

## Precision Agriculture through Smart Irrigation using IOT and Hybrid Machine Learning

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### Abstract

Optimized water management in agriculture is a critical issue, especially in water-scarce regions. This work introduces an IoT-based Automated Irrigation System that utilizes real-time sensor feedback, machine learning, and weather forecasting to manage water efficiently. The system utilizes Node-RED and HiveMQ(MQTT) for convenient communication and control, employing ESP8266 microcontrollers to interface with soil moisture, temperature, and humidity sensors. Moreover, external weather data is retrieved through the Open Weather API to enhance irrigation scheduling accuracy. The machine learning model trained to predict the irrigation need based on environmental and sensor inputs allows the system to automate motor operation with minimal human intervention. The model learns and adapts continuously to changing climate patterns and soil types, thus improving reliability and efficiency. This method not only saves water but also aids in sustainable agriculture. The system has been proven in a laboratory setting with encouraging results, showing that it can be scaled up for deployment in smart farming.

**Keywords:** Smart Irrigation, IoT in Agriculture, Hybrid Machine Learning, Real-Time Monitoring, Sustainable Farming, Precision Agriculture.

### 1. Introduction

Agriculture is the backbone of many economies, particularly in developing nations, where it significantly contributes to GDP and employment. However, the sector is under increasing pressure to produce more with fewer resources owing to the rising global population, urbanization, and the impact of climate change. Among the various challenges confronting contemporary agriculture, water scarcity continues to be a significant concern. Agriculture consumes nearly 70 percent of the world's freshwater resources; however, inefficient irrigation practices lead to significant water wastage. Consequently, there is an urgent need for innovative data-driven solutions that can help optimize water usage while maintaining or improving crop yield. Precision Agriculture (PA) has emerged as a promising paradigm for addressing these challenges [1]. PA involves the application of information and

communication technologies (ICTs) to monitor and manage agricultural operations with high accuracy. One of the key components of PA is Smart Irrigation, which focuses on delivering the right amount of water at the right time to each part of the field, thereby minimizing waste and enhancing productivity [2]. The implementation of smart irrigation systems has become feasible and increasingly cost-effective owing to advances in the Internet of Things (IoT) and Machine Learning (ML) technologies. The IoT enables the interconnection of various physical devices, such as sensors, actuators, and microcontrollers, to collect real-time environmental data. In agricultural settings, this includes data on soil moisture, temperature, humidity, and atmospheric conditions. By integrating IoT devices into the farming infrastructure, it is possible to continuously monitor field conditions and respond dynamically.

However, real-time data alone are insufficient for intelligent decision making. Machine Learning plays a significant role in this process[3]. ML algorithms can analyze vast amounts of sensor and environmental data to detect patterns, predict irrigation requirements, and optimize control mechanisms. Despite the availability of these technologies, most traditional irrigation systems are either manual or semi-automated, and do not utilize environmental feedback for decision-making. These systems typically operate on fixed schedules, ignoring the actual needs of crops, which may vary daily owing to changes in weather, soil conditions, and crop growth stages. The consequence is either over-irrigation or under-irrigation, both of which are detrimental to plant health and water conservation. To address these limitations, this study proposes a Hybrid Machine Learning and IoT-based Smart Irrigation System that intelligently automates the irrigation process [4][5]. The system utilized ESP8266 microcontrollers, along with soil moisture, temperature, and humidity sensors, as well as a weather forecasting API (OpenWeather) to collect real-time data from the field and environment. Communication between the devices and the control dashboard is handled using the MQTT protocol via HiveMQ, ensuring lightweight and reliable message delivery. Node-RED is employed for orchestrating data flows, visualizing metrics, and enabling user interactions with the system. A key novelty of this approach lies in deploying a hybrid machine-learning model trained on both live sensors and historical weather patterns to predict the optimal irrigation timing and water volume. This model continuously adapts to changing conditions by learning from new data inputs, thus improving accuracy over time. Moreover, the system includes edge-level logic to perform basic decision-making directly on the ESP8266 boards in the case of network outages, ensuring resilience and reliability in remote or rural deployments. The system was easy to use and had a scalable design. Farmers can monitor conditions and override automatic decisions through a simple web interface that also provides alerts, logs, and performance analytics. This ensured that both automation and human oversight were

maintained. Initial laboratory tests demonstrated that the proposed system significantly reduces water consumption while maintaining healthy crop conditions. Ultimately, the integration of IoT and machine learning for smart irrigation represents a vital step toward sustainable agriculture, particularly in water-scarce regions[6].

