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

25-26J-299

Final Thesis

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

Department of Information Technology

Sri Lanka Institute of Information Technology
Sri Lanka

August 2025

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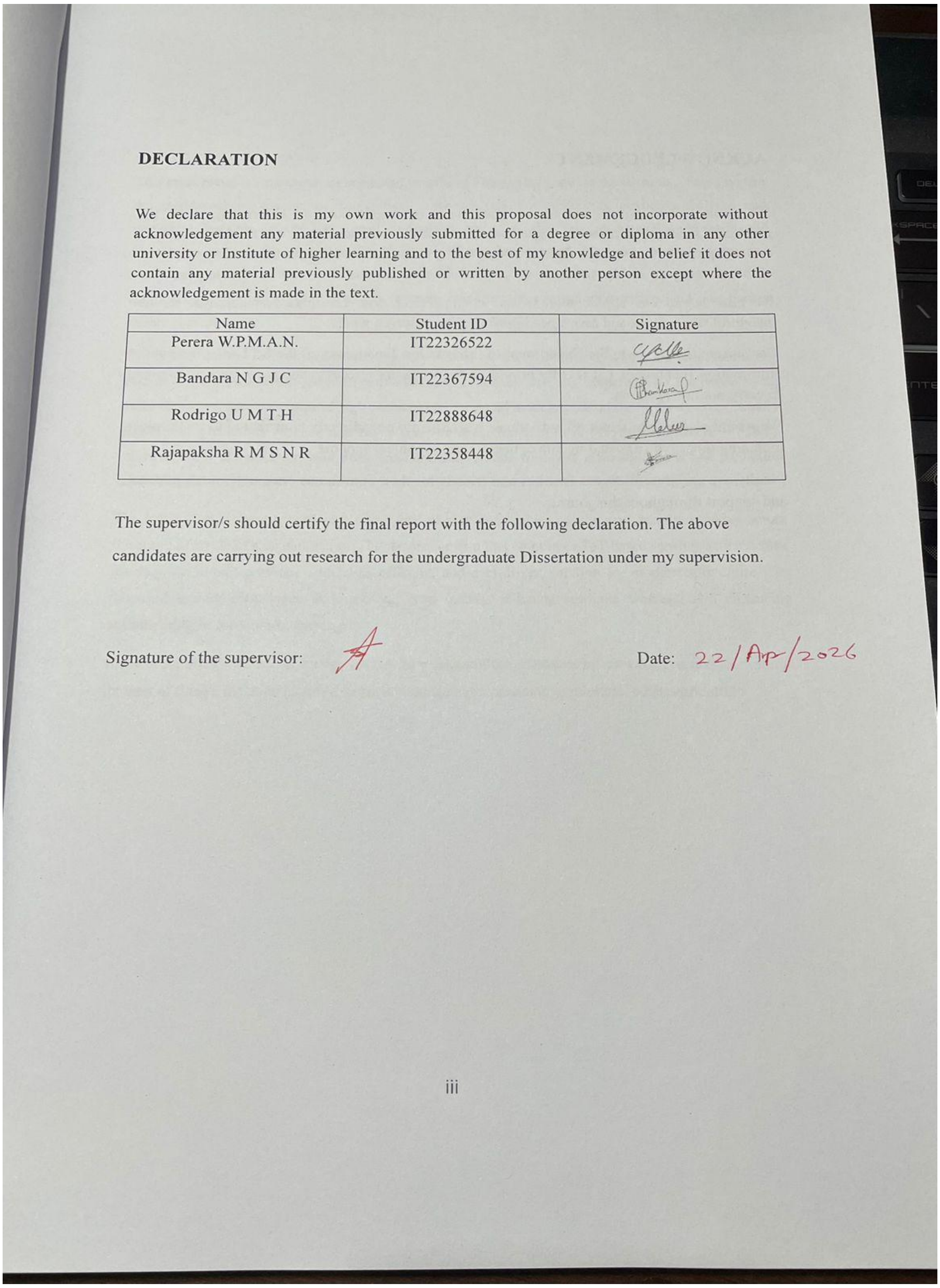
DECLARATION



DECLARATION

We 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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ABSTRACT

This study presents SmartRose, an integrated Internet of Things (IoT) and machine learning-based system designed to enhance greenhouse rose cultivation through real-time monitoring, predictive analytics, and intelligent decision support. Traditional floriculture practices often rely on manual observation and fragmented technological solutions, leading to inefficiencies, delayed responses to plant stress, and significant post-harvest losses. To address these challenges, the proposed system integrates four key components: early disease risk detection, nutrient management, energy optimization, and post-harvest freshness monitoring.

The system utilizes IoT sensors to continuously collect environmental data, which are processed using machine learning models to generate predictions and actionable insights. Experimental evaluation using real greenhouse data demonstrated high performance across all modules, including 100% accuracy in early disease risk prediction, superior nutrient forecasting using Random Forest regression (RMSE = 0.092), effective stress classification with 86% accuracy, and reliable freshness estimation with low prediction error.

The integration of these components into a unified platform enables coordinated decision-making across the entire lifecycle of rose cultivation. The results confirm that combining IoT-based sensing with machine learning techniques provides a scalable, efficient, and data-driven solution for modern agriculture. The proposed system contributes to improving crop quality, reducing resource wastage, and enhancing sustainability in greenhouse farming.

