SmartRose: A Unified AI-Driven IoT Platform for Optimised Greenhouse Rose Cultivation

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***Abstract*—The adoption of Artificial Intelligence and Internet of Things technologies in agriculture has enabled data-driven decision-making. However, most existing solutions address isolated problems rather than supporting the full crop lifecycle. High-value floriculture crops such as greenhouse roses require coordinated intelligence across cultivation, environmental management, nutrient optimization, and post-harvest quality preservation. To address this gap, this paper proposes SmartRose, an integrated AI-IoT-based platform for end-to-end intelligent management of greenhouse rose farming. The system unifies four functional modules within a single architecture: early disease risk prediction using physiological and environmental sensing with machine learning classification, intelligent nutrient forecasting and fertilizer optimization using regression-based modelling, stress prediction and energy-aware greenhouse monitoring using multi-class classification, and post-harvest freshness and vase life prediction using predictive analytics. Experimental evaluation demonstrates strong performance across all modules, including highly accurate early stress classification, effective nutrient prediction using Random Forest models, reliable stress-level detection, and low-error freshness estimation. The results confirm that integrated AI-IoT decision support can significantly enhance efficiency, reduce losses, and improve management in greenhouse floriculture.**

Keywords—floriculture, greenhouse monitoring, internet of things, machine learning, rose farming

I. Introduction

Floriculture is a high-value segment of modern agriculture, with rose cultivation contributing significantly to both domestic markets and international exports. The increasing demand for premium-quality flowers has accelerated the adoption of greenhouse-based farming practices worldwide, where environmental conditions can be partially controlled to enhance yield and quality [1]. However, rose cultivation remains highly sensitive to environmental fluctuations, nutrient imbalance, disease outbreaks, and post-harvest handling conditions, all of which can significantly reduce commercial value.

Recent developments in artificial intelligence (AI) and the Internet of Things (IoT) have demonstrated great promise for converting conventional agriculture into data-driven smart farming ecosystems. IoT technologies enable continuous monitoring of environmental and physiological parameters, while machine learning techniques provide predictive insights from complex agricultural data [2], [3]. Several studies highlight the effectiveness of AI-driven systems in crop monitoring, disease detection, and decision support, demonstrating improvements in productivity and resource efficiency [4].

Despite these advancements, existing smart agriculture solutions largely focus on isolated problems such as irrigation control, disease classification, or yield prediction. Surveys on AI and IoT in agriculture emphasize that most implementations are task-specific and lack integration across the full agricultural lifecycle [3], [5]. This limitation is particularly significant in greenhouse rose cultivation, where successful production depends on coordinated management of disease prevention, nutrient optimization, environmental control, and post-harvest quality preservation.

Rose farming presents a complex, multi-stage management challenge. Research indicates that early physiological stress often develops before visible symptoms appear, making early detection essential for preventing irreversible crop loss [6]. Nutrient imbalance can significantly affect flower quality, stem strength, and plant longevity. Furthermore, post-harvest factors such as temperature, humidity, and ethylene exposure strongly influence the vase life and market value of cut flowers. However, technological solutions addressing these aspects are typically developed independently, resulting in fragmented systems that do not support holistic decision-making.

This research addresses this gap by proposing SmartRose, an integrated AI-IoT platform for intelligent greenhouse rose farming. The proposed system combines multi-modal sensing, machine learning-driven analytics, and real-time decision support across four tightly coupled functional layers: early disease risk prediction using physiological and environmental indicators, intelligent nutrient forecasting for optimized fertilizer management, greenhouse stress prediction with energy-aware environmental control, and post-harvest freshness prediction for quality assessment and shelf-life estimation. By integrating these components within a single coherent architecture, SmartRose provides proactive monitoring, predictive insights, and actionable recommendations across the entire cultivation lifecycle. This makes SmartRose a scalable and practical solution for greenhouse rose cultivation, with particular relevance to medium-scale farmers and florists in Sri Lanka.

