DYNAMIC CROP MODELLING FOR SALAD CUCUMBERS USING BIOMASS AND IRRIGATION WEIGHTS AND VISUALS

24-25J-307

Project Proposal Report

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B.SC. (HONS) DEGREE IN INFORMATION TECHNOLOGY

SPECIALIZING IN DATA SCIENCE

DEPARTMENT OF COMPUTER SCIENCE

SRI LANKA INSTITUTE OF INFORMATION TECHNOLOGY

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DECLARATION

We declare that this is our 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 our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

23/08/2024

Signature of the supervisor: Date

23.08.2024

Signature of the co-supervisor: Date

23.08.2024

Signature of the external supervisor: Date

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I am truly grateful to all those who have contributed their time and expertise to assist me in this endeavour. Their collective guidance and support have been essential in laying the foundation for a meaningful and impactful research project.

ABSTRACT

This research focuses on the development of an on-demand irrigation system that leverages real-time crop biomass weight data to optimize water usage and enhance crop growth. Traditional irrigation systems, which often rely on periodic watering schedules or soil moisture sensors, can be inefficient and prone to inaccuracies. Our innovative approach integrates non-contact weight sensors and machine learning models to predict precise irrigation needs based on dynamic changes in the crop and system weight. By measuring both the top stress on plant training threads and the bottom weight of the crop system, we gain a comprehensive understanding of water requirements. Environmental factors such as humidity and temperature are also considered, with advanced machine learning models like reinforcement learning and Generative Recurrent Networks (GRN) employed to enhance prediction accuracy. This method represents a significant departure from traditional practices, offering a more sustainable and precise solution for modern agriculture. The system is tested on salad cucumbers in a tunnel environment, with potential applications to other crops, demonstrating its effectiveness in real-world agricultural settings.

Keywords

On-demand irrigation, crop biomass weight, machine learning, non-contact sensors, precision agriculture, sustainable water management.

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LIST OF ABBREVIATIONS

Abbreviation	Description
ML	Machine Learning
ANN	Artificial Neural Network
SVM	Support Vector Machine
GRN	Generative Recurrent Network
UI	User Interface
SaaS	system as a service

1. INTRODUCTION

In the era of smart agriculture, optimizing irrigation practices is essential to maximize crop yield while conserving water resources. Traditional irrigation systems, often based on fixed schedules or basic soil moisture readings, lack the precision required to meet the dynamic needs of crops. These conventional methods can result in both over- and under-watering, leading to wasted resources and suboptimal crop growth.

This research proposes an advanced, user-friendly on-demand irrigation system that leverages real-time data from non-contact weight sensors to provide precise water management tailored to the specific needs of crops. By analyzing the entire crop system's weight—encompassing the plant, growth medium, and water content—this innovative approach enables more accurate irrigation decisions, reducing water waste and enhancing crop health.

The system integrates machine learning algorithms to predict optimal irrigation times, ensuring that water is delivered exactly when and where it is needed. This technology not only simplifies the irrigation process for farmers but also introduces a scalable solution that can be adapted to various crops and farming environments, making it a valuable tool for sustainable agriculture.

2. BACKGROUND AND LITERATURE SURVEY

The global landscape of farming faces unprecedented challenges now. These challenges are driven by the twin pressures of increased food demand and diminishing water resources. Agriculture accounts for about 70% of the earth’s freshwater, thus it has come under criticism due to its significant contribution towards water scarcity concerns. This problem is exacerbated by climate change worsens water stress and affects crop yields around the world. The urgent need to enhance water use efficiency in agriculture has resulted in precision agriculture coming up as a viable solution. Among them, smart irrigation systems have been drawing attention for being capable of optimizing water usage by aligning irrigation schedules with crops’ real-time requirements [1].

Although they have been used for long, traditional practices of irrigation are often inefficient since they do not meet the precision required to conserve water and maximize crop productivity. Such methods as surface irrigation, sprinkler systems, or even drip irrigation use fixed schedules or elementary sensor inputs though popularly accepted ones (this does not make sense). As a result, these approaches can lead to either over-irrigation resulting in wastage of water plus runoff and soil degradation, or under-irrigation that causes crop stresses leading to low yields [2]. In response to these inefficiencies, the focus has shifted towards more complex systems that combine real-time data, automation, and machine learning (ML) for timely and precise irrigation decisions.

One of the emerging strategies in smart irrigation is using crop weight as an absolute indicator of water requirements. This idea suggests that the weight of a whole crop system including plant, its growth medium, and water content can be used as a good measure of a plant’s water status. Weight-based irrigation systems provide a more comprehensive picture than traditional approaches based on soil moisture alone; this allows for better management of water resources.

The proposed on-demand irrigation system deviates significantly from conventional methods and may establish new standards for precision agriculture. This study aims to improve sustainability and efficiency in farming by focusing on crop weight as a major determinant of water needs during irrigation to address the challenges of 21st-century agriculture.

