RESEARCH ARTICLE

AI-driven landscape design optimization based on geographical, environmental, and design-related characteristics

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By integrating environmental and geographic data to improve public satisfaction predictions, AI-driven landscape design optimization has become an important tool for sustainable rural planning. This study analyzed and optimized landscape design across protected zones using a Gaussian Kernel SVM-based Multi-Layer Perceptron (GKSVM-MLP) model based on land use, people density, nighttime light intensity, and climate characteristics. The research proposed an intelligent decision-making framework using multi-source datasets including China Land Use Dataset (CLCD), population density statistics, nighttime light data, and climate characteristics and excluding geological and paleontological reserves. With 97.3% accuracy, 96.1% precision, 96.6% recall, and 97.0% F1-score, the proposed GKSVM-MLP model performed better than conventional AI models like CNN, RNN, and Random Forest, proving its superior classification abilities in predicting ideal landscape topologies. Policymakers and urban planners could use the findings of this study to inform data-driven, ecologically sustainable landscape design that strikes a balance between environmental preservation and human well-being. To improve dynamic landscape optimization in response to changing environmental circumstances, future research should involve integrating real-time adaptive monitoring systems with reinforcement learning.

Keywords: AI-driven landscape design; Gaussian Kernel SVM-MLP; rural landscape optimization; geospatial data analysis; land use planning.

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Introduction

Artificial intelligence (AI) landscape design tools create aesthetically beautiful and incredibly useful landscape designs by analyzing data and user input using machine learning algorithms, which can swiftly create intricate, photorealistic landscape photos by combining real-time data with human preferences and simple sketches or text instructions [1]. The real appeal of AI is found in its capacity to increase productivity, automate processes, and save significant amounts of time. This automation turns into a potent friend for landscape designers in realizing their visions. Considering the crucial undertaking of choosing plants for a project, every decision must be customized for the location, which typically necessitates a great deal of research before the design process can even start. AI can quickly evaluate large datasets and provide recommendations based on predetermined criteria, soil types, and climate rather than requiring human data searches, which greatly accelerate the early design stage and release energy for innovative ideas [2]. In every design practice, AI allows clients and designers to visually enter a location before it is ever constructed with the aid of augmented reality (AR) and virtual reality (VR) technology. Landscape architects can adapt their work to suit particular needs without wasting valuable time on revisions [3]. As a link between natural ecosystems and man-made habitats, landscape design is an essential part of urban planning and environmental preservation, which moulds the regions and impacts not only the visual attractiveness of cities but also ecological well-being and practicality. Sustainable landscape strategies have grown increasingly important as cities continue to expand and the demands on natural resources increase [4]. The intricacies of contemporary environmental issues like resource scarcity, biodiversity loss, and climate change are frequently too complex for traditional landscape design techniques to handle. AI's enhanced capabilities in data analysis, predictive modeling, and automation allow landscape architects to design both beautifully and environmentally friendly [5]. Designers can forecast the results of their designs, maximize sustainability, and comprehend complicated environmental data more effectively by incorporating AI techniques [6].

