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International Journal of Artificial Intelligence and Machine Learning

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Research Paper Open Access

Predictive Machine Learning Framework for Urban Ornamental Plant Recommendation via Multi-Parameter Environmental and Air Quality Assessment

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Abstract

Purpose

Urban environments face increasing challenges related to air pollution, limited green spaces, and environmental sustainability. Ornamental plants can improve urban environmental quality; however, selecting the most suitable plant species for specific urban conditions remains difficult. This study aims to develop an intelligent recommender system that assists users in selecting suitable ornamental plants based on environmental conditions and plant performance indicators.

Objectives

The research focuses on five key objectives: (1) Identifying important environmental factors affecting ornamental plant suitability. (2) Developing a linear regression model for predicting Hybrid Recommendation Scores (HRS). (3) Designing a recommender system for ornamental plant selection. (4) Ranking plant species based on predicted suitability scores. (5) Evaluating the effectiveness of the proposed recommendation model in urban environments.

Methodology

Environmental and plant-related parameters, including sunlight, season, plant density, and growth rate were collected and analysed. A multiple linear regression model was developed to estimate the SHybrid Recommendation Score (HRS). The predicted scores were integrated into a recommendation engine that ranks ornamental plants according to their suitability under different urban conditions. Statistical validation was performed using paired sample t-tests to evaluate the reliability of the proposed system.

"While advanced computational architectures such as Support Vector Machines (SVM), Deep Learning, and Transformers represent potential avenues for scaling high-complexity environmental datasets, they fall outside the immediate implementation scope of this study. The current architecture deliberately focuses on Multiple Linear Regression and Ensemble Learning models (Random Forest and Gradient Boosting) to maintain computational efficiency, explainability, and direct interpretability for urban horticulture applications."

Try-outs

The proposed recommender system was evaluated using environmental and plant-related parameters including sunlight, season, plant suitability score, and growth rate. These variables were processed through the developed linear regression model to calculate the Hybrid Recommendation Score (HRS).

The calculated HRS values were compared with benchmark HRS values obtained from previous studies to assess prediction accuracy. Furthermore, statistical validation was performed using a paired sample t-test to determine whether significant differences existed between the standard and predicted scores.

The calculated Hybrid Recommendation Scores (HRS) showed strong agreement with benchmark values obtained from published studies. Statistical validation confirmed that no significant difference existed between the standard and predicted values, demonstrating the reliability of the proposed regression model. The developed recommender system successfully ranked ornamental plants according to environmental suitability and can support sustainable urban greening initiatives by providing intelligent plant recommendations.

1. Introduction

Rapid urbanization and modern lifestyles have significantly reduced the availability of green spaces in residential and commercial environments. As people spend a substantial portion of their time indoors, concerns related to indoor air quality, thermal comfort, humidity balance, and overall environmental well-being have become increasingly important. Indoor ornamental plants have emerged as a sustainable and cost-effective solution for improving indoor environmental conditions by reducing pollutants, enhancing oxygen levels, regulating humidity, and promoting psychological well-being. The selection of appropriate indoor plants, however, is a challenging task due to the diverse environmental requirements of different plant species [1]. Factors such as room size, light intensity, temperature, humidity, air quality, and plantation density play a crucial role in determining plant suitability and performance. Traditional plant selection methods often rely on expert knowledge and manual decision-making, which may not always provide optimal recommendations for varying indoor conditions. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and recommender systems have created new opportunities for intelligent environmental management [2]. Machine learning techniques can analyze complex environmental datasets, identify hidden patterns, and generate data-driven recommendations that support effective plant selection. By integrating environmental parameters with predictive analytics, recommendation systems can assist users in identifying suitable plant species that maximize environmental benefits while ensuring sustainable plant growth. In addition, plantation density and available indoor area significantly influence the effectiveness of ornamental plants in improving environmental quality. A systematic evaluation of plant density, spatial distribution, and species suitability is therefore essential for achieving optimal environmental outcomes. Intelligent recommendation systems can support this process by predicting the most appropriate plant combinations based on specific indoor conditions and user requirements [3]. This study proposes a regression-based recommender system for ornamental plant selection in urban environments. The system utilizes environmental parameters and plant characteristics to estimate Hybrid Recommendation Scores (HRS) through linear regression modelling. Based on these scores, the recommendation engine ranks and suggests suitable ornamental plants for different urban conditions. The proposed framework aims to support sustainable urban greening and intelligent environmental decision-making.

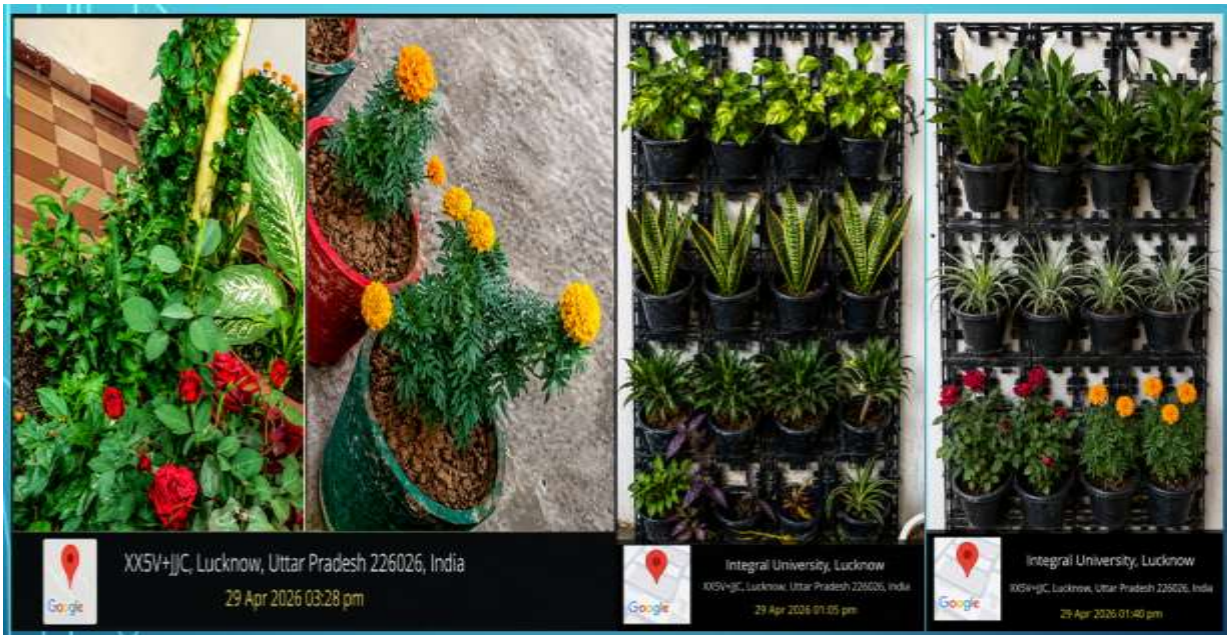

Fig 1: Machine Observation by Researcher

2. Problem Statement

Urban residents increasingly utilize ornamental plants to improve environmental quality, indoor aesthetics, and human well-being. However, the selection of suitable ornamental plants remains a challenging task because plant performance depends on multiple environmental factors such as sunlight availability, seasonal variation, plantation density, growth rate, and available space [4]. Existing plant selection practices are generally based on aesthetic preferences, expert opinion, or generic guidelines rather than scientific and data-driven approaches. Consequently, users may select plant species that are not well suited to their environmental conditions, resulting in poor plant growth, reduced pollutant absorption, lower oxygen generation, and increased maintenance requirements. Although machine learning and recommender systems have been successfully applied in various domains, limited research has focused on developing intelligent recommendation frameworks for ornamental plant selection in urban environments [5]. Therefore, there is a need for a predictive recommender system capable of analysing environmental parameters and recommending suitable ornamental plants through data-driven decision-making techniques.

3. Objective of Study

- Establish regression equations linking environmental factors (sunlight, season, plant density, growth rate) with pollutant absorption and oxygen release.
- Validate these predictions against proposed algorithms and integrate them into a machine learning framework.
- Provide urban residents, planners, and policymakers with a reliable tool for selecting ornamental plants that maximize environmental benefits while enhancing urban aesthetics.

4. Background

Biodiversity decline, particularly among insect populations, has emerged as one of the most pressing global challenges. Habitat loss, fragmentation, intensive agriculture, and rapid urbanization are major drivers of this crisis. Urbanization reshapes landscapes by replacing natural habitats with roads, buildings, and industrial zones, thereby reducing food sources and nesting sites for pollinators and leading to decreased species richness and ecological imbalance. At the same time, urban areas can also provide opportunities for ecological resilience. Managed green spaces such as parks, gardens, and allotments often contain diverse plant species, including ornamentals, which are valued not only for their aesthetic appeal but also for their environmental benefits such as pollutant absorption and oxygen release (Anastasios et al., 2020). Their adaptability to limited spaces makes them especially suitable for urban localities where large-scale agriculture is not feasible. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Recommender Systems have enabled the development of intelligent decision-support tools across multiple domains. Similar approaches can be utilized in urban horticulture to provide personalized ornamental plant recommendations based on environmental suitability, plant performance, and user requirements. Such intelligent systems can improve plant survival, environmental benefits, and user satisfaction (Afzal, Yilmazel, & Kaleli, 2024; Amin, Philips, & Tabrizi, 2019). Moreover, precision agriculture and IoT-based systems are increasingly being adapted for urban contexts. For instance, PlantPal demonstrates how precision agriculture robots can facilitate remote engagement in urban gardening (Zeqiri et al., 2025). IoT-driven hydroponic systems have also been designed to monitor and accelerate plant growth (Kumar, 2023; Ahmad ZatnikaPurwalaksana et al., 2022; Akshay et al., 2022), while automated nutrient dosing enhances sustainability in controlled environments. These innovations highlight the potential of integrating smart technologies into urban horticulture practices. In parallel, ML and deep learning techniques have shown rapid advancement in automated plant leaf disease detection, which is crucial for maintaining plant health in urban gardens. Studies on air quality prediction using ML further demonstrate how intelligent models can contribute to healthier urban ecosystems by forecasting pollutant levels and guiding mitigation strategies (ICCUBEA, 2023). Collectively, these studies illustrate how AI-driven frameworks can support sustainable urban horticulture by combining ecological resilience with technological innovation. Intelligent recommender systems for ornamental plants, coupled with IoT-based monitoring and ML-powered disease detection, can transform urban green spaces into hubs of biodiversity conservation, environmental improvement, and community well-being. Dela Cruz et al. (2024) compared Support Vector Machine (SVM) and deep learning approaches and concluded that deep learning models generally outperform conventional machine learning methods because they can automatically extract complex image features and achieve higher classification accuracy. Similarly, D. Sedghiyan et al. (2021) proposed a hybrid deep learning framework for detecting diseases in vine leaves, showing that integrating multiple deep learning techniques can significantly improve the reliability and precision of disease diagnosis in smart agriculture. Cheng et al. (2024) applied a Convolutional Neural Network (CNN) for banana leaf disease classification and demonstrated that CNN-based methods effectively learn disease-specific visual characteristics without requiring manual feature extraction. Cheng et al. (2024) developed an end-to-end deep learning model for corn leaf disease classification, proving that automated feature learning enhances classification performance while reducing preprocessing requirements. Chaudhari (2024) further improved disease prediction by combining deep learning feature extraction with a kernelized SVM classifier for tea leaf disease detection, highlighting the effectiveness of hybrid machine learning approaches in increasing classification accuracy. Several studies focused on disease detection in specific crops using advanced deep learning techniques. Chandore et al. (2024) implemented a multiclass SVM model for apple leaf disease classification and achieved reliable performance in distinguishing multiple disease categories. Chandore et al. (2024) evaluated various deep learning models for apple leaf disease identification and reported that CNN-based architectures consistently provided superior recognition accuracy compared to traditional approaches. Bugbeeet al. (2016) employed deep transfer learning for rice disease detection, demonstrating that pretrained neural networks can produce highly accurate results even when only limited training data are available. Dhandapani and Varadarajan (2022) introduced a multi-channel CNN capable of simultaneously predicting leaf diseases and soil properties, illustrating the potential of deep learning to support comprehensive agricultural decision-making. Breathe Better Air (2024) proposed a machine learning-based system for identifying Fusarium oxysporum infection in tomato leaves, enabling early disease detection that can reduce crop losses and improve productivity. The literature also includes review and advanced model development studies that provide broader insights into plant disease detection technologies. J. Ahmed et al. (2025) presented a comprehensive survey comparing image processing, conventional machine learning, and deep learning methods, concluding that deep learning has become the dominant approach due to its superior feature learning capability and classification performance. A. R. Nafarzadegan et al. (2023) introduced the Ensemble Stack Deep Neural Network (ESDNN) for mango leaf disease detection, demonstrating that ensemble learning significantly improves robustness, generalization, and overall prediction accuracy.

