



Investigating the Potential and Feasibility of Machine Learning and Biosensor-Enabled Water Quality Monitoring Systems in Uganda

By

GROUP BSE 25-30

NAME	STUDENT NUMBER	REG NUMBER
KISEJJERE RASHID	2100711543	21/U/11543/EVE
SSEMAGANDA TREVOUR	2100718348	21/U/18348/EVE
SSENTEZA EMMANUEL	2100713955	21/U/13955/PS
GUM PRISCILLA	2100717674	21/U/17674/EVE

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Abstract

Access to clean and safe water is a basic human right and a key-aspect of sustainable development. However, ensuring water quality remains a critical challenge in resource-constrained regions like Uganda, where traditional laboratory-based methods for monitoring water quality are usually inaccessible due to high costs, infrastructure demands, and time-consuming processes. This study investigates the potential of low-cost water quality monitoring systems as a practical solution to these challenges. Emerging technologies like biosensors, IoT devices, and machine learning algorithms are being leveraged toward developing systems that can offer real-time, affordable, and user-friendly water quality assessments. The study combines an extensive literature review with a survey that captures public perceptions in the growing demand for innovative cost-effective approaches to water quality monitoring in Uganda. Certain key elements of the analysis include technological advancements, exploring potential applications in rural and urban settings, and assessing implementation challenges around scalability, data accuracy, and user adoption. The findings indicate a need for the integration of low-cost monitoring systems within the national frameworks of Uganda for the management of water, to ensure that water is available and clean for all.

1. Introduction

Access to clean and safe water is essential for human health [1], environmental sustainability, and economic development. With the water having importances of serving as an ideal solvent for prebiotic and biochemical reactions due to its unique physical and chemical properties [2], enabling its interaction of carbon molecules and other essential compounds. Water is useful in living things biology because of its ability to generate small active clusters and macroscopic assemblies, which can both transmit information on different scales [3]. Small water bodies like ponds are also very crucial in bio-diversity as they often serve as refuges for species that have disappeared from larger, degraded water bodies [4]. Research found that in Europe, 70% of regional freshwater species are supported by water ponds [5]. Water is not only crucial to sustain life but also crucial in the industrial sector. For example water is used in the food and beverage industry for production processes, cleaning, and sanitation, while also contributing to significant wastewater generation that typically requires biological treatment, often through anaerobic digestion, due to its high organic content [6]. It's also used in the textile processing industries as a solvent, transfer medium, and for washing [7]. Given this extensive importance of water, high emphasis is needed on the water quality as well. In this study, we aim to discover the importance of low-cost water quality monitoring systems using bio-sensors and machine learning technologies.

1.1 Background

Monitoring water quality is a critical aspect of ensuring the sustainable use of water resources. Clean and safe water is vital for numerous ecological, industrial, and societal needs, yet the availability of uncontaminated water is increasingly threatened by anthropogenic activities, climate change, and natural pollutants [8]. A 2022 research survey utilizing the Absolute Principal Component Score-Multiple Linear Regression (APCS-MLR) method identified the major contributors to water pollution: industrial water (35.68%), rural wastewater (25.08%), municipal sewage (18.73%), phytoplankton growth and agricultural cultivation (15.13%), with unrecognized sources contributing a smaller fraction [9] as illustrated in the Figure 1 distribution. In Uganda, a water quality survey conducted in the Kampala and Mbarara districts classified 42% of sampled water bodies during the dry season as "Excellent" or "Good," while 58% were categorized as "Poor" or "Unfit for use" [10].

