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Advanced AI Driven Solution for Precise Water Management in Irrigation Systems

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Abstract: The research provides an artificial intelligence (AI) approach that uses data from temperature and soil moisture sensors stored in the cloud to provide precise water management in agricultural irrigation systems. To assess irrigation demands, the proposed method compares real-time sensor readings with specified threshold levels. This automated procedure increases crop productivity, conserves water, and supports environmentally friendly farming methods. Proactive intervention, accurate decision-making, and the combination of AI algorithms and IoT sensors enables real-time adjustments to irrigation processes. In order to accommodate different farm sizes and geographic locations, the suggested system offers scalability, adaptability, and user-friendly interfaces. This helps to promote sustainable agriculture and resource conservation.

Keywords: *Artificial intelligence, Soil Moisture sensor, Irrigation System, Threshold levels, Conserves Water, Geographic Locations, adaptability*

I. INTRODUCTION

Agricultural irrigation plays a crucial role in ensuring optimal crop growth and yield, yet inefficient water management practices often lead to resource wastage and environmental degradation. In response to these challenges, an innovative AI-driven solution tailored for precision water management in irrigation systems is required. This process helps to automate decision-making regarding irrigation needs, optimizing water usage, enhancing crop yield, and promoting sustainable farming practices[1].

A. *Artificial intelligence's (AI) part in smart irrigation systems*

Water scarcity is a problem that landowners and gardeners are facing, which means that in order to save water and lessen their influence on the environment, they must switch to sophisticated irrigation techniques. In order to maximize crop yields while effectively managing water resources, precise irrigation is now recognized as a crucial option in this area[2]. In today's era, where Artificial Intelligence (AI) is revolutionizing various industries, agriculture stands to benefit significantly from its applications[3].

AI performs a transformative role in the realm of precise irrigation by revolutionizing the management and maintenance of water resources for lush landscapes. By leveraging AI algorithms and sensors, smart irrigation systems can precisely determine the optimal amount of water required by plants at different stages of growth, thereby promoting healthy plant development while minimizing water wastage.

The integration of AI into irrigation systems offers sustainable solutions to growers who are challenged with the twin objectives of increasing yields and conserving water. Reports suggest that AI-based smart irrigation systems have been instrumental in reducing usage of water by up to ¼ or 25%, a significant conservation achievement in the face of escalating water scarcity [4]. Furthermore, AI technology's application in precision farming has yielded remarkable results, with crop yields boosted by 20 to 30%. Similarly, the role of digital farming tools and ML algorithms in managing irrigation schedules with higher precision—ensuring optimal crop growth and conserving resources—was emphasized [5-6]. Artificial Intelligence (AI) enables farmers to decide on crop management with knowledge, irrigation scheduling, and distribution of resources by using insights based on data and predictive analytics to guide them, thereby optimizing productivity while mitigating environmental impact.

Complementing irrigation management, deep learning techniques have been explored for crop disease detection, which is vital for early intervention. The application of convolutional neural networks (CNNs) for identifying diseases in turmeric plant leaves is discussed in [7], showcasing the potential of computer vision in enhancing crop productivity. In a related effort, integrated IoT and LSTM (Long Short-Term Memory) models to detect ripeness in dragon fruits under varying temperature conditions, highlighting the importance of temporal data analysis in agricultural monitoring. Additionally, scheduling irrigation remains a complex decision-making process. This was addressed using linear programming for optimized irrigation planning in [8], further demonstrating that intelligent algorithms can significantly refine agricultural operations. Together, these studies underscore a paradigm shift towards smart, sustainable, and autonomous agricultural systems, where IoT-enabled sensors, machine learning models, and digital analytics work in tandem to support real-time decision-making, improve yield quality, and optimize resource use.

B. *Need for smart irrigation systems*

The benefits of AI-powered smart irrigation extend beyond water conservation and yield optimization. These systems enable real-time monitoring and remote control, allowing farmers to adjust irrigation schedules and detect anomalies promptly[9]. Additionally, AI algorithms can examine environmental variables such as crop wellness indicators, moisture in the soil content, and forecasts for the weather to deliver tailored irrigation recommendations, enhancing operational efficiency and yield predictability. Conventional irrigation techniques may result in water usage that is inefficient, wasting water and decreasing crop yields.

