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IoT-Based Prediction of Ornamental Plant Water Needs Using Sugeno Fuzzy Algorithm

Reiza Hersa Dwitama [1]*, Novita Kurnia Ningrum[2]*
* Information Technology, Dian Nuswantoro University
reiza.dwitama12@gmail.com [1], novita.kn@dsn.dinus.ac.id [2]

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ABSTRACT

Urban plant care is increasingly important amid growing concerns about air pollution and limited time for manual maintenance. In Indonesia, air quality has deteriorated significantly, with PM2.5 pollution levels exceeding World Health Organization standards, particularly in major cities like Jakarta. Ornamental plants play a crucial role in improving air quality; however, urban residents often struggle to consistently water them. This study addresses that problem by developing an Internet of Things (IoT)-based smart irrigation system that utilizes the Sugeno fuzzy algorithm to predict the water needs of ornamental plants. The system combines a capacitive soil moisture sensor and a DHT11 temperature-humidity sensor with an ESP8266 microcontroller to monitor environmental conditions. Data is transmitted to Firebase and visualized in an Android application, which provides real-time monitoring and specific volume recommendations ranging from 10 ml to 240 ml, calibrated for medium-sized plant pots which is also based on 27 fuzzy rules derived from three input parameters: air temperature, humidity, and soil moisture. Real-world testing with the Aglaonema Snow White plant confirmed that the system functions reliably, helping users optimize water usage and support sustainable, data-driven plant care in urban environments. The system achieved an average prediction accuracy of 89.14% and a mean absolute error of 7.6% in guiding soil moisture toward a 70% target, confirming its practical effectiveness. While the system was tested on Aglaonema Snow White, the fuzzy rule base can be recalibrated for other ornamental plant species with different water needs.

I. Introduction

The rapid development of information technology has had a significant impact across various sectors, including agriculture. The Internet of Things (IoT) technology enables devices to communicate and exchange data via the internet, thereby enhancing efficiency and effectiveness in many fields—particularly agriculture. In Indonesia, the trend of cultivating ornamental plants is on the rise, with a wide variety of plant types and care methods tailored to each species. However, the busy urban lifestyle often prevents plant owners from consistently tending to their plants, which can lead to plant death.

This issue is further exacerbated by the increasing air pollution in major Indonesian cities, which negatively affects air quality and oxygen availability. According to an IQAir report, the average PM2.5 concentration in Indonesia in 2023 reached 37.1 µg/m³—far exceeding the WHO's recommended annual limit of 5 µg/m³. Specifically, Jakarta recorded a PM2.5 concentration of 43.8 µg/m³, making it one of the cities with the worst air quality in the world [1]. A major contributor to this pollution is emissions from motor vehicles, with approximately 21 million motorcycles and 4 million cars operating in Jakarta every day [2].

This situation highlights the crucial role of green plants in urban areas, as they absorb pollution and produce oxygen. However, urban residents often face challenges due to limited time for regularly watering and caring for plants. In this context, providing the right amount of water is essential.

Underwatering can cause the soil to dry out and damage the plant, while overwatering can lead to root rot [3].

Several studies have explored IoT-based plant monitoring and control systems. For example, students from the Malang State Polytechnic developed an IoT system for monitoring ornamental plants. This system uses the BH1750 light sensor and the DHT11 sensor to measure indoor temperature and humidit[4]. The sensor readings are processed using the Sugeno fuzzy method to determine irrigation needs. Similarly, students from the State Islamic University of North Sumatra developed a system using the YL-69 soil moisture sensor and the LM35 air temperature sensor for automated watering, also utilizing the Sugeno fuzzy method to predict water requirements [5].

Despite these advancements, existing systems still have certain limitations. Many studies focus on specific plant types or controlled environments, limiting the generalizability of their findings. Furthermore, while some systems employ the Sugeno fuzzy method for decision-making, they often lack integration with user-friendly mobile applications for real-time monitoring and control.

Therefore, this research aims to develop an IoT-based plant monitoring system that leverages the Sugeno fuzzy method to optimize water usage and improve plant care effectiveness. The system also seeks to encourage people to engage in planting by making plant care more accessible. It will include a soil moisture sensor and a DHT11 sensor to monitor air temperature and humidity, with data sent to Firebase at specified intervals. Users will be able to access real-time and historical data through an Android application. By applying the Sugeno fuzzy method, the system can accurately predict the plant's water needs based on real-time sensor data, ensuring optimal watering and preventing conditions that could harm the plants.

