SMART GREENHOUSES DECISION SUPPORT SYSTEM FOR

TOMATO CULTIVATION

24-25J-064

Project Proposal Report

Vishvi Dilthara Thrimavithana

BSc (Hons) in Information Technology Specialized in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology Sri Lanka

August – 2024

Smart Greenhouses Decision Support System for Tomato Cultivation

24-25J-064

Vishvi Dilthara Thrimavithana

BSc (Hons) in Information Technology Specialized in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology Sri Lanka

August 2024

1. DECLARATION

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

Name	Student ID	Signature
Thrimavithana V.D.	IT21181160	

Signature of the Supervisor: Date

(Mrs. Geethanjali Wimalaratne)

………………………………….. …………………….

it21181160 Thrimavithana V.D. <it21181160@my.sliit.lk>

Proposal Reports - Research Group 24-25J-064

Geethanjali Wimalaratne <geethanjali.w@sliit.lk> Fri, Aug 23, 2024 at 4:29 PM
To: "Thrimavithana V.D. it21181160" <it21181160@my.sliit.lk>

Dear Trimavithana
Accepted your document
Best regards,
Geethanjali

2. ABSTRACT

In modern agriculture, resource efficiency is critical to achieving a long-term high-yield crop production. This project component focuses on the development of an enhanced decision support system (DSS) for optimizing fertilization schedules in smart greenhouses specialized to tomato growing. The suggested system uses real-time environmental data, such as soil nutrient levels, temperature, and humidity, to calculate the optimal timing and amount of fertilizer delivery. The technology forecasts ideal fertilization times by combining Internet of Things (IoT) sensors and machine learning algorithms, guaranteeing that nutrients are provided at the optimal time for plant absorption. This method minimizes waste, improves crop quality, and increases productivity. The initiative not only solves the inefficiencies of traditional fertilization procedures, but it also helps to the overall aims of precision agriculture by improving resource utilization and minimizing environmental impact.

Keywords: Modern agriculture, Resource efficiency, High-yield crop production, Decision support system (DSS), Fertilization schedules, Smart greenhouses, Tomato growing, Real-time environmental data, Soil nutrient levels, Temperature, Humidity, Fertilizer delivery, Internet of Things (IoT), Machine learning algorithms, Precision agriculture, Nutrient absorption, Waste minimization, Crop quality, Productivity, Environmental impact

Table of Contents

4. LIST OF FIGURES

5. LIST OF TABLES

6. INTRODUCTION

The transition from traditional farming methods to smart, technology-driven practices has become essential in pursuing sustainable agriculture. Greenhouse cultivation, particularly for high-value crops like tomatoes, offers a controlled environment where variables such as temperature, humidity, and soil conditions can be closely monitored and managed. However, one of the most critical aspects of maintaining optimal growth and maximizing yield is the precise management of fertilization. [1]This project component aims to develop an optimized fertilization schedule using a decision support system (DSS) that leverages real-time data collected from IoT sensors within the greenhouse. By analyzing factors such as soil nutrient levels, temperature, humidity, and plant growth stages, the system will determine the precise timing and quantity of fertilizer application. This approach not only enhances nutrient uptake efficiency but also minimizes environmental impact by reducing waste and preventing nutrient leaching.

Through the integration of advanced technologies and data-driven insights, this project seeks to transform fertilization practices in smart greenhouses, contributing to more sustainable and productive tomato cultivation.

6.1 BACKGROUND & LITERATURE SURVEY

6.1.1 Background

Fertilization is a fundamental component of modern agriculture, ensuring that crops receive the vital nutrients required for growth, development, and production. In tomato agriculture, accurate fertilization is critical since it has a direct impact on crop quality, size, and health. Tomatoes are particularly vulnerable to nutrient imbalances, thus optimizing fertilization schedules is critical in greenhouse environments where conditions are regulated yet unpredictable owing to variables such as temperature swings and humidity changes.

Fertilization has traditionally been controlled manually using predetermined timetables or visual assessments of plant health. However, these approaches are typically ineffective and might result in dietary shortages or excesses. In terms of smart greenhouses, where technology allows for real-time monitoring of environmental variables, there is a great opportunity to enhance fertilization techniques through data-driven decision-making. Using sensors and advanced analytics, it is possible to develop a dynamic fertilization schedule that responds to the plants' current demands, therefore improving growth and decreasing waste.[2]

6.1.2 Literature Survey

Recent research in precision agriculture has highlighted the potential of integrating technology with traditional farming practices to enhance efficiency and sustainability. Several studies have focused on the use of Internet of Things (IoT) devices, machine learning algorithms, and decision support systems (DSS) to improve fertilization strategies in controlled environments like greenhouses.

IoT devices have become increasingly popular in smart agriculture, allowing for the continuous monitoring of soil moisture, nutrient levels, temperature, and humidity. For instance, studies by Tao et al. (2021) have demonstrated how IoT-based systems can provide real-time data that informs fertilization decisions, ensuring that plants receive the right nutrients at the right time.[2]

Despite these advances, there are still challenges in implementing fully optimized fertilization systems. One major gap identified in the literature is the integration of various data streams into a unified system that can adapt to the complex and dynamic environment of a greenhouse. Also, most current research focuses on single aspects of fertilization, such as nutrient levels or soil moisture, without considering the plant's holistic needs.[3]

6.2 RESEARCH GAP

Despite the advances in precision agriculture, particularly in the areas of IoT-based monitoring, machine learning algorithms, and decision support systems (DSS), there remains a significant gap in the integration and practical application of these technologies specifically for fertilization optimization in tomato cultivation within smart greenhouses.

