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ESP32-Based Flood Monitoring and Early Warning System Using the Sugeno Fuzzy Logic Method

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ABSTRACT

Floods remain one of the most frequent natural disasters in Indonesia, highlighting the need for reliable real-time monitoring and early warning systems. This study aims to develop an ESP32-based flood monitoring and early warning system integrated with a web-based monitoring platform using the Sugeno Fuzzy Logic method. The proposed system employs three environmental parameters, namely water level measured by the JSN-SR04T ultrasonic sensor, rainfall intensity measured by a tipping bucket rain gauge, and soil moisture measured by a capacitive soil moisture sensor. Sensor data are processed using the Sugeno Fuzzy Logic algorithm to classify flood conditions into Safe, Alert, and Danger, while the monitoring results are transmitted to Firebase Realtime Database for real-time website visualization and notification delivery through Telegram and Webpushr. Experimental results show that the ultrasonic, soil moisture, and tipping bucket rain gauge sensors achieved average accuracies of 99.35%, 98.01%, and 94.64%, respectively. The Sugeno implementation demonstrated excellent agreement with manual calculations, achieving an MSE of 0.00069, RMSE of 0.02627, and R^2 of 0.999998, while the flood status classification achieved 100% accuracy, precision, recall, and F1-score. In addition, the average notification response times were 1.63 s for Telegram and 2.35 s for Webpushr. These results demonstrate that the proposed system provides accurate flood monitoring, reliable flood status classification, and timely warning dissemination, making it suitable for real-time flood early warning applications.

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1. INTRODUCTION

Floods are among the most frequent natural disasters worldwide and continue to cause significant economic losses, infrastructure damage, and casualties. In Indonesia, floods occur due to a combination of natural and human-related factors, including high rainfall intensity, overflowing rivers, land-use changes, rapid urbanization, and inadequate drainage systems [1] [4]. According to the National Disaster Management Agency (BNPB), Indonesia recorded 1,652 flood events in 2025, indicating that flood disasters remain a major challenge requiring effective mitigation and early warning systems [3].

Flood occurrence is strongly influenced by several environmental parameters. Water level is widely used as the primary indicator of flood conditions because it directly reflects rising river or drainage water levels. However, flood events are also affected by rainfall intensity and soil moisture. High rainfall increases runoff volume, while saturated soil reduces infiltration capacity, accelerating surface runoff and increasing flood risk [4], [5]. Previous studies have shown that soil moisture has a significant relationship with flood occurrence, making it an important parameter in flood prediction systems [6], [7]. Therefore, integrating water level, rainfall intensity, and soil moisture provides a more comprehensive representation of flood conditions than relying solely on water level measurements.

Recent advances in the Internet of Things (IoT) have enabled the development of real-time environmental monitoring systems. IoT technology allows multiple sensors to communicate through wireless networks, enabling continuous monitoring and remote access to environmental data [8], [9]. By integrating sensors with cloud databases and web-based monitoring platforms, users can obtain flood information in real time and respond more quickly to potential disasters.

Several previous studies have proposed IoT-based flood monitoring systems. Kamali *et al.* developed an IoT-based flood early warning system integrated with social media notifications using fuzzy logic; however, the system depended heavily on Twitter services and only utilized two input parameters [10]. Ardani *et al.* designed an IoT-based flood monitoring system integrated with Blynk for monitoring flood barriers, but the study mainly focused on mechanical flood protection rather than intelligent flood prediction [11]. Akbar *et al.* implemented a Sugeno Fuzzy Logic-based flood monitoring system integrated with Telegram notifications, yet the system did not provide a dedicated web-based monitoring interface [12]. Rahardi *et al.* proposed a flood early warning system using water level, rainfall, and turbidity sensors with the Mamdani Fuzzy Logic method. Nevertheless, the turbidity sensor produced relatively high measurement errors, reducing overall system reliability [13].

Although previous studies have demonstrated the effectiveness of IoT and fuzzy logic for flood monitoring, several research gaps remain. First, many systems utilize only one or two environmental parameters, limiting the representation of actual flood conditions. Second, several studies employ Mamdani Fuzzy Logic, which requires more complex defuzzification processes than the Sugeno method. Third, many existing systems focus primarily on notification services without providing comprehensive web-based visualization for real-time monitoring. These limitations indicate the need for a more efficient and integrated flood monitoring system.