The novelty of this work resides in the integration of multiple AI-driven modules into a unified, end-to-end decision support system for greenhouse floriculture. Unlike existing approaches that focus on isolated tasks, the proposed SmartRose system enables continuous monitoring, predictive analysis, and coordinated management across cultivation, greenhouse operations, and post-harvest stages. This integrated architecture offers a workable and scalable solution. This is how the rest of the paper is structured. Section II summarizes relevant research and identifies gaps. The SmartRose system architecture and each module's methodology are presented in Section III. The evaluation and results are presented in Section IV. Limitations and implications are covered in Section V. The work is concluded in Section VI, and future research directions are outlined in Section VII.

II. Literature Review

Greenhouse rose cultivation is a high-value element of the floriculture sector in Sri Lanka, contributing to both domestic markets and export-oriented supply chains. Despite favourable climatic diversity and economic potential, rose productivity and quality remain constrained by environmental stress, inefficient energy utilization, delayed disease detection, suboptimal nutrient management, and significant post-harvest losses. Existing literature consistently indicates that these challenges are interrelated rather than isolated, with physiological stress often preceding disease outbreaks, nutrient imbalance, and deterioration in post-harvest quality. However, most prior studies address these issues independently, resulting in fragmented and reactive solutions that lack predictive intelligence and lifecycle-level integration.

Environmental stress significantly affects rose growth and yield under greenhouse conditions [7], [8]. Research on greenhouse shading and microclimate adaptation confirms that partial shading and controlled environments can significantly improve plant growth and yield; however, such approaches rely on static or manually controlled mechanisms that fail to respond dynamically to rapid environmental fluctuations [8]. At the national level, climate variability has intensified temperature extremes and rainfall irregularities, increased the energy burden of protected cultivation systems, exposing the limitations of reactive greenhouse management practices [9]. Although centralized energy optimization and predictive modelling have been shown to reduce operational expenses [10], these solutions are generally designed for large-scale, capital-intensive greenhouses and do not integrate plant-level physiological feedback, limiting their suitability for medium-scale rose farmers in Sri Lanka.

Physiological stress studies further demonstrate that measurable indicators such as leaf temperature, transpiration efficiency, and water potential change significantly before visible symptoms appear [11]. These findings validate the feasibility of early stress detection using non-invasive sensing techniques. Nevertheless, such studies remain largely confined to experimental environments and are not translated into deployable decision-support systems. As a result, existing literature lacks scalable frameworks that integrate real-time sensing, predictive stress analytics, and energy-aware greenhouse management tailored to diverse climatic zones.

Disease management remains another major challenge in greenhouse rose cultivation. Conventional practices rely heavily on visual inspection and farmer experience, often leading to delayed intervention and irreversible yield loss [12]. Early automated disease detection research employed classical image processing and data mining techniques, demonstrating feasibility but remaining reactive and dependent on controlled imaging conditions [13]. More recent deep learning-based approaches have achieved high accuracy in rose disease classification using convolutional neural networks trained on field images [6], supported by datasets such as RoseNet [15]. Despite these advancements, image-based systems inherently depend on visible disease progression and significant computational resources, limiting their effectiveness for early prevention and practical deployment. IoT-based disease alerting systems initially attempted to infer disease risk using environmental thresholds; however, such rule-based approaches lack predictive capability and specificity [16]. Recent smart greenhouse monitoring systems using IoT-based architectures have demonstrated improved environmental control and system efficiency [14]. Hybrid systems integrating computer vision and environmental sensing show promise but are often crop-agnostic, technologically complex, and economically inaccessible [17].

Nutrient management is another critical determinant of rose quality, flowering frequency, and vase life. Studies indicate that nutrient imbalance increases susceptibility to stress and disease, yet most Sri Lankan greenhouse rose farmers rely on fixed fertilizer schedules and experiential judgment [13], [18]. Sector-level analyses further highlight inefficient fertilizer usage and increased vulnerability following agrochemical import restrictions [19]. Although machine learning-based fertilizer recommendation systems have been explored, they are typically designed for other crops or ornamentals and function primarily as advisory tools without real-time integration of soil and environmental data [17]. Consequently, existing literature lacks dynamic, growth-stage-aware nutrient optimization frameworks specifically tailored to rose cultivation.

