RESEARCH ARTICLE

Application of interactive AI system based on image recognition in rural landscape design

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Rural landscape design plays a vital role in balancing ecological protection, cultural preservation, community development, and economic sustainability. However, current practices face significant challenges including inadequate ecological conservation, diminished cultural heritage, unequal distribution of design resources, and limited technological integration. This study aimed to address these issues by leveraging interactive AI systems based on image recognition to enhance the scientificity, efficiency, and inclusivity of rural landscape design. The research adopted a multi-method approach including questionnaire analysis, high-tech data collection such as satellite imagery, drones, and surveillance systems, and algorithm optimization. The study focused on four core applications of AI systems including ecological resource assessment and sustainable planning, identification and integration of vernacular architectural styles, tourist behavior analysis for public space optimization, and natural disaster risk assessment and prevention strategies. The results demonstrated significant improvements in design accuracy, resource allocation, and participatory decision-making, highlighting the transformative potential of AI in rural landscape planning. This research provided a framework for integrating AI into rural landscape design, promoting sustainable development, and offering valuable insights for researchers and practitioners in the field.

Keywords: image recognition; interactive AI system; rural landscape design.

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Introduction

Rural landscape design has gained increasing importance amidst the rapid globalization and urbanization of today’s world. It is not only concerned with the protection and restoration of the natural environment but also plays a crucial role in the transformation of rural social and economic structures, the preservation of local culture, and the improvement of residents' quality of life. As a bridge between nature and humanity, rural landscapes face multi-dimensional considerations and challenges during their design and restoration processes [1]. The primary goal of rural landscape design is to respect and protect the natural environment. Effective landscape planning helps to maintain ecological balance, conserve biodiversity, manage water resources, and mitigate the effects of climate change. For example, wetland restoration projects can improve water quality, provide wildlife habitats, and enhance the ecological resilience of rural areas. Moreover, rural landscapes attract tourism and promote agricultural development, contributing to local economic growth. Integrating local cultural features into design, such as traditional farming landscapes and rural tourism facilities, can add both economic value and industrial growth to rural areas [2].

The diversity and complexity of rural environments including topography, climate, soil types, and vegetation present high demands on the design process. Designers must account for regional environmental conditions to create solutions that respect both natural laws and practical needs. However, rural areas often lack the financial and technical resources to implement and maintain high-quality landscape designs, which affects both initial projects and their long-term viability. The acceleration of urbanization has led to demographic shifts such as population aging and labor loss, directly impacting rural landscape needs [3]. Rural landscape design must address several pressing challenges including population structure changes, the integration of local cultural identity, and the impact of globalization on traditional landscapes. Additionally, rural areas face resource constraints both financially and technically, which often result in the failure of landscape projects to meet their expected outcomes. How to preserve local characteristics and avoid the homogenization of landscapes under the influence of global trends remains a significant issue.

The basic principles and elements of rural landscape design include ecological priority, cultural integration, community participation, economic feasibility, and sustainable development. The ecological priority includes respecting nature, maintaining ecological balance, ensuring that design activities do not cause irreversible damage to the natural environment, and promoting biodiversity conservation. Cultural integration covers excavating and carrying forward local culture, conveying rural historical stories and cultural values through design language, and realizing cultural inheritance and innovation. Community participation will emphasize the dominant position of villagers, ensure that the program meets actual needs through participatory design, and enhance community cohesion. Economic feasibility needs to be considered. The design should be economical and efficient, promote rural economic development, and improve residents' living standards. For sustainable development, the design needs to be forward-looking, consider long-term impact, ensure rational use of resources, and promote harmonious coexistence of rural society, economy and environment. To understand the challenges faced by rural landscape design, the questionnaire is normally used with a combination of closed and open-ended questions to collect both quantitative data and qualitative feedback to ensure the comprehensiveness and depth of the survey [4]. To meet the actual needs of rural landscape design, it is necessary to improve the awareness of ecological environment protection and take effective measures to prevent soil erosion and biodiversity reduction and realize the sustainable development of rural landscape. It is also necessary to deepen the inheritance and innovation of local culture, combine traditional culture with modern design concepts, enhance the cultural connotation of rural landscape, and further optimize the allocation of design resources, increase capital investment in rural landscape design, train professional design talents, introduce advanced design technology, and realize reasonable allocation and efficient utilization of design resources. Meanwhile, it needs to improve the participation of villagers, give full play to the main position of villagers, make the design scheme more suitable for actual needs and enhance community cohesion through participatory design. To strengthen policy support, government departments should increase support for rural landscape design to provide a good policy environment for rural landscape design [5, 6]. In exploring the modern path of rural landscape design, interactive AI systems based on image recognition have become a powerful driving force. Through high-precision image recognition technology, AI systems can deeply analyze rural environments, provide data support for design decisions, and then realize more scientific, efficient, and humanized landscape design [7, 8].

