J. Electrical Systems 20-7s (2024): 3332-3346

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Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design

Journal of Electrical Systems

Abstract: - Environmental landscaping involves designing, planning, and managing landscapes that benefit both humans and the environment. Landscape design incorporates both landscaping and environmental considerations to address complicated issues holistically. Humans have a significant impact on the ecology by seeding native species and removing alien species.In this study, Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design(ISHGA-ELD-HOTNN) are proposed. Initially, the data gathered from Deep Globe Land cover classification dataset. To execute this input data is pre-processed using Multimodal Hierarchical Graph Collaborative Filtering (MHGCF). It is used to clean and normalize the data. Then, the pre-processed data are fed to Feature extraction segment using Newton Time Extracting Wavelet Transform (NTEWT), visual feature such as colour, texture and shape are extracted. In general, Higher-Order Topological Neural Networks (HOTNN) generates the landscape design. Hence, proposed utilize Harbor Seal Whiskers Optimization Algorithm (HSWOA) enhance Higher-Order Topological Neural Networks accurately generate the landscape design. Then, the Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design ISHGA-ELD-HOTNN is implemented to Python and the performance metrics such as, Accuracy, precision, Recall, F1-score, mean square error and error rate. Finally, the performance of ISHGA-ELD-HOTNN method provides 19.67%, 22.57% and 33.15% high accuracy, 23.17%, 26.62% and 28.68% higher Precision and 23.37%, 27.57% and 27.23% low error while compared with existing Mapping human perception of urban landscape from street-view images: A deep-learning approach (MHP-ULSVI-CNN) , Rural landscape design strategy based on deep learning model (RLDS-ELM) and Environmental landscape design and planning system based on computer vision and deep learning (ELD-PS-CV-DNN), respectively.

Keywords: Deep Globe Land Covers Classification Dataset, Harbor Seal Whiskers Optimization Algorithm, Higher-Order Topological Neural Networks, Multimodal Hierarchical Graph Collaborative Filtering, Newton Time Extracting Wavelet Transform.

I. INTRODUCTION

The countryside's natural beauty, wholesome agricultural goods, and age-old folk customs have made it a well-liked tourist destination. Tourism, when combined with agricultural resources, can better utilize rural resources, revitalize rural areas and promote resource integration, [1-3]. Rural construction has become less regional in recent years due to accelerated urbanization. As a result, we now have a thousand-villa landscape, a lopsided replica of urban growth, and the rural economy growing at the expense of the natural environment. People's quality of life and productivity have suffered as a result of the degradation of the rural environment [4-6]. The quest for economic growth and urbanisation has led to the disappearance of the lovely natural environment, the devastation of agricultural producing landscapes, and the loss of traditional rural cultural traits. Because they are not protected, traditional residential buildings with historical and cultural significance run the risk of vanishing and being replaced by Western-style homes and reinforced concrete structures. [7-9]. Tao Yuanming's perfect supply of peach blossoms is fading into the distance. Rural landscape resources require particular prerequisites and problems, necessitating a distinct set of theoretical and practical techniques that differ from urban planning [10]. Leveraging the natural, cultural, and regional benefits of the countryside, the central government seeks to encourage the sustainable growth of rural tourism by merging tourism, the environment, and other businesses. The German government implements programs to preserve traditional rural landscapes and promote harmony and coherence in rural landscape planning [11-13]. The strategy and planning for rural transformation development in Germany are the most valuable lessons to be learned. Planning and designing rural landscapes with an emphasis on "ecology, humanity, and beauty" combines scientific and artistic components to improve cultural, ecological, recreational, and economic aspects while encouraging sustainable development. [14]. The countryside landscape has become a major factor in protecting the environment and developing the economy throughout development and building, with emphasis on preserving its unique traits. The literature suggests that integrating agro-tourism can help alter the rural economic model in Tanzania [15-17]. Drainage ditches are a

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widespread forestry practice in northern European boreal forests and some regions of North America. Ditching aids in lowering groundwater levels in moist areas of the forest, which improves soil aeration and promotes tree growth [18]. In Finland, the Baltic States, and portions of Sweden, drained forest stands account for a significant portion of the overall forest area [19].

However, over time, the extensive use of ditches has altered the soil and wetland hydrology and harmed the total biological services provided by these areas. Intensive ditching has environmental problems, including wetland and soil degradation, greenhouse gas emissions, increased fertilizer and sediment loadings, and biodiversity loss. Research and action plans were developed to reduce environmental damage and rehabilitate damaged land in the ditched forest landscape [20]. However, precise and site-specific information about ditch networks is a major constraint for such programs. Artificial water bodies, including drainage ditches, are underrepresented in scientific inquiry and policy, despite their potential relevance.

While the use of deep learning models such as extreme learning machine, DBN-RBM, and DBN-DELM algorithms provides promising insights for rural landscape design, their effectiveness may be limited by data availability and quality, as well as the complexity of rural environments, which may not fully capture the nuanced preferences and needs of tourists and locals. The usage of drainage ditches in European boreal forests and North America has altered wetland and soil hydrology, impacting ecosystem function. With a growing understanding of the environmental concerns connected with forest ditches, mapping them has become a priority for sustainable forest and land use management. We describe the first rigorous deep learning-based system for mapping forest ditches on a regional scale.

This research provides novel rural landscape design strategies that use deep learning models such as the extreme learning machine algorithm and the HSWOA algorithm to answer the demand for scientific allocation of rural resources while preserving local character. It attempts to promote sustainable rural development by taking into account tourist preferences, balancing production, living, and ecological concerns while improving tourism experiences that are in tune with the natural surroundings and cultural heritage. This work provides a comprehensive approach to rural landscape design by integrating Higher-Order Topological Neural Networks models such as extreme learning machines and HSWOA algorithms, allowing for smart resource allocation while preserving native countryside charm. The research gives useful insights for rural planning and development by conducting a complete examination of visitor motives, supporting the sustainable integration of rural and tourism features in order to balance ecological concerns with societal needs.

Major contribution of this paper a follows;

- In this manuscript, Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design(ISHGA-ELD-HOTNN) is discussed.
- Initially, Deep Globe Land cover classification dataset, tocollection of high-resolution satellite imagery annotated with specific land cover classes.
- During the pre-processing stage, Multimodal Hierarchical Graph Collaborative Filtering would be used to data cleaning and normalization.
- The Higher-Order Topological Neural Networks (HOTNN) is used to generate the landscape design.
- The algorithm for Harbor Seal Whiskers Optimization Algorithm, which improves the performance of the HOTNN efficacy, was significantly enhanced generates the landscape design.