Keywords: disease detection, energy optimization, floriculture, freshness monitoring, greenhouse systems, internet of things, machine learning, nutrient management, precision agriculture, 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
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
ESP32	Espressif 32-bit Microcontroller

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1. INTRODUCTION

1.1. Background and Literature Review

Agriculture plays a critical role in the economic and social development of many countries, including Sri Lanka, where it contributes significantly to employment, food security, and export revenue [9], [12]. Within this sector, floriculture particularly greenhouse-based rose cultivation has gained increasing importance due to its high commercial value in both local and international markets [7], [8]. However, maintaining consistent quality and productivity in greenhouse environments remains a complex challenge due to the sensitivity of roses to environmental conditions such as temperature, humidity, soil nutrients, and light intensity.

Traditional floriculture practices largely rely on manual monitoring and experience-based decision-making, which often leads to delayed responses, inefficient resource utilization, and increased crop losses [3]. These limitations are particularly critical in greenhouse environments, where even minor fluctuations in microclimatic conditions can significantly affect plant health and yield.

Recent advancements in Internet of Things (IoT) technologies have enabled real-time monitoring of environmental parameters through distributed sensor networks. IoT-based systems can continuously collect data such as temperature, humidity, soil moisture, and air quality, providing a foundation for data-driven agricultural management [1], [14]. These systems reduce reliance on manual observation and improve the accuracy and timeliness of decision-making.

In parallel, machine learning (ML) techniques have demonstrated strong capabilities in predictive analytics within agriculture. Studies have shown that ML models can effectively identify plant diseases, predict crop stress, and optimize resource usage based on environmental and physiological data [2], [4]. For instance, deep learning and classification-based approaches have achieved high accuracy in plant disease detection, enabling early-stage intervention and improved crop protection [6], [13]. Similarly, smart greenhouse systems have been developed to optimize environmental control and energy consumption using sensor data and automated decision-making mechanisms [10], [17]. Such AI-IoT integration enables intelligent automation and real-time decision-making in smart environments [20].

Furthermore, post-harvest research highlights the importance of environmental monitoring in preserving flower quality. Parameters such as temperature, humidity, and ethylene gas concentration have been identified as key factors influencing the freshness and vase life of roses [21]. IoT-enabled monitoring combined with predictive models can significantly reduce post-harvest losses and improve supply chain efficiency.

A comparative summary of existing smart agriculture approaches and their limitations is presented in Table 1.

Table 1: Comparison Of Existing Smart Agriculture Systems

Study / Approach	Focus Area	Technique Used	Limitation
Mahlein (2014)	Disease Detection	Imaging-based methods	Requires visual symptoms, not real-time
Jones et al. (2020)	Plant Stress Detection	Thermal sensing	Lacks IoT integration and automation
IoT Monitoring Systems	Environmental Monitoring	Sensor-based data collection	No predictive analytics or decision support
Smart Greenhouse Systems	Climate Control	Rule-based / IoT	Limited integration with ML models
Post-Harvest Monitoring Studies	Freshness & Storage	Environmental analysis	Not connected to production-stage systems

Despite these advancements, most existing solutions focus on isolated functionalities such as disease detection, environmental monitoring, or post-harvest management. These systems often operate independently without cross-functional integration, limiting their ability to support holistic decision-making across the agricultural lifecycle [19]. As a result, farmers are required to interpret multiple data sources separately, reducing the effectiveness of decision-making and overall system efficiency.

Therefore, there is a clear need for an integrated and intelligent agricultural platform that combines IoT-based sensing with machine learning-driven analytics to provide unified, real-time decision support across all stages of rose cultivation. This research addresses this need by proposing SmartRose, a comprehensive AI-IoT platform that integrates disease detection, nutrient management, energy optimization, and post-harvest freshness monitoring into a single coordinated system.

1.2. Research Gap

Although significant advancements have been made in applying Internet of Things (IoT) and machine learning (ML) technologies in agriculture, existing solutions predominantly address individual challenges in isolation rather than providing a comprehensive and integrated system. Many current approaches focus on specific functionalities such as plant disease detection, irrigation control, environmental monitoring, or post-harvest management independently, without considering the interdependencies between these stages of the agricultural lifecycle [3], [19].

In the context of greenhouse-based floriculture, this fragmentation creates several limitations. First, most IoT-based systems primarily provide real-time sensor data without incorporating predictive analytics, requiring farmers to manually interpret environmental conditions and make decisions based on experience [18]. Second, machine learning models developed for agricultural applications are often task-specific and are not integrated into a unified decision-support framework, limiting their practical usability in real-world scenarios [2], [4]. Third, existing smart greenhouse solutions mainly focus on pre-harvest stages such as climate control and crop monitoring, while post-harvest processes such as freshness monitoring and vase life prediction remain underexplored and disconnected from production-level systems [21].

Furthermore, many of these systems are designed and evaluated in controlled or large-scale environments, making them less adaptable to the constraints of small- and medium-scale agricultural settings in developing countries such as Sri Lanka [16]. The lack of cost-effective, scalable, and integrated solutions limits the adoption of advanced technologies among local farmers and stakeholders.

Therefore, a significant research gap exists in the development of an end-to-end intelligent agricultural system that integrates real-time IoT sensing, machine learning-based predictive analytics, and coordinated decision support across multiple stages of crop management.

