# Sustania: A Digital Farming Ecosystem for Smart Agriculture


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**Abstract.** We have developed an innovative Smart Irrigation System to address recent challenges in agricultural water management while meeting the growing need for sustainable farming practices, particularly for small and medium-scale farmers. The system integrates Internet of Things (IoT)-based sensors, machine learning algorithms, and a user-friendly web interface to optimize water usage in agricultural settings. This system uses soil moisture and temperature sensors and a Random Forest classifier, ensuring precise and reliable scheduling. The platform has a modular architecture with an SQLite backend and a React-based frontend, making it a cost-effective solution. Initial testing was conducted using a DHT11 temperature sensor and a resistive soil moisture sensor; however, subsequent evaluations demonstrated that the DHT22 temperature sensor provided better performance and durability. Additionally, after extensive comparison, the Random Forest classifier was chosen for model training, proving to be the fastest and most accurate option. Core features of the model include the system's ability to provide real time temperature and moisture updates and to generate predictions based on these readings. Our system has been named "Sustania", owing to its potential to serve as a valuable tool for farmers to move towards the modern era of sustainable and innovative farming



**Keywords:** precision agriculture, sustainable agriculture, irrigation system, water conservation, agricultural technology, climate change, soil health, remote sensing, environmental impact assessment, smart irrigation, machine learning, IoT integration, real-time processing


## 1 Introduction

Farmers today, face a multitude of challenges that hinder agricultural productivity and sustainability. One of the key issues is the impact of climate change, which has altered weather patterns, reduced water availability, and affected crop yields[1]. The adoption of digital technologies in agriculture, such as IoT, machine learning, and precision farming, offers potential solutions to these challenges, but many farmers still struggle with the high costs and technical expertise required[2]. Furthermore, the shift towards more sustainable farming practices faces resistance due to economic constraints and the difficulty of implementing new techniques at scale[3].

Industry 4.0 has brought significant changes to agriculture by integrating advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), robotics, and big data analytics into farming practices. These technologies enable precision farming, which allows farmers to optimize crop yields, reduce resource consumption, and increase sustainability. For example, IoT sensors are used to monitor soil moisture and temperature, allowing for real-time data-driven decisions on irrigation and fertilization[2]. AI and machine learning models help analyze large datasets to predict crop diseases and pests, enabling farmers to take preventative measures before significant damage occurs[1]. Platforms like Climate FieldView offer farmers access to real-time data on weather patterns, soil health, and crop conditions, further enhancing decision-making capabilities[2]. These advancements have made agriculture more efficient, data-driven, and sustainable, marking a shift towards smarter, more connected farming practices.

Although technological advancements have transformed many industries, irrigation practices in agriculture still face significant barriers to modernization. Most existing solutions are tailored for large-scale operations and rely heavily on costly technologies, which are unaffordable and impractical for small-scale farmers [1, 2]. For instance, systems like Netafim Smart Irrigation Solutions use advanced drip irrigation technology and remote monitoring to optimize water use. However, their high installation costs and technical complexity make them inaccessible to many farmers. Similarly, RainMachine leverages weather data for irrigation scheduling but fails to incorporate real-time soil conditions and crop-specific requirements, limiting its precision. Another example, FarmBot, employs robotics for automated farming but remains prohibitively expensive and complex, restricting its use to niche markets.

In response, Sustania provides an affordable solution by integrating IoT sensors and machine learning to provide precise, data-driven irrigation recommendations tailored to local soil, crop, and climate conditions, optimizing water use and enhancing crop productivity[3]. Its user-friendly interface ensures accessibility for farmers with limited technical expertise, while also making it feasible and cost-effective[4]. This combination of precision, simplicity, and affordability positions Sustania as a viable solution to improve water efficiency and promote sustainable farming practices in the face of the ever-changing modern world[4].

