

IoT for Water Quality Categorization

Hermantoro Sastrohartono, Andreas Wahyu Krisdiarto, and Arief Ika Uktoro

Agricultural Engineering Department, Faculty of Agricultural Technology

Institute of Agriculture STIPER

Yogyakarta, Indonesia

hermantoro@instiperjogja.ac.id, andre@instiperjogja.ac.id, arief@instiperjogja.ac.id

Reza Rahutomo

Information System Department, School of Information Systems

Bina Nusantara University

Jakarta, Indonesia 11480

reza.rahutomo@binus.edu

Teddy Suparyanto

Bioinformatics & Data Science Research Center

Bina Nusantara University

Jakarta, Indonesia 11480

teddysup@binus.ac.id

Bens Pardamean

Computer Science Department, BINUS Graduate Program, Master of Computer Science

Bina Nusantara University

Jakarta, Indonesia 11480

bpardamean@binus.edu

Abstract

Water studies in the scope of agriculture have adopted Internet of Things (IoT) to become a new big data collection methodology. This research aimed to deliver a method in water quality categorization. The research methodology for this study used a combination of water quality parameter measurement with two integrated IoT water sensors (turbidity and TDS sensor) and manual categorization. Based on the water categorization standard, the measured turbidity and TDS were matched to one water category. In the sensor precision test, the integrated IoT water sensors showed 94.40% for the turbidity sensor and 97.95% for the TDS sensor. Compared to other water samples, drinking water was successfully distinguished with valid categorization. Other water samples namely groundwater, tea, and coffee showed invalid remarks.

Keywords

Water quality, data categorization, Internet of Things, water sensors

1. Introduction

As a substantial natural resource, water is facing risks that can be described as scarcity, pollution, and contamination. World Wildlife Fund (WWF) stated that the increase of water risks is not only caused by an environmental factor such as lack of precipitation or unmanageable water resources, but also the complex interaction with other domains such as industries (Orr et al. 2009). Schweitzer and Noblet defined that water pollution and contamination in the form of biological, chemical, and physical are threatening the safe-consumable water industry even though many initiatives have been established to protect water quality (Schweitzer and Noblet 2018).

Indicators of water quality, namely turbidity and total dissolved solids (TDS) are often utilized to categorize the quality of water samples beside biological oxygen demand, chemical oxygen demand, and conductivity (Alam et al. 2017; Pal et al. 2019; Khatri et al. 2020). Standard Methods for the Examination of Water and Wastewater organized analytical methods regarding water research (Federation et al. 2005). Not only classical wet chemical techniques, but the standard also covers modern instrumental techniques. Following the standard, Abbasnia et al. successfully assessed groundwater quality in three villages in Iran (Abbasnia et al. 2018). The result distinguishes 40 water samples into two classes, 40% are categorized as excellent water and the other 60% are categorized as good water samples.

On the other hand, the rapid development of Internet of Things (IoT) technology as an accurate data collection tool has been implemented in various water quality research. Aquaculture (Encinas et al. 2017; Huan et al. 2020) and coastal area management (Bresnahan et al. 2020) are two domains that have already implemented IoT sensors. NusaNet collaborates with Bina Nusantara University Bioinformatics and Data Science Research Center to research and develops several IoT implementation for smart pond (Darmalim et al. 2020; Darmalim et al. 2021).

1.1 Objectives

This research was motivated to find a way to identified polluted water. A design of integrated IoT water sensors was tested to support data collection process at first and followed by water samples examination to check the difference between several water quality categories using two approaches: manual and IoT-based.

2. Literature Review

2.1. Water Quality Assessment

The Water Quality Index (WQI) covered various mathematical formulas to assess surface water quality in many studies using measured chemical parameters. Elsayed et al. applied an example of WQI named Irrigation Water Quality (IWQ) to water samples in the northern part of the Nile delta, Egypt. The calculation shows that 82% of water samples are categorized in a higher category, which indicates an ideal water sample for irrigation (Elsayed et al. 2020).

Ewaid, Abed, Al-Ansari, and Salih constructed Iraqi Water Quality Index for consumable water evaluation. Applied in Tigris River, The Iraq WQI was run in two phases to find the most influential water quality parameters by using principal component analysis and the Delphi method. Based on the water quality standards, the WQI scores are calculated by extracting the quality curves of selected parameters. The proposed method discovers that some rivers (Diyala, Euphrates, Diwaniyah) need traditional purification treatment such as sedimentation, filtration, and disinfection while reverse osmosis treatment is recommended for Shatt Al-Arab River (Ewaid et al. 2020).

