



Smart Irrigation System for Precision Farming

Mr. Bhagyesh N Chaudhari¹, Dr. Dinesh D Puri²

Research Scholar, Department of Computer Applications, SSBT's COET, Jalgaon Maharashtra, India¹

Associate Professor, Department of Computer Applications, SSBT's COET, Jalgaon Maharashtra, India²

Abstract: Smart Irrigation System for Precision Farming is an IoT-based and sensor-driven approach designed to improve water management, crop productivity, and agricultural sustainability. Conventional irrigation practices often depend on fixed schedules or manual decisions, which can result in over-irrigation, under-irrigation, water wastage, and increased labour requirements. The proposed system integrates soil-moisture, temperature, humidity, and rainfall sensors with a microcontroller such as Arduino or ESP32 to continuously monitor field conditions in real time. Based on the collected data, the system automatically determines the irrigation requirement and controls water pumps or solenoid valves accordingly. Weather information can also be incorporated to avoid unnecessary irrigation during expected rainfall and to adapt watering according to environmental conditions. IoT connectivity enables farmers to remotely monitor soil and weather parameters through a web or mobile dashboard. The system provides a low-cost, scalable, and farmer-friendly solution that supports precision agriculture by delivering the right amount of water at the right time. Such intelligent irrigation can conserve water and energy, reduce manual effort, improve crop health, and contribute to sustainable agricultural development.

INTRODUCTION

Agriculture is one of the major consumers of freshwater resources, making efficient water management essential for sustainable food production. Water scarcity, climate change, irregular rainfall, population growth, and increasing agricultural demand have created significant challenges for farmers. Traditional irrigation methods, including manual and timer-based irrigation, frequently operate without considering the actual moisture condition of the soil or changing weather conditions. Consequently, crops may receive either excessive or insufficient water, resulting in water wastage, waterlogging, soil degradation, reduced crop productivity, and unnecessary energy consumption.

Recent developments in the Internet of Things (IoT), sensors, embedded systems, and automation provide an opportunity to address these limitations. IoT-based smart irrigation systems can continuously collect information about soil moisture, temperature, humidity, rainfall, and other environmental parameters. This real-time information can be processed by a microcontroller to determine when irrigation is required. The irrigation system can then automatically activate or deactivate pumps and valves according to the crop's water requirements.

Precision farming further improves this approach by applying water according to the specific conditions of a crop or field rather than following a fixed irrigation schedule. Integration with weather data can prevent irrigation when rainfall is expected and can help adjust irrigation according to temperature and environmental conditions. In addition, cloud-based monitoring and mobile or web interfaces allow farmers to observe field conditions and control the irrigation system remotely.

Existing smart irrigation solutions demonstrate the potential of IoT and sensor technologies for water conservation, but many systems can be expensive, complex, or unsuitable for small-scale farmers. Therefore, there is a need for an affordable, reliable, scalable, and farmer-friendly solution. The proposed Smart Irrigation System combines low-cost sensors, IoT connectivity, automated irrigation control, and environmental monitoring to provide precise water management. By supplying water only when and where it is required, the system aims to reduce water wastage, minimize human effort, improve crop health and productivity, and support sustainable precision agriculture.

LITERATURE REVIEW

Smart irrigation has emerged as an important application of precision agriculture because conventional irrigation often applies water according to fixed schedules rather than actual crop and soil requirements. Increasing water scarcity, climate variability, and the need to improve agricultural productivity have encouraged researchers to develop sensor-based and data-driven irrigation systems. The literature shows a transition from simple automatic irrigation systems toward IoT-, cloud-, and machine-learning-based solutions.



The Food and Agriculture Organization (FAO) has emphasized the importance of improving agricultural water-use efficiency. Irrigation is highly significant for agricultural production, but a large proportion of irrigated land is located in areas experiencing water stress. Therefore, efficient irrigation management is essential for sustainable agricultural development. FAO also highlights the importance of monitoring water use and improving irrigation practices rather than simply increasing the amount of irrigation water available.

Several researchers have investigated IoT-based irrigation systems using soil-moisture and environmental sensors. A 2022 study proposed an IoT and ARM-based soil-moisture monitoring and irrigation system using sensors, Raspberry Pi, a relay module, and cloud connectivity [1]. The system automatically activated irrigation when soil moisture became low and allowed information to be monitored through a web application. The study demonstrated that IoT technology can reduce manual intervention and help minimize unnecessary water consumption.