This research proposes an ESP32-Based Flood Monitoring and Early Warning System Using the Sugeno Fuzzy Logic Method. The proposed system integrates three environmental parameters: water level measured using the JSN-SR04T ultrasonic sensor, rainfall intensity measured using a tipping bucket rain gauge, and soil moisture measured using a capacitive soil moisture sensor. Sensor data are processed using the Sugeno Fuzzy Logic method to classify flood conditions into Safe, Alert, and Danger. The ESP32 microcontroller serves as the processing unit and transmits sensor data to Firebase Realtime Database, allowing real-time

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monitoring through a web-based dashboard while simultaneously activating local warning devices such as pilot lamps and a buzzer [9].

The objectives of this research are to (1) develop an IoT-based flood monitoring and early warning system using ESP32, (2) implement the Sugeno Fuzzy Logic method for flood status classification based on three environmental parameters, and (3) provide real-time monitoring through a website integrated with Firebase. The originality of this research lies in the integration of water level, rainfall intensity, and soil moisture sensors with the Sugeno Fuzzy Logic method and a web-based monitoring platform. This study contributes to the development of intelligent flood early warning systems by providing more comprehensive environmental monitoring, efficient fuzzy computation, and practical implementation for community-based flood disaster mitigation.

2. METHODS

2.1 Material

The proposed flood monitoring and early warning system integrates hardware and software to monitor environmental conditions, process sensor data, and provide real-time flood warnings. The hardware and software components used in this study are described as follows.

2.1.1 ESP32 Microcontroller

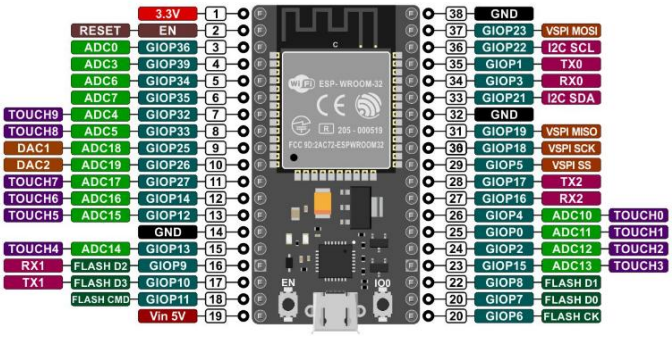


Figure 1. ESP Microcontroller

The ESP32 (**Figure 1**) serves as the main controller to acquire sensor data, execute the Sugeno Fuzzy Logic algorithm, and control the output devices. Its built-in Wi-Fi capability enables real-time data transmission, making it suitable for IoT-based flood monitoring applications [14].

2.1.2 JSN-SR04T Ultrasonic Sensor



Figure 2. JSN-SR04T Ulrasonic Sensor

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The JSN-SR04T ultrasonic sensor (**Figure 2**) measures the distance to the water surface to determine the water level. Its waterproof design makes it suitable for outdoor flood monitoring, and the measured distance is used as an input to the Sugeno Fuzzy Logic algorithm [15].

2.1.3 Tipping Bucket Rain Gauge Sensor

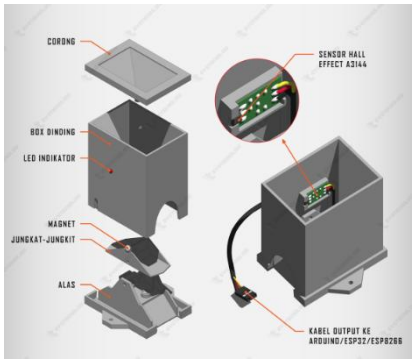


Figure 3. Tipping Bucket Rain Gauge Sensor

Rainfall intensity is measured using a tipping bucket rain gauge sensor (**Figure 3**), which converts rainfall into bucket tips representing a fixed rainfall volume. The measured rainfall intensity (mm/h) is used as an input variable for the Sugeno Fuzzy Logic algorithm [16].

2.1.4 Capacitive Soil Moisture Sensor



Figure 4. Capacitive Soil Moisture Sensor

A capacitive soil moisture sensor (**Figure 4**) measures soil moisture based on changes in soil capacitance. Its high corrosion resistance and stability make it suitable for long-term monitoring, and the measured soil moisture is used as an input to the Sugeno Fuzzy Logic algorithm [17].

