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Automated Rose Farming with IoT and Machine Learning: A Real-Time Predictive Irrigation System

Nur Zatil 'Ismah Hashim[1]*, Noramalina Abdullah[1] and Intan Sorfina Zainal Abidin[1]

[1]School of Electrical and Electronic Engineering, Universiti Sains Malaysia, 14300 Nibong Tebal, Pulau Pinang, Malaysia.

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ABSTRACT

Precision agriculture offers a practical solution to the limitations of traditional farming, particularly for delicate crops like roses. Manual irrigation methods often lead to inconsistent watering, resource wastage, and reduced crop health. This project introduces an IoT-based automated rose farming system enhanced with machine learning to enable real-time environmental monitoring and intelligent irrigation control. The system is built on the VisionFive2 RISC-V board and integrates SHT3x temperature-humidity and soil moisture sensors to capture real-time data. These inputs are transmitted via the MQTT protocol for live monitoring and processed using a Random Forest Regression model to predict optimal irrigation durations. The irrigation is automated through a DC water pump activated via a relay, with safeguards in place to avoid unnecessary cycles for predictions below one second. An alert feature also notifies users when soil moisture drops below critical thresholds. The model achieved 100% classification accuracy, with precision, recall, and F1-scores of 1.00, confirming high reliability in differentiating between above- and below-median irrigation needs. System testing validated accurate data acquisition, real-time dashboard integration, and responsive irrigation control. This work demonstrates a cost-effective, scalable solution for smart floriculture. Future improvements may include weather forecasting integration, adaptive learning for evolving plant needs, and automated fertigation to further optimize sustainability and yield.

Keywords: IoT platform, Machine learning, Rose cultivation, Soil moisture, Sustainable agriculture.

1. INTRODUCTION

Rose farming is a high-value sector in floriculture, with global demand driven by both ornamental appeal and economic significance [1,2]. However, roses are known to be sensitive to environmental stresses, particularly inconsistent irrigation, which can lead to stunted growth, reduced floral quality, and increased susceptibility to disease. Studies have shown that certain rose cultivars exhibit significant reductions in growth and visual quality under low irrigation frequency, highlighting the importance of precise water management in rose cultivation environments [3]. Manual irrigation, still prevalent in small- to medium-scale floriculture, is prone to inefficiencies such as overwatering, under-watering, and excessive labor requirements [4]. These practices not only waste water but also compromise plant health and yield consistency. In arid and semi-arid regions, improper scheduling and water losses through seepage or evaporation exacerbate the challenge [5]. Moreover, traditional irrigation methods fail to account for dynamic factors like microclimatic variation and short-term weather changes, making them unsustainable in precision agriculture systems. The integration of Internet of Things (IoT) and Machine Learning (ML) offers a promising solution to these challenges. IoT technologies enable

*Corresponding author: zatil.hashim@usm.my

real-time sensing of soil and environmental conditions [6-10], while ML algorithms enhance decision-making through predictive analysis [11]. By leveraging data-driven insights, automated irrigation systems can optimize water use, reduce operational costs, and increase crop productivity [12-14]. Specifically, in the context of smart agriculture, closed-loop systems combining sensor feedback and ML-driven control allow fine-tuned water application aligned with plant needs [15-20]. This work develops a real-time, low-cost predictive irrigation system for rose cultivation that converts IoT sensor streams (SHT3x temperature–humidity and resistive soil-moisture via MCP3008) into pump-duration commands on a VisionFive2 RISC-V controller, closing the loop from sensing to actuation. The aims are to: (i) build an end-to-end platform for continuous monitoring and MQTT-based telemetry, (ii) train and deploy a Random-Forest regression model that predicts irrigation time from soil moisture variables, and (iii) validate closed-loop actuation and skip-logic behaviour under controlled tests.

