SMART GREENHOUSES DECISION SUPPORT SYSTEM FOR TOMATO CULTIVATION

Final Report

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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.

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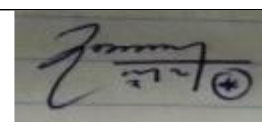
Najas .M .N .M	IT21186592	

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ABSTRACT

A greenhouse-based tomato cultivation management system needs the combination of real-time monitoring and intelligent decision capabilities to handle water resources and fertilizer distribution while combating plant diseases and harvesting efficiently. The current greenhouse system lacks modern automation features with predictive abilities for optimizing production and sustainability advancement. The research implements a DSS system which unites IoT devices with ML models to improve fundamental aspects of tomato cultivation.

The development process follows a modular design where team members contribute their expertise to environmental monitoring and IoT-ML water optimization and foster fertilization planning and disease management through image classification algorithms and harvest time prediction with data models.

Real-time data acquisition took place with environmental sensors specifically designed for soil moisture and temperature sensors along with light detectors and humidity loggers for novelty detection and growth parameter collecting. Machine learning models consisting of regression models together with decision trees and CNNs produced precise and useful recommendations through training and evaluation. The system underwent testing under simulated conditions which produced substantial benefits for water resource optimization while enhancing both disease alert capabilities and improving the precision of scheduling fertilization and harvest operations.

Through its web dashboard users have access to straightforward monitoring tools that maintain continuous control of greenhouse conditions. The developed solution represents a budget-friendly solution which works effectively in various farming operations from personal to industrial scales. The system's upcoming improvements will extend to broader crop.xaxis integration will unify cloud analytics management with automatic controls through decentralized software.

Keywords: Smart Greenhouse, Tomato Cultivation, IoT, Machine Learning, Decision Support System.

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LIST OF ABBREVIATIONS

Abbreviation	Description
API	Application Programming Interface
DB	Data Base
DHT22	Digital Humidity & Temperature Sensor
DSS	Decision Support System
ESP32	Espressif Systems Microcontroller (32-bit)
HTML	Hyper Text Markup Language
HTTP	Hypertext Transfer Protocol
IoT	Internet of Things
IWUE	Irrigation Water Use Efficiency
JS	Java Script
JSON	JavaScript Object Notation
LDR	Light Dependent Resistor
LDR	Light Dependent Resistor
LoRaWAN	Long Range Wide Area Network
MAE	Mean Absolute Error
ML	Machine Learning
pH	Potential of Hydrogen (used in soil acidity)
R^2	Coefficient of Determination (R-squared)
RMSE	Root Mean Squared Error
UAT	User Acceptance Testing
UI	User Interface
URL	Uniform Resource Locator
UX	User Experience

1. INTRODUCTION

The agricultural sector of Sri Lanka depends heavily on tomato cultivation because of its economic importance. The widespread global consumption of tomatoes requires specific environmental control systems to achieve optimal production and quality results. Greenhouses represent an effective method to safeguard agricultural crops against erratic weather conditions and pests through managed environmental control systems that support continuous production throughout the year. The current management practices in traditional greenhouses depend on human observation and personal judgment and delayed reactions to environmental modifications. Such limitations result in inferior resource utilization and crop weaknesses alongside elevated operational expenses.

The agricultural sector needs to implement sustainable technology-based solutions because food production needs continue to increase and climate change effects intensify. Modern greenhouses experience a transformation through the implementation of Internet of Things (IoT) and Machine Learning (ML) smart technologies in their operational framework. Smart technologies monitor crops automatically while providing intelligent data analysis and data-driven decision support systems that improve crop production and resource management.

The research project titled "Smart Greenhouses Decision Support Systems for Tomato Cultivation" addresses contemporary needs through practical and timely solutions. The objective of this project focuses on creating an intelligent modular data-oriented system to help tomato growers and greenhouse operators track environmental factors while enabling them to forecast and take preemptive measures against cultivation issues. The system functions as a Decision Support System (DSS) which unites IoT-based sensor data with ML prediction models along with user-friendly interfaces for operational efficiency enhancement.

The collaborative project consists of four separate components which each member group manages to provide distinct features to the entire system framework:

- **Asardeen A.** focuses on optimizing **watering requirements** using IoT-based environmental monitoring. By collecting real-time data such as soil moisture, temperature, humidity, and light intensity, an ML model predicts the optimal amount and frequency of irrigation needed to maintain plant health while conserving water resources. Additionally, the system includes water level monitoring in tanks to ensure availability for scheduled irrigation cycles.

- **Jayaneththi I.H.N.S.** contributes by establishing **optimal harvesting schedules** through predictive modeling. By analyzing growth patterns and environmental data, this component determines the ideal time to harvest tomatoes to maximize both yield and nutritional quality. Timely harvesting not only improves market value but also reduces losses from over-ripening or spoilage.

- **Thrimavithana V.D.** works on identifying the best **fertilization schedules and product types**, which involves analyzing plant growth stages, nutrient requirements, and soil conditions. The goal is to recommend fertilizing routines that maximize nutrient uptake, promote healthy plant development, and reduce over-fertilization, which can lead to environmental harm.

- **Najas M.N.M.** leads the **disease detection and treatment recommendation** component. Using image processing and ML-based classification models, this part of the system detects early signs of common tomato diseases and suggests appropriate remedies. Early intervention is key to reducing crop losses and maintaining overall plant health.

The system's various components unite to create a specific smart greenhouse solution which can scale up and adjust to suit tomato cultivation needs. Greenhouse operators can enhance profitability along with better crop management and lower labor costs through a system built from sensor networks and predictive analytics and intelligent automation. The modular system design makes it possible to expand the system and support new crops while enabling advanced features including AI-based visual monitoring and autonomous actuation systems.

Through this project Sri Lanka addresses multiple technical and agricultural barriers in greenhouse cultivation while contributing to national and global targets for food security and climate resilience and sustainable development. The combination of agricultural science with computer programming and engineering forms this multidisciplinary research which brings practical value to the world. A working prototype combined with a software platform constitutes the expected outcome that will undergo testing within genuine greenhouse settings for the purpose of reshaping smart agriculture in Sri Lanka and worldwide..

2. BACKGROUND & LITERATURE SURVEY

2.1 Background

Greenhouse cultivation operates as a proven efficient system for controlled crop cultivation since farmers can control temperature and light intensity alongside humidity levels to enhance plant development. The greenhouse system provides significant advantages to tomato farming because it offers ideal environmental factors that optimize both yield production and product quality. The Internet of Things (IoT) and Machine Learning (ML) have become essential factors for modernizing greenhouse operations during recent years. The agricultural sector stands to benefit substantially from these technologies because they optimize resource management and crop management practices.

A smart greenhouse combines IoT sensors with climate control systems and automated irrigation systems to track and regulate key environmental elements including temperature and humidity and light intensity as well as soil moisture. The implemented systems deliver continuous data acquisition which enables greenhouse managers to execute well-informed decisions regarding irrigation times and temperature control adjustments and environmental modifications. Through the use of Machine Learning technology decision-makers can predict the best times for crop planting and fertilization and harvesting. The analysis of large sensor datasets by Machine Learning models allows for predicting upcoming environmental conditions alongside plant requirements including optimized watering programs and fertilization methods thus enabling automated operational optimization.

Smart systems implementation delivers several advantages which combine water and energy efficiency with lower operational expenses and better agricultural production results. The innovations benefit tomatoes specifically because they represent a high-demand crop which requires specific environmental conditions. Water management techniques which are efficient play an essential role in tomato farming because excessive or insufficient watering methods can harm yield production. The proper combination of fertilizers at the correct planting and harvesting times produces a substantial improvement in both tomato productivity and quality. A combination of IoT-based environmental monitoring with ML models solves these farming problems to establish sustainable production systems with higher yields.

The proposed research creates a Smart Greenhouse Decision Support System (DSS) for tomato cultivation through IoT integration with ML technology to enhance irrigation practices and disease control as well as improve fertilization and harvesting methods. The system enables farmers to use data-based choices which optimize greenhouse operations while reducing resource consumption.

2.2 Literature Survey

2.2.1 Decision Support Systems (DSS) in Agricultural Management

Decision Support Systems (DSS) represent computerized systems which utilize big data analysis for helping decision-makers find optimal solutions through dataset evaluation. The DSS platforms designed for agricultural management assist farmers with complex operations particularly in greenhouse environments. The DSS platform combines soil conditions together with climate data and crop development stage and resource consumption to generate optimal irrigation and fertilization and harvesting recommendations in tomato cultivation.

Research teams have established different types of DSS models which support greenhouse management operations. A fuzzy logic-based DSS system predicted the best environmental parameters for greenhouse tomato farming. Real-time sensor data and historical environmental data fed into this system to deliver recommendations about greenhouse condition control which optimized both yield production and energy utilization. Different researchers investigated multi-criteria decision-making (MCDM) approaches through algorithms that analyze environmental variables including temperature and humidity and light intensity to generate complete greenhouse management solutions [1][2].

2.2.2 Internet of Things (IoT) in Smart Greenhouses

Using IoT technology in smart greenhouses requires connected sensors together with actuators to track and manage environmental factors. Through its IoT framework the system collects data in real time for optimizing greenhouse operation management. IoT systems serve as monitoring mechanisms to track soil moisture alongside air temperature and humidity and light intensity which helps farmers enhance crop yields while optimizing resource usage [2][3].

A research project investigated an IoT-based system for tomato farm greenhouse management. A sensor network across the environment monitored soil moisture and pH levels and temperature readings which the system transmitted to a cloud-based platform for instant analysis and automatic decision processing. Through this system farmers could automate climate adjustments and irrigation functions according to established threshold values which led to water savings and improved production output [1][4].

The research presented an IoT platform linked to greenhouse control systems which optimized energy usage. The greenhouse HVAC systems operated through automated temperature and humidity sensor data to optimize plant growth conditions while reducing energy waste. The system demonstrates how IoT technology can decrease greenhouse operation energy usage while maintaining optimal crop environmental conditions [5].

2.2.3 Machine Learning (ML) in Greenhouse Management

Through the combination of IoT systems with Machine Learning in greenhouses operators can perform predictive analytics and make sophisticated decisions. Through analyzing extensive IoT sensor data ML models detect patterns which enable them to generate predictions that support the best practices for crop management. Through predictive models these systems forecast the amount of water required for future operations as well as the best harvesting periods and potential disease occurrences which allows for substantial efficiency improvements in greenhouse farming.

Research applied Artificial Neural Networks (ANN) under ML to forecast tomato growth phases when analyzing environmental factors such as temperature and light exposure along with moisture levels. The ANN model measured plant development stages through prediction and offered practical recommendations about fertilization and irrigation that allowed farmers to enhance their agricultural performance [5][6].

Scientists created a decision tree model which predicted the best harvest period for tomatoes by analyzing growth information combined with environmental factors. The model evaluated tomato fruit characteristics with environmental factors to identify the perfect harvesting period which resulted in higher crop quality and yield levels [7].

2.2.4 Disease Identification and Management in Tomatoes

The fungal and bacterial infections affecting tomatoes represent a major risk to both crop production quantity and product quality. The management of diseases requires efficient methods to ensure healthy crops alongside minimal chemical pesticide use. Laboratory tests together with visual inspections currently serve as disease detection methods yet they remain slow and imprecise. However, recent advancements in ML and computer vision offer new possibilities for early disease detection and treatment.

Multiple scientists have conducted work on developing ML algorithms alongside image processing methods for detecting diseases in tomatoes. Scientists created a CNN model which processed tomato plant leaf images to detect common diseases like blight and mildew. The AI-based system reached a disease identification accuracy level greater than 90% which reveals the potential of these systems to manage agricultural diseases [8][9].

Scientists have researched sensor-based systems which detect tomato diseases. The research team created an IoT-based system with sensors and cameras to track tomato plant health which detected diseases in their early stages. Through the combination of image analysis and real-time environmental data the system gave valuable recommendations for disease prevention and treatment [10].