Remaining portion of this work structured follows: segment 2: literature survey, segment 3: describes proposed methodology, segment 4: illustrates results and discussion and segment 5: conclusion.

II. LITERATURE SURVEY

Among the frequent research work depends on generate the landscape design with the help of deep learning; some of the recent investigations were presented here

Chen,et.al, [21] have introduced a ELD-PS-CV-DNN. Environmental landscaping involves creating and managing landscapes that benefit both humans and the nature. Landscape design planning integrates landscaping and environmental considerations to address complicated concerns. Humans have a significant impact on the region's ecosystem by seeding native species and eliminating alien species. Landscape architecture involves designing and modifying landscapes, gardens or urban areas. It involves constructing urban and rural landscapes, managing open spaces and economy, creating employment, and adhering to project budgets. There was a lot of debate about global warming and water problems. It provides high accuracy and it provides low recall.

Liu,et.al, [22] have presented a RLDS-ELM. This paper explores deep learning-based strategies for designing rural landscapes to allocate resources, plan tourism space, and preserve local characteristics. The upgraded DBN-DELM algorithm, the DBN-RBM algorithm model, and the extreme learning machine algorithm are utilised to provide research data and parameter calibration findings for tourist planning and development. The planning concept and direction are determined by pre-analysis of rural landscape design. It provides high recall and it provides low accuracy.

Wei, et.al, [23] have presented MHP-ULSVI-CNN: A deep-learning approach.The widespread use of drainage ditches in European boreal forests and North America has altered wetland and soil hydrology, affecting ecosystem function. Mapping forest ditches has become critical for sustainable land use and forest management as awareness of the environmental issues associated with them has grown. They explain how forest ditches are mapped regionally using the first accurate deep learning-based technique. It provides high recall and it provides low precision.

Hu,et.al, [24] have presented Application of Digital Ceramic Art Elements in the Landscape Design of Rural Ecological Environment Based on Virtual Reality. Ceramic art has a long history in China and was considered one of the country's business cards. Excavated pottery dates back over 8,000 years to the Yangshao culture. And porcelain was discovered in Xia County, Shanxi, around four thousand two hundred years ago, making it the earliest primitive celadon uncovered in China. It is certain that pottery and porcelain in China have at least a thousand years of history, and through the continual evolution of history, ceramic items have now become an essential symbol of each cultural period.It provides high precision and it provides low accuracy.

Tongyun, et.al, [25] have presented The Role of Landscape Design in Enhancing Environmental Sustainability and Human Well-being.This study uses qualitative research to explore how landscape design might promote sustainability and improve human well-being. The researchers interviewed six pupils and three teachers individually. The study uses purposive sampling to identify existing difficulties and propose solutions related to landscape design. To guarantee a comprehensive research, the inquiry consists of nine sub-questions and three objectives. The study uses software and coding methodologies to find key themes. The research aims to identify challenges, offer solutions, and promote sustainable and harmonious ecosystems from the perspectives of both students and instructors. It provides high Matthews correlation coefficient and it provides low accuracy.

Melicher, et.al, [26] have presented Application of landscape-ecological approach for greenways planning in rural agricultural landscape. This paper offers a fresh method for incorporating greenways into environmentally friendly landscape designs. A landscape ecological concept can be used to plan greenways. This involves examining the existing landscape structure and state of linear components of green infrastructure, as well as analysing and synthesising specific abiotic, biotic, and socioeconomic landscape-ecological factors and recreation conditions. Designing the best greenways and other green infrastructure elements involves evaluating the ecological stability, aesthetic impact of agricultural fields, erosion hazards, and natural, cultural, and historical aspects of the area. It provides high recall and it provides low Matthews correlation coefficient

Li, et.al, [27] have presented Research on Urban Garden Landscape Planning and Construction Based on Ecological Concepts. Planning and constructing ecological landscape gardens is a crucial aspect of urban ecology and can significantly enhance the quality of life. This study evaluates the biodiversity of urban gardens using species diversity metrics such species richness, Simpson, Shan-Wiener, and Pielou evenness. A landscape dynamic change model was constructed utilising the patch transfer matrix, comprehensive dynamic attitude, and single dynamic attitude of the landscape to examine the pattern of plant cover in urban gardens and landscapes. The study's six urban regions were located in H City. object. It provides high Matthews correlation coefficient and it provides low error rate.

III. PROPOSED METHODOLOGY

In this section, Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design (ISHGA-ELD-HOTNN)is deliberated. Block diagram of proposed ISHGA-ELD-HOTNN presented in Figure 1. The proposed methodology Environmental gardening involves designing, developing, and managing landscapes that benefit both humans and the nature. Conservation is the first priority in ecological landscape design. More than just a creative way to enhance a landscape's aesthetic appeal, landscape gardening has practical and significant purposes. The Research Application of Integrating Small Habitat Genetic Algorithm in

Ecological Landscape Design (ISHGA-ELD-HOTNN), which uses Multimodal Hierarchical Graph Collaborative Filtering for data preprocessing and HOTNN for generate the landscape design. HOTNN's accuracy is improved by using the Harbor Seal Whiskers Optimization Algorithm (HSWOA). The entire process is written in Python, and performance is measured using metrics like precision, recall, accuracy Matthews's correlation coefficient and error rate.

