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An Edge–Cloud Integrated Smart Monitoring System for Sustainable Freshwater Fishpond Management

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ABSTRACT

Water quality is a critical determinant of fish health and productivity in freshwater aquaculture, with parameters such as pH, dissolved oxygen (DO), temperature, and turbidity directly influencing growth, metabolism, and disease susceptibility. Traditional monitoring methods, based on manual sampling and laboratory analysis, are often slow, labor-intensive, and unable to detect rapid environmental changes. This paper presents the design and implementation of a hybrid edge–cloud integrated smart monitoring system for sustainable freshwater fishpond management. The system employs an ESP32-based edge node to collect real-time water quality data, detect threshold violations locally, and trigger immediate responses, including LED/buzzer alarms and actuator activation, while simultaneously sending email alerts via SMTP. Long-term data storage, visualization, and remote access are enabled through a cloud platform integrated with MQTT-based data publishing. Experimental evaluation demonstrated a total detection-to-action latency of 3.4 s, local alerts in 1.0 s, email notifications within 7.0 s, and cloud synchronization latency of 150 ms. Sensor measurements achieved high accuracy, with maximum deviations of only ±0.11 pH units, 0.3 mg/L DO, 0.21 NTU turbidity, and 0.2°C temperature. The system maintained 100% uptime during stable network conditions, confirming its reliability for continuous aquaculture monitoring. By combining low-latency local decision-making with cloud-based analytics, the proposed solution enhances operational efficiency, supports proactive management, and aligns with SDG 6 (Clean Water and Sanitation) and SDG 14 (Life Below Water). Future work will focus on integrating machine learning models for predictive water quality analysis and expanding the platform to other aquaculture and smart farming applications.

Keywords: Water quality; water monitoring; cloud computing; edge computing

INTRODUCTION

Water quality is fundamental to the health and productivity of aquaculture systems, particularly freshwater fishponds. Key parameters, including pH, dissolved oxygen (DO), temperature, and turbidity, critically influence fish metabolism, behavior, and disease susceptibility (Hridoy et al. 2025). Even minor fluctuations in these metrics can trigger stress responses or health issues in pond-raised species (Zhang et al. 2025). Traditional water-quality monitoring relies on manual sampling and laboratory analysis, which are time-consuming and often unable to capture rapid environmental changes (Yunus et al. 2023). In response, IoT-based monitoring systems have emerged, enabling continuous, real-time collection of water-quality data in aquaculture environments, thereby enhancing management efficiency and reducing operator workload (Flores-Iwasaki et al. 2025; Recommendations 2025). While cloud-only IoT platforms offer centralized storage and remote visualization, they tend to suffer from latency, network dependency, and the inability to react promptly to sudden parameter deviations (Ajith Jerom et al. 2020; Jha, 2020). These limitations have prompted interest in edge computing, which brings lightweight data processing closer to the sensors. Edge-enabled systems can trigger on-site alarms or activate actuators instantly when water-quality thresholds are breached, even under poor network conditions (Chavhan et al. 2025; Dwarakanath et al. 2023; Hudda & Haribabu 2025).

Despite growing advancements in aquaculture technology, many small to medium scale freshwater fishpond operations, particularly in rural or developing regions, still rely on manual methods for water quality assessment. This introduces substantial risks of late detection, where deteriorating water conditions may lead to mass fish mortality or reduced growth rates, resulting in significant economic losses and environmental concerns. Recent studies emphasize the importance of real-time and automated monitoring to mitigate such risks (Durgun, 2024; Muthukumar et al. 2023; Zainurin et al. 2022). However, existing IoT systems often rely solely on cloud computing, which may introduce latency, network unreliability, and dependence on stable internet connections, all of which limit their effectiveness in dynamic and remote fishpond environments (Jha, 2020). Furthermore, many prior systems lack immediate response capabilities at the local level. Without edge-side decision-making, data must first travel to the cloud before any alarm or control action is taken, delaying potentially life-saving interventions for the aquatic ecosystem (Jha, 2020). In addition, most existing solutions do not offer integrated alert mechanisms, such as on-site alarms and email notifications, to actively inform pond managers about threshold violations. The absence of proactive communication limits the practicality of such systems, especially for operators who are not always physically present at the fishpond site. Motivated by these challenges, this work proposes a hybrid edge–cloud-based automated monitoring system that combines low-latency edge computing for on-site detection and alerts, with cloud-based storage and analytics for long-term water quality assessment and predictive analysis. By addressing both real-time responsiveness, this solution supports the foundational monitoring and control requirements of sustainable aquaculture and aligns with the objectives of SDG 6 (Clean Water and Sanitation) and SDG 14 (Life Below Water).

While IoT-based cloud monitoring systems have been proposed and adopted in some modernized setups, they largely depend on centralized cloud platforms to process sensor data and trigger responses. This centralized approach introduces multiple limitations such as latency and delay, since data must travel from sensors to the cloud and back before an action is taken, there is a potential delay that can prove detrimental in critical water quality events. Network dependence, since in many aquaculture settings, particularly rural areas, stable internet connectivity cannot be guaranteed. In such cases, cloud-only systems become unreliable or non-functional. Lack of local autonomy, since without the ability to process and act on data locally, current systems cannot deliver immediate alarms or corrective measures when thresholds are breached.

Additionally, existing systems often lack a scalable data management strategy that facilitates future integration with artificial intelligence (AI) or deep learning tools for trend analysis and prediction. Most traditional deployments either discard historical data or fail to leverage it effectively, limiting their value in long-term ecosystem monitoring and predictive insights (Essamlali et al. 2024). Another significant shortcoming is the absence of intelligent notification mechanisms. Farm operators are not always present at the pond site. A system that does not provide remote alerts, such as email notifications, limits the operator's ability to respond swiftly and efficiently. Taken together, these limitations highlight a critical need for an integrated, automated, and resilient monitoring solution that can:

1. Monitor vital water quality parameters in real time,
2. Perform on-site evaluation and issue immediate alarms when thresholds are violated,
3. Provide remote alerts through email,
4. Store historical data in the cloud for advanced analysis and model training, and
5. Function reliably in areas with unstable network connectivity by utilizing edge computing.

The proposed hybrid architecture that combines edge and cloud computing, coupled with sensors and actuators, is positioned to bridge this technological gap. It provides a smart, scalable, and autonomous platform for sustainable aquaculture monitoring, aligning with global goals such as SDG 6 (Clean Water and Sanitation) and SDG 14 (Life Below Water).