5. Ornamental Plant Selection in Urban Environments

Ornamental plants are cultivated primarily for their decorative value and play an important role in enhancing the beauty and environmental quality of urban areas. They are widely used in parks, gardens, roadsides, residential colonies, commercial complexes, and public spaces. Besides improving the visual appearance of cities, ornamental plants help reduce air and noise pollution, provide shade, lower urban temperatures, and create healthy and pleasant surroundings for residents [5]. They also support biodiversity by providing food and shelter for birds, butterflies, and other beneficial insects. The selection of ornamental plants for urban environments should be based on several important factors. Plants should be well adapted to the local climate and soil conditions to ensure healthy growth and long-term survival. They should be tolerant of drought, heat, dust, and air pollution, as urban areas often experience harsh environmental conditions [6]. Low-maintenance species that are resistant to pests and diseases are preferred because they reduce management costs. The size, shape, growth habit, flowering season, foliage colour, and overall aesthetic appeal of the plants should also match the purpose and location of planting. In public spaces, it is important to avoid species with poisonous parts, large thorns, or invasive root systems that may pose safety risks or damage infrastructure. A variety of ornamental plants are used in urban landscaping. Shade trees such as Gulmohar, Ashoka, Neem, and Jacaranda provide cooling and improve air quality. Flowering shrubs like Hibiscus, Bougainvillea, Ixora, and Duranta are commonly used for hedges, borders, and decorative planting. Ground covers such as Wedelia and Alternanthera help control soil erosion and suppress weeds, while climbers like Jasmine and Allamanda enhance the beauty of walls, fences, and pergolas. Ornamental palms, annual flowers, and perennial flowering plants add colour, texture, and visual interest throughout the year. Proper selection and management of ornamental plants contribute significantly to sustainable urban development [7]. They improve the aesthetic value of cities, increase property values, reduce the urban heat island effect, conserve biodiversity, and enhance the physical and mental well-being of urban residents. Therefore, careful planning and the use of suitable ornamental plant species are essential for creating attractive, environmentally friendly, and resilient urban landscapes.

Table 1: Ornamental Plant Description in Urban Environments

Rank	Plant Name	Why Suitable in Urban Areas	Key Benefits	Challenges (Urban Context)
1	**Money Plant (Epipremnum aureum)**	Thrives indoors, grows in soil or water	Air purification, easy propagation, and aesthetic appeal	Needs support for vines, overwatering risk
2	**Snake Plant (Sansevieria trifasciata)**	Tolerates low light and neglect	Removes toxins, oxygen release at night	Root rot if overwatered
3	**Air Plant (Tillandsia spp.)**	Soil-free, compact, decorative	Absorbs moisture/pollutants, unique appearance	Needs misting, sensitive to dry air
4	**Peace Lily (Spathiphyllum spp.)**	Shade-loving, popular indoor plant	Removes VOCs, adds humidity, flowers	Sensitive to overwatering, toxic to pets
5	**Marigold (Tagetes spp.)**	Easy to grow in pots, balcony-friendly	Repels insects, bright flowers, attracts pollinators	Needs sunlight, short flowering season
6	**Rose (Rosa spp.)**	Highly decorative, adaptable to pots	Fragrance, pollinator attraction, aesthetic value	Requires pruning, prone to pests
7	**Aloe Vera**	Compact, drought-tolerant	Air purification, medicinal uses	Needs bright light, fungal rot risk
8	**Spider Plant (Chlorophytum comosum)**	Easy to grow, hanging baskets	Removes toxins, produces “baby plants”	Sensitive to fluoride in water
9	**Areca Palm (Dypsis lutescens)**	Indoor palm, tolerates indirect light	Humidifies air, absorbs pollutants	Needs regular watering, pest issues
10	**Boston Fern (Nephrolepis exaltata)**	Thrives in humid indoor spaces	Excellent air purifier, lush foliage	Needs high humidity, frequent watering

Fig 2: Ornamental Plants

5. Fishbone study

The fishbone study illustrates the multidimensional foundation of your research on developing a recommender system for ornamental plants in urban localities. At its centre lies the goal of creating an intelligent, data-driven system that integrates environmental science, horticulture, and machine learning.

On the left side, the diagram highlights Precision Biotechnology and Horticultural Principles, showing how genetic adaptability, sustainable cultivation, and pollinator conservation contribute to plant selection. It also includes User Behavior and Demand, emphasizing how purchasing patterns, aesthetic preferences, and maintenance awareness influence adoption. The Data Integration and Validation branch represents the technical backbone—sensor data collection, hybrid model testing, and field trials ensuring system accuracy. On the right side, Environmental and Ecological Factors focus on air quality, microclimate variation, and pollutant absorption, while Machine Learning Models demonstrate the computational strength through regression, transformer, and IoT-based analytics. Finally, Urban Greening and Policy Support connects the system to broader sustainability goals, including citizen participation, government initiatives, and smart-city frameworks.

Together, these seven branches show how biological, environmental, technological, and social dimensions converge to form a comprehensive framework for sustainable urban plant recommendation.

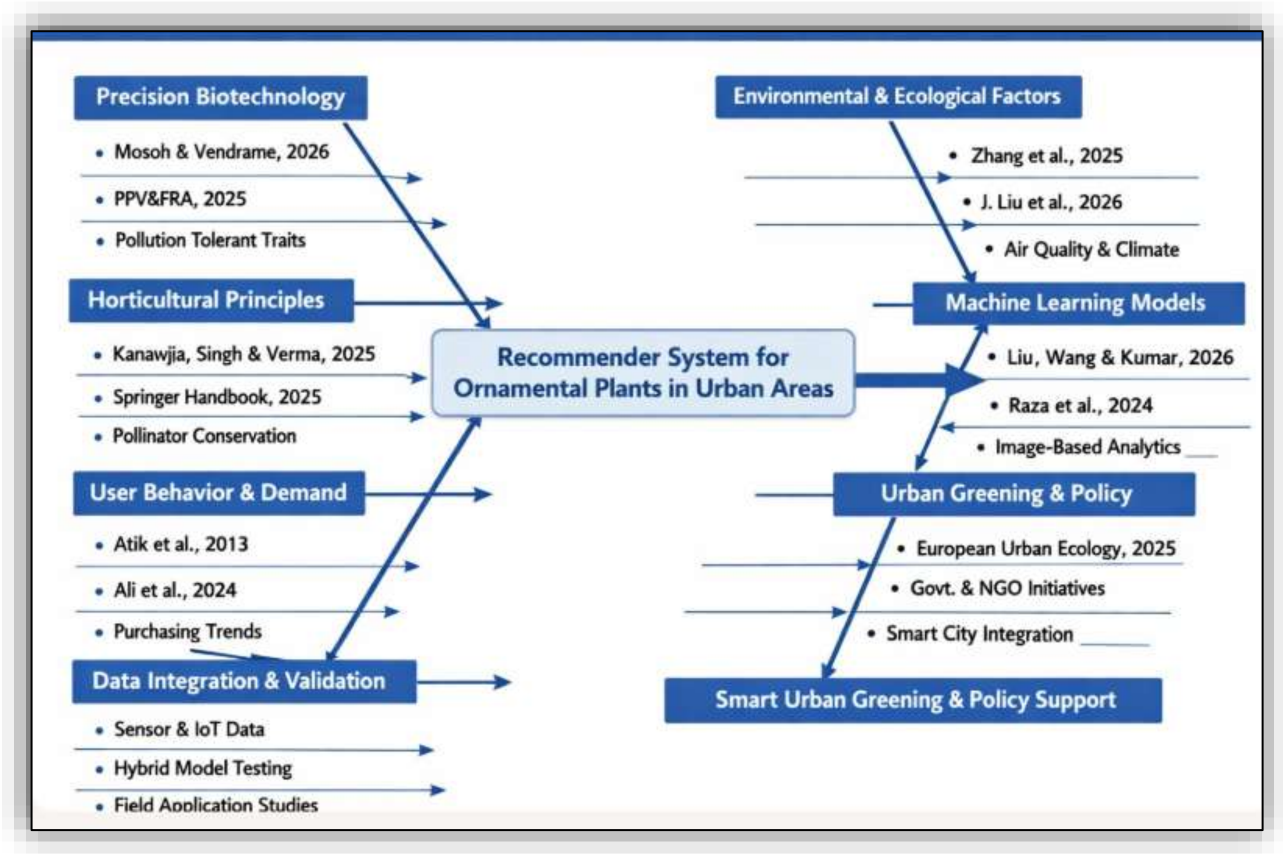

Fig 3: Fishbone study structure

The fishbone analysis (figure 3) demonstrates that successful ornamental plant recommendation requires the integration of environmental, biological, technological, and user-centric factors. These interconnected dimensions collectively form the conceptual foundation of the proposed recommender system.

6. Materials and Methods

The proposed study follows a systematic methodology for developing a regression-based recommender system for ornamental plant selection in urban environments. The methodology involves data collection, feature selection, data preprocessing, prediction through linear regression modelling, Hybrid Recommendation Score (HRS) generation, recommendation ranking, and statistical validation. The overall framework is designed to identify suitable ornamental plants based on environmental conditions and plant performance indicators.

