JoCoSiR
Journal of Computer Science Research ISSN 2986-2337 (Online)

Optimizing Sustainable Aquaculture via Internet of Things and Machine Learning

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ARTICLE INFO

Keywords:
IoT, Machine Learning, Aquaculture, Water Quality Prediction, Monitoring System

IEEE style in citing this article:
R. D Firmansyah, " Optimizing Sustainable Aquaculture via Internet of Things and Machine Learning," JoCoSiR: Jurnal Ilmiah Teknologi Sistem Informasi, vol. 3, no. 4, pp. 101-106, 2025.

ABSTRACT

This research aims to design and build an integrated system utilizing the Internet of Things (IoT) and Machine Learning (ML) for the optimization of sustainable aquaculture. The primary objective is to address key aquaculture challenges, including unstable water quality, feed inefficiency, and slow disease detection. The research design involves a real- time monitoring system using IoT sensors (pH, temperature, and dissolved oxygen) connected to an ESP32 microcontroller. The methodology consists of data collection from these sensors, which is then analyzed using machine learning algorithms: Linear Regression to predict water quality and a Decision Tree to classify fish health. The main outcomes show the system successfully monitors water quality in real-time. The Linear Regression model achieved a low Mean Squared Error (MSE) of 0.042 for predictions, and the Decision Tree model achieved a 93.7% accuracy in classifying fish health conditions. The conclusion is that this system is proven to be an effective decision support tool for enhancing the productivity and sustainability of aquaculture.

1. Introduction

Research Problem and Background

Aquaculture faces significant challenges in maintaining productivity while ensuring sustainability. Traditional farming methods often rely on manual monitoring, which leads to inefficiencies, such as unstable water quality, inefficient manual feeding, and late detection of diseases **[23]**. These factors contribute to high fish mortality rates and increased operational costs. The gap between current practices and the need for precision management demands innovative, technology-driven solutions. The integration of the Internet of Things (IoT) and Machine Learning (ML) offers a powerful approach to creating smart, automated, and predictive aquaculture systems.

Theoretical Studies and Related Work

The foundation of this research is built upon established and emerging technologies in IoT, ML, and sustainable aquaculture. The Internet of Things (IoT) is a concept where physical devices are connected via the internet to collect, process, and send data in real-time **[1]**. In aquaculture, IoT's role in monitoring the aquatic environment through sensors is well-documented [12], [14], [25]. Numerous studies have demonstrated the use of IoT for real-time monitoring of critical parameters like temperature, pH, and Dissolved Oxygen (DO) [11], [13], [17], [18], [19], [21], [24], [26]. Other systems have focused on smart feeding [6] or integrated eco-aquaculture control systems [9].

Machine Learning (ML) is a branch of AI that allows computers to learn from data to make predictions. In aquaculture, ML can be used for water quality prediction, fish growth estimation, and early disease detection [2]. The application of AI and ML for managing aquaculture is a rapidly growing field [16]**.** Specific models, including neural networks and deep learning, have been effectively used for predicting dissolved oxygen content [5], [7], [15], [22], predicting overall water quality [8], [20], and for fish health monitoring and diagnosis [23].

Sustainable aquaculture practices are crucial for long-term food security. These practices focus not only on productivity but also on ecological, economic, and social aspects [3], [10]. Key factors include stable water quality, feed efficiency, and disease prevention [3]. While many studies focus on either IoT for monitoring [12] or ML for prediction [21] separately, a research gap exists in the comprehensive integration of both systems into a single, cohesive decision support tool for farmers. This study addresses this gap by combining real-time data acquisition (IoT) with predictive analysis (ML) to optimize the entire cultivation process.

Research Objectives and Expected Benefits

Based on the problems identified, the research objectives are:

ISSN 2502-3357 (Online)

1. To design and implement an IoT system for real-time monitoring of water quality (pH, temperature, DO) and feed.
2. To analyze the application of machine learning for predicting water quality and classifying fish health status to support decision-making.
3. To evaluate the integrated IoT and ML system as a comprehensive solution for improving productivity and sustainability in aquaculture.

This research is expected to provide a practical, cost-effective, and efficient decision support tool for aquaculture farmers. The anticipated benefits include reduced fish mortality, optimized feed consumption, and improved environmental sustainability by maintaining optimal water conditions.

2. Method

The research methodology employs an experimental quantitative approach, focusing on system design, implementation, and evaluation of an integrated IoT and ML system. The procedure is explained chronologically below.

Research Framework

The study was conducted through sequential stages, as illustrated in the research framework (Figure 1). The process began with problem identification and a literature study, followed by system design, data collection, system implementation, and finally, testing and analysis to draw conclusions.

