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AI-POWERED SMART WATER QUALITY MONITORING SYSTEM USING IOT: A REVIEW-BASED FRAMEWORK FOR REAL-TIME CONTAMINATION DETECTION AND EARLY ALERTING

[1]Prajakta Arvind Totkar, [2]Prof. Jayshree Suryawanshi

[1]Student, [2]Professor
[1,2]Department of Artificial Intelligence and Data Science Engineering
[1,2]Ajeenkya DY Patil School of Engineering, Pune, India
[1]totkarprajakta17@gmail.com, [2]jayashreeyog@gmail.com

Abstract

Clean drinking water is fundamental for the welfare of humankind, and although many efforts are being made in the direction of automated water quality monitoring, the process of sampling sensors manually and sending them to a lab where their content undergoes chemical analysis is still predominantly aperiodic [6], [8], thus resulting in contamination of the water being discovered too late. Recent research has confirmed that inexpensive IoT devices can convey real-time data concerning the water's pH, turbidity, total dissolved solids (TDS), and temperature to the cloud [3], whereas ML has proven capable of classifying water quality as either good or bad, calculating the Water Quality Index (WQI), and detecting anomalies [2], [4]. We conducted a review of the literature consisting of eight relevant studies and found out that there are three recurring trends: the majority of IoT systems lack a prediction feature [3], [6], most ML studies utilize training data for their algorithms [7], and a consistent Internet connection is required for most systems [1], [4]. We propose a layered system consisting of Sensing Layer, Edge and Communication Layer, Cloud Layer, Intelligence Layer, and Application and Alert Layer using ESP32 microcontroller as the main element, with the methodology for data preprocessing, WQI calculation, ML classification, anomaly detection, and alert delivery being described in detail, including a representative example scenario. Since the research is currently at the conceptual stage, no implementation or performance evaluation is carried out, and an evaluation approach is provided for further research.

Keywords : Anomaly Detection, Artificial Intelligence, Cloud Computing, ESP32, Internet of Things, Machine Learning, Real-Time Monitoring, Smart Sensors, Water Quality Index, Water Quality Monitoring

I. INTRODUCTION

Access to and the quality of safe water could drastically vary. An incident of pollution in a village well, a school tank, or even the water chain in the hospital could quickly affect hundreds of individuals within hours [6], [8]. Conventional tests are periodically conducted by human beings. Therefore, there exists an

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enormous gap of blind period during which there would be no information about the quality of the water flowing through the tap [6], [8].

Development of the IoT paradigm has brought about incredible innovations in the sphere of environment monitoring. Inexpensive microcontrollers such as the ESP32 or NodeMCU could be equipped with pH, turbidity, TDS, and temperature sensors and sent data to the cloud server every few seconds [3], [8]. Such approach would give insights regarding the current state of the monitored that is impossible to obtain through conventional lab tests.

Yet sometimes, unprocessed raw data is not very helpful, and further analysis is required in order to detect useful patterns. The algorithms like Random Forest, SVM, XGBoost, and LSTM can be trained on the sensor data to classify a given water sample as drinkable or not drinkable, estimate its WQI, detect anomalies, and perform other tasks [2], [4], [7]. Also, it has been proved that the aforementioned algorithms can successfully make predictions about the water quality parameters based on the historical data [5]. used ML for predicting microbial contamination of water, which cannot be detected with a naked eye [5].

None of the techniques is enough on their own. Monitoring-only solutions accumulate the data without any intelligent alerting [3], [6]; studies of ML often use historical datasets instead of live sensor streams [7]; most integrated solutions require a constant internet connection [1], [4]. It leads to a multi-layered approach, where sensing, edge computation, cloud storage, and ML are combined with local fallback when the internet connection is poor. Such an approach is proposed in this paper, which is based on the literature review [1]–[8].

The contributions of the present paper include: (i) systematic literature review of eight papers related to IoT and ML enabled WQM; (ii) layered architecture of AI enabled smart WQM system; (iii) methodology for WQI computation, ML-based classification, and anomaly detection; and (iv) example scenario and evaluation strategy, not including any implementation details or measurement results for now.

