AIoT-Enabled Real-Time Water Quality and Fish Health Monitoring System for Smart Aquaculture

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Abstract

This study introduces a unified AIoT-enabled smart aquaculture system that integrates real-time water-quality monitoring, dissolved-oxygen (DO) prediction, and fish-disease detection within a single, low-cost, field-deployable framework. The system employs Arduino sensors to measure temperature, pH, and turbidity, combined with Raspberry Pi edge computing for continuous data acquisition and on-device analytics. A regression model predicts DO levels from low-cost sensor inputs, eliminating the need for expensive probes, while water quality is classified into three categories using machine-learning approaches. The baseline SVM model achieves 79% accuracy, whereas advanced ensemble methods improve performance to 92.46%. Fish health assessment utilizes a curated dataset of 1,000 veterinarian-verified images, augmented to 3,000 samples. Deep CNN models exhibit strong discriminative performance, with ResNet50 achieving 97.5% accuracy and surpassing MobileNetV2. The full pipeline operates efficiently on a Raspberry Pi, with an average end-to-end inference latency of 1.8 seconds, enabling automated control of pumps and aerators based on real-time predictions. A mobile dashboard provides live visualization, alerts, and historical data

M. S. Arefin et al. (eds.), *Proceedings of the International Conference on Intelligent Data Analysis and Applications (IDAA 2025)*, Advances in Intelligent Systems Research 206,
https://doi.org/10.2991/978-94-6239-664-7_81

tracking for remote farm supervision. Extensive field validation across 160 aquaculture farms, encompassing over 5,500 sensor records, demonstrates the system's robustness, scalability, and adaptability to diverse environmental conditions.

Keywords: AIoT; Smart Aquaculture; Water Quality Monitoring; Dissolved Oxygen Prediction; Edge Computing; Arduino; Raspberry Pi; Machine Learning

1 Introduction

Aquaculture has emerged as a vital contributor to global food security, supplying over half of the world's fish consumption [1]. Particularly in developing countries like Bangladesh, fish farming not only provides affordable protein but also plays a key role in rural employment and economic development [2]. However, the success of aquaculture is heavily dependent on maintaining optimal water quality, as fluctuations in temperature, pH, turbidity, and dissolved oxygen (DO) directly impact fish health and productivity [3], [4].

Advancements in Internet of Things (IoT) and artificial intelligence (AI) have introduced new opportunities for automating water quality monitoring and control. Smart aquaculture systems are now being developed to provide real-time insights, reduce manual labor, and optimize resource use [5]. Despite these innovations, many existing systems rely on fixed-location sensors and lack predictive intelligence or automation features required to maintain healthy aquatic environments dynamically.

Traditional water quality monitoring methods are largely manual, labor-intensive, and reactive rather than proactive. Farmers often rely on periodic testing with water kits or visual cues, which may fail to detect critical issues like low DO levels in time to prevent fish mortality [6]. While some IoT-based systems exist, they frequently fall short in three major areas: lack of predictive modeling for DO estimation, absence of automated response mechanisms (like actuator control), and limited user accessibility through mobile platforms [7].

Addressing these critical limitations the intelligent aquaculture system provides advance enables proactive interventions to stabilize water conditions before they become harmful. The system is depolyment and tested through over 5,500 valid data samples of 160 aquaculture farms across the Bangladesh. This solutions is a responsive aquaculture management system for the combination of multiple intelligent components, IoT protocols, spervised machine learning, deep learning and CNN classification models, automated actuator control with web and mobile-based monitoring system that ensures the practical effectiveness and reliability. The core contributions of this work are as follows:

1. Develop a unified AIoT framework that integrates real-time sensing, machine learning, and deep learning for smart aquaculture management.

2. Monitor essential water-quality parameters using low-cost sensors with continuous edge-based data collection.
3. Predict dissolved oxygen levels through a regression model to avoid dependency on expensive DO sensors.
4. Classify water quality and detect fish diseases using optimized ML models and high-accuracy CNN architectures.
5. Implement real-time edge deployment enabling autonomous actuator control and remote monitoring through a mobile dashboard.