This research addresses this gap by proposing SmartRose, an integrated AI-IoT platform that unifies four critical components: disease detection, nutrient management, energy optimization, and post-harvest freshness monitoring into a single system. By enabling cross-module data sharing, real-time prediction, and automated decision support, the proposed system provides a holistic solution for improving productivity, reducing resource wastage, and enhancing sustainability in greenhouse rose cultivation.

1.3. Research Problem

Greenhouse rose cultivation involves managing multiple interdependent factors, including plant health, nutrient levels, environmental conditions, and post-harvest quality. In practice, these factors are often monitored and managed independently using manual methods or fragmented technological solutions. This lack of coordination leads to delayed detection of plant stress, inefficient use of resources such as water, fertilizer, and energy, and significant post-harvest losses due to improper storage and handling conditions [7], [11].

Traditional approaches rely heavily on periodic observation and experience-based decision-making, which are insufficient for responding to rapid environmental changes within greenhouse systems. Although IoT-based monitoring systems can provide real-time data, they often fail to deliver predictive insights or actionable recommendations. Similarly, machine learning models developed for agricultural applications are typically designed for single tasks and are not integrated into a unified decision-support framework. As a result, farmers are unable to simultaneously manage multiple aspects of crop production in a timely and efficient manner.

These limitations create a critical challenge in modern floriculture: the inability to continuously monitor, predict, and optimize all stages of rose cultivation from growth and environmental control to post-harvest freshness within a single coordinated system.

Therefore, the core research problem addressed in this study is:

How can an integrated AI-IoT system be designed to enable real-time monitoring, predictive analysis, and intelligent decision support across multiple stages of greenhouse rose cultivation, to improve crop quality, reduce resource wastage, and minimize post-harvest losses?

1.4. Research Objectives

1.4.1. Main Objectives

The main objective of this research is to design, develop, and evaluate an integrated AI-IoT-based smart greenhouse system for rose cultivation that enables real-time environmental monitoring, machine learning-driven predictive analytics, and intelligent decision support across both pre-harvest and post-harvest stages of the agricultural lifecycle.

1.4.2. Specific Objectives

To achieve the main objective, the following specific objectives are defined:

- To develop a machine learning-based disease detection model that utilizes environmental sensor data to identify early-stage plant stress and disease risk conditions.
- To design and implement a data-driven nutrient management model that predicts optimal fertilizer requirements based on soil and environmental parameters.
- To develop a machine learning-based stress prediction and energy optimization module that classifies greenhouse conditions and recommends efficient environmental control strategies.
- To design and implement a predictive freshness monitoring model that estimates post-harvest freshness and remaining vase life using storage-related parameters.
- To integrate all functional modules into a unified IoT-based platform that supports real-time data acquisition, cross-module data sharing, and centralized decision support.
- To evaluate the performance of the proposed system using appropriate metrics, including classification accuracy, precision, recall, and regression-based error measures such as RMSE and MAE.

2. METHODOLOGY

2.1. Overall System Overview and Architecture

The SmartRose system is designed as an integrated AI-IoT-based framework to support intelligent greenhouse management for rose cultivation. The system enables real-time environmental monitoring, machine learning-driven predictive analytics, and coordinated decision support across multiple stages of the agricultural lifecycle, including plant growth, environmental control, nutrient management, and post-harvest handling [1], [2].

The overall system follows a continuous data-driven workflow consisting of several key stages: data acquisition, preprocessing, model development, prediction, and decision support. Environmental and crop-related data are continuously collected using IoT sensors deployed within the greenhouse environment [14]. These data are transmitted to a centralized processing unit, where they are stored, preprocessed, and analyzed.

The SmartRose system architecture is implemented as a multi-layered framework that integrates IoT sensing, communication, machine learning-based processing, and user-level application services. As illustrated in Figure 1, the system consists of three primary layers: the IoT sensing layer, the communication and control layer, and the AI processing and decision support layer.

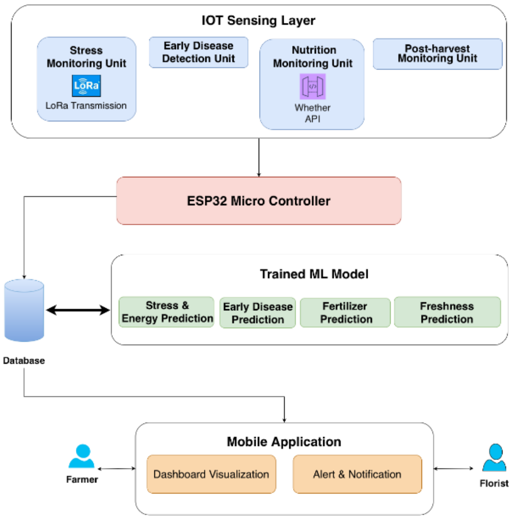

Figure 1: SmartRose Integrated System Architecture

The IoT sensing layer comprises multiple sensor modules deployed across the greenhouse environment to capture real-time environmental and physiological parameters. These include temperature, humidity, soil moisture, light intensity, and air quality for stress detection and energy optimization, as well as soil-related parameters such as NPK levels, electrical conductivity (EC), and pH for nutrient management [14], [17]. In addition, post-harvest freshness monitoring utilizes sensors measuring temperature, humidity, ethylene gas concentration, and water level [21].

