AI-Driven Construction and Application of Gardens: Optimizing Design and Sustainability with Machine Learning

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Abstract—**Artificial intelligence (AI) integration into environmental analysis has revolutionized various fields. Including the construction and application of gardens, by enabling precise classification and decision-making for sustainable practices. This paper presents a strong AI-driven framework uses convolutional neural network (CNN) and pretrained models like VGG16 and InceptionV3 to classify eight distinct environmental classes. The CNN achieved superior performance Among the tested models and reaching an impressive 98% accuracy with optimized batch sizes. This demonstrate its effectiveness for precise environmental condition classification. This work highlights the crucial role of AI in advancing the construction and application of gardens. It offers insights into optimizing garden design through accurate environmental data analysis. The diverse dataset used ensures the framework's adaptability to real-world applications, making it a valuable resource for sustainable development and eco-friendly design strategies. This paper not only contributes to the field of AI-driven environmental analysis but also provides a foundation for future innovations in garden management and sustainability, paving the way for intelligent solutions in the evolving landscape of ecological design.**

Keywords*—*Artificial intelligence; machine learning; construction and application of garden design; convolutional neural network; VGG16; InceptionV3

I. Introduction

The construction and application of gardens have long been intertwined with human civilization, serving as timeless symbols of beauty, solace, and ecological significance. From the glory of the Babylon Hanging Gardens, celebrated as one of the Seven Wonders of the Ancient World, to the serene and meticulously crafted Japanese Zen gardens [1]. These green spaces have continuously evolved to reflect cultural ideals, environmental adaptations, and technological advances [2]. More than just a testament to human creativity and harmony with nature, gardens also embody the intersection of sustainability and aesthetic appeal [3]. In today's rapidly urbanizing world, their role has expanded far beyond visual pleasure, as they now play a crucial part in addressing global challenges such as climate change, biodiversity loss, urban livability, and resource scarcity [4]. At the same time, they remain essential in promoting mental and physical well-being, offering spaces for relaxation, social interaction, and ecological balance. The integration of artificial intelligence has further revolutionized gardening, introducing data-driven solutions for optimizing garden layouts, automating maintenance, and enhancing biodiversity management. AI-powered systems now facilitate sustainable irrigation, real-time plant health monitoring, and predictive analysis for pest and disease control, making urban and rural green spaces more resilient and efficient. As technological advancements continue to shape the way gardens are designed and maintained, there is a growing need for ethical and sustainable approaches that balance innovation with ecological responsibility [5].

In this day and age of technological progress, the arrival of artificial intelligence (AI) and machine learning (ML) has opened evolutionary possibilities in the construction and application of gardens [6]. These cutting-edge technologies allow for the analysis of vast and complex datasets, enabling the optimization of garden design, the enhancement of sustainability, and the implementation of resource-efficient maintenance strategies. One good example of the potential of AI lies in land use scene classification, where ML models analyze satellite imagery as well as aerial photographs to classify various land types such as, *Forest*, *River*, agricultural areas etc. This capability is particularly instrumental in identifying suitable sites. This is useful for garden construction and to focus the design on specific ecological and climatic needs [7]. The application of these technologies marks the departure from traditional garden design practices, which often rely on manual analysis and experience methods. That can accidentally overlook crucial environmental and sustainability factors. The construction and application of gardens come with unique challenges. That AI is exceptionally well positioned to address. Traditional garden design methods, while rooted in artistic expression and intuition. Can be restricted by their ineffectiveness to integrate environmental and sustainability considerations widely [8].

By incorporating ML models into this process, designers can access data driven insights into land usability. And predict resource requirements and develop garden layouts that prioritize biodiversity and ecological harmony. For example, AI models can simulate various garden configurations. Taking into account variables such as sunlight exposure, water availability, soil quality, and plant compatibility ensures that

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the resulting designs are functional and sustainable [9]. In addition, these AI-powered systems extend their utility beyond design by enabling post-construction monitoring. Providing real-time data to support versatile maintenance strategies that reduce resource consumption and environmental impact. These systems enable garden planners to address not only immediate design concerns, but also long-term sustainability objectives, ensuring gardens remain thriving ecosystems over time [10].

This research focuses on using land use scene classification, which revolutionizes the construction and application of gardens. It offers a comprehensive framework that integrates sustainability, innovative design principles, and cutting-edge technological advancements. Using the Land-Use Scene Classification dataset, this study examines specific land categories, such as *Agriculture*, *Forest*s, *River*s, and residential zones, which are directly relevant to the sustainable design of the garden. ML models trained in these categories aim to provide actionable insights into site selection, resource allocation, and design optimization. The proposed approach bridges the gap between traditional garden design methods and the powerful capabilities of modern AI technologies, demonstrating the potential of AI to transform green space planning into a data-driven, scalable, and ecologically sound endeavor. The insights generated by these models will not only enhance the visual and functional aspects of gardens but will also align them with broader global sustainability goals, such as carbon sequestration, biodiversity conservation, and efficient water use. The significance of this work lies in its ability to reimagine the construction and application of gardens in an era defined by rapid urbanization and environmental degradation. By introducing a scalable, adaptable and data-driven approach, this research demonstrates how AI can be used to create gardens that are aesthetically pleasing, ecologically sustainable, and socially impactful. Beyond their immediate applications, such gardens contribute to the broader vision of fostering greener, more resilient urban and rural landscapes. In addition, this paper underscores the vital role of AI in the resolution of global environmental challenges, highlighting the importance of innovation and technological solutions to foster a harmonious coexistence between human development and nature. The key contributions of this work are:

- Introduces an AI-powered framework for garden construction that integrates the classification of the land use scene, enabling sustainable and efficient garden design.
- Demonstrate how AI can improve resource efficiency, biodiversity, and environmental sustainability in garden construction.
- Conducts a detailed evaluation of traditional garden design methods versus AI-driven approaches to highlight efficiency, accuracy, and sustainability gains.

II. Literature Review

Artificial intelligence (AI) and machine learning (ML) in the construction and application of gardens has gained substantial attention in recent years [11]. Cities continue to enlarge the importance of sustainable, efficient and ecologically sound garden designs is becoming increasingly clear. AI and ML present an opportunity to optimize garden layouts, improve resource use, and improve sustainability [12]. These technologies enable designers to analyze and classify land use more precisely, creating gardens that are not only aesthetic but also environmentally beneficial. One of the key areas where AI has shown promise is in land use classification. The ability to accurately classify different types of land, such as agricultural zones and urban areas. *Forest*s, and water bodies can significantly influence the construction and application of gardens [13]. AI models can provide insight into the bionomics and environmental characteristics of the area, using satellite images and aerial imagery for the construction of gardens [14]. These techniques allow for a deeper understanding of soil quality and water availability. Also, understands climate for ensuring that gardens are designed with the local environment in mind.

In addition to land-use classification, AI-driven tools are being applied to urban planning and landscape architecture [15]. These tools enable the creation of generative designs in which multiple garden layouts are explored and tested for optimal performance. AI algorithms can evaluate different configurations, considering factors such as compatibility, sunlight exposure, and soil health [16]. This process ensures that gardens are not only functional but also sustainable. The design iterations produced by AI can adapt to environmental changes, making gardens more resilient to challenges such as climate change, loss of biodiversity, and water scarcity. Such innovations allow for the creation of green spaces that can thrive in a variety of conditions, from urban rooftops to expansive rural landscapes [17].

Another critical application of AI is in the field of precision *Agriculture*, which shares many principles with the construction of sustainable gardens [18]. By monitoring soil moisture levels, weather patterns, and water use, AI systems help optimize resource allocation in agriculture. These technologies have proven to be effective in reducing water waste and maximizing crop yield. Similarly, in the construction and application of gardens, AI can monitor and manage resources such as water, fertilizers, and energy, ensuring that gardens are not only beautiful, but also efficient and sustainable [19]. The application of such technologies allows for adaptive maintenance strategies that minimize environmental impact while keeping gardens thriving.

AI also plays a crucial role in enhancing biodiversity and supporting the ecological balance within gardens [20]. By simulating various environmental conditions and plant interactions, AI can suggest garden layouts that support a diverse range of species and foster healthier ecosystems. This is particularly important in urban areas, where biodiversity is often limited. AI models can identify plant species that are compatible with each other and the local environment, promoting plant diversity and reducing the need for chemical interventions [21].

Through this, gardens can become vital ecosystems that support local wildlife and contribute to the overall health of the urban environment. Although much of the current research has focused on individual aspects of garden design or broader environmental planning, the potential for AI to integrate land use classification with garden construction remains largely unexplored. Most of the existing efforts have focused on urban planning or agricultural optimization, leaving a gap in the specific application of AI to the construction and application of gardens [22].

This presents an opportunity to bridge the gap and develop AI-driven tools that combine ecological sustainability with design optimization. By merging these two areas, AI can play a pivotal role in creating gardens that are not only functional and beautiful, but also environmentally resilient and resource-efficient [23].

The Motivation behind this research is to fill the gaps in existing research by specifically focusing on the intersection of AI-driven land use classification and the construction and application of gardens. although numerous researchers have explored human aspects of AI in urban planning, *Agriculture*, or ecological design, the application of these technologies in optimizing garden design and sustainability remains underexplored. This article aims to explain how AI can revolutionize the construction and application of gardens, ensuring that they are not only aesthetically pleasing but also ecologically viable and resource efficient. Using ML to integrate land-use classification with garden design, this research contributes to creating smarter, more sustainable green spaces that can adapt to the challenges posed by climate change, urbanization, and biodiversity loss. This paper seeks to push the boundaries of the construction and application of gardens, showing how AI can be harnessed to optimize both the process and the outcome of garden construction, thus fostering greener and more resilient landscapes.

