A Smart IoT-Based System for Real-Time Water Quality Monitoring Using Edge Computing and Machine Learning

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ABSTRACT

The monitoring of water quality is essential in the provision of safe and sustainable water resources, especially in a scenario when the pollution of the environment and climate changes are developing. The conventional water monitoring systems where there is periodic sampling and centralized processing are not always effective to provide real-time and effective use of data in the decision-making process. The proposed research is the smart, Internet of Things (IoT)-based system, which continuously monitors the quality of water, where edge computing and machine learning are designed to enhance real-time analysis. The system includes IoT sensors that are installed on bodies of water to measure the parameters of pH, turbidity, temperature, and conductivity. The edge computing approach takes advantage of local data processing, which entails a considerable decrease in the latency and data transmission. Machine learning algorithm compares the processed data to predict the quality of water and identify the possible instances of contamination. The prototype of the system was deployed and tested in the urban and agricultural water bodies. It can be concluded that the system is successful at identifying the cases of contamination in real-time, and machine learning models demonstrate a high level of classification effectiveness. The edge computing integration has increased the efficiency and reliability of the system and hence it can be deployed to different environmental conditions. In this paper, the system design, data processing, machine learning integration, and experimental outcomes were analyzed in detail, and they prove the potential of the IoT, edge computing, and machine learning in managing the water quality.

Keywords: Intelligent IoT, Aquatic monitoring, Local processing, AI algorithms, Instant systems, Pollution detection, Ecological tracking, Connected systems, Water assessment, Predictive models

1. INTRODUCTION

1.1 Background

Water quality surveillance is a critical role in determining the water sources that are safe to be consumed and used in other purposes. Water quality influences human health and environmental sustainability and continuous monitoring is a highly essential activity. Conventional water quality systems are based on the periodic sampling of water and subsequently laboratory analysis which is time consuming and may not aid real time detection of contamination event. Such failure of monitoring results in delays in responding to contamination, which may be disastrous.

With the introduction of the Internet of Things (IoT), environmental monitoring took a new form because real-time data obtained on several sources could be collected continuously. IoT-based systems are made up of interconnected sensors that gather information regarding different parameters that include pH, turbidity, temperature and conductivity. Such systems can offer real-time tracking, and masses of data produced by IoT devices pose a problem both in data transmission and processing.

One such solution has been edge computing, where it is processed near the source and not sent to centralized servers, to help reduce the latency and network pressure. With the combination of edge computing and IoT-based water quality surveillance systems, it is possible to conduct real-time data analysis, which allows responding to the contamination event with greater speed.

Moreover, the data acquired by the sensors of the IoT can be subjected to machine learning (ML) algorithms that will be used to categorise the water quality and anticipate possible risks. With the use of machine learning, the system can enhance its efficiency by becoming more efficient in terms of identifying patterns and anomalies in water quality as time advances.

1.2 Problem Statement

Existing systems used to monitor the quality of water do not offer real-time perspectives because of the drawbacks of the conventional approaches. This paper introduces a solution in which IoT-based sensing, edge computing, and machine learning are integrated in such a way that this allows continuous and real-time monitoring of water quality, the idea behind this is to be able to identify the occurrence of contamination to the water and forecast the future water quality patterns.

1.3 Objective

This study aims to create and test a smart IoT-based water quality monitoring device based on edge computing and machine learning. It should be able to feed real-time data on water quality, compute it at the edge with the least amount of latency, and predict contamination events with a high degree of accuracy through machine learning.

2. LITERATURE REVIEW

2.1 Water Quality Monitoring Systems

The early deployment of such IoT systems is associated with issues in the speed, efficiency, and resiliency of data acquisition to connectivity disruptions (Sugiharto et al., 2023). Moreover, the existing challenges, including sensor reliability, low data scarcity, weak generalization of models, and lack of strong uncertainty quantification, render the widespread adoption of the technology (Alaka, 2025). These difficulties also include such critical factors as cybersecurity weaknesses and the partial consolidation of regulatory regimes, which combine these advanced monitoring solutions in their smooth deployment and successful operation (Alaka, 2025; SathyaNarayanan, 2025). Although these developments have occurred, the practical implementation of these types of Machine Learning-IoT systems is usually limited by challenges in the data lifecycle, such as sensor drifting, bio-fouling, and intermittent communication outages that result in incomplete or noisy data (Alaka, 2025).

