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

25-26J-299

Final Thesis

Rodrigo U M T H

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

Department of Information Technology

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DECLARATION

I declare that this is my own work, and this report 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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The supervisor(s) should certify the proposal report with the following declaration:

The above candidate is carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor: Date

ABSTRACT

This research presents the design and development of a Centralized Stress Prediction and Energy Optimization System as a core component of the SmartRose AI–IoT platform for smart greenhouse rose cultivation in Sri Lanka. Greenhouse-based rose farming requires continuous monitoring and precise control of environmental conditions to maintain optimal plant health, improve flower quality, and ensure consistent yield. However, most middle-scale greenhouse farmers rely on manual observation and experience-based decision-making, which often leads to delayed stress detection, inefficient energy usage, and inconsistent environmental management across multiple greenhouse zones.

To address these challenges, the proposed system integrates Internet of Things (IoT) technologies with machine learning–based predictive analytics to enable real-time monitoring and intelligent decision support. A network of LoRa-enabled sensor nodes is deployed across greenhouse beds to continuously collect environmental data, including temperature, humidity, ultraviolet (UV) intensity, soil moisture, and air quality. These data are transmitted to a centralized ESP32-based gateway capable of both online and offline operation, ensuring system reliability in low-connectivity agricultural environments.

The collected data are preprocessed and analyzed using a Random Forest–based machine learning model to predict plant stress levels categorized as Low, Medium, and High. Based on the predicted stress conditions, the system generates energy optimization recommendations for greenhouse operations, including adjustments to lighting, ventilation, and irrigation systems. This enables proactive decision-making, reducing unnecessary energy consumption while maintaining optimal growth conditions.

Experimental evaluation demonstrates that the proposed model achieves an accuracy of approximately 86% in stress classification, indicating strong predictive performance and robustness under varying environmental conditions. The system also shows reliable operation under different scenarios, including normal conditions, missing data inputs, and environmental fluctuations.

The proposed solution contributes to precision agriculture by enabling early stress detection, improving resource efficiency, and supporting sustainable greenhouse management practices. Furthermore, the system demonstrates strong potential for scalability and commercialization as an intelligent, low-cost, and farmer-friendly solution tailored to the needs of Sri Lankan greenhouse rose cultivation.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
IoT	Internet of Things
LoRa	Long Range Communication
ESP32	Espressif 32-bit Microcontroller
RF	Random Forest
UV	Ultraviolet
API	Application Programming Interface
DB	Database
MQTT	Message Queuing Telemetry Transport
JSON	JavaScript Object Notation
CPU	Central Processing Unit
RAM	Random Access Memory
UI	User Interface
UX	User Experience
EC	Electrical Conductivity
CSV	Comma-Separated Values
HTTP	Hypertext Transfer Protocol

1. INTRODUCTION

Floriculture is a rapidly growing sector within modern agriculture, with greenhouse-based rose cultivation playing a significant role in both domestic markets and international exports. Roses are considered high-value crops that require precise environmental control to maintain quality, consistency, and market competitiveness. In countries like Sri Lanka, greenhouse cultivation is increasingly adopted to overcome climatic variability and enable year-round production. However, maintaining optimal conditions across greenhouse environments remains a complex and resource-intensive task [5], [12].

Greenhouse rose farming involves continuous monitoring and control of environmental parameters such as temperature, humidity, light intensity, soil moisture, and air quality. These factors directly influence plant physiology, growth rate, flower quality, and overall yield. Even slight deviations from optimal conditions can introduce plant stress, leading to reduced productivity, poor flower characteristics, and increased susceptibility to diseases. Research has shown that physiological stress often develops before visible symptoms appear, making early detection critical for effective intervention [11].

Despite the importance of environmental control, most middle-scale greenhouse farmers in Sri Lanka still rely heavily on manual observation and experience-based decision-making. This approach is often reactive rather than proactive, as farmers respond only after visible symptoms of stress or damage occur. Manual monitoring becomes increasingly inefficient as the number of greenhouse tunnels or flower beds increases, leading to inconsistent environmental management and delayed responses to critical conditions. Additionally, the lack of real-time data-driven insights results in inefficient utilization of resources such as lighting, ventilation, and irrigation systems [12].

Another major challenge in greenhouse rose cultivation is energy consumption. Systems such as grow lights, fans, misting units, and ventilation mechanisms consume significant amounts of electricity. Without intelligent control, these systems are often operated based on fixed schedules or assumptions, leading to unnecessary energy usage and increased operational costs. This not only reduces profitability but also contributes to unsustainable farming practices. Therefore, there is a strong need for systems that can optimize energy usage while maintaining optimal plant growth conditions [10].

Recent advancements in Artificial Intelligence (AI) and the Internet of Things (IoT) have introduced new opportunities for transforming traditional agriculture into data-driven smart farming systems. IoT technologies enable continuous real-time monitoring of environmental and soil parameters through sensor networks, while machine learning techniques allow for predictive analysis and intelligent decision-making. These technologies have been successfully applied in various agricultural domains, including crop monitoring, irrigation control, and disease detection [7], [8].

However, most existing smart agriculture solutions are designed to address isolated problems rather than providing a comprehensive and integrated system. Many IoT-based systems focus only on data collection and visualization, lacking predictive capabilities. Similarly, machine learning models are often developed using static datasets without real-time integration, limiting their effectiveness in dynamic greenhouse environments. Additionally, most solutions are designed for large-scale commercial farms and are not optimized for the needs, affordability, and infrastructure constraints of middle-scale farmers in developing regions [3], [9].

To address these challenges, the SmartRose platform was proposed as an integrated AI–IoT-based system for intelligent greenhouse rose cultivation. The platform consists of multiple interconnected components, including early disease detection, intelligent nutrient management, stress prediction and energy optimization, and post-harvest freshness monitoring. Each component focuses on a specific aspect of the rose cultivation lifecycle while contributing to a unified decision-support system [13].

This research focuses specifically on the development of the Centralized Stress Prediction and Energy Optimization System, which plays a critical role in maintaining optimal greenhouse conditions and improving resource efficiency. The system utilizes IoT-based sensors to collect real-time environmental data from multiple greenhouse zones and applies a machine learning model to predict plant stress levels categorized as Low, Medium, and High. Based on these predictions, the system generates energy optimization recommendations, enabling intelligent control of greenhouse resources such as lighting, ventilation, and irrigation.

A key feature of the proposed system is the use of LoRa-based communication, which allows long-range, low-power data transmission across multiple greenhouse units. This enables centralized monitoring and management of distributed greenhouse environments while maintaining low operational costs. Additionally, the system is designed to support offline operation through local data storage and synchronization, making it suitable for rural agricultural settings with limited internet connectivity [1], [2].

By integrating real-time sensing, machine learning-based prediction, and energy-aware decision support, the proposed system enables proactive greenhouse management. It allows farmers to detect stress conditions early, respond effectively, and optimize resource usage. This contributes to improved plant health, enhanced flower quality, reduced operational costs, and increased sustainability.

Overall, this research aims to demonstrate the feasibility and effectiveness of combining IoT and machine learning technologies to develop an intelligent, scalable, and cost-effective solution for greenhouse rose farming. The proposed system addresses key challenges faced by middle-scale farmers and contributes to the advancement of precision agriculture in developing regions.

