Design and Implementation of a Low-Cost IoT Model for Real-Time Water Quality Monitoring in Resource-Constrained Environments

[1]Samson O. Ooko*, [2]Laura Cheptegei and [3]Simon M. Karume
[1]Adventist University of Africa, P.O Box Private Bag Mbagathi -00503, Nairobi, Kenya
[1,2,3]Kabarak University, P.O Box 20157, Private Bag, Nakuru, Kenya
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ABSTRACT

Ensuring access to safe drinking water remains a major challenge in developing regions, where traditional water quality monitoring methods are often manual, time-consuming, and unable to provide real-time insights. These limitations delay detection of contamination and hinder timely intervention. The proposed model integrates low-cost sensors to measure pH, turbidity, temperature, and total dissolved solids (TDS), along with an embedded microcontroller for real-time data acquisition and processing. A four-layer architecture consisting of sensing, edge processing, GSM-based communication, and cloud visualisation was implemented. A mixed-methods approach was used, combining quantitative performance evaluation with qualitative stakeholder feedback. The model demonstrated reliable real-time monitoring with minimal measurement deviations (±0.1 pH, ±0.3 NTU, ±10 ppm TDS, ±0.2°C). Stable data transmission was maintained despite intermittent connectivity. Stakeholders reported improved usability, faster decision-making, and high confidence in system outputs. The results highlight the feasibility of deploying low-cost IoT devices for continuous water quality monitoring in resource-constrained environments.

*Corresponding author's e-mail address: ookosoft@gmail.com (Ooko S.O.)

1.0 Introduction

Access to clean water is essential to sustaining life worldwide and is among the Sustainable Development Goals (SDGs) (Mukonza & Chiang, 2023). However, water quality remains a global public health concern, with an estimated 2.3 billion people at risk of waterborne diseases due to poor management of drinking water sources and inadequate sanitation (Perveen & Amar-Ul-Haque, 2023).

Africa has also witnessed this worsening trend. A recent study that reviewed 42 research articles across 12 countries highlighted widespread pollution in both surface and groundwater (Lukhabi *et al.,* 2023). Surface water contamination, defined as pollution of water sources such as lakes, rivers, streams, and oceans, is more prevalent (66.7%) than groundwater contamination, which occurs when pollutants infiltrate the soil and reach water-bearing rocks (28.6%).

In Kenya, many commonly used water sources, including lakes and rivers, are experiencing rising levels of pollution, raising concerns about water quality and its adverse impacts on the environment and public health (Githaiga *et al.,* 2021). Water pollution leads to various health risks, which include waterborne diseases, toxic exposure, and food insecurity. The environmental risks include interference with ecosystems, reduced biodiversity, and threats to the sustainability of water sources. Key contributors to water pollution include heavy metals, runoff from agricultural activities, and waste from urban and industrial sources (Ngatia *et al.,* 2023; Anh *et al.,* 2023). Improving water monitoring and management is a key milestone in addressing water pollution.

Traditionally, water quality monitoring is conducted by collecting water samples from a specific location or water body and transporting them to a laboratory for analysis or by using field test kits to measure specific physicochemical parameters (pH, dissolved oxygen, and turbidity) at a given site at that particular time (Lukhabi *et al.,* 2023b). Parameters affecting water quality, such as chemical composition, nutrient content, and heavy metal content, are measured using spectrophotometry, chromatography, and titration.

Nonetheless, traditional methods of monitoring water quality have certain drawbacks that prevent them from providing timely assessments. Firstly, these methods combine multiple parameters affecting water quality into a single value to reduce dataset complexity, which makes it difficult to detect local variations or sudden changes in water quality that are crucial for real-time decision-making (Chidiac *et al.,* 2023). Additionally, sampling and laboratory testing are conducted manually, making the process time-consuming and costly. This hampers water quality monitoring in large areas, such as rural regions, and restricts real-time assessment capabilities (Uddin *et al.,* 2021). Moreover, traditional methods require specialised equipment, equipped laboratories, and trained personnel. These factors increase costs and make such methods inaccessible in resource-limited regions, particularly in developing countries (Syeed *et al.,* 2023). The limitations of traditional approaches render them unreliable for real-time monitoring of water sources, which are often subject to rapid environmental changes (Chidiac *et al.,* 2023). Furthermore, because these methods rely on periodic data collection and analysis, they pose challenges for managing pollution events that require immediate intervention.

The emergence of the Internet of Things (IoT) and advancements in sensor and software technologies have paved the way for innovative solutions in environmental monitoring. IoT devices with various sensors can continuously collect data on the physicochemical parameters of water, namely turbidity, pH, electrical conductivity, dissolved solids, dissolved oxygen, and temperature (Ushkov *et al.,* 2023; Bogdan *et al.,* 2023). The ability to collect data in real time can enable remote monitoring of water quality across large geographic areas. This approach overcomes the limitations of traditional methods for monitoring water quality, which involve taking manual samples and analysing them in a lab. IoT systems have proven to be effective in achieving accuracy rates of up to 95%, compared to 85% by some traditional methods (Jayaraman *et al.,* 2024).