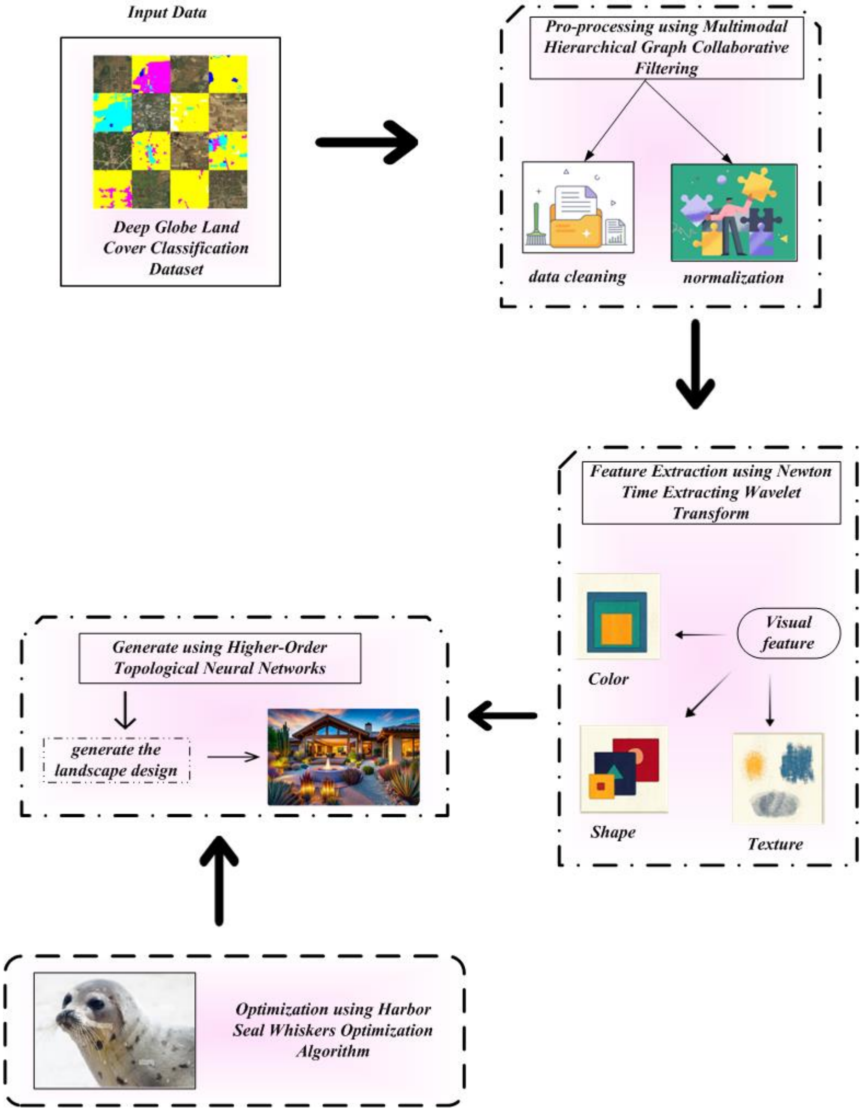

Figure 1: Block Diagram of the proposed ISHGA-ELD-HOTNN

A. Data Collection

Initially, the input image are collected from Deep Globe Land cover classification dataset [28]. The Deep Globe Land Cover Classification dataset is a comprehensive collection of high-resolution satellite imagery annotated with specific land cover classes, intended for training and assessing machine learning models in remote sensing and geographic information systems. This dataset covers a wide range of geographical regions and includes annotations for land cover categories such as forests, urban areas, and bodies of water, agricultural land, and barren terrain. It is a great resource for building algorithms that accurately classify land cover types, allowing for applications ranging from environmental monitoring to urban planning and catastrophe management.

B. Pre-processing Using Multimodal Hierarchical Graph Collaborative Filtering

In this section, Multimodal Hierarchical Graph Collaborative Filtering (MHGCF) [29] technique is utilized which used to resizing and normalizing of the collected input images. Multimodal Hierarchical Graph Collaborative Filtering (MHGCF) is a revolutionary improvement in recommendation systems that incorporate various modalities of user-item interactions into a hierarchical graph structure. MHGCF outperforms typical collaborative filtering algorithms in accuracy and robustness by harnessing the deep interaction of many types of data such as user preferences, item properties, and relational connections. Because of its hierarchical structure, the model can record complex relationships at various abstraction levels, allowing it to provide individualized recommendations even in sparse or cold-start conditions. Furthermore, MHGCF's capacity to handle a wide range of data formats improves interpretability and adaptability, making it a versatile solution for a variety of recommendation jobs in areas such as e-commerce, social networks, and content platformsand it given as equation (1).

$$F_u = \{ f^{(0)}{}_{v,v_1}, \ldots f^{(0)}{}_{v,v_1|u|}, f^{(0)}{}_{v,i_1}, \ldots, f^{(0)}{}_{v,i|x|} \} \tag{1}$$

Where, F_u denotes filter initialization; $f^{(0)}{}_{v,v_1}$ denotes image embedding for visual; $f^{(0)}{}_{v,i|x|}$ denotes final embedding images; i denotes filtering image. MHGCF creates a hierarchical graph representation of images by combining various data modalities, such as linked structures, visual characteristics, and textual descriptions. MHGCF uses collaborative filtering techniques to learn from image interactions and preferences. This enables it to suggest normalization and resizing options based on the specific needs of each image; and it given as equation (2).

$$h_{v1}^{(l)} = \sum_{j \in M_{v1} \cup vi} \frac{|M_j|^q}{|M_{v1}|^{0.5} |M_j|^{0.5}} \cdot h_j^{(l-1)} \tag{2}$$

Where, $h_{v1}^{(l)}$ denotes l graph convolution's embedding resizing image; v_1 denotes target image; j denotes images; M denotes the size of the image ; $h_j^{(l-1)}$ denotes embedding images at $(l-1)$ stage; i denotes filtering image; q denotes coefficient of image. MHGCF guarantees more accurate and individualized suggestions by utilizing the rich semantic and visual information stored within the graph. This improves image satisfaction and overall system performance in image processing jobs; and it given as equation (3).

$$h_{j1}^{(l)} = \sum_{j \in M_{j1} \cup ji} \frac{|M_j|^q}{|M_{j1}|^{0.5} |M_v|^{0.5}} \cdot h_v^{(l-1)} \tag{3}$$

Where, $h_{j1}^{(l)}$ denotes l graph convolution's embedding normalizing image; v denotes target image; j denotes images; M denotes the size of the image; $h_v^{(l-1)}$ denotes target embedding images at $(l-1)$ stage; i denotes filtering image; q denotes coefficient of image. Multiple data modalities, including picture features, textual descriptions, and image interactions, are integrated by MHGCF. In order to obtain both visual and semantic information about the image, resizing and normalizing them may need combining textual metadata such as image captions and tags with image content features such as colour histograms and deep neural network embedding; and it given as equation(4)

$$p_{v1}^{(l)} = \sum_{j \in M_{v1} \cup vi} \frac{|M_j|^q}{|M_{v1}|^{0.5} |M_j|^{0.5}} \cdot p_j^{(l-1)} \tag{4}$$

Where, $p_{v1}^{(l)}$ denotes initialized of the normalizing image; v denotes target image; j denotes images; M denotes the size of the image; $p_j^{(l-1)}$ denotes initialized of the resizing image; i denotes filtering image; q denotes coefficient of image. MHGCF bases its suggestions on image interactions and preferences with the image using collaborative filtering processes. This can entail using image input, such clicks or ratings, to customize the resizing and normalizing suggestions for certain images; and it given as equation (5).

$$p_{i1}^{(l)} = \sum_{v \in M_{v1} \cup vi} \frac{|M_v|^q p_v^{(l-1)}}{|M_v|^{0.5} |M_{j1}|^{0.5}} \cdot + \sum_{c \in M_{j1} C} \frac{|M_c|^q p_c^{(l-1)}}{|M_c|^{0.5} |M_{j1}|^{0.5}} \tag{5}$$

Where, $p_{i1}^{(l)}$ denotes final output images; v denotes target image; j denotes images; M denotes the size of the image; i denotes filtering image; q denotes coefficient of image; c denotes neighbouring images. Finally, the Multimodal Hierarchical Graph Collaborative Filtering improves the successive stages of recruitment. Then, the pre-processed output is fed to Feature Extraction.

