An IoT And Machine Learning Based Smart Irrigation System For Precision Agriculture

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***Abstract*—Agriculture is one of the major consumers of freshwater, and inefficient irrigation practices can lead to considerable water wastage, uneven crop growth, and increased energy consumption. Conventional irrigation methods commonly depend on fixed schedules or manual observation and may not adequately respond to variations in soil moisture and environmental conditions. The integration of the Internet of Things (IoT) and Machine Learning (ML) provides an opportunity to develop intelligent, automated, and data-driven irrigation systems. This paper proposes an IoT and Machine Learning Based Smart Irrigation System for Precision Agriculture. The proposed system combines field sensors, an ESP32-based controller, wireless communication, cloud/IoT monitoring, a machine learning model, and an automated irrigation actuator. Soil moisture, temperature, humidity, rainfall, and water-level information are collected from the agricultural field.**

The sensor data are transmitted to an IoT platform and used as input to a machine learning model to determine whether irrigation is required. Based on the prediction and predefined safety conditions, the water pump is automatically switched ON or OFF. The proposed framework is intended to improve irrigation decision-making, reduce unnecessary water application, minimize human intervention, and provide real-time monitoring. Existing research demonstrates that machine learning can improve irrigation decision-making and soil moisture prediction, while recent studies highlight the importance of reliable datasets, sensor calibration, scalability, and real-world field validation. S ScienceDirect+2 The proposed work addresses these requirements by combining sensing, prediction, and closed-loop irrigation control in a single framework.

I. INTRODUCTION

Agriculture plays an important role in food production and economic development. One of the major challenges faced by modern agriculture is efficient management of water resources. Conventional irrigation practices often depend on fixed schedules, manual inspection, or farmer experience. Such methods may apply water when it is not required or fail to provide adequate water when crop demand increases.

The development of precision agriculture has introduced technologies capable of monitoring agricultural conditions at a much finer scale. Internet of Things (IoT) devices can collect information from agricultural fields through sensors, while cloud platforms can store and visualize the collected data. Machine Learning (ML) can then be applied to identify relationships between environmental conditions and irrigation requirements. Research in smart irrigation has increasingly moved from simple threshold-based control toward predictive and data-driven irrigation.

A systematic literature review of machine-learning-based smart irrigation identified numerous ML techniques and concluded that ML approaches can outperform conventional approaches in several irrigation applications, while also emphasizing limitations related to generalization and data quality. S ScienceDirect An earlier IoT-based smart irrigation system demonstrated the integration of field sensors, weather information, machine learning-based soil-moisture prediction, cloud connectivity, and automated irrigation control. S ScienceDirect More recent research has investigated IoT and ML frameworks using multiple sensors and different soil types, demonstrating the importance of sensor calibration and soil-specific modeling. D DOI Therefore, this research focuses on developing an integrated IoT and ML framework capable of monitoring agricultural conditions and making intelligent irrigation decisions.

II. PROBLEM STATEMENT

Traditional irrigation systems have several limitations:

- Irrigation may be performed according to fixed schedules rather than actual soil conditions.
- Manual monitoring requires considerable time and effort.
- Excessive irrigation can waste water and energy.
- Insufficient irrigation can negatively affect crop development.
- Environmental parameters may not be considered during irrigation decisions.
- Conventional systems generally do not learn from historical field data. Therefore, an intelligent irrigation system is required that can continuously monitor field conditions, analyze multiple parameters, predict irrigation requirements, and automatically control water application.

III. RESEARCH OBJECTIVES

The major objectives of the proposed research are:

- To design an IoT-based system for real-time agricultural field monitoring
- To collect and store agricultural sensor data.
- To develop a machine learning model for irrigation prediction.
- To automatically control the irrigation pump.
- To reduce manual intervention.
- To provide remote monitoring of agricultural conditions.
- To evaluate the proposed system using experimentally collected data.