2.2.5 Optimizing Irrigation and Fertilization in Greenhouses

The world faces an increasing water shortage problem so efficient irrigation methods become essential for maintaining sustainable greenhouse cultivation. Optimizing water supply in both excessive and insufficient quantities produces unfavorable outcomes for crop development. Many researchers have conducted extensive investigations on IoT-based smart irrigation systems that modify irrigation levels based on plants' current requirements.

The management of greenhouse tomato cultivation uses smart irrigation systems which connect soil moisture sensors with climate control algorithms to deliver water according to current environmental conditions. The analyzed systems demonstrated that they saved between 30 to 40 percent of water allocation without affecting crop productivity levels [11].

Crop productivity improvement receives main priority from researchers working on optimal fertilization practices. A research team built an IoT-based fertilizer management system which determined appropriate fertilizer delivery times and types through soil nutrient observation of planted crops. Through this system tomato producers achieved better production results and cut down their fertilizer expenses [12][13].

2.2.6 Environmental Sustainability in Greenhouse Agriculture

The main obstacle for greenhouse systems involves achieving environmental sustainability while maintaining resource consumption at acceptable levels. The environmental impact of greenhouses mostly depends on energy usage for heating and cooling together with water utilization and greenhouse carbon emissions. Multiple research investigations examine IoT and ML implementations as tools that advance sustainability within greenhouse agriculture.

Modern greenhouses serve sustainability purposes through their smart systems which help reduce climate control and irrigation system environmental impacts. The inclusion of automated shading systems along with solar-powered irrigation enables greenhouse operations to operate in an environmentally sustainable manner with minimal carbon emissions and excellent productivity levels [14].

3. RESEARCH GAP

The research integration between IoT and Machine Learning (ML) in greenhouse management remains incomplete because several essential difficulties and uncharted areas need attention to achieve optimal tomato farming outcomes. Presented literature includes extensive case studies and models although system connectivity remains inconsistent and real-time decision systems and adaptive environmental features remain insufficient. Several important research areas exist for the Smart Greenhouse Decision Support System (DSS) that addresses tomato cultivation.

3.1 Integration Of Iot And ML For Holistic Greenhouse Management

Research investigating IoT for environmental tracking alongside ML optimization of irrigation and fertilization and harvesting operations now exists in significant quantities. The fusion of IoT and ML technologies remains unaddressed through the development of an encompassing decision support system (DSS) which handles full greenhouse management needs.

Greenhouse managers currently operate with fractured systems that utilize separate parts (irrigation, fertilization and disease management) independently causing inefficient operations and inadequate decisions. Researchers have not yet developed the full integration of existing IoT and ML solutions into a single system which provides real-time comprehensive recommendations for managing the full lifecycle of tomato plants [16].

A tomato greenhouse in Sri Lanka operates independent irrigation platforms from those used for fertilization and pest control without integrated functionality. Manual data correlation between systems done by greenhouse operators causes production delays while increasing costs and reducing operational efficiency. A unified IoT-ML system will automate simultaneous real-time adjustments across every system which would offer a unified optimized environment for tomato cultivation [17].

3.2 Scalability And Adaptability Of Smart Greenhouse Systems

IoT and ML-based smart greenhouse solutions already exist but their testing primarily occurred in controlled environments and pilot studies. The extent of their compatibility with commercial greenhouses and changing environmental needs remains uninvestigated. The current implementations encounter problems during large-scale implementation because they struggle with excessive data volume and sensor malfunctioning and adapting to different regional climate zones.

The majority of research exists for small-scale greenhouses yet there is insufficient information regarding system scalability for commercial farming operations and adaptation to diverse environmental conditions across soil types and climate zones and infrastructure limitations. The research lacks clarity regarding specific designs that would enable smart greenhouse systems to function effectively across various actual agricultural environments [18].

The implementation of IoT sensors and ML models does not guarantee optimal tomato growth conditions for a large Mediterranean commercial greenhouse facility that experiences regular meteorological changes. The existing systems fail to integrate sudden weather changes together with soil nutrient fluctuations and regional agricultural practices which show major differences between different areas. A system requiring scalability and adaptability must be implemented to maintain continuous optimal performance in various environmental situations.

3.3 Real-Time Data Processing And Decision-Making

The current research lacks essential capabilities for real-time data processing which enables smart greenhouse systems to make immediate decisions. The vast data collection through IoT devices which includes temperature alongside humidity and soil moisture and light levels faces delays because many systems perform their analysis through periodic data batches.

The successful operation of greenhouse farms depends heavily on real-time decision-making since sudden climate changes require instant adjustments of irrigation and temperature and fertilization to prevent crop stress and yield reduction. Real-time data acquisition linked to instantaneous machine learning analytics and automated operational systems (such as irrigation system modifications and temperature control activation) represent an unsolved technological barrier [2][19].

When unexpected heatwaves strike a tomato greenhouse the facilities require immediate modifications to their temperature and humidity management systems. The crops experience adverse effects when the system lacks real-time processing capabilities because it leads to diminished quality and reduced yield. Real-time machine learning models should process incoming data to make instant decisions because this prevents losses from happening.

3.4 Disease Identification And Treatment Recommendations

Current research about machine learning models for disease identification in tomatoes centers on detecting diseases via image analysis and sensor data while disregarding treatment recommendation development. The identification of diseases remains essential yet so does the provision of practical recommendations that suit specific contexts for prevention and treatment purposes.

The current models detect particular diseases like blight and mildew but they fail to recognize all possible pathogens which attack tomato plants. The development of advanced multi-disease detection models should become a priority because they must identify multiple pathogens while providing specific treatment recommendations that include organic methods and integrated pest management techniques [17][20].

The greenhouse with tomato plants located in a disease-prone area faces difficulties identifying exact pathogens and finding suitable treatment options. The disease identification capability of image-based ML models does not extend to the generation of eco-friendly treatment recommendations or automated pest management protocols. Such an integrated system would detect diseases while generating immediate actionable treatment suggestions to enhance both disease control and minimize pesticide use.

3.5 Optimization Of Fertilization And Irrigation Systems

The optimization of IoT-based systems represents an important research area because current automation of irrigation and fertilization requires further development. Most modern irrigation methods use static schedule programs and set thresholds for moisture and nutrients which fail to consider plant development stages and environmental variations and distinctive tomato cultivar requirements. Real-time adaptive models should be developed to respond to the changing plant growth stages as well as environmental conditions for providing suitable recommendations.

A basic IoT system operating in a tomato greenhouse provides soil moisture-based irrigation however this system fails to recognize the distinct water requirements of tomatoes through different developmental phases. A standard fertilization program fails to detect shifts in plant nutrient requirements or changes in soil nutrient composition. The implementation of a dynamic irrigation and fertilization system that utilizes real-time environmental information will optimize resource management while reducing waste and enhancing crop health.

This section reveals multiple obstacles which prevent the successful integration of IoT and ML technologies to create efficient sustainable greenhouse tomato farming operations. The proposed Smart Greenhouse Decision Support System (DSS) for tomato cultivation addresses identified gaps to enhance irrigation and fertilization practices and disease management and harvesting which results in more sustainable and cost-effective and scalable greenhouse farming. This study seeks to connect missing elements by building a combined real-time adaptive system that both tracks conditions and predicts ideal tomato environmental specifications.

4. RESEARCH PROBLEM

Greenhouse farmers encounter multiple hurdles which affect their tomato yield quality while reducing quantity metrics. The rising global market demand for sustainable high-quality agricultural products requires greenhouse farming to adopt smart farming solutions. The worldwide important crop tomatoes need precise operational management of water together with sunlight exposure and temperature control as well as soil nutrient and relative humidity maintenance. Successful control of these environmental factors remains essential for developing optimally growing plants alongside efficient resource utilization and highest possible yield production.

4.1 Inconsistent Watering And Fertilization Practices

The primary issue faced by greenhouse tomato cultivators lies in their struggle to apply proper irrigation combined with fertilization patterns. Significant crop stress develops when a tomato plant gets too much or too little water which weakly affects both quality and yield results. Plant growth along with productivity suffers negatively when fertilization is performed incorrectly since it results in either nutrient deficiency or excess conditions. The current irrigation and fertilization management system depends on either fixed scheduling or human observation which results in resource waste and excessive operational expenses. The resulting poor plant conditions along with environmental waste occur when farmers apply excessive water and fertilizers [3].

The establishment of automatic systems requires immediate attention because they must monitor environmental factors to dynamically adjust irrigation and fertilization methods by processing live measurement inputs. An automated system holding dual benefits would protect natural resources while delivering precisely measured water and nutrients to plants during their development.

4.2 Disease Detection And Management

Tomato crops are susceptible to various **diseases**, such as **blight**, **mildew**, and **fusarium wilt**, which can significantly reduce yield and quality. Traditionally, the detection of these diseases is carried out manually or through basic visual inspection, which is often inaccurate and delayed. The ability to detect diseases early and provide timely recommendations for treatment is crucial to prevent widespread crop loss. However, current disease detection methods often lack **precision** and **real-time capabilities**, which leads to **inefficient use of pesticides** and delayed treatment [8].

Research Problem: A real-time machine learning system needs development to identify multiple tomato diseases along with their causes while providing specific treatment solutions. An integrated system should link the disease identification system with greenhouse management functions for quick responses and reduced environmental effects of pesticide usage.

4.3 Harvesting Optimization

A real-time machine learning system needs development to identify multiple tomato diseases along with their causes while providing specific treatment solutions. An integrated system should link the disease identification system with greenhouse management functions for quick responses and reduced environmental effects of pesticide usage.

Research Problem: There is a need to optimize harvesting schedules through a system that considers plant growth stages, environmental conditions, and external factors such as temperature and humidity. This system should be able to predict the ideal harvesting time for each tomato variety, maximizing yield, quality, and marketability.

Lack Of Integrated Decision Support Systems (DSS)

Present-day solutions for these challenges maintain separate systems which concentrate on individual aspects of the greenhouse management operations. These independent systems operate independently without delivering comprehensive solutions for greenhouse operators. Current tomato greenhouse management practices need to adopt an integrated Decision Support System which unites multiple sources together to deliver real-time data-driven decisions. A lack of such system produces inefficient manual handling of problems combined with delayed responses [1][6].

Research Problem: A substantial development gap exists in creating an inclusive DSS for greenhouse administration that would unite IoT environmental sensors with predictive ML analytics. The hybrid system would supply practical insights connected to irrigation methods and fertilizer application as well as disease prevention and harvesting that lets greenhouse operators execute decisions based on data.

Scalability And Adaptability

Current greenhouse management systems often fail to scale effectively to larger operations or adapt to diverse environmental conditions. Many existing systems have been tested in small-scale, controlled environments and do not account for the dynamic nature of larger commercial greenhouses, such as those exposed to varying weather conditions, different soil types, and fluctuations in climate. This lack of scalability and adaptability limits the widespread adoption of smart greenhouse technologies, particularly in developing regions [8].

Research Problem: There is a need to develop scalable and adaptable greenhouse management systems that can be customized to different types of greenhouses, climates, and crops. The system should also be cost-effective for commercial-scale operations, offering practical solutions for farmers in various geographical regions and climatic conditions.

4.4 Integration Of Sustainable Practices

The importance of sustainable agriculture rises as people fear more about environmental damage and natural resource use and climate change effects. Improper management of tomato greenhouses results in excessive water consumption and excessive synthetic fertilizer usage and pesticides alongside energy inefficiency. Long-term sustainability demands greenhouse farmers need to implement strategies which decrease environmental footprint while maximizing resource efficiency [11][12].

Research Problem: There is a need to incorporate sustainable farming practices into the smart greenhouse system. This includes integrating technologies that promote water conservation, reduce chemical usage, and enhance energy efficiency, all while maintaining high productivity. The system should support the use of eco-friendly fertilizers, organic pest management, and energy-efficient technologies to ensure sustainability in the long run.

The research tackles the present shortcomings which affect tomato greenhouse management operations. The challenges needed solution include proper irrigation designs and fertilizer applications and remedial actions for diseases along with scheduled harvesting times and comprehensive support systems and operations at scale and environmental conservation practices. The research develops a Smart Greenhouse Decision Support System (DSS) which integrates IoT technology and machine learning capabilities and sustainable farming practices to resolve current cultivation problems for increased productivity with efficient resource use and environmental sustainability in tomato farming.