Post-harvest handling and freshness preservation remain among the most under-researched yet economically critical aspects of rose production. Empirical studies report post-harvest losses exceeding 30% [20], [21], driven by improper harvest timing, temperature mismanagement, water stress, and lack of monitoring during storage and transportation. Even where cold-chain infrastructure exists, rose quality deteriorates rapidly if environmental parameters are not continuously controlled throughout the supply chain. Value-chain analyses in Sri Lanka reveal losses across farm, transport, and retail stages due to information asymmetry and reliance on manual handling practices, while retail-level studies document widespread ambient storage and minimal preservation protocols leading to early wilting and reduced vase life. Notably, most smart floriculture systems terminate at the production stage and do not extend monitoring and decision support into post-harvest phases.

Overall, the reviewed literature reveals a clear research gap. Existing solutions address stress management, disease detection, nutrient optimization, and post-harvest handling as isolated problems. These approaches are largely reactive, crop-agnostic, or economically inaccessible to medium-scale farmers. Furthermore, most systems lack integration across the full lifecycle of rose cultivation and do not combine real-time sensing with predictive intelligence and decision support. To the best of our knowledge, no existing work proposes a unified, rose-specific AI-IoT platform that integrates early disease alerting, intelligent nutrient management, stress prediction with energy optimization, and post-harvest freshness monitoring within a single architecture. Therefore, there is a clear need for an integrated, intelligent system that combines sensing, prediction, and decision support across the entire lifecycle of greenhouse rose cultivation, which motivates the proposed SmartRose platform.

III. Methodology

The architecture and methodological design of the suggested SmartRose platform are explained in this section. The system is an end-to-end AI-IoT-based decision support framework for greenhouse rose cultivation, covering stages from growth monitoring to post-harvest management.

A. Overall System Architecture

Fig. 1 illustrates the SmartRose architecture, which follows a layered design consisting of Sensing, Communication, Intelligence, and Application layers. IoT sensor nodes collect environmental and physiological data, including temperature, humidity, soil moisture, pH, EC, NPK levels, light intensity, and leaf temperature. Data are transmitted via Wi-Fi and LoRa, enabling reliable and low-power communication. The Intelligence Layer processes data using machine learning models evaluated with metrics such as accuracy, recall, precision, F1-score, MAE, and RMSE. The Application Layer provides real-time monitoring, alerts, and decision support through a user interface. This architecture enables integrated, real-time data-driven decision-making across the greenhouse system.