Geographic Information System (GIS) is a framework for collecting, organizing, evaluating geographical and geographic data and becomes a potent tool for spatial analysis when paired with AI, giving designers a deeper understanding of spatial linkages and patterns [7]. Environmental factors that are essential for sustainable planning like resource distribution, habitat connectivity, and land use patterns can be analyzed. Designers may carry out intricate studies including identifying the region's most vulnerable to environmental hazards, optimizing green spaces, and predictively modelling urban expansion by using AI algorithms to GIS data. Parametric design tools react to ecological data inputs and automatically modify models depending on environmental data and control design parameters, which enables a more adaptable and responsive design process where modifications to environmental input data result in instantaneous changes to the design output, guaranteeing that the finished product stays in line with sustainability goals. Exploring a variety of design options is made possible by parametric tools, which foster creativity while ensuring that design decisions are grounded in ecological reality [8]. The integrated value of Ecosystem Service and Trade-off (InVEST) has been used to quantitatively examine the spatial relationship between environmental variables and landscape structure for the characteristics of the distribution pattern and the territorial spillovers of habitat quality. The geographical association between the land use index and ecosystem functioning was statistically revealed using an auto-regressive model [9]. Lu *et al*. created a three-dimensional imaging simulation environment with data-driven choices and a Rationale Judging Approach (RJA) to provide evidence in favor of a dynamic 3D model and found that the methods for matching image feature points were rather simple and that the approach produced a higher matching number and rate of environment features extracted [10]. Yu *et al*. used the MapReduce Parallel Processing Framework (MR-PPF) to study the use of digital tools and approaches for landscape design for improving the landscape model based on the chosen design, layout, internal and external surroundings, and professionalism [11]. Cohen *et al*. used the environmental circumstances of Models of Physiological and Mechanical Plant Growth (MPM) and Machine Learning (ML) algorithms to illustrate how a Dynamically Controlled Environment Agriculture (DCEA) paradigm may enhance productivity, human health, and urban resilience. By using MPM for false data inputs, the cost of sustaining ML design was reduced. The results demonstrated that the system required a lot of data for machine learning to produce accurate predictions about dynamic environments [12]. Li *et al*. proposed a landscape space environment with a reconstruction model for fuzzy, pixelated region featured an enhanced monitoring model for graphical picture representations, and an Interactive Genetic Algorithm (IGA) to optimize the gardening landscape space environment's structure and enhancing the design impact of the garden landscape environment system. The proposed algorithm combined the method of blocking regional features matching with the landscape space environment design of the image characteristics. The results showed that the visual restoration quality of the landscape spatial environmental design scenes and photos was improved by 15% and the signal-to-noise ratio was higher than the conventional method [13]. Castro *et al*. assessed evolutionary computing (EC) methods, particularly genetic algorithms (GA) and suggested that EC was used to create architectural, functional, innovative, creative, and visually stunning products, while GA was used in the development of partition procedures [14]. Eilola *et al*. proposed 3D visualizations for communicative urban and landscape design and presented a range of planning contexts, objectives, terminologies, and 3D technology options. The results suggested a common reporting framework for conducting comprehensive and systematic evaluation of the benefits and utility of collaborative and participatory 3D visualizations in landscape and urban planning [15]. To visualize environmental landscape design, Chen *et al*. suggested an immersive virtual reality experience and digital entertainment platform to freely browse and control virtual landscapes by including several interaction strategies into landscape design systems [16]. Further, scientists developed deep learning and computer vision for environmental landscape design and planning systems with a novel strategy that combined DL-DNN with landscape planning to address environmental contamination over the long run. Carbon dioxide levels were continuously checked when plants were present [17]. Web 4.0, a human-centered AI, was additionally enhanced and refined by Grêt-Regamey *et al*. The study identified key elements to improve the effectiveness of 3D digital settings for revolutionary landscape and urban design and proposed a collaborative knowledge platform that united scholars, developers, and stakeholders to promote social-ecological-technological system thinking [18]. Traditional methods often struggle with processing limitations and dynamic monitoring challenges. This study explored an innovative approach to landscape planning by integrating Gaussian Kernel-based SVM (GKSVM) with a Multilayer Perceptron (MLP). The proposed method was compared with CNN, RNN, and RF in areas of ecological risk assessment, public satisfaction prediction, and landscape feature extraction. This research would provide landscape architects with better decisions, improved sustainability, enhanced productivity, greater possibility for creativity through the investigation of non-traditional design approaches and pushing the limits of conventional landscape architecture, and improved collaboration and communication among stakeholders to create more resilient and sustainable urban environments. By incorporating AI capabilities, designers may proactively tackle intricate environmental issues and produce landscapes that can change with the times.