The collected sensor data are transmitted to an ESP32 microcontroller, which functions as the central control unit. The ESP32 aggregates sensor readings and facilitates communication through wireless technologies such as LoRa and web-based APIs. The use of LoRa communication enables long-range and low-power data transmission, making the system suitable for large-scale greenhouse environments [5]. Furthermore, architecture supports local data buffering and cloud synchronization, ensuring reliable system operation even in environments with intermittent connectivity.

The processed data are forwarded to the AI processing layer, where machine learning models perform predictive analysis for different functional modules, including disease detection, nutrient estimation, stress prediction, energy optimization, and freshness monitoring. Each model utilizes relevant environmental and physiological features to generate outputs such as risk classifications, prediction values, and actionable recommendations [2], [4].

A key aspect of the proposed system is the integration of outputs from multiple machine learning models into a unified decision support mechanism. The predictions generated by individual modules are combined and presented through a centralized interface, enabling coordinated and data-driven decision-making [19]. This cross-module integration allows the system to leverage shared environmental features across multiple prediction tasks, improving overall system efficiency and consistency in decision-making. For example, environmental parameters such as temperature and humidity are shared across multiple modules, allowing simultaneous analysis for disease detection, stress prediction, and freshness estimation.

The decision support layer provides user-facing functionalities through a web-based dashboard and alert notification system. Users can monitor real-time sensor data, view predictive insights, and receive alerts related to plant health, nutrient requirements, environmental stress, and post-harvest conditions. In addition, the system supports automated actions such as water refilling or environmental adjustments based on predefined conditions and model predictions.

This integrated architecture ensures seamless data flow from sensing to decision-making, enabling real-time monitoring and predictive analysis with coordinated system responses. By combining IoT-based sensing with machine learning-driven analytics in a unified framework, the SmartRose system enhances operational efficiency, improves crop health management, reduces resource wastage, and supports scalable smart agriculture practices [1], [2], [19].

2.2. Data Processing and Dataset Description

The SmartRose system employs a structured data processing pipeline to transform raw sensor readings into meaningful inputs for machine learning-based prediction and decision support. Environmental and physiological data are continuously collected from IoT sensor nodes deployed within the greenhouse and transmitted to a centralized processing unit for storage and analysis [14].

The dataset used in this study consists of approximately 2,500–6,000 samples collected under varying greenhouse conditions, representing diverse environmental scenarios. Each data instance includes multiple features such as temperature, humidity, soil moisture, light intensity, air quality, and nutrient-related parameters including nitrogen (N), phosphorus (P), potassium (K), electrical conductivity (EC), and soil pH. These features were selected based on their relevance to plant health, stress conditions, and post-harvest quality as identified in prior agricultural studies [1], [2].

The collected raw data undergo several preprocessing steps to ensure data quality and consistency. These steps include noise filtering, handling missing or inconsistent values, and normalization of feature ranges to enable effective model training. Feature engineering techniques are also applied to derive meaningful attributes and improve model performance, particularly in capturing relationships between environmental variables and plant responses.

Depending on the prediction task, the dataset is structured for both classification and regression problems. For disease detection and energy optimization modules, the dataset is formulated as a classification problem with labeled categories such as healthy, low stress, medium stress, and high stress. These labels are assigned based on observed environmental thresholds and domain-informed conditions. In contrast, nutrient management and freshness monitoring modules utilize regression-based datasets to predict continuous outputs such as optimal fertilizer requirements and remaining vase life.

To ensure reliable model evaluation, the dataset is divided into training and testing subsets using a 70:30 split ratio. This separation allows unbiased assessment of model performance on unseen data. During model development, multiple algorithms including Random Forest, Linear Regression, and Long Short-Term Memory (LSTM) networks were evaluated to identify the most suitable approach for each prediction task.

The preprocessing and dataset structuring approach enabled effective training of machine learning models, contributing to high predictive performance observed during evaluation. For instance, regression-based models achieved low prediction error (e.g., RMSE $\approx$ 0.092 for Random Forest in nutrient prediction), while classification models demonstrated strong accuracy in identifying plant stress conditions. These results indicate that the processed dataset effectively captures the underlying relationships between environmental factors and plant behavior.

Overall, this data-centric approach ensures that the SmartRose system can model complex interactions within greenhouse environments, enabling accurate predictions and supporting data-driven decision-making across all system components [1], [2].

2.3. Machine Learning Model Development

Machine learning models are developed within the SmartRose system to perform predictive analysis across multiple functional modules, including disease detection, nutrient management, energy optimization, and freshness monitoring. The model development process follows a structured pipeline consisting of data preparation, model training, validation, and performance evaluation.

Based on the nature of each prediction task, both classification and regression approaches are employed. Classification models are utilized for disease detection and stress prediction, where the objective is to categorize plant conditions into discrete classes such as healthy, low stress, medium stress, and high stress. Regression models are applied for nutrient management and freshness monitoring to predict continuous outputs such as optimal fertilizer requirements and remaining vase life.

Several machine learning algorithms were evaluated, including Random Forest, Linear Regression, and Long Short-Term Memory (LSTM) networks, to determine the most suitable model for each task. Among these, the Random Forest algorithm was selected as the primary model due to its robustness, ability to handle nonlinear relationships, and effectiveness in processing heterogeneous agricultural data [2], [4]. Additionally, Random Forest is less sensitive to noise and overfitting, making it well-suited for real-world sensor data environments.