The main objective of this research is to develop and deploy a smart water quality monitoring system for freshwater fishponds by integrating edge and cloud computing technologies. This system aims to automate the continuous assessment of essential water parameters, pH, temperature, DO, and turbidity, to ensure optimal conditions for fish health and aquaculture sustainability. The specific objectives of this research are: to design and implement a sensor-driven edge computing architecture capable of collecting real-time water quality data and autonomously detecting violations in safe operating ranges for pH, DO, temperature, and turbidity. To enable immediate local response using actuators and alarms triggered directly by the edge system, thereby minimizing dependency on cloud platforms and ensuring low-latency reaction to water quality hazards. To establish a cloud-based storage and processing platform for aggregating long-term water quality data, allowing scalability and potential integration with AI/deep learning models for future prediction and analysis. To incorporate automated remote notification mechanisms (e.g., email alerts) to inform fishpond operators promptly when water quality parameters deviate from acceptable thresholds, even if they are not physically present at the site. To ensure the system supports environmental sustainability goals, specifically contributing to SDG 6 (Clean Water and Sanitation, by promoting efficient and automated water quality monitoring practices) and SDG 14 (Life Below Water, by enabling better ecosystem management for freshwater fish and reducing aquaculture-related risks).

The primary contribution of this work lies in the realization and validation of a physically deployed, edge–cloud integrated monitoring system designed for real-world freshwater aquaculture environments. Rather than proposing a novel architectural paradigm, this research advances the state of the art through a performance- and deployment-driven contribution, demonstrating a complete end-to-end implementation that couples on-site sensing, local decision-making, autonomous actuation, and cloud connectivity within an operational fishpond setting. Through quantitative evaluation of end-to-end latency, sensing accuracy, and system reliability, the proposed solution provides empirical evidence of its practicality and deployment readiness, addressing critical gaps in existing edge–cloud aquaculture studies that largely remain conceptual, cloud-centric, or insufficiently validated under real operating conditions. This contribution establishes a robust and scalable technological foundation for sustainable aquaculture monitoring and future intelligent extensions, with potential alignment to the objectives of SDG 6 and SDG 14.

RELATED WORK

Recent advancements in aquaculture monitoring increasingly integrate Internet of Things (IoT) technologies, edge/cloud computing, and automated actuation to maintain optimal water quality. IoT-enabled sensing platforms have been deployed for continuous monitoring of critical parameters such as pH, DO, temperature, turbidity, and ammonia, enabling early detection of water quality degradation and supporting timely intervention (Recommendations 2025). Systematic reviews of sensing technologies in aquaculture report a diverse range of approaches, including optical, electrochemical, biosensors, and multi-parameter probes, each with specific trade-offs in measurement accuracy, energy efficiency, cost, and environmental robustness (Flores-Iwasaki et al. 2025; Zainurin et al. 2022).

Cloud-centric water quality monitoring solutions have gained significant attention for their ability to store, analyze, and visualize large-scale datasets, supporting long-term trend analysis and predictive modeling (Ajith Jerom et al. 2020; Muthukumar et al. 2023). However, their reliance on continuous internet connectivity introduces latency, reduces responsiveness, and poses operational risks in rural or remote environments where network stability is limited (Jha, 2020) demonstrated this limitation in EcoFan-technology–enabled ponds, where unstable connectivity impeded timely water quality management, reinforcing the need for distributed processing capabilities.

To address these issues, edge computing has emerged as a viable solution, enabling local analytics, threshold-based event detection, and immediate actuation without cloud dependency. Hybrid IoT–SCADA frameworks, such as APAH (Chavhan et al. 2025), process sensor data locally to control aerators, pumps, and alarms in real time. These architectures reduce bandwidth consumption, improve resilience, and ensure uninterrupted operation even under intermittent connectivity. Advanced implementations integrate AI-driven contamination detection and automated remediation processes, including UV disinfection (Durgun 2024).

Beyond digital infrastructure, mechanical water treatment innovations remain crucial. The EcoFan system evaluated by (Yunus et al. 2023) improved plankton mixing and DO levels but required optimization to maintain DO above 5 ppm and ammonia below 0.2 mg/L. Similarly, water quality interaction studies in Bangladesh highlight the synergistic effects between parameters such as temperature, pH, and CO_2 levels, where fluctuations can intensify DO depletion and stress aquatic organisms (Hridoy et al. 2025). From a biological perspective, (Zhang et al. 2025) demonstrated that deviations in water quality directly trigger stress behaviors, reduce feeding activity, and impair growth, underscoring the critical need for rapid corrective actions.

Collectively, the literature demonstrates a technological shift toward integrated IoT–edge–cloud ecosystems in aquaculture, with a growing emphasis on resilience, automation, and data-driven decision-making. However, most existing systems prioritize either local actuation or cloud-based analytics, with few offering a fully unified architecture that ensures both immediate on-site corrective measures and scalable, long-term data storage and analysis. This gap motivates the proposed dual-layer architecture in this study, combining low-latency edge-triggered alarms and actuator control with cloud-based logging, visualization, and automated operator notifications. To facilitate systematic comparison, Table 1 summarizes representative aquaculture monitoring systems and contrasts them with the proposed approach across key architectural, functional, and deployment-related dimensions.

As shown in Table 1, many existing systems lack local actuation, rely on cloud-centric processing, or omit quantitative performance reporting, which are explicitly addressed in this work.

SYSTEM ARCHITECTURE

This section presents the overall system architecture of the proposed solution and provides detailed descriptions of the technologies and components employed.

OVERVIEW OF THE ARCHITECTURE

Although the proposed edge–cloud architecture follows a widely adopted IoT design paradigm, the contribution of this work does not lie in introducing a novel architectural pattern. Instead, the emphasis is placed on the practical realization, system integration, and experimental validation of a hybrid edge–cloud monitoring platform specifically tailored for freshwater aquaculture environments. The architecture is deliberately kept lightweight to ensure low latency, operational robustness, and ease of deployment in resource-constrained and connectivity-unstable settings. Unlike many existing studies that present conceptual frameworks or partial implementations, this work demonstrates a fully deployed end-to-end system, quantitatively evaluated in terms of detection-to-action latency, sensing accuracy, system uptime, and real-time responsiveness under operational conditions.

