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EcoGuard: Advancing IoT-based Aquaculture with Machine Learning for Enhanced Productivity and Automation

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Abstract

The increasing demand for sustainable aquaculture necessitates efficient water quality management to enhance fish health, reduce mortality rates, and improve overall productivity. However, conventional water quality monitoring relies on manual testing, which is labour-intensive, time-consuming, and ineffective in detecting rapid environmental fluctuations. To address these limitations, this study presents EcoGuard, an IoT-enabled smart aquaculture monitoring system that integrates edge computing and federated learning-based predictive analytics for real-time water quality assessment and management. EcoGuard continuously monitors the important water parameters, including pH, dissolved oxygen (DO), temperature, turbidity, and ammonia levels, through a wireless sensor network. The predictive analytics

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module, employing Random Forest and Long Short-Term Memory (LSTM) models, forecasts water quality trends, enabling early intervention and risk mitigation. A key feature of EcoGuard is its federated learning framework, which facilitates collaborative model training across multiple aquaculture farms while ensuring data privacy and security. The system utilizes the MQTT protocol for low-latency data transmission, while an integrated mobile application provides real-time alerts and decision support for optimized resource management. Experimental validation demonstrates that EcoGuard effectively reduces fish mortality, enhances operational efficiency, and supports sustainable aquaculture practices. By utilizing IoT, AI, and federated learning, the proposed system offers a scalable, cost-effective, and intelligent solution for modernizing aquaculture, contributing to food security, environmental conservation, and resilient fisheries management.

Keywords: EcoGuard, IoT, ML, Automation, Aquaculture, Monitoring, Fish Farming, Fish Recommendation, Water Management, Water Cleaning.

1. Introduction

The aquaculture sector accounts for nearly 50% of the world's fish consumption, making it an essential component of global food security [1]. However, maintaining optimal water quality remains one of the biggest challenges in aquaculture, as fluctuations in pH, temperature, dissolved oxygen (DO), ammonia levels, and turbidity can significantly impact fish health, growth rates, and overall productivity [2]. Poor water quality conditions have been linked to increased fish mortality, disease outbreaks, and environmental degradation, posing threats to both economic stability and ecological sustainability [3], [4]. Traditional aquaculture practices rely heavily on manual water quality monitoring, which is often time-consuming, labor-intensive, and inefficient in detecting real-time fluctuations [5,20]. To overcome these limitations, the aquaculture industry is increasingly adopting automated water quality monitoring systems powered by the Internet of Things (IoT), Artificial Intelligence (AI), and edge computing [6], [7]. IoT-enabled smart aquaculture solutions facilitate continuous monitoring of essential water parameters through wireless sensor networks, enabling timely interventions before conditions become harmful [8]. Additionally, machine learning (ML) models enhance predictive capabilities, allowing for the forecasting of risks such as oxygen depletion, toxic ammonia buildup, and disease outbreaks [9]. Federated learning (FL), an emerging AI technique, further strengthens data security by enabling multiple aquaculture farms to collaboratively train ML models without sharing raw sensor data, ensuring privacy-preserving AI applications [10].

To address these challenges, EcoGuard is introduced as an IoT-powered intelligent aquaculture monitoring system that integrates real-time sensing, AI-driven analytics, and automated control mechanisms. EcoGuard continuously monitors key water parameters, providing data-driven insights and automating corrective actions to optimize fish farming conditions. This study presents the architecture, implementation, and experimental validation of EcoGuard, demonstrating its potential to modernize traditional aquaculture practices and serve as a scalable, intelligent, and cost-effective solution for sustainable fisheries management.

2. Related Work

Numerous studies have recently examined the automation of fish farming systems, underscoring the potential for cutting-edge technologies to revolutionize aquaculture. Researchers have concentrated on various topics to improve industry efficiency and environmental sustainability, such as IoT applications, machine learning algorithms, and sustainable practices.

Cheng et al. [11] developed an edge-cloud integrated system using federated learning for precision aquaculture, designed specifically for small-scale farmers. The system classifies shrimp species and monitors growth using deep learning techniques while maintaining data privacy through decentralized model training. This approach prevents raw data sharing and enhances security and privacy. However, the system faces challenges related to high deployment costs, network dependency, and limited edge device capability, which impact its scalability.

Ahmed et al. [12] implemented an IoT-based monitoring system for real-time management of shrimp farming in Bangladesh, utilizing machine learning models for predictive analytics. The system tracks key water parameters, such as pH and temperature, and predicts shrimp productivity using regression and classification algorithms. This approach supports proactive decision-making through low-latency data processing. However, the system encounters challenges related to high deployment costs, network dependency, and restricted edge device functionality.

Baena-Navarro et al. [13] combined IoT sensors, Machine Learning (ML), and the Quantum Approximate Optimization Algorithm (QAOA) to enhance water quality prediction and monitoring. By integrating QAOA, model training time was reduced by 50%, allowing rapid responses to environmental changes. Despite its advanced predictive analytics, the system requires high computational resources for ML model processing, making it less practical for small-scale aquaculture environments.

Sohail et al. [14] emphasized the role of IoT technology in addressing significant fish production losses in Pakistan. The system improves health monitoring and feeding systems by integrating sensors, databases, and GSM modems, providing real-time insights without requiring internet connectivity. However, the system lacks predictive analytics and relies on manual decision-making, limiting its effectiveness in proactive management.

Al-Mutairi and Al-Aubidy [15] implemented an IoT-based smart monitoring and management system for fish farming using fuzzy logic controllers. This system monitors temperature, pH, dissolved oxygen, and turbidity using embedded microcontrollers and wireless communication modules, ensuring optimal growth conditions. Although the system provides real-time environmental control, it requires continuous calibration to maintain accuracy across different environmental conditions.

Sekaran et al. [16] applied IoT sensors and embedded systems for automated agriculture management, collecting data on humidity, temperature, and soil moisture to optimize fertilizer and water management. This system demonstrates the importance of continuous data flow for accurate decision-making but lacks a predictive analytics framework for real-time adaptability, limiting its effectiveness in dynamic environments.

