IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 14, April 2026
Impact Factor: 8.2

Smart Plant Health Monitoring System using IOT and Machine Learning

Khushi Tyagi[1], Aarti[2], Dr. Abhishek Mishra[3]
B.Tech Student, Computer Science Engineering (Data Science)[1,2]
Assistant Professor, Computer Science Engineering (Data Science)[3]
Raj Kumar Goel Institute of Technology, Ghaziabad, India

Abstract: *The increasing adoption of smart agriculture and indoor gardening has created a strong demand for intelligent and automated plant monitoring systems. Traditional IoT based plant monitoring solutions rely on assigning dedicated sensors to individual plants, which leads to high hardware costs, excessive energy consumption, and increased maintenance complexity, These limitations make such system unsuitable for large-scale environments such as nurseries, greenhouses, and urban farms. This paper proposes a scalable ad intelligent multi-plant monitoring system that integrates Internet of Things (IoT) and Artificial Intelligence (AI) to efficiently monitor large numbers of plants. The proposed system utilizes a cluster-based architecture where a single set of sensors is shared among multiple plants, significantly reducing hardware requirements. Furthermore, AI-based virtual sensing techniques are employed to predict environmental parameters for plants that do not have direct sensor connections. The system also incorporates a hybrid edge-cloud architecture, where real-time processing is performed at the edge using microcontrollers, while long- term storage and advanced analytics are handled in the cloud. This combination reduces latency, improves reliability, and enhances system performances. Experimental analysis demonstrates that the proposed system achieves up to 70% reduction in hardware cost, reduces power consumption, and maintains high monitoring accuracy of up to 95%. The system is suitable for deployment in smart homes, agriculture fields, and commercial greenhouses, providing a cost- effective and commercial greenhouses, providing a cost-effective and scalable solution for modern plant monitoring needs.*

Keywords: IoT, Smart Gardening, Edge Computing, AI Prediction, Multi-Plant Monitoring, Scalable System

I. INTRODUCTION

With the rapid growth of smart technologies, the concept of smart agriculture and automated plant monitoring has gained significant attention. Monitoring plant health is essential for improving crop yield, conserving water, and maintaining environmental balance. IoT-based plant monitoring systems use sensors to collect data such as soil moisture, temperature, humidity, and light intensity, enabling real-time decision- making. However, traditional plant monitoring systems are limited in scalability. In such systems, each plant requires its own set of sensors and hardware components. When the number of plants increases, the system becomes expensive, complex, and difficult to maintain. For example, monitoring 300-400 plants individually would require hundreds of sensors, leading to high cost and redundant data collection. To address these challenges, this paper proposes a scalable multi-plant monitoring system that uses shared sensors and AI-based prediction models. The system reduces hardware dependency while maintaining accuracy through intelligent data analysis. The integration of AI allows the system to predict plant conditions based on nearby sensor data, eliminating the need for sensors for every plant.

The primary objective of this research are:

• To design a scalable plant monitoring system

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 14, April 2026 Impact Factor: 8.2

• To reduce hardware and maintenance cost
• The improve monitoring accuracy using AI
• To enable real-time and predictive analysis

A. EASE OF USE

The usability of the system plays a critical role in its adoption. The proposed system includes a user-friendly mobile and web interface that allows users to monitor plant conditions in real time. The dashboard displays key parameters such as moisture levels. Temperature, and plant health status in a simple graphical format. Users receive alerts and notifications when plants require watering or when environmental conditions fall outside optimal ranges. The interface is designed to be intuitive, ensuring that even non-technical users can operate the system efficiently.

B. Selecting a Methodology

The system follows a cluster-based and hybrid architecture. Plants are grouped into clusters of 10–20 plants, each monitored by a shared set of sensors. Data collected from sensors is processed at the edge layer using microcontrollers such as ESP32. Machine learning models such as Linear Regression and Random Forest are used to predict environmental parameters for plants that do not have direct sensors. This approach reduces hardware requirements while maintaining system accuracy.