The rest of the paper is organized as follows. Related work is discussed in Section II. The problem and objectives are stated in Section III. The proposed architecture is described in Section IV. The methodology is given in Section V. An example scenario is provided in Section VI. The expected outcomes are discussed in Section VII and compared with other approaches in Section VIII. Challenges and reliability issues are addressed in Section IX. Evaluation approach and future work are outlined in Section X. Conclusion is given in Section XI.

II. RELATED WORK

A. IoT Based Water Quality Monitoring System. In the first attempt at IoT, the sensing and remote viewing were carried out, where the microcontrollers were employed, and the cloud dashboards took the place of the manual sampling trip. For pond management purposes, Kumar et al. employed an ESP32 to integrate pH, TDS, and turbidity sensors into an IoT cloud, and real-time monitoring was performed, along with highly accurate results and remote access [3]. Bhardwaj and Kumar employed ESP32 sensors integrated with cloud platform for reliable remote monitoring [6], and Patel and Shah employed NodeMCU and cloud computing for remote monitoring and instant notifications to the users [8]. While all the above systems demonstrate the use of low-cost hardware for sensing tasks continuously, they do not employ any form of predictive analytics or water quality classification using machine learning [3], [6], [8].

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B. Machine Learning Approach for Water Quality Assessment. Zhang et al. tested the performance of Random Forest, Artificial Neural Network, and SVM on detecting water pollution, and reported improved accuracy of detection [7]. However, in the present study, the authors have employed historical datasets, not data from live IoT sensors [7].

C. IoT and Machine Learning Systems Integrated Together. The latest research includes both. Kushwaha and Pandey used ESP32, ThingSpeak, and employed such models as Random Forest, SVM, XGBoost, and LSTM for predicting water quality, anomalies detection and calculation of WQI; however, there is still the need for a big dataset and periodic sensors calibration [2]. Wiryasaputra et al. combined Arduino, NB-IoT and cloud computing with Decision Tree, Random Forest, and SVM models and found out that Decision Tree model gives high accuracy for the prediction of potable water, but the system requires NB-IoT and stable cloud connectivity [4]. Chakranaranyan and Shaikh integrated IoT sensors, AI, ML and cloud computing for contamination detection, trend prediction and automatic alerts; however, there are internet dependence, cybersecurity, and maintenance problems left unresolved [1].

D. Microbial Contamination Prediction. Singh and Walingo used wireless sensor networks and such models as Random Forest, AdaBoost, and SVM for microbial contamination prediction [5]. This study proves that the use of AI helps to detect threats which cannot be detected by physical sensors, however, it focuses only on microbial prediction [5].

E. Gaps in Research Identified. Table I outlines the research methodology, contributions, and remaining gaps for all the reviewed articles. There are five common gaps found in the literature reviewed: (1) numerous deployments end with mere monitoring with no predictive module [3], [6]; (2) many Internet of Things applications for water quality do not utilize ML to automatically classify water quality [8]; (3) there is little capacity for automatic alerting when the water becomes contaminated [1]; (4) some articles use very small datasets, historical or simulated datasets, which makes them less applicable in real life situations [2], [7]; and (5) most systems assume a working internet connection, which is quite rare in the rural areas where it is especially needed [1], [4]. Another common gap is sensor drift and periodic calibration [2], [5], [6].