IV. LITERATURE REVIEW

A. IoT-Based Smart Irrigation

IoT has become an important technology for precision agriculture because it allows distributed sensors and controllers to communicate with monitoring and decision-support systems. IoT-based agricultural systems commonly collect soil moisture, temperature, humidity, rainfall, light intensity, and other environmental parameters. These measurements can be transmitted to cloud platforms where they can be analyzed and visualized. Goap et al. developed an IoT-based smart irrigation management system using field sensing and weather information. Their system included soil and environmental sensing, cloud-based data collection, machine learning-based soil-moisture prediction, and automated irrigation control. S ScienceDirect

B. Machine Learning for Irrigation

Machine learning provides a mechanism for learning relationships between environmental variables and irrigation requirements. A systematic literature review covering 55 studies published between 2017 and 2023 found that several ML techniques have been applied to smart irrigation and reported the potential of ML based systems to improve irrigation decision-making. The review also highlighted the need for better-formed and more generalizable datasets. S ScienceDirect Machine learning has also been reviewed specifically for irrigation decision-making, including applications in crop water requirement estimation, irrigation scheduling, and water-demand prediction. S ScienceDirect

C. Soil Moisture Prediction

Soil moisture is one of the most important parameters for irrigation management. Recent research has investigated recurrent neural networks and LSTM models for real-time soil moisture prediction using IoT sensor data.

A 2026 study reported that an IoT-enabled RNN LSTM system could predict soil moisture in a precision-agriculture environment, while also identifying heavy rainfall as a source of larger prediction errors. S ScienceDirect Another 2026 study investigated multiple ML models across loam, sandy, and silt soils and reported strong performance from a stacking approach, emphasizing the importance of soil specific calibration and modeling.

D. Research Gap

Although many smart irrigation systems have been proposed, several challenges remain:

- Lack of standardized datasets.
- Differences in soil and climatic conditions.
- Sensor calibration problems.
- Network connectivity limitations.
- Difficulty in transferring models between agricultural environments.
- Limited long-term field validation.
- Security and interoperability issues.

V. PROPOSED SYSTEM

A. System Overview- The proposed smart irrigation system consists of five primary layers

- Sensing Layer
- IoT/Communication Layer
- Data Processing Layer
- Machine Learning Layer
- Actuation Layer

The overall process is:
Agricultural Field → Sensors → ESP32 → IoT Platform → ML Model
→ Irrigation Decision → Pump Control

B. Sensing Layer The sensing layer collects information about the agricultural environment.
The proposed sensors include:

- Soil moisture sensor
- Temperature sensor
- Humidity sensor
- Rain sensor
- Water-level sensor

The sensors are installed at suitable locations within the crop area.

1. Soil Moisture Sensor The soil moisture sensor provides information about the water content or moisture-related characteristics of the soil. Soil moisture is considered the primary input for irrigation decision-making.
2. Temperature Sensor Temperature provides information about environmental conditions that influence water demand.
3. Humidity Sensor Relative humidity can be used as an additional environmental feature for machine learning.
4. Rain Sensor Rain information can prevent unnecessary irrigation during or immediately after rainfall.
5. Water-Level Sensor The water-level sensor provides information about water availability in the storage tank and can be used as a safety condition for pump operation.

VI. SYSTEM ARCHITECTURE

1. Sensors collect soil and environmental data.
2. ESP32 receives the sensor readings.
3. Data is sent to the cloud using Wi-Fi.
4. Machine learning predicts whether water is needed.
5. The relay controls the water pump.
6. The pump supplies water to the crops automatically.

SOIL & ENVIRONMENTAL
SENSORS
|
▼
ESP32 CONTROLLER
|
▼
WI-FI / CLOUD
|
▼
MACHINE LEARNING
|
▼
RELAY MODULE
|
▼
WATER PUMP
|
▼
CROP FIELD

VII. HARDWARE IMPLEMENTATION

A. ESP32
An ESP32 microcontroller can be used as the central processing and communication unit.

Its functions include:

- Reading sensor values.
- Processing sensor measurements.
- Connecting to Wi-Fi. o Sending data to the IoT platform.
- Receiving or executing irrigation decisions.
- Controlling the pump through a relay.

ESP32-based IoT and ML architectures are also being investigated in recent smart-agriculture research

B. Relay Module
DOI The relay provides electrical isolation/control between the low-voltage controller and the pump switching circuit.

C. Water Pump

The pump supplies water to the agricultural field through an irrigation system such as drip irrigation.

VIII. DATA COLLECTION

The system collects data at predetermined time intervals.

A sample dataset structure is:

Sensor Data and Irrigation Status

Time	Soil Moisture (%)	Temperature (°C)	Humidity (%)	Rain	Water Level (%)	Pump
08:00	35	28	65	No	80	OFF
10:00	30	30	60	No	75	OFF
12:00	22	33	50	No	70	ON
14:00	45	31	55	No	65	ON
16:00	65	29	70	Yes	60	OFF

Note: The values marked XX must be replaced with measurements obtained from the actual experimental setup. The dataset should ideally be collected over multiple days and under different environmental conditions.

