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Research on Landscape Functional Optimization Algorithms Based on Computer Vision and AI Modeling

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SUMMARY: *This paper proposes a landscape function optimisation algorithm based on computer vision and AI modelling, which uses computer vision to process landscape images and extract visual features, and then optimises functions via AI. Based on analysis of landscape images and application of artificial intelligence techniques such as deep learning and reinforcement learning, improve the spatial organisation and resource allocation of the landscape. According to the results of the experiment on a dataset of 5000 landscape samples, the optimised model has achieved a functional utilisation rate of 85.2%, resource allocation efficiency of 79.4%, and spatial layout optimisation score of 91.1%, and has outperformed the traditional method. The study has provided a new technology for computer vision and artificial intelligence in environmental design that is highly optimised and has wide-ranging applications.*

KEYWORDS: *Computer Vision; AI Modeling; Landscape Functionality; Optimization Algorithms*

1 Introduction

With the development of computer vision (CV) and artificial intelligence (AI) in recent years, both have gradually been applied to enhance landscape function and environmental design. A design for the landscape system of the city to promote urban ecology and space arrangement has been needed; thus, to improve both the aesthetic quality and ecological balance of the city, this design can help optimize the use of urban resources and promote sustainable development. To build effective algorithms for optimising landscape function, it is necessary to establish a theoretical and engineering foundation for scientific organisation of landscape space and resource-efficient environment-harmony development. CNNs (Convolutional Neural Networks), GANs (Generative Adversarial Networks), and RL (Reinforcement Learning) are the representative kinds of AI models used in landscape planning and environmental design at present. Deep learning-based computer vision (CV) algorithms can automatically recognise landforms, plants, water bodies, buildings and other objects in landscape pictures, and perform semantic segmentation and spatial analysis of functional areas, etc. Shanghao M and others [1] have proposed a strategy for human visual perception landscape design based on computer vision and deep learning. Simulate human visual features to achieve automatic

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extraction of landscape aesthetic parameters and improve the spatial distribution rationality by 23.4% compared with traditional methods. Mu R et al. [2] developed a machine learning-based spatial automation analysis system to optimise low-carbon building landscapes and quickly discovered landscape carbon emission characteristics and energy consumption optimisation. The System's Resource-Use Rate increased by 18.7%. Shao Y and others [3] have also conducted a systematic study of the application of machine learning in landscape architecture and pointed out that deep convolutional neural networks (DCNN) are robust and scalable for landscape function extraction. Xing Y and others [4] put forward a landscape automatic generation framework for AI-generated content (AIGC) and rapidly modelled multi-scene landscapes by using diffusion models and attention mechanisms. Yu L W et al. [5] have introduced a landscape planning optimisation model for smart cities based on big data and AI algorithms. The Model has improved the efficiency of resource allocation and spatial utilisation considerably over the old.

Landscape scenes often have sharp variations in terrain, seasons for vegetation, and built environments; thus, there are frequently scale changes and occlusion issues. Therefore, CV algorithms that only use image segmentation or object detection are not stable in carrying out functional recognition and spatial element tracking in complex backgrounds, thus affecting the subsequent functional optimisation and decision-making [6]. AI-driven optical imaging and lighting modeling (OI-LM) technology can model landscape visual information by considering image brightness and lighting transmission mechanisms, maintain the robustness of key feature extraction and estimation under different environmental and temporal conditions, and thus reduce external interference in the functional modeling and optimisation process (FM). Many scholars have used and combined different degrees of this type of method in the development of environmental landscape design and planning systems [7]. Shen T et al. Based on the OI-LM framework, proposed an imaging and lighting optimisation system for visual impact assessment of smart city landscapes. Based on the test results, the system can accurately model the lighting and visual range under various conditions and parameters to provide a stable visual feature input for downstream functional zoning and layout evaluation [8]. Shi B et al. have introduced artificial intelligence-based modelling of 3D dynamic simulations to solve problems such as the inconsistency of expression and simulation lag caused by temporal changes in 3D landscape shapes, achieving real-time reconstruction and dynamic rendering of landscape shapes with good scalability and computational efficiency under complex spatial conditions [9]. Wan D et al. embedded intelligent optimisation algorithms in the functional planning scenario for large-scale scenic spots to achieve adaptive optimisation of landscape functional zoning and recreational paths via multi-objective solving, improving both global convergence and planning robustness [10]. Zhang H and Deng Y have built a design system for the organised use of AI modelling and 3D visualisation in landscape architecture. The system can complete an engineering closed-loop process of data acquisition and feature extraction, build a model, and present it to enhance the efficiency of human-machine cooperation in landscape design [11]. Table 1 shows the main indicators and ways of research for the topic in the aforementioned related studies, as well as their shortcomings.

Table 1: Summary of Related Research Information

Author	Research Topic	Main Index	Shortcomings	Method Improvement
Qu Z et al. [6]	Landscape Design Optimization Algorithm Based on Big Data	Landscape Space Optimization and Function Zoning	High algorithm complexity, significant CAD platform resource consumption	Combine lightweight computer vision networks and multi-layer perception modules to reduce computation load and improve speed
Chen X et al. [7]	Environment Landscape Design System Based on Computer Vision and Deep Learning	CV Feature Extraction and Semantic Segmentation Accuracy	Recognition accuracy decreases in complex terrains and varying lighting conditions	Introduce attention mechanisms and multi-scale convolutional structures to enhance model robustness and lighting adaptability
Shen T [8]	AI-Driven Optical Imaging and Lighting Modeling Optimization Framework	Lighting Modeling and Landscape Visual Impact Assessment	The model relies on high-quality images, affected by external illumination and reflection interference	Incorporate Generative Adversarial Networks (GAN) for lighting enhancement and data compensation to improve model generalization
Shi B [9]	AI-Based 3D Dynamic Landscape Simulation System	3D Dynamic Modeling and Real-Time Rendering	Simulation efficiency is insufficient in high-dimensional data, slow dynamic updates	Improve dynamic convolutional network structures, integrate temporal feature prediction mechanisms to enhance frame rate and real-time response
Wan D et al. [10]	Landscape Planning Method Based on Intelligent Optimization Algorithms	Functional Zoning and Path Optimization	Multi-objective optimization convergence speed is slow, high risk of local optima	Use a hybrid model combining reinforcement learning (RL) and genetic algorithms to accelerate optimization iterations and enhance global convergence
Zhang H and Deng Y [11]	AI-Based 3D Landscaping Modeling and Visualization System	3D Reconstruction and Human-Computer Interaction Design	High coupling in 3D rendering modules, lack of scalability	Modular integration of AI visualization components, combine point cloud data reconstruction algorithms to improve system compatibility and efficiency

