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# Smart watering of ornamental plants: exploring the potential of decision trees in precision agriculture based on IoT

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## Abstract

Ornamental plant farmers face various challenges due to climate change and environmental stress that significantly affect plant health and growth. This research overcomes these challenges by developing an intelligent watering system that uses internet of things (IoT) technology and decision trees (DTs) algorithms to optimize the use of planting land by ensuring plants grow in the most optimal conditions, both in terms of water and nutrients, and increase land productivity. The system is built by integrating various sensors to monitor soil moisture, air humidity, temperature, and light intensity in real-time. The collected data is used to automate watering schedules and provide recommendations on suitable plant species based on the soil nutrient content of nitrogen (N), phosphorus (P), and potassium (K). The use of the DTs algorithm helps in analyzing the data from the sensors and providing recommendations on the most suitable plants for the land. The smart watering system was tested in three zones, each simulating a different watering scenario, and successfully maintained optimal conditions for plant growth in each zone. The machine learning (ML) model with the DTs algorithm can predict the right type of ornamental plants based on the existing land conditions in three watering zones, with an accuracy of 89 %, 90 %, and 91 %, respectively. Furthermore, farmers can follow these recommendations to minimize damage and death of plants so that the level of productivity of the land becomes optimal.

Keywords: decision tree; precision agriculture; internet of things (IoT).

## I. Introduction

Ornamental plant farmers face many challenges, mainly due to climate change and environmental stress that are increasingly impacting plant health and growth. One of the challenges faced is fluctuations in temperature, light intensity, and water availability, which greatly affect plant development and productivity [1]. Improper watering and fertilization can cause health problems and even death in plants, especially in Indonesia, which often experiences a delayed rainy season due to the impact of climate

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change resulting from the El-Nino phenomenon [2][3]. Not knowing how to read soil conditions accurately can result in overwatering. In addition, the level of nutrient availability and pH in the soil can affect growth, thus requiring manual monitoring and adjustment of soil conditions by farmers [4].

The emerging internet of things (IoT) technology offers a promising solution to this challenge by enabling automatic and precise control over the growing environment. IoT systems can integrate various sensors to monitor soil moisture, air humidity, temperature, and light intensity in real-time, providing accurate data to ensure optimal conditions for plant growth [5][6]. These systems can automate watering and fertilization schedules based on real-time data, reducing the risk of over-watering or under-watering and ensuring that plants receive the right amount of nutrients. The presence of machine learning (ML) technology can also help predict early plant stress, optimize plant spacing, and predict image-based growth [7][8][9]. Overall, integrated IoT and ML can help farmers optimize crop production.

However, from the aspect of optimizing the availability of planting land, farmers also need to optimize production by determining the most suitable crops for cultivation on their limited planting land by considering the level of macronutrients such as nitrogen (N), phosphorus (P), and potassium (K) in the soil. Soil nutrient management is essential to maximize yield. For example, maize production in African smallholder agroecosystems often faces nutrient limitations, especially nitrogen (N) and potassium (K), which are critical for achieving high grain yields [10]. This research focuses on optimizing planting land by monitoring nutrients by utilizing sensors to read soil conditions and ML algorithms to predict plant seeds that match the available soil characteristics. Real-time soil condition data read by the sensors is communicated to the server that has been integrated with the ML model. Data is communicated using message queueing telemetry transport (MQTT) protocol and the ML training model is built by applying the decision trees (DTs) algorithm.

## II. Materials and Methods

### A. Smart watering monitoring system

The system is built using a series of components or devices that work together in an integrated manner to achieve specific goals such as measuring and analyzing nutrient content in the soil in real-time, automatically watering it, and providing recommendations. Such capabilities are very important in precision agriculture. The system consists of several main components, namely the soil sensor, data processing unit, communication module, and user interface [11]. Soil sensors are placed in the soil to measure various parameters such as nitrogen (N), phosphorus (P), potassium (K) levels, soil moisture, pH, and temperature [12]. The data collected by the soil sensor is forwarded to the data processing unit, in this case, a microprocessor or microcontroller [13]. The communication module serves to transmit the data that the sensors have collected for processing to the server [14][15]. This module can use various communication technologies such as Wi-Fi, Bluetooth, or cellular networks depending on the needs and field conditions [16][17]. The user interface is a component that allows users to monitor soil conditions in real-time [18][19]. This interface can be a mobile or web application that displays data in an easy-to-understand graphical form [20][21] to provide recommendations for crop types and watering times based on data analysis. It then sends notifications if certain nutrient deficiencies are found.

### B. Optimization of cropping land

To achieve the goal of optimizing planting land, in this research the system is able to recommend the selection of seeds that are suitable for the available soil conditions. The goal can be obtained by classifying suitable plant seeds that will grow well on the available land based on soil nutrients nitrogen (N), phosphorus (P), and potassium (K) in real-time. Decision trees (DTs) algorithms are a very popular and effective technique in ML, as they are easy to understand, require little data preparation, and can handle both numerical and categorical data [22].

DTs is a decision support tool by analogizing a tree represented in graph form. The branching of the trunk on the tree is a decision rule, which then the leaves are the results of a decision. The analogy of trunks and leaves in the graph theory of this algorithm is called internal nodes and leaf nodes [23]. Figure 1 shows that the DTs algorithm used in this research will give results when the soil nutrients meet the values corresponding to the classification of each ornamental plant species.

