IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 31, No. 2, February, 2026, pp. 381-388
Journal homepage: http://iieta.org/journals/isi

An IoT-Enabled Real-Time Water Quality Monitoring System with On-Device McCulloch–Pitts Neural Network Classification

Andi Rusdin[1*], Jumiyatun[2], Ratih Mar'atus Sholihah[2], Mery Subito[2], Irwan Mahmudi[2], Farhan[2],
Hideo Oshikawa[3]

[1] Department of Civil Engineering, Faculty of Engineering, Tadulako University, 94118, Indonesia
[2] Department of Electrical Engineering, Faculty of Engineering, Tadulako University, 94118, Indonesia
[3] Department of Civil Engineering and Architecture, Faculty of Science and Engineering, Saga University, 840-8502, Japan

Corresponding Author Email: andi.rusdin@untad.ac.id

https://doi.org/10.18280/isi.310206

Received: 19 September 2025
Revised: 1 December 2025
Accepted: 16 February 2026
Available online: 28 February 2026

Keywords:
water quality monitoring, Internet of Things, McCulloch–Pitts neural network, on-device classification, embedded system

ABSTRACT

This study presents an Internet of Things (IoT)-enabled real-time water quality monitoring and classification system that integrates a lightweight McCulloch–Pitts neural network for on-device inference on resource-constrained hardware. The proposed system employs pH, turbidity, Total Dissolved Solids (TDS), and temperature sensors connected to an Arduino-based platform, while measured data are transmitted to the ThingSpeak cloud for remote visualization and monitoring. A key contribution of the study is the embedded implementation of the classification model, which requires less than 5 KB SRAM and performs inference in under 10 ms per sample without relying on cloud-based computation. Experimental evaluation was conducted at three locations in Central Sulawesi, Indonesia, in order to assess both sensing performance and practical classification capability under real operating conditions. The results show that the sensing module achieved measurement accuracy ranging from 85% to 97% compared with a commercial reference device, and the proposed system successfully classified water into three practical categories: potable, suitable for washing, and unsuitable for daily use. In addition to supporting local display, the system enables remote and continuous monitoring through cloud-based data visualization. The developed framework provides a low-cost, real-time, and location-independent solution for water quality assessment. However, because the model relies on fixed threshold-based weighting, its adaptability to changing water conditions remains limited, indicating the need for future refinement through more adaptive classification strategies and the inclusion of additional water quality parameters.

1. INTRODUCTION

Water is a fundamental requirement for human and ecological life. In daily activities, water is used for drinking, cooking, bathing, washing, and in industrial and agricultural processes. However, rapid population growth and industrialization have led to declining water quality in many regions. Poor water quality can serve as a medium for the transmission of diseases, particularly those affecting the human digestive system. Therefore, water quality monitoring has become a crucial concern across multiple aspects of life, from household use to aquaculture practices [1]. Contaminated water may contain toxic compounds, leftover feed, organic materials, and pathogenic substances that can harm fish [2]. The government has established water quality standards through the Indonesian Ministry of Health Regulation No. 492/MENKES/PER/IV/2010, which includes parameters such as pH, temperature, Total Dissolved Solids (TDS), and turbidity [3]. Turbidity itself is not inherently hazardous, but it can indicate the presence of potentially harmful chemical compounds. These concerns drive researchers to develop innovative methods for reliably measuring water quality parameters, shifting from conventional methods to more efficient approaches [4]. One promising approach involves applying machine learning [5] to recognize environmental phenomena and improve water-quality assessment [6].

Several prior studies have focused on measuring basic water parameters [7]. Some have introduced monitoring systems to facilitate water quality observation through custom or existing web servers, enabling data storage and real-time monitoring via personal computers or smartphones [7, 8]. For instance, an IoT-based water monitoring system with pH, turbidity, salinity, temperature, and ultrasonic sensors [9, 10] connected to an Arduino Uno microcontroller has been developed to send data to Firebase and display real-time results in an Android application [5, 11]. However, these systems are often limited to local monitoring and lack robust remote access [9]. Other studies have developed online pH monitoring systems using the PH-4502C module and a web server, providing real-time visualization via a browser interface [12].

IoT-based systems present a modern solution for real-time water quality monitoring. Deploying sensor devices in the environment transforms it into a smart system capable of interacting with other devices via network connections [13, 14]. For example, a system using pH, temperature, and TDS sensors connected via an ESP32 microcontroller can be accessed through the Blynk application [15, 16]. Improving monitoring efficiency and preventing losses caused by fluctuations in water quality, particularly in aquaculture applications [17].

Beyond data acquisition, intelligent methods are needed for classification and decision-making regarding water quality. Artificial Neural Networks (ANNs), especially the McCulloch-Pitts model, can effectively classify water quality status. ANNs are classification algorithms that emulate the working principles of human neural networks [18]. They map input data to target outputs via neurons arranged across input, hidden, and output layers [19]. ANNs are highly effective for modeling complex, non-linear relationships [20]. The McCulloch-Pitts model represents one of the simplest ANN architectures, yet it remains effective for binary processing and basic classification tasks [21].

Intelligent computing methods, including fuzzy logic, have also been applied to water quality classification [22]. However, such methods often face limitations in field efficiency, especially in remote or hard-to-access locations, hindering real-time data acquisition. To overcome these limitations, this study proposes an IoT-based water quality detection and monitoring system using a McCulloch-Pitts Neural Network model. The system automatically collects sensor data and transmits it to a web-based server, enabling monitoring anytime, anywhere on computers or smartphones [23]. By integrating IoT technology with neural network methods, the proposed system aims to improve the efficiency of water quality classification, expand monitoring coverage, and help ensure the availability of safe water in accordance with health standards [24].

