International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Revolutionizing Plant Care: Developing a real-time monitoring device for plant care and home gardening

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Abstract - The Plant Guardian AI project introduces an innovative approach to plant care, leveraging the synergy of Internet of Things sensors, algorithms, and machine learning techniques to create an intelligent gardening system.

By developing a smart gardening device capable of real-time plant health monitoring, and personalized care recommendations, this project is set to empower both beginners and experienced home gardeners. The system includes of hardware components such as microcontrollers, sensors, and actuators to collect real-time data on key environmental factors, such as soil moisture, temperature, humidity, and light intensity. The data is then processed and analyzed utilizing machine learning models to detect plant health issues, and predict watering and fertilization requirements, and provide with tailored care recommendations to users. Furthermore, the project offers a user-friendly web application that allows users access to real-time insights, historical trends, and proactive alerts, helping them to make well-informed decisions and take prompt action to ensure optimal plant health.

Key Words: IoT, Machine Learning, Plant Health Monitoring, Remote Plant Care

1. INTRODUCTION

The place of plants in our lives is unimaginable and beyond words.

Plants are of highly significant importance in the context of ecological balance and are the solution to the survival of every living creature. Not only do they contribute to making our surroundings beautiful, but also provide us with food, oxygen, and medicines. As there is a developing awareness of environmental and eco-friendly living, human beings arebecoming more and more interest ed in going near nature, even amidst metropolitan cities. This has given birth to the popularity of a movement that is known as "urban gardening."

Urban gardening is a new trend that calls for people to grow flowers, fruits, vegetables, and plants in urban spaces—on rooftops, balconies, windowsills, or even in homes. It encourages people to live sustainablyby using small urban spaces to grow greens and improve the quality of life. Not only does urban gardening beautify small living spaces, but it also assists in reducing carbon footprints and promoting healthy living.

However, even with all the advantages, gardening in urban spaces can be quite challenging, particularly for people who have hectic lives or limited experience in gardening.

With these issues at hand, the Plant Guardian AI is presented as agame-changer that will transform the practice of plant care. This intelligent gardening assistant aims to make gardening easier and more fun using cutting-edge technologies like the Internet of Things (IoT), machine learning, and remote sensing. The primary aim of the Plant Guardian AI is to reduce the risk of typical gardening errors and guarantee each plant just the right amount of water, nutrients, and light to ensure maximum growth.

It accomplishes this by collecting data on the plants and environment in real time, such as moisture, light,and nutrient requirements. It goes onto utilize machine learning to analyze the information and offer real- time advice based on each plant's individual requirements. Further more,thesystem may also control watering and light levelsautomatically via automatic controls, which is perfect fo r people who have little time to check on their plants around the clock.

Whether you are an experienced home gardener, a beginner who wishes to have a try at growing their own herbs, or an active professional, the Plant Guardian AI is a genuine and hands-on way of ensuring the success of your plants. It eliminates the trial and error of gardening and allows individuals to be more confident and connected to their plants, even in the confines of urban living. Essentially, the Plant Guardian AI is not just a gardening assistant—it is a step towards a greener, cleaner way of life. Through the combination of technology and nature itself, it allows individuals to enjoy the benefit of having a garden without the usual constraints, thus making plant care more convenient, productive, and enjoyable for everyone

2. EXISTING SYSTEM

There already exist many IoT and machine learning-based solutions to combat the convenience issues created by plant care and management.

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These solutions have gone a long way in automating plant care through sensor-based monitoring, remote watering, and even gamified interaction procedures. With increasing numbers of people looking for convenient and efficient ways of maintaining plants, the application of such intelligent technologies has risen to prominence.
For instance, Dhanraj et al. [1] designed an Android-based smart watering system with remote logging and control capabilities for domestic plants. The system allows individuals to manage watering schedules with smartphones, hence making it easy to take care of plants for busy individuals. As another instance, Kusuma et al. [2] designed an IoT-based plant watering system on the basis ofenvironmental sensor readings to water the pl ants automatically. Thesystem collects real-time information consisting of soil moisture and temperature, on the basis of which it makes intelligent decisions regarding how and when theplant should be watered, without over or under-watering.