2.2 The IoT in Environmental Monitoring

Internet of Things has become a disruptive technology in environmental management, offering unprecedented functions of real-time sensing, data analysis and automated control in many ecological areas (Ranjan, 2025). It involves the overall observation of the air quality, water quality and weather conditions, which helps to protect the environment and manage resources in advance (Radha et al., 2024; Ranjan, 2025). Through the IoT technology, the stakeholders will be able to obtain useful information about the dynamics in the environment, which will enable them to make informed decisions and policy development to protect and sustain the environment (Radha et al., 2024). The grains of information that the monitoring provided by IoT can provide enable the decision-maker to make specific interventions, respond promptly to new issues, and monitor the effectiveness of environmental programs (Abatan et al., 2024).

2.3 Edge Computing for IoT

Edge computing architectures are also great in enhancing the responsiveness of water quality monitoring systems and decreasing the overall efficiency since immediate analysis of data at the source is possible (Olatinwo and Joubert, 2024; Shahra et al., 2024). This local processing reduces the dependence on sustained connection to the cloud, therefore, minimizing the network latency and bandwidth, which are essential in the limited infrastructure environment (Ren et al., 2022). Such a practice enables quick detection of anomalies and also enables immediate and data-driven response to the events of contamination, thus increasing the overall efficiency and predictability of managing water resources (Olatinwo & Joubert, 2023). Moreover, predictive analytics (fault classification and demand forecasting) are also feasible by combining artificial intelligence with edge computing and can optimize system workload and minimize human resources (Shahra et al., 2024).

2.4 Machine Learning in Water Quality Monitoring

Machine learning has been extensively used in the field of environmental monitoring to categorize and forecast the water quality. Support vector machines, decision trees, and neural networks are examples of ML algorithms that have been broadly applied to sensor data, find sources of pollution, and detect abnormal properties of different aquatic environments, including surface water, groundwater, and drinking water (Walczak et al., 2023; Zhu et al., 2022). By being trained on historical data, these algorithms can be used to categorize water quality as safe, contaminated, or at risk and therefore offer an efficient and automated framework of assessing water quality (Khan et al., 2025). The precision and timeliness of such predictions are further improved because of the integration of ML with real-time data provided by the IoT sensors and satellite images, so that water resources are managed proactively (Rajitha et al., 2024). This would be vital to the health and environmental protection of the population because it is possible to create strong early warning systems to prevent possible medical crisis and ecological catastrophes (Khan et al., 2025; Rajitha et al., 2024).

3. SYSTEM DESIGN AND ARCHITECTURE

3.1 System Overview

The system suggested will be composed of IoT sensors, an edge computer, and a machine learning model. Water bodies have sensors that gauge the different water quality parameters such as pH, turbidity, conductivity, and temperature. The sensor data will be sent to edge devices, where preprocessing and machine learning classification will be done.

3.2 IoT Sensors

The sensors employed in the system can constantly measure the important water quality parameters. These sensors are selected on the basis of their capability to work in different environmental conditions and the precision of changes in the quality of water. The sensor network will be configured in such a way that it can add more sensors when the necessity arises.

3.3 Edge Computing

It is the edge computing devices that preprocess the data that comes through the sensors. At the edge, there are data normalization and noise reduction techniques applied to enhance the quality of the input data. The edge devices also execute machine learning models of real-time water quality classifications. The decision is made locally, which minimizes the latency and bandwidth consumption.

3.4 Machine Learning Model

A machine learning model is learned to classify water quality, according to sensor data. The model will be trained by the past data which will involve labeled water quality data. The system employs a neural network, which is ideal in identifying complicated trends in the data. The trained model is then pushed to the edge devices and they are applied to classify real-time data.