2. METHODS

2.1 System design

The design of the water quality detection and monitoring system was carried out to simplify the integration and assembly of components for an Internet of Things (IoT)-based system. The design includes a complete system block diagram and an illustration of the system's primary components. A key feature of this study is the implementation of a McCulloch-Pitts Neural Network model directly on the microcontroller, enabling real-time, on-device water quality classification without relying on cloud-based computation.

Figure 1 shows the overall system design. The system consists of four primary sensors: a TDS Sensor, a pH Sensor, a Turbidity Sensor, and a Temperature Sensor. These sensors measure the essential parameters of water quality. The raw data collected by the sensors is sent to an Arduino microcontroller equipped with an integrated neural network algorithm [25]. The hardware components were selected based on availability, cost efficiency, and compatibility with embedded implementation. The Arduino Uno microcontroller was chosen due to its low power consumption and sufficient computational capability for implementing simple neural network inference. The McCulloch–Pitts neural network model was implemented using integer-based arithmetic to minimize memory usage and execution time. The total memory consumption required for neural network computation was less than 5 KB of SRAM, enabling stable operation on resource-constrained hardware.

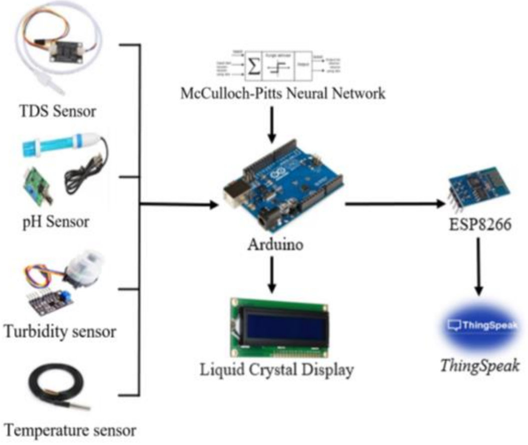

Figure 1. Diagram of the water quality monitoring system based on McCulloch-Pitts Neural Network

To support remote monitoring, the system uses an ESP8266 Wi-Fi module to transmit data to the ThingSpeak IoT platform. This architecture allows the local neural network model to perform water quality classification independently of cloud-based artificial intelligence, resulting in faster processing, reduced bandwidth usage, and the ability to operate offline. A local LCD interface provides instant visual feedback by displaying both sensor readings and water quality classification results.

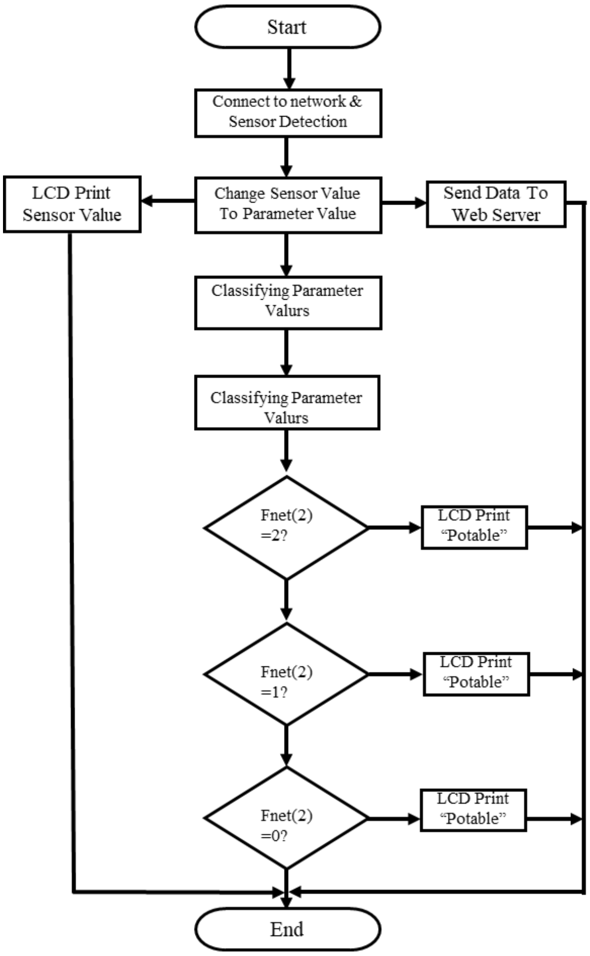

Figure 2. System flowchart of the water quality monitoring process

The water quality output is displayed in two ways, as shown in Figure 2:

1. Locally, via the LCD, showing sensor parameter values and the classified water quality category: Potable (drinking water), Suitable for washing, Unsuitable for daily use.
2. Online, by transmitting data to the ThingSpeak cloud server through the ESP8266 module. The data is visualized in real-time graphs, allowing users to observe trends and historical changes in water quality.

2.2 Neural network model for water quality classification

Water quality classification is performed using a McCulloch–Pitts neural network model due to its simplicity and suitability for embedded implementation. Figure 3 indicates that the input parameters include pH, turbidity (NTU), TDS, and temperature, which are key indicators of drinking water quality. Each parameter is first categorized into three numerical classes: potable (2), suitable for washing (1), and unsuitable for daily use (0), based on the drinking water quality standards.