2.1.5 Firebase Realtime Database

Firebase Realtime Database is used to store and synchronize sensor data in real time between the ESP32 and the monitoring website, enabling users to remotely access the latest environmental conditions through an internet connection [20].

2.1.6 Telegram and Webpushr Notification

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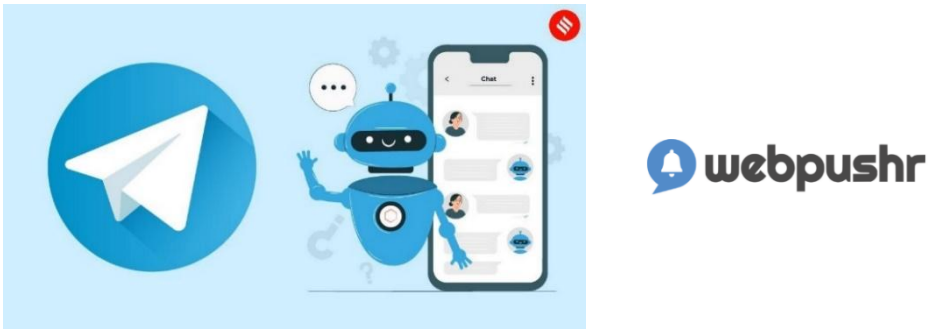


Figure 5. Telegram and Webpushr Notification

Telegram Bot and Webpushr are used to deliver real-time flood warnings. When the flood status changes to Alert or Danger, the ESP32 automatically sends notifications, allowing users to receive early warnings without accessing the monitoring website [21], [22].

2.2 Method

2.2.1 Hardware Design

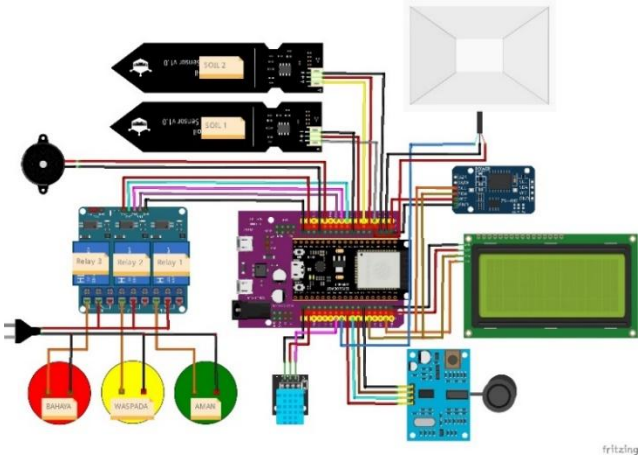


Figure 6. Circuit Design

Figure 9 shows the circuit design of the proposed flood monitoring and early warning system. The ESP32 serves as the main controller to acquire sensor data, execute the Sugeno Fuzzy Logic algorithm, control output devices, and transmit data to Firebase Realtime Database. The system utilizes JSN-SR04T ultrasonic sensors, capacitive soil moisture sensors, a tipping bucket rain gauge, and a DHT11 sensor to monitor environmental conditions. The monitoring results are displayed on a 20×4 I2C LCD, visualized on a web-based platform, and indicated through pilot lamps and a buzzer according to the classified flood status. This integrated design enables real-time monitoring, remote data transmission, and early flood warning.

2.2.2 Sugeno Fuzzy Logic Stages

2.2.2.1 Fuzzification

Fuzzification transforms sensor readings into fuzzy membership values (0–1). In this study, the input variables are water level (Low, Medium, High), rainfall intensity (No Rain, Light Rain, Heavy Rain), and soil moisture (Dry, Moist, Wet). The membership functions were designed using the MATLAB Fuzzy Logic Toolbox, as shown in **Figures 12–14**.