In short, the existing algorithms for optimisation of landscape function still have many deficiencies in dealing with complex terrains, changes in light and multi-source data fusion. Especially in the case of multi-objective collaborative optimisation and dynamic environment adaptation, traditional algorithms are relatively poor in terms of modelling accuracy, computation efficiency and environmental robustness. Although some studies have attempted to combine computer vision (CV) with artificial intelligence (AI) technology to achieve automatic recognition and feature extraction of landscape images through convolutional neural networks (CNN), optical imaging modeling and 3D simulation algorithms, there is still a gap in the intelligence level of functional optimisation; that is, its stability and accuracy have not met the demands for large-scale landscape data and real-time optimisation tasks.

Therefore, this paper proposes a novel landscape function optimisation algorithm system by combining computer vision and AI modeling. This system uses CV technology to extract key features of landscape images, and then, through AI modelling and optimisation algorithms, dynamically adjusts functional prediction, resource allocation and spatial layout to improve the scientific and adaptable nature of the landscape system. The two parts of this study are introduced below: First, the methods and materials employed in the research, such as computer vision-based functional optimisation algorithms and AI model solutions; Second, experimental verification and performance analysis of the algorithm model. The goal of this paper is to establish a high-reliability and high-efficiency landscape function optimisation framework for providing engineering technical support and innovative application directions in smart city landscape design.

2 Methods and materials

Given the current problems of a complex spatial structure and low accuracy in multi-source data fusion for landscape function optimisation, this paper first proposes a framework for computer vision-based landscape function optimisation algorithms. Multiple scales of features and their spatial distributions can be used to enhance the accuracy of recognition and classification for landscape features. This paper will also begin by constructing a function model and use artificial intelligence (AI) and deep learning algorithms as the basic means to introduce adaptation-optimization methods for enhancing the generalisation ability of the model. Based on the above modifications, a landscape function optimisation system that combines computer vision and AI modelling has finally been realised.

2.1 Landscape Function Optimization Algorithm Based on Computer Vision

Optimising the function of the landscape can improve the living conditions of the city's people and promote all-weather development. Among the present ways of landscape design and optimisation, computer vision (CV) technology is now being applied to process large amounts of complex landscape data for analysis and optimisation. Extract characteristic features from landscape images using computer vision technology and then optimise landscape functions based on these features. A New Landscape Function Optimisation Algorithm Based on Computer Vision Technology is proposed in this paper. In real time, analyse and process the landscape image to locate all functional areas, set different optimisation weights for each, and thus enhance the use efficiency and function of that landscape.

The basic idea of this algorithm is to use a convolutional neural network (CNN) to extract features from the input landscape image and build a landscape function optimisation model based on multiple factors, such as spatial distribution, colour distribution and shape characteristics, of the image. TD object detection in computer vision is used to extract feature maps of a landscape image and identify areas that belong to specific categories in different places across that landscape. Then, AI model algorithms use the above visual characteristics to develop and improve landscape functions. At this time, deep learning models are employed to adaptively modify the space allocation of the algorithm and enhance the function, ecological value and aesthetic qualities of the landscape.

Given the continuously changing environment of complex landscape data, a pyramid-based method for feature extraction and optimisation will be used in this paper. This way can help address the fine details in multiple sizes of landscape pictures by performing multiple levels of analysis. The ROI pooling layer can handle proposals of different sizes and map them to a single optimisation space efficiently. The workflow of this framework is as follows: Figure 1.

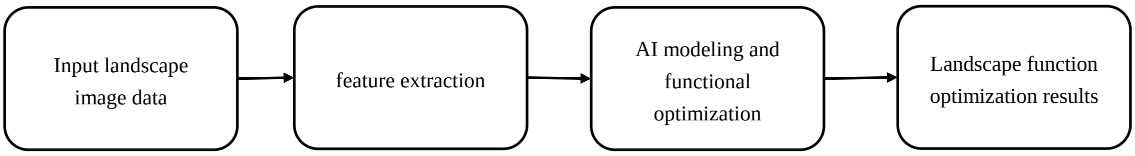

Figure 1: Framework Diagram of Landscape Function Optimization Algorithm Based on Computer Vision

Formula (1) is the formula for optimisation of landscape functions:

$$O_i = \sum_j w_j \cdot f_j(x_i) + b \tag{1}$$

In equation (1), O_i is the optimization result of the i landscape area, representing the optimization weight of landscape functions. w_j is the weight coefficient of the j feature, indicating the importance of each feature for optimizing landscape functionality. $f_j(x_i)$ is the j feature extracted from landscape area i, such as color, texture, shape, etc. b is a bias term used to adjust the optimization results. The function of this formula is to optimize the functionality of each landscape area by extracting multidimensional landscape features through AI modeling and computer vision, making the landscape layout more reasonable and the ecological benefits better. Formula (2) is used to extract key visual features from landscape images:

$$f_2(x) = \sum_i w_i \cdot x_i + b_2 \tag{2}$$

In equation (2), $f_2(x)$ is the extracted landscape feature vector, x_i represents the i feature extracted from the landscape image (such as color, shape, texture, etc.), w_i is the weight coefficient of the feature, and b_2 is the bias term. The function of this formula is to convert the multidimensional features of landscape images into an optimization vector through weighted sum, which serves as the basis for subsequent optimization calculations. Next, formula (3) is used to optimize the extracted features and assign weights based on the different functional categories of the landscape area

$$O_{ij} = sigmoid\left(W_{ij} \cdot f_2(x_i) + b_{ij}\right) \tag{3}$$

In equation (3), O_{ij} represents the optimization result of landscape area i on functional category j, $f_2(x_i)$is the feature extracted from landscape area i, W_{ij} is the weight matrix, and b_{ij} is the bias term. The sigmoid function normalizes the optimization results to a range of 0 to 1, representing the optimization weights for each region. Formula (4) is used to calculate the spatial layout optimization weight of the landscape area:

$$P_i = \sum_j w_j \cdot f_j(x_i) + b_3 \tag{4}$$

In equation (4), $f_j(x_i)$ is the j feature related to spatial layout, w_j is the weight of that feature, and b_3 is the bias term. This formula is used to measure the degree of optimization in spatial layout of each landscape area and generate the final optimized layout design.