The proposed system utilizes an Arduino-based sensor node to collect water quality data, which is transmitted to a Raspberry Pi for processing and storage. The Pi hosts machine learning models that predict DO levels and evaluate the overall quality status. Based on classification results, the system triggers actuators accordingly. All data and actions are logged and visualized through a cross-platform mobile application, enabling users to manage their ponds remotely.

2 Related Work

TRecent advancements in smart aquaculture have focused on integrating Internet of Things (IoT) and Artificial Intelligence (AI) to improve sustainability, reduce manual intervention, and enhance water quality management. Liu et al.[10] highlighted that IoT-based aquaculture systems can reduce water consumption by up to 50% and fish mortality by 40%, citing improvements in real-time monitoring and automated decision-making. Similarly, Huang and Khabusi[11] reviewed AIoT applications across ten aquaculture domains, including disease detection and feeding automation. Despite notable progress, challenges such as data sparsity and system integration complexity persist. Cui et al.[12] emphasized the growing use of vision and acoustic technologies for fish tracking and behavioral analysis but noted the absence of standardized datasets as a key barrier. Zhao et al.[13] discussed persistent issues in IoT deployments, including sensor degradation, network instability, and energy limitations. They proposed robust solutions such as energy harvesting and fault-tolerant architectures. Several works have explored predictive analytics and intelligent control in aquaculture. Singh et al.[16] introduced a freshwater recirculating aquaculture system integrating sensors, communication networks, and intelligent analytics. Their comparative analysis showed that the M5 model tree outperformed the Gradient Boosting Machine (GBM) in predictive accuracy. Rasheed Haq et al.[21] proposed hybrid deep learning models (CNN-LSTM, CNN-GRU) for water quality prediction, achieving notable improvements in both accuracy and computational efficiency. Mobile and cloud-enabled monitoring systems have also gained attention. Emmanuel et al.[17] developed an IoT-based water quality system with alerting and disease detection features. Zhu et al.[19] utilized artificial neural networks (ANNs) and VPN-based infrastructure for remote monitoring, while Gao et al.[20] proposed a modular system that separates data processing and visualization tasks for greater scalability. Other notable contributions include mobile-integrated systems for real-time user control [23], Android-based solutions leveraging Raspberry Pi and Arduino with remote access capabilities [22], and ZigBee-enabled wireless monitoring frameworks [5]. Additionally, Rapate et al.[24] and Ismail et al.[25] demonstrated automation through sensor-triggered pump control and multi-parameter sensing using commercially available modules. Some studies have explored domain-specific use cases. Darmalim et al.[28] focused on environmental monitoring for striped snakehead fish using a five-sensor IoT solution. Rohit et al.[31] developed a submersible ROV equipped with embedded sensors for underwater monitoring, transmitting real-time data to surface interfaces. Collectively, these works underscore the potential of AIoT in aquaculture. However, gaps remain in end-to-end automation, predictive dissolved oxygen estimation, integrated mobile control, and robust validation on large, real-world datasets. The system proposed in this paper addresses these challenges through a unified, intelligent, and scalable framework. [21] proposed a hybrid CNN-LSTM and CNN-GRU used for Water Quality Prediction (WQP). They use two different water quality datasets and compare their proposed hybrid model and other various (DL) models. As a result, the hybrid CNN-LSTM model significantly improves prediction accuracy and computation time.Saha et al. The authors introduces an IoT-based automated hydroponics system that measures water quality using very important sensors (moisture, pH, temperature, humidity, and water level) and an Arduino board. It monitors these parameters and initiates an automated water pump or nutrient disposal system when the parameters' values fall below predetermined thresholds [22] [23]. In the solutions use of an Android app, a Raspberry Pi, an Arduino, a number of sensors, and a smartphone camera to monitor the quality of aquaculture water and diseases prediction. Temperature, pH, turbidity were among the water quality metrics that were tracked. From anywhere in the world, users can use an Android app to monitor the water quality via Internet.

3 Proposed Methodology

This section presents the architecture, data acquisition, and techniques that are used in the development of this intelligent aquaculture monitoring system. The system combines embedded hardware, sensor integration, machine learning models, and cloud connectivity to enable automated water quality management.

3.1 System Architecture

As shown in Fig. 1, this system is designed for real-time water quality monitoring, fish disease detection, classification,and analysis of aquaculture environments. The hardware setup comprises the Raspberry Pi 4B(8GB) and Arduino UNO R3 used as the primary data acquisition unit, interfaced with the calibrated:

- pH Sensor
- DS18B20 Temperature Sensor
- Turbidity Sensor.