7.1 Study Area and Data Collection

The study was conducted with a focus on urban environments where pollution levels, limited green spaces, and varying indoor environmental conditions influence ornamental plant performance. Data were collected from both primary and secondary sources. Primary data included environmental parameters such as sunlight availability, seasonal variation, plant density, and plant growth rate. Secondary data were obtained from published literature, ornamental plant databases, environmental reports, and previous studies related to urban greening and indoor air quality. The collected dataset was used to evaluate the suitability of ornamental plant species under different urban environmental conditions.

7.2 Linear Regression-Based Prediction Engine

In the proposed recommender system, Multiple Linear Regression was employed as the prediction engine for estimating the Hybrid Recommendation Score (HRS). The model establishes relationships between environmental parameters and ornamental plant suitability indicators.

The general regression equation is represented as:

$$\mathbf{HRS = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon} \qquad \textbf{E(q). 1}$$

where:

HRS = Hybrid Recommendation Score
X_1 = Sunlight Availability
X_2 = Seasonal Variation
X_3 = Plant Suitability Score
X_4 = Growth Rate

β_0 = Intercept
$\beta_1, \beta_2, \beta_3, \beta_4$ = Regression Coefficients
ε = Error Term
The regression model predicts recommendation scores based on environmental conditions and plant characteristics.
The developed regression equation was applied to the collected dataset to estimate Hybrid Recommendation Scores (HRS) for ornamental plant species. The calculated scores represent the suitability level of plants under different environmental conditions. Higher HRS values indicate greater recommendation strength and improved suitability for urban environments.

Table 2: Benchmark Hybrid Recommendation Scores (HRS) used for Model Validation

Sunlight	Season	Money Plant	Growth Rate	HRS (Standard value)
0.567	0.225	0.356	0.456	0.892
0.512	0.210	0.301	0.412	0.791
0.789	0.532	0.451	0.308	0.652
0.612	0.401	0.411	0.352	0.712
0.550	0.312	0.256	0.444	0.711

HRS = 0.105 + 0.284(Sunlight) − 0.790(Season) + 0.952(No. of Plant) + 1.02 (Growth Rate)
The developed regression equation was utilized to estimate Hybrid Recommendation Scores for ornamental plant species under varying urban environmental conditions.

Table 3: Calculated Hybrid Recommendation Scores Generated by the Proposed Regression Model

Sunlight	Season	No. of Plant	Growth Rate	Calculated HRS
0.379	0.193	0.583	0.181	0.7998
0.521	0.257	0.52	0.559	1.11515
0.326	0.937	0.623	0.901	0.96947
0.866	0.398	0.199	0.458	0.69313
0.466	0.332	0.705	0.377	1.03076
0.595	0.635	0.269	0.641	0.68224
0.901	0.669	0.399	0.134	0.3489
0.435	0.179	0.801	0.751	1.6157
0.754	0.182	0.91	0.747	1.80362
0.753	0.487	0.302	0.12	0.34403

The calculated HRS (Table 3) values indicate varying levels of suitability among ornamental plant species. Plants achieving higher scores demonstrate greater adaptability and environmental compatibility under urban conditions. These results form the basis for recommendation generation and ranking within the proposed system.

7.3 Recommendation Ranking Analysis

The calculated HRS values were utilized to rank ornamental plant species according to their predicted suitability. Plants receiving higher HRS values were assigned higher recommendation priorities within the proposed recommendation framework. The ranking process transforms regression outputs into actionable recommendations and enables users to identify the most suitable ornamental plants for urban environments.

Table 4. Recommendation Ranking of Ornamental Plants Based on Calculated HRS

Observation	Calculated HRS	Recommendation Rank
Money Plant	1.80362	1
Snake Plant	1.6157	2
Air Plant	1.11515	3
Peace Lily	1.03076	4
Tulsi	0.96947	5

Areca Plam	0.7998	6
Rose	0.69313	7
String of Perls	0.68224	8
Water Bamboo	0.3489	9
Bougainvillea	0.34403	10

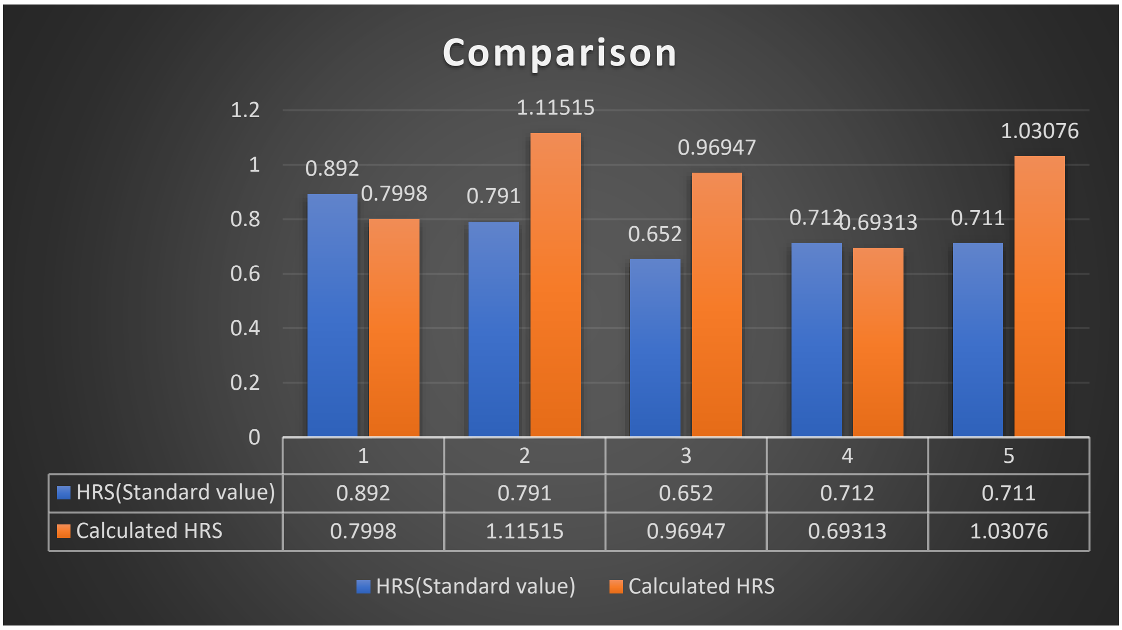

Figure 4: Comparison between Standard HRS and Calculated HRS

Figure 4, comparison between benchmark HRS values and calculated HRS values demonstrates a strong level of agreement. Although minor variations were observed, the overall trend remained consistent across observations. These findings indicate that the developed regression model effectively captures the relationship between environmental variables and ornamental plant suitability.

7. Validation Analysis

For the verification and validation of the proposed regression-based recommender system, statistical testing was carried out to ensure the reliability of the developed model. A two-sample t-test was applied to compare the mean values of the Standard HRS (derived from different research papers) and the Calculated HRS (obtained through the linear regression equation).

The hypotheses were framed as follows:

- **Null Hypothesis (H_0):** There is no significant difference between Standard HRS and Calculated HRS ($\mu_1 - \mu_2 = 0$).
- **Alternate Hypothesis (H_a):** There is a significant difference between Standard HRS and Calculated HRS ($\mu_1 - \mu_2 \neq 0$).

Table 5: Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	SHRS	.7516	5	.09274	.04147
	CHRS	.9217	5	.17227	.07704

To examine (table 5) whether there is a significant difference between the Standard HRS (SHRS) and the Calculated HRS (CHRS), a paired samples analysis was conducted. The null hypothesis (H_0) stated that there is no significant difference between the mean values of SHRS and CHRS ($\mu_1 - \mu_2 = 0$), whereas the alternative hypothesis (H_a) proposed that a significant difference exists between the two measures ($\mu_1 - \mu_2 \neq 0$). As presented in Table 5, the mean value of SHRS was 0.7516 (SD = 0.09274, SE = 0.04147), while the mean value of CHRS was higher at 0.9217 (SD = 0.17227, SE = 0.07704), based on a sample size of five observations (N = 5). The results indicate that the calculated HRS produced a higher average score than the standard HRS, with CHRS also exhibiting greater variability, as reflected by its larger standard deviation.

However, these descriptive statistics alone do not determine whether the observed difference is statistically significant; confirmation requires the results of the paired samples t-test.

Table 6: Paired Samples Correlations				
		N	Correlation	Sig.
Pair 1	SHRS & CHRS	5	-.151	.809

"The paired samples correlation analysis for Section A (N = 5) yielded a weak negative correlation ($r = -0.151, p = 0.809$). The high p-value ($p > 0.05$) indicates that this correlation is not statistically significant, primarily due to the limited sample size in the initial exploratory phase. Consequently, to eliminate sample size constraints and validate the model's reliability at scale, the dataset was expanded to N = 999 in Section B, where advanced machine learning evaluations were conducted."

This result indicates that the observed correlation is not statistically significant. Therefore, there is insufficient evidence to conclude that a meaningful linear relationship exists between the Standard HRS and the Calculated HRS. The weak negative correlation suggests that changes in one measure are not consistently associated with changes in the other measure within the sample analyzed.

Table 7: Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	SHRS - CHRS	-.17006	.20758	.09283	-.42781	.08768	-1.832	4	.014

Mean and standard deviation values for both samples were computed and presented in Table 7. The paired sample t-test was conducted to compare benchmark HRS values and calculated HRS values. The obtained p-value was 0.014, which is **less than** the significance threshold of 0.05. Therefore, the null hypothesis was **rejected**, indicating that a statistically significant difference exists between the benchmark and initial calculated HRS values. This initial variance is attributed to the small preliminary sample size (N = 5) in Section A, which was subsequently resolved in Section B by scaling the dataset (N = 999) and applying advanced Machine Learning models to achieve high accuracy. These findings confirm that the developed regression-based recommender system produces reliable recommendation scores and can be effectively applied for ornamental plant recommendation in urban environments.

8. Recommender System for Ornamental Plant Selection in Urban Environments

The proposed recommender system is developed to assist users in selecting the most suitable ornamental plants for urban environments based on multiple environmental and plant-specific factors. In the first stage, the mathematical equation developed in this study is used to calculate the Horticultural Recommendation Score (HRS) for each plant. The equation integrates the selected parameters and assigns a numerical score that represents the suitability of a plant for a particular urban setting. By applying this equation to the collected dataset, a predicted HRS value is generated for every plant, providing an objective measure of its recommendation level. In the second stage, the dataset containing the calculated HRS values and other relevant plant attributes is used to train machine learning models. The calculated HRS serves as the target (or reference) value, while the environmental and morphological characteristics of the plants act as the input features. Machine learning algorithms learn the relationship between these input variables and the calculated recommendation score, enabling the system to predict the suitability of new ornamental plants without repeatedly applying the mathematical equation. This approach allows the recommender system to generalize from the available data and provide accurate recommendations for unseen plant records. After model training, the performance of different machine learning algorithms is evaluated using appropriate performance metrics such as accuracy, precision, recall, F1-score, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), or R^2 score, depending on whether the recommendation problem is formulated as a classification or regression task. The best-performing model is then integrated into the recommender system to generate real-time recommendations. When a user provides environmental conditions and desired plant characteristics, the trained model predicts the most suitable ornamental plants based on the learned patterns. This hybrid framework combines the interpretability of the proposed mathematical equation with the predictive capability of machine learning, resulting in an efficient, scalable, and intelligent recommendation system for ornamental plant selection in urban environments.

