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IoT-enabled smart water quality monitoring system using embedded sensor analytics for environmental protection applications

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Abstract—**Due to the rapid industrialization and urbanization, the water quality has been reduced significantly, which poses a threat to the environment and human health. Manual collection of water samples by hand and laboratory testing is a time and labor-consuming process and does not provide any source of real-time information. To solve such issues, an IoT-based Smart Water Quality Monitoring System (SWQMS) was designed on IoT with sensor analytics. Conductivity, dissolved oxygen, turbidity, and pH sensors are deployed to post real-time data and identify anomalies together with edge processing through microcontrollers. The IoT communication protocols are used to transfer the received data to a cloud platform, where this data may be stored, viewed, and analyzed to give predictions. SWQMS in freshwater sources had a high correlation with laboratory measurements, which demonstrates why it accurately monitors and detects the occurrence of pollution in time. The environment can be proactively controlled by constant monitoring, and it also gives early notice of contamination. The suggested SWQMS will constantly measure pH (7.037.14), turbidity (3.23.6⁻ 7.037.14⁻ 3.23.6□NTU), dissolved oxygen (6.857.10 mg/L), and temperature (24.925.6 °C) with inbuilt multi-parameter sensors and edge analytics. IoT-based data collection and forecasting, real-time, and visualization on clouds allow the timely recognition of anomalies early and the delivery of warnings towards water quality management on ponds, industrial wastewater, and aquaculture facilities.**

Keywords—IoT-enabled water quality monitoring; Embedded sensor analytics; Real-time environmental monitoring; Predictive modeling; Edge computing; Smart water management

I. INTRODUCTION

A. Background

The world has been experiencing poor water quality as a result of rapid industrialization, growth in urbanization, and agricultural run-off [1]. Heavy metals, chemicals, and microbiological pollution are some of the contaminants that are a significant threat to the ecosystem and human health [2]. Traditional systems of monitoring water quality that involve a manual process of collecting samples and analyzing them at a laboratory are time-consuming, inefficient, and do not constitute real-time and continuous monitoring of water quality. The destruction of nature and human health hazards may become irreversible in case the contamination events have been unnoticed for too long [3].

B. Problem Statement

The conventional methods of monitoring the water quality possess several limitations, including failure to provide temporal information, unreasonable costs of operation, and inability to capture large or remote areas. The reactive actions are less effective against abrupt cases of pollution because they are usually not detected until the manifestations are experienced [4]. It is explained by the fact that without continuous monitoring and automated analysis, the need to consider proactive environmental management, as well as the ability to provide an early warning in case of pollution incidents, is underestimated, which is why the use of cutting-edge technical solutions is necessary to analyze the water quality accurately and in real-time [5].

C. Proposed Approach

The integration of IoT and embedded sensor analytics can be regarded as one of the potential solutions to the continuity of water quality monitoring. There is an array of real-time factors that sensors may measure, including conductivity, turbidity, dissolved oxygen, and pH. Anomaly detection can be performed in real-time by reducing centralized processing, applying edge computing with embedded microcontroller-based analytics. The information relayed to the cloud over the IoT networks is simpler to visualize, store, and analyze in a predictive manner. With such a system, it is possible to monitor the instances of pollution early, make judgmental decisions based on information, and control the environment in a sustainable manner.

D. *Significance*

The attempts to apply an IoT to implement the water quality monitoring system are advantageous as they offer more efficient early warning systems, less reliance on human factors, and increased coverage of a wide range of bodies of water [11]. Forecast insights and ongoing monitoring contribute to the implementation of regulatory norms, the safety of the population in terms of health, and environmental conservation [13]. The use of these technologies can result in the efficient organization of water resources and environmental safety in the long term [12].

E. *Research Gap*

Current IoT-based water quality monitoring systems typically have minimal predictive analytics and multi-parameter embedded sensors and are typically limited to single-environment use, such as ponds, industrial effluent, or aquaculture [14]. Lack of scalability studies on various water sources is limited, and real-time anomaly detection is often not sophisticated with edge-based processing [15]. Moreover, the current body of literature lacks total frameworks of proactive environmental management that can integrate the multi-head attentiveness, the IoT connection, as well as the cloud-based visualization [16].