Existing Products / Research Features Automated Fertilizer Application Real-Time Nutrient Monitoring Precision Nutrient Delivery Environmentall y Sustainable Practices Integration with IoT and Sensors Impact on Fruit Quality Predictive Analytics for Nutrient Needs IoT-Based Precision Fertilization System Smart Fertigation Management System Integrated Hydroponic Nutrient Solution Proposed System

	Features						
Existing Products / Research	Automated Fertilizer Application	Real-Time Nutrient Monitoring	Precision Nutrient Delivery	Environmentally Sustainable Practices	Integration with IoT	Impact on Fruit Quality	Predictive Analytics for Nutrient Needs
IoT-Based Precision Fertilization[1] System	✓	✗	✓	✗	✓	✗	✗

[1] (Lin et al., 2020) Lin, N., Wang, X., Zhang, Y., Hu, X., & Ruan, J. (2020). Fertigation management for sustainable precision agriculture based on Internet of Things. *Journal of Cleaner Production*, *277*, 124119. https://doi.org/10.1016/j.jclepro.2020.124119

Integrated Hydroponic Nutrient Solution System[2]	✗	✓	✓	✓	✗	✗	✓
Smart Fertigation Management System[3]	✓	✓	✗	✗	✗	✓	✗
Proposed System	✓	✓	✓	✓	✓	✓	✓

Table 6.1 Research Gap

To address the identified research gap, this project proposes the development of an integrated Decision Support System (DSS) specifically designed to optimize fertilization schedules in smart greenhouses used for tomato cultivation. The proposed system will combine real-time data collection, advanced data analytics, and adaptive decision-making to create a dynamic and responsive approach to fertilization management.

The system will utilize an IoT sensor strategically placed inside the greenhouse. These sensors will continuously monitor critical environmental parameters, such as soil

---

[2] Calabria, J. L., Lens, P. N., & Yeh, D. H. (2019). Zeolite ion exchange to facilitate anaerobic membrane bioreactor wastewater nitrogen recovery and reuse for lettuce fertigation in vertical hydroponic systems. *Environmental Engineering Science*, *36*(6), 690–698. https://doi.org/10.1089/ees.2018.0439

[3] Ahmad, U., Alvino, A., & Marino, S. (2022). Solar Fertigation: a sustainable and smart IoT-Based irrigation and fertilization system for efficient water and nutrient management. *Agronomy*, *12*(5), 1012. https://doi.org/10.3390/agronomy12051012

moisture, soil nutrient levels, temperature, humidity, and light intensity. Additionally, the sensors will track the growth stages of tomato plants, providing valuable data on plant health and development. The collected sensor data will be transmitted in real-time to a central processing unit, where it will undergo thorough analysis. Machine learning algorithms will be employed to identify patterns and correlations between environmental conditions and plant nutrient requirements. By incorporating both historical data and expert knowledge, the system will make informed decisions about fertilization, based on real-time conditions and predictive modeling.

To ensure the precise implementation of the DSS recommendations, the system will be connected to an automated fertilization delivery mechanism. This could be a fertigation system that mixes nutrients with irrigation water or a direct soil application system. The delivery mechanism will be controlled by the DSS, allowing for timely and accurate fertilizer application without manual intervention. Additionally, a user-friendly interface will be developed to provide real-time updates on greenhouse conditions, fertilization schedules, and system recommendations. This interface will be accessible via web and mobile platforms, ensuring ease of use for greenhouse managers. The system will also generate alerts and notifications for critical events, such as nutrient deficiencies or system malfunctions, allowing for prompt corrective actions.[5]

The proposed system offers numerous benefits. It will optimize nutrient management by ensuring that tomato plants receive the right nutrients at the right time, leading to improved plant health, higher yields, and better crop quality. The system will also enhance resource efficiency by preventing over-fertilization and reducing nutrient waste, contributing to more sustainable agricultural practices and lowering environmental impact. Furthermore, the integration of real-time data and machine learning will provide greenhouse managers with valuable insights into plant growth and fertilization needs, enabling more informed decision-making. Because it is designed to be scalable, the proposed system will allow for future expansion to other crops or additional greenhouse environments. It is also flexible, capable of adapting to different farming practices and conditions.

In summary, the proposed system leverages cutting-edge technology to revolutionize fertilization practices in smart greenhouses, offering a comprehensive solution to the challenges faced in tomato cultivation. This system will enhance productivity, sustainability, and profitability in modern greenhouse agriculture by optimizing fertilization schedules through a data-driven approach.

6.3 RESEARCH PROBLEM

How can we develop a decision support system for tomato greenhouses that optimizes fertilizing schedules and types that ensures nutrient balance based on real-time plant and environmental conditions?

In the context of modern agriculture, especially within controlled environments such as greenhouses, the optimization of fertilization schedules is critical for ensuring both the quality and quantity of crop yields. Traditional fertilization practices in greenhouse settings are predominantly based on generalized, time-based schedules that do not consider the complex and dynamic environmental factors that can significantly affect nutrient uptake by plants. These traditional methods often rely on predetermined quantities of fertilizers applied at fixed intervals, leading to a range of inefficiencies.