2.2. Integrated IoT Water Sensors Utilization

The IoT sensors have been used in many water-quality studies. Akhter, Siddiquei, Alahi, and Mukhopadhyay proposed a novel IoT sensor for nitrate concentration in the water (Vijayakumar et al. 2015). The novelty is completed with a wireless portable intelligent sensing system is developed for real-time monitoring purpose. Water samples that acquired through the system is utilized to train machine learning algorithm for determining temperature and nitrate concentrations.

Li, Xia, Chen, Zhao, and De Silva designed and developed an automated water quality survey tool with the mobile ability (Li et al. 2017). At least, six water quality parameters such as Chlorophyll A, Dissolved Oxygen, Turbidity, Conductivity, Salinity, and Temperature could be recorded and transmitted for further evaluation. The research interprets water quality surveys with Online Water Quality Index (OLWQI), so automatic online data processing is facilitated on the device when the IoT platform is deployed in the real water source.

3. Research Methodology

3.1. Integrated IoT Sensor

Hermantoro et al. proposed an integrated IoT sensor design for water quality data acquisition (Hermantoro et al. 2021). Figure 1 depicts the conceptual design of an integrated IoT sensor, there were three main parts to perform water sample characteristic measurements and data recording, namely: input sensors, processing units, and visualizations. The characteristics of water samples were divided into four different measurements such as temperature, pH, turbidity,

and TDS. The utilization of the Arduino Mega 2560 R3 microcontroller and SIM 800 module were combined as a processing unit to compile all measurements from water sensors. The design was included with a 0.96" wide LCD OLED screen for visualization. Figure 2 illustrates the realization of the conceptual design.