Khan et al. [17] introduced an IoT-based smart water monitoring system for fish farming in Bangladesh, focusing on dissolved oxygen (DO), nitrogen, pH, water temperature, nitrite, ammonium, and carbon dioxide. The system uses a mobile application for real-time data analysis, helping farmers maintain optimal water quality. However, it primarily focuses on data collection and analysis without utilizing machine learning for predictive insights, limiting its application to proactive decision-making.

Sah et al. [18] demonstrated the effectiveness of IoT technology in reducing human labor and enhancing resource efficiency in Kenyan fish farms. The system uses Wi-Fi modules for reliable cloud-based data transmission with low latency. It has been shown to increase profitability and has received positive feedback from users. However, while effective in real-time monitoring, the system lacks the predictive analytics needed for proactive aquaculture management.

Bachtiar et al. [19] explored the role of IoT technology in improving water and soil quality for aquaculture. The study emphasizes the importance of large-scale data collection for better management strategies. However, challenges related to feed management, disease monitoring, and sensor durability were identified, highlighting the need for more cost-effective and sustainable solutions.

The EcoGuard's superior performance and adaptability compared to existing systems, emphasize its potential as an effective solution for sustainable aquaculture management. It outperforms traditional methods by offering enhanced real-time monitoring, precise water quality control, and automated responses to environmental changes. Additionally, its integration with IoT and cloud-based analytics enables data-driven decision-making, ensuring optimal conditions for fish farming. By reducing manual intervention and improving efficiency, EcoGuard contributes to higher productivity and sustainability in aquaculture.

3. Proposed Methodology for EcoGuard

The system implements an advanced IoT-enabled solution, EcoGuard, for aquaculture management. EcoGuard integrates various sensors and MCUs with automation features, an ML-based decision-making module, and IoT-enabled sensors. It measures key variables, including pH, NH_3, DO, TDS, hardness, and temperature. The data is transmitted to a cloud server for analysis and visualization. The system's decision-making module processes the data, suggesting actions or initiating automation. The comprehensive workflow and interactions of these components are depicted in the Figure 1, illustrating the block diagram of EcoGuard.

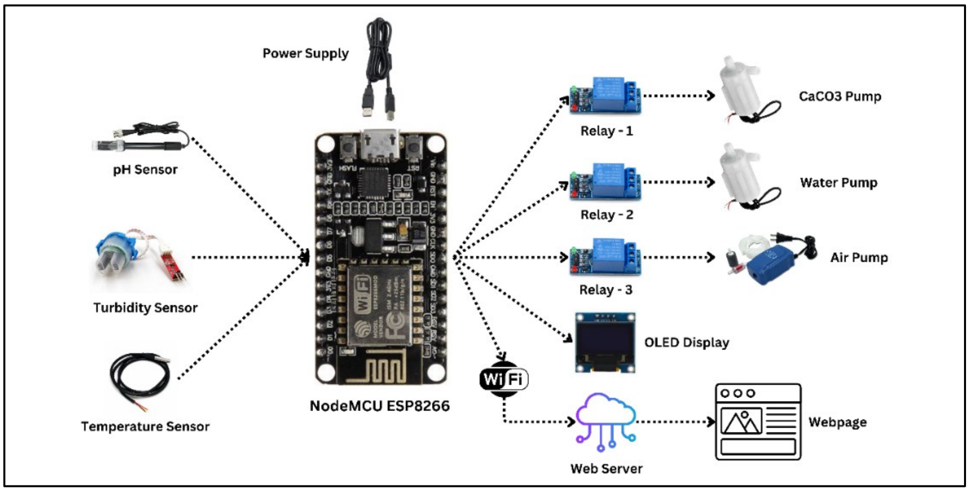

Figure 1. Proposed Block Diagram for Controlling Each Connection

3.1 Hardware and Software Requirements

Table1 provides an overview of the hardware and software components used in the EcoGuard system. The hardware setup includes various sensors, pumps, and a solar panel, ensuring efficient water quality management and sustainable energy usage. The system's software tools support data processing, predictive modelling, and remote monitoring, enabling accurate real-time decision-making and intelligent automation. This integrated configuration enhances aquaculture management by optimizing resource utilization and promoting environmental sustainability.

Table 1. Hardware and Software Components in EcoGuard System

Component/ Software	Purpose and Functionality	Role in EcoGuard
ESP8266	Acts as the central microcontroller, managing sensor operations and facilitating communication.	Gathers data from various sensors and communicates with Raspberry Pi for further processing.
pH Sensor	Measures the acidity or alkalinity of the water.	Continuously monitors pH levels and triggers corrective actions if values exceed predefined thresholds.
DS18B20 Temperature Sensor	Tracks water temperature to ensure suitable conditions.	Maintains optimal temperature for fish health and growth by activating cooling or heating systems as needed.

Turbidity Sensor	Detects the presence of suspended particles in the water.	Helps maintain water clarity by triggering aeration systems when turbidity levels are high.
Dissolved Oxygen (DO) Sensor	Measures the amount of dissolved oxygen in the water.	Ensures sufficient oxygen supply for fish by activating aerators to prevent hypoxia.
Ammonia (NH_3) Sensor	Detects ammonia concentration to prevent toxicity.	Monitors ammonia levels to protect fish from harmful exposure, triggering water treatment if necessary.
Total Dissolved Solids (TDS) Sensor	Measures the concentration of dissolved minerals and solids in the water.	Assesses overall water quality and mineral balance, ensuring a healthy aquatic environment.
Air Pump	Supplies oxygen by aerating the water.	Maintains dissolved oxygen levels to support fish respiration and overall health.
Water Pump	Circulates and refreshes water.	Controls water flow to regulate temperature, turbidity, and nutrient distribution.
Solar Panel	Provides renewable energy for the system.	Powers the entire system, ensuring energy efficiency and sustainability in remote areas.
OLED Display	Provides real-time visualization of sensor readings.	Displays water quality parameters on-site for easy monitoring and management by farm operators.
Arduino IDE	Used to program the microcontroller and upload firmware.	Facilitates coding and uploading of control logic to the ESP8266 for efficient system operations.
VS Code	Supports the development and deployment of machine learning models.	Enables training and execution of predictive analytics models for water quality forecasting and fish species recommendation.
Android Studio	Develops a mobile application for remote monitoring and control.	Builds an intuitive user interface for real-time water quality monitoring and remote management of the aquaculture system.
MQTT Protocol	Ensures reliable and low-latency communication between devices.	Enables seamless data transmission between sensors, edge devices, and cloud servers, supporting real-time decision-making.