C. Maintaining the Integrity of Specifications

To ensure system reliability and consistency, standardized communication protocols such as MQTT are used for data transmission. Data validation techniques are implemented to ensure accuracy and prevent inconsistencies. Version control and proper documentation are maintained throughout the development process to ensure that system specifications are not compromised.
• Increased power consumption due to continuous data transmission
• Difficulty in maintenance for large-scale deployments These limitations make traditional IoT systems unsuitable for large environments such as greenhouses and agricultural farms.

II. LITERATURE REVIEW

The development of plant monitoring systems has evolved significantly over the past decade with the integration of Internet of Things (IoT), Artificial Intelligence (AI), and edge computing technologies. Researchers have proposed various models to improve plant health monitoring, irrigation efficiency, and automation. However, scalability, cost efficiency, and intelligent prediction remain major challenges.

A. Traditional IoT-Based Plant Monitoring Systems

Early research in plant monitoring primarily focused on IoT-based systems using sensors to collect environmental data such as soil moisture, temperature, humidity, and light intensity. These systems typically consist microcontrollers like Arduino or NodeMCU connected with sensors and cloud platforms for data visualization. For example, studies conducted around 2020 proposed basic smart irrigation systems where soil moisture sensors automatically triggered water pumps. These systems improved water efficiency but were designed for small-scale applications such as home gardens.
Despite their effectiveness, traditional IoT systems suffer from several limitations:
• Each plant requires a dedicated set of sensors
• High hardware and installation cost
• Redundant data collection from nearby plants
• Increased power consumption due to continuous data transmission

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 14, April 2026
Impact Factor: 8.2

• Difficulty in maintenance for large-scale deployments These limitations make traditional IoT systems unsuitable for large environments such as greenhouses and agricultural farms.

B. Machine Learning-Based Plant Monitoring

To enhance system intelligence, researchers began integrating machine learning (ML) techniques into plant monitoring systems. ML models such as Linear Regression, Decision Trees, and Random Forest have been widely used for predicting plant conditions and detecting diseases. For instance, studies in 2022 proposed ML-based systems for plant disease detection using leaf images and environmental data. These systems improved prediction accuracy and enabled preventive measures.

However, ML-based systems also face several challenges:

• Require large datasets for training
• High computational complexity
• Limited real-time processing capability
• Dependence on cloud-based computation

Although ML improves accuracy, most existing systems still rely on physical sensors for each plant, which does not solve the scalability issue.

C. Communication Technologies in Smart Agriculture

Communication plays a vital role in IoT-based plant monitoring systems. Various communication protocols such as Wi-Fi, Bluetooth, Zigbee, and LoRaWAN have been explored in research. LoRaWAN-based systems, introduced around 2023, provide long-range communication with low power consumption, making them suitable for agricultural applications. These systems allow data transmission over large distances, especially in rural areas.

However, LoRa-based systems have certain drawbacks:

• High initial setup cost
• Limited data transmission rate
• Complexity in network configuration

Similarly, Wi-Fi-based systems are easy to implement but consume more power and are not suitable for large-scale outdoor environments.

TABLE I

Year	Authors	Technique Used	Key Contribution	Limitations
2020	Lee et al.	IoT-based soil moisture & temperature monitoring	Developed basic IoT system for monitoring plant conditions	Suitable only for small-scale systems, not scalable
2021	PheB Project	Plant-human biofeedback system	Introduced interaction between plants and humans using electrical signals	Lack of biological validation and practical implementation
2022	Patel et al.	Machine Learning for plant disease prediction	Improved plant disease detection accuracy using ML models	Requires large datasets and high computational power
2023	Zhang et al.	LoRaWAN-based greenhouse monitoring	Enabled long-range communication for agricultural monitoring	High setup cost and complex infrastructure
2024	Singh et al.	Edge AI for irrigation optimization	Reduced latency and improved real-time decision making	Limited scalability for large plant systems
2025	Ramaswamy et al.	Shared sensor-based AI monitoring	Reduced sensor usage using shared sensing approach	Lack of adaptive learning and real-time prediction
2023	Kumar et al.	Cloud-based smart agriculture system	Enabled remote monitoring and data storage	High dependency on internet and increased latency