F. *Contributions*

The proposed monitoring water quality in real-time solution incorporates embedded multi-parameter sensors and analytics facilitated by the edge, which is achievable through the Internet of Things. Attention-based techniques are used to do predictive modeling to detect the occurrence of contamination early. Cloud-based visualization and automated alarms make it possible to manage the environment in a manner that can be scaled across multiple sources of water.

II. RELATED WORKS

The threats of water pollution have increased due to rapid industrialization and urbanization, and it should be monitored all the time. There has been much recent development in IoT-enabled systems, which are capable of measuring water quality in real-time via a combination of predictive modeling, edge analytics, and embedded sensors. To illustrate scalable models that incorporate anomaly detection, cloud-based visualization, and machine learning for preventative water management and environmental conservation, several studies have been selected to focus on environmental and industrial applications.

Kumar et al. developed an Advanced Water Quality Monitoring System (IAWQMS) that is supported by the IoT to improve pond management and environmental protection. The system is fitted with different pH, turbidity, dissolved oxygen, and temperature sensors to monitor data continuously. To identify anomalies and create alerts for the environmental authorities, real-time analytics are based on the edge process sensor information. Cloud integration assists in sustainable water resource management by making decisions, as it enables the storage and presentation of past data. The study suggests that it is possible to protect the environment with the help of IoT-based monitoring.

Rahu et al. introduced the IoT-ML Water Quality Prediction Framework (IMWQPF) by combining the IoT sensor networks with machine learning algorithms to predict water quality indicators. The noise-reduction and calibration preprocessing are performed on the real-time data obtained by the sensors of freshwater and wastewater sources. Predictive models analyze trends throughout the time period to allow them to take proactive action to avert incidents of contamination. The framework is very precise and reliable in estimating the quality of water by demonstrating scalability to numerous water sources, anomaly detection, and predictive analytics.

The Smart Internet of Things Monitoring Framework (SIMF), developed by Bhardwaj et al., allows for the evaluation of water quality together with device-level monitoring. To measure critical water parameters in real-time and keep tabs on device health, the system makes use of sensors that are IoT-capable. Analytics built right in can spot out-of-the-ordinary data, sound alarms, and even let you see it all in the cloud. Pollution occurrences can be better predicted with the use of machine learning algorithms. Continuous, dependable, and scalable water monitoring across many conditions may be achieved through the convergence of IoT and ML, as demonstrated by SIMF.

For the purpose of evaluating water quality in real-time with the use of sophisticated sensors, Rani et al. introduced the Predictive Sensor IoT System (PSIS). A combination of IoT connections and edge computing allows for instant processing and cloud integration in the system. You can predict the levels of contamination by using predictive analytics on sensor data. Environmental management and prompt responses are aided by alerts and dashboards. PSIS is a real-world example of how to improve water safety and environmental protection by combining predictive modeling with real-time sensor monitoring.

To consider the water quality in real-time using advanced sensors, Rani et al. proposed the Predictive Sensor IoT System (PSIS). On-site processing and cloud connectivity can be achieved in the system through a combination of IoT connections and edge computing. Predictive analytics on sensor data can be used to predict the levels of contamination. Alerts and dashboards facilitate environmental management and immediate reactions. The case of PSIS demonstrates that, in the real world, to enhance water safety and environmental preservation, predictive modeling is used in conjunction with real-time sensor monitoring.

The ML-IoT-WM system is a system that has been developed by Nishan et al. to monitor industrial wastewater. The data is sent to a centralized cloud platform and is measured using a number of hierarchical sensor nodes that measure biological, chemical, and pH factors. Embedded analytics perform anomaly detection and trend analysis, whereas predictive algorithms forecast potential cases of pollution. Early interventions are facilitated through automated notifications. With the assistance of this scalable architecture, the quality of industrial water and environmental compliance can be successfully implemented with the focus on the multi-level implementation of IoT and predictive analytics.