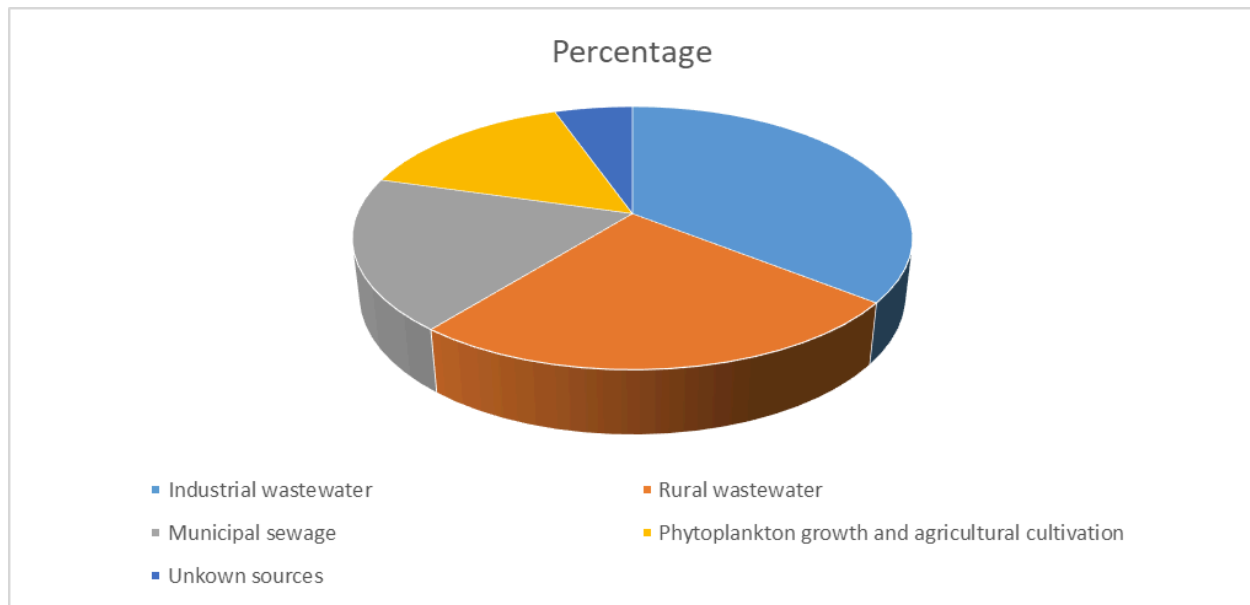


Figure 1 Illustration of the Water pollution Contributors

Conventional water quality monitoring methods rely heavily on sophisticated instruments and laboratory analysis, which are expensive, time-consuming, and require specialized expertise [11]. These limitations make such methods less accessible in resource-constrained regions like Uganda [12]. Laboratory-based analysis remains the predominant approach in Uganda, despite its challenges, often taking days or weeks to produce results [13] [14]. This delay hinders timely decision-making, leaving communities vulnerable to water-related health risks [15].

Emerging low-cost water quality monitoring systems aim to address these challenges by utilizing accessible technologies, such as affordable sensors, open-source software, and innovative data analysis techniques. However, these tools are not yet widely adopted in Uganda. Water sources, especially in rural and peri-urban areas, often lack routine monitoring, leaving populations

exposed to contaminants like bacteria, heavy metals, and agricultural runoff [16]. For example, a study in Lesotho found that unimproved water sources were major contributors to *Escherichia coli* contamination, a bacteria linked to diarrheal diseases [17]. In addition to their practical benefits, low-cost water quality monitoring systems contribute to achieving Sustainable Development Goal (SDG) 6, which aims to ensure the availability and sustainable management of water and sanitation for all [18]. By making water quality data more accessible and actionable, these systems empower local communities, enhance stakeholder decision-making, and facilitate evidence-based policymaking at regional and national levels.

1.2 Problem statement

Access to clean and safe water remains a critical challenge, particularly in resource-limited regions like Uganda. While water quality monitoring is essential to ensure the safety and sustainability of water resources, the predominant reliance on conventional methods poses significant barriers. Laboratory-based approaches, though accurate, are costly, time-intensive, and require specialized expertise. These challenges make such methods impractical for many communities, especially in rural and peri-urban areas where water sources like ponds, rivers, and wells are critical for drinking, irrigation, and other domestic uses.

The lack of timely and affordable water quality monitoring presents several pressing challenges. Contaminated water sources often remain undetected, exposing populations to harmful pollutants like *Escherichia coli*, heavy metals, and agricultural runoff, which contribute to waterborne diseases such as diarrhea, disproportionately affecting vulnerable groups like children [19] [20]. This unaddressed contamination also exacerbates environmental degradation, as pollutants from industrial, agricultural, and municipal sources harm ecosystems, threaten biodiversity, and disrupt natural water cycles [21]. Furthermore, the absence of real-time or near-real-time monitoring tools results in significant data gaps, limiting policymakers' and stakeholders' ability to respond effectively to water quality issues [22]. Together, these issues underscore the critical need for accessible and efficient water quality monitoring systems.