*1) Dataset*

The dataset in this study was obtained through measurements on ornamental plants, including Orchidaceae, Aglonema, and Monstera Adansonii, with a span of three months and measured weekly. The parameters measured were soil nutrients nitrogen (N), phosphorus (P), potassium (K), pH and soil moisture, shown in Table 1.

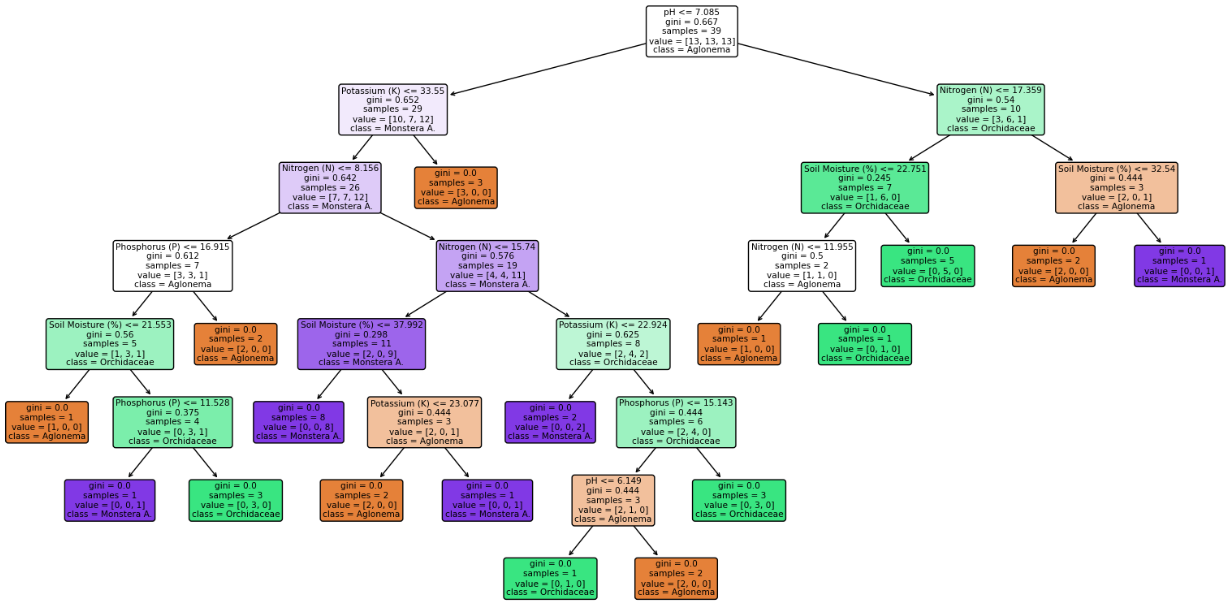


Figure 1. DTs algorithm.

*2) Decision tree modeling steps*

The steps in Figure 2 are the flow to create a Decision Trees model, starting from collecting datasets in the planting field. After that, data pre-processing is carried out by dividing the dataset into training data and test data.

The training results will produce a model that can predict the suitable type of ornamental plants. The model is evaluated using an accuracy metric and will be repeated until it gets the model with the best accuracy. Finally, the DTs model is built and ready for integration.

## C. System architecture design

As described in Figure 3, the flow of system architecture for the prototype in this study starts from data about soil conditions in plants read by sensors and then sent to sensor nodes, which then sensor data that has been received by sensor nodes will be forwarded to the HiveMQ website with the MQTT protocol. Sensor data from HiveMQ will be forwarded to several resources. If the data from the sensor has a value related to machine learning, the data from HiveMQ will be forwarded to the machine learning server to be predicted using the DTs model. Then, the prediction results will be forwarded back to HiveMQ and forwarded again to Node-RED to display the prediction results to the User Interface (UI) on the monitoring website. If the data from the sensor has values related to plant watering, the data from HiveMQ will be forwarded to the master node to water the plants if they meet certain conditions depending on the values obtained from the sensor, and HiveMQ will also forward the data to Node-RED to display the values from the sensor to the UI on the monitoring website. In addition to the sensor node, the master node also sends data in the form of watering time, watering duration, and estimated watering time to HiveMQ, which then the data will be forwarded to Node-RED to be displayed on the UI of the monitoring website.

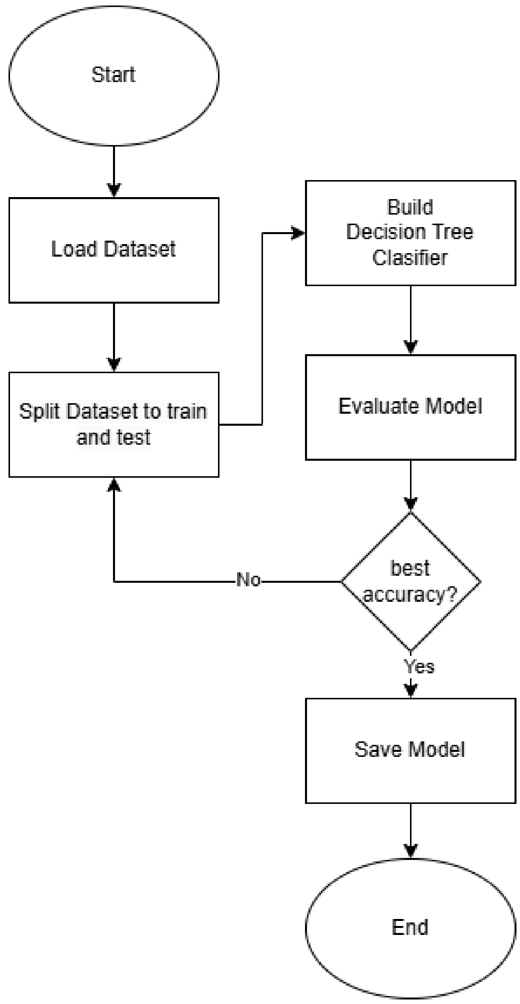


Figure 2. Flowchart for the DTs' model.