1.1. BACKGROUND & LITERATURE SURVEY

Greenhouse rose cultivation represents a high-value segment within the floriculture industry, contributing significantly to both domestic markets and export-oriented supply chains. In Sri Lanka, favorable climatic diversity supports the cultivation of premium rose varieties; however, productivity and quality remain constrained by several interrelated challenges, including environmental stress, inefficient energy utilization, delayed disease detection, nutrient imbalance, and post-harvest losses [5], [12]. These challenges highlight the need for intelligent, data-driven solutions capable of improving greenhouse management practices.

Environmental stress is one of the most critical factors affecting rose growth and productivity. Variations in temperature, humidity, light intensity, and soil moisture directly influence plant physiological processes such as transpiration, photosynthesis, and nutrient absorption. Studies have shown that physiological stress often develops before visible symptoms appear, making early detection essential for preventing irreversible crop damage [11]. Traditional greenhouse management approaches rely on manual monitoring and fixed control mechanisms, which are insufficient to respond dynamically to rapidly changing environmental conditions.

The integration of Internet of Things (IoT) technologies in agriculture has enabled real-time monitoring of environmental parameters through distributed sensor networks. IoT-based greenhouse monitoring systems can collect data such as temperature, humidity, soil moisture, and air quality, providing valuable insights into crop conditions. LoRa-based communication systems have been widely adopted in such applications due to their long-range, low-power capabilities, enabling reliable data transmission across multiple greenhouse zones [1], [2]. These systems have demonstrated effectiveness in large-scale greenhouse monitoring; however, many implementations are limited to data collection and visualization without incorporating predictive intelligence.

Machine learning (ML) techniques have further enhanced the capabilities of smart agriculture systems by enabling predictive analysis and automated decision-making. Algorithms such as Random Forest, Artificial Neural Networks, and Gradient Boosting have been applied to various agricultural problems, including climate control, irrigation prediction, and disease detection [3], [7]. In greenhouse environments, ML models can analyze complex relationships between environmental variables and plant conditions, allowing for more accurate prediction of stress and optimization of resource usage. However, many existing ML-based solutions rely on static datasets and are not integrated with real-time IoT systems, limiting their applicability in dynamic agricultural environments.

Energy consumption is another significant concern in greenhouse farming. Systems such as artificial lighting, ventilation, and irrigation consume considerable amounts of electricity, especially when operated continuously or inefficiently. Research has shown that intelligent energy management strategies can significantly reduce operational costs while maintaining optimal growing conditions [10]. However, most existing energy optimization systems are designed for large-scale commercial greenhouses and do not incorporate plant-level stress indicators, making them less suitable for medium-scale farming environments.

Disease detection in rose cultivation has also been extensively studied. Traditional approaches rely on visual inspection, which is often time-consuming and prone to human error. Recent advancements in deep learning have enabled automated disease detection using image-based techniques, achieving high accuracy in controlled environments [8]. However, these approaches are typically reactive, as they depend on visible symptoms that appear after the disease has already progressed. Additionally, image-based systems require high computational resources and controlled imaging conditions, limiting their practicality for real-time deployment in resource-constrained environments.

Nutrient management plays a crucial role in determining flower quality, growth rate, and plant health. Studies indicate that nutrient imbalance can increase susceptibility to stress and disease, affecting overall crop performance. While machine learning-based nutrient recommendation systems have been developed, most are designed for general agriculture or other crop types and lack real-time integration with greenhouse environmental data [3]. This limits their effectiveness in specialized domains such as rose cultivation.

Post-harvest management is another critical aspect of the floriculture supply chain, where significant losses occur due to improper storage conditions and lack of monitoring. Environmental factors such as temperature, humidity, and ethylene concentration directly affect the freshness and vase life of cut roses. Research indicates that post-harvest losses can exceed 30% due to inadequate monitoring and handling practices [5]. Despite its importance, this area remains underexplored in smart agriculture systems, which often focus primarily on the cultivation phase.

Overall, the existing literature demonstrates that while individual technologies such as IoT, machine learning, and LoRa communication have been successfully applied in agriculture, most solutions address specific problems in isolation. These systems are often reactive, lack integration across the crop lifecycle, and are not tailored to the specific requirements of greenhouse rose cultivation in developing regions [9]. Furthermore, many systems depend on continuous internet connectivity and do not support offline operation, limiting their usability in rural environments.

To address these limitations, recent research has emphasized the need for integrated platforms that combine real-time sensing, predictive analytics, and decision support. The SmartRose platform represents such an approach by unifying multiple functional modules, including disease prediction, nutrient management, stress prediction with energy optimization, and post-harvest monitoring within a single architecture [13]. This integrated framework enables holistic management of greenhouse operations, supporting proactive decision-making and improved resource efficiency.

In this context, the Centralized Stress Prediction and Energy Optimization System plays a vital role by focusing on real-time stress detection and energy-efficient greenhouse management. By combining IoT-based sensing, machine learning-based classification, and LoRa-enabled communication, the system addresses key gaps identified in existing research. It provides a scalable, cost-effective, and offline-capable solution tailored to the needs of middle-scale greenhouse rose farmers, contributing to the advancement of precision agriculture.

1.2. RESEARCH GAP

Recent advancements in smart agriculture have demonstrated the potential of integrating Internet of Things (IoT), machine learning (ML), and wireless communication technologies to improve crop monitoring and resource management. However, their application in greenhouse rose cultivation, particularly in developing regions such as Sri Lanka, remains limited and fragmented. Most existing systems are designed to address specific problems such as irrigation control, disease detection, or environmental monitoring in isolation, rather than providing a comprehensive and integrated solution across the entire cultivation lifecycle [3], [9].

IoT-based greenhouse monitoring systems have been widely adopted for collecting real-time environmental data, especially using long-range communication technologies such as LoRa [1], [2]. While these systems enable efficient data acquisition and visualization, they often lack predictive capabilities and intelligent decision support. Similarly, machine learning models have been successfully applied in agricultural domains for classification and prediction tasks; however, many of these models are developed using static datasets and are not integrated with real-time IoT systems, limiting their effectiveness in dynamic greenhouse environments [7].

In addition, most existing solutions are designed for large-scale commercial agriculture and are not suitable for middle-scale farmers due to high implementation costs, complex infrastructure requirements, and dependence on continuous internet connectivity. This creates a significant barrier for adoption in rural and semi-urban agricultural settings where connectivity is unreliable and resources are limited. Furthermore, many systems do not support offline operation or local data processing, which is critical for ensuring reliability in such environments [4].

Another important limitation in current research is the lack of focus on energy optimization in greenhouse farming. While environmental monitoring systems provide data insights, they do not actively support energy-aware decision-making. Existing energy management solutions are often not integrated with plant-level stress indicators, resulting in inefficient resource utilization and increased operational costs [10]. Additionally, most systems do not provide zone-specific or bed-level analysis, which is essential for accurate greenhouse management due to variations in microclimatic conditions.

Moreover, current approaches do not adequately address early stress detection in plants. Many systems rely on threshold-based rules or visual symptoms, which are reactive and fail to detect stress conditions at an early stage. This leads to delayed interventions and potential crop loss. The absence of predictive, data-driven stress analysis models tailored specifically for rose cultivation further highlights the gap in existing research [11].

Therefore, there is a clear need for an integrated, intelligent, and scalable system that combines real-time IoT-based sensing, machine learning-driven stress prediction, and energy optimization within a unified framework. Such a system should be capable of operating in low-connectivity environments, provide zone-level insights, and support proactive decision-making for greenhouse management.