The "Sustania" system is designed with several key components that work together to optimize irrigation. It starts with IoT sensors such as the DHT22 temperature and humidity sensor and a soil moisture sensor, which collect real-time data on temperature, humidity, and soil moisture, all of which are crucial to making accurate irrigation decisions. This data is sent to the Arduino Nano Controller, which acts as the central hub, collecting inputs from the sensors and passing them on for analysis. The Data Processing Unit then organizes and cleans the raw data, preparing it for the Machine Learning (ML) Pipeline, where a Random Forest algorithm predicts irrigation needs based on historical and current data. The Decision Engine takes these predictions and turns them into actionable irrigation recommendations. Users can view these recommendations and monitor system performance through an interactive User Interface Dashboard, which also allowsual adjustments if necessary. In addition, System Alerts and Notifications keep users informed about the status of the system, any issues that arise, and recommendations for immediate action, ensuring that the irrigation process remains efficient and easy to manage.

The objectives of this paper are as follows:

- To design a modular and scalable IoT-enabled irrigation system tailored to small- and medium-scale farming needs.
- To compare Sustania's Random Forest model with existing weather-dependent and robotics-based systems, highlighting its superior performance in cost and functionality.
- To assess the potential of Sustania to address water conservation, improve crop yields, and promote sustainable agricultural practices.

## 2 Literature Review

Recently, a lot of effort has been put into modernizing agriculture by exploring how technologies like IoT sensors, machine learning, and artificial intelligence can ease the workload for farmers and make their jobs less labour-intensive. A number of crucial studies that established the basis for precision agriculture explained the potential and limitations in this approach. Multiple survey papers provide a general overview of automated irrigation systems, highlighting the need to move beyond manual and scheduled irrigation and explore more intelligent systems. These papers emphasize the importance of reducing agricultural water usage, but do not delve into specific technological challenges or solutions[6].

Pandey and Agarwal emphasized the importance of intelligent software solutions for managing irrigation. They recognized the general need to move beyond manual and scheduled irrigation practices and towards more intelligent systems. They specifically addressed the necessity for smart software solutions to manage irrigation, highlighting that software plays a crucial role in optimizing water usage and crop production. While their research work focused on the software aspects, it did not delve into the practicalities of how this software would interface with physical sensors and actuators, which is needed for real-world applications. This included the type of sensors to use, the data acquisition methods, and the communication protocols necessary for interaction with the hardware components of an irrigation system[7].

Building on this limitation, Khan conducted extensive research on the idea of precision agriculture. Khan's research addressed the need to use IoT and smart technologies in irrigation. He discussed the integration of sensors, communication, and data analysis for precision agriculture. However, research faced significant challenges, particularly the high costs of technology and the complexity of integrating data effectively[8].

The next milestone in smart agriculture was incorporating sustainability into its core. Alongside automating farming processes, the focus shifted to preventing resource wastage, enhancing food security, and minimizing environmental harm. A key challenge highlighted was the inability of many systems to provide real-time updates, which often led to less-than-optimal outcomes. Additionally, integrating and managing vast amounts of data, coupled with high infrastructure costs, remained significant hurdles. There was also the pressing need to ensure that IoT devices themselves were energy-efficient and environmentally sustainable[9].

To tackle the financial challenges of adopting these technologies, efforts were made to address the economic constraints of implementing smart irrigation systems. Researchers proposed low-cost solutions for irrigation pivots and developed affordable sensors to make the technology more accessible. However, these systems needed to be compatible with various irrigation methods and crop types, which added complexity. Ensuring the reliability, durability, and accuracy of these cost-effective sensors also emerged as a significant challenge[10, 11].

The body of literature reviewed has underscored the remarkable progress achieved in the pursuit of smart and sustainable agricultural practices. These pioneering works have provided a strong conceptual and technological foundation, offering invaluable insights that have guided our research journey. While these studies have laid the groundwork, they have also revealed limitations and challenges that required further exploration. Drawing inspiration from their achievements, we sought to address these gaps by refining methodologies, optimizing models, and integrating cost-effective, practical solutions tailored to diverse agricultural contexts.