III. Methodology

A. Dataset Collection

Data collection is the most important aspect of the research. Dataset utilized in this research is a curated from kaggle. Which is subset of a land-use scene classification dataset and is specifically designed to facilitate the construction and application of gardens.The dataset consists satellite images which represents eight diverse land-use scenarios such as, *Agriculture*, *Forest*, *River*, urban areas and more. Each class is selected for its critical role in sustainable garden design. This dataset captures a range of ecological and environmental scenarios which provides valuable insights into land characteristics. Which is essential for tailored garden planning which include agricultural suitability urban density as well as water management. The dataset underwent preprocessing to standardize image resolution and format to ensure consistency. To increase diversity and simulate real-world variations advanced augmentation techniques such as rotation, scaling, and flipping, were applied. This diverse dataset forms a strong foundation for integrating AI into the construction and application of gardens which enhances their sustainability, efficiency, and resilience.

This dataset was chosen based on its comprehensive coverage of diverse land-use types relevant to garden planning. It provides high-quality satellite imagery, ensuring reliable data for AI-driven analysis. Compared to other datasets, this one offers a well-balanced mix of natural and urban environments, making it particularly suitable for evaluating ecological and spatial factors in sustainable garden construction. This directly align with the objectives of this work, integrating AI into the construction and application of gardens. The dataset diverse classes provide a basis for training ML models which is capable of optimizing garden designs, accounting for ecological and spatial demands. Furthermore, the dataset detailed depiction of environmental scenarios makes it ideal for testing new approaches to sustainable and efficient garden construction. Enhancing the practicality and adaptability of the methodology. Detailed description of the dataset is shown in Table I, which highlights its significance in the advancement of AI-driven garden design solutions. Despite its strengths, the dataset has some limitations. The fixed satellite image resolution may impact fine-grained analysis of smaller garden structures. Additionally, while the dataset covers multiple land-use types, real-time environmental variations such as seasonal changes or soil conditions are not explicitly captured. Addressing these challenges in future work could involve integrating real-time remote sensing data or expanding the dataset to include dynamic environmental parameters.

B. Preprocessing

1) Data resizing: We observed significant variations in the resolution of images within the dataset during preprocessing. This variation could negatively impact the consistency and accuracy of the model. In order to address this issue all images were uniformly resized to 224 × 224 pixels. By doing this, we observed that this standardization ensures the consistency of the input. Facilitating efficient processing by the model as well as helping with reducing computational complexity. Furthermore, this resizing helps in maintaining the balance not only image quality but also performance. Which ensures optimal feature extraction during the training.

2) Normalization of data: Data normalization is a crucial step in data preprocessing to enhance the performance of ML models. Where we standardize or rescales the input to fall within a specific range between 0 and 1 or sometimes between -1 and 1. The data normalization process minimizes the impact of varying not only pixel_intensity values, reduces training time but helps the model focus to learn meaningful patterns rather than being influenced by scale variance in the dataset.

C. Data Distribution and Quantitative Analysis

A well-structured dataset is the cornerstone of any successful deep learning model. For this study, we carefully curated

TABLE I. Dataset Description for the Construction and Application of Gardens

Class Name	Description
Agriculture	Areas used for farming, including crop fields and orchards, suitable for plant-rich designs.
Beach	Coastal sandy areas, often requiring salt-resistant plants and erosion control measures.
Denseresidential	Urban areas with closely packed houses or apartments, ideal for rooftop or small-space gardens
Forest	Large areas covered by trees, offering inspiration for natural, eco-friendly garden designs.
Golfcourse	Open green spaces maintained for recreational purposes, with efficient irrigation systems.
Mediumresidential	Suburban areas with moderately spaced housing, suitable for private gardens or community spaces.
Parkinglot	Large paved areas used for vehicle parking, often with potential for integrating green spaces.
River	Natural flowing water bodies, influencing designs with water management and riparian vegetation.

a dataset with eight distinct land-use classes: *Agriculture*, *Beach*, *Denseresidential*, *Forest*, *Golfcourse*, *Mediumresidential*, *Parkinglot*, and *River*. Each class is represented by 500 images, ensuring an equal distribution that prevents class imbalance, which is often a major challenge in classification tasks. The dataset is further divided into training and testing sets. Resulting in 400 images for training as well as 100 images for testing. This distribution strategy provides sufficient data for model training while preserving a fair portion for unbiased evaluation as shown in Table II. The dataset is balanced with a total of 4,000 images, distributed as 3,200 training images and 800 testing images. This balanced lays the foundation for fair and consistent model learning.

TABLE II. DATASET OVERVIEW SHOWING THE NUMBER OF IMAGES, TRAINING SET, AND TEST SET DISTRIBUTION ACROSS CLASSES

Class Name	No. of Images	Training Set	Test Set
Agriculture	500	400	100
Beach	500	400	100
Denseresidential	500	400	100
Forest	500	400	100
Golfcourse	500	400	100
Mediumresidential	500	400	100
Parkinglot	500	400	100
River	500	400	100
Total	**4000**	**3200**	**800**

To visualize this distribution, Fig. 1, presents a pie chart that illustrates the equal percentage of images contributed by each class. With each class forming exactly 12.5% of the dataset, the dataset achieves perfect equilibrium, eliminating any inherent bias toward a specific category. This balance is critical to ensure the model generalizes well across all land-use categories and does not overfit to any particular class.

