Reviewer 1 ● The abstract must clarify why categorizing water quality using IoT is necessary or significant. A good abstract must provide the background, research purpose, research method, results, and conclusion. ● The IoT for Water Quality Categorization introduction does not clarify your research's context or issues. Please clarify explicitly the reasoning behind the issue of research. Concerning previous research, clarifying the novelty and scientific contribution is necessary. ● Please provide the step-by-step research methodologies. ● We suggest developing more deeply the discussion (have to focus on analysis and interpretation) on the results. The discussions and conclusions do not fully relate to the research questions and objectives. This paper does not provide new ideas or research novelty. However, we suggest that the authors indicate the state-of-the-art field of the research. ● Please add the limitations of the research. ● The authors must follow the reference list template and update references with the latest!
Reviewer 2 ● Please add a detailed explanation of the specifications of the IoT hardware components used in the research methodology section.
Reviewer 3 ● Describe the novelty of the research in the abstract and the implications of the research results. ● The research method used needs to be explained in detail with a description of the stages of each research process. ● The implications of the research results and their novelty need to be explained in the discussion of the research results.
Reviewer 4 ● Your plagiarism score is 92%, if your paper is accepted, please revise it. We only accept papers that plagiarism score below 20%

IoT for Water Quality Categorization

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***Abstract* — In agricultural water research, the adoption of Internet of Things (IoT) technology has emerged as a pivotal approach for large-scale data collection. Water availability in the context of water quality is very important, both for domestic and industrial purposes. For domestic purposes, drinking water and bathing water are separated. Meanwhile, for the palm oil industry, boiler filler is differentiated from additional process water (dilution water). Water quality parameters can be assessed from turbidity and Total Dissolve Solid (TDS). Measurements using measuring instruments separately and repeatedly require significant energy, time, and costs. This research was conducted with the primary objective of presenting a novel method for categorizing water quality with the approach of IoT sensor technology. The research methodology entailed the utilization of an integrated IoT water sensors system in conjunction with manual water categorization. The methods consist of (1) system design, (2) design and installation of sensor and IoT-based microcontrollers, and (3) accuracy and precision testing compared with laboratory measurements. The precision of the integrated IoT water sensors was assessed through a dedicated sensor precision test, resulting in an accuracy rate of 94.4% for the turbidity sensor and 97.5% for the TDS sensor. Notably, this approach successfully discriminated drinking water with valid categorization, while other water types, including groundwater, water with tea, and water with coffee, yielded null categorization results.**

Keywords— Internet of Things, water quality, water sensors, data categorization

I. Introduction

Water, as a substantial natural resource, confronts multifaceted challenges characterized by issues of scarcity, pollution, and contamination. According to the World Wildlife Fund (WWF), the escalation of water-related risks cannot be attributed solely to environmental factors like inadequate precipitation or unsustainable water resources but also arises from intricate interactions with other sectors, including industries [1] . Schweitzer and Noblet's study further elucidate that water pollution and contamination, spanning biological, chemical, and physical dimensions, pose substantial threats to the potable water industry, despite the numerous initiatives implemented to safeguard water quality [2].

Water quality indicators, including turbidity and total dissolved solids (TDS), are frequently employed for the classification of water quality in addition to parameters such as biological oxygen demand, chemical oxygen demand, and conductivity [3],[4],[5] . The standard methods for the examination of water and wastewater provide a comprehensive framework for analytical techniques in water research, encompassing both traditional wet chemical methods and contemporary instrumental approaches [6] . Adhering to these standards, Abbasnia et al. conducted a successful assessment of groundwater quality across three villages in Iran [7]. Their findings were able to classify 40 water types into two categories. Forty-percentage were characterized as excellent water quality types, while the remaining sixty-percentage were categorized as good water quality types.

Conversely, the swift advancement of Internet of Things (IoT) technology as a precise data acquisition tool has found application in diverse studies related to water quality. Notably, IoT sensors have been deployed in the realms of aquaculture [8], [9] and coastal area management [10]. A collaborative effort between NusaNet and Bioinformatics & Data Science Research Center (BDSRC) has led to research endeavors focused on the development and implementation of various IoT solutions for smart pond management [11], [12].

This research was initiated with the aim of establishing a method for the detection of water pollution. Initially, an integrated IoT water sensor system was designed and deployed to facilitate the data collection process. Subsequently, a comparative analysis of water quality across various categories was conducted using two distinct approaches: the manual method and the IoT-based method.

