An Edge-Assisted IoT Framework for Intelligent Water Quality Anomaly Detection and Early Warning in Bangladesh Aquaculture

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***Abstract*—In sustainable aquaculture, maintaining optimal water quality is essential, as sudden environmental changes can lead to disease outbreaks, reduced productivity, and significant fish mortality. This paper presents an edge-assisted Internet of Things (IoT)-Cyber Physical System (CPS) framework for intelligent water quality monitoring and real-time anomaly detection. The proposed framework integrates IoT-enabled water quality sensors, an ESP32 edge device, and a Raspberry Pi 4 Model B to perform real-time data acquisition, preprocessing, and anomaly detection using the Isolation Forest algorithm. While the ESP32 is responsible for collecting and transmitting sensor data, the Raspberry Pi executes the computationally intensive anomaly detection process and supports intelligent early-warning generation with low communication latency. Four critical water quality parameters, namely temperature, dissolved oxygen (DO), pH, and turbidity, were selected from the publicly available IoTMLCQ dataset. After data preprocessing and feature normalization, the proposed framework was evaluated using confusion matrix analysis, receiver operating characteristic (ROC) analysis, and standard classification metrics. Experimental results demonstrate that the proposed model achieved an accuracy of 97.25%, a precision of 66.67%, a recall of 66.45%, an F1-score of 66.56%, and an ROC-AUC of 98.44%, outperforming One-Class Support Vector Machine and Local Outlier Factor under identical experimental conditions. The proposed low-cost edge-assisted architecture provides timely anomaly detection and intelligent early warning, offering a practical solution to reduce fish losses, improve aquaculture farm management, and support sustainable smart aquaculture.**

***Index Terms*—Internet of Things (IoT), Cyber-Physical System (CPS), Smart Aquaculture, Edge Computing, Isolation Forest, Anomaly Detection, Water Quality Monitoring.**

I. Introduction

In recent years, aquaculture has emerged as one of the fastest-growing food production industries in the world, offering a sustainable source of animal protein, a significant contribution towards food security, economic development and rural livelihoods. Bangladesh is one of the major inland fish-producing countries, where aquaculture contributes significantly to the fish production in the country and socio-economic development of millions of people. Intensive fish farming, which is very fast growing, has greatly increased production capacity, but optimal water quality is still a major challenge. Dissolved oxygen (DO), water temperature, pH, turbidity, ammonia concentration, and other water quality parameters directly affect fish metabolism, growth, immunity, feed utilization and survival. Of these parameters, dissolved oxygen is deemed most important as a short period of oxygen deficiency may cause physiological stress, decrease feeding activity and cause severe fish mortality. These values constantly change depending on the environmental conditions, biological activities and farming practices, so that regular manual monitoring becomes often impossible to detect the abnormal situations in time. Such a situation often leads to losses of production and higher operating expenses, making the need for intelligent and continuous water quality monitoring systems for sustainable aquaculture management apparent. [1]–[4].

The recent developments in Internet of Things (IoT), Artificial Intelligence (AI), Edge Computing and Cyber-Physical Systems (CPS) have revolutionized the traditional aquaculture management approach into intelligent and data-driven monitoring system. Sensor networks and IoT technology enable the continuous collection of environmental data, and cloud-based platforms enable remote visualization and storage of water quality information. Meanwhile, machine learning (ML) techniques have demonstrated great potential in predicting dissolved oxygen (DO) levels, detecting unusual water quality events, and providing intelligent decision making support. In addition, cloud-edge collaborative architectures have been proposed to minimize the latency of communication, computational efficiency, and the ability of real-time processing of