TABLE 1. Comparison of Existing Works and Identified Research Gaps

Reference	Key Technologies Used	Main Focus	Identified Limitations / Research Gaps	How This Work Addresses the Gap
Jha et al. (2020)	IoT sensors with cloud-based ML (Decision Tree), Ubidots platform	Continuous sensing and cloud-based water quality classification	Fully cloud-centric; no edge-level decision making or autonomous actuation; latency and network dependency not quantified	Introduces local edge intelligence for threshold detection and actuation with quantified latency and uptime
Ajith Jerom et al. (2020)	IoT water quality monitoring using cloud and deep learning	Real-time sensing and cloud-based prediction	Processing and alerts depend on cloud connectivity; lacks on-site alarms or actuator control	Enables immediate local alarms and actuator triggering independent of cloud availability
Muthukumar et al. (2023)	Cloud-based smart water management with SMS alerts	Centralized monitoring, visualization, and alerting	High reliance on continuous internet connectivity; limited discussion on latency and resilience	Employs a hybrid edge–cloud architecture to ensure low-latency response under unstable networks
Yunus et al. (2023)	EcoFan technology for freshwater fish ponds	Improved mixing and dissolved oxygen levels	Mechanical intervention not integrated with intelligent monitoring or automated control	Integrates sensing, decision logic, and actuator control in a unified monitoring platform
Hridoy et al. (2025)	Critical review of water quality interactions in aquaculture	Demonstrates synergistic effects between water parameters and fish health	Observational and analytical; lacks real-time monitoring or corrective mechanisms	Translates water quality interactions into actionable real-time monitoring and response
Durgun (2024)	AI-enabled spectroscopic sensors with UV disinfection	High-accuracy AI-based contamination detection	Computationally intensive and cloud-oriented; limited focus on deployment latency or uptime	Provides a lightweight edge–cloud framework suitable for future AI integration
Chavhan et al. (2025)	APAH IoT–edge system for industrial wastewater	Real-time monitoring with automated control	Application focused on industrial wastewater; limited emphasis on cloud-based analytics for aquaculture	Adapts edge intelligence to freshwater aquaculture with integrated cloud logging and notifications

The proposed system adopts a hybrid architecture that integrates edge computing with cloud computing to provide a comprehensive water quality monitoring solution for freshwater fishponds. This architecture ensures both real-time local feedback and long-term data storage and analysis capabilities. At the edge, a suite of sensors continuously monitors critical water parameters. These include the Gravity Analog pH Sensor/Meter Kit V2 (GVT-APH-KIT-V2) for measuring pH, the Waterproof Temperature Sensor (SN-DS18B20) for temperature, the Gravity Analog DO Sensor Kit (SEN0237-A) for DO, and the Gravity Analog Turbidity Sensor (GVT-TURBIDITY) for turbidity. These sensors are connected to an ESP32 microcontroller, which performs on-site processing and monitoring. Thresholds for each parameter (pH, temperature, DO, turbidity) are established based on recommended ranges from recent aquaculture studies (Yunus et al. 2023). These thresholds are used to trigger alerts via LED and buzzer alarms. Additionally, actuators such as water pumps and oxygen aerators are activated to address water quality issues autonomously. For remote accessibility and long-term analytics, all sensor readings are transmitted to the cloud using MQTT protocol through AWS IoT Core. The data is stored and visualized on a real-time dashboard accessible via web. The system also includes an email notification feature that alerts stakeholders when critical thresholds are exceeded.

Figure 1 illustrates the high-level architecture of the system, showing the interaction between sensors, the ESP32 controller, local actuators, cloud infrastructure, and user interfaces. Threshold-based alerting is implemented locally on the edge device. Each metric is evaluated against pre-defined thresholds to detect anomalies or hazardous conditions. When a threshold is breached, the system activates a local alarm system consisting of LEDs and a buzzer to alert nearby personnel. Simultaneously, the system sends an email notification to the person in charge using the SMTP protocol and triggers corresponding actuators, such as an aerator when DO levels drop or a water pump when turbidity rises.

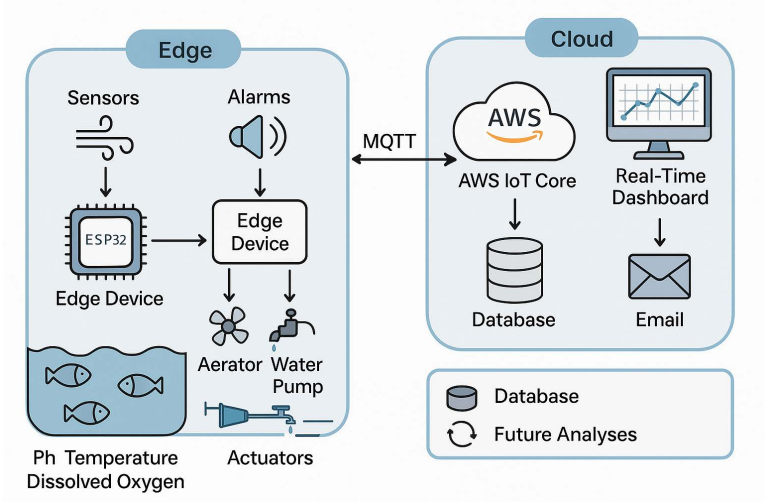


FIGURE 1. Overall Hybrid edge–cloud Architecture of the Proposed Water Quality Monitoring System

The ESP32 not only monitors but also performs basic validation by checking if each metric remains within the acceptable range. Although advanced preprocessing is not conducted at the edge, this simple logic ensures low-latency responses. Regardless of the alert status, all collected data is sent to the cloud via the MQTT protocol, where it is timestamped and stored for further analysis and historical tracking. Currently, the system is powered through a standard non-solar source. However, integrating solar power is considered as future work to enhance sustainability and facilitate deployment in remote locations lacking reliable electricity access. Figure 2 illustrates the schematic of the edge layer architecture used in the proposed system.

CLOUD INTEGRATION AND DATA FLOW

The proposed system leverages cloud computing to ensure reliable data storage, real-time visualization, and automated alerts. This section describes how the edge device communicates with the cloud and the services that manage the data pipeline from sensing to monitoring.

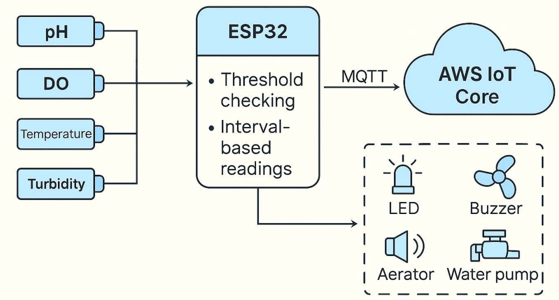


FIGURE 2: Edge-layer Schematic Showing Sensor Inputs, Threshold evaluation, and Actuator Control

Cloud Platform and Services: AWS IoT Core serves as the central gateway for receiving sensor data from the edge device. Once the data is received, AWS Lambda is triggered to process and forward the data to a Firebase Realtime Database, where it is stored in JSON format. No additional filtering, preprocessing, or classification is performed in the cloud. This setup enables a lightweight yet effective architecture suitable for real-time aquaculture monitoring.

Real-time Dashboard and Visualization: A custom HTML/CSS-based dashboard provides real-time visualization of the four monitored parameters: pH, DO, temperature, and turbidity. The dashboard is capable of displaying both live data and historical trends for each sensor, ensuring users can track water quality over time. Historical data access enhances decision-making and helps identify long-term changes in fishpond conditions. The web dashboard provides read-only visualization functionality and does not expose control or configuration interfaces, thereby minimizing potential misuse risks.