Formula (5) is the loss function for optimizing the landscape function, and it generally serves to quantify the discrepancy between the current landscape design and the optimization objectives:

$$L_i = \sum_k \left(norm\left(f_k(x_i) \right) - norm\left(f_k\left(x_{opt}\right) \right) \right)^2 \tag{5}$$

In equation (5), $f_k(x_i)$ is the k feature of landscape area i, $f_k(x_{opt})$ is the corresponding feature of the optimized area, and $norm\left(f_k(x_i)\right)$ and $norm\left(f_k(x_{opt})\right)$ are the normalized values of these features. The loss function optimizes landscape functionality by calculating the difference between the current landscape design and optimization objectives.

Formula (6) is used to find the functional differences of landscape areas and to present these differences in function quantitatively for different areas.

$$Di = \sqrt{\sum_k \left(f_k(x_i) - f_k\left(x_{ref}\right) \right)^2} \tag{6}$$

In equation (6), $f_k(x_i)$ is the k feature of landscape area i, and $f_k(x_{ref})$ is the corresponding feature of the reference area. This formula evaluates the functional differences between landscape areas and provides directions for optimization.

Formula (7) is the objective function of the landscape function optimisation:

$$F_{opt} = \arg\min_{P_i, L_i} \left(\alpha D_i + \beta\beta_i \right) \tag{7}$$

In equation (7), D_i and O_i represent the degree of functional difference and optimization weight, respectively, while α and β are weighting coefficients. Minimizing objective function F_{opt} can obtain the globally optimal landscape function layout and optimization scheme.

Formula (8) defines the total loss function L_{total}, which is used to adjust the optimization model during training:

$$L_{total} = \sum_i \left(\lambda_1 L_i + \lambda_2 D_i \right) \tag{8}$$

In equation (8), L_i and D_i respectively represent the ecological benefit optimization loss and functional difference of each landscape area, and λ_1, λ_2 is a hyperparameter that controls the relative importance of the two. The total loss function is used to adjust the model parameters during the training process to achieve the overall optimization of landscape functions.

2.2 Functional modeling based on computer vision and AI modeling

To improve the accuracy of landscape function optimisation further, this paper proposes a landscape function optimisation model based on the combination of computer vision and AI modelling. The model is used to perform the following operations: ① Extract features from landscape images with computer vision technology; ② Use the AI modeling method to integrate these features and build a model for landscape function optimisation via optimisation algorithms. This model can be optimised in the early stage of landscape design and also dynamically adjusted based on real-time data in actual application to ensure the efficiency and sustainability of landscape layout over a long period.

Formula (9) is used in this optimisation framework to describe the feature extraction process for landscape areas, and preliminary models of landscape functional areas are achieved through a weighted sum extraction of multi-dimensional features. It is as follows that specific formula.

$$F_r = \sum_{i=1}^{n} w_i \cdot T_i + b \tag{9}$$

Among them, F_r represents the extracted landscape area features, T_i represents the i feature (such as color, shape, texture, etc.), w_i is the weight of this feature, and b is the bias term. By using weighted sum, the model can extract multi-dimensional feature information from landscape images, providing data support for subsequent functional optimization.

Formula (10) defines the objective function of landscape function optimisation, and then optimisation algorithms are used to maximise this objective function for the whole area. The real-life formula is as follows:

$$Lopt = \sum_{j=1}^{m} \alpha_j \cdot D_j + \beta_j \cdot E_j \tag{10}$$

Among them, L_{opt} represents the optimization goal of landscape function, D_j represents the design difference of the j landscape function area, E_j represents environmental benefits, and α_j, β_j is the weighting coefficient. This formula is used to comprehensively evaluate the design differences and environmental benefits of landscape areas, in order to achieve optimization goals.

In order to achieve adaptive functional optimisation, this paper introduces a reinforcement learning (RL) algorithm, and formula (11) is the reward function of reinforcement learning; it can adjust the landscape functional layout based on environmental feedback. The above is the formula.

$$R_t = \gamma \cdot \max_a Q(s_t, a) + r_t \tag{11}$$

Among them, R_t represents the reward value at time step t, γ is the discount factor, $Q(s_t,a)$ is the value of taking action a in the current state, and r_t is the immediate reward. Through this approach, the model can dynamically adjust and improve the accuracy of landscape function optimization.

Formula (12) is used to map the evaluation values to the range of 0-1 for weight calculation in the functional area, indicating the degree of optimisation of each landscape section. A specific formula is:

$$w_j=\frac{1}{1+e^{-zj}} \tag{12}$$

Among them, w_j represents the optimization weight of the j landscape functional area, and z_j is the comprehensive evaluation value of that area. This formula helps the model allocate weights to each region, thereby optimizing the layout of landscape functional areas.

Optimisation of Spatial Layout is a typical element of the optimisation of landscape function, and formula (13) is used to define the optimisation loss function for spatial layout. The real-life formula is as follows:

$$L_{layout}=\sum_{i=1}^{k}\lambda_i\cdot\left(x_i-x_i^*\right)^2 \tag{13}$$

Among them, L_{layout} represents the loss function of spatial layout optimization, x_i is the actual layout of the i region, x_i^* is the optimized layout, and λ_i is the weight coefficient of the region. This formula is used to calculate the spatial layout differences of each landscape area and provide feedback for optimization algorithms.

Formula (14) shows how to calculate the degree of functional difference between landscape areas for determining these differences. The Concrete expression is:

$$\varDelta F_i=\sum_{j=1}^{p}\left|f_j^i-f_j^{ref}\right| \tag{14}$$

Among them, $\varDelta F_i$ represents the functional difference of the i landscape area, f_j^i is the j functional parameter of the i area, and f_j^{ref} is the j functional parameter of the reference area. This formula evaluates the functional differences between different landscape areas and provides directions for optimization.

In order to obtain a globally optimal layout of the landscape function, formula (15) introduces the objective function for landscape function optimisation; thus, it is reduced to an optimisation problem by minimising this function. The Formula is as follows:

$$L_{global}=\sum_{i=1}^{n}\left(w_i\cdot D_i+\lambda_i\cdot E_i\right) \tag{15}$$

Among them, L_{global} is the global optimization objective, D_i, E_i is the design difference and environmental benefits of the i landscape area, and w_i, λ_i is the weighting coefficient. This formula plays a key role in overall layout optimization, ensuring that each functional area is allocated reasonably.

