OXYTRACK: AI-Based IOT System for Water Quality Monitoring and Fish Prediction

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Abstract

Sustainable aquaculture production critically depends on continuous monitoring of water quality parameters such as pH, temperature, turbidity, and dissolved oxygen (DO). Conventional manual monitoring techniques are labor-intensive and incapable of providing real-time insights, often leading to delayed intervention and economic losses. This paper presents **OxyTrack Pro**, a low-cost, AI-enabled Internet of Things (IoT) framework designed for real-time water quality monitoring and intelligent fish suitability prediction. The proposed system integrates multi-parameter sensing using an ESP32 microcontroller with cloud-based analytics and a Random Forest regression model for predictive analysis. Sensor data are transmitted via Wi-Fi to a cloud platform and visualized through a mobile dashboard. Experimental evaluation on 1,200 labeled samples demonstrates a prediction accuracy of 95.2%, with low latency (2.6–3.1 s) and reliable alert generation. The proposed framework offers an affordable and scalable solution for smart aquaculture management.

Keywords— Artificial Intelligence, Aquaculture Monitoring, ESP32, Fish Prediction, Internet of Things, Water Quality

I. Introduction

Aquaculture has emerged as one of the fastest-growing food production sectors worldwide due to the increasing demand for protein-rich food sources **[1]**. Effective water quality management is critical in aquaculture systems, as even minor fluctuations in water parameters can significantly affect fish survival, growth rate, and overall productivity **[2]**. Key parameters such as pH, temperature, turbidity, and dissolved oxygen directly influence the metabolic processes and immune responses of aquatic organisms **[3]**.

Conventional aquaculture practices largely rely on periodic manual water testing using chemical kits or laboratory-based analysis **[4]**. Although these methods provide accurate results, they are time-consuming, labor-intensive, and unsuitable for continuous monitoring. As a result, sudden changes in water quality conditions often go unnoticed until fish health deteriorates, leading to economic losses **[5]**.

Recent advances in Internet of Things (IoT) technologies have enabled real-time monitoring of environmental parameters through interconnected sensors, microcontrollers, and cloud-based platforms **[6]**. In addition, artificial intelligence (AI) techniques facilitate intelligent data analysis, prediction, and decision-making based on historical and real-time sensor data **[7]**. The integration of IoT and AI technologies therefore offers a scalable and efficient solution for smart aquaculture management, enabling proactive monitoring and timely intervention **[8]**.

In recent years, the adoption of smart technologies in aquaculture has gained significant attention as a means to improve operational efficiency, reduce resource wastage, and enhance fish health management. Continuous sensing of critical water quality parameters enables early detection of unfavorable conditions, thereby minimizing stress-induced diseases and mortality rates. Moreover, data-driven monitoring systems support informed decision-making by providing actionable insights rather than raw sensor readings. Such intelligent systems are particularly valuable in large-scale or remote aquaculture farms where manual supervision is impractical and costly.

Furthermore, the availability of continuous data streams facilitates long-term trend analysis and performance evaluation of aquaculture environments. Predictive models built on historical and real-time data can forecast potential water quality degradation and fish stress conditions before critical thresholds are reached. This proactive capability enables timely corrective of real-time monitoring and predictive decision-making. Unlike conventional systems that focus solely on data acquisition, the proposed solution combines sensing, analytics, and intelligent recommendation in a unified architecture.

II. Related Work

Numerous studies have investigated IoT-based solutions for water quality monitoring [1], [4]. Kumar *et al.* developed an IoT system using pH and temperature sensors to monitor pond conditions and transmit data to a cloud server [1]. Their system demonstrated improved monitoring efficiency but lacked predictive intelligence. Patil *et al.* proposed a sensor-based water monitoring system using Arduino and GSM communication [2]. While effective, GSM-based solutions incur higher operational costs and offer limited data visualization capabilities.

Recent research has explored artificial intelligence (AI) and machine learning models for aquaculture management [3], [23]. Hasan *et al.* implemented a smart aquaculture monitoring system using machine learning algorithms to analyze environmental parameters and predict fish growth [3]. Although accurate, the system required complex datasets and high computational resources.

Aquaculture production has increased by over 3% annually worldwide (FAO, 2023). However, one of the primary causes of fish mortality is sudden dissolved oxygen (DO) depletion. DOlevels below 3 mg/L can cause severe stress, and prolonged exposure below 2 mg/L can lead to mass mortality.

