IoT and Machine Learning-Based Smart Watering Model for Water Optimization in Vegetable Gardens

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Abstract—Efficient water management has become increasingly important in modern agriculture due to growing increasing demand for finite water supplies and the necessity of promoting sustainable farming practices. Traditional time-based irrigation approaches often result in inefficient water use and limited adaptability to dynamic environmental conditions. This study presents the design and preliminary validation of an Internet of Things (IoT)- and Machine Learning (ML)-based smart irrigation framework at Technology Readiness Level (TRL) 3. The proposed framework integrates real-time sensor measurements, external weather information, and a Random Forest–based forecasting algorithm to determine crop water demand support adaptive irrigation scheduling. Experimental and simulation-based evaluations demonstrated that the Random Forest model achieved satisfactory predictive performance, with an RMSE of 0.19 L/m² and an MAE of 0.16 L/m². Furthermore, the proposed framework showed the potential to reduce irrigation water consumption by approximately 30% compared with conventional fixed-schedule irrigation while maintaining adequate water availability for crop growth. The integration of multi-source environmental data and predictive analytics enabled more accurate irrigation decisions, contributing to improved water-use efficiency and reduced irrigation-related operational costs. These findings highlight integrating connected sensing systems with machine learning techniques can facilitate evidence-based irrigation management while promoting long-term agricultural sustainability.

Keywords—Efficient water management; Smart Irrigation; Internet of Things; Machine Learning; Random Forest

I. Introduction

Sustainable utilization of agricultural water resources is increasingly important as farming systems face limited freshwater availability, unpredictable climatic conditions, and rising requirements for food production. Inefficient irrigation management may result in unnecessary water losses, lower agricultural yields, and higher expenditures associated with farm operations. Consequently, the development of intelligent irrigation systems has become essential to support sustainable agricultural production. The emergence of IoT-based sensing networks has made it possible to collect environmental information in real time, whereas ML algorithms provide analytical capabilities for generating intelligent irrigation recommendations from the acquired data. [1], [2].

The use of Machine Learning techniques in agricultural systems has shown considerable effectiveness in predicting crop water demand by analyzing environmental factors, including soil moisture content, air temperature, and relative humidity. Intelligent learning algorithms support dynamic irrigation management by adjusting water delivery according to environmental fluctuations, thereby reducing water wastage while sustaining agricultural output. [3], [4]. In parallel, IoT technologies have been increasingly adopted in precision agriculture to support automated monitoring and control through continuous environmental data collection [5], [6].

The convergence of IoT and ML technologies has emerged as a prominent research area in the development of intelligent irrigation systems. Previous studies have investigated machine learning-based irrigation scheduling using environmental data and demonstrated its effectiveness in improving irrigation management [7]. Several studies have proposed IoT-enabled irrigation frameworks that integrate soil moisture sensing devices with cloud-based communication platforms to support automated irrigation control and continuous field monitoring [8]. Despite their contribution to improving water-use efficiency, irrigation operations in these systems were generally triggered using fixed soil moisture criteria. In addition, meteorological forecast data have been incorporated into irrigation planning strategies to minimize unnecessary watering during rainfall events; however, irrigation recommendations remained dependent on rule-based mechanisms rather than predictive machine learning approaches [9]. Cloud-based IoT irrigation frameworks have also been developed to enable remote monitoring and management, although predictive models for estimating crop water demand were not comprehensively integrated into the irrigation decision-making process [10].

Despite these advances, several limitations remain. Most existing smart irrigation systems rely on static threshold-based approaches or simple rule-based decision mechanisms, which may not adequately respond to dynamic environmental conditions [9]. Furthermore, the integration of real-time sensor measurements, external weather information, and machine learning-based prediction within a unified irrigation decision-support framework remains limited. As a result, irrigation decisions may not fully reflect actual field conditions, reducing water-use efficiency and system adaptability [3], [5].

To address these limitations, this study proposes an IoT and Machine Learning-based smart irrigation framework for water optimization in vegetable cultivation. The proposed system integrates real-time environmental sensor data, external weather information, and a Random Forest prediction model to estimate crop water requirements and support adaptive irrigation scheduling. By combining multi-source environmental data with predictive analytics, the framework aims to improve irrigation accuracy, optimize water consumption, and contribute to sustainable agriculture through intelligent and data-driven water management [4], [7], [10].