1.3 Objectives

1.3.1 General Objective

To explore the theoretical aspects of low-cost water quality monitoring systems and evaluate their potential to address water quality challenges in resource-constrained regions.

1.3.2 Specific Objectives

1. To Analyze Key Water Quality Parameters: Identify and discuss the critical parameters that influence water quality and their significance in monitoring efforts.
2. To Review Existing Low-Cost Monitoring Technologies: Examine their capabilities, and limitations of various low-cost water quality monitoring technologies available globally.

3. To Assess Applicability in Resource-Constrained Settings: Evaluate the feasibility of adopting low-cost water quality monitoring systems in regions with limited financial and technical resources, such as Uganda.
4. To Investigate Challenges and Barriers: Highlight the logistical, technical, and socioeconomic challenges associated with implementing low-cost monitoring systems in underserved areas.
5. To Explore the Role of Stakeholders: Discuss the importance of local communities, policymakers, and other stakeholders in facilitating the adoption and sustainability of low-cost water quality monitoring systems.

In conclusion, ensuring access to clean and safe water is vital for health, biodiversity, and economic development, but the growing threats from pollution and inadequate monitoring pose significant challenges, particularly in resource-constrained regions like Uganda. While conventional water quality monitoring methods are accurate, they are costly, time-consuming, and impractical for many communities. Low-cost water quality monitoring systems offer a potential solution by providing affordable, real-time data that can help manage water resources more effectively. This report explores the theoretical aspects of these systems, assessing their capabilities, limitations, and feasibility in regions with limited resources.

2. Literature Review

Water quality monitoring is a critical component in ensuring the safety and sustainability of water resources [23]. However, resource-constrained regions, such as Uganda, face significant challenges in maintaining water quality due to limited infrastructure and high levels of pollution [24]. Poor water quality is always associated with waterborne diseases like Cholera, Dysentery, Typhoid, Escherichia Coli and Hepatitis A [25], disproportionately affecting vulnerable populations, particularly in rural areas [26]. Research to ensure the betterment of water quality is always continuously carried. This section reviews the available literature about water quality monitoring using machine learning.

2.1. Water Quality and Human Health

Water diseases account for a significant portion of global disease burdens. The World Health Organization(WHO) estimates that over 2 billion people consume contaminated water leading to diseases like Cholera, dysentery and many more [27]. In Uganda, studies have shown that water sources in districts like Kamapala and Mbarara are categorized as “Poor” or “Unfit for use” during the dry season [28]. Below is curated literature on water quality monitoring used in different countries.

Traditional water quality monitoring relies on laboratory-based analysis, which, while accurate, is resource-intensive and often inaccessible to rural and underserved communities [29]. These methods require advanced equipment, technical expertise and significant financial investment, making them unsuitable for widespread application in resource-constrained regions like Uganda.

Despite their accuracy, traditional water monitoring techniques are time-consuming, require skilled personnel, are not user-friendly and are incompatible with operating on-site [30].

R. Bogdan et al. [31] presented a low-cost internet of things system that was capable of measuring and reporting the quality of different water sources. It comprised the following components like Arduino UNO board, Bluetooth module BT04, temperature sensor DS18B20, pH sensor–SEN0161, TDS sensor–SEN0244, turbidity sensor–SKU SEN0189. The system was to be controlled and managed from a mobile application, which monitored the actual status of water sources. A proposal to monitor and evaluate the quality of water from five different water sources in a rural settlement was made. The results showed that most

A. U. Alam et al. [32] Another study carried out experimental work where a multi-parameter water quality monitoring system was developed that included an array of low cost, easy to use, high sensitivity electrochemical sensors, as well as custom designed sensor readout circuitry and smartphone application with wireless connectivity. This proposed Multi-Parameter Water Quality Monitoring System could simultaneously monitor pH, free chlorine, and temperature with sensitivities of 57.5 mv/pH and 186 nA/ppm. This system also provided seamless interconnection between transduction of the sensors' signal, signal processing, wireless data transfer and smartphone app-based operation. This interconnection was accomplished by fabricating nanomaterial and carbon nanotube-based sensors on a common substrate, integrating these sensors to the readout circuit and transmitting the sensor data to an Android application.

