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Research on simulation system of landscape art design based on computer learning and virtual reality technology

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Abstract. The increasing growth of urbanization has created significant prospects for the advancement of architectural landscape design. However, the existing machine learning and image processing methods provide partial solutions, because they struggle with noise, overlapping landscape features, and poor segmentation accuracy. To address these limitations, we propose a hybrid simulation and classification model that integrates the advantages of computer learning with immersive virtual reality (VR) environments. First, wavelet-based denoising and intensity normalization are applied to enhance 360° landscape image quality. A multi-orientation segmentation method is then used to accurately classify the complex visual features. Texture features are extracted using a combination of Grey Level Co-occurrence Matrix (GLCM) and Bayesian-optimized Gauss Markov Random Field (GMRF), which helps to capture both spatial and statistical relationships. These features are classified using a hybrid approach combining logistic regression (LR) and K-nearest neighbor (KNN), which allows strong observation of landscape features. Simulation of the model is conducted using real world immersive VR studies. The experiments demonstrate the superiority of the model in terms of accuracy (98%), precision (99.5%), and sensitivity (98.5%), respectively.

Keywords: Landscape simulation / virtual reality (VR) / wavelet denoising / multi-orientation segmentation / GLCM / Gauss Markov random field (GMRF) / Bayesian optimization / hybrid classification / logistic regression / K-nearest neighbor (KNN) / 360° panoramic imagery / urban planning

1 Introduction

Information technology has developed quickly in tandem with the rapid advancements in science and technology. In the surroundings, a range of novel technological display approaches were used. Scientific and technological methods are continuously being incorporated into environmental art design with the rise of virtual reality (VR) technology. This eliminates the original work's dull aura for the general public and significantly increases the appeal and visibility of environmental art. Virtual reality served as the foundation for the development of augmented reality as a research area. The amiable HCI interface has a wide variety of potential uses in augmented reality technologies [1,2]. This paper suggests realizing the digital design application of planning through VR technology in order to foster the organic fusion of virtual reality (VR) technology with planning and design, improve the authenticity and intuitiveness of designers in space vision, and better execute computer-aided scene design [3]. Individuals turn these straightforward concepts and well-wishes into joyful and prosperous creative forms. Folk activities such as dress and dwelling customs, witchcraft beliefs, life etiquette, and many more are influenced by these images of auspicious themes, which people see as the great magic weapon for all souls [4]. It is clear that students are limited to using images or films to explain these works due to the pandemic's impact. If students just react to the teacher's exposition of images or films on the other end of the computer, they will never be able to sympathize with the works and develop their creative inspiration [5]. To improve student engagement and training, virtual reality will be used. The creation of learning content might be completely changed by virtual reality education, which is predicated on the idea of presenting participants with an actual or imagined digital world that they can interact with in addition to seeing. You can better understand what you're learning if you immerse yourself in it. Less computing complexity may be used to process the data [6]. Assert that the two interact in reverse, with unjustified growth leading to the subsequent destruction of cultural landscape resources. Thus, there is ongoing disagreement about how to preserve and advance cultural heritage, particularly in China. There are gaps in the wealth of domestic research that has recently been conducted on the development and protection of cultural assets.

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A dearth of focused debates on individual cultural landscape resources, particularly in places with a minority population, is evident in the viewpoints.

Which mostly concentrate on the big picture of the general development of cultural heritage [7]. By using computer simulation technology, computer graphics, and picture software, a virtual simulation system of the three-dimensional simulation model is established, and several three-dimensional models of experimental testing technology are created [8]. Shape, size, scale, proportion, and direction/orientation are the adjectives used to characterize the qualities of design, which are crucial. And the design quality, which is characterized by hierarchy, balance, harmony, unity, order, and rhythm. Early in the design process, design students take these factors into account together [9]. The phrase "visualization" encompasses integrating geographical data, thematic information, and geospatial information and the realistic rendering of the physical world. The geographical organization of this data may be complex, including temporal and thematic aspects of the data together with geographic information (positioning). One instance of a 3D visualization of geographical data that is interactive is the project [10]. According to one definition, virtual reality (VR) is really "the use of computers and human-computer interfaces to create the effect of a three-dimensional world containing interactive objects with a strong sense of three-dimensional presence [11,12]." However, we offer a complete method to tackle these problems, first improving picture quality via Wavelet denoising and normalization, then multi-segmentation according to orientation. We utilize the Gauss Markov Random Field (GMRF) with Bayesian optimization to ascertain statistical correlations between nearby pixels and the Grey Level Co-occurrence Matrix (GLCM) to extract spatial texture attributes. A hybrid approach combining K-Nearest Neighbor and Logistic Regression is then used to classify the combined GLCM-GMRF texture characteristics and picture intensity vectors to improve the overall performance and accuracy.

1.1 Motivation

As per the overall problem description, there exist many significant issues that require innovative solutions in contrast to the existing approaches.

- **Complexity of Landscape Design Aggregation:** The intricate combination of many landscape aspects makes it difficult to identify and classify landscape designs, making it difficult for current image processing and machine learning approaches to classify them effectively.
- **Problems with Image Quality:** Noise and irregularities in the quality of the photos used to classify landscape designs frequently occur, which has a detrimental effect on the classification process' accuracy and dependability.
- **Insufficient Feature Extraction Techniques:** Extant techniques for feature extraction, such texture and intensity analysis could not fully capture the intricate correlation properties between adjacent pixels, resulting in less-than-ideal performance when it comes to differentiating various landscape aspects.
- **Limitations of Classification Techniques:** Achieving high sensitivity, specificity, recall, accuracy, and precision in practical applications can be difficult due to the complex and high-dimensional nature of landscape design data, which may be beyond the scope of existing classification techniques.

1.2 Contributions

This extensive study includes the following major points of emphasis:

- This study proposed a hybrid landscape simulation and classification model that integrates computer learning and VR technology for immersive landscape design analysis.
- The model involves wavelet-based noising and intensity normalization techniques to enhance the consistency of the input images.
- Also, introduced a multi-orientation segmentation strategy to accurately classify overlapping and spatially complex landscape features.
- Combined GLCM with Bayesian optimized GMRF modeling to extract both spatial and statistical texture features.
- Utilized the strength of LR and KNN algorithms to improve the accuracy of landscape feature classification.
- The model was simulated using the real-time VR landscape samples, and demonstrates the efficacy in terms of accuracy, precision, and recall with 98%, 99.5%, and 98.5%, respectively.

1.3 Paper organizations

The remaining components of the study are arranged as follows: In Section 2, the inadequacies of the current research are assessed. Section 3 provides a detailed explanation of the proposed work complete with pseudo-code and pictures. In Section 4, the experimental setup is given together with comprehensive descriptions of the simulation setup and comparison analysis. A comprehensive analysis of the recommended works' conclusion and upcoming projects is given in Section 5.

2 Literature Survey

The research gaps from these earlier articles are outlined below. The author in [13] outline the factors to consider when designing an immersive virtual landscape, such as creating animated 3D plants that transition between seasons and soundscapes that evolve throughout a simulated day. To evaluate the potential of immersive VR landscape modeling, we conducted a heuristic evaluation with experts. This study [14] presents application research on the merging of interactive 3D dynamic scene virtual reality technology with multi-source information art painting. This essay provides a thorough analysis of the requirements for art painting education reform and concludes that the current state of virtual reality technology is ill-suited to the art painting classroom.