II. Research Methods

A. Research Stages

This research uses a systems engineering and quantitative experimental approach. The aim is to design and validate the initial concept of an IoT and ML-based smart watering system that can be controlled in real time via mobile devices. The research methodology includes the following stages:

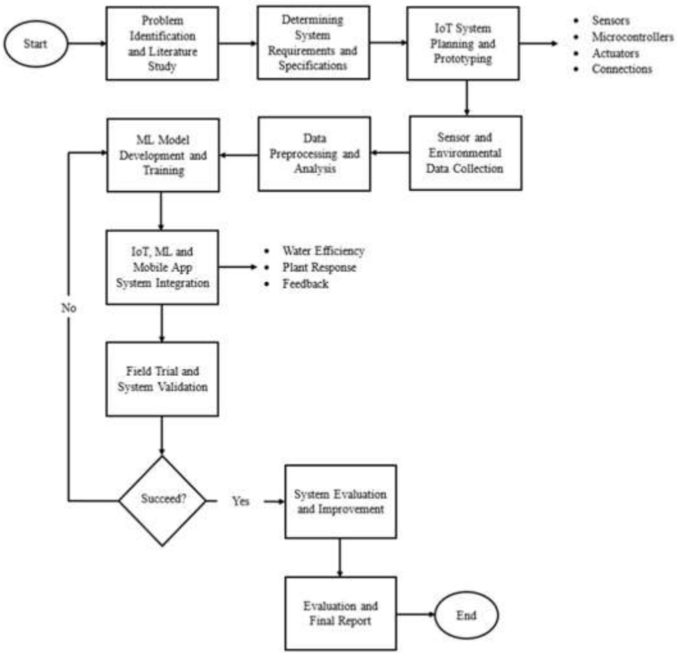

Figure 1. Research Stages

Figure 1 presents the research workflow adopted in this study. The research process comprises problem identification, literature review, system requirements analysis, system design and simulation, machine learning model development, and validation of the proposed IoT-based smart irrigation system. This research process was designed to design and validate the initial concept of an Internet of Things (IoT) and Machine Learning (ML)-based smart irrigation system that can be controlled in real time via mobile devices. The process began with identifying problems related to inefficient plant watering, followed by a literature review to assess relevant technologies and approaches. Next, research objectives were formulated, leading to efficient water use and environmental data-driven irrigation automation [3], [11], [12].

After establishing the objectives, a system requirements analysis was conducted to determine key components such as soil moisture and temperature sensors, a microcontroller, and cloud connectivity. The next stage was system simulation and design, which included modeling ML algorithms, integrating sensor data, and simulating functional testing [11].

B. *Sytem Design*

1. *The Design of System Architecture*

This system was designed by integrating) Internet of Things (IoT) and Machine Learning (ML) to automate and optimize precision irrigation for vegetable gardens. The architecture consists of three interconnected layers: data collection (IoT), intelligent processing (ML), and the user interface (Mobile App). The system's workflow is explained below [13], [6]:

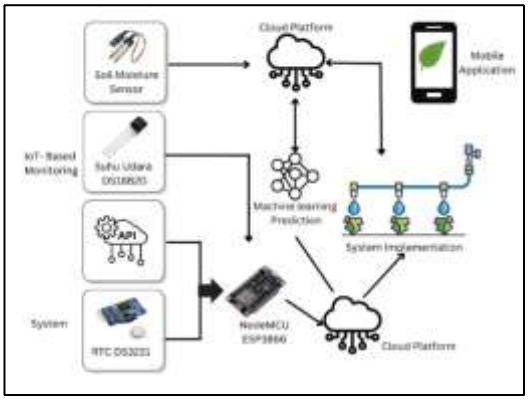

Figure 2. System Architecture

Figure 2 provides an overview of the proposed data-driven irrigation system, highlighting the integration of IoT infrastructure and Machine Learning components. The architecture integrates environmental sensing, cloud-based data processing, machine learning-based water requirement prediction, and mobile-based monitoring and control to support adaptive and efficient irrigation management. An IoT-based and machine learning-based smart irrigation system designed to optimize water use in vegetable gardens. The system begins with data acquisition through several sensors, including a soil moisture sensor, a DS18B20 temperature sensor, and a DS3231 RTC module, which determines watering times. The system can also utilize external data via an API as supporting data. All data obtained from the sensors is sent to a NodeMCU ESP8266 microcontroller device, which acts as a control center in the field [1], [2].