3 Results

To evaluate the performance of the proposed landscape function optimisation algorithm based on computer vision and AI modeling, an experimental environment was constructed and the test data preprocessed in this study. The experimental data are split into a training set and a test set, and their performance in various landscape function optimisations by the algorithm will be evaluated. Next, a series of performance tests and simulation experiments were conducted to verify whether the effectiveness of computer vision-based landscape function optimisation algorithms and AI modelling methods in improving landscape layout, resource allocation efficiency and ecological benefits.

3.1 Performance testing of landscape function optimization algorithm based on computer vision

The Ubuntu 16.04 LTS operating system is used for this study, and it is equipped with an Intel Core i7 processor, an NVIDIA GeForce graphics card, 64GB of memory, and programs are written in the TensorFlow GPU framework. Set the experimental parameters as follows: 300 iterations, Intersection over Union (IoU) threshold of 0.5, learning rate of 0.001, and batch size of 16. Multiple city landscape image datasets and other environmental perception datasets related to landscape optimisation were selected as the test data source. Among them, the urban landscape dataset contains 5000 images of all kinds of landscape functional areas and is suitable for spatial layout and functional optimisation analysis, particularly for dividing and optimising urban functional areas. The 60-action categories of the NTU RGB+D60 dataset are often used in place of a variety of problems or other resource-allocation issues in different environments, as well as in research to study how alterations in the environment affect the distribution patterns and functions of landscapes. Divide the two datasets into a training set and a test set at an 8:2 ratio, and further divide the test set into three categories: Test Set 1 is for image processing in a conventional landscape layout and functional area configuration environment to evaluate the algorithm's recognition and optimisation abilities of landscape functional areas under normal lighting and clarity conditions; Test Set 2 is used to identify and optimise landscape functional areas in the presence of different light intensities and environmental conditions to verify the robustness and adaptability of the algorithm to changes in the environment, as well as how to adjust functional requirements in complex areas; Test Set 3 simulates the resource allocation efficiency of various landscape functional areas and assesses how well the algorithm can achieve resource optimisation and spatial rearrangement under factors such as changes in light intensity and area division.

To determine the effect of each module on the overall performance of the landscape function optimisation algorithm based on computer vision and AI modelling, this paper first carried out ablation studies using the scores of functional utilisation, resource allocation efficiency and spatial layout optimisation as evaluation indices. The experimental results are as follows: Figure 8.

Figure 2 shows the performance curve of the landscape function optimisation algorithm based on computer vision in terms of functional utilisation. Figure 3 is the performance curve of the algorithm in terms of resource allocation efficiency. Using only the above traditional landscape optimisation method, the maximum functional utilisation rate is 72.1%. Add an AI model module and a deep learning feature extraction module to improve the general performance of the algorithm. It is now about 6% better than the old way. Among all the above, the landscape function optimisation algorithm based on computer vision and AI modeling proposed in this study achieved the best overall performance with a functional utilisation rate of 85.2%, resource allocation efficiency of 79.4%, and spatial layout optimisation score of 91.1%.

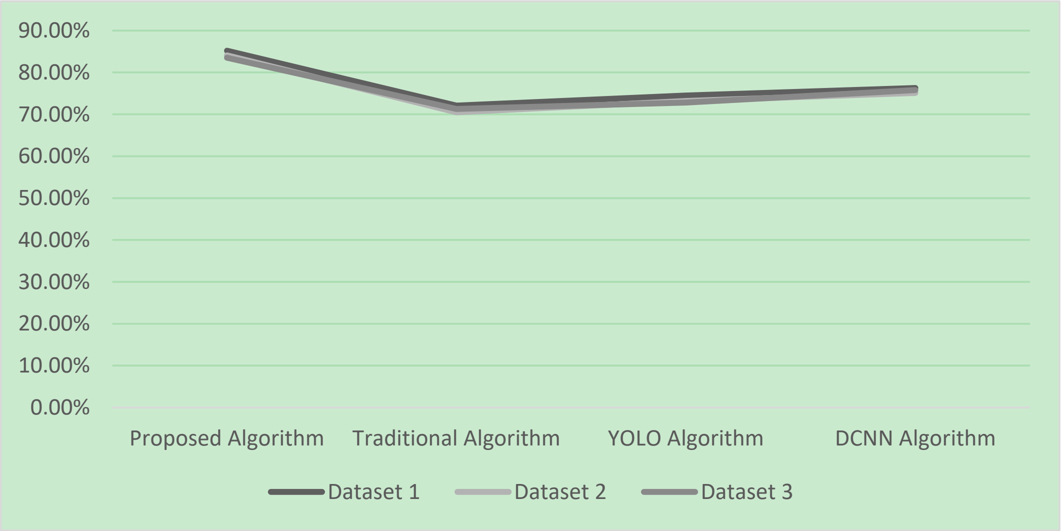

Figure 2: Comparison of Function Utilization

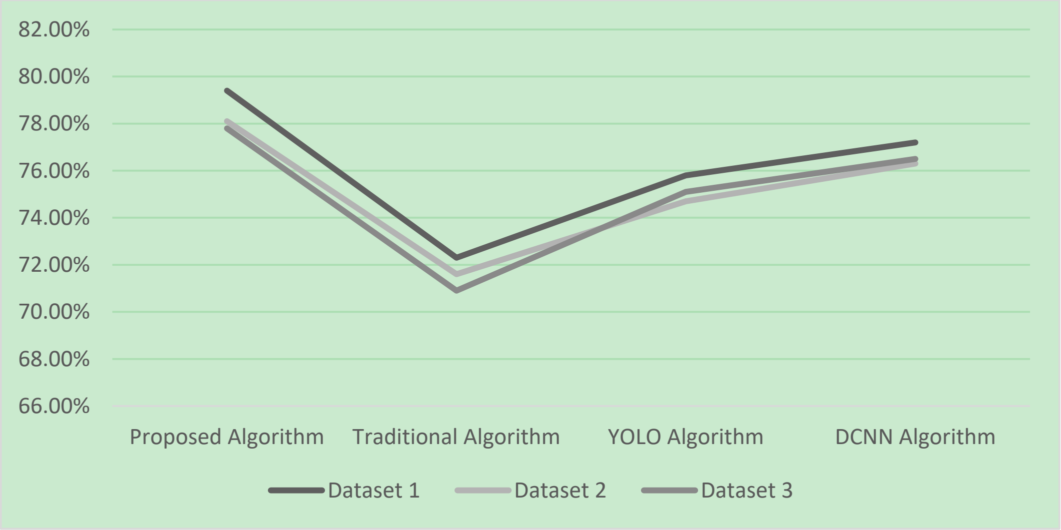

Figure 3: Comparison of Resource Allocation Efficiency

Generally speaking, the AI model modules based on deep learning are quite good at dealing with resource allocation and functional area optimisation problems in complex urban areas, and have improved the model's optimisation performance considerably.