In light of potential calculation errors as well as other issues, this research proposes an optimization technique. The main goal of the plan is to enhance the image quality of virtual reality technology by utilizing the benefits of multi-source information fusion for information integration in order to supply more thorough and full object information for 3D modeling. This study modifies the conventional higher vocational art teaching mode, enhances the immersion of art education, and increases the effectiveness of higher vocational art teaching by incorporating artificial intelligence virtual reality technology into the design of higher vocational schools [15]. Furthermore, virtual reality algorithm display in the teaching system has been improved. This paper describes the process of implementing the system's features, which are mainly shown as interface diagrams and flowcharts, in order to realize the state-of-the-art curriculum design system for higher vocational education based on virtual reality technology. These features include homework management, virtual scenes, personal spaces, resource management, online examinations, and teacher-student communication. This study examines the design of urban comprehensive parks with an eye on aging-friendliness [16]. Drawing on computer virtual simulation technologies, the design scheme for urban park landscapes is based on four considerations: layout, type, distribution, and construction. An urban park landscape virtual simulation display impact was achieved by methodical study on the activity space system for the aged. According to research, the design scheme put forth in this paper breaks with traditional landscape design presentation forms, solves the issue of how buildings and users interact, and requires less money to produce and modify than traditional models. It also serves as a useful guide for upcoming urban park projects as they get older.

Through computer processing, the panoramic video is created and presented, allowing visitors to view the scene while wearing a display device somewhere and viewing virtual information added to the recording [17]. Technical challenges include the high complexity of the algorithm in the panoramic video stitching system, the occurrence of stitching cracks and the "GHOST" phenomenon in the stitched video, and the ease with which the time-consuming environment and target tracking detection algorithm can affect 3D registration. These issues are resolved by this solution. The outcomes of the simulation demonstrate that the augmented reality 3D registration approach works well for the local augmentation of the panoramic video, while the panoramic video stitching method works well in real time and efficiently suppresses stitching cracks and the "GHOST" phenomena. They introduce the landscape workshop, which makes use of the Unity 3D game engine in this post [18].

Working with an interactive 3D geovisualization low-immersion desktop screen environment, 25 architecture students completed landscape design assignments. By using the Intrinsic Motivation Inventory to measure motivation, the Questionnaire on User eXperience in Immersive Virtual Environments was used to assess how the geovisualization process affected the perception of the 3D world. All fields are being impacted by technological growth, which is also increasing accessibility to works [19]. They have also started to dabble in crafts and the arts. Digital technology may revitalize traditional arts and crafts. Art photographs are transformed into three-dimensional image art with the use of artificial intelligence and three-dimensional digital technology. The process involves determining the image's frequency and storing the associated information in a database. Wireless sensor networks are used to transport the picture data in this operation. The sensors that are part of digital technology help to transform regular photographs into three-dimensional digital images. The simple identification of the photographs will be made possible by this data. The efficacy of combining artificial intelligence with three-dimensional technology is assessed through the use of the Surface Wavefront Reconstruction on Fast Fourier Transform (SWRFFT) Method. This article also uses a landscape design method based on 3D image processing technologies [20]. In order to achieve 3D landscape picture feature improvement and increase the clarity of the landscape design image, a 3D landscape image can be preprocessed throughout the design process to eliminate redundant and noisy information.

When the parametric plant modeling method is applied to the example of a garden green space, the morphological structure parameters of green plants are obtained, and the three-dimensional models of various plant modeling are established. The oculus rift virtual reality equipment is integrated, and the rules of parametric description of plant spatial layout are adopted, based on the open scene graph rendering engine, to realize the virtual construction and display of a three-dimensional garden vegetation landscape. The use of computers as auxiliary tools in digital art creation has led to fast development and application across many societal domains [21]. The subject of education has seen a surge in research interest in digital art design instruction at the same time. Modern display design is altered in both look and meaning. This piece creates a digital art design system based on big data and interactive virtual technologies in an effort to advance digital technology and apply contemporary technology to the area of art design. The big data, interactive virtual, digital art design, and 3D file formats are all introduced in this article's technique section, along with the algorithm's SVM support vector machine's relevant information. The study findings section of this article examines a number of time-consuming topics, including gesture recognition, function recognition, average CPU use, speedup and data volume relationships, and accuracy comparisons among approaches. The field of design and research for new energy landscape architecture is booming as the field develops at an accelerating rate. Modern principles of aesthetics, technology, and design will always encourage and support the ongoing enrichment of urban landscape design. Designing new urban landscapes with multimedia technologies is therefore a new area of investigation. Via the processing of text, graphics, pictures, music, animation, video, and other data, multimedia technology creates logical connections and facilitates human–computer interaction [22].

Table 1. Analysis of the studies integrating machine learning and virtual reality (VR) in landscape design.

Source	Model	Improvements	Limitations
Lin et al. [28]	VR-ML-BIM clash detection	Reduced design clashes up to 16%	Small project sample
Ha et al. [29]	Immersive design learning VR	Enhanced spatial realism	Limited group
Tan et al. [30]	YOLO-v3 on VR images	High detection precision of 97%	Focused only on turbine objects
Shan et al. [31]	Oculus-3D image processing VR	Cost-efficient immersive visualization	Simplified case example
Vijayakumar et al. [32]	Comparative XR-ML review	Review	Review

The most recent advancements in artificial intelligence, computer graphics, multimedia, multi-sensory perception, networking, parallel computing, and other technologies are all integrated into virtual reality technology. With the use of multimedia technology, individuals may easily be deeply affected by the color of the environment, making it one of the most visually striking elements. The purpose of this study is to give references for the design of current gardens by examining the landscape design techniques that mimic painting in contemporary gardens. Virtual reality technology primarily uses simulation techniques to give users an interactive three-dimensional image environment [23]. These techniques can accurately represent the movements and interactions of operating objects, creating a virtual world and a connection between users and the virtual environment. This study chooses an appropriate virtual reality system based on the features of garden landscape design, based on a comparison of popular engine systems. Based on this, it investigates the operations of the engine system that the research institution chose and looks into virtual reality systems that fit the requirements for developing garden landscape engineering. In the actual work process, a three-dimensional virtual landscape is ultimately chosen in order to establish a strong basis for utilizing virtual reality technology in garden landscape design and to work toward gaining an edge in this field of application. The use of contemporary instruments to improve the landscape impression has been included into traditional garden design [24]. The scene depth algorithm and the three-dimensional reconstruction method are provided, and a three-dimensional reconstruction of the scene based on the depth image algorithm is suggested. By calibrating the camera, the scene depth is determined.

The introduction of each person's geographical position has been pointed out, based on the depth of information. Reconstruction efficiency is great and an easily understood and implementable adaptive 3D reconstruction approach based on multi-source information is suggested. For viewers, the majority of techniques try to recreate artworks as 3D virtual objects. But these approaches do not tell the important historical facts and tales that the paintings omit, nor do they allow viewers to engage with the historical events that are portrayed in the paintings. In this work [25], they present an augmented reality system that serves historical context experiences of royal events and offers 3D virtual restorations of information required to comprehend court artworks. To put it more precisely, we turn the historical narratives that are absent from the picture into a virtual three-dimensional object by restoring the information needed for its interpretation. Visitors can also participate in a variety of interactions with the system to experience royal events. This study [26] focuses on developing a gesture-controlled, open-source augmented reality (AR) tool for remote industrial assistance. It aims to improve communication and task execution in real time by allowing users to interact with virtual elements. The system provides the immersive support for complex maintenance and assembling tasks in industrial environments. This work [27] proposes a real-time IoT-based monitoring framework for predictive maintenance in industrial systems. It integrates data from multiple sensors and applies intelligent algorithms to detect system faults. This framework helps to enhance the operational efficiency through continuous, data-driven decision-making.

Most of the recent studies implements the combination of VR nad machine learning models in the landscape designs. Some of them are illustrated in Table 1.

2.1 Research gap analysis

By thoroughly analyzing the existing literatures, many studies have explored VR and 3D modeling for landscape design, education, and urban planning; however, most of them are mainly focused on basic virtual scenes. Also, they do not include any smart techniques to handle real-world image noise, complex scene segmentation, and accurate classification of landscape features. Particularly, few works only combine real 360° panoramic data with machine learning methods for automatic landscape recognition in VR environments. Some systems show how users interact with virtual scenes, but they rarely provide a complete technical solution. This creates a gap to develop an intelligent and immersive model that can be used in real-time landscape data analysis. Our proposed method addresses this gap by combining the novelty of wavelet denoising, multi-angle segmentation, GLCM and GMRF feature extraction, and a hybrid strategy for immersive and accurate landscape simulation.