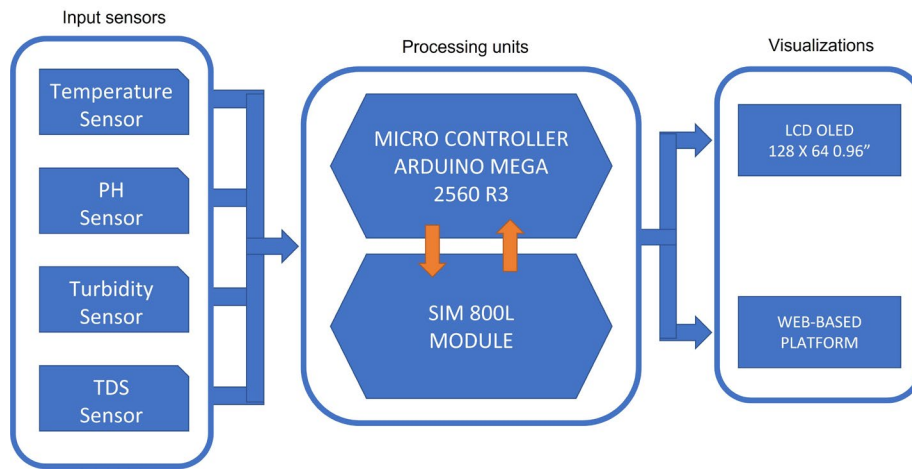


Figure 1. Conceptual Design of Integrated IoT Water Sensor

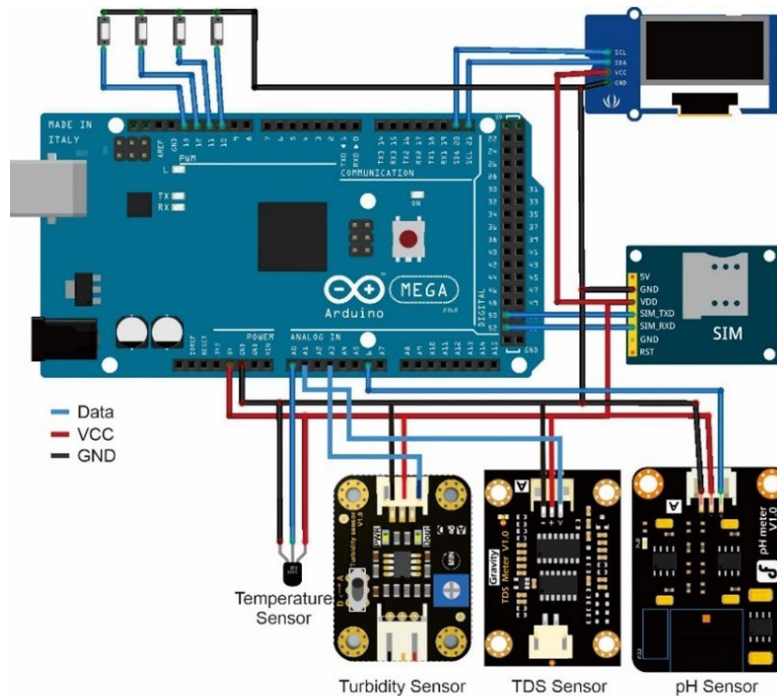


Figure 2. Realization of Integrated IoT Water Sensor

3.2. Water Samples

This research utilized five different water samples as listed in Table 1. Overall, two types of water were prepared, namely consumable water (sample 1,3,5) and water for agricultural purposes (sample 2 and 4). A number of water characteristic measurements namely temperature, pH, turbidity, and TDS were recorded from laboratory examination and compared to measurements generated from integrated water IoT sensors.

Table 1. Water Samples

Water Sample	Description	Temp. (°C)	pH (pH)	Turbidity (NTU)	TDS (PPM)
1	Drinking water	30.13	6.16	0.48	132
2	Groundwater with sugar	29.53	1.13	20.13	206
3	Tea	29.86	5.26	81.67	274
4	Groundwater with dirt	29.50	5.40	1350	354
5	Coffee	29.73	2.66	1160	545

3.3. Sensor Accuracy and Precision test

There are three mathematical equations employed in this study to measure sensor accuracy and precision. Equation 1 and 2 generate accuracy rate and error rate respectively. Meanwhile equation 3 generates sensors' precision. The sensors were tested with water samples as described on Table I. All of the equations are described as follows:

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

$$Error = \frac{Lab - Sensor}{Lab} 100\% \quad (2)$$

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

Where 'Lab' equals to data collected from laboratory trials, 'Sensor' equals to data measured by sensors, and 'Average Sensor' equals to division the sum total of a set of sensor data by the number of sensors to record activities.

3.4. Water Categorization

To perform water quality categorization, each turbidity and TDS record was validated to a water quality category which was defined in Table 2. Each class had a range of tolerable measurements for turbidity and TDS. A valid categorization was defined when turbidity and TDS were in the same row. A categorization task was marked as 'invalid' if both turbidity and TDS measurements were not located in the same row.

Table 2. Water Categorization

Category	Turbidity (NTU)	TDS (PPM)
A	1-5	1-600
B	5-25	600-900
C	26-100	900-1200
D	100+	1200+

4. Results and Discussion

4.1 Sensor Accuracy and Precision Test

A precision test was run on water sample 2 in the separate research laboratory. The test was focused to ensure the precision of the integrated IoT sensor. Two of four sensors were activated in the precision test since the necessity of water categorization only require both NTU and TDS. The examinations were run for 15 trials, and illustrates in Figure 3 for turbidity and Figure 4 for TDS. Overall, both sensor tests have contrast results. When turbidity sensor shows a stable performance from the beginning, TDS sensor shows dynamic performance until meet a stable performance on

trial 11 to 15. Table 3 showed that turbidity and TDS sensors were performing precisely with 94.40% and 97.95% precision according to the calculation of Equation 3.