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The increasing global population and the climate change's consequences on water supply have made the application of smart water technologies crucial. In addition to saving money, smart irrigation cuts labour expenses, conserves water, and enhances the health of the landscape[10].

C. *AI integration with various irrigation system types*

Sprinkler Irrigation:

Artificial intelligence (AI) has made sprinkler systems smarter than they were before. In order to schedule the next watering, an AI-powered sprinkler irrigation system gathers real-time meteorological data from rain sensors that gauge the quantity of rainfall and the condition of the soil. Following analysis of this data, the system notifies sprinklers to prevent excessive watering or over consumption of water[11-12].

Drip irrigation:

It provides water to the plant's roots directly, minimizes runoff, guarantees uniform distribution, and boosts irrigation efficiency, this is the most effective irrigation technique[13]. AI improves this approach even more. AI algorithms can accurately manage the water flow in drip irrigation systems by monitoring soil moisture levels using sensors buried in the soil.

Center pivot irrigation:

This is a typical large-scale farming irrigation technique. On mobile irrigation equipment, in-field sensors gather information on crop and soil health[14]. This data is sent by sensors to an AI-based system, which utilizes it to regulate the pivot's water flow velocity, stream, and angle as well as the circle irrigation sprinklers.

The bottom line:

Artificial intelligence must be incorporated into irrigation systems to maximize irrigation and solve issues with managing water in agriculture. AI has provided crops with protection against several challenges such as population growth, water scarcity, and climate change. Reducing the climate change's impacts and conserving water are combined with this. Using water properly is one way to do this. Smart irrigation systems based on artificial intelligence (AI) can help farmers conserve water, boost agricultural output, and promote sustainable development [15].

II. PROPOSED SYSTEM

The proposed project entails integrating temperature and moisture sensors, a Raspberry Pi with machine learning model, and a relay module controlling a solenoid valve is shown in Fig 1. The collected sensor data, tailored to the specific geographical location of the farm, is transmitted to the cloud for storage and analysis. Over time, the accumulated data is structured into a dataset, which serves as the foundation for training a machine learning model to optimize farm water usage. The work is carried out by following the below mentioned steps.

A. *Data Collection and Storage*

By placing sensors for soil moisture and temperature in agricultural land to gather data in real time. The collected data from sensors is send to a cloud-based storage platform so that it may be accessed and analyzed centrally.

B. *Threshold Determination*

By analyzing the water usage level based on the soil type and the plant variety that has to be grown in the field, threshold value has to be fixed. Temperature thresholds have to be fixed if necessary to account for environmental factors affecting irrigation needs

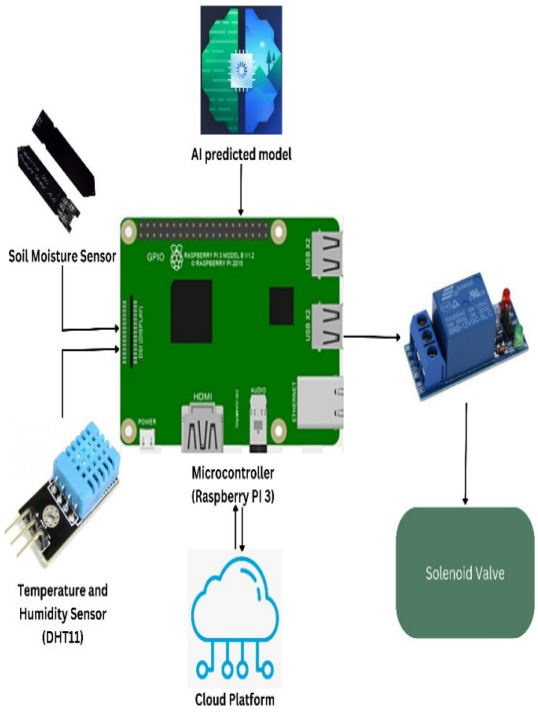
C. *Data Comparison and Decision Making*

The AI algorithms developed compare real-time sensor readings with predefined threshold values. Based on the current soil moisture level relative to the defined thresholds, irrigation is done.