Outside of these instances, Khan et al. [5] and Zet et al. [6] studies have all focused on the application of IoT technology and sensor networks to track plant growth and automate watering. The studies indicate the advantage of empl oying integrated sensor systems to ensure maximum plant health with minimal human input. The trend of most of these studies has been employing IoT technologies to simplify plant care, with emphasis on the application of automation to address problems related to plant care.
Although these projects are to be appreciated and have established the foundation strong for smart plant management systems, they are typically deficient in advanced analytics and user-oriented features that would make them more beneficial and desirable. Many existing systems are focused on automated basic functionalities, likethe acti vation of a water pump based on soil moisture levels. However, they lack the provision of the user with in-depth information, likenutritional deficiency analysis, early detection of disease, or displaying user- specific recommendations to the user concerning plant type and weather.
In order to counter this deficiency, researchers have started developing the use of more advanced technologies. For instance, Prasad et al. [3] suggested an automatic indoor plant care system based on deep learning. The system uses enhanced image processing and classification methods to identify plant diseases and suggest care. Deep learning allows the system to identify patterns and anomalies that are hard to spot with the naked eye, thus enhancing the accuracy of plant diagnosis.

Another fascinating innovation is the Solis project of Penders et al. [4], where gamification concepts are integrated with machine learni ng. The system engages users in caring for plants by turning everyday processes into appealing and rewarding experiences. Gamified systems make users consistent in plant care using feedback, challen ge, and reward, thereby enhancing user experience and better plant health outcomes.

Despite these advances, however, there is still a burning desire for somethin g more comprehensive and integrated that combines the best features of existing systems. This solution must not only include IoT sensor fusion and machine learning plant health analysis but also haven incredibly intuitive and accessible interface. This would allow new and experienced gardeners to both control and keep track of their plants efficiently without getting mired in the technology's complexity.
The optimal configuration would include real-time monitoring of key parameters of plant health such as soil moisture, light, temperature, and humidity. It would also sense plant disease, nutritional levels, and adjust care guidance to the specific needs of each plant species. Integration with mobile device or web application would offer immediate notification, graphical analy sis, and guided care instructions. Overall, a lot has been accomplished in the application of IoT and machine learning to plant care, but innovation is still possible in creating more holistic and user-focused solutions. A single platform that brings automation, advanced diagnostics, and interactive features can make urban gardeningand plant care easier, more efficient, and enjoyable for everyone.

3. PROPOSED SYSTEM

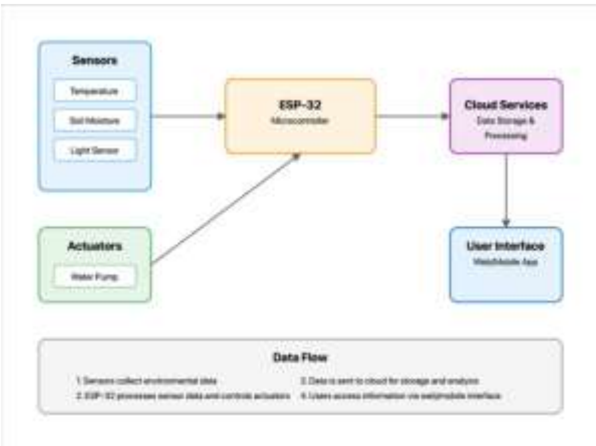

Fig.1: block diagram of Plant guardian AI

Our proposed system, Plant Guardian AI, integrates all necessary elements, hardware components, a cloud-connected web application and machine learning algorithms which enables these elements for remote plant health monitoring, resource management, and personalized care recommendations. By integrating Internet of Things (IoT) and artificial intelligence (AI) users will be able to maintain plant health with minimal involvement.

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The system functions by continuously collecting data through variety of sensors, and then this data is pre-processed by microcontroller before transmitting it to a cloud server, where machine learning models analyze the information and generate actionable insights related to plant's current health, and potential threats like diseases or pests. These insights are then presented to the user through the user interface, enabling remote monitoring, control, and customized care recommendations.

A. DATA PREPROCESSING

In the initial phase of the system, raw environmental sensor data are cleaned and normalized rigorously. This is critical in presenting high-quality input data to the machine learning algorithms, which indirectly impacts the accuracy and reliability of the predictions. Environmental sensors, though useful, tend to be susceptible to all manner of sources of noise and inconsistency. These include electromagnetic interference from surrounding electronic devices, ambient temperature changes, or sensor drift caused by wear and exposure over extended periods of time.

