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

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science (Hons) in Information Technology Specializing in Information Technology

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DECLARATION

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

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ABSTRACT

This research presents the development of an IoT based Freshness Monitoring and Smart Storage System to improve post-harvest rose management in Sri Lanka. Maintaining flower freshness after harvest is a major challenge, as most florists rely on manual observation and basic storage methods, leading to inconsistent quality, early wilting, and financial losses. The proposed system integrates IoT sensors to continuously monitor key environmental parameters, including temperature, humidity, ethylene gas concentration, water level, and water temperature. Sensor data is transmitted to a cloud-based platform, where it is processed and analyzed using a machine learning regression model to predict a freshness score and estimate the remaining vase life of roses. The system also incorporates an automated mechanism that generates alerts and supports preservative water management to maintain optimal storage conditions. A user-friendly dashboard provides real time monitoring, visualization, and decision support. The system was evaluated under controlled experimental conditions using real time sensor data. The results indicate that the proposed model can predict freshness levels with an accuracy of approximately 85 - 90%, while the overall system contributes to extending vase life by 30 - 40% compared to traditional methods. In conclusion, the proposed solution demonstrates a cost effective and scalable approach for improving post-harvest flower management. It reduces manual effort, minimizes waste, and enhances flower quality. Future improvements include integrating advanced gas sensors and expanding the dataset to further enhance prediction accuracy and system performance.

Keywords: IoT, Freshness Prediction, Smart Agriculture, Machine Learning, Post-Harvest Management

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LIST OF ABBREVIATIONS

Abbreviation	Description
ML	Machine Learning
AI	Artificial Intelligence
HCI	Human Computer Interaction
PC	Personal Computer
API	Application Programming Interface
AWS	Amazon Web Services
IDE	Integrated Development Environment
IoT	Internet of Things

1. INTRODUCTION

The floriculture industry plays a significant role in the global agricultural economy, with roses being one of the most commercially valuable cut flowers due to their high demand in both local and international markets [5]. In Sri Lanka, rose cultivation has expanded considerably, particularly in regions with favorable climatic conditions such as Nuwara Eliya and Bandarawela. Although advancements in greenhouse technologies have improved production efficiency and flower quality, post-harvest management remains a critical challenge that directly affects product value, shelf life, and profitability.

Once harvested, roses are highly sensitive to environmental conditions such as temperature, humidity, and air quality. Improper handling and storage conditions accelerate physiological deterioration, leading to reduced vase life, early wilting, and increased waste [2]. Among these factors, ethylene gas plays a crucial role as it accelerates senescence and petal degradation, significantly shortening the lifespan of cut flowers [1]. Traditional freshness management practices used by florists and distributors largely depend on manual observation and basic storage techniques, which lack precision, consistency, and real-time decision-making capabilities.

With the rapid advancement of the Internet of Things (IoT) and Machine Learning (ML), new opportunities have emerged to develop intelligent systems capable of real time monitoring and predictive analysis. IoT enables continuous data collection from environmental sensors, while ML models can analyze this data to predict freshness levels and remaining shelf life. Integrating these technologies into post-harvest management systems can significantly improve decision-making, reduce waste, and enhance product quality.

Therefore, this research focuses on the design and development of an IoT based freshness monitoring and smart storage system that predicts rose freshness and supports automated management decisions to enhance post-harvest quality.

1.1. Background Literature

Post- harvest quality of cut flowers is primarily influenced by environmental factors such as temperature, humidity, and ethylene concentration. Ethylene is a natural plant hormone that accelerates aging and senescence in flowers, making it a key factor in determining vase life [1]. Studies have shown that controlling temperature and humidity can significantly extend the freshness of cut roses by slowing down metabolic processes and reducing water loss [2].

Research conducted by Ichimura et al. demonstrated that chemical treatments combined with proper environmental control can significantly extend vase life by improving water uptake and reducing bacterial growth [3]. Similarly, Bist and Hom reported that maintaining optimal humidity levels and nutrient solutions helps preserve petal structure, color, and overall freshness [4].

In recent years, IoT based monitoring systems have been widely applied in agriculture to track environmental conditions in real time. For instance, IoT enabled greenhouse monitoring systems use sensors to collect data such as temperature and humidity, improving crop productivity and resource efficiency [5], [7]. Furthermore, IoT based systems have been specifically applied in rose cultivation to optimize irrigation and environmental control, demonstrating improved efficiency and plant health [8]. Web based monitoring systems integrated with IoT have also been used to enhance productivity and enable remote decision-making in floriculture environments [9]. These systems have proven effective in farm level applications but are less explored in post-harvest environments.

