

IoT-based Water Monitoring with Geologic Mapping

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Abstract

This study focused on real-time water quality monitoring that is useful to local water source facilities using the benefits of IoT. The system implementation with Arduino Uno, turbidity, total dissolved solids, odor, and colorimetric sensors ensures that the water supplied to the consumers is clean and potable. Also, the platform uses a web application to monitor the real-time data from the devices with geologic mapping to provide findings needed for decision-making. Moreover, the accuracy testing of the device based on the ten samples resulted in a 97.5% accuracy rate, which denotes that the sensors passed the standard requirement as stipulated by the World Health Organization. Furthermore, for the accuracy of the individual sensors, the testing for turbidity is 90%, total dissolved solids is 100%, odor is 100%, and color is 100% based on the given samples. Furthermore, the system evaluation showed that the system is accurate in its real-time data gathering through the sensor, has commendable functionality and reliability, and is very usable in guiding the users and identifying the roles of each user in the system.

Keywords: IoT, Arduino, Turbidity, Total Dissolved Solids, Sensors, Colorimetric

Introduction

Progressive industrialization, overpopulation, and climate change are factors in the problems of pollution, global warming, and other environmental problems. Many of these environmental problems affect the waterways, resulting in scarcity of water (Razzaq et al., 2020; Salih & Muhammad, 2022) and unsafe water for drinking (Ahmed et al., 2020; Geetha, 2021). Point and non-point sources of pollution, including sewerage and industrial discharges, and runoff from urban and agricultural fields impacted the water quality (Srinivas et al., 2020; Guo et al., 2021; Xu et al., 2022). Hence, these impacts result in health problems such as waterborne diseases, especially after flooding and typhoons in areas with high population densities (Ntajal et al., 2022).

Water is one of the basic needs for all living things to survive. For instance, in Malaysia and other countries, access to potable water is an issue because of some polluted water sources, which need an immediate decision tool on whether the water is safe to consume (Ahmed et al., 2020; Rahman, 2021). However, more than 30% of developing countries encounter problems in accessing safe potable water (WHO and UNICEF, 2015; Adelodun et al., 2021). Diseases connected with poor water and sterilization conditions are a concern, resulting in various waterborne diseases (Adelodun et al., 2021; Lee et al., 2023). Hence, it is advantageous to have a water monitoring system that monitors and controls water parameters such as total dissolved solids (TDS), turbidity, odor, and colorimetric (Smitha & Kumar, 2023). Monitoring water quality has become essential to clean and safe water (Adelodun et al., 2021; Lee et al., 2023). Water treatment provides significant benefits to safe and quality water, like biofilm (Hasan & Muhammad, 2020), removal of microplastics (Shen et al., 2020), and nanofiltration (Guo et al., 2022). Yet, water quality monitoring in developing countries is less efficient (Adelodun et al., 2021). Conventional monitoring processes such as screening, filtration, and chlorination cannot effectively provide treatment (Hasan & Muhammad, 2020).

The Internet of Things (IoT) helps determine water safety by remotely monitoring its sources as the sensors send water parameter data to the base station for analysis and decision-making (Alipio, 2020). Thus, IoT analyzes the sensor data gathered to identify the water quality and transmits the information to a cloud server for distant data storage and monitoring (Liu et al., 2019; Alipio, 2020; Mezni et al., 2022). Therefore, water quality data is essential for water safety management and for preventing water-related diseases (Ahmed et al., 2020; Lakshmikantha et al., 2021).

Implementing and adopting the Internet of Things (IoT) is beneficial in reducing inconveniences, including water monitoring. Connecting everything in the Cloud has become one of the leading advanced technologies of the 21st century. The rise of smart cities become a trend adopted by sensitive urban areas and governments (Javed et al., 2022). The continuing innovation of IoT opens a significant scope for smart and tiny wireless devices to accomplish various processes in diverse environments, allowing an interface to monitor and operate remotely from anywhere and anytime (Lombardi et al., 2021). This interface associates everything from individuals, associations, and organizations to things in the physical and virtual world, thereby interconnecting devices to share data across stages in a unified framework (Dutta et al., 2019; Sharma et al., 2021). Along these lines, the IoT aims to work on one's comfort and effectiveness by empowering participation and cooperation among smart objects (Lombardi et al., 2021; Shammam & Zahary, 2021). Furthermore, IoT visualizes the sustainable community to develop the designed frameworks that enable sustainability by ensuring the natural and environmental systems (Salam, 2020; Lombardi et al., 2021). Through the interconnection of frameworks, detecting, and communication technologies, IoT for sustainability gives a worldview that balances the community's need to provide ecological and environmental security and maintains a secure economic society (Mondejar et al., 2021).