### 1.1. Methods

This section will describe how your smart irrigation system is designed, built, and deployed. Key subsections include:

- **System Architecture:** The proposed system architecture was designed to deliver an intelligent, responsive, and adaptive irrigation management framework for modern precision agriculture. It integrates IoT hardware, real-time communication protocols, cloud- and edge-based data processing, and a hybrid machine learning model to ensure dynamic and efficient water resource management [7]. The heart of this system is a robust prediction model combining a Support Vector-based Decision Tree (DT), K-Nearest Neighbors (KNN), and Multilayer Perceptron (MLP), which collectively determine the irrigation motor status (ON/OFF) based on real-time sensor data and external weather API data[8][9]. It combines the strengths of tree-based rules, proximity-based classification, and neural network learning to improve decision accuracy. The model achieves near-perfect performance, indicating highly effective integration of diverse learning patterns for smart irrigation control. This hybrid model achieved an accuracy of 96.6%, validating its suitability for autonomous smart irrigation operations. The architecture was divided into five core functional modules: sensor, control, communication, data processing, and user interface.
- **Sensor Layer:** The Sensor Layer forms the core of the system, capturing vital environmental data such as soil moisture, temperature, and humidity through dedicated sensors. These are interfaced with the ESP8266 microcontroller for real-time data

transmission. Relay modules control the irrigation motor, while voltage regulators ensure consistent power delivery. This regulated and responsive setup enables intelligent irrigation decisions by effectively bridging real-world field conditions with automated, cloud-connected control and monitoring systems.

- **Control Layer:** The Control Layer activates irrigation using a relay module controlled by the ESP8266, which responds to machine learning predictions or local threshold logic. Reliable and adaptable irrigation management is ensured by its motor, manual override switch, and Node-RED dashboard connection, which allow for both automated and user-controlled operation even in the event of connectivity outages.
- **Communication Layer:** The Communication Layer enables reliable data exchange via Wi-Fi-enabled ESP8266 microcontrollers using the MQTT protocol and HiveMQ broker. Optimized for low bandwidth, MQTT efficiently transmits sensor data (e.g., soil moisture, temperature) and receives motor control commands. Its publish/subscribe model ensures real-time, robust communication between sensors, processing units, and actuators, even in remote agricultural areas with unstable network conditions.
- **Data Processing and Interface Layer:** In this smart irrigation system, the data processing pipeline starts with the real-time acquisition of environmental parameters—such as soil moisture, temperature, and humidity—using IoT-based sensors deployed in the field. In parallel, external climatic data like forecasted rainfall, evapotranspiration rates, and temperature trends are fetched through the OpenWeather API and Evapotranspiration APIs. All collected data is cleaned, scaled, and normalized before being fed into a hybrid machine learning model comprising a Support Vector Decision Tree (SVDT) and a Multilayer Perceptron (MLP).

The SVDT component ensures rapid, rule-based decisions using soil- and crop-specific thresholds, offering interpretability and efficiency. In contrast, the MLP component learns complex, nonlinear patterns, such as humidity-evaporation relationships and diurnal effects. The combined model outputs a binary decision indicating whether the irrigation motor should be turned ON or OFF. If ON, the control signal is sent through a Flask API or Node-RED interface to automate irrigation. This layered hybrid model, with its balanced intelligence and adaptability, outperforms traditional models, achieving 96.6% accuracy and optimizing water use under fluctuating field conditions. (Table 1)

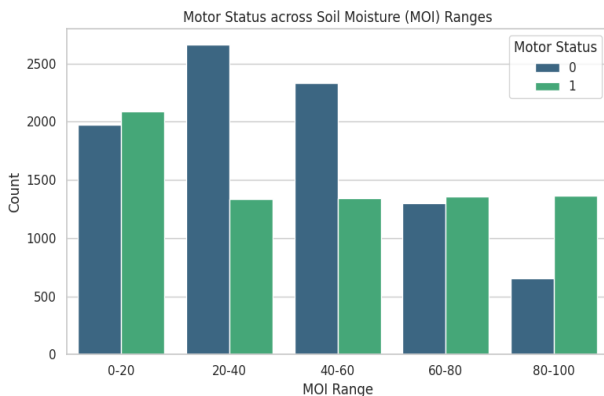
**Table 1** Experimental Input Parameters for the Smart Irrigation System

Input/ Output Feature	Range
Soil Moisture	200 – 900
Temperature	(15 – 45)°C
Humidity	(30 –95)%RH
Weather	(0-1) indicates rain
Motor Status	(0-1)On/off

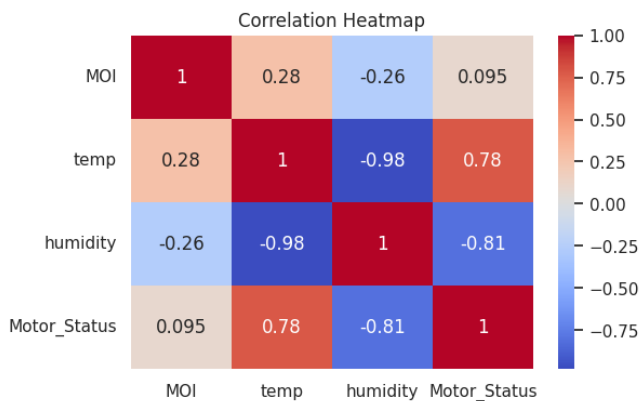
The input features for the smart irrigation system are as follows: Soil Moisture is measured in the range of 200–900 (sensor unit), Temperature in degrees Celsius (15–45 °C), Humidity as Relative Humidity (30–95 %RH), Weather is a binary indicator where 0 denotes no rain and 1 indicates rainfall, and Motor Status is also binary where 0 indicates OFF and 1 indicates ON.