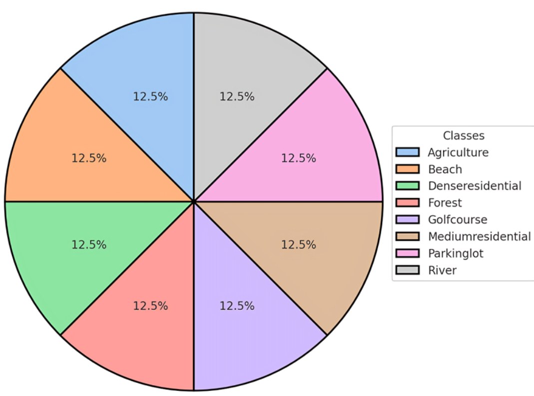

Fig. 1. Class distribution in the dataset, showing balanced contributions from each class.

To further validate this equal distribution, Fig. 2 shows a bar chart displaying the total number of images per class. The uniform height of the bars emphasizes that every class has exactly 500 images, underscoring the equal composition of the dataset. This visual confirmation strengthens confidence in the integrity of the dataset and its suitability for training a robust classification model.

In addition to the overall distribution, it is crucial to examine the segregation of the dataset into training and testing

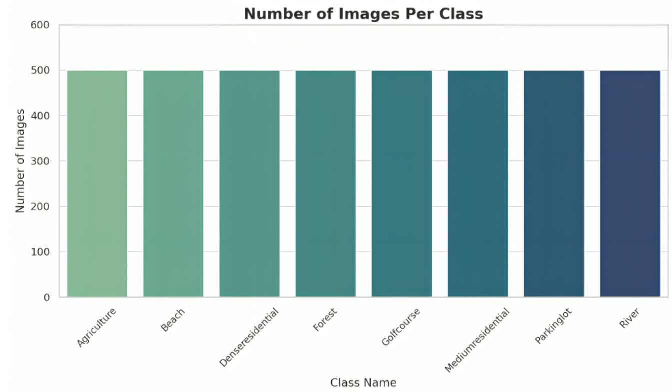

Fig. 2. Total number of images per class.

subsets. Fig. 3 provides a detailed visualization of the training and testing distribution for each class. Training set consists of 400 images for each class in the dataset and 100 images to the testing set which shows the 80% split for training and 20% split for test set. This distribution ensures that the model is trained on a substantial portion of the data while reserving enough samples for an objective evaluation of its performance. The design of this dataset ensures a harmonious blend of diversity and balance. The balance representation of all classes guarantees that the model receives varied inputs, preventing any single class from dominating the learning process. Moreover, the structured division into training and testing subsets aligns with best-practices in machine learning, facilitating reliable and unbiased performance assessment.

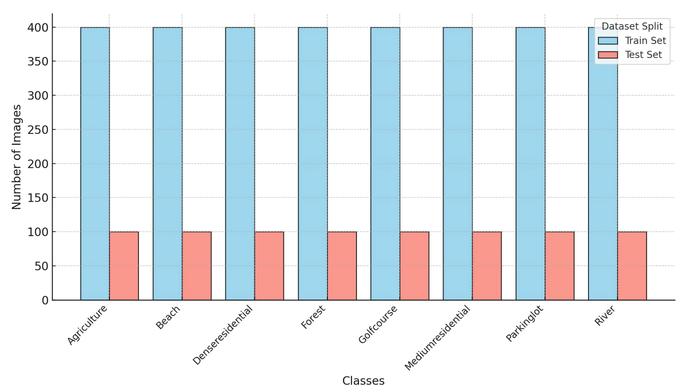

Fig. 3. Total number of images in train and test set.

By combining these quantitative analysis with visual insights, we can conclude that the dataset is well prepared to support the development of an effective classification model. This precise approach of distribution of data improves the reliability of the study and also emplace a solid foundation for future research on land use classification.

D. Proposed Framework

The proposed classification framework uses advanced machine learning to provide an effective and efficient solution. The training and testing workflow is presented in Fig. 4. The system begins by receiving image inputs from the dataset, which are then divided into training, testing, and validation sets.

Furthermore, the proposed framework for this work is presented in Fig. 5, designed to optimize the construction and application of gardens using satellite image classification. It categorizes images into eight distinct classes Agriculture, Beach, Denseresidential, Forest, Golfcourse, Mediumresidential, Parkinglot, and River enabling precise and efficient landscape planning.

The process begins with preprocessing, where satellite images are resized and normalized to ensure consistency. These preprocessed images are then passed through a custom Convolutional Neural Network (CNN) that extracts key spatial features, such as textures, patterns, and vegetation density. Convolutional and max-pooling layers work together to identify and retain essential features while reducing data complexity. The extracted features are then mapped through fully connected layers, where the softmax activation function ensures accurate classification by assigning probabilities to each class. The framework not only enhances the classification of land instances. But also supports AI_driven decisions for garden construction and sustainability. For instance identifying agricultural regions or *River* landscapes allows for informed garden designs tailored to specific environmental contexts. By integrating both automation as well as precision the proposed framework transforms traditional garden planning into more effective and sustainable process.