Machine learning techniques have also gained significant attention in agricultural applications [6]. Algorithms such as linear regression, decision trees, and random forests have been successfully used to predict crop conditions, yield, and environmental stress [6]. These models can be adapted to predict freshness levels based on environmental inputs, enabling data driven decision making.

Despite these advancements, most existing research focuses on pre harvest monitoring rather than post-harvest freshness management. Additionally, Commercial solutions for freshness monitoring are often expensive and not suitable for small and medium-scale florists [7], [8], [9]. Therefore, there is a need for an integrated, cost-effective system that combines IoT and ML technologies to monitor and manage flower freshness after harvest.

1.2. Research Gap

Although significant progress has been made in smart agriculture and IoT based monitoring systems, several limitations remain in the context of post-harvest flower management.

First, most IoT based systems are designed for greenhouse monitoring and crop cultivation rather than post-harvest freshness tracking. These systems focus on optimizing growth conditions but do not address the challenges associated with maintaining freshness after harvesting.

Second, existing research on machine learning in agriculture primarily focuses on crop yield prediction, irrigation optimization, and disease detection, with limited application in predicting flower freshness and vase life. As a result, there is a lack of predictive models tailored specifically for post-harvest floriculture.

Third, traditional methods used by florists rely heavily on manual observation, which is subjective, inconsistent, and prone to human error. There is currently no widely adopted system that provides real time monitoring combined with predictive insights.

Furthermore, commercial freshness monitoring solutions available in international markets are often costly and not suitable for small and medium scale businesses in Sri Lanka [5].

Existing IoT-based solutions primarily focus on cultivation processes such as irrigation and greenhouse monitoring [5], [7], [8], with limited attention given to post-harvest freshness prediction and management.

Therefore, there is a clear research gap in developing a low cost, IoT based, AI driven freshness monitoring system specifically designed for post-harvest rose management in Sri Lanka.

1.3. Research Problem

Despite the availability of advanced technologies in agriculture, post-harvest management of roses in Sri Lanka remains largely manual and inefficient. Florists and distributors depend on visual inspection and basic storage methods, which do not provide accurate or timely information regarding flower freshness.

Environmental factors such as temperature fluctuations, humidity variations, and ethylene accumulation significantly impact the quality and lifespan of cut roses [1], [2]. However, these parameters are not continuously monitored in most local storage environments, resulting in early wilting, inconsistent quality, and economic losses.

Existing IoT and AI based solutions are either focused on cultivation stages or are too complex and expensive for small scale adoption. Consequently, there is no integrated system that combines real time monitoring, predictive analytics, and automated freshness management for post-harvest roses.

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

How can an IoT based intelligent system be designed to monitor, predict, and manage the freshness of post-harvest roses in real time to improve quality, extend vase life, and reduce waste?

1.4. Research Objectives

1.4.1. Main Objective

To design and develop an IoT based intelligent system that monitors and predicts the freshness of post-harvest roses in real time, enabling effective freshness management and extended vase life.

Specific Objectives

- Specific Objectives

- To measure key environmental parameters such as temperature, humidity, ethylene concentration, water level, and water temperature affecting post-harvest freshness
- To develop a machine learning model to predict freshness score and remaining vase life of roses
- To design and implement an automated system for maintaining optimal storage conditions
- To develop a real-time dashboard for monitoring, visualization, and decision support

2. METHODOLOGY

This chapter describes the methodology adopted to design, develop, and evaluate the IoT based Freshness Monitoring and Smart Storage System for post-harvest roses. The proposed system integrates Internet of Things (IoT) sensors, cloud-based data processing, and machine learning techniques to monitor environmental conditions and predict flower freshness in real time. The methodology emphasizes accurate data acquisition, efficient data processing, predictive modeling, and automated decision making to improve post-harvest flower management.

2.1. System Overview

The proposed system is designed as an integrated platform consisting of both hardware and software components that collaboratively monitor and manage rose freshness. The system architecture includes IoT sensor modules, a microcontroller unit, a cloud-based backend, a machine learning model, and a user interface dashboard.