2. METHODOLOGY

This study implements a closed-loop IoT-based smart irrigation system optimized through machine learning (ML) to automate water application based on real-time environmental conditions. The architecture integrates sensor data acquisition, model inference, actuator control, and wireless communication into a single embedded platform.

2.1 System design and operation

The proposed system is designed to automate irrigation using real-time environmental sensing and machine learning–based control. At the core of the system is a VisionFive 2 single-board computer, which serves as the central controller. It collects data from two types of sensors: a Sensirion SHT3x for measuring ambient temperature and humidity, and a resistive soil moisture sensor. The soil moisture sensor produces an analog signal that is digitized using an MCP3008 analog-to-digital converter (ADC). Communication with these sensors is handled through standard I2C and SPI interfaces. To apply irrigation, the system uses a DC water pump powered by an external battery. The pump is controlled through a relay module triggered by the VisionFive 2. When irrigation is required, the relay is activated to power the pump for a specific duration. This duration is determined by a trained machine learning model running on the board. All sensor readings and control actions are published to a public MQTT broker, enabling real-time monitoring and potential manual override. Figure 1 provides a block diagram of the complete system, showing the connection between sensors, controller, actuator, and communication interface.

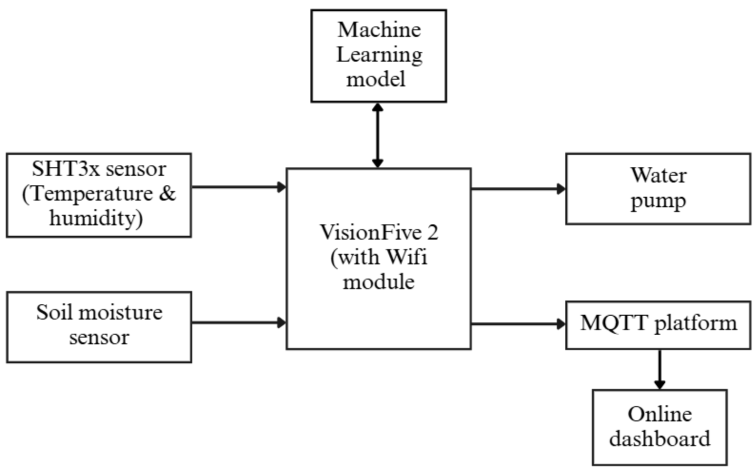

Figure 1: Block diagram of the proposed irrigation system.

The system operates in a continuous loop, beginning with the initialization of hardware interfaces and software components. This includes GPIO for relay control, I2C and SPI for sensor data, and the MQTT client for communication. A pre-trained machine learning model, stored locally, is loaded during startup. During each cycle, the system reads current sensor values. The raw moisture reading is converted into a percentage, while temperature and humidity values are collected directly. These readings, along with a preset target soil moisture value, are used to form a feature vector that is passed to the machine learning model. The model then predicts the required irrigation time in seconds. If the predicted irrigation time is less than one second, the system skips actuation and waits for the next cycle. This threshold prevents unnecessary short activations and reduces mechanical wear. If the predicted time is one second or more, the relay is triggered to power the pump for the exact duration. After irrigation, the system enforces a five-minute waiting period before restarting the loop. This delay allows time for water absorption and avoids frequent switching. Figure 2 shows the operational flow of the system, from initialization to data acquisition, model inference, decision-making, actuation, and wait interval. This logic ensures the system responds appropriately to changing environmental conditions and applies water only when necessary.