K. Murphy et al. [33] presented a low-cost optical sensor for monitoring the aquatic environment where an autonomous optical sensor was devised to be environmentally robust, easily deployable and simple to operate. This consisted of a multi-wavelength light source with two photodiode detectors capable of measuring the transmission and side-scattering of the light in the detector head. This enabled the sensor to give qualitative data on the changes in the optical opacity of the water. Laboratory tests to confirm colour and turbidity-related responses were described and results given. The application of this low-cost optical sensor is in the area of environmental pollution alerts to support a water monitoring programme, where multiple such sensors could be deployed as part of a network.

N. Kumar Koditala et al. [34] proposed a low-cost water monitoring system using emerging technologies such as IoT, Machine Learning and Cloud Computing which replaced traditional ways of water quality monitoring. The proposed model also had a capacity to control temperature of water and adjust it so as to suit environment temperature.

S. Hafeez et al. [35] addressed the importance of monitoring case II classified coastal waters. Here, the authors focused on Hong Kong coastal waters and proposed a solution for improving water quality estimates by using machine learning. It has been concluded that the most accurate indicators were provided by the artificial neural network machine-learning model and satellite data.

Ch. Sowmya et al. [36] described their paper as a solution with wireless sensor network technology. Their system incorporated Arduino-based microcontrollers paired with sensors,

enabling continuous measurement of critical water parameters such as pH, temperature and conductivity.

Numerous real-time systems leverage IoT technology, including a solution introduced by Sabari. M et al. [37] which employs an Arduino microcontroller and Wi-Fi module to enable cloud-based visualization of water quality parameters. Similarly, A. H. Abdulwahid. [38] developed an IoT-based system that facilitates data visualization on the cloud. Another solution, presented by N. R. Moparthy et al. [39] utilizes Arduino to notify relevant authorities about water contamination. This approach incorporates a GSM module for messaging and extends functionality by transmitting sensor data to the cloud.

A. Alqahtani et al. [40] proposed an innovative method for determining a water index by utilizing inputs such as temperature, pH, total dissolved solids and turbidity evaluated through various machine learning algorithms. Their findings revealed that the most accurate results for the water index were obtained using gradient boosting with a learning rate of 0.1 and polynomial regression of degree 2.

S. Stajkowski et al. [41] proposed an innovative approach leveraging a genetic algorithm-optimized long short-term memory model to forecast river water temperatures.

Additionally, L. Lakshmanan et al. [42] implemented a GSM module integrated with Arduino to measure water quality parameters using sensors, display the results on the web page, and store the data on the cloud for shared access. In this project, analysis for a water quality monitoring system was done to give data about the quality of water, on a webpage. The quality of water is determined using various sensors like pH sensors and turbidity sensors, connected to the Arduino board microcontroller. The Arduino software, developed using Embedded C, worked in conjunction with a GSM module connected to the Arduino Board. Sensor data continuously transmitted from the remote sensor network through the microcontroller and a Wi-Fi module. The Wi-Fi module enables the transfer of data to a webpage via the internet, which is integrated with the microcontroller.

In summary, the reviewed literature highlights the critical role of water quality monitoring in safeguarding public health and sustaining water resources. While traditional methods offer high accuracy, their limitations in terms of cost, time and accessibility underscore the need for innovative solutions, particularly in resource-constrained regions like Uganda. However, gaps remain in the integration of predictive analytics and adaptive algorithms to enhance the efficiency and accuracy of these systems. Moreover, the existing studies often lack comprehensive evaluation in diverse environmental settings, particularly in developing regions. Using these insights, this research focuses on analyzing existing water quality monitoring systems and comparing their methodologies, technologies and outcomes with data collected in this study. This assessment contributes to advancing sustainable water resource management by bridging the knowledge gap between theoretical advancements and practical implementations.

Methodology

This section outlines the methods and approaches used to gather data, analyze results, and validate the potential of the low-cost water quality monitoring system. Our methodology

includes online surveys to assess public perception and interest, along with a review of relevant technologies and literature.

Research Design

The study employed a mixed-methods approach, combining quantitative and qualitative techniques. Quantitative data was collected using an online survey administered through Google Forms, while qualitative insights were derived from literature reviews. This approach allowed for comprehensive analysis of public needs, existing technologies, and feasibility in resource-constrained settings.

Data Collection Methods

Online Survey

An online survey was designed and distributed via Google Forms to gather public opinions, awareness, and expectations regarding water quality monitoring systems. The survey included questions targeting the following:

- Awareness of water quality issues.
- Perceived importance of real-time water quality monitoring.
- Willingness to adopt and use low-cost systems.
- Suggestions for improvement or additional features.