Model training was performed using the preprocessed dataset, with appropriate splitting into training and testing subsets to ensure unbiased evaluation. During training, models were optimized to learn the relationships between environmental parameters and target outputs. Validation techniques were applied to monitor model performance and prevent overfitting.

The performance of the developed models was evaluated using appropriate metrics based on the task type. For classification tasks, evaluation metrics such as accuracy, precision, recall, and F1-score were used to assess prediction performance. For regression tasks, error-based metrics including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were employed to quantify prediction accuracy.

Comparative analysis of the evaluated models demonstrated that the Random Forest approach consistently achieved superior performance across both classification and regression tasks. In particular, regression models achieved low prediction error (e.g., RMSE ≈ 0.092 in nutrient prediction), while classification models showed strong accuracy in identifying plant stress conditions. These results indicate that ensemble-based methods are highly effective for modeling complex relationships in greenhouse environments.

The trained models were subsequently integrated into the SmartRose system to enable real-time prediction and decision support. This model development approach ensures reliable, scalable, and accurate predictive capabilities, supporting intelligent greenhouse management through data-driven insights.

2.4. Component-wise Methodologies

The SmartRose system consists of four primary functional components: disease detection, nutrient management, energy optimization, and post-harvest freshness monitoring. Each component is developed using machine learning models and operates on shared environmental data collected through the IoT sensing infrastructure. Although each module performs a specific task, they are integrated within a unified framework to enable coordinated and data-driven decision-making.

The disease detection component utilizes environmental parameters such as temperature, humidity, soil moisture, and light intensity to identify early signs of plant stress and disease risk. A classification-based machine learning model, primarily Random Forest, is trained on labeled data representing different plant health conditions. The model analyzes real-time sensor data and predicts the likelihood of disease occurrence, enabling early intervention through alert notifications and preventive actions.

The nutrient management component focuses on optimizing fertilizer usage by predicting nutrient requirements based on soil and environmental conditions. This module uses input features including soil moisture, NPK levels, electrical conductivity (EC), pH, temperature, and humidity. A regression-based model is employed to estimate optimal fertilizer quantities and detect potential nutrient deficiencies. The system provides actionable recommendations to farmers, improving resource efficiency and promoting sustainable agricultural practices.

The energy optimization component is designed to enhance greenhouse environmental control while minimizing energy consumption. This module analyzes environmental parameters such as temperature, humidity, and light intensity to classify greenhouse conditions into different stress levels. Based on the predicted stress category, the system generates recommendations for controlling ventilation, cooling, heating, and lighting systems. This approach enables efficient energy usage while maintaining optimal conditions for plant growth.

The freshness monitoring component addresses post-harvest challenges by predicting the quality and remaining vase life of harvested roses. This module utilizes storage-related parameters such as temperature, humidity, ethylene gas concentration, and water levels. A regression-based model estimates freshness scores and vase life duration, allowing stakeholders such as florists and distributors to make informed decisions regarding storage, transportation, and sales.

A key strength of the SmartRose system lies in the integration of these components through shared data and centralized processing. Environmental features collected from the greenhouse are simultaneously utilized across multiple modules, enabling consistent and synchronized predictions. For example, temperature and humidity data contribute not only to disease detection but also to stress prediction and freshness estimation, ensuring efficient utilization of sensor data.

Overall, the component-level implementation demonstrates a modular yet interconnected system design, where each functional unit contributes to a comprehensive decision-support platform. This integrated approach enhances system scalability, improves prediction accuracy, and enables holistic management of greenhouse rose cultivation from growth to post-harvest stages.

2.5. System Implementation, Integration and Testing

The SmartRose system was implemented as an integrated AI-IoT platform combining hardware-based data acquisition, machine learning-based prediction, and a web-based decision support interface. The implementation was carried out in a modular manner to ensure scalability, maintainability, and seamless integration of all system components.

2.5.1. System Implementation

The data acquisition layer was implemented using IoT sensor nodes connected to ESP32 microcontrollers. These nodes were configured to collect real-time environmental and soil parameters, including temperature, humidity, soil moisture, light intensity, air quality, and nutrient-related indicators such as NPK, EC, and ph. For post-harvest monitoring, additional sensors were used to capture temperature, humidity, ethylene gas levels, and water conditions.

Sensor data were transmitted to a centralized processing unit using wireless communication protocols such as LoRa and Wi-Fi. The use of LoRa enabled reliable long-range communication with low power consumption, making the system suitable for distributed greenhouse environments. The ESP32 acted as the central controller, aggregating sensor data and forwarding them to the backend system. In addition, local storage mechanisms were implemented to buffer data during connectivity interruptions, ensuring continuous system operation.

The backend system was developed using Python-based frameworks, where data preprocessing and machine learning inference were performed. Machine learning models were implemented using libraries such as Scikit-learn and TensorFlow, enabling both classification and regression-based predictions. A MongoDB database was used to store real-time and historical data, supporting efficient data retrieval and analysis.

A web-based dashboard was developed as the user interface to visualize system outputs and provide decision support. The dashboard displays real-time sensor readings, predicted outputs from machine learning models, and alert notifications for abnormal conditions. Users can monitor greenhouse conditions, receive recommendations, and take timely actions based on system insights. The interface was designed to be simple and intuitive to ensure usability for non-technical users such as farmers.

All system components were integrated to operate as a unified platform, where sensor data, machine learning predictions, and user interface functionalities are synchronized in real time. This integration ensures seamless data flow and coordinated system behavior across all modules.