TABLE 1: RELATED WORKS SUMMARY

Reference	Focus	Advantages	Limitations
Kumar et al., 2024 (IAWQMS)	IoT-enabled water quality monitoring for pond management	Real-time monitoring; cloud visualization; threshold-based alerts; multi-parameter sensors	Limited predictive analytics; mostly for small-scale ponds; less focus on industrial wastewater
Rahu et al., 2023 (ML-IoT-WM)	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)	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	Real-time water quality assessment using advanced sensors	Predictive analytics; multi-parameter sensing; fast real-time alerts	Short-term deployment; less focus on cloud integration; small dataset size
Nishan et al., 2024	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

III. PROPOSED METHODOLOGY

Water quality has been deteriorating due to fast industrialization, urbanization, and agricultural runoff, which poses a hazard to ecosystems and human health. Traditional techniques of monitoring, which include collecting data by hand and analyzing it in a lab, are time-consuming, labor-intensive, and don't provide any insights in real-time. Key water parameters may be continuously monitored, anomalies can be detected in real-time, and predictive evaluation can be performed with the help of embedded sensor analytics and the Internet of Things. The use of cloud-based visualization and automated alarms allows for the proactive management of the environment and the scalable monitoring of many water sources.

Equation 1 adjusts the measurements of the raw sensors by utilizing past data to fix measurement noise and drift.

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

$\hat{s}_{i_t}$is the raw sensor reading, μ_i is the mean of all historical readings for sensor i, and σ is the standard deviation of all historical readings for sensor i. It is the calibrated sensor value for sensor i at time t.

Equation 2 determines if sensor values are significantly off from noise handling standards beyond three standard deviations.

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

If condition identifying readings that considerably depart from typical behavior for anomaly replacement or smoothing. The current sensor reading is represented by sit, the historical mean and standard deviation are denoted by $\boldsymbol{\mu i}$ ***and*** $\boldsymbol{\sigma i}$, respectively.

Equation 3 determines how much weight to give to the correlation between sensors in the prediction model.

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

The formula n represents the total number of sensors, α_{ij} stands for the attention weight of sensor j for sensors i, Q_i for query vector, K_i for the key vector, and $\sqrt{d_k}$ for the dimension of key vectors.