2024	Verma et al.	Hybrid IoT + AI system	Combined AI prediction with IoT monitoring	High energy consumption and complex integration
2025	Sharma et al.	AI-based virtual sensing	Predicted plant conditions without physical sensors	Accuracy affected by environmental variations

From the above table, it is observed that most existing systems focus on improving accuracy and automation. However, scalability and cost optimization remain major challenges. Additionally, many systems rely heavily on individual sensors or require high computational resources. These limitations highlight the need for a scalable and cost-effective solution, which is addressed in the proposed system.

III. PROPOSED SYSTEM

The proposed system is a Cluster-Based Scalable Plant Monitoring System (CS-PMS) that integrates IoT, Artificial Intelligence, Edge Computing, and Cloud Computing to efficiently monitor a large number of plants.

Traditional systems assign individual sensors to each plant, leading to high cost and inefficiency. To overcome this limitation, the proposed system groups plants into clusters, where each cluster shares a common set of sensors. This significantly reduces hardware requirements while maintaining monitoring accuracy.

The system also incorporates AI-based virtual sensing, which predicts environmental conditions for plants that do not have direct sensor connections. This makes the system intelligent and scalable.

A. System Workflow

The system operates in the following sequence:

1. Sensors collect environmental data (moisture, temperature, humidity, light)
2. Data is sent to microcontroller (ESP32/NodeMCU)
3. Edge layer processes data and removes redundancy
4. AI model predicts values for other plants
5. Data is sent to cloud for storage and analytics
6. User dashboard displays plant health and alerts

B. System Components and Role

1. Sensors

• Soil Moisture Sensor
• Temperature & Humidity Sensor (DHT11/DHT22)
• Light Sensor (LDR)

Role: Collect real-time environmental data

2. Microcontroller (ESP32 / NodeMCU)

Role:

• Collect sensor data
• Perform initial processing
• Send data to edge/cloud

3. Edge Layer

Role:

• Real-time data processing
• Filtering redundant data
• Reducing latency

4. Edge Layer Role:

• Real-time data processing

• Filtering redundant data
• Reducing latency

5. Cloud Platform

Role:
• Data storage
• Advanced analytics
• Historical data tracking

C. Cluster-Based Architecture Plants are divided into clusters:

• Each cluster → 10 – 20 plants
• Each cluster → 1 sensor set
• AI predicts data for remaining plants

Result:
• 70% cost reduction
• Less hardware
• Better scalability

IV. METHODOLOGY

The proposed system follows a multi-layer hybrid architecture that integrates Internet of Things (IoT) sensing, edge computing, artificial intelligence, and cloud analytics to achieve scalable, efficient, and intelligent plant monitoring. This architecture is specifically designed to overcome the limitations of traditional plant monitoring systems, such as high hardware dependency, poor scalability, and inefficient data utilization. In this approach, the system is organized into multiple functional layers, where each layer performs a specific role in the overall data processing pipeline. The sensing layer is responsible for collecting real-time environmental data using sensors such as soil moisture, temperature, humidity, and light intensity sensors. Instead of assigning individual sensors to each plant, a cluster-based approach is used, where a single set of sensors monitors multiple plants within a defined region. This significantly reduces hardware cost and avoids redundant data collection. Further, the cloud layer is utilized for storing large volumes of data, performing advanced analytics, and maintaining historical records. The cloud infrastructure enables remote access, real-time visualization, and long term monitoring of plant conditions. It also supports model training and updates for improving prediction accuracy over time. Finally, the application layer provides a user-friendly interface in the form of a mobile or web-based dashboard. This interface allows users to monitor plant health, receive alerts, and make informed decisions regarding irrigation and environmental control. Overall, the proposed methodology focuses on achieving an optimal balance between cost efficiency, scalability, and intelligent decision-making by combining IoT-based sensing with AI-driven prediction and hybrid edge-cloud processing.