The NodeMCU collects, pre-processes, and transmits the data to a cloud platform via the internet. On the cloud platform, the data is stored as a historical database and then analyzed using machine learning methods to predict plant water needs based on environmental conditions and soil moisture. The results of this analysis serve as the basis for decision-making in determining the optimal watering time and duration [14].

The watering command is then relayed to the field implementation system, which consists of actuators such as water pumps and irrigation valves that operate automatically. This ensures that watering is only carried out when plants truly need water, reducing waste and increasing the efficiency of water resource use. In addition to running automatically, the system is also integrated with a mobile application that allows users to monitor garden conditions in real time, view historical data, and perform manual control if necessary.

Overall, this architecture demonstrates the integration of sensor technology, IoT devices, cloud computing, and machine learning to support an adaptive, efficient, and data-driven irrigation system to support smart farming practices in vegetable gardens.

2. *System Implementation*

The smart irrigation system was conceptually designed through device-based modeling and simulation, which is planned for use in the next implementation phase. The system design includes the placement of soil moisture, air temperature, and time-sensitive (RTC) sensors at strategic points to represent environmental conditions comprehensively. All sensors are designed to be connected to a NodeMCU ESP8266 microcontroller, which will serve as a data acquisition center and send information to a cloud platform via a Wi-Fi connection [15].

The collected environmental data is designed to be analyzed using a simulated machine-learning model to predict irrigation needs based on temperature, soil moisture, and weather data. This model is designed to be integrated into a cloud platform or local server to generate automated decisions regarding irrigation schedules and volumes. The concept of automatic water valve or pump control was also incorporated into the system simulation [7].

As a user interface, a mobile application design was conceptually developed to enable real-time garden monitoring.

3. *Data Collection and Validation*

The dataset used in this study was obtained from three sources: IoT sensor measurements, open-source environmental datasets, and synthetic data. IoT data represented real-time field conditions, including soil moisture and temperature measurements, while open-source data provided complementary weather information such as rainfall, humidity, and temperature records. Synthetic data were generated to increase dataset diversity and compensate for the limited availability of real-world observations during the initial development phase [16], [17].

To ensure data reliability, the synthetic data were validated by comparing their statistical characteristics, including mean values, standard deviations, minimum values, and maximum values, with those of the original datasets. The generated data remained within realistic environmental ranges and followed similar distributions to the observed data, making them suitable for simulation and machine learning model development, [18], [19].

4. *Data Preprocessing*

Prior to model development, the collected data underwent preprocessing, including data cleaning, normalization, transformation, and integration. Missing values and inconsistent records were handled during the cleaning process, while numerical variables were normalized to ensure consistent feature scales. Subsequently, data from multiple sources were synchronized and integrated into a unified dataset for model training and evaluation.

5. *Machine Learning Model Development*

A Random Forest algorithm was employed to predict crop water requirements based on environmental variables, including soil moisture, temperature, humidity, and weather-related data [3], [4], [7]. The dataset was divided into training and testing subsets using an 80:20 ratio to evaluate the model's predictive capability.

The model was developed using 100 decision trees, where each tree was trained on a randomly selected subset of the available data. The final prediction was generated by combining the outputs of all trees, thereby improving prediction stability and robustness.

Since this study focused on the conceptual design and initial validation of the proposed framework, hyperparameter tuning was not performed. The trained model was subsequently integrated into the IoT-based smart irrigation system to support adaptive irrigation scheduling and improve water-use efficiency based on real-time environmental conditions [9], [14].

