

**SMARTROSE: AI-IOT PLATFORM FOR SMART
GREENHOUSE ROSE FARMING IN SRI LANKA**

25-26J-299

Final Thesis

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**B.Sc. (Hons) Degree in Information Technology Specialized in Information
Technology**

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

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Supervised by Mr. Junius Anjana

Co-supervised by Ms. Kaushika Kahatapitiya

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
**Department of Information Technology
Sri Lanka Institute of Information Technology
Sri Lanka**

August 2025

DECLARATION

DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Date:

22/AP/2026

ABSTRACT

This research presents the design and development of an intelligent nutrient management component for rose cultivation, integrating Internet of Things (IoT) technology with machine learning techniques to enable data-driven fertilizer recommendations. Traditional nutrient management practices rely on manual observations and generalized guidelines, often resulting in inefficient fertilizer usage and inconsistent crop performance. To address these limitations, the proposed system utilizes IoT-based sensors to collect real-time environmental and soil data, including parameters such as pH, temperature, humidity, and nutrient levels.

The collected data are processed and analyzed using a Random Forest-based machine learning model to predict nutrient requirements accurately. Based on these predictions, the system generates optimized fertilizer recommendations, including type, dosage, and application timing. The implementation integrates data acquisition, preprocessing, prediction, and user interaction through a mobile application, ensuring real-time and adaptive decision-making.

Experimental results demonstrate that the proposed model achieves low error rates in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), indicating high prediction accuracy and reliability. Compared to traditional methods and other machine learning approaches, the system provides improved performance and better adaptability to varying environmental conditions.

The proposed solution contributes to precision agriculture by enhancing fertilizer efficiency, reducing environmental impact, and improving crop yield and quality. Furthermore, the system demonstrates strong potential for commercialization as an Intelligent Nutrient Management (INM) product, supporting scalable and sustainable smart farming practices.

Keywords: Fertilizer Recommendation, Internet of Things (IoT), Machine Learning, Nutrient Management, Random Forest, Smart Agriculture

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LIST OF ABBREVIATIONS

Abbreviation	Description
IoT	Internet of Things
ML	Machine Learning
AI	Artificial Intelligence
NPK	Nitrogen, Phosphorus, and Potassium
pH	Potential of Hydrogen
EC	Electrical Conductivity
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
INM	Intelligent Nutrient Management

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1. INTRODUCTION

1.1. Background and Literature Review

The agricultural sector is increasingly transitioning toward intelligent, data-driven systems to improve productivity, efficiency, and sustainability. Greenhouse cultivation of high-value crops such as roses requires precise control of environmental and nutrient conditions to ensure consistent yield and quality. However, traditional farming practices still rely heavily on manual observation, fixed fertilizer schedules, and farmer experience, which often lead to inefficient resource utilization, nutrient imbalances, and reduced crop performance [1], [6].

The emergence of the Internet of Things (IoT) has significantly transformed modern agriculture by enabling real-time monitoring of environmental and soil parameters such as temperature, humidity, pH, and moisture levels. IoT-based systems facilitate continuous data collection and remote monitoring, supporting precision agriculture practices [1], [5]. Several studies have demonstrated that IoT-enabled greenhouse and irrigation systems improve operational efficiency and crop productivity through automated monitoring and control mechanisms [9]-[11]. However, most of these systems are limited to data acquisition and threshold-based automation, lacking predictive intelligence for proactive decision-making.

In parallel, Artificial Intelligence (AI) and Machine Learning (ML) have introduced advanced capabilities for analyzing complex agricultural data and generating predictive insights. Machine learning techniques such as artificial neural networks, regression models, and ensemble methods have been applied to fertilizer recommendation, crop monitoring, and yield prediction tasks [2], [3], [13]. These approaches improve accuracy compared to traditional methods, but they are often developed using static datasets and lack integration with real-time IoT data, limiting their adaptability in dynamic greenhouse environments.

Recent studies emphasize the importance of integrating AI with IoT to develop intelligent agricultural systems capable of both sensing and decision-making [7], [8]. Despite this, most existing solutions remain crop-agnostic and are not optimized for specific crops such as roses, which require precise nutrient balance and environmental control. Agronomic studies highlight that factors such as NPK levels, soil pH, electrical conductivity (EC), and environmental conditions significantly influence rose growth, flower quality, and yield [17]-[20]. However,

these findings are largely experimental and have not been effectively translated into real-time automated systems.

Furthermore, existing smart agriculture solutions typically address isolated problems such as irrigation control, fertilizer recommendation, or environmental monitoring independently. This lack of integration limits their effectiveness in real-world applications, where crop management requires coordinated decision-making across multiple factors. Therefore, there is a growing need for integrated systems that combine real-time sensing with predictive intelligence to support comprehensive and adaptive agricultural decision-making. Recent research has also explored nutrient optimization and sustainable soil management strategies in rose cultivation, highlighting the importance of balanced nutrient supply and environmentally responsible farming practices [19]-[22]. To provide a clearer comparison of existing approaches, Table 1 summarizes their strengths and limitations in relation to nutrient management and decision support.

Table 1: Summary of Existing Approaches and Limitations

Category	Approach	Strengths	Limitations
IoT Systems	Monitoring & irrigation [1], [10]	Real-time data collection	No prediction
ML Models	Fertilizer prediction [13]	Data-driven decisions	No real-time integration
Smart Fertilizers	Sustainable inputs [15], [16]	Improve soil & yield	Not automated
Rose Studies	Nutrient research [18]-[20]	Accurate domain knowledge	No system implementation
Proposed Work	IoT + ML integration	Predictive + adaptive	Not applicable

As shown in Table 1, existing IoT-based systems primarily focus on real-time monitoring and automation but lack predictive capabilities for proactive decision-making. Similarly, machine learning-based approaches provide data-driven insights but are often developed using static datasets and do not integrate real-time environmental data. Although smart fertilizers improve soil health and sustainability, they are not supported by automated decision systems.