This study therefore aims to address the challenges of traditional water quality monitoring in resource-constrained settings by designing an IoT-driven model for real-time water quality monitoring in distribution networks. This approach marks a shift from existing solutions, which are primarily deployed in treatment plants and do not account for energy, computing, and infrastructure constraints in distribution networks. Such a solution can still be implemented at water treatment points, community water collection and distribution points, and for monitoring various water sources.

The key contributions include (1) development of a modular and energy-efficient sensing device, (2) integration of GSM-based communication for operation in low-connectivity environments, (3) implementation of edge-based data processing for real-time monitoring, and (4) validation of the system under real-world deployment conditions. The implementation of the proposed model will contribute to achieving Sustainable Development Goal 6 by ensuring access to safe and clean water and will align with Kenya's Vision 2030.

1.1 Water Quality Monitoring Using IoT

Recent review studies indicate that IoT is increasingly being applied to water quality monitoring across different environments (Thakur & Devi, 2024; de Camargo *et al.,* 2023). IoT sensors are inexpensive and can measure pH, temperature, turbidity, TDO, TDS, and electrical conductivity, with microcontrollers used to integrate and interface with the sensors. Wi-Fi, cellular networks, LPWAN technologies, and Bluetooth are used for connectivity in remote monitoring and for transmitting data to the cloud for analysis and real-time decision-making.

An IoT-based smart water quality assessment framework for aqua-ponds management was recently developed (Arepalli & Jairam Naik, 2024). This solution uses different water quality sensors, including nitrate, pH, temperature, DO, ammonia, turbidity, and manganese sensors. Wi-Fi was used to send data to Google Drive cloud storage. This shows the ability of IoT sensors to collect water quality data. This is further supported by a related study that presents an IoT-based system for monitoring water quality in aquaculture. The solution measures key parameters, including dissolved oxygen (DO), pH, and temperature in real time (Shete *et al.,* 2024). An Arduino Uno board is used as the microcontroller with a GSM communication module to transmit data to the cloud infrastructure for storage.

The IoT-driven solutions have also been applied in monitoring water bodies. A study presents an IoT-driven solution for monitoring the water quality in a river. This is done using a sensor to collect data, followed by statistical analysis to calculate the WQI, which is then used to classify water quality for different uses (Kumar *et al.,* 2023). The sensors used in the solution include pH, dissolved oxygen, conductivity, ORP, and temperature. A gateway is used to collect data from Waspmotes and send it to the cloud via Bluetooth, WiFi, and 4G (Kumar *et al.,* 2023). In a similar approach, a low-cost IoT-driven solution has been proposed for monitoring lake water quality. This model is a solar-powered model with the capability of monitoring five water quality parameters. The monitored parameters include dissolved oxygen, total dissolved solids, pH, turbidity, and temperature. An Arduino board is used as a microcontroller, with a Wi-Fi module that sends the collected data to a web server and a Micro-SD card for storing sensor data locally.

IoT-based solutions tailored for deployment in rural areas have also been proposed in some studies. To begin with, a solution for monitoring water quality in rural areas using IoT is presented (Bogdan *et al.,* 2023). The study presents the development of a low-cost IoT-based system for monitoring water quality in rural areas. In the solution, an Arduino is used as a microcontroller, with temperature, turbidity, pH, and TDS sensors for data collection. The users used a mobile application to view the collected data and recommendations with Bluetooth as the communication protocol. In addition, in a related study (Jabbar *et al.,* 2024).

An Arduino Uno microcontroller board and a LoRa shield were used for wireless communication. The sensors measured water quality parameters, including temperature, pH, turbidity, and TDS. The Things Network (TTN), ThingSpeak, and ThingView were used for cloud-based data storage and visualisation. Moreover, an IoT-based solution for early warning of abnormal water conditions in developing countries is presented (Flores-Cortez, 2024). Sensors used include pH, temperature, and TDO sensors, with an ATmega328 microcontroller. An ESP8266 Wi-Fi module with an external antenna is used for wireless communication. A cloud-based platform (Thinger.io) is used to store and analyse the data. Table two presents a summary of the solutions used in water quality monitoring.

In an endeavour to enhance the capabilities of the solutions, the IoT-driven solutions have also been integrated with ML for water quality prediction (Rahu *et al.,* 2023; Rawat, 2022). A study presents a smart water quality monitoring framework that uses an intelligent IoT wireless sensor network to predict E. coli concentrations in water using ML algorithms (Singh & Walingo, 2024). Various communication technologies, including LTE-M, Zigbee, WiFi, Bluetooth, cellular, SigFox, LoRa, and NB-IoT, are used to send data to the cloud.

IoT-based systems for monitoring water quality face different challenges in areas with connectivity and resource constraints, such as many regions in Africa. To begin with, limited internet connectivity interferes with real-time data transmission to cloud servers where data is usually stored for analysis, energy problems, including unreliable power supplies, affect continuous operation, and high operational costs, which may include expenses for data plans and maintenance. In addition, a shortage of technical expertise complicates the installation and maintenance of the solutions. These factors have made it difficult to scale and sustain traditional IoT solutions in such settings.