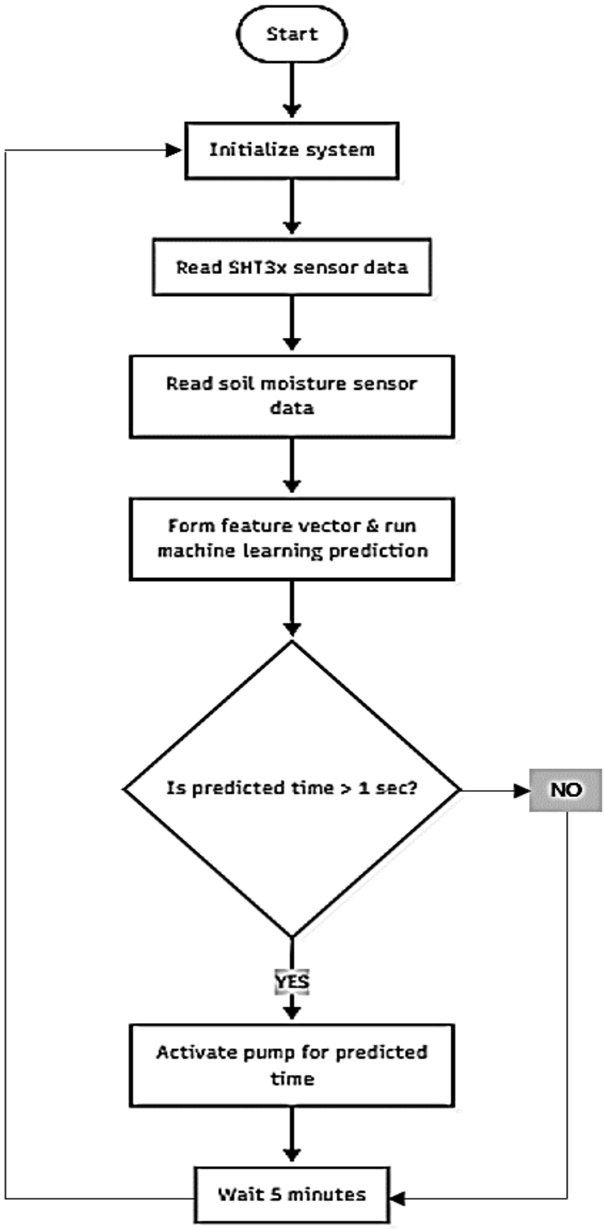

Figure 2: Operational flow chart of the proposed setup.

2.2 Machine learning and software implementation

The decision-making in the system is driven by a supervised machine learning model trained to predict irrigation time based on real-time environmental inputs. To develop the model, a dataset was manually constructed by recording the time required for the pump to raise the soil moisture level under various conditions. Each entry in the dataset consists of four input features: ambient temperature, humidity, current soil moisture, and a fixed target soil moisture level (In this case, 50% is used for an optimal moisture level). The output is the corresponding irrigation time in seconds. Based on observations during data collection, it was estimated that a one-second pump activation typically results in a 10% increase in soil moisture. This relationship was used as a guideline for labelling and target assignment. The dataset was split into 80% training and 20% testing sets using a fixed random seed to ensure reproducibility. A Random Forest regression model was chosen due to its robustness and ability to handle non-linear relationships between features. The model was configured with 100 decision trees and trained using the training set. Its performance was evaluated on the test set using mean squared error (MSE) as the primary metric. Once the model demonstrated satisfactory accuracy, it was serialized in the library and saved as a trained model for deployment on the embedded system. Due to the package-compatibility constraints on the VisionFive2 stack, a fixed configuration was used in this prototype.

On the software side, the system was developed using Python and configured to operate the hardware components and communication protocols reliably. The program initializes the necessary interfaces to interact with the sensors, relay module, and network broker. The key components include *joblib* for loading the trained model, *spidev* for communicating with the MCP3008 ADC, *VisionFive.gpio* for controlling the GPIO relay pin, and *paho.mqtt.client* for MQTT communication. *Sensirion_i2c_driver* library is used for interfaces with the SHT3x sensor for temperature and humidity data via I2C Protocol, whilst SPI is configured for the MCP3008 ADC that converts the raw moisture sensor data into percentage forms.

3. RESULTS AND DISCUSSION

Based on the methodology described in Section 2, results are presented in three parts: (i) model performance, (ii) plausibility of single-point predictions, and (iii) end-to-end system validation.