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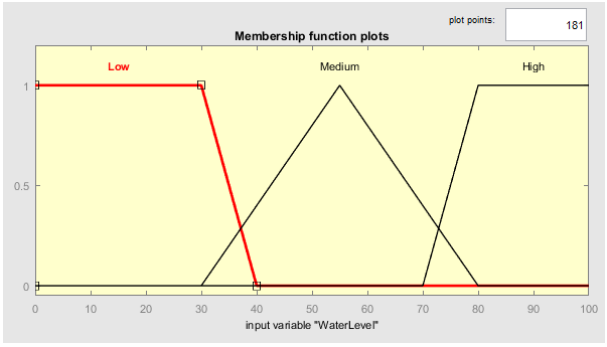


Figure 7. Membership Function WaterLevel

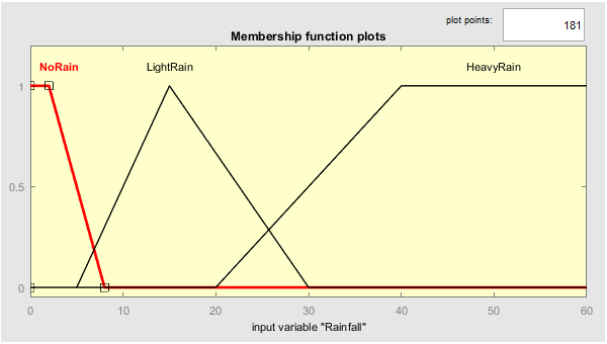


Figure 8. Membership Function Rainfall

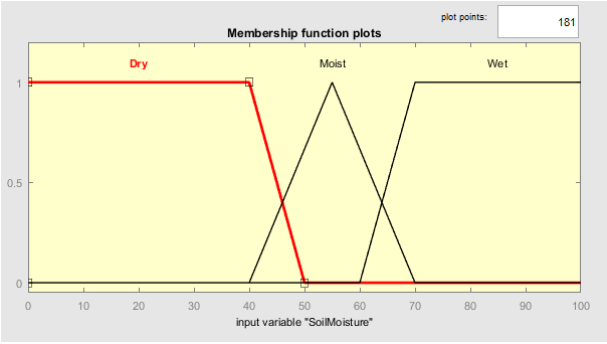


Figure 9. Membership Function SoilMoisture

2.2.2.2 Rule Base

The rule base consists of a collection of IF–THEN rules that define the relationship between the three input variables and the flood status. In this study, each input variable contains three linguistic terms, resulting in a total of 27 fuzzy rules (3 × 3 × 3).

2.2.2.3 Defuzzification

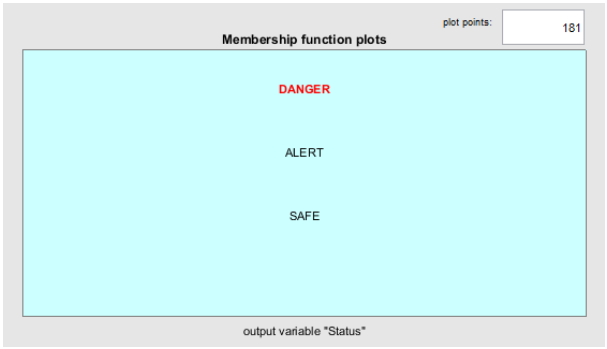


Figure 10. Defuzzification

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Defuzzification converts the fuzzy inference results into a crisp output using the zero-order Sugeno Weighted Average method:

$$Z = \frac{\sum(\alpha_i \,.\, z_i)}{\sum \alpha_i}$$

where Z is the final output, α_i is the firing strength, and z_i is the rule output (25 = Safe, 50 = Alert, 75 = Danger). The resulting value is used by the ESP32 to determine the flood status and activate the monitoring and warning system.

2.3 Evaluation

2.3.1 Sensor Accuracy Evaluation

The accuracy evaluation was performed by comparing the sensor measurements with their reference values. Soil moisture references were converted into percentages using Min–Max normalization [24], while rainfall references were calculated from the collected water volume and funnel area [25].

The Min–Max normalization is expressed as

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \; x \; (Y_{max} - Y_{min}) + Y_{min} \tag{1}$$

Where X is the original hygrometer value, X_{min} and X_{max} are the minimum and maximum hygrometer scales, respectively, and Y is the normalized soil moisture value.

The reference rainfall value was calculated using

$$Y = \frac{X - 1}{9} \; x \; 100 \tag{2}$$

Where CH is the rainfall (mm), V is the collected water volume (mL), and A is the funnel area (cm^2) [25].