II. METHODOLOGY

This study proposes the development of an IoT-based plant monitoring system that leverages fuzzy sugeno to optimize water usage and enhance plant care. The system integrates various sensors to monitor environmental parameters essential for plant. Specifically, soil moisture sensors, air temperature sensors, and humidity sensors are deployed to collect real-time data. These sensors interface with a microcontroller unit, such as the ESP8266, known for its Wi-Fi capabilities and suitability for IoT applications [6]. The collected data are transmitted to a cloud-based platform, Firebase, facilitating remote access and storage. How the system is built can be seen in figure 1.

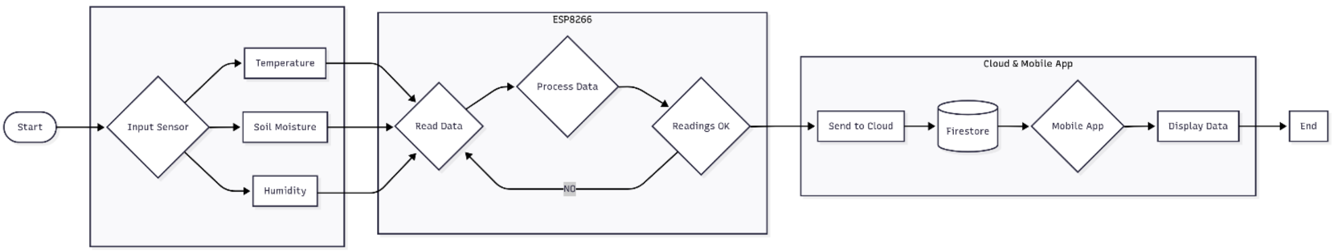

Figure 1. System Flow Chart

A. Microcontroller and Sensors

The ESP8266 is a microcontroller-based Wi-Fi module developed by Espressif Systems. Since its release in 2014, it has become widely used in Internet of Things (IoT) projects due to its integrated Wi-Fi, 32-bit RISC architecture, and multiple I/O pins [6]. It supports communication protocols such as SPI, I2C, UART, PWM, and GPIO, enabling connection with external devices and sensors, including the DHT11 and the Precision Capacitive Soil Moisture Sensor.

The DHT11 is a low-cost digital sensor used to measure temperature and humidity. It operates using a resistive humidity sensor and an NTC thermistor, with data processed by an internal microcontroller and transmitted as a digital signal via a single data line [7].

The Precision Capacitive Soil Moisture Sensor detects soil moisture using capacitance changes. It is preferred in agricultural applications for its corrosion resistance and stability compared to resistive sensors [8].

The ESP8266 can operate in Station (STA), Access Point (AP), or both modes simultaneously (STA+AP), allowing it to connect to or create Wi-Fi networks for transmitting sensor data to a server [6].

B. Firebase Service

Firebase is a platform developed by Google for building and scaling mobile and web applications. It offers backend services, tools, and SDKs that simplify development without the need to manage complex infrastructure [9]. In Android apps, Firebase is commonly used for user authentication and data management. Firebase Authentication provides backend services, easy-to-integrate SDKs, and UI libraries to support authentication methods such as email/password, phone number, and third-party providers like Google, Facebook, and Twitter [9]. This allows each user to securely connect and manage multiple IoT devices under a single account.

For data storage, Cloud Firestore is used—a scalable, document-based NoSQL database designed for mobile, web, and server development via Firebase and Google Cloud [10]. Firestore ensures real-time data synchronization across clients, supports offline access, and organizes data into documents and collections. Each document can store structured data including subcollections and nested objects [10]. This is ideal for IoT applications, enabling each device to maintain its own history of status and sensor readings.

Firestore also supports range and inequality filters on multiple fields in a single query , allowing efficient retrieval of time-ordered IoT data using timestamps [11]. This reduces the need for additional client-side processing, improves performance, and simplifies development when handling large datasets.

This service will be implemented in the mobile application to display real-time sensor data as well as its historical records, enabling users to monitor and track their IoT devices efficiently.

C. Fuzzy Sugeno

Fuzzy is a mathematical approach that enables the handling of uncertainty and imprecision in decision-making—unlike classical binary logic, which only recognizes values of true (1) or false (0) [12]. In contrast, fuzzy logic allows variables to take on continuous values between 0 and 1, representing degrees of truth or membership in a given fuzzy set [13]. This makes fuzzy especially effective for modeling complex real-world phenomena where information is incomplete, imprecise, or linguistically defined.