Literature Survey

The urge to improve resource efficiency and agricultural productivity towards global challenges has been the driving force behind the development of precision agriculture, especially as regards irrigation. In this case, smart irrigation systems have represented the vanguard of these changes, with many studies exploring how advanced technologies can be integrated into water management.

Traditional Irrigation Systems and Their Limitations

Farmers have used old-school watering methods like surface irrigation, sprinklers, and drip systems for many years. Surface irrigation, which puts water right on the soil, is one of the oldest ways and is still common in many places because it's simple and cheap [5]. But it's also one of the least effective methods of wasting a lot of water through evaporation, runoff, and deep seepage [6].

Sprinkler systems, which distribute water through a network of pipes and emitters, offer better control over water application but are still subject to inefficiencies, particularly in windy conditions where water drift can reduce application uniformity [7]. Drip irrigation, which delivers water directly to the root zone of plants through a network of tubes and emitters, is considered one of the most efficient methods, reducing evaporation losses and allowing for precise control of water application [8]. However, even drip irrigation systems are not without limitations, as they often rely on fixed schedules that do not account for the real-time water needs of crops.

The Emergence of Precision Agriculture and Smart Irrigation Systems

The concept of precision agriculture has introduced a new approach to farming, characterized by the use of technology and data to optimize agricultural practices. Smart irrigation systems, a key component of precision agriculture, have been developed to address the inefficiencies of traditional irrigation methods by providing real-time data on crop and soil conditions [9]. These systems utilize a range of sensors to monitor parameters such as soil moisture, temperature, and humidity, enabling farmers to adjust irrigation schedules based on the specific needs of their crops.

One of the most significant advancements in smart irrigation technology has been the integration of machine learning algorithms, which can analyze large datasets to predict optimal irrigation times and amounts. Studies have shown that machine learning models, such as artificial neural networks (ANNs) and support vector machines (SVMs), can significantly improve the accuracy of irrigation predictions compared to traditional methods [10]. These models are trained on historical data and continuously updated with real-time inputs, allowing them to adapt to changing environmental conditions and crop requirements.

Crop Weight as a Parameter for Irrigation Management

The use of crop weight as a parameter for irrigation management is a relatively new approach that offers several advantages over traditional soil moisture-based methods. Crop weight provides a direct measure of the plant's water status, as it reflects both the water content of the plant and the growing media. This method is particularly effective in controlled environments, such as greenhouses and tunnels, where the conditions can be tightly regulated [11].

Recent studies have explored the use of non-contact sensors to measure crop weight, highlighting the benefits of this approach in terms of accuracy, reliability, and cost-effectiveness. Non-contact sensors, such as load cells and tension sensors, are less prone to the degradation issues that affect traditional soil moisture sensors, making them a more durable option for long-term use in agricultural settings [12].

The dual-weight measurement approach, which involves monitoring both the tension on the plant training thread and the weight of the entire crop system, has been shown to provide a comprehensive understanding of the crop's water needs. By combining these measurements with machine learning models, it is possible to develop an on-demand irrigation system that can dynamically adjust water application to match the precise requirements of the crop [13].

Machine Learning and Predictive Modeling in Irrigation Systems

Machine learning has become an integral part of modern irrigation systems, providing the ability to predict irrigation needs based on a wide range of data inputs. Studies have demonstrated the effectiveness of various machine-learning techniques in improving irrigation efficiency and crop yields. For example, reinforcement learning models have been used to optimize irrigation schedules by continuously learning from real-time data and adjusting watering times accordingly [14].

Generative Recurrent Networks (GRNs) are another promising machine learning approach, particularly for handling time-series data, which is critical in irrigation management. GRNs can capture the temporal dependencies in the data, allowing for more accurate predictions of future irrigation needs based on past trends [15]. These models can also incorporate environmental data, such as temperature and humidity, to enhance their predictive capabilities.

Challenges and Future Directions

While the integration of crop weight analysis and machine learning into irrigation systems offers significant potential, some challenges must be addressed. Sensor calibration and data reliability are critical factors that can affect the accuracy of the system. Additionally, the high cost of advanced sensors and the complexity of implementing machine learning models in real-world agricultural settings may limit their widespread adoption.

Future research should focus on refining sensor technology to improve accuracy and reduce costs, as well as developing user-friendly interfaces that make advanced irrigation systems more accessible to farmers. There is also a need for further studies to validate the effectiveness of these systems across different crop types and environmental conditions.

the development of an on-demand irrigation system based on crop weight analysis represents a significant advancement in precision agriculture. By leveraging the latest sensor technologies and machine learning techniques, this approach has the potential to revolutionize irrigation practices, leading to more efficient water use, higher crop yields, and a reduction in the environmental impact of agriculture.