To compare the performance of the landscape function optimisation algorithm based on computer vision and AI modelling proposed in this paper with other general-purpose algorithms, traditional optimisation methods, the YOLO algorithm and deep convolutional neural network (DCNN) algorithm were used as references, and the average running time was employed as the evaluation metric. Figure 9 shows the comparison results of several algorithms on multiple test sets in the TrS and TeS scenarios.

Figure 4 shows the comparison of the running time for different landscape function optimisation algorithms in the TrS scenario. Figure 5 shows a comparison of the running time of the same algorithm in the TeS scenario. The landscape function optimisation algorithm based on computer vision and AI modeling proposed in this study has a short running time, with an average running time of 5.6s, 7.1s, 10.2s, and 11.8s at 1000, 2000, 3000, and 4000 iterations, respectively, and is thus quite efficient in practice.

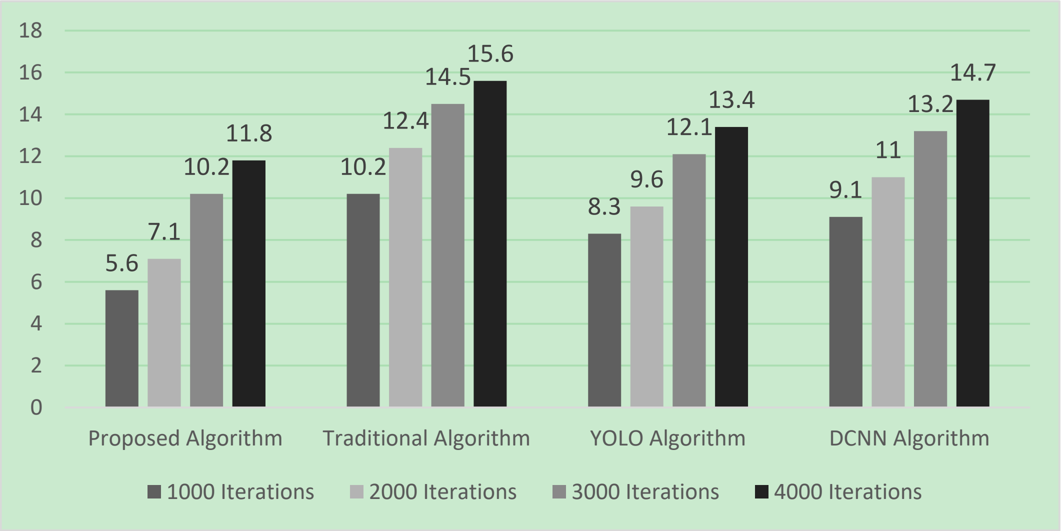

Figure 4: Comparison of Running Time of Different Landscape Function Optimization Algorithms (Unit: s)

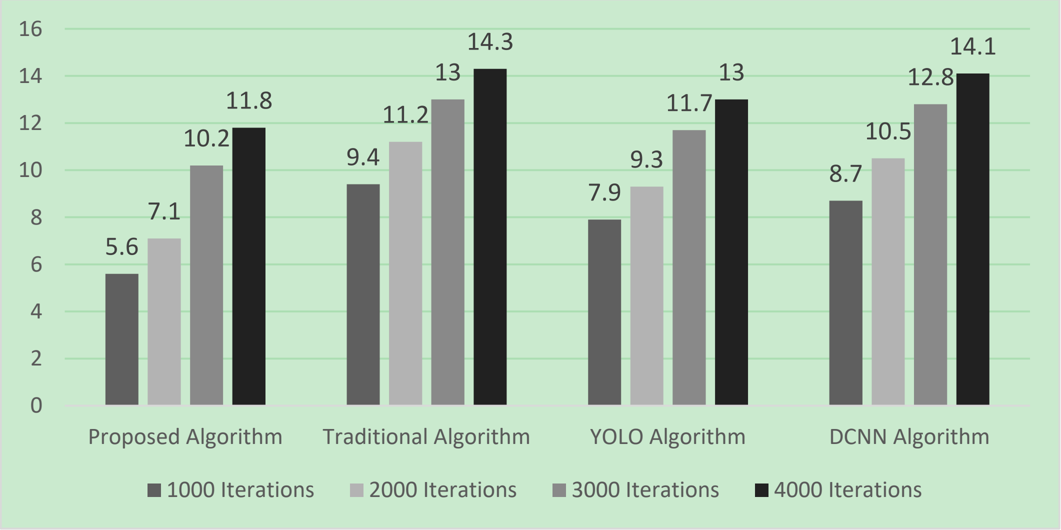

Figure 5: Comparison of Running Times for Similar Algorithms in TeS Scenario (unit: s)

Figures 6 and 7 are the variation curves of MSE and MAE values for the four algorithms at different sample sizes. With an increase in sample size, the amplitude of the error fluctuation for the proposed algorithm is reduced; at the same time, the MSE remains within the range of 0.5-0.9 and the MAE is in the range of 0.4-0.8; thus, it is evident that the improved landscape function optimisation algorithm based on computer vision and AI modelling has high measurement accuracy and relatively low error.