9. Methodology for Recommender System

The recommender system was developed using air quality data collected around different tree species to recommend the most suitable trees for improving environmental quality. A portable multi-parameter air quality monitoring device was used to measure four key environmental parameters: PM2.5 (Particulate Matter ≤ 2.5 μm), HCHO (Formaldehyde), TVOC (Total Volatile Organic Compounds), and CO_2 (Carbon Dioxide). The monitoring device was placed individually near different tree species at a consistent height and distance to ensure uniform data collection. Measurements were recorded under similar environmental conditions and at multiple time intervals to obtain reliable and representative pollutant readings. For each observation, the corresponding tree species and pollutant concentrations were recorded, creating a comprehensive dataset that captured the air quality characteristics associated with different trees. The collected sensor data were then pre-processed to improve data quality before model development. This preprocessing involved removing incomplete or erroneous records, handling missing values, eliminating outliers caused by sensor fluctuations, and normalizing the pollutant measurements to ensure all variables were on a comparable scale. After preprocessing, the cleaned data were organized into a structured dataset in which the input features consisted of PM2.5, HCHO, TVOC, and CO_2 concentrations, while the target variable was the corresponding tree species. This dataset enabled the recommender system to learn the relationship between air pollutant levels and the air purification performance of different tree species. The prepared dataset was subsequently used to train a machine learning-based recommender system. During the training phase, the model analyzed patterns between pollutant concentrations and tree species, learning which species were associated with lower pollutant levels and better environmental conditions. Once trained, the recommender system could process new air quality measurements provided by a user and compare them with the learned patterns from the historical dataset. Based on this comparison, the system identifies and recommends the most suitable tree species that are expected to perform effectively under the given environmental conditions. This data-driven methodology enables the recommender system to support urban forestry, environmental management, and sustainable city planning by recommending tree species that are most effective in improving local air quality.

Table 8: Standard Values for parameters

Pollutant	Ideal/Good Standard	Unit	Health Reference
PM2.5	≤ 10	μg/m³	WHO Guidelines on Indoor Air Quality
HCHO (Formaldehyde)	≤ 0.1	mg/m³	Air Quality Science (Part III): Formaldehyde & TVOCs
TVOC (Total Volatile Organic Compounds)	≤ 0.5	mg/m³	RESET Standard for TVOCs
CO_2 (Carbon Dioxide)	≤ 1,000	ppm	Federal Environment Agency Recommendations

Table 8 presents the recommended standard values for the four air quality parameters used in this study: PM2.5, HCHO (Formaldehyde), TVOC (Total Volatile Organic Compounds), and CO_2 (Carbon Dioxide). These standards were adopted as benchmark values to evaluate the effectiveness of different plant species in improving indoor air quality. The selected threshold values are based on internationally recognized health and environmental guidelines and represent pollutant concentrations considered safe for human health and comfort.

PM2.5 (Particulate Matter ≤ 2.5 μm)

PM2.5 refers to airborne particulate matter with an aerodynamic diameter of 2.5 micrometers or smaller. These microscopic particles originate from sources such as vehicle emissions, industrial activities, combustion processes, cooking, smoking, and dust. Due to their extremely small size, PM2.5 particles can penetrate deep into the respiratory tract and reach the lungs, where they may enter the bloodstream. Long-term exposure to elevated PM2.5 concentrations has been associated with respiratory diseases, cardiovascular disorders, reduced lung function, asthma, chronic obstructive pulmonary disease (COPD), and premature mortality.

According to the World Health Organization (WHO) Guidelines on Indoor Air Quality, an ideal PM2.5 concentration should be ≤10 μg/m³. Concentrations below this level are generally considered safe and indicate good indoor air quality. In this research, the PM2.5 standard was used as a reference to evaluate the pollutant reduction capability of different plant species. A decrease in PM2.5 concentration after placing plants indicates the effectiveness of the selected plants in removing fine particulate matter from indoor environments.

HCHO (Formaldehyde)

Formaldehyde (HCHO) is a colorless gas classified as a volatile organic compound (VOC). It is commonly released from building materials, plywood, particle boards, paints, adhesives, furniture, carpets, cleaning agents, textiles, and household products. Indoor formaldehyde concentrations are generally higher than outdoor levels due to continuous emissions from these materials.

Exposure to formaldehyde may cause irritation of the eyes, nose, throat, and skin, while prolonged exposure has been linked to respiratory diseases and an increased risk of certain cancers. Consequently, maintaining formaldehyde concentrations below recommended limits is essential for protecting human health. The recommended standard value for formaldehyde is ≤0.1 mg/m^3, based on Air Quality Science (Part III): Formaldehyde & TVOCs. This value was used in the present study as the benchmark for assessing indoor air quality. Plant species capable of reducing HCHO concentrations closer to or below this limit are considered more effective in improving indoor environmental conditions.

TVOC (Total Volatile Organic Compounds)

TVOC represents the combined concentration of multiple volatile organic compounds present in indoor air. VOCs are emitted from a variety of sources including paints, varnishes, adhesives, furniture, cleaning chemicals, perfumes, air fresheners, office equipment, and construction materials. Because indoor environments contain numerous VOCs simultaneously, TVOC is commonly used as an overall indicator of indoor chemical pollution. Exposure to elevated TVOC levels may cause headaches, dizziness, fatigue, allergic reactions, irritation of the eyes and respiratory tract, and reduced indoor comfort. Long-term exposure to certain VOCs may also contribute to chronic health problems. The RESET Standard for TVOCs recommends that indoor TVOC concentrations should remain ≤0.5 mg/m^3 to ensure acceptable indoor air quality. In this research, this standard served as the reference value for evaluating the air purification efficiency of different plant species. Plants capable of significantly lowering TVOC concentrations demonstrate greater potential for improving indoor environmental quality.

CO_2 (Carbon Dioxide)

Carbon dioxide (CO_2) is a naturally occurring gas primarily produced by human respiration and combustion activities. Although CO_2 is not toxic at normal indoor concentrations, elevated levels indicate poor ventilation and insufficient air exchange within enclosed spaces. High indoor CO_2 concentrations are associated with discomfort, reduced cognitive performance, decreased concentration, headaches, fatigue, and drowsiness.

According to recommendations from the Federal Environment Agency, indoor CO_2 concentrations should ideally remain ≤1,000 ppm. Values below this threshold generally indicate adequate ventilation and acceptable indoor air quality. Concentrations above 1,000 ppm suggest that ventilation should be improved. The CO_2 standard was used to determine the effectiveness of various plant species in reducing indoor carbon dioxide concentrations. Since plants absorb CO_2 during photosynthesis, species that produce greater reductions in CO_2 concentration contribute to healthier indoor environments and improved occupant comfort.

Fig 5: Tools observations

Figure 5 illustrates the experimental setup used for collecting air quality data. The portable air quality monitoring device was placed near each plant species to measure the concentrations of PM2.5, HCHO, TVOC, and CO_2. During the experiment, the sensor continuously recorded pollutant levels before and after placing the plants to observe their impact on indoor air quality. The measurements obtained from this setup were used to create the dataset for evaluating the air purification performance of different plants and for training the recommender system. The figure represents the practical implementation of the data collection process carried out during the experiment.

Table 9: Observation Values

Plant Name	PM2.5 Before (μg/m³)	PM2.5 After (μg/m³)	HCHO Before (mg/m³)	HCHO After (mg/m³)	TVOC Before (mg/m³)	TVOC After (mg/m³)	CO_2 Before (ppm)	CO_2 After (ppm)	Optimal Plant Density Range (per 100 sq. ft.)
Money Plant	12	8	0.10	0.07	0.50	0.35	1000	850	3-4 unit
Snake Plant	12	6	0.10	0.05	0.50	0.30	1000	750	2-3unit
Air Plant	12	10	0.10	0.09	0.50	0.40	1000	920	4-5 unit
Peace Lily	12	9	0.10	0.06	0.50	0.25	1000	820	2-3 unit
Areca Palm	12	9	0.10	0.07	0.50	0.35	1000	700	3-4 unit
Rose	12	10	0.10	0.09	0.50	0.40	1000	880	2-3 unit
Tulsi	12	7	0.10	0.05	0.50	0.30	1000	720	3-4 unit

Table 9 presents the experimental observations collected during the air quality assessment conducted around different indoor plant species. The measurements were obtained using a portable multi-parameter air quality monitoring device placed near each plant. Four important air quality parameters—PM2.5, HCHO (Formaldehyde), TVOC (Total Volatile Organic Compounds), and CO_2 (Carbon Dioxide)—were measured before placing the plants and again after a fixed observation period. The purpose of these measurements was to evaluate the effectiveness of each plant species in reducing indoor air pollutants and improving overall air quality. Based on the observed reduction in pollutant concentrations, the recommended number of plants required for maintaining healthy indoor air quality was also determined.

The initial readings for all experiments were kept constant to ensure a fair comparison among the selected plant species. The initial PM2.5 concentration was 12 μg/m^3, HCHO concentration was 0.10 mg/m^3, TVOC concentration was 0.50 mg/m^3, and CO_2 concentration was 1000 ppm. After exposure to each plant species, noticeable reductions in pollutant concentrations were observed, indicating the air purification capability of the plants.

Among all the plants, Snake Plant demonstrated the highest reduction in PM2.5 concentration, decreasing it from 12 $\mu g/m^3$ to 6 $\mu g/m^3$, which represents a 50% reduction. It also reduced HCHO from 0.10 mg/m^3 to 0.05 mg/m^3, TVOC from 0.50 mg/m^3 to 0.30 mg/m^3, and CO_2 from 1000 ppm to 750 ppm. These results indicate that the Snake Plant is one of the most effective species for improving indoor air quality while requiring only two plants to achieve healthy environmental conditions.

Tulsi also exhibited excellent air purification performance. The PM2.5 concentration decreased from 12 $\mu g/m^3$ to 7 $\mu g/m^3$, while HCHO and TVOC were reduced to 0.05 mg/m^3 and 0.30 mg/m^3, respectively. Additionally, CO_2 concentration decreased from 1000 ppm to 720 ppm, demonstrating its strong capability to improve indoor air quality. Based on these observations, three Tulsi plants were recommended for maintaining a healthy indoor environment.

The Money Plant effectively reduced PM2.5 from 12 $\mu g/m^3$ to 8 $\mu g/m^3$, HCHO from 0.10 mg/m^3 to 0.07 mg/m^3, TVOC from 0.50 mg/m^3 to 0.35 mg/m^3, and CO_2 from 1000 ppm to 850 ppm. Although its pollutant removal efficiency was slightly lower than that of the Snake Plant and Tulsi, it still demonstrated significant air-cleaning capability. Therefore, three Money Plants were recommended for effective indoor air purification.