III. Results and Discussion

A. *Overview of the System Model*

This research produces a smart watering system model based on the Internet of Things (IoT) with Machine Learning (ML) algorithms, specifically the Random Forest model, to predict water needs in vegetable plants, namely mustard greens and lettuce. The modeling of the smart watering system based on the Internet of Things (IoT) was made using a DS18B20 temperature sensor, a soil moisture sensor, and a real-time RTC DS3231 module. Each sensor is used to be able to analyze various environmental parameters, such as air temperature, soil moisture, and weather conditions, to automatically adjust the volume and time of watering [16].

The main objective of this model is to help farmers optimize water use and ensure that crops receive watering appropriate to their environmental conditions. The system modeling is developed with three main parts, namely data collection, analysis and processing, and decision making. A DS18B20 temperature sensor, a soil moisture sensor, and a DS3231

RTC real-time module are used to read the system in real time [16].

B. *Data Set*

The data used in this study comes from three main data sources, namely:

1. Open-source datasets, such as WeatherAPI, NASA Power, and FAO CLIMWAT, which provide daily historical climate data including air temperature, humidity, rainfall, and solar radiation parameters at various agricultural locations [17], [18], [19].

Table 1. Dataset Open Source (WeatherAPI, NASA POWER, FAO CLIMWAT) (ex. for 5 data)

No	Air Temperature (°C)	Humidity (%)	Rainfall (mm)	Weather Status	Data Source
1	30.8	72.4	2.1	Bright	WeatherAPI
2	28.5	78.2	4.8	Overcast	NASA POWER
3	26.9	82.1	0.0	Bright	FAO CLIMWAT
4	31.1	68.9	5.5	Rain	Weather API
5	29.3	75.0	1.3	Overcast	NASA POWER

The data presented in Table 1 demonstrate the variability of environmental conditions obtained from different open-source platforms. These data serve as an important source for training and validating the crop water requirement prediction model.

2.Experimental results from a similar study that monitored environmental conditions in an IoT-based agricultural system. This data was used to strengthen the validity and variability of the analyzed environmental conditions.

Table 2. IoT Experiment Data (ex. for 5 data)

No	Soil Temperature (°C)	Soil Moisture (%)	Air Temperature (°C)	Air Humidity (%)	Rainfall (mm)	Location
1	27.3	61.5	29.4	73.2	0.0	Mustard Garden
2	29.1	55.8	31.2	68.4	1.2	Lettuce Garden
3	28.6	63.0	30.1	70.1	0.4	Mustard Garden
4	30.2	58.9	32.0	65.3	4.8	Lettuce Garden
5	27.9	66.2	29.7	75.5	0.0	Mustard Garden

The experimental data shown in Table 2 complement the open-source weather data by providing field-level environmental observations relevant to crop water requirement prediction.

3. Synthetic data, generated based on local climate conditions by adjusting the range of temperature, humidity, and weather status (sunny, cloudy, rainy). Generated to depict variations in Ketapang's climate conditions during August–September 2025.

The data generation process was carried out using a scientific approach based on statistical distributions and local climatological parameters, namely:

a. parameters based on NASA POWER and FAO CLIMWAT data to determine realistic temperature, humidity, and rainfall limits.
b. Simulation of environmental variable values using a normal distribution with mean parameters adapted to local conditions (e.g., an average temperature of 29°C with a deviation of 2°C).
c. Correlations between variables were maintained logically, such as increasing air humidity and decreasing radiation during rainfall.
d. Visual and statistical validation were performed to ensure the synthetic data remained representative of actual weather trends in Ketapang.

Table 3. Synthetic data generated based on local climate conditions

No	Air Temperature (°C)	Air Humidity (%)	Soil Moisture (%)	Weather Status	Location
1	27.1	83.4	65.2	Bright	Mustard Garden
2	31.3	75.2	58.5	Overcast	Lettuce Garden
3	29.6	78.1	67.8	Bright	Mustard Garden
4	32.4	71.5	55.3	Rain	Lettuce Garden
5	26.5	85.9	71.4	Bright	Mustard Garden

As shown in Table 3, the synthetic dataset reflects realistic variations in temperature, humidity, soil moisture, and weather conditions, making it suitable for machine learning model training.