IV. Results and Discussion

A. Experimental Setup

The experiments were conducted using intel(R) Core(TM) i5-6500 CPU running at 2.60 GHz, along with 16 GB, RAM on the windows 10 operating system. Anaconda-based python 3.11 environment configured with TensorFlow-and PyTorch.

B. Evaluation Metrics

The performance of the model is evaluated using various metrics such as, accuracy, precision, recall as well as F1-score. Which together offers a detailed understanding of the proposed model classification capabilities. Firstly ,accuracy calculated using Eq. 1, determines the overall correctness of the model by measuring the ratio of correctly predicted instances. True positives (TP) and True negatives (TN) to the total predicted result. Secondly, precision defined in Eq. 2, evaluates the proportion of true positive predictions among all positive predictions.High precision is very important in such cases where minimizing false positives is crucial. Third metric is recall computed using Eq. 3, reflects the models ability to accurately identify all actual positive instances. Lastly, F1-score as presented in Eq. 4, shows the harmonic mean of precision and recall which strikes a balance between precision and recall.

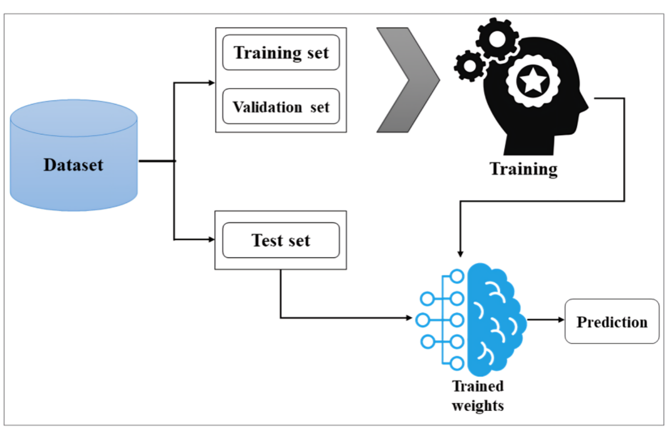

Fig. 4. Workflow for training and evaluating model using the dataset. The dataset is divided into training, validation, and test sets, which are utilized for model evaluation. The trained model then makes predictions, demonstrating the pipeline from data preparation to deployment.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

C. Performance Comparison of Pre-trained Models

Performance evaluation of pretrained models is performed to get insights into their robustness in addressing the classification difficulties in the construction as well as application of gardens. These models include include Artificial Neural Network (ANN) [24], VGG16 [25], and Inception V3 [26]. The metrics used for comparison were accuracy, loss, validation accuracy (Val_Accuracy), validation loss (Va_Loss), precision, recall, and F1-score were the metrics used for comparison. which collectively provide a holistic view of each model's performance. Table III, displays the results of the ANN model. It achieved an accuracy of 0.88 with a validation accuracy of 0.83, indicating reasonable performance for a baseline model.

TABLE III. Performance Metrics of ANN, Including Accuracy, Loss, Precision, Recall, and F1-score

Metric	Accuracy	Loss	Val_Accuracy	Val_Loss	Precision	Recall	F1_Score
Values	0.88	0.19	0.83	0.21	0.85	0.82	0.83

However, the higher validation loss (0.21) compared to its training loss (0.19) suggests some overfitting, limiting its ability to generalize effectively to unseen data. The precision, recall, and F1-score of 0.85, 0.82, and 0.83, respectively, further highlight that while ANN performs decently, it falls short in addressing the complexities of the dataset. Table IV, showcases the performance of the VGG16 model, which marked a significant improvement over ANN.

With an accuracy of 0.93 and a validation accuracy of 0.91, VGG16 demonstrated strong generalization capabilities. The low training loss (0.10) and validation loss (0.13) reflect its ability to learn meaningful features from the data efficiently. Precision, recall, and F1-score values of 0.92, 0.91, and 0.91,