Additionally, agronomic studies on roses provide valuable domain knowledge but lack practical system-level implementation.

These limitations highlight a clear research gap in the development of integrated systems that combine real-time IoT sensing with machine learning-based prediction to enable intelligent and adaptive nutrient management. Addressing this gap forms the foundation of the proposed system.

1.2. Research Gap

Despite the advancements in IoT-based monitoring and machine learning-based prediction systems, several key limitations remain. Most IoT-based agricultural systems focus primarily on data collection and visualization, without incorporating predictive analytics for intelligent decision support [1], [5]. Similarly, many machine learning-based fertilizer recommendation systems operate on static datasets and do not utilize real-time environmental data, reducing their effectiveness under dynamic conditions [12], [13].

In addition, existing solutions are largely crop-independent and fail to address the specific requirements of greenhouse rose cultivation, where precise nutrient control is essential for maintaining flower quality and productivity. Although agronomic research provides detailed insights into nutrient management for roses, these findings have not been integrated into automated, real-time decision-support systems [17], [18].

Therefore, the primary research gap lies in the lack of an integrated, real-time, and crop-specific nutrient management system that combines IoT-based environmental sensing with machine learning-driven prediction to provide adaptive and accurate fertilizer recommendations for greenhouse rose cultivation.

1.3. Research Problem

Efficient nutrient management is a critical factor in achieving optimal growth, yield quality, and sustainability in greenhouse rose cultivation. However, conventional farming practices rely on manual decision-making and generalized fertilizer guidelines, which often lead to inefficient fertilizer usage, increased operational costs, and environmental impact [14]-[16].

Although IoT technologies enable real-time monitoring and machine learning techniques provide predictive capabilities, existing systems fail to integrate these technologies into a

unified solution for nutrient management. As a result, there is no comprehensive system capable of delivering accurate, data-driven, and adaptive fertilizer recommendations tailored to dynamic environmental conditions and crop-specific requirements.

This research addresses the problem of developing an integrated intelligent nutrient management system that leverages real-time IoT data and machine learning techniques to provide precise, adaptive, and crop-specific fertilizer recommendations for greenhouse rose cultivation.

1.4. Objectives

1.4.1. Main Objectives

To develop an intelligent nutrient management component that integrates IoT-based environmental sensing with machine learning techniques to provide accurate, data-driven, and adaptive fertilizer recommendations for greenhouse rose cultivation.

1.4.2. Specific Objectives

- To collect and analyze real-time environmental and soil data using IoT-based sensors.
- To preprocess and prepare collected data for machine learning model development.
- To design and develop a predictive machine learning model for nutrient requirement estimation.
- To generate optimized fertilizer recommendations based on predicted nutrient levels.
- To evaluate the performance of the developed model using appropriate evaluation metrics.
- To integrate the solution into a scalable smart agriculture framework for real-time decision support.

1.5. Novelty and Contribution of the Study

The novelty of this research lies in the integration of IoT-based real-time data acquisition with machine learning-driven nutrient prediction to develop a crop-specific and adaptive fertilizer recommendation system for greenhouse rose cultivation.

Unlike existing approaches that focus on monitoring or prediction independently, the proposed system combines both capabilities into a unified framework, enabling real-time, data-driven decision-making. Furthermore, the system is specifically tailored to rose cultivation,

incorporating domain-specific agronomic knowledge to improve accuracy and practical applicability.

This integrated approach contributes to precision agriculture by enhancing fertilizer efficiency, reducing environmental impact, and supporting sustainable and scalable smart farming practices.

2. METHODOLOGY

2.1. System Overview

The proposed system is designed as an intelligent, data-driven nutrient management component within the SmartRose platform, integrating Internet of Things (IoT) sensing with machine learning-based predictive analytics. The system enables real-time monitoring, analysis, and decision support for greenhouse rose cultivation by combining environmental and soil data with predictive modeling techniques.

The architecture follows a layered approach consisting of data acquisition, data processing, intelligence, and application layers, enabling seamless interaction between physical sensors and decision-support mechanisms. This design aligns with modern smart agriculture frameworks, where IoT devices collect real-time data and machine learning models generate actionable insights for improved agricultural decision-making [1], [7].

2.2. System Architecture

Figure 1 illustrates the overall system architecture of the proposed intelligent nutrient management component, highlighting the interaction between IoT sensing, data processing, machine learning prediction, and user interface layers.

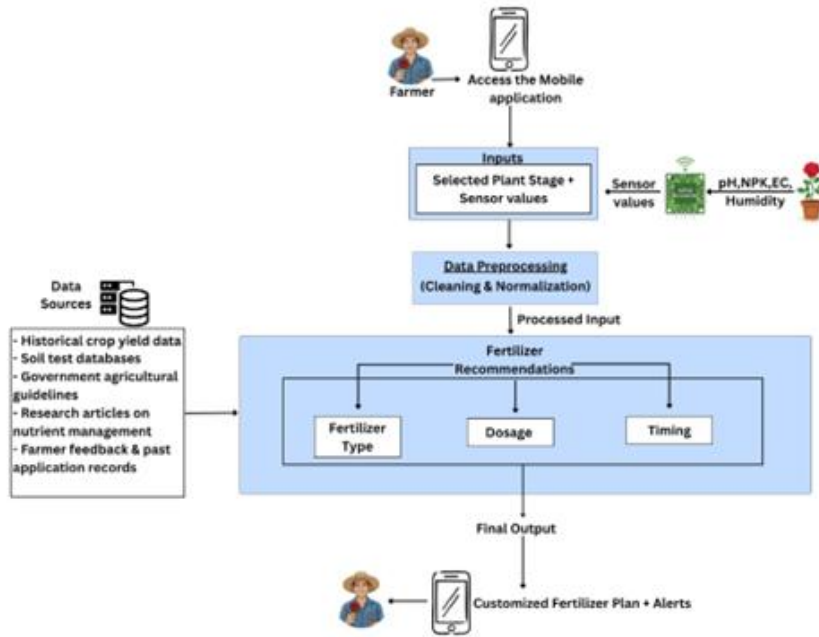


Figure 1: System Architecture Diagram of INM Component

As shown in Figure 1, the system is organized into four main layers, each responsible for a specific function within the overall architecture. This layered architecture ensures modularity, scalability, and efficient integration of IoT sensing with machine learning-based decision-making, making the system suitable for real-time smart agriculture applications.