Next, all data from the three sources were combined based on the same collection time (every 30 minutes). The merging process was performed using Python in Google Colab to create a single, unified dataset ready for use in training a Machine Learning model to predict plant water needs.

After integrating data from the three main sources (open-source, IoT experiments, and synthetic data), a total of 1,200 data sets were obtained, representing environmental conditions during the period from August to September in the Ketapang region. Each data set contained parameters such as time, air temperature, soil moisture, rainfall, and solar radiation.

The dataset was then divided into two parts:

1. The training set, 80% of which, or 960 data sets, was used to train the Machine Learning model to recognize

patterns of relationships between environmental parameters.
2. The testing set, 20% of which, or 240 data sets, was used to evaluate the model's performance on new, previously unseen data.

This split is done randomly using the train_test_split function from the Scikit-learn library in Google Colab, to ensure the model has good generalization capabilities to variations in data in the field.

1. Data Preprocessing
   Next, after the data is obtained, a preprocessing stage is performed to ensure the training and test data are high-quality, consistent, and representative of actual environmental conditions. This stage is necessary because the data comes from open-source sources and previous research. The data preprocessing stages include:
   a. Data Cleaning
      This stage detects and handles missing values, duplicates, and outliers. Incomplete weather data, such as missing daily temperature or humidity data, is filled using linear interpolation or moving average-based estimation to avoid disrupting the model training process.
   b. Data Normalization
      Each variable used in temperature, humidity, and rainfall sensor data has different units, necessitating a data normalization process. In this research, data normalization was performed using the Mix-Max scaling method or standardization with Z-score normalization. This method aims to ensure each feature contributes equally to the training process using the Machine Learning algorithm with the Random Forest model [7], [9].
2. Time and Weather Data Transformation
   The data transformation stage is a crucial process in preparing datasets for machine learning modeling. Data obtained from various sources, such as WeatherAPI, NASA POWER, and FAO CLIMWAT, have different time formats, value ranges, and units [18], [20].
   Several steps are required to transform the data: (1) converting the time format to standard, (2) transforming weather units, (3) converting radiation, (4) extracting time features, and (5) combining sensor and weather data based on the nearest time.
3. Multi-Source Data Integration and Synchronization
   Research using data from various sources requires a multi-source data integration and synchronization process to ensure that all data used in modeling has a uniform format, time, and units. Each data set has a different recording frequency, column structure, and time zone [17]. Each data point is converted to the local time zone (WIB/UTC+7). This time alignment process aims to align the measurement points between external weather data and sensor readings in the IoT system.
   Next, a data merging process is performed to combine parameters from various sources into a single, integrated dataset containing air temperature, soil moisture, rainfall, and light intensity. Each time entry (time stamp) serves as the primary key in the merging process to prevent duplication or data loss.
4. Data Separation for Training and Testing
   The final stage of data pre-processing is the separation of the data into training and test data. In machine learning, this stage is crucial and fundamental to ensuring that the developed model can generalize to new data.
   The process of dividing the training and test data is carried out randomly using a random split to avoid bias in the time sequence or crop type; in this study, mustard greens and lettuce were used.

C. Modeling and Training of ML Algorithms

This stage is the core of the research, namely, building a machine learning-based plant water requirement prediction model. The model's goal is to analyze the relationship between environmental variables such as air temperature, soil moisture, rainfall, and light intensity with the water requirements of mustard and lettuce plants [9].

The algorithm used is Random Forest, an ensemble learning method that combines multiple decision trees to produce more stable and accurate predictions. This algorithm was chosen because of its ability to handle highly variable data and minimize the risk of overfitting compared to a single model, such as a decision tree [4].

Random Forest was chosen as the prediction model because of its ability to effectively capture nonlinear interactions among environmental parameters and improve generalization performance through ensemble learning. Compared with conventional machine learning approaches, such as a single Decision Tree or Support Vector Machine (SVM), Random Forest offers greater robustness against overfitting and can efficiently process heterogeneous agricultural datasets with minimal parameter adjustment. Therefore, it is well suited for estimating crop water requirements based on integrated environmental data obtained from multiple sources.[4], [9].