Table 1.
Dataset.

| Date | Nitrogen (N) (mg/L) | Phosphorus (P) (mg/L) | Potassium (K) (mg/L) | pH | Soil moisture (%) | Plant |
|---|---|---|---|---|---|---|
| 01-01-2023 | 10.61 | 14.24 | 15.99 | 6.66 | 38.78 | Aglonema |
| 08-01-2023 | 19.26 | 13.64 | 25.43 | 6.18 | 37.90 | Aglonema |
| 15-01-2023 | 15.98 | 13.67 | 27.77 | 6.74 | 31.96 | Aglonema |
| 22-01-2023 | 13.98 | 16.08 | 11.39 | 6.05 | 38.44 | Aglonema |
| 29-01-2023 | 7.34 | 20.50 | 28.23 | 7.36 | 21.77 | Aglonema |
| 05-02-2023 | 7.34 | 18.64 | 15.12 | 6.39 | 23.92 | Aglonema |
| 12-02-2023 | 5.87 | 15.82 | 11.95 | 6.99 | 20.90 | Aglonema |
| 19-02-2023 | 17.99 | 22.24 | 38.47 | 6.47 | 26.51 | Aglonema |
| 26-02-2023 | 14.02 | 12.79 | 38.97 | 6.78 | 27.77 | Aglonema |
| 05-03-2023 | 15.62 | 15.84 | 34.25 | 6.82 | 25.43 | Aglonema |
| 12-03-2023 | 5.31 | 17.33 | 19.14 | 6.28 | 36.57 | Aglonema |
| 19-03-2023 | 19.55 | 19.12 | 12.93 | 7.45 | 27.14 | Aglonema |
| 26-03-2023 | 17.49 | 25.70 | 30.53 | 7.16 | 25.62 | Aglonema |
| 01-01-2023 | 13.14 | 17.17 | 31.40 | 7.36 | 23.73 | Monstera Adansonii |
| 08-01-2023 | 7.11 | 12.32 | 32.82 | 6.37 | 37.85 | Monstera Adansonii |
| 15-01-2023 | 17.03 | 27.26 | 26.84 | 6.62 | 30.79 | Monstera Adansonii |
| 22-01-2023 | 6.12 | 22.47 | 33.13 | 7.13 | 36.15 | Monstera Adansonii |
| 29-01-2023 | 19.80 | 16.62 | 24.81 | 6.34 | 37.92 | Monstera Adansonii |
| 05-02-2023 | 16.58 | 11.27 | 25.68 | 6.12 | 26.36 | Monstera Adansonii |
| 12-02-2023 | 7.98 | 16.22 | 22.83 | 6.43 | 22.20 | Monstera Adansonii |
| 19-02-2023 | 5.08 | 16.50 | 10.76 | 6.24 | 24.56 | Monstera Adansonii |
| 26-02-2023 | 17.23 | 24.59 | 13.24 | 7.39 | 28.54 | Monstera Adansonii |
| 05-03-2023 | 15.60 | 22.75 | 10.94 | 7.21 | 36.36 | Monstera Adansonii |
| 12-03-2023 | 15.94 | 27.74 | 29.09 | 6.95 | 37.21 | Monstera Adansonii |
| 19-03-2023 | 16.57 | 19.44 | 19.43 | 7.31 | 20.14 | Monstera Adansonii |
| 26-03-2023 | 6.11 | 12.39 | 25.26 | 7.21 | 30.21 | Monstera Adansonii |
| 01-01-2023 | 11.26 | 16.02 | 30.16 | 6.89 | 38.49 | Orchidaceae |
| 08-01-2023 | 8.33 | 15.70 | 32.85 | 7.02 | 37.55 | Orchidaceae |
| 15-01-2023 | 6.80 | 10.74 | 17.13 | 6.02 | 25.16 | Orchidaceae |
| 22-01-2023 | 10.06 | 22.19 | 31.85 | 6.77 | 33.20 | Orchidaceae |
| 29-01-2023 | 19.14 | 20.05 | 21.03 | 6.34 | 36.34 | Orchidaceae |
| 05-02-2023 | 9.85 | 11.03 | 28.97 | 6.97 | 31.10 | Orchidaceae |
| 12-02-2023 | 12.78 | 15.57 | 29.01 | 6.26 | 30.59 | Orchidaceae |
| 19-02-2023 | 15.55 | 28.17 | 26.07 | 7.04 | 4.84 | Orchidaceae |
| 26-02-2023 | 10.45 | 14.79 | 12.71 | 6.58 | 21.86 | Orchidaceae |
| 05-03-2023 | 19.58 | 12.90 | 35.06 | 7.41 | 37.94 | Orchidaceae |
| 12-03-2023 | 19.44 | 19.79 | 19.62 | 6.21 | 38.01 | Orchidaceae |
| 19-03-2023 | 8.78 | 29.71 | 15.60 | 6.51 | 32.66 | Orchidaceae |
| 26-03-2023 | 12.46 | 14.84 | 11.22 | 6.17 | 26.78 | Orchidaceae |