Among the various fuzzy inference systems (FIS), the Sugeno fuzzy inference method—introduced by Takagi, Sugeno, and Kang in 1985—is one of the most widely used due to its computational efficiency, precision, and suitability for optimization and control applications [14]. The Sugeno method, also known as Takagi–Sugeno–Kang (TSK) fuzzy model, differs from the Mamdani model in that its rule consequents are mathematical functions (typically linear or constant) rather than fuzzy sets. As a result, it can produce crisp numerical outputs directly, making it ideal for systems that require continuous output values. One practical example is the implementation of the Fuzzy Sugeno method in a room security system using ultrasonic sensors and a microcontroller, which intelligently determines the presence of movement or intrusion based on measured distance fluctuations [15]. Another application can be found in determining optimal routes to tourist destinations in Surabaya by analyzing real-time traffic conditions and user preferences through fuzzy rules [16]. Moreover, Fuzzy Sugeno has also been used in an IoT-based automatic fire extinguisher system that utilizes smoke, temperature, and flame sensors to assess risk levels and trigger safety mechanisms accordingly [17].

The Sugeno fuzzy system follows three main steps, first is fuzzification. In this stage, crisp input values are converted into fuzzy values by applying membership functions. A membership function $\mu_A(x)$ maps an input x to a degree of membership in a fuzzy set A:

$$\mu_A(x) : X \to [0,1] \dots (1)$$

Each input variable may have multiple fuzzy sets (e.g., Low, Medium, High), each defined by its own membership function.

The second step is rule evaluation. The sugeno method uses fuzzy rules of the form:

$$IF\ x_1\ is\ A_1^i\ AND\ x_2\ is\ A_2^i\ AND \cdots THEN\ y_i = f_i(\ x_1, x_2, \cdots\ x_n) \dots (2)$$

Here:
A_k^i is the fuzzy set for the k-th input in the i-th rule.
$f_i(\ x_1, x_2, \cdots\ x_n)$ is typically a linear or constant function that defines the rule's output.

The firing strength ω_i of the i-th rule is computed using a T-norm (commonly the product or minimum) of the degrees of membership of all input variables:

$$w_i = T(\mu_{A_1^i}(x_1), \mu_{A_2^i}(x_2), \cdots, \mu_{A_n^i}(x_n)) \dots (3)$$

If the product T-norm is used:

$$w_i = \prod_{k=1}^{n} \mu_{A_k^i}(x_k) \dots (4)$$

The rule's output is given by the function:

$$z_i = f_i(x_1, x_2, \cdots, x_n) \dots (5)$$

Commonly used output functions are:
Constant model: $z_i = c_i$
Linear model: $z_i = a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n + b_i$

The final step is deffuzification. The final crisp output y is computed as a weighted average of the outputs of all activated rules, using their firing strengths as weights:

$$y = \frac{\sum_{i=1}^{R} w_i \cdot z_i}{\sum_{i=1}^{R} w_i} \dots (6)$$

Where:
R is the total number of rules,
w_i is the firing strength of rule I,
z_i is the output of the rue function $f_i(x_1, x_2, \cdots, x_n)$

This form of defuzzification ensures a smooth and continuous mapping from inputs to output, which is especially advantageous in control systems and real-time applications [16].

III. Result And Discussion

A. IoT Design

Environmental data is obtained by connecting the DHT11 and Capacitive Soil Moisture sensors to the NodeMCU ESP8266 microcontroller. The NodeMCU ESP8266 will be configured to handle the inputs.

The DHT11 sensor is used to read air temperature and humidity. The reading process is carried out digitally using the DHT library which has provided built-in functions to obtain temperature and humidity data directly and efficiently [7]. Meanwhile, soil moisture data is taken using the Capacitive Soil Moisture sensor which produces an analog signal [8]. This raw analog voltage value is then converted and calibrated so that it can be displayed in percentage units (%), so that it is more representative in describing soil moisture conditions.

Before the ESP8266 can send data to Firestore, the device needs to be configured to connect to a Wi-Fi network. For this reason, the system is designed so that the ESP8266 can operate as a temporary access point and run a local HTTP server. Users can connect an Android device to the ESP8266 network, then access a simple configuration page to enter the Wi-Fi SSID and password [7]. This process is handled by the handleClient() function which is executed continuously inside the main loop() function. This function detects HTTP requests and extracts the configuration data sent via the POST method. After the data is saved, the ESP8266 will try to connect to the configured Wi-Fi network. If the connection is successful, the device will start sending sensor data to Firestore periodically.