Data Transmission and MQTT Communication: Sensor readings are transmitted from the edge device to AWS IoT Core via the MQTT protocol. Although a presentation setting used a 5 ms interval, the realistic and stable operating interval is 10 minutes. This frequency is currently hardcoded in the NodeMCU firmware, and changes require firmware re-upload. MQTT communication is secured using TLS 1.2, as enforced by AWS IoT Core. Acknowledgment messages confirming connectivity (e.g., 'WiFi Connected', 'AWS IoT Connected') are logged on the Arduino IDE's serial monitor during operation.

Automated Email Notifications: An SMTP-based notification system is integrated into the edge layer to provide immediate alerts via email whenever a sensor value breaches its defined threshold. These alerts are synchronized with the local alarms (LED and buzzer). Currently, there is no logging mechanism for sent emails in the cloud. A time-based throttling mechanism is implemented at the edge to limit the frequency of email alerts, preventing alert flooding during prolonged abnormal conditions.

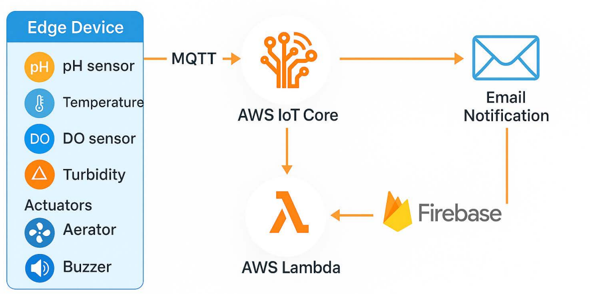


FIGURE 3. Cloud Integration and Data Flow for Storage, Visualization, and Notifications

Security and Reliability Considerations: All MQTT communications between the edge and cloud are encrypted using TLS 1.2, ensuring secure transmission of sensitive sensor data. However, the current system does not implement a backup mechanism in the event of internet connectivity failures. Incorporating offline caching or redundant communication paths can be considered in future work to improve reliability. Figure 3 shows the cloud integration dataflow. Each ESP32 device is authenticated to AWS IoT Core using unique X.509 certificates, enabling secure device identity management and mutual authentication over TLS 1.2–encrypted MQTT communication.

In the current prototype, system parameters such as the MQTT publish interval and threshold values are statically defined in the firmware to ensure stable operation during evaluation; dynamic remote configuration is considered as future enhancement.

COMMUNICATION TECHNOLOGY

The proposed freshwater fishpond monitoring system utilizes Wi-Fi as its primary communication technology to transmit sensor data from the edge device to the cloud. The system is connected to a local Wi-Fi access point, typically a home or office router, which provides reliable internet connectivity within the deployment area. Due to the nature of Wi-Fi connectivity, the system's network performance is contingent on the signal availability and strength at the specific location. In the tested deployment area, no connectivity issues were observed. However, the stability and availability of Wi-Fi may vary depending on the location's network infrastructure. In the event of a temporary network failure or disconnection, the edge device is programmed to continuously attempt reconnection to the network. It is important to note that any sensor data collected during the disconnection period is not backed up or transmitted retroactively. Communication between the edge device and the cloud platform is established using the MQTT protocol. This lightweight publish-subscribe messaging protocol supports efficient and real-time data transmission suitable for IoT-based systems. The device publishes data to the MQTT topic `esp32/water_qual/pub`, and if necessary, it can also subscribe to commands or configuration updates via the topic `esp32/water_qual/sub`. This communication approach enables low-latency, scalable, and flexible data handling between the physical sensing infrastructure and the cloud-based monitoring system.

SYSTEM WORKFLOW

This section outlines the complete system workflow from sensing to alerting, including both edge-side and cloud-side processes. The workflow is designed to operate autonomously and cyclically based on a fixed time interval (typically 10 minutes), ensuring continuous monitoring of water quality parameters in the fishpond.

Edge-side Workflow:

1. System Initialization: The ESP32 device establishes a stable Wi-Fi connection before initiating any data collection. This is essential to ensure uninterrupted MQTT communication with the cloud platform.
2. Sensor Data Collection: Once connected, the system sequentially reads data from four sensors: pH (GVT-APH-KIT-V2), Temperature (SN-DS18B20), DO (SEN0237-A), and Turbidity (GVT-TURBIDITY). These readings are gathered in real time.
3. Threshold Comparison: The ESP32 compares the measured values against pre-set thresholds for each parameter. These thresholds are determined based on water quality standards, such as those referenced in Yunus et al. (2023).
4. Local Alert Triggering: If any parameter violates its threshold, local alerts are activated using a buzzer and LED indicators. The system also logs the timestamp of the last triggered email to prevent repetitive alerts within a short window.
5. Actuator Activation: Corresponding to the type of violation, the system activates relevant actuators. For example, low DO triggers the aerator, and high turbidity activates the water pump.
6. Data Transmission: All collected sensor data, regardless of threshold breach, is sent to AWS IoT Core using the MQTT protocol. The transmission includes sensor values in JSON format.

Cloud-side Workflow:

1. Data Reception and Processing: AWS IoT Core receives MQTT messages. AWS Lambda is triggered to process and forward the data to Firebase Realtime Database.
2. Dashboard Update: A real-time dashboard (developed using HTML/CSS) displays live sensor values. Historical data views are also accessible per sensor type.

3. Email Notification: If threshold violations are present, and sufficient time has passed since the last alert, the cloud system sends email notifications using SMTP to the responsible personnel.
4. User Authentication: Authorized users are required to sign up with a username, email, and password. Upon successful registration, users can log in using their email and password to access the monitoring dashboard and historical logs.

This end-to-end loop repeats at regular intervals, ensuring responsive alerts, real-time monitoring, and historical tracking, all while minimizing manual intervention through automated edge-cloud orchestration.

METHODOLOGY

This section outlines the systematic approach adopted in the development and deployment of the edge–cloud water quality monitoring system. It includes the calibration of sensors, configuration of thresholds for each water quality parameter, the deployment architecture, data flow mechanisms, and the operational logic for alerts and actuation. The methodology ensures that the system not only provides real-time monitoring but also delivers timely and automated responses to maintain optimal pond conditions.

DESIGN RATIONALE AND EXPERIMENTAL SCOPE

The methodological choices in this study were guided by the primary objective of developing a low-latency, resilient, and practically deployable water quality monitoring system for freshwater aquaculture. Threshold values for pH, dissolved oxygen, temperature, and turbidity were adopted from established aquaculture studies to ensure biological relevance and safe operating conditions for commonly cultured freshwater species. Rather than optimizing thresholds for a specific species or pond configuration, the study emphasizes system-level responsiveness and operational feasibility under representative field conditions.