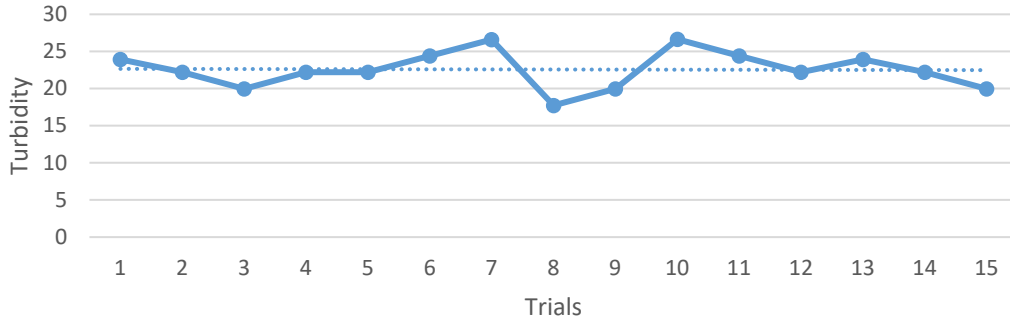


Figure 3. Turbidity Sensor Accuracy and Precision Test

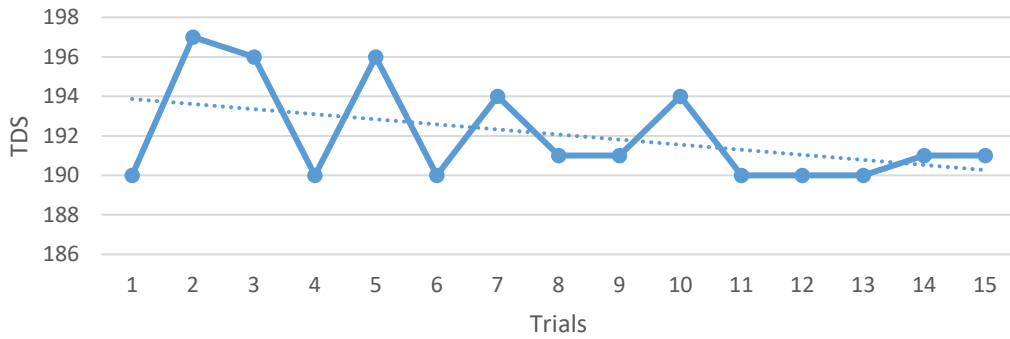


Figure 4. NTU Sensor Accuracy and Precision Test

Table 3. Sensor Precision Test

Trial	NTU	TDS
1	23.93	190
2	22.19	197
3	19.97	196
4	22.19	190
5	22.19	196
6	24.42	190
7	26.62	194
8	17.74	191
9	19.97	191
10	26.64	194
11	24.42	190
12	22.19	190
13	23.93	190
14	22.19	191
15	19.97	191
Average	22.59	192
Precision (%)	94.40	97.95

4.2 Water Quality Categorization

Table 4 shows the result of water quality categorization that was applied to water samples 1-5. The integrated water sensor was only capable to categorize water sample 1 as category A. Unlike the result from manual categorization, the integrated sensors showed invalid remarks for samples 2-5 due to unmatched turbidity and TDS categorization. On the other hand, according to manual categorization, samples 4 and 5 was categorized as category D indicate that the samples were polluted since they contain a large number of materials. While sample 1 was indicated as pure water with the least material contained, samples 2 and 3 were categorized as category B and C respectively.

Table 4. Water Categorization Results

Water Sample	Manual Categorization	Sensor Categorization
1	A	A
2	B	Invalid
3	C	Invalid
4	D	Invalid
5	D	Invalid

4.3 Discussion

The capability of Integrated IoT Water Sensor was limited to support in categorizing whether the water was drinkable using turbidity and TDS sensor. If Integrated IoT Water Sensor was well established and applied, all necessary water parameters required by WQI were able to be captured and managed in a reliable repository. Utilization of WQI models was facilitated once the database was established as well.

Compared to the integrated IoT platform by Li, Xia, Chen, Zhao, and De Silva, this proposed design and categorization method were surpassed (Li et al. 2017). The utilization of varied sensors and a more advanced water quality index generated a more reliable analysis of an aquatic territory. Furthermore, mobile ability enabled the IoT platform to survey certain water territories without requiring a coordinate input.

This research reveals several opportunities in water studies if the integrated IoT water sensor was established with a more mature data repository infrastructure. Several studies by Caraka et al. that applying the statistical approach to forecast rainfall and water balance could enrich with data collection supported by IoT sensors (Caraka et al. 2018a; Caraka et al. 2018b; Caraka et al. 2019a; Caraka et al. 2019b; Caraka et al. 2019c; Caraka et al. 2020). In the scope of the monitoring system, the collected water quality parameters could be monitored in a comprehensible interface that was studied by Cenggoro (Cenggoro et al. 2018), Baurley (Baurley et al. 2018), and Budiarto et al. (Budiarto et al. 2018). The last, there was an opportunity that enables people to study the characteristics of water through a learning management system proposed by Pardamean et al. (Firmansyah et al.; Pardamean et al. 2018).