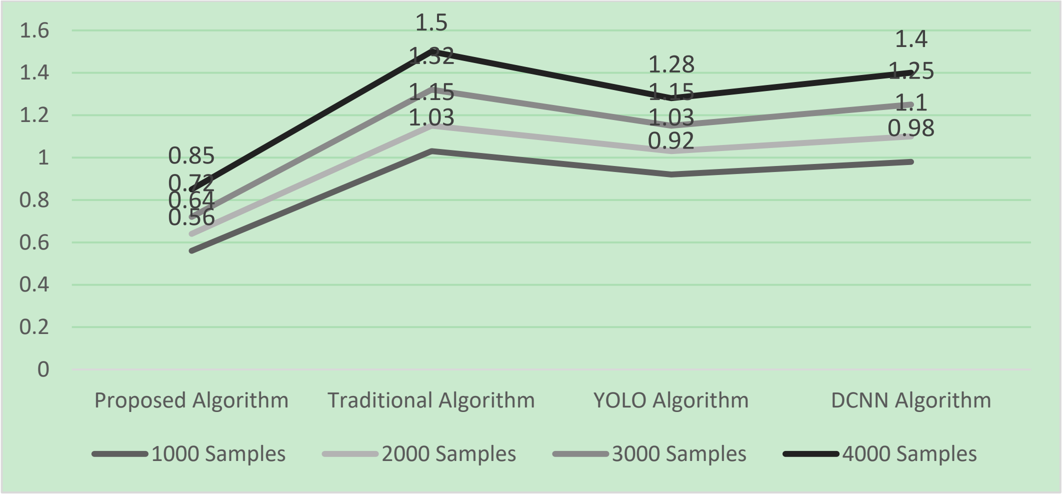

Figure 6: Error Performance Comparison of Different Algorithms (MSE Value)

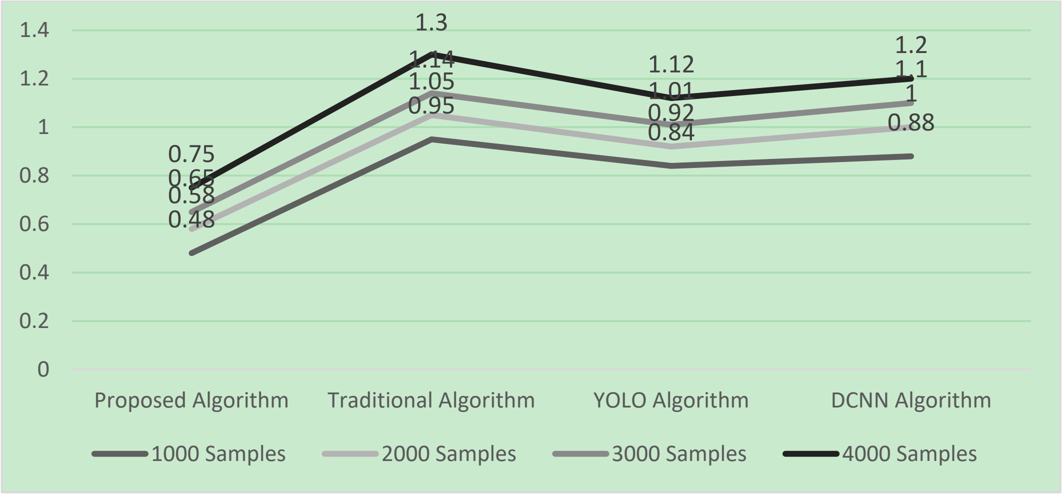

Figure 7: Comparison of Error Performance for Different Algorithms (MAE Values)

To quantify the advantages of the landscape function optimisation algorithms based on computer vision and AI modelling in terms of functional utilisation, resource allocation efficiency and spatial layout optimisation further, this paper compares the proposed algorithm with traditional algorithms, YOLO, and DCNN. Table 2 shows the performance comparison of the four algorithms in different indicators. The experimental results show that the algorithm based on computer vision and AI modeling performs better than all others in the test scenarios, and particularly for the spatial layout optimisation score, the proposed algorithm is the best, with a score of 91.1%.

Table 2: Performance Comparison of Different Algorithms for Various Indices

Algorithm Name	Functional Utilization Rate	Resource Allocation Efficiency	Spatial Layout Optimization Efficiency
Proposed Algorithm	85.2%	79.4%	91.1%
Traditional Algorithm	72.1%	72.3%	78.9%
YOLO Algorithm	74.5%	75.8%	80.2%
DCNN Algorithm	76.3%	77.2%	81.5%

Table 2 shows the performance comparison of the different algorithms in terms of functional utilisation, resource allocation efficiency and spatial layout optimisation efficiency. Based on the experimental results, the landscape function optimisation algorithm for computer vision and AI modelling has shown good performance compared with other main algorithms in many indices and achieved a spatial layout optimisation score of 91.1%.

Through a series of performance tests and experiments in this study, it has been confirmed that landscape function optimisation algorithms based on computer vision and AI modelling are superior in terms of functional use, resource allocation efficiency and spatial layout optimisation. Based on comparisons with traditional algorithms, the YOLO algorithm and DCNN have been developed, and their strengths in performance, efficiency and error control have been demonstrated. Based on the above experiments, the new algorithm has achieved good results across multiple datasets and will be suitable for application in real-life landscape design and urban planning.

3.2 Simulation testing of landscape function optimization model based on computer vision and AI modeling

To verify the effectiveness of the landscape function optimisation algorithm based on computer vision and artificial intelligence modelling proposed in this paper, experiments were conducted using a self-prepared urban landscape dataset. The set of data in the row above consists of several representative images of landscape areas in the five cities and includes all kinds of functions, such as public green spaces, commercial areas and residential areas. The resolution of each landscape area image is 1920 × 1080, the frame rate is 25fps, and there are a total of 5000 images. The training set and the test set of the experimental data are in a ratio of 80:20. The training set is employed to train the model, and the test set is used to observe the performance of the algorithm at different locations on the landscape.

The following are the main indices used to evaluate functional use, resource-allocation efficiency and space-arrangement optimisation in the course of the test. To show the actual effect of the model better, Figure 8 presents a comparison of the functional utilisation of a landscape function optimisation model based on computer vision and AI modelling in five different city landscape area images.