- **Sensing Layer**

This layer consists of IoT-based sensors deployed within the greenhouse environment to collect real-time data. The sensors include:

- NPK sensor (Nitrogen, Phosphorus, Potassium)
- pH sensor
- Electrical Conductivity (EC) sensor
- Soil moisture sensor
- Temperature and humidity sensor (SHT31)

These sensors continuously monitor soil and environmental conditions that directly influence nutrient availability and plant health. IoT-based sensing has been widely adopted in precision agriculture due to its ability to provide continuous, real-time data for informed decision-making [5], [6].

- **Communication Layer**

The collected sensor data are transmitted to a cloud-based system using an ESP32 microcontroller with built-in Wi-Fi capability. The ESP32 serves as a low-cost and energy-efficient communication module suitable for agricultural IoT deployments.

The use of wireless communication enables remote monitoring and supports scalability across multiple greenhouse units. Similar IoT communication architectures have been successfully applied in smart irrigation and greenhouse monitoring systems [9], [10].

- **Data Processing and Intelligence Layer**

This layer is responsible for data preprocessing and predictive analysis. Raw sensor data undergo several preprocessing steps, including:

- Noise filtering
- Missing value handling
- Data normalization

These preprocessing techniques improve data quality and ensure consistency for machine learning model training [2].

Following preprocessing, the data are processed using a machine learning-based prediction model. A Random Forest regression model is selected as the primary predictive model due to its robustness, ability to handle nonlinear relationships, and resistance to overfitting compared to traditional regression techniques [2], [3].

The model predicts key nutrient-related parameters, including:

- Nutrient trends (NPK levels)
- Electrical conductivity (EC) trends
- Potential nutrient deficiencies or imbalances

The selection of Random Forest is further justified by its superior performance in agricultural prediction tasks, where complex interactions exist between environmental variables and crop responses [2].

- **Application Layer**

The application layer provides a user interface for farmers through a mobile or web-based dashboard. This interface displays:

- Real-time sensor readings
- Predicted nutrient trends
- Fertilizer recommendations (type, dosage, timing)
- Alerts and notifications

The integration of user-friendly interfaces in smart agriculture systems enhances usability and supports decision-making for farmers with varying levels of technical expertise [8].

2.3. Data Collection and Preprocessing

Data collection is performed using IoT sensors deployed in a controlled greenhouse environment. The dataset includes key environmental and soil parameters such as NPK levels, pH, electrical conductivity (EC), soil moisture, temperature, and humidity, which are essential for nutrient prediction in greenhouse cultivation.

In addition to real-time sensor data, agronomic reference data and fertilizer application records are incorporated to enrich the dataset. Synthetic data generation techniques are also applied to increase dataset diversity and improve model generalization.

The collected dataset consists of approximately 500-1000 samples, providing sufficient variability for model training and evaluation. Prior to model development, the data undergo preprocessing steps including noise filtering, handling of missing values, and normalization to ensure consistency and improve model performance. The dataset is divided into training (80%) and testing (20%) subsets, following standard machine learning practices for reliable evaluation [2]. Table 2 summarizes the key features used for model training.

Table 2: Dataset Features Used for Model Training

Feature	Description
pH	Soil acidity/alkalinity
NPK	Nutrient levels
EC	Soil conductivity
Temperature	Ambient temperature

Feature	Description
Humidity	Air moisture
Soil Moisture	Water content

2.4. Model Development and Recommendation System

The nutrient prediction component is developed using a supervised machine learning approach. Multiple models, including Linear Regression, Long Short-Term Memory (LSTM), and Random Forest, are evaluated to determine the most suitable approach.

Among these, the Random Forest regression model is selected due to its high prediction accuracy, ability to model nonlinear relationships, and robustness to noise in agricultural datasets [2], [3]. Random Forest is an ensemble learning method that constructs multiple decision trees during training and combines their outputs to improve predictive performance, reduce variance, and prevent overfitting. This makes it particularly effective for agricultural datasets, which often exhibit complex and nonlinear patterns.

Based on the predicted nutrient levels, the system generates fertilizer recommendations by considering soil conditions (pH, EC), plant growth stage, and environmental factors. The recommendations include fertilizer type (N:P:K ratio), dosage, and application timing, ensuring precise and context-aware nutrient management.

To further enhance decision accuracy, the system integrates weather forecast data using an external API. Environmental factors such as rainfall probability, humidity, and temperature are considered to avoid fertilizer application under unfavorable conditions. This improves fertilizer efficiency and supports sustainable smart agriculture practices [14]-[16].

2.5. System Implementation Technologies

The system is implemented using a combination of hardware and software technologies, as summarized below in table 3:

Table 3: Technologies used for INM Component

Component	Technology	Justification
Microcontroller	ESP32	Low cost, Wi-Fi enabled, energy efficient
Sensors	NPK, pH, EC, SHT31	Real-time environmental monitoring
Backend	Python	Strong support for ML development

Component	Technology	Justification
ML Library	Scikit-learn	Efficient implementation of Random Forest
Database	MongoDB	Scalable data management
Frontend	Mobile/Web dashboard	User-friendly interface

The selected technologies are widely used in IoT and machine learning applications due to their reliability, scalability, and cost-effectiveness [1], [8].