D. *Control Mechanism*

A relay system connected in the model acts as a switch based on the decision made by the AI algorithm. The relay connected in the circuit trigger the solenoid valve as soon as the soil's moisture content falls beneath the specified dry condition limit, indicating the need for watering and also when the soil moisture level reaches the minimum wetness threshold, indicating sufficient irrigation.

Fig.1. Block diagram of smart irrigation system



E. *Automation and Real-time Monitoring*

For automated operation and real-time monitoring, the control mechanism is integrated with IoT devices. It ensures the continuous communication between the sensors, AI algorithm, relay, and solenoid valve and enables seamless irrigation control.

F. *Testing and Validation*

The designed system has to be tested in various environmental conditions and crop types to validate its effectiveness and reliability. Fine-tuning AI algorithms and threshold values based on feedback from field testing is done to optimize performance.

G. *User Interface Development*

The designed system acts as a user-friendly interface for farmers to monitor the system status, view sensor data, and adjust settings if necessary. It provides alerts and notifications to inform users about irrigation activities and system malfunctions.

III. DATA FROM SURVEY REPORT

The real time data taken from the survey done in the field near Tiruchengode for maize crop is shown in Fig 2.

Time	Id	Humidity	Temperature	Soil Moisture
2024-04-11T10:42:52+05:30	71	63	31	15691
2024-04-11T10:46:05+05:30	72	61	31	15235
2024-04-11T10:51:15+05:30	73	60	31	8599
2024-04-11T10:56:17+05:30	74	61	31	10204
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.	.	.	.	.
2024-04-11T11:01:19+05:30	75	60	31	9363
2024-04-11T11:12:38+05:30	76	60	32	9963
2024-04-11T11:17:41+05:30	77	58	32	9802
2024-04-11T11:22:47+05:30	78	57	32	9097
2024-04-11T11:27:50+05:30	79	57	32	7540

Fig.2. Survey data taken from red Soil for Maize plant

The temperature, and soil moisture values were recorded over a period in a maize field. Among these values, 7540 represents the lowest recorded value, while 15691 stands as the highest recorded value.

To establish thresholds for categorizing conditions within the maize field, it was decided that a value of 15691 would delineate dry conditions, indicating when the temperature, humidity, or soil moisture levels are low, and 7300 would mark wet conditions, signifying lower levels of these parameters. This categorization assessing the environmental conditions within the maize field helps in facilitating better management and decision-making processes related to crop growth and maintenance. The real time data taken from the survey done in the field near Tiruchengode for sugarcane crop is shown in Fig 3 below.

Time	Id	Humidity	Temperature	Soil Moisture
2024-04-11T11:47:57+05:30	80	56	32	15532
2024-04-11T11:53:04+05:30	81	57	32	15817
2024-04-11T11:58:12+05:30	82	57	32	15896
2024-04-11T12:03:14+05:30	83	57	32	7789
2024-04-11T12:08:16+05:30	84	58	32	7713
2024-04-11T12:13:18+05:30	85	57	32	7583
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
2024-04-11T12:18:21+05:30	86	58	32	7469
2024-04-11T12:23:24+05:30	87	60	32	7286
2024-04-11T12:28:26+05:30	88	61	32	7356
2024-04-11T12:33:30+05:30	89	59	32	7359
2024-04-11T12:38:35+05:30	90	60	32	7315
2024-04-11T12:43:38+05:30	91	60	32	7337
2024-04-11T12:48:45+05:30	92	60	32	7290

Fig 3 Survey data taken from black Soil for sugarcane plant

Using the sensor modules connected to the raspberry pi board the temperature, and soil moisture values were gathered over the course of one month in a sugarcane field. The highest recorded value is 15896, while the lowest stands at 7286. To effectively classify the environmental conditions within the sugarcane field, threshold values were used in proposed work. Specifically, a threshold greater than 8000 was designated to indicate dry conditions, indicating elevated levels of temperature, humidity, or soil moisture, while a threshold less than of 8000 was set for wet conditions, signifying lower levels of these parameters. These threshold values serve as reference points to evaluate and manage the conditions within the sugarcane field, aiding in decision-making processes related to irrigation, fertilization, and overall crop health.