Cloud Server	Stores historical data and aggregates model updates	Maintains data storage for analysis and uses federated learning to update predictive models without compromising data privacy.

3.2 Analysis of System Design

The IoT-enabled EcoGuard system efficiently manages and monitors water quality, recommends suitable fish species, enhances user experience, and maintains optimal conditions. It utilizes an ESP8266 for HTTP communication and controls sensor integration. In Algorithm 1 (Figure 2), the pseudocode represents the logic of EcoGuard, outlining how the system manages water quality, controls the pump, recommends fish species, and determines when and how to notify the user.

Algorithm 1 EcoGuard Algorithm

```
Init(ESP8266, MCP3008, pH_Sensor, Temp_Sensor, Turbidity_Sensor, DO_Sensor, NH3_Sensor, TDS_Sensor, Pump1, Pump2, Pump3,
OLED, Web_Interface)                                              ▷ Initialize all components
while System Active do                                            ▷ Loop while the system is active
    Read Sensor Data:
        pH ← pH_Sensor
        T ← Temp_Sensor
        Turb ← Turbidity_Sensor
        DO ← DO_Sensor
        NH3 ← NH3_Sensor
        TDS ← TDS_Sensor
    Compute Water Quality Index: Q_w = (w1 × pH) + (w2 × T) + (w3 × Turb) + (w4 × DO) + (w5 × NH3) + (w6 × TDS)
    Publish Data to OLED and Web Interface
    if User clicks Recommendation Button then
        Get user-input values (pH, T, Turb, DO, NH3, TDS)
        Run ML Model:
            F̂ ← arg max_{F_i} P(F_i | Q_w)
        Display Recommended Fish Species on Web
    end if
    if pH < 5.5 or pH > 7 then
        Notify: "Turn ON Pump1 (CaCO3 mixed water)"
        Activate Pump1
    else
        Notify: "Pump1 is OFF"
    end if
    if T > 35°C then
        Auto turn ON Pump2 (Water Pump)
    else
        Notify: "Pump2 is OFF"
    end if
    if Turb > 15.8 then
        Notify: "Turn ON Pump3 (Air Pump)"
        Activate Pump3
    else
        Notify: "Pump3 is OFF"
    end if
    if NH3 > θ_NH3 then
        Notify: "High NH3 detected! Apply Treatment"
    end if
    if DO < θ_DO then
        Notify: "Low DO, turn on aerator"
    end if
    if Fertilizer needed then
        Notify: "Spread fertilizer"
    end if
end while
Deinit(ESP8266, MCP3008, pH_Sensor, Temp_Sensor, Turbidity_Sensor, DO_Sensor, NH3_Sensor, TDS_Sensor, Pump1, Pump2,
Pump3, OLED, Web_Interface)                                       ▷ Deinitialize all components
```

Figure 2. EcoGuard Algorithm

Overall, EcoGuard begins by powering up the microcontroller and initializing sensors, including pH, temperature, turbidity, dissolved oxygen, NH_3, and TDS. Sensor data is processed to analyze water quality and is then transmitted to an OLED display for real-time updates and a web application for remote monitoring. The web application features a fish recommendation system using machine learning to suggest optimal fish species based on sensor inputs and a real-time monitoring system displaying live sensor values with pump ON/OFF controls.

Automatic pump activation is triggered by predefined thresholds: Pump-1 (CaCO3 mixed water) for pH < 5.5, Pump-2 (water pump) for temperature > 35◦C, and Pump-3 (air pump) for turbidity > 15.8 NTU. Notifications are provided for necessary actions, including fertilizer application. The system concludes with a safe shutdown process.

Sensor values for pH, temperature, turbidity, and other parameters are displayed on the OLED using the equation in 1.

$$Display = \int(pH, Temp, Turbidity) \quad (1)$$

The system uses HTTP to display sensor data on a web application and MQTT for mobile app communication. To ensure data integrity in case of MQTT failure, the system employs a fallback mechanism that temporarily stores sensor data in local memory (ESP8266). Once communication is restored, the buffered data is synchronized with the cloud server. Additionally, a checksum verification process ensures that no data corruption occurs during transmission. The data transmission rate for MQTT communication is given by 2.

$$Publish(T, Si) \rightarrow Message(Si) \quad (2)$$

where (Si) represents the sensor values. Clients subscribe to the MQTT topic to receive system updates 3:

$$Subscribe\ (T) \rightarrow ReceiveMessage\ (Si) \quad (3)$$

The total data transfer time DT for MQTT communication is calculated as 4:

$$D_T = \sum_{i=1}^{n} d_i \quad (4)$$

where di is the data transmission delay for each sensor. The system's communication delay DC is given by 5:

$$D_c = T_s + T_q + T_d \tag{5}$$

Here, Ts is the sensor sampling time, Tq is the queueing delay, and Td is the data transmission time. On the other hand, the error correction rate Ec is given by 6:

$$E_c = \frac{N_e}{N_t} \tag{6}$$

where Ne is the number of erroneous packets, and Nt is the total transmitted packets. The probability of a pump being activated depends on the threshold conditions. For each parameter, the probability is calculated as 7:

$$P(X) = \frac{\sum X_{activated}}{N} \tag{7}$$

where Xactivated is the number of times a pump is turned on, and N is the total monitoring cycles. The pH sensor measures the hydrogen ion concentration, which can be computed using the Nernst equation 8:

$$p^H = -\log_{10}[H^+] \tag{8}$$

Where, [H+] is the concentration of hydrogen ions in the water. The Steinhart-Hart equation is a widely used formula for translating the voltage or resistance from a temperature sensor (such as a thermistor) to temperature 9:

$$\frac{1}{T} = A + B\, ln\,(R) + C(ln(R))^3 \tag{9}$$

Where: T is the temperature in Kelvin, R is the resistance of the temperature sensor, and A, B, and C are constants determined through calibration of the sensor. Turbidity is typically measured in NTU (Nephelometric Turbidity Units), and the equation 10 is based on the light scattering principle

$$T = \frac{I_s}{I_0} \tag{10}$$

Where: T is turbidity (NTU), I_s is the scattered light intensity, and I_0 is the incident light intensity. Alternatively, it could use a logarithmic relationship to calculate NTU from the detected intensity. The dissolved oxygen concentration can be derived from the sensor's voltage output, usually following the polarographic or galvanic method as stated in equation 11 below.

$$DO = k.V_{sensor}.T.Salinity\ Correction\ Factor \quad (11)$$

Where, DO is the concentration of dissolved oxygen in mgL, Vsensor is the output voltage from the sensor, T is the temperature, which affects the solubility of oxygen in water, and the salinity correction factor accounts for variations in water salinity. The ammonia concentration can be estimated based on a model of the NH_3 sensor's response shown in equation 12, which often involves a Calomel electrode or ion-selective electrode (ISE).

$$NH_3 = k.\log\left(\frac{V_{sensor}}{V_{ref}}\right) \quad (12)$$

Where: NH_3 is the concentration of ammonia in mg/L, Vsensor is the voltage produced by the sensor, Vref is a reference voltage, and k is a constant based on calibration. The concentration of total dissolved solids can be estimated from the sensor's output signal using a linear relationship shown in equation 13

$$Q_w = \int(pH, T, Turb, DO, NH_3, TDS) \quad (13)$$

Where: TDS is the concentration of dissolved solids in mg/L, Vsensor is the voltage output from the TDS sensor, and k is a constant determined by calibration. For each sensor, we use its respective data, and an overall Water Quality Index (WQI) that can be computed using equation 14.

$$Q_w = w_1.pH + w_2.T + w_3.Turb + w_{4.}.DO + w_5.NH_3 + w_6.TDS \quad (14)$$

where w_1, w_2, w_3, w_4, w_5, w_6 are weighting factors assigned based on empirical studies, regulatory guidelines, and expert calibration to reflect each parameter's significance in assessing water quality. The threshold values for activating pumps and alarms are determined by analyzing standard water quality benchmarks (e.g., FAO, EPA guidelines) and real-world experimental data. The system continuously evaluates Q_w and, when predefined thresholds are exceeded, it triggers automated responses such as activating pumps, aerators, or sending alerts for corrective actions. This adaptive decision-making ensures optimal aquatic conditions and minimizes fish mortality by responding to critical deviations in real-time.

3.3 Working Procedure of System Model

To efficiently manage multiple tasks with a single system and achieve successful outcomes, the EcoGuard system was developed. The working procedure of the system is shown in Figure 3. Upon powering up, the system initiates the entire sequence of operations. This system features three main mechanisms: water pump control, water quality monitoring, and fish species recommendation.