3. RESEARCH GAP

The rise of smart agriculture is really catching people's attention because it has become less and less possible to do just this: farm without technology. Now, the primary task of the farmer is to make such machines and vehicles reliable and learn how to install and use software and applications as well. Modern agriculture is incomplete without them. What can be the first difference we can spot after they are implemented in the first place? These questions will be first ones coming up when we say technology in agriculture.

Water Capacity in Media: Generally, in agriculture practices, the outcome comes with much data. However, while this data helps the beam, it is not able to help the farmer take the cow where the farmer wants it to go. In the end, there is a big difference when you add water sensors at the top and sensors at the bottom and combine them to check out soil water movement. Not only that, but these devices are not flexible in changing positions when needed. If we analyze the design-based approach, we will see that the team may make the recommendations, which might or might not work. Furthermore, in high-speed computers or phone-like small computers, the great warehouse of instruments in the field provided 24-hour weather and soil monitoring. The main issue the research deals with is the issue of water capacity in the soil and its effect on plant water requirements. Exploring the use of already existing remote sensing data for the applications of precision agriculture is yet to be researched in the existing literature and released as an open-source dataset for the interest of the community.

Machine Learning Models: Furthermore, while machine learning (ML) has been increasingly applied to optimize irrigation, most of the research focuses on traditional models such as linear regression, support vector machines (SVM), or basic decision trees. These models, while useful in controlled environments, often fail to capture the complex, non-linear relationships that exist in real-world agricultural settings, particularly when dealing with dynamic variables such as real-time water content and crop growth stages. Additionally, these models are prone to overfitting, especially when applied across different crops and environmental conditions, leading to reduced robustness and adaptability. The current literature lacks an in-depth exploration of advanced ML techniques that could more effectively model the complexities of real-time irrigation needs, particularly those that incorporate multiple, dynamically changing inputs like water capacity in the media, biomass weight, and other environmental factors.

Machine Learning Models: Moreover, while machine learning (ML) is being applied to irrigation more and more, most of the research is focused on traditional models like linear regression, support vector machines (SVM) or basic decision trees. These models are good in controlled environments but fail to capture the complex non-linear relationships in real world agricultural settings, especially when dealing with dynamic variables like real time water content and crop growth stages. Moreover, these models are prone to overfitting especially when applied across different crops and environmental conditions, resulting to reduced robustness and adaptability. The literature lacks in-depth exploration of advanced ML techniques that can model real time irrigation needs more effectively, especially those that include multiple dynamic inputs like water capacity in the media, biomass weight and other environmental factors.

Fixed-Schedule Irrigation: Traditional irrigation systems run on fixed schedules with watering times predetermined based on historical weather patterns or general crop requirements. This does not account for the real time variability in crop water needs which can be influenced by daily weather changes, crop growth stage or water content in the growing media. As a result, these systems often over irrigate resulting to water waste or under irrigate which can harm crop health. Despite the recognition of these limitations, there is a big gap in research on developing systems that can adjust irrigation schedules based on real time data especially using non-invasive and continuous monitoring methods.

Our research aims to address these gaps by introducing an innovative approach that integrates real time monitoring of water capacity in the growing media with focus on water weight and biomass weight. This dual approach allows for more precise and holistic assessment of crop irrigation needs, addressing the limitations of current methods that rely only on environmental data or contact based soil moisture sensors.

Real-Time Monitoring of Water Capacity in Media: Our approach uses non-contact sensors to monitor the water content in the growing media, specifically the weight of water in the media and the overall system weight which includes the crop and its growing environment. By focusing on water weight as a direct indicator of available moisture, our system can determine the actual water needs of the crop more accurately. This method overcomes the limitations of traditional soil moisture sensors which are prone to degradation and often fails to provide reliable data over time. Moreover, by using non-contact sensors we eliminate the corrosion and maintenance issues of contact-based sensors, providing a more durable and cost-effective solution for long term use.

Advanced Machine Learning Models: Unlike the basic ML models used in existing research, we use advanced techniques like reinforcement learning and generative recurrent networks (GRN). We chose these models because they can handle complex non-linear relationships and are robust across different crops and environmental conditions. Reinforcement learning allows the system to learn optimal irrigation strategies over time and improve based on real-world feedback. GRN models are great for sequential data so are perfect for predicting irrigation needs based on time series data of water weight and environmental factors. By using these advanced ML techniques, our system can adjust irrigation schedules in real-time and give crops exactly the right amount of water for optimal growth.

Dynamic Irrigation Scheduling: We move away from the fixed schedule approach and use a dynamic approach that adjusts irrigation based on real-time data. By monitoring the water content in the media and the overall crop weight, our system can detect changes in water availability and adjust irrigation accordingly. For example, as the water evaporates from the media and the weight of the media goes down, the system can sense this as a signal that the crop needs more water. This dynamic scheduling prevents over and under irrigation and supports healthier crop development by giving water exactly when and where it’s needed.

