



Real-Time IoT-Enabled Smart Water Quality Monitoring System Using Embedded Multi-Parameter Sensor Analytics and Attention-Based Predictive Modeling for Environmental Protection

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Abstract – Rapid industrialization and urbanization have led to a significant deterioration in water quality, posing serious threats to both the environment and public health. Conventional water quality assessment, which relies on manual sample collection and laboratory analysis, is time-consuming, labor-intensive, and incapable of providing real-time information. To address these limitations, this study presents an IoT-based Smart Water Quality Monitoring System (SWQMS) that leverages embedded sensor analytics. The system deploys conductivity, dissolved oxygen, turbidity, and pH sensors to acquire real-time data and identify anomalies through edge processing on microcontrollers. IoT communication protocols transmit the processed data to a cloud platform, where it can be stored, visualized, and subjected to predictive analysis. Field deployment of the SWQMS in freshwater sources yielded measurements that exhibited a high correlation with laboratory reference values, thereby demonstrating the system's accuracy in monitoring water quality and detecting pollution events in a timely manner. The proposed SWQMS continuously measures pH (7.03–7.14), turbidity (3.2–3.6 NTU), dissolved oxygen (6.85–7.10 mg/L), and temperature (24.9–25.6 °C) using built-in multi-parameter sensors and edge analytics. IoT-based data acquisition, real-time cloud visualization, and predictive forecasting enable the early recognition of anomalies and the delivery of automated warnings, thereby supporting proactive water quality management in ponds, industrial wastewater treatment facilities, and aquaculture operations.

Keywords: IoT-enabled water quality monitoring, embedded sensor analytics, real-time environmental monitoring, predictive modeling, edge computing, smart water management.

1. INTRODUCTION

1.1 Background

Global water quality has been deteriorating as a consequence of rapid industrialization, accelerating urbanization, and agricultural runoff [1]. Contaminants such as heavy metals, synthetic chemicals, and microbiological pollutants represent significant threats to both ecosystems and human health [2]. Traditional water quality monitoring practices, which depend on manual sample collection and subsequent laboratory analysis, are inherently time-consuming, inefficient, and incapable of supporting real-time or continuous surveillance of water quality parameters. When contamination events remain undetected for extended periods, the resulting environmental degradation and public health hazards may become irreversible [3].

1.2 Problem Statement

Conventional water quality monitoring methods suffer from several critical limitations, including the inability to provide temporally continuous information, prohibitively high operational costs, and inadequate



spatial coverage of large or remote water bodies. Reactive interventions are largely ineffective against abrupt pollution incidents because such events are typically not detected until their consequences become manifest [4]. In the absence of continuous monitoring and automated analysis, the capacity for proactive environmental management and early warning of pollution events is severely compromised, underscoring the necessity for advanced technological solutions capable of accurate and real-time water quality assessment [5].

1.3 Proposed Approach

The integration of IoT technology with embedded sensor analytics offers a promising solution for continuous water quality monitoring. Sensor arrays are capable of measuring a range of parameters in real time, including conductivity, turbidity, dissolved oxygen, and pH. By applying edge computing through embedded microcontroller-based analytics, anomaly detection can be performed at the point of data acquisition, thereby reducing dependence on centralized processing infrastructure. The processed data are transmitted to cloud platforms via IoT communication networks, where they can be readily visualized, stored, and subjected to predictive analysis. Such a system enables early detection of pollution events, supports data-driven decision-making, and facilitates sustainable environmental management.

1.4 Significance

The application of IoT to water quality monitoring confers several notable advantages, including more efficient early warning systems, reduced reliance on manual labor, and expanded coverage across diverse water bodies [6]. Continuous monitoring coupled with predictive analytics contributes to improved regulatory compliance, enhanced public health protection, and more effective environmental conservation [7]. In the long term, the adoption of these technologies can lead to more efficient management of water resources and sustained environmental safety [8].