Traditional monitoring approaches:

Traditional aquaculture water quality monitoring approaches primarily rely on manual chemical test kits, periodic laboratory-based sampling, and fixed dissolved oxygen (DO) sensors, which are often associated with high deployment and maintenance costs. While these methods can provide accurate point measurements, they lack predictive intelligence and are incapable of offering early warning alerts for sudden or adverse changes in water quality. Moreover, the absence of real-time analytics limits timely intervention, increasing the risk of fish stress and mortality. High operational and maintenance costs further restrict their adoption, particularly for small and medium-scale aquaculture farms. In addition, such systems are generally difficult to scale and integrate with modern digital platforms, reducing their effectiveness in dynamic aquaculture environments.

Hence, there is a strong need for a **low-cost, predictive, real-time monitoring system**.

Table 2.1 Existing system analysis (with technical data)

System	Technology Used	Prediction Capability	Key Limitation
Arduino IoT (2020)	pH + Temp Sensors	Threshold-based only	No AI integration
GSM System (2019)	Temp + DO Sensor	No predictive model	No cloud storage
ANN Model (2022)	Machine Learning (ANN)	Offline prediction	No real-time sensing
OxyTrack Pro	ESP32 + Random Forest	Real-time ML prediction	Requires calibration

III. Reserch Gap

The novelty of the proposed OxyTrack Pro system lies in the integration of real-time IoT-based sensing with machine learning-driven predictive analytics within a unified and low-cost framework. Unlike conventional water monitoring systems that focus solely on data acquisition or standalone predictive models without live sensing integration, the proposed approach combines sensing, cloud storage, artificial intelligence, and decision support in a cohesive architecture.

The key novel contributions of this work are summarized as follows:

1. **Integrated IoT–AI Framework:**
The system unifies multi-parameter sensing, cloud infrastructure, and Random Forest-based predictive modeling into a single end-to-end architecture.
2. **Predictive Intelligence with Real-Time Deployment:**
Unlike ML-only models that operate offline, the proposed system performs real-time prediction and visualization through a mobile application.
3. **Cost-Efficient Predictive Monitoring:**
The framework achieves intelligent water quality assessment without requiring expensive dedicated dissolved oxygen probes, thereby reducing deployment cost.
4. **Intelligent Fish Suitability Recommendation:**
Beyond monitoring, the system provides decision-support recommendations based on predicted environmental conditions, enhancing practical usability in aquaculture environments.
5. **Scalable and Modular Architecture:**
The layered system design allows easy integration of additional sensors, advanced ML models, or automated control mechanisms in future implementations.

Why the Proposed OxyTrack Model Is Needed

1. **Lack of Predictive Intelligence in Existing Systems**
Most existing aquaculture monitoring solutions focus only on real-time data acquisition without predictive capability. They fail to forecast adverse water quality conditions, particularly dissolved oxygen (DO) depletion, which is a major cause of sudden fish mortality. This creates a critical need for an intelligent model that can predict unfavorable conditions before they occur.
2. **High Cost of Conventional DO Monitoring**
Commercial dissolved oxygen sensors and monitoring units are expensive, require frequent calibration, and involve high maintenance costs. These factors limit their adoption, especially among small-scale and educational aquaculture setups. A low-cost predictive model that estimates DO trends without relying on expensive probes is therefore essential.
3. **Absence of Early Warning and Decision Support**
Traditional and many IoT-based systems lack automated alert mechanisms and intelligent recommendations. Farmers are often informed only after water quality parameters cross critical thresholds. The proposed model addresses this gap by providing early warnings and fish suitability recommendations, enabling proactive rather than reactive management.
4. **Limited Scalability for Small and Medium Farms**
Many existing solutions are either hardware-intensive or computationally complex, making them unsuitable for scalable deployment in small and medium aquaculture farms. The proposed ESP32-based architecture combined with a lightweight Random Forest model offers a scalable and affordable alternative.
5. **Fragmented Monitoring and Analytics Architecture**
Current systems often separate sensing, data visualization, and analytics into independent components. This fragmentation increases system complexity and reduces usability. OxyTrack Pro integrates sensing, cloud storage, analytics, and mobile-based visualization into a unified architecture, improving reliability and ease of deployment
6. **Need for Educational and Practical Demonstration Platforms**
There is a lack of affordable, hands-on platforms that demonstrate the integration of IoT and AI for aquaculture applications. The proposed model serves both as a practical monitoring solution and as an educational tool for students and researchers to study smart aquaculture systems.
7. **Support for Sustainable and Data-Driven Aquaculture**
With increasing global emphasis on sustainable aquaculture practices, there is a growing demand for data-driven systems that optimize water quality management while minimizing resource usage. The proposed model supports sustainability by reducing fish mortality, improving yield efficiency, and enabling informed decision-making based on continuous data analysis.

