction standards. The conversion of algorithm outputs into engineering parameters still requires manual intervention and does not form an automated tool chain. (3) Cultural adaptation limitations: Color quantification does not consider regional cultural characteristics and residents aesthetic preferences, and there is a tendency for “technology orientation” to be superior to “cultural orientation”, which may weaken regional cultural identity. Therefore, in the future, this research will consider expanding the range of multi-source data collection channels and integrating regional cultural elements to further improve the universality and humanistic adaptability of the method.

5. Conclusion

In response to the demand for accurate analysis and efficient quantification in rural landscape optimization, this study proposed a method based on improved DeepLab v3+ and improved KMC quantification to achieve color optimization of rural landscapes. This method stylized landscape images by improving DeepLab v3+ and using improved K-means to quantize the color of the segmented images. In terms of landscape image segmentation, DeepLab v3+ was improved by introducing cross-stripe pooling, CBAM, and residual feature fusion modules, which solved the problems of the original model's insufficient processing of multi-scale targets and loss of boundary details. Experiments showed that the average IoU of this model reached 0.881, and the average segmentation speed was 0.22s/image, both of which were better than those of DAGU-Net++ and PMA-PSPNet. It could accurately segment natural, cultural, and artificial landscapes, and other types of targets. In terms of color quantification optimization, the node index method, elbow rule, and average error vector were used to improve the KMA, which overcomes the shortcomings of random initial cluster centers and slow convergence of large clusters. This method had the highest weighted average PSNR (32.4-36.6dB) among the three types of rural landscapes. The average quantization speed was 1.6s/photo, and the error was lower. It can effectively enrich the color levels of the landscape and improve the ornamental value. In summary, the method proposed in this study can effectively enhance the appreciation of rural landscapes and enrich their color palette.

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Declaration of Artificial Intelligence (AI) Tools

The authors used AI tools solely for language editing and readability improvement. The authors reviewed and verified all content and take full responsibility for the accuracy and integrity of the manuscript.

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