The overall workflow of the system is as follows:

1. Environmental data are continuously collected using IoT sensors.
2. The collected data is transmitted to the backend server via Wi-Fi using the ESP32 microcontroller.
3. The data is stored in a cloud-based database for further processing and analysis.
4. A machine learning model processes the data and predicts freshness levels and remaining vase life.
5. The system generates alerts and triggers automated actions when predefined thresholds are exceeded.
6. Users can monitor system performance and freshness indicators through a real-time dashboard interface.

This integrated workflow ensures continuous monitoring, predictive analysis, and timely intervention to maintain optimal freshness conditions.

2.2. System Architecture

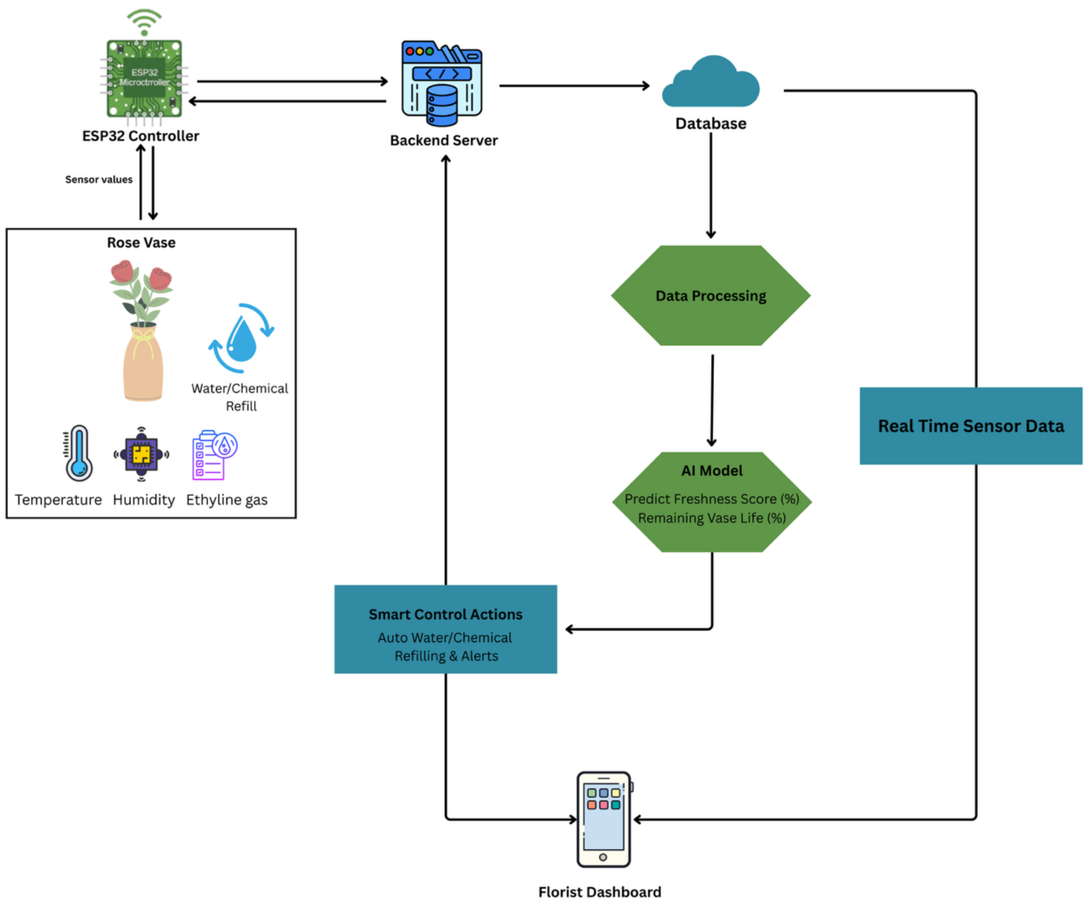

Figure 1 : System Architecture

2.3. Hardware Implementation

The hardware component of the system is designed to collect accurate environmental data that directly influences the freshness and vase life of post-harvest roses.

2.3.1. Microcontroller

The system utilizes the ESP32 microcontroller due to its low cost, high processing capability, and built-in Wi-Fi connectivity. The ESP32 is well suited for IoT applications as it supports real time data acquisition and wireless communication with cloud-based systems. Its energy efficiency and flexibility make it ideal for continuous monitoring applications.