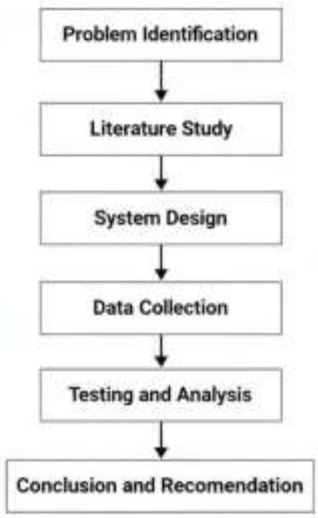

Figure 1. Research Framework

The workflow is divided into three main phases:

1. Input (Data Acquisition): Real-time data (temperature, pH, DO) is collected from IoT sensors placed in a simulated pond.
2. Process (Processing & Analysis): Data is transmitted via Wi-Fi to a server/cloud. ML algorithms process this data to generate predictions and classifications.
3. Output (Decision Support): The analysis results are displayed on a monitoring dashboard, providing actionable recommendations.

Data Acquisition

Data for this study was obtained from two sources:

1. Primary Data: Collected in real-time from a hardware prototype built for this research. The prototype, simulating a small-scale aquaculture environment, used a DS18B20 Temperature Sensor, a DFRobot pH Sensor, and a Dissolved Oxygen (DO) Sensor. ANodeMCU ESP32 microcontroller managed data collection.
2. Secondary Data: Supporting datasets from previous, related research were used as training data to build the initial machine learning models, ensuring a robust baseline before testing with live primary data.

Methodological Analysis

The data analysis method followed several steps:

1. Data Collection: Sensor data (pH, temperature, DO) was recorded periodically.
2. Data Preprocessing: Raw sensor data was cleaned and normalized to prepare it for model training.
3. Model Training: Based on the literature review, Linear Regression and Decision Trees were selected. Linear Regression is widely used and effective for predictive tasks [2], making it suitable for predicting water quality parameters. Decision Trees are robust and interpretable for classification tasks [2], making them ideal for classifying fish health status.
4. Model Evaluation: The system's performance was measured using standard metrics. Mean Squared

DOI: https://doi.org/10.65126/jocosir.v3i4

ISSN 2502-3357 (Online)

Error (MSE) was used to evaluate the accuracy of the Linear Regression model, while Accuracy was used to evaluate the performance of the Decision Tree classification model.

The formulas used for Linear Regression and MSE evaluation are as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - Y^{\wedge}_i)^2$$

System Analysis and Design

The system was designed with three primary layers:

1. Device Layer: Consists of the sensors (pH, DO, temperature) and the ESP32 microcontroller for data acquisition.
2. Network Layer: Uses Wi-Fi to transmit data from the microcontroller to the application server.
3. Application Layer: Includes the cloud server, database, ML processing module, and the user-facing monitoring dashboard.

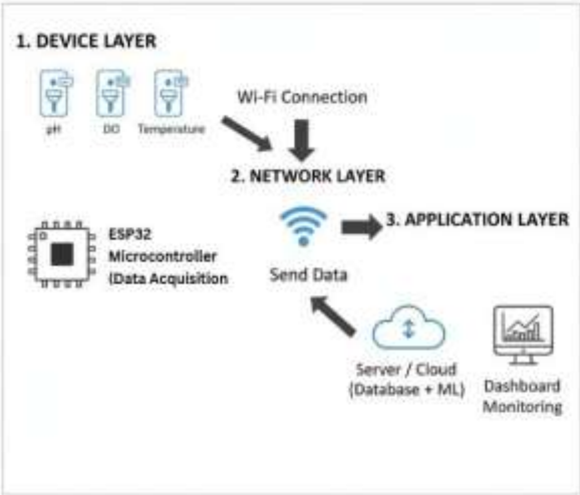

Figure 2. System Architecture

3. Results and Discussion

System Implementation

Hardware: The prototype was assembled using an ESP32 microcontroller, DS18B20 Temperature Sensor, DFRobot pH Sensor, and a DO Sensor, all installed in a ±20-liter water container to simulate a small pond environment.

Software:

1. Microcontroller: Programmed using the Arduino IDE to read sensors every 10-30 seconds and transmit data to the server.
2. Backend: A MySQL database was used to store sensor readings and ML prediction results.
3. Machine Learning Model: Developed in Python using Scikit-learn, Pandas, and NumPy libraries to implement the Linear Regression and Decision Tree algorithms.

System Testing and Results

The system was tested for hardware functionality, software connectivity, and model performance.

Hardware and Software Testing: All sensors were verified to be functional and provided stable data within expected normal ranges, as shown in Table 1. Data was successfully transmitted to the database and displayed on the dashboard in real-time without significant delay.

Table 1. Hardware Sensor Verification

Sensor	Normal Value	Data Read	Status
Temperature	26-30°C	27.1-28.9°C	Success
pH	6.5-8.5	7.12-7.90	Success
DO	5-8 mg/L	5.3-6.1 mg/L	Success

Machine Learning Model Performance:

1. Linear Regression (Prediction): The model's performance in predicting pH values was evaluated. As shown in Figure 3 and Table 2, the model achieved a Mean Squared Error (MSE) of 0.042, indicating a very low error rate and high predictive accuracy.