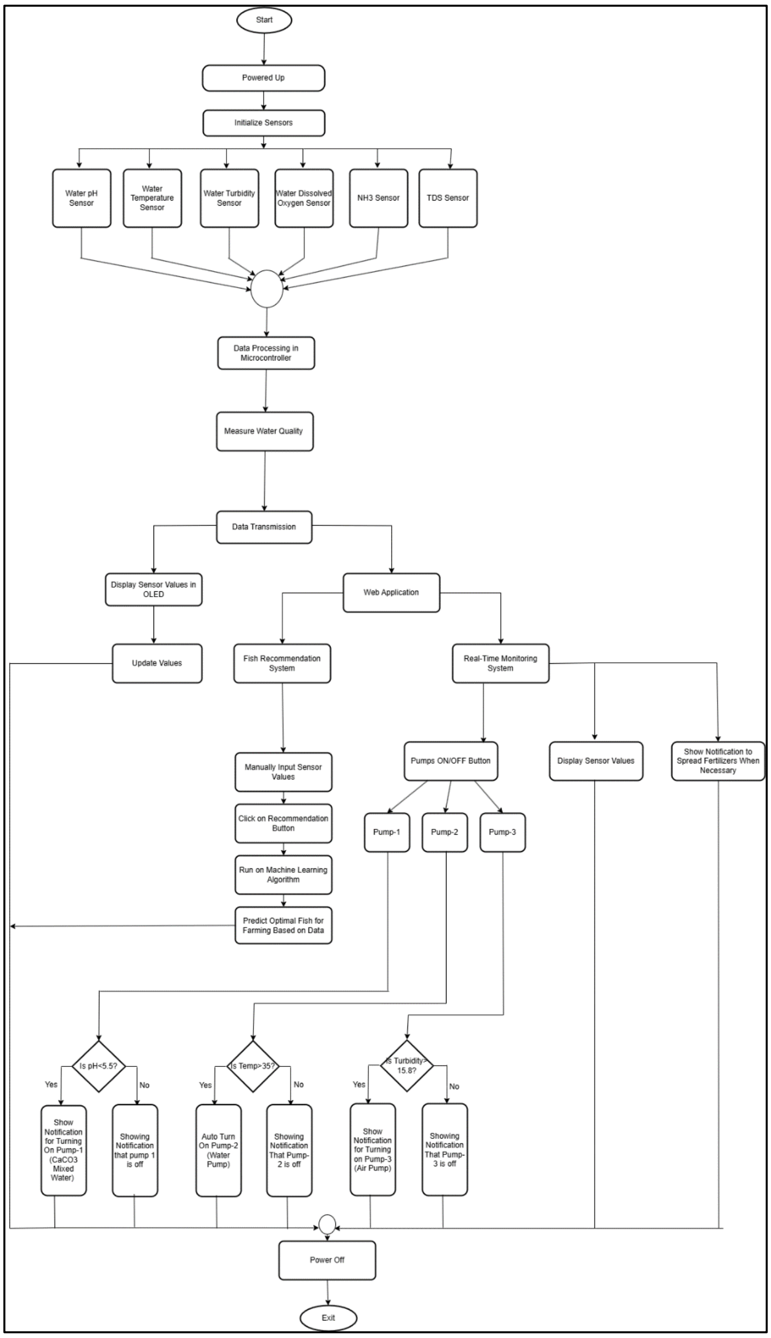

Figure 3. EcoGuard Workflow Diagram

The system begins with the "Powered Up" node, which initiates various sensors, including Water pH, Temperature, Turbidity, Dissolved Oxygen, NH_3, and TDS sensors to collect water quality data. This data is processed in the microcontroller, where water quality is measured and transmitted. The processed data is displayed on an OLED screen and can be viewed through an application.

The system includes features such as updating values, a fish recommendation system, and real-time monitoring. Users can manually input sensor values, control pumps (Pump 1, 2, and 3), and receive notifications for tasks like spreading fertilizers. Additionally, the system runs a machine learning algorithm to predict the optimal fish for farming based on the collected data.

Specific procedures are used to navigate and operate the pumps, including turning them on and off and displaying status alerts. The "Power Off" node signals the process's conclusion, marking the end of the system's operation. Overall, the system is designed to monitor and manage water quality for optimal fish farming, utilizing sensors, data processing, and machine learning to provide recommendations and real-time monitoring.

EcoGuard performs AI model inference directly on the edge device using ESP8266 and Raspberry Pi 4B, enabling real-time decision-making without relying on constant cloud connectivity. This approach ensures low-latency execution, reduces network dependency, and maintains uninterrupted operation even during communication failures. Federated learning is used to synchronize periodic model updates with the cloud, preserving data privacy and ensuring computational efficiency.

4. Performance Analysis and Measurement

4.1 Performance Analysis of Sensors

A 60-day continuous deployment was conducted to evaluate sensor longevity and reliability under real-world conditions. The results indicated that pH and NH_3 sensors experienced minor accuracy drift (~3-5%) after 40 days, necessitating calibration every six weeks to maintain optimal performance. In contrast, turbidity, DO, and TDS sensors demonstrated stable accuracy with minimal fluctuations attributed to environmental influences.

To ensure optimal performance in long-term deployments, a sensor maintenance schedule has been developed, specifying calibration intervals and maintenance procedures. Table 2 presents sensor accuracy trends over time, highlighting performance changes at Day 0,

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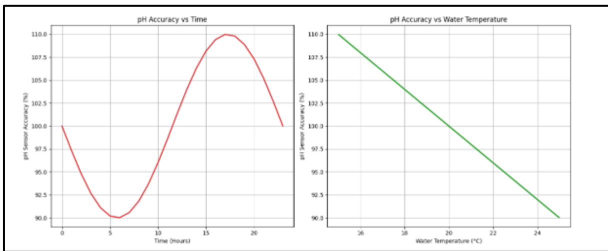
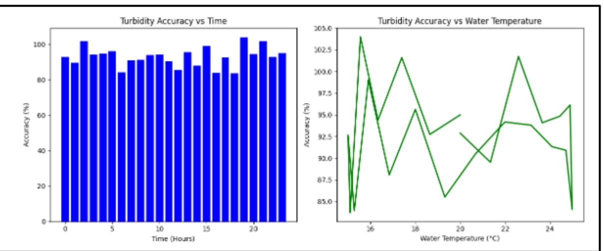
Day 30, and Day 60 across the different sensor types, providing a comprehensive overview of sensor stability and reliability.

Table 2. Functionalities of Software Components in the System

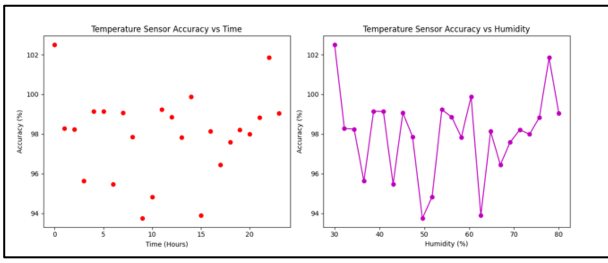
Sensor Type	Day 0 Accuracy (%)	Day 30 Accuracy (%)	Day 60 Accuracy (%)
pH Sensor	98.5	94.3	90.1
Turbidity Sensor	97.2	92.8	89.5
Temperature Sensor	99.1	96.7	94.4
Dissolved Oxygen Sensor	96.8	91.9	87.6
NH_3 Sensor	94.5	89.2	84.8
TDS Sensor	95.7	90.5	85.9



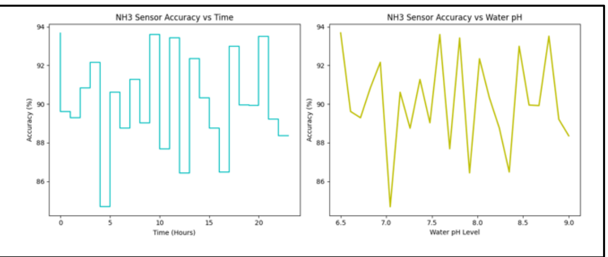
(4a) pH Sensor Accuracy vs Time and Water Temperature