One significant issue with these traditional methods is the lack of responsiveness to real-time environmental variations within greenhouses. For instance, factors such as temperature, humidity, soil moisture, light intensity, and plant growth stage can all influence the optimal timing and quantity of fertilization. Without the ability to adjust fertilization schedules dynamically in response to these factors, several problems can arise:

Over-fertilization: Applying more nutrients than the plants can absorb leads to nutrient leaching, which not only wastes resources but also poses environmental risks, such as contamination of water bodies through runoff. Over-fertilization can also result in salt accumulation in the soil, which can harm plant roots and reduce the overall fertility of the soil over time. [6]

Under-fertilization: Conversely, applying insufficient nutrients can lead to nutrient deficiencies, which impair plant growth, reduce yields, and degrade the quality of the produce. Inadequate fertilization can also weaken plants, making them more susceptible to diseases and pests. [6]

Environmental Impact: Inefficient use of fertilizers contributes to broader environmental issues, including greenhouse gas emissions from the production and application of fertilizers, soil degradation, and water pollution. These environmental concerns are increasingly important in the context of sustainable agriculture.

There is a pressing need for an intelligent system that can optimize fertilization schedules in real-time, considering the specific conditions of each greenhouse. This system should leverage real-time data from various sensors that monitor environmental parameters such as soil moisture, temperature, light intensity, and plant nutrient status. By integrating this data with advanced predictive algorithms, the system could determine the precise amount and timing of fertilizer application required to maximize plant health and productivity.

However, the development of such a system presents several technical and practical challenges. These include the accurate modeling of nutrient dynamics within the greenhouse environment, the integration of diverse data sources, the design of effective machine learning models that can predict nutrient needs based on real-time data, and the creation of a user-friendly interface that can provide actionable recommendations to greenhouse managers.

7. OBJECTIVES

7.1 Main Objective:

The primary objective of this research is to develop an optimized fertilization schedule within a decision support system tailored for tomato cultivation in smart greenhouses. This system aims to enhance tomato yield and quality by precisely managing nutrient delivery, minimizing waste, and ensuring the sustainability of the fertilization process. By leveraging real-time environmental data and advanced predictive analytics, the system will provide recommendations that are responsive to the dynamic needs of the plants, thereby optimizing the growth environment and improving overall agricultural efficiency.

7.2 Specific Objectives:

I. Monitor soil nutrient levels in real-time using advanced sensors.

II. Integrate data from environmental sensors (e.g., temperature, humidity) to adjust fertilization schedules dynamically.

III. Develop a machine learning model to predict optimal fertilization times and quantities based on historical and real-time data.

IV. Minimize nutrient waste by ensuring precise and timely nutrient delivery according to plant growth stages.

V. Ensure the sustainability of the fertilization process by reducing environmental impact and resource use.

VI. Provide real-time alerts and recommendations through a user-friendly dashboard.

VII. Validate the system's effectiveness through controlled experiments in smart greenhouse environments.

8. METHODOLOGY

8.1 System Architecture Diagram

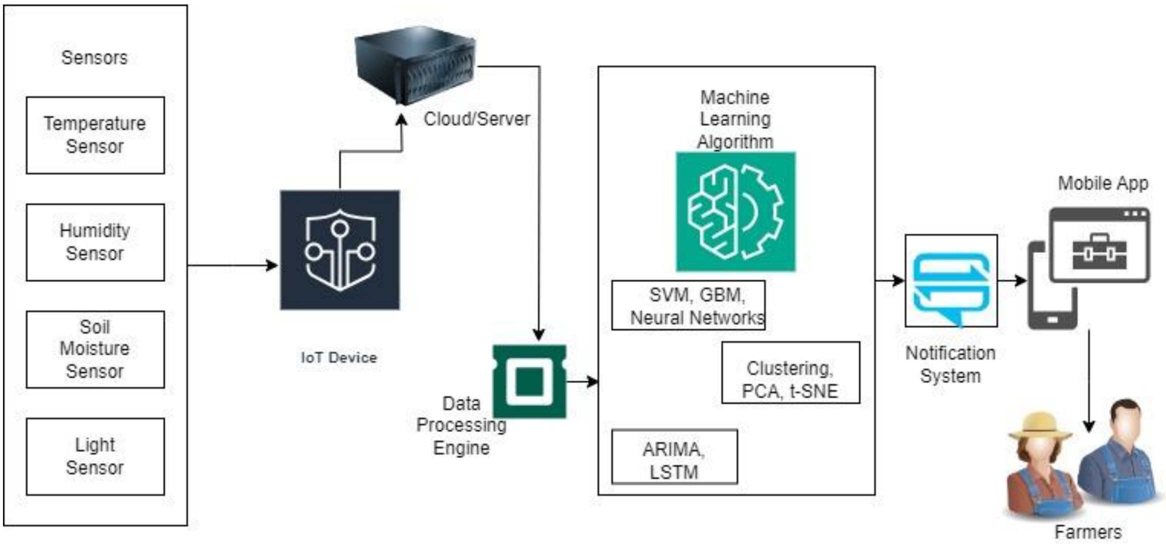

Figure 8.1 System Architecture Diagram

To achieve the objective of optimizing fertilization schedules for tomato cultivation in smart greenhouses, the following methodology will be implemented:

8.2 System Design and Architecture:

I. Requirements Gathering: Identify and document the system requirements, including the types of sensors, data inputs, and user interface needs. Collaborate with agricultural experts to determine the critical parameters influencing tomato growth.