In addition to handling network configuration, the ESP8266 also provides several additional handlers that allow for further interaction with Android applications. One of them is a feature to send a list of SSIDs from Wi-Fi networks detected around the device, so that users can select a network directly through the application interface. There is also a handler that allows disconnecting from the current Wi-Fi network, if the user wants to change the network used.

Cloud Firestore is used as a cloud storage medium to store sensor reading data. Data is sent by the ESP8266 in JSON format and stored in a simple document collection. In addition to storing current data, the system also records historical data into a separate collection if the time difference from the previous data exceeds one hour. Each historical data is equipped with a timestamp to support the process of analyzing and tracking environmental conditions over a certain period of time. Firestore was chosen because of its ease of integration with the Android platform and its ability to synchronize data in real time.

B. Development of the Sugeno Fuzzy Algorithm

In the development of a plant water requirement prediction system, the fuzzy approach based on the Sugeno method has been implemented. The system receives three environmental input parameters: air temperature, air humidity, and soil moisture. Each of these input parameters is transformed into corresponding linguistic variables using predefined membership functions. These linguistic variables represent qualitative states that simplify the decision-making process within the fuzzy inference system.

For the humidity parameter, the value range is divided into three linguistic categories: Low, Medium, and High. Each category is associated with a triangular or trapezoidal membership function that determines the degree of membership for each specific humidity value. The graphical representation of these membership functions is shown in the corresponding figure. The Low membership function is represented by a decreasing linear curve covering humidity values from 30% to 50%. The Medium category is defined by a triangular function peaking at 50% and spanning the range from 30% to 70%. Meanwhile, the High membership function is represented by an increasing linear curve from 50% to 70% as it can be seen in figure 2.

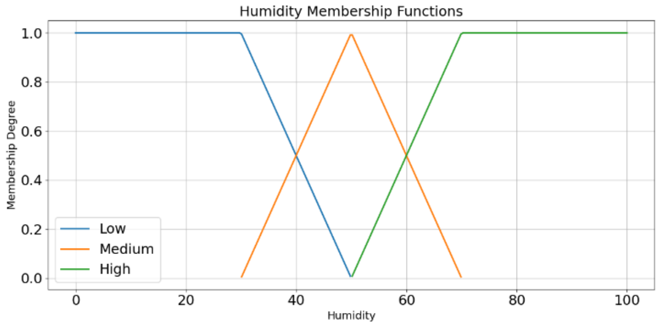

Figure 2. Humidity Membership Function

Here is the mathematical equation for the humidity membership function.

$$\mu_{Low}(h) = \begin{cases} 1, & h \leq 30 \\ \frac{50-h}{20}, & 30 < h \leq 50 \\ 0, & h > 50 \end{cases} \quad \dots(7)$$

$$\mu_{Medium}(h) = \begin{cases} 0, & h \leq 30 \\ \frac{h-30}{20}, & 30 < h \leq 50 \\ \frac{70-h}{20}, & 50 < h \leq 70 \\ 0, & h > 70 \end{cases} \quad \dots(8)$$

$$\mu_{High}(h) = \begin{cases} 0, & h \leq 50 \\ \frac{h-50}{20}, & 50 < h \leq 70 \\ 1, & h > 70 \end{cases} \quad \dots(9)$$

With:
h = value of humidity

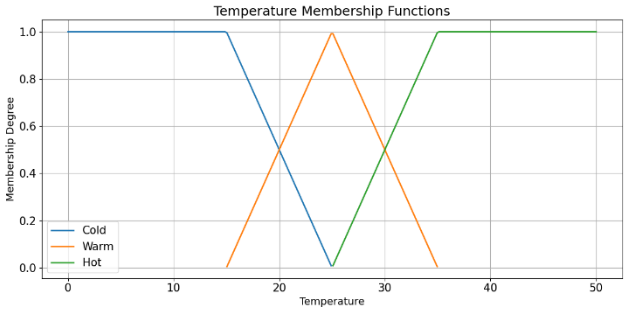

Figure 3. Temperature Membership Function

Similarly, the temperature parameter is divided into three linguistic categories: Cold, Warm, and Hot. Each category is defined using membership functions that map temperature values to corresponding degrees of membership.Figure 3 illustrates the membership functions used to represent linguistic variables for temperature. The Cold category is represented by a decreasing linear curve within the temperature range of 15°C to 25°C. Warm is represented by a triangular function peaking at 25°C and covering temperatures from 15°C to 35°C. Meanwhile, Hot is illustrated by an increasing linear function ranging from 25°C to 35°C.