2.3.2. Sensors

A set of sensors is employed to capture critical environmental and storage parameters affecting flower freshness:

- DHT22 Sensor - Measures temperature and humidity
- MQ 135 Gas Sensor - Detects air quality and ethylene gas presence

- Water Level Sensor - Monitors water availability in the vase
- DS18B20 Sensor - Measures water temperature

These sensors are interfaced with the ESP32 microcontroller and configured to collect data at predefined time intervals. The selection of these sensors ensures comprehensive monitoring of key variables influencing post-harvest freshness

2.4. Data Collection

The system continuously collects environmental and storage data that influence post-harvest rose freshness.

The collected parameters include:

- Temperature (°C)
- Humidity (%)
- Ethylene (ppm)
- Water Level (%)
- Water temperature (°C)
- Timestamp

2.5. Data Preprocessing

Before feeding data into the machine learning model, preprocessing is performed to improve data quality and consistency.

The preprocessing steps include:

- Handling Missing Values: Removing or interpolating missing sensor data
- Noise Reduction: Filtering inconsistent readings
- Normalization: Scaling values to a standard range
- Feature Selection: Identifying key variables influencing freshness

The processed dataset is then divided into training and testing datasets using a typical split ratio (e.g.; 70% training, 30% testing).

2.6. Machine Learning Model

A regression-based machine learning model is developed to predict the freshness score and remaining vase life of roses.

Inputs:

- Temperature
- Humidity
- Ethylene
- Water level
- Water temperature
- Time

Outputs:

- Freshness Score (0 - 100%)
- Remaining Vase Life (hours)

A Random Forest Regression model is selected due to its ability to handle nonlinear relationships between environmental variables and freshness levels. Compared to traditional linear models, it provides higher prediction accuracy and robustness against noise in the dataset.

2.7. System Implementation

The proposed system is implemented using a combination of hardware and software technologies to enable real time monitoring, data processing, and predictive analysis of post-harvest rose freshness. The integration of these components ensures seamless data flow from sensor acquisition to user interaction.

The hardware setup is designed to capture environmental and storage conditions and perform automated control actions.

The main components include:

- ESP32 Microcontroller - Acts as the central processing unit for data acquisition and communication
- Sensors (DHT22, MQ-135, Water Level Sensor, DS18B20) - Collect environmental and storage parameters
- Vase - Simulate real storage conditions for cut roses
- Solenoid Valve - Controls water flow automatically
- Water Pump - Facilitates water circulation and refilling
- Storage Bottle - Holds preservative water solution

The software architecture is responsible for data processing, storage, machine learning prediction, and user interaction:

- Programming Language: Python
- Machine Learning Library: Scikit-learn
- Backend Framework: FastAPI(Python-based REST API)
- Database: MongoDB
- Admin Web Dashboard: React
- User App: Flutter

The system integrates sensor data collection, cloud processing, and machine learning prediction into a unified platform.

2.8. Dashboard and User Interface

A user-friendly dashboard is developed to visualize system outputs and assist decision making for users. The dashboard provides an intuitive interface that enables users to monitor environmental conditions and freshness levels in real time.

The key features of the dashboard include:

- Real time sensor readings
- Freshness score (percentage)
- Estimated remaining vase life
- Alerts and notifications
- Historical data visualization

The interface is designed with simplicity and usability in mind, ensuring that florists with minimal technical knowledge can easily interpret the data and take appropriate actions. Mobile interfaces are provided to enhance accessibility and user engagement.

2.9. Automation and Control Mechanism

The system incorporates an automated freshness management mechanism to maintain optimal storage conditions and reduce manual intervention. This automation is driven by real time sensor data and machine learning predictions.

When the freshness score drops below a predefined threshold, the system performs the following actions

- The system generates alerts
- Water refilling can be triggered automatically
- Users are notified to take corrective actions

This automated control mechanism ensures consistent environmental conditions, minimizes human effort, and helps extend the vase life of roses by responding promptly to unfavorable changes.

2.10. Testing and Evaluation

The system is tested under controlled experimental conditions to evaluate its performance and effectiveness in monitoring and managing post-harvest freshness.