The sensor error was calculated as

$$Error(\%) = \left| \frac{X_{ref} - X_{Sensor}}{X_{ref}} \right| \; x \; 100\% \tag{3}$$

Where X_{ref} is the reference value and X_{Sensor} is the sensor measurement [26].

The sensor accuracy was then obtained by

$$\text{Akurasi } (\%) = 100\% - \text{Error } (\%) \tag{4}$$

Higher accuracy and lower error indicate better sensor performance [26].

2.3.2 Sugeno Fuzzy Logic Performance Evaluation

The performance of the Sugeno Fuzzy Logic algorithm was evaluated by comparing the system output with manually calculated Sugeno values. The manual calculation follows the three stages of the Sugeno inference process, namely fuzzification, rule evaluation, and defuzzification [18], [19].

2.3.2.1 Fuzzification Stage

The fuzzification stage converts sensor inputs into fuzzy membership values (0–1) using predefined membership functions. In this study, the membership functions for water level, rainfall intensity, and soil moisture were designed based on previous studies and relevant standards [5], [6], [23], using increasing, decreasing, and triangular membership functions.

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The increasing membership function is defined as

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \dfrac{\mathrm{x} - a}{\mathrm{b} - a}, & a < x < \mathrm{b} \\ 1, & x \geq \mathrm{b} \end{cases} \tag{5}$$

The decreasing membership function is defined as

$$\mu(x) = \begin{cases} 1, & x \leq a \\ \dfrac{\mathrm{b} - x}{\mathrm{b} - a}, & a < x < \mathrm{b} \\ 0, & x \geq \mathrm{b} \end{cases} \tag{6}$$

The triangular membership function is expressed as

$$\mu(x) = \begin{cases} 0, & x \leq a \; or \; x \geq c \\ \dfrac{x - a}{b - a}, & a < x < b \\ \dfrac{c - x}{c - b}, & b \leq x < \; c \\ 1, & x = b \end{cases} \tag{7}$$

Where a, b, and c denote the boundary parameters of the membership functions.

2.3.2.2 Rule Evaluation

The firing strength of each rule was determined using the MIN operator,

$$\alpha_i = \mathrm{MIN}\ (\mu_1, \mu_1, .., \mu_n) \tag{8}$$

Where α_i is the firing strength of the *i*-th rule and μ_n represents the membership degree of each input variable [18], [19].

2.3.2.3 Defuzzification Stage

The final Sugeno output was calculated using the Weighted Average method,

$$Z = \frac{\sum(\alpha_i \; . \; \mathrm{z}_i)}{\sum \alpha_i} \tag{9}$$

Where Z is the crisp output, α_i is the firing strength, and z_i is the constant output of the corresponding rule [19].

To evaluate the agreement between the manually calculated Sugeno values and the system output, three regression metrics were used, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) [27].

The MSE is calculated as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Xi)^2 \tag{10}$$

The RMSE is calculated as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Xi)^2} \tag{11}$$

The coefficient of determination is expressed as

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$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - Xi)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \quad (12)$$

Where Y_i is the manually calculated Sugeno value, Xi is the system output, $\bar{Y}$ is the average manual Sugeno value, and n is the number of testing samples.

The flood classification performance was further evaluated using a confusion matrix consisting of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The evaluation metrics include Accuracy, Precision, Recall, and F1-score [27].

The classification accuracy is calculated as

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (13)$$

Precision is expressed as

$$Precision = \frac{TP}{(TP + FP)} \quad (14)$$

Recall is calculated as

$$Recall = \frac{TP}{(TP + FN)} \quad (15)$$

While the F1-score is

$$F1 - Score = \frac{2\ x\ (Precision\ x\ Recall)}{(Precision + Recall)} \quad (16)$$

Higher values of these metrics indicate better flood classification performance [27].

2.3.3 Response Time Evaluation

The notification response time was evaluated by measuring the transmission time of Telegram and Webpushr notifications using the ESP32 millis() function after the flood status was determined [28]. The response time is calculated as:

$$RT = t_{finish} - t_{start} \quad (17)$$

where RT is the response time (ms), t_{start} is the timestamp before notification transmission, and t_{finish} is the timestamp after transmission is completed [28].