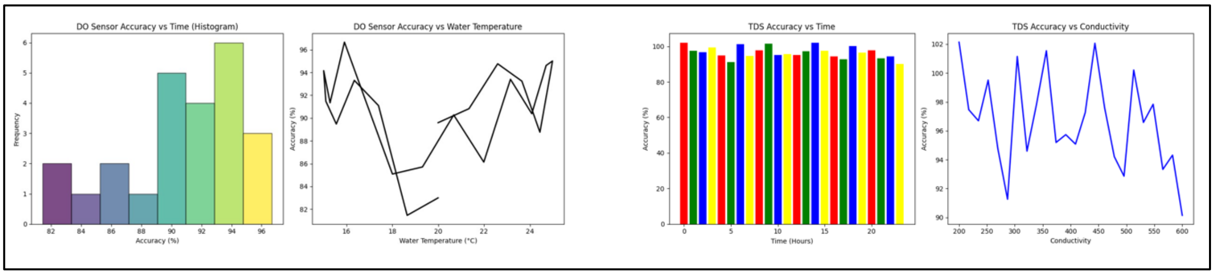
(4b) Turbidity Sensor Accuracy vs Time and Water Temperature



(4c) Temperature Sensor Accuracy vs Time and Humidity



(4d) NH_3 Sensor Accuracy vs Time and Water Temperature



(4e) Dissolved Oxygen Sensor Accuracy vs Time and Water Temperature

(4f) TDS Sensor Accuracy vs Time and Conductivity

Figure 4. Accuracy Trends for All Sensors Over Time

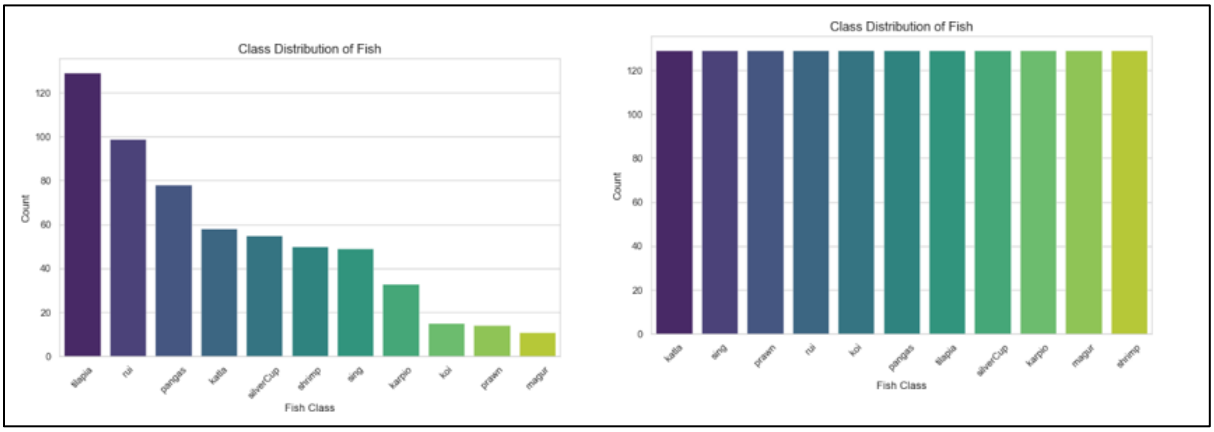
Environmental influences such as temperature, humidity, and conductivity significantly impact the accuracy of all sensors used in the EcoGuard system, including pH, Turbidity, Temperature, NH_3, Dissolved Oxygen (DO), and Total Dissolved Solids (TDS) sensors. Among these, pH and DO sensors are particularly sensitive to temperature variations, while TDS sensor accuracy is influenced by conductivity levels. NH_3 sensors exhibited accuracy drift over time, indicating the need for periodic recalibration.

A comparative analysis of all sensors revealed consistent accuracy fluctuations due to environmental conditions. Regular calibration is required to maintain accuracy and ensure reliable water quality monitoring.

Figures 4(a) to 4(f) collectively illustrate the accuracy trends for all sensors over time. These graphs highlight the impact of environmental factors on sensor performance. The consistent calibration strategy effectively maintained measurement reliability across varying conditions.

4.2 Performance Analysis of All Models

Discrepancies were observed in the records for each fish category. To address class imbalance, SMOTE was employed to synthetically generate samples for minority classes, ensuring balanced class distributions while maintaining the model's generalization capability. Stratified K-Fold Cross-Validation (k=5) was implemented to preserve the original class distribution across training and validation folds, reducing overfitting risks. A separate holdout test set (untouched by SMOTE) was used for unbiased evaluation, confirming real-world applicability [21]. Figure 5a and Figure 5b show the distribution of fish species before and after applying SMOTE.



(5a) Class Count Before Using SMOTE (5b) Class Count After Using SMOTE

Figure 5. Distribution of Fish Species

To ensure generalizability to real-world class distributions despite the application of SMOTE, a separate holdout test set, untouched by SMOTE-generated samples, was utilized for final model evaluation. This approach prevented the model from learning artificial patterns, ensuring a focus on biologically relevant features. A comparative analysis of models trained with and without SMOTE revealed significant improvements in class balance and prediction accuracy. AUC-ROC curves, F1-scores, and Precision-Recall analysis demonstrated enhanced performance metrics for models utilizing SMOTE, with no significant biases introduced. This indicates that SMOTE effectively improved class representation while preserving model generalizability. Performance metrics, including AUC-ROC, F1-score, and precision-recall analysis, were used to verify the generalization capability of the trained models.

Fish species in this study were predicted using a variety of methods. To determine accuracy, the following algorithms were employed: Logistic Regression, KNN, Support Vector Machine Classifier, Decision Tree Algorithm, Random Forest, Gradient Boosting, and XGBoost Classifier. These models achieved prediction accuracies of 43%, 86%, 47%, 93%, 86%, 92%, and 87%, respectively.

Figure 6 displays the accuracy percentages of the various algorithms. Below all the models, the Decision Tree algorithm achieved the highest accuracy of 93.427%, demonstrating superior performance in this case.