A rule-based edge algorithm was intentionally selected to prioritize interpretability, reliability, and deterministic behavior in resource-constrained environments. Such logic enables immediate decision making and actuation without reliance on cloud connectivity, directly supporting the research objective of minimizing response latency and ensuring autonomous operation. Sensitivity analysis and adaptive threshold tuning were considered beyond the scope of this deployment-focused study and are identified as directions for future work.

Cloud-side processing was deliberately kept lightweight to avoid introducing additional latency and dependency on continuous network availability. The cloud layer primarily supports data aggregation, visualization, and historical logging, while safety-critical decisions are executed locally at the edge. This separation of responsibilities aligns with the study's focus on evaluating real-time edge responsiveness and field deployment readiness rather than cloud-centric analytics.

SENSOR CALIBRATION AND RANGE DEFINITION

To maintain optimal environmental conditions in aquaculture settings, each sensor in the proposed system is configured with reference to established thresholds. These thresholds serve as the basis for both on-site and remote alert mechanisms. The selected parameters, pH, temperature, DO, and turbidity, are known to have significant impacts on fish health and overall water quality. Table 2 summarizes the recommended operational ranges for each parameter based on established aquaculture guidelines. The selected ranges represent commonly accepted operational thresholds for freshwater aquaculture and are used to evaluate system responsiveness rather than species-specific optimization.

TABLE 2. Recommended Operating Ranges for Water Quality Parameters

Parameter	Optimal Range	Source
pH	6.7 – 9.5	Yunus et al. (2023)
Temp.	24°C – 30°C	Yunus et al. (2023)
DO	> 5.0 mg/L	Yunus et al. (2023)
Turbidity	0 – 10 NTU	In-Situ, Inc. (n.d.)

EDGE ALGORITHM

The edge layer is responsible for conducting real-time analysis of sensor readings and executing rule-based logic to maintain optimal pond conditions. Once the edge device (ESP32) is powered on and connected to the Wi-Fi network, it enters a loop where data from all four sensors (pH, temperature, DO, and turbidity) is continuously monitored. For each parameter, the sensor reading is compared against predefined threshold values to determine if the pond conditions deviate from acceptable ranges.

When a breach is detected in any parameter:

1. Local Alarm Activation: A buzzer and LED are triggered on-site to immediately alert nearby personnel.

2. Actuator Response: The edge device activates the appropriate actuator, an aerator for low DO levels and a water pump for high turbidity, to rectify the abnormal condition.
3. Email Notification: An automated email alert is sent via the SMTP protocol to the registered user. To avoid alert spamming, a timing mechanism is implemented based on the timestamp of the last email sent, ensuring a minimum interval between notifications.

This edge algorithm runs on a fixed cycle (set to 10 minutes in this implementation), and the entire loop is repeated continuously. Even if no threshold is breached, the sensor data is transmitted to the cloud at every cycle for storage and visualization. This dual function, local automation and cloud synchronization, ensures responsiveness and traceability within the aquaculture monitoring system. The use of fixed thresholds prioritizes conservative detection to avoid missed hazardous events, with alert throttling employed to mitigate excessive notifications. The complete operational workflow executed at the edge is summarized in Algorithm 1, including threshold evaluation, alarms, actuator control, email throttling, and cloud publishing.

Algorithm 1. Edge-Level Monitoring, Alerting, and Actuation Logic (ESP32)

Input:
Sensor readings: pH(t), Temp(t), DO(t), Turb(t)
Thresholds: pH_min, pH_max, Temp_min, Temp_max, DO_min, Turb_max
Actuators: Aerator, WaterPump
Local alarms: LED, Buzzer
Cloud endpoint: AWS IoT Core (MQTT topic: esp32/water_qual/pub)
Email server: SMTP credentials + recipient address
Timing parameters: sampling interval ΔT = 10 minutes, minimum email interval ΔE
Output:
Local alarms, actuator commands, email alerts, cloud-published sensor records

Initialization
1.1 Configure ESP32 GPIO pins for LED, buzzer, aerator relay, and pump relay
1.2 Initialize sensors (pH, temperature, DO, turbidity) and load calibration constants
1.3 Load thresholds from Table 2: (pH_min, pH_max, Temp_min, Temp_max, DO_min, Turb_max)
1.4 Connect to Wi-Fi network
1.5 Establish secure MQTT session with AWS IoT Core (TLS 1.2)
1.6 Set lastEmailTime ← 0

Main Loop (executed every ΔT)
2.1 If Wi-Fi not connected:
  Attempt reconnection until connected
2.2 Acquire sensor readings:
  Read pH(t), Temp(t), DO(t), Turb(t)
2.3 Perform threshold evaluation:
  Set violation ← FALSE
  If pH(t) < pH_min OR pH(t) > pH_max: violation ← TRUE
  If Temp(t) < Temp_min OR Temp(t) > Temp_max: violation ← TRUE
  If DO(t) < DO_min: violation ← TRUE
  If Turb(t) > Turb_max: violation ← TRUE
Local Response and Actuation
3.1 If violation = TRUE then:
  Activate LED and Buzzer
3.2 Actuator rules:
  If DO(t) < DO_min: Turn ON Aerator, else turn OFF Aerator (or keep safe default)
  If Turb(t) > Turb_max: Turn ON WaterPump, else turn OFF WaterPump (or keep safe default)
Remote Notification (Email Throttling)
4.1 If violation = TRUE AND (currentTime − lastEmailTime ≥ ΔE) then:
  Compose alert message including parameter values and violated thresholds
  Send email via SMTP
  Update lastEmailTime ← currentTime
Cloud Publishing (Always executed)
5.1 Create JSON payload: {pH(t), Temp(t), DO(t), Turb(t), deviceID, statusFlag}
5.2 Publish payload to AWS IoT Core via MQTT topic esp32/water_qual/pub
5.3 (Cloud-side) AWS Lambda appends timestamp and forwards to Firebase Realtime Database
Wait
6.1 Delay/sleep until next cycle (ΔT), then repeat Step 2

DATA FLOW AND SYNCHRONIZATION

The data flow from the edge device to the cloud is designed to ensure that water quality readings are reliably captured, timestamped, and stored for both real-time monitoring and future analysis. The process begins with the edge device (ESP32), which collects data from four water quality sensors: pH, temperature, DO, and turbidity.

Timestamping:

While the edge device performs local threshold evaluation and real-time actuation, the actual timestamping of sensor readings occurs in the cloud. When data is received at the cloud endpoint (AWS IoT Core), it is passed through an AWS Lambda function, which attaches the current timestamp and forwards the data to the Firebase Realtime Database for storage.

Sync Frequency:

Sensor readings are published to AWS IoT Core using the MQTT protocol. Although the hardware was initially configured for testing at a high frequency (every 5 milliseconds), the system is now tuned for a practical 10-minute interval between each data transmission. This fixed frequency ensures that data is consistently logged without overwhelming network or cloud resources.