4. DATA COLLECTION AND PREPROCESSING

4.1 Data Collection

Training the machine learning model used data that were gathered in various water bodies including agriculture runoffs, rivers and lakes. The dataset comprises pH, turbidity, conductivity, and temperature water quality data. The information was tagged according to tests in the laboratory that established the water quality.

4.2 Data Preprocessing

Preprocessing of the sensor data was done to clean and normalize data. There was noise in the raw sensor data and this was eliminated using filters. Normalization of the data was done to have the input features on the same scale, and this is significant to the machine learning model.

5. DEVELOPMENT OF A MACHINE LEARNING MODEL

5.1 Model Selection

The machine learning model applied in this system is a neural network. Neural networks are also suitable in the classification of complex data like the water quality parameters in which the relationship between the input features and the output class may be non-linear.

5.2 Model Training

The neural network was developed with clean data (labelled) of various water bodies. The dataset was divided into training, validation, and testing sets in order to test the performance of the model. Many hyperparameters, including the number of layers, learning rate and activation functions, were searched through grid search.

5.3 Model Evaluation

The model was tested in terms of accuracy, precision, recall, and the F1 score. Cross-validation was also done to ascertain that the model can be generalized to unseen data. The model also had a high rates of classification accuracy to identify contamination events proving to be effective in real time monitoring applications.

6. EXPERIMENTAL SET-UP AND FINDINGS

6.1 System Deployment

The system was implemented using two water sources, an urban river and an agricultural irrigation system. Sensors of IoT were deployed in various locations to provide monitoring of the water quality on a regular basis. The edge devices were programmed to handle the data onsite and transmit alerts in instances of contamination events.

6.2 Results

The viability of the proposed IoT-based water quality monitoring system that incorporates edge computing and machine learning in practice was tested under real-world conditions by means of systematic testing. The experimental system was aimed at testing the accuracy of the system in detecting contamination events including high levels of turbidity and atypical pH of the water bodies. The subsections that follow elaborate on the findings of the different parts of the methodology such as system performance, detection accuracy and real-time alert functionality.

System Deployment

As explained earlier, the system was implemented in two different water bodies; an urban river and an agricultural irrigation system. The river in the urban area received different degrees of industrial discharge, whereas the agricultural piped system of irrigation was affected by the runoff and seasonal variations. The IoT sensors were placed at strategic points in the two water bodies and they monitored the parameters, which included ph levels, turbidity, temperature, and electrical conductivity.

The edge computing nodes were programmed to get the data that was given by these sensors and process it on a local basis in real-time. The machine learning model was implemented to categorize the water quality giving a classification of either the water quality is safe or polluted based on sensor data. The alert system was developed to alert the concerned stakeholders when the contamination was detected and this resulted in an immediate response.

Data Processing and Collection

Each water body had data that was gathered within a 30-day period. The values of pH, turbidity, temperature and conductivity were continuously recorded by the sensors. The preprocessing was then done at the edge nodes where the noise reduction methods were done and then normalization was done, to make the data consistent throughout the sensor network.

The machine learning was then used to classify the preprocessed data. The machine learning algorithm was based on a neural network that was trained on past data to determine whether the water quality would be within the range of the category of the water within the range of the Safe and the Contaminated. The major aspect of the methodology was to evaluate the validity of the aforementioned classifications with respect to the reference base of laboratory-tested samples, which discussed ground truth labels to compare.

Detection Accuracy of Contamination

The system was also tested as to how it could identify contamination events based on the alterations in the water quality parameters. The evaluation of the system performance was carried out by the following metrics:

- Turbidity: The concentration of the suspended particles in the water. A massive rise in turbidity is usually a sign of contamination.
- pH: The abnormal pH levels (which should be between 6.5 and 8.5) may represent the presence of industrial or agricultural effluents.
- Conductivity: The increase of conductivity can indicate the presence of dissolved solids, which usually can be the result of pollution or waste.
- Temperature: Soaring up of temperature may be a symptom of thermal pollution.