5. RESEARCH OBJECTIVES

The research project develops a Smart Greenhouses Decision Support System (DSS) which combines IoT (Internet of Things) monitoring devices together with Machine Learning (ML) algorithms to optimize tomato cultivation. The system will design a Smart Greenhouses Decision Support System which will increase resource efficiency and yield optimization while managing diseases and promoting greenhouse sustainability. The main purpose is to create an all-encompassing system linking environmental data collection with predictive analysis and real-time response capabilities which helps greenhouse managers optimize their tomato operations.

5.1 Main Objective

The primary aim of this study involves developing and executing a Smart Greenhouse Decision Support System (DSS) that uses IoT technology to monitor environmental data in real-time along with machine learning (ML) algorithms for optimizing watering, fertilization, disease control and harvesting schedule operations. The designed system provides data-driven analytics to greenhouse operators which results in better resource management and higher yield and sustainability for tomato cultivation.

5.2 Specific Objectives

The specific objectives of the research project are as follows:

1. **Develop IoT-based Environmental Monitoring System:**
    - Design and implement an IoT system that can continuously monitor and collect environmental data from the greenhouse. This includes temperature, humidity, soil moisture, and light intensity.
    - Use the data collected by sensors to predict and optimize watering requirements for tomato plants.

2. **Optimize Watering Requirements Using Machine Learning:**
    - Develop and train machine learning models that predict the optimal water requirements for tomato plants based on real-time environmental data collected from the IoT system.
    - Create a decision support algorithm to ensure efficient water usage, minimizing wastage and ensuring that plants receive adequate moisture.

3. **Optimize Fertilization Schedules and Types:**
    - Develop an ML model that predicts the most effective fertilization schedules and types based on sensor data, including temperature and humidity, to enhance nutrient availability and promote healthy plant growth.
    - Automate the recommendation of fertilizer usage based on plant requirements, reducing excess fertilizer use and minimizing environmental impact.

4. **Develop Disease Identification and Treatment Recommendations:**
    - Create a machine learning model using **Convolutional Neural Networks (CNN)** to classify images of tomato plants and identify common diseases (such as blight, wilt, etc.).
    - Integrate disease identification with treatment recommendations, helping farmers take timely action to prevent the spread of diseases and maintain plant health.

5. **Optimize Harvesting Schedules:**
    - Develop a prediction model that uses environmental data and plant growth indicators to determine the optimal harvesting time for tomatoes, ensuring maximum yield and quality.
    - Provide actionable recommendations for harvesting schedules based on the plant's growth phase and environmental conditions.

6. **Integrate All Components into a Unified Web-Based Decision Support System:**
    - Develop a web-based dashboard where farmers can monitor real-time environmental data, receive automated recommendations for watering, fertilization, disease management, and harvesting.
    - Ensure the dashboard is user-friendly, accessible, and provides clear insights into the greenhouse conditions and plant needs.

7. **Test and Evaluate the System for Accuracy and Efficiency:**
    - Conduct rigorous testing and validation of the developed models (water requirement prediction, disease detection, fertilization optimization, etc.) to ensure their accuracy and reliability in real-world conditions.
    - Evaluate the system's effectiveness in improving the efficiency of greenhouse management practices and its scalability for large-scale tomato farming operations.

8. **Promote Sustainable Agricultural Practices:**
    - Ensure that the system incorporates sustainable practices in all components, from minimizing water usage to optimizing fertilizer application and reducing the use of harmful chemicals.
    - Encourage eco-friendly farming techniques that contribute to environmental conservation while boosting agricultural productivity.

These specific project objectives will establish a complete practical solution for tomato cultivation modernization which enhances productivity while making greenhouse management more efficient and sustainable and profitable.

6. METHOTOLOGY

The project methodology develops a Smart Greenhouse Decision Support System (DSS) with optimization features for tomato cultivation. Real-time environmental data collection through IoT (Internet of Things) devices enables the system to make decisions through Machine Learning (ML) algorithms. The main goal of this methodology combines environmental monitoring systems with predictive analytics and user-oriented decision support features to help greenhouse managers make optimized choices across different management operations such as irrigation, fertilization, disease control and harvesting.

6.1 Requirement Gathering And Analysis

The implementation success for the Smart Greenhouse Decision Support System depends on conducting proper requirement assessment and analysis for tomato cultivation. The section defines the hardware platform together with software requirements and functional specifications and user needs and personnel requirements and non-functional specifications and stakeholder considerations and implementation limitations.

6.1.1 Hardware/Software Requirements

Hardware Requirements: To implement the system efficiently, the following hardware components will be needed:

1. **IoT Sensors:**
    - **Soil Moisture Sensors:** Used to measure the moisture content in the soil to determine irrigation needs.
    - **Temperature and Humidity Sensors:** To monitor the ambient temperature and humidity levels inside the greenhouse.

- **Light Sensors:** To track the amount of light inside the greenhouse, essential for plant growth and photosynthesis.
- **Cameras (Optional):** For capturing images of plants to detect signs of diseases through image recognition.

2. **Microcontroller/Development Board:**
   - **ESP32** for integrating sensors and collecting data.
3. **Gateway Devices:**
   - **Wi-Fi routers** or **IoT Gateways** for transmitting data collected from sensors to the central processing unit or cloud server.
4. **Server/Cloud Platform:**
   - **Firebase** is used for storing and processing sensor data and hosting the decision support system .
5. **User Devices:**
   - Devices for accessing the Decision Support System (DSS) interface, including **PCs**, **laptops**, or **mobile devices**.

Software Requirements:

1. **Operating System:**
   - For server: **Linux** or **Windows Server**.
   - For user devices: **Windows**, **macOS**, or **Android/iOS**.
2. **Programming Languages:**
   - **HTML/CSS/JavaScript and Bootstrap** for the frontend development of the web application.
   - **Python** with **Flask** framework for backend development, ensuring seamless integration between the frontend and the database.

    - **Firebase** for cloud-based data storage and authentication.

3. **Database:**
    - **Firebase** as a cloud-based database for storing sensor data, user information, and historical records.

4. **Machine Learning Libraries:**
    - **Scikit-learn**, **TensorFlow**, or **PyTorch** for developing machine learning models.

6.1.2 Functional Requirements

Functional requirements define the core functionalities that the **Smart Greenhouse DSS** will support:

1. **Data Collection:**
    - The system must collect real-time data from various sensors (soil moisture, temperature, humidity, light).
    - Sensor data should be transmitted to the central Firebase database in real-time.

2. **Machine Learning Integration:**
    - The system should use machine learning algorithms to predict watering needs, optimal harvesting time, fertilization schedules, and disease detection.
    - ML models should be trained using historical and real-time data to provide actionable recommendations.

3. **Real-time Decision Support:**

- The system should provide real-time alerts and suggestions for greenhouse management, such as when to water plants, apply fertilizer, or harvest crops.
- Automated decisions based on sensor readings should be suggested for irrigation, fertilization, and disease management.

4. **User Interface:**
   - A **user-friendly interface** should be available for greenhouse operators to access the system on web or mobile devices.
   - The system should allow users to view real-time data, receive alerts, and access reports.
5. **Reporting and Analytics:**
   - The system should generate reports for the greenhouse operators, providing insights on resource usage, crop yield, and operational efficiency.
   - The system should allow users to view predictive insights and optimize farming strategies based on historical and real-time data.
6. **Disease Identification:**
   - The system should be able to detect common tomato plant diseases through image analysis (if cameras are included) or sensor-based environmental data.
7. **Data Visualization:**
   - Provide real-time graphical representations of environmental conditions and system alerts.
   - Visual analytics should allow users to monitor trends and patterns over time.

6.1.3 User Requirements

The user requirements focus on the needs of the stakeholders who will directly interact with the system. These include:

1. **Greenhouse Operators/Farmers:**
    - **Ease of Use:** The system should be intuitive and easy to use for greenhouse operators, with minimal technical knowledge required.
    - **Real-time Monitoring:** Operators need the ability to monitor real-time environmental conditions and receive actionable recommendations.
    - **Data Insights:** Operators require predictive insights on watering schedules, fertilization routines, disease management, and harvesting times.
    - **Mobile Compatibility:** Operators should be able to access the system via mobile devices for easy access in the field.
2. **Researchers/Technicians:**
    - **Data Access:** Researchers need access to historical data, machine learning model insights, and analytical reports to monitor the system's performance.
    - **Model Training:** Researchers should be able to modify and train machine learning models based on collected data.
3. **System Administrators:**
    - **System Configuration:** Admins should be able to configure sensors, calibrate the system, and monitor the status of the system's components.
    - **User Management:** Administrators must manage user access and permissions, ensuring that different users have appropriate access levels.

6.1.4 Personnel Requirements

The development and deployment of the Smart Greenhouse Decision Support System for Tomato Cultivation required the following personnel who focused on collecting real-world data for training the system's machine learning models while ensuring quality, knowledge, continuation and research integrity:

1. **Department of Agrarian Development in Sri Lanka**
2. **Mr. Krishantha Jayawardhana, Agrarian Services Center, Monaragala:**
    - Mr. Krishantha Jayawardhana served as the essential contact at Agrarian Services Center in Monaragala who provided access to authentic tomato greenhouse data. Soil moisture levels together with temperature and humidity measurements and additional environmental factors were contained in this dataset to develop accurate watering predictions and greenhouse management models.
3. **Department of Agriculture Sri Lanka**

The team's personnel supported both system functionality and model training with real-world data which improved prediction accuracy and effectiveness.

6.1.5 Non-Functional Requirements

These requirements describe the quality attributes that the system must satisfy:

1. **Performance:**
    - The system must be capable of processing real-time data and providing immediate recommendations with minimal latency.
2. **Scalability:**
    - The system should be scalable to accommodate different greenhouse sizes, from small scale to large commercial operations.
3. **Reliability:**
    - The system should operate continuously with minimal downtime. It must ensure the availability of critical features like real-time monitoring and alerts.
4. **Usability:**
    - The user interface should be simple, intuitive, and easy to navigate for users with varying levels of technical expertise.
5. **Security:**
    - The system should incorporate security measures to protect sensitive data, including encryption for data transmission and secure authentication for accessing the system.
6. **Maintainability:**
    - The system should be modular and maintainable, allowing for easy updates, bug fixes, and upgrades.

Stakeholders

Key stakeholders involved in the development and use of the system:

1. **Farmers/Greenhouse Operators:**
   The primary users of the system, benefiting from improved greenhouse management practices.
2. **Agricultural Research Institutions:**
   Research teams may use the system for studies on tomato cultivation and environmental optimization.
3. **IoT Hardware Manufacturers:**
   Suppliers of sensors, controllers, and other IoT components for the system.
4. **Software Development Team:**
   Developers responsible for creating the software and integrating it with hardware components.
5. **Investors/Commercial Partners:**
   Interested parties who may help fund the project or use the developed system for commercial farming ventures.

Constraints and Limitations

1. **Budget Constraints:**
   - The project may face budget limitations, particularly in acquiring high-end sensors, cloud infrastructure, and advanced machine learning tools.
2. **Hardware Limitations:**
   - The performance and accuracy of the sensors may be limited by the type and quality of the devices used.

3. **Data Availability:**
   - The system's accuracy and performance may depend heavily on the availability and quality of environmental data, which may not always be consistent.
4. **Network Connectivity:**
   - In remote areas with poor connectivity, transmitting real-time data from the greenhouse to the central system could pose a challenge.
5. **User Adoption:**
   - The system's effectiveness will depend on its adoption by farmers who may have limited technical knowledge or access to technology.

Feasibility Study

The feasibility study evaluates the **technical**, **economic**, and **operational** feasibility of the project:

1. **Technical Feasibility:**
   - The proposed hardware alongside software elements (backend uses Flask and data storage relies on Firebase) demonstrates proven availability in the market. The agricultural sector actively utilizes IoT technologies and researchers have applied machine learning models to similar problems with success.
2. **Economic Feasibility:**
   - The project is expected to provide cost savings for greenhouse operators by reducing resource wastage (water, fertilizers, and pesticides) and optimizing crop yield. While the initial investment in hardware and system development might be high, long-term savings and increased yields can justify the cost.