Materials and methods

Data resources

The Zenodo community platform (https://doi.org/10.5281/zenodo.5210928) was employed in this research, which covered the China land use dataset (CLCD) at a resolution of 30 m from 2020 to 2024 [19]. Further, the Resource and Environment Science and statistics Centre of Chinese Academy of Sciences provided population density statistics at a resolution of 1 km (https://www.resdc.cn/), while the National Tibetan Plateau Science and Data Centre supplied nighttime light data at a resolution of 1 km (http://data.tpdc.ac.cn/zh-hans/), and the China Meteorological Data Service Centre provided climate parameters including mean annual temperature and mean annual precipitation with a 1 km precision (http://data.cma.cn/). The raster data of each protected region were gathered including land use, population density, nighttime light, mean annual temperature, and mean annual precipitation. The data was divided into two main phases to obtain comprehensive data to satisfy the needs of rural landscape design and public satisfaction forecast. Natural ecosystems were classified into five categories including forest, grassland, wetland, desert, and coastal, while nature reserves of geological and paleontological relic types were excluded. Besides about 30,000 raster tiles were obtained from the CLCD, a total of over 3,000 raster files were retrieved from the population density, nighttime light, and climatic parameter datasets. After data integration and preprocessing, 25,000 composite data samples were created and divided into three categories including 70% for training (17,500 samples), 15% for validation (3,750 samples), and 15% for testing (3,750 samples) to create and assess the proposed GKSVM-MLP model for landscape optimization and public satisfaction predictions.

Data pre-processing using Min-Max normalization

The research was carried out using the Python 3.11 (https://www.python.org/) in a laptop computer with an Intel i7 12th Gen processor, 64 GB RAM, and Windows 11 system. The input features of the landscape prediction dataset were regularized using min-max regularization to scale numerical features within a certain range, using linear modifications to the original data to provide a fair comparison of the before and after values of the procedure as below.

$$X_{new} = \frac{x=min}{max(x)-min(x)} \quad (1)$$

where X_{new} was the adjusted value obtained after scaling the data. X was outdated value. $max(x)$ was Dataset's highest possible value. $min(x)$ was dataset's lowest possible value.

Construction of proposed method

A Gaussian kernel support vectorized multi-layer perceptron network (GKSVM-MLP) was proposed in this study, which leveraged the deep learning potential of MLP and the powerful feature extraction capabilities of Gaussian SVM to improve classification and regression tasks.

(1) Gaussian kernel-based support vector machine (GKSVM)

Gaussian support vector machine GSV, a well-known kernel-based learning systems, could be used as a substitute for neural networks, which had been effectively used to address clustering issues, particularly in landscape protection. To classify the data, it built an N-dimensional hyperplane that divided it into two groups as efficiently as possible. A few data samples usually made up the testing and training data for an identification ecological task. Furthermore, for one class label, every instance in the training set included many characteristics. The purpose of the support vector machine was to build a model that, given the test set's occurrences, could predict the target value. Considering a collection of instance-label pairings for training $(w, z) = \{(w_1, z_1), (w_2, z_2) \dots \dots (w_m, z_m)\}$ where $w_m \in R^z$ and $z_m \in \{-1,1\}$, GSV needed to solve the following optimization issue, where $\min_{x,a,\xi} \frac{1}{2} x^S x + D \sum_{j=1}^{k} \xi_j$ was presented as below.

$$z_j \left(\frac{x^S}{w_j} + a \right) \geq 1 - \xi_j \xi_j \geq 0 \quad (2)$$

where the function Φ mapped the training vectors w_j onto a higher-dimensional space, which might even be infinite. In this higher dimensional space, GSV located a linear separating hyperplane with the maximum margin. The error term's penalty parameter was $D > 0$. $L(w_j, w_i) = \Phi \backsim w_j \Phi \backsim w_i$ was known as the kernel function. Data was transformed from the input and independent to the space of features using the kernel. The four fundamental categories of kernel functions were as follows.

Polynomial:

$$L(w_j, w_i) = (\gamma w_j^S w_i + q)^c, \gamma > 0 \quad (3)$$

Linear:

$$L(w_j, w_i) = w_j^S \quad (4)$$

Sigmoid:

$$L(w_j, w_i) = \tanh(\gamma w_j^S w_i + q) \quad (5)$$

RBF:

$$L(w_j, w_i) = \exp\left(-\gamma \left|\left|w_j - w_i\right|\right|^2\right), \gamma > 0 \quad (6)$$

where the kernel characteristics were c, q, and γ. Gaussian RBF kernel thus was provided by the follows.

$$L(w_j, w_i) = \exp\left(-\frac{\left|\left|w_j - w_i\right|\right|}{2\sigma^2}\right) \quad (7)$$

where σ was GSV kernel width. The goal was to change the width to get rid of the inconsistent results caused by coexisting under and over-fitting in GSV. Global kernels such as polynomial kernels were insufficient for image classification since the association between picture pixels was confined landscape. The two image kernels included in the study were Hausdorff and histogram kernels. Gaussian RBF kernel was utilized in this study by the motivation of RBF kernel's positive findings.