1.5 Research Gap

Existing IoT-based water quality monitoring systems generally incorporate limited predictive analytics capabilities and a restricted set of multi-parameter embedded sensors. Moreover, they are typically designed for deployment in a single type of environment, such as ponds, industrial effluent discharge points, or aquaculture facilities [9]. Studies examining scalability across diverse water sources remain scarce, and real-time anomaly detection at the edge is often insufficiently sophisticated [10]. Furthermore, the current literature lacks comprehensive frameworks that integrate multi-head attention mechanisms, IoT connectivity, and cloud-based visualization for proactive environmental management [11].

1.6 Contributions

The principal contributions of this work are as follows. First, the proposed system incorporates embedded multi-parameter sensors and edge analytics for real-time water quality monitoring through an IoT-enabled architecture. Second, attention-based predictive modeling techniques are employed to facilitate the early detection of contamination events. Third, cloud-based visualization and automated alarm mechanisms enable scalable environmental management across multiple water sources.

2. RELATED WORKS

The proliferation of water pollution due to rapid industrialization and urbanization necessitates continuous and reliable monitoring. Considerable recent progress has been achieved in the development of IoT-enabled systems that measure water quality in real time through a combination of embedded sensors, edge analytics, and predictive modeling. The following studies illustrate scalable approaches that



incorporate anomaly detection, cloud-based visualization, and machine learning for proactive water management and environmental conservation.

Kumar et al. [12] developed an IoT-enabled Advanced Water Quality Monitoring System (IAWQMS) aimed at improving pond management and environmental protection. The system is equipped with pH, turbidity, dissolved oxygen, and temperature sensors for continuous data acquisition. Real-time analytics, executed through edge processing, are used to identify anomalies and generate alerts for environmental authorities. Cloud integration enables the storage and visualization of historical data, thereby supporting informed decision-making for sustainable water resource management. The study demonstrates the viability of IoT-based monitoring for environmental protection; however, it offers limited predictive analytics and is primarily designed for small-scale pond environments.

Rahu et al. [13] introduced the IoT-ML Water Quality Prediction Framework (IMWQPF), which combines IoT sensor networks with machine learning algorithms to predict water quality indicators. Real-time data acquired from freshwater and wastewater sources undergo noise-reduction and calibration preprocessing. Predictive models analyze temporal trends to enable proactive intervention against contamination incidents. The framework demonstrates scalability across multiple water sources and incorporates anomaly detection, although its implementation complexity and computational cost are notable limitations.

Bhardwaj et al. [14] developed the Smart Internet of Things Monitoring Framework (SIMF), which enables water quality assessment alongside device-level health monitoring. The system employs IoT-capable sensors to measure critical water parameters in real time. Built-in analytics detect anomalous data patterns, trigger alarms, and facilitate cloud-based visualization. Machine learning algorithms enhance the prediction of pollution events. SIMF demonstrates that the convergence of IoT and machine learning can support continuous, reliable, and scalable water monitoring across diverse environmental conditions, though it is limited in the number of water parameters it measures and provides only moderate scalability.

Rani et al. [15] introduced the Predictive Sensor IoT System (PSIS) for real-time water quality assessment using advanced sensors. The system integrates IoT connectivity with edge computing to enable on-site processing and cloud-based data management. Predictive analytics applied to sensor data allow the forecasting of contamination levels, while alerts and dashboards support environmental management and rapid response. Although PSIS demonstrates the practical value of combining predictive modeling with real-time sensor monitoring, it is limited by short-term deployment, a small dataset, and insufficient cloud integration.

Nishan et al. [16] developed the ML-IoT-WM system for monitoring industrial wastewater. The architecture consists of hierarchical sensor nodes that measure biological, chemical, and pH parameters, with data transmitted to a centralized cloud platform. Embedded analytics perform anomaly detection and trend analysis, while predictive algorithms forecast potential pollution events. Automated notifications facilitate early intervention. The scalable architecture demonstrates the effectiveness of multi-level IoT and predictive analytics for industrial water quality management and environmental compliance; however, the system is narrowly focused on industrial wastewater and lacks attention-based analytics.