This research addresses these gaps by proposing a Centralized Stress Prediction and Energy Optimization System that integrates LoRa-based multi-zone sensing, offline-capable data processing, and machine learning-based stress classification. The system provides real-time insights and energy optimization recommendations, offering a cost-effective and practical solution tailored to the needs of middle-scale greenhouse rose farmers in Sri Lanka.

1.3. RESEARCH PROBLEM

Despite the increasing adoption of greenhouse-based rose cultivation, many middle-scale farmers continue to face significant challenges in maintaining optimal environmental conditions and managing resource utilization efficiently. Greenhouse environments require continuous monitoring of multiple parameters such as temperature, humidity, soil moisture, light intensity, and air quality. However, in practical scenarios, these parameters are often monitored manually or through basic sensor systems without intelligent analysis, leading to delayed detection of unfavorable conditions and inconsistent greenhouse management [12].

One of the primary issues in greenhouse rose farming is the inability to detect plant stress at an early stage. Stress conditions typically develop before visible symptoms appear, and by the time farmers recognize these signs, the impact on plant health and flower quality may already be significant [11]. Existing approaches largely rely on threshold-based monitoring or visual inspection, which are reactive and do not provide predictive insights. This results in delayed intervention, reduced crop yield, and increased susceptibility to diseases.

Another critical challenge is the inefficient use of energy within greenhouse systems. Devices such as grow lights, ventilation systems, and misting units are often operated based on fixed schedules or manual decisions rather than real-time environmental conditions. This leads to unnecessary energy consumption, increased operational costs, and suboptimal environmental control. Current systems lack the ability to dynamically adjust energy usage based on plant conditions and environmental changes, limiting their effectiveness in achieving sustainable greenhouse management [10].

Furthermore, existing smart agriculture solutions are often designed for large-scale operations and require continuous internet connectivity for cloud-based processing. Such systems are not suitable for many rural and semi-urban agricultural environments in Sri Lanka, where internet access can be unreliable. The absence of offline-capable systems and localized data processing limits the adoption of advanced technologies among middle-scale farmers [4].

In addition, most existing systems do not provide centralized monitoring across multiple greenhouse zones or flower beds. Variations in microclimatic conditions within different areas of a greenhouse can lead to uneven plant growth and inconsistent output quality. Without zone-level analysis and centralized decision support, farmers are unable to effectively manage distributed greenhouse environments.

Therefore, the core research problem can be defined as the lack of an integrated, intelligent, and scalable system that can:

- Detect plant stress conditions at an early stage using real-time environmental data
- Provide predictive insights rather than reactive monitoring
- Optimize energy usage based on plant and environmental conditions
- Support centralized monitoring across multiple greenhouse zones
- Operate reliably in low-connectivity environments with offline capabilities

This research addresses the identified problem by developing a Centralized Stress Prediction and Energy Optimization System that integrates IoT-based sensing, machine learning-based stress prediction, and energy-aware decision support within a unified architecture. The proposed system aims to enable proactive greenhouse management, improve resource efficiency, and enhance the overall productivity and sustainability of greenhouse rose farming.

1.4. SIGNIFICANCE OF THE STUDY

The proposed research holds significant importance in advancing intelligent greenhouse management practices, particularly within the context of greenhouse rose cultivation in developing regions such as Sri Lanka. Traditional farming methods rely heavily on manual monitoring and experience-based decision-making, which often leads to delayed responses, inefficient resource utilization, and inconsistent crop quality. By introducing a data-driven and automated approach, this study contributes to transforming conventional greenhouse systems into smart and adaptive environments.

One of the key contributions of this research is the ability to detect plant stress at an early stage using real-time environmental data and machine learning techniques. Early stress detection enables timely intervention, reducing the risk of crop damage and improving overall plant health and flower quality. This proactive approach helps farmers maintain consistent production standards and enhances market competitiveness.

Another important contribution is the optimization of energy usage within greenhouse operations. By generating intelligent recommendations for controlling systems such as lighting, ventilation, and irrigation, the proposed system reduces unnecessary energy consumption. This not only lowers operational costs but also promotes environmentally sustainable farming practices.

The use of LoRa-based communication and offline-capable system design further enhances the practical applicability of the solution. The system is specifically tailored for middle-scale farmers who may face limitations in infrastructure and internet connectivity. By ensuring reliable operation in low-connectivity environments, the research increases accessibility and adoption of smart agriculture technologies.

Additionally, the integration of IoT and machine learning within a centralized framework provides a scalable and extensible platform. The system can be expanded to support additional agricultural functions such as disease prediction, nutrient management, and post-harvest monitoring, contributing to a holistic precision agriculture ecosystem.

Overall, this study contributes to improving productivity, reducing costs, enhancing sustainability, and enabling data-driven decision-making in greenhouse rose cultivation. It bridges the gap between advanced technological solutions and real-world agricultural needs, making it highly relevant for modern agriculture development.

1.5. SCOPE AND LIMITATIONS

This research focuses on the design and development of a Centralized Stress Prediction and Energy Optimization System specifically for greenhouse rose cultivation. The system is intended to operate within controlled greenhouse environments and utilizes IoT-based sensor data combined with machine learning techniques to predict plant stress levels and optimize energy usage.

The scope of the study includes the monitoring of key environmental parameters such as temperature, humidity, ultraviolet (UV) intensity, soil moisture, and air quality. These parameters are used as inputs to a machine learning model that classifies plant stress into three categories: Low, Medium, and High. Based on the predicted stress levels, the system provides recommendations for adjusting greenhouse systems such as lighting, ventilation, and irrigation.

The system also incorporates LoRa-based communication to enable long-range data transmission across multiple greenhouse zones, along with a centralized gateway that supports data aggregation, local storage, and offline operation. A user-friendly dashboard is included to visualize real-time data and system recommendations, allowing farmers to make informed decisions.

However, this research has certain limitations. The system is designed specifically for greenhouse-grown roses and may require modifications to be applied to other crops or open-field farming environments. The accuracy of the stress prediction model depends on the quality and diversity of the collected dataset, which may vary under different environmental conditions. Additionally, while the system provides energy optimization recommendations, it does not include fully automated control of greenhouse devices.

The study also focuses primarily on environmental stress prediction and energy optimization, and does not deeply integrate other aspects such as disease detection, nutrient optimization, or post-harvest management within the same module. Furthermore, although offline functionality is supported, real-time cloud-based analytics may be limited in low-connectivity scenarios.

Despite these limitations, the proposed system provides a strong foundation for intelligent greenhouse management and can be further enhanced in future research to support broader agricultural applications.

2. OBJECTIVES

2.1. MAIN OBJECTIVES

The main objective of this research is to develop a centralized, intelligent decision-support system that predicts plant stress levels and optimizes energy usage in greenhouse rose cultivation using real-time IoT sensor data, machine learning techniques, and LoRa-based communication with offline operational capability.