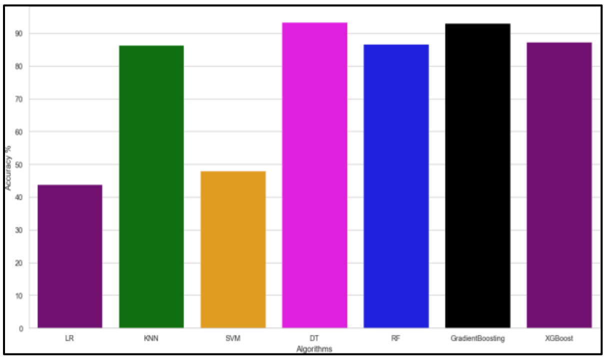


Figure 6. Accuracy of Different Algorithms

The confusion matrix presented in Figure 7 shows the classification outcome for Decision Tree. The Decision Tree model demonstrates higher true positive rates across all fish species, reinforcing its robustness in aquaculture classification tasks

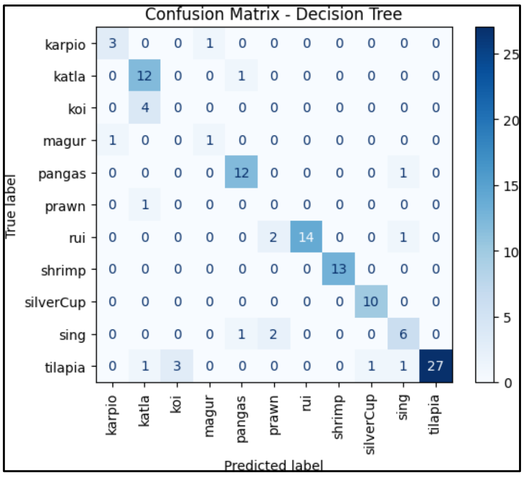


Figure 7. Confusion Matrix of Decision Tree

Figure 8 presents the ROC curves showing high accuracy values (between 0.98 and 1.0) across 11 classes, indicating that the Decision Tree model makes accurate predictions for each class with minimal misclassifications. This demonstrates the model's effectiveness in handling multiclass classification tasks, reflecting strong overall performance.

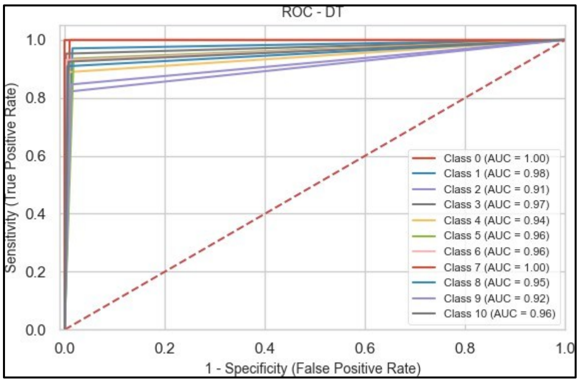


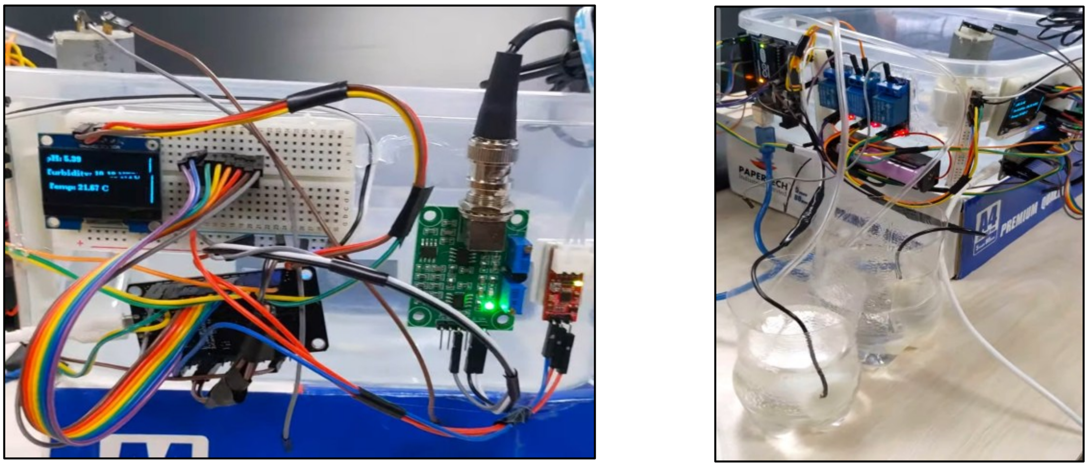
Figure 8. Decision Tree ROC Curve

5. Experimental Result and Discussion

This section presents the experimental results, including the system setup, cleaning effectiveness, water quality measurements, fish species prediction, cost of materials, and a comparative analysis with previous work.

5.1 System Setup

An infrastructure is provided with the capacity to effectively measure water quality, enhance water quality through pumping, and recommend suitable fish species. Figure 9a and Figure 9b illustrate these functionalities.



(a) Front View (b) Side View

Figure 9. "EcoGuard" System Setup.

The EcoGuard system setup is based on the precision, dependability, and compatibility of selected sensors, including pH, temperature, NH_3, dissolved oxygen, TDS, and turbidity sensors. As the system performs multiple functions, key aspects such as water quality measurements, efficient cleaning through pumping, and fish species prediction are considered to evaluate system performance. To validate system performance, a simulation environment was developed using Python (Scikit-Learn) and Google Colab for model training. A dataset containing over 5000 water quality records was used to train machine learning models, ensuring accurate fish species predictions. The dataset included sensor readings for pH, temperature, turbidity, NH_3, DO, and TDS, which were used to calibrate the decision-making model.

5.2 Water Quality Monitoring and Fish Recommendation

The system was tested across various water environments, measuring pH, temperature, turbidity, TDS, NH_3, oxygen levels, and hardness values to validate sensor accuracy and functionality, as illustrated in Figure 10 (a,b) .