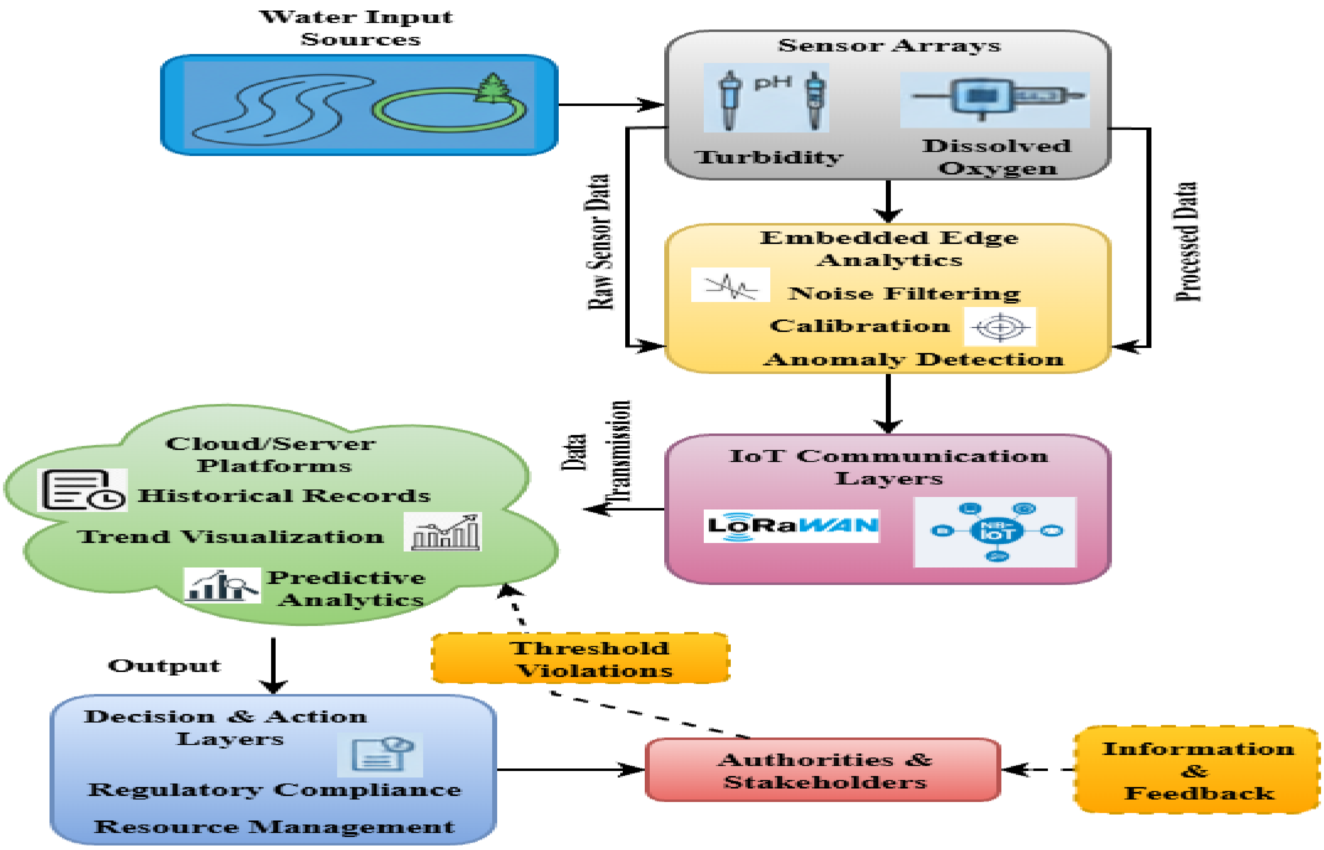

Fig. 1 Proposed system overview

The main input for continuous monitoring is water, which comes from places like rivers, lakes, and municipal supply systems. This water contains factors that affect public and environmental health, including physical and chemical ones, and the process is shown in Fig.1. Through the use of sensor arrays, vital signs such as conductivity, dissolved oxygen, turbidity, and pH can be measured and transformed into processable electrical signals. To assure data accuracy and real-time identification of anomalies, embedded edge analytics perform noise filtering, calibration, and anomaly detection immediately upon receiving the raw sensor data. Reliable transfer of processed data from dispersed or remote monitoring stations to centralized platforms is made possible through IoT communication layers employing protocols like Wi-Fi, LoRaWAN, or NB-IoT. To foresee contamination incidents, platforms in the cloud or on servers keep historical records, display trends through dashboards, and perform predictive analytics. Threshold violation alerts provide stakeholders and authorities with the information they need to take appropriate measures. Compliance with regulations, corrective actions, and strategies for managing resources are all influenced by insights interpreted by decision and action layers. Water quality can be efficiently and continuously monitored for environmental protection through the integration of sensors, embedded analytics, IoT connections, and cloud-based analysis.

Algorithm 1: IoT-Enabled Smart Water Quality Monitoring Algorithm

Input:
S_t list of current sensor readings $[s1, s2, \ldots, sn]$
H: list of historical readings $[s1_{history}], [s2_{history}], \ldots, [sn_{history}]$
T: threshold values for each sensor $[T1, T2, \ldots, Tn]$

Output:
P_t: processed sensor data
Q_t: predicted water quality index
A_t: alert flags for each sensor

def $SWQMS(S_t, H, T, W_{query}, W_{key}, W_{value}, d_k)$
$n = len(S_t)$
$P_t = [n]$
$A_t = np.zeros(n)$