Despite these advancements, most existing systems rely heavily on continuous connectivity and centralised processing, limiting their applicability in resource-constrained environments. Additionally, many solutions focus on data collection without addressing real-time processing, energy efficiency, and deployment challenges in distribution networks. This study addresses these gaps by designing a self-contained IoT device optimised for low-resource settings.

2.0 Materials and Methods

2.1 Research Design

A mixed research design was used in the study. It integrates both quantitative and qualitative approaches to solving a problem (Kothari, 2017). The mixed methods design was chosen to comprehensively understand the research problem by combining the depth of qualitative analysis with the precision of quantitative data. This approach ensured a holistic evaluation of the IoT-based water quality monitoring model by addressing both technical performance and practical usability in resource-constrained environments.

The quantitative component of the study focused on collecting and analysing numerical data related to the system's technical performance. IoT sensors collected real-time water-quality data by measuring physicochemical parameters, including pH, turbidity, TDS, and temperature. Experiments were conducted in a controlled setting to assess the system's performance under different conditions. This helped accurately evaluate the model's technical capabilities. The model will also be deployed in environments with resource constraints to evaluate real-world functionality and scalability. Performance metrics were evaluated, including the time taken for the system to process data and produce results.

The qualitative component comprised two phases. The first explored existing water monitoring practices, user needs, and operational constraints, while the second examined the contextual and user-centric aspects of the model evaluation. Water authorities, community members, and technical staff were interviewed to gain insights into current practices and the model's usability, scalability, and relevance. In addition, direct observations during deployment captured practical challenges and system interactions in real-world settings. The qualitative data were analysed using descriptive statistics and thematic analysis to identify recurring patterns and themes.

2.2 Population and Sampling

The target population of this study comprised professionals directly involved in water quality assessment, management, and regulatory oversight in Kenya. These respondents were essential for testing the IoT-driven model and for providing critical feedback on its usability, reliability, and applicability in real-world contexts. They were drawn from the six selected study counties in Kenya.

In each selected county, one respondent was purposively sampled from each of the following categories: Water Quality Assurance Officer or Laboratory Technician; Plant Operator or Technician; ICT/IoT Officer; Instrumentation or Maintenance Engineer; Water Services/Utility Manager; and NEMA Environmental Compliance Officer. This yielded a total of six respondents per county, resulting in an overall sample of 36 professionals across the study. Purposive sampling was appropriate given the specialised technical knowledge required and the roles these individuals play in both operationalising and evaluating water quality solutions. These professionals tested the model and participated in system evaluations during lab simulations and real-world field deployments.

2.3 Ethical Considerations

Ethical principles governing research involving human participants were observed throughout the study. Participation in interviews and stakeholder validation was voluntary, and informed consent was obtained from all participants before data collection. Participants were informed about the purpose of the study and assured that their responses would be treated confidentially and used solely for research purposes. Personal identifiers were excluded from the analysis to maintain anonymity. Participants were free to withdraw from the study at any stage without any consequences. Where required, permission to conduct the study was obtained from the relevant water authorities and participating institutions.

3.0 Results and Discussion

3.1 Qualitative Results and Discussion

The qualitative findings presented in this subsection are based on semi-structured interviews with county water officers, water treatment plant operators, ICT personnel, and environmental regulators. Although 36 professionals were purposively sampled across the six study counties, only 29 participants completed the interviews and participated in the qualitative evaluation. Seven participants were unavailable during the interview period because of operational commitments and scheduling constraints. Data collection was concluded after the 29 completed interviews because thematic saturation had been achieved, with no substantially new themes emerging. The prototype evaluation and technical validation were conducted independently and were therefore not affected by the reduced number of interview participants.

Interview data were analysed using thematic analysis. Transcripts and field notes were reviewed iteratively, with initial open coding used to identify recurring issues and concerns. These codes were subsequently grouped into broader themes that reflect shared patterns across stakeholder roles and institutional contexts. Five dominant themes emerged from this analysis:

Theme 1: Monitoring practices are predominantly reactive. A dominant theme across all stakeholder groups was the reactive nature of current water quality monitoring practices. Participants consistently described monitoring as driven by scheduled testing routines, regulatory requirements, or responses to reported incidents rather than continuous risk detection. Water samples are often collected at predetermined intervals, and laboratory analysis may take several days, during which time contaminated water may already have been consumed by the public. This theme highlights a fundamental mismatch between existing monitoring practices and the need for timely, preventive intervention in real-world water supply systems.

Theme 2: Infrastructure and resource constraints. Infrastructure and resource limitations emerged as a second major theme, shaping both the scope and effectiveness of water quality monitoring. Stakeholders working in rural and peri-urban settings described unreliable power supply and intermittent internet connectivity as persistent challenges. ICT personnel explained that many existing monitoring systems assume stable connectivity and continuous access to cloud-based platforms, assumptions that are rarely met in these environments. This theme illustrates how resource constraints directly influence the feasibility, scalability, and sustainability of monitoring systems.

Theme 3: Collected data and decision-making.

A third theme concerned the limited integration of collected data into operational decision-making processes. Although water quality data are routinely collected, stakeholders reported that the information is often stored for compliance or reporting purposes rather than actively used to guide real-time interventions. Environmental regulators noted that reporting frameworks tend to emphasise periodic summaries over continuous assessment, thereby diminishing the practical value of monitoring data. This disconnect between data collection and decision-making reinforces the reactive nature of current monitoring practices and limits authorities' ability to respond promptly to emerging risks.