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sensor data; conversely, CPS-based architectures have been used as a basis for developing sensor-integrated computing, communication and control in smart farming environments. The technology developments described here all suggest that combining IoT, edge intelligence and machine learning with smart aquaculture systems can have a meaningful impact on operational efficiency and the sustainability of modern aquaculture systems. [5]–[13].Yet, there are still a number of research questions yet to be answered. Past research has mainly concentrated on data acquisition solutions using the IoT, monitoring platforms in the cloud or predictive solutions based on machine learning as isolated solutions. The above-mentioned techniques have improved the accuracy of monitoring and the prediction performance, but many of them still use centralized cloud processing which creates a lot of communication latency and causes low responsiveness to time-critical aquaculture applications. Furthermore, most existing systems are based on monitoring environmental conditions and offer no intelligent decision support or practical recovery guidance for farmers. This can mean the farm manager must estimate the readings themselves on the sensors and make decisions about how to correct the water quality according to their personal experience, thus failing to take corrective action when water quality changes quickly conditions [14]–[17].

Recent review studies emphasize that integrating edge intelligence, lightweight communication, and cyber-physical architectures is essential for next-generation smart aquaculture [1], [4], [12]. Nevertheless, existing solutions largely focus on monitoring or prediction independently, with limited efforts toward a unified framework integrating IoT sensing, edge-based anomaly detection, MQTT communication, cloud visualization, and intelligent decision support. In addition, the practical requirements of resource-constrained aquaculture farms in developing countries such as Bangladesh remain insufficiently addressed. Therefore, this work proposes an edge-assisted cyber-physical system that combines these technologies into a unified framework for real-time water quality monitoring, anomaly detection, and intelligent early warning.

The main contributions of this work are summarized as follows:

- An edge-assisted CPS framework for real-time aquaculture water quality monitoring is proposed.
- A lightweight edge-based anomaly detection mechanism is developed for real-time water quality assessment.
- An MQTT-enabled early-warning system is introduced to provide timely alerts and recovery recommendations.
- The proposed framework is designed as a scalable and low-cost solution for Bangladesh aquaculture.

II. Proposed System Architecture

This section explains the proposed edge-assisted cyber-physical system for real-time aquaculture water quality monitoring and early-warning. The framework is designed to combine various components of the IoT ecosystem, such as sensing, edge processing, MQTT communication, cloud services, and intelligent decision-making, into a cohesive architecture. The system architecture and operation is described in the following subsections

A. Overall Architecture

The proposed edge-assisted cyber-physical system is designed to provide real-time water quality monitoring and intelligent early warning for aquaculture environments. The overall architecture of the proposed framework is illustrated in Fig. 1.

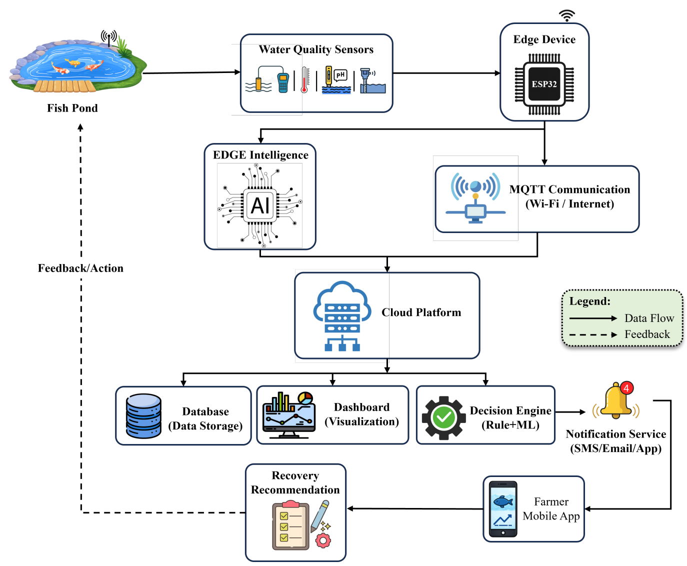

Fig. 1. Overall architecture of the proposed edge-assisted IoT-CPS framework.