The overall system workflow describes the interaction between system components from data acquisition to decision support. Sensors collect real-time environmental data, which are transmitted to the cloud via the ESP32 module. The data are then preprocessed and fed into the machine learning model to predict nutrient trends. Based on these predictions, the recommendation engine generates fertilizer suggestions, which are delivered to the user through the mobile application interface.

This workflow establishes a complete pipeline from data acquisition to intelligent decision-making, forming a closed-loop system for real-time nutrient management.

2.6. Commercialization aspect of the product

2.6.1. Product Overview and Value Proposition

The proposed solution can be commercialized as a standalone product named the Intelligent Nutrient Management (INM) System, designed to support precision agriculture in greenhouse rose cultivation and other high-value crops. The system integrates Internet of Things (IoT)-based sensing with machine learning-driven predictive analytics to deliver real-time, data-driven fertilizer recommendations.

The product is structured as a complete end-to-end smart farming solution consisting of three core components: an IoT-based data acquisition unit equipped with sensors (NPK, pH, EC, moisture, temperature, humidity), a cloud-based analytics platform for processing data using machine learning models, and a mobile or web-based application interface that provides real-time visualization, alerts, and actionable fertilizer recommendations.

The INM system delivers significant value by optimizing fertilizer usage, reducing operational costs, improving crop yield and quality, and supporting sustainable farming practices. By replacing manual decision-making with accurate, data-driven recommendations, the system enhances productivity while minimizing environmental impact, aligning with modern smart agriculture trends [14]-[16].

2.6.2. Business Model and Target Market

The primary target market includes greenhouse rose farmers, commercial floriculture producers, agricultural enterprises, and research institutions seeking data-driven cultivation solutions. The system is particularly relevant in Sri Lanka and similar developing agricultural economies, where challenges such as inefficient fertilizer usage and limited access to precision farming technologies are prevalent.

From a business perspective, the system follows a hybrid hardware-software model. This includes a one-time hardware purchase for the IoT sensor kit and a subscription-based Software-as-a-Service (SaaS) model for analytics and recommendation services. The mobile application provides both free basic features and premium functionalities for advanced insights. This model ensures affordability while enabling scalable and sustainable revenue generation.

2.6.3. Feasibility and Scalability

The feasibility of the proposed solution is supported by using low-cost IoT hardware, cloud-based infrastructure, and open-source machine learning frameworks, making it economically viable for widespread adoption.

The system also offers several competitive advantages, including crop-specific optimization for rose cultivation, integration of IoT and AI technologies, and adaptability to local agricultural conditions. Furthermore, the scalable architecture enables expansion to other crops, integration with irrigation and climate control systems, and deployment across large-scale agricultural environments.

The increasing global demand for precision agriculture and sustainable farming practices further strengthens the market potential of the INM system. By addressing real-world challenges in nutrient management, the system demonstrates strong potential as a practical, scalable, and commercially viable solution for modern agriculture.

2.7. Implementation And Testing

2.7.1. System Implementation and Workflow

The proposed Intelligent Nutrient Management (INM) component was implemented as an integrated system combining IoT-based data acquisition, machine learning-driven prediction, and a user-friendly mobile application interface for delivering fertilizer recommendations.

The system utilizes IoT sensors to continuously collect environmental and soil parameters, including pH, NPK levels, electrical conductivity (EC), soil moisture, temperature, and humidity. These sensor readings are transmitted via an ESP32 microcontroller to a cloud-based processing environment for storage and analysis. The use of IoT-based sensing enables real-time monitoring and supports data-driven decision-making in precision agriculture [1], [5].

The machine learning component was developed using Python and the Scikit-learn library, with a Random Forest regression model selected due to its robustness and ability to model nonlinear relationships in agricultural datasets [2], [3]. Cloud-based storage solutions were used to ensure efficient data management, scalability, and accessibility.

A mobile application interface was designed to allow users to interact with the system, visualize real-time data, and receive actionable fertilizer recommendations. The integration of a user-friendly interface enhances usability and supports practical adoption in real-world farming environments [8]. The system follows a structured workflow:

- IoT sensors collect real-time environmental and soil data
- Data are transmitted to the cloud via the ESP32 microcontroller
- Data preprocessing is performed (cleaning, normalization, and validation)
- The machine learning model predicts nutrient trends and requirements
- The recommendation engine generates fertilizer suggestions (type, dosage, timing)
- Results are delivered to the user through the mobile application

This workflow enables a complete pipeline from data acquisition to decision support, ensuring real-time and adaptive nutrient management.

2.7.2. System Design

The functional behavior of the system is illustrated in Figure 2, which presents the use case diagram of the Intelligent Nutrient Management system, highlighting the interaction between the farmer and system functionalities.