Our research focuses on optimizing water usage while maintaining crop yield through the integration of a low-cost moisture sensor [7]. Additionally, we have incorporated a temperature sensor into our system. Both sensors are designed to provide real-time data updates, which are used to make predictions based on the collected information. We employed the Random Forest Classifier as the machine learning model for training our data, drawing inspiration from the works of Priyanka, Joseph, and Naik. Their research utilized various machine learning models to analyze data from smart sensors to predict crop stages, irrigation schedules, and fertilizer requirements. However, their work did not validate or optimize the machine learning models for application across diverse crops and farming practices [12]. In our study, we successfully optimized the Random Forest Classifier to accommodate multiple crop patterns. Nonetheless, significant opportunities remain for further improvement and research in this field.

Our contributions extend beyond incremental improvements, aiming to enhance the technological framework of smart agriculture while prioritizing sustainability and accessibility. By tackling key challenges such as scalability, resource efficiency, and adaptability, we have added depth to the existing body of knowledge and advanced the practical application of these technologies. Furthermore, we have endeavored to pave a clear path for future research, offering a robust platform for exploring innovative strategies that address the evolving needs of global agriculture. In doing so, we hope to inspire continued progress in this vital field, bridging the gap between emerging technologies and the practical realities faced by farmers worldwide.

## 3 Proposed Methodology

This section outlines the various stages involved in the implementation of our proposed system. The first subsection provides a diagrammatic overview of the system's fundamental architecture and offers a brief description of its core functionalities. The second and third subsections explore the key procedures of the system, including the integration of various IoT devices and a comparative analysis of the machine learning models employed. Additionally, we provide an in-depth discussion of the dataset utilized to train the aforementioned models, highlighting its significance in the system's development.

### 3.1 System Architecture

Sustania's architecture is designed for scalability and user-focused efficiency, integrating the key modules as shown in the following diagram.

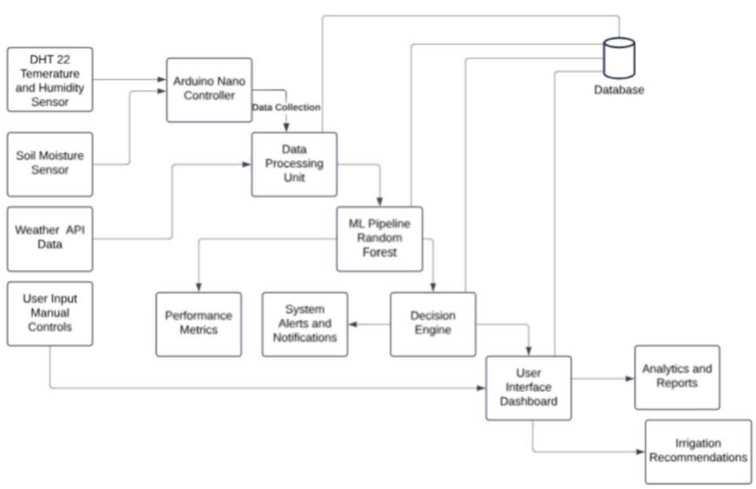


**Fig. 1.** System Architecture Diagram

Fig. 1 illustrates a smart irrigation system that uses sensors (for temperature, humidity, and soil moisture), weather data, and an Arduino Nano controller to collect and process data. A machine learning pipeline (Random Forest) analyzes the data to generate irrigation recommendations via a decision engine. The system integrates a user dashboard for monitoring, manual controls, and reports, while storing data in a database for analytics and performance tracking. It ensures efficient water usage with real-time alerts and insights.