Machine learning has further improved the capabilities of smart irrigation systems. Togneri et al. investigated machine-learning approaches for soil-moisture forecasting using data collected from multiple agricultural fields and crops. Their research showed that machine-learning models can be used to predict future soil-moisture conditions and support irrigation decisions. The study also found that boosting and blended models could provide strong forecasting performance.

Another study developed an IoT-based smart irrigation system using soil humidity, temperature, and rainfall sensors [2]. Different machine-learning algorithms, including KNN, Logistic Regression, Neural Networks, SVM, and Naïve Bayes, were evaluated. The reported results showed strong performance from the KNN model, demonstrating the potential of combining sensor data with machine learning for intelligent irrigation decisions.

Recent research has also focused on integrating IoT with predictive algorithms. A 2025 study developed an automated irrigation system using soil-moisture, temperature, and humidity sensors connected to an Arduino-based controller. The system used historical and real-time data to predict irrigation requirements and reported a reduction in water usage while maintaining appropriate soilmoisture conditions. Such systems demonstrate that predictive irrigation can be more efficient than fixed irrigation schedules.

Wireless sensor networks have also been applied to precision irrigation. A study conducted in a commercial pear orchard used soil-moisture-based wireless sensors and spatial information to maintain soil water content within an appropriate range. The researchers reported water savings of up to 50% compared with conventional irrigation scheduling while maintaining acceptable fruit quality. This indicates that precision irrigation can consider spatial variation in fields rather than treating the entire field uniformly.

More recent research has incorporated deep learning for soil-moisture prediction. A 2026 study developed an IoT-enabled irrigation system using subsurface soil-moisture sensors and an RNN-LSTM model. The model was used to predict soil moisture in real time and support irrigation scheduling [8]. However, the researchers identified heavy rainfall and spatial variability as challenges, indicating that machine-learning irrigation systems still require larger and more diverse datasets for reliable deployment.

A 2026 review of soil-moisture monitoring technologies further highlights the integration of IoT, machine learning, remote sensing, edge computing, and TinyML in smart agriculture. The review identifies sensor calibration, connectivity, energy consumption, scalability, and cost as important challenges for practical implementation, particularly for small-scale farmers.

Table 1 summarises the studies discussed above.

Table 1: Summary of the reviewed studies

Study	Technology / approach	Reported finding or observation
IoT and ARM-based study, 2022 [1]	Soil-moisture sensors, Raspberry Pi, relay module, cloud connectivity, web application	Irrigation activated automatically when soil moisture became low; reduced manual intervention and helped minimise unnecessary water use



IoT and machinelearning study, 2022 [2]	Soil humidity, temperature, and rainfall sensors; KNN, Logistic Regression, Neural Networks, SVM, and Naïve Bayes	KNN model showed strong performance
Togneri et al.	Machine-learning soil-moisture forecasting using data from multiple fields and crops	Boosting and blended models gave strong forecasting performance
Arduino-based study, 2025	Soil-moisture, temperature, and humidity sensors with historical and real-time data for prediction	Reduction in water usage reported while appropriate soil moisture was maintained
Pear orchard study	Wireless soil-moisture sensors with spatial information	Water savings of up to 50% compared with conventional scheduling; acceptable fruit quality maintained
IoT RNN-LSTM study, 2026 [8]	Subsurface soil-moisture sensors and RNN-LSTM model	Real-time soil-moisture prediction; heavy rainfall and spatial variability identified as challenges
Soil-moisture monitoring review, 2026	IoT, machine learning, remote sensing, edge computing, and Tiny ML	Sensor calibration, connectivity, energy consumption, scalability, and cost identified as challenges

2.1 Research Gap

From the reviewed literature, it can be observed that existing systems successfully use individual technologies such as soil-moisture sensors, IoT, machine learning, weather information, and automated control. However, there is still a need for an integrated, low-cost system that combines real-time soil and environmental sensing, weather information, predictive analytics, and automatic irrigation control. The proposed Smart Irrigation System for Precision Farming aims to address this gap by using sensor data and intelligent decision-making to provide water according to actual crop requirements, thereby improving water-use efficiency and supporting sustainable farming.