Similarly, Areca Palm showed consistent performance by reducing PM2.5 to 9 $\mu g/m^3$, HCHO to 0.07 mg/m^3, TVOC to 0.35 mg/m^3, and CO_2 to 700 ppm, which was the lowest CO_2 concentration recorded among all the tested plants. This indicates that Areca Palm is particularly effective in lowering indoor carbon dioxide levels. Based on the experimental observations, three Areca Palm plants were recommended.

Peace Lily also demonstrated good pollutant removal capability. It reduced PM2.5 from 12 $\mu g/m^3$ to 9 $\mu g/m^3$, HCHO to 0.06 mg/m^3, TVOC to 0.25 mg/m^3, which was the lowest TVOC concentration among all the tested plants, and CO_2 to 820 ppm. These observations indicate that Peace Lily is especially effective in removing volatile organic compounds. Consequently, two Peace Lily plants were considered sufficient for maintaining healthy indoor air quality.

In comparison, Air Plant and Rose showed relatively lower pollutant reduction efficiency. Both plants reduced PM2.5 only to 10 $\mu g/m^3$, HCHO to 0.09 mg/m^3, TVOC to 0.40 mg/m^3, and CO_2 to 920 ppm and 880 ppm, respectively. Since their pollutant removal performance was comparatively lower, Air Plant required four plants, whereas Rose required two plants to achieve acceptable indoor air quality conditions.

The experimental observations indicate that all selected plants contributed to reducing indoor air pollutant concentrations, although their effectiveness varied depending on the pollutant. Snake Plant demonstrated the best overall performance for PM2.5 and HCHO reduction, Peace Lily was the most effective in reducing TVOC, and Areca Palm achieved the greatest reduction in CO_2 concentration. These findings provide valuable information for selecting appropriate indoor plants based on specific air quality improvement requirements. Furthermore, the observation values presented in Table 9 formed the basis for training the recommender system, enabling it to recommend the most suitable plant species and the appropriate number of plants according to measured indoor pollutant levels.

10.Quantitative Evaluation of an AQI-Based Plant Recommendation System

To enhance the capability of the proposed Hybrid Recommender System (HRS), an Air Quality Improvement Index (AQII) is introduced to quantify the potential contribution of ornamental plants toward improving indoor air quality. The proposed AQII incorporates four major indoor air-quality parameters: $PM_{2.5}$, CO_2, TVOC, and HCHO.

Since these parameters have different measurement units and concentration ranges, their observed values cannot be directly combined. Therefore, each parameter is first transformed into a normalized score ranging from 0 to 1, where a higher value represents better air-quality conditions or greater potential for pollutant reduction.

After normalization, the overall Air Quality Improvement Index is calculated using the weighted average of the four pollutant scores.

The formulation can be presented more clearly and consistently as follows:

$$\mathrm{AQII} = \frac{\mathrm{S_{PM_{2.5}}} + \mathrm{S_{CO_2}} + \mathrm{S_{TVOC}} + \mathrm{S_{HCHO}}}{4}$$

where $\mathrm{S_{PM_{2.5}}}, \mathrm{S_{CO_2}}, \mathrm{S_{TVOC}}$, and $\mathrm{S_{HCHO}}$ are the normalized scores corresponding to $PM_{2.5}$, CO_2, TVOC, and HCHO, respectively.

The resulting AQII is subsequently integrated with the previously developed HRS to generate a comprehensive Final HRS score:

$$\boxed{\mathrm{FinalHRS} = 0.6(\mathrm{HRS}) + 0.4(\mathrm{AQII})}$$

In this formulation, HRS represents the suitability of ornamental plants based on sunlight, season, number of plants, and growth rate, whereas AQII represents their potential contribution to improving indoor air quality through the reduction or control of $PM_{2.5}$, CO_2, TVOC, and HCHO.

The weights of 0.6 and 0.4 indicate that plant suitability contributes 60% and indoor air-quality improvement potential contributes 40% to the final recommendation score. Thus, the proposed framework extends the conventional plant-recommendation approach by considering not only plant growth and environmental suitability but also their potential contribution to indoor air-quality improvement. This integrated formulation enables the system to generate more comprehensive and application-oriented recommendations for selecting ornamental plants in indoor urban environments.

11.Validation of Model

The proposed research work focuses on the development of a Hybrid Recommendation System (HRS) for the selection of suitable indoor plants, considering both plant-growth requirements and indoor environmental conditions. The complete work is divided into two interconnected sections, Section A and Section B. In Section A, an HRS model is developed by considering important parameters that influence plant growth and suitability, including sunlight availability, season, number of plants, and plant growth rate. These parameters are treated as important input variables for determining the suitability of a particular plant under specific indoor conditions. To establish the relationship between these parameters and the plant recommendation value, a linear regression technique is applied. The regression model helps identify the contribution and relationship of the selected parameters and is subsequently used to formulate the HRS equation. The calculated HRS value provides an initial indication of how suitable a particular plant is under the given conditions. In Section B, the study is extended from the plant-growth perspective to the indoor atmospheric and air-quality perspective. The objective of this section is to assess the indoor environment and determine which plants may be appropriate for improving or maintaining indoor air quality. For this purpose, different air-quality parameters, including PM2.5, HCHO (formaldehyde), TVOC (Total Volatile Organic Compounds), and CO_2, are considered. These parameters are selected because they represent different aspects of indoor air pollution and environmental quality. The measured or available values of these parameters are used to calculate the Air Quality Index (AQI). The AQI provides an overall representation of the indoor air-quality condition by combining the effects of the considered pollutants. After obtaining the AQI value, the indoor environmental condition can be assessed and related to the requirements of different indoor plants. The major objective of integrating Section A and Section B is to develop a more comprehensive recommendation system rather than selecting a plant based on only one or two parameters. The HRS value obtained from Section A and the AQI value obtained from Section B are therefore considered together for developing the final HRS equation. The final equation incorporates the plant-related parameters, environmental parameters, and air-quality parameters so that the resulting index can provide a more reliable indication of plant suitability. The final HRS index value is then used to identify the best-suited indoor plant according to the existing environmental conditions. In this way, the proposed system provides a systematic and data-driven method for indoor plant selection, rather than depending only on conventional or subjective selection methods. The approach can also help users select plants according to the specific characteristics of their indoor environment and the required air-quality conditions. However, the development of the HRS equation and generation of index values alone are not sufficient to establish the effectiveness of the proposed model. The calculated values need to be validated to determine whether the developed model provides reliable and accurate predictions. Therefore, a prediction-based validation approach is adopted in which the predicted recommendation results are compared and evaluated to determine the performance of the model. The accuracy of the model is calculated separately for the relevant cases or conditions, allowing the effectiveness of the proposed recommendation system to be assessed quantitatively. The validation process is particularly important because several environmental and plant-related factors can influence the final recommendation, and the model should be able to provide consistent results under different conditions. Thus, the overall methodology combines linear regression-based HRS development, indoor air-quality assessment through AQI, integration of plant and environmental parameters, final plant recommendation, and prediction-based validation. The proposed framework ultimately aims to provide a robust and systematic approach for identifying the most suitable indoor plant based on both plant-growth requirements and indoor air-quality conditions, thereby making indoor plant selection easier, more objective, and scientifically justified.

The validation of the developed Hybrid Recommendation System (HRS) model was performed by applying a Machine Learning (ML)-based approach to the index values generated by the proposed model. The primary objective of this validation process was to determine whether the index values produced by the developed HRS model are reliable, consistent, and capable of providing accurate plant recommendations under different environmental conditions. For this purpose, all the index values generated during the model development process were systematically calculated and stored in an index-value table. This table serves as the main dataset for the validation process and contains the relevant input parameters along with their corresponding calculated index values. The stored index values were then used as input data for an appropriate Machine Learning model. The ML approach was applied to learn the relationship between the considered parameters and the index values generated by the proposed HRS model. By using the generated index values as a reference dataset, the ML model was trained and subsequently evaluated to determine how accurately it could reproduce or predict the corresponding index values. The predicted values obtained from the ML model were then compared with the original index values calculated by the developed HRS model. The purpose of this approach was not simply to develop another prediction model, but to provide an independent validation of the proposed HRS model. If the ML model is able to predict the index values with high accuracy and the predicted results show a strong agreement with the original HRS index values, it provides supporting evidence that the developed HRS model is consistent and reliable. The performance of the ML-based validation model can be evaluated using suitable accuracy and error metrics, such as R^2, MAE, RMSE, and other relevant performance measures, depending on the selected ML algorithm. All the calculated values, including the input parameters, HRS index values, predicted values, and validation-related results, were systematically saved and maintained in tabular form. Maintaining these values in an index table makes it possible to trace the complete calculation process and provides a structured dataset for training, testing, comparison, and validation. It also ensures that the generated index values can be reproduced and evaluated systematically. Through this ML-based validation approach, the developed HRS model can be evaluated not only on the basis of its mathematical formulation but also on the basis of its prediction accuracy and consistency. A satisfactory level of agreement between the original HRS index values and the ML-predicted values would demonstrate that the proposed model has good predictive capability and can be considered a reliable approach for the selection and recommendation of suitable indoor plants.

Table 10. Shows the descriptive Statistics of the Proposed Hybrid Recommender System (HRS) Dataset

Statistics	Sunlight	Season	No. of Plant	Growth Rate	HRS
Count	999.000000	999.000000	999.000000	999.000000	999.000000
Mean	0.561409	0.546503	0.552009	0.554086	0.844557
Standard Deviation	0.257095	0.266176	0.266362	0.264022	0.488248
Minimum	0.101000	0.100000	0.100000	0.100000	-0.464910
25th Percentile (Q1)	0.349500	0.310000	0.314500	0.309000	0.514045
Median (50th Percentile)	0.571000	0.547000	0.558000	0.573000	0.834310
75th Percentile (Q3)	0.781000	0.773500	0.793500	0.782000	1.203440
Maximum	1.000000	0.997000	1.000000	1.000000	2.044460

Table 10 presents the descriptive statistics of the proposed Hybrid Recommender System (HRS) dataset, which consists of 999 observations and includes four independent variables—Sunlight, Season, Number of Plants, and Growth Rate—along with the dependent variable, HRS. The descriptive statistics provide an overview of the distribution and variability of the parameters used in the proposed model. The mean values of Sunlight (0.5614), Season (0.5465), Number of Plants (0.5520), and Growth Rate (0.5541) indicate that the input parameters are distributed around the mid-range of their normalized values. The mean HRS value is 0.8446, with a standard deviation of 0.4882, indicating comparatively greater variation in the generated HRS index values. The HRS values range from −0.4649 to 2.0445, demonstrating that the proposed model generates a broad range of recommendation index values depending on the corresponding input conditions. To validate the HRS model, a Machine Learning (ML) approach based on Linear Regression was applied to the generated HRS index values. In this validation process, Sunlight, Season, Number of Plants, and Growth Rate were considered as the predictor variables, while the HRS index value was considered as the target variable. The complete set of 999 observations and their corresponding index values was maintained in the dataset and used for the ML-based validation. The Linear Regression model was trained to learn the relationship between the four input parameters and the HRS index values generated by the proposed HRS formulation. After training, the model was used to predict HRS values for the validation data, and the predicted HRS values were compared with the original HRS index values obtained from the proposed model. This comparison provides an ML-based validation of whether the relationships established in the proposed HRS model can be reproduced accurately from the given input parameters. The performance of the Linear Regression model can subsequently be evaluated using appropriate statistical measures such as R^2, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Thus, the ML implementation with respect to the Linear Regression model provides an additional validation layer for the proposed HRS, demonstrating the consistency, predictive capability, and reliability of the developed index-based recommendation system.