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TABLE I
SUMMARY OF LITERATURE SURVEY AND RESEARCH GAPS

Ref.	Author(s) / Year	Methodology	Key Contribution	Residual Research Gap
[1]	Chakranaranyan & Shaikh (2026)	IoT sensors with AI, machine learning, and cloud computing	Detects contamination, predicts trends, and provides automatic alerts	Internet dependency, cybersecurity concerns, and maintenance issues
[2]	Kushwaha & Pandey (2025)	ESP32 with ThingSpeak; Random Forest, SVM, XGBoost, LSTM	Predicts water quality, detects anomalies, and calculates the Water Quality Index (WQI)	Requires large datasets and periodic sensor calibration
[3]	Kumar et al. (2024)	ESP32 with pH, TDS, and turbidity sensors connected to an IoT cloud	Real-time monitoring of pond water with high accuracy and remote access	Focuses on monitoring; no machine learning prediction layer
[4]	Wiryasaputra et al. (2024)	Arduino with NB-IoT and cloud computing; Decision Tree, Random Forest, SVM	Decision Tree achieved high accuracy for potable water prediction with cloud monitoring	Depends on NB-IoT infrastructure and stable cloud connectivity
[5]	Singh & Walingo (2024)	Wireless sensor networks with Random Forest, AdaBoost, SVM	Predicts microbial contamination using AI techniques	Focuses on microbial prediction rather than overall water quality
[6]	Bhardwaj & Kumar (2021)	IoT sensors with ESP32 and a cloud platform	Enables reliable remote water quality monitoring	No predictive analytics or AI integration
[7]	Zhang et al. (2021)	Random Forest, Artificial Neural Networks, SVM	Machine learning improved pollution detection accuracy	Uses historical datasets rather than real-time IoT sensor data
[8]	Patel & Shah (2019)	NodeMCU with IoT sensors and cloud computing	Remote monitoring and instant notification to users	No AI-based classification of water quality

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III. PROBLEM STATEMENT AND DESIGN

A large number of villages, schools, hospitals, industries and residential complexes have no provision for constant monitoring of water quality. Traditional methods of testing are cumbersome, expensive and incapable of providing a warning of contaminated water in time causing consumption of unsafe water [6], [8]. Low cost water quality monitoring systems capable of measuring continuously and analyzing parameters intelligently and providing alerts if water is polluted are necessary [1], [2]. Hence the need for the following design goals:

1. **Continuous Monitoring** – Measurement of water quality parameters like pH, Turbidity, TDS and temperature needs to be done at short intervals [3], [6].
2. **Intelligent Classification** – The water quality status must be classified by using ML techniques such as Random Forest, SVM, XGBoost, and LSTM [2], [4], [7].
3. **Quality Indexing and Anomaly Detection** – Calculate water quality index and detect anomalies in sensor readings [2].
4. **Immediate Notification** – The system must give instant warnings to respective authorities [1], [8].
5. **Cost-effectiveness and Scalability** – The system must use cheap hardware and be compact enough to adopt it in smart cities and rural areas [4].
6. **Resiliency** – The system must provide local notifications and buffer the data if it is disconnected from the internet [1], [4].

The abovementioned design goals are desirable for building the proposed framework. However, their implementation and experimentation are not the goal of the current research paper and will be done in future (please see Section X).