Buffering and Reliability:

The edge device continuously attempts to maintain an active Wi-Fi connection. In the event of a network disruption, the device enters a reconnection loop until the connection is re-established. However, due to the limited memory capacity of the ESP32, no local buffering or data caching is implemented; thus, any readings captured during disconnection are not stored. Once the device reconnects, it resumes normal operation and cloud synchronization.

The use of MQTT with TLS 1.2 ensures secure data transmission, while topic-based publish/subscribe patterns (esp32/water_qual/pub) provide structured routing of messages. This approach enables real-time visualization of all four parameters on a custom HTML/CSS-based dashboard and allows users to review historical trends via dedicated data views per sensor.

Due to the limited on-chip memory of the ESP32, local buffering or data caching during network outages is not implemented in the current prototype; however, all edge-level monitoring and actuation functions remain fully operational during connectivity loss.

EXPERIMENTAL SETUP

This section describes the setup used for the deployment and testing of the edge-cloud integrated smart monitoring system for sustainable freshwater fishpond management. The experimental setup was designed to assess the performance and efficiency of the system in a real-world environment, highlighting the key components, environment, software, and testing scenarios. The setup includes the location of the fishpond, the hardware and software used, and the different scenarios under which the system was tested to ensure its reliability and functionality.

DEPLOYMENT ENVIRONMENT

The fishpond for this experimental setup is located at Cafe Damai Desasiswa, Universiti Sains Malaysia (USM). The pond layout is asymmetrical and constructed from cement, which provides a stable and durable structure for the system's installation. This project is highly suitable for indoor environments due to the controlled conditions that can be provided. While it is possible to deploy the system in an open-air space, doing so would require additional infrastructure to ensure reliable operation of the IoT system, particularly in terms of maintaining a stable Wi-Fi connection. Environmental factors, such as temperature and humidity fluctuations, should also be considered in outdoor deployments to ensure consistent data collection.

HARDWARE COMPONENTS

The hardware setup for the edge-cloud integrated monitoring system consists of various sensors, microcontrollers, and connectivity modules that work together to collect and transmit data from the fishpond. The system is built around an ESP32-based NodeMCU microcontroller interfaced with an expansion board and four water quality sensors, namely pH, DO, temperature, and turbidity sensors.

Hardware Visuals:

A clear photo of the fishpond with sensors installed, showing the system in its real-world setup is shown in Figure 4 and a close-up of each sensor separately, including the pH sensor, DO sensor, temperature sensor, turbidity sensor, buzzer, LEDs, water filter pump, and aerator are shown in Figure 5.

FIGURE 4: Fishpond with Sensors Installed

SOFTWARE STACK

The software stack used in this project includes programming languages, libraries, and cloud services that enable secure communication, data handling, and visualization for the edge-cloud integrated smart monitoring system.

Programming Languages Used:

1. Arduino C++: Used for programming the NodeMCU (ESP32) to interface with sensors, control actuators, and handle communication with cloud services.
2. JavaScript: Utilized for the front-end development of the web interface, allowing real-time data visualization.
3. HTML/CSS: Used for creating and styling the web-based user interface for data presentation.

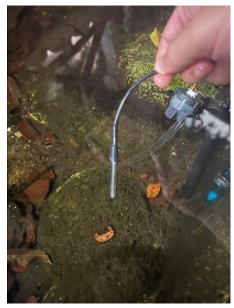
TESTING SCENARIO

Threshold Violation (DO Drop)

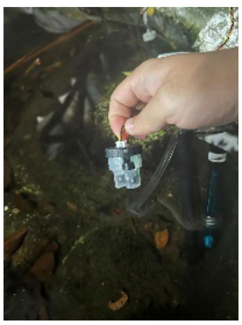
To evaluate the system's responsiveness to critical water quality changes, the DO level was deliberately reduced below the configured threshold of 2.5 mg/L. Upon detection, the ESP32-based edge device immediately processed the sensor reading, confirmed the threshold breach, and initiated two concurrent actions: (1) activation of the aerator to restore DO levels, and (2) transmission of an automated email alert to the farmer via the Simple SMTP service. The alert email clearly specifies the sensor type, measured value, and an explicit message indicating "DO too low." Simultaneously, the violation was visually reflected in the developed web application dashboard, where the DO level indicator turned red to highlight the abnormal condition. This dual-channel notification mechanism, combining real-time visual dashboard updates with instant email alerts, ensures rapid awareness and timely intervention, thereby mitigating risks of fish stress or mortality.

a: pH Sensor

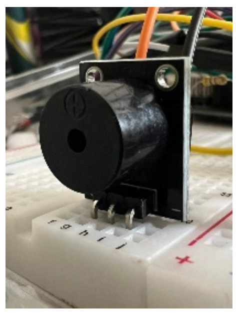
b: DO Sensor



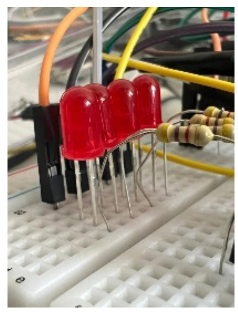
c: Temp. Sensor



d: Turbidity Sensor



e: Buzzer



f: LEDs

g: Water Filter Pump

h: Aerator

FIGURE 5: Sensor and Actuators Closeup

RESULTS AND ANALYSIS

This section presents a comprehensive evaluation of the proposed edge–cloud integrated smart monitoring system, focusing on its operational performance, measurement accuracy, reliability, and data visualization capabilities. The analysis begins with an assessment of system responsiveness, which includes quantifying the latency from anomaly detection at the edge to the corresponding alert notification received by the end user. Subsequently, the accuracy of sensor measurements is examined through calibration experiments and a comparison with ground truth data obtained from standardized measurement instruments. The system's stability and reliability are then evaluated based on extended operational uptime and the success rate of data transmissions across the communication pipeline. Finally, the data storage and visualization capabilities of the cloud platform are showcased through representative dashboard snapshots and log entries, demonstrating the system's ability to provide continuous, real-time monitoring and historical data access for informed decision-making in sustainable freshwater fishpond management.

SYSTEM RESPONSIVENESS

The responsiveness of the proposed monitoring system was evaluated by measuring the latency across the complete operational chain, from sensing an event to executing local and remote responses. When a threshold violation was detected, the time taken from sensor data acquisition to the initiation of both actuator control and alert generation was recorded at 3.4 seconds. Local edge alerts, such as LED illumination and buzzer activation, were triggered within 1.0 second of event detection, ensuring immediate on-site feedback. The email alert, sent via the Simple Mail Transfer Protocol SMTP, exhibited an average delivery delay of 7.0 seconds, which remains within acceptable bounds for timely user notification in aquaculture operations. Additionally, the MQTT-based data publishing to the cloud demonstrated a minimal latency of approximately 150 milliseconds, enabling near real-time synchronization between the edge device and the cloud dashboard. These results confirm that the system achieves a low-latency response across all communication channels, balancing rapid local intervention with prompt remote awareness.