Through our proposed system we aim to achieve several key objectives that address the gaps in existing research:

Optimized Water Management: By monitoring real-time water content in the media and overall crop weight, our system gives crops exactly the right amount of water they need, based on their current condition. This reduces waste and optimizes water usage and contributes to more sustainable agriculture.

Enhanced Predictive Capabilities: By using advanced ML models like reinforcement learning and GRN, our system can predict irrigation needs more accurately even in complex and dynamic environments. These models can adapt to changes in environmental conditions and crop growth stages and provide a more reliable and robust irrigation solution that can be applied across different crops and conditions.

More Durable and Cost Effective: By using non-contact sensors for water weight and crop weight monitoring, we address the durability issues of traditional irrigation systems. These sensors are less prone to degradation and require less maintenance making the system more cost effective in the long run. And by eliminating expensive high precision contact sensors, the overall cost of the system is reduced and can be applied to a wider range of agricultural applications.

Holistic Crop Health Monitoring: Our system not only focuses on delivering water but also provides comprehensive insights into the overall health of the crop. By analyzing both the biomass weight and the water content in the media, the system can offer valuable data on crop growth and health, enabling more informed decision-making in crop management and irrigation practices.

Contribution to the Field of Smart Agriculture: Our system represents a significant advancement in smart agriculture by addressing the critical gaps in existing research. It offers a more precise, adaptive, and sustainable approach to irrigation, which is essential for meeting the growing global demand for food while conserving water resources. Our research contributes to developing more resilient and efficient agricultural systems, paving the way for future innovations in the field.

Research Gap	Research 1	Research 2	Research 3	Availability in Proposed Solution
Limited Use of Weight-Based Metrics	No	No	No	our solution introduces biomass weight as a critical input, addressing this gap
Real-time Monitoring and Adaptation	No	Yes	No	Real-time monitoring dashboard with adaptive learning.
Dependency on Fixed Schedules	No	No	No	our solution eliminates fixed schedules by basing irrigation on real-time biomass weight and environmental data.
Advanced Machine Learning Techniques	No	No	No	Utilizes cutting-edge ML for growth and defect modeling.
Lack of Precision in Water Shutoff Points	Yes	No	No	our solution uses biomass weight to precisely identify shutdown points, improving water efficiency..
Overfitting and Model Robustness	No	No	No	our solution includes cross-validation and data diversity to prevent overfitting and ensure robustness.

Figure 1:Research Gap Analysis

4. RESEARCH PROBLEM

Modern agriculture requires efficient management of water, considering the growing worldwide water shortage. Traditional systems of irrigation, mainly fixed or time-based scheduling, can't efficiently serve the dynamic requirements of crops; most of them result in excess application or inadequate watering. It typically relies on environmental data like soil moisture, temperature, and humidity again, good data, but unable to provide direct and precise measurement of a crop's immediate water needs.

With the current technology for monitoring these parameters mostly touch sensors it is not simple, though. Contact sensors deteriorate over time owing to corrosion, even though some are initially functional. This leads to inaccurate data and ultimately erroneous irrigation decisions. Second, high-precision touch sensors, which might likely lessen such issues, are typically quite costly and hence impractical for use in routine farming applications, particularly in environments with limited resources.

Other key challenges are in the deployment of ML models within such systems. Given the complexity and variability of agricultural environments, most of the ML models applied in irrigation management and deployed today either suffer from overfitting or are otherwise incapable of generalization across different crops, environments, and real-world scenarios. What has come out of these models so far in terms of their robustness and adaptability is not quite effective for proper irrigation advice in various agricultural situations.

Given such challenges, there is an obvious requirement for an innovative irrigation management approach that addresses these limitations. An approach which shall be able to:

- **Provide Direct and Accurate Measurement of Crop Water Needs:** A method that goes beyond environmental proxies to directly measure the crop's immediate requirements, like its biomass weight, offers a more reliable indicator of water necessity.
- **Affordable and corrosion-free technology** is realized using non-contact sensors, avoiding the pitfalls of corrosion and reducing costs for a wider diffusion and sustainability of advanced irrigation technology.
- **Develop strong machine learning models:** It is very important to guarantee reliable irrigation management by developing ML models that generalize across different scenarios concerning various crops and environments without overfitting.

Problem Statement

Problems occur due to the lack of a method that will effectively, efficiently, and economically manage water resources in agriculture with existing irrigation systems and technologies. This design project focuses on an on-demand irrigation system that exploits biomass weight analysis and non-contact sensor technology via advanced machine learning models to meet dynamic and exact water requirements for crops in agriculture. By doing this, the research will ensure water efficiency, reduced resource wastage, and the health of crops necessary for sustainable agriculture.

The prevalent problems that would be addressed in this research are:

- Inefficient time-based irrigation systems due to a lack of adaptations to real-time needs of the crops.
- Contact sensors are unreliable for long-time use in agriculture mainly due to potential corrosion and high costs
- Current ML models applied in irrigation are found to be suffering from overfitting, less robust, and hence incapable of functioning effectively in most diversified agricultural environments.