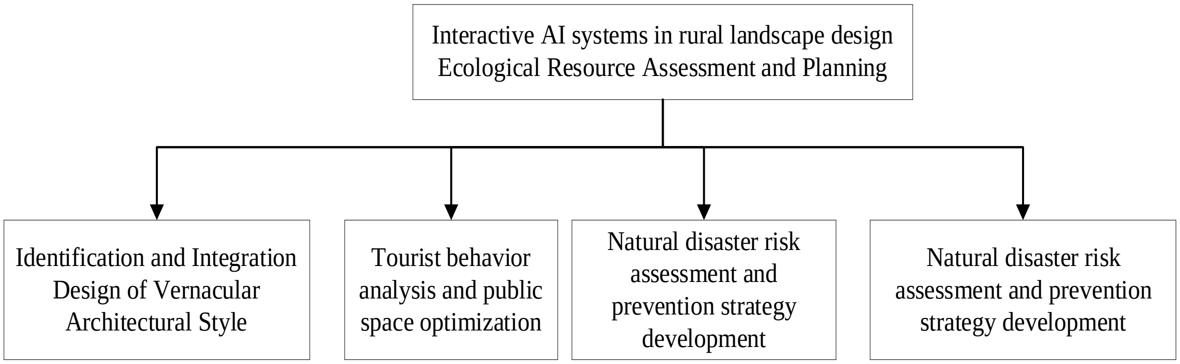

Figure 1. Application framework of interactive AI system in rural landscape design.

The core objectives of this study were to investigate how to integrate image recognition, machine learning, and Geographic Information Systems (GIS) into a cohesive platform capable of analyzing rural landscape features and providing actionable design solutions. Additionally, the study aimed to explore the use of unmanned aerial vehicle (UAV) aerial photography, satellite remote sensing, and other data sources for efficient rural landscape data collection, while optimizing algorithms to ensure the accuracy and timeliness of the data, thereby supporting informed and effective design decisions. This research involved developing an interactive AI system that utilized image recognition technologies to analyze rural landscape features, which included integrating various data sources like satellite imagery and UAV footage, applying machine learning algorithms to recognize patterns, and providing real-time design feedback through an interactive user interface. This study would contribute to the field of rural landscape design by providing a technological framework that improved the precision and efficiency of design processes. By integrating AI-driven image recognition, the study would enhance landscape design's scientific nature, offering insights into ecological protection, cultural preservation, and economic development. Furthermore, this research would foster the development of AI tools that helped bridge the gap between traditional rural landscapes and modern technological advancements.

Materials and methods

Application of interactive AI system

A questionnaire covering ecological environment protection and utilization, local cultural inheritance and innovation, and unequal distribution of design resources was designed in this study. The application framework of interactive AI system in rural landscape design was shown in Figure 1.