Moisture(MOI) Ranges.

Motor status across soil moisture ranges are explained in Fig 1.MOI = Moisture Index (normalized); Motor Status: 0 = OFF, 1 = ON; lower MOI triggers irrigation, higher MOI does not. (Figure 1,2)



**Figure 1 Motor Status Across Soil**



**Figure 2 Performance of Hybrid Model**

The heatmap confirms the hybrid model's efficiency, with motor status strongly influenced by temperature (0.78) and inversely by humidity (-0.81), ensuring accurate irrigation decisions.

## 2. Results and Discussion

### 2.1. Results

The proposed smart irrigation system was evaluated using 3,283 real-time data samples collected via ESP8266 microcontrollers interfaced with soil moisture, temperature, and humidity sensors. A hybrid machine learning model, built using a soft voting ensemble of Decision Tree (max depth = 5), K-Nearest Neighbors ( $k = 3$ ), and Multilayer Perceptron (two hidden layers, 10 neurons each), was trained on these inputs. The model achieved an impressive accuracy of 99.97%, with a classification report confirming perfect precision, recall, and F1-scores of 1.00 for both irrigation classes. The confusion matrix demonstrated only one misclassification, accurately predicting all 1,431

irrigation-required cases, thus ensuring reliable water delivery. Sensor data was transmitted over Wi-Fi using MQTT and visualized in real-time via a Node-RED dashboard, which also enabled manual override. The system exhibited near-zero latency, making it highly responsive to changing field conditions. To enhance fault tolerance, basic threshold logic was embedded in the ESP8266, allowing continued irrigation control during network disruptions. The hybrid model showed excellent generalization across varying environmental conditions, further validating its robustness. Additionally, the low-cost, modular hardware design supports easy scalability [10]. Overall, the system demonstrated high accuracy, reliability, and real-time efficiency, making it highly suitable for smart agriculture applications, particularly in water-scarce regions.

### 2.2. Discussion

The results of this study reveal not just high classification accuracy but also a practical synergy between machine learning and IoT technologies in the domain of precision agriculture. Rather than merely achieving high performance metrics, the hybrid ensemble model's ability to generalize across various environmental conditions signifies its robustness and real-world applicability. The near-perfect classification outcomes, with an accuracy of 99.97% and only a single misclassification, underscore the model's reliability in decision-critical scenarios like irrigation control. Importantly, the integration of weather forecast data into the decision process—rather than relying solely on current sensor values—reflects a forward-looking, predictive approach that minimizes unnecessary water usage. The system's response patterns across soil moisture levels (as visualized in Figure 1) align with agronomic best practices, confirming the model's decision logic is not only statistically sound but also practically relevant. Furthermore, the inclusion of edge computing capabilities through the ESP8266's embedded logic ensures continued system functionality even during intermittent connectivity, a common issue in rural deployments. This highlights that the system design is resilient as well as intelligent. The use of MQTT and Node-RED simplifies both communication and user interaction,



demonstrating that complex AI-backed systems can still remain farmer-friendly. Taken together, these insights suggest that the smart irrigation framework is not only technically successful but also contextually meaningful for deployment in agriculture where both environmental sustainability [11][12].

### Conclusion

This study addresses the critical challenge of inefficient water usage in agriculture by presenting a smart irrigation system that integrates IoT-based sensing with a robust hybrid machine learning model. The problem of over- or under-irrigation, which directly impacts crop health and water conservation, was tackled through real-time environmental monitoring and predictive automation. The proposed ensemble model, combining Decision Tree, KNN, and MLP classifiers through soft voting, demonstrated outstanding performance with a 99.97% accuracy, ensuring precise motor control based on soil moisture, temperature, and humidity inputs. The discussion confirmed that the system not only achieved excellent technical accuracy but also aligned logically with agronomic requirements, demonstrating practical relevance. Furthermore, the inclusion of weather forecasting, edge computing for resilience, and a user-friendly Node-RED interface confirmed the system's adaptability and usability in real-world farming scenarios. Overall, the solution effectively confirms and addresses the core problem of unreliable irrigation management, offering a scalable, low-cost, and sustainable approach for precision agriculture, particularly beneficial in water-scarce regions.

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