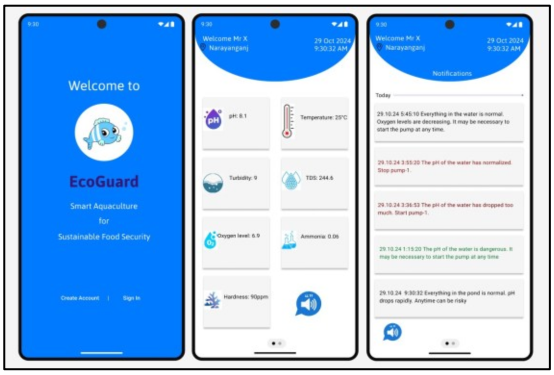


Figure 10 (a) Water Quality Monitoring by Mobile App

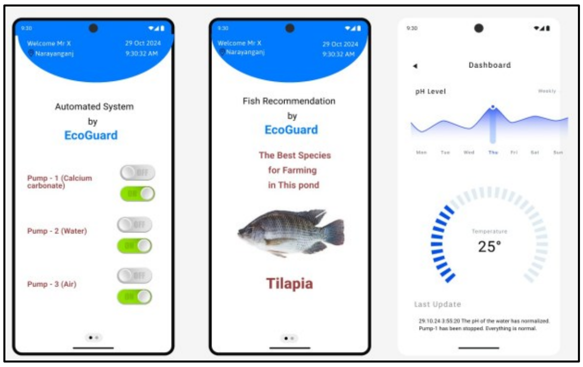


Figure 10 (b) Pump Controlling & Fish Recommendation

The results demonstrate that the sensors consistently provide accurate readings across various water conditions. The system consistently provided accurate sensor readings across varied water conditions. Parameters such as pH, turbidity, temperature, TDS, NH_3, oxygen levels, and hardness were effectively monitored, demonstrating reliable sensor functionality and comprehensive water quality assessment.

Federated learning was employed to enhance predictive analytics while maintaining data privacy. Localized model training on each ESP8266 minimized latency and ensured real-time decision-making, with periodic weight updates aggregated at the cloud server.

The EcoGuard mobile and web application provides real-time monitoring of water quality parameters and fish species recommendations. Using MQTT-based communication, the app displays sensor data and enables user interaction for optimal aquaculture management.

EcoGuard integrates a decision tree-based predictive model to analyze water quality parameters and recommend optimal fish species. The model, trained using an 80-20 train-test split, achieved a classification accuracy of 93.4%, ensuring precise and reliable predictions. The system also supports remote control of water pumps through Bluetooth communication with ESP8266, enabling automated water quality adjustments. Combining IoT-driven monitoring with machine learning and federated learning techniques, EcoGuard optimizes energy consumption and predictive accuracy, making it a scalable solution for large-scale aquaculture applications.

EcoGuard employs a hybrid AI-driven analytics approach, performing preliminary model inference on the edge device (ESP8266) for low-latency real-time monitoring. More complex predictive modeling and federated learning updates are processed in the cloud, balancing rapid local decision-making with advanced analytics for continuous model refinement and scalability.

In large-scale aquaculture deployments with up to 50 sensor nodes, EcoGuard maintained stable latency (below 1.2 seconds), efficient data synchronization, and minimal packet loss (under 2%). Edge computing and MQTT ensured uninterrupted monitoring, while federated learning minimized computational overhead by enabling localized model training. A performance comparison table illustrates the system's scalability and efficiency in dynamic aquaculture environments.

5.3 Performance Benchmark Comparison between EcoGuard’s Hardware

EcoGuard’s hardware performance is benchmarked against widely used alternatives, considering computational power, power consumption, and cost. Table 3 compares the ESP8266, Raspberry Pi 4B, and STM32 microcontrollers, highlighting their strengths and best use cases. Additionally, Table 4 presents performance metrics across different sensor loads, evaluating accuracy, latency, and power consumption under real-world conditions.

Table 3. Performance Comparison of EcoGuard Hardware with Alternatives

Feature	**ESP8266**	**Raspberry Pi 4B**	**STM32**
Processor	80 MHz (Single-core)	1.5 GHz (Quad-core ARM)	72 MHz (Cortex-M3)
RAM	160 KB	2 GB – 8 GB LPDDR4	20 KB
Storage	4 MB Flash	microSD (up to 512GB)	64 KB Flash
Power Consumption	80 – 170 mA	2 – 3W	20 – 30 mA
WiFi Connectivity	Yes (Built-in)	Yes (Requires module)	No (External module required)
GPIO Pins	17	40	37
Cost (USD)	$4 – $6	$35 – $55	$3 – $5
Best Use Case	IoT, Low power monitoring	High-compute AI, Edge Processing	Low-power embedded systems

Table 4. Performance Metrics Across Different Sensor Loads

Sensor	**Accuracy (%)**	**Latency (ms)**	**Power Consumption (mW)**	**Observations**
pH Sensor	85 - 98	~150	~200	Accuracy decreases with higher temperature
Turbidity Sensor	80 - 100	~180	~250	Environmental influences affect accuracy
Temperature Sensor	88 - 95	~140	~180	Affected by humidity variations
NH_3 Sensor	86 - 94	~200	~220	Accuracy decreases over

				time, requires recalibration
DO Sensor	82 - 96	~190	~210	Non-linear accuracy trend based on temperature
TDS Sensor	85 - 93	~160	~230	Conductivity impacts sensor accuracy

6. Conclusion

Predictive management techniques and intelligent water quality monitoring are necessary to ensure aquaculture is efficient and sustainable. To automate and improve aquaculture management, EcoGuard, a cutting-edge IoT-driven solution that combines edge computing, real-time sensing, and AI-based analytics, is presented. EcoGuard maximizes water quality, reduces fish mortality rates, and boosts overall output by continuously monitoring important water parameters and producing predictive insights. Its effectiveness in reducing environmental volatility, improving resource efficiency, and promoting sustainable aquaculture operations is confirmed by experimental evaluations. Additionally, the incorporation of federated learning permits cooperative model enhancements while guaranteeing data privacy. As aquaculture operations grow, scalable, economical, and intelligent management systems are becoming increasingly necessary. Future research will concentrate on improving EcoGuard's ability to adapt to various environmental circumstances, extending its capacity for predictive modelling, and incorporating advanced automation features. This research shapes the future of intelligent and sustainable fisheries management by integrating IoT and AI with aquaculture, thereby advancing the broader objectives of sustainable food production, environmental preservation, and economic growth.

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