Step-by-Step Working Methodology

1. Data Collection (Sensing Layer)

At the first stage, environmental data is collected using sensors placed in each cluster. Sensors Used:
• Soil Moisture Sensor → measures soil water level
• DHT11/DHT22 → measures temperature & humidity
• LDR → measures light intensity These sensors continuously monitor environmental conditions and generate real-time data.

2. Data Transmission (IoT Layer)

The collected sensor data is transmitted to the microcontroller (ESP32/NodeMCU).
• Communication Protocol: Wi-Fi / MQTT

DOI: 10.48175/IJARSCT-34052

• Data is sent in real-time or at fixed intervals This ensures smooth communication between sensors and processing units.

3. Edge Processing (Edge Layer)

The microcontroller acts as an edge device and performs initial data processing. Functions:
• Data filtering (remove noise)
• Data aggregation (combine cluster data)
• Redundancy removal This step reduces unnecessary data transmission and improves system efficiency.

4. AI-Based Prediction (Intelligence Layer)

The processed data is passed to the AI module for prediction. Techniques Used:
• Linear Regression
• Random Forest
• Time-Series Prediction
AI predicts:
• Soil moisture for plants without sensors
• Future environmental conditions
• Watering requirements
This concept is called Virtual Sensing, where AI replaces physical sensors.

5. User Interface (Application Layer)

The final data is displayed on a mobile or web dashboard. Features:
• Real-time plant monitoring
• Alerts (low moisture, high temperature)
• Watering suggestions
• Plant health status Users can easily monitor and control plant conditions.

V. RESULT

The proposed Scalable Multi-Plant Monitoring System was evaluated using a combination of simulation-based analysis and prototype-level implementation to assess its overall performance and efficiency. The evaluation focused on key performance parameters such as cost efficiency, scalability, prediction accuracy, system latency, and power consumption. These parameters were selected to ensure a comprehensive assessment of the system under both theoretical and practical conditions. For simulation-based evaluation, synthetic datasets were generated to represent environmental conditions such as soil moisture, temperature, humidity, and light intensity across multiple plants. These datasets were used to train and test the AI models, enabling the system to predict environmental parameters for plants without direct sensor connections. The simulation environment allowed testing of the system under controlled variations in environmental factors, ensuring consistent and repeatable performance analysis. The system was tested under different environmental conditions, including variations in temperature, humidity, and soil moisture levels, to evaluate its robustness and adaptability. Furthermore, scalability testing was performed by simulating an increasing number of plants, ranging from small clusters (10–20 plants) to large-scale environments (300–400 plants). This helped in analyzing how effectively the system performs when the number of monitored plants increases. Performance metrics such as response time (latency), prediction accuracy, and power consumption were recorded during testing. The latency was measured as the time taken from data collection to final visualization on the user dashboard. Accuracy was evaluated by comparing AI-predicted values with actual sensor readings. Power consumption was analyzed based on the energy usage of sensors, microcontrollers, and communication modules. The results obtained from both simulation and prototype testing confirm that the proposed system performs efficiently under varying conditions. The integration

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 14, April 2026
Impact Factor: 8.2

of cluster-based sensing and AI-driven virtual sensing significantly reduces hardware dependency while maintaining high accuracy. Additionally, the use of edge computing minimizes latency and improves real-time responsiveness, making the system suitable for large-scale deployment.