This is an architecture that combines the IoT-based sensing, edge computing, lightweight MQTT communication, cloud services, and intelligent decision support. The IoT sensors continuously monitor water quality parameters such as dissolved oxygen (DO), water temperature, pH and turbidity, which are then transmitted to an ESP32 edge device for real-time data acquisition and communication. The collected data are forwarded to a Raspberry Pi 4 Model B, where preprocessing, Isolation Forest-based anomaly detection, and decision support are performed.

Processed data is then pushed to the cloud platform using the MQTT protocol for storage, visualization and centralized monitoring. The decision engine, according to the received information, makes a judgment on the water quality and when an abnormal event is detected, it triggers the notification service. Lastly, real-time warning notifications and suitable recovery recommendations are sent to the farmer's mobile app, allowing them to take timely action and manage aquaculture efficiently.

B. Operational Workflow

The proposed system operates through an iterative sensing and decision-making process. Water quality sensors continuously measure four critical parameters, namely dissolved oxygen (DO), temperature, pH, and turbidity. The collected sensor data are acquired and transmitted by the ESP32 edge device to a Raspberry Pi 4 Model B, where data preprocessing and Isolation Forest-based anomaly detection are performed. The processed data are then forwarded to the cloud platform via the MQTT communication protocol for remote monitoring and data management.

The cloud platform stores and visualizes the processed data, enabling continuous monitoring of water quality conditions. The decision engine evaluates the anomaly detection results and determines the water quality status. When abnormal conditions are identified, the notification service is activated to generate real-time alerts and recovery recommendations. These notifications are delivered to the farmer's mobile application, enabling timely intervention, reducing potential fish losses, and supporting efficient aquaculture management.

III. Proposed Methodology

The proposed methodology enables intelligent water quality monitoring by integrating data preprocessing, edge-based anomaly detection, and an early warning mechanism. As illustrated in Fig. 2, the workflow begins with the acquisition of IoT water quality data, followed by data cleaning and feature normalization to improve data quality and ensure consistent feature representation.

The normalized data are then analyzed using an Isolation Forest model deployed at the edge to detect abnormal water quality conditions. Once an anomaly is identified, a rule-based decision engine generates an early warning and recommends appropriate recovery actions to support timely intervention.

A. Data Acquisition and Preprocessing

The proposed framework takes the publicly available IoTMLCQ aquaculture dataset, with measurements of water quality collected from monitoring systems that are implemented via the IoT. The data set contains the following environmental measures: water temperature, dissolved oxygen (DO), pH, turbidity, and other water quality components which are critical for evaluating pond health and effects of abnormal environmental conditions. The proposed edge-assisted anomaly detection framework takes these parameters as its input features.

The data are collected and preprocessed before anomaly detection to enhance the quality of the data and ensure uniform representation of the features. Firstly, missing or incomplete records are identified and removed; and then, duplicate samples are discarded to ensure data integrity. Because of the difference in the numerical range and the units used for the measurement of the selected features, the technique of feature normalization is adopted using the technique of StandardScaler, which is used to scale the features to zero mean and unit variance. This process helps to reduce feature-scale bias and makes the anomaly detection by the Isolation Forest model more stable.

The normalized feature set is then passed to the edge-based anomaly detection module to analyze the data in real time, shown in Fig. 2. This pre-processing pipeline gives the