The Sensors collect data from water and transmitted to the Raspberry Pi via USB, which serves as the computational hub of the system. For adopting an intelligent decision the Pi aggregates, processes and analyzes these data by using machine learning

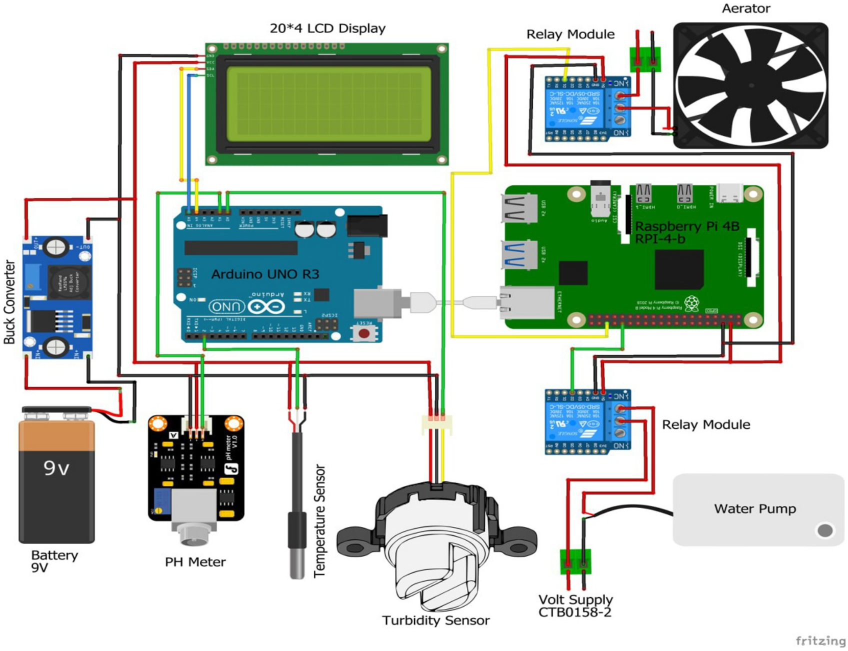

Fig. 1 Pin Configuration Diagram of the Proposed System

models. Based on the result of the decision, Pi controls an aerator and a water pump that interfaced with its GPIO pin (General Purpose Input Output) through the relay module to maintain optimal water quality of aquaculture environments. All sensor readings, classification results, and decision are displayed on a 20×4 LCD display to locally view the real-time water quality and aquaculture environment status, and also automatically upload to ThingSpeak cloud by sing Internet of Things(IoT) protocols for more analysis and future improvement, and access the system remotely. A Web dashboard includes mobile apps for Android and iOS that provide real-time visualizations, alerts, and remote control options to improve user interaction and system transparency.

3.2 Data Collection, Pre-processing and Validation

Data collection and pre-processing is a critical issue in image classification, and deep learning model. Data pre-processing, parameters, and thresholds directly impact the model performance, behavior, accuracy, and decision boundaries. To develop a reliable predictive system for water quality management, a comprehensive data set was collected over a period of seven months from 160 different fish farms. The data set comprises approximately 5500 records that capture essential parameters such as temperature (°C), pH, turbidity (NTU), and dissolved oxygen (DO in mg/L). Data acquisition was performed using real-time sensors connected to an Arduino UNO and

Raspberry Pi for processing and analysis. Our research team visited multiple aquaculture farms to collect data manually using standard water testing kits to validate sensor accuracy. The combination of sensor readings and physical kit measurements ensured high-quality and reliable data. To prepare the water quality data set for machine learning, several pre-processing techniques were applied to ensure that the data were clean, consistent, and meaningful. The key parameter and thresolds of water quality is presented in Table 1.