3 Proposed method

The method that is given is used to recognize landscapes. Images are cleaned, normalized, and divided into training, validation, and test datasets as part of this inquiry. The proposed approach includes pre-processing, segmentation,

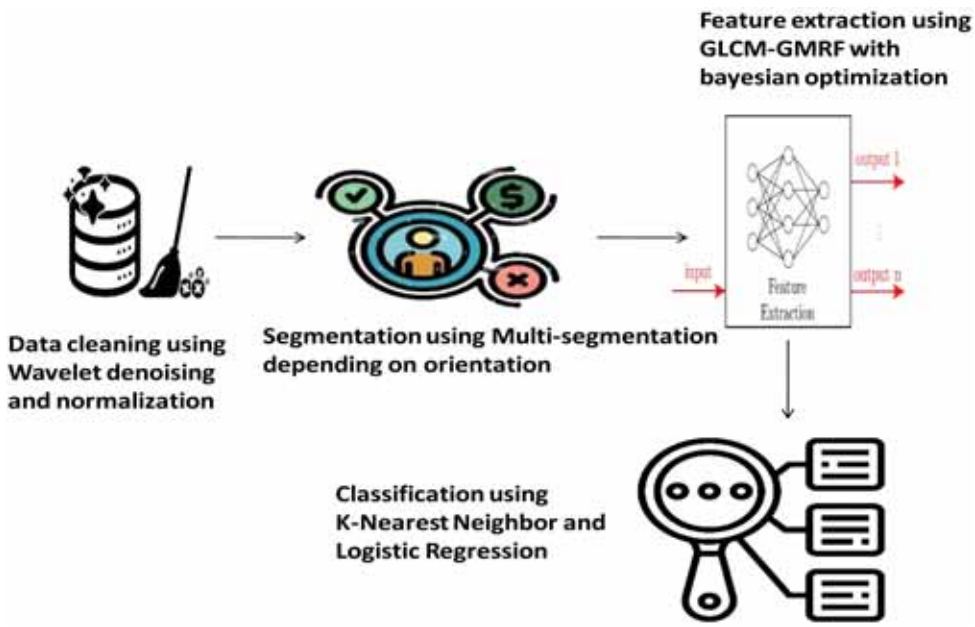

Fig 1. Proposed architecture.

extraction features, classification, training, optimization, and model assessment Figure 1 represents the proposed design. This section provides a brief discussion of the five main processes that make up the planned work. These processes are as follows:

– Data collection.
– Pre-processing.
– Segmentation.
– Feature extraction.
– Classification.

3.1 Data collection

The dataset used in this study was inspired by [5], which developed a spherical video-based immersive virtual reality (SV-IVR) learning system for landscape architecture education. The data is collected from real-world outdoor campus scenes through 360° spherical video imagery, which allows immersive viewing through VR headsets and mobile devices. These scenes are designed to reflect the views captured from five different landscape-oriented camera angles by maintaining the 360° panoramic view, similar to the various viewpoints used in the original SV-IVR footage. This setup encourages some practical terms like urban planning which involves immersive city layout reviews, interactive heritage site visualization which reconstruct the historical landscapes ad provides engaging visitor experience, and educational tools with interactive design simulations. We collected around 3,000 image frames, each carefully labeled into seven landscape-related categories such as road, sidewalk, curb, vegetation, open grass, path, and built structure. To train and evaluate our model, the dataset was split into 70% for training, 15% for validation, and 15% for testing.

Let the dataset is defined as collection of labeled image samples $D = \{(x_i, y_i)\}_{i=1}^{n}$, where each $x_i \in X$ denotes a preprocessed panoramic image, with the corresponding label $y_i \in Y$, belongs o the set of landscape classes C. Each image is preprocessed to using wavelet denoising and normalization to enhance visual quality. Then, the feature extraction is performed using GLCM and GMRF models, to obtain a spatial texture representation of $F(x_i)$. The classification tasks aim to learn the function of $f_\theta : F(x_i) \rightarrow C$. Here, θ denotes the parameters of the hybrid classification models which involves LR and KNN. The goal of the model is to improve these parameters to reduce classification error of all image samples, which is expressed as

$$\theta^* = arg \max_{\theta} \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}(f_\theta : F(x_i) = y_i). \quad (1)$$

Here, $\mathbb{I}$ denotes the predicted label that indicates 1 if the image is matched with the ground truth otherwise, it indicates 0.

3.2 Preprocessing

3.2.1 Data cleaning

We have collected the environmental sensors, GIS, satellite images, and user comments. Preprocess the picture first. To improve the clarity of visual data before analysis, a three-step preprocessing approach is used in the study: wavelet denoising, image normalization, and spatial

information extraction. Wavelet denoising helps to remove unwanted noise from the image and helps to prevent the important features like edges and textures. After denoising, normalization adjusts the color background uniformly, particularly it helps to convert the inconsistent regions to the accessible areas. Finally, spatial distribution information is extracted to capture the different landscape features like roads, vegetation, or buildings.

Wavelet denoising of images: The image was denoised using the wavelet transform technique, supposing that the visual image included the following noise signals:

$$\varepsilon(t) = \omega(t) + \alpha(t). \tag{2}$$

Two of them are the original signal of the picture, represented by $\omega(t)$, and the image's noise, represented by $\alpha(t)$.

To produce the discrete signal $m(t)$, where $t = 0, 1, \ldots .. T$, discretize the noise signal in the visual picture. Then, sample some of the signals in the discrete signal using the wavelet transform method:

$$\mathcal{C}_i = \frac{1}{t(|\mathcal{Y}_{1i} - AVG_i|) + |\mathcal{Y}_{2i} - AVG_i| +, \ldots, +|\mathcal{Y}_{ti} - AVG_i|.} \tag{3}$$

Among these, AVG_i stands for the wavelet coefficient, $\mathcal{C}_i$ for the wavelet decomposition outcome of the image, and $\mathcal{Y}_{ti}$ for the scale function. The wavelet coeAcients may then be transformed to provide the following results:

$$AVG_i = \frac{1}{t(\mathcal{Y}_{1i} + \mathcal{Y}_{2i} +, \ldots, +\mathcal{Y}_{ti})}. \tag{4}$$

Given the wavelet function to be $\mathcal{Y}_{ji}$, the filter coefficient matrices $\mathcal{W}_{ti}$ and $\mathcal{L}_{ji}$, which are represented by formulas (5) and (6), respectively, relate to the scaling function $\mathcal{Y}_{ti}$ and the wavelet function $\mathcal{X}_{ji}$:

$$\mathcal{W}_{ti} = \begin{pmatrix} 1 & \mathcal{W}_{11} & \ldots & \mathcal{W}_{1i} \\ 1 & \mathcal{W}_{21} & \ldots & \mathcal{W}_{2i} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \mathcal{W}_{t1} & \ldots & \mathcal{W}_{ti} \end{pmatrix} \tag{5}$$

$$\mathcal{L}_{ji} = \begin{bmatrix} l_{1j} & 0 & \cdots & 0 \\ 0 & l_{2j} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & l_{ji} \end{bmatrix}. \tag{6}$$

The picture is designated as $\mathcal{V}(\mathcal{W}_{ti}, \mathcal{L}_{ji})$ in accordance with formulae (5) and (6). The discretized picture is still made up of two components, the coefficient $\mathcal{W}(m)$ corresponding to the original signal $\omega(t)$ and the coeAcient $\mathcal{Y}(m)$ relating to the noise signal $\alpha(t)$, as can be observed due to the linear nature of the wavelet transform.

The normal signal in the picture is significantly focused on the Security and Communication Networks following the wavelet decomposition of the image.