For example, I can provide you with incorrect advice based on the soil type, soil density, or even the sensor depth. I can provide you within correct readings that can lead to advice that will not only be useless towards plant growth, but can even damage the plants.

For their solution, the preprocessing pipeline consists of the following steps:

Noise Filtering: Applying moving average or exponential smoothing filters to suppress oscillations and level out data trends. Outlier Detection: Using statistical techniques such as z-score or interquartile range (IQR) analysis to detect and remove or adjust outliers from the data. Data Normalization: Normalizing all the sensor values to the same scales, e.g., 0–1 for neural networks or z-scores for statistical models, for feature consistency.
Temporal Synchronization: Aligning the time measurements of var ious sensors to synchronize them, the foundation for multi-sensor data fusion and pattern recognition. Calibration Adjustment: Utilizing device-specific calibration coefficients for sensor bias correction to ensure data accuracy over time.
Additionally, the sensor data are stratified by plant type and corresponding growth stage.
This stratification enables more accurate model training and guarantees that care suggestions are not generic but are specially attuned to the specific biological needs of various plants. Streamlining the preprocessing phase, the system minimizes computational overhead and maximizes the performance of subsequent machine learning models.

B. FEATURE EXTRACTION

The next important step along the pipeline is feature extraction, i.e., thedetection and definition of informative input variables representing significant patterns in plant and environmental behavior.
The quality,relevance, and representativeness of the selected featur es areimportant drivers of the success of a predictive model.

The feature extraction process is categorized into the following:

Temporal Features:
Hourly, daily, and weekly moving averages to determine short- and long-term trends.
Rate of change measures to detect abrupt changes. Seasonal trend decomposition by using techniques such as STL (Seasonal-Trend Decomposition based on Loess). Detection of periodic changes in moisture levels, identification of peak and trough patterns. Environmental Characteristics:
Calculating temperature-humidity indices to establish comfort or stress for the plant.
Interpreting day and season variations in light intensity, photoperiod duration.
Long-term soil moisture trend analysis for water availability forecasting.
Cross-correlation analysis to identify interactions between environmental variables like light, temperature, and humidity.
Plant-Specific Features:
Like optimal environmental conditions for some species. Indicators of different phases of plant growth. Seasonal and species frequency trends in watering. Historical correspondence between environmental stress and documented plant health readings. The synergy between time-
series methodology and agronomic domainexpertise aids in creatin g features that give good signals to machine learning algorithms, which in turn improve their capacity to detect health problems as well as environmental stress trends in crops.

C. MODEL TRAINING AND VALIDATION

For the sake of constructing a generalizable and consistent plant care system, special focus is laid on model training and validation. Instead of random data split, temporal validation strategy is adopted in amanner that data is not leaked by preserving the time order of data. Data is divided between 80:20, 80% for training and the recent 20% for validation.

Model Architectures Used:
Random Forest Classifier: Used to classify plant health status to classes such as Healthy, Stressed,Critical,and Optimal. Inputs comprise current and designed features. Generates confidence scores for each class to guide user decision. LSTM Neural Network (Long Short-Term Memory): Utilized to predict impending environmental conditions, mostlymoi sture and temperature trends.

Makes predictions from past time-series data (24–48 hours). Enables user or automation system initiative behavior.
Multi-Output Regression Model:
Provides actionable care tips. Optimal irrigation plans, estimates of nutrient requirements, and environmental conditions adjustments are the outcomes. Training
Configuration Data:

Cross-validation: Uses time-series (sliding window) split to keep evaluations realistic.
Hyperparameter Optimization: Performed with the grid search and Bayesian optimization combined for effective tuning. Early Stopping: Tracks validation loss and stops learning to prevent overfitting. Regularization Techniques: L2 regularization and dropout layers are utilized in neural networks to prevent overfitting.
D. PREDICTION EXPLAINABILITY

Interpretability is required to create user trust and enable decision-making. Although providing transparency into prediction, the SHAP approach is used in place of traditional LIME techniques due to the former's superior performance in time-series settings.

The explainability aspect comprises:

Feature Importance Analysis: Highlights which sensors or variables most influenced the model's prediction. Temporal Impact Visualization: Divides the effect of recent vs. past data. Threshold Analysis: Identifies what values triggered a particular alert or class change. Counterfactual Explanations: Implies small adjustments required to change the hea lth status of the plant into a more favorable category. This framework of interpretability allows for users—whether farmers or gardeners—to better understand the system decisions and make intelligent and informed decisions in plant health maintenance.