Table 1 Key Water Quality Parameters and Thresholds

Parameter	**Optimal**	**Tolerance**	**Stress**	**Remarks**
Temp (°C)	25–30	20–35	<25/>30	Affects growth, DO
pH	6.5–8.5	6.0–9.0	<6.5/>8.5	Alters toxicity
Turbidity (NTU)	<30	–	>30	Limits light, DO

The dataset was first cleaned by handling missing values using linear interpolation, preserving time-series continuity. Outliers were treated using both the IQR method (based on quartile range) and the Z-score method (based on deviation from the mean). For better model performance, normalization and scaling were applied—using Min-Max normalization for rescaling to [0, 1] and Z-score standardization for zero-centered data. In addition, temporal features like time of day and season were engineered, and highly correlated features (correlation>0.8) were removed to reduce redundancy and overfitting. Sample data and summary of preprocessing techniques are presented in Table 2 and Table 3, respectively.

Table 2 Sample Water Quality Dataset Collected from the Field

Temp (°C)	**pH**	**Turbidity (NTU)**	**DO (mg/L)**
28.29	6.51	2.54	5.32
30.13	7.18	2.14	7.28
29.21	6.36	3.14	4.96
26.41	7.46	2.57	6.68
25.79	8.12	4.03	5.11
23.08	6.99	4.33	8.10
27.11	6.56	3.66	3.82
22.00	5.22	2.80	5.85
31.12	7.45	5.66	2.77

3.3 Water Quality Management System

The system developed with the combination of Arduino UNO, Raspberry Pi, pH sensor, Temperature sensor, and Turbidity sensor to collect continuously critical water parameters from aquaculture pond.

Table 3 Summary of Data Pre-processing Steps

Step	Description
Missing Values	Linear interpolation used to fill gaps in time-series data.
Outlier Treatment	IQR and Z-score methods applied to detect and handle outliers.
Normalization	Min-Max scaling to [0,1] for uniform feature range.
Standardization	Z-score transformation to center data with unit variance.
Feature Engineering	Extracted time-based features (e.g., time of day, season).
Feature Selection	Removed features with correlation ¿ 0.8 to reduce redundancy.

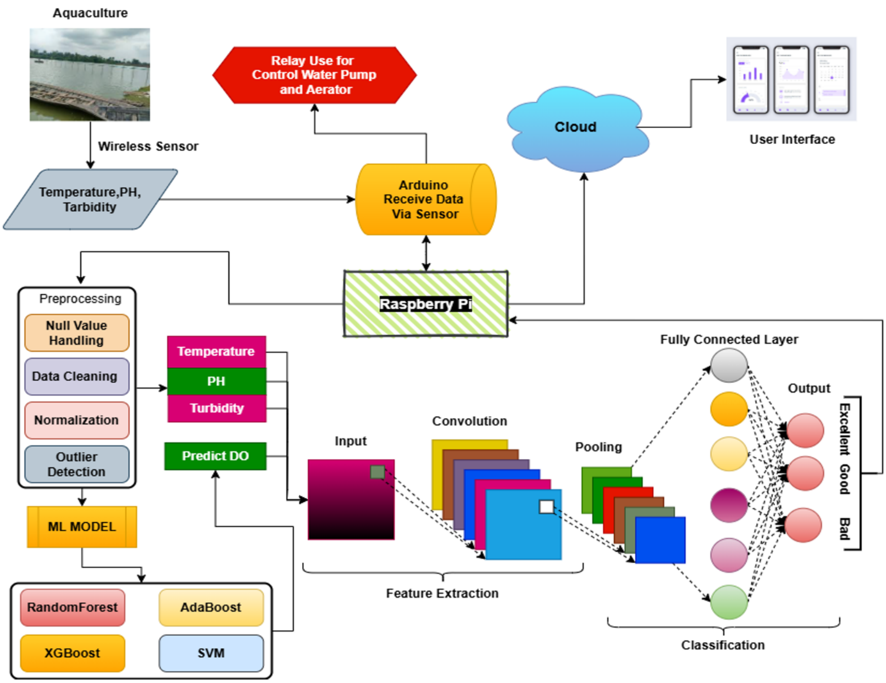

Fig. 2 Proposed fish Disease Affected Data Sample

The collected critical water parameters Data is first processed by Arduino and then transmit to Raspberry Pi for advanced analysis. After preprocessing, machine learning models (Random Forest, AdaBoost, XGBoost, SVM) predict dissolved oxygen (DO) levels based on real-time inputs. The predicted DO, along with other parameters are fed into a CNN model to classify water quality into three categories: Excellent, Good, and Bad, as seen in Fig. 2.