(1) Ecological resources assessment and planning

Vegetation cover was one of the basic indexes for evaluating rural ecological status. The AI system used convolutional neural networks (CNN) (https://www.tensorflow.org/) to process satellite images or high-definition photos taken by drones, identify different types of vegetation through pixel classification algorithms, and calculate vegetation coverage area and density using the following formula.

$$VCA = \sum_{i=1}^{N} p_i \cdot A_i \qquad (1)$$

where p_i was the pixel proportion of the i^{th} vegetation type. A_i was the average pixel area of the corresponding vegetation category. N was the total number of vegetation types. VCA was the vegetation coverage area [9, 10]. Biodiversity monitoring was to identify the presence of specific species through image recognition technology and assess the health of ecosystems. AI systems identified animal and plant species in images through deep learning models, combined spatiotemporal sequence data, analyzed species distribution and quantity changes, and assisted designers in formulating protection measures. By using a CNN model improved by transfer learning to identify rare birds, the loss function could be expressed as below.

$$L = -\sum_{c=1}^{C} y_c \, log(p_c) \quad (2)$$

where *L* was the loss value. y_c was the one-hot code of the true label. p_c was the probability distribution predicted by the model. *C* was the total number of categories.

(2) Vernacular architecture style identification and fusion design

AI system automatically extracted feature elements from a large number of local architectural pictures through image recognition technology including roof shape, door and window style, decoration details, *etc*. to provide inspiration for design. Using feature extraction algorithms of principal component analysis (PCA) or autoencoder, images could be converted into low-dimensional feature vectors as follows.

$$F = f(I; \theta) \quad (3)$$

where *F* was the feature vector. *I* was the input image. f was the feature extraction function. θ was the model parameter [11, 12]. On the basis of extracting traditional elements, AI systems combined machine learning algorithms such as collaborative filtering or deep learning recommendation systems to analyze design case libraries and proposed design recommendations that integrated modern and tradition. The recommendation algorithm was expressed as below.

$$S = argmax_d P(d|T, C; \phi) \quad (4)$$

where *S* was the optimal design proposal. *T* was the set of extracted traditional elements. *C* was the modern design constraint. *P* was the prediction probability. ϕ was the algorithm parameter [13].

(3) Visitor behavior analysis and public space optimization

AI system used image recognition and video analysis technology to capture tourist movement lines and gathering points through surveillance cameras to generate thermal maps of people flow. The calculation formula of the thermal map was simplified as follows.

$$H(x, y) = \sum_{i=1}^{M} w_i \cdot K(x - x_i, y - y_i; \sigma) \quad (5)$$

where *H (x, y)* was the heat of the location *(x, y)*. *M* was the total number of visitors. w_i was the weight of the i^{th} visitor. *K* was the Gaussian kernel function, which controlled the smoothness of the thermal map. Thermal maps helped identify areas of high traffic and optimize the visitor experience. Based on the results of crowd analysis, the AI system simulated a variety of public facilities layout schemes through optimization algorithms such as genetic algorithms or particle swarm optimization with the goal of minimizing visitor waiting time and improving convenience. The optimization objective function was defined as follows.

$$min\, J = \sum_{j=1}^{J_f} \sum_{k=1}^{K_j} d_{jk}^2 \quad (6)$$

where *min J* was the total inconvenience. *J* was the number of facility types, J_f was the number of facilities of each type. K_j was the square of the distance from the k^{th} facility point to the nearest demand point. The optimized layout was closer to the needs of tourists and promoted the effective use of public space. The process of tourist behavior analysis and public space optimization was shown in Figure 2 [14, 15].

(4) Natural disaster risk assessment and prevention strategy formulation

In rural landscape design, natural disaster risk assessment is an important link to ensure residents' safety and environmental protection. AI systems based on image recognition technology could effectively analyze geospatial image data and identify potential natural disaster risk areas such as flood-prone areas, landslide