Theme 4: Usability and expertise. Usability and human capacity emerged as critical socio-technical factors influencing the adoption and sustained use of monitoring systems. Field technicians and plant operators expressed concern that many existing systems are complex and require specialised technical expertise that is not consistently available at the local level. Systems designed primarily for technical specialists were viewed as difficult to operate and maintain, particularly in settings with high staff turnover. This theme shows the need to align system design with end users' skills, workflows, and operational realities, rather than assuming ideal conditions or high levels of technical expertise.

Theme 5: Accountability and Regulatory Acceptance. The final theme relates to trust, accountability, and regulatory acceptance. Environmental regulators and policy stakeholders emphasised that any automated monitoring system must demonstrate reliability and consistency comparable to established laboratory-based methods. Concerns were raised about data accuracy, validation, and traceability, particularly where monitoring results may inform enforcement actions or public communication. This theme highlights the need for monitoring solutions that balance innovation with credibility and institutional acceptance.

The qualitative themes identified in this study reinforce and extend the gaps highlighted in the literature. Together, they demonstrate that the limitations of existing water quality monitoring models are not solely technical but are deeply embedded within infrastructural constraints, organisational practices, human capacity, and regulatory expectations. Existing systems struggle to deliver timely, actionable information in real-world conditions, leading to delayed detection and reactive intervention. These findings directly informed the design decisions adopted in this study.

3.2 System Requirements

The system requirements and design considerations were informed by findings from interviews, observation, and document analysis. These findings confirmed the need for a low-cost, energy-efficient, real-time, and locally deployable water quality monitoring model that can operate under intermittent connectivity and limited technical capacity. Respondents confirmed delays, manual processes, and a lack of real-time visibility during the qualitative inquiry. The goal of the model is therefore to enhance the timeliness, reliability, and accessibility of water quality monitoring in resource-constrained settings.

Based on stakeholder expectations and observed operational challenges, the functional requirements for the proposed model were defined as follows. The system should be able to measure key physicochemical water quality parameters, including pH, turbidity, temperature, and total dissolved solids, at configurable sampling intervals. To improve data quality, it should also perform basic data preprocessing on the embedded device before transmission.

In terms of communication and alerting, the system should be able to generate appropriate alerts and transmit processed data, alerts, and summaries to the cloud using GSM connectivity at periodic intervals. To maintain reliability during connectivity issues, it should store data locally during network outages and synchronise automatically once connectivity is restored. Once received, the data should be visualised through the Thing Speak platform using dashboards, charts, and alerts.

Finally, given the operational context, the system should be powered by a renewable energy source and designed to use as little energy as possible.

In addition to core functionality, the system must satisfy several non-functional requirements to ensure long-term usability and sustainability. Non-functional requirements are quality attributes that describe the ways the system should behave. The system shall operate with low power consumption to support battery- or solar-powered deployment, and function effectively under unreliable network connectivity. To enable scalability, it shall utilise low-cost and readily available hardware components while supporting the deployment of multiple sensor nodes across different geographic locations.

Data reliability and measurement accuracy shall be ensured through calibration and validation mechanisms, and secure communication channels shall be maintained between edge devices and the cloud platform. From a usability standpoint, the system shall be easy to use by different stakeholders and shall ensure optimal responsiveness to various user interactions at all times.

Finally, in the event of failure, the system shall have a self-recovery backup procedure, and it shall be designed using miniaturised devices to support portability. It shall also confirm compliance with relevant traffic regulatory requirements.

3.3 System Architecture

A 4-layer, edge-driven architecture was adopted for an edge-based-driven water quality monitoring model. The architecture is designed to support real-time monitoring, edge-based intelligence, intermittent connectivity, and scalability when deploying the model in resource-constrained environments. The architecture prioritises on-device processing and decision-making while leveraging cloud services for visualisation, long-term storage, and analysis. The four primary layers of the architecture include (i) the sensing layer, (ii) the edge intelligence layer, (iii) the network layer, and (iv) the application layer.

The proposed architecture reflects insights from the study's problem-definition stage. The user emphasised the need for real-time alerts, low maintenance, offline capability, and scalability. By centring intelligence at the edge and using the cloud primarily for visualisation and long-term analysis, the system balances technical feasibility with operational sustainability. In addition, the architecture supports incremental deployment, allowing counties to start with a small number of nodes and scale over time without major infrastructure changes.