3.1 Machine-learning model performance

Figure 3 displays the confusion matrix for the test set. All 400 samples were placed on the main diagonal, yielding 100 % accuracy and demonstrating perfect separation between the "Above Median" (True Positive) and "Below Median" (True Negative) classes. This outcome is reinforced by the precision–recall curve in Figure 4, where the area under the curve (AUC) equals 1.00; both precision and recall remain at 1.0 across every threshold, indicating no trade-off between false positives and false negatives. A full classification report (Figure 5) confirms these findings, showing precision = 1.00, recall = 1.00, and F1-score = 1.00 for both classes.

3.2 Sanity-Check of Prediction Plausibility

To ensure the model's outputs align with irrigation practice, a single-input validation was carried out (Figure 6). Manually entered values for temperature, humidity and current soil moisture produced a prediction consistent with the project's heuristic of roughly one second of pump activation per 10 % moisture increase. This sanity check confirmed that the algorithm avoids unrealistic durations such as sub-second activations, which the relay cannot reliably deliver and suggests that the model's internal mapping between environmental inputs and irrigation time is physically meaningful.

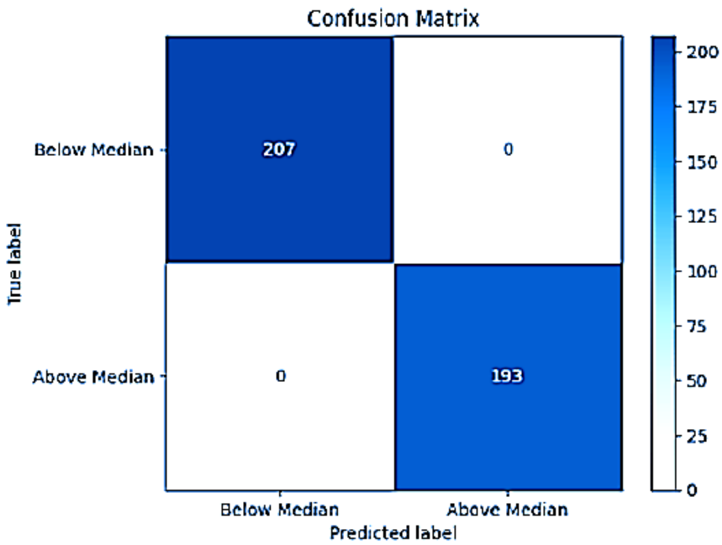

Figure 3: Confusion matrix. 207 instances for True Negative and 193 instances for True Positive.