## D. Hardware design

Hardware design consists of two parts, namely the sensor node and the master node. The sensor node is designed to know the soil conditions that will be read by the sensor capacitive soil, DHT11, and raindrop, while the master node is designed to be able to water according to soil conditions. The soil conditions are taken through the sensor node data. The design of the sensor node and master node is presented in Figure 3 and Figure 4.

As presented in Figure 4, the sensor node design requires one NodeMCU, two DHT11, one capacitive soil, and one battery. Based on this design, the sensor node can read soil moisture from the capacitive soil sensor, temperature from the DHT11 sensor, and macronutrient levels (NPK) in the soil from the DHT11

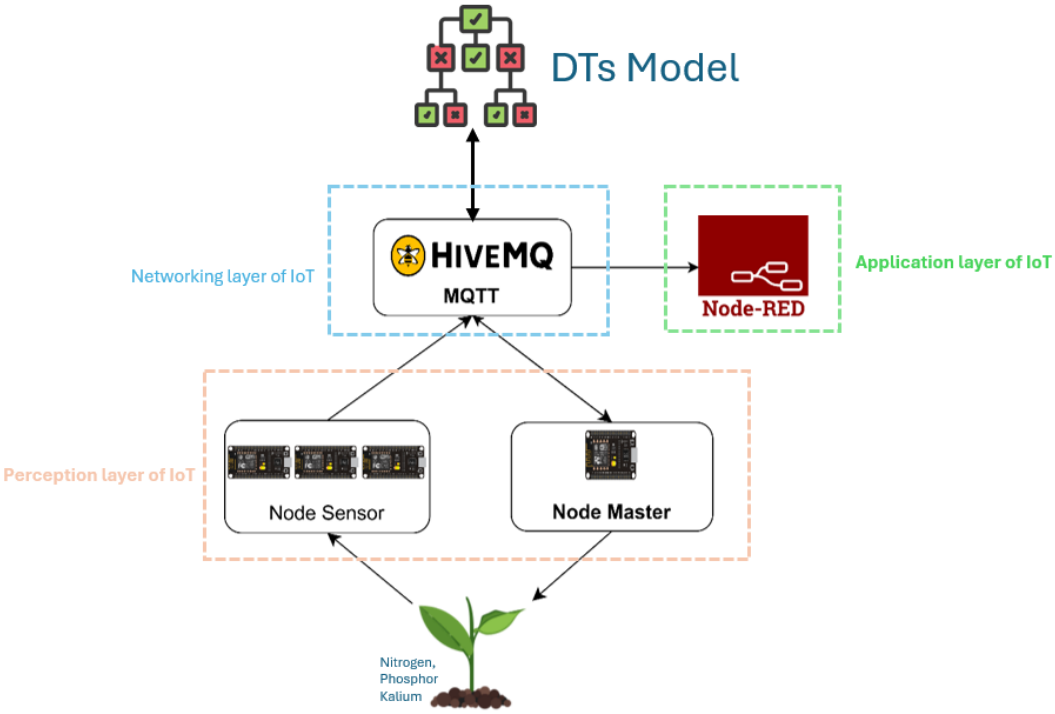

Figure 3. System architecture flowchart.

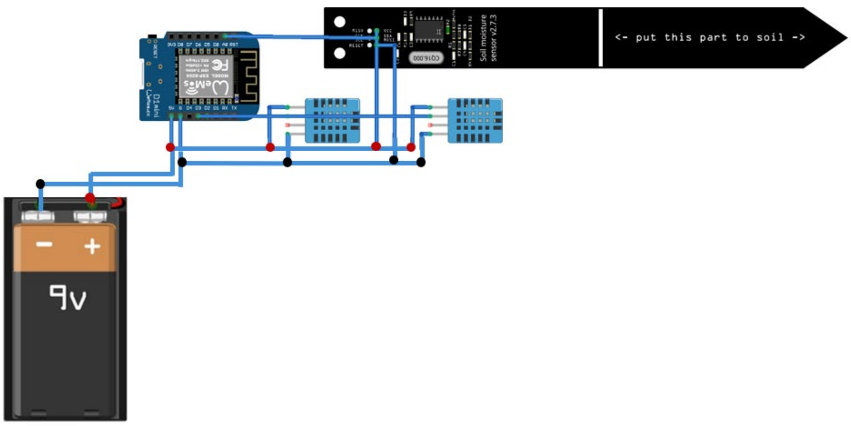

Figure 4. Design of sensor nodes.

