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An AI-Based Multi-Depth Water Quality Monitoring and Early Warning System for Storage Tanks

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***Abstract*—**
Water stored in tanks may change in quality because of sediment accumulation, mixing, temperature variations, and other local disturbances. However, many existing monitoring approaches rely on periodic sampling or on measurements taken at a single location. This paper proposes AquaWatch, an IoT- and AI-based system that monitors water quality at three depths within a tank. The proposed AquaWatch system uses three sensing stations positioned at different depths of the tank: 0.40 m, 1.30 m, and 2.10 m. Each station is designed to monitor important water-quality parameters, including pH, turbidity, electrical conductivity (EC), estimated total dissolved solids (TDS), temperature, dissolved oxygen (DO), and oxidation-reduction potential (ORP). The collected readings are processed by an ESP32 and transmitted to a gateway through LoRa communication. From there, the data are forwarded to a cloud database for further analysis. To identify unusual changes in water quality, the cloud platform uses Isolation Forest, Z-score, exponentially weighted moving average (EWMA), and cumulative sum (CUSUM) techniques. These methods work together with cross-depth analysis to determine whether a change affects the entire tank or occurs only at a particular depth. The monitoring information is then displayed on a dashboard, while mobile notifications inform users. The system is also designed to support solar-assisted operation in remote locations. This paper describes the proposed system design, methodology, implementation plan, and evaluation approach. Experimental measurements are not included at this stage and will be considered during prototype testing. The generated alerts indicate abnormal patterns only and require further inspection and confirmatory laboratory testing.

***Index Terms*— water quality monitoring, multi-depth sensing, cross-depth analysis, anomaly detection, Isolation Forest, EWMA, CUSUM, ESP32, LoRa, IoT, early warning.**

I. INTRODUCTION

Water quality is influenced not only by its source but also by the way it is stored. In many homes, institutions, and rural areas, water remains in storage tanks for several days before it is used. During this time, its quality may gradually change. Sediments can settle at the bottom of the tank, unwanted substances may enter from outside, and temperature changes can also affect the stored water. For this reason, public health guidelines Sensor-based online monitoring offers a way to observe water quality more frequently and identify unusual patterns[1]

The conventional way of checking stored water is to collect samples and send them to a laboratory for testing.Although this approach gives results testing is usually carried out at fixed intervals and the results may take some time to arrive. As a result changes that occur between two tests may go unnoticed. Online sensor-based monitoring reduces this delay; however many existing systems still depend on a sensor at one location and raise an alert only when a predefined threshold is exceeded. A single measurement point may not represent the condition of the tank because water quality can vary between the surface, middle and bottom layers. Similarly fixed thresholds may generate alerts or may fail to identify unusual combinations of readings when each individual value remains within its specified limit.

Monitoring water tanks in remote areas is not easy. Limited electricity and poor network connectivity make it difficult to monitor water quality continuously and receive timely updates. A monitoring system for such environments should therefore consume little energy and keep operating during temporary network interruptions.

To address these issues, this paper proposes AquaWatch, a water quality monitoring system that uses three sensor stations positioned at different depths in the same tank and analyzes their readings together. The major contributions of this work are:

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- A three-level sensing arrangement with illustrative depths of 0.40 m, 1.30 m, and 2.10 m, designed to monitor seven water quality parameters at each level;
- A hybrid anomaly detection layer that uses Isolation Forest, Z-score, EWMA, and CUSUM techniques;
- A cross-depth comparison method to identify overall changes in tank water quality and distinguish them from changes limited to specific depths;A low-power, solar-assisted monitoring architecture based on ESP32, LoRa, a gateway, and a cloud dashboard with mobile alert support;
- A testing approach that compares single-depth and multi-depth monitoring methods, along with traditional fixed-threshold alerts and advanced hybrid analytics.

AquaWatch is developed to monitor water quality and provide early warnings when unusual changes are detected. However, these alerts do not confirm whether the water is safe or unsafe to drink. If an alert occurs, the tank should be inspected, and the water must be tested in a certified laboratory to confirm its actual quality. The rest of this paper is structured as follows. Section II discusses previous research and related work. Section III explains the existing methods and their limitations. Section IV introduces the proposed AquaWatch system. Section V describes the methodology used, while Section VI explains how the system is implemented.. Section VII discusses the evaluation plan, expected behavior, and limitations. Sections VIII to X present the advantages and applications, the conclusion, and the future scope.