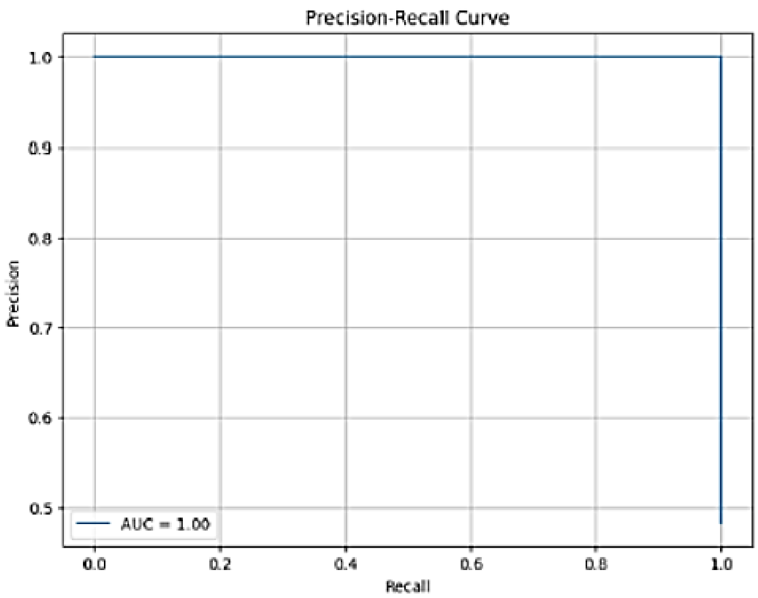

Figure 4: Precision-recall curve with an AUC = 1.0.

```
Classification Report:
              precision    recall  f1-score   support

Below Median       1.00      1.00      1.00       207
Above Median       1.00      1.00      1.00       193

    accuracy                           1.00       400
   macro avg       1.00      1.00      1.00       400
weighted avg       1.00      1.00      1.00       400

F1 Score: 1.00
```

Figure 5: Classification report showing precision = 1.00, recall = 1.00, and f1-score = 1.00 for both below median and above median classes.

```
Enter the following details to predict irrigation time:
Temperature (°C): 30
Humidity (%): 70
Current Soil Moisture (%): 40
Target Soil Moisture (%): 50
Predicted irrigation time: 1.00 seconds
```

Figure 6: Irrigation time predicted by the model using user input for testing purposes.

3.3 End-to-End System Validation

Table 1 summarizes the runtime logs and corresponding system actions during end-to-end validation. The first log confirms MQTT broker linkage, enabling cloud telemetry. The second shows the Random-Forest model loaded in memory, signaling readiness for inference. The third entry reports raw soil-moisture (30.98 %), temperature (31.03 °C), and humidity (66.57 %) data, evidence that I2C (for SHT3x sensor) and SPI (for digitized soil moisture sensor) channels operate correctly. The fourth log displays the predicted irrigation time (1.9 s), proving the model processed live features. The fifth records the relay energizing the DC pump for exactly 1.9 s, validating prediction-to-actuation integrity. The final log captures a subsequent cycle in which soil moisture had risen to 49.09 %, the model predicted 0.1 s, and the program correctly suppressed irrigation (<1 s threshold), confirming skip logic. Collectively, these sequential checkpoints demonstrate seamless sensing, inference, actuation, and cloud reporting across the entire control loop.

Figure 7 captures the MQTT Explorer interface during system operation. In the topic tree on the left, four payloads; temperature, humidity, soil moisture, and valve status appear under the predefined root topic irrigation, confirming that each sensor channel and pump state is being published in real time to the public broker (broker.emqx.io). The right-hand panel displays the most recent value (31.08 °C for temperature) and a time-stamped history graph, demonstrating that historical data are also retained for trend inspection. Together, these elements verify end-to-end cloud connectivity: the VisionFive 2 board is successfully transmitting telemetry to the MQTT cloud, and the user can subscribe to each topic to visualize live readings and past messages.