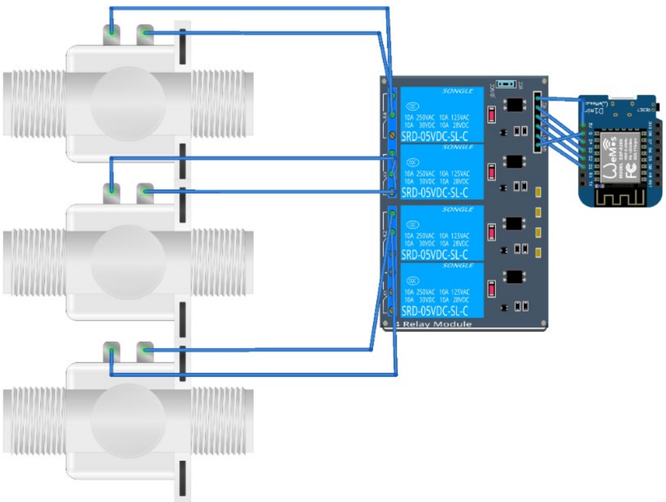
Figure 5. Design of master node.

sensor that is plugged into the ground. The reading results from the sensor will be sent to the NodeMCU.

As presented in Figure 5, the master node design requires one NodeMCU, one 4-channel relay module,

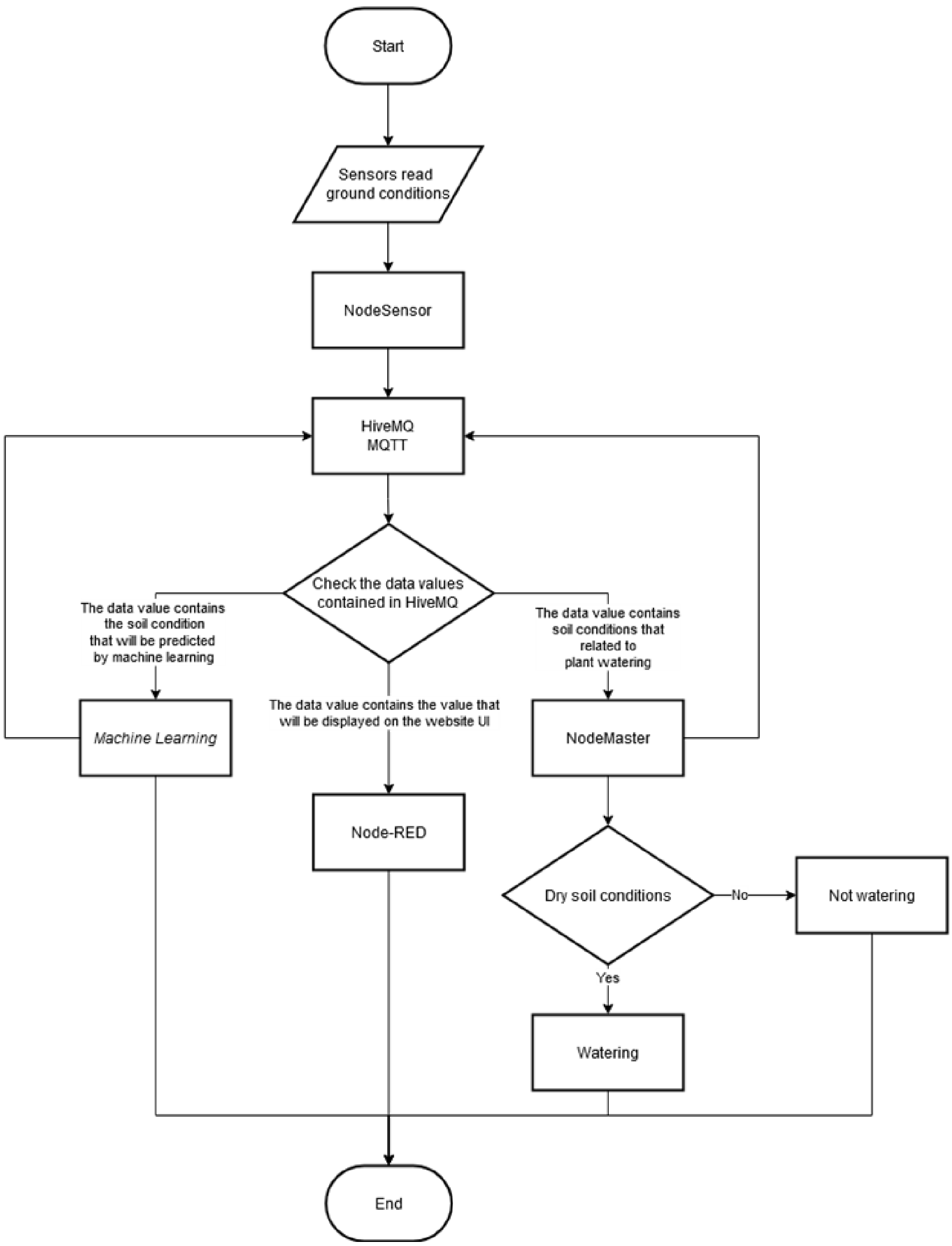


Figure 6. Software design flowchart.

and three solenoids. The relay and solenoid will be connected to the AC voltage. Then the three solenoids will be connected to the pump and to the sprinkler via a small pipe in order to water the plants.

### E. Software design

Software design is divided into four parts: software design for sensor nodes, master nodes, machine learning, and monitoring app. Sensor node and master node software were developed using C++. Meanwhile, machine learning software was developed using python and the monitoring app was built using Node-RED. An outline of the software design is presented in Figure 6.