ACCURACY OF SENSOR MEASUREMENT

The accuracy of each water quality sensor was evaluated by comparing its readings against known reference standards under controlled test conditions. For the pH sensor, measurements were taken using standard buffer solutions at pH 4.0, 7.0, and 10.0, yielding maximum deviations of +0.11, −0.01, and −0.02, respectively, from the reference values. The calibration followed a linear model, $\text{pH} = -3.716 \times \text{voltage} + 20.58$, derived from empirical fitting against the known standards. Turbidity measurements were validated using clear water (0 NTU) and cloudy water (20 NTU), resulting in errors of +0.21 NTU and −0.14 NTU, respectively. A voltage–turbidity relationship was established between 2.10 V (0 NTU) and 1.67 V (20 NTU), consistent with the sensor's response curve. The DS18B20 temperature sensor, which comes factory-calibrated with a typical accuracy of ±0.5°C, demonstrated deviations of +0.2°C at 20°C and −0.1°C at 30°C. DO measurements were verified using deoxygenated water (0 mg/L) and air-saturated water (~20 mg/L), with a calibration range of 0 V to 5 V corresponding to 0 mg/L to 20 mg/L DO. The observed maximum DO error was +0.3 mg/L. Overall, all sensors exhibited minimal deviations from the ground truth, validating the reliability of the calibration methods and confirming their suitability for continuous aquaculture monitoring applications. Table 3 represents the measurement accuracy of the sensors.

Overall, all sensors exhibited minimal deviations from the ground truth, validating the reliability of the calibration methods and confirming their suitability for continuous aquaculture monitoring applications. Table 3 summarizes the measurement accuracy of the deployed sensors. While Table 3 quantitatively validates the accuracy of the sensing layer in the proposed system, direct numerical benchmarking against existing systems is constrained by the limited availability of comparable performance metrics in prior studies. As summarized in Table 4, most related works do not report experimental sensor calibration errors, end-to-end latency, or system uptime, and in some cases only provide nominal sensor specifications without empirical validation. Consequently, direct cross-system quantitative comparison is not feasible, and the evaluation in this study emphasizes transparent reporting of measurable performance indicators obtained from real deployment.

The experimental evaluation presented in this section is intended to demonstrate system feasibility, responsiveness, and operational stability in a real aquaculture environment rather than to provide exhaustive statistical characterization. Due to practical constraints of field deployment, repeated trials, confidence interval analysis, and controlled stress testing were not conducted. During the deployment period, only dissolved oxygen levels naturally crossed the defined threshold, while pH, temperature, and turbidity remained within recommended ranges, reflecting realistic pond conditions rather than selective testing.

TABLE 3. Comparison with Lab-Grade Tools

Sensor	Test Condition	Known Standard	Sensor Reading	Error	Notes
pH	pH 4.0 Buffer Solution	4.0 (Kecler-Pietrzyk 2017)	4.11	+0.11	Use the formula pH = -3.716 * voltage + 20.58 which is a linear equation derived from calibrating sensor against known pH standard.
	pH 7.0 Buffer Solution	7.0(Kecler-Pietrzyk 2017)	6.99	-0.01	
	pH 10.0 Buffer Solution	10.0 (Kecler-Pietrzyk 2017)	9.98	-0.02	
Turbidity	0 NTU (Clear Water)	0 NTU (Specification, n.d.)	0.21 NTU	+0.21 NTU	Voltages were recorded at these points (2.10V at 0 NTU, 1.67V at 20 NTU), and a linear relationship was established. The range (2.10V to 1.67V) was chosen based on the sensor's response curve, likely determined by testing multiple turbidity levels.
	20 NTU (Claudy Water)	20 NTU (Specification, n.d.)	19.86 NTU	-0.14 NTU	
Tem.	20°C Water Bath	20.0 °C	20.2 °C	+0.2 °C	DS18B20 came with factory calibration and accuracy of typical reading is ±0.5°C
	30°C Water Bath	30.0 °C	29.9 °C	-0.1 °C	
DO	0 mg/L (Deoxygenated)	0.0 mg/L (Probe, n.d.)	0.3 mg/L	+0.3 mg/L	Voltages were recorded at these points (0V at 0 mg/L, 5V at 20 mg/L), and a linear relationship was established. The range (0V to 5V) was chosen based on the sensor's response curve, likely determined by testing deoxygenated water and air-saturated water conditions at the operating temperature.
	10 mg/L (Air-Saturated)	10.0 mg/L (Probe, n.d.)	10.2 mg/L	+0.2 mg/L	

STABILITY AND RELIABILITY

The stability and reliability of the monitoring system were assessed through continuous observation of sensor readings and actuator states over extended operation. A representative log excerpt from the serial monitor demonstrates consistent data acquisition for all parameters, including temperature, pH, turbidity, and DO, without fluctuations outside expected ranges under stable pond conditions. Actuator status messages confirm that the water filter and oxygen aerator remained in their normal "OFF" states when no threshold violations occurred. The uninterrupted sequence of records and the absence of communication errors indicate a robust data transmission pipeline from the edge device to the AWS IoT Core, ensuring high uptime and dependable operation for real-time aquaculture monitoring.

TABLE 4. Availability of Quantitative Performance Metrics in Related Works

Reference	Sensor Accuracy	Latency	Uptime
Yunus et al. (2023)	Not reported	Not reported	Not reported
Chavhan et al. (2025)	Partial (Specification-level only)	Not reported	Not reported
Durgun (2024)	Not reported	Not reported	Not reported
This work	Reported (Table 3)	Reported	Reported

The system's cloud integration and data logging capabilities were assessed by capturing serial monitor outputs alongside tabulated performance metrics (Table 5). Each time-stamped entry in the table is supported by a corresponding screenshot, illustrating the published JSON payload, MQTT transmission status, publish time, and packet loss percentage. During stable network conditions (e.g., 10:10 AM and 10:15 AM), the system consistently achieved 100% uptime with 0.00% packet loss, and MQTT messages were successfully published within 13–14 ms. However, intermittent connectivity issues were observed at specific intervals, such as 10:20 AM and 10:25 AM, where MQTT publish attempts failed, resulting in 33.33% and 50.00% packet loss, respectively. In other cases (e.g., 10:30 AM, 10:35 AM, and 10:40 AM), MQTT publishing remained functional, but packet loss ranged from 28.57% to 40.00%, likely due to transient Wi-Fi signal fluctuations or bandwidth contention. These results demonstrate that, while the system performs reliably under optimal network conditions, occasional packet loss events can occur under unstable connectivity, reinforcing the importance of implementing buffering or retransmission mechanisms for mission-critical aquaculture monitoring.