$\# \, Calibration \; and \; anomaly \; detection$
$for \; i \; in \; range(n)$
$s = S_{t[i]}$
$\mu, \sigma = np.mean(H[i]), np.std(H[i])$
$if \; abs(s - mu) > 3 * sigma$
$s = np.median(H[i])$
$P_t.append(s)$
$\# \, Attention \; computation$
$Q, K, V = [i], [i], [i]$
$for \; i \; in \; range(n)$
$Q.append(P_{t[i]} @ \, W_{query})$
$K.append(P_{t[i]} @ \, W_{key})$
$V.append(P_{t[i]} @ \, W_{value})$
$\alpha = np.zeros((n, n))$
$for \; i \; in \; range(n)$
$for \; j \; in \; range(n)$
$$\alpha[i, j] = np.\exp\left(\frac{Q[i] @ \, K[j].T}{np}.sqrt(d_k)\right)$$
$\alpha[i] \mathrel{/}= np.suma[i])$

$\# \, Multi-head \; aggregation \; and \; prediction$
$multihead_{output} = np.sum([\alpha[i, j] * V[j] for \; i \; in \; range(n) for \; j \; in \; range(n)], axis = 0)$
$Q_t = FeedForward(multihead_{output})$
$\# \, Alert \; generation$
$for \; i \; in \; range(n)$
$if \; P_{t[i]} > T[i]$
$A_{t[i]} = 1$
$return \; P_t, Q_t, A_t$

The initialization of processed sensor data alarm flags is the first step of Algorithm 1. The measurement drift is corrected by collecting sensor readings from various parameters and calibrating them using historical data. If the result is more than three standard deviations out of the ordinary, anomaly detection will flag it and replace it with the median from the past to bring the noise level down. To uncover inter-sensor dependencies, embedded attention-based analytics converts each calibrated reading into query, key, and value vectors. A multi-head system can capture complicated relationships by aggregating weighted sensor contributions and computing attention weights using scaled dot-product Soft Max. The water quality index is predicted by passing the aggregated representation through a feed forward layer. Notifications are generated by comparing each parameter to predetermined thresholds. And lastly, for storage, visualization, and decision-making, processed data, forecasts, and warnings are sent via IoT communication to server or cloud platforms. This algorithm allows for the automatic, precise, and real-time monitoring of water quality.

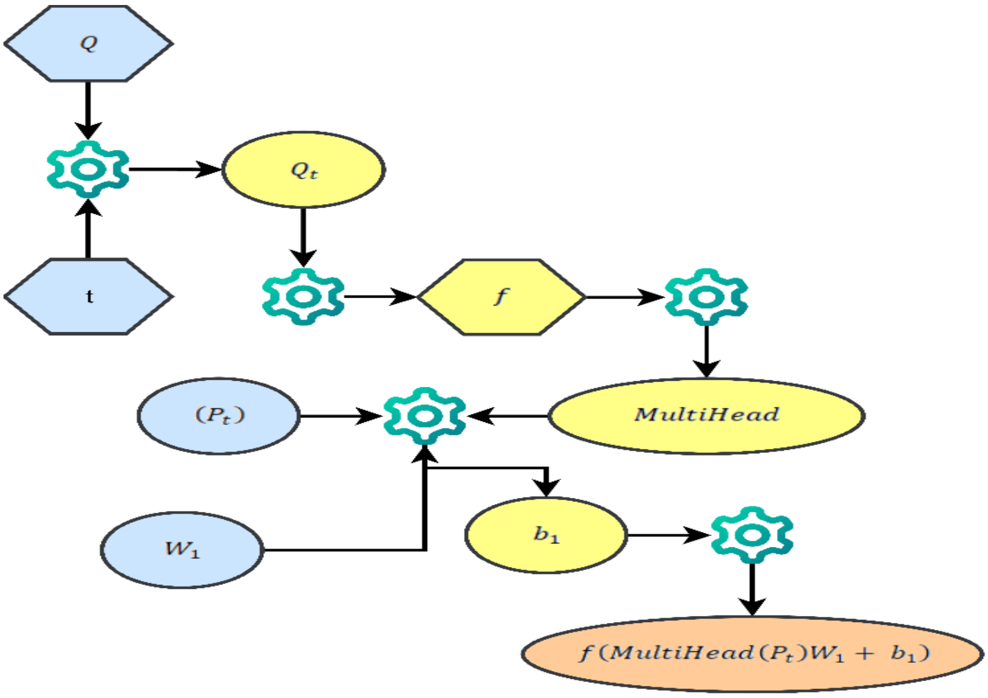

Fig.1.a Process of the feed forward layer

Equation 4 is utilized as a feed forward layer that processes the outputs from several heads and uses them to generate the final water quality index.