The sensing layer is responsible for measuring physicochemical water-quality parameters. It consists of low-cost sensors deployed at water sources, treatment facilities, or distribution points. Sensors are selected based on affordability, compatibility with low-power microcontrollers, and ease of calibration. The modular design allows individual sensors to be replaced or upgraded without affecting the entire system. The components of this layer include:

i. pH sensors for acidity and alkalinity measurement
ii. Turbidity sensors for suspended solids detection
iii. Temperature sensors for thermal variation monitoring
iv. Total Dissolved Solids sensors for measuring the levels of dissolved solids

The edge intelligence layer is the core of the system and runs on a resource-constrained microcontroller. This layer is responsible for local data processing, decision-making, and energy optimisation. By performing inference locally, the system minimises latency and reduces dependence on continuous connectivity. The functions at the edge include:

i. Periodic acquisition of raw sensor readings
ii. Preprocessing operations such as noise filtering, normalisation, and aggregation
iii. Execution of edge-based models to detect abnormal water quality patterns
iv. Local storage of data during periods of network unavailability
v. Triggering of alerts without the need for connectivity

The network layer is the communication layer of the system that enables data exchange between edge devices and remote services over GSM. Given the variability of network coverage and the cost of cellular data, the architecture adopts a hybrid communication strategy. This layer is responsible for:

i. Transmission of summarised data and inference results instead of raw high-frequency measurements
ii. Store-and-forward mechanisms to handle intermittent connectivity
iii. Secure data transmission protocols to ensure data integrity and confidentiality

The Thing Speak platform was selected as the cloud platform due to its low bandwidth requirements, ease of integration with microcontroller platforms, and suitability for rapid prototyping and academic research. The cloud platform is used for

i. Centralised data aggregation and storage
ii. Visualisation of time-series water quality trends
iii. Remote access by authorised users across institutions

The application layer provides interfaces through which users interact with the system. It supports multiple stakeholder roles identified in the system analysis. The features of this layer include:

i. Real-time dashboards displaying current and historical water quality parameters
ii. Colour-coded visualisations and threshold indicators for quick interpretation
iii. Alert notifications delivered via LEDs, buzzer or SMS for abnormal conditions
iv. Exportable datasets and summary reports for research and policy use

3.4 System Hardware and Components

The proposed system presents a low-cost, embedded, edge-based architecture for real-time water quality monitoring in resource-constrained environments. It integrates multiple analogue sensors, including a pH sensor for assessing acidity and alkalinity, a turbidity sensor for detecting suspended particles, a waterproof temperature sensor for environmental context and compensation, and a total dissolved solids (TDS) sensor for estimating mineral and salinity levels. These sensors are interfaced with microcontroller units, primarily the ESP32-S3, selected for its dual-core processing capability, energy efficiency, and support for on-device machine learning inference, with the Raspberry Pi Pico serving as a comparative platform for evaluating system performance. Data communication is enabled through a SIM800L GSM/GPRS module, allowing remote transmission of sensor readings and inference results in areas lacking reliable internet infrastructure. The system incorporates local alert mechanisms, including a buzzer and RGB LEDs, to provide immediate feedback on abnormal water quality conditions independent of network connectivity. Power is supplied via a rechargeable battery with optional solar integration, supported by energy-efficient strategies such as duty cycling and low-power operation to ensure long-term deployment. The software stack spans Arduino IDE for embedded firmware development, Google Colab for model training and evaluation, Edge Impulse for model optimisation and deployment in edge-based environments, and Thing Speak for cloud-based data visualisation and storage.

The design of the proposed system responds intentionally to the operational and contextual challenges identified during the problem-definition stage. Instead of following a purely technology-driven approach, the system architecture and component selection are shaped by practical constraints observed in the field, such as unreliable connectivity, limited power resources, and the need for prompt decision-making. This alignment between system requirements and environmental realities is essential, as it ensures that the proposed solution is not only technically sound but also feasible under the conditions in which it is meant to operate.

A key design choice in this study is placing intelligence at the edge. By enabling local processing and inference within the microcontroller, the system decreases dependence on continuous network connectivity and external computational resources. This approach directly addresses the delays and inefficiencies of traditional monitoring systems, in which data must be sent and processed remotely before actionable insights can be produced. The event-driven data flow further supports this choice, ensuring communication occurs only when necessary, thus saving energy and bandwidth. Consequently, the system shifts from a passive data-collection model to a more responsive, context-aware monitoring framework.

The layered architecture used in the system also enhances both flexibility and scalability. By dividing sensing, processing, communication, and application functions, the design allows individual components to be updated without affecting the entire system. For example, sensors can be replaced or upgraded separately, and new nodes can be added to expand coverage without major modifications to the existing infrastructure. This modular approach is especially important in distributed water monitoring setups, where deployment conditions can vary between locations.

It also facilitates gradual adoption, enabling stakeholders to deploy the system step by step while controlling costs and operational complexity.

Hardware selection further illustrates a balance between capability and constraint. Choosing microcontrollers with sufficient processing power to support embedded inference, while maintaining low energy consumption, shows an understanding of the trade-offs inherent in edge-based systems. Similarly, using widely available and cost-effective sensors ensures the system remains accessible for large-scale deployment. Although these components may not match the precision of laboratory instruments, their purpose is continuous monitoring and trend detection, which are more relevant to early warning and operational decision-making.

The communication strategy used in the system further showcases this balance between performance and practicality. By sending summarised data rather than continuous raw streams, the system reduces communication overhead while still providing sufficient information for remote monitoring and analysis. The use of local storage ensures data continuity even during network disruptions, addressing a key limitation of existing systems. This hybrid approach enables the system to function efficiently in environments with changing connectivity, without losing its main capabilities.