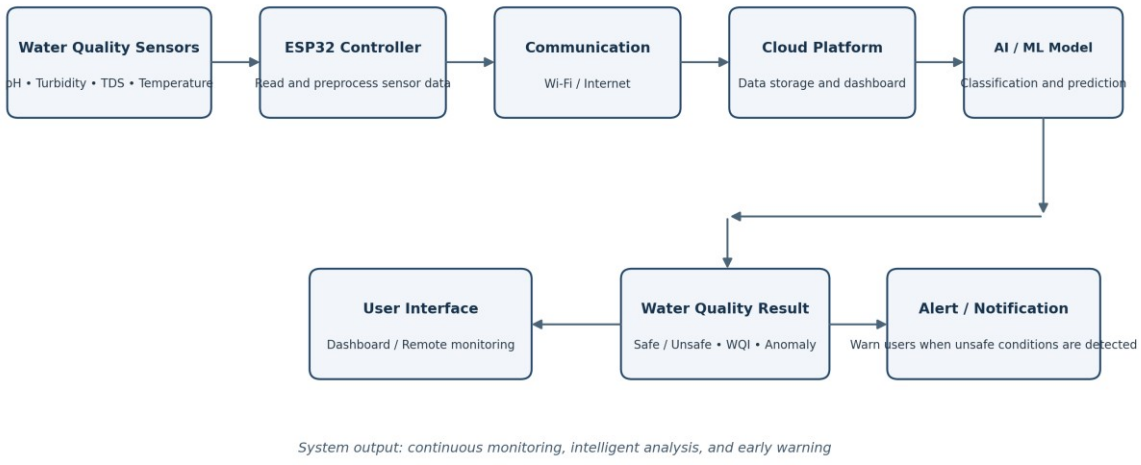


Fig. 3. Block diagram of the proposed AI-powered smart water quality monitoring system

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IV. PROPOSED SYSTEM ARCHITECTURE

A. Architecture Overview. The proposed system consists of five interacting layers: Sensing, Edge and Communication, Cloud, Intelligence, and Application and Alert Layers (Figure 1). Sensor data moves from the source to the user in an upward direction, whereas control and calibration signals move downward.

Fig. 1. Layered architecture of the proposed

C. Edge and Communication Layer. The ESP32-based system reads the sensor values, performs initial filtering, and sends them via Wi-Fi to the cloud periodically, per [2], [3], and [6]. The Edge Layer also implements the buffer and the threshold check, to make sure that the sensor readings are not lost and an alert can be triggered locally in case the cloud connection goes down. If there is no Wi-Fi connection, other communication options like NB-IoT can be utilized, per [4].

D. Cloud Layer. Cloud IoT Platform is responsible for storing the input time-series data and making it accessible to the Intelligence Layer and dashboards, as implemented by the ThingSpeak platform per [2]. The cloud layer ensures remote access to the current and historical sensor readings; this is the major advantage of the cloud-connected monitoring systems, per [3] and [8].

E. Intelligence Layer. This layer holds the analytical elements: data pre-processing, WQI calculation, ML-based water quality classification, and anomaly detection. These analytical elements implement the integrated approaches presented in [2] and [4] and explained in Section V.

F. Application and Alert Layer. The layer shows live readings, WQI value, and safe/unsafe state on a dashboard and alerts in case unsafe values are found [1], [8]. The user, which acts as a caretaker or a water supply provider, can check the alert and confirm it using laboratory test in case required.

G. SACA Operating Loop. The proposed system works according to the following four-stages loop, named SACA (Fig. 2). In the sensing stage, readings are acquired by the sensors. In the analyzing stage, readings are filtered and the WQI is computed. In the classification stage, ML model classifies the water and anomaly detector checks the latest trend. Lastly, in the alerting stage, any unsafe/abnormal condition triggers an alert. Review and backup mechanism is placed at the heart of the loop, to enable human operator to review alerts and for local alerts to be provided in case the connection is lost.

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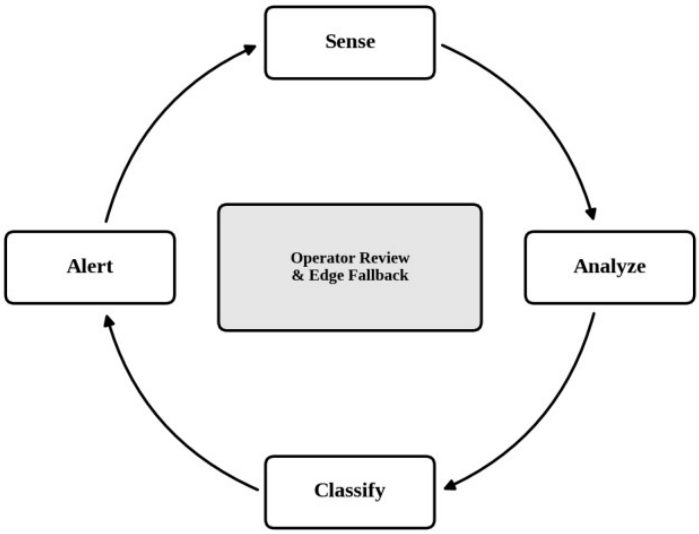


Fig. 2. The Sense–Analyze–Classify–Alert (SACA) loop, with operator review and edge fallback at its center.