THEORETICAL BACKGROUND

This section presents the theoretical background on which the proposed Smart Irrigation System for Precision Farming is built. It covers the soil–water relationship, crop water requirement, the architecture of IoT-based irrigation systems, the sensing and communication technologies involved, the machine-learning techniques used for prediction, and the measures used to evaluate model performance.

3.1 Soil–Water Relationship and Water Balance

Soil functions as a reservoir from which crop roots extract water. The amount of water held in the soil is commonly expressed as the volumetric water content, defined as the ratio of the volume of water to the total volume of soil, as given in Eq. (1).

$$\theta = \frac{V_w}{V_t} \quad (1)$$

where θ is the volumetric water content, V_w is the volume of water, and V_t is the total volume of the soil sample. The value is often expressed as a percentage.

Two characteristic soil–water limits are important for irrigation management. Field capacity is the water content retained by the soil after excess water has drained under gravity, whereas the permanent wilting point is the water content below which plants can no longer extract water. The water held between these limits is called plant-available water. Effective irrigation aims to keep the root zone within this range: water applied beyond field capacity is lost through drainage or causes waterlogging, while allowing the soil to approach the wilting point exposes the crop to water stress. These limits depend on soil texture; sandy soils drain quickly and store less water, whereas clay soils retain more water but release it



more slowly. Because of this variability, measuring the actual soil condition is more reliable than following a fixed schedule.

The overall behaviour of water in the root zone can be described by the soil-water balance in Eq. (2).

$$\Delta S = P + I - ET - D - R \quad (2)$$

where ΔS is the change in soil-water storage, P is precipitation, I is irrigation, ET is evapotranspiration, D is deep drainage, and R is surface runoff. In a sensor-based system, irrigation I is the controllable term. By adjusting I according to measured soil moisture and expected rainfall, the system attempts to keep the root-zone storage within the desired range while minimising drainage and runoff losses. Table 2 contrasts conventional irrigation practice with the sensor-driven approach considered in this work.

Table 2: Conventional irrigation versus sensor-driven smart irrigation

Aspect	Conventional irrigation	Smart (sensor-driven) irrigation
Basis of decision	Fixed schedule or manual judgement	Measured soil and weather data
Response to rainfall	Usually none unless adjusted by the farmer	Can be suspended or reduced using rainfall sensing or forecast data
Water application	Uniform; may cause over- or underirrigation	Adjusted to the actual crop and soil requirement
Labour requirement	Continuous manual operation and inspection	Automatic control of pumps and valves
Monitoring	Physical presence in the field	Remote, through a web or mobile dashboard
Use of data	Limited or none	Continuous records for analysis and prediction

3.2 Crop Water Requirement

The water requirement of a crop is governed by the evaporative demand of the atmosphere and by crop characteristics. Reference evapotranspiration (ET_0) expresses the evaporative power of the atmosphere for a standard reference surface and is estimated from meteorological variables such as temperature, humidity, solar radiation, and wind speed; the Penman–Monteith method is widely used for this purpose. The crop evapotranspiration is then obtained using a crop coefficient, as shown in Eq. (3).

$$ET_c = K_c \times ET_0 \quad (3)$$

where ET_c is the crop evapotranspiration, K_c is the crop coefficient, which varies with crop type and growth stage, and ET_0 is the reference evapotranspiration. In its simplest form, the net irrigation requirement is the part of the crop water demand that is not met by effective rainfall, as given in Eq. (4).

$$IR = ET_c - P_e \quad (4)$$

where IR is the irrigation requirement and P_e is the effective rainfall, that is, the portion of rainfall actually stored in the root zone. Temperature and humidity measurements therefore influence the estimated demand, and rainfall measurements or forecasts reduce the amount of irrigation that needs to be applied. This is why the proposed system combines soil-moisture, temperature, humidity, and rainfall information.