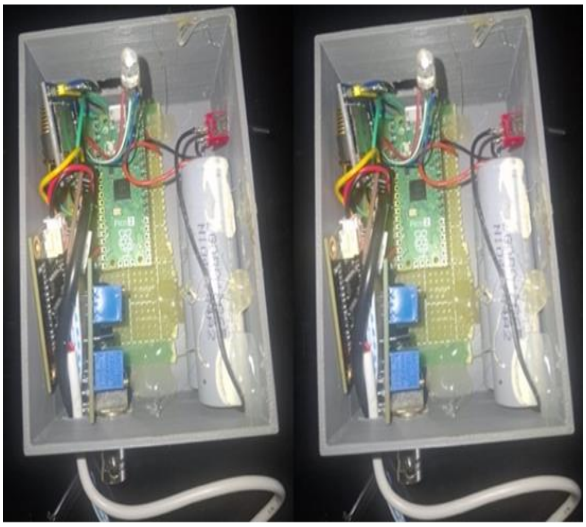
Despite these strengths, certain limitations inherent in the design must be recognised. The reliance on low-cost sensors introduces potential variability in measurements, necessitating regular calibration and maintenance. Environmental factors such as sensor fouling and exposure to harsh conditions may also affect long-term reliability. In addition, while edge-based processing reduces dependency on connectivity, it imposes restrictions on model complexity, requiring careful selection and optimisation of machine learning algorithms. These limitations emphasise the need for ongoing system refinement and adaptive maintenance strategies.

The design showcased in this study illustrates a shift from traditional, infrastructure-reliant monitoring systems to a more distributed and resilient method. By integrating sensing, edge intelligence, and selective communication into a unified framework, the system addresses both technical and contextual challenges associated with water quality monitoring. The design not only fulfils the functional and non-functional requirements outlined in the study but also lays a foundation for scalable and sustainable deployment in environments with limited resources.

3.5 Prototype Assembly

The prototype consists of a compact, self-contained water-quality monitoring unit assembled within a 3D-printed enclosure. At the core is a Raspberry Pi Pico 2 mounted on a perforated prototyping board, with neatly soldered interconnections linking it to the communication and interface modules. A rechargeable 18650 battery pack is secured within the enclosure and connected through a panel-mounted toggle switch for power control. Status indication is provided by an external LED mounted at the top of the casing. The internal layout shows deliberate component placement to minimise loose wiring while maintaining access to power, signal, and communication lines. Externally, the system interfaces with water via probes and sensor modules positioned outside the enclosure, enabling real-time measurements during testing. The 3D-printed housing, produced using a Creality printer, provides structural support and electrical insulation while keeping the assembly portable. The prototype demonstrates a functional integration of embedded control, power management, and external sensing within a compact, field-deployable design.

Figure 1
Assembled Prototype



All sensors were calibrated prior to deployment using standard reference solutions. The pH sensor was calibrated with buffer solutions (pH 4, 7, and 10), and turbidity was calibrated with standard NTU solutions. TDS calibration was conducted using known conductivity solutions. Calibration was repeated periodically to ensure measurement accuracy during field deployment.

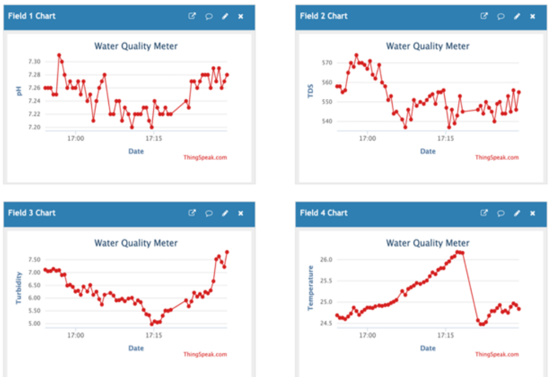
3.6 Cloud Environment

After deploying the model, the edge device was configured to send sensor readings and locally generated inference outputs to ThingSpeak via the GSM/GPRS communication module. Results from the initial integration tests confirmed that the device could establish a stable connection to the cloud platform and authenticate successfully using the assigned channel credentials.

Each transmission packet contained time-stamped measurements of pH, turbidity, temperature, and total dissolved solids (TDS), along with the predicted water quality status from the Edge-based model running on the microcontroller. Upon transmission, these parameters were correctly mapped to their respective fields within the ThingSpeak channel. No misalignment between sensor variables and channel fields was observed, indicating that the data formatting and upload configuration were correctly implemented. The populated dashboard confirmed that the cloud platform consistently received multi-parameter data streams from the edge device, validating the correctness of the end-to-end communication pipeline.

Once integration was confirmed, the model was allowed to operate continuously to evaluate the reliability of cloud-based data logging. The results show that ThingSpeak successfully stored sequential records for each upload event. All received entries were automatically time-stamped by the platform, enabling chronological ordering of observations without manual intervention. Inspection of the stored records revealed consistent temporal alignment across all sensor fields. Measurements recorded at a given sampling instance appeared simultaneously across pH, turbidity, temperature, TDS, and inference output plots. This temporal consistency indicates that sensor sampling, local processing, and data transmission occurred as a coordinated process rather than as independent or asynchronous events. The absence of missing values or partially populated records further demonstrates that the cloud environment reliably captured complete data packets during normal system operation.