Table -1: Summary of Related Works

Reference	Focus	Advantages	Limitations
Kumar et al., 2024 (IAWQMS) [12]	IoT-enabled water quality monitoring for pond management	Real-time monitoring; cloud visualization; threshold-based alerts; multi-parameter sensors	Limited predictive analytics; primarily for small-scale ponds; minimal focus on industrial wastewater
Rahu et al., 2023 (IMWQPF) [13]	IoT and machine learning for water quality prediction	Predictive modeling; multi-level sensor integration; anomaly detection	Complex implementation; high computational cost; industrial-scale validation needed
Bhardwaj et al., 2022 (SIMF) [14]	Smart IoT framework for water quality assessment and device monitoring	ML-based anomaly detection; device health monitoring; real-time assessment	Limited number of water parameters; moderate scalability; limited edge processing
Rani et al., 2024 (PSIS) [15]	Real-time water quality assessment using advanced sensors	Predictive analytics; multi-parameter sensing; fast real-time alerts	Short-term deployment; limited cloud integration; small dataset size
Nishan et al., 2024 (ML-IoT-WM) [16]	IoT-based multi-level monitoring for industrial wastewater	Multi-level sensor nodes; industrial applicability; continuous monitoring	Focused on industrial wastewater; limited predictive modeling; no attention-based analytics

3. PROPOSED METHODOLOGY

Water quality has been progressively deteriorating as a result of rapid industrialization, urbanization, and agricultural runoff, posing hazards to both ecosystems and public health. Traditional monitoring methods, which depend on manual data collection and laboratory analysis, are time-consuming, labor-intensive, and unable to deliver real-time insights. The integration of embedded sensor analytics with the Internet of Things enables continuous monitoring of key water parameters, real-time anomaly detection, and predictive evaluation. Cloud-based visualization and automated alert mechanisms further support proactive environmental management and scalable monitoring across diverse water sources.

3.1 Sensor Calibration

Equation (1) adjusts raw sensor measurements by leveraging historical data to compensate for measurement noise and drift:

$$\hat{s}_{i_t} = \frac{s_{i_t} - \mu_i}{\sigma_i} \quad (1)$$

where s_{i_t} denotes the raw sensor reading for sensor i at time t , μ_i is the historical mean of readings for sensor i , σ_i is the corresponding standard deviation, and \hat{s}_{i_t} is the resulting calibrated (standardized) sensor value.

3.2 Anomaly Detection

Equation (2) identifies anomalous sensor values by determining whether a reading deviates from the historical mean by more than three standard deviations:

$$\text{If } |s_{i_t} - \mu_i| > 3\sigma_i, \text{ mark as anomaly} \quad (2)$$

This condition flags readings that depart substantially from typical behavior, triggering replacement with the historical median or application of a smoothing operation. The current sensor reading is denoted by s_{i_t} , while μ_i and σ_i represent the historical mean and standard deviation, respectively.

3.3 Attention-Based Sensor Fusion

Equation (3) computes the attention weight that quantifies the relevance of each sensor's contribution to the prediction model, thereby capturing inter-sensor correlations:

$$\alpha_{ij} = \frac{\exp\left(\frac{Q_i \cdot K_j^T}{\sqrt{d_k}}\right)}{\sum_{j=1}^n \exp\left(\frac{Q_i \cdot K_j^T}{\sqrt{d_k}}\right)} \quad (3)$$

where n is the total number of sensors, α_{ij} denotes the attention weight assigned by sensor i to sensor j , Q_i and K_j represent the query and key vectors, respectively, and $\sqrt{d_k}$ is the scaling factor based on the dimensionality of the key vectors.