II. LITERATURE REVIEW

A. Water Quality Assessment

The assessment of surface water quality in numerous studies relies on the application of mathematical formulas within the framework of the water quality index (WQI). For instance, Elsayed et al. employed a specific WQI known as the irrigation water quality (IWQ) index to evaluate water types collected from the northern region of the Nile Delta in Egypt. The calculations revealed that 82% of the water types fell into a higher category, signifying their suitability for irrigation purposes [13].

Ewaid et al. developed the Iraqi water quality index (WQI) for the assessment of potable water quality. In their study conducted at the Tigris River, the Iraq WQI was implemented in a two-phase approach aimed at identifying the most influential water quality parameters. This was achieved through the utilization of principal component analysis and the Delphi method. Subsequently, WQI scores were computed by extracting the quality curves of the selected parameters in accordance with established water quality standards. The findings of this methodological approach indicated that certain rivers, namely Diyala, Euphrates, and Diwaniyah, require conventional water purification treatments such as sedimentation, filtration, and disinfection. In contrast, it was recommended for the implementation of reverse osmosis treatment plan for the Shatt Al-Arab river [14].

B. Integrated IoT Water Sensors Utilization

In numerous studies focused on water quality assessment, Internet of Things (IoT) sensors have played a pivotal role. Akhter et al. for instance, introduced an innovative IoT sensor designed specifically for monitoring nitrate concentration in water [15] . This pioneering sensor is accompanied by the development of a wireless as well as portable intelligent sensing system designed for real-time measuring applications. The system facilitates the collection of water types, which are subsequently employed to train machine learning algorithms capable of accurately determining both temperature and nitrate concentrations.

Li et al. undertook the development of an automated water quality measuring tool system endowed with mobile capabilities technology [16]. This sophisticated tool enables the collection and transmission of data pertaining to six crucial water quality parameters, namely chlorophyll, dissolved oxygen (O2), salinity, conductivity, turbidity, and temperature for subsequent analysis. The research incorporates the interpretation of water quality surveys through the utilization of the online water quality index (OLWQI). Consequently, when the IoT system is implemented in typical water sources, it facilitates automatic online data processing directly on the device.

III. RESEARCH METHODOLOGY

The research methods consist of three parts, they are (1) system design, (2) design and installation of sensor and IoT-based microcontrollers, and (3) accuracy and precision testing compared with laboratory measurements. Figure 1 shows the detailed activity diagram according to the research methodology. This research pointed to quickly differentiating various air qualities based on turbidity and TDS values. The limitations of this research were (1) water turbidity value from 0 to 5000 NTU, (2) TDS value from 0 to 10000 PPM, and internet required.

A. IoT Water Quality Sensor

Hermantoro et al. introduced an innovative integrated IoT sensor system designed for the data acquisition of water quality [17] . As portrayed in Figure 2, the design of this integrated IoT sensor system encompasses three primary components responsible for characterizing water types and recording data. The system consists of input sensors, data processing units, and visualization interfaces. The types of water were categorized into four distinct measurements, including water temperature, pH level, turbidity, and total dissolved solids (TDS). To gather data and read all the measurements from these sensors, Hermantoro et al. employed a processing unit that combined the Arduino Mega 2560 R3 microcontroller and the SIM 800 module. Additionally, the design was equipped with an inch size of LCD OLED screen to facilitate data visualization, as illustrated in Figure 3.