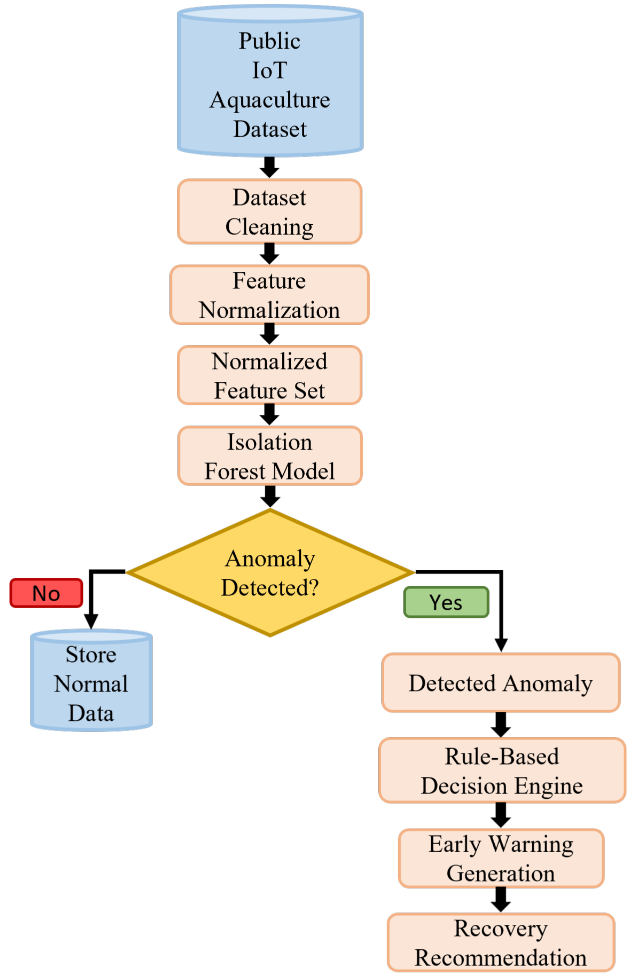

Fig. 2. Workflow of the proposed methodology for edge-based anomaly detection and early warning using the Isolation Forest model.

standardized input data in the next stage, which is the anomaly detection process.

B. Edge-Based Anomaly Detection

The proposed edge-assisted anomaly detection framework integrates an ESP32 edge device with a Raspberry Pi 4 Model B to enable efficient real-time water quality monitoring in aquaculture. The ESP32 interfaces with the water quality sensors to continuously collect measurements of dissolved oxygen (DO), temperature, pH, and turbidity. After performing basic preprocessing, including data formatting and validation, the ESP32 transmits the collected measurements to the Raspberry Pi 4 Model B through the local network.

The Raspberry Pi performs feature normalization and executes the Isolation Forest algorithm to identify anomalous water quality conditions. Compared with deploying machine learning models directly on low-power microcontrollers, the Raspberry Pi provides greater computational capability while maintaining low processing latency, making it suitable for real-time edge intelligence. Since the anomaly detection process is performed locally, the framework significantly reduces communication overhead and minimizes the response time required for early warning.

The Isolation Forest algorithm is an unsupervised machine learning technique that detects anomalies by recursively partitioning the feature space using randomly selected features and split values. Because anomalous observations are isolated with fewer partitions than normal observations, the algorithm efficiently identifies abnormal water quality conditions without requiring labeled training data. The anomaly score of each observation is calculated as

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{1}$$

where $E(h(x))$ denotes the average path length of sample x, $c(n)$ is the average path length of unsuccessful searches in a binary search tree with n samples, and $s(x,n)$ represents the anomaly score. A score approaching 1 indicates a higher probability of an anomaly, whereas values closer to 0.5 generally correspond to normal observations.

Based on the anomaly detection results, the decision engine evaluates the overall water quality status and determines whether abnormal environmental conditions exist. When an anomaly is detected, the processed data and decision results are transmitted to the cloud platform via the MQTT communication protocol for visualization and remote monitoring. Simultaneously, real-time warning notifications together with appropriate recovery recommendations are delivered to the farmer's mobile application, enabling timely intervention, reducing fish mortality, and supporting sustainable aquaculture management.

C. Early Warning and Decision Support

If an anomalous water quality condition is detected, the detected event is passed to the rule based decision engine for further analysis. The system uses the anomaly detection result to decide the warning level and to output the appropriate warning to alert the farmer to possible water quality degradation.

A recovery recommendation is provided with the generated warning based on the detected water quality condition. The system will suggest corrective measures (for example water changes, increase aeration, adjust water pH) if an anomaly has been detected, to improve the aquarium water quality. These recommendations help farmers take immediate action to minimise fish stress and mortality.