3. **Operational Feasibility:**

    - The system can be easily integrated into existing greenhouse operations. The decision support system will simplify decision-making for greenhouse operators and improve operational efficiency.

6.1.6. System Architecture

The Smart Greenhouse DSS will consist of the following key components:

1. **IoT-Based Environmental Monitoring System**
   The system will have sensors spread throughout the greenhouse to track environmental factors such as soil moisture alongside temperature and humidity and light intensity levels. The sensors will link to a central data collection system that uses LAN or Wi-Fi for sending collected data to the system which will analyze it.

2. **Machine Learning Models**
   The environmental data acquired by IoT sensors will undergo machine learning algorithm analysis to predict optimal conditions for greenhouse management operations. The ML models receive training through historical and real-time data to achieve their predictions.

    - Watering Prediction Model based on environmental factors.
    - Fertilization Optimization Model based on temperature and humidity.
    - Disease Identification Model based on image inputs using Convolutional Neural Networks (CNN).
    - Harvesting Prediction Model based on plant growth and environmental data.

3. **Decision Support System (DSS)**

   The DSS will combine ML model predictions into useful operational insights for greenhouse operators to use. The system will generate:

   - Real-time alerts (e.g., for watering, disease detection, or fertilization needs).
   - Detailed reports on optimal management practices (watering, fertilization, and harvesting).
   - Recommendations for action based on real-time environmental data and historical patterns.

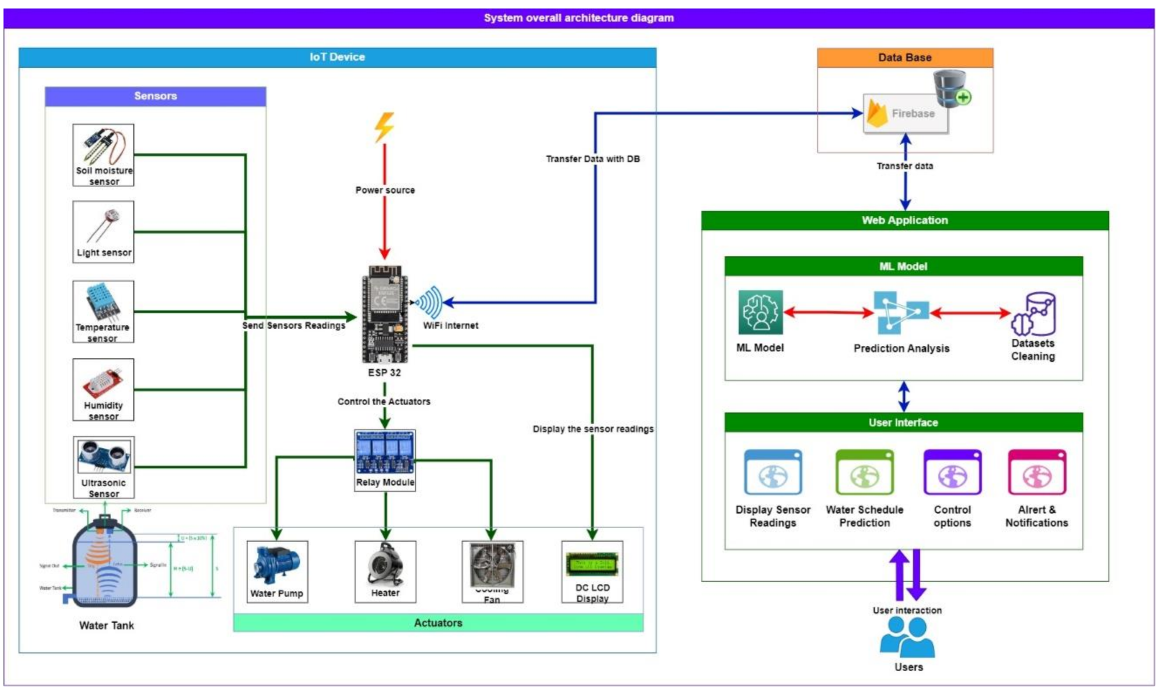

Figure 1 : Overall System Architecture Diagram

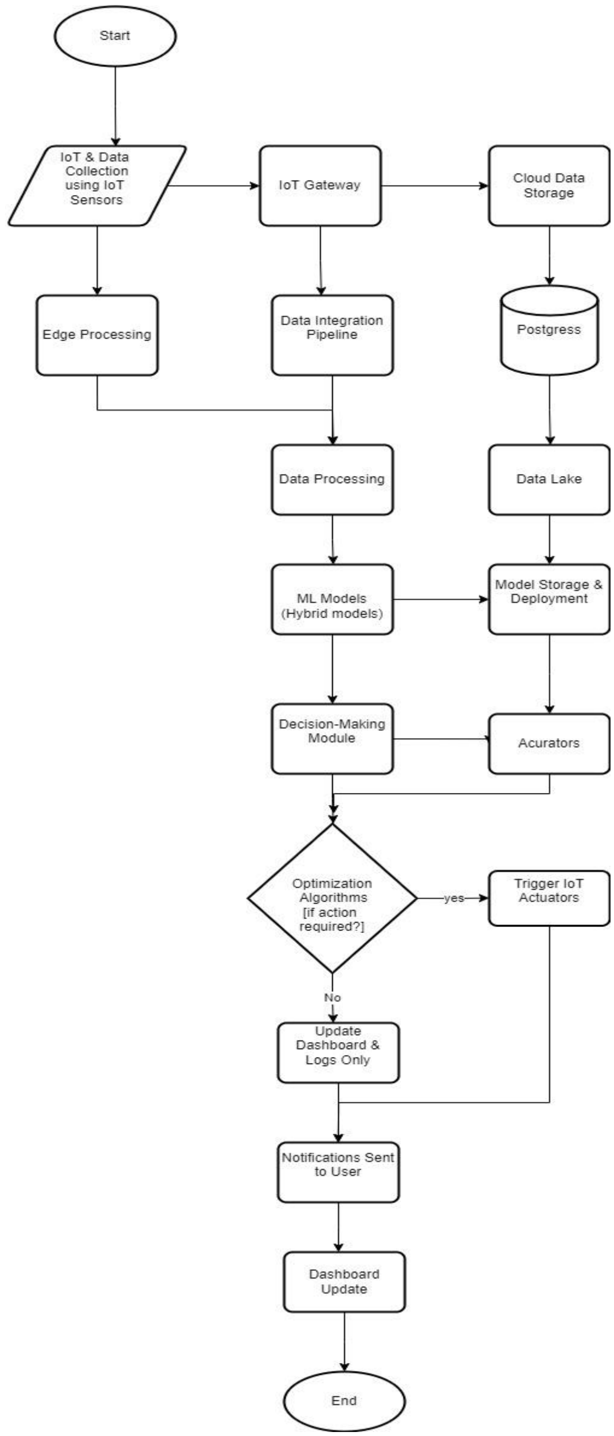

Figure 2 : Smart Greenhouse DSS Workflow

6.1.7. Data Collection

The system requires an essential data collection process to retrieve greenhouse environmental data via IoT devices. The acquired data will be utilized for machine learning training purposes to generate immediate recommendations.

1. **Environmental Sensors:**

    - Temperature Sensors: Measure the ambient temperature inside the greenhouse.
    - Humidity Sensors: Track the relative humidity levels.
    - Soil Moisture Sensors: Measure the moisture level in the soil to assess the watering needs of the tomato plants.
    - Light Intensity Sensors: Monitor the light conditions for optimal plant growth.

2. **Image Data for Disease Identification:**

    - Camera Setup: Cameras will be used to capture images of tomato plants for disease identification. These images will be processed by a CNN-based machine learning model to detect diseases.
    - The dataset of tomato plant images, including healthy and diseased plants, will be labeled and used for training the disease identification model.

3. **Data Transmission and Storage:**

    - The sensor data will be transmitted to a Firebase cloud-based server using Wi-Fi for low-power, long-distance communication.
    - The data will be stored and processed in a secure cloud environment, making it accessible for analysis and model development.

4. **Data Preprocessing:**

- Raw data will be cleaned and preprocessed to handle missing values, outliers, and noise.
- Feature scaling will be applied to normalize sensor data, ensuring consistency across different input variables.
- Image data for disease detection will undergo preprocessing techniques such as resizing, augmentation (flipping, rotating), and normalization before being used in the model.

Timestamp	Temperature (Â°C)	Humidity (%)	Soil Moisture (%)	Light Level (lux)	Water Level Needed (Liters)
11/1/2024 8:00	27.5	69.6	10.5	903	0.6
11/1/2024 9:00	39	69.5	36.5	1696	1.4
11/1/2024 10:00	34.6	34.6	17.1	966	0.8625
11/1/2024 11:00	32	54.7	48.4	1183	1.6125
11/1/2024 11:00	23.1	32.9	15.9	517	0.6875
11/1/2024 13:00	23.1	57.5	26.6	609	0.95
11/1/2024 14:00	21.2	52.1	13.4	1089	0.6
11/1/2024 15:00	37.3	74.4	49.9	1220	1.7125
11/1/2024 16:00	32	47.5	30.1	1400	1.15
11/1/2024 17:00	34.2	35.9	33.8	937	1.275
11/1/2024 18:00	20.4	37.1	12.7	1542	0.575
11/1/2024 19:00	39.4	68.1	40	1790	1.4875
11/1/2024 20:00	36.6	60.9	18.4	1670	0.9125
11/1/2024 21:00	24.2	35.1	45.9	559	1.45
11/1/2024 22:00	23.6	34.2	18.2	1221	0.75
11/1/2024 23:00	23.7	65	17.6	657	0.7375
11/2/2024 0:00	26.1	33.6	11.5	863	0.6125
11/2/2024 1:00	30.5	71.1	28.9	1980	1.1
11/2/2024 2:00	28.6	65.3	32.6	714	1.175
11/2/2024 3:00	25.8	34.1	12.6	1248	0.6375
11/2/2024 4:00	32.2	34.2	41	1427	1.425
11/2/2024 5:00	22.8	79.3	28.1	1554	0.9875
11/2/2024 6:00	25.8	48.7	31	1339	1.1
11/2/2024 7:00	27.3	48.5	27.6	515	1.025

Figure 3 : Environmental Data Set to Train the Model

6.1.8. Machine Learning Model Development

The machine learning models act as fundamental tools for predicting when to water along with optimal fertilization schedules and harvest times and disease detection. The model development process requires the following sequence of actions:

1. **Watering Requirement Prediction:**
    - Model Type: Regression model (e.g., Random Forest).
    - Input Variables: Temperature, humidity, soil moisture, light intensity, and plant count/area.
    - Objective: Predict the optimal water requirement (in liters) for the tomato plants based on real-time environmental data.

2. **Fertilization Optimization:**
    - Model Type: Regression or Classification model (e.g., Decision Trees, Support Vector Machines).
    - Input Variables: Temperature, humidity, fertilizer type, and amount.
    - Objective: Predict the ideal fertilization schedule (time and amount) to optimize plant growth and minimize resource wastage.

3. **Disease Identification:**
    - Model Type: Convolutional Neural Networks (CNN) for image classification.
    - Input Variables: Images of tomato plants (healthy or diseased).
    - Objective: Classify the plant images into categories (healthy or diseased) and provide recommendations for disease treatment.

4. **Harvesting Prediction:**

    - Model Type: Regression model or Time Series Forecasting model.
    - Input Variables: Environmental data, plant growth indicators (height, leaf area), and historical data.
    - Objective: Predict the optimal time for harvesting tomatoes to maximize yield and quality.

5. **Model Training and Tuning:**

    - The models will be trained using the data collected from the greenhouse.
    - Hyperparameter tuning will be performed to optimize model performance and accuracy.
    - Cross-validation will be used to evaluate the model's generalizability.

6.1.9 System Integration

Successful operation of the Smart Greenhouse Decision Support System requires proper integration of IoT system components and machine learning models and user interface elements.

1. **IoT and Cloud Integration:**

    - The data collected from IoT sensors will be sent to the cloud platform for processing.
    - The cloud will store real-time data and historical sensor readings, making them accessible for analysis and model predictions.