3.3 Architecture of IoT-Based Smart Irrigation

An IoT-based smart irrigation system is usually organised into four layers. The perception layer consists of the sensors that measure soil and environmental parameters and the actuators, such as pumps and solenoid valves, that apply water. The network layer transfers data between the field devices and remote services using wireless communication. The processing layer includes the microcontroller, which performs local decisions, and cloud or server resources that store



data and run analytics and machine-learning models. The application layer provides web or mobile interfaces through which farmers monitor conditions, receive recommendations, and control the system remotely.

The layers form a closed control loop, as illustrated in Figure 1. Sensor readings are acquired by the microcontroller, compared with the irrigation requirement of the crop, and used to switch the pump or valve on or off. The same data are sent to the cloud for storage and visualisation, and weather information can be used to postpone irrigation when rainfall is expected. The effect of each irrigation action appears in the next round of sensor readings, which completes the feedback loop.

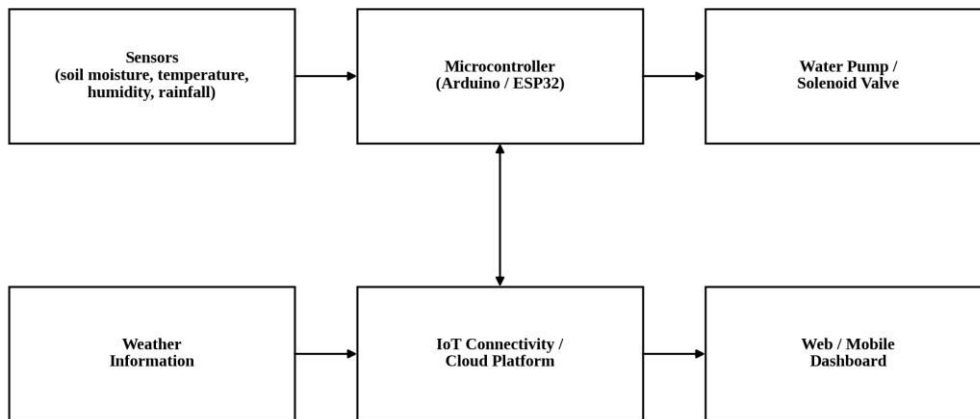


Figure 1: General architecture of the proposed IoT-based smart irrigation system

3.4 Sensors and Actuators

Sensors convert physical quantities into electrical signals that a microcontroller can read. Soilmoisture sensors are commonly of the resistive or capacitive type. Resistive sensors estimate moisture from the electrical conduction between two probes, but the probes are prone to corrosion in wet soil. Capacitive sensors respond to the change in dielectric permittivity of the soil, which depends on its water content, and are generally more durable. The output of any soil-moisture sensor depends on soil type, salinity, and temperature; therefore, calibration against the soil in which it is installed is necessary for dependable readings. Table 3 lists the main parameters considered in the proposed system, the type of device typically used to measure them, and their role in the irrigation decision.

Parameter	Typical sensing device	Role in the irrigation decision
Soil moisture	Resistive or capacitive soil-moisture sensor	Indicates the water status of the root zone; main trigger for irrigation
Soil temperature	Soil temperature probe	Influences root activity and water uptake
Air temperature	Digital temperature sensor	Influences evapotranspiration and hence crop water demand
Humidity	Humidity sensor	Affects the evaporation rate; used together with temperature
Rainfall	Rain sensor or rain gauge; weather forecast data	Prevents unnecessary irrigation when rain has occurred or is expected
Soil pH	pH probe	Indicates the chemical condition of the soil, which affects nutrient availability
Nutrient levels	Soil nutrient sensing or laboratory analysis	Supports fertilizer management recommendations

Table 3: Parameters, sensing devices, and their role in irrigation

The actuators are pumps and solenoid valves. Since the output pins of a microcontroller cannot supply the current required by these devices, they are switched through relay or driver circuits, and the pump or valve is turned on and off according to the irrigation decision.



3.5 Microcontrollers and Communication Technologies

The microcontroller acquires sensor data, executes the control logic, and communicates with remote services. Arduino boards are widely used because of their low cost and simplicity, but basic models do not provide built-in wireless connectivity and need an additional communication module. The ESP32 integrates Wi-Fi and Bluetooth, provides several analogue input channels, and supports low-power operating modes, which makes it well suited for battery- or solar-powered field nodes. Single-board computers such as the Raspberry Pi offer greater processing capability and can be used as local gateways where more computation is required.