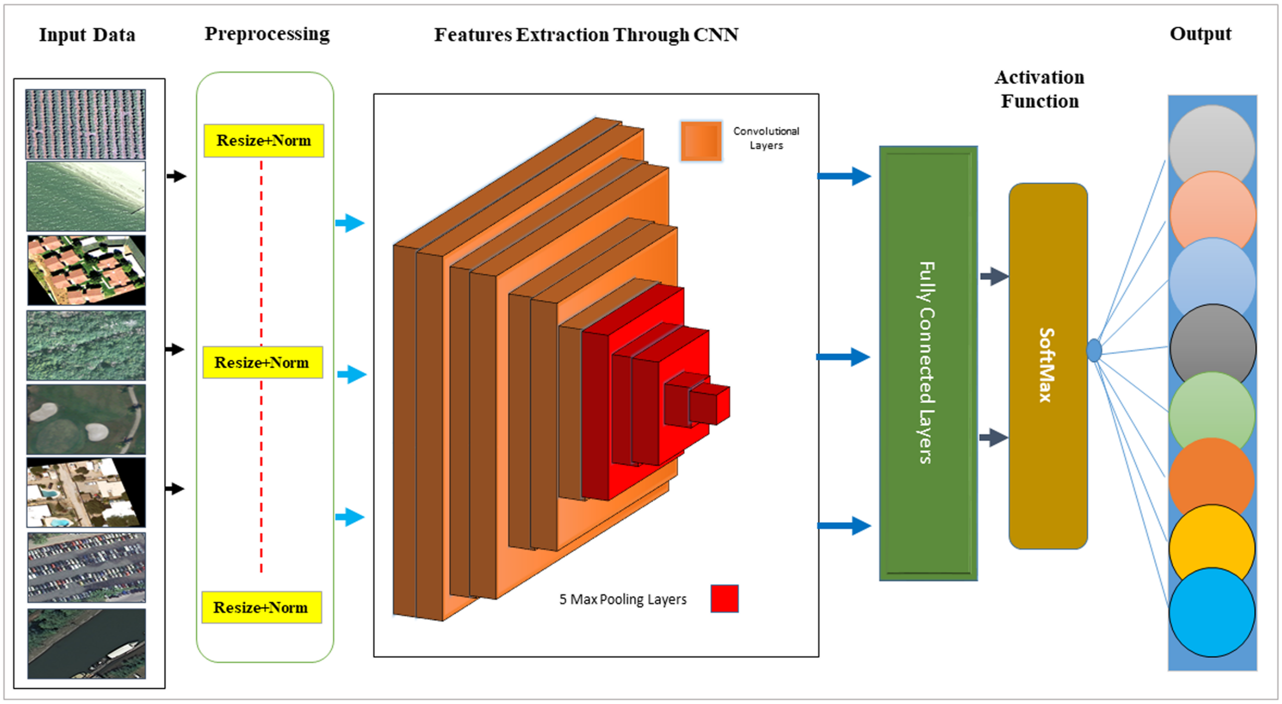

Fig. 5. Proposed framework for optimizing the construction and application of gardens through satellite image classification using a custom CNN, featuring preprocessing, feature extraction, and class-specific predictions for precise landscape planning.

TABLE IV. PERFORMANCE METRICS OF THE VGG16 MODEL, INCLUDING ACCURACY, LOSS, PRECISION, RECALL, AND F1-SCORE

Metric	Accuracy	Loss	Val_Accuracy	Val_Loss	Precision	Recall	F1_Score
Values	0.93	0.10	0.91	0.13	0.92	0.91	0.91

respectively, indicate that VGG16 reliably classifies the data with fewer false positives and negatives, making it well-suited for this task. Table V, presents the results for the Inception V3 model, which outperformed both ANN and VGG16.

TABLE V. PERFORMANCE METRICS OF THE INCEPTIONV3 MODEL, INCLUDING ACCURACY, LOSS, PRECISION, RECALL, AND F1-SCORE

Metric	Accuracy	Loss	Val_Accuracy	Val_Loss	Precision	Recall	F1_Score
Values	0.96	0.11	0.91	0.17	0.92	0.90	0.91

Inception V3 achieved an accuracy of 0.96 and a validation accuracy of 0.91, indicating its robustness in identifying intricate patterns and features within the dataset. While its validation loss (0.17) was slightly higher than that of VGG16, its precision (0.92), recall (0.90), and F1-score (0.91) demonstrate a strong balance between sensitivity and specificity. The superior performance of Inception V3 can be attributed to its advanced architecture, which excels in multi-scale feature extraction. To better illustrate the comparative performance, Fig. 6, presents a bar chart highlighting the accuracy of all three models. The progression from ANN to VGG16 and Inception V3 emphasizes the importance of employing deeper and more sophisticated architectures for tackling complex classification tasks. While ANN serves as a useful baseline, the results of VGG16 and Inception V3 underscore the potential of pretrained models in achieving higher performance levels.

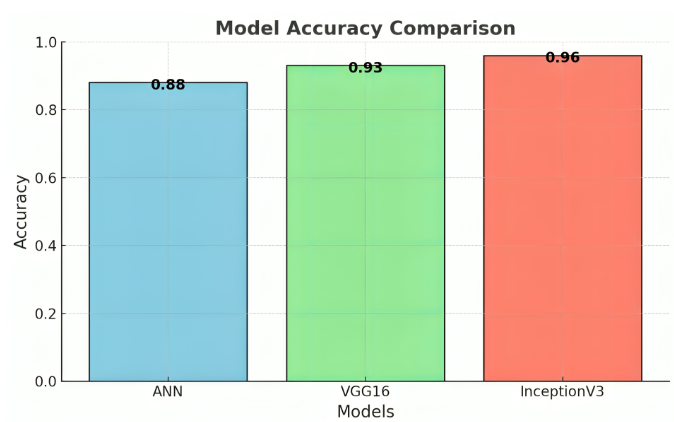

Fig. 6. Comparison of accuracy across pretrained models.