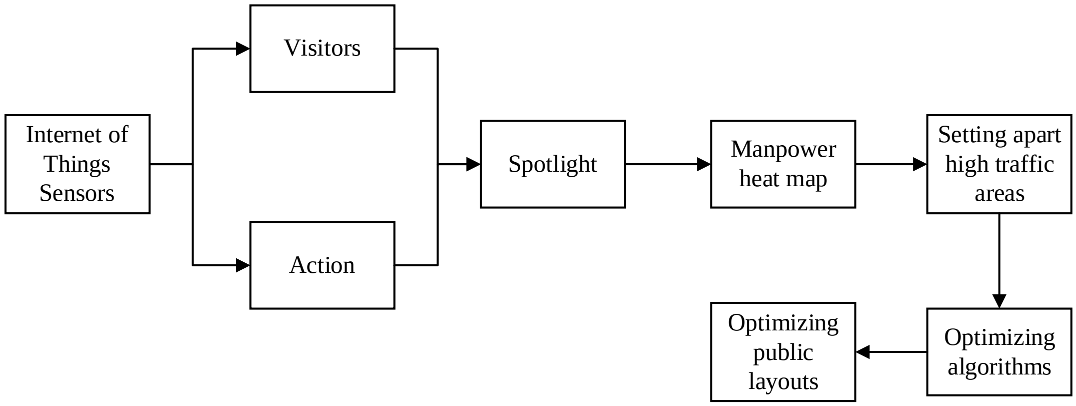

Figure 2. Flow chart of tourist behavior analysis and public space optimization.

sites or forest fire hazard zones, thus providing scientific basis for preventive measures and emergency planning. AI system used deep learning models to predict flood inundation range by analyzing satellite images of historical flood events and combining topographic data, which was based on a U-Net architecture with a loss function that took into account pixel-level segmentation accuracy for flood regions as follows.

$$L=-\sum_{i=1}^{N}\sum_{j=1}^{W}\sum_{k=1}^{H}[y_{ijk}\log(p_{ijk})+(1-y_{ijk})\log(1-p_{ijk})] \quad (7)$$

where L was the loss value. N was the number of samples. W and H were the image width and height, respectively. y_{ijk} was the true label. p_{ijk} was prediction probability. By using this model, designers could accurately mark flood risk areas and provide basis for flood dike and drainage system design. For landslide recognition, the AI system used time-series image analysis technology to monitor slope stability changes combined with geological radar data and predicted landslide possibility through long-term memory network (LSTM) viewed in PyTorch (https://pytorch.org/). The loss function of the LSTM unit could be expressed as cross-entropy loss in equation (8).

$$L=-\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}y_{it}\log(p_{it})+(1-y_{it})\log(1-p_{it}) \quad (8)$$

where N was the number of training samples. T was the time step. P was the label of the actual landslide. y_{it} was prediction probability. The model helped decision makers deploy monitoring equipment in advance, develop emergency evacuation plans, and reduce disaster losses [16]. AI system identified forest fire precursors such as dry vegetation coverage and temperature anomaly through multi-spectral remote sensing images and predicted forest fire risk level by CNN. The risk rating function was defined as follows.

$$R=f(I_{\text{vegetation}},I_{\text{temperature}},\ldots;\theta) \quad (9)$$

where R was the forest fire risk rating. $I_{\text{vegetation}}$ and $I_{\text{temperature}}$ were input image features. θ was model parameter. Based on the risk level map, designers could plan fire isolation zones, set fire monitoring points, and improve the fire prevention capability of villages [17]. The process of algorithm optimization and model training included multiple steps. First, the model parameters were adjusted to minimize the error by selecting a suitable loss function and optimization algorithm. For CNN, the image features were extracted through multi-layer convolution and pooling operations and used the back-propagation algorithm for training to improve the classification or recognition accuracy of the model. For LSTM, the optimization focused on adjusting the network's gating mechanism and memory units to improve the prediction effect of time series data. You Only

Look Once v3 (YOLOv3) (https://github.com /AlexeyAB/darknet) optimized real-time object detection capabilities through an improved CNN architecture and had high accuracy and speed in target detection.

Datasets

All data used in this study included 150 GB data from drone imagery collected from March 2023 to February 2024, 2 TB data from satellite remote sensing collected from May 2019 to October 2023 through geographic information systems (GIS) (https://earthexplorer.usgs.gov). The locations of the data collection involved multiple countries and regions including rural areas in Jiangsu, China and Kerala, India, and agricultural areas in California, USA. The datasets from China included vegetation cover data and topographic maps of a county in Jiangsu Province, while the Indian dataset contained architectural styles and land use data in rural Kerala. The USA dataset included climate and soil data in agricultural areas of California.