5. OBJECTIVES

5.1. Main Objective

The objective of this research would be to develop a resource-efficient, economically viable, and sustainable on-demand irrigation system that responds to changes in available water supply concerning real-time biomass weight analysis and environmental data. It would integrate state-of-the-art non-contact sensor technology coupled with robust machine learning models for optimization in water usage, ensuring the right amount of water at the right time is delivered to crops for optimum health, without an inch of extra or unnecessary water spent.

5.2. Specific Objectives

1. Integration of Biomass Weight Monitoring with Environment Data:

   To design and develop a contactless, continuous weight measuring system of the entire crop system crop, media, and water. Parallel measurement of environmental data, such as temperature, humidity, and soil moisture, so that they can provide a comprehensive and efficient understanding of irrigation requirements of the crop.

2. Development and Evaluation of Machine Learning Models:

   To developing machine-learning models for crop irrigation needs predictions using the integrated data. The models should learn from real-time data and test accuracy, precision, recall, and F1-score metrics so that they can reliably predict the best times for irrigation and quantify water requirements.

3. Development of a Resilient and Agile Model:

   To this would involve the optimization of machine learning models to be strong and flexible regarding different crops and varying environmental conditions. Tests were run on other crops such as salad cucumbers, tomatoes, and green chilies. Preventing overfitting by adjusting the model increases generalizability.

4. Water Usage Optimization and Crop Health:

   To design a control mechanism in the irrigation system to dynamically adjust the quantity of water supply using this prediction from the machine learning model. This will make sure that crops get the exact amount of water and avoid any kind of wastage, assuring optimal growing conditions.

5. Real-World Testing and Validation

   To test the irrigation system developed in a real agricultural situation by applying this to salad cucumbers cultivated in a tunnel environment. The objective of this study will be to prove the effectiveness of this system in bringing about enhancement of water efficiency and improvement of crop health, with the intention to generalize to other crops and environments.

6. METHODOLOGY

The proposed research methodology for developing an on-demand irrigation system based on crop weight analysis involves multiple stages, each focused on ensuring accurate data collection, processing, model training, and system implementation. The methodology is designed to provide a reliable and scalable solution for optimizing water usage in agricultural systems.

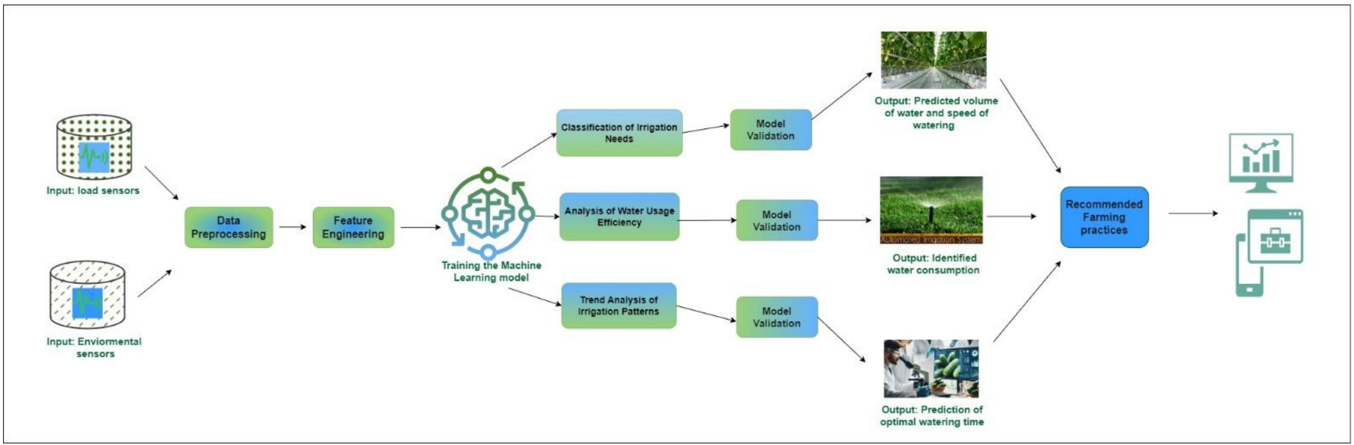

Figure 2:Component System Diagram

1. System Design and Setup

1.1 Crop System Setup:

Create a controlled tunnel environment with salad cucumbers as the test crop. This setup will fit 25 crops within an area of 17 square feet.

Mount each crop with a dual-weight measurement system:

> Top Measurement: Place a sensor on the plant training thread that is going to measure the stress caused by to weight of the crop. This sensor captures dynamic changes in the weight of biomass.
> Bottom Measurements: Load sensors installed at the base of the crop, to determine the total system weight, as including crop, media, for example, coir bags, and water content.