2.2. SPECIFIC OBJECTIVES

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

- To design and implement IoT-based sensor nodes capable of monitoring key environmental parameters including temperature, humidity, UV intensity, soil moisture, and air quality in real time
- To develop a LoRa-based communication system for reliable, long-range data transmission across multiple greenhouse zones
- To build a centralized gateway system using ESP32 for data aggregation, local storage, and offline operation with cloud synchronization capability
- To collect and preprocess multi-sensor environmental data for machine learning model training and evaluation
- To design and train a machine learning model (Random Forest Classifier) to predict plant stress levels categorized as Low, Medium, and High
- To evaluate the performance of the stress prediction model using appropriate metrics such as accuracy, precision, recall, and F1-score
- To develop an energy optimization mechanism that generates recommendations for controlling greenhouse systems such as lighting, ventilation, and irrigation based on predicted stress conditions
- To design and implement a centralized dashboard for real-time visualization of environmental data, stress levels, and system recommendations
- To ensure system reliability through offline data buffering and synchronization for operation in low-connectivity environments

- To validate the system through testing under different environmental conditions and evaluate its effectiveness in improving greenhouse management and reducing energy consumption

3. METHODOLOGY

This research adopts a structured and phased approach to design, develop, and evaluate a Centralized Stress Prediction and Energy Optimization System for greenhouse rose cultivation. The system integrates Internet of Things (IoT) - based sensing, long-range wireless communication, machine learning–based stress prediction, and a centralized decision-support interface. The methodology is designed to ensure scalability, reliability, and applicability in real-world agricultural environments, particularly for middle-scale greenhouse farmers in Sri Lanka.

The overall system is developed using a layered architecture consisting of four main components: the sensing layer, communication layer, processing layer, and application layer. Each layer plays a critical role in enabling real-time data acquisition, transmission, analysis, and visualization.

3.1. SYSTEM ARCHITECTURE

The proposed system follows a centralized architecture where multiple IoT sensor nodes are deployed across different greenhouse zones or flower beds. These sensor nodes continuously monitor environmental parameters such as temperature, humidity, ultraviolet (UV) intensity, soil moisture, and air quality.

The architecture consists of the following layers:

- **Sensing Layer**

This layer includes IoT-based sensor nodes built using ESP32 microcontrollers integrated with environmental sensors. These sensors collect real-time data related to greenhouse conditions, which directly influence plant health and stress levels.

- **Communication Layer**

The collected data is transmitted using LoRa (Long Range) communication technology. LoRa enables low-power, long-distance data transmission, making it suitable for monitoring multiple greenhouse zones from a centralized location. This ensures reliable communication even in large or distributed greenhouse environments.

- **Processing Layer**

A centralized gateway, implemented using an ESP32 device, receives data from all sensor nodes. This gateway performs data aggregation, preprocessing, and storage. It also supports offline functionality by storing data locally when internet connectivity is unavailable and synchronizing with the cloud when connectivity is restored.

The machine learning model for stress prediction is deployed at this layer or integrated through backend services. The model processes incoming sensor data and predicts plant stress levels categorized as Low, Medium, or High.

- **Application Layer**

The application layer provides a user interface for farmers through a mobile or web-based dashboard. It displays real-time sensor readings, predicted stress levels, and energy optimization recommendations. Alerts and notifications are also generated to inform users of critical conditions.

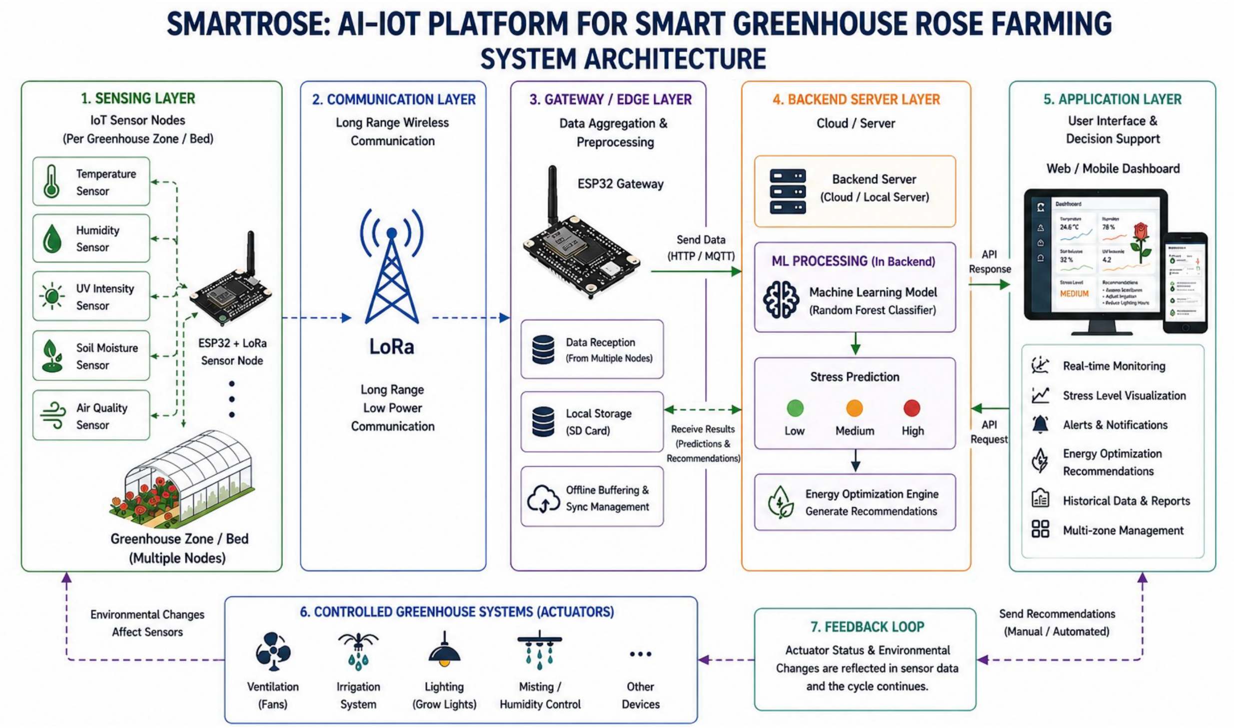


Figure 3.1.1: SmartRose System Architecture

3.2. PROJECT EXECUTION APPROACH

The development of the system is carried out through multiple phases to ensure systematic implementation and evaluation.

3.2.1. Requirement Analysis and Planning

This phase involves identifying the challenges faced by greenhouse rose farmers and defining the system requirements. Functional and non-functional requirements are established based on real-world farming conditions, including the need for real-time monitoring, predictive analysis, offline operation, and energy optimization.

3.2.2. Hardware Design and Sensor Integration

In this phase, appropriate sensors are selected to measure environmental parameters such as temperature, humidity, UV intensity, soil moisture, and air quality. These sensors are interfaced with ESP32 microcontrollers to form IoT sensor nodes. Each node is programmed to collect and transmit data at regular intervals.

3.2.3. Communication and Gateway Development

A LoRa-based communication system is implemented to enable long-range data transmission. A centralized gateway is developed to receive data from multiple sensor nodes. The gateway is configured to store data locally and support synchronization with cloud services when internet connectivity is available.

3.2.4. Data Collection and Preprocessing

Environmental data is collected from sensor nodes over a period of time to build a dataset for machine learning. Data preprocessing techniques such as normalization, handling missing values, and noise filtering are applied to ensure data quality and consistency.

3.2.5. Machine Learning Model Development

A Random Forest classifier is selected for stress prediction due to its ability to handle nonlinear relationships and noisy sensor data. The model is trained using labeled environmental data, where stress levels are categorized into Low, Medium, and High. The model is evaluated using metrics such as accuracy, precision, recall, and F1-score.

3.2.6. Dashboard Development and System Integration

A centralized dashboard is developed to visualize real-time data, predicted stress levels, and system recommendations. The dashboard provides a user-friendly interface for farmers to monitor greenhouse conditions and make informed decisions.