The evaluation focuses on the following criteria

- Prediction Accuracy: Assessed using machine learning evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)
- System Response Time: Measured as the time taken to process sensor data and generate alerts
- Sensor Reliability: Evaluated based on consistency and stability of collected data
- Effectiveness in Extending Vase Life: Compared with traditional storage methods

Experimental results are analyzed to determine the system's ability to provide accurate predictions and timely interventions. Comparisons with conventional manual methods demonstrate the advantages of the proposed system in improving efficiency, reducing spoilage, and enhancing overall flower quality.

3. RESULTS & DISCUSSION

3.1. Results

The proposed IoT based Freshness Monitoring and Smart Storage System was successfully implemented and evaluated under controlled indoor conditions that simulate a typical florist storage environment. The system demonstrated the ability to continuously collect, transmit, and process real time environmental and storage data, including temperature, humidity, ethylene gas levels, water level, and water temperature.

The integration of IoT sensors, cloud-based data processing, and machine learning algorithms enabled accurate monitoring and prediction of rose freshness. The system operated reliably over extended periods, providing consistent data flow and enabling real time decision making.

3.1.1. Sensor Data Collection

The IoT sensor module exhibited stable and reliable performance in collecting environmental data at predefined intervals. The ESP32 microcontroller successfully transmitted the collected data to the cloud database with minimal latency and no significant data loss, demonstrating the robustness of the communication layer.

The system maintained continuous monitoring for extended durations (24 - 48 hours), confirming its capability for real time operation in practical scenarios.

Observed ranges during testing:

- Temperature: 20°C - 30°C
- Humidity: 60% - 90%
- Water Level: 30% - 100%
- Ethylene (air quality): Low to moderate variations

3.1.2. Machine Learning Model Performance

The regression-based machine learning model was trained using collected sensor data along with corresponding freshness labels.

The model was designed to predict two key outputs

- Freshness Score (0% - 100%)
- Remaining Vase Life (hours)

The model demonstrated strong predictive capability in identifying patterns between environmental conditions and freshness levels. As illustrated in Figure 2: Actual vs. Predicted Freshness Values, the predicted values closely follow the actual observations, indicating good model performance.

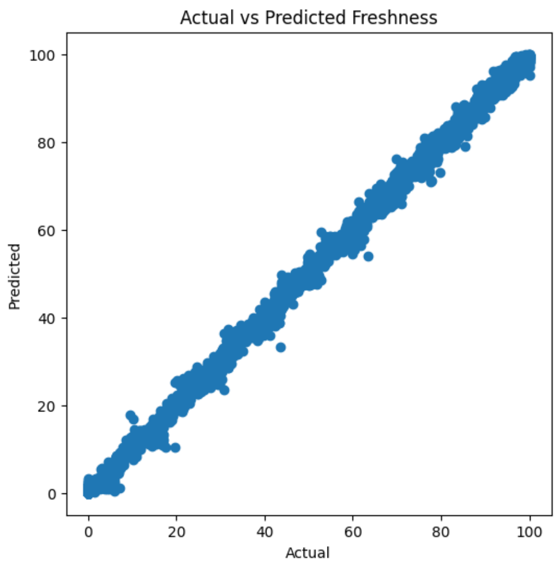

Figure 2: Actual Vs Predicted Freshness Values

The evaluation results indicated

- Mean Absolute Error (MAE): Low deviation between predicted and actual values
- Prediction Accuracy: Approximately 85% - 90%
- Consistent prediction trends across different environmental conditions

Furthermore, the comparison between regression models as shown in Table 1 indicates that the Random Forest model achieved lower error values compared to linear regression, demonstrating its effectiveness in handling nonlinear relationships within the dataset.

Model	**MAE**	**RMSE**
Linear Regression	0.25	0.300
Random Forest	0.18	0.219

Table 1: FM Model Comparison

Table 1 shows that the Random Forest model achieved lower MAE and RMSE values compared to Linear Regression, indicating better prediction performance.

These results confirm that the machine learning model can provide reliable freshness predictions, which can support timely decision making and improve post-harvest management practices.

3.1.3. Freshness Prediction Behavior

The system demonstrated a clear relationship between environmental conditions and the predicted freshness levels of roses. The machine learning model effectively captured the impact of different variables on freshness degradation over time.