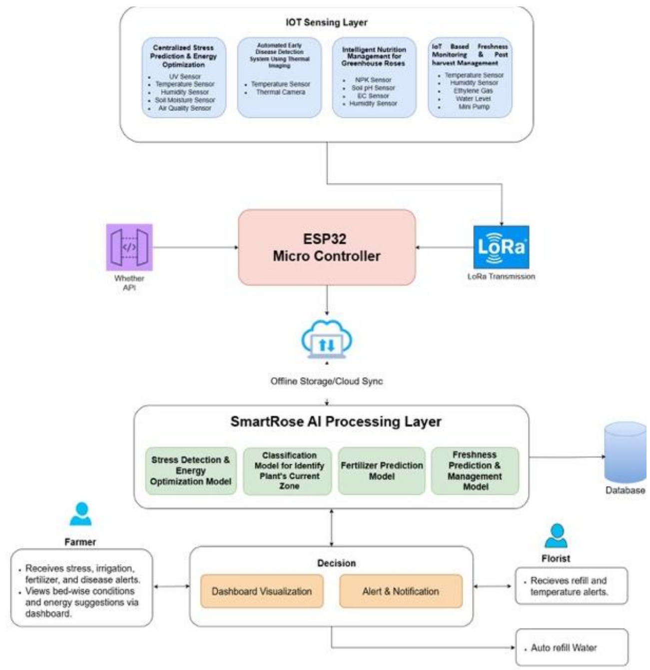

Fig. 1. Overall SmartRose System Architecture

B. Data Collection and Preprocessing

Data were collected from a greenhouse rose cultivation environment in Sri Lanka under real operating conditions. A total of 2,592 samples were recorded and labeled based on plant condition and environmental observations. The dataset was categorized into two classes: healthy (2,185 samples) and stress-risk (407 samples). The dataset includes environmental, soil, and physiological parameters such as temperature, humidity, leaf temperature, soil moisture, pH, EC, and NPK levels. Data preprocessing included noise filtering, normalization, and handling missing values.

C. Early Disease Risk Prediction Module

The Early Disease Risk Prediction module detects early physiological stress in greenhouse roses before visible disease symptoms appear using IoT sensing and supervised binary classification. Plant temperature is measured using an MLX90614 sensor, while ambient air temperature and relative humidity are measured using an SHT30-D sensor. An ESP32 microcontroller oversees data acquisition and wireless transmission, and all sensor data are stored in a MongoDB database. Data preprocessing includes noise filtering, missing value handling, and normalization. A derived feature, ΔT (plant-air temperature difference), is calculated and used as the primary stress indicator. A Random Forest classifier was employed for binary classification due to its robustness in handling nonlinear relationships and sensor noise [2], [3]. The model was trained using attributes such as air temperature, humidity, leaf temperature, and the derived ΔT parameter. The model outputs a classification label indicating either healthy or stress-risk condition, which is translated into early warning alerts for farmers to enable timely intervention.

D. Intelligent Nutrient Management Module

The nutrient management module aims to optimize fertilizer application based on real-time soil and environmental conditions. This component utilizes soil parameters such as NPK levels, pH, EC, and moisture, along with growth stage information. A Random Forest Regressor was selected as the final model for nutrient prediction due to its excellent performance compared to Linear Regression and LSTM models in capturing nonlinear relationships in greenhouse nutrient dynamics. Based on the model outputs, the system generates fertilizer recommendations tailored to the current crop status. This approach supports efficient fertilizer usage, reduces over application, and improves overall flower quality.

E. Stress Prediction and Energy Optimization Module

This module focuses on identifying greenhouse plant stress conditions and supporting energy-aware environmental control decisions. Sensor data related to temperature, light intensity, humidity, soil moisture, and air quality is analyzed using a Random Forest classifier to categorize plant stress into LOW, MEDIUM, and HIGH levels. The model was trained using environmental features collected from greenhouse conditions. Stress levels were defined using threshold-based ranges derived from observed environmental conditions. Based on predicted stress levels, the system provides energy optimization recommendations such as adjusting ventilation, cooling, irrigation, and lighting operations to reduce unnecessary energy consumption. The module supports proactive intervention by issuing alerts when stress thresholds are exceeded. In LoRa-enabled deployments, centralized monitoring of multiple greenhouses is achieved through a single base station, ensuring scalable and low-power operation suitable for medium-scale greenhouse farming.

F. Post-Harvest Freshness Prediction Module

The post-harvest freshness prediction module uses IoT-based sensing and machine learning to monitor cut roses during storage and display. Environmental parameters such as temperature, humidity, ethylene concentration, water level, water temperature, and storage duration are collected via sensors connected to an ESP32 microcontroller. A Random Forest Regressor was used to predict freshness score and remaining vase life based on environmental and storage conditions. The model enables real-time estimation of freshness and remaining vase life, supporting improved post-harvest decision-making.

G. Decision Support and Alert Mechanism

All modules feed into a centralized decision support engine. Based on model outputs, the system generates: Early warning alerts (e.g., disease risk, stress risk), Fertilizer recommendations, Environmental adjustment suggestions, Freshness status indicators. These recommendations are presented to users via the application layer in a simplified, user-friendly format.