II. System Architecture: Design the overall architecture of the decision support system, incorporating sensors, data processing units, machine learning algorithms, and the user interface. The system will integrate IoT devices for data collection and cloud-based services for data storage and analysis.

8.3 Data Collection and Sensor Deployment

I. Deploy soil sensors capable of monitoring nutrient levels (e.g., nitrogen, phosphorus, potassium) in real-time. Additional environmental sensors will measure temperature, humidity, light intensity, and other relevant parameters.

The following data will be required for optimizing fertilizing schedules in tomato cultivation:

I. Soil Nutrient Levels: Regularly measured levels of nitrogen, phosphorus, and potassium.
II. Tomato Plant Growth Stages: Data on plant growth stages to adjust fertilizing schedules accordingly.
III. Weather Conditions: Historical and real-time weather data, including temperature, humidity, and rainfall.
IV. Water Quality: Data on the purity and composition of irrigation water.
V. Fertilizer Application Records: Historical records of fertilizer usage and application methods.

8.4 Data Collection Methods:

I. Interviews: Conduct interviews with local farmers and agronomists to gather insights on current fertilizing practices and challenges. This can be done using structured questionnaires and semi-structured interviews.
II. Sensors and Monitoring Devices: Utilize sensors to measure soil nutrient levels and weather conditions in real-time.
III. Historical Data: Gather historical data from the Department of Agrarian Development.

8.5 Data Processing and Analysis:

I. Data Preprocessing: Clean and preprocess the collected data to remove noise and ensure consistency. This step will include data normalization, outlier detection, and handling missing values.

II. Feature Engineering: Extract relevant features from the data that are indicative of the tomato plants' fertilization needs. These features may include soil nutrient levels, environmental conditions, and plant growth stages.

III. Machine Learning Model Development:

i. Model Selection: Choose appropriate machine learning algorithms (e.g., regression models, decision trees, or neural networks) to predict optimal fertilization schedules. The choice of model will be based on the nature of the data and the complexity of the relationships between variables.

ii. Model Training and Validation: Split the dataset into training and validation sets. Train the model using historical data and validate its performance using the validation set. Hyperparameter tuning will be performed to optimize the model's accuracy and generalization ability.

8.6 System Integration and Testing:

I. System Integration: Integrate the trained machine learning model with the decision support system. The system will use real-time data to make predictions and provide fertilization recommendations.

II. Testing and Calibration: Conduct controlled experiments in a smart greenhouse to test the system's performance. Calibration of the system will be done by comparing the recommended fertilization schedules with actual plant responses. Adjustments will be made as necessary.

8.7 Dashboard Development and User Interface:

I. Dashboard Design: Develop a user-friendly dashboard to visualize real-time data, predicted fertilization schedules, and system alerts. The dashboard will provide users with actionable insights and allow manual overrides if needed.

8.8 Evaluation and Validation:

I. Field Trials: Conduct field trials in various greenhouse settings to evaluate the system's effectiveness in optimizing tomato growth and yield. Performance metrics will include yield improvement, nutrient use efficiency, and reduction in environmental impact.

II. Comparison with Traditional Methods: Compare the results obtained from the decision support system with traditional fertilization methods to demonstrate the system's advantages.

8.9 Final Implementation and Deployment:

I. System Deployment: Once validated, deploy the decision support system across multiple smart greenhouses. Provide training and support to users for system adoption.

II. Continuous Monitoring and Updates: Establish a continuous monitoring mechanism to ensure the system's performance remains optimal. Regular updates and improvements will be made based on ongoing data collection and user feedback.

8.10 Software Solution

8.10.1 Development Process

In the traditional software development approach, teams often follow a linear sequence where each phase must be completed before moving on to the next. This method, commonly known as the Waterfall model, is rigid and can be inefficient when requirements evolve during the development cycle. Changes in requirements often necessitate revisiting previous stages, which can be costly and time-consuming. In contrast, Agile methodologies embrace flexibility and responsiveness to change, allowing teams to adapt to new requirements even in the later stages of development.

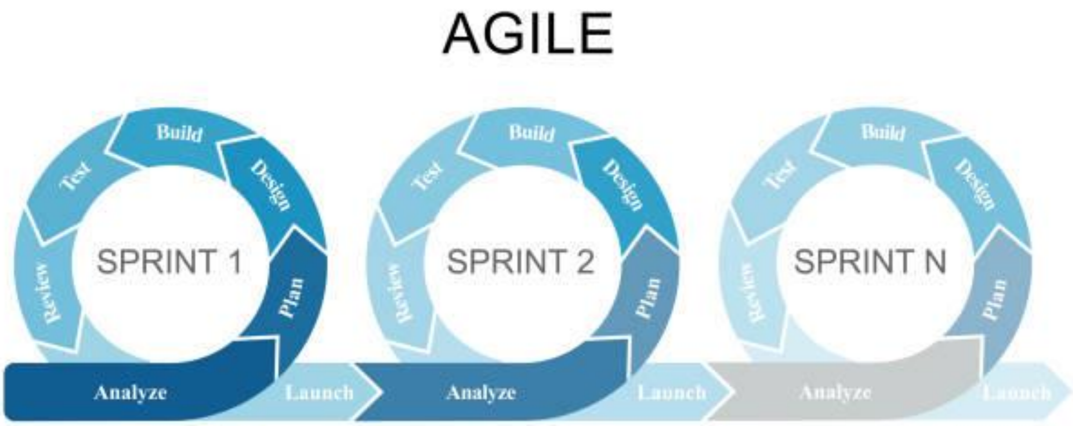

Figure 8.1 Agile Methodology

8.11 Time Frame

8.11.1 Agile Methodology

The timeline for the proposed project is structured to emphasize the development, training, and validation of the machine learning model for optimizing the fertilization schedule system. The project begins with a data collection phase, where existing environmental and plant growth data will be gathered from available sources and databases. This phase also includes data preprocessing, ensuring the data is clean and ready for analysis.