2.5.2. System Testing and Validation

The SmartRose system was evaluated through both module-level and system-level testing to ensure reliability, accuracy, and practical applicability. Module-level testing was conducted to verify the functionality and performance of individual components, including sensor data acquisition, preprocessing, and machine learning prediction.

Machine learning models were evaluated using standard performance metrics. Classification models were assessed using accuracy, precision, recall, and F1-score, while regression models were evaluated using RMSE and MAE. The results demonstrated strong predictive performance across all modules, confirming the effectiveness of the selected models.

System-level testing was conducted by simulating real greenhouse conditions using continuous sensor data streams. The system was tested for its ability to process incoming data, generate predictions, and deliver timely recommendations through the dashboard interface. The performance of the system in handling real-time data, maintaining stability, and providing accurate outputs was carefully observed.

In addition, integration testing was performed to ensure that all modules function cohesively within the unified platform. The system successfully demonstrated the ability to combine predictions from multiple models and provide coordinated decision support. For example, environmental parameters were simultaneously utilized for disease detection, stress prediction, and freshness estimation without data inconsistency.

Overall, the implementation and testing results confirm that the SmartRose system can operate as a reliable, scalable, and efficient smart greenhouse management solution. The integration of

IoT-based sensing with machine learning-driven analytics enables real-time monitoring, accurate prediction, and intelligent decision-making, supporting improved productivity and sustainability in greenhouse rose cultivation.

2.6. Commercialization Aspects of the Product

2.6.1. Product Structure and Target Users

The SmartRose system is designed as a modular platform consisting of four distinct yet interconnected components targeting different stakeholders within the floriculture value chain. These components are categorized based on their primary users and the value they provide, as summarized in Table 2.

Table 2: SmartRose Product Modules and Target Users

Product	**Target User**	**Value Provided**
Disease Detection	Farmer	Reduces crop loss
Nutrient Management	Farmer	Optimize fertilizer use
Energy Optimization	Farmer	Reduces operational cost
Freshness Monitoring	Florist/Exporter	Extends shelf life

As shown in Table 2, three modules disease detection, nutrient management, and energy optimization are primarily designed for greenhouse rose farmers, focusing on improving crop health, optimizing resource utilization, and reducing operational costs. In contrast, the freshness monitoring module targets florists, distributors, and exporters, enabling improved post-harvest management and quality preservation.

Each module can operate as a standalone solution, allowing users to adopt specific functionalities based on their operational needs. This modular architecture enhances flexibility, affordability, and accessibility, particularly for small- and medium-scale users, while also supporting full system integration for comprehensive end-to-end decision support.

2.6.2. Deployment and Business Model

The SmartRose system supports both standalone and fully integrated deployment strategies. Individual modules can be deployed independently, while the complete system provides end-to-end support across the entire lifecycle of rose cultivation, from growth monitoring to post-harvest handling.

The system can be commercialized using a subscription-based or service-oriented business model, where users pay for access to real-time monitoring, predictive analytics, and decision support functionalities. Flexible pricing tiers can be introduced based on system scale, number of sensor nodes, and level of functionality, enabling adoption across different user segments.

Additionally, the platform can be deployed through partnerships with agricultural organizations, cooperatives, and government initiatives to facilitate large-scale adoption. Such collaborations can improve accessibility for farmers and promote the use of smart agriculture technologies in developing regions.

2.6.3. Cost and Market Potential

From a cost perspective, the SmartRose system is designed to be affordable, scalable, and practical for real-world deployment. Hardware components such as IoT sensors and ESP32 microcontrollers are relatively low-cost and widely available, reducing the initial investment required for system implementation. Software-related costs are primarily associated with machine learning model development, system integration, and maintenance.

The system demonstrates strong market potential due to its ability to address critical challenges across both pre-harvest and post-harvest stages of floriculture. The increasing demand for high-quality flower production, combined with the need to reduce operational costs and resource wastage, further supports its commercial viability particularly in regions such as Sri Lanka, where floriculture contributes significantly to economic development [12], [16].

Furthermore, with the growing global emphasis on smart agriculture and sustainability, the SmartRose system provides a scalable and extensible solution that can be adapted to other crops and agricultural domains. This adaptability enhances its long-term commercial potential and relevance in the evolving agri-tech landscape [18].

3. RESULTS AND DISCUSSION

3.1. Results

This section presents the performance evaluation of the SmartRose system across its four primary components: disease detection, nutrient management, energy optimization, and freshness monitoring. The models were trained and tested using real greenhouse datasets, and their performance was evaluated using appropriate metrics for both classification and regression tasks.

3.1.1. Disease Detection Performance

The performance of the disease detection model was evaluated using classification metrics, including precision, recall, F1-score, and accuracy. The results are presented in Table 3.

Table 3: Disease Risk Prediction Results

	Precision	**Recall**	**F1-Score**	**Support**
0	1.00	1.00	1.00	2185
1	1.00	1.00	1.00	407
Accuracy			1.00	2592
Micro Avg	1.00	1.00	1.00	2592
Weighted Avg	1.00	1.00	1.00	2592

The model achieved near-perfect classification performance under controlled conditions, with precision, recall, and F1-scores approaching 1.00. This indicates that the selected environmental features are highly effective in distinguishing between healthy and stressed plant conditions. However, it is important to note that such high performance is influenced by the controlled dataset used in this study, and performance may vary under more diverse real-world conditions.