Figure 2
Things Speak Graphs



The cloud setup was also evaluated under realistic connectivity conditions, including periods of reduced or intermittent cellular network availability. Results indicate that when connectivity was stable, data uploads occurred at the configured sampling interval and appeared on the Thing Speak dashboard shortly after local acquisition. During brief network interruptions, uploads were delayed; however, once connectivity was restored, subsequent data entries appeared without a system reset or manual intervention.

Although delayed uploads resulted in non-uniform spacing between cloud timestamps, no permanent data loss was observed during the test period. This behaviour confirms that the system maintained internal operation independently of the cloud connection and that the cloud environment functioned primarily as a data aggregation and visualisation layer. These results demonstrate that the cloud setup supported asynchronous data reception without disrupting ongoing sensing and inference processes at the edge.

In addition to raw sensor measurements, the system successfully transmitted and stored the categorical output of the edge-based inference process. Each data record included a field representing the predicted water quality state at the time of sampling. The consistent appearance of this field alongside sensor values confirms that the cloud platform was able to handle both numerical measurements and higher-level decision outputs. The inference field remained synchronised with the corresponding sensor readings, ensuring that each classification could be directly associated with the environmental conditions under which it was generated. This result establishes a clear foundation for later evaluation of model behaviour and decision consistency using cloud-stored records. Analysis of the collected data shows that the measured water quality parameters varied significantly by water source type. Table 1 summarises the observed ranges in the dataset. These variations reflect differences in environmental conditions across the monitored locations.

Table 1
Observed Parameter Ranges

Parameter	Observed Range
pH	6.1 – 10.0
TDS	50 – 3000 ppm
Turbidity	0 – 35 NTU
Temperature	18 – 30 °C

pH measurements in treated water sources were generally near neutral, typically between 6.8 and 7.6. In contrast, higher pH values were observed in alkaline lakes within the Rift Valley region, where mineral content influences water chemistry. TDS values varied widely across the dataset. Bottled water and treated municipal water sources generally exhibited relatively low TDS concentrations, while groundwater sources and marine environments displayed substantially higher values due to dissolved salts and minerals. Turbidity measurements were lowest in treated water sources where filtration processes remove suspended particles. Surface water samples, particularly river samples, exhibited higher turbidity due to sediment and organic matter. Water temperatures across the different locations ranged from 18°C to 30°C, reflecting typical environmental conditions in the study regions during the monitoring period.

3.7 Validation against Lab Results

A key requirement of this study was to determine whether the system could produce results that are not only computationally consistent but also aligned with established laboratory standards. To address this, the classifications generated by the deployed model were directly compared with those from laboratory analysis, which served as the reference for accuracy. Figure 3 shows an image taken from a validation exercise in one of the laboratories.

Figure 3
Validation Setup

The comparison shows that the system achieved full agreement across all sampled cases. As observed, the values recorded by the device closely match those obtained from laboratory measurements, with only minor differences across parameters. These variations are expected and can be attributed to factors such as sensor precision limits, slight environmental fluctuations during measurement, and differences between real-time sensing and controlled laboratory conditions. To better quantify these differences, the average deviation across parameters was calculated, as shown in Table 2.

Table 2
Measurement Deviation Summary

Parameter	Difference
pH	±0.1
Turbidity (NTU)	±0.3
TDS (ppm)	±10
Temperature (°C)	±0.2

The deviations stay within acceptable operational ranges for field-based monitoring systems and, importantly, do not influence the final classification results. This shows that the model is resilient to small variations in input values and can keep consistent decision boundaries even when measurements differ from laboratory readings. These results provide strong evidence of the model's reliability. The complete agreement in classification outcomes demonstrates that the model effectively captures the underlying relationships among water quality parameters, while the close alignment of measured values confirms that the sensing component operates within acceptable accuracy limits.

This validation highlights a key contribution of the study. It shows that laboratory-level classification can be performed in real time via on-device processing without relying on centralised analysis. This has important implications for practical deployment, especially in settings where laboratory access is limited or where delays in analysis could affect decision-making. The validation confirms that the system delivers results that are both accurate and operationally reliable, supporting its use as a practical alternative for continuous water quality monitoring in real-world environments.

3.8 Stakeholder Validation

To complement the quantitative evaluation, qualitative data were collected through semi-structured interviews and direct field observations during the system's pilot deployment. A total of 29 participants were involved, including plant operators, technicians, environmental officers, and ICT personnel. The participants were selected for their direct involvement in water monitoring, ensuring that the insights reflect real operational experiences. In addition to interviews, direct observations were conducted during system installation and use at both treatment and distribution points. These observations focused on how users interacted with the system, how the system behaved under real environmental conditions, and how it fit within existing workflows. The combination of interviews and observation allowed for triangulation of findings, strengthening the credibility of the results.

The data were analysed thematically, leading to the identification of five key themes: usability, real-time capability, perceived reliability, adoption potential, and deployment challenges.