The noise signal is randomly distributed in the transform domain, but the wavelet coefficients have greater amplitude. At this point, more denoising can be done to the wavelet coefficient noise. The detailed procedure for denoising is as follows:

- Step 1: breakdown the visual picture to be denoised, choose suitable wavelet coefficients, and extract the o-level image hierarchy
- Step 2: Quantify the various levels of images by selecting an acceptable threshold.
- Step 3: The pictures of each layer are subjected to denoising processing in accordance with the quantization processing result to obtain the overall denoising result.

Normalization: The backdrop of each input image should be uniformly white in order to normalize it, but the color-depth relationships between the contents of each image should be kept intact. To set the backdrop to pure white, we create a linear function denoted by $\phi_{\gamma,\varepsilon}$.

$$\phi_{\gamma,\varepsilon} = \boldsymbol{b}_{ji}.\gamma/\varepsilon \tag{7}$$

where γ is the RGB value of white, which is 255. A mapping must be created so that points larger than μ are mapped to a location near γ and points less than μ are mapped to a location near 0. This will increase the contrast between the lines. We create a mapping to increase the image's color contrast after being inspired by:

$$\mathcal{D}_{\phi}(\boldsymbol{b}_{ji}) = \mu\, arctan\left(\phi\left(\boldsymbol{b}_{ji} - \frac{\gamma}{2}\right)\right) + \gamma/2 \tag{8}$$

where the mapping range is controlled by a parameter called ϕ. This ensures that the new pixel intensities for the normalized image will primarily fall between -1and1.

3.2.2 Segmentation

We suggested a landscape perception system that would use GPS, inertial measurement, odometer, speedometer, wheel speed sensor, time pressure sensor, pedestrian warning, lane departure, night vision mode, and steering angle sensor in addition to satellite photos and radio detection. The improved perception system assesses the state of the vehicle using sensor data. We processed 360° images from five landscape cameras in a timely and precise manner. Roads, sidewalks, curbs, lane markings, buildings, and participants are all recognized by the perception module. Panoptic, instance, and semantic data are extracted using image segmentation. Compared to narrow FoV cameras, wide-angle area view cameras look smaller. For big datasets, this fast-training approach is suitable. It divides up well too. From 95° to 30°, we employed three segmentation techniques. Semantic segmentation is used for 30°–95° FoV images and panoptic segmentation, which separates images based on color differences, for 30°–30° FoV images. For more accurate route selection, panoptic segmentation performs superior front-view FoV segmentation. As a result, we were able to segment every little, thin item in every direction of the field of view.

3.2.3 Feature extraction

Short extraction times, strong discrimination, and good robustness are indicators for extracting texture features. This paper extracts the GLCM and GMRF features of the texture image to describe the properties of the distorted texture image. Feature extraction is the most important step in texture image classification and detection.

GLCM-Based Texture Feature Extraction:

GLCM texture feature is derived from the GLCM statistics. GLCM is computed by determining the joint. The calculation formula is the probability density of two pixels in the $\mathcal{P}$ direction separated by v.

$$\mathrm{II}_{\boldsymbol{b}a}(\mathcal{P}, v) = \frac{\mathcal{E}_{\boldsymbol{b}a}}{\sum_{\boldsymbol{b}=1,a=1}^{t} \mathcal{E}_{\boldsymbol{b}a}} \tag{9}$$

These are: t is the image's grey level; $\mathcal{P}$ typically selects 0°, 45°, 90°, and 135°; $\varepsilon_{\boldsymbol{b}a}$ is the number of instances of both grey levels a and b. GLCM typically uses fourteen different types of texture feature statistics. This research employs four unrelated feature statistics that are not necessary to calculate all features due to the connection between different feature statistics.

(1) Energy. The formula for computation is

$$\mathcal{F}h = \sum_{b=1}^{t} \sum_{a=1}^{t} \{q_{ba}(\mathcal{P}, v)^2\} \tag{10}$$

(2) Entropy. The formula for calculating this

$$\mathcal{F}q = \sum_{b=1}^{t} \sum_{a=1}^{t} q_{ba}(\mathcal{P}, v) log_{10}(q_{ba}(\mathcal{P}, v)\Big) \tag{11}$$

(3) In contrast, the formula for calculation is

$$\mathcal{D}n = \sum_{b=1}^{t} \sum_{a=1}^{t} (b-a)^2 q(b, a) \tag{12}$$

(4) Correlation: The equation for computation is

(5) *See equation (13) below*

The value of the GLCM element at $(\boldsymbol{b}, a)$ is represented by $q(\boldsymbol{b}, a)$ among them.

Extraction of texture features using the Bayesian optimized GMRF model

In this study, Bayesian optimization is applied to fine-tune the parameters of the GMRF-based texture feature extraction process. This method explores the parameter space using entropy-based acquisition functions to identify combinations that increase the classification accuracy. Also, this helps the system to extract clear features from images, which makes the hybrid classifier work better and reduces the chances of incorrect results. Every pixel an in the image has an intensity value $\mathcal{H}(\boldsymbol{b})$ that is associated to every neighboring pixel around it in the Markov random field. This relationship may be written as conditional probability so that $q(\mathcal{H}(\boldsymbol{b})) \,|\, \mathcal{H}(\boldsymbol{b}+n)\,,\ n\varepsilon t)$.

A symmetric differential equation may be used to represent the GMRF process. Let U be the point set on the picture block, $U=\{\,(m,\ g\}\,,\ 1 \le m \le t,\ 1 \le g < t\,\}$.

$$\mathcal{H}(b) = \sum_{n=1}^{t} \alpha_n (\mathcal{H}(b+n)). \tag{14}$$

The weight of the symmetric neighborhood pixel is α, the point in U is $\mathcal{H}(\boldsymbol{b}+n)$, and $t$is the GMRF neighborhood of point $\boldsymbol{b}$. The difference equation is determined by substituting each pixel in area U into equation (14):

$$\mathcal{H}(b) = \mathcal{H}(U)(\alpha + \beta). \tag{15}$$

The model's feature vector that has to be estimated is number β among them. The following may be produced by estimating and solving using the least square error criteria:

$$\beta = \Big(\sum \mathcal{H}(U)(\mathcal{H}(U))^N\Big)^{-1} \Big(\sum \mathcal{H}(U)(\mathcal{H}(b))\Big). \tag{16}$$

GMRF texture feature defining the picture block is the obtained model parameter β.

To the process of optimizing using statistical models of an objective function. It is composed of a group of data-efficient optimization techniques with the goal of locating the global optimum of costly to assess cost functions. In our situation, the robot experiences wear in the system from each cost evaluation that it performs with specific controller parameters, and it may take a long time. When evaluating novel parameters that show promise as candidates for the global optimum, the mean and variance of the GP models might be employed. For instance, employs higher confidence boundaries that permit verifiable convergence assurances.

We expand on the Entropy Search (ES) method in this study, which chooses parameters to minimize the uncertainty on the location of $\mathcal{J}(\theta)$ minimum in each phase. This uncertainty is measured using the entropy of the distribution across the minimal location.

$$q_{min}(\theta) = \mathbb{q}(\theta \varepsilon \underset{\theta \varepsilon \mathcal{C}}{argmin}\, \mathcal{J}(\theta) \tag{17}$$

Once q_{min} is approximated on a non-uniform grid, the method becomes tractable, with greater resolution in regions where the minimum is more likely to be found. Essentially, the main point is that we anticipate q_{min} having low entropy after convergence as it is peaked at the minima. The amount of information about the position of the global minimum that we acquire with each assessment of the cost function depends on the rate of change in the entropy of q_{min}. In light of this measure, the most

$$\mathcal{D}e = \frac{\sum_{b=1}^{t} \sum_{a=1}^{t} (b, a) q(b, a) - \sum_{b=1}^{t} \sum_{a=1}^{t} bq(b, a) \sum_{b=1}^{t} \sum_{a=1}^{t} aq(b, a)}{\sum_{b=1}^{t} \sum_{a=1}^{t} \Big(b - \sum_{b=1}^{t} \sum_{a=1}^{t} bq(b, a) bq(b, a)\Big)^2 q(b, a) \sum_{b=1}^{t} \sum_{a=1}^{t} \Big(a - \sum_{b=1}^{t} \sum_{a=1}^{t} bq(b, a) bq(b, a)\Big)^2 q(b, a)} \tag{13}$$

instructive parameter to use while evaluating the cost function in the following iteration is:

$$\theta_{t+1} = arg \max_{\theta \varepsilon \mathcal{C}} \mathcal{F}\Delta[\mathcal{G}(\theta)]. \tag{18}$$

The change in $\mathscr{g}_{min}$'s entropy produced by getting a new cost value at point θ is denoted by $\Delta\mathcal{G}(\theta)$. It makes sense to us to gradually reduce the entropy in $\mathscr{g}_{min}$ until it reaches a peak at the optima by gathering cost values at the most instructive sites (18). By minimizing the current GP posterior at iteration t, we calculate the best estimate $\theta_{a\mathscr{k}}$ about the ideal parameters:

$$\theta_{ah} = ar\,g\,\underset{\theta \varepsilon \mathcal{C}}{min}\,\mu_t(\theta). \tag{19}$$

There are several estimates needed to calculate $\Delta\mathcal{G}$ given the GP model of $\mathcal{J}(.)$. The scope of the paper does not allow for a thorough derivation, although all the information is available.