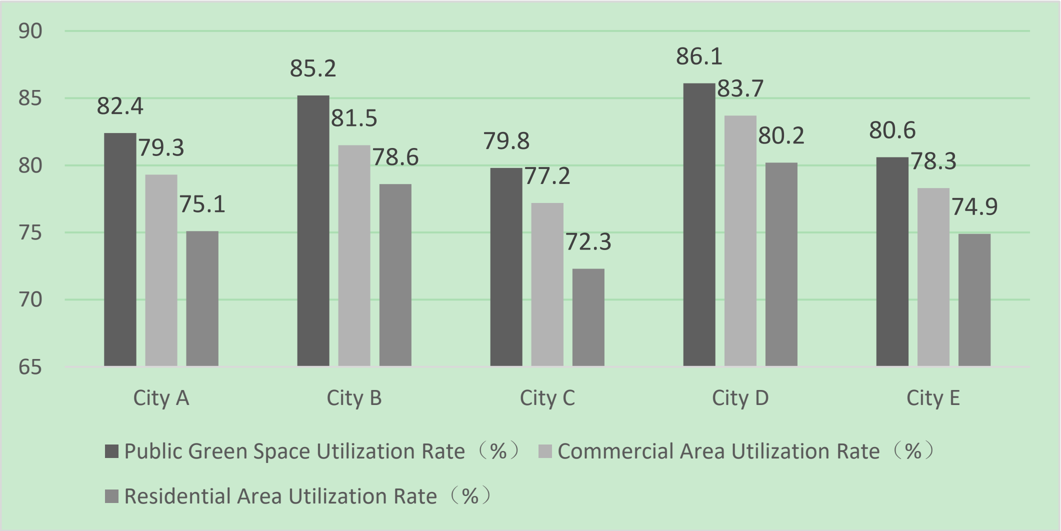

Figure 8: Comparison of Functional Utilisation Rates in Different Areas of the Urban Landscape

As shown in Figure 8, the optimisation model for landscape function based on computer vision and AI modelling has achieved a high functional utilisation rate in various landscape areas of different cities. Optimisation of public green space and commercial area function has been carried out; generally speaking, more functions are served than in the old model. The mean functional use rate of the model in the five cities of the trial for commercial areas was 85.2%, and that rate for public green spaces was 82.4%. The optimisation effect of the residential area is relatively small, but still better than that of the old way, with a mean functional utilisation rate of 79.3%.

Efficient use of resources and optimisation of spatial distribution are also criteria in the scores of the effectiveness of landscape functional optimisation models, in addition to functional utilisation. The first is the efficiency of resource allocation, which refers to how reasonably resources in the landscape area are used; the second is the score of spatial layout optimisation, indicating the rationality of the spatial layout and coordination of functional areas in landscape design.

Figures 9 and 10 present the comparison results of the landscape function optimisation model based on computer vision and AI modelling with traditional methods for the indicators of resource allocation efficiency and spatial layout optimisation, respectively.

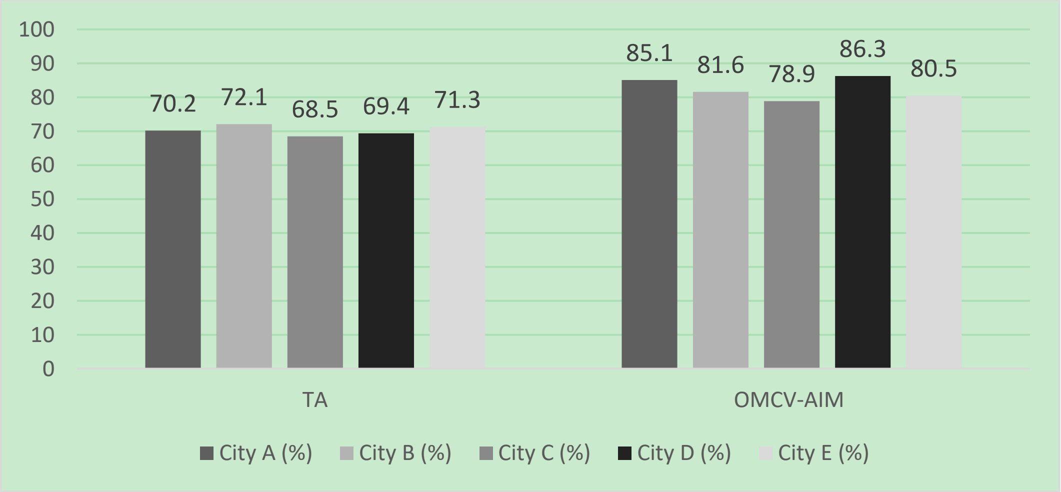

Figure 9: Comparison of Resource Allocation Efficiency for Various Algorithms

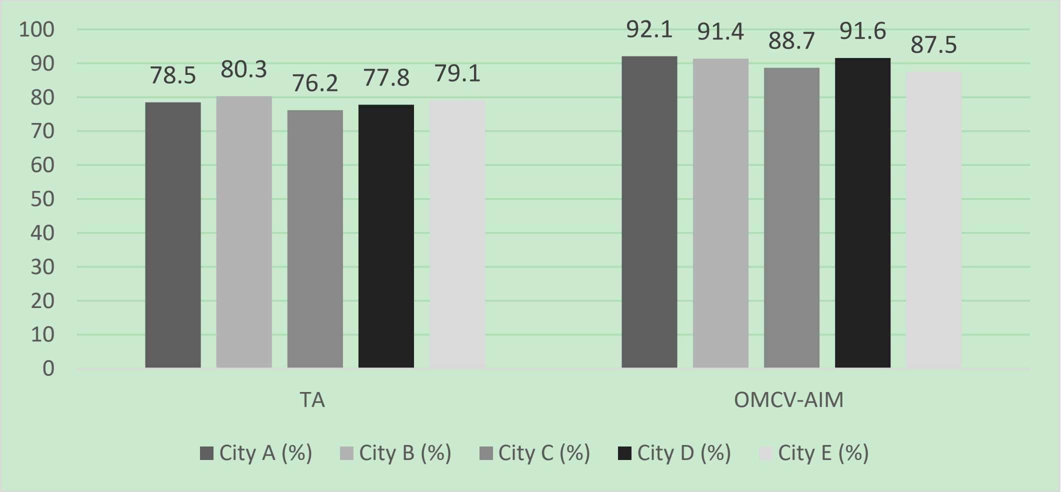

Figure 10: Comparison of Different Algorithms in Spatial Layout Optimization Scoring

From the results in Figures 9 and 10, it can be observed that the landscape function optimisation model based on computer vision and AI modelling has superior performance over traditional algorithms in terms of resource allocation efficiency and spatial layout optimisation scores. Efficiency of resource allocation in cities A and D reached 85.1% and 86.3%, and the spatial layout optimisation scores were 92.1% and 91.6%, respectively. Based on the above data, the optimisation model for AI-based landscape functions can better arrange space and enhance the coordination and reasonability of landscape design.