$$\mu_{Cold}(t) = \begin{cases} 1, & t \leq 15 \\ \frac{25 - t}{10}, & 15 < t \leq 25 \\ 0, & t > 25 \end{cases} \dots(10)$$

$$\mu_{Warm}(t) = \begin{cases} 1, & t \leq 30 \\ \frac{t - 15}{10}, & 15 < t \leq 25 \\ \frac{35 - t}{10}, & 25 < t \leq 35 \\ 0, & t > 35 \end{cases} \dots(11)$$

$$\mu_{Hot}(t) = \begin{cases} 0, & t \leq 25 \\ \frac{t - 25}{10}, & 25 < t \leq 35 \\ 1, & t > 35 \end{cases} \dots(12)$$

With:
t = value of the temperature

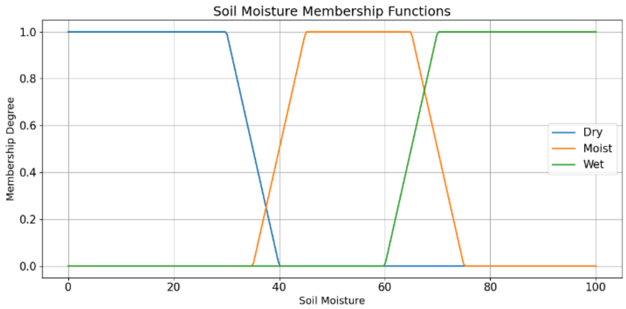

Figure 4. Soil Moisture Membership Function

The soil moisture parameter is divided into three linguistic categories: Dry, Moist, and Wet [18]. As illustrated in figure 4, each category is defined using triangular or trapezoidal membership functions that map moisture values to specific degrees of membership. The Dry category is represented by a decreasing linear curve from 30% to 40%, with full membership for values below 30%. The Moist category is represented by a triangular function peaking between 45% and 65%, gradually decreasing toward zero near 35% and 75%. Meanwhile, the Wet category is defined by an increasing linear function from 60% to 70%, with full membership for values above 70%. These ranges form a fuzzy system that allows a more flexible evaluation of soil moisture.

$$\mu_{Dry}(s) = \begin{cases} 1, & s \leq 30 \\ \frac{40 - s}{10}, & 30 < s \leq 40 \\ 0, & s \geq 40 \end{cases} \dots(13)$$

$$\mu_{Humid}(s) = \begin{cases} 0, & 35 \leq or\ s \geq 75 \\ \frac{s - 35}{10}, & 35 < s < 45 \\ 1, & 45 \leq s \leq 65 \\ \frac{75 - s}{10}, & s > 35 \end{cases} \dots(14)$$

$$\mu_{Wet}(s) = \begin{cases} 0, & s \leq 60 \\ \frac{s - 60}{10}, & 60 < s < 70 \\ 1, & s \geq 70 \end{cases} \dots(15)$$

These ranges form a fuzzy system that allows a more flexible evaluation of soil moisture. This categorization of soil moisture is especially critical in ornamental plant care, where excessive watering can be detrimental. According to Rosliana Eso et al. [19], Aglaonema has succulent stems and is intolerant of excessively moist growing media, requiring highly precise and measured irrigation. Therefore, in this system, fuzzy rules are specifically constructed to provide watering recommendations only when soil moisture drops below a safe threshold, minimizing the risk of overwatering and supporting optimal plant health.

By converting numerical sensor inputs into fuzzy linguistic terms using these membership functions, the system simplifies complex environmental data into interpretable states. This enables the design of fuzzy inference rules that link various combinations of temperature, humidity, and soil moisture to specific levels of water requirement. In the next stage of the Sugeno fuzzy inference system, these membership functions serve as the basis for rule evaluation and output computation using the Sugeno method. Each input parameter contributes to a rule base that determines the estimated water requirement for plants under different environmental conditions.

The inference process is carried out using fuzzy rules constructed based on combinations of three variables: temperature, soil moisture, and humidity. Based on the research by Rosliana Eso et al.[19],the rules used in this model are shown in the table below.