IX. MACHINE LEARNING METHODOLOGY

A. Feature Selection

The proposed model can use the following input features:

X=[SM,T,H,R,W]

where:

- SM = Soil Moisture
- T = Temperature
- H = Humidity
- R = Rain condition
- W = Water availability

The target variable can be:

Y= {1, Irrigation Required

{0, Irrigation Not Required

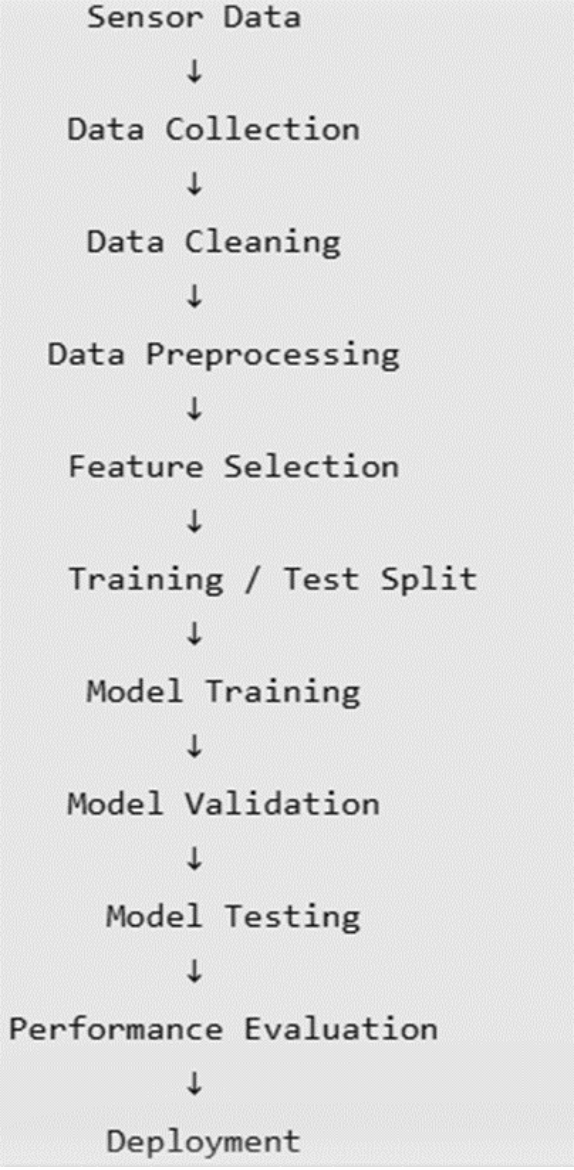
B. Candidate Algorithms

The following algorithms can be evaluated:

- Logistic Regression
- Decision Tree
- Random Forest
- Support Vector Machine
- K-Nearest Neighbors
- Gradient Boosting
- Artificial Neural Network

Random Forest is a suitable baseline because it can model nonlinear relationships and handle multiple environmental features. For more advanced research, LSTM-based models can be investigated when the objective is to predict future soil moisture using time-series data. Recent research has demonstrated the application of RNN-LSTM models for this purpose.

X. MACHINE LEARNING WORKFLOW



Data Preprocessing

Data preprocessing may include:

- Missing-value handling
- Removal of invalid sensor readings

- Noise filtering
- Outlier analysis
- Feature scaling where required
- Encoding categorical variables
- o Dataset balancing where necessary

A. Model Training

The collected dataset can be divided into training and testing subsets.

For example:

- 80% training
- 20% testing

The final split should be determined based on the size and characteristics of the actual dataset.

XI. IRRIGATION DECISION ALGORITHM

The proposed algorithm is:

START

Initialize ESP32 and sensors Read soil moisture

Read temperature Read humidity

Read rainfall condition Read water level Validate sensor data

Send data to IoT platform Provide sensor data to ML model Predict irrigation requirement

IF water level is insufficient:

Pump = OFF

ELSE IF irrigation requirement = NO: Pump = OFF

ELSE:

Pump = ON

Monitor soil moisture

IF target moisture condition is reached: Pump = OFF

Store sensor and irrigation data Repeat after predefined interval END

The ML prediction should preferably be combined with safety constraints rather than allowing a prediction model alone to control a pump without safeguards.

XII. PERFORMANCE EVALUATION

The proposed system can be evaluated using two groups of performance parameters.