The dataset was divided into two parts:
1) Training data (80% of the total data),
2) Test data (20% of the total data).

The algorithm used is Random Forest Regressor, because it is able to handle non-linear relationships and produce stable predictions despite fluctuating sensor data. The model was trained using variables such as air temperature, soil moisture, and reading time to predict plant water requirements (ml).

Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) to assess the accuracy of crop water requirement predictions.

Through this approach, the system is expected to provide automatic water requirement estimates based on actual environmental conditions, thereby helping to improve water use efficiency and supporting the implementation of sustainable smart irrigation systems in the modern agricultural sector [10].

Next, a comparison curve is displayed between actual and predicted crop water requirements, Figure 3 shows the comparison between actual and predicted crop water requirements generated by the Random Forest model.

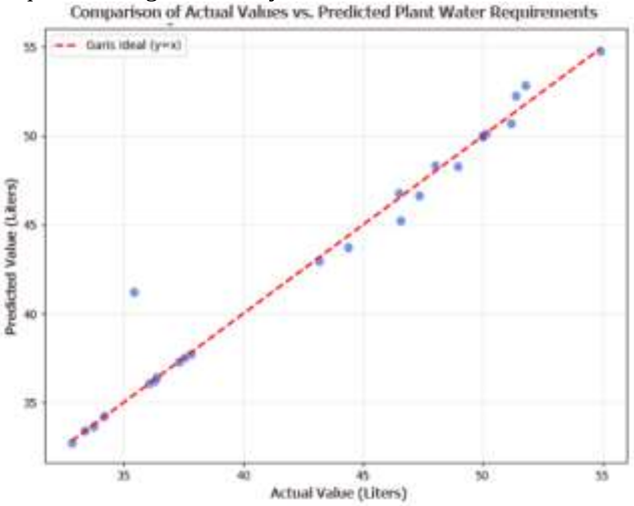

Figure 3. Comparison Curve between Actual and Predicted Plant Water Requirements

Curve Interpretation:

1. The data points are spread very closely around the diagonal line, indicating that the predicted results are nearly identical to the actual values.
2. Small deviations around the line indicate a very low error rate.
3. The central distribution pattern indicates the model has high predictive consistency across the entire test data range.

The following figure shows the relationship between temperature, soil moisture, and predicted water requirements:

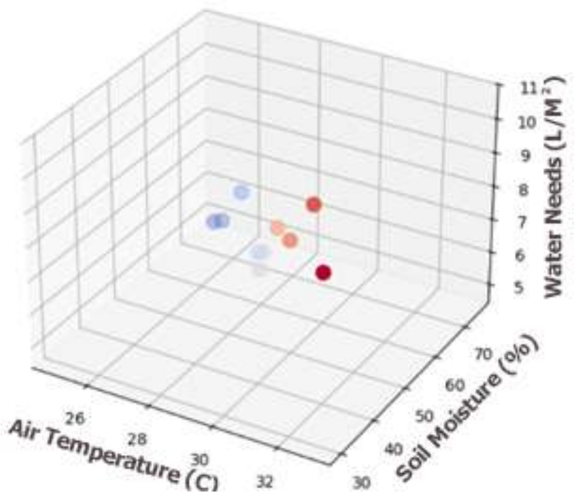

Figure 4. The Relationship Between Tribes, Soil Humidity, and Water Need Prediction

Figure 4 shows the relationship between air temperature, soil moisture, and predicted crop water requirements. The figure shows the relationship between air temperature (°C), soil moisture (%), and plant water requirements (L/m²) based on the prediction results of the Random Forest Regressor model. Each point on the three-dimensional graph represents environmental conditions recorded by the IoT sensor system.

It can be seen that increasing air temperature is directly proportional to increasing plant water requirements due to increased evapotranspiration rates. Conversely, high soil moisture correlates with decreased water requirements, as moist soil conditions adequately meet plant needs.

The color gradient in the graph indicates temperature variations, with reddish colors indicating higher temperatures and greater water requirements. These results demonstrate that the machine learning model is capable of capturing nonlinear relationships between environmental variables and plant water requirements, which form the basis for adaptive decision-making in an IoT-based smart watering system.