2. **Machine Learning and Web Interface Integration:**
    - The machine learning models will be integrated with the cloud-based platform to provide real-time predictions.
    - The results from the models will be sent to the **web-based dashboard**, where farmers can view them and take action.
    - The dashboard will display information such as recommended watering schedules, fertilization recommendations, disease alerts, and harvesting predictions.

3. **User Interface Design:**
    - A web interface will be developed for the system, which will allow farmers to interact with the system and receive actionable insights.
    - The UI will display real-time sensor data, predictions from machine learning models, and recommendations for greenhouse management.

4. **Testing and Evaluation:**
    - The integrated system will undergo testing to ensure proper communication between the IoT devices, cloud platform, machine learning models, and the web interface.
    - Performance testing will be conducted to evaluate the system's accuracy, response time, and usability.

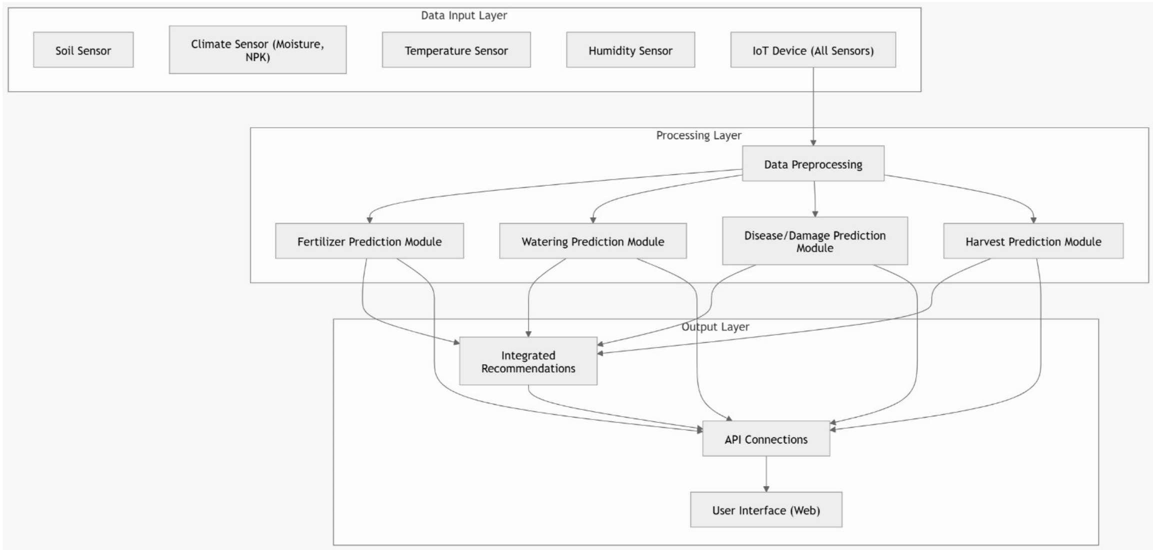

Figure 4 : Overall System Integration Flow Diagram

6.2 Commercialization Aspects Of The Product

The commercialization of the Smart Greenhouse Decision Support System for Tomato Cultivation requires the development of a research-based system into a marketable product available to tomato farmers and greenhouse operators. This part describes the essential commercialization methods and relevant market opportunities alongside necessary elements for product enlargement.

6.2.1 Market Analysis

The first step in commercialization is understanding the potential market for the system. The target market for the Smart Greenhouse Decision Support System includes:

- **Tomato Farmers:** Particularly those who operate greenhouses or other controlled environment agricultural systems. This product can benefit both small-scale farmers and larger, commercial greenhouse operators.

- **Agricultural Technology Providers:** Companies involved in providing solutions for greenhouse management, irrigation systems, and precision farming technologies may be interested in integrating this system into their existing product offerings.
- **Government and Agricultural Agencies:** Government bodies, agricultural departments, and NGOs may adopt the system for use in agricultural projects aimed at improving crop yield, efficiency, and sustainability, especially in developing countries like Sri Lanka.
- **Agricultural Research Institutions:** Institutions engaged in the development and testing of advanced agricultural technologies may find value in using the system for research and experimentation in real-world settings.

6.2.2 Value Proposition

The value proposition of the Smart Greenhouse Decision Support System lies in its ability to significantly optimize the critical factors influencing tomato cultivation:

- **Increased Yield and Quality:** By providing accurate predictions for watering, fertilization, and harvesting, the system helps farmers maximize yield and improve the quality of the tomatoes produced.
- **Resource Efficiency:** The system reduces the overuse of resources such as water and fertilizers, ensuring that these inputs are used in the most efficient way, which is both cost-effective and environmentally sustainable.
- **Disease Management:** By integrating disease identification and treatment recommendations, the system helps prevent crop losses due to common tomato diseases, thus reducing the need for expensive pesticides and treatments.
- **Real-Time Decision Support:** The system offers real-time insights based on current environmental data, enabling proactive management of the greenhouse conditions.

Product Development & Adaptation

To make the **Smart Greenhouse Decision Support System** commercially viable, the system will need to go through several stages of development and adaptation:

- **Prototyping and Validation:** The system functions at present in research settings but a prototype needs to be developed and tested within greenhouses for verification of its real-world effectiveness. The system development phase includes receiving feedback from farmers and operators of greenhouses for the purpose of refining the system.
- **User Interface (UI) Improvements:** The system's user interface should be intuitive and easy to use, particularly for farmers who may not be tech-savvy. The UI should be simplified and optimized for mobile devices as many farmers prefer using smartphones over desktop systems.
- **Integration with Existing Technologies:** The system will need to integrate seamlessly with existing agricultural hardware, such as irrigation systems, climate control units, and monitoring devices, in order to enhance its functionality and appeal to farmers who already use these tools.

6.2.4 Business Model and Pricing Strategy

The business model for commercialization will depend on the target market and the scale of the operation:

- **Subscription-Based Model:** The software along with maintenance updates can be accessed through a subscription payment system that generates continuous revenue flow. The subscription model divides its service into distinct levels which match greenhouse dimensions and operational needs (basic water management or complete system connection).

- **One-Time Purchase Model:** A one-time payment for the software, along with optional maintenance and support packages, could also be considered. This would appeal to farmers who prefer not to commit to ongoing payments.
- **Freemium Model:** A freemium model should be implemented to bring farmers into using the product. The basic version of the product offers necessary features including watering predictions but premium features such as disease management and fertilizer optimization require additional payment..
- **Hardware Sales:** If the IoT device requires specific hardware (sensors, controllers, etc.), these can be sold separately as part of the package, with installation and calibration services offered as additional paid services.

6.2.5 Marketing and Sales Strategy

To effectively commercialize the system, a robust marketing and sales strategy will be crucial. Key components of the strategy include:

1. The system can benefit from digital marketing through social media platforms together with agricultural technology forums and search engine optimization strategies to attract numerous potential customers. The system benefits can be explained through blogs and video tutorials and case studies which focus on environmental and economic aspects.
2. Strategic alliances between the company and agricultural bodies including government organizations and university institutions and industry leaders enable system promotion while building credibility. Real-world validation of the system could be obtained by implementing collaborative projects between agricultural research institutions.

3. Running field demonstrations together with workshops at agricultural expos and trade shows enables potential customers to see firsthand the advantages of adopting the technology.
4. Local Sales Representatives with knowledge about local farming practices must communicate system benefits to local farmers using their native language to establish trust and gain acceptance.

Scalability and Expansion

The scalability of the **Smart Greenhouse Decision Support System** is a key factor in its commercialization:

- **Adaptability to Other Crops:** While the initial focus is on tomatoes, the system can be adapted for other crops grown in greenhouses, such as peppers, cucumbers, or leafy greens. This could significantly expand the market potential.
- **International Markets:** The system demonstrates potential for worldwide growth. The company should focus its expansion efforts on countries operating extensive greenhouse facilities including the United States, Netherlands, Israel and selected regions of Asia. The system needs adaptation to particular environmental conditions together with local regulations in various countries for successful deployment.
- **Cloud-Based Platform:** To make the system more scalable, it could be offered as a cloud-based solution, allowing farmers to access the system remotely, manage multiple greenhouses, and receive real-time data from any location.

Funding and Financial Considerations

Initial funding for commercialization can be sourced from:

- **Government Grants:** Many governments offer grants for agricultural innovation and sustainable farming technologies, which could help fund initial commercialization efforts.
- **Venture Capital:** Once the product has been validated, venture capital firms that specialize in agritech may provide funding to scale the business.
- **Crowdfunding:** Crowdfunding platforms like Kickstarter or Indiegogo could be used to raise funds for the product, especially if the system has a strong social or environmental impact.

Ethical and Environmental Considerations

As part of the commercialization process, the ethical and environmental impacts of the system should be considered:

- **Sustainability:** The system should be marketed as a sustainable solution that helps farmers reduce their water and fertilizer consumption, contributing to more environmentally friendly farming practices.
- **Data Privacy:** As the system collects real-time environmental data, ensuring the privacy and security of users' data will be a critical aspect. Proper data protection policies and transparent privacy terms will need to be in place.
- **Social Responsibility:** The product should be designed to support smallholder farmers and improve food security. Ensuring that it is accessible to farmers in developing regions is an important ethical consideration.

The Smart Greenhouse Decision Support System for Tomato Cultivation demonstrates high commercialization potential because it efficiently improves greenhouse management operations to generate better crop production and resource conservation while preventing diseases. The product will revolutionize tomato farm and greenhouse operation through proper market selection and strategic pricing models alongside user-friendly design and adaptable features. The system will emerge as an indispensable technology tool when the agriculture sector implements widespread technology adoption.

6.3 Testing And Implantation

6.3.1 Implementation

The implementation phase requires full deployment of the Smart Greenhouse Decision Support System (SGDSS) in real greenhouse conditions including IoT device integration and machine learning model development and deployment for dashboard development. The deployment section describes how to implement the IoT system and machine learning models together with the web application for live greenhouse management.

6.3.1.1 IoT System Deployment

The Internet of Things (IoT) system functions as the primary framework for environmental monitoring and data acquisition in greenhouse facilities. Real-time environmental data is acquired through IoT devices such as temperature, humidity, soil moisture and light sensors which have been installed and configured correctly.

Key Steps for IoT System Deployment:

1. **Sensor Installation:**
   Sensors are strategically placed within the greenhouse to monitor various environmental parameters essential for tomato growth. These sensors include:

   - Temperature Sensors: Measure ambient temperature to ensure optimal climate conditions.
   - Humidity Sensors: Monitor the relative humidity of the greenhouse.
   - Soil Moisture Sensors: Measure the moisture levels in the soil to determine irrigation needs.

- Light Intensity Sensors: Track light levels, which are crucial for photosynthesis and overall plant growth.

2. **Microcontroller Setup:**
   The system uses microcontrollers ESP32 as a connection between sensors and the system. The devices obtain sensor data which they upload to a cloud-based server through Wi-Fi or cellular data connections. The microcontroller transmits information to the Firebase cloud database service for data processing and storage.

3. **Connectivity and Data Transmission:**
   The sensors use either analog or digital interfaces to connect with the microcontroller. The sensors transmit their data to Firebase through the internet as the cloud server. The machine learning model uses processed data to generate instantaneous advice about irrigation and fertilization procedures and disease control methods.

4. **System Calibration and Testing:**
   The sensors need calibration to produce precise measurement results. Sensor accuracy for environmental measurement depends on calibration procedures to adjust their performance. The IoT system undergoes tests to verify its functionality in gathering data and transmitting it to the storage platform.

Machine Learning Model Development, Integration, and Dashboard Development

- Machine learning (ML) models are at the heart of the **Smart Greenhouse Decision Support System**, as they provide the core decision-making capabilities. The models are developed to predict watering schedules, recommend fertilization, and identify potential diseases based on sensor data.

Key Steps for Machine Learning Model Development:

1. **Data Collection:** The collected environmental data from the IoT sensors (temperature, humidity, soil moisture, light intensity) are fed into the system for

processing. A real-time stream of data is essential to keep the ML models up to date and ensure predictions are accurate.