In the southern part of the Philippines, most of the local water sources are springs and rivers (Galang et al., 2023), and monitoring these water sources will provide sustainable solutions to these areas; however,

it is highly indeterminate. Waterborne diseases are the primary problems of smaller communities, which have no guarantee of safe and quality drinking water. Besides, monitoring water sources is exhausting and does not give timely results. Therefore, it is necessary to have a competent model to predict water status to avoid any contamination that results in waterborne diseases. Besides, the model will help improve water resource management as it provides information that makes local resource managers accountable to higher authorities (Buntaine et al., 2021). The most common parameters for water quality include turbidity, color, odor, and TDS. Using modern technologies and the Internet of Things (IoT), monitoring the status of the water's quality can lessen the time and the burden of assessment and checking. Besides, IoT helps make it easier to do things quickly; hence, its implementation for water source management is beneficial (Ntajal et al., 2022).

Methods

The study focused on monitoring the water quality of a particular water source facility using the turbidity, color, odor, and total dissolved solids sensors placed in the water sources they managed. Figure 1 presents the conceptual framework of the system.

Figure 1 shows how water quality monitoring, through IoT, implements the process of gathering data from all the sensors and providing inputs for possible decision-making. The turbidity, color, odor, and TDS sensors obtain real-time data and send them to the API, which the web monitoring system displays. The system equipped the sensors with tracking codes to track the location of the sensors that produce data that needs immediate attention. These water quality data help the water source facility in its decision-making on whether to stop the supply, momentarily, of the affected distribution channel and to provide immediate water treatment.

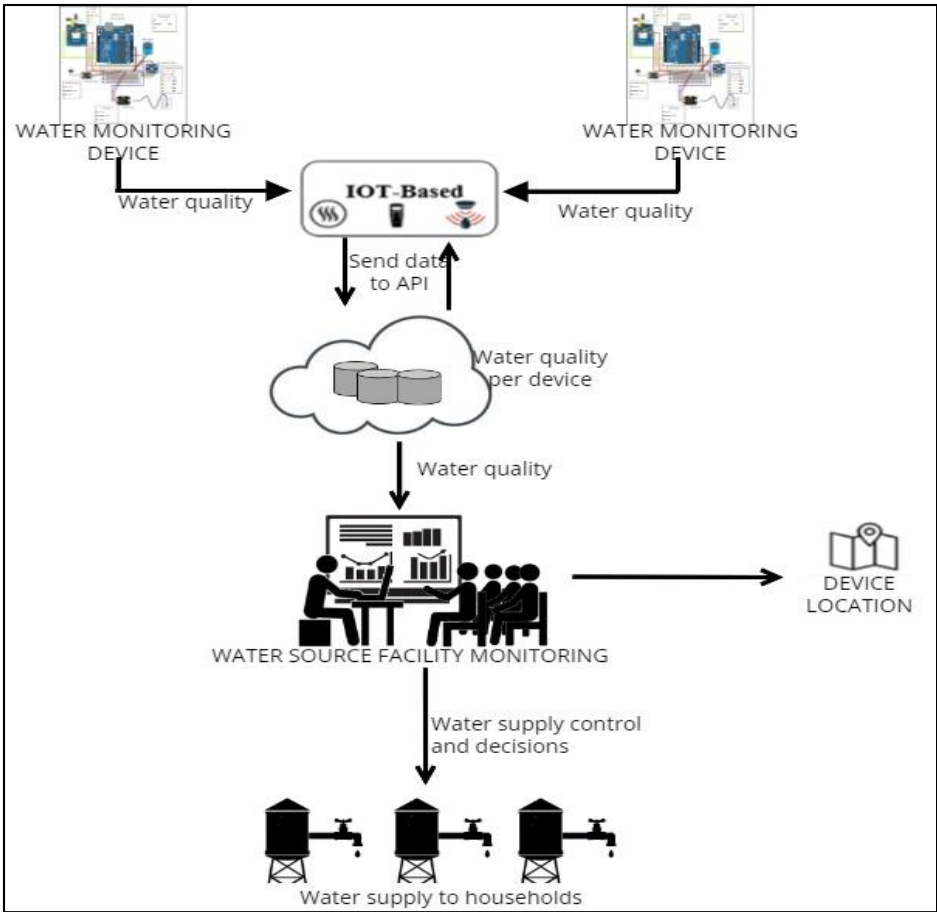


Figure 1. Water Monitoring System Conceptual Framework

To realize the implementation of the IoT-based water quality monitoring, the designers created the circuit diagram, shown in Figure 2.