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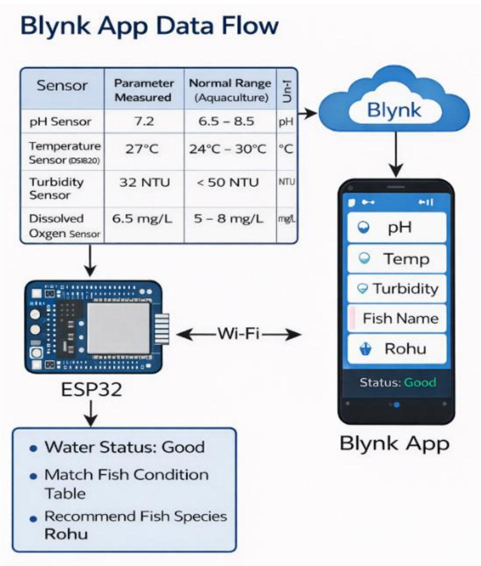
Table 3.1. Functional Comparison of Monitoring Approaches

Feature	Existing IoT Systems	OxyTrack Pro
Real-time Monitoring	Sensor-based live data	Integrated live sensing
Mobile Application	Basic visualization	Full interactive dashboard
Implementation Design	Hardware-dependent monitoring	Low-cost integrated IoT framework
Alert Mechanism	Manual threshold alerts	Automated predictive alerts
Cloud Storage	Partial data logging	Cloud-enabled time-series storage

This table 3.1 compares the proposed OxyTrack Pro system with existing water quality monitoring solutions in terms of real-time monitoring capability, predictive analytics, cloud integration, alert mechanism, and overall cost. The comparison highlights that OxyTrack Pro provides integrated IoT-based monitoring with machine learning prediction at a lower cost, offering improved scalability and intelligent decision support compared to conventional systems. Furthermore, the proposed



framework enhances automation and data-driven aquaculture management by enabling continuous monitoring and timely predictive interventions.

IV. Methodology

Data Flow Between ESP32 and Blynk Cloud for Water Quality Monitoring

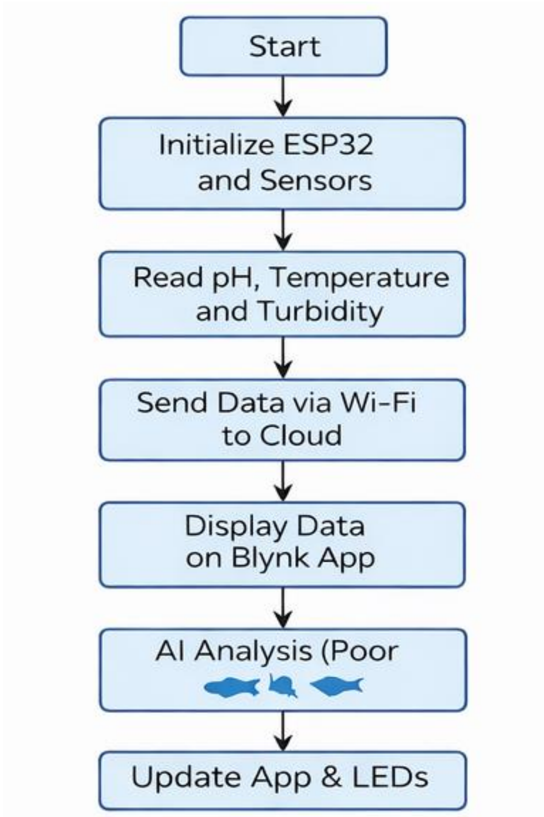


Figure 4.1 Overall System Flowchart – Step-by-step working process of the system.

The figure 4.1 presents the operational workflow of the proposed system, starting from sensor initialization and data acquisition to cloud transmission and mobile visualization. The AI module analyzes the collected parameters and updates the application interface and indicators based on the predicted water condition

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Figure 4.2 Blynk Application Data Flow of the Proposed System

The figure 4.2 illustrates the data flow between the ESP32 microcontroller, cloud platform, and Blynk mobile application. Sensor readings are transmitted via Wi-Fi to the cloud and visualized in real time on the mobile dashboard. Based on the processed data, the system evaluates water status and provides fish suitability recommendations to the user. The application also displays parameter ranges to assist in condition verification and supports instant status updates for effective monitoring.