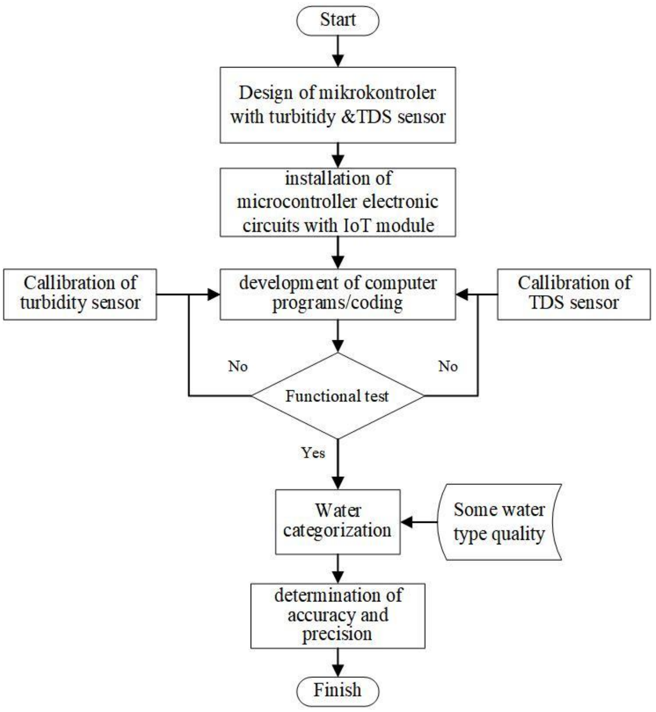

Fig. 1. Research activity

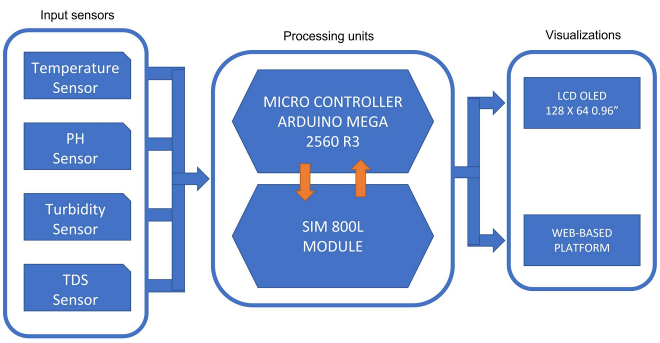

Fig. 2. Conceptual Framework for the Integrated IoT Water Sensor Design

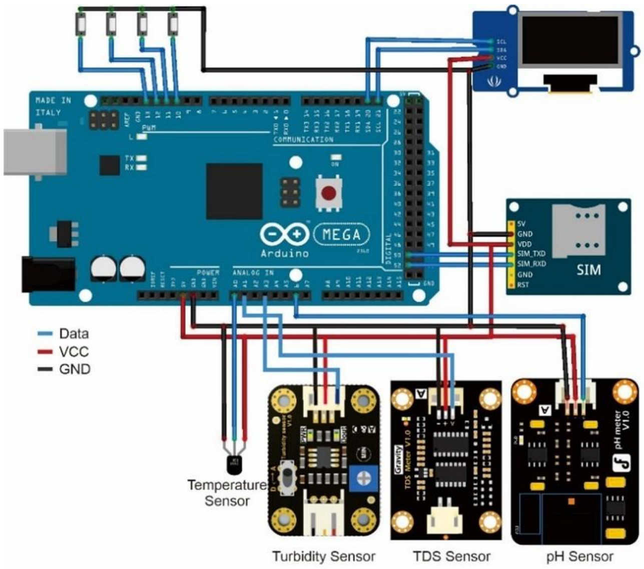

Fig. 3. Implementation of the Integrated Internet of Things (IoT) Water Sensor

TABLE I. WATER TYPES

Water Type	Description	Tempe-rature (°C)	pH Level	Turbidity (ntu)	TDS (ppm)
A	Tap water	30.1	6.2	0.5	132.0
B	Ground water with sugar	29.5	1.1	20.1	206.0
C	Water with tea	29.9	5.3	81.7	274.0
D	Ground water with dirt	29.5	5.4	1350.0	354.0
E	Water with coffee	29.7	2.7	1160.0	545.0

B. Water Types

In this study, a total of five distinct water types were employed, as detailed in Table I. These water types were broadly categorized into two types: potable water (type A, C, E) and water intended for agricultural use (type B and D). Comprehensive water quality assessments were conducted, encompassing measurements of temperature, pH, turbidity, and Total Dissolved Solids (TDS). The data obtained from these laboratory analyses were subsequently compared with measurements acquired through integrated IoT water sensors.

C. IoT Sensor Accuracy and Precision

In this research, three mathematical equations have been deployed to assess the accuracy and precision of the sensors. Equation 1 and Equation 2 are utilized to calculate the accuracy rate and error rate, respectively. Conversely, Equation 3 is employed to determine the precision of the sensors. These sensor evaluations were conducted using the water types outlined in Table I. The mathematical expressions for these equations are elaborated below:

$$Accuracy = 1 - \left(\frac{Lab - Sensor}{Lab}\right) 100\% \tag{1}$$

$$Error = \frac{Lab - Sensor}{Lab} 100\% \tag{2}$$

$$Precision = 1 - \left(\frac{Sensor - Avg\ Sensor}{Sensor}\right) 100\% \tag{3}$$

In the context of this study, 'Lab' represents data acquired from laboratory experiments, 'Sensor' corresponds to data obtained from the sensors, and 'Avg Sensor' pertains to the calculation achieved by dividing the cumulative sensor data by the number of sensors used in the data collection process.