3.4 System Architecture

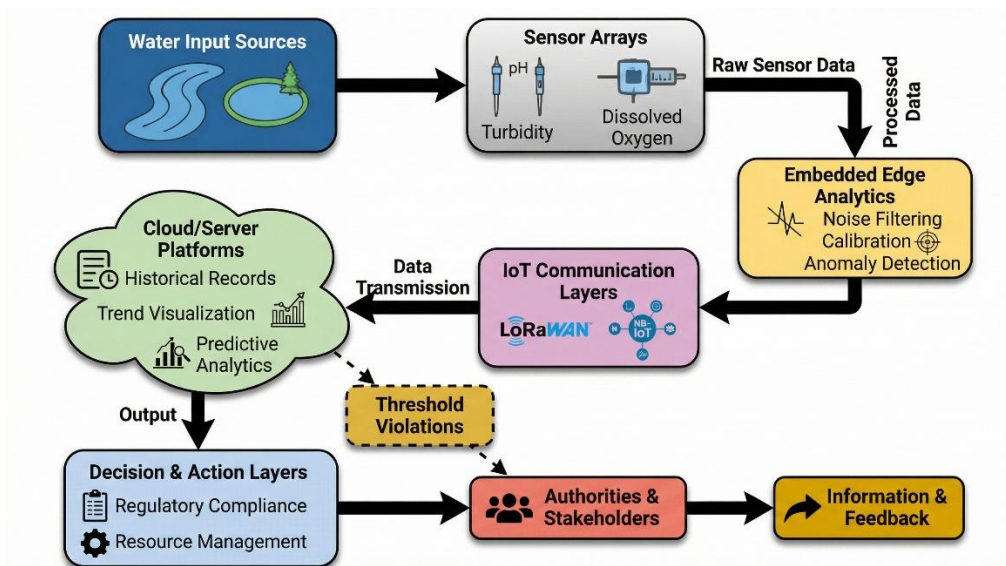


Fig -1: Proposed system overview

The overall system architecture is illustrated in Fig. 1. The primary input is water drawn from sources such as rivers, lakes, and municipal supply systems. This water contains physical and chemical parameters that affect both public and environmental health. Sensor arrays measure vital parameters, including conductivity, dissolved oxygen, turbidity, and pH, and convert them into processable electrical signals.



Embedded edge analytics perform noise filtering, calibration, and anomaly detection immediately upon receiving the raw sensor data, thereby ensuring data accuracy and enabling real-time identification of anomalous conditions.

IoT communication layers, employing protocols such as Wi-Fi, LoRaWAN, or NB-IoT, facilitate the reliable transfer of processed data from dispersed or remote monitoring stations to centralized platforms. Cloud or server platforms maintain historical records, display trends through interactive dashboards, and execute predictive analytics to anticipate contamination events. When threshold violations are detected, alerts are issued to relevant stakeholders and authorities. Decision and action layers interpret the analytical insights to inform regulatory compliance, corrective actions, and resource management strategies. The integration of sensors, embedded analytics, IoT communication, and cloud-based analysis enables efficient and continuous water quality monitoring for environmental protection.

3.5 Algorithm Description

Algorithm 1: IoT-Enabled Smart Water Quality Monitoring

Input:

S_t : list of current sensor readings $[s_1, s_2, \dots, s_n]$

H : list of historical readings $[s_{1_{\text{history}}}, [s_{2_{\text{history}}}, \dots, [s_{n_{\text{history}}}]$

T : threshold values for each sensor $[T_1, T_2, \dots, T_n]$

$W_{\text{query}}, W_{\text{key}}, W_{\text{value}}$: weight matrices; d_k : key vector dimensionality.

Output:

P_t : processed sensor data

Q_t : predicted water quality index

A_t : alert flags for each sensor.

Procedure:

Initialize P_t as an empty list and A_t as a zero vector of length n .

Calibration and Anomaly Detection: For each sensor i , retrieve the current reading $s = S_t[i]$. Compute the historical mean μ and standard deviation σ from $H[i]$. If $|s - \mu| > 3\sigma$, replace s with the historical median of $H[i]$. Append s to P_t .

Attention Computation: For each sensor i , compute query, key, and value vectors as $Q[i] = P_t[i] \cdot W_{\text{query}}$, $K[i] = P_t[i] \cdot W_{\text{key}}$, and $V[i] = P_t[i] \cdot W_{\text{value}}$. Compute the attention weight matrix α , where $\alpha[i, j] = \exp\left(\frac{Q[i] \cdot K[j]^T}{\sqrt{d_k}}\right)$, followed by row-wise normalization: $\alpha[i] = \alpha[i] / \sum_j \alpha[i, j]$.