(2) Multi-layer perceptron network (MLP)

One of the most common types of FFNNs was MLP. The first processing elements of MLP were preset in a one-directional fashion. The output, hidden, and input layers were the three kinds of matching layers that interacted with one another to create new information in these networks. There were several weighting values that varied within [-1, 1] for the sensor network that connected these landscape levels. Summation and activation functions were two types of functions that might be performed on each node in an MLP. The summing function might be used to get the product of the values given as inputs, weight values, and bias values as follows.

$$T_i = \sum_{j=1}^{m} \omega_{ji} J_j + \beta_i \quad (8)$$

where ω_{ji} was the connection weight. β_i was a bias value. J_j was an input variable$j$. m was the total quantity of inputs. The MLP might be activated using a variety of techniques with the most popular one being the S-shaped sigmoid function as below.

$$e_i(w) = \frac{1}{1+e^{-T_i}} \quad (9)$$

Thus, Equation (10) was used to determine the neuron i's ultimate output as follows.

$$z_j = e_j\left(\sum_{j=1}^{m} \omega_{ji} J_j + \beta_i\right) \quad (10)$$

Learning was initiated after the final structure was built to refine and evolve the weighting vectors of the network. These weighting vectors needed to be adjusted to estimate the results and maximize the overall error of the network. The efficacy and problem-solving abilities of the MLP were significantly impacted by the computationally demanding training phase.

(3) Gaussian kernel support vectorized machine based multi-layer perceptron network (GKSVM-MLP)

The use of SVMs contributed to the model's high accuracy and adaptability to various fault conditions and networks. The MLP component was the landscape protection network, which contained neurons arranged in layers and connected to each other with weights on the edges. The MLP enabled the GKSVM-MLP network to have the ability that helped to learn various representations of the input data with high precision to predict fault locations. The knowledge of the network was updated in a supervised manner until it recalled the previous fault data in real-time exercises based on historical data. By incorporating these three parts, the GKSVM-MLP network could predict fault locations and repairs. From this forecast capability, the integrity of landscape distribution systems was well sustained since faults were detected immediately and isolated apace without compromising on the entire landscape design. Furthermore, the GKSVM-MLP network was capable of predicting future state and withstands shifts that might be observed in the network topology and varied levels ecosystem penetration, which made the GSVM-MLP network relevant in the modern landscape protection. The accuracy and timeliness of the landscape detection of the proposed method contributed to the shift towards more reliable and sustainability. Due to the ongoing demand for high dependability and efficiency in methods, advanced networks will remain paramount in guaranteeing the stability of the landscape protection. Three popular models including random forest (RF), recurrent neural network (RNN), and convolutional neural network (CNN) were compared with the proposed GKSVM-MLP model to assess its efficacy. These models were chosen because they are applicable to the analysis of structured and geographical data. Four major performance indicators were adopted to determine accuracy, precision, recall, and F1-score during models' comparison.

Results and discussion

Performance analysis of different models

The results showed that, in AI-driven landscape design optimization, the proposed Gaussian kernel SVM-based MLP (GKSVM-MLP) performed better than other models, getting the best accuracy of 97.3%, precision of 96.1%, recall of 96.6%, and F1-score of 97.0% (Table 1). The Gaussian kernel SVM that successfully captured intricate, non-linear correlations in geospatial, environmental, and design-related variables was responsible for this high performance, enabling accurate land suitability categorization. Furthermore, by understanding high-level patterns in landscape attributes and streamlining design solution decision-making, the MLP component improved predictive modelling. In contrast, random forest (RF) offered robust classification but lacked deep flexibility, while CNNs exceled at extracting spatial features but struggled with long-term pattern recognition, and RNNs had trouble understanding structured spatial relationships. GKSVM-MLP was a powerful model for optimizing landscape designs because it combined the deep learning capacity of MLP with the robust feature extraction of SVM. Further enhancements could be achieved by adjusting hyperparameters, integrating real-time monitoring based on the Internet of Things, and utilizing reinforcement learning for adaptive landscape alterations.