Communication technology is selected according to the distance and the availability of network coverage. Wi-Fi provides high data rates over short distances and is suitable where the field is close to an access point. GSM or cellular networks provide wide-area coverage in locations without Wi-Fi, and hybrid GSM and Wi-Fi arrangements can be used to improve reliability. Low-power wide-area technologies such as LoRa support long-range transmission of small data packets at low energy cost. At the application level, lightweight publish-subscribe protocols such as MQTT, or HTTP-based interfaces, are commonly used to send sensor data to cloud platforms, which store the time-series data, generate alerts, and present dashboards to the user.

3.6 Machine-Learning Techniques

Machine learning allows the system to learn relationships between agricultural parameters and outcomes from data rather than relying only on fixed rules. Supervised learning is used when labelled data are available. Classification algorithms assign an input to a category, for example, recommending a suitable crop for given soil and weather conditions, whereas regression algorithms predict a continuous value, such as crop yield or future soil moisture.

Several algorithms are commonly applied for these tasks. K-nearest neighbours (KNN) assigns a sample to the class most common among its k closest samples in the feature space and requires no explicit training stage. Logistic regression models the probability of a class using the logistic function. Naïve Bayes applies Bayes' theorem under the assumption that features are conditionally independent given the class. Support vector machines (SVM) find the decision boundary that maximises the margin between classes and can handle non-linear problems through kernel functions. Artificial neural networks consist of interconnected layers of neurons that learn non-linear relationships, and ensemble methods such as boosting combine several weak learners to obtain a stronger predictor.

Soil moisture and weather variables form time series, in which current values depend on previous ones. Recurrent neural networks, and in particular long short-term memory (LSTM) networks, are designed for such sequential data because their gating mechanism allows information to be retained over longer periods. For deployment in the field, compact models can be executed directly on microcontrollers using Tiny ML techniques, which reduces dependence on network connectivity and cloud processing.

3.7 Data Preprocessing and Feature Scaling

Sensor data often contain missing readings, duplicates, and noise, which must be handled before model training. Features measured on different scales, such as rainfall and soil pH, can also bias distance-based and gradient-based algorithms. Two common scaling methods are considered. Min-max normalisation rescales each feature to the range 0 to 1, as shown in Eq. (5).

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (5)$$

where x is the original value and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the feature. Standardisation transforms the feature to zero mean and unit variance, as given in Eq. (6).

$$z = \frac{x - \mu}{\sigma} \quad (6)$$

where μ is the mean and σ is the standard deviation of the feature. Feature selection is applied in addition to scaling: it removes attributes that contribute little to the prediction, which reduces model complexity and training time and can improve generalisation.

3.8 Performance Evaluation Measures

The performance of classification and prediction models is measured on data that were not used for training. For classification, the confusion matrix records the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). For regression, the measures are based on the difference between the actual values y_i and the predicted values $\hat{y}_i$ over n samples. Table 4 lists the measures considered in this work.



Measure	Formula	Interpretation
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$	Proportion of all predictions that are correct
Precision	$TP / (TP + FP)$	Proportion of predicted positives that are actually positive
Recall	$TP / (TP + FN)$	Proportion of actual positives that are correctly identified
F1-score	$2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$	Harmonic mean of precision and recall
MAE	$(1/n) \sum y_i - \hat{y}_i $	Average absolute prediction error
MSE	$(1/n) \sum (y_i - \hat{y}_i)^2$	Average squared error; penalises large errors
RMSE	$\sqrt{\text{MSE}}$	Error expressed in the unit of the predicted variable
R ² score	$1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2$	Proportion of the variance in the data explained by the model

Table 4: Performance evaluation measures

METHODOLOGY

The proposed precision farming methodology aims to improve agricultural productivity, optimize the use of resources, and support farmers in making data-driven decisions. The system integrates agricultural data, sensors, machine learning techniques, and intelligent recommendations to monitor crop and soil conditions and provide suitable farming decisions.

4.1 Data Collection

The first stage involves collecting relevant agricultural data such as soil moisture, soil temperature, humidity, rainfall, temperature, pH value, crop type, and nutrient levels. Historical agricultural datasets can also be collected from reliable agricultural databases and government sources.