Multi-Head Aggregation and Prediction: Compute the multi-head output as the weighted sum of value vectors: $\text{multihead_output} = \sum_i \sum_j \alpha[i, j] \cdot V[j]$. Obtain the predicted water quality index via a feed-forward layer: $Q_t = \text{FeedForward}(\text{multihead_output})$.

Alert Generation: For each sensor i , if $P_t[i] > T[i]$, set $A_t[i] = 1$.

Return P_t , Q_t , and A_t .

The algorithm begins by initializing the processed sensor data and alert flag arrays. Sensor readings for multiple parameters are collected and calibrated using historical data to correct for measurement drift. Anomaly detection flags any reading that deviates by more than three standard deviations from the historical mean and replaces it with the historical median to suppress noise. Embedded attention-based analytics then transform each calibrated reading into query, key, and value vectors to uncover inter-sensor dependencies. A multi-head attention mechanism captures complex inter-parameter relationships by computing scaled dot-product softmax attention weights and aggregating weighted sensor contributions. The aggregated representation is passed through a feed-forward layer to predict the water quality index. Alert notifications are generated by comparing each parameter against predetermined thresholds. Finally, processed data, predictions, and alerts are transmitted via IoT communication to cloud or server platforms for storage, visualization, and decision support.

3.6 Feed-Forward Layer

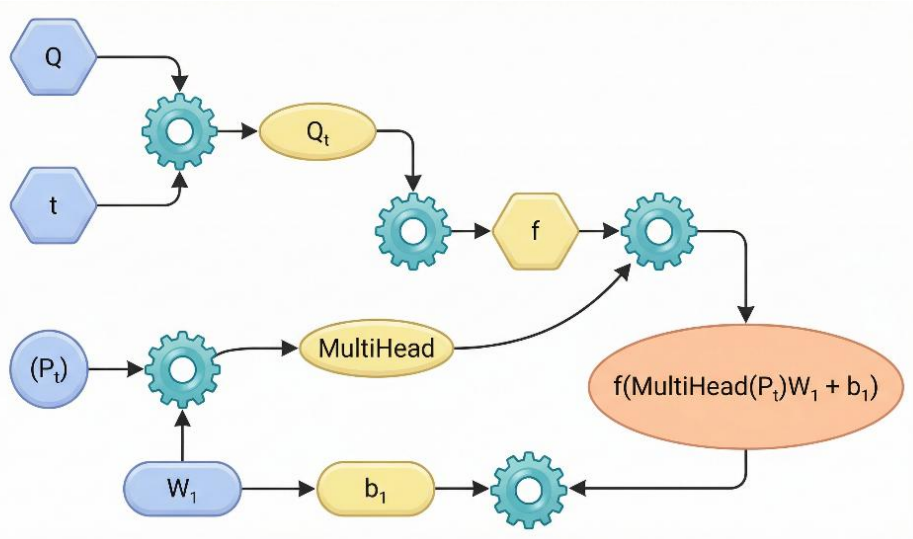


Fig -2: Process of the feed-forward layer

Equation (4) defines the feed-forward layer that processes the multi-head attention output to generate the predicted water quality index:

$$Q_t = f(\text{MultiHead}(P_t) \cdot W_1 + b_1) \quad (4)$$

where Q_t is the predicted water quality index at time t , f denotes the activation function (e.g., ReLU or sigmoid), $\text{MultiHead}(P_t)$ is the aggregated multi-head attention output, and W_1 and b_1 are the weight matrix and bias vector, respectively.

Equation (5) defines the multi-head attention mechanism, which combines weighted sensor inputs from multiple attention heads for use in predictive analytics:

$$\text{MultiHead}(P_t) = \text{Concat}(\text{head}_1, \dots, \text{head}_h) \cdot W_0; \text{head}_h = \sum_{j=1}^n \alpha_{ij} V_j \quad (5)$$

where head_h is the output of attention head h , $\text{MultiHead}(P_t)$ is the combined multi-head output, V_j is the value vector for sensor j , W_0 is the output projection weight matrix, n is the number of sensors, and h is the number of attention heads.