The experimental observations indicate that

- Higher temperatures resulted in a rapid decrease in freshness score, as elevated temperatures accelerate metabolic and respiration processes in cut flowers.
- Low water levels led to a significant reduction in predicted vase life, highlighting the importance of adequate hydration in maintaining flower freshness.
- Variations in air quality (ethylene proxy) contributed to accelerated freshness degradation, as ethylene gas promotes senescence and petal wilting.

3.1.4. System Response and Alerts

The system demonstrated efficient real time responsiveness in detecting changes in environmental conditions and freshness levels. Alerts were automatically generated when the predicted freshness score dropped below predefined threshold values.

The response time of the system was observed to be within 5 - 10 seconds after receiving updated sensor data, indicating low latency and effective real time processing capabilities.

The dashboard displayed

- Real time sensor readings
- Freshness percentage
- Estimated remaining vase life
- Alert notifications

3.1.5. Automation Performance

The automated control mechanism was evaluated to assess its effectiveness in maintaining optimal storage conditions. The system successfully triggered automated actions, such as preservative water refilling, when water levels dropped below predefined thresholds.

The integration of the solenoid valve and water pump allowed the system to respond immediately to unfavorable conditions without requiring manual intervention. This contributed to maintaining stable environmental conditions and reducing fluctuations that negatively impact freshness.

As a result, the automation mechanism played a significant role in improving freshness duration and ensuring consistency in storage conditions, demonstrating the practical effectiveness of the proposed system.

3.2. Research Findings

Based on the experimental results and system evaluation, several key findings were identified regarding the effectiveness of the proposed IoT-based freshness monitoring system.

3.2.1. Impact of Environmental Factors

- Temperature has a direct impact on freshness. Higher temperatures accelerate metabolic processes, reducing vase life.
- Humidity plays a critical role in maintaining moisture balance and preventing dehydration.
- Ethylene (air quality) contributes significantly to flower aging and early wilting.
- Water availability is one of the most critical factors affecting freshness and longevity.

3.2.2. Effectiveness of IOT Based Monitoring

The implementation of IoT based monitoring demonstrated significant advantages over traditional manual methods. Continuous real time data collection provided accurate and reliable insights into environmental conditions affecting flower freshness.

Unlike manual observation, which is subjective and intermittent, the IoT system ensures

- Continuous monitoring without human intervention
- High accuracy and consistency in data collection
- Early detection of unfavorable environmental changes
- Immediate response through alerts and automation

These capabilities enable proactive freshness management, reducing the risk of spoilage and improving overall efficiency in post-harvest handling.

3.2.3. Machine Learning Prediction Capability

The machine learning model demonstrated strong capability in identifying patterns and relationships between environmental parameters and flower freshness levels. By analyzing variables such as temperature, humidity, ethylene concentration, and water conditions, the model was able to accurately predict both the freshness score and the remaining vase life of roses.

The predictive nature of the model provides a significant advantage over traditional manual methods, which rely on visual inspection and subjective judgment. In contrast, the proposed system delivers data driven insights that enable early detection of freshness degradation and support timely decision making. Furthermore, the model's ability to generalize across varying environmental conditions highlights its robustness and suitability for real world applications.

3.2.4. Automation Benefits

The integration of automation within the system significantly enhances its efficiency and usability. Automated features, such as water refill triggers and alert notifications, allow the system to maintain optimal storage conditions without requiring continuous human intervention.

By responding promptly to changes in environmental conditions, the system minimizes the risk of sudden freshness degradation. This reduces the dependency on manual monitoring and lowers the likelihood of human error. Additionally, automation ensures consistency in maintaining environmental parameters, leading to improved reliability and prolonged vase life of roses.

Overall, the automation mechanism contributes to increased operational efficiency, reduced workload for users, and more effective freshness management.

3.2.5. Practical Applicability

The proposed system demonstrates strong practical applicability, particularly for small and medium scale florists. It is designed to be cost effective, user friendly, and easy to deploy in real world environments.

The system is suitable for small and medium scale florists due to

- Low-cost hardware components
- Simple dashboard interface
- Minimal technical requirements

These characteristics make the system a scalable and adaptable solution for improving post-harvest freshness management in the floriculture industry.

3.3. Discussion

The results of this study demonstrate that integrating IoT and machine learning technologies into post-harvest flower management can significantly improve freshness monitoring and decision making.

Traditional freshness management methods rely heavily on visual inspection and experience, which are subjective and inconsistent. In contrast, the proposed system provides objective, data driven insights in real time.