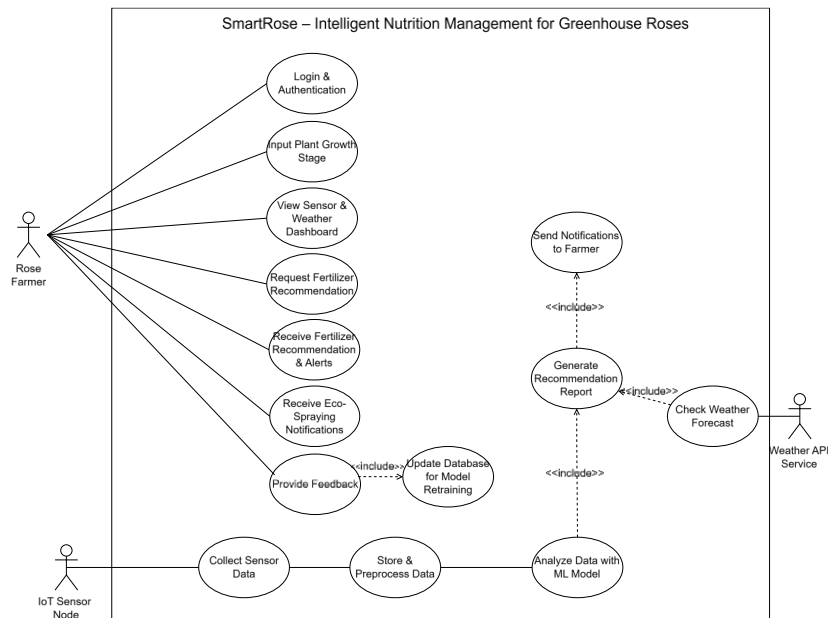


Figure 2: Use Case Diagram of Intelligent Nutrient Management for Greenhouse Roses

The primary actor in the system is the farmer, who interacts with the system through the mobile application interface. The system supports several key functionalities, including input of plant growth stages, visualization of real-time environmental and soil data, generation of fertilizer recommendations, and receipt of alerts and notifications.

The system processes sensor data and user inputs to generate customized fertilizer plans. This ensures that recommendations are tailored to both environmental conditions and plant growth stages, improving accuracy and usability.

The overall system design emphasizes simplicity, accessibility, and practical applicability, enabling farmers with minimal technical expertise to effectively utilize the system in real-world agricultural settings.

2.7.3. Testing and Evaluation

To evaluate the performance, reliability, and robustness of the proposed system, both functional testing and model performance evaluation were conducted under multiple operating conditions.

Functional testing was carried out to verify system behavior under different input scenarios, including normal, incomplete, and extreme environmental conditions. Table 4 summarizes the functional testing results of the INM system.

Table 4: Functional Testing Results of the INM System

Test Case ID	Input Scenario	Expected Outcome	Actual Outcome	Status
TC01	Valid sensor data (normal range)	Accurate nutrient prediction	MAE = 0.060324, RMSE = 0.092321 indicating high accuracy	Pass
TC02	Missing sensor values	System handles missing data without failure	Missing values successfully handled during preprocessing	Pass
TC03	Extreme environmental values	Stable prediction without system crash	Model produced consistent outputs with no instability	Pass
TC04	Different plant growth stages	Recommendations vary based on growth stage	Stage-specific fertilizer plans correctly generated	Pass

The results demonstrate that the system maintains stable and reliable performance across all tested conditions, even in the presence of incomplete or extreme input data.

In addition to functional validation, the performance of the machine learning model was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which are standard metrics for regression-based prediction tasks in agriculture [2].

The Random Forest model achieved an MAE of 0.060324 and an RMSE of 0.092321, indicating high prediction accuracy. These results demonstrate the model's ability to effectively capture complex relationships between environmental variables and nutrient dynamics. Furthermore, comparative evaluation with Linear Regression and Long Short-Term Memory (LSTM) models confirmed the superior performance of the Random Forest approach, consistent with findings in previous studies [2], [3].

The system was further evaluated under multiple real-world scenarios, including normal operating conditions, missing data inputs, and extreme environmental variations. The results indicate that the system maintains both stability and accuracy across all scenarios. The preprocessing techniques ensure effective handling of noisy and incomplete data, while the integration of real-time IoT data enables adaptive and context-aware fertilizer recommendations.

Overall, the implementation and testing results confirm that the proposed INM system is accurate, robust, scalable, and practical for real-world deployment in greenhouse agriculture.

3. RESULTS AND DISCUSSION

3.1. Results and Discussion

The performance of the proposed intelligent nutrient management system was evaluated using standard regression metrics, namely Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which are widely used to assess prediction accuracy in machine learning-based agricultural systems [2].

The experimental results indicate that the Random Forest model achieved a Mean Absolute Error (MAE) of 0.060324 and a Root Mean Square Error (RMSE) of 0.092321, demonstrating high prediction accuracy and consistency. These low error values indicate that the model is capable of effectively capturing the complex relationships between environmental parameters and nutrient dynamics, making it suitable for real-time agricultural decision support.

To further validate model performance, a comparative analysis was conducted using multiple machine learning algorithms, including Linear Regression and Long Short-Term Memory (LSTM). The results are summarized in Table 5.

Table 5: INM Model Comparison

Model	MAE	RMSE
Linear Regression	0.061728	0.094674
Random Forest	0.060324	0.092321
LSTM	0.096262	0.118461

The comparison demonstrates that the Random Forest model achieved the lowest error values among all evaluated models, confirming its superior predictive performance. This can be attributed to its ensemble learning mechanism, which combines multiple decision trees to reduce variance and improve generalization. In contrast, Linear Regression is limited by its assumption of linear relationships, while LSTM models require larger datasets and higher computational resources to achieve optimal performance [2], [3].

Figure 3 illustrates the comparison between actual and predicted EC values using the Random Forest model, further validating the model's accuracy.

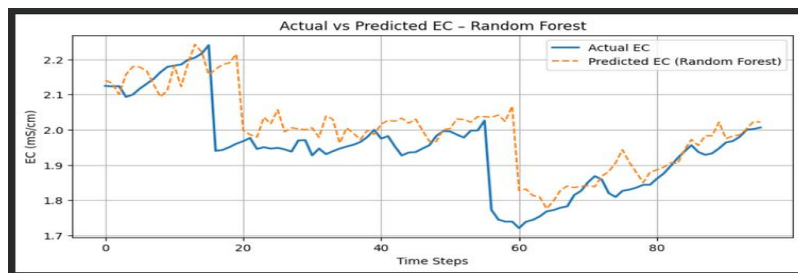


Figure 3: Actual vs Predicted EC Values using Random Forest Model

The close alignment between actual and predicted values indicates that the model performs reliably under varying environmental conditions, reinforcing its suitability for real-world deployment.