Here the snapshot of the survey that have been conducted in two different fields for two crops to identify the moisture level and temperature level is shown below in Fig 4 and 5.



Fig 4 Snapshot for the survey conducted in field 1

In the survey, soil moisture sensors would have been strategically placed in the soil can determine the moisture content at different depths, giving data on the distribution and Water content of the soil. Meanwhile, temperature sensors would have been deployed to monitor ambient temperature conditions, helping assess thermal conditions affecting crop growth and influencing various physiological processes. These sensors are deployed at different locations to measure soil moisture levels and temperature variations across the study area. As the sensors collect data, measurements of soil moisture content and temperature are recorded at each location.



Fig 5 Snapshot for the survey conducted in field 2

This data is typically collected over a period of time to capture variations in soil conditions and temperature throughout the day or across different seasons. The data obtained from these sensors would serve as valuable input for training a model aimed at optimizing irrigation scheduling and crop management practices. By incorporating this data into the model, it learns to interpret soil moisture and temperature dynamics, allowing for more accurate predictions and recommendations regarding irrigation timing, frequency, and other agronomic interventions.

IV. COMPARISON BETWEEN EXISTING AND PROPOSED WORK

It's important to clarify that the data provided pertains specifically to crop requirements, but the proposed collection process takes into account the geographical conditions such as soil type, climate, etc.. to ensure that water usage does not exceed threshold values. These thresholds are established based on a combination of existing data and newly collected data, which are found to be consistent. This approach ensures that the prototype being designed can effectively conserve water without the need for manual supervision. Moreover, it's worth noting that the data and water requirements may vary from one location to another due to differences in geographical factors such as soil type, climate, and topography.

To capture a representative set of data, the survey focused on areas with various soil types which used drip irrigation as their irrigation technique. This choice of location and irrigation method allows for the collection of data that is relevant and applicable to similar agricultural settings where drip irrigation and red soil are prevalent are given in Table 1 below. By considering geographical conditions and utilizing appropriate irrigation methods, the survey aims to gather data that accurately reflects crop water requirements while ensuring efficient water management practices. This approach not only facilitates the development of a prototype that conserves water effectively but also lays the groundwork for sustainable agricultural practices tailored to specific geographical contexts.

Table.1. Comparison between Existing and Proposed Work

Existing data (Internet source)	Proposed work
Water management is available only for a particular variety of crop	Water management for different crop can be obtained
Geographical conditions are not considered	Geographical conditions such as soil type, climate, etc… are considered with the help of sensor's data
Water may exceed the limit given while irrigating	Excess water usage can be avoided by fixing the threshold vales
Water requirement alone is considered e.g. 2000mm for sugarcane	All parameters i.e. temperature, moisture level are considered for irrigation
Lack of water management details	Efficient water management can be done by the proposed model

V. SIMULATION OUTPUT

The trained machine learning model provides a detailed classification report, showcasing the performance of multiple algorithms, including Logistic Regression, Decision Tree, AdaBoost, XGBoost, and Random Forest. The report outlines the precision, recall, F1-score, and support for each class label: Dry, More Dry, More Wet, and Wet. The model assigns label for each category randomly. Here the model assigns 0,1,3 & 2 for soil status Dry, More dry, Wet and More Wet conditions respectively. These metrics help evaluate the model's effectiveness in correctly predicting irrigation requirements. Among the models tested, XGBoost demonstrate superior performance for unseen data, achieving perfect precision, recall, and F1-scores for all class labels. The Logistic Regression model shows a lower overall accuracy (0.87), while the Decision Tree, AdaBoost, XGBoost, and Random Forest models achieve higher accuracies, with the latter two reaching 1.00.

The resultant accuracy metrics before and after hyperparameter tuning of various machine learning models are given in Table 2 below.