## III. Results and Discussions

### A. Accuracy score

The DTs model has been built through a training and testing process. The process was carried out several times, and it was found that the portion of the training and test dataset division had an effect on the resulted accuracy level [24]. The results shown in Figure 7 show that the evaluation metrics measured in the forms of accuracy, precision, recall, and F1-score increase as the portion of the training dataset increases. The 90:10 portion is the best choice in this case as it produces a value of 0.91.

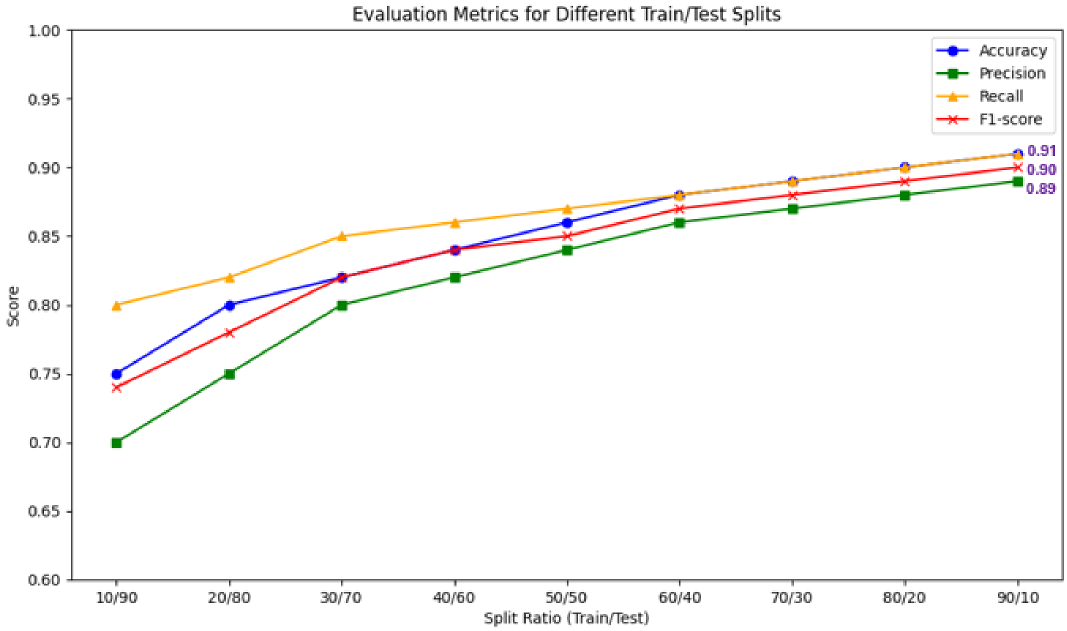


Figure 7. Result of training.

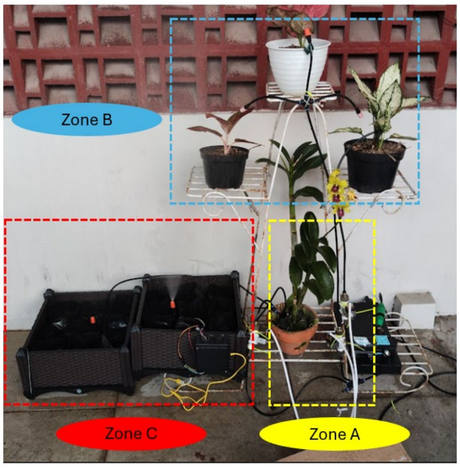


Figure 8. Prototype system.

Although the accuracy value is good, modeling with the DTs algorithm can have an over-fitting problem [25]. Nevertheless, this research has limitation to overcome over-fitting, which usually can be done in either two ways: Pre-pruning or post-pruning

## B. Three watering zones

The smart watering prototype has been implemented into three watering zones called zone A, zone B, and zone C, as shown in Figure 8.

Zone A is set to simulate the automatic watering of fields with scheduled rules. Zone B and zone C simulate automatic watering when the soil moisture parameter value is below the threshold value. What distinguishes zone C from the other zones is that it is also used to simulate the prediction process to recommend the type of plants that are suitable for the soil nutrient value of the land. The sensors in each zone were tested for three days, and the data is in Table 2.

## C. Integration of the DTs model with the prototype

The integration between smart watering has been successful, shown by real-time test data in zone C that sends nutrient values to the DTs model to obtain recommendations for plants suitable for planting in zone C soil. The DTs model deployment process is carried out by creating a publish-subscribe paradigm application programmable interface (API) that serves plant recommendation predictions [26].

System testing was conducted by subscribing nutrient values from plants via HiveMQ and the recommendation was published back to HiveMQ to be obtained and shown at the Node-RED monitoring app. Data was obtained for three days and can be seen in Table 3, Table 4, Table 5. Based on Table 3, Table 4, and Table 5, it can be seen that the initial data of the new recommendation is constant after several predictions,

Table 2.
Sensor testing results (22/09/2023).