The results also highlight the effectiveness of integrating IoT-based data collection with machine learning techniques for nutrient prediction in greenhouse rose cultivation. Unlike traditional farming practices, which rely on fixed fertilizer schedules and manual decision-making, the proposed system provides a data-driven and adaptive approach. This aligns with recent advancements in smart agriculture, where the integration of AI and IoT technologies enables more precise and efficient resource management [7], [8].

Furthermore, existing IoT-based agricultural systems primarily focus on monitoring and threshold-based control without predictive capabilities [1], [5]. In contrast, the proposed system integrates predictive modeling with real-time sensing, enabling proactive nutrient management. This directly addresses limitations identified in previous studies and enhances decision-making accuracy.

The inclusion of crop-specific agronomic knowledge further strengthens the system's applicability. Studies have shown that factors such as NPK levels, pH, and electrical conductivity significantly influence rose growth, flower quality, and yield [17], [18]. By

incorporating these parameters into the prediction model, the system provides more accurate and context-aware fertilizer recommendations compared to generic solutions.

From a practical perspective, the system has significant potential to improve fertilizer efficiency by reducing over-application and minimizing nutrient loss. This contributes to sustainable agricultural practices by lowering environmental impact and optimizing resource usage, as emphasized in smart fertilizer management research [14]-[16].

In terms of system performance, the model was evaluated under multiple operating conditions, including normal scenarios, missing sensor data, and extreme environmental values. The results indicate that the system maintains stable and reliable performance across all conditions. The preprocessing techniques, including data cleaning and normalization, ensure robustness by effectively handling incomplete and noisy data. Additionally, the integration of real-time IoT data enables the system to adapt dynamically to changing environmental conditions, improving consistency and reliability in prediction outcomes.

Overall, the findings demonstrate that the integration of IoT sensing with machine learning provides an effective and scalable solution for intelligent nutrient management. The proposed system enhances decision-making, improves fertilizer efficiency, and supports sustainable and precision agriculture practices. These results confirm that the proposed system successfully achieves the stated objectives of accurate nutrient prediction and data-driven fertilizer recommendation.

3.2. Limitations and Future Work

Despite the promising results, several limitations were identified in this study. The dataset used for model training was relatively limited and partially generated using synthetic data, which may affect the generalizability of the model. Additionally, the system was evaluated under controlled greenhouse conditions, which may not fully represent real-world variability. Model performance may also vary under different climatic regions and soil conditions.

These limitations highlight the need for further validation using larger and more diverse datasets collected from real-world agricultural environments.

Future improvements may include the integration of additional data sources such as weather forecasting and image-based plant analysis, deployment in large-scale greenhouse environments, and the use of advanced machine learning models to enhance prediction

accuracy. These enhancements would further strengthen the system's ability to support precision agriculture and intelligent farming practices.

3.3. Individual Contribution

This research was conducted as an individual component of the SmartRose AI-IoT platform, focusing specifically on the development of an intelligent nutrient management system for greenhouse rose cultivation.

The author was responsible for the following key tasks:

- Conducting a comprehensive literature review on smart agriculture, IoT-based monitoring systems, and machine learning applications in nutrient management
- Identifying the research gap and defining the problem statement and objectives of the study
- Designing the system architecture, including the integration of IoT sensors, data processing modules, and machine learning components
- Developing and implementing the machine learning model (Random Forest) for nutrient prediction using Python and Scikit-learn
- Performing data preprocessing, including data cleaning, normalization, and feature selection
- Conducting model training, evaluation, and comparative analysis with alternative models such as Linear Regression and LSTM
- Designing the fertilizer recommendation logic based on predicted nutrient values and agronomic guidelines
- Implementing and testing the system under different input scenarios to evaluate performance and reliability
- Analyzing and interpreting experimental results, including performance metrics such as MAE and RMSE
- Documenting the research work, including methodology, results, discussion, and conclusions

Through these contributions, the author successfully developed a functional and scalable intelligent nutrient management component that integrates IoT sensing with machine learning-based decision support.

4. CONCLUSION

This research presented the design and development of an intelligent nutrient management component for greenhouse rose cultivation by integrating Internet of Things (IoT)-based data acquisition with machine learning-driven predictive analytics. The proposed system addresses the limitations of traditional nutrient management practices, which rely on manual decision-making and generalized fertilizer schedules, often leading to inefficient resource utilization and inconsistent crop performance [1], [14].

The implementation of a Random Forest-based prediction model demonstrated high accuracy in estimating nutrient requirements using environmental and soil parameters. The low error values obtained in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) confirm the effectiveness and reliability of the model in capturing complex relationships within agricultural data. This supports findings from previous studies that highlight the suitability of ensemble learning methods for agricultural prediction tasks involving nonlinear and high-variability datasets [2], [3].

Furthermore, the integration of real-time IoT sensing with machine learning enables the system to adapt dynamically to changing environmental conditions, providing more precise and context-aware fertilizer recommendations compared to static and rule-based approaches. This aligns with recent advancements in smart agriculture, where the combination of IoT and AI technologies enhances decision-making and operational efficiency [7], [8].

A key contribution of this research is the development of a crop-specific solution tailored to greenhouse rose cultivation. By incorporating agronomic knowledge related to parameters such as NPK levels, pH, and electrical conductivity (EC), the system provides practical and relevant recommendations that improve fertilizer efficiency and crop quality. This addresses a significant gap in existing systems, which are often generalized and lack crop-specific optimization [17], [18].