Following the data collection, another time period is dedicated to data analysis and model development. During this phase, advanced machine learning algorithms will be employed to analyze the data, identify patterns, and develop a predictive model that optimizes the fertilization schedule. This phase will also include hyperparameter tuning and model validation to ensure the model's accuracy and effectiveness.

The next month will focus on model integration and testing. Here, the machine learning model will be integrated into the decision support system (DSS), and its performance will be rigorously tested in a simulated greenhouse environment. Any necessary adjustments or improvements to the model will be made during this period.

The final phase, lasting 1 month, will involve preparing a comprehensive report that details the project's outcomes, including the performance metrics of the machine learning model, the impact on fertilization efficiency, and recommendations for future improvements. This phase will also include the presentation of the results to stakeholders.

In total, the project is estimated to take 09 months from start to finish, allowing sufficient time for each critical stage of development to be completed successfully.

Data Collection	3 weeks

Sensor Installation and Calibration	1 month
Data Analysis and Model Development	3, 1/2 months
Fertilizing Schedule Optimization	1 month
Testing and Validation	1 month
Report Preparation and Presentation	1 week
Total estimated time	09 months

Table 8.1 Time Frame

9. SYSTEM REQUIREMENTS

9.1 Hardware Requirements

I. High-Performance Server or Cloud Computing Resources - Required for processing large datasets and training machine learning models efficiently.

II. GPU (Graphics Processing Unit) - For accelerating machine learning model training, especially for deep learning models.

III. Storage Solutions (HDD/SSD) - Ample storage capacity to handle large datasets and model files.

IV. Network Infrastructure - Reliable and high-speed internet connection to facilitate data transfer between databases, cloud services, and local servers.

V. Backup Systems - RAID or cloud-based backup solutions to ensure data integrity and prevent loss during processing or storage.

9.2 Software Requirements

Database Management System (DBMS)

i. MongoDB: For structured data management and query operations.

ii. Firebase: For real-time database management and cloud storage.

Data Integration Tool

i. Talend: To aggregate and transform data from multiple sources before processing.

Programming Languages

i. Python: Primary language for machine learning and data processing tasks, utilizing libraries such as Pandas, NumPy, and Scikit-Learn.
ii. R: For statistical analysis and advanced data visualizations.

Data Processing Libraries

i. Pandas, NumPy, SciPy: Essential libraries for data manipulation, numerical computations, and statistical analysis.

Machine Learning Frameworks

i. Scikit-Learn: For implementing traditional machine learning models.
ii. TensorFlow: For developing and deploying deep learning models.

Data Visualization Tools

i. Matplotlib, Plotly: For creating visualizations to interpret model outcomes and data trends.

Notification Services

i. Firebase Cloud Messaging (FCM): For sending notifications related to data updates, model training statuses, and system alerts.

Backend Framework

i. Node.js: For developing the backend services that interact with the database and manage API requests.

Frontend Frameworks

i. React.js, Vue.js: To build responsive and interactive user interfaces for the web application.

APIs

i. RESTful APIs: For communication between the frontend, backend, and external services.

Version Control

i. Git/GitHub: For managing code versions and collaborating with the team.

9.3 Functional and Non-Functional Requirements

9.3.1 Functional Requirements

I. Data Integration and Processing - The system should integrate data from various sources, clean and preprocess it, and store it in a structured format.

II. Machine Learning Model Training - The system should support the training of hybrid machine learning models using processed data.

III. Real-Time Data Updates - The system should support real-time data updates from the IoT devices through Firebase.

IV. Visualization and Reporting - The system should generate visual reports and dashboards that provide insights into the data and model performance.

V. Mobile Application Functionality - The mobile app should allow users to monitor system status, receive notifications, and access reports.

9.3.2 Non-Functional Requirements

I. Scalability - The system should be scalable to handle an increasing volume of data and more complex models as the project evolves.

II. Performance - The system should ensure high performance, with minimal latency in processing and real-time data handling.

III. Security - The system must ensure data security and user authentication, especially when dealing with sensitive agricultural data.

IV. Reliability - The system should be reliable, with mechanisms for backup and recovery in case of failures.

V. Usability - The user interfaces, both on the web and mobile platforms, should be intuitive and easy to use for the greenhouse manager and other stakeholders.

VI. Maintainability - The system should be easy to maintain and update, with clear documentation and version control in place.