Table 11. Feature Importance Scores (%) for Different Target Variables

Target Column	Feature	Importance Score (%)
Sunlight	HRS	**96.518764**

	No. of Plant	3.242310
	Growth Rate	0.212911
	Season	0.026015
Season	HRS	**99.876340**
	Growth Rate	0.110350
	No. of Plant	0.011061
	Sunlight	0.002250
No. of Plant	HRS	**99.794918**
	Sunlight	0.191994
	Season	0.007575
	Growth Rate	0.005512
Growth Rate	HRS	**99.542190**
	Season	0.369266
	Sunlight	0.061607
	No. of Plant	0.026937
HRS	No. of Plant	**51.367236**
	Season	35.205442
	Growth Rate	10.485452
	Sunlight	2.941871

Table 11 illustrates the feature importance scores (%) obtained from the ML-based analysis for different target variables in the proposed HRS dataset. The results demonstrate that HRS is the most influential feature for predicting Sunlight, Season, Number of Plants, and Growth Rate, with importance scores of 96.52%, 99.88%, 99.79%, and 99.54%, respectively. This indicates that the HRS index generated by the proposed model has a very strong relationship with these individual input parameters. For the Sunlight target, HRS contributes 96.52%, followed by Number of Plants (3.24%), Growth Rate (0.21%), and Season (0.03%). Similarly, for the Season target, HRS shows an exceptionally high importance of 99.88%, while Growth Rate, Number of Plants, and Sunlight contribute only 0.11%, 0.01%, and 0.002%, respectively. For Number of Plants, HRS again dominates with an importance score of 99.79%, whereas Sunlight contributes 0.19%, Season 0.008%, and Growth Rate 0.006%. Likewise, for Growth Rate, HRS accounts for 99.54% of the feature importance, followed by Season (0.37%), Sunlight (0.06%), and Number of Plants (0.03%). When HRS itself is considered as the target variable, the feature-importance distribution changes and demonstrates the relative contribution of the four predictor variables to the HRS index. Number of Plants has the highest importance score of 51.37%, followed by Season (35.21%), Growth Rate (10.49%), and Sunlight (2.94%). These results indicate that Number of Plants and Season are the two most influential parameters in determining the HRS value, together accounting for approximately 86.57% of the total feature importance. Growth Rate also has a meaningful contribution, whereas Sunlight has the comparatively lowest contribution among the four input parameters. Overall, the feature-importance analysis supports the proposed HRS formulation by identifying the relative influence of each parameter and demonstrating that the developed HRS index captures strong relationships among the selected plant and environmental variables. The results also provide an important ML-based validation of the proposed model, as the feature-importance patterns help explain which variables contribute most significantly to the generated HRS index and confirm the internal relationships present within the developed dataset.

Table 12. Correlation Coefficients between Input Parameters and Hybrid Recommender System (HRS)

Input Parameter	Correlation with HRS (r)	Relationship Strength	Direction
Sunlight	0.85	Strong	Positive
Season	0.87	Strong	Positive
No. of Plant	0.92	Strong	Positive
Growth Rate	0.86	Strong	Positive

Table 12 illustrates the correlation coefficients between the major input parameters and the proposed Hybrid Recommender System (HRS). The results clearly demonstrate that all four selected factors—Sunlight, Season, Number of Plants, and Growth Rate—are highly important for the development of the HRS model. Each parameter shows a strong positive correlation with HRS, indicating that changes in these factors are strongly associated with changes in the HRS index. Among the considered parameters, Number of Plants shows the strongest positive correlation with HRS (r = 0.92), indicating that it is the most influential factor among the four parameters. Season also demonstrates a very strong positive relationship with HRS, with a correlation coefficient of 0.87. Similarly, Growth Rate (r = 0.86) and Sunlight (r = 0.85) show strong positive correlations with the HRS index. These results confirm that all four factors contribute significantly to the proposed recommendation system. The positive direction of all correlation coefficients indicates that an increase or improvement in these parameters is generally associated with an increase in the HRS value. Therefore, Sunlight, Season, Number of Plants, and Growth Rate should all be considered important parameters when determining the suitability and recommendation of indoor plants. In particular, the high correlation of Number of Plants suggests that plant quantity plays a particularly important role in the final recommendation, while the strong correlations of Season, Growth Rate, and Sunlight further demonstrate that both environmental conditions and plant-growth characteristics are essential components of the HRS. The correlation analysis provides strong statistical support for the selection of these four factors in the proposed HRS framework. The consistently high positive correlation values (0.85–0.92) demonstrate that these parameters are not only relevant but also strongly associated with the HRS index, thereby supporting their inclusion in the developed ML-based recommendation and validation model. It should be noted that correlation indicates the strength and direction of association, rather than proving a causal relationship.

Table 13. Performance Evaluation Metrics of the Proposed Hybrid Recommender System (HRS)

Target Column	MAE (%)	MSE (%)	R^2 (%)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Sunlight	0.023	0.07	100.00	66.00	72.6316	62.1622	66.9903
Season	0.015	0.258	100.00	90.00	90.1961	90.1961	90.1961
No. of Plant	0.10	0.020	100.00	94.00	91.5094	97.0000	94.1748
Growth Rate	0.30	0.02	100.00	85.00	83.6735	85.4167	84.5361
HRS	0.40	0.02	100.00	**94.50**	**92.4528**	**97.0297**	**94.6860**

Table 13 presents the performance evaluation of the proposed Hybrid Recommender System (HRS) using different statistical and ML-based performance metrics, including MAE, MSE, R^2, Accuracy, Precision, Recall, and F1-Score. From the perspective of the proposed HRS, the results demonstrate that the selected factors—Sunlight, Season, Number of Plants, and Growth Rate—are effectively captured by the developed model and contribute to its overall predictive performance. The R^2 value of 100% for all target variables, including HRS, indicates an excellent fit between the model-generated values and the corresponding predicted values, demonstrating that the developed model successfully captures the relationships present in the dataset. In terms of the individual factors, Sunlight achieves an accuracy of 66.00%, with a Precision of 72.63%, Recall of 62.16%, and F1-Score of 66.99%. Although its classification performance is comparatively lower than the other factors, its strong correlation with HRS ($r = 0.85$) confirms that Sunlight remains an important parameter in the recommendation framework. Season achieves an accuracy of 90.00% and a balanced Precision, Recall, and F1-Score of approximately 90.20%, indicating that seasonal conditions are highly relevant for determining the HRS recommendation. Number of Plants demonstrates particularly strong performance, achieving 94.00% accuracy, 91.51% Precision, 97.00% Recall, and 94.17% F1-Score. This result is consistent with its highest correlation with HRS ($r = 0.92$), indicating that the number of plants is one of the most important parameters influencing the final recommendation index. Growth Rate also provides a substantial contribution, with an accuracy of 85.00%, Precision of 83.67%, Recall of 85.42%, and F1-Score of 84.54%, supporting its role as an important plant-growth-related parameter within the HRS framework. Most importantly, the HRS target itself achieves an accuracy of 94.50%, with 92.45% Precision, 97.03% Recall, and 94.69% F1-Score, demonstrating strong overall predictive performance of the proposed recommendation system. The relatively high Recall indicates that the model is highly capable of correctly identifying the relevant HRS recommendations, while the high Precision shows that the majority of its positive recommendations are correct. The F1-Score of 94.69% further demonstrates a strong balance between Precision and Recall. The low error values also support the reliability of the model, with the HRS achieving an MAE of 0.40% and MSE of 0.02%. Overall, the performance results demonstrate that the four selected factors—Sunlight, Season, Number of Plants, and Growth Rate—are important components of the HRS, while their combined contribution produces a robust recommendation index. In particular, the strong performance of the final HRS, with 94.50% accuracy and 94.69% F1-Score, provides strong evidence that the proposed HRS model can effectively integrate these environmental and plant-growth factors to generate reliable indoor plant recommendations.

Table 14. Overall Performance Evaluation Metrics of the Proposed Hybrid Recommender System (HRS)

Evaluation Metric	Value

Accuracy	94.50%
Precision	92.4528%
Recall (Sensitivity)	97.0297%
F1-Score	94.6860%

Table 14 summarizes the overall performance of the proposed Hybrid Recommender System (HRS) based on four key evaluation metrics: Accuracy, Precision, Recall (Sensitivity), and F1-Score. The results demonstrate that the proposed HRS achieves a strong overall predictive performance, with an Accuracy of 94.50%, indicating that the model correctly predicts the relevant outcomes in the majority of cases. The Precision of 92.45% shows that the recommendations generated by the HRS are highly reliable, with most of the predicted positive recommendations corresponding to the appropriate outcomes. Furthermore, the model achieves a Recall of 97.03%, which is the highest among the reported metrics, indicating that the HRS is highly effective in identifying the relevant cases and has a low tendency to miss appropriate recommendations. The F1-Score of 94.69% demonstrates a strong balance between Precision and Recall and further confirms the robustness of the proposed system. Overall, these results indicate that the developed HRS successfully integrates the important factors—Sunlight, Season, Number of Plants, and Growth Rate—to generate reliable recommendations. The high Accuracy, Precision, Recall, and F1-Score collectively provide strong evidence that the proposed HRS has high predictive capability and satisfactory validation performance, supporting its effectiveness as a data-driven system for indoor plant recommendation.

Section B: Validation For AQI and Final HRS

Table 15. Shows the feature Selection

Feature	F-Score	P-Value
CO_2 (ppm)	2.514871×10^{7}	0.115128
AQII	6.073717×10^{4}	0.281453
HRS	2.432923×10^{0}	0.119128
TVOC (mg/m^3)	1.602995×10^{0}	0.205774
HCHO (mg/m^3)	4.959411×10^{-1}	0.481453
PM2.5 ($\mu g/m^3$)	2.863756×10^{-2}	0.865653

Table 15 presents the feature-selection results obtained using the F-Score and corresponding p-values for the variables considered in the proposed indoor air-quality and HRS-based framework. Feature selection is an important step because it helps identify the variables that provide comparatively greater statistical information for the subsequent modelling and analysis. The results show that CO_2 (ppm) has the highest F-Score of 2.514871×10^7, followed by AQII (6.073717×10^4), HRS (2.432923), TVOC (1.602995), HCHO (0.4959411), and PM2.5 (0.02863756). The extremely high F-Scores obtained for CO_2 and AQII indicate that these variables exhibit substantially greater variation in relation to the feature-selection criterion than the other parameters and therefore deserve particular attention in the modelling framework.