In addition to its technical contributions, the proposed system demonstrates strong potential for real-world application and commercialization. By optimizing fertilizer usage and reducing environmental impact, the system supports sustainable agricultural practices, which are increasingly emphasized in modern smart farming solutions [14]-[16].

However, the study is subject to certain limitations, including the use of a relatively limited dataset and testing under controlled greenhouse conditions. Future work should focus on large-scale deployment, integration with additional data sources such as weather forecasting and image-based analysis, and validation across diverse environmental conditions to improve model generalizability.

Overall, this research validates the feasibility and effectiveness of integrating IoT and machine learning for intelligent nutrient management. The proposed system contributes to the advancement of precision agriculture by enabling data-driven, adaptive, and sustainable farming practices, particularly in the context of greenhouse rose cultivation.

5. REFERENCE LIST

- [1] K. A. Patil and N. R. Kale, "A model for smart agriculture using IoT," 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC), Dec. 2016, doi: <https://doi.org/10.1109/icgtspicc.2016.7955360>.
- [2] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine Learning in Agriculture: A Review," *Sensors* (Basel, Switzerland), vol. 18, no. 8, p. 2674, Aug. 2018, doi: <https://doi.org/10.3390/s18082674>.
- [3] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70-90, Apr. 2018, doi: <https://doi.org/10.1016/j.compag.2018.02.016>.
- [4] K. R. Shyamalee, S. Srikrishnah, K. P. Somachandra, and S. Sutharsan, "Effect of pruning height on growth and cut flower production of rose (*Rosa hybrid L.*) variety 'White Success,'" *AGRIEAST: Journal of Agricultural Sciences*, vol. 15, no. 2, p. 12, Dec. 2021, doi: <https://doi.org/10.4038/agrieast.v15i2.103>.
- [5] C. Visvesvaran, S. Kamalakannan, K. N. Kumar, K. M. Sundaram, S. M. S. S. Vasam, and S. Jafrrin, "Smart Greenhouse Monitoring System using Wireless Sensor Networks," *IEEE Xplore*, Oct. 01, 2021. <https://ieeexplore.ieee.org/abstract/document/9591680>
- [6] G. D. G. P. P. Gamage and R. M. N. Rathnayaka, "The Role of IoT in Agriculture in Sri Lankan Context: A Comprehensive Review," *Journal of Agriculture and Value Addition*, vol. 8, no. 1, pp. 20-43, Jun. 2025, doi: <https://doi.org/10.4038/java.v8i1.149>.
- [7] N. Y. Mulongo, "Artificial Intelligence For Smart Agriculture Industry," 2022 IEEE World AI IoT Congress (AIIoT), pp. 0892-0895, May 2025, doi: <https://doi.org/10.1109/aiiot65859.2025.11105360>.
- [8] S. Hans, R. Kumar, Saloni Manhas, Arti Badhouthiya, Ashima Juyal, and A. Alkhayyat, "AI Integration in IoT: A Comprehensive Overview of Applications and Implications," pp. 1-6, May 2024, doi: <https://doi.org/10.1109/icmica61068.2024.10732321>.
- [9] C. R. Laksiri et al., IoT-Based Smart Irrigation System for Sri Lankan Agriculture, *IRJMETS*,

vol.4,no.3,2022.https://www.irjmets.com/uploadedfiles/paper/issue_3_march_2022/20397/financial/fin_irjmets1648731851.pdf

[10] O. Moreira et al., Development of an Intelligent Irrigation System for a Rose Cultivation Based on IoT, IEEE ANDESCON, 2024. <https://ieeexplore.ieee.org/abstract/document/10755850>

[11] A. Suyanto et al., The Role of IoT and Web Monitoring to Improve Productivity in Rose Cultivation, IEEE ICONDBTM, 2023. <https://ieeexplore.ieee.org/abstract/document/10327205>

[12] L. G, R. C, and G. P, “An automated low cost IoT based Fertilizer Intimation System for smart agriculture,” Sustainable Computing: Informatics and Systems, Jan. 2019, doi: <https://doi.org/10.1016/j.suscom.2019.01.002>.

[13] F. Siva, “Smart fertilizer recommendation through NPK analysis using Artificial Neural Networks,” Strathmore.edu, 2019. doi: <https://su-plus.strathmore.edu/handle/11071/6702>.

[14] J.-J. Liu, H. Wu, and I. Riaz, “Advanced technologies for smart fertilizer management in agriculture: A Review,” IEEE Access, pp. 1-1, Jan. 2025, doi: <https://doi.org/10.1109/access.2025.3594361>.

[15] Divya Shanmugavel, I. Rusyn, O. Solorza-Feria, and S. Kamaraj, “Sustainable SMART fertilizers in agriculture systems: A review on fundamentals to in-field applications,” Science of The Total Environment, vol. 904, pp. 166729-166729, Dec. 2023, doi: <https://doi.org/10.1016/j.scitotenv.2023.166729>.

[16] S. Singh et al., “Smart fertilizer technologies: An environmental impact assessment for sustainable agriculture,” Smart Agricultural Technology, vol. 8, p. 100504, Aug. 2024, doi: <https://doi.org/10.1016/j.atech.2024.100504>.

[17] X. Liu et al., “Micro-moistening irrigation combined with bio-organic fertilizer: An adaptive irrigation and fertilization strategy to improve soil environment, edible Rose yield, and nutritional quality,” Industrial Crops and Products, vol. 196, p. 116487, Jun. 2023, doi: <https://doi.org/10.1016/j.indcrop.2023.116487>.

[18] S. Sujatha, P. Tejaswini, R. H. Laxman, and G. R. Smitha, “Flower Yield, Physiology, Nutrient Acquisition and Soil Fertility Variations in Cut Flower Rose (*Rosa hybrida* L.) as

Influenced by Rootstocks,” *Journal of Plant Growth Regulation*, Jun. 2024, doi: <https://doi.org/10.1007/s00344-024-11386-9>.