DATA STORAGE AND VISUALIZATION SNAPSHOTS

The developed cloud-based dashboard provides both real-time and historical visualization of fishpond water quality parameters, enabling effective monitoring and decision-making. The main dashboard interface displays all four critical metrics, turbidity, pH, DO, and temperature, in real time, with intuitive color-coded indicators reflecting parameter status. For in-depth analysis, users can access historical trend charts for individual parameters, such as the DO history page, which presents both a time-series graph and a detailed data table for past readings. All readings, alerts, and user profile information are persistently stored in a structured Firebase Realtime Database, which includes distinct sections for alert history, user profiles, and sensor readings, each timestamped for traceability. This integration of real-time monitoring, historical analysis, and structured cloud storage ensures that operators can track environmental changes, identify trends, and maintain a permanent data record for long-term aquaculture management.

TABLE 5. Uptime and Packet Loss

Time	Uptime(%)	Packet Loss (%)
10.10 AM	100.00	0.00
10.15 AM	100.00	0.00
10.20 AM	66.70	33.33
10.25 AM	66.70	50.00
10.30 AM	100.00	40.00
10.35 AM	100.00	33.33
10.40 AM	100.00	28.57

DISCUSSION

The implementation of the proposed edge–cloud integrated monitoring system has important implications for practical freshwater aquaculture management, particularly in contexts where rapid response, operational simplicity, and cost efficiency are critical. The measured end-to-end latency of 3.4 s, with local edge alerts triggered within 1.0 s, is well within acceptable bounds for common aquaculture risk scenarios such as dissolved oxygen depletion, where timely aeration can prevent acute fish stress or mortality. While some cloud-centric monitoring systems prioritize long-term analytics, their reliance on continuous connectivity can delay corrective action; in contrast, the proposed system demonstrates that edge-level autonomy is sufficient to support time-critical interventions in real pond environments.

The achieved sensing accuracy, with deviations limited to ±0.11 pH units, ±0.3 mg/L dissolved oxygen, ±0.21 NTU turbidity, and ±0.2 °C temperature, is appropriate for operational decision-making in freshwater fishponds, where management actions are typically triggered by threshold crossings rather than fine-grained fluctuations. However, these results also highlight an inherent trade-off between affordability and precision when deploying low-cost sensors at scale. While the accuracy is adequate for real-time monitoring and alerting, long-term deployment may be affected by sensor drift, biofouling, and environmental exposure, necessitating periodic recalibration and maintenance to preserve measurement reliability.

The use of a rule-based edge algorithm represents a deliberate design choice favoring deterministic behavior, transparency, and low computational overhead over adaptive or data-driven approaches. This choice minimizes false negatives in safety-critical conditions and ensures predictable system behavior under constrained hardware and network conditions. However, it also limits adaptability to gradual environmental changes or species-specific requirements, suggesting that future extensions could incorporate adaptive thresholds or learning-based models while preserving the current system's low-latency edge response.

Cloud-side processing in the proposed system is intentionally lightweight, serving primarily for data aggregation, visualization, and historical logging rather than real-time decision making. This design reduces dependency on network stability and prevents cloud-induced latency from affecting emergency responses. The observed packet loss during unstable connectivity further reinforces the importance of this design separation, as critical actuation remains functional even when cloud synchronization is partially disrupted. At the same time, the absence of buffering and retransmission mechanisms highlights a trade-off between system simplicity and data completeness, particularly for long-term analytics.

Study Limitations. Despite these advantages, several limitations of the current implementation should be acknowledged. During the field deployment, dissolved oxygen was the only parameter that naturally crossed its predefined threshold, while pH, temperature, and turbidity remained within recommended operating ranges; consequently, system responses to multiple or extreme parameter violations were not experimentally evaluated. The prototype does not implement local data buffering or caching during network outages due to hardware memory constraints, which may affect data continuity under prolonged connectivity disruptions. Key operational parameters, such as threshold values and MQTT publish intervals, are statically defined in the firmware, limiting runtime configurability. Furthermore, sensor fault scenarios, long-term diurnal or seasonal dynamics, and extended multi-site deployments were not analyzed in this study.

Addressing these limitations through controlled stress testing, adaptive threshold mechanisms, enhanced fault tolerance, and longer-term, multi-pond deployments will further strengthen the system's robustness and generalizability. Nonetheless, the present results demonstrate that a carefully designed edge–cloud architecture can deliver reliable, low-latency, and practically deployable monitoring for freshwater aquaculture, supporting operational requirements relevant to sustainable fish farming and aligning with the broader objectives of SDG 6 and SDG 14. The alignment with SDG 6 and SDG 14 in this study should be interpreted as enabling and infrastructural, rather than as a direct quantitative assessment of sustainability outcomes.

CONCLUSION

This study addressed critical limitations in traditional and cloud-only aquaculture monitoring systems by designing and implementing a hybrid edge–cloud architecture for real-time water quality management in freshwater fishponds. The developed system continuously monitored four essential parameters, pH, DO, temperature, and turbidity, while integrating low-latency edge computing for immediate threshold violation detection, automated local actuation, and remote alerting via email. Experimental results demonstrated strong performance, with total detection-to-action latency of 3.4 s, local LED/buzzer alerts in 1.0 s, and email notifications delivered within 7.0 s on average. MQTT-based cloud synchronization achieved an average latency of 150 ms, while uptime reached 100% during stable connectivity periods. Sensor measurements showed high accuracy, with maximum deviations of only ±0.11 pH units, 0.3 mg/L DO, 0.21 NTU turbidity, and 0.2°C temperature compared to reference standards. These findings validate the system's potential to reduce operational costs, minimize fish mortality risks, and improve aquaculture sustainability. Beyond addressing immediate intervention needs, the cloud integration enabled long-term data storage and visualization, providing a foundation for predictive analytics and informed decision-making. Future enhancements will include controlled stress testing of multiple water quality parameters and long-term seasonal deployments to further evaluate system robustness under diverse environmental conditions and will also integrate lightweight store-and-forward mechanisms using external non-volatile storage to improve data continuity under intermittent network conditions. Future enhancements will incorporate remote configuration capabilities using cloud-based parameter management, enabling dynamic adjustment of thresholds, sampling intervals, and operational policies without firmware re-deployment. Finally, Future work will include the integration of machine learning models to forecast water quality trends, enabling proactive management before critical thresholds are reached. Additionally, the system's modular design allows for expansion to other aquaculture types, such as shrimp farms or marine cages, and broader smart farming applications, positioning the platform as an adaptable and scalable monitoring solution with long-term relevance to sustainability objectives, including SDG 6 and SDG 14.

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DECLARATION OF COMPETING INTEREST

None.

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