IV. Results and Analysis

The experimental findings from every SmartRose platform intelligent module are shown in this part. Model performance, predicted accuracy, and the efficiency of machine learning methods for decision assistance are the main areas of assessment. An 80:20 ratio was used to split the dataset into training and testing sets. To guarantee generalization, the models were tested on untested data after being trained on the training set. Python and machine learning libraries like Scikit-learn were used in every experiment.

A. Early Disease Risk Prediction Results

The Early Disease Risk Prediction module was evaluated using a labeled dataset containing 2,592 samples, including 2,185 healthy samples and 407 stress-risk samples. The model made use of physiological and environmental features such leaf temperature, relative humidity, air temperature, and the estimated ΔT parameter. For binary classification, a Random Forest classifier was employed. Under the current experimental conditions, the accuracy of the model on the test dataset was 100%. While this indicates strong feature separability, further validation using larger and more diverse datasets is required to cnfirm generalizability. The evaluation metrics are summarized in Table I. The confusion matrix indicated no misclassifications across both classes. These results demonstrate that physiological and environmental features can effectively support early detection of plant stress before visible symptoms appear. Compared to traditional threshold-based approaches, the proposed model provides significantly improved predictive accuracy and robustness.

TABLE I. 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

B. Post Harvest Freshness Prediction Results

The post-harvest freshness prediction module uses a regression-based machine learning approach to estimate freshness score and remaining vase life of cut roses. Environmental features such as temperature, humidity, ethylene concentration, water temperature, and water level were used for model training. Because of its capacity to represent nonlinear connections in multivariate sensor data, a Random Forest Regressor was chosen. The Root Mean Square Error (RMSE) was used to evaluate the model's performance. The results summarized in Table II show low prediction error, with an RMSE of 0.22 for freshness prediction and 1.95 hours for vase life estimation. These results indicate that the model provides reliable predictions for post-harvest monitoring. Compared to traditional visual inspection methods, the proposed approach offers quantitative and consistent estimation of freshness, supporting improved storage management and decision-making.

TABLE II. POST-HARVEST FRESHNESS RESULTS

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

C. Intelligent Nutrient Management Results

For the nutrient management module, multiple models were evaluated to identify the best performing predictive technique for EC forecasting. The following models were compared: Random Forest regression, Long-Short-Term Memory (LSTM), and linear regression. The performance comparison is summarized in Table III. The Random Forest Regressor had the lowest MAE and RMSE, according to the results. The Random Forest model closely resembles the real EC patterns, according to the numerical data. Random Forest was chosen as the final model for nutrient forecasting based on both quantitative measurements and graphical analysis. The Random Forest Regressor achieved the lowest MAE (0.060324) and RMSE (0.092321), outperforming both Linear Regression and LSTM models, according to the results. This demonstrates how well ensemble-based models capture nonlinear interactions in the dynamics of greenhouse nutrients. Compared to traditional fertilizer scheduling methods based on fixed intervals or farmer experience, the proposed data-driven approach provides more accurate and adaptive nutrient recommendations.

TABLE III. INTELLIGENT NUTRIENT MANAGEMENT RESULTS

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

D. Stress Prediction and Energy Optimization Results

The stress prediction module classified greenhouse plant stress levels into three categories: LOW, MEDIUM, and HIGH using sensor inputs including temperature, humidity, UV intensity, soil moisture, and air quality. A Random Forest classifier was employed for multi-class stress prediction and achieved an overall accuracy of 86%. Detailed evaluation metrics indicate strong classification performance across all classes is shown in Table IV. The model obtained precision, recall, and F1-score values of 0.87, 0.93, and 0.90 for HIGH stress, 0.85, 0.92, and 0.88 for LOW stress, and 0.85, 0.73, and 0.79 for MEDIUM stress. The confusion matrix provides additional evidence that the model effectively distinguishes between different stress levels, with particularly strong performance in identifying both LOW and HIGH stress conditions. The model reliably detects both normal and critical greenhouse states. Accurate stress classification supports timely decision-making and enables energy-aware environmental control actions such as optimized ventilation, cooling, and irrigation. Compared to rule-based threshold systems, the machine learning-based approach provides improved classification accuracy and adaptability to dynamic greenhouse conditions.