The experimental results confirm that environmental factors such as temperature, humidity, ethylene levels, and water availability directly influence the freshness of roses. The ability of the system to continuously monitor these parameters allows for early detection of unfavorable conditions and timely intervention.

The machine learning model plays a crucial role in transforming raw sensor data into meaningful predictions. By estimating freshness score and remaining vase life, the system provides actionable insights that help users optimize storage conditions and reduce spoilage.

Furthermore, the automation feature enhances system efficiency by reducing the need for constant manual monitoring. This is particularly beneficial for florists managing multiple flower batches simultaneously.

However, there are some limitations in the current system. The accuracy of the machine learning model depends on the quality and size of the dataset. In real world scenarios, more diverse data collected under varying environmental conditions would further improve prediction accuracy. Additionally, the system currently relies on indirect measurement of ethylene using air quality sensors, which may not provide exact gas concentration levels.

These findings are consistent with previous research on IoT based agricultural systems, where real-time monitoring has been shown to improve environmental control and productivity [5], [7]. Similarly, studies on rose cultivation using IoT based irrigation and monitoring systems have demonstrated improved efficiency and plant health [8], [9]. However, unlike these studies, the proposed system focuses on post-harvest freshness prediction, highlighting its novel contribution.

Despite these limitations, the proposed system demonstrates strong potential as a cost effective and scalable solution for post-harvest freshness management. It can be further enhanced by integrating advanced sensors, improving machine learning models, and expanding to other types of flowers.

This demonstrates the practical importance of integrating IoT and machine learning technologies for post-harvest freshness management, an area that remains less explored compared to cultivation-focused systems.

4. CONCLUSION

This research successfully designed and developed an IoT based Freshness Monitoring and Smart Storage System for post-harvest rose management. The system integrates IoT sensors, cloud-based data processing, and machine learning techniques to monitor environmental conditions and predict flower freshness in real time.

The results demonstrate that environmental factors such as temperature, humidity, ethylene concentration, and water availability have a significant impact on the freshness and vase life of roses. By continuously monitoring these parameters, the proposed system provides accurate and reliable data that supports informed decision making.

The machine learning model developed in this study was able to predict freshness scores and estimate remaining vase life with a satisfactory level of accuracy. This predictive capability offers a major improvement over traditional manual methods, which rely on visual inspection and experience. The inclusion of a real time dashboard further enhances usability by presenting clear and actionable insights to users.

In addition, the system's automation features, such as alert notifications and water management mechanisms, contribute to maintaining optimal storage conditions and reducing manual effort. This helps improve consistency in freshness management and reduces the risk of early spoilage.

Overall, the proposed solution provides a cost effective and scalable approach for florists and distributors to improve post-harvest flower quality. It has the potential to reduce economic losses, enhance customer satisfaction, and promote the adoption of smart technologies in the floriculture industry.