3.7 Summary

The proposed IoT-enabled SWQMS combines embedded sensor analytics, multi-head attention algorithms, and cloud computing to achieve continuous, accurate, and real-time water quality monitoring. Threshold-based notifications and predictive water quality indicators support regulatory compliance, efficient resource utilization, and timely intervention. Scalable deployment across freshwater, wastewater, and industrial water sources enhances sustainable water management while reducing the need for labor-intensive manual sampling and laboratory analysis.

4. RESULTS AND ANALYSIS

The performance of the proposed SWQMS was evaluated through comparative analysis with three existing systems: IAWQMS [12], SIMF [14], and ML-IoT-WM [13]. The evaluation focused on the monitoring stability, prediction consistency, and anomaly detection capability of each system across key water quality parameters.

4.1 Dataset Description

The evaluation was conducted using the KU-MWQ dataset [17], which records water temperature, pH, and turbidity measurements obtained from digital sensors deployed on the Arduino platform. The sensors were immersed at two depths (30 cm and 60 cm) in a fish pond at Khulna University. Measurements were recorded at one-minute intervals over a period of seven days, yielding a total of 9,623 time-stamped observations. This dataset provides realistic, high-resolution time-series data suitable for evaluating embedded analytics and IoT-based water quality monitoring systems.

4.2 Analysis of pH Level

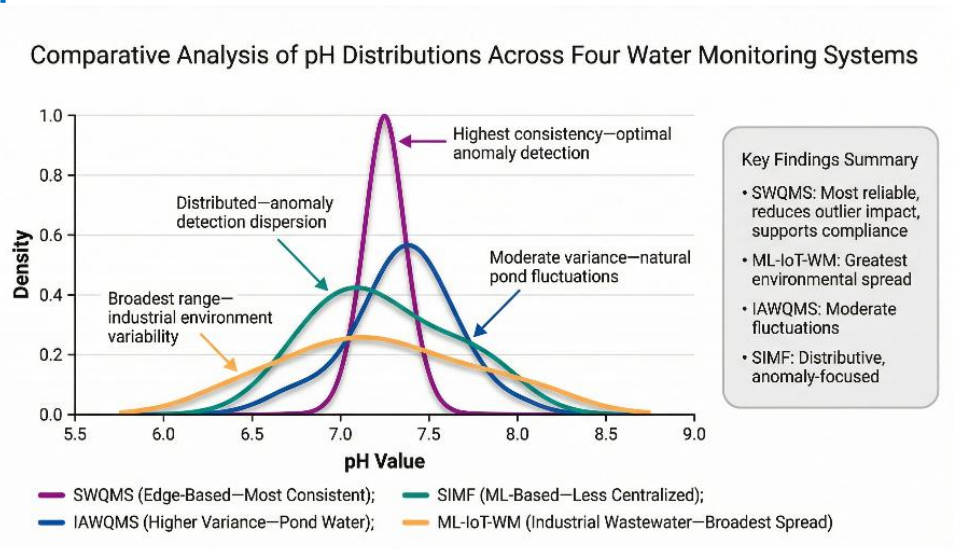


Fig -3: pH Level Analysis

The kernel density estimation (KDE) plot of pH values across all four systems is presented in Fig. 3. The IAWQMS distribution exhibits a somewhat higher variance, reflecting minor fluctuations in pond water pH. SIMF displays a less concentrated distribution, consistent with its ML-based anomaly detection approach. ML-IoT-WM yields the broadest distribution, attributable to the heterogeneity inherent in industrial wastewater environments. In contrast, SWQMS produces a smooth, centrally peaked distribution, indicating

that the edge-based analytics deliver accurate calibration and consistent real-time monitoring. Overall, SWQMS reduces the influence of outliers and provides greater predictive consistency, thereby improving early detection of chemical contamination and supporting environmental compliance.