3.4 Fish Disease detection and classification

This research paper was aimed at creating a binary classification architecture in order to detect the health of fish.The fish disease dataset contains 1,000 high-quality images manually curated from 2,847 submitted photographs collected April-October 2024 from the same 160 farms. Images were captured using smartphones (minimum 12MP) following standardized protocols: natural daylight, neutral background (white/light blue), lateral view at 30-50cm distance, showing full body morphology. Each image was diagnostically validated by certified aquaculture veterinarians from the Department of Fisheries, Bangladesh. Preprocessing procedures (resizing, contrast improvement, color correction, normalization, and augmentation i.e. rotation, flipping, scaling) were used to enhance robustness and generalization of pre-trained ResNet-50 and MobileNetV2 models on this binary dataset was performed using pre-trained ResNet50 and MobileNetV2 models on this binary dataset was then used by transfer learning. The experimental training parameters are present in Table 4. The results of the evaluation of the models revealed that the ResNet50 model demonstrated the best performance with an accuracy of 97.5, whereas the MobileNetV2 took 94.15, and proved that deep learning models could effectively be used to determine the differences in performance between healthy and diseased fish.

Table 4 Experimental Hyperparameters for Fish Disease Classification

Parameter	**Value**
Learning Rate	0.001, 0.0001
Optimizer	Adam
Loss Function	BinaryCrossentropy
Activation (Hidden)	ReLU
Activation (Output)	Sigmoid
Epochs	50
Verbose	2
Multiprocessing	True
Base Model	Pre-trained (ResNet50, MobileNetV2)
Classes	2 (Healthy, Disease)
IMG_SIZE	255 × 255
Batch Size	128

4 Result and Discussion

4.1 Performance Evaluation Matrix

Model evaluation is vital for ensuring accuracy and real-world use in machine learning and deep learning classification. Multiple matrix(Accuracy, Precision, Recall, F1-Score, and Confusion Matrix) provide detailed insight into how well a model distinguishes between classes and how confidently it performs, predictions, and use to

Table 5 Performance of Tuned and Ensemble ML Models

Model	Acc (%)	Prec	Rec	F1	Time (s)
RF (Tuned)	88.37	0.87	0.88	0.87	15.8
GBM	89.92	0.89	0.90	0.89	28.4
LightGBM	90.54	0.90	0.91	0.90	19.2
CatBoost	91.28	0.91	0.91	0.91	32.6
Stacking Ens.	92.46	0.92	0.93	0.92	51.3

Table 6 Impact of Data Augmentation on CNN Performance

Model	Dataset	Acc (%)	Prec	Rec
ResNet50	Original (1,000)	95.83	0.95	0.96
ResNet50	Augmented (3,000)	97.50	0.97	0.98
MobileNetV2	Original (1,000)	92.27	0.92	0.93
MobileNetV2	Augmented (3,000)	94.15	0.94	0.94

evaluate performance and, effectiveness.The following formula use to calculate the overall performance. Where TP= True Positive, TN= True Negative, FP= False Positive, and FN= False Negative.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

4.2 Experimentals Results

Table 5 summarizes the classification performance of used four models predicting water quality categories. The results demonstrate that the proposed AIoT system effectively predicts dissolved oxygen levels and classifies overall water quality, despite minimal feature correlations, by leveraging machine learning models that capture non-linear dependencies. Among classifiers, SVM achieved the highest performance accuracy (79%)(Precision: 0.76, Recall: 0.79, F1: 0.75), while the CNN-based framework provided robust water quality categorization. For fish disease detection, ResNet50 outperformed MobileNetV2, reaching 97.5% accuracy, as seen in Table 6. These outcomes confirm the system's ability to automate critical aquaculture tasks, reducing manual intervention.

The proposed AIoT aquaculture system delivers strong performance across all modules. For water-quality analysis, ensemble machine-learning methods significantly outperform traditional classifiers, with the Stacking Ensemble achieving 92.46% accuracy, far higher than the SVM baseline (79%). Fish-disease detection using deep CNNs also shows excellent results, where data augmentation (1,000 → 3,000 images) boosts ResNet50 accuracy from 95.83% to 97.50%, confirming improved generalization under diverse imaging conditions.