In summary, the performance evaluation highlights the effectiveness of VGG16 and Inception V3 as pretrained models, with Inception V3 emerging as the most accurate. These findings provide a benchmark for understanding the capabilities of pretrained architectures in similar applications, paving the way for further exploration and optimization in the Construction and Application of Gardens through deep learning approaches.

D. Performance Analysis of Proposed Model

The proposed Custom CNN [27] model was evaluated across varying batch sizes to analyze its performance comprehensively, with the results summarized in Table VI. Key metrics such as accuracy, loss, validation accuracy (Val-Accuracy), validation loss (Val-Loss), precision, recall, and F1-score were employed to assess the model's efficacy in handling classification tasks. Fig. 7, depicts the trends in accuracy and loss, while Fig. 8, presents a bar chart showcasing the model's performance across different batch sizes. Starting from the batch size of 4, the proposed model achieved an accuracy of 0.96 as well as validation-accuracy of 0.94. Additionally, minimal loss values of 0.04 for train and 0.03 for validation. These metrics showcases the model's best initial learning and generalization capabilities. Moreover, the model achieved the values for Precision as 0.95, recall (0.93), and F1-score 0.94. Respectively which further depicts its ability to give balanced and reliable results at this structure. At the batch of 8, the proposed model performance improved more and achieved Training accuracy of 0.97 and 0.95 of validation. Training loss and validation loss decreased to 0.03 for training and 0.02 for validation, which indicates more stable learning. Metrics such as Precision and recall rise up to 0.96 and 0.94. While F1-score reached to 0.95 which reflects the models high predictive capabilities and reduced error rate.

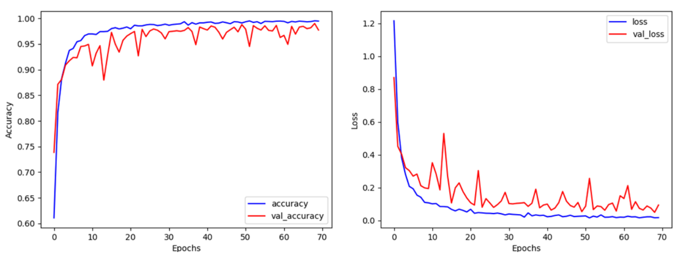

Fig. 7. Accuracy and loss curves of the proposed CNN model at different batch sizes.

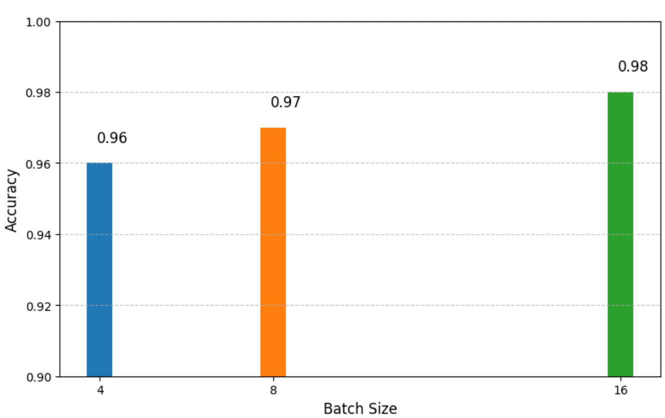

Fig. 8. Comparison of the proposed model across different batch sizes, highlighting accuracy improvements with increasing batch size.

Best results were achieved when the batch-size reached to 16. This is where the model achieved the highest accuracy of Training as 0.98 and for validation as 0.96. Training loss and validation loss were decreased to 0.02 for training and 0.01 for validation. Which depicting the model's best generalization and convergence. Metrics Precision reached at 0.97, recall rise to 0.95, and F1-score maintains its position height at 0.95. Fig. 10 highlights the comparison of metrics among the model and highlights that CNN shows superiority among the others.

TABLE VI. Performance Metrics of the Proposed Model for Different Batch Sizes

Batch Size	Accuracy	Loss	Val_Accuracy	Val_Loss	Precision	Recall	F1_Score
4	0.96	0.04	0.94	0.03	0.95	0.93	0.94
8	0.97	0.03	0.95	0.02	0.96	0.94	0.95
16	**0.98**	**0.02**	**0.96**	**0.01**	**0.97**	**0.95**	**0.95**

In conclusion, the results shows the effectiveness of the proposed model, with a 16 batch size emerging as the best performer. The proposed model shows high accuracy, minimum loss. And a balanced precision, recall, and F1-score, making it more suitable for applications in the Construction and Application of Gardens. This analysis underscores the robustness of the model and its potential to facilitate sustainable garden design and management. Fig. 9, shows the accuracy of the proposed model with all ML models.