| | Temperature (°C) | | | Moisture (%) | | | Humidity (%) | | |
|---|---|---|---|---|---|---|---|---|---|
| Time | Zone A | Zone B | Zone C | Zone A | Zone B | Zone C | Zone A | Zone B | Zone C |
| 14:20:01 | 25 | 33 | 26 | - | 47 | 72 | 95 | 20 | 95 |
| 14:39:43 | 25 | 33 | 27 | - | 59 | 73 | 95 | 33 | 95 |
| 14:49:25 | 27 | 33 | 27 | - | 59 | 72 | 95 | 27 | 95 |
| 15:05:30 | 27 | 33 | 28 | - | 59 | 72 | 95 | 20 | 95 |
| 15:19:16 | 28 | 33 | 28 | - | 59 | 72 | 95 | 48 | 95 |
| 15:34:38 | 27 | 33 | 29 | - | 58 | 72 | 95 | 20 | 95 |
| 15:49:21 | -1 | 33 | 30 | - | 58 | 72 | 75 | 20 | 98 |
| 16:05:18 | -19 | 32 | 31 | - | 58 | 72 | 20 | 20 | 61 |
| 16:19:22 | -18 | 32 | 31 | - | 58 | 72 | 20 | 20 | 51 |
| 16:35:34 | -16 | 31 | 31 | - | 58 | 71 | 20 | 20 | 48 |
| 16:49:20 | -17 | 32 | 30 | - | 58 | 72 | 20 | 20 | 48 |

Table 3.
System testing results (22/09/2023).

| No | N (mg/L) | P (mg/L) | K (mg/L) | pH | Rainfall (rF) | Recommendation |
|---|---|---|---|---|---|---|
| 1 | 22 | 75 | 87 | 7 | 103 | Orchidaceae |
| 2 | 2 | 100 | 162 | 7 | 89 | Orchidaceae |
| 3 | 2 | 100 | 162 | 7 | 89 | Orchidaceae |
| 4 | 40 | 110 | 27 | 7 | 37 | Monstera Adansonii |
| 5 | 40 | 75 | 35 | 7 | 26 | Aglonema |
| 6 | 35 | 50 | 100 | 7 | 22 | Aglonema |
| 7 | 57 | 115 | 122 | 7 | 20 | Aglonema |
| 8 | 55 | 22 | 25 | 7 | 17 | Aglonema |
| 9 | 67 | 80 | 97 | 7 | 13 | Aglonema |
| 10 | 50 | 17 | 77 | 7 | 9 | Aglonema |
| 11 | 77 | 27 | 137 | 7 | 9 | Aglonema |

Table 4.
Machine learning testing results (25/09/2023).

| No | N (mg/L) | P (mg/L) | K (mg/L) | pH | Rainfall (rF) | Recommendation |
|---|---|---|---|---|---|---|
| 1 | 63 | 105 | 163 | 7 | 7 | Aglonema |
| 2 | 63 | 105 | 163 | 7 | 7 | Aglonema |
| 3 | 42 | 36 | 52 | 7 | 6 | Aglonema |
| 4 | 29 | 89 | 47 | 7 | 6 | Aglonema |
| 5 | 79 | 34 | 79 | 7 | 8 | Aglonema |
| 6 | 50 | 42 | 163 | 7 | 8 | Aglonema |
| 7 | 10 | 121 | 134 | 7 | 14 | Aglonema |
| 8 | 21 | 26 | 15 | 7 | 24 | Aglonema |
| 9 | 13 | 102 | 134 | 7 | 23 | Aglonema |
| 10 | 29 | 52 | 116 | 7 | 24 | Aglonema |
| 11 | 29 | 52 | 116 | 7 | 24 | Aglonema |
| 12 | 44 | 100 | 60 | 7 | 24 | Aglonema |
| 13 | 13 | 36 | 92 | 7 | 22 | Aglonema |
| 14 | 44 | 105 | 126 | 7 | 21 | Aglonema |
| 15 | 44 | 105 | 126 | 7 | 21 | Aglonema |
| 16 | 10 | 31 | 4 | 7 | 19 | Aglonema |

the initial recommendation value of Orchidaceae. However, it then changed to Monstera Adansonii and then constant to Aglonema. This is influenced by the condition of soil moisture in zone C, which is starting

Table 5.
Machine learning testing results (26/09/2023).

| No | N (mg/L) | P (mg/L) | K (mg/L) | pH | Rainfall (rF) | Recommendation |
|---|---|---|---|---|---|---|
| 1 | 33 | 20 | 128 | 7 | 1 | Aglonema |
| 2 | 11 | 67 | 19 | 7 | 1 | Aglonema |
| 3 | 16 | 5 | 78 | 7 | 0 | Aglonema |
| 4 | 42 | 39 | 129 | 7 | 2 | Aglonema |
| 5 | 28 | 44 | 67 | 7 | 0 | Aglonema |
| 6 | 84 | 11 | 104 | 7 | 0 | Aglonema |
| 7 | 5 | 101 | 33 | 7 | 0 | Aglonema |
| 8 | 76 | 93 | 121 | 7 | 0 | Aglonema |
| 9 | 76 | 11 | 119 | 7 | 0 | Aglonema |
| 10 | 19 | 133 | 57 | 7 | 0 | Aglonema |
| 11 | 45 | 74 | 185 | 7 | 0 | Aglonema |
| 12 | 68 | 119 | 168 | 7 | 0 | Aglonema |
| 13 | 28 | 88 | 142 | 7 | 0 | Aglonema |
| 14 | 22 | 82 | 17 | 7 | 0 | Aglonema |
| 15 | 31 | 43 | 80 | 7 | 0 | Aglonema |
| 16 | 83 | 132 | 154 | 7 | 0 | Aglonema |
| 17 | 88 | 54 | 97 | 7 | 0 | Aglonema |
| 18 | 2 | 45 | 28 | 7 | 0 | Aglonema |
| 19 | 43 | 141 | 37 | 7 | 0 | Aglonema |