3.1.2. Nutrient Management Performance

The nutrient management module was evaluated using multiple regression models, including Linear Regression, Random Forest, and Long Short-Term Memory (LSTM). The performance comparison is shown in Table 4.

Table 4: Intelligent Nutrient Management Results

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

The Random Forest model achieved the lowest prediction error (RMSE ≈ 0.092), outperforming both Linear Regression and LSTM models. This demonstrates the effectiveness of ensemble-based methods in capturing nonlinear relationships between environmental and soil parameters. In contrast, the higher error observed in LSTM suggests that deep learning approaches may require larger datasets to perform optimally in this context.

3.1.3. Energy Optimization Performance

The energy optimization module was evaluated as a classification problem to predict greenhouse stress levels. The results are summarized in Table 5.

Table 5: Stress Prediction Results

	Precision	**Recall**	**F1-Score**	**Support**
High	0.87	0.93	0.90	2505
Low	0.85	0.92	0.88	1434
Medium	0.85	0.73	0.79	2109
Accuracy			0.86	6048
Micro Avg	0.86	0.86	0.86	6048
Weighted Avg	0.86	0.86	0.86	6048

The model achieved an overall accuracy of approximately 86%, indicating reliable performance in identifying greenhouse stress conditions. The model performed particularly well in detecting high and low stress levels, while performance for medium stress conditions was comparatively lower. This suggests that moderate environmental variations are more difficult to distinguish, which is a common challenge in classification tasks involving overlapping feature distributions.

3.1.4. Freshness Monitoring Performance

The freshness monitoring module was evaluated using regression metrics to predict freshness score and vase life. The results are presented in Table 6.

Table 6: Post-Harvest Freshness Results

Metric	**Value**
RMSE (Freshness)	0.22
RMSE (Vase Life)	1.95 hours

The model achieved low prediction error, with RMSE values of approximately 0.22 for freshness score and 1.95 hours for vase life estimation. These results indicate that the model can reliably predict post-harvest quality based on environmental conditions, supporting improved storage and transportation decisions.

3.2. Research Findings

The experimental results highlight several key findings. First, environmental and physiological features are highly effective for early-stage plant stress detection, enabling proactive intervention. Second, ensemble-based models such as Random Forest consistently demonstrated superior performance across both classification and regression tasks. Third, the integration of IoT-based sensing with machine learning models enables accurate and reliable predictions across multiple aspects of greenhouse management. Finally, the unified system approach enhances decision-making by providing coordinated insights across the entire cultivation lifecycle.

3.3. Discussion

The results demonstrate that the SmartRose system provides a comprehensive and effective solution for intelligent greenhouse management. The high performance observed in disease detection indicates the strong correlation between environmental parameters and plant stress conditions. However, the near-perfect accuracy achieved in controlled environments may not fully generalize to more complex real-world scenarios, where environmental variability and sensor noise can affect prediction accuracy.

The superior performance of the Random Forest model in nutrient prediction confirms its suitability for handling heterogeneous agricultural data. Its ability to model nonlinear relationships makes it particularly effective in environments where multiple factors interact simultaneously.

The energy optimization module demonstrates practical applicability, with strong performance in identifying critical stress conditions. The relatively lower performance for medium stress levels suggests the need for further refinement of classification boundaries or additional feature engineering.

The freshness monitoring component extends the system beyond traditional greenhouse management by addressing post-harvest challenges. The low prediction error indicates that environmental conditions play a significant role in determining vase life, and predictive modeling can effectively support supply chain decision-making.

Compared to traditional manual methods and rule-based systems, the SmartRose platform provides real-time monitoring, predictive analytics, and integrated decision support. This represents a significant advancement in smart agriculture, particularly in the context of greenhouse floriculture.

3.4. Individual Contribution

The SmartRose system was developed collaboratively, with each team member responsible for a specific component of the system. The contributions are outlined below:

- **IT22358448 – RAJAPAKSHA R M S N R**

  Responsible for the development of the *Automated Early Disease Alerting System*. This included collecting and preprocessing environmental data, designing and implementing classification models for early disease and stress detection, and evaluating model performance using metrics such as accuracy, precision, and recall. Additionally contributed to integrating sensor data for real-time disease prediction and alert generation.

- **IT22326522 – PERERA W P M A N**

  Led the development of the *Intelligent Nutrition Management System for Greenhouse Roses*. This involved dataset preparation, feature engineering, and implementation of regression models to predict optimal fertilizer requirements. The contribution also included evaluating model performance using error metrics such as RMSE and MAE, and integrating soil sensor data (NPK, EC, pH) into the system.

- **IT22888648 – RODRIGO U M T H**

  Developed the *Centralized Stress Prediction and Energy Optimization System*. Responsibilities included designing classification models to predict greenhouse stress levels, analyzing environmental parameters such as temperature, humidity, and light intensity, and generating recommendations for energy-efficient greenhouse control. Also contributed to system integration and ensuring coordination between multiple modules.

- **IT22367594 – BANDARA N G J C**

  Responsible for the *IoT-Based Freshness Monitoring and Post-Harvest Management System*. This included developing regression models to predict freshness scores and vase life, processing storage-related sensor data, and validating prediction outputs.

Additionally contributed to the development of the user dashboard and visualization of system outputs.