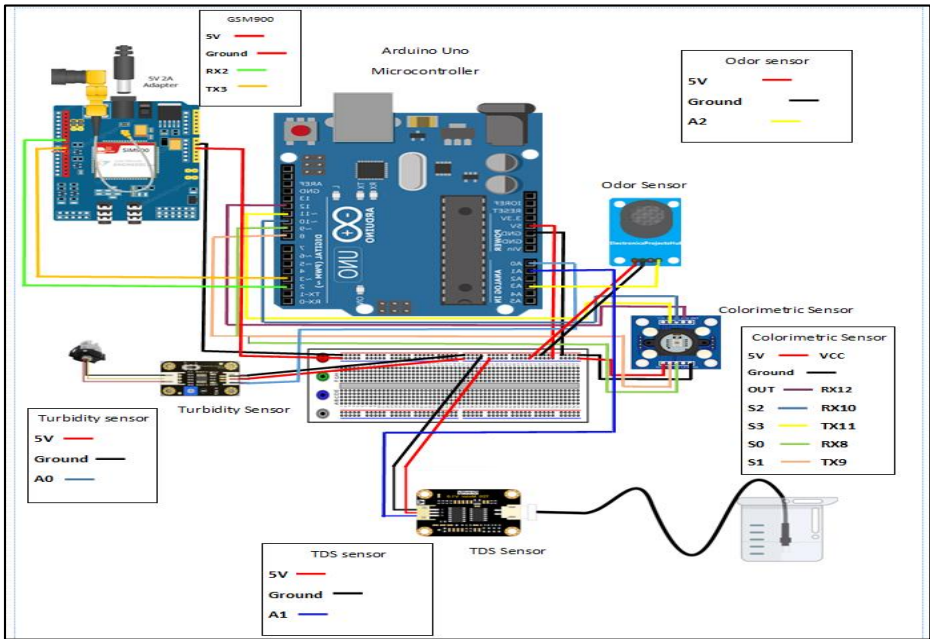


Figure 2. Water Quality Monitoring Device Circuit Diagram

Figure 2 shows the circuit diagram of the water quality monitoring device that connects the four sensors and other necessary peripherals to make the device work. The system used the Arduino Uno microcontroller with the following components – the odor, TDS, colorimetric, and turbidity sensors, and the GSM900a module for data transmission. The circuit diagram also illustrates the connections of the sensors’ pins to the Arduino’s analog port and the power supply connected to the breadboard with a usable voltage of 5V.

The water source facility monitors the real-time data obtained from the sensors through a web-based system. The system’s context diagram, shown in Figure 3, and the top-level data flow diagram, shown in Figure 4, show the overall data flowing from entities, data stores, and processes.

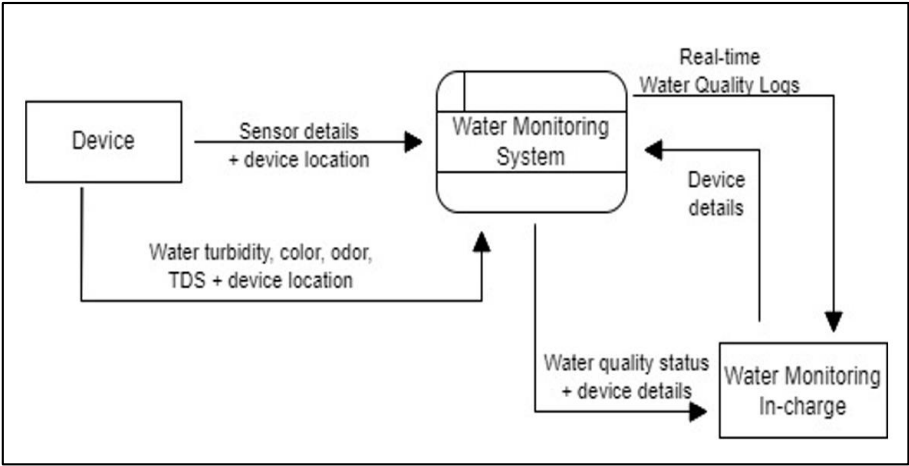


Figure 3. Context Diagram of the Water Monitoring System Website

Figure 3 shows the general picture of the entities interacting with the system. The device, which contains the turbidity, colorimetric, odor, and TDS sensors, sends real-time data, including the device location, to web-based monitoring. These collected data provide information on which device sent alarming information through its progressive visualization. This information is significant to the decision-making of the administration and water monitoring in-charge to provide intervention when needed.