9.4 Personnel Requirements

I. Department of Agrarian Development in Sri Lanka

II. Mr. Krishantha Jayawardhana, Agrarian Services Center, Monaragala.

III. Department of Agriculture Sri Lanka

9.5 Use Case Diagram

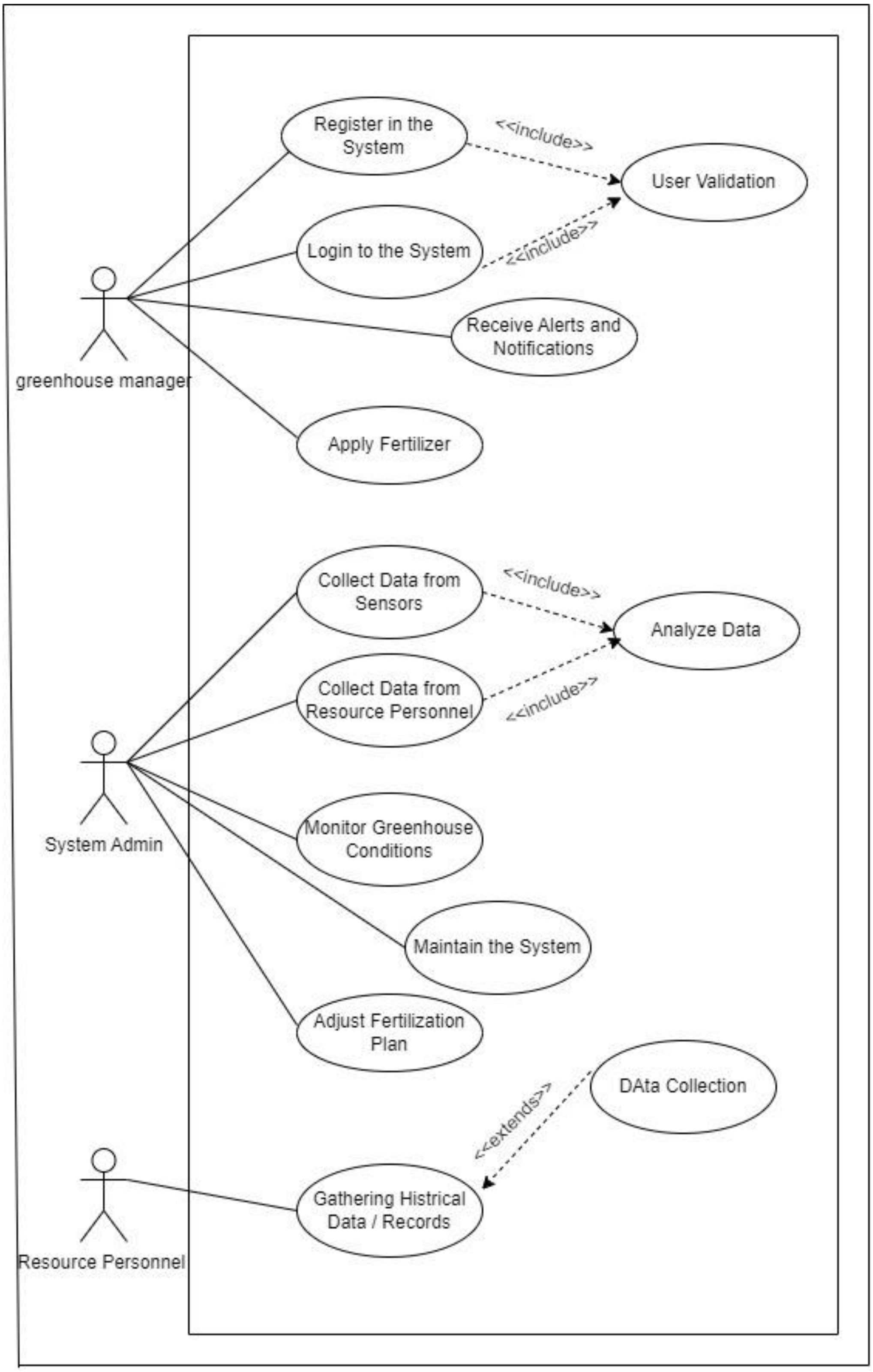

Figure 9.1 Use Case Diagram

10. PROJECT TIMELINE AND TASK ASSIGNMENT

10.1 Project Timeline

Task	Start Date	End Date	Duration
Data Collection	01-Jul-2024	31-Aug-2024	2 months
Sensor Installation and Calibration	01-Sep-2024	31-Oct-2024	2 months
Data Analysis and Model Development	01-Nov-2024	31-Jan-2025	3 months
Fertilizing Schedule Optimization	01-Feb-2025	31-Mar-2025	2 months
Testing and Validation	01-Apr-2025	30-Apr-2025	1 month
Report Preparation and Presentation	01-May-2025	31-May-2025	1 month