1.2 Environmental Data Collection:

Integrate sensors that will measure internal humidity, internal temperature, and other relevant parameters related to the environment. This information will be very important in contextualizing the measurements of weight and understanding their implications on water requirements.

2. Data Collection and Preprocessing

2.1 Real-Time Weight Data Acquisition:

Obtain a continuous record of weight data from both top and bottom sensors. The bottom sensor will capture the total system weight, for example 5 kg, and the top sensor will capture the biomass weight, say 1 kg.

Add water to the system, say 500 ml, and observe how the sensors change over time. Note the initial weight increase and the subsequent evaporation process.

2.2 Data Preprocessing:

Data Cleaning: Identify any outliers or anomalous data points which are going to skew the analysis and remove them. This ensures that data fed into the model is accurate and reliable.

Normalization: Weight data needs to be standardized in order to keep all measurements consistent with crops of varying sizes and growth stages.

Feature Engineering: Engineer the rest of the features from raw weight data, such as rate of weight change, time intervals between weight changes, and correlation between top and bottom sensor readings. These features will enhance the predictive capability of the Machine Learning models.

3. Machine Learning Model Development

3.1 Model Selection:

Develop learned models to predict irrigation needs from the obtained data. Reinforcement learning and generative recurrent networks will be tested for their suitability in modeling these complex patterns hidden in the data.

Train the chosen models to learn when and how much water to add, given the weight variations read by the sensors.

3.2 Model Training and Evaluation:

Train the machine learning models on instances of historical data from the controlled environment, including the addition of water, the resultant changes in weight, and the environmental conditions.

Model performance metrics will be evaluated in terms of accuracy, precision, recall, and the F1 score. Cross-validation will be carried out to guarantee the robustness and generalizability of the built models across a large variety of conditions.

Example: The model will predict when the bottom sensor weight drops below 5 kg, therefore requiring irrigation. It will also indicate how much water needs to be added to bring the crop to an optimal healthy status.

4. System Implementation and Testing

4.1 Integration of Real-Time System:

Integrate the trained machine learning models into a real-time system for dynamic irrigation based on weight data and environmental conditions. This system keeps probing to sensors and automatically triggers an irrigation once it is necessary.

Example: The bottom sensor weight falls below 5 kg, and the top sensor reveals that there is a constant decrease in biomass weight; the system will automatically initiate irrigation to recharge its water content.

4.2 Field Testing and Validation

The fully integrated system shall be tested on the salad cucumber crops in a tunnel environment. The performance monitoring of the system over some extended period will be focused on maintaining optimal levels of water, leading to the promotion of healthy crop growth.

System effectiveness shall be validated with crop yield and water usage compared to that of conventional irrigation techniques. This will further realize the advantages brought about by the on-demand irrigation system concerning the efficiency of the water used and crop productivity.

5. Continuity in improvement and adaptation

5.1 Model Refining:

Keep collecting data from the field tests to train the machine learning models. Up-to-date data will update the models and improve the accuracy of the predictions. It should accommodate changes in behavior of crops, or environmental conditions.

Research in scaling up this system to other crops and environments that could generalize in other agricultural contexts

5.2 System Optimization:

Optimize the hardware and software parts of the system with respect to cost-effectiveness and reliability. This shall be done by finding alternative sensors, optimizing data processing algorithms, and developing a better UI to get an easier way of managing the irrigation system.

7. PROJECT REQUIREMENTS

This section highlights the different types of requirements that must be necessary for developing an on-demand irrigation system based on crop weight analysis. The requirements have been segmented into functional, non-functional, user, and system requirements.

7.4 Functional Requirements

The functional requirements point out the key capabilities and functions that the on-demand irrigation system must execute towards the realization of the set objectives. In this specific project, these include:

I. Data Acquisition:
   - display real-time data from the load sensors, placed under the crop structure, constantly monitoring the total weight.
   - Download data from sensors controlling the level of stress in training threads of plants and variations in biomass weight.
   - Record temperature, humidity, and light intensity uninterruptedly.

II. Data processing
   - Clean the data that is gathered by filtering out anomalies and errors.
   - It should standardize the data to have constant measures in respect of different conditions.
   - It should extract more relevant features from raw data, such as the rate of change of weight concerning time, by feature engineering.

III. Implementation of Machine Learning Models:
   - The system shall be implemented with the help of machine learning models like Reinforcement learning or Genetic Regulatory Networks for predicting optimal irrigation schedules and amount of water quantities.
   - It must be trained with historical data and then tested and validated. Their accuracy against different metrics such as precision, recall, and the F1-score should be checked.

IV. Automated Irrigation Control:
   - The machine learning models shall be integrated into the irrigation control unit to adjust the irrigation in real-time according to current weight data and environmental parameters.
   - It shall generate an alert or trigger irrigation in case the crop weight is below the threshold critical value.