5. Conclusion

The variety of water risks urges the application of IoT in categorizing water quality. In the scope of agriculture, the proposed solution was expected to find whether a water sample is polluted or pure. If all results in this paper were compiled very well, it can be seen that the objective of the research is obtained because the integrated IoT water sensor was capable to categorize pure water. However, the limitation of categorizing various contaminations still needs to be solved. The rest of the water samples namely groundwater, tea, and coffee were showing invalid remarks. There are two recommendations for further development: first, water purity detection is recommended for enhancement with modern classification techniques like artificial neural networks. Second, in order to categorize more water types, it is recommended to enhance the proposed design with combinations of water sensors. The findings of this research that concluded in this part remarked that with the proposed IoT sensor integration we can categorize the purity of a water sample in a proper experiment that involved the latest sensory technology instead of manual approach.

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Biography

Dr. Hermantoro has a strong background in agriculture engineering with more than thirty years of experience. He started his educational path at Universitas Gadjah Mada for the bachelor and magister program. In 2003, he obtained his doctoral degree from the faculty of Agricultural Engineering at Institut Pertanian Bogor. In the last five years, he finished various agricultural research that combined with recent technology such as Decision Support Systems, Artificial Neural Networks, Geographical Information Systems, and Drone. Based on the research, he regularly published research papers and textbooks about the science of agriculture and agricultural engineering.

Dr. Andreas Wahyu Krisdiarto received his Doctoral degree in Agricultural Mechanization from Universitas Gadjah Mada. His educational path in Agricultural Mechanization was started at Universitas Gadjah Mada and was followed by finishing the Magister Program of Agroindustry at the Asian Institute of Technology, Thailand. In the last ten years, his research discussed many technology applications like database systems, business intelligence, and decision support systems in the scope of agricultural research. He also conducted community services regularly in the last ten years in several areas in Java such as Pacitan, and Cilacap.

Arief Ika Uktoro earned his bachelor degree of agricultural engineering from Instiper on 2006. He pursued Magister of Remote Sensing in Universitas Gadjah Mada from 2010 and graduated on 2012. In the last five years, he led many applied research of geographical information systems and database systems in the scope of agriculture. Regularly, he published agricultural engineering papers that covered discussions namely early agriculture education, decision support system for oil palm industry, drone image analysis, and geographical information systems.

Reza Rahutomo earned both his Bachelor's and Master of Information System from Binus University. He worked in Japan for an AI developer company as a Technology Development Consultant until he returned to Indonesia in 2017 to apply his AI and data science experience and knowledge. Besides machine learning, his expertise and curiosity covered data engineering, time series analysis, and public speaking as well. Starting in 2020, he becomes a faculty member of the School of Information System and teaches database systems and data warehouses regularly.

Teddy Suparyanto has a deep understanding of developing and managing IT systems in the educational and agro-industry sectors. He currently holds an appointment as a Research Associate at Bioinformatics & Data Science Research Center (BDSRC) | AI Research & Development Center (AIRDC) and as a Lecturer of agricultural informatics engineering at STIPER Agricultural University in Yogyakarta, Indonesia. Graduated from the mathematics teacher education faculty, he has an educational background in mathematics, teaching skills, educational psychology, pedagogy philosophy, teaching strategy, and learning media. His expertise in statistics is very helpful in the data analysis process. He completed his master's degree program in information technology at Bina Nusantara University.

Dr. Bens Pardamean has over thirty years of global experience in information technology, bioinformatics, and education, including a strong background in database systems, computer networks, and quantitative research. His

professional experience includes being a practitioner, researcher, consultant, entrepreneur, and lecturer. His current research interests are in developing and analyzing genetic data in cancer studies and genome-wide association studies (GWAS) for agriculture genetic research. After successfully leading the Bioinformatics Research Interest Group, he currently holds a dual appointment as the Director of Bioinformatics & Data Science Research Center (BDSRC) and as an Associate Professor of Computer Science at the University of Bina Nusantara (BINUS) in Jakarta, Indonesia. He earned a doctoral degree in informative research from the University of Southern California (USC), as well as a master's degree in computer education and a bachelor's degree in computer science from California State University, Los Angeles.