Survey Participants

The survey targeted a diverse demographic, including urban (82.1%), rural (10.7%) and sub-urban(7.1%) respondents as illustrated in figure 2, to ensure representation of different water quality challenges . Participation was voluntary, and the [form](#) was distributed through social media platforms.

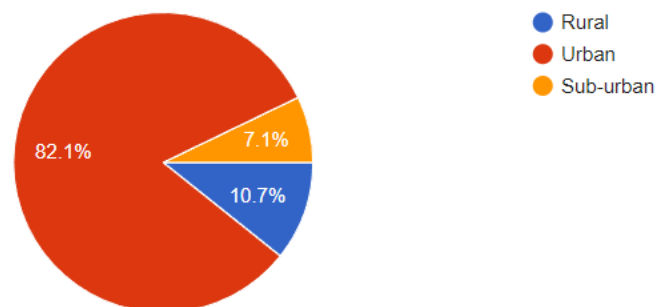


Figure 2 Pie-chart showing the region distribution of the respondents

Sample Size

A total of 61 responses were collected over a period of four weeks. Among the respondents, the majority (91%) were aged 18-25 years, with a representation from urban, sub-urban and rural areas.

Questionnaire Design

The questionnaire consisted of multiple-choice questions, Likert scale items, and open-ended questions to capture a wide range of data. It was divided into the following sections:

- **Demographics:** Age, location of the different respondents of the survey.
- **Water Quality Awareness:** Understanding of water contamination and monitoring practices.
- **User Preferences:** Desired features such as real-time alerts for contamination were suggested and acceptable costs.
- **Feedback:** Challenges such as cost and equipment accessibility, and suggestions for improvement.

Literature Review

A comprehensive literature review was conducted to identify existing low-cost water quality monitoring technologies and their applications in similar contexts. Sources included peer-reviewed journals, technical reports, and case studies focusing on biosensors, machine learning applications, and real-time monitoring systems.

Results

The survey results provide critical insights into the usage patterns and perceptions of water quality monitoring in low-resource areas of Uganda. These findings underscore the necessity for advanced and accessible water monitoring systems.

Primary Source of Water

The majority of respondents (86%) indicated **tap water** as their primary source. Other sources included **boreholes** (5%), and less commonly, **tank water, rain-harvested water, and wells** (collectively 13%). This distribution reflects a reliance on centralized water systems while highlighting the diversity in access points as illustrated in the figure 2 below.

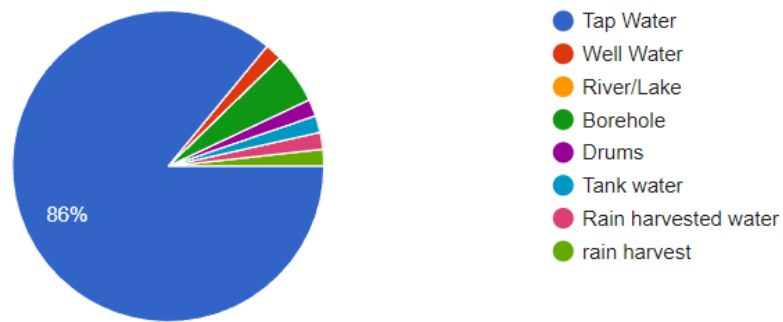


Figure 3, Pie-chart showing the primary source of water

Filtration Practices

Only 16% of participants reported using water filtration methods at home, whereas 84% did not. This lack of filtration underscores the potential vulnerability to waterborne diseases and contamination, emphasizing the need for robust water quality monitoring systems as shown in figure 3 below.

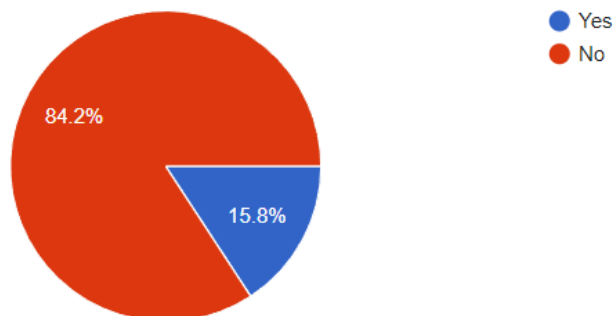


Figure 4 Pie-chart showing the distribution of individuals using filtration

Perception of Water Safety

Respondents ranked the safety of their existing water sources on a scale of 1 (extremely unsafe) to 5 (very safe), with 45.6% rating it moderately safe (3/5), 42.1% rating it safe to very safe (4-5/5), and 12.3% rating it unsafe to very unsafe (1-2/5).