TABLE IV. 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

E. Overall System Performance Discussion

Across all four modules, Random Forest-based models demonstrated robust performance in both classification and regression tasks. The results confirm that environmental and physiological features are effective for early disease and stress prediction, while IoT-based sensing enables reliable freshness estimation and data-driven nutrient forecasting. Compared to traditional approaches, the system provides improved predictive capability and decision support. Overall, these results validate the effectiveness of the SmartRose platform as an integrated AI-IoT solution for greenhouse rose farming. However, since the models were evaluated under controlled conditions, further validation using larger and more diverse datasets is required to ensure real-world generalizability.

F. Comparative Analysis with Existing Systems

Most existing smart agriculture systems focus on isolated tasks such as disease detection, irrigation control, or nutrient recommendation [2], [3], and lack integration across the crop lifecycle. In contrast, the proposed SmartRose system integrates disease prediction, nutrient management, stress monitoring, and post-harvest freshness estimation within a unified AI-IoT framework. This enables continuous monitoring and data-driven decision support across all stages of greenhouse rose cultivation. Compared to traditional rule-based or manual approaches, the system provides more adaptive and accurate predictions, improving resource efficiency and overall crop management. These findings demonstrate that integrated multi-module systems offer more comprehensive and scalable solutions than task-specific approaches.

V. DISCUSSION

This section discusses the significance of the experimental results, practical implications of the proposed system, strengths of the approach, and observed limitations of the SmartRose platform. The results demonstrate that integrating IoT-based sensing with machine learning techniques can provide reliable and meaningful decision support across multiple stages of rose cultivation and post-harvest management. Across all four modules, the models were able to learn useful patterns from environmental and physiological data, validating the overall feasibility of the proposed architecture.

The Early Disease Risk Prediction module achieved exceptionally strong classification performance, indicating that features such as air temperature, humidity, leaf temperature provide highly discriminative information for identifying plant stress conditions. This finding is important because it confirms that early physiological indicators can be used to detect potential problems before visible symptoms appear, enabling proactive rather than reactive farm management. From a practical perspective, this can significantly reduce crop loss by allowing farmers to intervene early.

The Intelligent Nutrient Management module indicated that Random Forest regression models are highly effective for predicting EC trends and nutrient related parameters in greenhouse environments. The comparison between Linear Regression, LSTM, and Random Forest models shows that ensemble-based methods are better suited for capturing the nonlinear dynamics of soil and nutrient behaviour. This supports the argument that data-driven fertilizer recommendations can outperform traditional manual judgment, leading to more efficient fertilizer usage, cost reduction, and improved flower quality.

The Stress Prediction and Energy Optimization module showed strong overall classification performance in a three-class stress scenario comprising LOW, MEDIUM, and HIGH stress levels. This outcome is significant because greenhouse management requires continuous balancing between maintaining optimal plant conditions and minimizing energy consumption. Accurate stress prediction using multi-sensor environmental data forms a reliable decision layer for intelligent and energy-aware control strategies. Based on predicted stress levels, the system can support optimized operation of actuators such as ventilation, cooling, and irrigation systems. Furthermore, the use of LoRa-based communication enables centralized and scalable monitoring across multiple greenhouse units, making the proposed solution practical and cost effective for medium scale agricultural deployments.

The Post-Harvest Freshness Prediction module demonstrates that environmental sensing combined with regression based modelling can effectively estimate freshness and remaining vase life. This is a critical contribution because post-harvest losses are a major economic issue in floriculture, yet they are rarely addressed using intelligent systems. The ability to predict freshness allows better stock management, prioritization of distribution, and reduction of waste, offering direct commercial benefits to growers and sellers.