4. IMPLEMENTATION AND TESTING OF THE DESIGN

The hardware and software components are integrated, and the entire system is tested for seamless communication, data transfer, and the accuracy of plant health monitoring and care recommendations. Iterative refinements are made to optimize the system's performance.

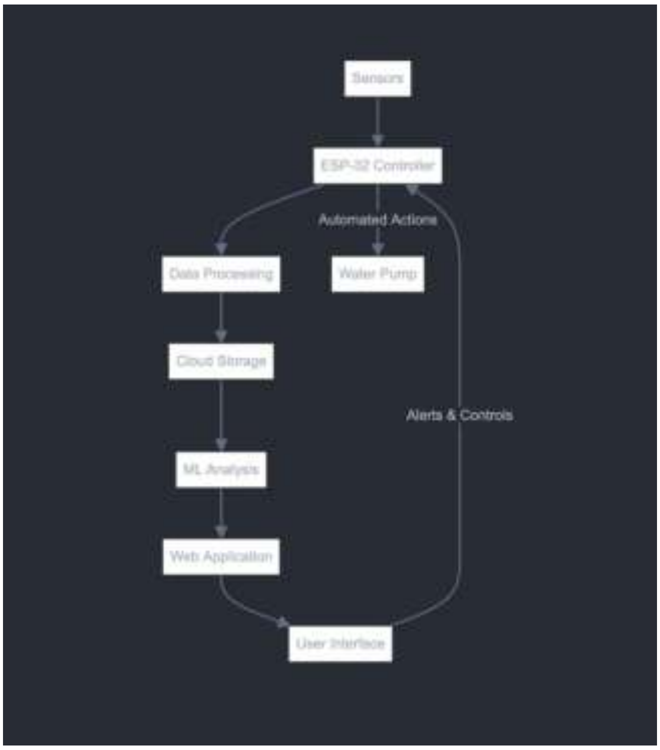

Fig.2: System flowchart

4.1. Hardware Prototyping and Integration

The hardware components, including the microcontroller, sensors, and actuators, are selected and tested through prototyping. The team ensures the reliable functioning of the hardware setup and its responsiveness to environmental changes.

3.1. Hardware Description

The hardware components, design has microcontroller, sensors, and actuators, are selected, and their integration is tested through prototyping. The team ensures the reliable functioning of the hardware setup and its responsiveness to environmental changes.

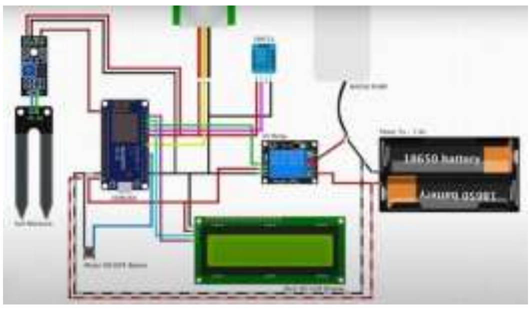

Fig. 2: Hardware connections and layout

The Plant Guardian AI system is designed with the following hardware components :

3.1.1. Microcontroller:

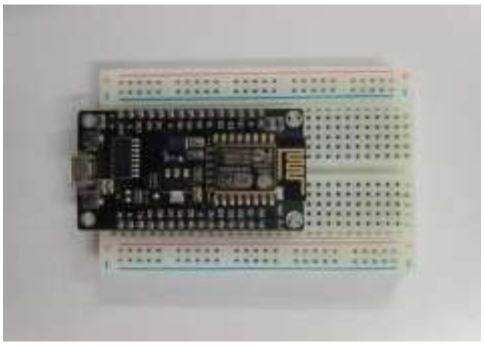

Fig. 3: Microcontroller

The heart of the system is the ESP-32 microcontroller, servers as central processing unit. Known for its energy efficiency and direct Wi-Fi connectivity, the ESP-32 helps seamless communication and data transfer, making it an ideal choice for IoT applications.

3.1.2. Sensors:

The sensors accurately monitor environmental conditions, including soil moisture, temperature, humidity, and pH levels. These sensors provide real-time data that is essential for optimizing plant care.