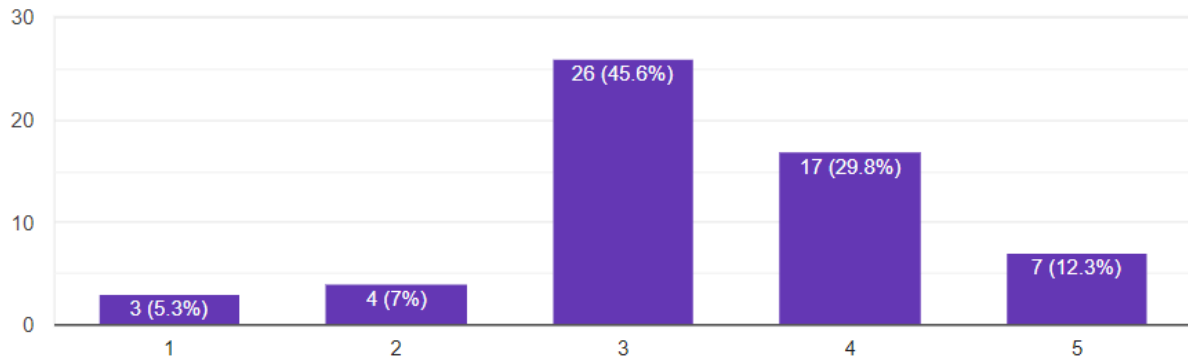


Figure 5 Illustration of the respondent's perception of water safety

These findings suggest varied perceptions of water safety, with a notable portion expressing significant concerns.

Incidence of Waterborne Diseases

Approximately 23% of respondents reported experiencing waterborne diseases in their communities within the past year. This highlights the potential health risks associated with inadequate water quality.

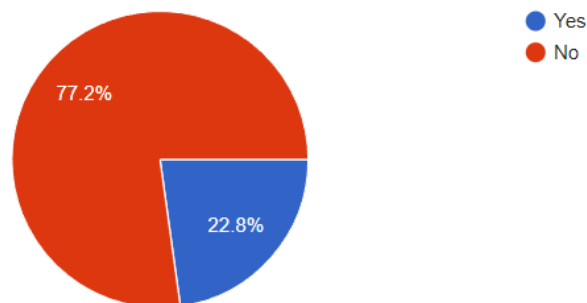


Figure 6 Distribution of respondents that reported experiencing waterborne diseases

Current Water Testing Practices

The majority of respondents (54%) reported **no testing** of their water. A significant proportion (52%) relied on **visual inspections** for indicators such as color or odor. Few respondents (7%) utilized home testing kits, and even fewer depended on laboratory tests. This indicates limited access to reliable water testing methods and tools.

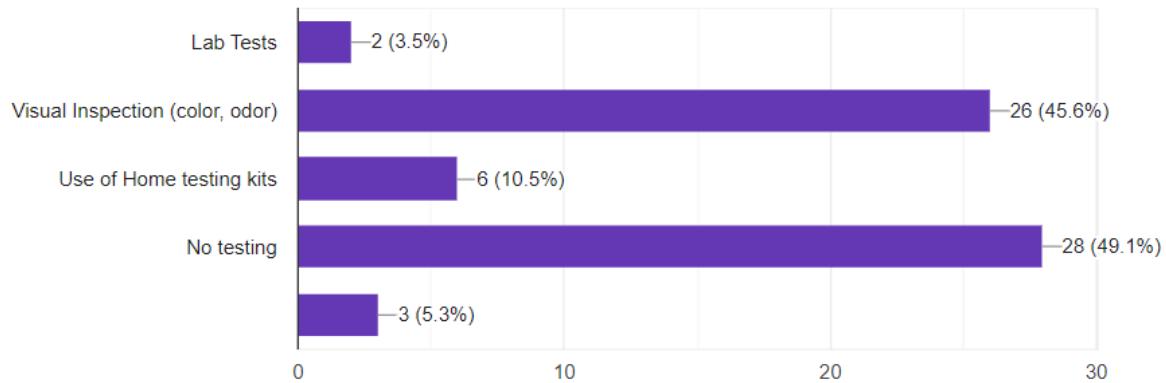


Figure 7 Bar graph showing the water testing practices of the respondents

Belief in Biosensors and Machine Learning

When questioned about the importance of biosensors and machine learning in enhancing water quality monitoring, 63% agreed, while 35% were unsure, demonstrating a significant desire to recognize the potential of these technologies.