C. Feature Extraction using Newton Time Extracting Wavelet Transform

In this section, NTEWT [29] is discussed to extract the visual features are extract from input data such as colour, texture and shape. The advantage of the NTEWT is its ability to accurately capture and analyse non-stationary data's with high time-varying resolution. NTEWT is an innovative data processing method created to reliably assess non-stationary data. It does this by combining the Newton interpolation method with the concept of wavelet analysis. This technique makes it possible to accurately represent and analyse data that exhibit dynamic behaviour over time, which makes it extremely useful in a variety of fields. A spectral-varying linear chirp data's Group Delay (GD) is the amount of time that each of the information's various wavelengths experiences as a delay. GD indicates the relative delays between the various incidences as the amplitude of the chirp data varies linearly with time. In order to understand the chirp data's behaviour over the band spectrum, it is essential to analyse its time-varying attribute. The group delay of the spectral-varying linear chirp data is defined as equation (6),

$$F(\omega) = Ez^{-i\phi(\omega)} \tag{6}$$

Where, $F(\omega)$ denotes the group delay of the spectral-varying linear chirp data; E denotes the amplitude of the data and $z^{-i\phi(\omega)}$ denotes the complex exponential term representing the phase shift of the data at duration. In wavelet analysis, the "instantaneous" time associated with a specific scale and data translation can be used for time-duration analysis of non-stationary transmissions. With a harmonic oscillation in the frequency domain and a Gaussian envelope in the time domain, this wavelet function is complex-valued and oscillatory. It is defined as the following equation (7),

$$\bar{l}_Y(c,\alpha) = c - \frac{c - \bar{t}_Y(c,\alpha)}{1 - \partial_c \bar{t}_Y(c,\alpha)} \tag{7}$$

Where, $\bar{l}_Y(c,\alpha)$ denotes the accurate GD estimation of the data $F(\omega)$; c denotes the position in time varying space and ∂_c denotes the partial derivative with respect to c. The group delay's variation across different bandwidths or scales is referred to as the data's GD trajectory. It explains how different components of bandwidth from the data change in phase across time or scale. Analysis of the data's behaviour and attributes over a range of wavelengths or time scales is made easier by this trajectory, which offers insightful information about the data's time-varying characteristics. GD trajectory of data is defined as equation (8),

$$c = \alpha \frac{\omega_\varphi}{\alpha} + \beta \tag{8}$$

Where, c denotes the position in time varying space; $\alpha \, and \, \beta$ denotes the scaling parameters governing the trajectory of the group delay and ω_φ denotes the central wavelength of the wavelet. NTEWT is a second-order case extension of the Time Extracting Wavelet Transform that makes use of the Newton GD estimator. Utilizing the wavelet analysis and group delay estimation to improve the analysis's accuracy, this method makes it possible to extract time-varying characteristics from data. The NTEWT is defined as equation (9),

$$NTz\,(c,\alpha) = W_Y^{\hat{\psi}}(c,\alpha) \cdot \delta(c - \bar{l}_Y(c,\alpha)) \tag{9}$$

Where, $NTz(c,\alpha)$ denotes the Newton time extracting wavelet transform; $W_Y^{\hat{\psi}}(c,\alpha)$ denotes the wavelet transform of data Y using the Morlet wavelet and $\delta(c - \bar{l}_Y(c,\alpha)$ denotes the delta function cantered at the "instantaneous" time $\bar{l}_Y(c,\alpha)$. Data reconstruction is the process of regaining or creating a data from its representation that has been altered or examined. In the context of processing data, reconstruction can involve reversing the data change in an effort to precisely restore the original data. The data reconstruction of NTEWT is defined as equation (10),

$$F\left(\frac{\omega_{\psi}}{\alpha}\right)=\frac{\alpha NTz\left(\phi'\left(\frac{\omega_{\psi}}{\alpha}\right),\alpha\right)z^{-i\frac{\omega\psi}{\alpha}c}}{N_{y}\left(\phi'\left(\frac{\omega_{\psi}}{\alpha}\right),\alpha\right)} \tag{10}$$

Where, $F\left(\frac{\omega_{\psi}}{\alpha}\right)$ denotes the data F reconstructed from the Newton Time Extracting Wavelet Transform; $\alpha NTz(\phi')$ denotes the NTEWT coefficient at the adjusted duration $\left(\frac{\omega_{\psi}}{\alpha}\right),\alpha$; $z^{-i\frac{\omega\psi}{\alpha}b}$ denotes the complex exponential term representing the phase shift of the data at duration and $N_{y}(\phi')$ denotes complex conjugate of the NTEWT coefficient corresponding to the adjusted timing and scale. Finally, visual features are extracting from input data such as colour, texture and shape are extracted with NTEWT. Then these extracted features are fed to HOTNN for generate the landscape design.

D. Generate the Landscape Design Using Higher-Order Topological Neural Networks

In this section, Higher-order topological neural network (HOTNN) [30] is discussed. For generate the landscape design. Higher-order topological neural networks provide a significant advantage in pattern recognition and sophisticated data processing. These networks excel in capturing complicated relationships and contextual dependencies within data by leveraging higher-order topological features, allowing them to identify subtle patterns that traditional neural networks. This innovative architecture not only improves classification accuracy but also increases resistance to noise and unpredictability, making it especially competent at dealing with complicated real-world datasets. Furthermore, higher-order topological neural networks have stronger generalization capabilities, allowing them to extrapolate insights from limited data, pushing the boundaries of machine learning applications in domains as diverse as healthcare, finance, and autonomous systems. Thus, it is given equation (11)

$$Y_{G}=\oplus\left(Y_{G}^{2},...,Y_{G}^{\mho}\right) \tag{11}$$

Where, Y_{G} is represent the topological and electrical characteristics of the distribution grid, $\oplus$ denotes as concatenate operation. In our investigation, they employ a CNN to learn the geometrical characteristics of persistence the images. Given an on-going depiction of given equation (12)