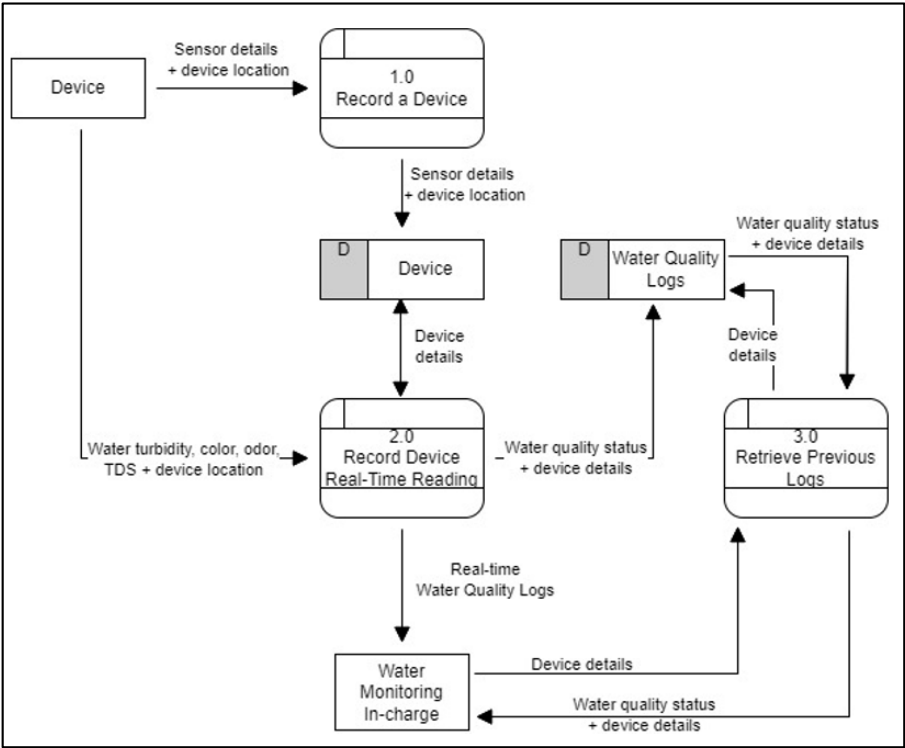


Figure 4. Top Level Data Flow Diagram of the Water Monitoring Website

Figure 4 shows the details of the implementation of the water monitoring website, which includes obtaining real-time data from the sensors deployed in specific locations. The system records all the devices and the details of the turbidity, color, odor, and TDS sensors interconnected in the device and its location. The device sends water quality readings and logs, which the website displays in real-time. The Water Monitoring In-charge can monitor the real-time logs directly from the dashboard display; however, he can also view previous readings when necessary. The study used a geologic mapping feature to easily track and locate the devices and stations.

In doing the simulation to test the accuracy of the sensors, the researchers used the trial-and-error method, ensuring that the sensors’s performance obtained a 100% passing percentage using the formula.

$$\begin{aligned} ¶meterPercentage = requiredPercentage / No. of resources \\ &(1) \\ &overallResult(\%) = requiredPercentage - (parameterPercentage * No. of \\ &failed results) \end{aligned}$$

Regarding accuracy testing, the results were obtained from the sensor readings and error rate. Each sensor has its standard requirement or parameters to pass the required result. The following formula was used to get the accuracy of the device’s result after calculating the error rate.

$$\begin{aligned} &Error Rate = (No. of Error Sample / No. of Total Sample) * 100 \\ &(2) \\ &Accuracy Rate (\%) = 100 - Error Rate \end{aligned}$$

The testing of monitoring real-time device performance uses individual sensors to determine the water turbidity, total dissolved solids in water, the color of the water, and the water odor. The study used the World Health Organization’s recommended standard limits for safe waters, as shown in Table 1.

Table 1. World Health Organization’s Recommended Standard Limits for Safe Waters.