3.2.7. System Testing and Evaluation

The final system is tested under different environmental conditions to evaluate its performance, reliability, and usability. The effectiveness of stress prediction and energy optimization recommendations is analyzed to validate the system.

3.3. WORK BREAKDOWN STRUCTURE (WBS)

The Work Breakdown Structure (WBS) defines the hierarchical decomposition of the SmartRose Centralized Stress Prediction and Energy Optimization System into manageable components. It provides a structured view of the tasks involved in the development and implementation of the system.

The project is divided into the following major phases:

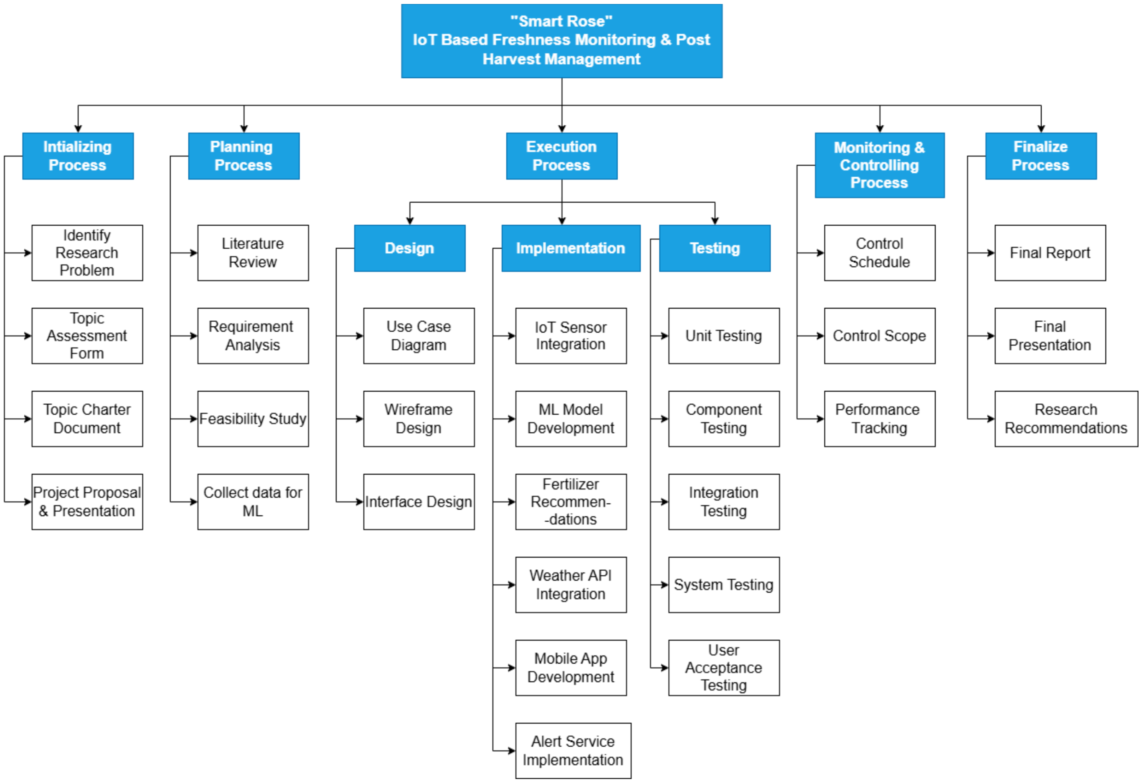


Figure 3.3.1: Work Breakdown Structure (WBS)

3.4. PROJECT TIMELINE (GANTT CHART)

The project timeline illustrates the scheduling and duration of each phase involved in the development of the SmartRose system. A Gantt chart is used to represent the sequence of activities and their respective timeframes, ensuring proper planning and execution.

The project was carried out over multiple stages, beginning with requirement analysis and progressing through system design, development, testing, and evaluation.

The timeline includes the following phases:

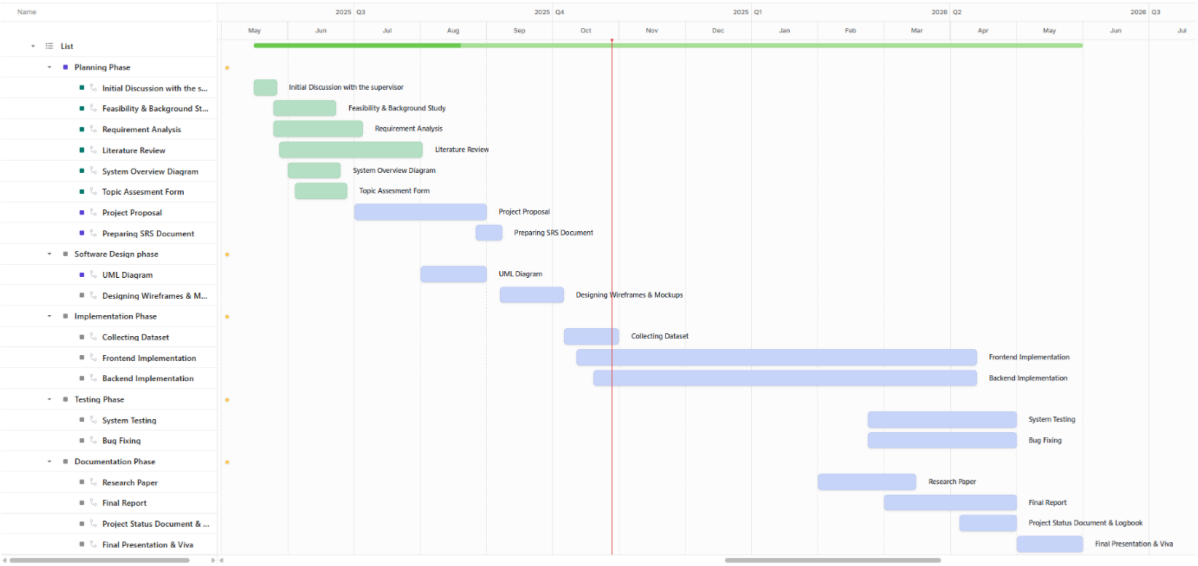


Figure 3.4.1: Project Timeline (Gantt Chart)

Each phase was scheduled with overlapping periods where necessary to optimize development time and ensure efficient resource utilization. Iterative development practices were followed, allowing continuous improvement and refinement of system components throughout the project lifecycle.

3.5. SYSTEM WORKFLOW AND DATA FLOW

The overall workflow of the proposed system illustrates how data flows from sensor acquisition to intelligent decision-making.

Initially, IoT sensor nodes collect environmental data from different greenhouse zones. These data are transmitted via LoRa communication to a centralized gateway, where they are stored and preprocessed.

The processed data are then passed to the machine learning model, which predicts plant stress levels. Based on these predictions, the system generates energy optimization recommendations such as adjusting lighting, ventilation, and irrigation systems.

Finally, all processed information, including sensor readings, predicted stress levels, and recommendations, is displayed on a centralized dashboard. Alerts are generated when critical stress conditions are detected, enabling proactive intervention.

This workflow ensures real-time monitoring, predictive analysis, and efficient decision-making, supporting intelligent greenhouse management.

4. IMPLEMENTATION AND SYSTEM DESIGN

This chapter describes the detailed implementation of the Centralized Stress Prediction and Energy Optimization System. Unlike the methodology, which outlines the overall approach, this section focuses on the practical realization of the system, including data collection, preprocessing, machine learning model development, and system integration.