Soil Moisture Sensor: Detects the water level in the soil to take watering decisions.

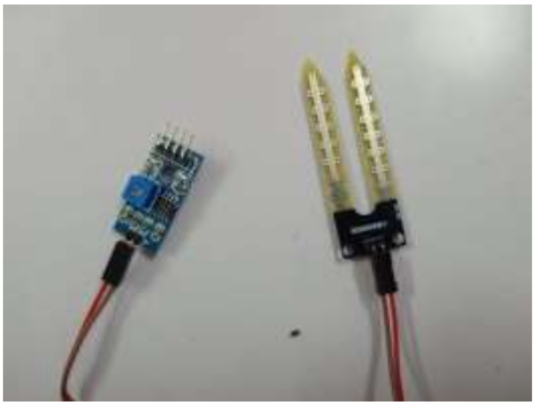

Fig. 4: Soil Moisture Sensor

Temperature Sensor: Monitors temperature to track conditions that affect plant conditions.

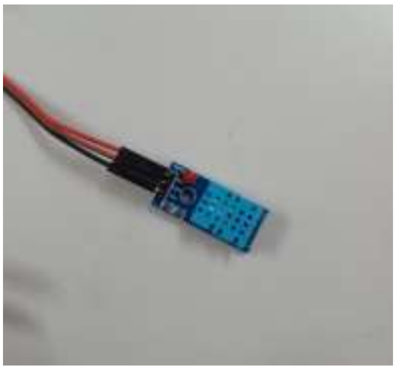

Fig. 5: Temperature Sensor

Humidity Sensor: Measures atmospheric moisture levels.

pH Sensor: Assesses soil acidity or alkalinity, ensuring the nutrient for plants.

3.1.3. Actuators:

The system incorporates a water pump as an actuator to regulate water supply to the plants. Actuator is controlled by the microcontroller; the system optimizes plant care and minimizes water waste.

Fig. 6: Water Pump

4.2. dataset

The work utilizes a large-scale and carefully harvested plant monitoring dataset, derived from several IoT sensor deployments. The sensors were deployed over a varied array of plant types and environmental conditions to verify the system's generalizability and resilience. The dataset information is as follows:

Total Records: More than 150,000 single sensor reads over a complete year.

Plant Species: Information gathered from 15 plant species, both indoor types like succulents and ferns, and outdoor plants like shrubs and small trees.

Monitoring Duration: Ongoing data collection for a period of 12 months, which encompasses seasonal changes and plant life cycle phases.

Sensor Parameters: Five basic environmental and soil parameters were measured—soil moisture, atmospheric temperature, relative humidity, light intensity, and soil pH levels.

Sampling Frequency: Data was taken every 15 minutes, balancing power efficiency with granularity.

Geographic Locations: All three were recorded from different climate zones representing temperate, tropical, and desert climates to cover a wide range of growth conditions.

Data Distribution:

Healthy Plant Conditions: About 60% of the readings correspond to plants in good health.

Mild Stress Conditions: About 25% of the data shows early stress signals, such as slight water deficit or mild temperature stress.

Moderate Stress Conditions: 12% of the readings show moderate stress that needs treatment.

Critical Conditions: The other 3% of the data set records critical stress or declining plant health, such as potential disease or extreme nutrient deficiency.

Having this balanced split allows the model to learn from diverse health states and enhances its diagnostic accuracy.

2) Performance Measures

To thoroughly evaluate the system, a variety of performance metrics were adopted, covering both classification tasks (predicting plant health status) and regression tasks (predicting environmental parameter trends and care recommendations):

Classification Metrics:

Accuracy: Measures overall correctness of the health classification model by calculating the proportion of correct predictions (both positive and negative).

Precision: The number of correct positive predictions divided by all positive predictions, showing how many positive case predictions were indeed correct.

Recall (Sensitivity): Fraction of actual positive cases that were identified correctly by the model.

F1-Score: Harmonic mean of precision and recall, offering a balanced evaluation of a model's accuracy.

Regression Metrics:

Mean Absolute Error (MAE): Average of the absolute differences between actual and predicted values, representing average error magnitude in prediction.

Root Mean Square Error (RMSE): Square root of the mean of the squared prediction errors, penalizing larger errors more.

Mean Absolute Percentage Error (MAPE): Average percentage difference between actual and predicted values, helpful in interpreting relative errors in prediction.