The neural network processes the classified inputs by calculating the weighted sum at each neuron. The net input value is determined using the following equation:

$$net = \sum x_i \, w_i \tag{1}$$

where, x_i represents the classified input value, and w_i denotes the corresponding weight. The weight values were manually assigned based on the relative importance of each parameter according to drinking water quality standards. pH and TDS were given higher weights ($w_1 = 1$, $w_3 = 1$) because they directly affect human health, while turbidity and temperature were assigned lower weights ($w_2 = 0.25$, $w_4 = 0.25$) as supporting indicators. Compared to multilayer perceptron (MLP) models, the McCulloch–Pitts model offers lower computational complexity, deterministic behavior, and suitability for real-time embedded implementation, though it lacks adaptive learning.

Figure 4 illustrates the structure of the proposed McCulloch–Pitts neural network. The first neuron combines the pH and turbidity inputs to produce an intermediate output, which is then forwarded to the second neuron along with the TDS input to generate the final water quality classification. This hierarchical structure enables efficient classification while maintaining low computational overhead, making it suitable for deployment on resource-constrained IoT devices.

3. RESULTS AND DISCUSSION

The developed water quality detection and monitoring system was tested to verify its functionality and accuracy in real conditions. System performance was evaluated based on sensor accuracy testing and water quality classification in accordance with the Indonesian Ministry of Health Regulation, No. 492/MENKES/PER/IV/2010 [3]. Table 1 shows the reference standard for drinking water quality, as defined by the Ministry of Health.

Before system testing, individual sensor calibration and accuracy tests were conducted by comparing the readings with a commercial standard device (HANNA brand). The results of the sensor testing are shown in Tables 2 to 4. These results indicate that the sensors have an accuracy range between 85% and 97%, which is acceptable for IoT-based water quality monitoring.

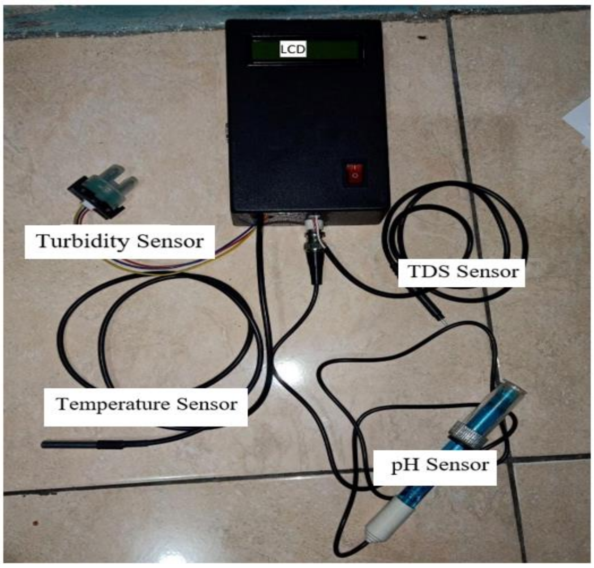

Figure 3. Water quality detection and monitoring prototype

Table 1. Standard drinking water quality

No.	Parameter	Standard Value	Unit
1.	TDS	< 500	Ppm
2.	pH	6,5 – 8,5	pH
3.	Turbidity	< 5	NTU

Table 2. Total Dissolved Solids (TDS) sensor accuracy

Sample	TDS (Standard)	TDS (Prototype)	Accuracy (%)
1.	129	153	81.4
2.	1741	1361	78.17
3.	377	385	97.88
	Average		85.82

Table 3. pH sensor accuracy

Sample	pH (Standard)	pH (Prototype)	Accuracy (%)
1.	6.6	6.3	95.45
2.	7.3	7.2	98.63
3.	7.8	8	97.44
	Average		97.17

Table 4. Temperature sensor accuracy

Sample	Temp (°C Standard)	Temp (°C Prototype)	Accuracy (%)
1.	27.9	27.5	98.92
2.	32.4	31	95.68
3.	33.5	32.3	96.42
	Average		97.01

The data generated from the sensors is used as the basis for water quality classification using the Neural Network method with the McCulloch-Pitts model. Water quality is classified into three categories: potable (suitable for drinking), suitable for washing, and unsuitable for daily use. The classification table for each parameter is presented in Table 5. The values of each parameter are entered into a mathematical function, multiplied by their respective weights, to produce an output that is then activated to generate the final classification. Consequently, each parameter classification is represented numerically as follows:

1. Potable = 2
2. Suitable for washing = 1
3. Unsuitable for daily use = 0

Table 5. Water parameter classification

pH	Classification		Turbidity (NTU)	Classification		TDS (ppm)	Classification	
	Description	**No.**		**Description**	**No.**		**Description**	**No.**
4-< 6,5	Washing	1	0-5	Potable	2	0-500	Potable	2
6,5-8,5	Potable	2	> 5-20	Washing	1	>500-100	Washing	1
> 8,5-11	Washing	1	Other	Unsuitable	0	Other	Unsuitable	0
Other	Unsuitable	0						