D. *Results of the Water Needs Prediction Model Evaluation*

Based on the results of testing the Machine Learning-based water demand prediction model, comparative data were obtained between actual water demand and predicted water demand, as shown in the following table.

Table 4. Comparison of Actual and Predicted Water Needs

No	Air Tempe-rature (°C)	Soil Moisture (%)	Actual Water Require-ments (L/M²)	Predicted Water Require-ments (L/M²)	Water Savings (L/M²)	Savings (%)
1	25.5	70	5.0	3.6	1.4	28.0%
2	27.2	62	6.3	4.4	1.9	30.2%
3	28.9	55	7.6	5.3	2.3	30.3%
4	30.4	47	8.9	6.2	2.7	30.3%
5	32.0	40	10.1	7.0	3.1	30.7%

As shown in Table 4, the predicted water requirements are consistently lower than the actual irrigation volumes, resulting in water savings ranging from 28% to 30.7%, with an average saving of approximately 30%. These results demonstrate the effectiveness of the proposed system in optimizing water use. The table above shows that the IoT and Machine Learning-based smart watering system significantly optimizes water use. The predicted water requirements are lower than the actual water requirements, with savings ranging from 28% to 30.7%, with an average water savings of 30%.

When evaluated against traditional irrigation practices that operate using predetermined schedules, the proposed intelligent irrigation solution demonstrated superior flexibility in regulating water distribution. By leveraging real-time environmental observations and predictive analysis, irrigation decisions were tailored to the actual conditions of the cultivation area rather than relying on static rules. The findings from the simulation study revealed that this strategy could achieve substantial water savings, with total irrigation demand reduced by nearly one-third, while still maintaining adequate moisture levels required for healthy crop development.

These results indicate that the prediction model successfully adjusts the water volume applied based on actual environmental conditions (air temperature and soil moisture), allowing for more efficient watering without reducing plant water requirements.

To evaluate the model's accuracy, calculations were performed using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE). Based on the calculation results on the test data

1. RMSE = 0.19 L/m^2
2. MAE = 0.16 L/m^2
3. MSE = 0.036 L^2/m^4

This relatively small error indicates that the model has good and stable predictive ability in estimating plant water requirements. Thus, the implementation of the proposed system demonstrates the potential to reduce irrigation water consumption by approximately 30% compared with conventional irrigation practices. From a practical perspective, this reduction can lower water pumping and energy costs, particularly in areas where irrigation depends on electrically powered pumps. Improved irrigation accuracy may also reduce the risks of overwatering and water stress, thereby supporting healthier crop growth and potentially improving crop productivity. These benefits highlight the potential contribution of the proposed framework to sustainable and resource-efficient agricultural management.

IV. Conclusion

1. This study presents the design and preliminary validation of an Internet of Things (IoT)- and Machine Learning-based smart irrigation framework that employs a Random Forest algorithm to estimate the water requirements of mustard and lettuce crops.
2. A comprehensive dataset comprising 1,200 records was constructed through the integration of multiple data sources, including open-source environmental datasets, IoT-based sensor observations, and synthetically generated data. This integrated dataset provided a robust foundation for model training and performance evaluation.
3. The Random Forest model effectively captured the complex nonlinear relationships among environmental variables, including air temperature, soil moisture, and crop water requirements. The model demonstrated satisfactory predictive performance, achieving an RMSE of 0.19 L/m^2, an MAE of 0.16 L/m^2, and an MSE of 0.036 L^2/m^4.
4. Simulation-based evaluation indicated that the proposed framework has the potential to reduce irrigation water consumption by approximately 30% compared with conventional irrigation approaches, while maintaining sufficient water availability to support crop growth and development.
5. The comparison between observed and predicted values revealed low prediction errors and consistent model performance under varying environmental conditions, indicating strong model stability and generalization capability.
6. Overall, the proposed IoT- and Machine Learning-based irrigation framework demonstrates considerable potential for enhancing water-use efficiency and supporting data-driven irrigation management. Future research should focus on large-scale field validation, the integration of additional environmental sensing parameters, and advanced model optimization techniques to further improve prediction accuracy, system reliability, and agricultural sustainability.

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