The system architecture integrates several key components to enable efficient and data-driven irrigation management. Sensors, including the DHT22 Temperature and Humidity Sensor and a Soil Moisture Sensor, collect real-time environmental data, complemented by Weather API inputs for forecasts and rainfall trends. An Arduino Nano microcontroller acts as the central hub, gathering raw sensor data and forwarding it to the Data Processing Unit, where the data is cleaned and organized for analysis. A Machine Learning pipeline, using the Random Forest algorithm, predicts irrigation needs based on historical and real-time inputs, while the Decision Engine translates these predictions into actionable recommendations, such as irrigation schedules and amounts[12]. The User Interface Dashboard provides users with real-time metrics, analysis, and manual parameter adjustment options, ensuring transparency and control. In addition, a notification system delivers timely alerts and updates about system performance and conditions, enhancing user awareness and system reliability.

### 3.2 IoT Integration

Our system utilizes a resistive soil moisture sensor alongside a temperature and humidity sensor to provide real-time data and generate predictions. During the initial stages of the project, the sensors were configured on a Raspberry Pi. However, due to the lack of an integrated analog-to-digital converter necessary to process the analog readings from the soil moisture sensor, we transitioned to an Arduino Nano controller.

For the temperature and humidity sensor, we initially employed the DHT11 model. Through repeated testing and evaluation, we identified the DHT22 sensor as a more durable and reliable alternative, leading to its adoption in place of the DHT11. This adjustment improved the system's overall performance and longevity[13].

### 3.3 Model Comparison and Training

The initial dataset for our project, sourced from Kaggle, contained data on moisture and temperature levels for cotton plants, along with predictions on whether irrigation was required. To adapt this dataset for our study, we developed a Python script to modify and scale the temperature and irrigation values to align with the requirements of wheat crops. Additionally, we expanded the original dataset, which consisted of approximately 500 entries, to 5,000 entries, creating a new semi-synthesized dataset. This process ensured a more comprehensive dataset for training and validating our system.

This newly generated dataset was first pre-processed and then used to train multiple machine learning models. On running these models parallelly, all models initially showed a 100% accuracy indicating signs of overfitting. Subsequently, bias was introduced, thereby decreasing the variance and reducing overfitting. This modified dataset was again used to retrain all the machine learning models. Among these, the Random Forest model emerged as the most effective, achieving the highest accuracy while maintaining optimal cross-validation time[14, 15].

## 4 Evaluation and Analysis

In this section, we talk about the results obtained and conduct a detailed analysis about the performance of the system. The subsection "Results", contains a screenshot of the main Farmer Dashboard and a brief description of the contents displayed. The subsection "Performance Analysis", displays the ROC curves and graphs for the different machine learning models as well as the confusion matrix for the chosen model.

### 4.1 Results

The system generates detailed performance metrics and analytics reports, offering insights into environmental conditions and the system's efficiency. Based on these insights, it provides irrigation recommendations, helping users implement precise and optimal watering strategies tailored to the specific needs of their crops or plants.

**Fig. 2.** Real-Time Implementation of Irrigation Prediction System

Fig. 2 shows the real-time implementation of our irrigation prediction system, where the moisture and temperature sensors connected to the Arduino Nano controller provide real-time updates on the Farmer Dashboard along with irrigation predictions based on these readings.

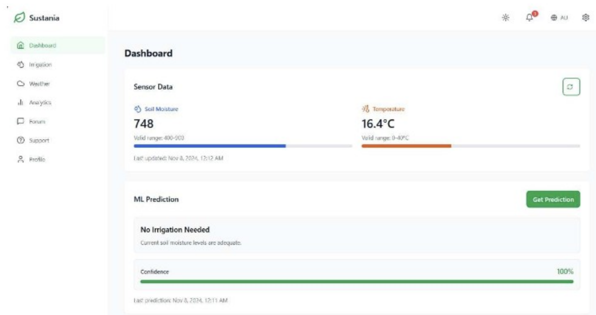


**Fig. 3.** Sensor Readings along with the Predicted Outcome

Fig. 3 shows the Farmer Dashboard page, which provides real-time readings of soil moisture and temperature along with irrigation predictions.