TABLE I
FUZZY RULES

No	Soil Moisture	Temperature	Humidity	Water Requirement (ml)
1	Dry	Cold	Low	120
2	Dry	Cold	Medium	140
3	Dry	Cold	High	160
4	Dry	Warm	Low	180
5	Dry	Warm	Medium	200
6	Dry	Warm	High	220
7	Dry	Hot	Low	240
8	Dry	Hot	Medium	230
9	Dry	Hot	High	220
10	Moist	Cold	Low	60
11	Moist	Cold	Medium	75
12	Moist	Cold	High	90
13	Moist	Warm	Low	100
14	Moist	Warm	Medium	120
15	Moist	Warm	High	130
16	Moist	Hot	Low	140
17	Moist	Hot	Medium	130
18	Moist	Hot	High	120
19	Wet	Cold	Low	20
20	Wet	Cold	Medium	15
21	Wet	Cold	High	10
22	Wet	Warm	Low	20
23	Wet	Warm	Medium	15
24	Wet	Warm	High	10
25	Wet	Hot	Low	20
26	Wet	Hot	Medium	15
27	Wet	Hot	High	10

There are a total of 27 fuzzy rules applied. For each rule, the degree of truth is calculated using the minimum membership value of the two inputs, for example:

$$\omega_i = \min(\min(\mu_{sDry}(s), \mu_{tHot}(t)), \mu_{hLow}(h)) \dots (16)$$

After evaluating all rules, the final predicted value is calculated using the Sugeno defuzzification formula as follows:

$$Output = \frac{\sum_{i=1}^{7} \omega_i \cdot z_i}{\sum_{i=1}^{7} \omega_i} \dots (17)$$

where the firing strength of the i-th rule is represented by the membership value, and the constant output value for each rule corresponds to specific water volumes.

The result of this process is an estimated volume of water required (in milliliters) based on current environmental conditions. This predicted value can later be displayed in an Android application to provide watering suggestions to users.

To validate the effectiveness and efficiency of the 27 fuzzy rules, a computational sensitivity analysis was performed. The analysis process began with the creation of a systematic test dataset covering the entire operational range of inputs: temperature (15°C-35°C), air humidity (30%-70%), and soil moisture (30%-75%). For each input combination, the trigger strength (ωi) of each rule was calculated to identify 'dead rules', i.e., rules with ωi that are consistently zero. Next, a redundancy test was performed by simulating the removal of each rule individually and observing its impact on the final output. The results of this process showed that no dead rules were found and all rules, even the weakest ones, proved to be non-redundant due to their role in handling specific input scenarios.

Although some rules associated with high soil moisture (e.g., 'Wet' category) tend to result in low water recommendations, they are not considered dead rules technically, as they still produce non-zero firing strength under specific input combinations. Their contribution, albeit small, ensures consistent fuzzy reasoning at the edges of the membership functions.

This system was developed and tested using Aglaonema Snow White as the target plant, it is important to note that water requirements may vary significantly among different plant species due to differences in stem structure, leaf surface area, and root system. Therefore, the current implementation is specifically calibrated for Aglaonema, and the fuzzy rules, particularly the output constants in each rule, are based on its specific water tolerance and pot size.

For adaptation to other plant species, users or developers may adjust the output values of the fuzzy rules based on empirical observations or horticultural guidelines related to the specific plant's water needs. The membership functions for soil moisture, temperature, and humidity can also be redefined to match the environmental preferences of the target plant. Future work may focus on creating dynamic calibration methods or integrating plant-specific profiles into the application to support a broader range of ornamental plants.

The water volume range produced by the system is between 10 ml and 240 ml, depending on the combination of three input parameters: soil moisture, air temperature, and air humidity. These values are the output of 27 Sugeno fuzzy rules that have been designed based on the water requirements of the Aglaonema Snow White plant.

This recommended volume is assumed for a medium-sized pot with a diameter of approximately 15–20 cm, 12-15 cm tall and a porous growing medium commonly used for indoor ornamental plants. If used in a larger or smaller pot, the output can be proportionally recalibrated by changing the constants in the output rules or by adjusting the fuzzy membership functions.

C. System Testing

System testing was conducted to validate the functionality of each component, starting from sensor data acquisition to data visualization on the Android application. The purpose of this testing was to ensure that the system operates in an integrated and reliable manner, in accordance with the design specifications.

The initial phase of testing focused on verifying the sensor and microcontroller. The DHT11 sensor and capacitive soil moisture sensor were connected to the NodeMCU ESP8266. Sensor readings were displayed through the Serial Monitor to ensure that temperature, air humidity, and soil moisture data were accurately and consistently received by the microcontroller. This test confirmed that the sensors functioned properly and that the raw data could be processed.

Next, the ESP8266 is tested its ability to connect to a Wi-Fi network and transmit data to Firebase. The Wi-Fi configuration process via a local access point was tested to ensure users could easily connect the device to their home internet network. Once connected, the system was verified to periodically send sensor data in JSON format to Cloud Firestore. This test ensured that data from the IoT device successfully reached the cloud. These steps run in loop every 30 seconds if there is no error readings in the sensors.