II. Literature Review

A. Wireless Water Quality Monitoring

Wireless sensor networks have been widely explored for water quality monitoring. Adu-Manu et al. reviewed recent developments and open research challenges in this field, including the practical difficulties of deploying sensors in water [2]. Similarly, Pule et al. presented a survey of wireless sensor network techniques used for water quality monitoring [3]. These studies highlight the importance of remote and continuous monitoring and provide a foundation for the approach adopted in AquaWatch.

B. Anomaly Detection

Chandola et al. presented a detailed survey of anomaly detection methods and explained that the choice of a suitable technique depends on the data characteristics and on the type of abnormal behavior being investigated [4]. One such technique is Isolation Forest, which identifies unusual data points through random partitioning rather than relying on a predefined model of normal behavior [5]. This approach is useful for detecting unusual combinations of values collected from multiple sensors.

C. Statistical Change Detection

The CUSUM method introduced by Page identifies persistent changes by accumulating small deviations over time [6]. Roberts proposed control charts based on geometric moving averages, which form the foundation of the EWMA technique [7]. Montgomery's textbook on statistical quality control further explains these control charts and their practical applications [8]. The Z-score is another commonly used statistical measure that indicates how far an observed reading differs from the mean in terms of standard deviations.

D. Low-Power Communication

Augustin et al. examined LoRa technology and discussed its long-range communication capability and low power requirements for Internet of Things applications, along with its limitations [9]. These characteristics make LoRa a suitable communication option for monitoring tanks located far from conventional network infrastructure.

E. Research Gap

From the literature reviewed, wireless water quality monitoring and anomaly detection techniques are generally discussed as separate aspects, with less attention given to the influence of sensor placement at different depths within a tank. AquaWatch addresses this aspect by combining multi-depth sensing with anomaly detection and by comparing measurements collected from different levels of the same tank. However, a broader and more systematic literature review is required before making strong claims about the novelty of this approach. Its effectiveness should also be established through measurable comparisons, as outlined in Section VII.

III. Existing System

Current methods for monitoring stored water can generally be divided into two categories. The first involves manual or periodic sampling, in which water samples are collected and examined using field testing kits or laboratory methods. The second category includes online sensor-based monitoring systems, in which sensors are installed at a fixed location and transmit measurements to a remote server [2], [3]. However, the existing approaches still have some drawbacks:

- Monitoring water from a single point may not provide a clear understanding of its quality throughout the tank.
- Water conditions can differ at various depths due to sediment settling, mixing, temperature changes, incoming water, and other local disturbances. Because of this, changes near the bottom of the tank may not be noticed.
- In manual sampling, test results are available only after the collected samples have been examined in a laboratory. This delay makes it difficult to keep track of water quality continuously.
- Systems that rely only on fixed threshold values may miss unusual changes involving multiple sensor readings. In some cases, they may also produce unnecessary alerts.
- Maintaining continuous monitoring in remote areas is difficult because power supply may be limited and network connections may not always be reliable.

These limitations highlight the need for a multi-depth monitoring approach supported by data analysis, which is described in the following section. Table I compares conventional monitoring methods with the proposed approach.

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TABLE I
CONVENTIONAL MONITORING VERSUS AQUAWATCH

Aspect	Conventional	AquaWatch
Measurement location	One position or manual sample	Three depths in the same tank
Monitoring	Periodic, with delay before results	Continuous readings with remote dashboard
Alert logic	Fixed thresholds	Hybrid statistical and machine-learning analysis with cross-depth comparison
Remote use	Difficult where power and network are limited	LoRa link with solar-assisted power and local buffering

IV. Proposed System

A. Multi-Depth Monitoring Design

AquaWatch uses three sensor stations installed at different depths within the same tank. Each station has a specific monitoring role, as shown in Table II. Since all three sensor stations measure the same water quality parameters, their readings can be easily compared. If similar changes are detected at all three depths, it may indicate a change affecting the entire tank. However, if a change appears at only one depth, it could be due to a local water condition, differences in water layers, a sensor problem, or a temporary disturbance during measurement..

TABLE II
SENSOR STATIONS AND THEIR PURPOSE

Station	Depth	Purpose
Top	0.40 m	Observe conditions near the water surface
Middle	1.30 m	Observe conditions in the central water column
Bottom	2.10 m	Observe conditions near the tank floor, where settling may occur

The depths in Table II are example design values selected for the prototype. In a real-world installation, the sensor positions can be adjusted based on the tank's height, water level, sensor size, and mounting requirements. Each probe should remain properly submerged at its assigned depth. The arrangement should also make it easy to access the sensors whenever maintenance or calibration is needed.

B. water quality paramater

Each sensor station is designed to measure seven important water quality parameters, as shown in Table III. These measurements help identify changes in water conditions at different depths of the tank. To obtain reliable results, each sensor must be properly installed, regularly maintained, and calibrated when required. This helps ensure that the collected data is accurate and useful for further analysis..