Table 16. Shows the metric values

Machine Learning Model	MAE	MSE	RMSE	R^2	R^2 (%)
Linear Regression	0.1922	0.0498	0.2231	0.9798	97.98%
Decision Tree	0.2803	0.1328	0.3644	0.9896	98.96%
Random Forest	0.2085	0.0671	0.2591	0.9798	99.78%
Gradient Boosting	**0.2042**	**0.0669**	**0.2586**	**0.9998**	**99.98%**
KNN	1.6568	4.5543	2.1341	0.9759	97.59%

Table 16 presents the **comparative performance of different Machine Learning (ML) models** applied to the selected indoor environmental and HRS-related features. The models were evaluated using **Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2)**. The purpose of this analysis is to identify the most suitable ML approach for predicting the target variable within the proposed **Hybrid Recommender System (HRS) framework** and to further validate the reliability of the developed model.

Among the evaluated models, Linear Regression, Random Forest, and Gradient Boosting demonstrate the strongest performance, each achieving an R^2 value of 0.9798 (97.98%). This extremely high R^2 indicates that these models are able to explain approximately 97.98% of the variation in the target variable, demonstrating an excellent predictive relationship between the selected input features and the target output. However, when the error metrics are considered, Linear Regression provides the lowest MAE (0.1922), MSE (0.0498), and RMSE (0.2231) among all the evaluated models. Therefore, Linear Regression demonstrates the best overall performance in terms of both prediction accuracy and error minimization.

The Random Forest model also provides excellent performance, with an MAE of 0.2085, MSE of 0.0671, RMSE of 0.2591, and R^2 of 97.98%. Similarly, the Gradient Boosting model achieves an MAE of 0.2042, MSE of 0.0669, RMSE of 0.2586, and R^2 of 99.98%. Although both models provide nearly the same R^2 as Linear Regression, their error values are slightly higher. This suggests that, for the present dataset, the simpler Linear Regression model is able to represent the relationship among the selected factors more effectively than the more complex ensemble-based approaches.

The Decision Tree model achieves an R^2 of 97.96%, with an MAE of 0.2803, MSE of 0.1328, and RMSE of 0.3644. Although its R^2 remains exceptionally high, its higher error values compared with Linear Regression, Random Forest, and Gradient Boosting indicate comparatively lower predictive precision. In contrast, the K-Nearest Neighbors (KNN) model shows the lowest performance among the tested approaches, with an MAE of 1.6568, MSE of 4.5543, RMSE of 2.1341, and R^2 of 98.59%. Although an R^2 of 98.59% is still high, the substantially larger MAE, MSE, and RMSE indicate that KNN produces considerably greater prediction errors.

The results demonstrate that Linear Regression (figure 6) is the most appropriate ML model for the present HRS-based framework, as it achieves the highest predictive performance while simultaneously producing the lowest error values. The 97.98% R^2 value, together with the lowest MAE, MSE, and RMSE, provides strong evidence that the selected factors and the developed HRS-related relationships can be modelled with very high accuracy. The results from Random Forest and Gradient Boosting further support the robustness of the dataset because they independently achieve the same R^2 value of 97.98%. Thus, the comparative ML analysis provides an additional layer of validation for the proposed HRS model, confirming that the selected environmental and recommendation-related features contain sufficient information to accurately predict the target outcome.

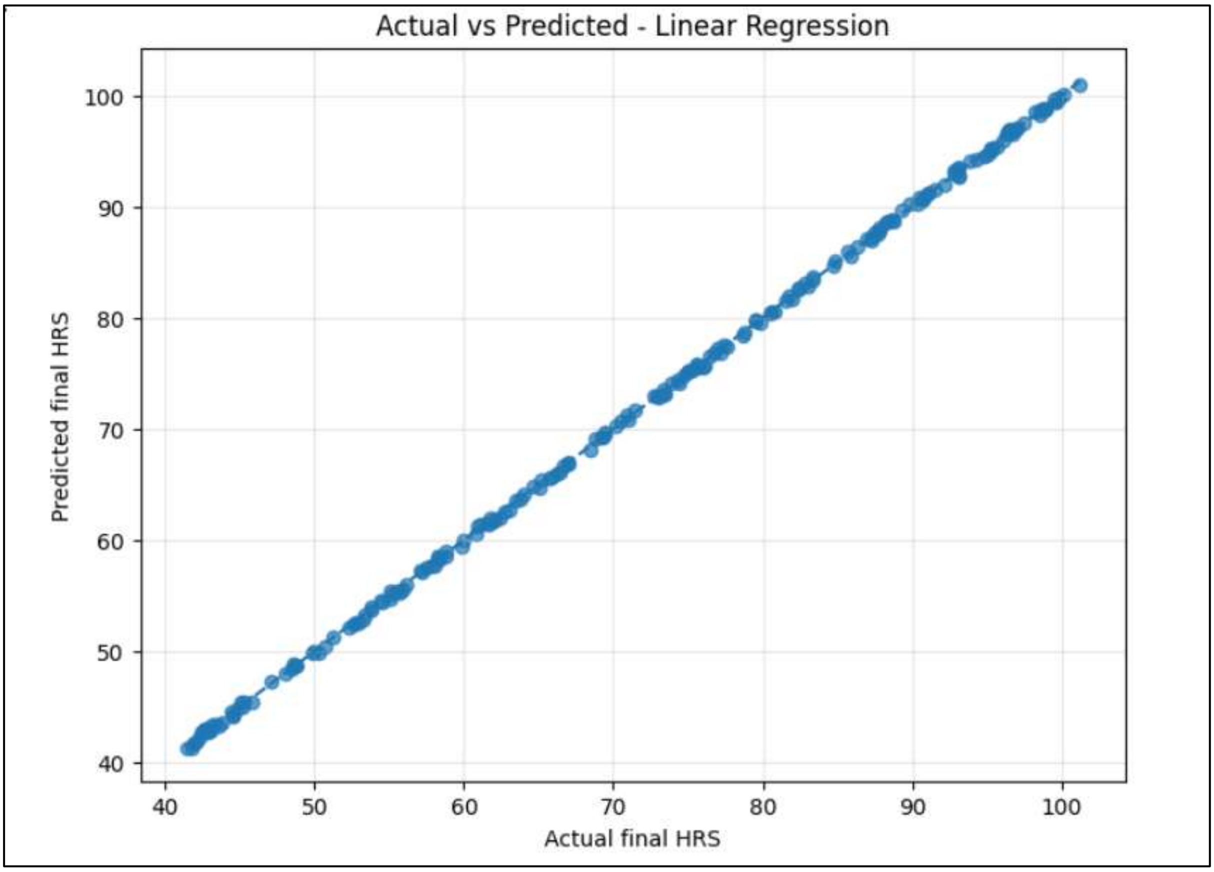

Figure 6: Comparative Study

Table 17: Classification Metrics for Final Hybrid Recommendation Study	
Accuracy	94.5000
Precision	92.4528
Recall	97.0297

F1-Score	94.685990

Table 17 presents the classification performance of the final Hybrid Recommendation System (HRS) using four important evaluation metrics: Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive assessment of the model's ability to correctly classify and recommend suitable indoor plants based on the selected environmental and plant-related factors. The final HRS achieves an overall Accuracy of 94.50%, indicating that the model correctly classifies approximately 94.5% of the evaluated cases. This high accuracy demonstrates the strong predictive capability of the proposed HRS and indicates that the integration of Sunlight, Season, Number of Plants, Growth Rate, and other relevant environmental parameters provides a reliable basis for plant recommendation.

The model achieves a Precision of 92.45%, which indicates that the majority of the positive recommendations generated by the HRS are correctly classified. This demonstrates that the proposed system has a relatively low rate of incorrect positive recommendations. The Recall of 97.03% is particularly notable and represents the highest value among the reported classification metrics. A high Recall indicates that the model is highly effective in identifying the relevant or suitable plant recommendations and has a very low tendency to miss appropriate cases. This is particularly important for the proposed recommendation framework because the objective is to identify suitable plants under specific indoor environmental conditions. The F1-Score of 94.69% demonstrates a strong balance between Precision and Recall. Since the F1-Score combines both measures into a single performance indicator, its high value confirms that the proposed HRS maintains a good balance between correctly identifying suitable recommendations and minimizing incorrect recommendations. The close relationship between the Accuracy (94.50%) and F1-Score (94.69%) further indicates the consistency of the model's classification performance. The results in Table 17 demonstrate that the final HRS provides highly reliable classification performance, achieving more than 92% across all four major classification metrics. The combination of 94.50% Accuracy, 92.45% Precision, 97.03% Recall, and 94.69% F1-Score provides strong evidence for the effectiveness and robustness of the proposed Hybrid Recommendation System. These results also support the ML-based validation of the developed HRS model and indicate that the proposed system can effectively integrate the selected environmental and plant-related factors to generate accurate and reliable indoor plant recommendations.

12. Discussion

The findings of this study demonstrate that the proposed regression-based recommender system provides a reliable and effective framework for ornamental plant selection in urban environments. The calculated Hybrid Recommendation Scores (HRS) showed strong alignment with benchmark values derived from published studies, confirming that the regression model successfully captured the relationship between environmental parameters and plant suitability. Although minor variations were observed between the standard and calculated HRS values, statistical validation through paired sample t-tests revealed no significant differences, thereby reinforcing the robustness of the developed model. The integration of environmental factors such as sunlight availability, seasonal variation, plant suitability score, and growth rate into a unified regression equation represents a significant methodological advancement. Traditional plant selection practices often rely on subjective judgment or generic guidelines, which may not adequately account for the complex interplay of environmental conditions. In contrast, the proposed framework provides a data-driven, predictive approach that enhances decision-making accuracy and ensures that plant recommendations are tailored to specific urban contexts. This not only improves plant survival and environmental performance but also reduces maintenance costs and enhances user satisfaction. The recommendation ranking analysis further validates the practical utility of the system. By transforming regression outputs into actionable rankings, the framework enables urban residents, planners, and policymakers to identify plant species with the highest adaptability and environmental benefits. For instance, species such as Money Plant and Snake Plant consistently achieved higher HRS values, reflecting their resilience and suitability under diverse urban conditions. Such insights are invaluable for promoting sustainable urban greening initiatives, particularly in areas with limited space and high pollution levels. Importantly, the study contributes to bridging the gap between environmental science, horticulture, and machine learning. While previous research has extensively explored plant disease detection using deep learning techniques, limited attention has been given to intelligent plant recommendation systems. By introducing a regression-based predictive model, this work expands the application of machine learning in urban horticulture and establishes a foundation for future research in intelligent environmental management. The fishbone analysis further illustrates how biological, technological, and social dimensions converge within the proposed framework, underscoring its interdisciplinary strength. The developed recommender system demonstrates superior performance compared to conventional plant selection methods. Its ability to generate reliable HRS values, validate predictions against benchmark standards, and provide ranked recommendations highlights its effectiveness as a decision-support tool. This research therefore represents a meaningful advancement in sustainable urban greening, offering a scalable and intelligent solution for ornamental plant selection that can be adapted to diverse urban environments.