### 4.2 Performance Analysis

The machine learning model applied in Sustania proactively predicts irrigation needs with high accuracy. According to the evaluation metrics, the system provides an accuracy of 93.94%, which means that almost all predictions made by the model are correct. Furthermore, the precision score of 1.0000 accounts for every irrigation event predicted as needed; thus, it extenuates all assumptive water waste. The recall score is 0.8788, which for most instances where irrigation was required and thereby ensures minimal risk of under-irrigation. These results testify to the robustness of the Random Forest algorithm while managing diverse environmental inputs for accurate prediction.

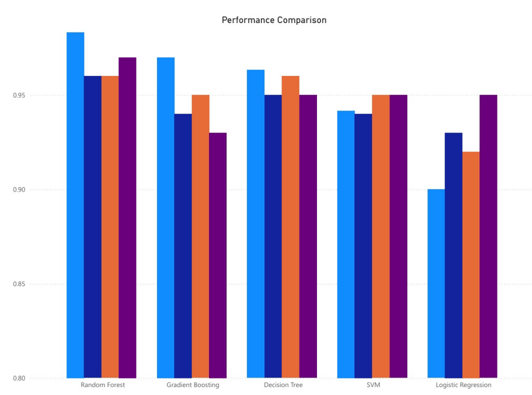


**Fig. 4.** Performance Comparison Graph

Fig. 4 shows a comparison of performance metrics—accuracy, F1 score, precision, and recall—for several machine learning models. By laying out these details, it helps in identifying which model is the most effective for the task, making it easier to understand the trade-offs and choose the best approach.

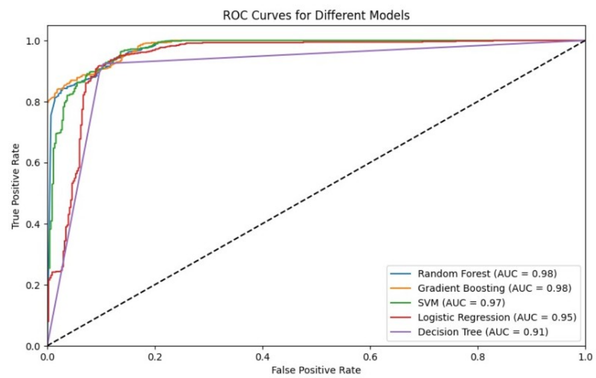


**Fig. 5.** ROC Curve

Fig. 5 shows the ROC curve for different ML Models. The figure clearly shows why Random Forest was selected for our system. AUC for Random Forest is one of the highest among all the models we had tested. Though Gradient Boosting too has the same AUC, Random Forest was selected because it is a little faster than Gradient Boosting.

**Table 1.** Classification Report

| Decision | Precision | Recall | F1-Score |
|---|---|---|---|
| 0 | 0.87 | 0.93 | 0.90 |
| 1 | 0.94 | 0.89 | 0.92 |
| Accuracy | | | 0.91 |
| Macro avg | 0.91 | 0.91 | 0.91 |
| Weighted avg | 0.91 | 0.91 | 0.91 |

Table I shows the performance assessment of the trained ML Model. The output shows a machine learning model trained with 91% accuracy, highlighting "moisture" as the top feature. The best parameters were tuned, and the model was saved as irrigation model.joblib.

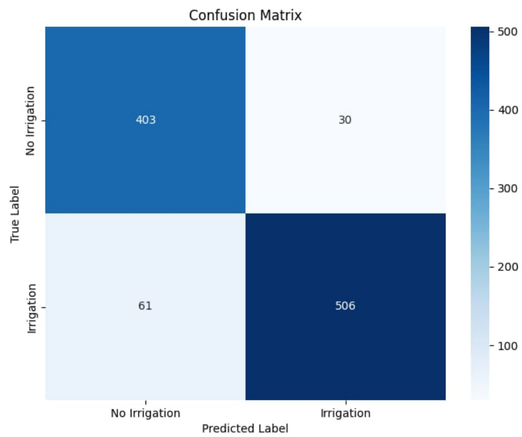


**Fig. 6.** Confusion Matrix

Fig. 6 shows the confusion matrix of the Random Forest model which was selected for training. The confusion matrix visualizes the performance of the Random Forest classifier by displaying the counts of true positive, true negative, false positive, and false negative predictions. It provides a comprehensive summary of the classifier's accuracy and error distribution across predicted and actual classes.