The proposed decision support mechanism is an extension to the anomaly detection process along the edge as it provides actionable, timely recommendations instead of just the anomaly. The integrated workflow as shown in Fig. 2 enables quick response and reliable water quality management in IoT-based aquaculture systems.

IV. Results and Discussion

This section presents the experimental evaluation of the proposed edge-assisted IoT-CPS framework using the publicly available IoTMLCQ dataset. The performance of the proposed Isolation Forest model is assessed through quantitative evaluation metrics, confusion matrix analysis, ROC analysis, and comparison with baseline unsupervised anomaly detection methods. In addition, the practical deployment feasibility of the proposed framework is discussed through a deployment cost analysis.

A. Experimental Setup

An edge-assisted anomaly detection algorithm was developed in Python using Scikit-learn package of machine learning library, and tested with the publicly available IoTMLCQ aquaculture dataset. Water temperature, dissolved oxygen (DO), pH and turbidity were chosen as input features because they directly affect the water quality parameters of the aquatic environment. Data cleaning involved removing missing and duplicate records and applying the StandardScaler method to normalize the data features, ensuring consistent scales across the data and enhancing model stability prior to model training.

TABLE I
Experimental Configuration

Parameter	Value
Dataset	IoTMLCQ
Selected Features	Temperature, DO, pH, Turbidity
Data Preprocessing	Cleaning + StandardScaler
Reference Labeling	IQR-based
Training/Testing Split	80% / 20%
Detection Model	Isolation Forest
Number of Trees	200
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, ROC-AUC

A reference label was created using the Interquartile Range (IQR) approach, as no ground-truth anomaly labels are available in the dataset, so as to enable the quantitative evaluation of the performance. Processed data was subsequently split in an 80:20 ratio between training and testing datasets in a stratified manner, which guarantees the same class distribution in both sets. The model proposed here is Isolation Forest model with 200 isolation trees and trained with the contamination ratio on the training data. The model performance was assessed by using Accuracy, Precision, Recall, F1-Score and ROC-AUC to get a thorough evaluation of the model's ability to detect anomalies. All the experimental setup is summarized in Table I.

The adopted experimental configuration provides a consistent evaluation framework for assessing the proposed edge-assisted anomaly detection model and enables a fair comparison with other unsupervised anomaly detection techniques.

B. Performance Evaluation

The performance of the proposed edge-assisted IoT-CPS framework was assessed using confusion matrix analysis and receiver operating characteristic (ROC) evaluation. As illustrated in Fig. 3, the proposed Isolation Forest model correctly identified 7,048 normal samples and 204 anomalous samples, while misclassifying only 102 normal samples as anomalies and 103 anomalous samples as normal. The relatively small number of misclassified instances demonstrates the effectiveness of the proposed framework in accurately distinguishing abnormal water quality conditions from normal operating states.

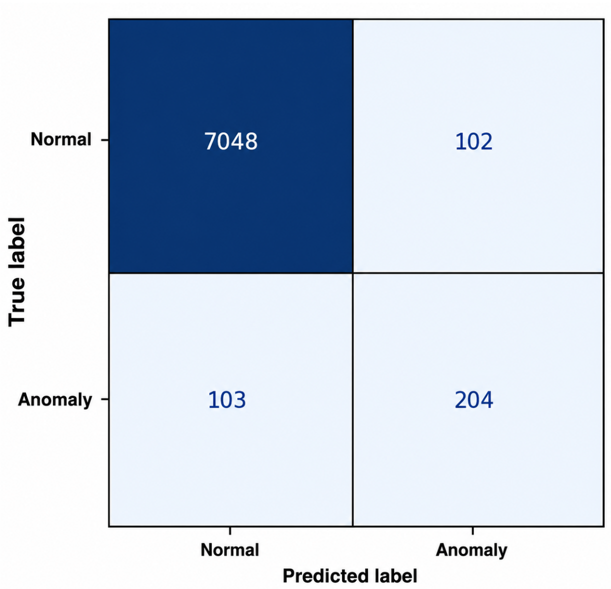

Fig. 3. Confusion matrix of the proposed Isolation Forest model.