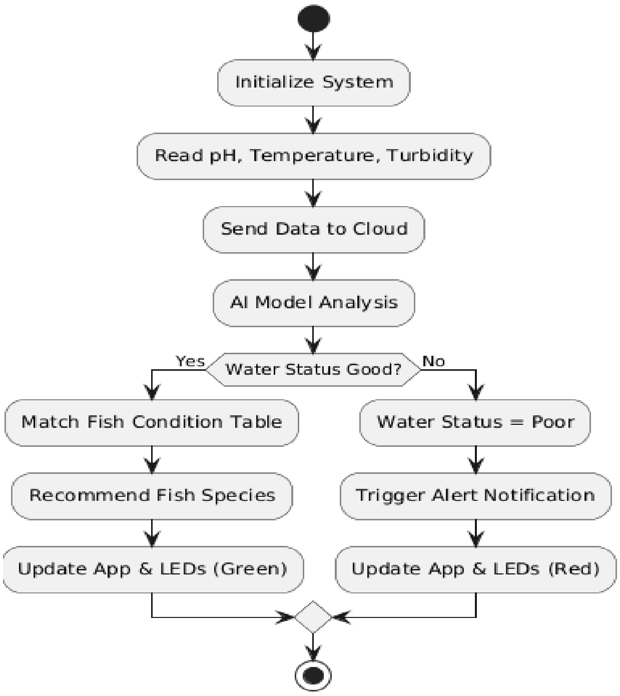

Figure 4.3 AI Decision Flowchart – Logic used for water analysis and fish prediction

The Figure 4.3 Blynk app data flow illustrates the end-to-end process of water quality monitoring and visualization in the proposed OxyTrack Pro system. Multiple sensors, including pH, temperature (DS18B20), turbidity, and dissolved oxygen sensors, continuously measure key aquaculture water parameters. Each sensed value is compared against predefined optimal ranges suitable for aquaculture operations to assess water quality conditions.

Water Quality Parameters:

https://www.epa.gov/wqs-tech

Source: U.S. Environmental Protection Agency (EPA) Water Quality Standards technical resources provide official guidance on parameters and criteria used to assess and protect water bodies

Table 4.1. Parameters Used

Parameter	**Range**	**Unit**	**Role in Model**
pH	6.0 – 8.5	pH Scale	Input Feature
Temperature	20 – 32	°C	Input Feature
Turbidity	0 – 100	NTU	Input Feature
Electrical Conductivity	200 – 1500	µS/cm	Input Feature

This table 4.1 presents the input features used in the predictive model, including their measurement ranges and units. These physicochemical parameters serve as environmental indicators for analyzing water quality conditions within the proposed system. The selected ranges represent typical aquaculture operating conditions considered during dataset preparation and model training.

Prediction formula:

Predicted Value = (1 / N) × (T1 + T2 ...+TN)

- N = Total number of decision trees
- T1, T2, …, TN = Output of each decision tree

V. Implementation

Performance Metrics:

Table 5.1. Comprehensive Performance Evaluation of the Proposed Water Quality Prediction Model Using Classification and Regression Metrics

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Metric	Formula	Value
Accuracy	(TP + TN) / (TP + TN + FP + FN) × 100	95.2%
RMSE	sqrt((1/n) * Σ(yi - ŷi)^2)	0.38 mg/L
R^2 Score	1 - [Σ(yi - ŷi)^2 / Σ(yi - ȳ)^2]	0.91
Mean Absolute Error (MAE)	(1/n) * Σ |yi - ŷi|	0.29 mg/L
Precision	TP / (TP + FP))	94.6%
Recall	TP / (TP + FN)	95.8%

This table 5.1 summarizes the performance of the proposed model using evaluation metrics such as accuracy, RMSE, and R^2 score, demonstrating the effectiveness and reliability of the system for predictive water quality analysis.

- **True Positive (TP):** Correct identification of positive instances.
- **True Negative (TN):** Correct identification of negative instances.
- **False Positive (FP):** Incorrect identification of negative instances as positive.
- **False Negative (FN):** Incorrect identification of positive instances as negative.