$$Y_{S_{j}}=e_{GMP}\left(e_{\theta_{j}}\left(OH_{j}\right)\right) \tag{12}$$

Where, $Y_{S_{j}}$ is represent the reference current and voltage ; e_{GMP} is represent the global max pooling, $e_{\theta_{j}}$ is represent the CNN-based neural network using the parameter set θ_{j}. Equivalent orderings involve those that differ by an even number of combinations. Thus it is given equation (13)

$$K_{j}=A_{j}^{\mathrm{P}}A_{j}+A_{j+2}A_{j+2}^{\mathrm{P}} \tag{13}$$

Where, K_{j} is represent the technical voltage; $A_{j}^{\mathrm{P}}A_{j}$ is represent a special case of the above technical voltage. The normalized Hodge-1-Laplacian, sometimes referred to as the higher-order simplices convolution module, has a propagation rule that is established by equation (14).

$$A_{F}^{(k+2)}=\max\left(\Psi\left(\widetilde{P}_{2}A_{F}^{(k)}\Theta_{F}^{(k)}\right)\right) \tag{14}$$

In this case, $A_{F}^{(k)}$ indicates the input activation matrix of the k-th hidden layer, max for the element-wise $\max(\cdot)$ operator, and $\Psi(\cdot)$ for a forward current. In practice, the attention coefficient is determined using the following equation to adaptively detect the inherent relationships across many greater-order simplices and topological representations (15).

$$\alpha_{j}=soft\max{}_{j}\left(\tanh\left(\Xi A_{j}\right)\right) \tag{15}$$

Where, Ξ is denotes the trainable weight matrix; $soft\max_{j}$ is represent the used to normalize the attention vector; A_{j} is represent the combining all embeddings. Finally, HOTNN generate the landscape design. Here, HSWOA is employed to optimize the HOTNN. Here, HSWOA is employed for tuning the weight and bias parameter of HOTNN.

E. Optimization Using Harbor Seal Whiskers Optimization Algorithm

The proposed HSWOA [31] is utilized to enhance weights parameters Y_G *and* K_j of proposed HOTNN. The parameter Y_G *and* K_j is implemented for increasing the accuracy and recall. Through the use of robust sensing and data processing concepts inspired by nature, the Harbor Seal Whiskers Optimization Algorithm provides advantage of improved efficiency and accuracy in the detection of outdoor trash, hence permitting efficient waste management solutions. HSWOA is a bio-inspired optimization algorithm that tracks its prey by utilizing the high-sensing capacity of seal whiskers. Unlike humans, most mammals have whiskers. Because there are a lot of nerve endings at the base of each dense, wiry hair, they are very sensitive to any movement. Not only can a marine mammal like a seal use its whiskers to feel and inspect objects, but it can also detect vibrations in the water. The whiskers on mammals are usually circular and uniformly formed. Nonetheless, the whiskers of practically every seal species are wavy and unevenly formed. The uneven form of the seal's whisker helps to keep it steady when it swims. The whisker vibrates only in reaction to hydrodynamic trails. Here, step by step procedure for obtaining appropriate HOTNN values using HSWOA is described here. To creates a uniformly distributed population for optimizing the ideal HOTNN parameters. The entire step method is then presented in below,

Step1: Initialization

Initial population of HSWOA is, initially generated by randomness. Then the initialization is derived in equation (16).

$$i = \begin{bmatrix} i_{1,1} & i_{1,2} & \cdots & i_{1,N} \\ i_{2,1} & i_{2,2} & \cdots & i_{1,N} \\ \cdots & \cdots & \cdots & \cdots \\ i_{M,1} & i_{M,2} & \cdots & i_{M,P} \end{bmatrix} \tag{16}$$

Where, i denotes the total population of seals whiskers in the tracks; M denotes the n^{thh} number of HSWOA while attacking towards its prey and P represents the distance between the prey and HSWOA.

Step2: Random Generation

Randomly generated input parameters. Optimal fitness values were selected based on obvious hyperparameter conditions.

Step 3: Fitness Function

The system's fitness is determined by the objective function. To determine the fitness function,

$$Fitness\,Function = optimizing\ [Y_G\ and\ K_j] \tag{17}$$

Where, Y_G is used for increasing the Precision and K_j is used for increasing the recall.

Step 4: Current Sensing Function Y_G

Harbor seals utilize their whiskers to identify and attack their prey at a precise velocity. The seal raises its whiskers and keeps them away from its face when it follows sensations below the surface. When a prey moves, the water stirs. A seal can track the movement of its meal by using its whiskers to detect the hydrodynamic trails the prey leaves behind. The seal may utilise equation (18) to ascertain the prey's direction, vicinity, and even size.

$$u_i = \frac{n}{2\pi} \frac{\left(2b_i^2 - H^2 + Y_G\right)}{\left(b_i^2 + H^2\right)^{5/2}} \tag{18}$$

Where, b_i^2 denotes the position of HSWOA in seal; Y_G is represent the topological and electrical characteristics of the distribution grid; H indicates the seal whisker's high sensing capacity; π denotes the parameter of seal and n denotes the inspect objects of its prey and Figure 2 shows the corresponding flowchart.