TABLE III
WATER QUALITY PARAMETERs AT EACH DEPTH

Parameter	What it indicates	Implementation note
pH	Acidity or alkalinity	Use a suitable, calibrated probe
Turbidity	Cloudiness from suspended particles	Optical sensor; avoid bubbles and fouling
EC	Conductivity; related to dissolved ions	Temperature compensation may be needed
TDS (estimate)	Approximate dissolved solids	Usually derived from EC; an estimate only
Temperature	Thermal condition of water	Helps interpret the other readings
DO	Oxygen dissolved in water	Select probe type and maintenance carefully
ORP	Broad indicator of chemical conditions	Interpret with context; not a direct contaminant detector

A microcontroller such as the ESP32 collects sensor readings along with the time and depth at which they are recorded. The collected data is sent to a gateway through LoRa communication, which then transfers it to the cloud for further analysis. The analytics system examines the sensor readings, tracks changes over time, and compares water quality conditions across different depths. The results are displayed on a dashboard, and alerts are sent whenever unusual changes or patterns are detected..

C. Overall Operation

A microcontroller such as the ESP32 gathers sensor readings along with the corresponding time and depth details. This information is sent to a nearby gateway using LoRa communication. The gateway then transfers the data to the cloud, where further analysis takes place. The system checks individual readings, monitors changes over time, and compares the measurements collected from different depths. The analysed results are displayed on a dashboard, and alerts are generated whenever the system detects unusual changes in water quality.. A solar-assisted power supply is also planned to support operation in remote locations. Fluorescence sensors and optical sensors other than the turbidity probe are not included in the current system design.

V. Methodology

The operation of AquaWatch is organized into five main stages: data collection, baseline learning, anomaly scoring, cross-depth decision-making, and alert generation. Data quality management is also considered throughout these stages to improve the reliability of the monitoring process.

A. Data Collection

At every sampling interval, the sensor stations placed at the top, middle, and bottom of the tank collect readings for the selected water quality parameters. The ESP32 then records the time and depth details along with each set of readings before sending the data for further processing.. This allows readings from all three stations to be matched and compared by sampling time.

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B. Tank-Specific Baseline Learning

Normal water quality conditions may vary from one tank to another. AquaWatch therefore establishes a separate baseline for each tank and monitoring depth using previously collected reliable readings. Once a sufficient amount of valid data is available, the system determines the mean and standard deviation of each monitored parameter. These baseline statistics are then used by the statistical anomaly detection methods described below.

C. Anomaly Scoring

Z-score: The Z-score method measures how far an individual sensor reading lies from its previously established mean, using the standard deviation of the collected data. Readings that deviate considerably from the normal range are treated as potential anomalies. This method is particularly useful when the data follow a relatively stable distribution.

EWMA: The exponentially weighted moving average method is used to identify gradual changes in sensor readings over time. It gives greater weight to recent measurements while still considering earlier readings. This helps the system recognize slow variations that may not be detected through individual measurements [7].

CUSUM: The cumulative sum method identifies persistent changes by continuously tracking small deviations from the established baseline. It considers both upward and downward changes in the readings. When the accumulated deviation exceeds a selected decision limit, the system identifies a possible change in water quality. This method is useful for detecting small but continuous variations that may otherwise remain unnoticed [6].

Isolation Forest: Unlike the statistical methods, which examine individual parameters separately, Isolation Forest analyzes the complete set of sensor readings together. It identifies unusual data patterns by separating observations using randomly constructed decision trees, and data points that can be isolated more easily are considered potential anomalies [5]. In AquaWatch, this method helps detect uncommon combinations of sensor readings, even when individual parameter values remain within their predefined limits.

These methods are proposed components of the AquaWatch monitoring system and do not represent experimentally verified performance. The smoothing values, acceptable deviation limits, decision thresholds, and model settings have not yet been fixed in this study. These values will be determined using actual sensor readings, calibration records, and controlled testing. AquaWatch uses four different techniques that work together to identify changes in water quality. Isolation Forest helps identify unusual combinations of sensor readings, while Z-score detects values that differ significantly from the average. EWMA helps track gradual changes over time, and CUSUM is used to identify small changes that continue for a longer period. By combining these techniques, the system can identify different types of unusual water quality patterns more effectively.

D. Cross-Depth Decision Making.

Table IV explains how the system compares sensor readings from the top, middle, and bottom of the tank to identify and understand changes in water quality at different depths..