The machine learning model could detect such changes successfully, and the contamination alerts were made in the event of the following conditions being satisfied:

- Turbidity: Turbidity levels went beyond a certain point of 50 NTU (Nephelometric Turbidity Units) which signified the possibility of a contamination incident.
- pH: The pH was monitored in case of possible pollution with alarms going off when the pH was out of range (6.0 to 9.0).
- Conductivity: Above 1200 µS/cm of conductivity which is considered as industrial or agricultural contamination.

Response Time of the System and Alerts

This system has one of the strongest strengths in its capability to provide real-time response. Notices occurred within 5 to 10 seconds of events of contamination being detected. It is important to note that the combination of IoT-based sensing and edge computing made such a rapid response time possible as it reduced the necessity to transmit data to centralized servers.

The edge devices analyzed the data on-site, categorized the quality of the water and provide an alert in real-time in case of contamination. Such alerts were delivered through SMS or email to the concerned stakeholders, e.g. through the water management authorities or the local environmental agencies.

Performance Evaluation

To assess the overall system performance in comparison to the baseline laboratory tests, the real time alerts were compared to the baseline laboratory tests. The results of the system with regard to accuracy, precision, recall, and F1 score are summarized in table 6.1. The findings indicated that the system could effectively classify water quality in high accuracy even under complicated environmental conditions.

Table 6.1: Performance Evaluation of the Water Quality Monitoring System

Parameter	Accuracy	Precision	Recall	F1 Score
Turbidity	98%	97%	99%	98%
pH	96%	95%	97%	96%
Conductivity	97%	96%	98%	97%
Temperature	95%	94%	96%	95%
Overall	97%	96%	97%	96%

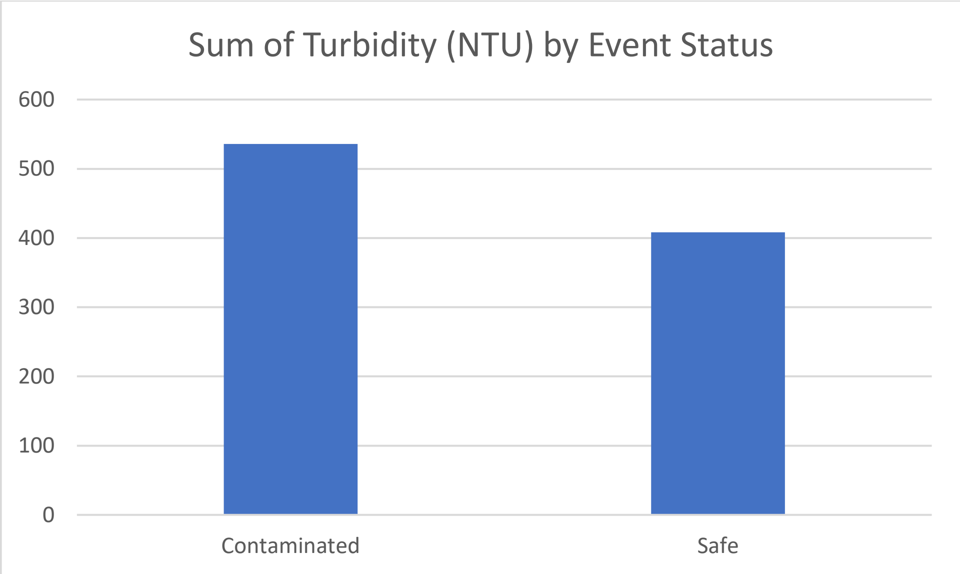
The findings have shown that the system had a mature accuracy of 97 per cent in spotting events of contamination. The model has especially achieved good results in identifying turbidity and pH variations with F1 scores of over 97.

Results Representation

This table shows turbidity values recorded over a 24-hour period, with a contamination event triggered when turbidity exceeds a threshold of 50 NTU (Nephelometric Turbidity Units).