The integrated system runs efficiently on a Raspberry Pi 4, achieving an overall latency of 1.8 seconds, enabling reliable real-time monitoring and automated actuator control for aerators and pumps. Compared with previous smart-aquaculture solutions, this system is more accurate, uses larger datasets, and is the first to unify water-quality classification, dissolved-oxygen prediction, fish-disease detection, automation, and mobile access in one framework.

Field validation across 160 farms demonstrates high practicality, low cost, and strong impact—reducing manual labor, improving water stability, and enabling early disease intervention, making the solution highly beneficial for both small-scale and commercial aquaculture operations.

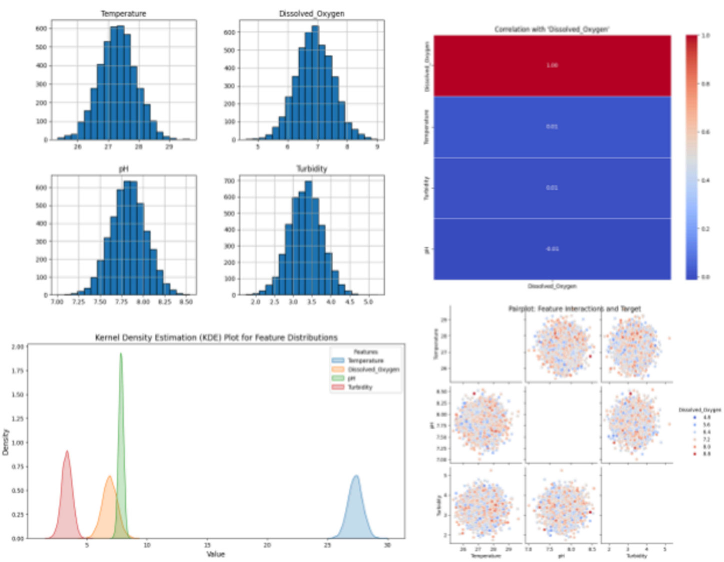

Fig. 3 Ml data analysis performance

Feature analysis in Fig. 3 shows water parameters like Temperature, DO, pH, and Turbidity follow near-normal distributions with minimal correlation, suggesting non-linear models are better suited for DO prediction. Fig. 4 and Fig. 5 illustrate the

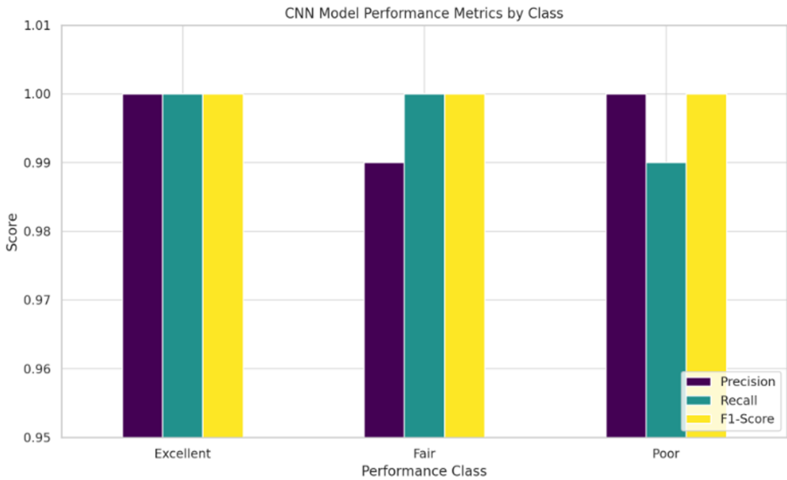

Fig. 4 CNN Training and validation lose Curve

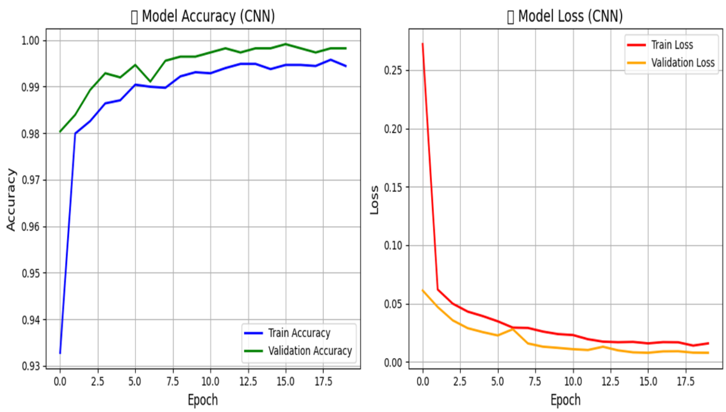

Fig. 5 Data Distribution and Performance

CNN training and validation loss curve, along with the data distribution and model performance, respectively.