TABLE IV
CROSS-DEPTH INTERPRETATION OF OBSERVED PATTERNs

Observed pattern	Interpretation
Turbidity rises at all three depths	May suggest a tank-wide change
Change at one depth only	May be a localized condition, stratification, sensor issue, or disturbance
Turbidity, EC, and DO change together	Stronger evidence of an anomaly
Change persists over time	Higher confidence than a single-reading change

VI. IMPLEMENTATION

This section describes the planned implementation of the AquaWatch prototype. The final selection of components should consider sensor accuracy, compatibility with water, power requirements, communication range, and overall cost. The specific component models and sampling intervals will be finalized and documented during prototype development.

The AquaWatch system mainly consists of sensor probes placed at three different depths of the tank, an ESP32 or a similar microcontroller, and a LoRa module for data transmission. It also uses a gateway, with optional 4G connectivity, to send the collected data to the cloud. A solar power setup, including a solar panel, charge controller, and rechargeable battery, is used to supply power to the system. For actual field installation, additional items such as a weather-resistant enclosure, cable glands, mounting frame, and protective covers for the sensors are also needed. Regular cleaning, proper calibration, good waterproofing, and secure installation are essential to keep the system working reliably over time..

Firmware: The ESP32 collects data from the connected sensors and records the corresponding time and depth details for each reading. It then sends the collected data to the gateway through LoRa communication. If the network connection is unavailable, the system temporarily stores the readings in local memory and sends them once the connection is restored.

Practical Considerations: Proper sensor handling and maintenance are important to ensure accurate readings. Turbidity sensors may be affected by air bubbles or dirt collecting on their surfaces. EC readings may need temperature compensation, while temperature measurements also help in understanding changes in other water quality parameters. Dissolved oxygen (DO) sensors require regular maintenance, so their maintenance needs should be considered when selecting the sensor type. ORP readings should be checked along with other sensor measurements, as they provide a general indication of water conditions but cannot identify specific contaminants. All sensors must be properly installed at their assigned depths and kept submerged, with enough space for cleaning and calibration. Maintenance and calibration dates should also be recorded regularly.

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Cloud and Analytics: The cloud database stores the sensor readings collected from the top, middle, and bottom of the tank. The analytics system uses this data to establish a normal water quality baseline for each tank. It then applies the four selected anomaly detection techniques and compares the readings across all three depths. The system also keeps separate records of sensor data issues and unusual water quality patterns, as explained in Section V.

Dashboard: The dashboard is designed to show both current and previous sensor readings from all three depths of the tank. It allows users to compare the readings side by side, view changes in individual water quality parameters over time, and understand detected anomalies through their severity levels and explanations. It will also provide information about sensor conditions, network connectivity, battery level, and solar power status.

Development Phases: Prototype development is planned in six phases, summarized in Table V.

TABLE V
PROTOTYPE DEVELOPMENT PHASES

Phase	Activity
1. Sensor validation	Select and calibrate probes; check repeatability in controlled water samples
2. Three-depth assembly	Build a safe tank fixture; collect synchronized readings at the chosen depths
3. IoT communication	ESP32 acquisition, LoRa transmission, gateway link, local buffering
4. Cloud and dashboard	Store time-stamped readings; show depth-wise trends; keep sensor-health records
5. Analytics	Learn baselines; implement statistical methods and Isolation Forest; tune alerts with labeled test scenarios
6. Evaluation	Compare detection performance, false alarms, missed events, response time, power use, and data availability

VII. Results and Discussion

At this stage, the AquaWatch prototype has not yet been fully tested, so experimental results are not available. For this reason, performance values such as accuracy, detection time, and false alarm rates have not been included. Reporting these values without conducting proper experiments would not be reliable. Instead, this section explains how the system will be evaluated, what results are expected during testing, and the limitations that should be considered.

A. Evaluation Plan

The proposed system will be evaluated by comparing the results obtained from single-depth and multi-depth monitoring methods, as well as fixed-threshold detection and hybrid analytics. Different water quality disturbances will also be introduced under controlled conditions to observe how the system responds. The evaluation will focus on important performance measures such as precision, recall, F1-score, false-positive rate, detection time, sensor measurement error, system uptime, successful data transmission rate, and power consumption. These measurements will help determine how effectively AquaWatch detects unusual water quality changes and performs under real-world conditions.. The test scenarios planned for this evaluation are listed in Table VI.