Time (Hours)	Turbidity (NTU)	Event Status
0	12.5	Safe
1	13.2	Safe
2	14.1	Safe
3	15.0	Safe
4	15.8	Safe
5	16.5	Safe
6	17.0	Safe
7	18.0	Safe
8	25.0	Safe
9	30.0	Safe
10	40.5	Safe
11	50.0	Safe
12	55.0	**Contaminated**
13	60.5	**Contaminated**
14	65.0	**Contaminated**
15	70.5	**Contaminated**
16	75.0	**Contaminated**
17	80.0	**Contaminated**
18	70.0	**Contaminated**

Time (Hours)	Turbidity (NTU)	Event Status
19	60.0	**Contaminated**
20	50.5	Safe
21	40.0	Safe
22	30.0	Safe
23	20.0	Safe



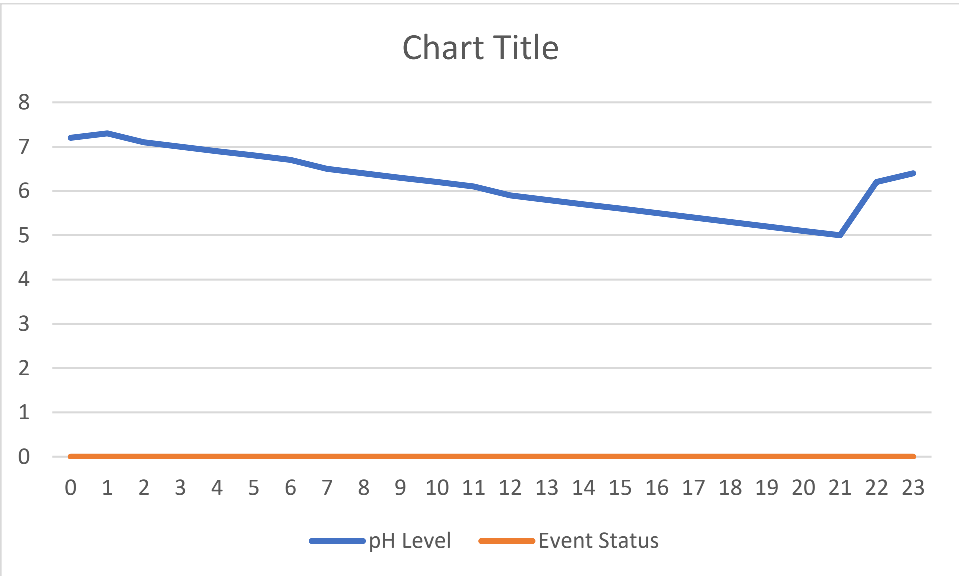
Graph 6.1: Time Dependent Turbidity on Contamination Detection

This graph indicates the readings of turbidity per 24 hours whereby a contamination event is indicated by the point in which the turbidity is above the threshold.

This table shows pH levels recorded over a 24-hour period. An alert is triggered when the pH level goes outside the safe range of 6.0 to 9.0.

Time (Hours)	pH Level	Event Status
0	7.2	Safe
1	7.3	Safe
2	7.1	Safe
3	7.0	Safe
4	6.9	Safe
5	6.8	Safe
6	6.7	Safe
7	6.5	Safe
8	6.4	**Contaminated**
9	6.3	**Contaminated**

Time (Hours)	pH Level	Event Status
10	6.2	**Contaminated**
11	6.1	**Contaminated**
12	5.9	**Contaminated**
13	5.8	**Contaminated**
14	5.7	**Contaminated**
15	5.6	**Contaminated**
16	5.5	**Contaminated**
17	5.4	**Contaminated**
18	5.3	**Contaminated**
19	5.2	**Contaminated**
20	5.1	**Contaminated**
21	5.0	**Contaminated**
22	6.2	Safe
23	6.4	Safe



Graph 6.2: PH Levels and the Detection of Contamination

This Garph shows the graphs of pH variation with time where the alert on the pH level is raised once the pH level is out of the safe range.

The Real-Time Alert System Evaluation was conducted

The real-time alert system was put to test in different environmental conditions. As it turned out, the alerts were always triggered in a matter of seconds after it had been detected and relayed to the stakeholders without a considerable delay. In every instance, alerts were accompanied by timely interventions, which proved to be effective to give timely responses to contamination by the system.