$$Q_t = f(MultiHead(P_t)W_1 + b_1) \quad (4)$$

The projected water quality index at time b is denoted as Q_t. The activation function is represented by f and can be ReLU or sigmoid. The aggregated multi-head output is called $MultiHead(P_t)$. The weight matrix and bias vector are denoted by W_1 and b_1, respectively shown in Fig. 1.a.

Equation 5 combines the weighted sensor inputs from various attention heads for use in predictive analytics.

$$MultiHead(P_t) = Concat(head_1, \dots, head_h)W_O; head_h = \sum_{j=1}^{n} \alpha_{ij} V_j \quad (5)$$

Head h is the output of the attention head h, $MultiHead(P_t)$ is the combined multi-head output, V_j is the value vector of the sensor j, W_O is the output weight matrix, n is the number of sensors, and h is the number of heads.

With the help of IoT-enabled smart water quality monitoring systems, the air can be safer, and the ecological environment can be better preserved, as it will help identify and prevent pollution accidents quickly. Combining cloud computing, multi-head attention algorithms, and embedded sensor analytics allows for generating alerts in real-time and providing constant and accurate monitoring.

Threshold-based notifications and predictive indicators of water quality help to comply with regulations, efficiently use resources, and take action in time. Scalable deployment across freshwater sources enhances sustainable management of water and decreases the quantity of water that requires laboratory analysis and manual sampling.

IV. RESULTS AND ANALYSIS

The water quality has been seriously impacted due to the high rate of industrialization, urbanization, and agricultural runoff, as this is a threat to the ecosystem and human health. Conventional monitoring methods are time-consuming, and they do not give any information in real time. IoT-enabled systems with multi-parameter sensors embedded on them wear edge analytics and can automatically and constantly evaluate water quality. Early detection of contamination events can be done through a mix of cloud-based visualization, real-time notifications, and a combination with predictive models. This allows environmental proactive management and scalable monitoring of the different sources of water, such as freshwater, wastewater, and industrial water.

A. Dataset Description

The KU-MWQ dataset measures water temperature, pH, and turbidity using the digital sensors designed using the Arduino platform and immersed at two different depths of 30 and 60 cm in a fish pond of Khulna University. Measurements were taken every minute over a period of seven days, and the total sets taken were 9,623 with time stamps. This dataset is realistic and has high-resolution time series data, which can be used in embedded analytics and water quality monitoring based on the Internet of Things [18].