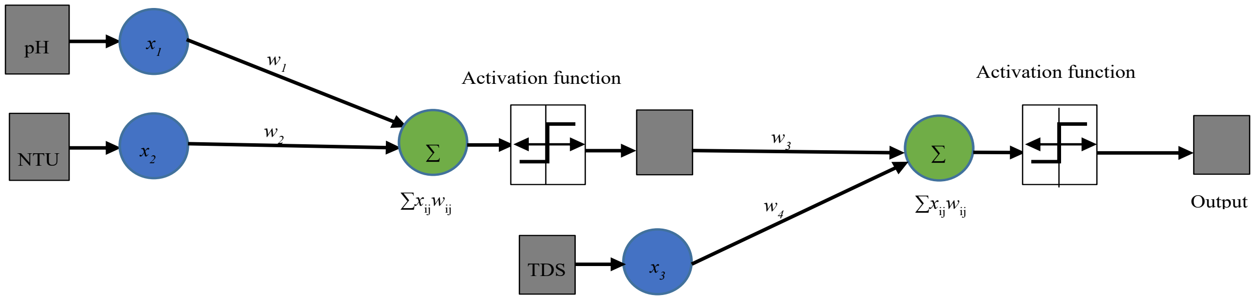

Figure 4. Water quality neural network structure

Each parameter value, represented numerically as 0, 1, or 2, is treated as an input to the neuron and multiplied by its corresponding weight (w) to produce an intermediate output. The McCulloch-Pitts model then sums the weighted inputs according to the following formula:

$$net = \sum x_{ij}\, w_{ij} \quad (2)$$

where, x_{ij} is the input value from the classified water parameter (pH, turbidity, or TDS); w_{ij} is the weight assigned to the corresponding input.

The resulting net value is then passed through an activation function to determine the final classification output of the system. In this study, the weights for the McCulloch-Pitts neural network were assigned manually as $w_1 = 1$, $w_2 = 0.25$, $w_3 = 1$ and $w_4 = 0.25$. The water quality neural network structure is shown in Figure 4. The first neuron combines the pH and turbidity (NTU) inputs, each multiplied by its respective weight, to produce an intermediate output. This output is then activated by the following formula:

$$f(net1)\begin{cases} 2, & \text{jika} \quad net1 = 2{,}5 \\ 1, & \text{jika} \quad 1 < net1 < 2 < net1 < 2{,}5 \\ 0, & \text{jika} \quad net1 \leq 1, net1 = 2 \end{cases} \quad (3)$$

The intermediate output is then activated and passed to the second neuron, which combines it with the TDS input to produce the final water quality classification. The activation function is as follows:

$$f(net2)\begin{cases} 2, & \text{jika} \quad net2 = 2{,}5 \\ 1, & \text{jika} \quad 1 < net2 < 2 < net2 < 2{,}5 \\ 0, & \text{jika} \quad net2 \leq 1, net2 = 2 \end{cases} \quad (4)$$

The system was tested in three locations in Palu City, Central Sulawesi, Indonesia:

1. Palu Bangga Streat (Location 1)
2. Tondo sub-District (Location 2)
3. Duyu, Tatanga District (Location 3)

The measurement results for Locations 1, 2, and 3 are presented sequentially in Tables 6, 7, and 8, respectively. Meanwhile, the monitoring graphs displayed on the web interface are shown in Figures 5, 6, and 7.

Table 6. Water quality at Location 1

TDS (ppm)	pH	Turbidity (NTU)	Temp (℃)	System Output
153	6,3	101,2993	27,597	Unsuitable
156,6	5,85	97,0661	26,117	Unsuitable
187,1	5,5	93,1508	27,413	Unsuitable
156,6	5,5	92,1404	26,958	Unsuitable
190,1	5,6	92,8982	26,359	Unsuitable
156,6	5,82	99,7184	26,585	Unsuitable
159,6	5,6	96,0557	26,161	Unsuitable
159,6	5,64	96,0557	27,2	Unsuitable
199,3	5,87	98,4554	27,547	Unsuitable
168,8	5,4	93,1508	27,45	Unsuitable
171,8	5,3	93,5297	27,245	Unsuitable

The final water quality classification at Location 2 is unsuitable, due to the very high TDS level, indicating a high concentration of dissolved particles in the water. The turbidity and pH, which range between 6 and 7, are relatively acceptable for drinking water. Therefore, this water quality can be classified as suitable for washing or can be consumed after proper treatment.

The final water quality classification at Location 3 is suitable for washing. The TDS values in the samples are below 500 ppm, with pH values ranging between 7 and 8, indicating that the water is generally in good condition for drinking purposes. However, the turbidity at Location 3 is slightly higher, so the water quality is classified as suitable for washing, although it can still be consumed after appropriate processing.