The final testing phase involved Fuzzy algorithm and android application. Sensor data stored in Firestore was accessed by the Android application and displayed on the main dashboard. These sensor values were then processed using the Sugeno Fuzzy algorithm implemented within the app to generate watering volume recommendations. Test scenarios were created by varying input conditions (e.g., dry soil and high temperature). The results were observed to ensure that the app produced logical recommendations (e.g., a higher water volume) according to the predefined fuzzy rules. The data history feature was also tested to verify that the graphs correctly displayed historical data.

The results of this series of functional tests demonstrated that the system can operate cohesively—from environmental data acquisition and cloud transmission to visualization and intelligent recommendation delivery to users via the Android application.

D. Accuracy and Efficiency Comparison

To evaluate the predictive accuracy of the system, this study focuses exclusively on the soil moisture parameter. While air temperature and humidity serve as fuzzy inputs, only soil moisture is directly and measurably affected by irrigation and thus most relevant for evaluating system effectiveness. The evaluation was performed by recording moisture levels before and after watering, based on the system's recommended water volume.

The post-watering soil moisture was then compared to an ideal target moisture level of 70%, selected because it lies at the boundary between the Moist and Wet fuzzy categories. This level is considered optimal to ensure sufficient hydration without exceeding the safe threshold that may cause root rot—particularly in water-sensitive plants like Aglaonema Snow White. The value also provides a conservative margin that aligns with typical indoor plant care needs.

The evaluation was conducted using 15 test cases. For each test, the error and accuracy were calculated using the following equations:

$$Error_i = \left| M_{after,i} - M_{target} \right| \ldots (18)$$

$$Accuracy_i = 100 - \left(\frac{Error_i}{M_{target}} \times 100\right) \ldots (19)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} Error_i \ldots (20)$$

where $M_{after,i}$ is the post-watering soil moisture for the i-th test, and M_{target} is the ideal value (70%). This method allows for a quantitative assessment of how closely the system's recommendation brings the soil moisture to the desired level.

TABLE III
SOIL MOISTURE EVALUATION RESULTS

Temp (°C)	Humid (%)	Moist Before (%)	Recommen-dation(ml)	Moist After (%)
29.5	51	56	124.55	74
29.7	65	64	38.95	85
29.6	43	55	122.43	77
30.5	39	18	214.58	92
28.4	51	55	123.56	65
…	…	…	…	…

Based on the 15 test cases conducted, the system achieved a mean absolute error (MAE) of 7.6%, meaning that the average deviation from the ideal soil moisture target (70%) was approximately 7 percentage points. The average accuracy across all tests was calculated to be 89.14%, indicating a moderate level of precision in guiding post-watering soil moisture toward the optimal threshold. While the system does not fully guarantee exact outcomes due to environmental variability and differences in absorption rates, these results demonstrate that the fuzzy-based recommendation system provides a reasonably effective approximation to guide plant watering needs in a controlled indoor setting.

TABLE III
MANUAL VS SYSTEM COMPARISON

Parameter	Manual Watering	Fuzzy-Based System
Water Volume per Day	~250ml	~120ml (avg.)
Fixed or Adaptive	Fixed	Adaptive
Based on Sensor	No	Yes
Risk of Overwatering	High	Low
Water Efficiency	-	~50% saving

In addition to verifying functional performance, a theoretical comparison was conducted to evaluate the potential benefits of this system over traditional manual watering methods. Based on on the studies [19], Aglaonema is known to be highly sensitive to excess moisture due to its succulent stems, and overwatering can lead to root rot. Manual watering practices often involve giving a fixed amount of water—such as one ladle (approximately 250 ml)—daily, regardless of actual soil moisture.

In contrast, the fuzzy-based system developed in this study provides adaptive volume recommendations ranging from 10 ml to 240 ml, depending on real-time environmental conditions. Observations showed that the average suggested volume was around 120 ml per day, indicating a potential reduction in water usage of up to 50%. This suggests the system not only helps prevent overwatering but also supports water use efficiency tailored to the plant's actual needs.

This system does not automatically water, but rather provides water volume recommendations based on current environmental conditions. The final decision on watering remains with the user.

This approach was chosen to allow for greater system flexibility and avoid the risk of overwatering during initial implementation. However, the system is modularly designed, allowing for easy integration with automatic watering devices such as water pumps or solenoid valves in future developments.