Parameters	Unit	Requirements	Sensor
Color	Pt. Co scale	<15 (White)	Colorimetric Sensor
Odor	Pt. Co scale	<300 (Negative)	
Turbidity	NTU	< 5	Turbidity
Total Dissolved Solids	ppm	< 500	TDS Sensor

Results and Discussion

Sensor Testing

The researchers used ten water samples during the testing, including cases of clear water and water with color, odor, and sediments. Among the water samples, samples 1, 2, 3, and 4 are clear water with no odor and sediments, and the readings passed the standard parameters of WHO. Water samples 5, 6, and 7 have slight contaminants like some particles of rice, salt, vinegar, and a few drops of ink. This set of samples resulted in slightly high readings. Additionally, water samples 8, 9, and 10 represent unsafe water quality where the samples showed many particles of rice, increased amount of salt and vinegar, and more drops of ink that changed the color of the water to the ink’s color.

Using all the water samples, testing for water turbidity focused only on determining the presence of some particles in the water. Table 2 shows the results of the water turbidity samples.

Table 2. Test results of the water turbidity samples within a specific time (acceptable value is less than 5 NTU).

Sample No.	Turbidity Value (NTU)	Acceptability	Timestamps (Sensor sending data)
1	3	Yes	11:28:11 pm
2	2	Yes	11:31:00 pm
3	1	Yes	11:33:49 pm
4	0	Yes	11:36:38 pm
5	4	Yes	11:39:28 pm
6	7	No	11:42:18 pm
7	7	No	11:45:07 pm
8	27	No	11:47:49 pm
9	43	No	11:50:39 pm
10	51	No	11:53:29 pm

Using the recommended standard limits for safe water, five samples presented in Table 2 yield an acceptable result, while the other five samples are not acceptable. This result implies that despite Sample 5

having a bit of water contaminants, it still yields a reading within the limits. On the other hand, testing for water’s total dissolved solids focused on determining the presence of some sediments in the water. Table 3 presents the results of the sensor testing for total dissolved solids.

Table 3. Test results of the total dissolved solids in water within a specific time (acceptable value is less than 500 ppm).

Sample No.	Total Dissolved Solids (ppm)	Acceptability	Timestamps (Sensor sending data)
1	134	Yes	11:28:11 pm
2	134	Yes	11:31:00 pm
3	134	Yes	11:33:49 pm
4	132	Yes	11:36:38 pm
5	1243	No	11:39:28 pm
6	1243	No	11:42:18 pm
7	1243	No	11:45:07 pm
8	1243	No	11:47:49 pm
9	1243	No	11:50:39 pm
10	1243	No	11:53:29 pm

Based on the recommended standard limits for safe water, the test resulted in four acceptable water samples and six unacceptable water samples. This result implies that once the sensor detects a solid contaminant, even in a small amount, it will result in a change in the quality of the water. Regarding color testing, testing for water’s color focused on checking the change of color of the water from transparent to a different color. Table 4 presents the results of the colorimetric testing.

Table 4. Test results of the color in water within a specific time (acceptable value is less than 15 pt. co.)

Sample No.	Color (pt. co.)	Acceptability	Timestamps (Sensor sending data)
1	8	Yes	11:28:11 pm
2	6	Yes	11:31:00 pm
3	6	Yes	11:33:49 pm
4	6	Yes	11:36:38 pm
5	53	No	11:39:28 pm
6	54	No	11:42:18 pm
7	51	No	11:45:07 pm
8	57	No	11:47:49 pm
9	103	No	11:50:39 pm
10	112	No	11:53:29 pm

Based on the recommended standard limits for safe water, the test resulted in four acceptable water samples and six unacceptable water samples. This result implies that once the sensor detects a color change, it will result in a change in the quality of the water. Regarding color testing, testing for water’s color focused on checking the change of color of the water from transparent to a different color. Table 5 presents the results of the odor testing.

Table 5. Test results of the color in water within a specific time (acceptable value is less than 300 pt. co.).

Sample No.	Odor (pt. co.)	Acceptability	Timestamps (Sensor sending data)
1	5	Yes	11:28:11 pm
2	6	Yes	11:31:00 pm
3	7	Yes	11:33:49 pm
4	5	Yes	11:36:38 pm
5	403	No	11:39:28 pm
6	521	No	11:42:18 pm
7	733	No	11:45:07 pm
8	1022	No	11:47:49 pm
9	1023	No	11:50:39 pm
10	1023	No	11:53:29 pm

Based on the recommended standard limits for safe water, the test resulted in four acceptable water samples and six unacceptable water samples. This result implies that once the sensor detects an odor in the water, it will result in a change in the quality of the water.