The quantitative performance further validates the proposed framework. The model achieved an overall accuracy of 97.25%, together with a precision of 66.67%, a recall of 66.45%, and an F1-score of 66.56%. Although the precision and recall are lower than the overall accuracy, this outcome is expected because anomalous observations represent only a limited portion of the dataset, resulting in an inherently imbalanced anomaly detection problem.

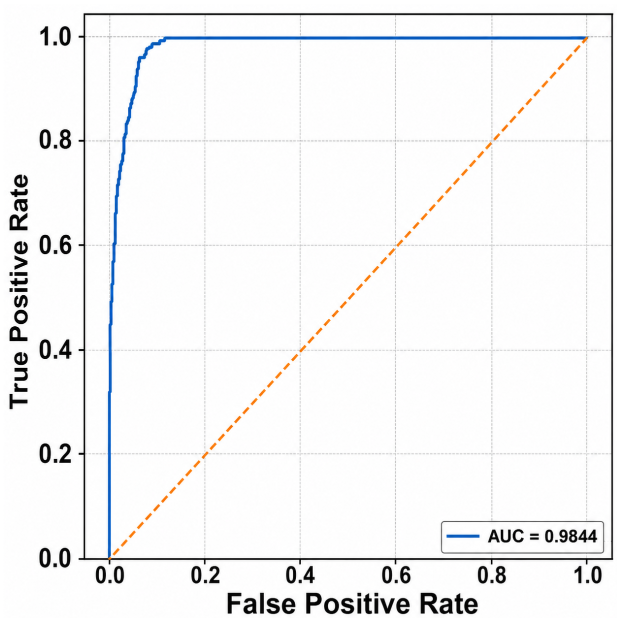

Fig. 4. ROC curve of the proposed Isolation Forest model.

To further evaluate the discrimination capability of the proposed model, the ROC curve is presented in Fig. 4. The proposed Isolation Forest achieved an ROC-AUC of 98.44%, indicating excellent separation between normal and anomalous observations over a wide range of decision thresholds. The high ROC-AUC value demonstrates the robustness of the proposed framework and confirms its capability to provide reliable anomaly detection while maintaining a low false alarm rate in real-time aquaculture monitoring applications.

C. Comparative Performance Analysis

To further validate the effectiveness of the proposed framework, its performance was compared with two widely used unsupervised anomaly detection algorithms, namely One-Class Support Vector Machine (OC-SVM) and Local Outlier Factor (LOF). All models were evaluated using the same preprocessed dataset, identical training and testing partitions, and the same evaluation metrics to ensure a fair and consistent comparison. The comparative results are summarized in Table II.

TABLE II
COMPARISON OF THE PROPOSED MODEL WITH BASELINE UNSUPERVISED METHODS

Method	**Acc.**	**Pre.**	**Rec.**	**F1**	**ROC**
One-Class SVM	96.42	56.49	56.68	56.59	94.22
Local Outlier Factor	93.70	24.29	25.08	24.68	70.47
Proposed Isolation Forest	97.25	66.67	66.45	66.56	98.44

Table II compares the proposed Isolation Forest model with two widely used unsupervised anomaly detection methods, namely One-Class Support Vector Machine (OC-SVM) and Local Outlier Factor (LOF), under identical experimental settings. The proposed model achieved the highest performance across all evaluation metrics, including an accuracy of 97.25%, a precision of 66.67%, a recall of 66.45%, an F1-score of 66.56%, and an ROC-AUC of 98.44%. These results demonstrate that the proposed edge-assisted anomaly detection framework provides more reliable and robust detection of abnormal water quality conditions than the selected baseline methods, making it well suited for real-time smart aquaculture applications.