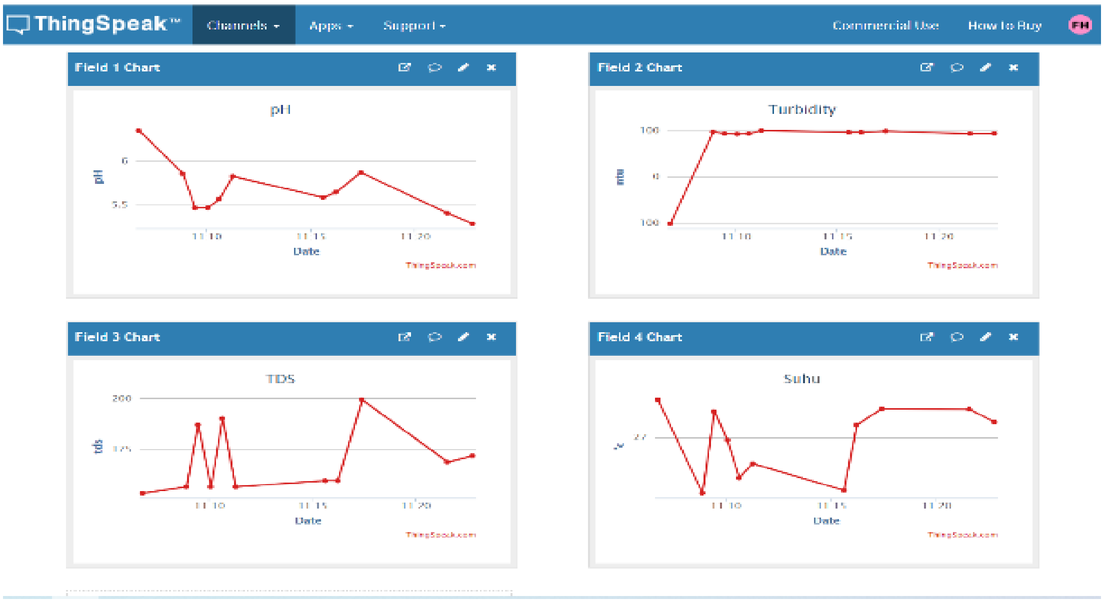

Figure 5. Water quality monitoring graph at Location 1

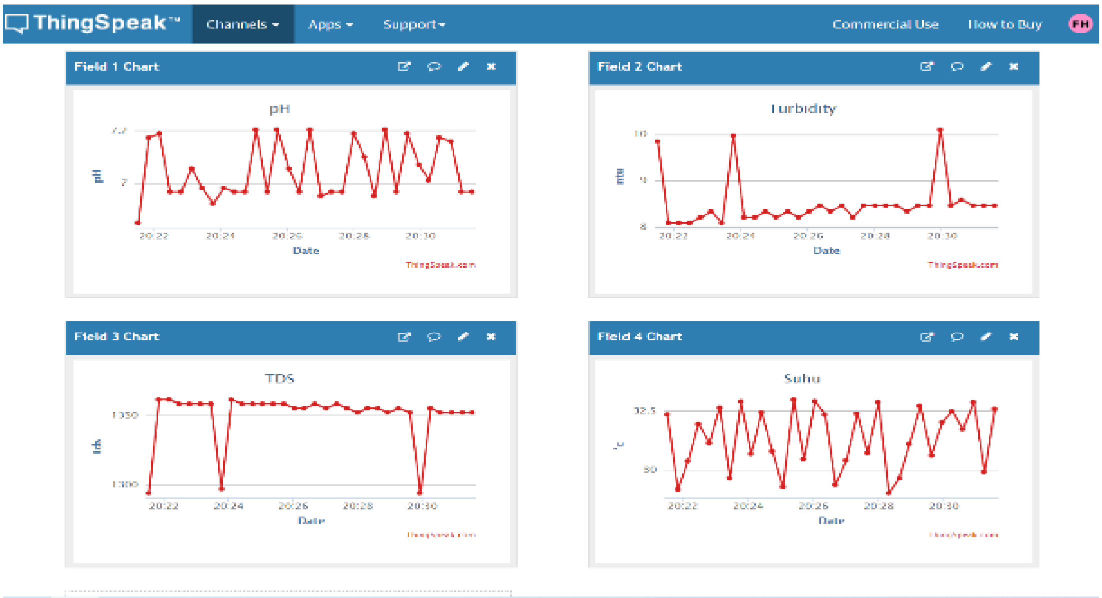

Figure 6. Water quality monitoring graph at Location 2

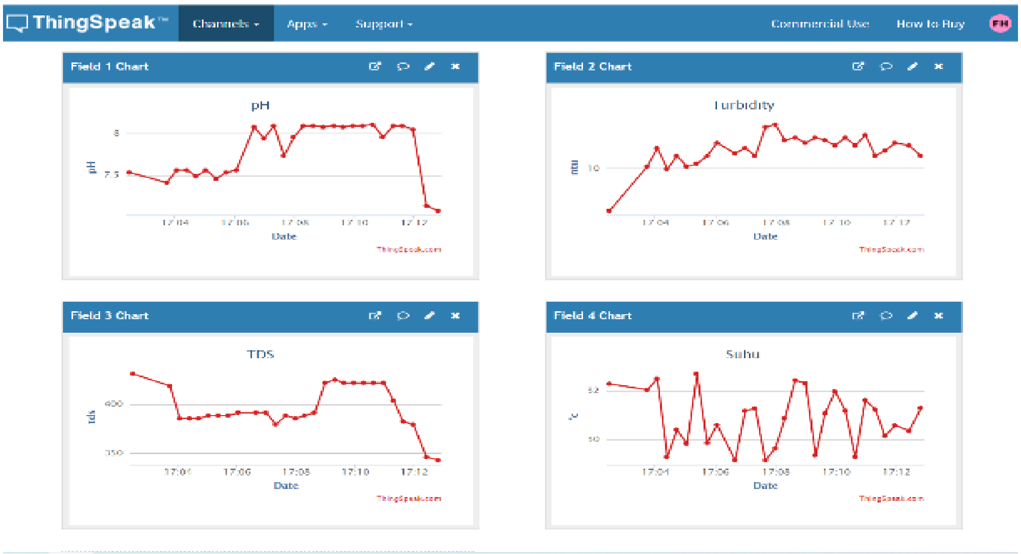

Figure 7. Water quality monitoring graph at Location 3

Table 7. Water quality at Location 2

TDS (ppm)	pH	Turbidity (NTU)	Temp (°C)	System Output
1294,000	6,84	9,8447	32,359	Unsuitable
1361,042	7,175	8,0765	29,166	Unsuitable
1361,042	7,19	8,0765	30,368	Unsuitable
1357,993	6,965	8,0765	31,953	Unsuitable
1357,993	6,965	8,2028	31,143	Unsuitable
1357,993	7,055	8,3291	32,645	Unsuitable
1357,993	6,98	8,0765	29,642	Unsuitable
1297,007	6,92	9,971	32,903	Unsuitable
1361,042	6,98	8,2028	30,679	Unsuitable
1357,993	6,965	8,2028	32,445	Unsuitable
1357,993	6,965	8,3291	30,783	Unsuitable
1357,993	7,205	8,2028	29,281	Unsuitable
1357,993	6,965	8,3291	32,982	Unsuitable
1357,993	7,205	8,2028	30,46	Unsuitable
1354,944	7,055	8,3291	32,911	Unsuitable
1354,944	6,965	8,4554	32,353	Unsuitable
1357,993	7,205	8,3291	29,364	Unsuitable
1354,944	6,950	8,4554	30,405	Unsuitable
1357,993	6,965	8,2028	32,390	Unsuitable
1354,944	6,965	8,4554	30,719	Unsuitable
1351,894	7,190	8,4554	32,875	Unsuitable
1354,994	7,100	8,4554	29,005	Unsuitable
1354,994	6,950	8,4554	29,642	Unsuitable
1351,894	7,205	8,3291	31,013	Unsuitable

Table 8. Water quality at Location 3

TDS (ppm)	pH	Turbidity (NTU)	Temp (°C)	System Output
431,006	7,53	7,95	32,3	Washing
418,808	7,41	10,10	32	Washing
385,266	7,56	10,98	32,5	Washing
385,266	7,56	9,97	29,3	Washing
385,266	7,49	10,60	30,4	Washing
388,315	7,56	10,10	29,8	Washing
388,315	7,46	10,22	32,7	Washing
388,315	7,53	10,60	29,9	Washing
391,365	7,56	11,23	30,6	Washing
391,365	8,08	10,73	29,2	Washing
391,365	7,94	10,98	31,2	Washing
379,167	8,09	10,60	31,3	Washing
388,315	7,73	11,99	29,2	Washing
385,266	7,96	12,12	29,6	Washing
388,315	8,09	11,36	30,9	Washing
391,365	8,09	11,49	32,4	Washing
4218587	8,08	11,23	32,3	Washing
424,907	8,09	11,49	29,4	Washing
421,858	8,08	11,36	31,1	Washing
421,858	8,09	11,11	32	Washing
421,858	8,09	11,49	31,2	Washing
421,858	8,11	11,12	29,3	Washing
421,858	7,96	11,61	31,6	Washing
403,562	8,09	10,60	31,2	Washing
382,217	8,09	10,86	30,1	Washing
379,167	8,05	11,23	30,6	Washing
345,625	7,03	11,12	30,4	Washing
342,578	7,07	10,60	31,1	Washing