Table 1. Analysis of different models' performance.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	88.4	86.1	87.4	87.8
RNN	77.7	75.4	76.2	76.5
RF	82.1	79.3	80.2	79.7
GKSVM-MLP	97.3	96.1	96.6	97.0

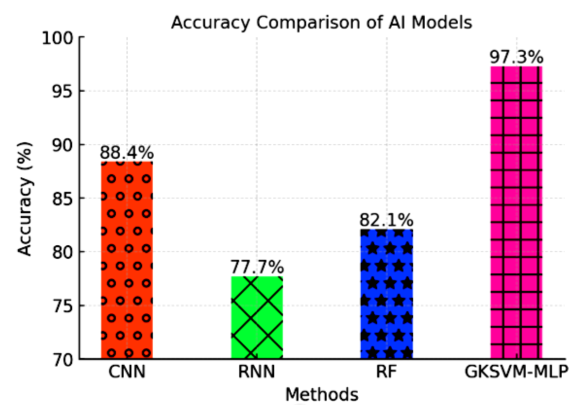

Figure 1. Accuracy comparison of proposed model with other Existing methods

Accuracy comparison

A comparison of the accuracy of four AI models for landscape design optimization showed that, with an accuracy of 97.3%, the proposed GKSVM-MLP model outperformed the others in capturing intricate landscape patterns and optimizing design choices. The combination of Gaussian kernel SVM for feature extraction and MLP for predictive modelling improved classification and adaptability and was the contribution to the performance (Figure 1). By using its spatial data processing skills, CNN performed well in comparison, achieving an accuracy of 88.4%. However, its restricted capacity to adapt to dynamic design caused it to fall short of GKSVM-MLP. RNN was less successful for geospatial optimization because it struggled with complex spatial relationships as evidenced by its lowest accuracy of 77.7%. With an accuracy of 82.1%, RF performed somewhat well, gaining from its structured data categorization capabilities but lacking the deep learning adaptability needed for extremely complicated landscape designs.

Precision comparison

The precisions of four AI models utilized in landscape design optimization were compared using bright colors and unique hatch patterns to ensure accessibility and clarity for each model. the results demonstrated that, with the maximum precision of 96.1%, the GKSVM-MLP model demonstrated its exceptional capacity to classify landscape elements accurately while minimizing false positives (Figure 2).

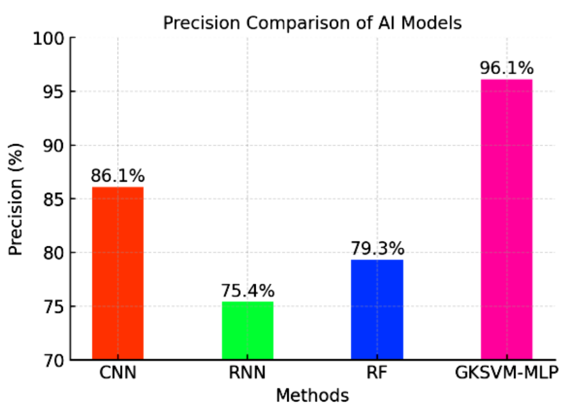

Figure 2. Precision comparison of proposed model with other existing methods.

Comparison of recalls and F1 scores

The results demonstrated that, with the best recall of 96.6% and F1 score of 97.0%, the GKSVM-MLP model performed noticeably better than the other models, proving its greater capacity to accurately identify pertinent landscape characteristics while reducing misclassification. In terms of models' powerful spatial feature extraction capabilities, CNN outperformed the other models with a recall of 87.4% and an F1 score of 87.8%, while RF was ranked as the second one, demonstrating its dependability but lacking deep learning optimization. The RNN model appeared to be the less successful one with structured geographic data due to its sequential learning methodology (Figure 3).