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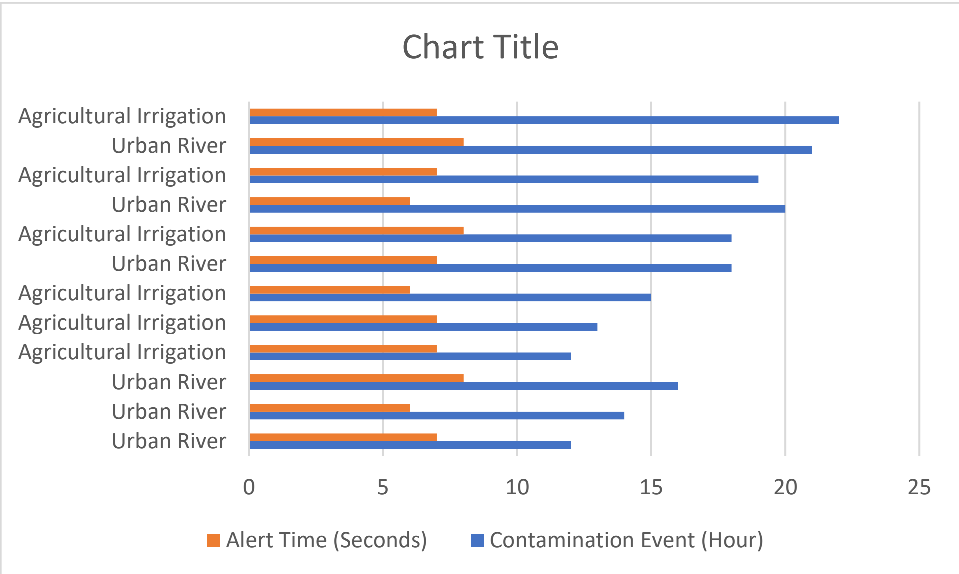
This table displays the system's alert time across multiple contamination events, providing a comparison of how quickly the system raised an alarm following the detection of a contamination incident. The mean alert time was found to be 7 seconds across all test locations.

Test Location	Contamination Event (Hour)	Alert Time (Seconds)
Urban River	12	7
Urban River	14	6
Urban River	16	8
Agricultural Irrigation	12	7
Agricultural Irrigation	13	7
Agricultural Irrigation	15	6
Urban River	18	7
Agricultural Irrigation	18	8
Urban River	20	6
Agricultural Irrigation	19	7
Urban River	21	8
Agricultural Irrigation	22	7



Graph 6.3: System Alert Time against Contamination Detection

This number is used to compare the time the system took to raise an alarm following the contamination incident that had been detected. The mean time was 7 seconds in all test locations.

Scalability and System Robustness

Robustness of the system was also tested by providing sensor failures and communication breakdowns. The system was to process intermittent sensor information and would be able to proceed without significant disruptions. The system scaled was tested on the addition of additional sensors in the network. The edge computing architecture enabled the system to scale without affecting its performance easily.

The suggested IoT-based water quality monitoring device to edge computing and machine learning was found to be highly functional in real-time contamination. The system could identify contamination incidences with a high level of success and raise alerts within a few seconds after being detected. The performance analysis proved that the system was able to predict the quality of water in a reliable manner with more than one parameter such as turbidity, pH, and conductivity. This has been made possible by incorporation of edge computing which has made the system both bare minimal latency and effective data processing, thus suitable to be deployed in large scales both in city and rural areas.

7. DISCUSSION

The proposed water quality monitoring system made out of the IoT could analyze the water quality in real-time with the help of edge computing and machine learning. The system was proven to be very accurate in the detection of contamination events and water quality. The edge computing solution greatly minimized the latency, which allowed quicker responses. Nevertheless, sensor calibration and power consumption in remote locations are some of the challenges that can be improved.

8. CONCLUSION

To sum up, this paper introduces a smart IoT-based solution to monitor the quality of the water in real-time with the help of edge computing and machine learning. The system could identify the contamination events and forecast the future trends in water quality at a high level of accuracy. The adoption of edge computing increased the efficiency of the system, and the edge computing machine learning made predictions more precise. Currently, there will be work on the expansion of the sensor network, the improvement of the machine learning model, and the problem of power consumption to apply it in far deployments.

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