DOI: https://doi.org/10.65126/jocosir.v3i4

ISSN 2502-3357 (Online)

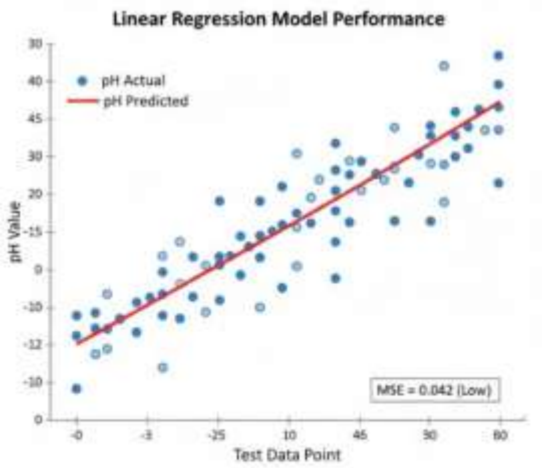

Figure 3. Linear Regression Model Performance

Table 2. Comparison of Actual vs. Predicted pH

Test Data Point	Actual pH	Predicted pH	Difference/Error
1	7.50	7.48	0.02
2	7.30	7.34	-0.04
…	…	…	…
8	7.35	7.38	-0.03

2. Decision Tree (Classification): The model achieved an accuracy of 93.7% in classifying fish health status (Normal, Caution, Unhealthy) based on the real-time water quality data. Figure 4 visualizes the distribution of classifications during the test period.

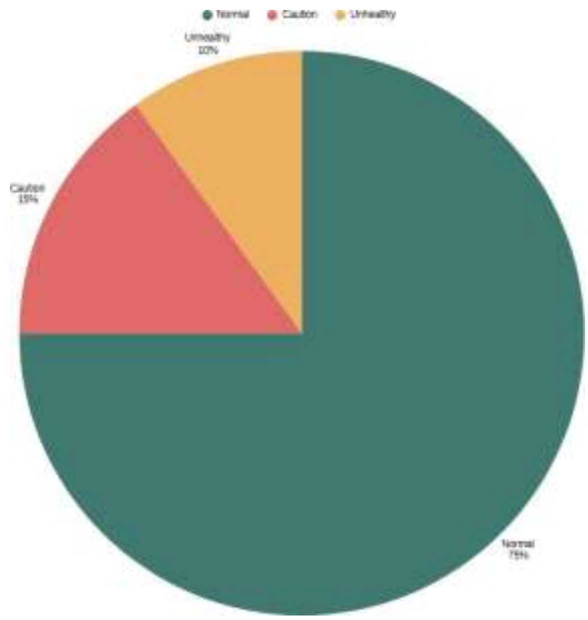
Figure 4. Fish Health Classification Results

Discussion

The implementation results demonstrate that the integrated system is valid and performs effectively. The IoT hardware provided stable and reliable real-time data, as shown in Table 1, which is essential for accurate ML analysis.

The ML models showed strong performance. The low MSE of the Linear Regression model confirms its suitability for predicting water quality trends, giving farmers advance warning. The high accuracy of the Decision Tree model (93.7%) is particularly significant, as it provides a reliable automated system for detecting conditions that could lead to fish stress or disease, far exceeding the reliability of manual, periodic checks.

This system successfully transforms raw data into actionable insights, such as "Activate aerator, DO level is low," effectively creating a decision support system. This directly addresses the research problem by reducing manual labor and enhancing the farmer's ability to maintain an optimal and sustainable aquaculture environment.

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ISSN 2502-3357 (Online)

4. Conclusion

Summary of Main Findings

This research successfully designed, implemented, and tested an integrated IoT and Machine Learning system for sustainable aquaculture. The key findings are: The IoT prototype accurately and reliably collected real-time data for water temperature, pH, and dissolved oxygen. The machine learning models performed with high efficacy: the Linear Regression model predicted water quality with a low MSE of 0.042, and the Decision Tree model classified fish health status with 93.7% accuracy.

Research Contribution and Implication

The primary contribution of this work is the creation of a practical, integrated, and low-cost decision support system. Unlike studies focusing on single components, this research provides a complete, end-to-end solution from data acquisition to predictive recommendation. The implication for aquaculture is a potential shift from reactive, manual management to proactive, data-driven, and automated cultivation, which can significantly increase productivity and reduce resource waste.

Research Limitation

This study has several limitations. First, the implementation was conducted in a small-scale, simulated environment (±20L container), not in a large-scale commercial pond. Second, the parameters were limited to temperature, pH, and DO, excluding other critical indicators like ammonia, nitrite, or water turbidity. Third, the system currently provides recommendations, but does not include a closed-loop system for automatic control (e.g., automatically activating aerators).

5. Future Research

Based on the limitations, future research should focus on:

1. Scaling and Deployment: Testing the system's durability and effectiveness in real-world, large-scale commercial aquaculture ponds.
2. Sensor Expansion: Integrating additional sensors for ammonia, nitrite, and turbidity to create a more comprehensive water quality profile.
3. Advanced Models: Exploring more complex ML models, such as Neural Networks [5], [7], [20] or ensemble methods [4], to potentially improve prediction accuracy.
4. Automation: Implementing automated control mechanisms (actuators) that respond directly to the ML model's recommendations.
5. Mobility: Developing a mobile application to provide farmers with remote monitoring and instant alerts.

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