3.2.4 Classification

The benefits and drawbacks of each component model must be carefully considered before developing a hybrid model. Logistic regression is effective for evaluating linear relationships, but KNN may capture complicated non-linear patterns. By making use of both of these variables, the hybrid strategy aims to increase prediction accuracy. By applying LR to the combined characteristics of each subcluster, discrete models for students in different subgroups are produced. Assuming that students in the same subgroup exhibit comparable traits and behaviors, this makes it possible to identify linear correlations within each subcluster.

When using quantitative or qualitative independent variables to explain a binary response variable, statistical modeling is often used. It is a member of the generalized linear model's category. For instance, the usual form of the log odds for an LR typical with a single autonomous variable, $\mathcal{W}$, which can be either binary or continuous, is $k = \beta_0 + \beta_1 w$, where the coefficients β_0 *and* β_1 are the regression parameters and z is the observed value of $\mathcal{W}$. This is non-linear model so that the odds are the exponent $d = b^{\beta_0+\beta_1 w}$, representing a non-linear typical as the chances are a non-linear mixture of autonomous variables, with the exponential function being assumed to be the base a. Then, the associated probability function of $\mathcal{Y} = 1$ is

$$\begin{aligned} p = \mathcal{P}(\mathcal{Y} = 1) &= \frac{\exp(\beta_0 + \beta_1 w)}{(\exp(\beta_0 + \beta_1 z) + 1)} \\ &= \frac{1}{(1 + exp(-\beta_0 - \beta_1))}. \end{aligned} \tag{20}$$

However, in order to find complex non-linear patterns inside these finely detailed land subgroups, K-Nearest Neighbors is also applied to each subcluster separately. The last phase, known as hybridization, integrates the predictions of the LR and KNN models in each subcluster. This combination uses a weighted average or other relevant methods to leverage the models' linear and nonlinear characteristics.

K-NN approach plays a key role in machine learning. It is contingent upon the supervised learning approach. The K-NN method maintains all of the available data and classifies newly added data points based on their similarity to previously classified data. It implies that the K-NN approach may be used to swiftly classify fresh data into a well-defined category. Although it may also be used for regression, the KNN approach is most frequently applied to classification problems. The KNN algorithm groups newly gathered data into groups that closely resemble previously stored data from the training phase. K-NN is used to categorize the clustered data into categories A and B after clustering is employed to group comparable properties.

The hybrid KNN architecture enables high precision and accuracy in detecting students who are at-risk at every subcluster level. It provides in-depth understanding of the Lan environment and enhances the prediction accuracy in detecting at-risk landscape art. Moreover, it supports both linear and nonlinear patterns across various landscape art categories. KNN is a useful ML algorithm for categorizing student data according to an achievement. Benefits of both K-NN, a non-parametric approach that takes data point similarity into account, and logistic regression, a potent classification tool, are combined in this method. By employing this hybrid approach, educators may successfully place students into various performance groups. This makes it possible for them to offer focused interventions and support in order to foster a successful landscape art environment. Figure 2 clearly illustrates the overall pipeline of the model.

3.2.5 Proposed algorithm

Input: Image dataset $D = \{x_i\}_{i=1}^N$
Output: Predicted labels $\hat{y}_i$
for each image $x_i \in D$ do
Apply wavelet denoising Equation. (2)
Compute wavelet decomposition $\mathcal{C}_i$ and average coefficient AVG_i using Equation. (3)–(5)
Normalize using linear mapping $\phi_{\gamma,\varepsilon}$ and contrast function $\mathcal{D}_\phi(\,_{ji})$using Equation. (7)–(8)
Choose segmentation method based on FoV angle and segment regions accordingly
Extract GLCM co-occurrence features $(\mathcal{P},)$using Equation. (9)
Calculate energy $\mathcal{F}$, entropy $\mathcal{F}$, contrast $\mathcal{D}n$, correlation $\mathcal{D}e$ using Equation. (10)–(13)
Model spatial relations using GMRF using Equation. (14)–(15)
Estimate β using least squares using Eq. (16)
Optimize parameters through entropy-based search using Equation. (17)–(19)
Use hybrid classifiers of LR using Equation. (20) and combine the predictions with KNN based on distance
Predict class label $\hat{y}_i$ from feature vector
end for
Return, all predictions $\{\hat{y}_i\}_{i=1}^N$.

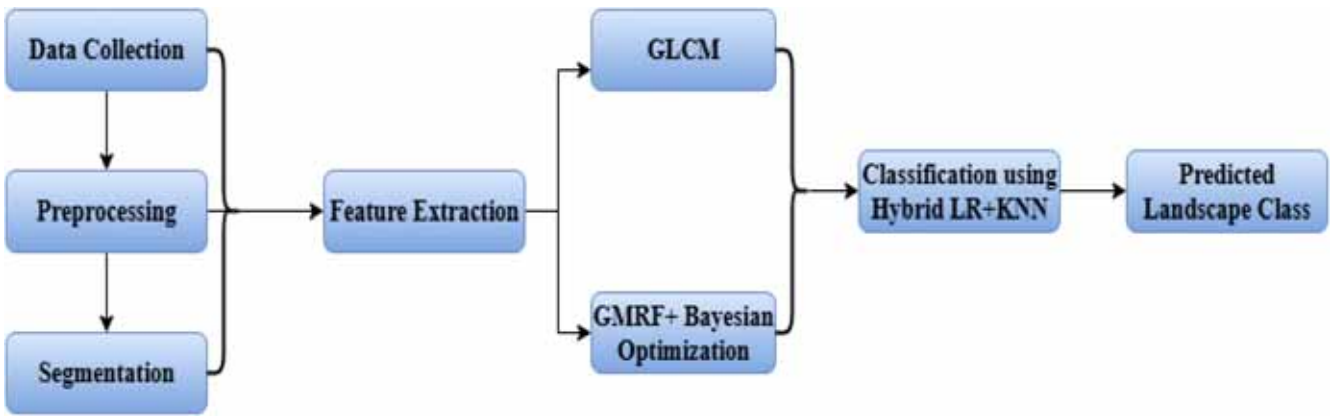

Fig 2. Schematic illustration of the proposed pipeline.

Table 2. System specifications.

Hardware configuration	Random Access Memory	8GB
	Hard Disk	1TB
	CPU Processor	Intel(R) Core (TM) i5-4590S CPU @ 3.00GHz
Software configuration	Operating System	Windows 10 Pro
	Simulation Tool	Python − IDLE 3.11(64-bit)

Table 3. Hyperparameters of the model.

Parameter	Range
Image Size	(64 × 64)
Number of Samples	3000
Class Labels	[0,1]
Wavelet Type	'db2'
Threshold Value	0.2
Distance	1 pixel
KNN	5
Distance Metric	Euclidean
LR Regularization Type	L2
LR Solver	Liblinear
Train-Test Split	70% Train, 15 Validation, 15% Test

4 Experimental results

The experimental analysis of the proposed research plan for performance evaluation is presented in this part. There are three subsections in this section: comparative analysis, simulation study, and study.