V. User Interface:
   - The system shall be provided with a user interface that ensures real-time monitoring of the system, irrigation forecasts viewing, and—in case of necessity—the possibility of manual control.
   - Data View of trend history, system performance metrics, and other relevant insights.

7.4 Non-Functional Requirements

Nonfunctional requirements are constraints on the performance of the system, quality attributes, and operational constraints. For this project, they involve:

I. Performance:
   - The system shall deal with real-time data and decide on irrigation with minimum delay.
   - Refreshing of predictions by machines in learning should be as often as possible every 1 minutes to show the latest conditions.

II. Scalability:
   - The system should scale up for big, different agricultural operations with various crops and configurations of sensors.
   - It should be able to maintain performance integrity even with increasing volumes of data.

III. Reliability:
   - The system shall provide an uninterrupted operation, especially during critical growth periods of the crops.
   - All sensors and hardware components should be rugged to withstand environmental impacts such as dust, moisture, and temperature changes.

IV. Usability:
   - The user interface shall be user-friendly with a minimum need for training to be used by farmers and agricultural technicians.
   - Responsibility: The system should provide data in such a format that it is easily readable, and the user can, without much hassle, arrive at a conclusion.

V. Security:
   - All data transference and storage shall be secured by the system, while sensitive information is kept secure against unauthorized viewing.
   - Procedures for authentication and role-based access controls that ensure access to key system functionalities is restricted

VI. Maintainability:
   - The system should be designed with modularity in mind. This shall make updating, maintenance, and solving problems easier when required.
   - Any constituent part of the system, including machine learning models, shall be accompanied by extensive documentation that will help in its improvement in the future.

7.3. User Requirements

User needs are requirements from the viewpoint of the people who will use the system. In this project, they are:

I. Farmers:
   - The system should automate irrigation making it minimal for human control.
   - Farmers need timely and accurate alerts concerning irrigation and water needs.
   - The system should be easy to configure and integrate with established practices easily.

II. Agricultural Technicians:
   - Technicians shall have access to the details in the data—sensor readings, environmental conditions, and outputs from any machine learning.
   - System parameters—like sensor thresholds, or irrigation schedules should be tunable for optimization
   - Tools for troubleshooting/diagnostics shall be available to detect and solve the problem quickly

III. Agricultural Researchers
   - Having access of historical data and trend analysis for performance evaluation of system
   - View and export data for further analysis and experimentation.
   - The system should be able to test different machine learning models and configurations.

7.4 System Requirements

System Requirements: System requirements are those hardware, software, or other kinds of infrastructure that would be needed to implement a project. System requirements for this on-demand irrigation system include the following.

I. Hardware Requirements
- Sensors: sensing weight measurements using load cells, stress in plant thread using tension sensors, environmental factors like temperature, humidity, and light.
- Microcontrollers: Interface with the sensors using a microcontroller such as Arduino or Raspberry Pi, process real-time data.
- Irrigation Controller: An automated irrigation controller with the ability to receive system commands to turn on/off the water flow.
- Communication Modules: Wireless communication modules such as Wi-Fi to be used in sending data from sensors to the control unit.

II. Software Requirements
- Operating System: Any strong operating system that can run on the microcontroller. For instance, in the case of Raspberry Pi microcomputer, Raspbian.
- Data Processing Software: Applications for cleaning data, normalization, feature engineering. Example: Python with its libraries such as Pandas and NumPy.
- Machine Learning Platform: A platform to train and deploy machine learning models. Example: TensorFlow or Scikit-learn.
- User Interface (Ui): Web or mobile application framework for user interface. Example: React, Angular, Android Studio.

III. Network Requirements:
- Connectivity: Reliable Internet connectivity to enable remote monitoring and data analysis.
- Local Network: Secure local network allowing communication between sensors, microcontrollers, and an irrigation controller.

IV. Storage Requirements:
- Collection of Data: Cloud-based or local database storing real-time data, historical data, and machine learning models, such as MySQL or MongoDB.
- Backup System: A backup solution in order not to lose data in case of a system failure.

8. COMMERCIALIZATION

The proposed on-demand irrigation system offers significant potential for commercialization within the agricultural sector, particularly in precision farming. By integrating machine learning and real-time data analysis from weight sensors, the system optimizes water usage, reducing both resource consumption and costs. This innovative approach addresses a critical need in modern agriculture for efficient and sustainable irrigation solutions, making it attractive to farmers and agricultural enterprises.

The system can be commercialized in multiple ways:

I. **Direct Sales to Farmers:** The system can be marketed as a cost-effective solution for medium- to large-scale farms, providing immediate savings on water usage and improving crop yield through precise irrigation.

II. **Licensing to Agricultural Technology Companies:** The technology could be licensed to agricultural tech firms, allowing them to integrate it into existing precision farming systems, thus expanding their product offerings.

III. **Subscription-Based Model:** Offering the system as a service (SaaS), with ongoing monitoring, updates, and support, could provide a recurring revenue stream while ensuring users benefit from continuous system improvements.