Sustania is modular and flexible, which makes it easily adaptable to diverse farming conditions and scales. In terms of design, it is open to additional sensors that can be integrated into the system, like those measuring soil nutrients or weather conditions; thus, making it suitable for more complex farming operations. On small-scale farms versus large agricultural estates, Sustania's scalability ensures compatibility at various farm sizes and crop types. This gives a major advantage in the system's potential for widespread adoption as it can be tailored to the specific needs of different farming communities. Moreover, the affordability and ease of use of the solution make it accessible to small and medium-scale farmers who usually cannot afford to pay for high-end technology solutions. Because of its efficiency while operating under various agricultural conditions, it can be considered a truly versatile solution that can be applied worldwide, especially in areas where water is scarce or resources are constrained. Hence these characteristics would highlight Sustania as a sustainable and viable tool for modern agriculture to provide better water management and productivity on an immense scale.

## 5 Conclusion and Future Scope

Sustania is a solution that embodies the evolution of precision farming; it combines Internet of Things, machine learning, and an interactive interface to tackle irrigation challenges for small to medium-scale farmers. While dealing with water usage, wastage in terms of sustainability and keeping crops hydrated optimally, it proves itself a sustainable along with a cost-effective solution in various scenarios. With these two parameters at its core, Sustania connects advanced agricultural technology with resource-constrained farming communities which will soon be widespread Smart Irrigation Systems adoption. One of the challenges we faced during the implementation of our system was the question of how it could be used in varying environmental and regional conditions. The answer is to use localized training data for the ML model to improve regional accuracy. Partnering with agricultural experts to fine-tune the system for specific crop needs and soil profiles is a more long-term and stable solution to this issue. Another problem was the issue of scalability of the system. How the system could adapt to varying farm sizes and different crops, and the challenge of adding more sensors to the system without making it complicated, both come under the issue of scalability. The solution lies in implementing a modular design, which enables incremental hardware upgrades for additional functionality. Training machine-learning models with datasets representing varied conditions would also help in increasing adaptability of the system. Regardless of these challenges, Sustania has a great potential of growing and innovating. Advanced sensors could be added, for instance, those detecting soil nutrient levels, thereby enhancing the system's capability to manage crops more effectively- only not through water usage alone. Long-term irrigation needs could be forecasted using AI by analyzing data history, weather patterns, and crop cycles. This would enable the farmer to plan better and ensure sustainability in water management over time. A mobile application would further enhance the accessibility of Sustania by offering farmers instant updates, control options, and information directly on their smartphones. These additions would not only make the system more user-friendly but also help it reach agricultural communities that are quite far from the main areas. Moreover, alliances with governmental agencies and non-governmental organizations would further sustain any impact because it could ease the wide adoption through financial support or subsidies for farmers. Partnership with research institutions in agriculture would also spice up the platform by offering models designed for specific regions that will cater to diverse area needs. All these would encourage the smart irrigation system's adoption while equipping the farmers with customized solutions and know-how to enhance productivity alongside sustainability. Sustania could standardize itself as a cornerstone in the innovation of precision agriculture by amenities making supportive networks of innovation and collaboration that drive economic growth together with environmental stewardship principles.

These future developments will reinforce Sustania's role in promoting sustainable farming practices, helping to address global challenges such as water scarcity, food security, and climate change. By continuously evolving and incorporating new technologies, Sustania has the potential to redefine irrigation management and support the long-term growth of agriculture worldwide.

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