Table 10.1 Project Timeline

10.1 Work breakdown Chart

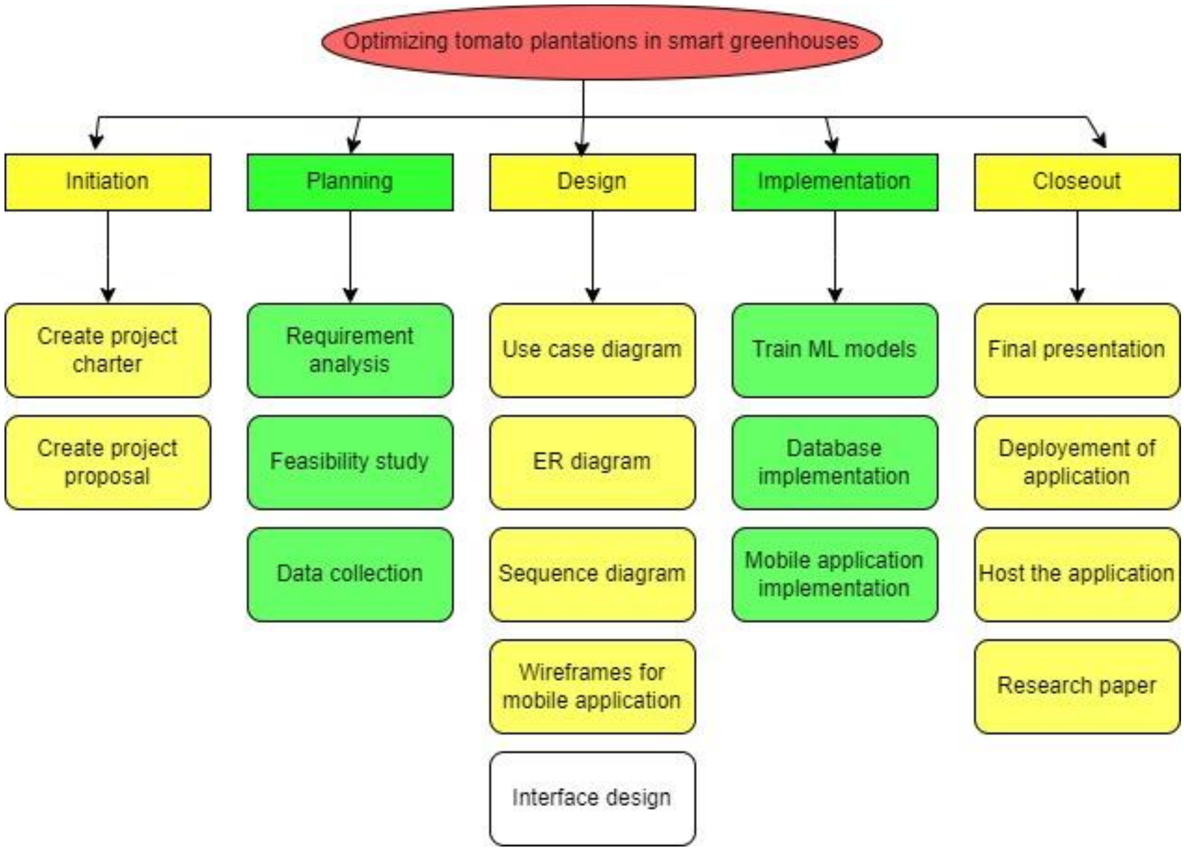

Figure 5 Work breakdown Chart

11. FEASIBILITY STUDY

11.1 Technical Feasibility

This project is technically feasible given the availability of advanced tools and frameworks that support the development of complex decision support systems. Existing literature and previous research indicate that similar systems have been successfully implemented using machine learning and IoT technologies to monitor and optimize agricultural processes. The project team has extensive experience in developing cloud-based applications, integrating IoT devices, and implementing machine learning models. Additionally, the technical infrastructure required for this project, including cloud services for data storage and processing, is readily available and can be efficiently utilized. Therefore, the project is technically feasible and can be successfully executed with the available resources and expertise.

11.2 Scheduling Feasibility

The proposed system's development is structured into clearly defined phases, each with specific deliverables and milestones. A detailed project timeline has been established, ensuring that each phase progresses on schedule and within the allocated time frame. The Agile methodology, particularly Scrum, will be employed to manage the development process, allowing for flexibility and iterative progress. The project timeline has been developed considering all potential risks and contingencies to ensure that the final product is delivered by the predefined due date. Regular sprint reviews and retrospectives will be conducted to monitor progress and make necessary adjustments to keep the project on track.

11.3 Description of Personal and Facilities

11.3.1 Personnel Requirements

Mr. Krishantha Jayawardhana

Position: Agronomist

Organization: Agrarian Services Center, Monaragala

Mr. Krishantha Jayawardhana is a key external collaborator for your project. With his role at the Agrarian Services Center in Monaragala, Mr. Jayawardhana brings valuable expertise in agricultural practices, particularly in the region's specific cultivation challenges. His experience and knowledge will be instrumental in providing accurate and relevant data for optimizing fertilizing schedules in your decision support system. His insights into local agricultural conditions and practices will enhance the project's effectiveness and relevance.

11.3.2 Facilities
Agrarian Services Center, Monaragala

The Agrarian Services Center in Monaragala serves as a crucial facility for your project, providing access to a wealth of agricultural data and resources. This center specializes in supporting local farming practices and can offer critical information regarding soil conditions, crop management, and environmental factors pertinent to tomato cultivation. The center's facilities include data collection tools, research resources, and expert personnel like Mr. Jayawardhana, all of which will support the development and implementation of your decision support system. [7]

Figure 11.1 Agrarian Services Center

12. COMMERCIALIZATION OF THE PRODUCT

12.1 Market Opportunity

The Smart Greenhouse Decision Support System addresses the critical need for innovation in modern tomato cultivation. With the increasing global emphasis on sustainable farming practices and the demand for high-efficiency agricultural solutions, our system is positioned to cater to a growing market of greenhouse operators and agribusinesses focused on maximizing yields while minimizing resource consumption.

12.1.1 Key Market Drivers

I. Sustainability and Efficiency: As the agricultural sector moves towards sustainable practices, our system offers a solution that aligns with this trend by optimizing water usage and reducing waste.

II. Technological Adoption: The integration of IoT and data-driven decision-making is becoming standard in agriculture, creating a ripe market for advanced technologies like ours that enhance operational efficiency and productivity.