4.1. DATA COLLECTION

Environmental data were collected using IoT sensor nodes deployed within greenhouse environments. Each node was equipped with sensors to monitor key parameters affecting plant stress, including temperature, humidity, ultraviolet (UV) intensity, soil moisture, and air quality.

The sensor nodes continuously capture real-time data and transmit it to a centralized gateway using LoRa communication. The gateway aggregates data from multiple greenhouse zones and stores them in a structured format for further processing.

The collected dataset was organized as a time-series dataset, ensuring that temporal relationships between environmental conditions were preserved. This is important for accurately modeling plant stress patterns over time.

4.2. DATA PREPROCESSING

Before training the machine learning model, the collected data were preprocessed to improve quality and consistency.

The preprocessing steps include:

- Handling missing values using interpolation and default replacement methods
- Noise filtering to remove inconsistencies caused by sensor fluctuations
- Outlier detection and removal to eliminate abnormal readings
- Feature normalization to ensure consistency during analysis

Additionally, to simulate real-world conditions where sensor data may be imperfect, controlled label noise of approximately 8% was introduced into the dataset. This improves the robustness of the model and its ability to generalize to unseen data.

4.3. FEATURE SELECTION

The input features used for model training were selected based on their relevance to plant stress conditions. These features represent key environmental factors that influence plant health.

Feature Name	Description
Temperature	Ambient temperature inside greenhouse
Humidity	Relative humidity level
UV Intensity	Light exposure level
Soil Moisture	Soil water content
Air Quality	Air condition and pollutant level

Figure 4.3.1: Input Features Used for Model Training

The target variable is the plant stress level, categorized into three classes:

- Low Stress
- Medium Stress
- High Stress

4.4. MACHINE LEARNING MODEL IMPLEMENTATION

A Random Forest Classifier was implemented to predict plant stress levels. The model was selected due to its ability to handle nonlinear relationships, robustness to noisy data, and effectiveness in multi-class classification problems.

The dataset was divided using a time-based splitting approach, where 80% of the data were used for training and 20% for testing. This approach prevents data leakage and preserves temporal dependencies, making the evaluation more realistic.

The model was configured with the following parameters:

Parameter	Value
Number of Trees	200
Maximum Depth	6
Minimum Samples Leaf	15
Class Weight	Balanced
Random State	42

Figure 4.4.1: Random Forest Model Parameters

The model was trained using labeled environmental data and then used to predict stress levels based on new incoming sensor data.

4.5. MODEL EVALUATION

The performance of the model was evaluated using standard classification metrics.

Metric	Description
Accuracy	Overall correctness of predictions
Precision	Correctness of positive predictions
Recall	Ability to identify actual stress conditions
F1-Score	Balance between precision and recall

Figure 4.5.1: Evaluation Metrics for Stress Prediction Model

The model achieved an accuracy of approximately 86%, indicating reliable performance in classifying plant stress levels under varying environmental conditions.

A confusion matrix was used to visualize prediction performance and analyze classification errors. The results show that the model performs well across all three stress categories, with minimal misclassification.

4.6. SYSTEM INTEGRATION

The complete system integrates IoT hardware, communication modules, machine learning models, and a user interface into a unified architecture.

The implementation flow is as follows:

- Sensor nodes collect environmental data
- Data are transmitted via LoRa to the gateway
- The gateway stores and preprocesses the data
- The machine learning model predicts stress levels
- Recommendations are generated based on predictions
- Results are displayed on the dashboard

This integration ensures real-time monitoring and intelligent decision-making within the greenhouse environment.

4.7. DASHBOARD IMPLEMENTATION

A centralized dashboard was developed to visualize system outputs and provide decision support to users.

The dashboard displays:

- Real-time sensor data
- Predicted stress levels
- Energy optimization recommendations
- Alerts for critical conditions

The interface is designed to be user-friendly, with clear visual indicators and color-coded alerts to help farmers quickly understand system outputs.

4.8. ENERGY OPTIMIZATION IMPLEMENTATION

Based on predicted stress levels, the system generates recommendations to optimize energy usage in greenhouse operations.

Examples include:

- Activating ventilation systems during high temperature conditions

- Adjusting irrigation when soil moisture is low
- Controlling lighting based on UV intensity levels

These recommendations help reduce unnecessary energy consumption while maintaining optimal plant growth conditions.

4.9. SYSTEM DEPLOYMENT

The system is designed for deployment in real greenhouse environments. The use of ESP32 microcontrollers and LoRa communication ensures low power consumption and long-range connectivity.

The system also supports offline operation by storing data locally and synchronizing with the backend when internet connectivity is available. This makes it suitable for rural agricultural environments with limited connectivity.

5. RESULTS AND DISCUSSION

5.1. INTRODUCTION

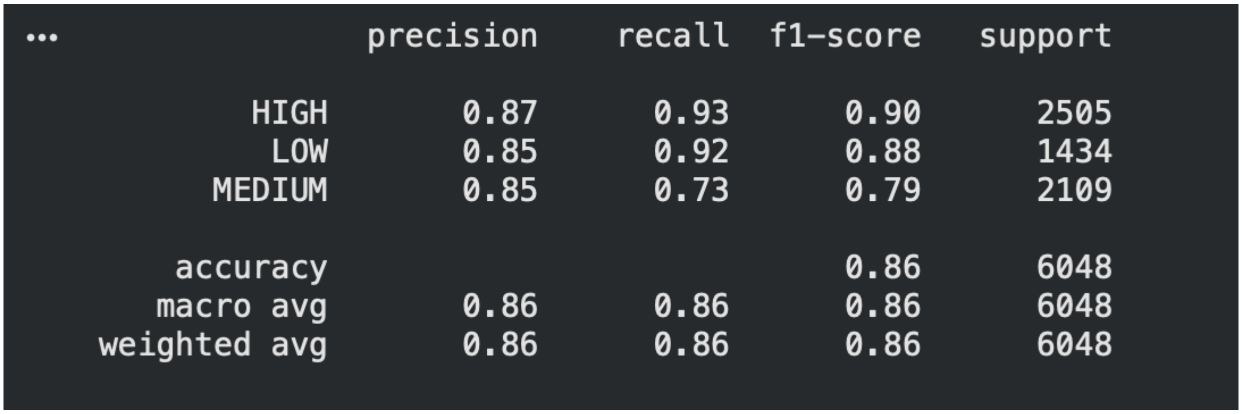
This chapter presents the evaluation results of the Centralized Stress Prediction and Energy Optimization System developed for greenhouse rose cultivation. The performance of the machine learning model, system reliability, and effectiveness of energy optimization recommendations are analyzed. The discussion focuses on how well the system meets the research objectives and addresses the identified problem.

5.2. MODEL PERFORMANCE EVALUATION

The Random Forest classifier was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The model achieved an overall accuracy of approximately 86%, indicating strong performance in predicting plant stress levels.

The evaluation results demonstrate that the model is capable of effectively classifying stress into three categories: Low, Medium, and High. The balanced class weighting and controlled noise introduction contributed to improved generalization and robustness.