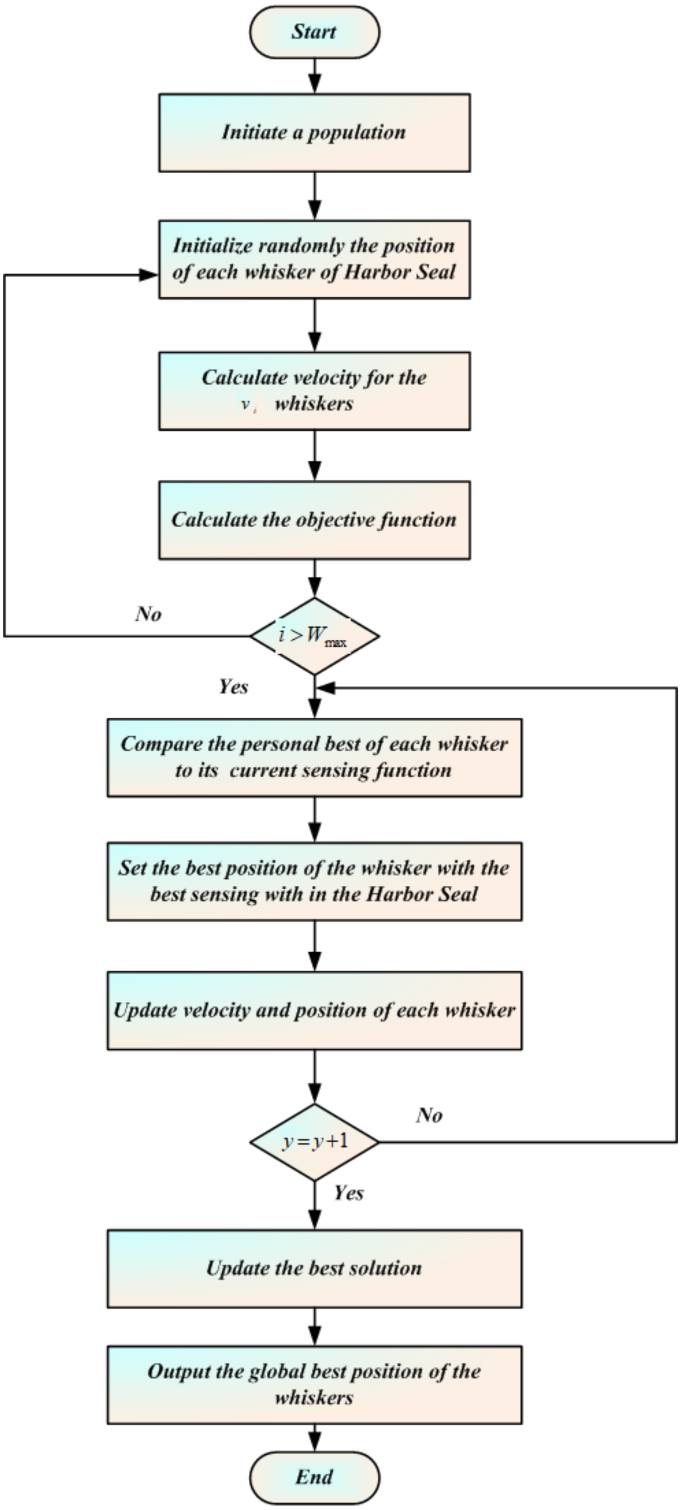

Figure2: Flow Chart of HSWOAfor Optimizing HOTNN

Step5: Update Velocity and Position of Each Whisker K_j

A biologically inspired of whisker structure diagram in the exploitation phase. A nerve in a harbor seal's cheek is stimulated when its whiskers move simultaneously, sending information to the seal's brain. Because of this, the seal is able to recognise and comprehend complicated situations, such the tracks left by obstacles and targets. The ability to differentiate between the attack angle and the water flow is attributed to the elliptical cross section of the whiskers of harbour seals. Equation (19) is used by the seals to exploit potentially advantageous postures of their prey once they receive an update to their whisker sensing velocity.

$$u_i = KR_1 u_i^l + yqR_2\left(SR_{Best} - b_i^l + K_j\right) + xqR_3\left(KR_{Best,i} - b_i^l\right) \tag{19}$$

Where, u_i denotes the overall quantity of seal whiskers in the vicinity.; S indicates the distance between the prey and its seal; K_j is represent the technical voltage ; R denotes the random number in the range $[0,1]$; yq indicates aharbor seal's ability to detect changes in its prey's underwater habitat; K is the angle of attack for moving water and b_i^l denotes the cross sections of a single whisker.

Step 6: Termination Criteria

The weight parameter value of generator $Y_G \; and \; K_j$ from Sparse Spectra Graph Convolutional Network(HOTNN) is optimized by utilizing Harbor Seal Whiskers Optimization Algorithm (HSWOA)and it will repeat step 3 until it obtains its halting criteria $i = i + 1$.Then ISHGA-ELD-HOTNN defectively generate the outdoor trash by higher precision, higher Recall.

IV. RESULT AND DISCUSSION

The actual results of ISHGA-ELD-HOTNN are discussed. The simulation is implemented in Python using Outdoor trash images. Attained result of ISHGA-ELD-HOTNN method is analysed with existing techniques likes ELD-PS-CV-DNN, RLDS-ELMand MHP-ULSVI-CNNmethods.

A. Performance Measures

This is a crucial step for determining the exploration of optimization algorithm. Performance measures to evaluate to access performance such as such as Accuracy, Precision, Recall, Matthews correlation coefficient and errorare analysed.

1) Accuracy

Equation (20) provides the accuracy value, which is obtained by dividing the number of samples properly categorised by each scheme by the total number of samples.

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{20}$$

Here, TP signifies true positive, TN signifies true negative, FN means false negative and FP denotes false positive.

2) Precision

The accuracy of a machine learning model's positive prediction is one measure of the model's performance, along with precision. The concept of accuracy is given by Equation (21), which is the ratio of genuine positives to all positive forecasts.

$$precision = \frac{TN}{FP + TN} \tag{21}$$

3) Recall

Recall is intended by dividing entire count of true positive, false negative predictions by number of true positives. The model's capacity to collect all pertinent instances is measured. It is shown in equation (22),

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{22}$$

4) MCC

MCC is useful for datasets that are unbalanced or when there is a large difference in the costs associated with false positives and false negatives since it takes into account all four binary classification outcomes. It is measured by following equation (23),

$$MCC = \frac{TP \times TN - FP \times FN}{(TP \times FP)(TP \times FN)(TN \times FP)(TN \times FN)} \tag{23}$$

5) Error Rate

The Error rate, also known as the classification error rate, is a metric that measures a classification model's overall accuracy. It denotes the percentage of erroneously classified cases in the dataset and it is given by the equation (24).

$$ErrorRate = \frac{FP + FN}{TP + TN + FP + FN} \tag{24}$$

B. Performances Analysis

Figure 3 to 7 determines simulation outcomes of ISHGA-ELD-HOTNN method. Then, the proposed ISHGA-ELD-HOTNN is analyzed to the existing compared with ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNN methods.