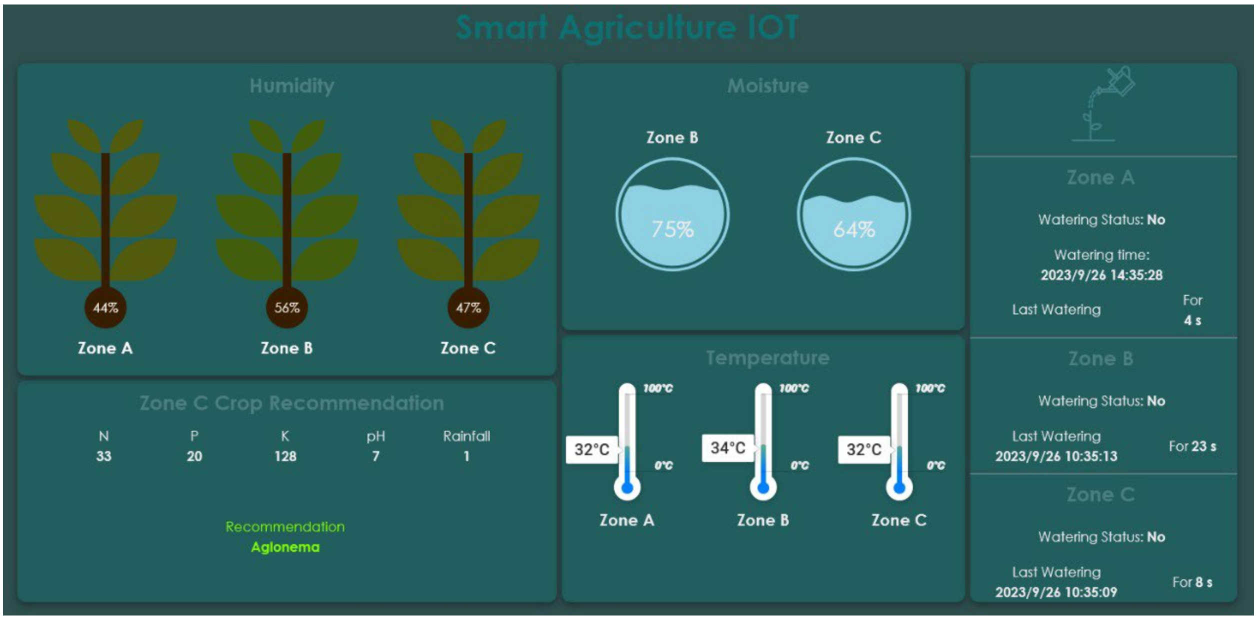


Figure 9. Dashboard data 26/09/2023 (Node-RED).

to be controlled into good conditions because it has experienced automatic watering when the value is less than the threshold.

## D. Data visualization on monitoring app

The monitoring application is developed using Node-RED. Plant recommendations, humidity, and temperature values of each zone will change according to the real-time situation. Meanwhile, the watering status value will change when the plant moisture in zone B and zone C is below the threshold, while zone A will change once every four hours after automatic watering. The monitoring application also provides the last watering time and watering duration for each zone. An example can be seen on the Node-RED dashboard on the 1st data of September 26, 2023, as shown in Figure 9.

# IV. Conclusion

Based on the results of the design and testing of the system, it can be concluded that machine learning based on the DTs algorithm has been implemented well in the IoT-based ornamental plant smart watering system. Tests on three watering zones show that the system can maintain optimal conditions for plant growth, reduce the risk of overwatering or underwatering, and ensure the plants receive the right amount of nutrients. The results show that the use of the DTs algorithm can predict the type of ornamental plants that are suitable based on soil nutrient content, with an accuracy of 89 %, 90 %, and 91 %, respectively. Farmers can follow the recommendations given to minimize damage and death of plants so that the level of productivity of the field becomes optimal. The accuracy value of the ML model with the DTs algorithm is influenced by the portion of the separation of the data set and test data. Although the accuracy value is good, this research has limitations in that it has not overcome overfitting that may occur. It is necessary to increase the number of training datasets with various types of plants. This study also did not measure the production yield compared to the land area, how many plants failed to harvest, and how many were successfully harvested on that land area, which should be measured during the harvest season. The implementation of the DTs algorithm in this smart watering system has great potential to improve agricultural efficiency and productivity, especially when climate change impacts rainfall patterns. The DTs algorithm can accurately analyze sensor data to provide optimal watering and crop selection recommendations. As such, this research makes a significant contribution to the field of Precision Agriculture, paving the way for further innovations in the use of machine learning for automated and intelligent management of ornamental plants.


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# Declarations

## Author contribution

**H.P. Pratama**: Writing - conceptualization - algorithm developer. **E.N. Irawan**: software designer and algorithm developer. **H.E. Putri**: Data Analysis - Review & Editing. **D.I.H. Putri**: hardware designer - system integrator. **M.A. Kautsar**: hardware assembler - algorithm developer.


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## Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

During the preparation of this work, the authors used Elicit to help find and organize research papers. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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