[19] Johnn Jairo Franco Hermida, Martha Cecilia Henao Toro, Miguel Guzman, and Raul I. Cabrera, “Determining Nutrient Diagnostic Norms for Greenhouse Roses,” Nov. 01, 2013. <https://journals.ashs.org/view/journals/hortsci/48/11/article-p1403.xml>

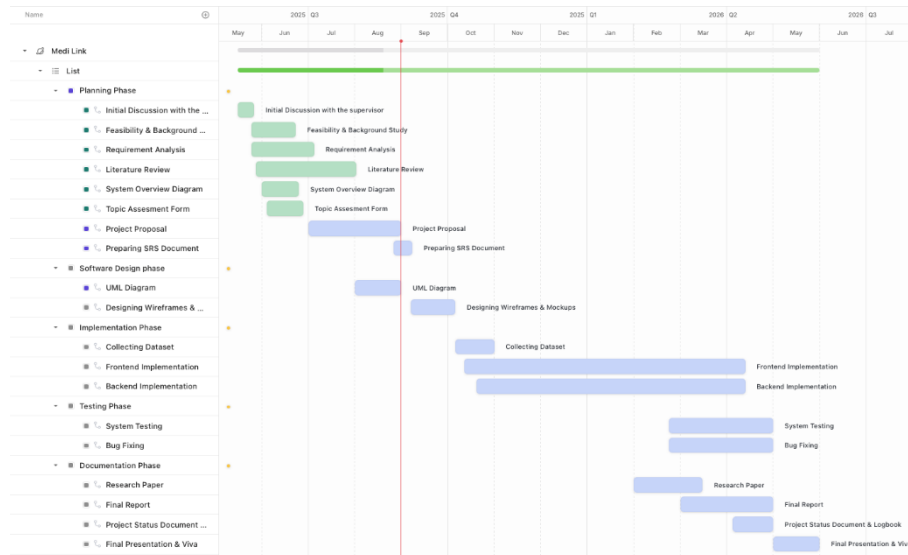
[20] Youbin Zheng, Diane Feliciano Cayanan, and Mike Dixon, “Optimum Feeding Nutrient Solution Concentration for Greenhouse Potted Miniature Rose Production in a Recirculating Subirrigation System,” Sep. 01, 2010. <https://journals.ashs.org/view/journals/hortsci/45/9/article-p1378.xml>

[21] S. Rezai, M. R. Sabzalian, A. Nikbakht, H. Zarei, S. Baroodkoo, and F. Beshkar, “Roses exhibited higher production and postharvest longevity in response to nano-nutrients of Fe, Ca and Zn under LED supplemental lighting,” *BMC Plant Biology*, vol. 25, no. 1, Sep. 2025, doi: <https://doi.org/10.1186/s12870-025-07000-z>.

[22] E. F. A. Almeida, M. A. Lessa, I.C.S. Curvelo, T.C. Taques, and D. A. Nogueira, “Soil sustainable management in rose integrated production,” *Acta Horticulturae*, vol. 970, no. 970, pp. 355-360, Jan. 2013, doi: <https://doi.org/10.17660/ActaHortic.2013.970.43>.

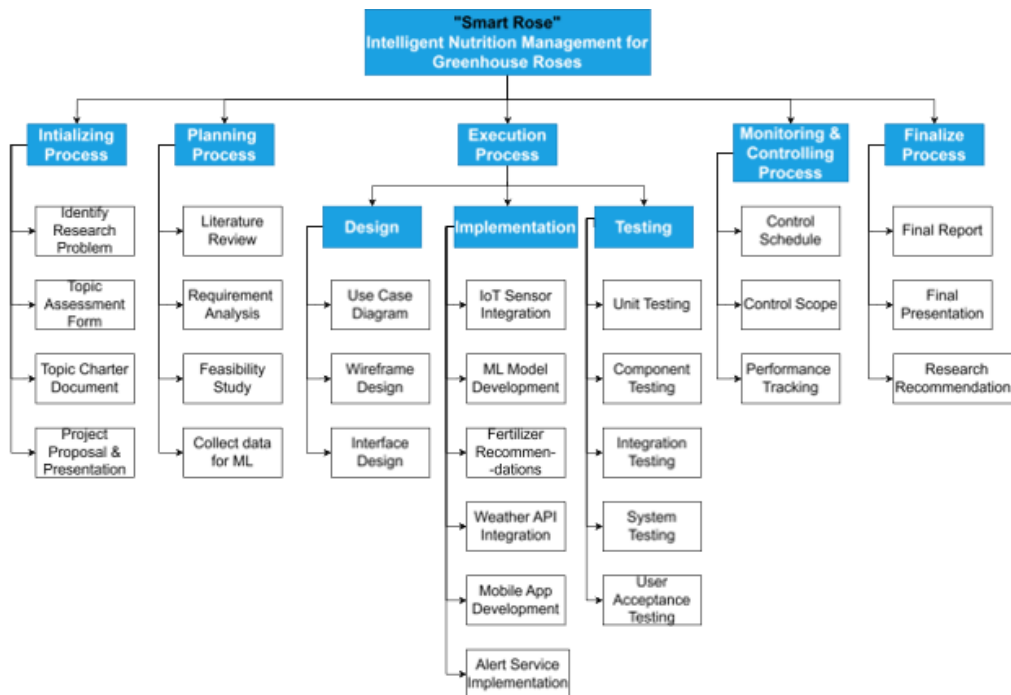
6. APPENDICES

6.1. Appendix A: Gantt Chart



Appendix A: Gantt Chart

6.2. Appendix B: Work Breakdown Chart



Appendix B: Work Breakdown Chart