Some misclassification cases were observed, particularly when turbidity sensor readings were unstable due to calibration drift or environmental interference. High turbidity values occasionally dominated the classification outcome despite acceptable pH and TDS levels. This limitation highlights the sensitivity of threshold-based neural models to sensor noise. Nevertheless, the classification results remain consistent with local water usage practices, where water with high turbidity is typically avoided for direct consumption.

- **Sample 1 Analysis**

The first sample shows significant sensor value fluctuations due to unstable network conditions. The measured TDS is low with pH between 5–6, but the turbidity reading experienced calibration errors. In general, the water could still be used after treatment, but the neural network model classified it as not suitable.

a. Neural Network Formulation:

$$net1 = x\_\mathrm{pH} \cdot w_1 + x\_\mathrm{NTU} \cdot w_2 \tag{5}$$

$$net2 = \hat{y}_1 \cdot w_3 + x\_\mathrm{TDS} \cdot w_4 \tag{6}$$

b. Calculation results:

$$\begin{gathered} net1 = (1.0 \times 1.0) + (0.0 \times 0.25 \times) = 1.0 \\ \rightarrow f(net1) = 0.0 \end{gathered} \tag{7}$$

$$\begin{gathered} net2 = (0.0 \times 1.0) + (2.0 \times 0.25 \times) = 0.5 \\ \rightarrow f(net2) = 0.0 \text{ (Not suitable)} \end{gathered} \tag{8}$$

Interpretation: The final classification is 'Not Suitable' because the NTU error reduced the output. Practically, the water could still be used for washing or even drinking after proper treatment.

- **Sample 2 Analysis**

The second sample shows stable monitoring results with good network conditions. The pH value is between 6–7 (good), NTU is good, but TDS is very high. The final neural network output classified the water as not suitable.

a. Neural Network Formulation:

$$net1 = x\_\mathrm{pH} \cdot w_1 + x\_\mathrm{NTU} \cdot w_2 \tag{9}$$

$$net2 = \hat{y}_1 \cdot w_3 + x\_\mathrm{TDS} \cdot w_4 \tag{10}$$

b. Calculation results:

$$\begin{gathered} net1 = (2.0 \times 1.0) + (0.0 \times 0.25 \times) = 2\ .5 \\ \rightarrow f(net1) = 2.0 \end{gathered} \tag{11}$$

$$\begin{gathered} net2 = (2.0 \times 1.0) + (0.0 \times 0.25 \times) = 2.0 \\ \rightarrow f(net2) = 0.0 \text{ (Not suitable, exact threshold)} \end{gathered} \tag{12}$$

Interpretation: Although pH and NTU are good, the very high TDS dominates the final decision. The net2 value being at the threshold produced a strict 'Not Suitable' classification.