A. Machine Learning Metrics

$$\textbf{Accuracy} \quad \frac{TP+TN}{TP+TN+FP+FN}$$

$$\textbf{Precision} \quad \frac{TP}{TP+FP}$$

$$\textbf{Recall} \quad \frac{TP}{TP+FN}$$

$$F1 = 2\,\frac{Precision \times Recall}{Precision + Recall} \qquad (1)$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

For soil-moisture regression models, metrics such as MAE, RMSE, and $R2$ can be used instead.

XIII. EXPERIMENTAL RESULTS

The experimental results must be obtained from the actual prototype and dataset.

Model Comparison

The following table can be used in the final paper:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	XX%	XX%	XX%	XX%
Decision Tree	XX%	XX%	XX%	XX%
Random Forest	XX%	XX%	XX%	XX%
SVM	XX%	XX%	XX%	XX%

The model providing the best balance of predictive performance, computational requirements, and deployment suitability should be selected.

Water Consumption

Water consumption should be measured under both conventional and proposed irrigation conditions.

Parameter	Conventional Method	Proposed Method
Total water used	XX L	XX L
Irrigation events	XX	XX
Average irrigation duration	XX min	XX min
Manual intervention	High	Low
Automatic control	No/Partial	Yes

Water saving can be calculated as:

$$Water\ Saving(\%) = \frac{W_c - W_s}{W_c} \times 100$$

where:

- Wc = water consumed by conventional irrigation
- Ws = water consumed by smart irrigation

Soil Moisture Analysis
A graph should be plotted showing:
Time vs Soil Moisture
The expected behavior is that soil moisture decreases due to evaporation, plant uptake, and environmental conditions, and increases after irrigation.
The objective of the proposed system is not simply to maximize soil moisture but to maintain it within an appropriate range for the selected

XIV. DISCUSSION

The proposed IoT and ML framework provides an integrated approach to irrigation management. Unlike a simple timer-based system, the proposed system considers real-time field conditions before making an irrigation decision. The use of multiple parameters allows the model to consider environmental conditions in addition to soil moisture. IoT connectivity enables remote monitoring, while machine learning provides the possibility of adapting irrigation decisions based on historical patterns. Recent literature supports this direction. Research has demonstrated IoT-based soil-moisture prediction, ML-driven irrigation scheduling, and sensor-based precision irrigation.

XV. ADVANTAGES OF THE PROPOSED SYSTEM

The major advantages are:

- Real-time monitoring.
- Automated irrigation.
- Reduced manual intervention.
- Data-driven decision-making.
- Potential reduction in water wastage.
- Remote monitoring.
- Historical data storage.

XVI. LIMITATIONS

The proposed system has several limitations: Sensor readings may be affected by soil conditions and sensor placement.

- Sensor calibration is necessary for reliable measurements.
- Machine learning requires sufficient high-quality data.
- Internet connectivity may not always be available in rural areas.
- The trained model may not generalize to different crops or soil types.
- Initial implementation cost may be higher than a conventional irrigation system.
- Long-term field testing is necessary. Security and privacy issues must be considered for connected agricultural systems.

XVII. FUTURE SCOPE

The proposed system can be extended in several directions.

A. Weather Forecast Integration
Weather forecast data can be integrated into the ML model to anticipate rainfall and changing environmental conditions.

B. LSTM-Based Soil Moisture Prediction
LSTM models can be used to predict future soil moisture from historical time-series measurements. Recent research has investigated this approach in real agricultural

C. Solar-Powered Irrigation
Solar panels can be integrated to operate sensors, communication devices, and irrigation pumps.

D. Long-RangeCommunication LoRa/LoRaWAN or cellular communication can be investigated for farms where Wi-Fi coverage is limited.

E. Computer Vision
Camera-based crop monitoring can be combined with IoT sensor data to identify crop stress and improve irrigation decisions.

F. Edge AI
The ML model can be deployed directly on an edge device to reduce dependence on cloud connectivity and decrease response time.

XVIII. CONCLUSION

This paper proposed an IoT and Machine Learning

Based Smart Irrigation System for Precision Agriculture. The proposed framework combines IoT sensors, ESP32-based data acquisition, wireless communication, machine learning, and automated pump control. The system continuously monitors soil and environmental parameters such as soil moisture, temperature, humidity, rainfall, and water availability. These parameters are transmitted to an IoT platform and used by a machine learning model to determine irrigation requirements. The main contribution of the proposed work is the integration of real-time sensing and ML based decision-making with automatic irrigation control. This approach can overcome some limitations of conventional fixed-schedule irrigation by making decisions according to actual field conditions. The literature indicates strong potential for IoT and ML in precision irrigation, while also emphasizing the importance of data quality, calibration, generalization, scalability, and field validation

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REFERENCES

[1] A. Goap, D. Sharma, A. K. Shukla, and C. R. Krishna, “An IoT based smart irrigation management system using machine learning and open-source technologies,” *Computers and Electronics in Agriculture*, vol. 155, pp. 41–49, 2018, doi: 10.1016/j.compag.2018.09.040.