3. RESULTS AND DISCUSSION

3.1 Hardware Design Results

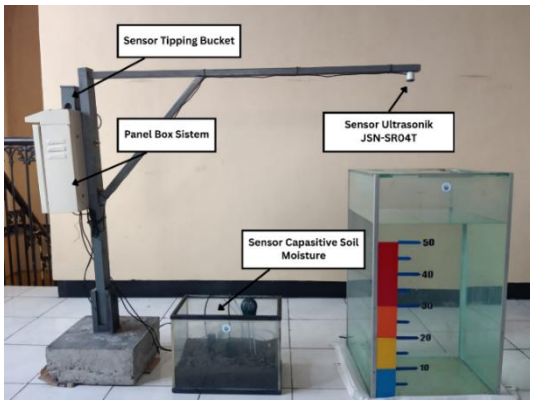


Figure 11. Hardware Design Results

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Figure 11 shows the developed hardware prototype of the proposed flood monitoring and early warning system. The prototype integrates an ESP32, JSN-SR04T ultrasonic sensor, tipping bucket rain gauge, capacitive soil moisture sensors, LCD, and supporting modules. Sensor data are processed using the Sugeno Fuzzy Logic algorithm and transmitted to the monitoring website, while warning indicators and notifications are activated according to the detected flood status.

3.3 Sensor Accuracy Evaluation

3.3.1 JSN-SR04T Ultrasonic Sensor

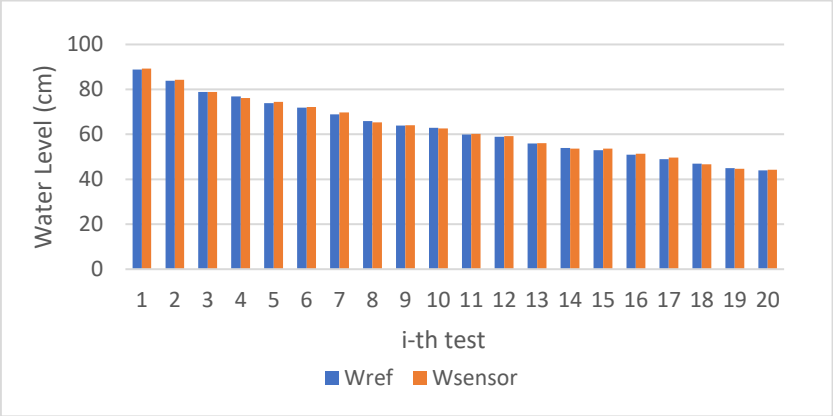


Figure 12. Comparison Chart of Reference Water Level and Water Level Sensor

As shown in **Figure 12** the sensor measurements closely follow the reference values throughout all testing conditions, indicating excellent agreement between the two datasets. The maximum measurement error was 1.43%, while the minimum error was 0.13%, resulting in an average error of 0.65% and an average accuracy of 99.35%. The small deviation between the reference and measured values demonstrates that the JSN-SR04T ultrasonic sensor provides stable and reliable distance measurements. Therefore, the sensor is suitable for water level monitoring and provides dependable input data for the Sugeno Fuzzy Logic algorithm, contributing to accurate flood status classification.

3.3.2 Tipping Bucker Rain Gauge Sensor

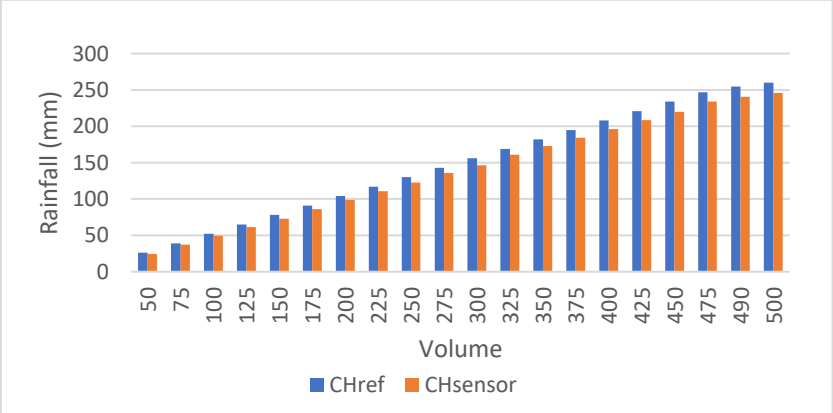


Figure 13. Comparison Chart of Reference Rainfall and Sensor Rainfall

As shown in **Figure 13** the measured rainfall values closely follow the reference values throughout the 20 testing conditions, demonstrating a consistent measurement trend. The measurement error ranged from 4.33% to 6.57%, with an average error of 5.36% and an average accuracy of 94.64%. The slight differences between the reference and measured values