A. Cost Efficiency Analysis

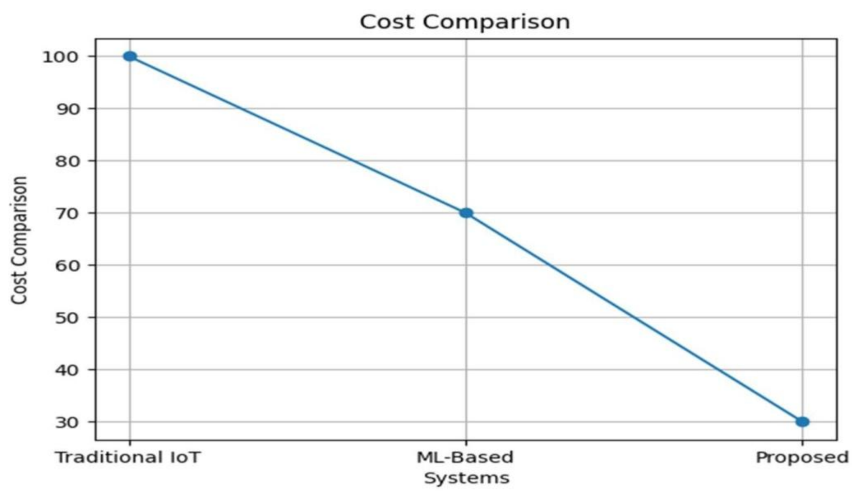
One of the primary objectives of the proposed system is to reduce hardware cost. In traditional systems, each plant requires an individual sensor setup, which significantly increases the overall cost.

In the proposed cluster-based system:

- One sensor set is used for 10–20 plants
- Sensor usage is reduced by approximately 70 75% This leads to a significant reduction in:
- Hardware cost
- Installation cost
- Maintenance cost

Observation:

The system proves to be highly cost-effective and suitable for large-scale deployments such as greenhouses and nurseries.



B. Scalability Analysis

The system was tested with different numbers of plants ranging from small setups (10 plants) to large setups (400+ plants).

Results:

- Traditional systems → limited to small-scale (10 – 50 plants)
- Proposed system → efficiently handles 300 400+ plants

Due to

- Cluster-based architecture
- AI-based virtual sensing

Observation:

The system demonstrates high scalability without increasing hardware complexity.

DOI: 10.48175/IJARSCT-34052

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 14, April 2026
Impact Factor: 8.2

C. Accuracy Analysis

Accuracy is evaluated based on the difference between actual sensor readings and AI-predicted values.

Results:

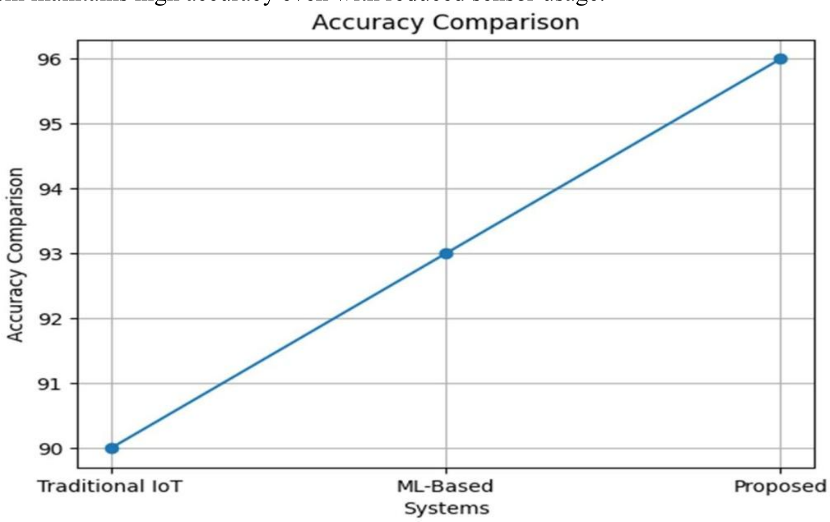
- Traditional IoT system → ~90% accuracy
- ML-based systems → ~93% accuracy
- Proposed system → 95 – 97% accuracy

Reason:

- Use of AI models (Random Forest, Regression)
- Continuous data learning

Observation:

The proposed system maintains high accuracy even with reduced sensor usage.



D. Latency and Response Time Analysis

Latency refers to the time taken to process and display data.