- **Sample 3 Analysis**

The third sample provides stable data with TDS < 500 ppm and pH 7–8 (good), but NTU is slightly higher. The neural network classified the water as suitable for washing.

a. Neural Network Formulation:

$$net1 = x\_\mathrm{pH} \cdot w_1 + x\_\mathrm{NTU} \cdot w_2 \tag{13}$$

$$net2 = \hat{y}_1 \cdot w_3 + x\_\mathrm{TDS} \cdot w_4 \tag{14}$$

b. Calculation results:

$$net1 = (2.0 \times 1.0) + (1.0 \times 0.25 \times) = 2\ .25 \\ \rightarrow f(net1) = 1.0 \tag{15}$$

$$net2 = (1.0 \times 1.0) + (2.0 \times 0.25 \times) = 1.5 \\ \rightarrow f(net2) = 1.0 \text{ (Suitable for washing)} \tag{16}$$

Interpretation: The combination of good pH and TDS was limited by higher NTU, resulting in the final classification 'Suitable for Washing'. Practically, the water could still be consumed after turbidity treatment.

4. CONCLUSION

The IoT-based Water Quality Monitoring System designed using the Neural Network method implemented in the Arduino IDE, was successfully developed and functioned effectively. The system can reliably determine the classification of water quality parameters for drinking water. This reliability is achieved because the neural network-based classification utilizes fixed value ranges referring to drinking water quality standards, although it does not provide flexible classification outside these ranges.

The real-time monitoring of water quality parameters through the ThingSpeak web server significantly facilitates remote observation of water conditions. However, the stability of the network connection greatly affects the speed and success of data transmission to the web server. Overall, the integration of IoT technology with a lightweight neural network model provides a cost-effective, real-time, and location-independent solution for water quality detection and monitoring, contributing to better decision-making in water utilization and public health protection.

Despite its effectiveness, the proposed system has several limitations, including dependence on fixed classification thresholds, limited adaptability to varying water conditions, and sensitivity to sensor calibration errors. Future work will focus on incorporating adaptive weight mechanisms, additional water quality parameters such as dissolved oxygen and conductivity, and comparative evaluation with more advanced neural network models while maintaining low computational complexity. These improvements are expected to enhance classification robustness and system scalability.

ACKNOWLEDGMENT

This work was funded by the Tadulako University Excellence Research Grant (Contract No. 0604/UN28.16/AL.04/2025). The authors also wish to express their gratitude to the Power Electronics and Control System Laboratory at the Faculty of Engineering, Tadulako University, for providing the necessary research facilities and support.

REFERENCES

[1] Nagothu, S.K., Bindu Sri, P., Anitha, G. et al. (2025). Advancing aquaculture: fuzzy logic-based water quality monitoring and maintenance system for precision aquaculture. Aquaculture International, 33: 32. https://doi.org/10.1007/s10499-024-01701-2

[2] Keshipeddi, S.B. (2021). IoT based smart water quality monitoring system. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3904842

[3] Ministry of Health of the Republic of Indonesia. (2010). Peraturan Menteri Kesehatan Republik Indonesia nomor 492/Menkes/Per/IV/2010 tentang persyaratan kualitas air minum [Regulation of the Minister of Health of the Republic of Indonesia number 492/Menkes/Per/IV/2010 concerning drinking water quality requirements].

[4] Jerbi, H., Gnana Vincy, V.G.A., Ben Aoun, S., Abbassi, R., Kchaou, M. (2026). Optimizing waste management in smart cities: An IoT-based approach using dynamic bald eagle search optimization algorithm (DBESO) and machine learning. Journal of Urban Management, 15(1): 114-130. https://doi.org/10.1016/j.jum.2025.05.015

[5] Sembiring, J.P., Pranita, E., Putri, N.U., Jayadi, A., Fadli, R. (2023). Water quality control and monitoring systems in VANAME shrimp ponds using the fuzzy method. In 2023 International Conference on Networking, Electrical Engineering, Computer Science, and Technology (IConNECT), Bandar Lampung, Indonesia, pp. 103-108. https://doi.org/10.1109/IConNECT56593.2023.10326751

[6] Chourlias, A., Violos, J., Leivadeas, A. (2025). Virtual sensors for smart farming: An IoT- and AI-enabled approach. Internet of Things, 32: 101611. https://doi.org/10.1016/j.iot.2025.101611

[7] Ekundayo, O.S., Ezugwu, A.E. (2025). Deep learning: Historical overview from inception to actualization, models, applications and future trends. Applied Soft Computing, 181: 113378. https://doi.org/10.1016/j.asoc.2025.113378

[8] Nvs, B., Saranya, P.L. (2020). Water pollutants monitoring based on Internet of Things. In Inorganic Pollutants in Water, pp. 371-397. https://doi.org/10.1016/B978-0-12-818965-8.00018-4

[9] Jan, F., Min-Allah, N., Düştegör, D. (2021). IoT based smart water quality monitoring: Recent techniques, trends and challenges for domestic applications. Water, 13(13): 1729. https://doi.org/10.3390/w13131729

[10] Lyu, Z., Zhou, W.L., Gao, X.L., Zheng, H.W., Jia, J.L. (2025). Remediation of toluene-contaminated soils by sequential treatment: Soil vapor extraction systems and internal combustion engine units. Journal of Contaminant Hydrology, 271: 104532. https://doi.org/10.1016/j.jconhyd.2025.104532