D. Water Categorization

In order to categorize water quality, the recorded values for turbidity and TDS were cross-referenced with predefined categories as outlined in Table II. Each category specified permissible ranges for turbidity and TDS measurements. A categorization was considered valid if both the turbidity and TDS measurements fell within the same category. Conversely, a categorization was deemed 'Null' when the measurements for turbidity and TDS did not correspond to the same category.

TABLE II. CATEGORY OF WATER

Category	Turbidity (NTU)	TDS (PPM)
1	1.0 – 4.9	1.0 – 599.9
2	5.0 – 25.9	600,0 – 899.9
3	26.0 – 99.9	900.0 -1,199.9
4	>= 100.0	>= 1200.0

IV. RESULTS AND DISCUSSION

A. Sensor Accuracy and Precision Test

A precision test was conducted using water type B to assess the accuracy of the integrated IoT sensor. In this test, two out of the four sensors were measured, as the categorization of water quality only required measurements for both NTU and TDS. A total of 10 trials were conducted, and the outcomes of the test are presented in Table III. The results indicate that the turbidity and TDS sensors exhibited a high degree of precision, with accuracy rates of 94.4% and 97.5%, respectively, as calculated using Equation 3.

TABLE III SENSOR TRIAL TEST

Trial	NTU	TDS
1	23.9	190.0
2	22.2	197.0
3	20.0	196.0
4	22.2	190.0
5	22.2	196.0
6	24.4	190.0
7	26.6	194.0
8	17.7	191.0
9	20.0	191.0
10	26.6	194.0
Average	22.6	192.9
Accuracy (%)	94.4	97.5

B. Water Quality Categorization Test Results

Table IV presents the results of water quality categorization tests applied to water type A-E. The integrated water sensor was only able to categorize type A as category 1. However, unlike the results obtained through manual categorization, the integrated sensors provided null results for type B, C, D, and E due to discrepancies in turbidity and TDS categorization. In contrast, according to manual test, type D and E were categorized as category 4, indicating that these water types were polluted due to their high material content. Type A was classified as pure water with the lowest material content, while type B and C fell into category 2 and 3, respectively, signifying different levels of water quality.

TABLE IV WATER CATEGORIZATION TEST RESULTS

Water Type	Manual Test Results	Sensor-based Test Results
A	1	1
B	2	Null
C	3	Null
D	4	Null
E	4	Null

C. Discussion

The functionality of the integrated system of IoT water sensor was constrained to its ability to determine the drinkability of water, relying solely on the turbidity and TDS sensors. However, with proper establishment and deployment of the integrated IoT water sensor, it would be feasible to capture and store all essential water parameters needed for water quality index (WQI) calculations in a robust database. This, in turn, would streamline the utilization of WQI models once the comprehensive data repository was developed.

In comparison to the integrated IoT platform developed by Li et al. the proposed design and categorization method exhibited superior performance [16]. This was attributed to the incorporation of diverse sensors and the utilization of a more sophisticated water quality index, resulting in a more dependable analysis of aquatic environments. Additionally, the mobile capabilities of the IoT system enabled it to conduct surveys of specific water areas without the need for manual coordinate input.

This research highlights numerous opportunities in the field of water research, particularly if the integrated IoT water sensor system was to be implemented alongside a mature data repository infrastructure. A series of research have demonstrated the potential for enhancing rainfall and water balance forecasting through statistical approaches, with the integration of IoT sensor data playing a pivotal role [18]–[23] . In the realm of monitoring systems, the comprehensive collection of water quality parameters could be visualized through an intuitive interface, as explored in studies by Cenggoro et al. [24] , Baurley et al. [25] , and Budiarto et al. [26] . Lastly, there exists an opportunity to facilitate the study of water characteristics through information technology agricultural infrastructure [27], [28].

V. CONCLUSION

The performance of the integrated IoT water sensor was assessed through a series of 10 trials conducted on groundwater, revealing a accuracy rate of 94.4% for the turbidity sensor and 97.5% for the TDS sensor. While the integrated IoT water sensor successfully categorized pure water, it encountered challenges in categorizing the remaining water types, including groundwater, tea, and coffee, leading to invalid categorization. This suggests that in future applications, an integrated IoT water sensor can be employed not only for water quality assessment but also for functions such as water forecasting, monitoring, and educational purposes.

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