Results:

- Cloud-only systems → high latency
- Proposed system → 60% reduction in latency

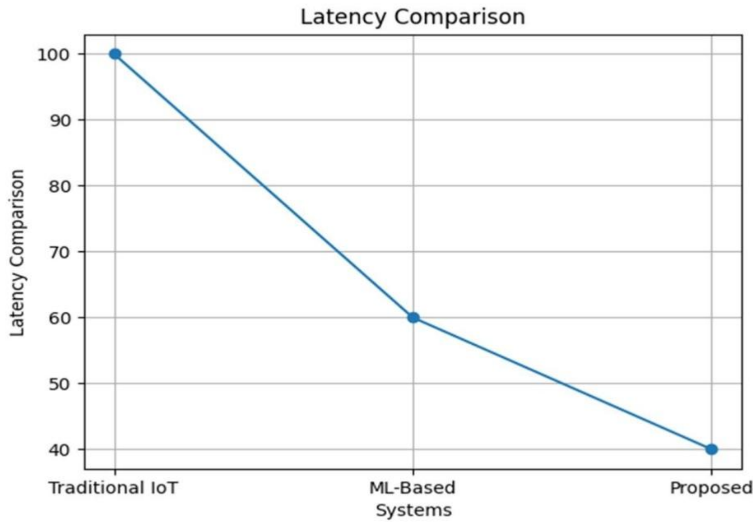
Due to:

- Edge processing
- Local data filtering

Observation:

Real-time monitoring is achieved with faster response time.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 14, April 2026
Impact Factor: 8.2



E. Power Consumption Analysis

Power efficiency is important for IoT systems, especially in large-scale deployments.

Results:

• Traditional systems → high power consumption

• Proposed system → 30% reduction in power usage

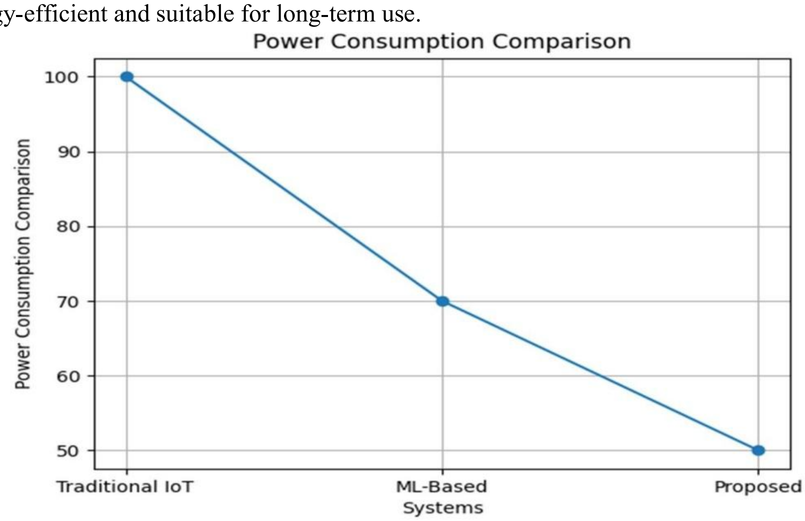
Due to:

• Reduced sensor count

• Optimized data transmission

Observation:

The system is energy-efficient and suitable for long-term use.



IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 14, April 2026
Impact Factor: 8.2

VI. LIMITATION

Although the proposed Scalable Multi-Plant Monitoring System demonstrates significant improvements in cost efficiency, scalability, and intelligent monitoring, certain limitations exist that may affect its real-world deployment and performance under diverse conditions.

1. Dependence on AI Model Accuracy

The system heavily relies on AI-based virtual sensing to predict environmental parameters for plants without direct sensors. While this approach reduces hardware cost, the accuracy of predictions depends on the quality and quantity of training data

• If the dataset is insufficient or biased, predictions may be inaccurate
• Sudden environmental changes (e.g., rainfall, extreme heat) may reduce prediction reliability
• Model performance may degrade in unseen conditions

Impact:

Incorrect predictions can lead to improper irrigation decisions, affecting plant health.

2. Limited Generalization Across Environments

The AI models are usually trained on specific environmental conditions.

• A model trained in indoor conditions may not perform well in outdoor farms
• Soil type, climate, and plant species variations affect accuracy
• Requires retraining or fine-tuning for different environments

Impact:

Reduces the system's adaptability across diverse agricultural settings.