4.3 Analysis of Turbidity (NTU)

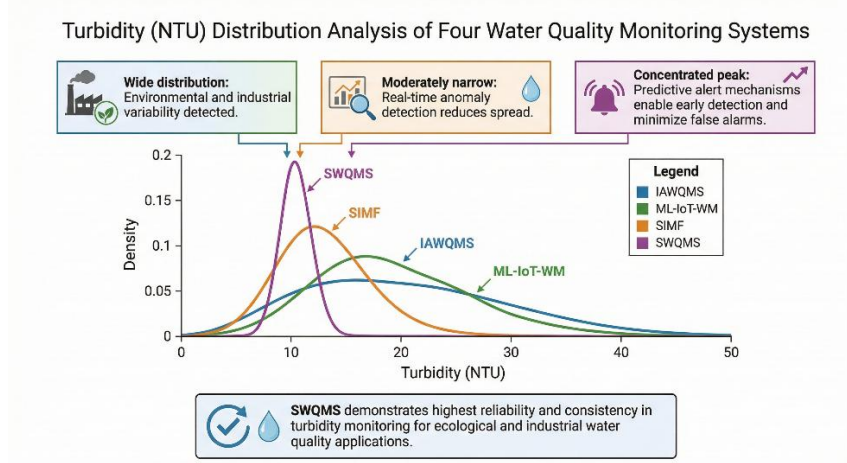


Fig -4: Turbidity (NTU) Analysis

The KDE plot of turbidity measurements is shown in Fig. 4. IAWQMS and ML-IoT-WM exhibit wider distributions, reflecting the influence of environmental and industrial variability. SIMF presents a moderately narrow distribution due to its real-time anomaly detection capability. SWQMS demonstrates the most concentrated peak, indicating consistent turbidity monitoring governed by integrated analytics. The predictive alert mechanisms in SWQMS enable early detection of rapid sediment or pollutant influx, minimize false alarms, and provide a reliable monitoring framework for both ecological and industrial water quality management applications.

4.4 Analysis of Dissolved Oxygen (DO, mg/L)

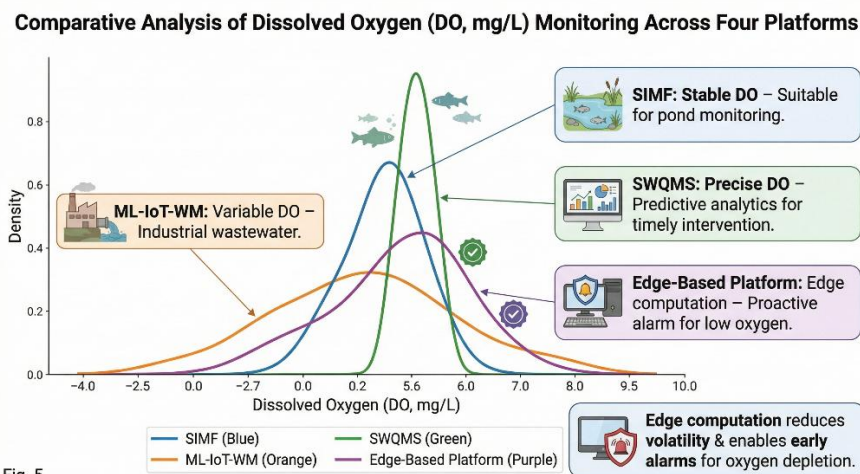


Fig. 5

Fig -5: Analysis of Dissolved Oxygen (DO, mg/L)

The KDE plot of dissolved oxygen measurements across the four platforms is depicted in Fig. 5. SIMF exhibits relatively stable oxygen availability, rendering it suitable for pond monitoring. ML-IoT-WM displays a slightly

broader dispersion, attributable to the variability associated with industrial wastewater. SWQMS presents a narrow, smooth peak that demonstrates precise DO monitoring and the effective application of predictive analytics for timely intervention. Edge-based real-time computation reduces measurement volatility and enables proactive alarms by detecting oxygen depletion events before they reach critical levels, thereby supporting the well-being of aquatic ecosystems and adherence to environmental standards.