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are mainly caused by the mechanical characteristics of the tipping bucket mechanism, such as bucket tipping tolerance and residual water remaining in the funnel after each tipping event. Nevertheless, these deviations remain within an acceptable range for rainfall monitoring applications. Therefore, the Tipping Bucket Rain Gauge sensor provides reliable rainfall measurements and is suitable as the rainfall input sensor for the proposed IoT-based flood monitoring and early warning system, ensuring dependable input data for the Sugeno Fuzzy Logic algorithm.

1.3.1 Capacitive Soil Moisture

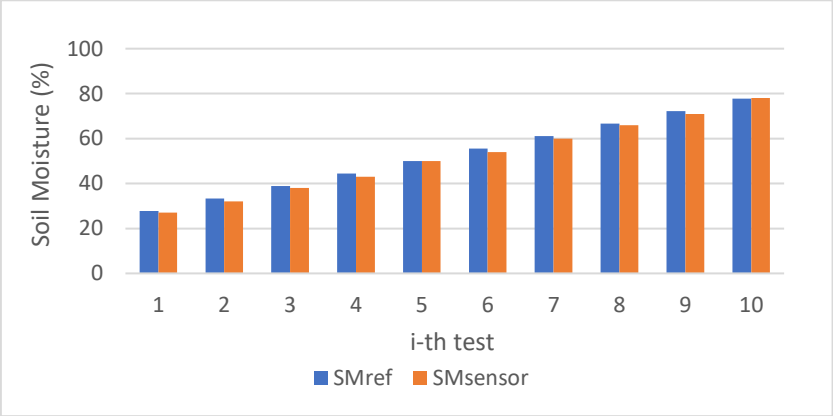


Figure 14. Comparison Chart of Reference Soil Moisture and Sensor Soil Moisture

As shown in Table 14. the capacitive soil moisture sensor exhibited high measurement accuracy under different soil moisture conditions. The measurement error ranged from 0.00% to 3.99%, with an average error of 1.99% and an average accuracy of 98.01%. The comparison between the normalized reference values and the sensor measurements also showed a very similar trend, indicating excellent agreement between both datasets. These results demonstrate that the capacitive soil moisture sensor provides reliable and consistent soil moisture measurements, making it suitable for use in the proposed flood monitoring and early warning system. The high measurement accuracy ensures that the soil moisture data supplied to the Sugeno Fuzzy Logic algorithm are dependable, thereby improving the accuracy of flood condition classification.

3.4 Sugeno Fuzzy Logic Performance

3.4.1 Testing the Sugeno Value Calculation

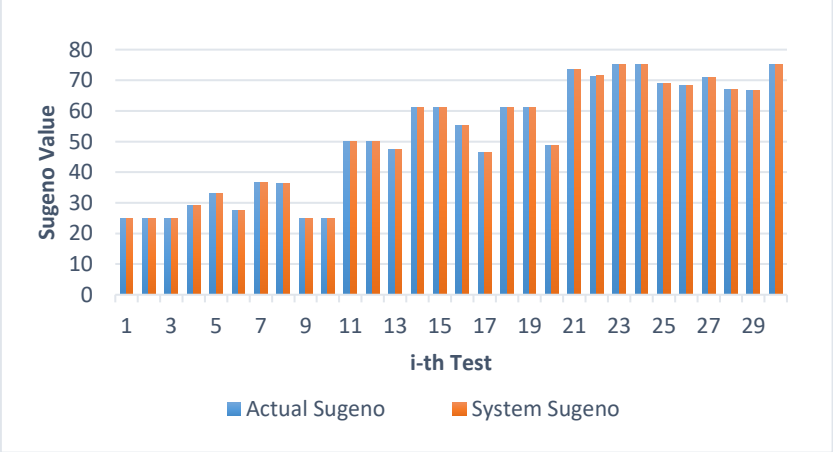


Figure 15. Comparison of Actual Sugeno Values and System Sugeno Values

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As shown in **Figure 15**, the Sugeno values generated by the proposed system closely match the manually calculated values for all 30 testing scenarios. Only negligible numerical differences were observed due to decimal rounding during the computation process. Furthermore, every testing scenario produced the same flood status classification (Safe, Alert, or Danger) as the manual calculation, resulting in 100% agreement between the theoretical Sugeno inference and the implemented system. These results confirm that the fuzzification process, rule evaluation, and Weighted Average defuzzification were correctly implemented. Therefore, the proposed ESP32-based system is capable of accurately executing the Sugeno Fuzzy Logic algorithm and providing reliable flood status decisions based on water level, rainfall intensity, and soil moisture measurements.