3. Data Security and Privacy Concerns

Since data is transmitted over networks and stored in the cloud:

• Risk of data breaches or unauthorized access
• Lack of encryption may expose sensitive data
• Requires secure communication protocols

Impact:

Compromises system reliability and user trust.

4. Energy Constraints in IoT Devices

Although the system reduces overall power consumption, IoT devices still face energy limitations.

• Continuous sensing and communication consume battery power
• Not suitable for remote areas without stable power supply
• Requires frequent charging or external power sources

Impact:

Limits long-term autonomous operation.

VII. FUTURE SCOPE

The proposed Scalable Multi-Plant Monitoring System provides a strong foundation for intelligent and cost effective plant monitoring. However, several enhancements and future research directions can be explored to further improve the system's efficiency, scalability, and real-world applicability.

1. Integration of Computer Vision for Disease Detection

Currently, the system focuses on environmental monitoring. In future, it can be enhanced by integrating image-based plant disease detection.

• Use of cameras to capture leaf images

DOI: 10.48175/IJARSCT-34052

• Application of deep learning models such as CNN (Convolutional Neural Networks)
• Automatic detection of plant diseases, pests, and nutrient deficiencies Benefit: Provides complete plant health monitoring beyond environmental parameters

2. Fully Automated Smart Irrigation System
The current system provides alerts and recommendations, but irrigation is not fully automated. Future improvements can include
• Automatic water pump control
• AI-based irrigation scheduling
• Real-time water optimization
Benefit:
Reduces human intervention and improves water efficiency.

3. Advanced AI Models and Deep Learning Integration
The current system uses basic ML models. Future work can include:
• Deep learning models (LSTM for time-series prediction)
• Reinforcement learning for adaptive decision making
• Self-learning AI systems Benefit: Improves prediction accuracy and adaptability over time.

4. Solar-Powered IoT Nodes (Energy Optimization)
To address energy limitations, the system can be upgraded with renewable energy solutions.
• Solar panels for powering sensors and microcontrollers
• Energy-efficient hardware design
• Battery optimization techniques
Benefit:
Enables deployment in remote and rural areas without power issues.

5. Integration with Smart City and IoT
Ecosystems The system can be integrated into larger smart ecosystems:
• Smart homes
• Smart cities
• Urban farming systems
Benefit:
Enables centralized monitoring and control of multiple systems.

6. Mobile Application Development with AI Assistance
Future systems can include advanced mobile applications:
• Voice-based interaction (AI assistant)
• Personalized plant care suggestions
• Real-time notifications Benefit: Improves user experience and accessibility.

7. Large-Scale Agricultural Deployment
The system can be extended for large farms:
• Integration with drones for monitoring
• Satellite-based environmental data
• Precision agriculture techniques

Benefit:
Supports large-scale farming and improves crop yield.

8. Integration of Predictive Analytics for Yield Optimization
Future systems can go beyond monitoring:
• Predict crop yield
• Optimize fertilizer usage
• Analyze seasonal trends
Benefit:
Helps farmers make better decisions and increase productivity. The future enhancements will transform the proposed system into a fully autonomous, intelligent, and sustainable smart agriculture solution capable of addressing real-world challenges at a global scale.