Precision and recall values were consistently high across all classes, showing that the model can both correctly identify stress conditions and minimize false predictions. The F1-score further confirms that the model maintains a good balance between precision and recall.



```
...              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
    macro avg       0.86      0.86      0.86      6048
 weighted avg       0.86      0.86      0.86      6048
```

Figure 5.2.1: Classification Report of Stress Prediction Model

5.3. CONFUSION MATRIX ANALYSIS

A confusion matrix was used to analyze classification performance in detail. The results indicate that:

- Most predictions fall along the diagonal, confirming correct classification
- Minor misclassifications occur mainly between Medium and High stress levels
- Very few cases of Low stress are misclassified as High stress

This pattern suggests that the model effectively distinguishes between extreme conditions but occasionally overlaps in borderline scenarios. Such behavior is expected due to gradual transitions between stress levels in real-world environments.

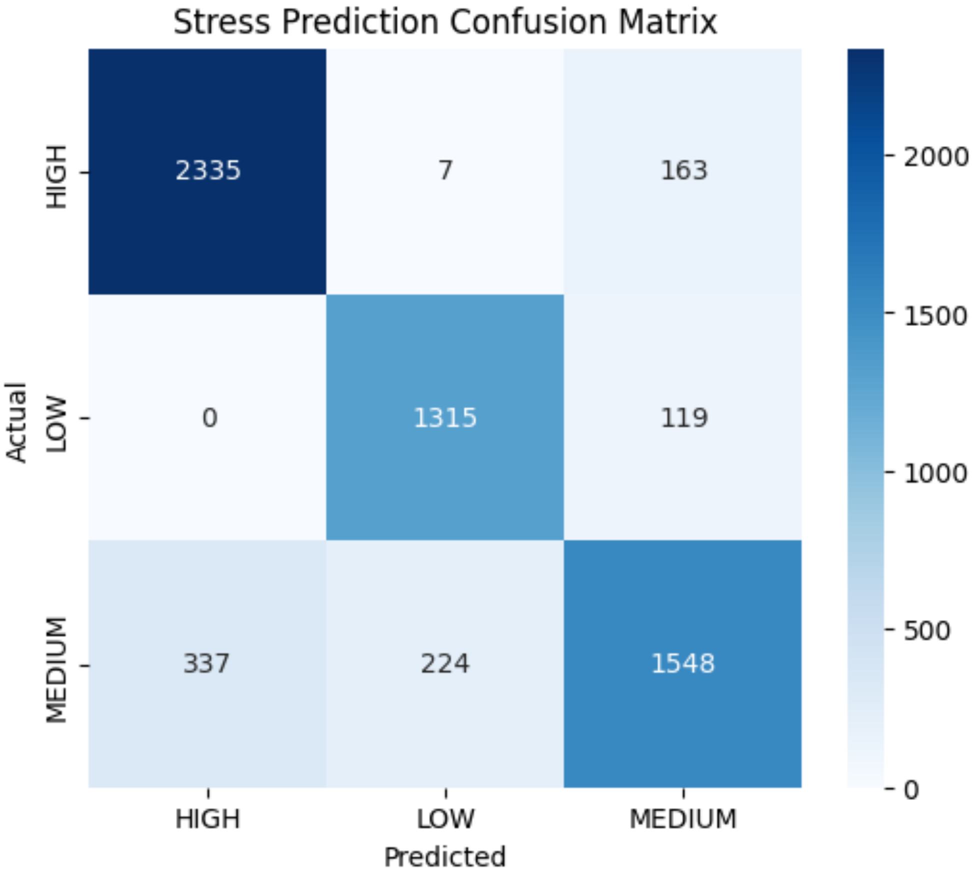


Figure 5.3.1: Confusion Matrix for Stress Prediction

5.4. SYSTEM RELIABILITY AND ROBUSTNESS

The system was tested under multiple operational conditions to evaluate reliability.

Normal Conditions

Under stable environmental conditions, the system consistently provided accurate predictions and real-time monitoring without delays.

Missing Data Scenarios

The preprocessing techniques, including interpolation and default value handling, ensured that the system remained functional even when some sensor data were missing. The model maintained stable performance with minimal accuracy degradation.

Environmental Fluctuations

During rapid environmental changes, the system successfully adapted to new data inputs and generated updated predictions in real time. This demonstrates the model's ability to handle dynamic greenhouse conditions.

Offline Operation

The system successfully stored data locally during connectivity loss and synchronized with the cloud once the connection was restored. This confirms the suitability of the system for rural environments.

5.5. ENERGY OPTIMIZATION EFFECTIVENESS

The energy optimization component was evaluated based on its ability to generate relevant and practical recommendations.

The system successfully provided:

- Ventilation control suggestions during high temperature conditions
- Irrigation adjustments based on soil moisture levels
- Lighting control recommendations based on UV intensity

These recommendations help reduce unnecessary energy usage by avoiding fixed schedules and enabling condition-based operation.

Although the system does not implement automated control, the decision-support mechanism enables farmers to make informed and timely actions, contributing to improved efficiency.

5.6. SYSTEM INTEGRATION PERFORMANCE

The integration of IoT sensors, LoRa communication, machine learning, and the dashboard was evaluated as a complete system.

Key observations include:

- Reliable data transmission across multiple greenhouse zones using LoRa
- Efficient data aggregation and preprocessing at the gateway
- Real-time prediction and visualization through the dashboard
- Minimal latency in system response

The layered architecture ensured smooth interaction between components, validating the feasibility of the proposed design.

5.7. DISCUSSION

The results demonstrate that the proposed system effectively addresses the key challenges identified in the research problem.

- The machine learning model enables early stress detection, reducing reliance on visual observation
- The system provides predictive insights, shifting from reactive to proactive management
- Energy optimization recommendations contribute to cost reduction and sustainability
- LoRa communication and offline functionality ensure reliability in low-connectivity environments
- Centralized monitoring supports multi-zone greenhouse management

However, some limitations were observed. The model may experience minor classification overlaps in borderline stress conditions, and the system currently relies on user action rather than full automation.

Despite these limitations, the system demonstrates strong practical applicability and aligns well with the objectives of precision agriculture.