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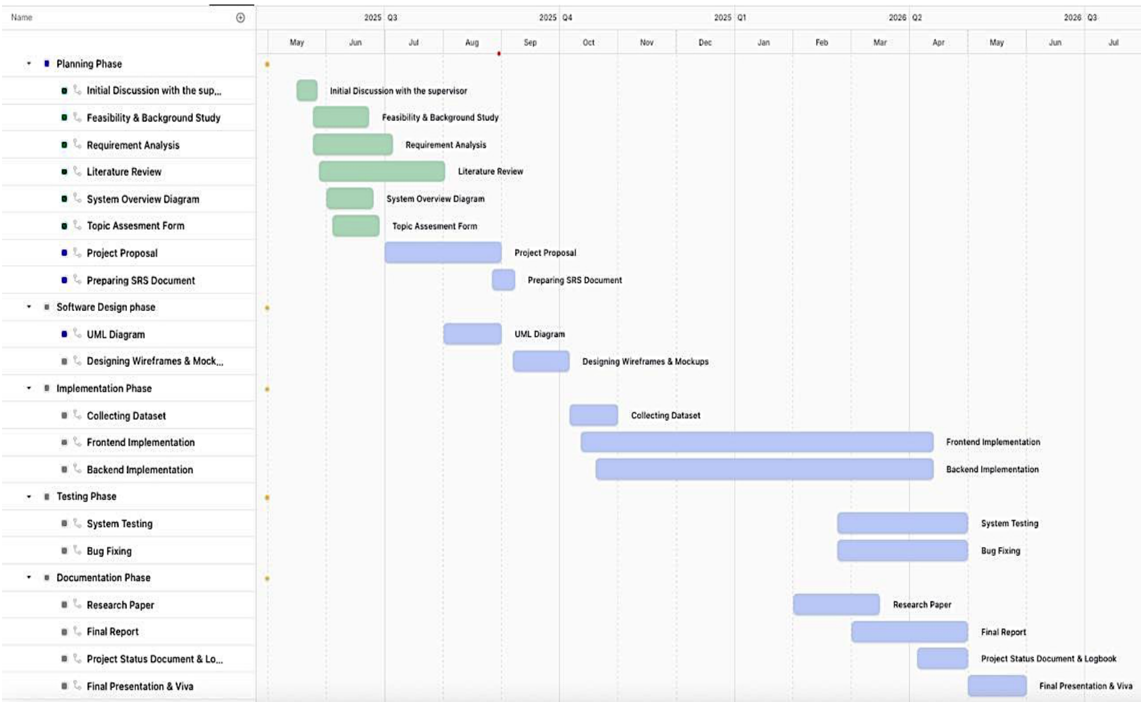
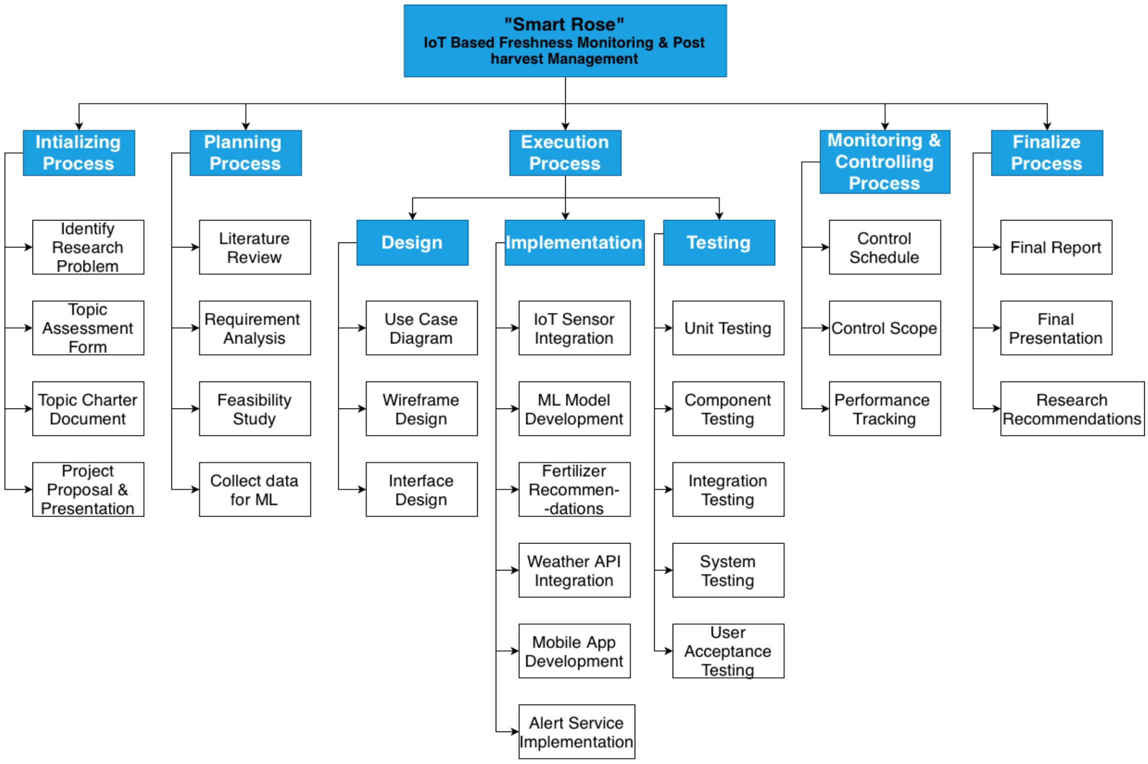
6. APPENDICES

6.1. Appendix A: Gantt Chart



Appendix A: Gantt Chart

6.2. Appendix B: Work Breakdown Chart



Appendix B: Work Breakdown Chart