Table 2 Training & Testing Accuracy of the Various Model

Model Accuracy	Accuracy before Hyper parameter tuning		Accuracy after Hyper parameter tuning
	Training	Testing	Testing
Logistic Regression	87.9	89	92.17
Decision Tree	100	100	100
Adaboost	94	94	99.83
XG Boost	100	100	99.5
Random forest	100	100	99.83

In order to validate the model for unseen data and to overcome the class imbalance of the dataset, stratified k-fold validation is carried out and the testing accuracy was determined. The results are tabulated below in Table 3

Table 3 Accuracy of the Various Model for Unseen Data

Model	Testing accuracy with stratified k-fold validation	Testing Accuracy for unseen data
Logistic Regression	99.83	80.30
Decision Tree	99.3	84.24
Adaboost	99.83	85.24
XG Boost	99.5	94.09
Random forest	99.83	85.24

This output highlights the successful integration of the AI-driven smart irrigation system. The system combines various essential modules, including a relay, temperature sensor, soil moisture sensor, and Raspberry Pi, to provide real-time data on soil conditions. After training and loading the best machine learning model into the Raspberry Pi, the system accurately classifies soil moisture levels, ensuring optimal irrigation. The classification report demonstrates the reliability and effectiveness of the proposed system, particularly when using ensemble methods like XGBoost, which provide flawless predictions for precise irrigation control. The opening and closing of the solenoid valve depend on the threshold value set based on the survey conducted in the real field. The snapshot of the hardware output is shown in Fig 6.

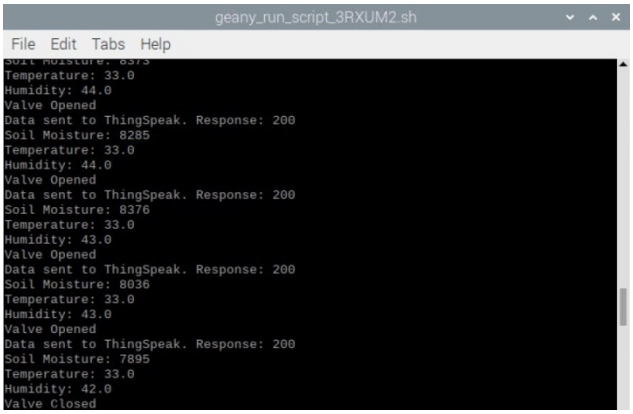


Fig.6. Snapshot of the hardware output

The below Table 4 explains the output analysis of AI driven smart irrigation system.

Table 4 Output Analysis

Soil moisture	Temperature	Humidity	Valve status
8285	33	44	Opened
8376	33	43	Opened
8036	33	43	Opened
7895	33	42	Closed

The graph of the Raspberry pi microcontroller for Soil moisture, Humidity and Temperature are shown in below Fig 7, Fig 8 and Fig 9 below.

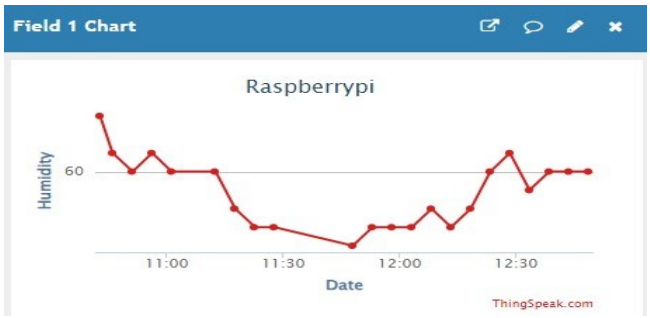


Fig.7. Graph of the Raspberry pi for soil moisture

In the provided figures, the X-axis shows the date and time, indicating the chronological progression of the data collection period. Meanwhile, the Y-axis displays different parameters depending on the respective figures: temperature is represented in Fig 10, humidity in Fig 9, and soil moisture in Fig 8. The graphing process entails plotting the data points based on real-time measurements obtained during the data collection period.