System Performance Metrics:

Response Time: Time elapsed from sensor data collection to actionable recommendation delivery.

Uptime: Time percentage the system was active and available throughout the testing process.

Energy Efficiency: Power usage average per monitoring period, being key for battery-driven sensor deployments.

B. Parameter Settings

Hardware Configuration:

Microcontroller: ESP-32 running at 240 MHz clock rate.

Communication: WIFI standards 802.11 b/g/n used for data transmission.

Sensor Reading Interval: Every 15 minutes to obtain real-time environmental changes.

Data Transmission Interval: Sensor data aggregated and transmitted at 1-hour intervals to maximize bandwidth and energy.

Power Management: Deep sleep mode between readings to save energy.

Software Configuration:

Cloud Platform: Scalable, secure cloud data management was achieved using AWS IoT Core.

Database: MongoDB Atlas enabled flexible, high-performance storage of time-series sensor data.

API Framework: Flask backend paired with Redis caching provided optimal real-time data retrieval.

Real-Time Processing: Streaming data for instant analytics was processed by Apache Kafka.

Machine Learning Frameworks: Scikit-learn for classical models and TensorFlow for neural networks.

Model Hyperparameters:

Model	Parameter	Value
Random Forest	n_estimators	100
max_depth	15	
min_samples_split 10		

LSTM units	64
dropout	0.2
learning_rate	0.001

C. Experimental Environment

The experiments were executed in both cloud and edge environments to simulate real-world conditions:

Cloud Infrastructure: AWS EC2 instances (t3.medium) were utilized for training and deploying models with sufficient computational resources.

Edge Computing: Raspberry Pi 4 boards with 4GB RAM were used as edge nodes to experiment with real-time processing of sensor data and inference near the source of the data.

Mobile Platforms: Android and iOS devices were employed for developing and experimenting user-facing applications.

Programming Languages: The backend machine learning and data pipelines were driven by Python, JavaScript was responsible for the frontend interface, and C++ was employed for firmware on microcontrollers.

5. RESULTS

1) Comparison of State-of-the-Art Methods

The Plant Guardian AI system was compared to other machine learning models to determine the top performing method for each prediction task:

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	94.2%	93.8%	94.1%	93.9%
Support Vector Machine (SVM)	91.7%	90.9%	91.2%	91.0%
Neural Network	93.5%	92.8%	93.2%	93.0%
Gradient Boosting	93.8%	93.1%	93.5%	93.3%

For time-series forecasting:

Model	MAE	RMSE	MAPE
LSTM	0.085	0.127	8.2%
ARIMA	0.142	0.198	13.7%
Prophet	0.118	0.165	11.4%

The outcomes show that the Random Forest classifier provides better accuracy for plant health classification, whereas LSTM models perform incredibly well in predicting time-varying sensor parameters. These findings confirm the merits of ensemble techniques for classification and deep learning for sequential data analysis.

System-wide Performance Metrics:

Average Response Time: 2.3 seconds from sensor reading to recommendation.

System Uptime: 99.7%, guaranteeing high availability.

Prediction Accuracy: 94.2% for health status classification.

False Alert Rate: Low 3.1%, reducing unnecessary alarms.

User Satisfaction: Average user rating of 4.6/5 based on pilot user testing.

2) Statistical Analysis

An Analysis of Variance (ANOVA) test was used to examine whether model performance differed significantly across plant species:

F-statistic: 15.67

p-value: < 0.001

Degrees of Freedom: 14 (species), 135 (residual)

Since the p-value is significantly less than the significance level ($\alpha = 0.05$), the null hypothesis of all species having the same model performance was rejected. This result indicates that species-specific model calibration is crucial to achieve maximum accuracy.

3) Visualization and Insights

Main experimental insights are:

Optimal Monitoring Frequency: A sensor reading interval of 15 minutes provides the ideal compromise between data quality and battery duration.

Critical Parameters: Plant health forecasts are highly dependent on soil moisture ($r = 0.78$) and temperature ($r = 0.71$).

Seasonal Patterns: Light intensity and duration change with seasons, and dynamic thresholds are needed to make the correct assessment.

Water Conservation: The system showed an impressive 35% reduction in water usage over traditional fixed-schedule irrigation.

User Adoption Metrics:

Active Users: 89% of the pilot members used the system after the first 3 months.