V. METHODOLOGY

A. Data Collection and Representations. In every sample interval, edge device records a tuple r_t = (time stamp, pH, turbidity, TDS, temperature). Recent tuples are saved in a sliding window W to enable inspection of short term trends. These tuples are saved in a time series in cloud and used as input features in the ML model.

B. Preprocessing. Sensor readings collected by the system contain noise. Every reading is filtered by its physically meaningful range and invalid ones are dropped. Moving median filter is applied to remove short term peaks, and TDS is adjusted based on temperature. Values of sensors are scaled before being fed into distance based models such as SVM, or neural based models such as LSTM. Offset calibration is performed at the edge node using recent values [2], [5].

C. Water Quality Index. Water Quality Index is a condensed value of a few parameters. In our approach, we propose a weighted arithmetic one as follows:

$$WQI = \Sigma (q_i w_i) / \Sigma w_i \quad (1)$$

where the quality rating is defined as $q_i = 100 (V_i - V_i^o) / (S_i - V_i^o)$, unit weight as $w_i = K / S_i$, V_i is the value of parameter i measured by sensors, S_i is its permissible standard value, V_i^o is its ideal value, and K is the proportionality constant. The standard values are calculated from the drinking water specification, such as BIS IS 10500 [9]; e.g., the generally accepted range for pH is from 6.5 to 8.5. The smaller the value of WQI is, the better is the quality of water, and the ranges correspond to the categories of good, poor, and unsuitable for drinking.

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D. Machine Learning Classification. The drinking water is classified as safe or unsafe (potable or non-potable) using a supervised classifier taking as input the processed values of the sensor data and WQI. The four machine learning methods will be explored: Random Forest, SVM, XGBoost, and LSTM [2], [4], [7]. The tree-based models can be considered attractive because of their low complexity and suitability for small tabular datasets; Decision Tree and Random Forest have proved efficient in potable water prediction in [4]. The LSTME

vthe water as unsafe, while the anomaly detector picks up a sudden increase of turbidity. Coming to the Alert stage, if the Internet connection is lost (not unlikely in a stormy weather), a local alarm rings and the alert is stored in the edge device memory until the connection is re-established. The caretaker can then take action: halt the supply and request a lab confirmation before any water is drunk.

The benefit of such a system is reflected in the scenario: a warning is issued when the condition starts, not when the caretaker will perform the next planned test.

VII. EXPECTED OUTCOMES AND DISCUSSION

Since the framework is not in place, the paper cannot claim to measure the performance outcomes in terms of its effectiveness. Therefore, the expected advantages come from the results achieved by techniques, on which the system is based. The cloud-enabled systems using Decision Tree and Random Forest models for potable water prediction were shown to be very accurate [4], which supports the Classify step. The systems, which used ESP32 and ThingSpeak, calculated the WQI and found anomalies in near real-time [2], which supports the Analyze step. IoT systems, which utilized the sensors of pH, TDS, and turbidity levels, have proven to be accurate in real-time sensing and remote monitoring [3], which supports the Sense and Cloud layers, whereas automatic notifications were shown in [1] and [8]. The wireless sensor networks coupled with the ensemble methods predicted the contamination with microbes [5]. All those results show that the implementation of these techniques in one affordable framework is a reasonable choice for the proposed system.

VIII. COMPARISON TO EXISTING APPROACHES

Table II below illustrates the comparisons between the proposed approach and previous approaches through six criteria including real time sensing, cloud platform, machine learning classification, water quality index, anomalies detection, and automatic notifications and offline resiliency. Comparison is qualitative according to the information provided by the review of each paper, and NR means Not Reported.