TABLE VI
PLANNED TEST SCENARIOS

Scenario	Purpose
Normal operation	Learn the baseline and measure false alarms
Controlled turbidity change	Test detection of changes in suspended particles
Change in conductivity	Test response to a dissolved-ion change
Temperature variation	Check the effect on the other readings
Depth-localized disturbance	Test separation of local and tank-wide patterns
Simulated sensor faults	Check that faults are reported separately

For each labelled test scenario, the system's detection results will be checked using four outcomes: true positives, false positives, false negatives, and true negatives. These results will then be used to calculate precision, recall, F1-score, and false-positive rate. This evaluation will help understand how accurately AquaWatch identifies unusual water quality conditions while avoiding unnecessary alerts.

Precision shows how many of the alerts generated by AquaWatch correctly identify actual abnormal water quality conditions. It helps determine how reliable the system's alerts are and how often they indicate a genuine issue. Recall measures how effectively the system identifies the abnormal conditions present in the test data. The F1-score combines precision and recall into a single measure, and the false-positive rate is the proportion of normal conditions incorrectly identified as anomalies.

Detection delay is the time between the beginning of a controlled change and the generation of the first alert. Packet delivery rate is the proportion of transmitted data packets successfully received by the gateway, and system uptime is the portion of the testing period during which valid data are successfully produced. To ensure a fair comparison, both single-depth and multi-depth detection methods will be tested using the same recorded scenarios. This will help identify the actual differences in their performance without any variation in the test conditions.

B.. Expected Behavior

In the proposed system, EWMA and CUSUM are expected to help identify slow and continuous changes in water quality that might go unnoticed when only individual sensor readings are examined. The Z-score is intended to identify significant deviations from the established baseline, while Isolation Forest is designed to detect unusual combinations of multiple sensor parameters. The cross-depth comparison is expected to give more meaningful alerts by indicating the specific depth at which an unusual pattern occurs. However, these results are only expected based on the proposed system design and must be verified through the planned experiments..

C. Limitations and Responsible Uses

- Sensor readings help monitor changes in water quality, but they cannot detect or identify every type of pathogen, toxin, or chemical contaminant present in the water.
- Anomaly detection methods help identify unusual changes in sensor readings, but they cannot independently

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determine whether the water is safe to drink or contaminated..

- Factors such as sensor drift, dirt buildup, air bubbles, improper calibration, and incorrect sensor placement can affect the accuracy and reliability of the collected data.
- Before using the system in real-world conditions, its performance should be tested in different types of tanks, across various seasons, and under different operating conditions.
- Decisions about drinking water safety should be made according to the relevant water quality standards and confirmed through proper laboratory testing..

VIII. Advantages and Applications

A. Advantages,

- Monitoring water at three different depths provides a better understanding of the overall tank conditions compared to collecting readings from just one location.
- Combining machine learning with statistical methods may help reduce unnecessary alerts compared to traditional fixed-threshold methods. However, this improvement needs to be confirmed through proper experiments.
- Whenever an unusual condition is detected, the generated alert provides details about the affected sensors, the time of detection, and the related measurements. This helps users better understand the issue and identify what may have caused it.
- Continuous remote monitoring helps reduce the need for frequent manual inspections and repeated water sampling.
- The use of low-power LoRa communication and solar power helps make AquaWatch suitable for monitoring water tanks in remote areas where electricity and network connectivity may be limited..

B. Applications

AquaWatch can be used to monitor water storage tanks in rural and remote communities where grid-powered continuous monitoring and immediate access to water testing facilities may be limited. It can also support timely tank inspection and help users arrange confirmatory water testing whenever unusual conditions are detected.

IX. Conclusion

This paper presented AquaWatch, an IoT-enabled and AI-assisted approach for monitoring water quality at multiple depths within storage tanks. The proposed system uses three sensor stations to collect water quality parameters and transfers the readings through an ESP32, a LoRa communication module, and a gateway to a cloud platform. The collected data are analyzed using Isolation Forest, Z-score, EWMA, and CUSUM techniques, together with cross-depth comparison, to identify unusual patterns. Monitoring results are made available to users through a web dashboard and mobile alerts, while solar-assisted power supports the proposed operation in remote locations. This work describes the system design, methodology, implementation approach, and planned evaluation process. Further prototype development and experimental testing are required to measure its actual performance. Any alert generated by the system should be followed by physical inspection and confirmatory laboratory testing.

X. Future Scope

The following improvements are considered possible extensions of the proposed system and are not included in the minimum prototype implementation:

- Development of sensor-drift detection and diagnosis techniques.
- Introduction of adaptive, tank-specific baselines using previously collected historical data.
- Addition of predictive warning features to identify developing changes in water quality.
- Integration of additional optical or fluorescence-based sensing technologies.
- Optional camera-based monitoring for visual inspection of tank conditions.
- Development of a centralized monitoring network that can manage multiple water tanks through a single dashboard.

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