D. Deployment Cost Analysis

The proposed edge-assisted IoT-CPS framework is designed using commercially available hardware components, making it a practical and cost-effective solution for smart aquaculture applications. The deployment cost includes the ESP32 edge device, Raspberry Pi-based cloud server, water quality sensors, and essential supporting accessories required for prototype implementation. The estimated hardware cost was calculated based on the prevailing market prices of commercially available components at the time of this study, and the complete cost breakdown is presented in Table III.

The total estimated deployment cost of the proposed prototype is approximately USD 404.90. Although the framework incorporates multiple sensing and processing units, the overall

TABLE III
APPROXIMATE DEPLOYMENT COST OF THE PROPOSED SYSTEM

Component	**Specific Item**	**Price (USD)**
ESP32 Edge Device (Data Acquisition)	ESP32 DevKit V1 (USB Type-C, 30-pin)	5.04
Raspberry Pi (ML Inference, Cloud Sync)	Raspberry Pi 4 Model B, 4 GB RAM	150.41
Temperature Sensor	DS18B20 waterproof probe, 1 m cable	2.68
pH Sensor	Analog pH sensor/meter kit with BNC probe (Gravity type)	21.01
Dissolved Oxygen Sensor	Gravity Analog DO sensor/meter kit for Arduino	199.02
Turbidity Sensor	Gravity Analog Turbidity Sensor for Arduino	12.11
Miscellaneous Accessories	Breadboard, jumper wires, miscellaneous wiring (bundle estimate)	14.63
Total		**404.90**

cost remains reasonable for research laboratories, pilot-scale deployments, and commercial aquaculture farms. Furthermore, by performing anomaly detection locally on the ESP32 edge device, the proposed framework significantly reduces communication overhead and cloud processing requirements. This edge-assisted architecture not only enables timely early warning generation but also lowers long-term operational costs compared with conventional cloud-centric monitoring systems.

V. FUTURE WORK

Future work will focus on implementing and validating the proposed edge-assisted IoT-CPS framework in real aquaculture environments using IoT-enabled water quality sensors, an ESP32 edge device, and a Raspberry Pi 4 Model B for continuous real-time monitoring and edge intelligence. Further research will investigate advanced machine learning and edge AI techniques to enhance anomaly detection accuracy and develop a more intelligent decision support system capable of providing adaptive recovery recommendations with minimal human intervention. In addition, integrating automated control mechanisms, such as aerators and water pumps, will be explored to establish a closed-loop cyber-physical system for autonomous water quality management. These enhancements are expected to improve the robustness, adaptability, and practical applicability of the proposed framework for sustainable smart aquaculture.

VI. CONCLUSION

In this paper, an edge-assisted IoT-CPS framework for intelligent water quality monitoring and real-time anomaly detection in aquaculture was presented using the publicly available IoTMLCQ dataset. The proposed framework integrates IoT-enabled water quality sensors, an ESP32 edge device, and a Raspberry Pi 4 Model B to perform real-time data acquisition, edge-assisted processing, and Isolation Forest-based anomaly detection with low computational overhead. Experimental results demonstrated that the proposed model achieved an accuracy of 97.25%, a precision of 66.67%, a recall of 66.45%, an F1-score of 66.56%, and an ROC-AUC of 98.44%, outperforming the One-Class Support Vector Machine and Local Outlier Factor under identical experimental conditions. The edge-assisted architecture further reduces communication overhead by performing anomaly detection close to the data source, enabling timely responses for real-time aquaculture monitoring. Furthermore, the proposed low-cost architecture can be implemented using commercially available hardware components, making it suitable for deployment in small- and medium-scale aquaculture farms.

The proposed framework enables timely detection of abnormal water quality conditions and provides intelligent early-warning notifications to support rapid decision-making. By reducing fish mortality, minimizing economic losses associated with poor water quality, and improving overall farm management, the system offers a practical and scalable solution for smart aquaculture. The proposed framework has the potential to support sustainable fish production and promote the adoption of intelligent aquaculture technologies in Bangladesh.

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