[11] Lee, Y.W. (2020). A stochastic model of particulate matters with AI-enabled technique-based IoT gas detectors for air quality assessment. Microelectronic Engineering, 229: 111346. https://doi.org/10.1016/j.mee.2020.111346

[12] Sharma, M., Mahajan, P., Alsubaie, A.S., Khanna, V., et al. (2025). Next-generation nanomaterials-based biosensors: Real-time biosensing devices for detecting emerging environmental pollutants. Materials Today Sustainability, 29: 101068. https://doi.org/10.1016/j.mtsust.2024.101068

[13] Lakshmikantha, V., Hiriyannagowda, A., Manjunath, A., Patted, A., Basavaiah, J., Anthony, A.A. (2021). IoT based smart water quality monitoring system. Global Transitions Proceedings, 2(2): 181-186. https://doi.org/10.1016/j.gltp.2021.08.062

[14] Silvanir, Foo, W.H., Chia, W.Y., Ende, S., Chia, S.R.,

Chew, K.W. (2024). Nanomaterials in aquaculture disinfection, water quality monitoring and wastewater remediation. Journal of Environmental Chemical Engineering, 12(5): 113947. https://doi.org/10.1016/j.jece.2024.113947

[15] Saputri, F.R., Linelson, R., Salehuddin, M. (2025). Portable off-grid solar power generation system for emergency energy supply. In 2025 15th International Conference on Power, Energy, and Electrical Engineering (CPEEE), Fukuoka, Japan, pp. 439-443. https://doi.org/10.1109/CPEEE64598.2025.10987391

[16] Budiman, F., Ismardi, A., Hardinah, T., Muhammad, R., Nurwijayadi, Hartaman, A., Nurhidayat, A., Sasto, I.H.S., Sutapa, I.D.A. (2024). Strengthening oil pollution monitoring system in aquatic environment through development of IoT-based Oil-Water Separator Device. Ecohydrology & Hydrobiology, 24(3): 617-623. https://doi.org/10.1016/j.ecohyd.2023.06.002

[17] Al Mamun, M.R., Ashik-E-Rabbani, M., Haque, M.M., Upoma, S.M. (2024). IoT-based real-time biofloc monitoring and controlling system. Smart Agricultural Technology, 9: 100598. https://doi.org/10.1016/j.atech.2024.100598

[18] Li, G., Tan, Z., Xu, W., Xu, F., Wang, L., Chen, J., Wu, K. (2021). A particle swarm optimization improved BP neural network intelligent model for electrocardiogram classification. BMC Medical Informatics and Decision Making, 21(Suppl 2): 99. https://doi.org/10.1186/s12911-021-01453-6

[19] Plumb, A.P., Rowe, R.C., York, P., Brown, M. (2005). Optimisation of the predictive ability of artificial neural network (ANN) models: A comparison of three ANN programs and four classes of training algorithm. European Journal of Pharmaceutical Sciences, 25(4-5): 395-405. https://doi.org/10.1016/j.ejps.2005.04.010

[20] Irwan, I., Mohamad, J.N., Galih, V., Putra, V.G.V. (2023). FT-IR spectral model of polyester-cotton fabrics with corona plasma treatment using artificial neural networks (ANNs). Indonesian Journal of Applied Physics (IJAP), 13(1): 128-146. https://doi.org/10.13057/ijap.v13i1.67873

[21] Chakraverty, S., Sahoo, D.M., Mahato, N.R. (2019). McCulloch–Pitts neural network model. In Concepts of Soft Computing: Fuzzy and ANN with Programming, pp. 167-173. https://doi.org/10.1007/978-981-13-7430-2_11

[22] Indrawati, E.M., Andrianto, C., Kurniawan, A. (2025). Detection of water quality fluctuation patterns with fuzzy logic controller. Journal of Intelligent System and Telecommunication, 1(2): 175-188. https://doi.org/10.26740/jistel.v1n2.p175-188

[23] Hemamalini, R. R., Vinodhini, R., Shanthini, B., Partheeban, P., Charumathy, M., Cornelius, K. (2022). Air quality monitoring and forecasting using smart drones and recurrent neural network for sustainable development in Chennai city. Sustainable Cities and Society, 85: 104077. https://doi.org/10.1016/j.scs.2022.104077

[24] Pally, R.J., Samadi, S. (2022). Application of image processing and convolutional neural networks for flood image classification and semantic segmentation. Environmental Modelling & Software, 148: 105285. https://doi.org/10.1016/j.envsoft.2021.105285

[25] Sridhar, K., Radhakrishnan, P., Swapna, G., Kesavamoorthy, R., Pallavi, L., Thiagarajan, R. (2023). A modular IOT sensing platform using hybrid learning ability for air quality prediction. Measurement: Sensors, 25: 100609. https://doi.org/10.1016/j.measen.2022.100609

NOMENCLATURE

x_i	Classified input value of water quality parameter (pH, turbidity, TDS, temperature)
w_i	Weight assigned to input parameter
net	Weighted sum input of neuron
TDS	Total Dissolved Solids concentration
pH	Potential of hydrogen
NTU	Turbidity value
Temp	Water temperature
SRAM	Static Random Access Memory usage

Subscripts

i	Index of input parameter
1	First neuron (pH and turbidity processing)
2	Second neuron (final classification neuron)