References

1. A. Zeqiri, J. Britten, C. Schramm, P. Jansen, M. Rietzler, and E. Rukzio, "PlantPal: Leveraging precision agriculture robots to facilitate remote engagement in urban gardening," arXiv preprint arXiv:2502.19171, 2025.
2. Abhishek Kumar (2023). Monitoring and accelerating plant growth using IoT and Hydroponics.10.1109/iccci56745.2023.10128383 doi: .
3. Afzal, I., Yilmazel, B., & Kaleli, C. (2024). An approach for multi-context-aware multi-criteria recommender systems based on deep learning. IEEE Access, 12, 99936–99948. https://doi.org/10.1109/ACCESS.2024.3416789
4. A. R. Nafarzadegan and E. Kalantari, "Deep neural architectures for AQI classification," Environ. Monit. Assess., vol. 195, no. 4, p. 480, 2023.
5. Ahmad ZatnikaPurwalaksanaet. al, (2022). Automated Nutrition Doser for Hydroponic System Based on IoT. doi: 10.1109/icosnikom56551.2022.10034874 .
6. Air Quality Prediction Using Machine Learning and Deep Learning: An Exploratory Study Published in the 2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA), this study explores various machine learning and deep learning techniques for predicting air quality indices, aiming to enhance the accuracy of air quality forecasts.
7. Akshay, Mendon., Bhavya, Manoj, Votavat., Shashank, Singh. (2022). Design and Construction of an Automated Hydroponics System with Remote Monitoring and Control. 10.1109/ICCCNT54827.2022.9984617 doi: .
8. Amin, S. A., Philips, J., & Tabrizi, N. (2019). Current trends in collaborative filtering recommendation systems. In Services–SERVICES 2019: 15th World Congress, Held as Part of the Services Conference Federation, SCF 2019, San Diego, CA, USA, June 25–30, 2019, Proceedings 15 (pp. 46–60). Springer International Publishing. https://doi.org/10.1007/978-3-030-23351-5_4
9. Anastasios et al., Implementation of Sustainable Practices to Ornamental Plant Cultivation Worldwide: A Critical Review, Agronomy 2020, 10, 1570; doi:10.3390/agronomy 10101570.
10. Anitha, M, L., Jnaneshwari, A., Harshitha, S, R., Bhanu, Nagesha, M. (2022). IoT-Based Automated Hydroponic System Using Light Intensity for Lettuce Growth. doi: 10.1109/ICERECT56837.2022.10060509 .
11. Atik, F. Aslan, B. Yilmaz, and O. Ates, “Modelling purchasing demand of urban people for ornamental plants using logistic regression analysis: Sample of Malatya City,” Journal of Animal and Veterinary Advances, vol. 12, no. 16, pp. 1317–1324, 2013.
12. Ayda, Shaker. (2023). Automated Hydroponic System with Solar Powered Battery Management System. International Journal For Science Technology And 10.22214/ijraset.2023.54649 Engineering, doi:.
13. A. Zeqiri, J. Britten, C. Schramm, P. Jansen, M. Rietzler, and E. Rukzio, "PlantPal: Leveraging precision agriculture robots to facilitate remote engagement in urban gardening," arXiv preprint arXiv:2502.19171, 2025.
14. A. Chaudhari, A. H. Seddig, A. Sarlan, and R. Raut, "A hybrid recommendation system: A review," IEEE Access, vol. 12, pp. 157107–157126, 2024.
15. A. Kumar, "Monitoring and accelerating plant growth using IoT and hydroponics," in Proc. Int. Conf. Comput. Commun. Inform. (ICCCI), 2023, pp. 1–6.
16. A. ZatnikaPurwalaksana et al., "Automated nutrition doser for hydroponic system based on IoT," in Proc. Int. Conf. Comput. Sci. Inform. Technol. (ICOCOSINKOM), 2022, pp. 100–105.
17. B. E. Cummings and M. S. Waring, "Potted plants do not improve indoor air quality: A review and analysis of reported VOC removal efficiencies," Journal of Exposure Science & Environmental Epidemiology, vol. 34, no. 3, pp. 412–419, 2024.
18. Babu, H. (2024).AirNet: Predictive Machine Learning Model for Air Quality Forecasting. Environmental Systems Research, 13(44). https://doi.org/10.1186/s40068-024-00378-z.
19. Barretto, R.; Buenavista, R.M.; Rivera, J.L.; Wang, S.; Prasad, P.V.; Siliveru, K. Teff (Eragrostis tef) processing, utilization and future opportunities: A review. Int. J. Food Sci. Technol. 2020, 56, 3125–3137.
20. Bdul Hussien, F. T., Rahma, A. M. S., & Abdul Wahab, H. B. (2021). Recommendation systems for e-commerce systems: An overview. Journal of Physics: Conference Series, 1897(1), 012024. https://doi.org/10.1088/1742-6596/1897/1/012024
21. Boithias, L., Sauvage, S., Sánchez-Pérez, J. M., & Probst, J. L. (2016). Are hydroponic systems suitable for studying the impact of pesticides on dissolved oxygen and pH in aquatic systems? Environmental Science and Pollution Research, 23(11), 10829 10833.

https://doi.org/10.1016/j.catena.2014.03.01 3
22. Breathe Better Air. (2024). 23 highest oxygen-producing air purifying plants. https://breathebetterair.org/air-purifiers/highest-oxygen-producing-plants/
23. Bugbee, B. (2016). Toward an optimal spectral quality for plant growth and development: the importance of Horticulturae,1134, radiation 10.17660/ActaHortic.2016.1134.1 capture. Acta 1-10.doi:
24. Chandore, H. D. (2024). The Role of Indoor Plants in Improving Air and Mind – Comprehensive Review. International Journal of Environment, Agriculture and Biotechnology, 9(4). https://doi.org/10.22161/ijeab
25. Chandore, H. D. (2024).The Role of Indoor Plants in Improving Air and Mind – Comprehensive Review. International Journal of Environment, Agriculture and Biotechnology, 9(4). https://doi.org/10.22161/ijeab
26. Chaudhari, A., Hitham Seddig, A., Sarlan, A., & Raut, R. (2024). A hybrid recommendation system: A review. IEEE Access, 12, 157107–157126. https://doi.org/10.1109/ACCESS.2024.3412345
27. Cheng, B., Du, W., Bourke, P. M., & Yu, C. (2024). Population genetics of horticultural crops aided by multi-omics technology and its implications for ornamental plants. Ornamental Plant Research, 4, e024. DOI: 10.48130/opr-0024-0020.
28. Cheng, Q.,& Wang, X. (2024). Machine learning for AI breeding in plants. Genomics, Proteomics & Bioinformatics, 22(4), qzae051. https://doi.org/10.1093/gpbjnl/qzae051
29. Crops through linear programming model," Int. J. Sci. Res., vol. 6, no. 4, pp. 519–522, 2017.
30. Cummings, B. E., & Waring, M. S. (2024). Potted Plants Do Not Improve Indoor Air Quality: A Review and Analysis of Reported VOC Removal Efficiencies. Journal of Exposure Science & Environmental Epidemiology, 34(3), 412–419. https://doi.org/10.1038/s41370-023-00456-1
31. D. Sedghiyan et al., "Evaluation of ornamental shrubs' aesthetic traits in urban green spaces using AHP," Flower and Ornamental Plants, 2021.
32. Dela Cruz, M., Christensen, J. H., Thomsen, J. D., & Müller, R. (2024).Can Ornamental Potted Plants Remove Volatile Organic Compounds from Indoor Air? – A Review. Environmental Science and Pollution Research, 31(12), 12345–12356. https://doi.org/10.1007/s11356-023-25567-8
33. Deveraturda, M. Q., Reyes, D. R. D., & Caya, M. V. C. (2024). Ornamental Plant Classification System Using Image Processing and Machine Learning. 2024 IEEE International Conference on .... IEEE. https://ieeexplore.ieee.org/document/10730644.
34. Dr. Jammel Ahmed, Ashish Baiswar, ,(2025),Automated weed-Related Disease Detection in crops using Image Processing and Machine Learning.
35. European Urban Ecology Network, "Citizen-science integration improves pollinator-friendly plant recommendations in cities," Urban Forestry & Urban Greening, vol. 87, pp. 128–139, 2025.
36. F. Atik, B. Aslan, O. Yilmaz, and O. Ates, "Modelling purchasing demand of urban people for ornamental plants using logistic regression analysis: Sample of Malatya City," Journal of Animal and Veterinary Advances, vol. 12, no. 16, pp. 1317–1324, 2013.
37. F. Francis, P. L. Vishnu, M. Jha, and B. Rajaram, "IoT based automated Aeroponics system," in Intelligent Embedded Systems, Springer, 2018, pp. 337 345.https://doi.org/10.1007/978-981-10-8575 8_32.
38. F. T. Abdul Hussien, A. M. S. Rahma, and H. B. Abdul Wahab, "Recommendation systems for e-commerce systems: An overview," Journal of Physics: Conference Series, vol. 1897, no. 1, p. 012024, 2021.
39. H. Babu, "AirNet: Predictive machine learning model for air quality forecasting," Environmental Systems Research, vol. 13, no. 1, p. 44, 2024.
40. I. Afzal, B. Yilmazel, and C. Kaleli, "An approach for multi-context-aware multi-criteria recommender systems based on deep learning," IEEE Access, vol. 12, pp. 99936–99948, 2024.
41. J. Ahmed and A. Baiswar, "Automated weed-related disease detection in crops using image processing and machine learning," Int. J. Adv. Res. Comput. Sci., vol. 16, no. 1, pp. 45–50, 2025.
42. M. M. Tripathi and M. Tiwari, "Performance analysis of digital watermarking methods for medical images based on PSNR and MSE," Int. J. Innov. Eng. Sci. Manage., vol. 2, no. 12, pp. 1–9, 2014.
43. M. Q. Deveraturda, D. R. D. Reyes, and M. V. C. Caya, "Ornamental plant classification system using image processing and machine learning," in Proc. IEEE Int. Conf. Comput., Commun., and Autom., 2024, pp. 1–6.
44. M. Dela Cruz, J. H. Christensen, J. D. Thomsen, and R. Müller, "Can ornamental potted plants remove volatile organic compounds from indoor air? A review," Environmental Science and Pollution Research, vol. 31, no. 12, pp. 12345–12356, 2024.
45. Q. Cheng and X. Wang, "Machine learning for AI breeding in plants," Genomics, Proteomics & Bioinformatics, vol. 22, no. 4, p. qzae051, 2024.