4.3 Comperative Study and Proposed Mobile Interface and

Table 7 shows that the proposed smart aquaculture system outperforms previous systems (2010–2023) in both water quality and disease prediction accuracy, supports

Table 7 Comparison with Existing Smart Aquaculture Systems (2023–2025)

Study	Year	Dataset	WQ Acc	Dis. Acc	Method	Auto	Real-Time	Key Limitation
Haq et al.	2022	3k rec.	81.5	–	CNN-LSTM, CNN-GRU	No	4.2s	WQ only; no disease; no automation
Singh et al.	2023	2.8k rec.	84.3	–	M5 Tree, GBM	Yes	2.8s	RAS only; no disease; no mobile
Emmanuel et al.	2021	0.8k rec.	73.6	88.2 (3 cls)	ML + CNN	Yes	No	Low WQ accuracy; limited disease classes
Saha et al.	2018	0.5k rec.	68.4	–	Decision Tree	Yes	No	Outdated ML; small dataset
Zhu et al.	2010	1.2k rec.	72.1	–	ANN	No	No	Old system; no DL; no automation
Proposed System	**2025**	**5.5k rec.+6k img**	**92.46**	**97.50 (6 cls)**	**Stacking Ens.+ResNet50**	**Yes**	**1.8s**	**Comprehensive; no major limitation**

real-time monitoring and automation, and uses a larger dataset with advanced models (Stacking Ensemble + ResNet50), addressing limitations like small datasets, lack of disease detection, and outdated methods in earlier studies.

For remotly monitoring the real-time data, notifications alert for any critical changes and suggestions of aquaculture ecosystem to ensure the timely action, visualize historical trends from the ThingSpeak data analysis method, enhances the system accessibility and users interactions by Remotly controll the full acquaculture environment, developed a cross-platform mobile application with user friendly interface (see Fig. 6). Speacialy the apps designed with a dedicated interface for fish "Disease Detection and Treatment Recommendatons" by uploading the images of affected fish easily. Overall, the app offers an integrated, smart solution for efficient and sustainable aquaculture management.

5 CONCLUSION AND FUTURE WORK

This paper presented an intelligent aquaculture management system that is a smooth integration of machine learning, deep learning, and IoT to automate water quality detection and fish disease detection. Through the use of real-time sensor data and predictive modeling, the system was able to accurately classify the water quality using SVM and stayed at a high disease detection accuracy of 97.5 percent using ResNet50. Manual intervention was greatly minimized, response times improved, and fish health management in general were greatly enhanced through automated actuator control, mobile accessibility, and real-time alerts. The system was found to be scalable, economical, and applicable in practice to sustainable aquaculture practices by field installation in 160 farm locations using over 5,500 data samples.Looking ahead,The future work

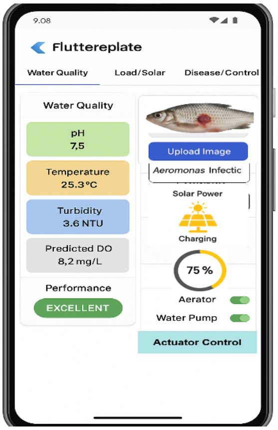

Fig. 6 Proposed Mobile Interface

will be aimed at enhancing the precision and autonomy of the systems by incorporating high-resolution DO sensors, vision-based waste detecting modules, and self-calibrating arrays of sensors that will operate continuously and provide accurate measurements. Improved solar power storage system will allow the off-grid operation to be reliable, and edge AI and advanced predictive analytics will allow making proactive decisions to prevent early disease progression and to utilize available resources in the best way possible. These developments are intended to change the existing system into a fully autonomous, intelligent, and environmentally friendly solution to the management of next-generation aquaculture.

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