[2] “The application of machine learning techniques for smart irrigation systems: A systematic literature review,” *Smart Agricultural Technology*, vol. 7, Art. no. 100425, 2024.

[3] “Application of machine learning approaches in supporting irrigation decision making: A review,” *Agricultural Water Management*, vol. 294, Art. no. 108710, 2024.

[4] B. Nsoh et al., “Internet of Things-based automated solutions utilizing machine learning for smart and real-time irrigation management: A review,” *Sensors*, 2024.

[5] “Smart drip irrigation systems using IoT: A review of architectures, machine learning models, and emerging trends,” *Discover Agriculture*, vol. 3, Art. no. 253, 2025.

[6] “AI-driven irrigation systems for sustainable water management: A systematic review and meta-analytical insights,” *Smart Agricultural Technology*, vol. 11, Art. no. 100982, 2025.

[7] “Smart irrigation management: IoT-based RNN-LSTM model for soil moisture prediction in precision agriculture,” *Smart Agricultural Technology*, vol. 13, Art. no. 101866, 2026.

[8] K. Lata, S. K. Soni, and S. K. Yadav, “Machine learning-driven IoT framework for soil moisture prediction in precision irrigation systems,” *Engineering Research Express*, vol. 8, Art. no.

105201, 2026.
[9] “Design of machine learning based smart irrigation system for precision agriculture,” *Computers, Materials & Continua*, 2022, doi: 10.32604/cmc.2022.022648.
[10] “Implementation of smart agriculture using ESP32-based IoT and machine learning for monitoring crop,” in *Proc. IEEE*, 2026, doi: 10.1109/ICTMIM68190.2026.11507902.
[11] S. P. Sudha and J. B. Shajilin Loret, “A review on machine learning-based precision agriculture techniques for crop farming monitoring with IoT,” *Discover Environment*.
[12] “Innovative applications of internet of things and machine learning in sustainable agricultural irrigation management: Benefits and challenges,” *Smart Agricultural Technology*, 2025.
[13] A. E. G. and G. J. Bala, “IoT and ML-based automatic irrigation system for smart agriculture system,” *Agronomy Journal*, vol. 116, pp. 1187–1203, 2024.
[14] L. P. Challa, C. D. Singh, K. V. R. Rao, A. Subeesh, and M. Srilakshmi, “Prediction of soil moisture using machine learning techniques: A case study of an IoT-based irrigation system in a naturally ventilated polyhouse,” *Irrigation and Drainage*, vol. 73, no. 3, pp. 1138–1150, 2024.
[15] R. Togneri, R. Prati, H. Nagano, and C. Kamienski, “Data-driven water need estimation for IoT-based smart irrigation: A survey,” *Expert Systems with Applications*, vol. 225, Art. no. 120194, 2023.
[16] “Development of a wireless sensor network and IoT-based smart irrigation system,” *Wireless Communications and Mobile Computing*, 2022.
[17] “An intelligent irrigation scheduling system using low-cost wireless sensor network toward sustainable and precision agriculture,” *IEEE Access*, vol. 8, pp. 172756–172769, 2020.
[18] “IoT-enabled adaptive watering system with ARIMA-based soil moisture prediction for smart agriculture,” *IEEE Access*, vol. 13, pp. 27714–27728, 2025.
[19] “A data-driven bibliometric review on precision irrigation,” *Smart Agricultural Technology*, vol. 5, Art. no. 100320, 2023.
[20] “An environmental remote sensing and prediction model for an IoT smart irrigation system based on an enhanced wind-driven optimization algorithm,” *Computers and Electrical Engineering*, vol. 122, Art. no. 109889, 2025.
[21] “AI-driven irrigation systems for sustainable water management: A systematic review and meta-analytical insights,” *Smart Agricultural Technology*, vol. 11, Art. no. 100982, 2025.
[22] “Application of machine learning approaches in supporting irrigation decision making: A review,” *Agricultural Water Management*, vol. 294, Art. no. 108710, 2024.