In summary, the comparative analysis of ANN, VGG16, Inception V3, and the proposed Custom CNN demonstrates a clear progression in performance, emphasizing the influence of architectural complexity and feature extraction capabilities. The relatively lower performance of ANN highlights its limitations in capturing complex patterns due to its simpler structure and limited feature learning capacity. In contrast, the balanced performance of VGG16 shows the effectiveness of moderate depth and transfer learning. Inception V3 outperforms both models by leveraging its advanced architecture for multiscale feature extraction. The proposed Custom CNN achieves the highest accuracy, particularly with a batch size of 16, due to its custom design that optimizes learning and generalization for this domain-specific application. These results underscore the importance of selecting appropriate model architectures and hyperparameters to effectively address classification challenges, paving the way for optimized solutions in the Construction and Application of Gardens.

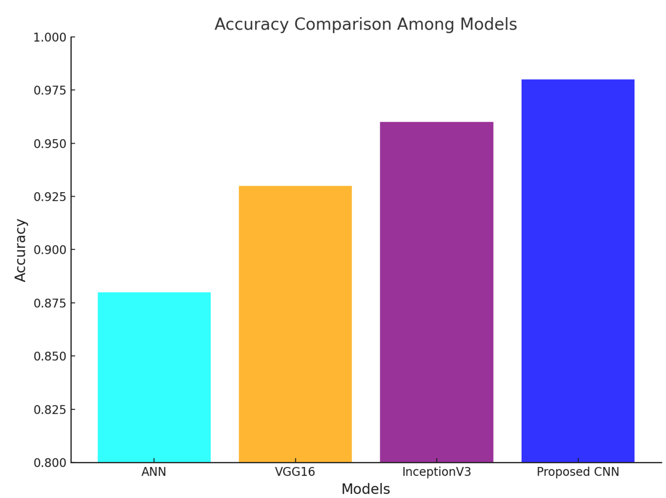

Fig. 9. Comparison accuracy of the proposed model with all ML models.

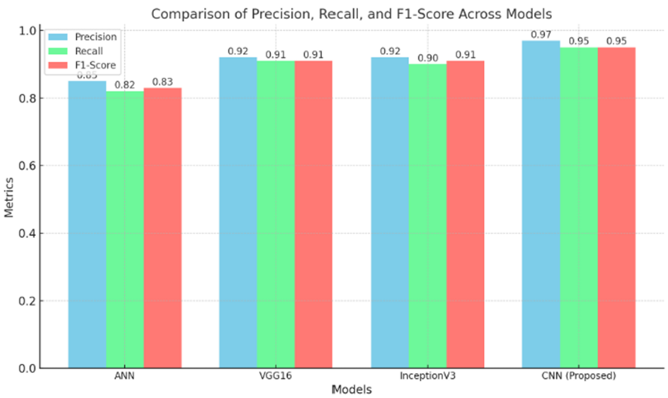

Fig. 10. Comparison accuracy of the proposed model with different models.

V. Conclusion

In conclusion,this research demonstrates the transformative potential of AI in revolutionizing garden design and sustainability through precise environmental classification and analysis. By utilizing advanced machine learning (ML) models, including both pretrained architectures and a custom CNN, this paper highlights the effectiveness of ML in accurately categorizing diverse landscape types, such as Agriculture, Beaches, Forests, and residential areas. The comprehensive evaluation of models, coupled with the use of a robust and diverse dataset, ensures the applicability of the findings across different real-world scenarios, making the work not just theoretical but practically impactful. The importance of this article lies in its ability to address pressing challenges in sustainable garden design by offering a data-driven approach to optimize planning and resource management. The results, supported by detailed performance analysis, reveal the strengths of different models while showcasing the custom CNN's superior capability in achieving high accuracy and efficient processing. The use of graphical analysis further enhances the papers clarity and accessibility, providing actionable insights for researchers and practitioners alike. This work not only sets a strong foundation for integrating AI into environmental and garden applications, but also opens doors for future advancements. The dataset can be expanded to include more complex and varied environments, and the models can be refined to handle real-time applications. By bridging the gap between technology and nature, this article paves the way for innovative, sustainable, and scalable solutions in garden construction and environmental optimization.

However, despite its promising contributions, this study is not without limitations. The dataset focuses mainly on specific landscape types like Agriculture, Beaches, Forests, and Residential areas, which may limit model generalization to more complex or mixed environments. Additionally, the current implementation lacks real-time processing capabilities, which are crucial for dynamic garden management and environmental monitoring. The models may also struggle with classification accuracy under extreme weather, varying light, or seasonal changes. Moreover, human intervention may still be required in complex or ambiguous scenarios to ensure classification accuracy. Addressing these limitations provides a balanced perspective and opens avenues for future research. Enhancing dataset diversity and improving model adaptability to extreme weather, varying light, and seasonal changes can enhance classification accuracy. Optimizing real-time processing capabilities and reducing computational demands will improve usability in dynamic garden management and environmental monitoring. Expanding the geographical scope and exploring edge computing solutions can boost scalability and practical deployment. Additionally, addressing the need for human validation in complex scenarios can refine automation accuracy. By transparently addressing these challenges, this study not only contributes to the academic field but also drives innovation at the intersection of AI and sustainable garden construction. It lays a solid foundation for future research focused on achieving environmental harmony through intelligent design and resource optimization.

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