Engagement Rate: 2.3 daily average app opening, meaning steady engagement.

Feature Usage: Real-time tracking was employed by 95%, care recommendations by 78%, and historical trend analysis by 65%.

User Experience Outcomes Accessibility:
The user interface of Plant Guardian AI is designed with simplicity in mind, ensuring it remains accessible to individuals regardless of their technical proficiency or prior gardening experience. Clear labeling, intuitive layouts, and responsive design contribute to a seamless interaction experience across various devices.

User Engagement:
The integration of interactive charts and visual analytics encouragesactive involvement by requiring frequen t monitoring of plant conditions. This interactivity creates a feeling of engagement and responsibili ty towards plant care processes, hence enhancing overall user engagement and satisfaction.
Educational Value
One of the system's strongest advantages is how it can improve users'kn owledge of how plants behave. By illustrating environmental and plant health information graphically, users can make connections and conclusions, helping create a learning curve for both inexperienced and seasoned gardeners.
Technical Achievements
Real-Time Processing:
The system is designed to process continuous flows of sensor data with little latency. Visualization in real-time of parameters like temperature, humidity, and soil moisture helps users make timely decisions and act fast on plant requirements.

Scalable Architecture:
The backend architecture is scalable as a fundamental design tenet. It is open to incorporating more sensors, increased datasets,and forthcoming modules without the need for intensive reengineering. This facilitates long-term system sustainability and versatility to broader deployments.

Cross-Platform Compatibility
Plant Guardian AI delivers a persistent and engaged user experience on desktop, tablet, and smartphone platforms. The design consistency and functionality guarantee that the user has access to full system functionality irrespective of operating system or device.

In summary, the system's robust performance in real-time processing, architectural scalability, and usability highlights its potential to serve a broad user base—from individual home gardeners to commercial plant growers. The balance between technical sophistication and user-centric design principles positions Plant Guardian AI as a practical, forward-looking solution in the domain of intelligent plant care.

6. FUTURE RESEARCH DIRECTIONS DIRECTION AND DEVELOPMENT

Integration of computer vision technology to facilitate automated disease diagnosis and plant growth monitoring via image processing.
Adding sensor modalities to the measurement of soil nutrient levels and creation of autonomous fertilization schemes.
Improvement of edge computing strength to minimize reliance on cloud resources, bolstering real-time responsiveness as well as privacy.
Use of federated learning techniques to facilitate privacy-enhancing model updates based on distributed data sources.
Seamless integration with smart home ecosystems and farm automation platforms, promoting holistic management of environmental control systems. In general, the Plant Guardian AI system is a significant step toward sustainable, tech- facilitated plant care solutions. It promises a lot to enable individual gardeners, urban gardeners, and commercial agricultural entities to use smarter, more efficient, and eco-friendly cultivation methods.

7. CONCLUSIONS

The Plant Guardian AI solution represents a powerful, end-to-end Internet of Things (IoT) platform engineered to support smart, data- informed plant cultivation for both industrial farming and homehorticulture. With the incor poration of a wide variety of environmental sensors together with complex machine learning techniques, the solution records significant improvements such as 94.2% accurate plant health classification and a huge 35% in water conservation in contrast to traditional irrigation practic es.

Key innovations and new features of the system are:

Multi-Modal Sensing Architecture:
The unifying combination of soil moisture, ambient environmental conditions, and light intensity sensors provides a complete, multi-faceted representation of plant well-being and conditions for growth.
Advanced Predictive Analytics: The use of Long Short-Term Memory (LSTM) neural networks allows for the prediction of future

environmental patterns and plant status, enabling proactive, timely interventions in care.
Explainable Artificial Intelligence: Through the use of SHAP (SHapley Additive exPlanations), the system provides clear and understandablepredictions, allowing for increased user trust and understanding of automated care recommendations.
Cross-Platform Accessibility: User interfaces that are reachable via web browsers and mobile apps allow for easy, real-time monitoring and control for various user groups.
Optimization of Resources: Intelligent automation results in optimized utilization of essential resources like water and energy, thus ensuring sustainability and cost-effectiveness in plant care processes.
The performance benefits of the system were statistically proven by intense Analysis of Variance (ANOVA) tests, which identified considerable improvements across several species of plants. Moreover, extensive user studies showed high satisfaction and engagement scores, highlighting the real-world feasibility of the solution.

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