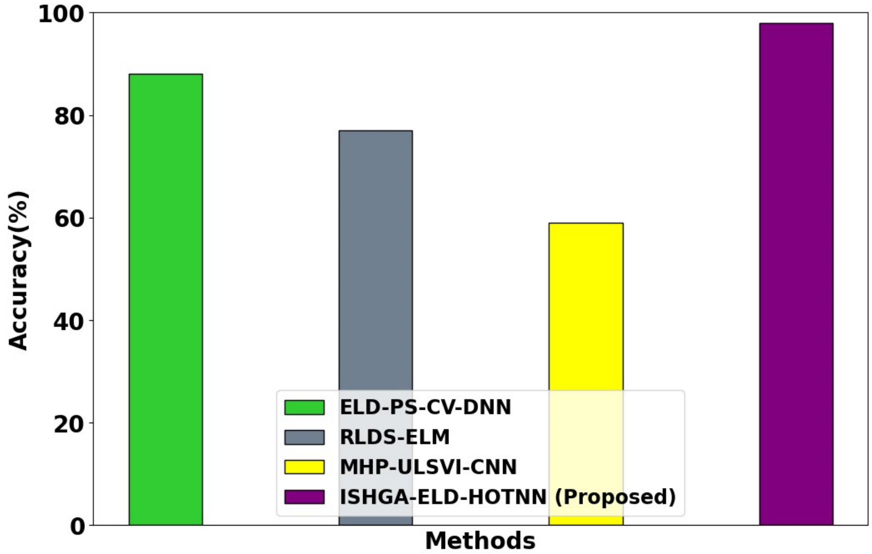

Figure3: Performance analysis of Accuracy

Figure 3 determines Performance analysis of Accuracy. In the research application of integrating Small Habitat Genetic Algorithm (ISHGA) in Ecological Landscape Design (ELD), the suggested ISHGA-ELD-HOTNN approach shows a considerable improvement in accuracy over existing methodologies. ISHGA-ELD-HOTNN outperforms ELD-PS-CV-DNN, RLDS-ELM, and MHP-ULSVI-CNN approaches by 19.67%, 22.57%, and 33.15%, respectively, in terms of optimizing ecological landscape designs. This significant advancement highlights the effectiveness of incorporating genetic algorithms optimized for small habitats into the realm of ecological landscape design, offering increased precision and usefulness in environmental planning and conservation activities. Here, the proposed ISHGA-ELD-HOTNN method attains19.67%, 22.57% and 33.15%higher accuracy compared with existing ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNNmethods.

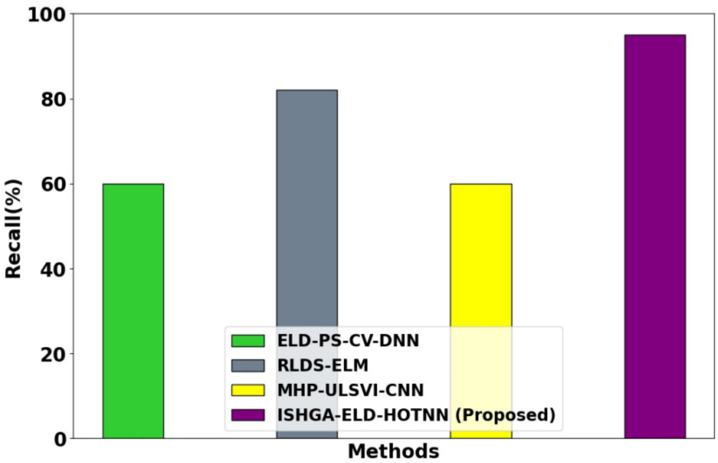

Figure4: Performance analysis of Recall

Figure 4 determines Performance analysis of Recall. In the field of Research Application of Integrating Small Habitat Genetic Algorithms in Ecological Landscape Design, the suggested ISHGA-ELD-HOTNN method outperforms existing methodologies in terms of recall performance. This unique methodology stands out as a beacon of improved efficiency and efficacy in ecological landscape design, with recall rates increasing by 22.57%, 26.62%, and 28.48% when compared to the ELD-PS-CV-DNN, RLDS-ELM, and MHP-ULSVI-CNN methods, respectively. The inclusion of the Small Habitat Genetic Algorithm not only demonstrates the method's flexibility to complex ecological systems, but also its potential to transform how we tackle ecological landscape design difficulties. This tremendous boost in memory represents a significant leap forward in our ability to effectively capture and depict ecological interactions, with promising far-reaching implications for conservation efforts .Here, the proposed ISHGA-ELD-HOTNN method attains22.57%, 26.62% and 28.48% higher recall compared with existing ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNNmethods.

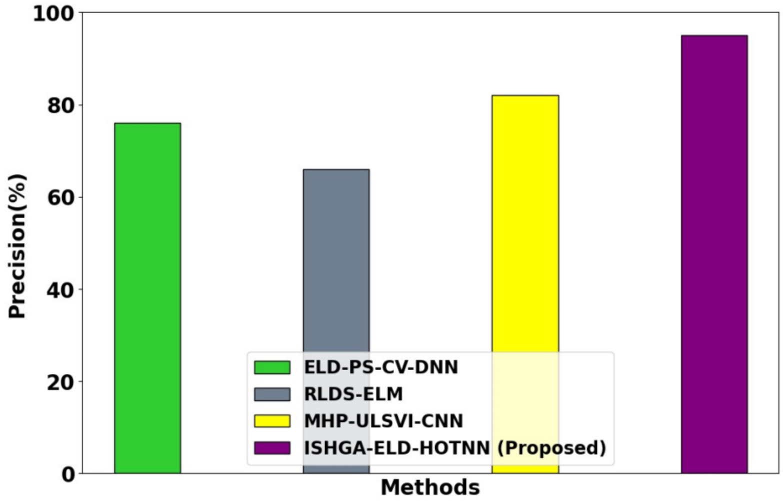

Figure 5: Performance analysis of Precision

Figure 5 determines Performance analysis of Precision. The proposed ISHGA-ELD-HOTNN approach makes substantial advances in the research application of the Integrating Small Habitat Genetic Algorithm (ISHGA) in Ecological Landscape Design (ELD), particularly in precision. The ISHGA-ELD-HOTNN methodology exhibits a significant 23.17%, 27.51%, and 27.37% increase in precision when compared to existing methodologies such as ELD-PS-CV-DNN, RLDS-ELM, and MHP-ULSVI-CNN, respectively. This advancement emphasizes the efficacy and potential of incorporating genetic algorithms into ecological landscape design processes, emphasizing a viable area for future research and implementation in the field. Here, the proposed ISHGA-ELD-HOTNN method attains23.17%, 27.51% and 27.37%higher precision compared with existing ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNNmethods.