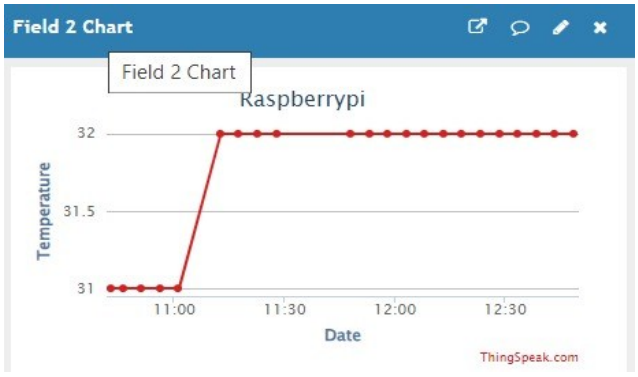


Fig 8 Graph of the Raspberry pi for humidity

xFor temperature (Fig 10), each data point represents the temperature recorded at a specific date and time. Similarly, for humidity (Fig 9) and soil moisture (Fig 8), data points correspond to the respective measurements taken at different instances during the observation period.

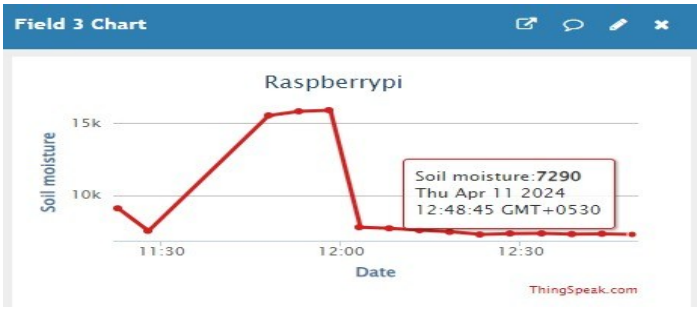


Fig.9. Graph of the Raspberry pi for temperature

By visualizing these data points on the graph, it becomes possible to discern patterns, trends, and fluctuations in temperature, humidity, and soil moisture levels over time. This graphical representation facilitates analysis and interpretation of environmental conditions within the field, aiding in decision-making processes related to agricultural management and crop health.

VI. HARDWARE SETUP

The hardware setup of the project is given in Fig.10. below.

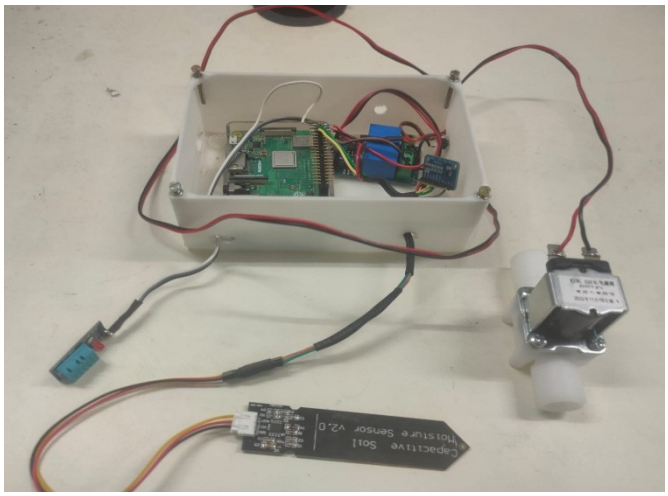


Fig.10. Hardware setup (Prototype)

The above image describes the hardware setup of the proposed work titled Advanced AI Driven solution for precise water management in irrigation systems. It includes the Microcontroller, Sensors, Solenoid valve and Relay, to control the operation of the Solenoid valve. ADS1115 converter is used for transmitting the analogue values of the sensor to the Microcontroller.

V. CONCLUSION

Utilizing an AI-driven solution employing XGboost for precise water management in irrigation systems provides significant advantages. By leveraging machine learning techniques, historical data and environmental factors are analyzed to predict optimal irrigation schedules with high accuracy. By analysis, for a sugarcane plant to be grown in red soil type in the area of Tiruchengode a threshold value of 8000 is considered for wet and 15000 for more dry conditions. This approach enables farmers to reduce costs, minimize water usage, and enhance crop yields by precisely matching water supply to crop demand. The deigned system architecture is scalable to accommodate varying farm sizes and adaptable to different geographical locations and crop

types. Therefore, the proposed model, with a prediction accuracy of 0.9883, outperforms other inventions, demonstrating its efficacy in optimizing irrigation practices in real life with a detected accuracy of 94.03% for unseen data for improved agricultural outcomes.

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