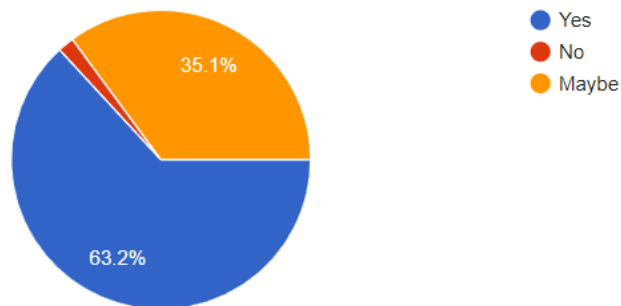


Figure 8 Distribution of Respondent's interest in AIoT powered water quality monitoring system

These results suggest openness to leveraging advanced technologies for water quality improvements.

In conclusion, These findings demonstrate a clear need for accessible, affordable, and advanced water quality monitoring systems in low-resource areas. With high levels of community concern, significant health risks, and willingness to adopt new technologies, the implementation of systems leveraging biosensors and machine learning offers a promising pathway to addressing water quality challenges in Uganda.

Discussion

The outcomes of this study highlight the important need for accessible, low-cost water quality monitoring devices in resource-constrained areas such as Uganda. The study results show a strong reliance on centralized water systems, such as tap water, with 86% of respondents citing these as their major source. However, alternative sources such as boreholes, wells, and rainwater harvesting remain important, particularly in rural regions. This range of water access sites highlights the complexities of providing safe and clean water to all populations.

Addressing Gaps in Monitoring

The survey found that only 16% of participants actively filtered drinking water, highlighting the lack of widespread procedures to reduce contamination concerns. This finding is consistent with the literature, which shows that a lack of accessible water quality monitoring exposes populations to pollutants such as heavy metals, agricultural runoff, and pathogens like *Escherichia coli*. Conventional laboratory-based procedures, while precise, are excessively expensive and time-consuming, rendering them unsuitable for most communities. These restrictions highlight the importance of implementing alternative technologies that provide real-time, cost-effective, and user-friendly solutions.

Potential of Low-Cost Technologies

Emerging low-cost water quality monitoring systems that use sensors, IoT technology, and machine learning algorithms offer potential options. These systems can assess crucial factors including pH, turbidity, temperature, and dissolved solids, providing actionable information to help reduce hazards. For example, IoT-based systems demonstrated in the literature enable real-time data collecting and cloud-based display, allowing for quicker reactions to pollution. Furthermore, machine learning models have showed promise in predicting water quality trends, increasing their usefulness for decision-making in resource-constrained settings.

Applicability to Uganda

The feasibility of deploying these systems in Uganda is promising but not without challenges. The socio-economic barriers, such as limited technical expertise and initial investment costs, remain significant obstacles. Moreover, the survey responses indicated a general lack of awareness regarding water contamination risks and the importance of monitoring systems. Addressing these gaps will require targeted capacity-building initiatives, community engagement, and stakeholder collaboration to ensure adoption and sustainability.

Conclusion

This study highlights the pressing need for innovative, low-cost water quality monitoring solutions to address the challenges faced by resource-constrained regions like Uganda. The findings underscore the limitations of conventional laboratory-based methods and the potential of emerging technologies to bridge these gaps. By leveraging IoT, biosensors, and machine

learning, low-cost monitoring systems can provide real-time, actionable data, empowering communities to safeguard their water resources. The integration of these systems into national water management strategies can enhance resilience against waterborne diseases and environmental degradation, ultimately contributing to sustainable development and improved quality of life.

In conclusion, low-cost water quality monitoring systems represent a transformative opportunity to address the urgent water quality challenges in Uganda and similar contexts. By bridging the gap between theoretical advancements and practical applications, these systems can ensure equitable access to safe and clean water, supporting both human and environmental well-being.

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