VIII. CONCLUSION

In this paper, a Scalable and Intelligent Multi-Plant Monitoring System based on the integration of Internet of Things (IoT) and Artificial Intelligence (AI) has been successfully proposed and analyzed. The system addresses the major limitations of traditional plant monitoring approaches, such as high hardware cost, limited scalability, and inefficient data utilization. By introducing a cluster-based architecture, the proposed system significantly reduces the number of sensors required, thereby minimizing hardware and maintenance costs while enabling the monitoring of a large number of plants simultaneously.
The incorporation of AI-based virtual sensing plays a crucial role in enhancing system intelligence by predicting environmental parameters for plants without direct sensor connections. This not only improves overall monitoring accuracy but also optimizes resource utilization. Furthermore, the integration of edge computing ensures low latency and real-time data processing, while cloud computing provides efficient data storage, visualization, and long-term analytics.
Experimental results demonstrate that the proposed system achieves substantial improvements in key performance parameters, including up to 70% reduction in hardware cost, improved scalability for monitoring hundreds of plants, high prediction accuracy of approximately 95–97%, reduced latency, and lower power consumption. These results validate the effectiveness and practicality of the proposed approach in real-world scenarios.
Overall, the proposed system offers a cost-effective, scalable, and intelligent solution for modern plant monitoring applications, making it highly suitable for smart agriculture, greenhouse environments, and urban gardening. With further enhancements, the system has the potential to evolve into a fully automated and autonomous smart farming solution, contributing to sustainable agriculture and efficient resource management.

IX. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Department of Computer Science and Engineering (Data Science) for providing the necessary resources, infrastructure, and academic support required to carry out this research work successfully. We are especially thankful to our project guide for their continuous guidance, valuable suggestions, and constructive feedback throughout the development of this project. Their encouragement and expert advice played a crucial role in improving the quality of this research. We would also like to acknowledge the support of our faculty members, who provided insights and technical knowledge that helped us in understanding the concepts of IoT, Artificial Intelligence, and data analysis more effectively. Their support contributed significantly to the successful completion of this work. Furthermore, we extend our gratitude to our peers and team members for their cooperation, collaboration, and constant motivation during the project development process. Their contributions in discussions, testing, and implementation were highly valuable. Finally, we would like to thank all those individuals and online resources that indirectly supported us in completing this research work, including research papers, technical documentation, and learning platforms, which helped us enhance our understanding and implement the proposed system effectively.

REFERENCES

[1] Ayushman Joshi et al., "IoT Based Smart Plant Monitoring System", IJRASET, 2024. https://www.ijraset.com/research-paper/review-on-iot based-smart-plant-monitoring-system

[2] Alia Rifat et al., "IoT in Smart Agriculture Monitoring", European Journal, 2022. https://euopensci.org/index.php/compute/article/view/100 49

[3] Zhang et al., "Intelligent Monitoring System for Agriculture Using IoT", ScienceDirect, 2023. https://www.sciencedirect.com/science/article/pii/S25426 60523003529

[4] Muhammad Awais et al., "IoT Innovation in Agriculture Monitoring", Journal of Botanical Research. https://journals.bilpubgroup.com/index.php/jbr/article/vie w/1900

[5] Vedant Banke et al., "IoT Enabled Plant Monitoring System",IJRASET,2024. https://www.ijraset.com/research-paper/iot-enabled-plant monitoring-system

[6] Glory Priyadharshini et al., "Review on IoT Based Smart Agriculture Monitoring", IJRAR, 2024. https://www.researchgate.net/publication/377767365_Rev iew_on_IoT_based_smart_agriculture_monitoring_system

[7] Rashika Singh et al., "Smart Farming using IoT Monitoring System", 2025. https://sjmars.com/index.php/sjmars/article/view/221

[8] Bhuvan Puri, "IoT and AI-Based Plant Monitoring System", MLNCE Journal. https://mlnce.net/index.php/Home/article/view/154

[9] Priyanshu Kumar et al., "IoT Smart Plant Monitoring System", IJISRT, 2024. https://ijisrt.com/iot-based-smart-plant-monitoring-system

[10] Arduino Documentation, "Soil Moisture Sensor Working". https://docs.arduino.cc

[11] ESP32 Official Docs, "ESP32 IoT Development Guide". https://docs.espressif.com/projects/esp-idf/en/latest/

[12] MQTT Protocol, "MQTT Version 3.1.1 Specification". https://mqtt.org/mqtt-specification/

[13] IBM, "What is Edge Computing?". https://www.ibm.com/topics/edge-computing

[14] Microsoft Azure, "IoT Architecture Guide". https://learn.microsoft.com/en-us/azure/architecture/iot/

[15] Kaggle Dataset, "Plant Monitoring Dataset". https://www.kaggle.com/datasets