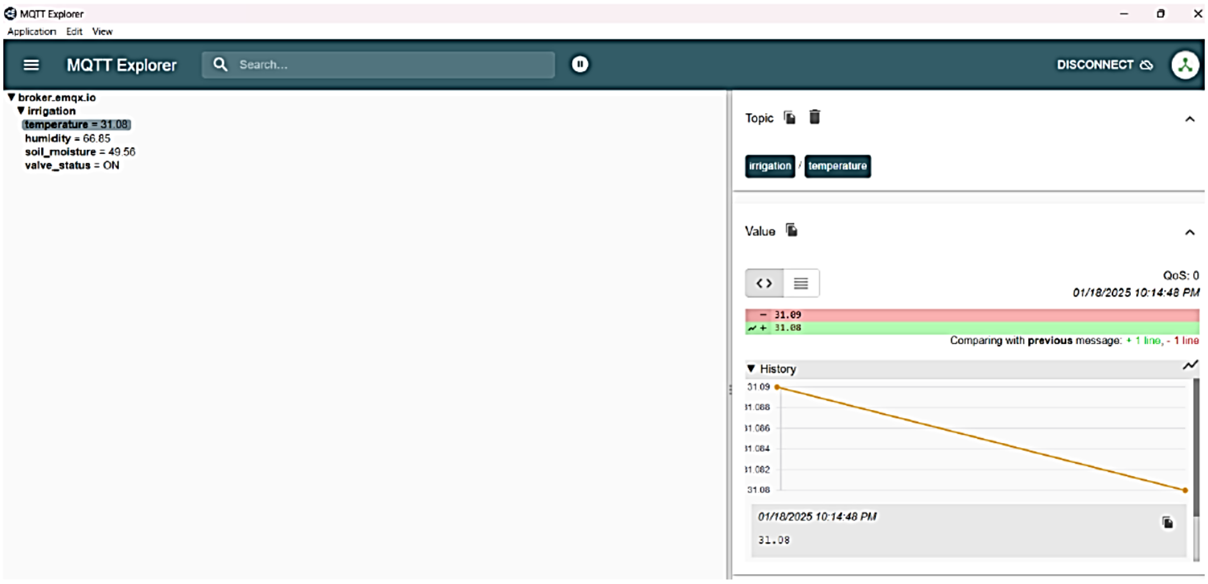

Figure 7: MQTT Explorer interface during system operation showing the temperature, humidity, soil moisture and valve status.

Table 1: Runtime logs and corresponding system actions during end-to-end validation.

Runtime logs	Details
`client = mqtt.Client()` `Connected to MQTT Broker!`	The program successfully connected to the MQTT broker, allowing sensor data to be published to the cloud and viewed in MQTT Explorer.
`Model loaded successfully.`	The trained machine-learning model loaded successfully on the VisionFive 2 board, indicating that the program is ready to generate predictions as soon as sensor data are received.
`Soil Moisture: 30.98%` `Temperature: 31.03 °C, Humidity: 66.57 %`	The VisionFive 2 board successfully retrieved temperature and humidity readings from the SHT3x sensor via the I2C protocol and displayed them in the terminal. In addition, the analog output from the soil-moisture probe was digitized by the MCP3008 ADC, read by the board, and converted to a percentage soil-moisture value.
`Predicted irrigation time: 1.9 seconds`	The collected temperature, humidity, and soil-moisture data for the rose plant were fed into the machine-learning model, which then successfully predicted the required irrigation time.
`Valve opened to water the plants for 1.9 seconds.` `Valve closed.`	The DC water pump activated precisely for the duration specified by the model's predicted irrigation time.

`Soil Moisture: 49.09%`
`Temperature: 31.02 °C, Humidity: 66.65 %`
`Predicted irrigation time: 0.1 seconds`
`No irrigation needed.`
	If the predicted irrigation time is under one second, the program interprets this as "no irrigation needed" and keeps the pump off.

4. CONCLUSION

This work addressed the limitation of manual irrigation by developing a data-driven system that predicts irrigation time using sensor inputs processed on a VisionFive 2 board with a trained Random Forest model. The embedded controller achieved AUC = 1.00 on a binary above/below-median diagnostic, with precision = 1.00, recall = 1.00, and F1-score = 1.00; end-to-end logs showed 0 s timing error on a 1.9 s command and correct skip-logic for <1s predictions. The system maintains soil moisture around a target set-point, avoids unnecessary short cycling via a < 1s guard, provides live remote monitoring through MQTT, and is built from low-cost, off-the-shelf components, making it feasible for small and medium rose cultivators. However, the dataset was limited in size and diversity, potentially affecting generalizability. The system was tested indoors with uniform soil and static conditions, which may not reflect real-world variability. Future priorities include multi-cultivar greenhouse and outdoor trials to quantify water savings, water-use efficiency (WUE), and flower quality/yield relative to threshold and fixed-schedule controls; the curation of season-spanning datasets with k-fold cross-validated Random-Forest tuning and lightweight baselines; integration of weather-aware control with fertigation; and robust battery/solar operation with fail-safe moisture overrides and transfer learning across soils and cultivars.

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