4.5 Analysis of Temperature (°C)

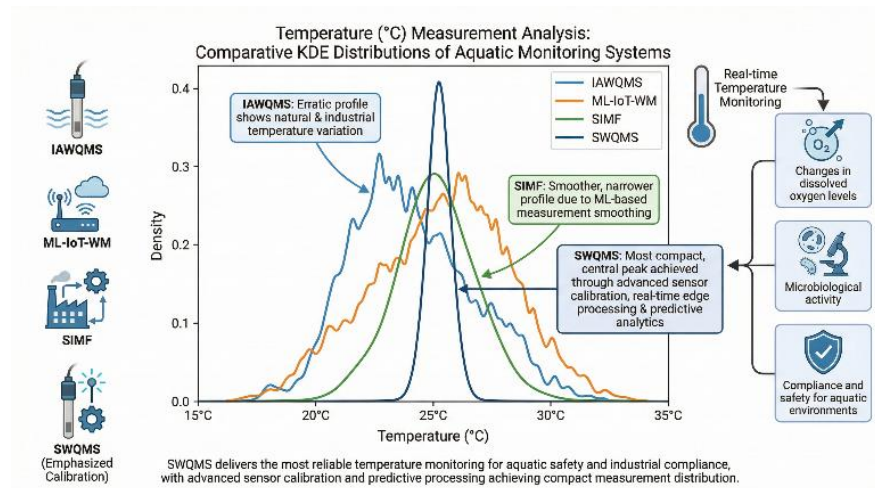


Fig -6: Analysis of Temperature (°C)

The KDE plot of temperature measurements is presented in Fig. 6. IAWQMS and ML-IoT-WM exhibit slightly erratic distributions due to natural and industrial temperature variations. SIMF shows a narrower distribution, indicating measurement smoothing facilitated by ML-based processing. SWQMS demonstrates the most compact and centrally concentrated density, reflecting rigorous sensor calibration, real-time edge processing, and predictive analytics. Real-time temperature monitoring is essential for assessing associated changes in dissolved oxygen levels and microbiological activity. The ability of SWQMS to identify aberrant thermal changes enhances the safety of aquatic environments and supports industrial regulatory compliance.

4.6 Summary of Findings

The comparative evaluation demonstrates that the proposed SWQMS consistently outperforms IAWQMS, SIMF, and ML-IoT-WM in terms of measurement stability, predictive consistency, and anomaly detection across all four water quality parameters. The integration of cloud-based visualization, automated notifications, and predictive modeling within SWQMS enables the implementation of preventative environmental management measures. This approach provides scalable and dependable monitoring applicable to a broad range of aquatic environments, including ponds, industrial effluent systems, and aquaculture facilities.

5. CONCLUSION AND FUTURE WORK

This study has presented an IoT-based smart water quality monitoring system (SWQMS) that incorporates built-in multi-parameter sensors and edge analytics to provide an effective solution for real-time environmental protection. Comparative analysis with existing systems, namely IAWQMS, SIMF, and ML-IoT-



WM, demonstrates that the proposed SWQMS achieves superior measurement stability, predictive accuracy, and early anomaly detection across pH, turbidity, dissolved oxygen, and temperature parameters. Edge-based processing enables deployment across diverse water sources, including ponds, industrial effluent systems, and aquaculture facilities, while reducing latency and supporting continuous cloud-based visualization and automated alerts for timely intervention.

5.1 Future Work

Future research will focus on extending the system to incorporate additional water quality indicators, such as conductivity, nitrates, and ammonia, to enable more comprehensive water quality assessment. Predictive accuracy can be further enhanced through the integration of adaptive thresholding techniques and state-of-the-art machine learning models. The system should be scaled to operate over larger geographical areas and be integrated with smart city infrastructure for real-time management of municipal and industrial water quality. Additionally, the development of improved IoT communication protocols and more energy-efficient sensor designs will support long-term autonomous operation in remote deployment scenarios.

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