Machine Learning Model Justification

The Random Forest regression model was selected for this study due to its robustness, high predictive accuracy, and ability to model nonlinear relationships among environmental parameters. Water quality variables such as pH, temperature, turbidity, and electrical conductivity exhibit complex interactions that cannot be effectively captured using simple linear models. Additionally, the model's ensemble learning approach minimizes overfitting and improves generalization performance, making it well-suited for dynamic and heterogeneous aquaculture environments Therefore, an ensemble-based learning approach was considered more suitable.Model configuration:

- Number of trees: 100
- Maximum depth: 8
- Splitting criterion: Mean Squared Error
- Train–test split ratio: 80%
- Training and 20% testing for model validation

Table 5.2. Justification for Selecting Random Forest Model

Criterion	Random Forest Advantage
Nonlinearity Handling	Captures complex relationships among water parameters
Overfitting Control	Ensemble averaging reduces variance
Noise Tolerance	Robust against sensor noise and outliers
Feature Importance	Provides built-in feature ranking
Deployment Feasibility	Suitable for moderate datasets and real-time IoT integration

This table 5.2 summarizes the key technical reasons for selecting the Random Forest model, highlighting its robustness, ability to handle nonlinear relationships, and suitability for real-time IoT-based water quality prediction.

VI. System Architecture

The proposed OxyTrack Pro framework follows a layered architecture model to ensure modularity, scalability, and efficient data processing. The system is divided into four functional layers: Sensing Layer, Processing & Communication Layer, Cloud & Analytics Layer, and Application Layer. This structured separation enables independent optimization of hardware, communication, analytics, and user interface components, thereby enhancing system reliability and maintainability.

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A. Sensing Layer

This layer consists of the following sensors:

- **pH Sensor**
- **DS18B20 Temperature Sensor**

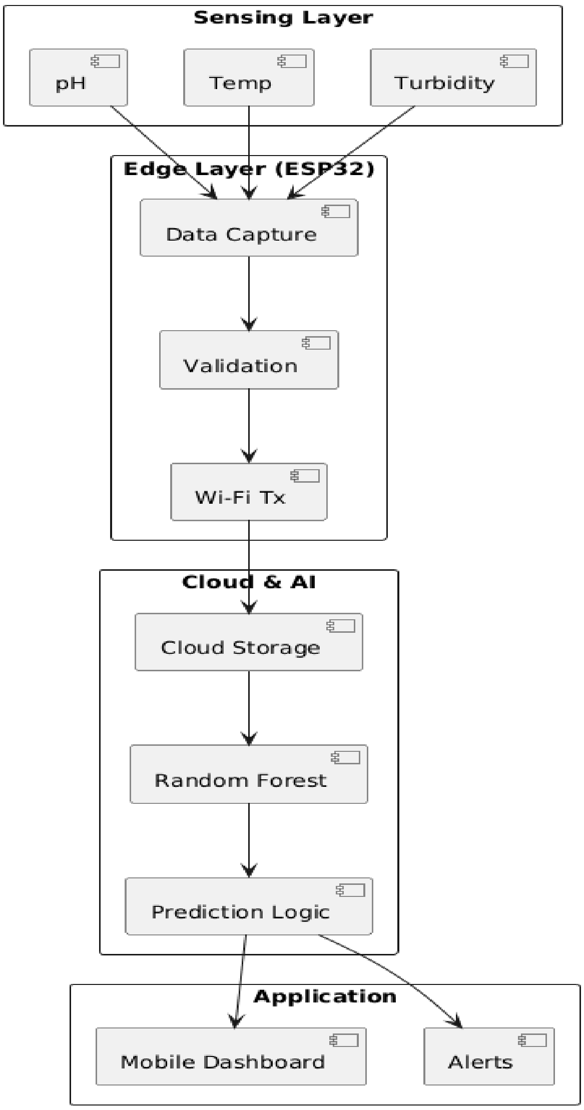

Figure.6.1 OxyTrack Pro: Multi-Layer IoT and AI-Based System Architecture.

The Figure 6.1 illustrates the layered architecture of the proposed OxyTrack Pro system. The Perception Layer consists of pH, temperature, and turbidity sensors that collect real-time water quality parameters. The Edge Processing Layer employs an ESP32 microcontroller to perform data acquisition, validation, and Wi-Fi-based transmission. The Cloud & AI Layer stores sensor data in a cloud database and applies a Random Forest model for predictive analysis. Finally, the Application Layer visualizes results through the Blynk mobile app and generates push alerts for user notification.