Most participants described the system as easy to operate, noting that the outputs were clear and required little interpretation. The classification of water quality into simple categories reduced the need for technical analysis, enabling users to make swift decisions. From an observational perspective, users were able to interact with the system with minimal assistance after initial setup. In many cases, the interaction was limited to checking sensor readings and interpreting the classification output, confirming that the system does not demand advanced technical skills. *"The system is simple. Once you see the result, you already know what to do."* This simplicity is especially valuable in field environments, where users may have varying levels of technical expertise.

The ability to obtain immediate results has become one of the most valued features. Participants consistently emphasised the contrast between this system and traditional laboratory-based techniques, which often involve delays. *"Before, we had to wait for lab results. Now you can see immediately if something is wrong."* Observations during deployment confirmed that the system responds instantly to incoming data, with classification results generated without noticeable delay. This real-time feedback enables quicker decision-making and shifts monitoring from a reactive process to a more proactive one.

Participants showed high confidence in the system, mainly because it consistently matched laboratory results. Once users saw that device outputs aligned with lab findings, their trust in the system grew considerably. *"When we compared with lab results, and they matched, that gave us confidence."* This belief was reinforced by observation. Repeated measurements under similar conditions produced stable outputs, with no unexpected fluctuations. The system's consistent behaviour helped establish its reputation as a dependable monitoring tool.

There was considerable interest in expanding the system's use, especially for ongoing monitoring across multiple locations. Participants noted that the system could be beneficial beyond the pilot site, particularly in areas with limited laboratory access. Additionally, several participants proposed expanding the system's features to include detection of leakage and blockage in water distribution networks. These suggestions show that users regard the system not just as a monitoring tool but as part of a wider water management framework.

Despite the positive feedback, several practical concerns were identified. These were mainly related to deployment conditions rather than system functionality. Participants raised concerns about:

i. Physical security of the device at distribution points
ii. Exposure to environmental conditions such as dust, moisture, and weather
iii. Placement and accessibility in open or public areas

Observations supported these concerns. At some deployment points, the device was exposed to environmental elements and potential physical interference. These findings highlight the importance of incorporating protective housing and secure installation strategies in future deployments.

The qualitative findings offer a deeper understanding of how the system performs in real-world settings. While the quantitative results show technical accuracy, the qualitative insights demonstrate that the system is also usable, reliable, and relevant in practice. There is strong consistency between interview responses and observed system behaviour. Users not only said that the system is easy to use and dependable, but this was also clear during actual operation. This agreement enhances the credibility of the findings and supports the validity of the evaluation. The identified challenges emphasise that successful deployment depends not only on system performance but also on how well the system is adapted to its environment. Addressing security and environmental protection issues will be essential to scaling the solution. The results indicate that the system has the potential to support a shift from periodic, laboratory-based monitoring towards continuous, real-time, and decentralised water quality management, while remaining aligned with user needs and operational realities.

4.0 Conclusion

This study successfully designed and validated an IoT-based, water quality monitoring system tailored for deployment in resource-constrained environments. The findings demonstrate that the proposed system overcomes key limitations of traditional monitoring approaches by enabling continuous, real-time data acquisition, on-device processing, and immediate classification of water quality conditions.

The system achieved high reliability, as evidenced by strong agreement between device-generated results and laboratory measurements, with only minimal deviations that did not affect classification outcomes. The integration of edge intelligence significantly reduced dependence on continuous connectivity while ensuring timely detection of anomalies. Furthermore, the modular and layered architecture supports scalability, flexibility, and incremental deployment across diverse geographic locations.

Qualitative evaluation confirmed that the system is not only technically effective but also practical and user-friendly. Stakeholders reported improved decision-making capability due to real-time feedback, increased trust in system outputs, and strong potential for adoption in wider water management contexts. However, deployment challenges such as environmental exposure, device security, and maintenance requirements highlight the importance of contextual adaptation in real-world implementation.

This study establishes that combining IoT, edge computing, and edge-based provides a viable and sustainable alternative to conventional water quality monitoring methods. The proposed model contributes to the transition from reactive to proactive water management systems, with significant implications for improving water safety, especially in underserved regions.

5.0 Recommendations

Based on the findings of this study, several recommendations are proposed. Future work should focus on improving sensor calibration mechanisms and incorporating automated self-calibration techniques to enhance long-term measurement accuracy. In addition, integrating further parameters, such as dissolved oxygen and heavy metals, is recommended to provide a more comprehensive assessment of water quality.

To validate the system's broader applicability, it should be deployed at a larger scale across multiple counties to evaluate performance under diverse environmental and infrastructural conditions. Alongside this expansion, robust enclosure designs and anti-tampering mechanisms should be developed to address physical security and environmental exposure challenges. It is also recommended that alternative communication technologies, such as LoRaWAN or NB-IoT, be explored to improve connectivity reliability and reduce operational costs. At the policy level, regulatory frameworks should be developed to support the adoption of IoT-based monitoring systems alongside traditional laboratory methods.

Looking ahead, several directions for future research are proposed. Future studies should investigate the integration of predictive analytics to provide early warnings of contamination events, and research should explore combining water quality monitoring with other smart water management systems, such as leak detection and demand forecasting. Finally, long-term field studies should be conducted to assess system durability, maintenance requirements, and cost-effectiveness over time.

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8.0 Declaration of Conflicting Interests

The authors declare no conflict of interest.

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