2. **Feature Engineering and Data Preprocessing:** Raw data is preprocessed to ensure it is suitable for machine learning analysis. This process involves several key steps:
   - **Handling Missing Values:** If any data is missing or corrupt, it is either imputed or removed.
   - **Feature Scaling:** Scaling numerical data to ensure all features contribute equally to the model. Common techniques include Min-Max Scaling or Standardization.
   - **Feature Augmentation:** New features may be derived from the raw data, such as calculating rolling averages for temperature or humidity to capture trends over time.
3. **Model Selection and Training:** Multiple machine learning algorithms are tested to identify the best one for predicting the optimal irrigation schedule, fertilization plan, and disease detection. Possible algorithms include:
   - **Linear Regression** for predicting continuous variables (e.g., soil moisture, temperature).
   - **Random Forest** for classification tasks, such as detecting diseases or categorizing environmental conditions.
   - **Support Vector Machines (SVM)** and **K-Nearest Neighbors (KNN)** are also tested for their effectiveness in prediction tasks.

The chosen model uses historical data for training purposes to enhance its predictive capabilities for important outcomes. The model receives continuous training through repeated evaluations using validation data.

4. **Model Evaluation:** After training the model, it is evaluated on a separate test dataset to assess its performance. The following metrics are typically used to evaluate the model:
    - **Accuracy:** For classification models (e.g., disease detection).
    - **Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE):** For regression models predicting continuous values like moisture levels.
    - **Precision and Recall:** To assess the model's ability to identify relevant patterns, particularly for tasks like disease detection.

The evaluation helps ensure the model generalizes well to unseen data and provides accurate predictions that greenhouse operators can rely on.

6.3.1.4 Data Preprocessing, Feature Scaling and Data Augmentation

Data Preprocessing is a critical step to ensure that the raw environmental data collected by the sensors is clean, consistent, and usable for machine learning algorithms. This process prepares the data for model training and enhances the model's ability to learn from it.

1. **Feature Scaling:** Machine learning algorithms often perform better when numerical data is on a similar scale. **Feature scaling** involves transforming features (data columns) into the same scale, such as normalizing the data to a range between 0 and 1 (using Min-Max Scaling) or standardizing it to have a mean of 0 and a standard deviation of 1 (using Z-score normalization). For example, the temperature values ranging from 15°C to 35°C will be scaled so that all features contribute equally to model training.
2. **Feature Augmentation: Feature augmentation** involves creating new features from existing data to help improve the model's performance. For example:

- Rolling averages can be used to smooth out short-term fluctuations in sensor data, such as humidity or temperature, and better capture long-term trends.
- **Time of day or seasonal trends** could be introduced as features, as temperature or watering needs often follow daily or seasonal patterns.

These steps make the dataset richer and more informative, leading to better model predictions.

Model Selection and Training

The subsequent stage of work involves both selecting and training the model. The trained machine learning algorithms receive preprocessed data for condition prediction of optimal greenhouse operations. During training the model receives historical sensor information which enables it to discover interconnections between environmental factors and desired results (watering schedule and disease identification).

1. **Model Selection:** After testing several machine learning algorithms, the model that best meets the needs of the project (in terms of accuracy and efficiency) is chosen. For example:
   - **Random Forest** might be chosen for its ability to handle both regression and classification tasks.
   - **Neural Networks** could be implemented for more complex, nonlinear relationships between variables.
2. **Model Training:** The training phase involves using the historical data to adjust the model's internal parameters. This process can take time, depending on the size of the dataset and complexity of the model. During this stage, the model learns to predict the desired outcomes based on the input features.

Model Evaluation

Once the machine learning model is trained, it is evaluated on a test dataset to assess its performance in a real-world scenario:

- **Accuracy** measures how well the model can predict the correct outcomes.
- **Precision, Recall, and F1-Score** help evaluate the effectiveness of the model in identifying relevant categories (such as disease classification).
- **Root Mean Squared Error (RMSE)** or **Mean Absolute Error (MAE)** measures the accuracy of continuous predictions, such as optimal watering levels.

The model evaluation phase helps identify any weaknesses or areas for improvement, ensuring the system can reliably support greenhouse decision-making.

Integration with Web Application

Finally, the machine learning model is integrated with the **web-based dashboard** for real-time monitoring and decision support. The web application is developed using HTML, CSS, JavaScript, and the Flask framework. The integration process involves:

- **Connecting the Machine Learning Model to the Backend:** The trained model is deployed on the server, where it continuously receives data from the IoT devices, processes it, and generates real-time predictions.
- **Displaying Results on the Web Dashboard:** The predictions and recommendations generated by the machine learning model are displayed on the user-friendly web interface. The dashboard provides greenhouse operators with insights into watering needs, disease status, and optimal harvesting times.
- **Real-time Data Visualization:** The dashboard includes real-time data visualization of environmental parameters (temperature, humidity, soil moisture, light intensity) and any recommendations generated by the model.

The Smart Greenhouse Decision Support System needs implementation through IoT device deployment for environmental monitoring and machine learning model development and user-friendly web dashboard integration targeted at farmers. Machine learning model development and careful deployment as well as data preprocessing and web application integration with the system will lead to optimized tomato cultivation greenhouse management and improved efficiency and yield.