- **Group Contribution**

  All team members collaboratively contributed to the overall system integration, implementation of the IoT infrastructure, model testing and validation, and preparation of the final report. The development of the SmartRose platform, including data collection, machine learning integration, and user interface design, was carried out as a coordinated effort to ensure seamless operation across all system components.

4. CONCLUSION AND FUTURE WORK

This research presented the design, development, and evaluation of SmartRose, an integrated AI-IoT-based smart greenhouse system for rose cultivation. The system successfully combines real-time environmental monitoring with machine learning-driven predictive analytics to provide intelligent decision support across multiple stages of the agricultural lifecycle, including disease detection, nutrient management, energy optimization, and post-harvest freshness monitoring.

The experimental results demonstrate that the proposed system can effectively model the complex relationships between environmental conditions and plant responses. Classification models achieved high accuracy in identifying plant stress and disease risk, while regression models produced low prediction errors in estimating nutrient requirements and freshness levels. Among the evaluated approaches, the Random Forest algorithm consistently delivered superior performance, highlighting its suitability for agricultural prediction tasks involving nonlinear and heterogeneous data.

A key contribution of this research is the integration of multiple functional modules into a unified platform. Unlike traditional systems that address isolated aspects of agriculture, SmartRose provides a comprehensive solution that enables coordinated decision-making across the entire cultivation and post-harvest process. The use of shared environmental data across modules enhances system efficiency and supports more consistent and reliable predictions.

The implementation of the SmartRose system demonstrates its practical feasibility as a scalable and cost-effective solution for smart greenhouse management. By leveraging IoT-based sensing and machine learning techniques, the system reduces reliance on manual monitoring, improves resource utilization, and minimizes crop loss and post-harvest waste. This makes it particularly valuable for regions such as Sri Lanka, where floriculture plays an important role in economic development.

Despite these contributions, certain limitations remain. The system was evaluated using a controlled dataset, which may not fully capture the variability of real-world greenhouse environments. Additionally, the performance of some models, particularly for moderate stress conditions, indicates the need for further refinement and expanded datasets.

Future work will focus on enhancing the system's robustness and scalability by incorporating larger and more diverse datasets, improving model generalization, and exploring advanced deep learning techniques. The integration of automated control mechanisms for irrigation, climate regulation, and energy management can further extend the system's capabilities. In addition, the SmartRose platform can be adapted to support other crops and agricultural domains, increasing its applicability and commercial potential.

In conclusion, the SmartRose system demonstrates the effectiveness of integrating IoT and machine learning technologies in modern agriculture. The proposed approach provides a practical, scalable, and intelligent solution for improving productivity, sustainability, and decision-making in greenhouse rose cultivation.

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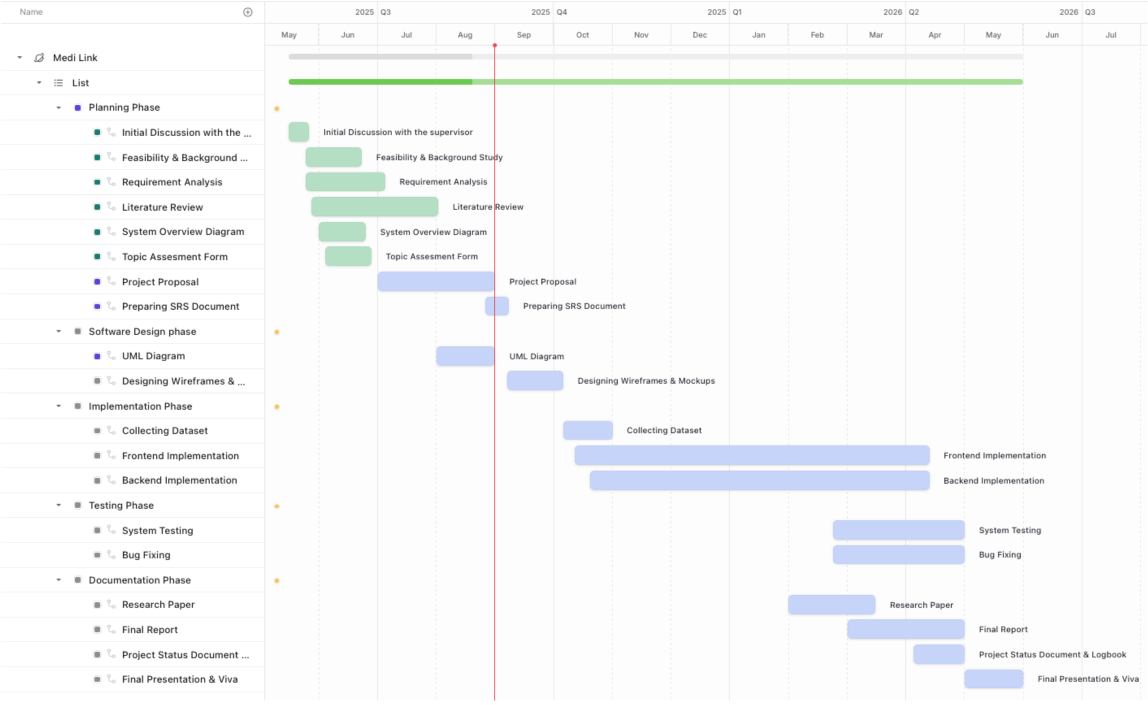
6. APPENDICES

6.1. Appendix A: Gantt Chart



Appendix A: Gantt Chart