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TABLE II

QUALITATIVE COMPARISON OF WATER QUALITY MONITORING APPROACHES

Approach	Real-Time Sensing	Cloud Platform	ML Classification	WQI / Anomaly Detection	Automatic Alerts	Offline Resilience
Chakranaranyan & Shaikh [1]	Yes	Yes	Yes	Partial	Yes	No
Kushwaha & Pandey [2]	Yes	Yes	Yes	Yes	NR	NR
Kumar et al. [3]	Yes	Yes	No	No	NR	NR
Wiryasaputra et al. [4]	Yes	Yes	Yes	NR	NR	No
Singh & Walingo [5]	Yes	NR	Partial	NR	NR	NR
Bhardwaj & Kumar [6]	Yes	Yes	No	No	NR	NR
Zhang et al. [7]	No	NR	Yes	NR	NR	NR
Patel & Shah [8]	Yes	Yes	No	No	Yes	NR
Proposed Framework (this paper)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes (planned)**

NR = not reported in the reviewed source.

IX. CHALLENGES AND RELIABILITY CONSIDERATIONS

Given that decisions regarding water quality affect people's health, the proposed framework was developed in such a way as to complement, not substitute, the laboratory tests. Considerations that can be found in the literature reviewed include the following:

1) Dependence on the Internet. Most of the systems reviewed depend on the Internet connection [1], [4].

2) Sensor drift and calibration. Over time, sensors tend to lose accuracy and require calibration [2], [5], [6]. As such, the framework plans regular calibration check-ins and will flag suspicious readings.

3) Data requirement and generalization capability. Well-trained ML models generally need to be fed with many data in order to be able to work properly, and they may suffer from brittleness when dealing with new scenarios [2], [7]. Therefore, a model needs to be tested in the target environment prior to any deployment.

4) Security issues. Connected devices represent a threat to networks [1]. It is necessary to use secure communication protocols for cloud-connected systems.

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5) Cost and maintenance. The cost and maintenance demands of the system constitute an important constraint especially in rural areas [1], [4]. Therefore, low cost and simplicity are essential for the design.

6) False positives. Too many false positives may cause the operator to become indifferent to them. The threshold for the anomaly detector and alerts should be carefully set up. Positive alerts should be verified through laboratory tests.

X. EVALUATION PLAN AND FUTURE WORK

As the next step, it is necessary to build a prototype for the Sensing, Edge, Cloud, and Intelligence layers and perform an initial evaluation before implementing the project in the field. Evaluation should include the following aspects: (i) sensor accuracy which can be assessed by comparing it with a reference calibrated measuring instrument or with the laboratory analysis; (ii) classification performance measured as accuracy, precision, recall, and F1 by applying the model comparison method from [2], [4] to labeled laboratory samples; (iii) alert latency from the moment of detecting the dangerous situation until receiving the alert; (iv) system robustness measured in terms of data storage and local alerts in case of link failure; and (v) cost estimated as the hardware price of each monitoring node.

Further development of the project includes implementation of lightweight ML models on the edge to allow independent classification, use of low-power long-range communication technology for remote areas, adding new sensors such as residual chlorine, and microbial risk prediction using the approach described in [5].

XI. CONCLUSION

The present paper offers a review-based approach to developing an AI-based smart system for water quality monitoring based on IoT. Considering the following eight articles [3], [6], [8] on IoT sensors [2], [4], [5], [7], [8], and [1] concerning ML application, smart systems [1], [2], [4], [1], [6], and models of microbial water quality prediction [5], the current trends in the field of research were identified. They include neglecting the necessity of incorporating predictive abilities into the monitoring system, applying machine learning methods without IoT data, lack of automatic alerts, and Internet dependency. A concept of smart water ecosystem was offered that includes, along with the main system components, the methodology of pre-processing, calculation of the WQI, classification with the help of ML, anomaly detection, and alerts. Also, a scenario of system functionality demonstration and evaluation of its prototype was suggested. The major results of the research are the combination of IoT, cloud computing, and ML, together with a backup

Among all types of ML algorithms available locally, it emerges as the most promising direction for the creation of intelligent systems that will be used for monitoring water quality in future urban and rural settlements.

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