B. Analysis of pH Level

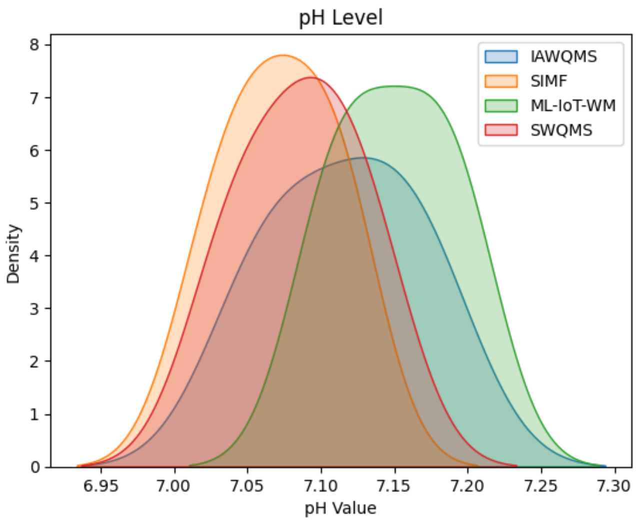

Fig. 2 pH Level Analysis

Acidity and alkalinity readings from all four systems are shown in the KDE pH graphic in Fig. 2. There are small variations in the pond water, as shown by the somewhat higher variance in IAWQMS. SIMF shows a less dense distribution, which is consistent with values obtained using ML-based anomaly detection. The heterogeneity of industrial wastewater has led to ML-IoT-WM having a greater distribution. SWQMS shows a centralized peak that is smooth, which means that the analytics at the edge are correct and that real-time monitoring is consistent. In general, SWQMS helps to lessen outliers and offers predictable consistency, which improves chemical contamination detection in the early stages and keeps environmental compliance under check.

C. Analysis of Turbidity (NTU)

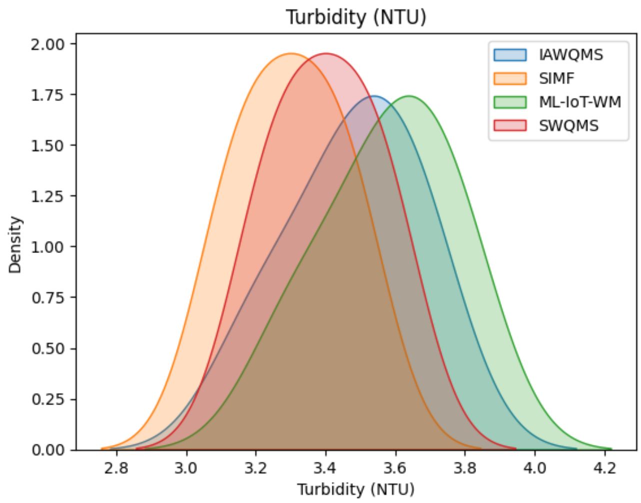

Fig. 3 Turbidity (NTU) Analysis

A time series of observations of suspended particle density is shown by the turbidity in Fig. 3. Environmental and industrial variables contribute to the wider distributions seen in IAWQMS and ML-IoT-WM. Because of the real-time anomaly detection, SIMF has a somewhat narrow distribution. The most concentrated peak is shown by SWQMS, which means that the turbidity is being monitored consistently and regulated by integrated analytics. Supporting real-time water quality management for ecological and industrial applications, predictive alert mechanisms in SWQMS enable early detection of rapid sediment or pollution influx, minimize false alarms, and provide a reliable water quality monitoring system.

D. Analysis of Dissolved Oxygen (DO, mg/L)

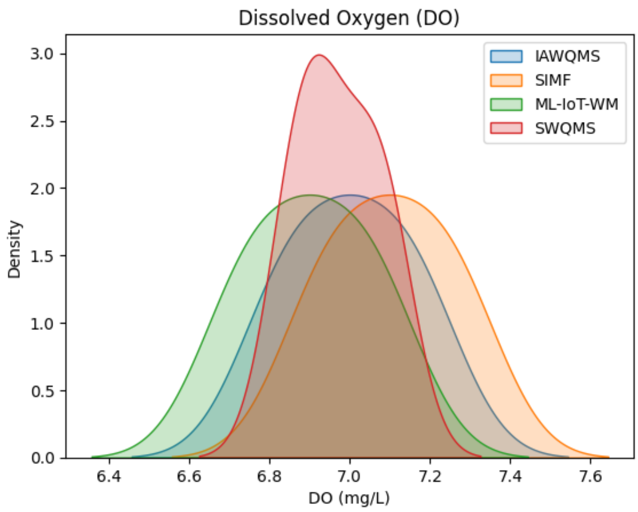

Fig**. 4 Analysis of Dissolved Oxygen (DO, mg/L)**

The trends of oxygen availability on different platforms are depicted in Fig. 4, and SIMF can be used in monitoring the pond because oxygen availability is fairly constant. Even the slightly larger dispersion of ML-IoT-WM is attributable to the variability of industrial wastewater. In SWQMS, a narrow and smooth peak is presented, which demonstrates the accurate monitoring of DO and the application of predictive analytics to take action in time. Prolonging the well-being of aquatic ecosystems and ensuring that the environmental standards are followed, the edge-based real-time computation makes the volatility subsidence lower and proactive alarms possible because it detects the oxygen depletion cases prior to reaching critical levels.