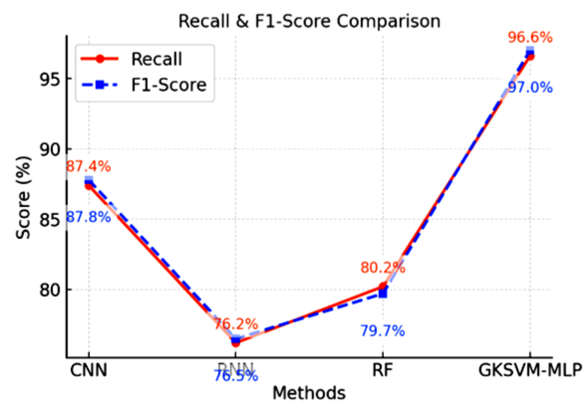

Figure 3. Comparison of recall and F1 score of proposed model with other existing methods.

The investigation of how public satisfaction with rural landscape design was affected by environmental and design-related elements employed a satisfaction score (%) based on AI-driven forecasts to evaluate each of the factors including green space, urbanization, population density, nighttime light, and climate comfort. The satisfaction score of green space was 85% with the highest satisfaction ratings of parks, woods, and plants as the considerably improving the general well-being of the populace. The satisfaction score for urbanization was 72%, which indicated that, while excessive construction might degrade the environment, moderate urban development increased satisfaction. The satisfaction score of nighttime light was 78%, indicating that too bright lighting might result in light pollution, while enough lighting increased accessibility and security and raised satisfaction. Climate comfort was counted as 69%. Since harsh weather reduced public comfort, favorable temperature and precipitation conditions were important factors in satisfaction levels. The satisfaction score of population density was 60%. According to the lowest satisfaction rating, places with a lot of people and little open space seemed to have less general well-being (Figure 4).

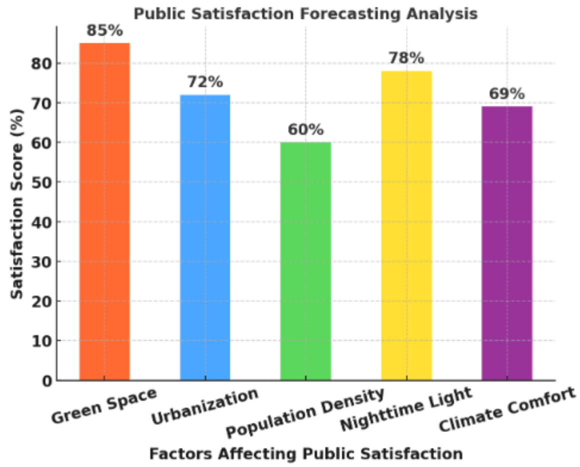

Figure 4. Public satisfaction forecasting.

Based on the results of this research, improving public satisfaction required balanced landscape planning that emphasized green spaces, moderate urbanization, and climate-adaptive architecture. To enhance rural environments, policymakers and urban planners may use AI-driven forecasting model to guide their data-driven judgements.

Conclusion

To improve rural landscape planning and public satisfaction predictions, this research effectively combined multi-source geospatial datasets with AI-driven landscape design optimization. While excluding geological and paleontological reserves, the study offered a thorough picture of landscape dynamics throughout protected zones by utilizing data from land use, population density, nighttime light, and temperature characteristics. When compared to the other traditional AI models like CNN, RNN, and random forest, the proposed Gaussian Kernel SVM-based Multi-Layer Perceptron (GKSVM-MLP) model demonstrated better accuracy, precision, recall, and F1 score. Its efficacy in optimizing landscape designs that strike a compromise between ecological sustainability and human enjoyment was confirmed by its outstanding classification performance. This study advanced AI-assisted rural landscape planning by combining demographic, environmental, and spatial elements, provided policymakers and urban planners with data-driven and sustainable design solutions. To further improve landscape adaption techniques under shifting environmental conditions, future research may concentrate on integrating real-time monitoring systems, reinforcement learning techniques, and generative AI models.

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