4.2 Data Preprocessing

The collected data is cleaned and prepared before being used by the machine learning model. Missing values, duplicate records, inconsistent values, and noisy data are identified and handled. Numerical features are normalized or standardized when required.

4.3 Feature Selection

Important features affecting crop growth and productivity are selected from the available dataset. Parameters such as rainfall, temperature, humidity, soil moisture, soil pH, and nutrient availability are considered to identify the factors that have the greatest influence on crop performance.

4.4 Crop and Soil Analysis

The processed data is analyzed to understand the current agricultural conditions. The system compares environmental and soil parameters with the requirements of different crops. This helps identify suitable crops and determine whether the existing conditions are favourable for cultivation.

4.5 Machine Learning Model Development

Machine learning algorithms are trained using the processed agricultural dataset. Depending on the application, classification algorithms can be used for crop recommendation, while regression algorithms can be used for crop-yield prediction. The dataset is divided into training and testing sets to evaluate model performance.

4.6 Precision Irrigation and Resource Management

The system uses soil moisture and weather-related information to determine irrigation requirements. Instead of applying the same amount of water to the entire field, irrigation recommendations can be generated according to the actual requirements of the crop and soil. This helps reduce unnecessary water consumption.



4.7 Prediction and Recommendation

After training, the machine learning model receives current agricultural parameters and generates predictions. Based on these predictions, the system can recommend suitable crops, irrigation requirements, fertilizer management, and other farming practices.

4.8 Model Evaluation

The performance of the developed model is evaluated using appropriate performance metrics. For classification problems, accuracy, precision, recall, and F1-score can be used. Precision is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

where TP = True Positive and FP = False Positive.

For crop-yield prediction, metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R² score can be used.

4.9 System Implementation

The final model is integrated into the Smart Agriculture application. A user-friendly interface allows farmers or users to enter agricultural parameters and receive recommendations. The system can be implemented using technologies such as Python, Flask/Django, MySQL, HTML, CSS, JavaScript, and machine learning libraries such as Scikit-learn.

4.10 Continuous Monitoring

The system can continuously monitor agricultural conditions when real-time sensor data is available. Changes in soil moisture, temperature, humidity, and weather conditions can be analyzed to update recommendations and improve resource management.

The workflow of these stages is shown in Figure 2, and Table 5 summarises the input and output of each stage.

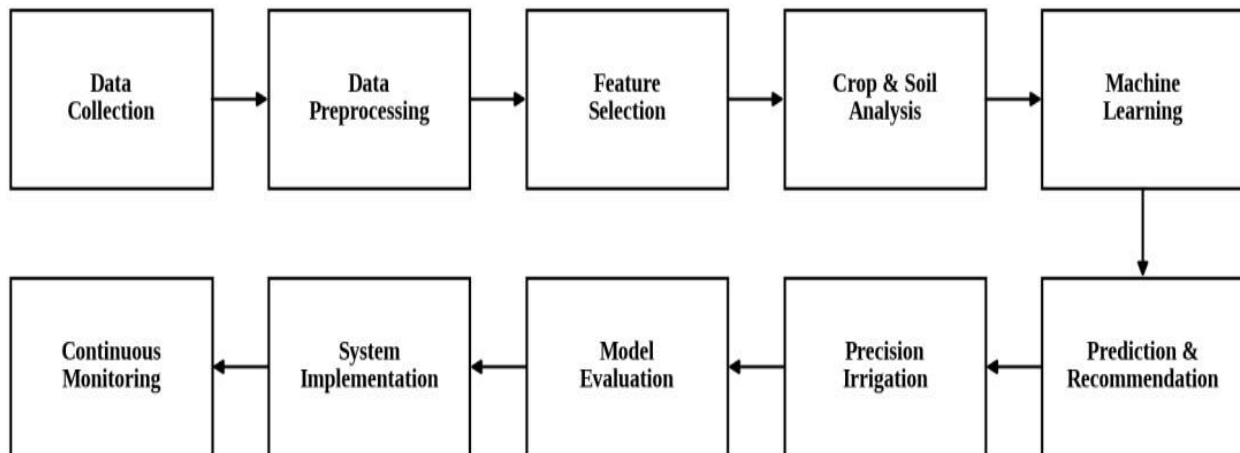


Figure 2: Workflow of the proposed Smart Irrigation System methodology

Stage	Main input	Output / purpose
Data collection	Sensor readings; historical agricultural datasets	Raw agricultural dataset
Data preprocessing	Raw dataset	Cleaned and normalised data
Feature selection	Processed dataset	Features with the greatest influence on crop performance
Crop and soil analysis	Selected features; crop requirements	Assessment of suitable crops and field conditions
Machine-learning model development	Training and testing sets	Trained classification or regression model