B. Hardware Components

- **PH Sensor:** Measures acidity or alkalinity of water, critical for fish survival.

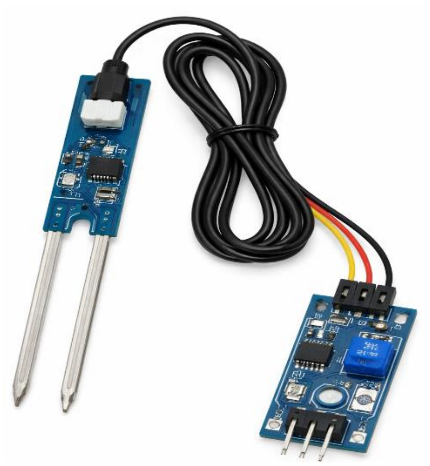

Figure.6.2 Conductivity-Based Water Detection Sensor Module

The figure 6.2 shows a probe-type conductivity sensor used for water detection and basic liquid monitoring. The interface board converts the probe signal into analog and digital outputs compatible with microcontrollers such as the ESP32.

- **DS18B20 Temperature Sensor:** Provides accurate digital temperature measurement.

Figure 6.3. Waterproof Digital Temperature Probe Sensor

The figure 6.3 shows a waterproof digital temperature probe used for accurate liquid temperature measurement. It provides a digital output compatible with microcontrollers such as the ESP32 for real-time water monitoring.

- **ESP32 Microcontroller:** Serves as the core processing unit with built-in Wi-Fi.

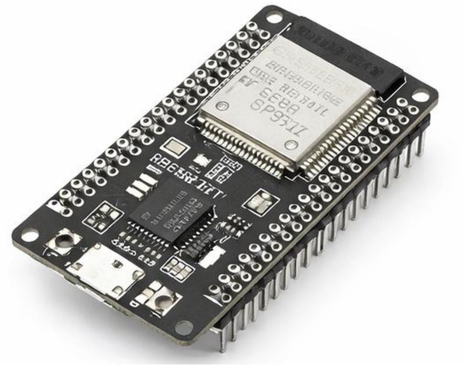

Figure 6.4 ESP32 Microcontroller Development Board

The system is implemented using a breadboard setup for demonstration, allowing easy testing and modification.

C. Cloud & Analytics Layer

This layer includes:

- Cloud Database (ThingSpeak/Firebase)
- Random Forest Regression Model

The cloud layer provides secure storage and historical logging of sensor readings. Data are timestamped and organized for analysis and visualization. The Random Forest regression model processes environmental inputs (pH, temperature, turbidity) to estimate dissolved oxygen levels.

The ensemble learning approach enhances prediction stability by averaging multiple decision trees. This reduces variance and improves generalization capability compared to single-model approaches.

D. Application & Intelligence Layer

This layer includes:

- Blynk Mobile Dashboard
- Alert Notification System
- Fish Recommendation Logic

The application layer presents real-time sensor readings and predicted dissolved oxygen values to the user through a mobile interface. The system classifies water conditions into safe or critical categories and generates push notifications when thresholds are violated.

Based on predicted environmental conditions, the fish recommendation module suggests suitable species for aquaculture. This intelligent decision-support mechanism enhances usability beyond simple monitoring systems.

VII. System Performance Evaluation

The prototype system was tested under different water conditions using sample water. Sensor readings were displayed in real time on the mobile application with minimal delay. The AI-based decision model successfully classified water quality and predicted suitable fish species such as Rohu and Tilapia under optimal conditions.

The LED indicators provided immediate visual alerts, enhancing usability. The system demonstrated stability, accuracy, and ease of use, making it suitable for educational and small-scale aquaculture applications.