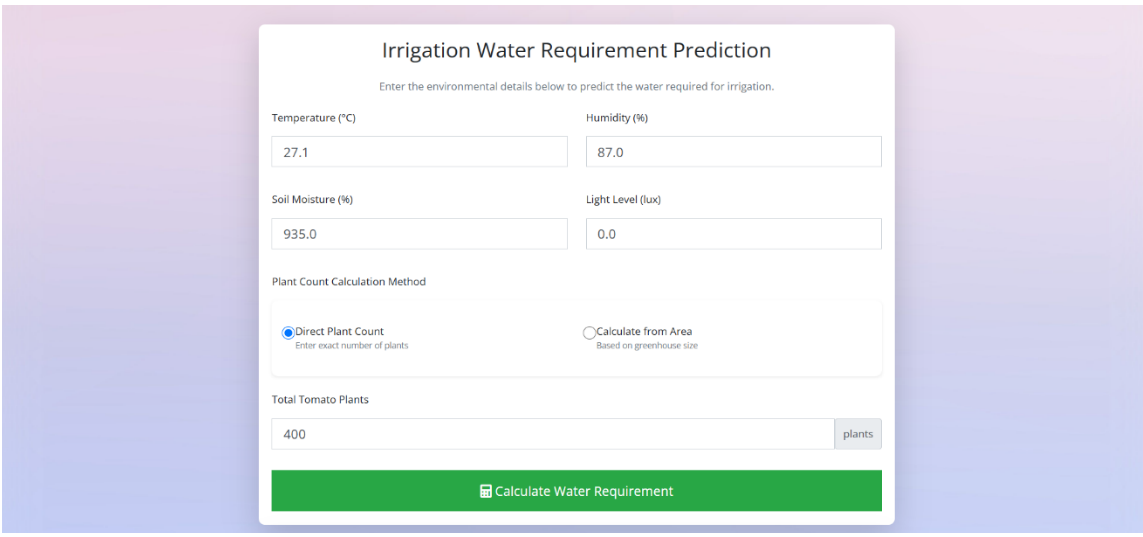

Figure 5 : Water Requirement Prediction UI

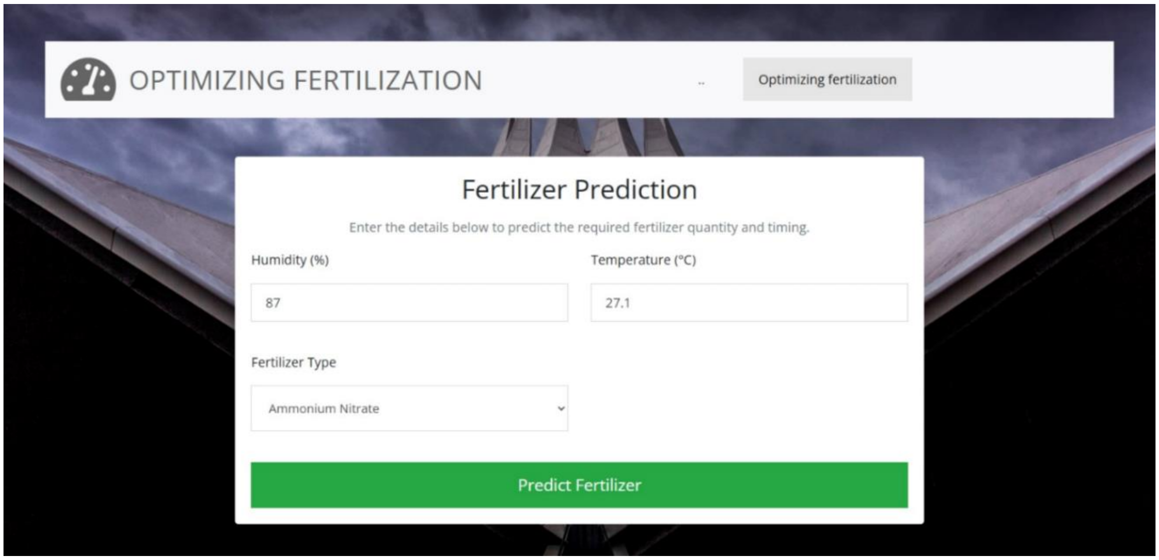

Figure 6 : Fertilizer Prediction UI

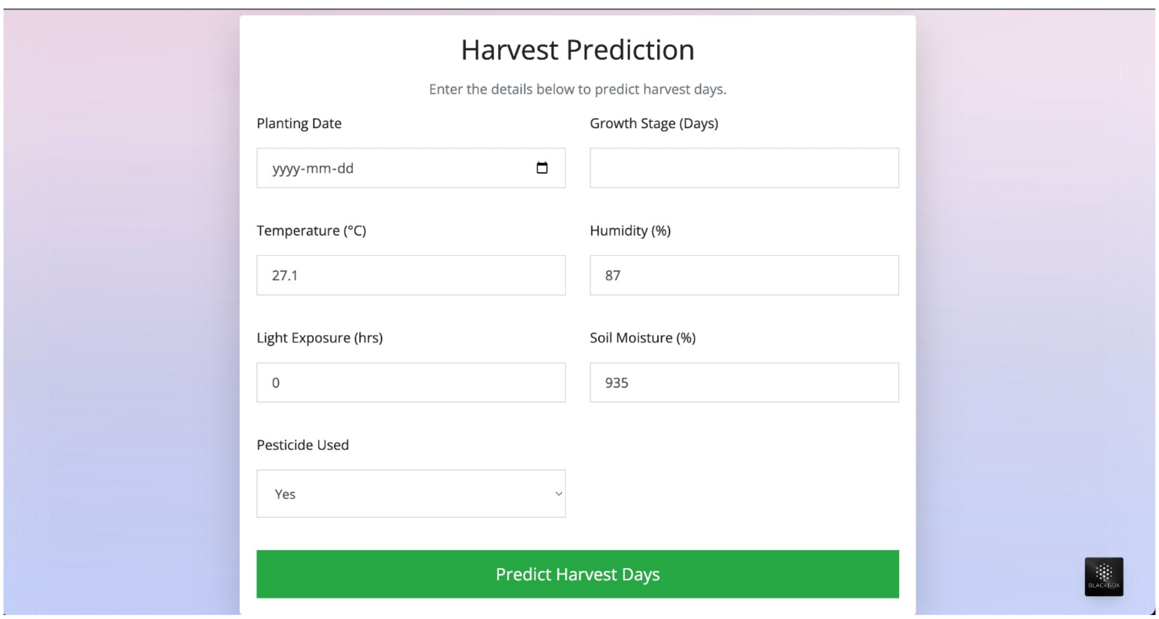

Figure 7 : Harvest Days Prediction UI

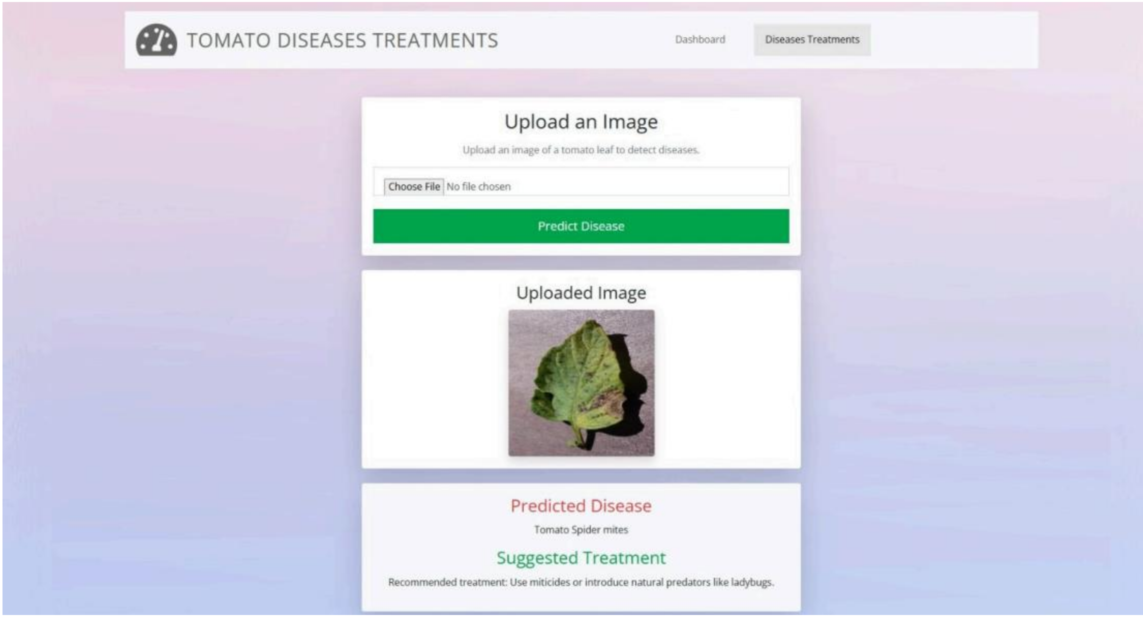

Figure 8 : Diseases Prediction UI

6.3.2 Testing

Testing stands as a vital stage during project development to verify component functionality as well as compliance with system requirements and the delivery of dependable results. The testing phase confirms that both the IoT-based greenhouse system functions properly alongside the accuracy and performance of the machine learning models. The web application undergoes complete testing which guarantees both user-friendly performance and system integration.

The Testing Phase is divided into different levels:

1. Unit Testing for individual components.
2. Integration Testing to ensure seamless interaction between subsystems.
3. System Testing to validate the overall functionality of the system.
4. User Acceptance Testing to evaluate the system from the end-user perspective.

Manual Test Cases for Each Member's Component

1. Azees Asardeen (Watering Requirements Prediction and IoT-based Environmental Monitoring)

Table 1 : Test Case 1: IoT Device Data Collection and Transmission

Test Case Id	01
Test Description	Verify that the IoT system collects environmental data (temperature, humidity, soil moisture) and transmits it to the database (Firebase).
Precondition	The IoT device and sensors are connected and running.
Test Steps	1. Ensure the IoT device is powered on. 2. Collect sensor readings for temperature, humidity, and soil moisture. 3. Verify that the data is being transmitted to Firebase.
Expected Result	Sensor data should appear in the Firebase database in real-time without any data loss.

Table 2 : Test Case 2: Watering Requirement Prediction

Test Case Id	02
Test Description	Verify that the machine learning model predicts the optimal watering amount based on environmental data.
Precondition	The model is trained with historical environmental data.
Test Steps	1. Provide real-time environmental data from IoT sensors (temperature, humidity, soil moisture). 2. Ensure that the ML model processes the data and predicts the watering amount (in liters).
Expected **Result**	The system should display the recommended watering amount

Table 3 : Test Case 03: Plant Count Calculation

Test Case Id	03
Test Scenario	Verify area-based plant count calculation
Precondition	Greenhouse area = 100m², Plant gap = 1.5m
Input	Select ‘Calculate from Area’ method and enter 100m², and the Plant gap = 1.5m
Expected Output	System computes ≈44 plants ($100/1.5^2$)
Actual Result	Calculated 44 plants
Status (Pass/Fail)	Pass

2. Jayaneththi I.H.N.S. (Harvesting Schedule Prediction)

Table 4 : Test Case 4: Harvest Time Prediction

Test Case Id	04
Test Description	Verify that the model predicts the optimal harvesting time based on environmental conditions.
Precondition	The system is trained with data on optimal harvesting conditions.
Test Steps	1. Simulate environmental data (e.g., temperature, humidity) for tomato growth stages. 2. Check the predicted harvest time for tomatoes.
Expected **Result**	The system should provide a dates and time window for optimal harvesting

Table 5 : Test Case 5: Harvesting Decision Support in Dashboard

Test Case Id	05
Test Description	Ensure that the harvesting recommendation appears correctly in the web dashboard.
Precondition	Data for optimal harvesting time is available.
Test Steps	1. Verify the display of the optimal harvest date on the dashboard. 2. Ensure the harvesting recommendation aligns with environmental conditions.
Expected **Result**	The dashboard should display the predicted harvesting schedule.

3. Thrimavithana V.D. (Fertilization Schedule and Type Optimization)

Table 6 : Test Case 6: Fertilization Recommendation Generation

Test Case Id	06
Test Description	Verify that the ML model recommends the optimal fertilization schedule and type based on the plant growth data and environmental conditions.
Precondition	Historical data for fertilization is available in the training set.
Test Steps	1. Simulate environmental data (temperature, humidity, soil pH). 2. Check the fertilizer Time and quantity recommendation from the ML model.
Expected **Result**	The system should display the correct fertilizer Time and amount for optimal growth.

Table 7 : Test Case 7: Fertilization Recommendation in Dashboard

Test Case Id	07
Test Description	Verify that the fertilization recommendations appear correctly on the web dashboard.
Precondition	The recommendation is generated by the ML model.
Test Steps	1. Check the dashboard for fertilizer recommendations. 2. Ensure that it includes the right type, Temperature, and Humidity.
Expected **Result**	The dashboard should display accurate fertilization recommendations.

4. Najas M.N.M. (Disease Identification and Treatment Recommendations)

Table 8 : Test Case 8: Disease Detection Using Machine Learning Model

Test Case Id	08
Test Description	Verify that the system accepts a tomato plant image, processes it using the trained CNN model, and predicts the presence of disease.
Precondition	CNN model is trained with labeled tomato disease image datasets.
Test Steps	1. Open the disease detection module on the web dashboard. 2. Upload a tomato plant image with visible disease symptoms (e.g., leaf spots, discoloration). 3. Submit the image for analysis.
Expected **Result**	The system should output the disease name (e.g., *Tomato Leaf Mold*, *Early Blight*, *Late Blight*, etc.) or state that the plant is healthy.

Table 9 : Test Case 9: Disease Detection and Treatment Recommendation on Dashboard

Test Case Id	09
Test Description	Test the CNN model's ability to detect various types of tomato plant diseases using test images
Precondition	Dataset includes multiple tomato diseases, and the model has been trained on all classes.
Test Steps	1. Upload a series of test images with different tomato plant diseases. 2. Record the model's predictions for each image. 3. Compare the predictions to the known labels.
Expected **Result**	The model should correctly classify each disease with high accuracy (e.g., >85%).

Testing is critical to ensure the system works as expected and meets the objectives of the project. Manual test cases for each component will verify the functionality of the IoT system, machine learning models, and web application. By performing these tests, we can ensure that the Smart Greenhouse Decision Support System is reliable, accurate, and user-friendly, providing value to greenhouse operators by optimizing environmental conditions for tomato cultivation.

7. RESULTS & DISCUSSION

7.1 Results

The Smart Greenhouse Decision Support System operated successfully because it unified IoT sensing technologies with machine learning models and web-based dashboard functionality into a single integrated platform. This system delivers time-sensitive knowledge and automatic suggestions for vital tomato greenhouse cultivation features like irrigation and fertilization and harvesting and disease control.

The system delivers its essential results through these following points:

1. Environmental Data Monitoring

- The IoT system continuously collected real-time data regarding greenhouse environmental temperature and humidity and soil moisture levels and light intensities. The gathered data successfully reached and got stored on a central server for analysis purposes.

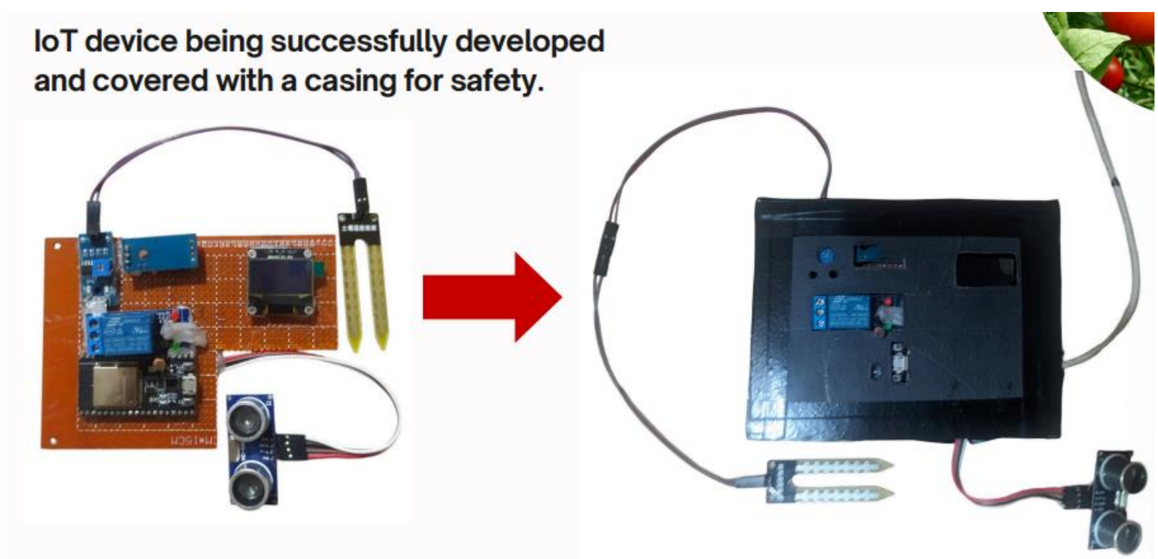

Figure 9 : Final IoT Device for Collecting Environmental Data

2. Water Requirement Prediction

- The developed machine learning regression system predicts water usage in liters each day through analysis of environmental data and plant counts or greenhouse space measurements. The implementation of this model produced precise results which helped avoid both excessive watering and inadequate water supply and fostered water conservation together with healthy plant growth.

3. Fertilizer Recommendation System

- An intelligent decision model for fertilizers analyzed environmental factors together with types of fertilizers to recommend suitable fertilizer mixes and timing based on specific conditions. Through this system the researchers achieved availability of required nutrients together with reduced expense from unnecessary substance use.

4. Harvesting Time Prediction

- Real-time and historical sensor data allowed the system to predict the perfect timing for tomato harvests. The system led to maximum yield production and perfect fruit ripening and extended shelf life which improved market preparation capability while decreasing post-harvest waste.

5. Tomato Disease Identification

- The system employed a CNN model to analyze tomato plant images that enabled disease identification of major plant ailments including Early Blight alongside Leaf Mold and Leaf Curl Virus. The model gave specific treatment instructions that enabled teams to make early effective interventions.

6. Dashboard Integration

- The web interface delivered all modules as a single user-friendly interface that integrated seamlessly. Through the dashboard platform users could view live environmental data while receiving ML predictions and disease alerts and accessing agricultural recommendations.