4.1 Simulation setup

The proposed simulation system of landscape art design based on computer learning and virtual reality technology is implemented and simulated using Python, we tend to tune the system configurations in terms of hardware and software configurations respectively. The hardware configurations involve 1TB hard disk capacity and 8GB RAM respectively. On the simulation case, the model is executed using Python − IDLE 3.11(64-bit) within a Windows 10 Pro operating system. Furthermore, the system specifications utilized are listed in Table 2. And the hyperparameter details are shown in Table 3.

4.2 Evaluation criteria

This section provides a concise summary of the comparative analysis conducted between the existing works and the proposed framework. We examine past studies, including the Hierarchical rate splitting-based macro base station supported cooperative content distribution system, the RCNN, and the LSTM. A comparison is conducted between the proposed work and assessment criteria, which include the comparison of users and accuracy, sensitivity, recall, precision. These metrics are specifically selected to assess the overall classification performance of the image samples. Accuracy reflects the accurate predictions, where sensitivity and recall help to assess the model identified images patterns. Precision indicates the model's ability to avoid misclassifying unrelated images.

4.2.1 Accuracy

To improve image quality, we proposed image quality enhancement which includes processes such as noise removal, normalization which increase segmentation accuracy.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{21}$$

Table 4. Numeric results of accuracy (%).

No of images	Accuracy (%)		
	RCNN	LSTM	Proposed
10	72	84	92
20	74	86	93
30	76	87	95
40	77	89	97
50	78	92	98

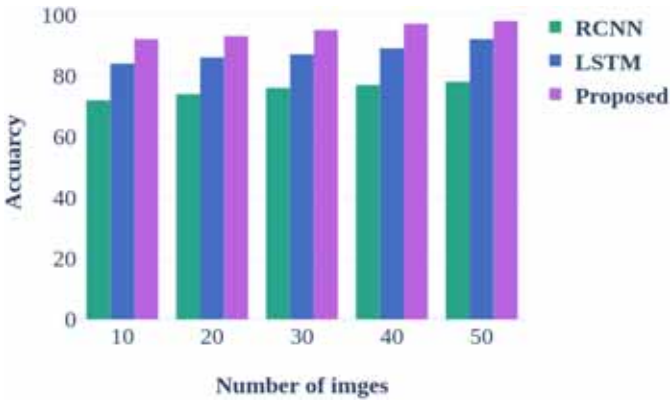

Fig 3. Number of images vs accuracy.

where TP (true positives) represents images correctly identified as landscape, $F\ N$ (false negatives) represents images incorrectly identified as such, and TN (true negatives) represents images correctly identified as such.

Table 4 provides the quantitative accuracy findings, and Figure 3 shows the categorization accuracy as the number of images grows. On the other hand, when compared to other existing techniques like RCNN and LSTM, the suggested method shows better detection accuracy. The suggested techniques may categorize items with a maximum detection accuracy of 98% after fifty images. When it comes to object detection, RCNN and LSTM reach a maximum accuracy of 92%, whereas LSTM only reaches a maximum accuracy of 78%. Our developed approach outperforms other currently used techniques in terms of accuracy.

4.2.2 Sensitivity

Sensitivity also known as True Positive Rate (T) measures the model's ability to detect positive instances, or more accurately, the landscape. The following is the matrices equation:

$$\mathcal{S} = \frac{\mathcal{T}}{\mathcal{T} + f} \tag{22}$$

where $\mathcal{T}$ (*True positives*) represents the number of images that were correctly identified as positive. f(*False Negatives*) denote the number of actual landscape that the model mistakenly dismissed as being free of the image.

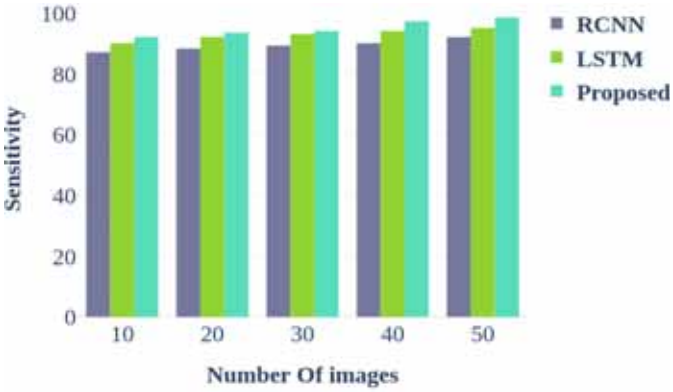

Fig 4. Number of images vs sensitivity.

Table 5. Numeric results of sensitivity (%).

No of images	Sensitivity (%)		
	RCNN	LSTM	Proposed
10	87	90	92
20	88.2	92	93.5
30	89.2	93	94
40	90	94	97.2
50	92	95	98.5

Figure 4 shows the recall, while Table 5 shows the sensitivity's numerical findings. Compared to other existing systems like RCNN and LSTM, the proposed method shows a strong sensitivity. The sensitivity also rises with the amount of images. In terms of the quantity of photos, the recommended procedures acquire the highest sensitivity of all the investigated approaches, which is 98.5%. More specifically, the greatest sensitivity achieved by the LSTM strategy is 95%, but the RCNN approach only manages a maximum sensitivity of 92%. Our proposed method performs more sensitively than existing methods.

4.2.3 Recall

A statistical metric called recall is used in binary and multiclass classification to assess how well a model can identify all pertinent occurrences of a given class. It goes by the names true positive rate and sensitivity as well. The ratio of true positive results to the total number of false negative results and genuine positive results is defined as follows. The equation for recall is given by:

$$\mathcal{R}_{\mathcal{C}} = \frac{\mathcal{T}}{\mathcal{T} + f}. \tag{23}$$

Let $\mathcal{T}$ be the number of true positives and f be the number of false negatives

The recall is shown in Figure 5, and the recall's numerical findings are shown in Table 6. In comparison to other existing systems like RCNN and LSTM, the proposed method shows a strong recall rate. Recall rises in

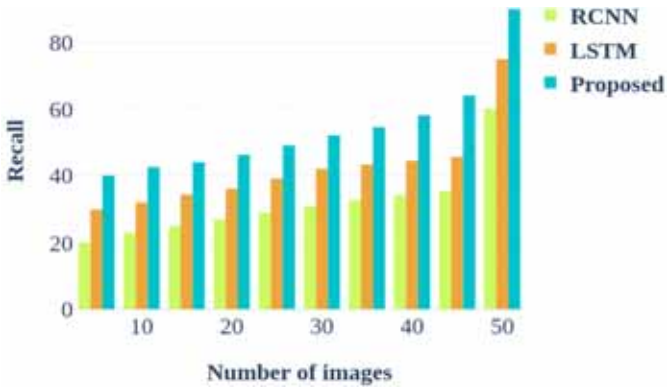

Fig 5. Number of images vs recall.

Table 6. Numeric results of recall.

No of images	Recall		
	RCNN	LSTM	Proposed
5	20	30	40
10	23	32	42.5
15	25	34.2	44
20	27	36	46.2
25	29	39	49
30	31	42	52
35	32.5	43.2	54.5
40	34	44.3	58
45	35.2	45.5	64
50	60	75	90

proportion to the amount of pictures. In terms of the quantity of pictures, the recommended strategies attain the highest recall of 90 out of all the examined methods. More specifically, the maximum recall for the RCNN strategy is 75, whereas the maximum recall for the LSTM approach is 60. We find that our proposed method performs better in recall than the existing ones.