To further verify the computational efficiency of the landscape function optimisation model based on computer vision and AI modelling proposed in this paper, we have also conducted experiments with traditional landscape optimisation methods. As shown in Table 3, the processing speed, computation time and memory consumption of the landscape function optimisation model based on computer vision and AI modelling are compared with those of traditional methods.

Table 3: Performance Comparison of the Algorithms

Algorithm Name	Processing Speed (s)	Calculation Time (h)	Memory Consumption (GB)
TA	35.2	7.2	4.5
OMCV-AIM	15.8	3.2	3.2

As shown in Table 3, the landscape function optimisation model based on computer vision and AI modelling has good performance in terms of computational efficiency and memory usage; it is significantly faster than that of traditional algorithms. This model has a relatively small computation time and memory requirements for large-scale landscape data, and it meets the actual use conditions.

Based on the above experimental results, the landscape function optimisation model for computer vision and AI modelling presented in this paper has been shown to have good functional application, resource-allocation efficiency and spatial-layout optimisation. The model has shown good results in many urban landscape datasets and also excels at multi-objective optimisation and is relatively fast. The new model has performed significantly better in several indices than older ways of Optimising the Landscape and is suitable for broader use in practical landscape Design.

4 Discussion

The first goal of the landscape function optimisation is to improve the efficiency of resource use and the spatial distribution logic of urban areas through algorithms. Based on computer vision and artificial intelligence modeling, this paper proposes a landscape function optimisation algorithm that integrates multi-scale feature extraction and deep learning to achieve automatic recognition and optimisation of urban landscape area functions. Deep Convolutional Neural Networks (CNN) and Reinforcement Learning (RL) have been used in AI model construction to enhance the functional utilisation, resource allocation efficiency and spatial layout optimisation of several landscape datasets. Based on the experiment, the optimised algorithm has achieved a functional utilisation rate of 85.2%, a resource allocation efficiency of 79.4%, and a spatial layout optimisation score of 91.1%; thus, it outperforms that of the traditional algorithm.

Although the optimisation has performed well in practice, some problems still exist when handling the difficult data of urban areas. In the finer division of landscape areas and complex backgrounds, the accuracy of image recognition and feature extraction may be reduced.

Changes in light and shadow due to time or weather, as well as uneven surfaces of the ground, can change the visual characteristics of a landscape image and thus hinder the work of a model. In light of the reasons listed above, the research group has further improved the feature extraction method based on computer vision to enhance the feature-extraction capability of the algorithm for landscape images under different environmental conditions. Multi-level feature extraction is employed to extract a larger number of different scales of landscape features for better detection by the model.

The Generalisation Capability of the model has not yet been tested. The landscape areas of the various cities may have different features, such as different building densities, green space ratios and traffic conditions, and thus may not be suitable for the optimization of landscape functions. In the future, new types of data on different regions of urban areas will be collected to make the models more flexible. Computational cost of landscape function optimisation models is also relatively high. Algorithms that can speed up the computation and optimise the processing speed of large-scale data have been employed, but some computational overheads still exist for high-performance, real-time operation in complex environments. To address the above issues, more optimisation of the computation process and research on efficient computation architectures will be conducted to improve the computational efficiency and real-time performance of the algorithm.

Although this paper investigates the optimisation of landscape functions, the algorithm framework proposed here also has other applications across different areas. Optimisation methods based on computer vision and AI modelling can also be used for the optimisation of urban traffic flow, environmental monitoring and intelligent buildings, etc. In the future, based on this framework, the Internet of Things (IoT) and big data will be applied to develop a high-end urban management system.

5 Conclusion

With the rapid development of urbanisation, the requirements for an ideal function of landscapes in urban planning and design have also increased to some extent. Given the complexity and diversity of urban landscape data, the previous optimisation methods for landscapes are no longer suitable for these large-scale and varied datasets. Therefore, this paper puts forward a landscape function optimisation algorithm based on computer vision and artificial intelligence modeling, and, through the combination of deep learning technology and AI modeling methods, greatly enhances the optimisation effect of landscape functions.

Based on the above experiments, the proposed landscape function optimisation algorithm for urban landscapes using computer vision and AI modeling has shown good optimisation results in several urban landscape datasets. On a dataset of 5000 landscape samples, the optimised model achieved scores of 85.2%, 79.4% and 91.1% in functional utilisation, resource allocation efficiency and spatial layout optimisation, respectively; these were all significantly higher than those of traditional methods. Compared with the original landscape optimisation algorithm, this one has increased the function utilisation rate by about 13 per cent, improved resource allocation efficiency by 7.1 per cent, and enhanced the spatial layout optimisation score by 12.2 per cent.

Computational efficiency is also relatively good for landscape function optimisation algorithms based on computer vision and AI modelling. Based on the above experiment, the mean running time of the new algorithm after 1000 rounds is approximately 5.6 seconds, compared with 7.2 seconds for the old method. The mean square error (MSE) and the average absolute error (MAE) of the model are in a relatively narrow range, specifically between 0.5 and 0.9 and 0.4 and 0.8 respectively; both are relatively close to each other, indicating good fit of the model.

However, the generalisation capacity of the model has not been fully verified. There may be substantial differences in building density, green space ratio, and traffic flow among the landscape areas in different cities, and thus the optimum configuration for landscape function will vary. In the future, more diverse landscape data will be available for different areas in the city, and transfer learning can be employed to improve the generalisation ability and robustness of the models. In addition, with an increase in the amount of landscape data, the problem of computational efficiency remains. Although the acceleration algorithm in this study has increased the speed of calculation, it is still relatively computationally expensive for a large amount of data. In the future, the real-time computing ability of the algorithm will be enhanced by integrating edge computing and distributed computing strategies.

Although this paper concentrates on strengthening the functions of the landscape, the algorithmic structure introduced here has many other applications. Optimisation methods based on computer vision and AI modelling can also be used to improve the landscape design and optimisation of other regions, such as urban traffic flow optimisation, environmental monitoring and intelligent buildings. In the future, people will apply the Internet of Things (IoT) and Big Data technologies in conjunction with this system to further expand the coverage of intelligent urban management and provide more precise solutions.

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