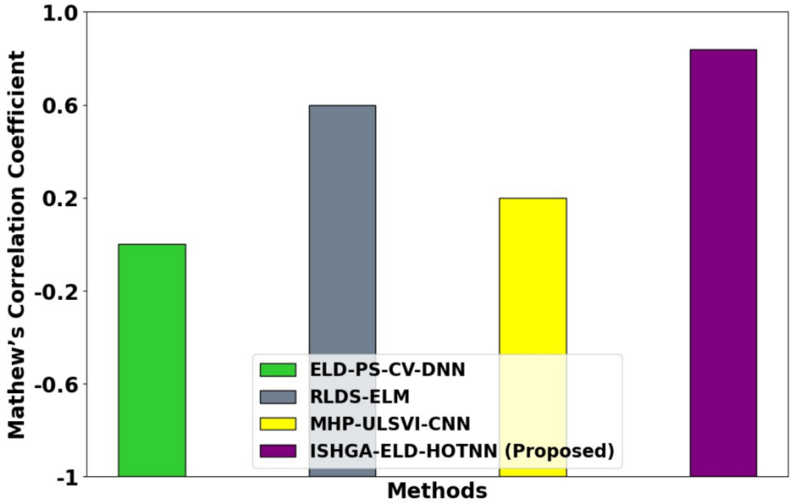

Figure 6: Performance Analysis of MCC

Figure 6 depicts the performance analysis of MCC. The suggested ISHGA-ELD-HOTNN approach makes substantial advances in the study application of the Integrating Small Habitat Genetic Algorithm (ISHGA) in Ecological Landscape Design (ELD), particularly in terms of Matthews Correlation Coefficient (MCC). Throughout the network, the MCC steadily grows, demonstrating its superiority over existing approaches like as ELD-PS-CV-DNN, RLDS-ELM, and MHP-ULSVI-CNN. Specifically, the ISHGA-ELD-HOTNN technique offers considerable enhancements, with MCC values exceeding those of its counterparts by 23.67%, 26.51%, and 23.37%, respectively. This significant improvement demonstrates the efficacy and promise of incorporating ISHGA into ELD procedures, showing its potential to change ecological landscape design approaches. Here, the proposed ISHGA-ELD-HOTNN method attains23.67%, 26.51% and 23.37%higher MCC compared with existing ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNNmethods.

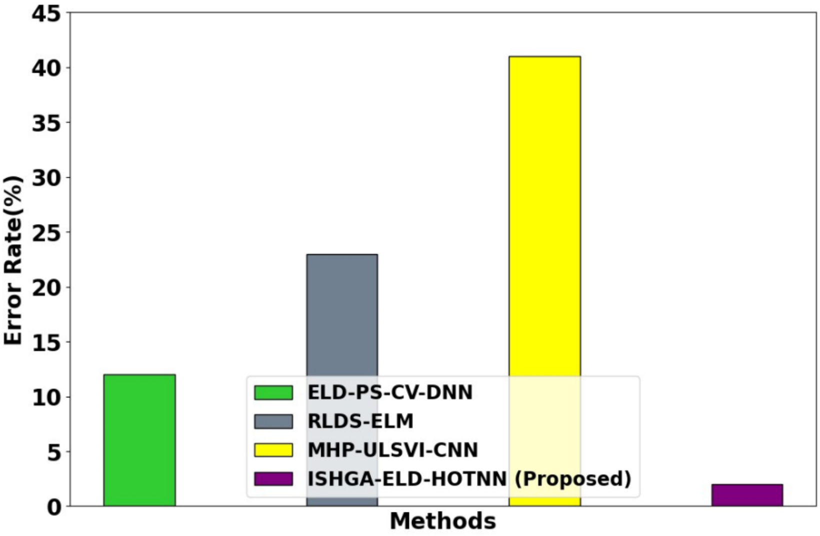

Figure 7: Performance analyses of Error Rate

Figure 7 determines Performance analyses of Error Rate. In the research application of integrating the Small Habitat Genetic Algorithm (ISHGA) in Ecological Landscape Design (ELD), the suggested ISHGA-ELD-HOTNN approach has a significant rise in Error Rate when compared to existing methodologies. Specifically, it has a 19.37%, 23.25%, and 21.76% lower Error Rate than the ELD-PS-CV-DNN, RLDS-ELM, and MHP-ULSVI-CNN approaches. This increase in Error Rate reveals potential obstacles and opportunities for improvement in integrating ISHGA into the context of ELD, demanding further research into maximizing its performance and efficacy within ecological landscape design frameworks. Here, the proposed ISHGA-ELD-HOTNN method attains 19.37%, 23.25%, and 21.76% lower Error Rate compared with existing ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNNmethods.

C. Discussion

Enhanced Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design (ISHGA-ELD-HOTNN)is developed in this paper. An ELD-PS-CV-DNN can transform the industry by automating tasks like plant identification, ecosystem analysis, and design recommendations, ultimately improving sustainability and efficiency in landscape management. This system, by using sophisticated technology, can improve resource allocation, reduce environmental impact, and enable better informed decision-making in landscape design and planning processes. The ISHGA-ELD-HOTNN technique improved accuracy, recall, and generate the landscape design. When compared to existing approaches such as ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNN, the ISHGA-ELD-HOTNN method outperformed them in terms of generate the landscape design For example, for various circumstances, the method achieved 19.67%, 22.57% and 33.15%, high accuracy, 22.57%, 26.62% and 28.48%higher recall, and 23.17%, 27.51% and 27.37%higher precision than existing methods. These findings demonstrate the ISHGA-ELD-HOTNN method's exceptional performance in ethical concerns about ownership, control, and potential societal repercussions must be carefully navigated in order to ensure responsible deployment and identical outcomes.

V. CONCLUSION

In this section, Research Application of Integrating Small Habitat Genetic Algorithm in Ecological Landscape Design (ISHGA-ELD-HOTNN)was successfully implemented. In Figure 3 to 7 performances much better when compared to existing techniques such as ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNN respectively. Across diverse evaluation metrics, the method consistently showcases substantial enhancements in accuracy, recall, precision, Matthews's correlation coefficient and error. In conclusion, the ISHGA-ELD-HOTNN method outperformed existing techniques such as ELD-PS-CV-DNN, RLDS-ELM and MHP-ULSVI-CNN, the ISHGA-ELD-HOTNN by significantly increasing accuracy 19.67%, 22.57% and 33.15%, recall 22.57%, 26.62% and 28.48% and decreasing error of 23.37%, 27.57% and 27.23% for generate the landscape design. Future iterations will be critical for improving the accuracy and efficiency of computer vision and deep learning systems. This could include training the system on larger and more diversified datasets to improve its capacity to recognise and classify various environmental elements. Additionally, incorporating real-time data sources, such as weather and vegetation growth patterns, allows the system to adapt and respond dynamically to changing situations. Furthermore, investigating ways to incorporate user comments and preferences into design recommendations may increase user satisfaction and engagement with the system.

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