III. Increasing Greenhouse Cultivation: The rise in greenhouse farming, driven by its ability to control environmental factors and extend growing seasons, presents a growing market for our tailored solutions.

12.1.2 Target Market Segments

I. Commercial Greenhouse Operators: Large-scale operations seeking to enhance productivity and reduce operational costs. [6]

II. Agricultural Technology Providers: Companies looking to integrate advanced decision support systems into their product offerings.

III. Research Institutions: Organizations focused on agricultural innovation and research that require sophisticated data analysis tools. [7]

IV. Our system stands out by providing a unique combination of advanced data analytics, ease of use, and integration capabilities, positioning it as an essential tool for modern greenhouse management.

12.2 Commercial Strategy

12.2.1 Product Development and Validation

I. Pilot Programs: Initiate pilot programs with select greenhouse operators to validate system performance, gather user feedback, and refine the product based on real-world use cases.

II. Continuous Improvement: Implement an agile development approach to incorporate feedback and continuously enhance system features and reliability.

10.2.2 Strategic Partnerships

I. AgTech Collaborations: Forge partnerships with agricultural technology companies to integrate our system into broader solutions and leverage their distribution networks. [9] [1]

II. Greenhouse Manufacturers: Collaborate with greenhouse manufacturers to bundle our system with their infrastructure, offering a complete solution to end-users. [10]

12.2.3 Marketing and Outreach

I. Digital Marketing Campaigns: Utilize SEO, content marketing, and targeted ads to reach potential customers online and drive traffic to our website.

II. Industry Events and Trade Shows: Participate in relevant agricultural and technology events to showcase our system and engage with key stakeholders.

III. Customer Testimonials and Case Studies: Highlight successful implementations and customer success stories to build credibility and attract new clients.

12.2.4 Target Audience

I. Researchers: Academics and industry professionals studying agricultural optimization, smart greenhouses, or related fields.

II. Greenhouse Operators: Individuals or organizations managing smart greenhouses where the decision support system will be applied.

III. Farmers: Both small-scale and large-scale tomato growers looking for optimized fertilizing solutions.

IV. Agricultural Consultants: Experts providing advice and solutions to improve farming practices and greenhouse management.

V. Technology Providers: Companies offering technological solutions for agriculture, including sensor manufacturers and data analytics firms.

12.2.5 Market Space

I. Accessibility: The system is designed to be user-friendly, requiring minimal technical knowledge from users.

II. Age Limitation: There are no age restrictions; the system is suitable for users of all ages involved in tomato cultivation.

III. Prior Knowledge: Users do not need prior knowledge of advanced agricultural techniques or technology to benefit from the system. The focus is on practical, actionable insights derived from the data provided.

13. BUDGET AND BUDGET JUSTIFICATION

13.1 Budget

I. Travel Costs

Travel from Colombo to Monaragala: LKR 10,000

(Includes transportation expenses for travel by car or public transport to meet Mr. Jayawardhana. This estimate covers round-trip fuel costs or ticket fares.)

I. Miscellaneous Expenses

Meals and Incidentals: LKR 10,000

(Daily expenses for meals and minor incidentals during the visit.)

[Total Estimated Budget: LKR 20,000]

13.2 Budget Justification

1. Travel Costs

The travel expenses are necessary for meeting Mr. Krishantha Jayawardhana in person. This cost covers the round-trip journey from Colombo to Monaragala, ensuring that the project team can gather firsthand information and establish a strong working relationship with the consultant.

2. Miscellaneous Expenses

Meals and incidental expenses are included to cover daily costs during the visit. This ensures that all aspects of the trip, including food and minor unplanned expenses, are accounted for.

14. REFERENCES

[1] F. Lops, Tomato Cultivation and Consumption - Innovation and Sustainability. 2024. doi: 10.5772/intechopen.111285.

[2] Oumnia Ennaji, Machine learning in nutrient management: A review, Artificial Intelligence in Agriculture, Volume 9, September 2023, Pages 1-11

[3] Ayubu Jacob Churi, A Decision Support System for Enhancing Crop Productivity of Smallholder Farmers in Semi-Arid Agriculture, Volume 3 No. 8, July-August 2013

[2] C. Pahmeyer , 'Fruchtfolge': A crop rotation decision support system for optimizing cropping choices with big data and spatially explicit modeling¸ Computers and Electronics in Agriculture, Volume 181, February 2021, 105948

[7] Ren Wang, Andrea Sonnino, Agricultural Innovation, Agricultural Innovation Systems, Environmental and socioeconomic triggers, Sustainable Food and Agriculture, 2019

[6] Martin J. Luna Juncal, Pietro Masino , Edoardo Bertone, Rodney A. Stewart a b, Towards nutrient neutrality: A review of agricultural runoff mitigation strategies and the development of a decision-making framework, Science of The Total Environment, Volume 874, 20 May 2023, 162408

[9] "Recipes for success: policy innovations to transform Africa's food systems and build resilience," Nov. 2021. doi: 10.54067/9781737916420.

[10] S. Hallstedt, O. Isaksson, and A. Ö. Rönnbäck, "The Need for New Product Development Capabilities from Digitalization, Sustainability, and Servitization Trends," Sustainability, vol. 12, no. 23, p. 10222, Dec. 2020, doi: 10.3390/su122310222.

[7] J. Brow, "The Incorporation of a Marginal Community within the Sinhalese Nation," Anthropological Quarterly, vol. 63, no. 1, p. 7, Jan. 1990, doi: 10.2307/3317956.