3.4.2 Sugeno Value Regression Analysis

The regression analysis demonstrated excellent agreement between the manually calculated Sugeno values and the system outputs. The proposed system achieved an MSE of 0.00069 and an RMSE of 0.02627, indicating negligible prediction errors. In addition, the coefficient of determination (R^2) reached 0.999998 (99.9998%), confirming an almost perfect correlation between the manual calculations and the implemented Sugeno Fuzzy Logic algorithm. These results demonstrate that the proposed system accurately reproduces the theoretical Sugeno calculations and provides highly reliable outputs for flood status determination.

3.4.3 Flood Status Classification Analysis

The flood status classification performance was evaluated by comparing the flood status obtained from manual Sugeno calculations with the classifications generated by the proposed system. A total of 30 testing scenarios, consisting of 10 Safe, 10 Alert, and 10 Danger conditions, were used in the evaluation. The corresponding confusion matrix is presented in Table 10.

Table 1. Confusion Matrix of Flood Status Classification

		Actual			
		SAFE	ALERT	DANGER	Amount
Predicted	SAFE	10	0	0	10
	ALERT	0	10	0	10
	DANGER	0	0	10	10
	Amount	10	10	10	30

The confusion matrix shows that all testing samples were correctly classified without any false positive or false negative predictions. Based on these results, the classification performance metrics are summarized in Table 11.

Table 2. Flood Status Classification Performance

Status	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SAFE	100	100	100	100
ALERT	100	100	100	100
DANGER	100	100	100	100

The proposed system achieved 100% accuracy, precision, recall, and F1-score, demonstrating reliable flood status classification for real-time monitoring and early warning applications.

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3.5 Notification Response Time

The notification response time was evaluated to measure the speed of the proposed system in delivering flood warning notifications through Telegram and Webpushr after the flood status was determined. Based on 10 testing trials for each notification service, Telegram achieved an average response time of 1.63 s, while Webpushr achieved 2.35 s. Although Webpushr required slightly longer transmission time due to additional server-side processing, both services successfully delivered all notifications. These results demonstrate that the proposed system can provide timely and reliable flood warning notifications for real-time monitoring and early warning applications.

4. CONCLUSION

This study successfully developed an ESP32-based flood monitoring and early warning system integrated with a real-time monitoring website using the Sugeno Fuzzy Logic method. The proposed system accurately classified flood conditions into Safe, Alert, and Danger using water level, rainfall intensity, and soil moisture as input parameters. Experimental results showed high sensor accuracies of 99.35%, 98.01%, and 94.64% for the ultrasonic, soil moisture, and tipping bucket rain gauge sensors, respectively. The Sugeno implementation achieved excellent agreement with manual calculations (MSE = 0.00069, RMSE = 0.02627, R^2 = 0.999998) and 100% accuracy, precision, recall, and F1-score for flood status classification. In addition, the average notification response times were 1.63 s for Telegram and 2.35 s for Webpushr, demonstrating the capability of the proposed system for reliable real-time flood monitoring and early warning. Future work may focus on deploying multiple monitoring nodes and integrating additional sensors or artificial intelligence techniques to further improve flood prediction performance.

5. ACKNOWLEDGMENT

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

7. AUTHORS' CONTRIBUTION/ROLE

Galeh Rizky Alifviansyah: Conceptualization, Methodology, Hardware, Software (IoT & Fuzzy Logic Sugeno), Investigation, Data Curation, Writing Original Draft. Lilik Anifah: Formal Analysis and Supervision.

8. DECLARATION OF THE USE GENERATIVE AI IN THE MANUSCRIPT PREPARATION PROCESS

Authors declare that did not use Generative AI in the manuscript preparation process upon submission of the paper.

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