Precision irrigation and resource management	Soil moisture; weather-related information	Irrigation recommendation based on actual requirement
Prediction and recommendation	Current agricultural parameters	Crop, irrigation, and fertilizer recommendations
Model evaluation	Test data; model predictions	Performance measures
System implementation	Trained model	User interface for farmers
Continuous monitoring	Real-time sensor data	Updated recommendations

Table 5: Summary of the methodology stages

RESULTS

The proposed Smart Irrigation System for Precision Farming provides an integrated approach for monitoring soil and environmental conditions and supporting intelligent irrigation decisions. The system uses parameters such as soil moisture, temperature, humidity, rainfall, pH, crop type, and nutrient levels to generate suitable farming recommendations.

The expected results are:

1. Improved Water Management: Irrigation can be provided according to actual soil-moisture and crop requirements, helping reduce unnecessary water consumption.
2. Better Crop Decisions: Machine learning can analyze agricultural parameters and provide crop and farming recommendations.
3. Reduced Manual Effort: Sensor-based monitoring and automated irrigation can reduce the need for continuous manual monitoring.
4. Efficient Resource Utilization: Soil, weather, and crop information can be used to manage water and other agricultural resources more efficiently.
5. Continuous Monitoring: Real-time sensor data can help monitor changes in soil moisture, temperature, humidity, and weather conditions and update recommendations accordingly.
6. Model Performance Evaluation: The system can evaluate machine-learning performance using accuracy, precision, recall, F1-score, MAE, RMSE, and R^2 , depending on the prediction task.

Overall, the proposed system is expected to support precision agriculture by improving irrigation management, reducing resource wastage, and providing data-driven recommendations to farmers.

DISCUSSION

The proposed precision farming system integrates IoT sensors, machine learning, and data analysis to improve agricultural decision-making. Soil and weather data are collected and processed to recommend suitable crops, irrigation, and fertilizer requirements.

Machine learning helps provide accurate crop and yield predictions, while real-time monitoring allows recommendations to be updated according to changing field conditions. Overall, the system can reduce water and fertilizer wastage, improve crop productivity, and support sustainable farming.

6.1 Challenges and Limitations

Although sensor-based and machine-learning-based irrigation offers clear advantages, several practical challenges must be considered. Sensor calibration is necessary because readings vary with soil type and installation conditions, and sensors may drift over time. Reliable connectivity is required for remote monitoring, and network coverage in rural areas can be limited. The energy consumption of field nodes needs to be controlled, particularly when they operate on batteries or solar power. Cost and complexity influence adoption by small-scale farmers, so the system should use low-cost components and remain simple to operate. In addition, the literature indicates that heavy rainfall and spatial variability in soil conditions can reduce the reliability of prediction models, and that larger and more diverse datasets are needed for dependable deployment.

6.2 Future Scope

The present work describes the proposed methodology and the outcomes expected from it; quantitative validation through field experiments remains to be carried out. Future work can therefore evaluate the system on real sensor data from different crops and soil types and report water use, crop health, and model performance measures. Further directions



include running compact models on the microcontroller using edge computing and TinyML, adding remote-sensing data to capture spatial variability, and extending the dashboard with alerts and farmer-friendly interfaces.

CONCLUSION

Precision farming provides an effective approach to modern agriculture by combining IoT sensors, machine learning, data analysis, and intelligent decision-making. The proposed system helps monitor soil and environmental conditions and provides suitable recommendations for crop selection, irrigation, and fertilizer management.

By using real-time and historical agricultural data, the system can help farmers reduce water and fertilizer wastage, improve crop productivity, lower unnecessary costs, and make better farming decisions. Overall, precision farming contributes to efficient resource utilization, sustainable agriculture, and improved farm management.

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