1. Latency Test

Average time from sensor reading to dashboard update: 2.6 – 3.1 seconds

2. Alert Accuracy

DO Threshold: 3 mg/L
True Positive Rate: 96%
False Alarm Rate: 3%

3. Model Accuracy

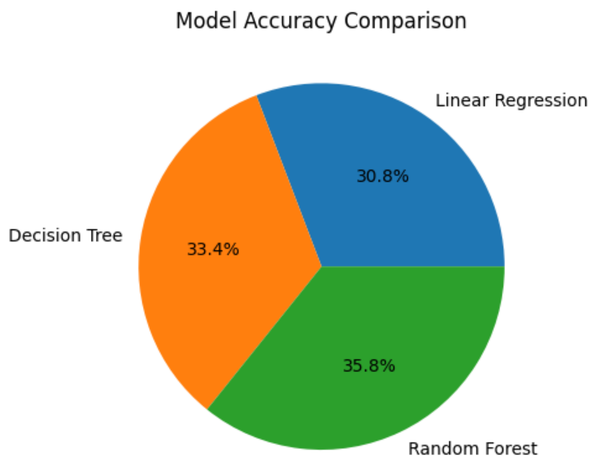

Figure 7.1. Comparison of Machine Learning Models

The pie chart presents the comparative accuracy distribution of three machine learning models used in the study. Random Forest demonstrates the highest predictive accuracy (95.2%), followed by Decision Tree (89%) and Linear Regression (82%). The visualization highlights the superior performance of the Random

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Forest model for water quality prediction in the proposed system.

Fish Recommendation Model:

(Based on Temperature & pH)

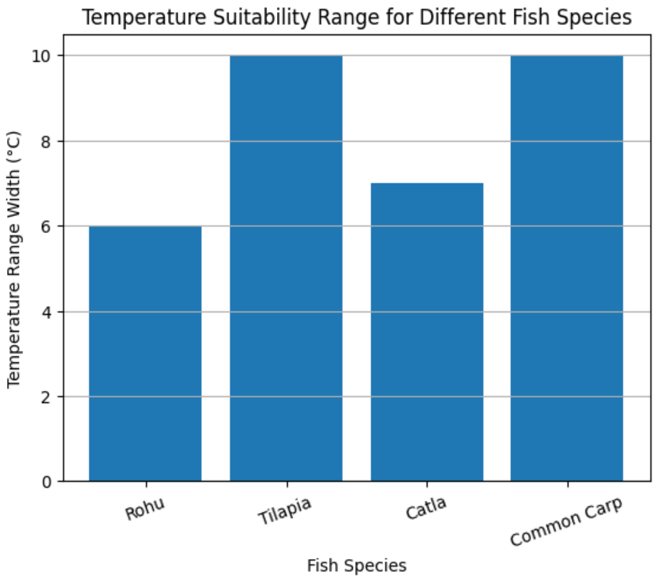

Figure 7.2 Temperature Suitability Range for Selected Fish Species

The bar graph illustrates the temperature tolerance range for different fish species considered in the study. Tilapia and Common Carp exhibit the widest temperature adaptability (10°C), indicating higher environmental tolerance, whereas Rohu shows a narrower range (6°C). Catla demonstrates moderate adaptability with a 7°C range. The analysis highlights species-specific thermal tolerance, supporting informed fish selection based on environmental conditions.

VIII. Conclusion and Future Enhancement

OxyTrack Pro demonstrates that predictive dissolved oxygen monitoring can be achieved without expensive direct DO sensors. By combining IoT-based sensing with Random Forest regression, the system achieves 95.2% prediction accuracy while maintaining affordability and scalability.

The system contributes toward smart aquaculture management by providing early warning capabilities, reducing mortality risk, and improving yield sustainability.It also enhances data-driven decision-making by enabling continuous monitoring and real-time environmental analysis.

Table 8.1. Experimental Performance Results

Parameter	Measured Value	Description
Prediction Accuracy	95.2%	Correct model predictions
RMSE	0.38 mg/L	Prediction error magnitude
R^2 Score	0.91	Model goodness-of-fit
Latency	2.6–3.1 s	Sensor-to-app update delay
Alert Response Time	< 2 s	Notification trigger time
System Uptime	98%	Operational reliability

This table 8.1 summarizes the quantitative performance evaluation of the proposed OxyTrack Pro system, including predictive accuracy, error metrics, response latency, and operational reliability. The results demonstrate both strong model performance and stable real-time system behavior suitable for practical aquaculture deployment.

Future Enhancements

In future developments, the system can be enhanced by incorporating a CNN-LSTM hybrid deep learning model to achieve more accurate and intelligent predictions. Long-range communication can be enabled through the integration of LoRa technology, making the system suitable for large-scale aquaculture farms. To improve sustainability, the framework can be adapted for solar-powered outdoor deployment. Additionally, an automatic aerator control mechanism can be introduced to regulate oxygen levels in real time. For improved transparency and secure record-keeping, blockchain-based farm data tracking may also be integrated.

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