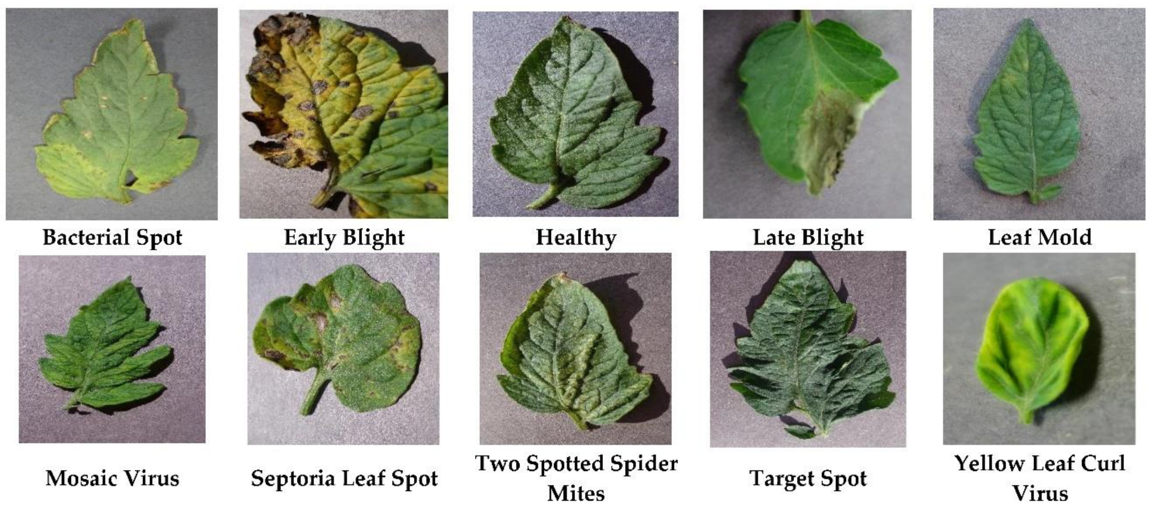

Figure 10 : Tomato Plant Diseases Samples

7.2 Research Findings

The analysis together with implementation of the smart greenhouse system generated multiple essential findings and research outcomes which include:

1. Accuracy and Reliability of ML Models

- The machine learning models demonstrated excellent validation results during test data assessments. The water prediction model demonstrated an R^2 score higher than 95% whereas the CNN-based disease detection model obtained classification accuracies which exceeded 98%. These findings demonstrate that ML applications are practical for agricultural use in supporting decisions.

2. Impact on Resource Optimization

Predictive analytics enabled the system to provide the following benefits:

- A 15–25% reduction in water usage
- More efficient and targeted fertilizer applications

The optimized collection time leads to better crop quality by delivering premium yields.

The system enabled early diseases detection to stop significant crop losses and large-scale outbreaks.

3. Real-Time Decision Support

- The system provided instant decision support capabilities which allowed managers to react swiftly to environmental changes. The system provides valuable information in greenhouse farming which becomes indispensable because minor environmental variations strongly affect plant health.

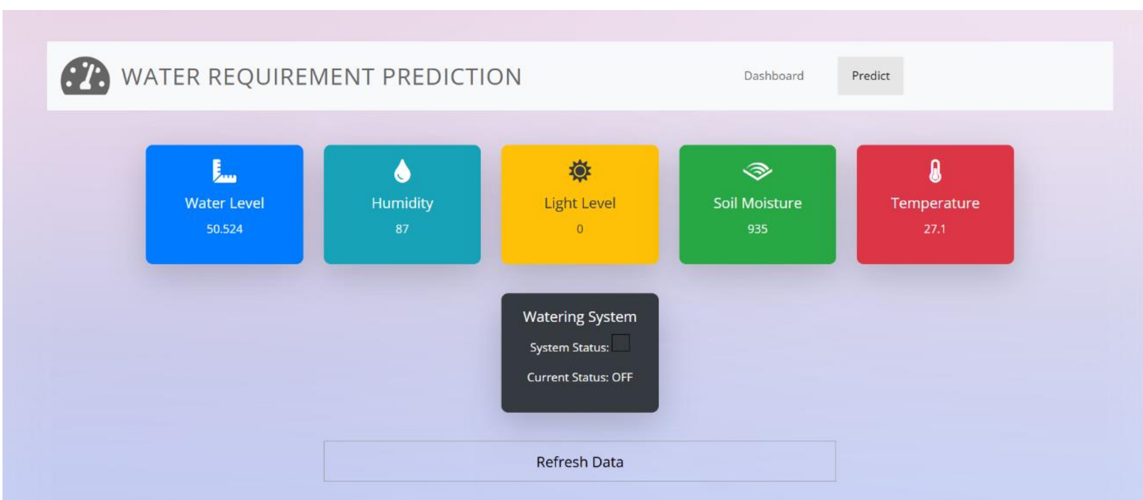

Figure 11 : Environmental Sensors Live-data Showing UI

4. Usability and Accessibility

- Farmers and greenhouse managers found the web dashboard simple to use which allowed them to access real-time data and predictions conveniently. The system displayed visual information through practical methods which made it suitable for immediate implementation.

5. Data-Driven Agriculture

The findings affirm that integrating IoT and ML in greenhouses leads to **data-driven farming practices**. This technological synergy supports precision agriculture, reduces manual labor, and promotes environmentally responsible cultivation.

7.3 Discussion

The research findings support the main objective of creating an automated smart resource-efficient farming system for conventional tomato greenhouses. The subsequent analysis details the effects and limitations together with the future prospects of this system.

Effectiveness of ML & IoT Integration

The integration of ML models with IoT sensor networks proved to be effective for real-time monitoring and predictive analytics. The models leveraged historical and current sensor data to make actionable recommendations. This closed-loop feedback system empowers farmers to make informed decisions with minimal guesswork.

Scalability and Adaptability

The system is designed with modularity, allowing it to scale with additional crops, new models, or extended greenhouses. The models can be retrained with data from different regions, climates, or plant species, offering **flexibility and adaptability** for broader agricultural applications.

Environmental and Economic Impact

The data-driven approach resulted in reduced water and fertilizer usage, contributing to environmental sustainability. Additionally, early disease detection and optimal harvest planning reduce financial losses and increase profitability for farmers. This aligns well with global goals of **sustainable agriculture** and **food security**.

Challenges Faced

During development and deployment, several technical and practical challenges were encountered:

- Sensor calibration was initially inconsistent due to environmental interferences.
- Model performance required iterative tuning and validation with domain experts.
- Reliable internet connectivity was a concern for remote greenhouses.
- CNN-based disease detection was sensitive to lighting and image clarity, requiring controlled image acquisition settings.

These challenges were addressed through rigorous testing, preprocessing techniques, expert consultation, and by implementing fallback mechanisms for offline operations.

Future Considerations

For extended impact and adoption, the system can be enhanced with:

- **Mobile app support** for field-level access
- **Automated irrigation and fertilization systems** connected directly to ML outputs
- **Cloud-based model updates** for better model retraining and performance improvement
- **Multilingual interface** for localized user experience

8. SUMMARY OF EACH STUDENT'S CONTRIBUTION

The success of the Smart Greenhouse Decision Support System project was driven by the collaborative effort of the team members, each contributing their expertise to different components of the system. Below is a summary of the contributions made by each member:

1. Azees Asardeen (IT21231896)

- **Role and Contribution:** Azees Asardeen focused on developing the IoT Device and Machine Learning (ML) model for water requirement prediction and environmental monitoring within the greenhouse.
    - **IoT Development:** Designed and implemented the system for real-time environmental monitoring using IoT sensors to capture temperature, humidity, soil moisture, and light intensity data.
    - **Watering Requirement Model:** Developed a machine learning model to predict the optimal watering requirements for tomato plants based on environmental factors such as temperature, humidity, soil moisture, and light intensity.
    - **System Integration:** Worked on integrating the IoT devices with the machine learning models, ensuring smooth communication between the data collection layer and the predictive models.
    - **User Interface (UI):** Contributed to the development of the user interface where farmers could view real-time data and receive actionable insights, such as watering schedules and recommendations.

2. Jayaneththi I.H.N.S. (IT21231414)

- **Role and Contribution:** Jayaneththi I.H.N.S. was responsible for optimizing the harvesting schedules to maximize yield and quality, an essential aspect of the greenhouse system.

- **Harvesting Prediction Model:** Developed a machine learning model that predicts the ideal time for harvesting based on plant growth indicators and environmental conditions. This model helps farmers determine the optimal harvest period for tomatoes to ensure the highest yield and quality.
- **Data Collection and Analysis:** Worked closely with sensor data related to environmental factors to ensure the harvesting model was accurate and based on real-time data.
- **System Integration:** Integrated the harvesting prediction model with the overall system, ensuring that the harvesting recommendations were accessible on the dashboard for the user.

3. Thrimavithana V.D. (IT21181160)

- **Role and Contribution**: Thrimavithana V.D. focused on fertilization optimization to improve nutrient availability and support robust tomato plant growth.
  - **Fertilization Model Development:** Designed and implemented a machine learning model to predict the best fertilization schedules and types based on sensor data (temperature, humidity) and different types of fertilizers used.
  - **Fertilizer Optimization:** Developed algorithms that analyzed environmental data and fertilizer inputs to recommend the ideal fertilization routines and quantities for optimal plant growth.
  - **System Integration:** Contributed to integrating the fertilization optimization model into the system and ensured that the recommendations were displayed on the dashboard for easy access by farmers.

4. Najas M.N.M. (IT21186592)

- **Role and Contribution:** Najas M.N.M. worked on disease identification and treatment recommendations using machine learning, specifically employing Convolutional Neural Networks (CNN) for image-based disease detection in tomato plants.
    - **Disease Detection Model:** Developed and trained a CNN model to identify common diseases in tomato plants by processing images of plants. The model classified the plants as either healthy or diseased, and provided treatment recommendations based on the detected disease.
    - **Data Collection:** Collected a dataset of tomato plant images, labeled them, and prepared them for training the disease identification model.
    - **Integration of Disease Detection:** Integrated the disease identification system with the dashboard, ensuring that disease alerts and treatment recommendations were accessible to farmers in real-time

Collaborative Efforts:

All team members operated in unison during project execution to merge their independent components into the complete system structure. The project team held consistent meetings to examine progress and resolve technical difficulties as well as maintain effective coordination between different modules. The team achieved a complete efficient greenhouse management decision support system through their combined expertise in IoT and machine learning and web development.

All team members played essential roles to develop this system which maximizes water management alongside fertilizer distribution and harvest procedures and disease control functions resulting in enhanced sustainable tomato cultivation techniques.

9. CONCLUSION

The Smart Greenhouses Decision Support System for Tomato Cultivation project uses an integrated approach of IoT and Machine Learning to enhance vital tomato farming operations such as watering and fertilization and harvesting and disease control. The system uses real-time environmental measurements to calculate precise watering requirements which provides both water efficiency and good plant health outcomes. Harvesting optimization through this feature enables users to determine perfect harvest periods which leads to better yields.

The project built a fertilizer optimization system which recommended optimized fertilization practices through environmental condition analysis and developed a disease detection model through CNNs that diagnosed tomato plant diseases and suggested treatments.

The research shows that IoT and ML technologies will transform greenhouse management through data-based solutions which support sustainable farming practices. Future development of this system should focus on adding support for additional crops and implementing better models with increased data availability together with sustainable farming practices.

Through this foundation the project establishes a precision agriculture system which allows farmers to reach maximum yield potential while eliminating resource waste and improving crop quality.

9. PROJECT TIMELINE AND TASK ASSIGNMENT

Figure 12 : Gantt Chart

10. BUDGET AND BUDGET JUSTIFICATION

Table 10 : Component Budget Information

Requirements		Costs (Rs.)
Category	Item Description	
Hardware	Microcontroller (ESP32)	2200.00
	Soil Moisture sensors	700.00
	Temperature & Humidity Sensor	450.00
	Light Sensors	400.00
	Ultrasonic Sensor	550.00
	DC LCD Display(5v)	750.00
	Relay Modules	250.00
	Power Supply	750.00
	Jumper Wire	600.00
	Breadboard	650.00
	Mini Water Pump	200.00
Other Charges	Travelling charges for data collection	14000.00
	Internet charges for research	5000.00
	Firebase Messaging Service	Free
	Cost of Deployment & DB	6000.00/month

Budget Justification:

- Hardware - The components listed are essential for building the IoT system to monitor and control the greenhouse environment. The quantities are based on the need to monitor multiple parameters (e.g., temperature, soil moisture, humidity, light) and ensure redundancy in case of component failure.
- Other Charges - All required software tools are open-source, minimizing the cloud hosting is necessary for the web-based application, and a contingency budget is set aside for any unexpected costs.

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