4.2.4 Precision

The accuracy of a model is a statistical measure that evaluates its ability to accurately anticipate positive outcomes in both binary and multiclass classification tasks. The definition of it is the ratio of true positives ($\mathcal{P} = \frac{\mathcal{TP}}{\mathcal{TP}+\mathcal{FP}}$) to the sum of false positives ($\mathcal{FP}$) and true positives. The formula for precision is given by:

$$\mathcal{P} = \frac{\mathcal{TP}}{\mathcal{TP} + \mathcal{FP}} \tag{24}$$

When the cost of false positives is high and you need a high level of confidence in the accuracy of positive forecasts, precision becomes a crucial factor.

The results of the thorough graphical analysis are shown in Table 7 and Figure 6. In contrast to previous studies on RCNN and LSTM, the suggested method produced precision values of 96.2, 95.5, and 92 when the

Table 7. Numeric results of precision.

No of images	Precision (%)		
	RCNN	LSTM	Proposed
10	73	85	92
20	75	86	94
30	76.2	87.2	96
40	78	89	97.5
50	80	91	99.5

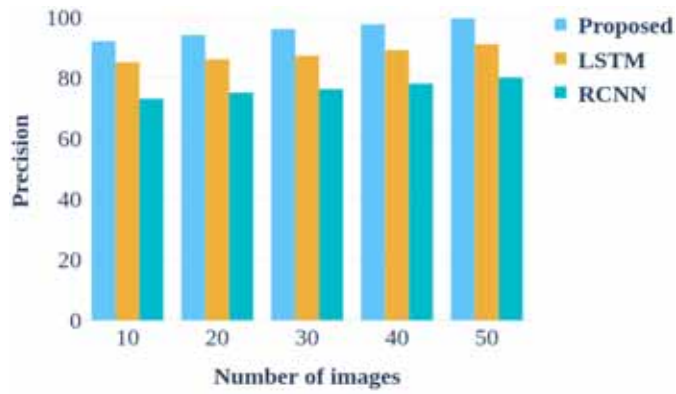

Fig. 6. Number of images vs. precision.

number of precision epochs was set at 10. When the maximum number of photos is set to fifty, the suggested approach produces 98 images, whereas previous research produces 99.5 and 50 images, respectively. In summary, it is anticipated that the current projects will provide average results of 80 and 91, respectively, and that the forthcoming project will yield estimated outcomes of 73 and 85. As a result, the average accuracy of the suggested approach is higher than that of the current methods.

Figure 7 illustrates the latency, throughput, and energy efficiency performance of the proposed model over increasing image batch sizes of 10 to 50. From the figure we observe that latency per image decreases consistently from 15.2ms at 10 images to 13.2ms at 50 images, which indicates a 13% reduction in processing time. Similarly, throughput improves steadily from 65.8 samples/sec at 10 images to 75.8 samples/sec at 50 images, which highlights 15.2% improvement. And finally, energy efficiency shows a 25W CPU power assumption. The energy needs for the sample drop from 0.38 J to 0.33 J; therefore, the energy improvement is up to 13.2%.

Figure 8 shows the error analysis of the model, was conducted across five experimental runs using the key metrics of accuracy, precision, sensitivity, and specificity. The results are consistently high, which indicates the model's reliability. Error bars clearly indicate the variability. Among all metrics, precision and sensitivity shows minimum variations, suggesting that the model consistently identified landscape features with low false positives and high true positives. Specificity had slight fluctuations, which indicate the difficulty in correctly rejecting

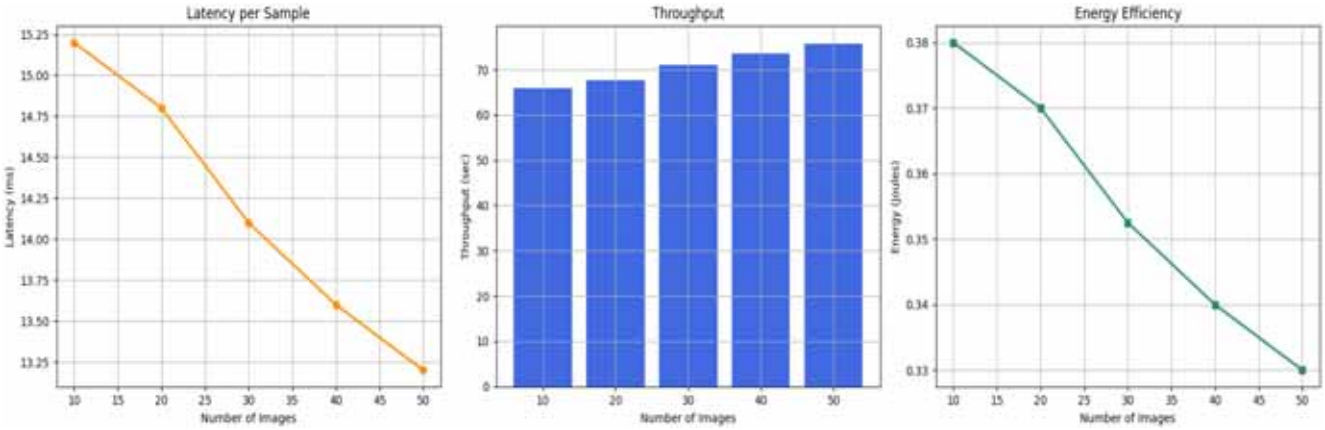

Fig. 7. Performance analysis of the proposed model in terms of latency, throughput and energy efficiency over increasing image batch sizes.

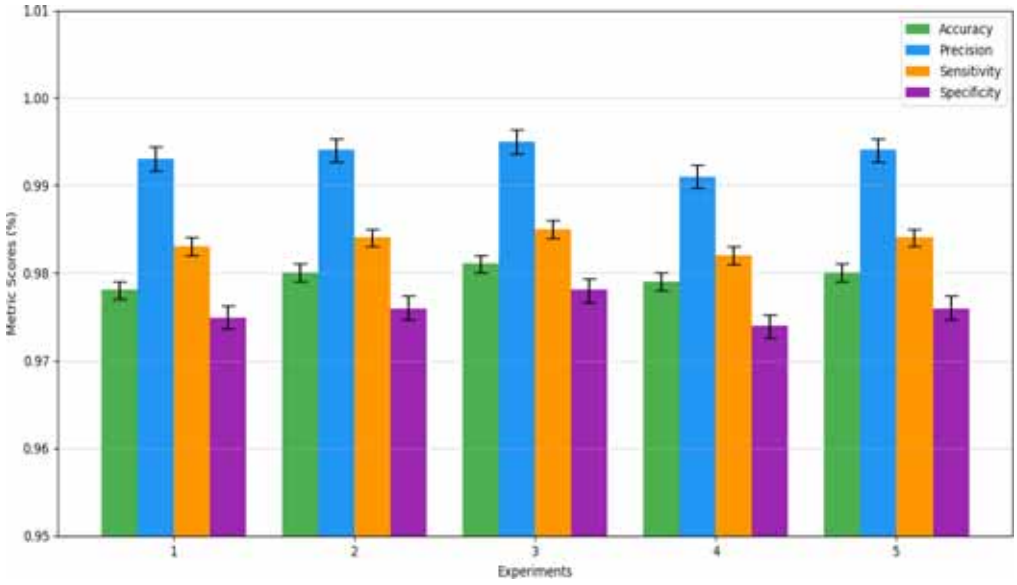

Fig. 8. Error analysis over 5 experimental runs.

Table 8. Comparison with benchmark models.

Study	Domain	Accuracy	Precision	Recall
Fan et al., [33]	VR experience prediction	75.32%	87.64%	57.47%
Cappellazzo et al., [34]	LiDAR landscape mapping	80.15%	89.99%	87.67%
Proposed	Landscape image classification	98%	99.50%	98.50%

non-target classes. This analysis highlights the model's stability and performance consistency in real-time immersive simulation tasks in complex landscape environments.

Finally, Table 8 shows the benchmark comparisons of the models.