Time Interval Monitoring

Time complexity refers to the sensor's number of actions to achieve its task of sending the data to the web server, considering that each operation takes the same amount of time. The algorithm that completes the task with the fewest actions has the most efficient time complexity. Based on the result, the lowest time interval in the sample is for Samples 7 and 8, which yield a 162-second time interval when sending the data to the web server. Implementing the time complexity metric is important to get the average time interval of all the sample datasets based on these datasets. To obtain the average time intervals, sum up all the intervals and divide them by the samples. On average, it takes a 152-second time interval from getting the data from the sensors to receiving the data from the webserver. Table 6 presents the time intervals of data sending and receiving for the 10 samples.

Table 6. Time intervals of data received by the web server from the sensors.

Sample No.	Timestamps	Intervals (seconds)
1	11:28:11 pm	
		Between Samples 1 & 2
2	11:31:00 pm	169 seconds
		Between Samples 2 & 3
3	11:33:49 pm	169 seconds
		Between Samples 3 & 4
4	11:36:38 pm	169 seconds
		Between Samples 4 & 5
5	11:39:28 pm	170 seconds
		Between Samples 5 & 6
6	11:42:18 pm	170 seconds
		Between Samples 6 & 7
7	11:45:07 pm	169 seconds
		Between Samples 7 & 8
8	11:47:49 pm	162 seconds
		Between Samples 8 & 9
9	11:50:39 pm	170 seconds
		Between Samples 9 & 10
10	11:53:29 pm	170 seconds
Total		= 1,518 seconds
		= 1,518 / 10
Average = total / no. of samples		= 152 seconds
		(2 minutes and 32 seconds)

Accuracy Testing

The study calculated the accuracy of the detection of the individual sensors. Due to the delay in detection for the turbidity sensor on Sample 5, the accuracy result decreases. Based on the calculated accuracy, the turbidity sensor has an accuracy rate of 90%, the odor sensor is 100%, the colorimetric sensor is 100%, and the TDS sensor has

a 100% accuracy rate. Table 7 presents the summary of the device’s accuracy rate per sample.

Table 7. Summary of the device’s accuracy rate per sample.

Sample No.	Acceptability	Percentage Error Rate (%)
1	✓	0
2	✓	0
3	✓	0
4	✓	0
5	✗	25
6	✓	0
7	✓	0
8	✓	0
9	✓	0
10	✓	0
Accuracy Rate (%) = 100 – (Average Error		= 100 – (25 / 10)
Percentage (%) / No. of Samples		= 100 – 2.5
		= 97.5

The average error rate percentage of all the sensors on the given samples is 2.5, resulting in an accuracy rate of 97.5%, based on the given ten (10) samples with the different classifications of water tests.

Acceptance Testing

The researchers conducted the system’s acceptance testing among the personnel and consumers of the local water district of a town in the southern part of the Philippines. The acceptance test includes the system’s functionality, reliability, and usability. The system’s functionality includes user credentials, authentication and authorization, geologic mapping, real-time data transmission and monitoring, data and notification logging, and device mapping. These features were found to be very functional among the users. On the other hand, the system’s usability was tested, which includes learnability, understandability, ease of use, and responsiveness through labels and feedback. This usability aspect of the system was found to be very usable among users. Lastly, the system’s reliability acceptance testing includes error trapping, detection,

and prompting, as well as the accuracy of the data, which were found to be somewhat reliable. Overall, the local water district personnel found the system to be a working system that can deliver the needed functionalities necessary for water quality management.

Conclusion and Recommendation

Waterborne disease is one of the main problems of communities due to the presence of undetected contaminants. The local water facility continuously monitors the safety of the water sources; however, the results of monitoring take time to generate as samples are retrieved from the water sources. With the IoT-based water monitoring device and a web application system to monitor the water's real-time data of its color, odor, turbidity, and total dissolved solids, the monitoring becomes timely, up-to-date, and comprehensive. With the device's performance in sending data with an average interval of 2 minutes and 32 seconds and with an average accuracy rate of 97.5%, the system showed a significant alternative tool for monitoring water safety and quality. Likewise, with its geologic mapping feature, the system can easily identify and locate the water sources that require immediate attention.

This innovation provides real-time water monitoring to help the local water source facility ensure real-time checking. Besides, water quality monitoring is not only limited to the attributes used in the study. Hence, future endeavors to improve the process may include other water quality sensors for improved water quality management. Also, incorporating data analytics helps determine patterns of changes in water quality in specific periods.

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