E. *Android Interfaces*

To bridge the technical functionality of the system with the end user, an Android application was developed as the main user interface. The application is designed to present data intuitively and provide actionable plant care recommendations. The main interface of the application serves as a monitoring dashboard, presenting real-time environmental data such as temperature and humidity from the DHT11 sensor, as well as soil moisture percentage from the capacitive sensor. By utilizing real-time data synchronization from Firebase, users can monitor the condition of their plants remotely.

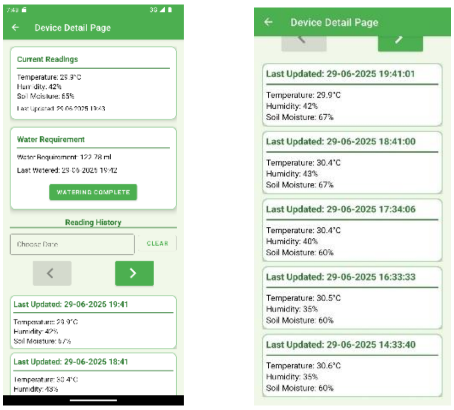

Figure 5. Sensor Readings Interfaces

The most crucial feature of the application is the visualization of the results of the Fuzzy Sugeno algorithm. The application not only displays the raw data but also translates it into specific watering volume recommendations in milliliters (ml). These recommendations are direct outputs from the developed fuzzy model, which processes sensor data to accurately predict the water needs of plants. In addition, the application also provides a feature to view historical data, which is stored in a separate collection in Firestore. This historical data is visualized in the form of graphs to help users track trends in environmental conditions over a period of time, providing deeper insights into plant health. The interface can be seen in figure 9.

F. *System Implementation*

After all components were successfully set up, a real-world usage scenario was simulated to evaluate the overall performance of the system. The ornamental plant Aglaonema Snow White was chosen as the test subject. This variety is one of the most popular ornamental plants in Indonesia and is known for being quite sensitive to watering conditions—it requires consistently moist soil without being waterlogged—making it an ideal candidate for this study.

Figure 6. IoT Implementation

In preparation for the test, the capacitive soil moisture sensor was inserted into the planting medium near the root zone, while the DHT11 sensor was positioned to measure the ambient temperature and humidity around the plant. The entire setup was placed indoors to replicate a typical urban household environment, in line with the system's target users. Over the course of several days, sensor data was monitored in real-time through the Android application. This test aimed to observe how the system generated watering volume recommendations in response to natural fluctuations in soil moisture and surrounding environmental conditions.

IV. CONCLUSION

This study successfully developed a smart system based on the Internet of Things (IoT), utilizing the Sugeno fuzzy algorithm approach to predict the water needs of ornamental plants in urban agricultural areas. The system integrates a DHT11 sensor and a capacitive soil moisture sensor connected to an ESP8266 microcontroller. The Sugeno fuzzy algorithm enables the system to accurately determine the required water volume based on air temperature, air humidity, and soil moisture.

Evaluation of the system through functional testing confirmed that all components operate reliably and in an integrated manner. The testing validated the successful operation from sensor data acquisition, data transmission to the cloud, to the display of logical recommendations on the Android application. This demonstrates the system's effectiveness in providing a practical solution for plant irrigation.

Quantitative evaluation showed that the system achieved an average prediction accuracy of 89.14% and a mean absolute error (MAE) of 7.6%, indicating a high level of precision in aligning the recommended water volume with the ideal soil moisture target.

It is important to note that the current system does not perform automatic watering, but rather provides recommendations for water volume based on environmental conditions. This design choice allows users to retain full control of the watering process, minimizing the risk of overwatering. The system is also designed in a modular fashion, making it technically ready to be extended into a fully automated irrigation system in future development.

The technical recommendations from this study include applying the fuzzy Sugeno-based automatic irrigation system on a larger scale, such as in urban parks or community gardens, to improve water use efficiency and support sustainable plant care. From an academic perspective, this research can serve as a foundation for further development in integrating artificial intelligence methods with IoT technology in the field of precision agriculture. Policy implications that may be considered include regulatory support and government incentives to encourage the adoption of smart agricultural technologies as a means to address water crises and pollution in urban areas.

However, this system has only been tested on Aglaonema Snow White. Since different plant species have varying water requirements, the fuzzy logic rules—particularly the output values—should be adapted accordingly. Future work may involve developing calibration guidelines or plant-specific profiles to extend the applicability of this system to a wider range of ornamental plants.

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