The system’s scalability and adaptability make it suitable for diverse crops and farming environments, positioning it well for widespread adoption in the global agricultural market.

9. BUDGET & BUDGET JUSTIFICATION

Type	Price Per Unit	Quantity	Total Price
Load Beam Sensors	Rs 700.00	20	Rs. 14 000.00
Relative Humidity (RH) Sensors	Rs 6000.00	2	Rs. 12 000.00
Arduino Boards	Rs.3500.00	1	Rs. 3 500.00
Wi-Fi Router	Rs. 2000.00	1	Rs.2 000.00
Metal Plates	Rs.750	20	Rs.15 000.00
Stress detectable sensos	Rs.5000.00	20	Rs. 10 000.00
Cloud Deployment		Pay as you go	
Total			**Rs.56 500.00**

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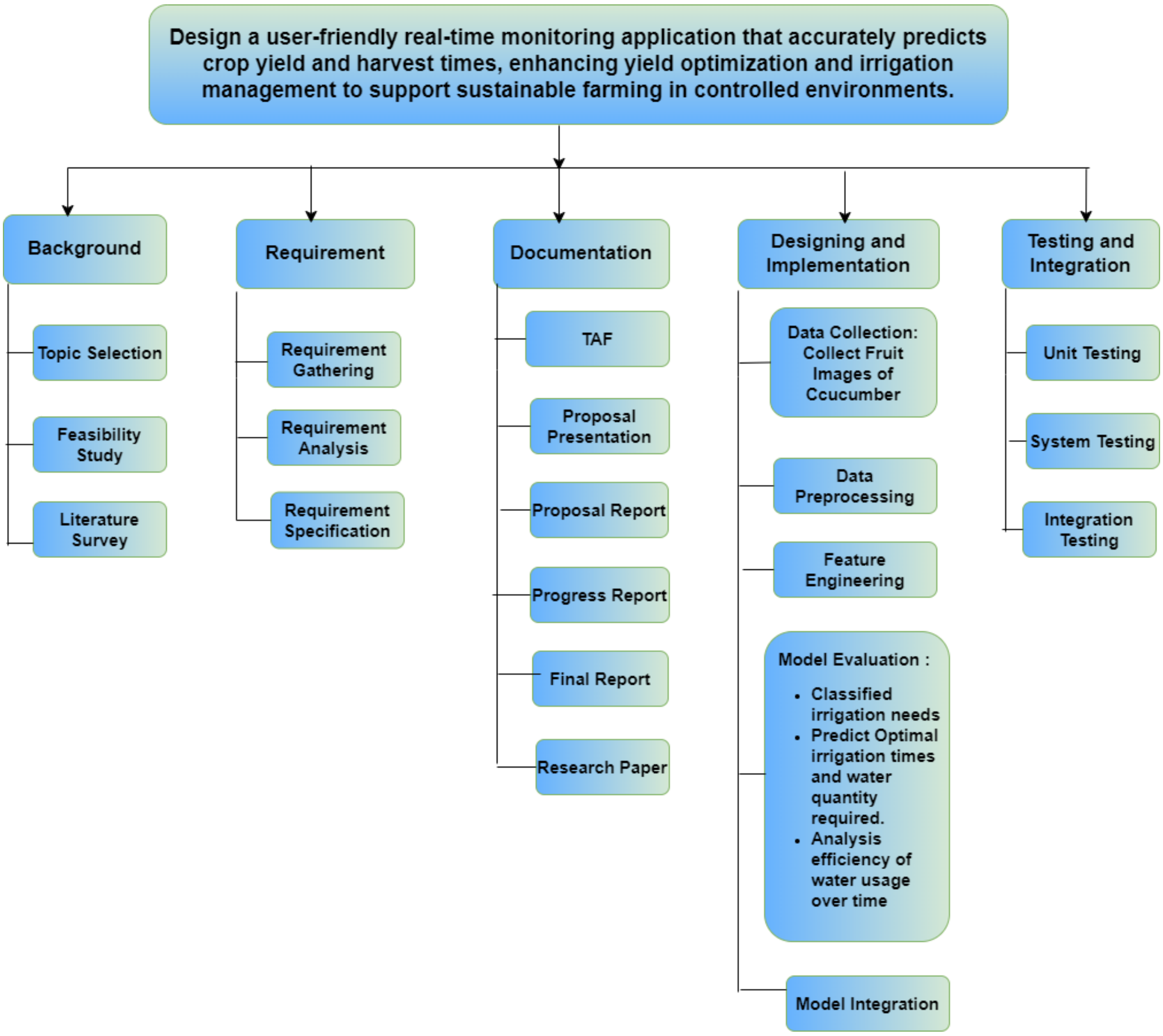
11. APPENDICES

11.1. Work Breakdown Chart



11.2. Gant Chart