5.8. Feature Importance Analysis

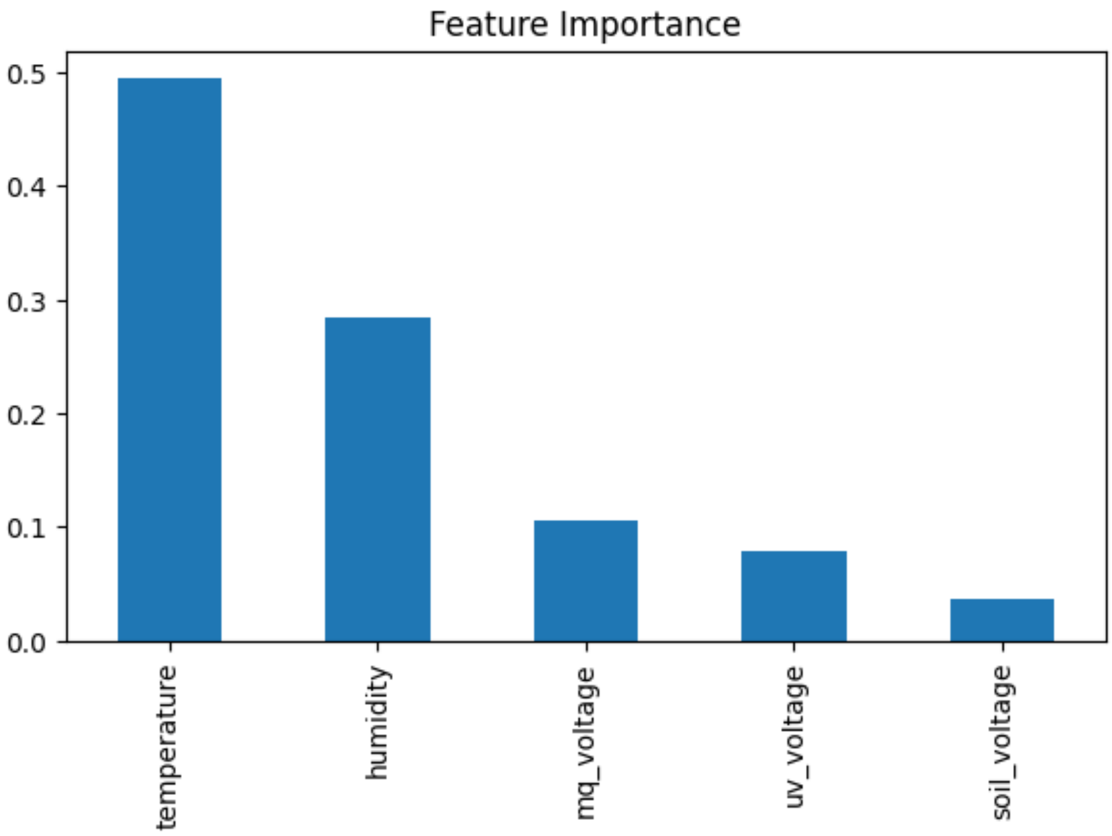


Figure 5.8.1: Feature Importance in Stress Prediction Model

The feature importance analysis illustrates the contribution of each environmental parameter to the stress prediction model.

As shown in Figure 5.3, temperature is the most influential feature, followed by humidity, indicating that these factors play a dominant role in determining plant stress levels. Other features such as air quality (mq), UV intensity, and soil moisture have comparatively lower contributions but still provide valuable contextual information.

This result aligns with agricultural studies, where temperature and humidity are known to have the strongest impact on plant physiological stress.

6. CONCLUSION AND FUTURE WORK

6.1. CONCLUSION

This research presented the design and development of a Centralized Stress Prediction and Energy Optimization System as part of the SmartRose AI–IoT platform for greenhouse rose cultivation.

The study successfully demonstrated the integration of IoT-based sensing, LoRa communication, and machine learning to create an intelligent decision-support system. The Random Forest model achieved an accuracy of approximately 86%, confirming its effectiveness in predicting plant stress levels under varying environmental conditions.

The system enables real-time monitoring, early stress detection, and energy-aware recommendations, addressing key challenges faced by middle-scale greenhouse farmers. The inclusion of offline functionality further enhances system reliability in low-connectivity environments, making it suitable for practical deployment in Sri Lanka.

Overall, the research achieved its main objective by developing a scalable, cost-effective, and intelligent solution that improves greenhouse management, enhances productivity, and supports sustainable agricultural practices.

6.2. CONTRIBUTIONS OF THE STUDY

This research makes several important contributions:

- Development of an integrated AI–IoT system for greenhouse rose farming
- Implementation of a machine learning model for real-time stress prediction
- Introduction of an energy optimization approach based on plant conditions
- Design of a LoRa-based multi-zone monitoring system
- Support for offline operation in rural agricultural environments

These contributions bridge the gap between advanced technologies and real-world farming needs.

6.3. LIMITATIONS

Despite its strengths, the study has several limitations:

- The system is limited to greenhouse rose cultivation and may require adaptation for other crops
- The accuracy of the model depends on the quality and diversity of collected data
- The system provides recommendations but does not include automated control mechanisms
- Other components such as disease detection and nutrient optimization are not fully integrated into this module

6.4. FUTURE WORK

Future research can extend this work in several directions:

Automation of Control Systems

Integrating actuators to automatically control lighting, irrigation, and ventilation based on model predictions.

Advanced Machine Learning Models

Exploring deep learning or hybrid models to improve prediction accuracy and handle more complex patterns.

Multi-Module Integration

Combining stress prediction with disease detection, nutrient management, and post-harvest monitoring into a unified platform.

Scalability and Cloud Integration

Enhancing cloud-based analytics and enabling large-scale deployment across multiple farms.

Mobile Application Development

Developing a dedicated mobile application to improve accessibility and user interaction for farmers.

Real-World Deployment and Long-Term Testing

Conducting extended field testing to validate system performance over different seasons and environmental conditions.

6.5. FINAL REMARKS

The SmartRose system represents a significant step toward intelligent and sustainable greenhouse farming. By combining real-time sensing, predictive analytics, and energy optimization, the proposed solution demonstrates the potential of AI and IoT technologies in transforming traditional agriculture into a data-driven ecosystem.

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8. APPENDICES

APPENDIX A : SYSTEM COMPONENT DETAILS

This appendix provides a detailed description of the hardware and software components used in the SmartRose prototype system.

A.1 Hardware Components

The system utilizes low-cost and energy-efficient hardware suitable for greenhouse environments.

- ESP32 Microcontroller
    - Used as the core processing unit in sensor nodes and gateway
    - Supports Wi-Fi and low-power operation
- LoRa Module (e.g., SX1278)
    - Enables long-range wireless communication between sensor nodes and gateway
    - Suitable for multi-zone greenhouse monitoring
- Environmental Sensors
    - Temperature and Humidity Sensor (e.g., DHT22)
    - Soil Moisture Sensor
    - UV Sensor
    - Air Quality Sensor (e.g., MQ135)

A.2 Software Components

- Embedded C / Arduino IDE for ESP32 programming
- Python for machine learning model development
- Scikit-learn library for Random Forest implementation

- Web technologies (HTML, CSS, JavaScript) for dashboard
- Backend (Flask / Node.js – depending on your implementation)

A.3 Communication Protocols

- LoRa – Sensor node to gateway communication
- MQTT / HTTP – Gateway to cloud/dashboard communication
- JSON format – Data transmission format

APPENDIX A : SAMPLE DATASET

This appendix presents a sample of the environmental dataset collected from IoT sensor nodes deployed within the greenhouse. The dataset was used for training and evaluating the machine learning model for plant stress prediction.

The data include readings from multiple sensors such as temperature, humidity, UV intensity, soil moisture, and air quality. Each record is timestamped and associated with a specific greenhouse and base station.

Sample Dataset

basestation_id	greenhouse_id	timestamp	temperature	humidity	uv_raw	soil_raw	mq_raw	stress_score	stress_label
BS_01	GH01	1764527400	17.28	76.47	13	3308	324	0.28	LOW
BS_01	GH01	1764527520	17.25	76.42	4	3316	322	0.28	LOW
BS_01	GH01	1764527640	17.34	76.82	0	3312	323	0.28	LOW
BS_01	GH01	1764527760	17.36	76.14	0	3298	331	0.28	LOW
BS_01	GH01	1764527880	17.32	76.39	7	3306	328	0.28	LOW

APPENDIX B : PSEUDOCODE

```
“Input: Sensor Data (Temperature, Humidity, UV, Soil Moisture, Air Quality)
Step 1: Collect data from IoT sensors
Step 2: Preprocess data
    - Handle missing values
    - Normalize features
Step 3: Load trained Random Forest model
Step 4: Predict stress level
Step 5: If stress == High:
    Recommend ventilation + irrigation
Else if stress == Medium:
    Monitor and adjust lighting
Else:
    Maintain current conditions
Step 6: Display results on dashboard”
```