E. *Analysis of Temperature (°C)*

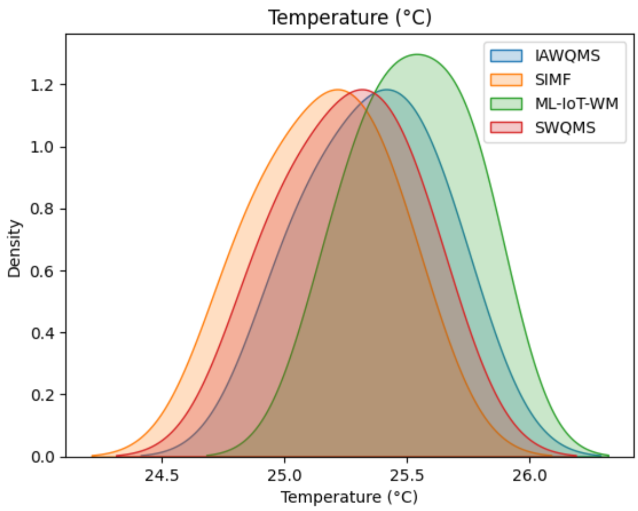

Fig. 5 Analysis of Temperature (°C)

The temperature of systems shows the thermal trends in Fig. 5. IAWQMS and ML-IoT-WM show slightly erratic spreads due to variations in industrial and natural temperature. SIMF is also a narrower concept that points to the fact that the measurements were smoothed with the assistance of ML. SWQMS demonstrates the leanest and centralized density, with a focus on the strict calibration of sensors and real-time processing at the edge and predictive analytics. Water quality management systems (SWQMS) enhance the safety of aquatic environments and industrial adherence in real-time through the identification of aberrant thermal changes, and real-time temperature monitoring is used to assess the changes in dissolved oxygen and microbiological activity.

Smart water quality monitoring systems provided by the Internet of Things, made possible through the use of embedded multi-parameter sensors and edge analytics, also provide a continuous and real-time evaluation process. Findings indicate that ML-IoT-WM is better than IAWQMS, SIMF, and IAWQMS in measuring stability, predictability, and anomalies. SWQMS is able to integrate cloud visualization, automatic notifications, and predictive modeling, so as to enable preventative measures to be implemented. This method, in addition to enhancing environmental safety and control in such cases as environmental regulations, provides scalable and dependable monitoring to a broad range of aquatic ecosystems, such as ponds and industrial wastes.

V. CONCLUSION AND FUTURE WORK

IoT-based smart water quality monitoring systems with built-in multi-parameter sensors and edge analytics offer an effective solution to the dilemma concerning environmental protection in real-time. The SWQMS proposed improves the stability of measurements, prediction, and provides an early indication of anomalies in pH, turbidity, dissolved oxygen, and temperature parameters, as it was proved in a comparative analysis with the already existing current systems like IAWQMS, SIMF, and ML-IoT-WM. The edge-based processing can also be used in diverse water sources, including ponds, industrial effluent, and aquaculture, reducing the latency and enabling the continuous view and automatic alarms, respectively, to implement timely interventions.

A. *Future works*

To enable scientists to conduct a more comprehensive analysis of the system, future research will focus on improving the system to incorporate additional water quality indicators, such as conductivity, nitrates, and ammonia. Even greater predictive accuracy can be boosted by combining adaptive thresholding and state-of-the-art machine learning models. The water quality of municipal and industrial can be administered in real-time and scaled to operate over larger geographical locations and engage with smart city infrastructure. Better protocols on how the IoT should be connected and more energy-efficient sensor designs will enable it to operate autonomously in the long term..

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Author Contributions:
G. MANIKANDAN, Problem Selection, Algorithm, Implementation, Results Implementation,

Coding and Testing

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