A key strength of this research lies in the holistic integration of multiple intelligent components into a single unified platform. Unlike many existing systems that focus on only one aspect of agriculture, SmartRose provides end-to-end support across the full lifecycle of rose production. This integrated design improves practical usability and aligns better with real-world farming needs, where decisions are interconnected rather than isolated. However, several limitations were also identified. The models were trained and evaluated on datasets collected within controlled experimental settings, which may limit generalization across different geographical regions, greenhouse designs, and rose varieties. In addition, although the system demonstrates strong predictive capability, long term field deployment and real-world farmer interaction studies are still required to fully evaluate usability and long-term impact. These limitations highlight important opportunities for future enhancement.

These findings directly address the limitations identified in the literature, where existing systems lack integration, predictive capability, and lifecycle-level decision support. The proposed SmartRose platform overcomes these limitations by providing a unified, data-driven framework that connects sensing, prediction, and control across multiple stages of rose cultivation. Overall, the discussion confirms that SmartRose is not only technically feasible but also practically meaningful. The experimental results provide compelling evidence that integrated AI-IoT platforms can significantly improve precision, efficiency, and decision-making in greenhouse rose farming. This integrated approach differentiates SmartRose from existing systems, which typically address only a single aspect of agriculture. Future work will focus on large-scale field deployment, model generalization across diverse climatic conditions, and integration with automated actuation systems for fully autonomous greenhouse management. This demonstrates the potential of SmartRose as a scalable and practical solution for advancing precision floriculture in emerging agricultural markets.

VI. Future Work

Building on the identified limitations, several opportunities exist for further improvement and extension. First, the system can be strengthened through long-term deployment in real-world greenhouse environments to evaluate robustness across different seasons, rose varieties, and geographical conditions. Larger and more diverse datasets would further improve the generalization capability of the machine learning models. Second, future work may incorporate additional data sources such as image-based disease detection, solar radiation sensors, and advanced gas sensing technologies to improve predictive accuracy and system intelligence. Third, the platform can be extended to support automated control mechanisms, such as intelligent irrigation, fertigation, ventilation, and climate control, enabling a transition from decision support toward fully autonomous greenhouse management. Finally, the architecture can be generalized and adapted to support other floriculture and high-value crops, increasing the broader applicability and impact of the SmartRose platform.

VII. Conclusion

This paper presented SmartRose, an integrated AI-IoT-based intelligent platform for end-to-end management of greenhouse rose farming. The proposed system addresses key challenges across the entire rose production lifecycle by unifying early disease risk prediction, intelligent nutrient management, stress-aware greenhouse optimization, and post-harvest freshness prediction within a single coherent architecture. Unlike fragmented existing solutions that focus on isolated tasks, SmartRose provides holistic decision support that better aligns with real-world farming practices.

The efficiency of the suggested strategy was shown by the experimental evaluation. The early disease prediction module achieved highly reliable classification performance, confirming that physiological and environmental features can support proactive stress detection. The nutrient management module showed that Random Forest regression models perform effectively for EC and nutrient forecasting, enabling more accurate fertilizer recommendations. The stress prediction module demonstrated dependable multi-class classification for greenhouse condition monitoring, while the post-harvest module confirmed that machine learning models can successfully estimate freshness and vase life using environmental data.

Overall, the findings demonstrate that combining machine learning and IoT sensing on unified platform can significantly enhance precision, efficiency, and decision-making in floriculture. The SmartRose system shows strong potential as an affordable, scalable, and useful approach to intelligent greenhouse rose farming. This work demonstrates that integrated AI-IoT systems can bridge the gap between fragmented agricultural technologies and practical, real-world farming needs. The proposed SmartRose system demonstrates the potential of integrated AI-IoT platforms to transform greenhouse floriculture through predictive, data-driven decision support.

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