Results and discussion

Challenges in rural landscape design

In the field of rural landscape design, several key challenges were identified through a questionnaire survey along with their specific manifestations. The main issues related to ecological environment protection and utilization included severe soil erosion (65%), reduction of biodiversity (79%), and agricultural pollution (56%). In terms of cultural heritage preservation, the challenges were significant, which included the serious damage to traditional buildings (82%), the reduction of folk activities (71%), and the decreasing interest of the younger generation in traditional culture (68%). Furthermore, the uneven distribution of design resources was a major concern with a lack of professional design talent (90%), insufficient capital investment (85%), and outdated design technology (70%). Additional problems included insufficient policy support (75%), low participation of villagers (62%), and information asymmetry leading to a disconnect between design and actual needs (73%). Traditional rural landscape design practices were also limited by static planning methods, which failed to account for the dynamic evolution of rural environments and the continuous development of community needs and made it difficult to adapt to the rapidly changing development of rural areas. The inefficient use of resources not only occurred in design and construction but also sometimes exacerbated environmental burdens, counteracting sustainability goals. Additionally, the lag in adoption of technology, particularly the limited use of modern information technologies like GIS and building information modeling (BIM), contributed to inefficiency in the design process and insufficient refined management.

Data collection and labeling for AI-based design

To address the above challenges and ensure the accuracy of the analysis, high-tech, diversified approaches were employed to data collection in this research, which included satellite imagery to capture the macro-ecological patterns of the entire village, drone photography for close-ups of local buildings, and fixed cameras to continuously monitor tourist behavior (Table 1). In the data preprocessing phase, all data was meticulously labeled, which included that the vegetation coverage was categorized by type, the structure and details of vernacular buildings were outlined using bounding boxes, and tourist behavior including aggregation and flow direction was recorded. This created a rich and high-quality training dataset, providing a solid foundation for subsequent model learning and application.

Algorithm optimization and system design for rural landscape

To address the challenges of rural landscape design, a range of algorithms tailored to specific tasks were selected and optimized. CNN was used to accurately identify and analyze vegetation cover, aiding in ecological planning. LSTM was utilized for predicting visitor traffic trends, optimizing travel management and resource allocation. YOLOv3, a real-time object detection model, was employed for fast and

Table 1. Data collection and labeling.

Data type	Collection methods	Labeled content	Sample size	Remarks
Satellite imagery	Satellite download	Vegetation types	500 sheets	Categorical tags
Ground photographs	Drone shooting	Architectural elements	1,000 sheets	Bounding box annotation
Video surveillance	Fixed camera	Flow dynamics	20 hours	Behavior markup

Table 2. Algorithm optimization and model training parameters.

Model type	Optimization algorithm	Loss function	Batch size	Training rounds	Accuracy
CNN	Adam	Cross-entropy	64	100	92%
LSTM	RMSprop	Mean squared error	32	200	89%
YOLOv3	SGD	Intersection over union	16	50	85%

accurate object detection, enhancing scene understanding and security. Optimization strategies such as adjusting key parameters like learning rate and regularization were applied to avoid overfitting, enhancing the generalization performance of the model. A high-performance system architecture based on distributed processing and cloud computing technologies was constructed. This design efficiently allocated computing resources and enhanced data processing capabilities, ensuring quick responses even for large-scale image analysis tasks. The integration of graphics processing unit (GPU) acceleration technology further boosted image recognition speed, while model pruning optimized computational efficiency, ensuring both high-speed and high-precision image recognition. This technological combination supported rural landscape design and accelerated the implementation of design decisions, which not only improved the efficiency and accuracy of rural landscape design but also laid a strong foundation for sustainable rural development (Table 2). By integrating advanced technologies such as AI-driven image recognition and analysis with optimized algorithms, the system ensured precise ecological planning, cultural preservation, and resource allocation. The use of distributed processing and cloud computing further enhanced scalability, enabling rapid responses to dynamic design needs. Additionally, GPU acceleration and model pruning strategies optimized computational efficiency, reducing costs and environmental impact. This holistic approach bridged traditional design limitations, aligned closely with actual rural needs, and accelerated the realization of sustainable, resilient rural landscapes.

Acknowledgements

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