5 Conclusions

This study proposed a hybrid simulation and classification framework that integrates VR with computer learning techniques to enhance the landscape design analysis. The model begins with the image preprocessing using wavelet-based denoising and normalization to enhance visual clarity. A multi-orientation segmentation approach is then applied to improve spatial boundary detection in 360° panoramic scenes. For feature extraction, the system combines GLCM to capture spatial texture patterns with GMRF to extract the statistical relations between neighboring pixels. Classification is performed through a hybrid strategy which combines LR and KNN to capture both linear and non-linear landscape patterns effectively. The simulation was conducted on a VR dataset consists of 3,000 annotated 360° images, the model achieved the

classification accuracy of 98%, precision of 99.5%, and sensitivity of 98.5% when compared with the traditional models like RCNN and LSTM. Apart from the advantages, the model has some critical limitations to be considered. The model mostly depends on high-resolution panoramic images and sensor input, which require significant computational resources. Then, manual annotation of complex landscape scenes is time-consuming. Therefore, the future work will focus on expanding the dataset to include real-time, sensor-integrated outdoor scenes and an automatic annotation process using semi-supervised learning techniques. Also plan to enhance system scalability through lightweight deployment on edge devices. Further exploration of deep learning and fusion with LiDAR and 3D mapping data is also considered to improve spatial awareness and depth insight in simulated environments.

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Conflicts of interest

The authors declare that they have no competing interests.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Author contribution statement

Ke Deng : Conceptualization, Methodology, Formal analysis, Validation, Resources, Supervision, Writing - original draft, Writing - review & editing.

References

1. T. Zhang, Research on environmental landscape design based on virtual reality technology and deep learning, Microprocess. Microsyst. **81**, 103796 (2021)
2. Y. Wang, X.B. Hu, Three-dimensional virtual VR technology in environmental art design, Int. J. Commun. Syst. **35**, e4736 (2022)
3. P. Shan, W. Sun, Auxiliary use and detail optimization of computer VR technology in landscape design, Arab. J. Geosci. **14**, 798 (2021)
4. Z. He, Study on the application of traditional chinese auspicious images in environmental art design based on VR Senses Comput. Intell. Neurosci. **2022** (2022)
5. W.L. Wu, Y. Hsu, Q.F. Yang, J.J. Chen, A spherical video-based immersive virtual reality learning system to support landscape architecture students' learning performance during the COVID-19 era, Land **10**, 561 (2021)
6. Y. Gong, Application of virtual reality teaching method and artificial intelligence technology in digital media art creation, Ecolog. Inform. **63**, 101304 (2021)
7. Z. Lin, L. Zhang, S. Tang, Y. Song, X. Ye, Evaluating cultural landscape remediation design based on VR technology, ISPRS Int. J. Geo-Information **10**, 423 (2021)
8. G. Luo, Y. Guo, L. Wang, N. Li, Y. Zou, Application of computer simulation and high-precision visual matching technology in green city garden landscape design, Environ. Technol. Innov. **24**, 101801 (2021)
9. S.D. Özgen, Y. Afacan, E. Sürer, Usability of virtual reality for basic design education: a comparative study with paper-based design, Int. J. Technol. Des. Educ. **31**, 357–377 (2021)
10. C. Carbonell-Carrera, J.L. Saorin, D. Melián Díaz, User VR experience and motivation study in an immersive 3D geovisualization environment using a game engine for landscape design teaching, Land **10**, 492 (2021)
11. G.W. Scurati, M. Bertoni, S. Graziosi, F. Ferrise, Exploring the use of virtual reality to support environmentally sustainable behavior: a framework to design experiences, Sustainability **13**, 943 (2021)
12. Y. Deng, L. Xie, C. Xing, L. Cai, Digital city landscape planning and design based on spatial information technology, Neural Comput. Appl. **34**, 9429–9440 (2022)
13. T. Chandler, A.E. Richards, B. Jenny, F. Dickson, J. Huang, A. Klippel, S.M. Prober, Immersive landscapes: modelling ecosystem reference conditions in virtual reality, Landscape Ecol. 1–17 (2022)
14. J. Pan, X. Deng, Multi-source information art painting fusion interactive 3d dynamic scene virtual reality technology application research, Int. J. Commun. Syst. **35**, e4705 (2022)
15. Q. Cao, Curriculum design of art higher vocational education based on artificial intelligence assisted virtual reality technology, Secur. Commun. Netw. **2022**, 1–9 (2022)
16. Y. Huang, B. Ye, T. Liu, Research on an aging-friendly design of urban park landscape based on computer virtual simulation technology, Wireless Commun. Mobile Comput. **2022** (2022)
17. Y. Kong, Research on the application of environmental art design based on the combination of VR and panoramic video technology, Sci. Program. **2021**, 1–11 (2021)
18. C. Carbonell-Carrera, J.L. Saorin, D. Melián Díaz, User VR experience and motivation study in an immersive 3D geovisualization environment using a game engine for landscape design teaching, Land **10**, 492 (2021)
19. Z. Niu, S. Xiang, M. Zhang, Retracted] Application of artificial intelligence combined with three-dimensional digital technology in the design of complex works of art, Wireless Commun. Mobile Comput. **2022**, 6444441 (2022)
20. J. Li, T. Hou, Application of virtual reality technology in analysis of the three-dimensional evaluation system of rural landscape planning, Math. Probl. Eng. **2021**, 1–16 (2021)
21. L. Li, Digital art design system based on big data technology and interactive virtual technology, IEEE Consumer Electr. Mag. **12**, 49–55 (2021)
22. B. Ma, Y. Dong, H. Liu, Z. Cao, Soft multimedia assisted new energy productive landscape design based on environmental analysis and edge-driven artificial intelligence, Soft Comput. **26**, 12957–12967 (2022)

23. C. Sun, L. Dong, Virtual reality technology in landscape design at the exit of rail transit using smart sensors, Wireless Commun. Mobile Comput. **2022** (2022)
24. W. Chuan, Research on interactive landscape design based on virtual reality technology, in 2022 *IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)* (pp. 253–257). IEEE.
25. E. Yoo, O. Kwon, J. Yu, Evaluation of an augmented reality for historical context experiences of 3D restored court paintings, *IEEE Access* (2023)
26. C. Sharma, K. Sharma, M. Kumar, P. Garg, N. Goyal, Open-source gesture-powered augmented reality-based remote assistance tool for industrial application: challenges and improvisation, in International Conference on Emergent Converging Technologies and Biomedical Systems. Springer Nature Singapore (2023), pp. 337–347
27. M. Uppal, D. Gupta, N. Goyal, A.L. Imoize, A. Kumar, S. Ojo, S.K. Pani, Y. Kim, J. Choi, A real-time data monitoring framework for predictive maintenance based on the internet of things, Complexity **2023**, 9991029 (2023)
28. Z. Lin, L. Zhang, S. Tang, Y. Song, X. Ye, Evaluating cultural landscape remediation design based on VR technology, ISPRS Int. J. Geo-Inform. **10**, 423 (2021)
29. J. Ha, K. Alrayyan, M.L. Alam, Virtual reality technology for learning detailed design in landscape architecture, Discover Educ. **3**, 39 (2024)
30. H. Tan, Design of 3D garden landscape design simulation system based on virtual reality and neural network model, in 2023 International Conference on Telecommunications, Electronics and Informatics (ICTEI). IEEE (2023), pp. 541–545
31. P. Shan, W. Sun, Research on landscape design system based on 3D virtual reality and image processing technology, Ecolog. Inform. **63**, 101287 (2021)
32. P. Vijayakumar, E. Dilliraj, A comparative review on image analysis with machine learning for extended reality (XR) applications, in International Conference on Ubiquitous Computing and Intelligent Information Systems. Singapore: Springer Nature Singapore (2021), pp. 307–328
33. M. Cappellazzo, G. Patrucco, G. Sammartano, M. Baldo, A. Spanò, Semantic mapping of landscape morphologies: tuning ML/DL classification approaches for airborne LiDAR data, Remote Sensing **16**, 3572 (2024)
34. W. Fan, Z. Ding, R. Huang, C. Zhou, X. Zhang, Improved AdaBoost for virtual reality experience prediction based on long short-term memory network (2024). arXiv:2405.10515

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