ADVANCED IOT-INTEGRATED SUSTAINABLE AQUACULTURE SYSTEM FOR COMMERCIAL SCALE OPERATIONS

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CERTIFICATE

This is to certify that the work entitled '***Advanced IoT-Integrated Sustainable Aquaculture System for Commercial Scale Operations***' authored by K Karthik, M Udaya Siva Kiran, and R Raja Rajeswari, has been carried out under my supervision. To the best of our knowledge, this work is original and has not been submitted elsewhere for any diploma or degree.

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DECLARATION

The work entitled '***Advanced IoT-Integrated Sustainable Aquaculture System for Commercial Scale Operations***' which has been carried out in the Department of Electronics and Communication Engineering at Velagapudi Ramakrishna Siddhartha Engineering College, is original and conforms to the regulations of this Institute.

We understand the Institute's policy on plagiarism and declare that no part of this work has been copied from other sources or previously submitted elsewhere for any degree or diploma.

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Abstract

In Andhra Pradesh, small-scale fish farmers, especially from the East Godavari district, are facing significant losses due to high fish mortality, which also impacts the economy of the country. This high mortality is primarily caused by inadequate monitoring of water parameters such as pH, temperature, turbidity, TDS (total dissolved salts), Dissolved Oxygen(DO), Ammonia and harmful gases. By monitoring these parameters, precautions can be taken to reduce the fish mortality rate and minimize losses for small-scale fish farmers.

This project aims to revolutionize sustainable fish farming by enhancing and commercializing a prototype for real-time aquaculture monitoring. The system integrates IoT sensors and machine learning algorithms to continuously monitor water quality parameters such as pH, temperature, turbidity, TDS (total dissolved salts), Dissolved Oxygen(DO), Ammonia and harmful gases. Through iterative development and advanced deployment strategies, the project focuses on refining the system for field scalability and robustness. The outcome is a high-precision, user-friendly system capable of real-time alerts and predictive analysis, empowering farmers to achieve higher productivity and sustainability.

Keywords: *IoT-based Aquaculture, Water Quality Management, Machine Learning, Sustainability, Real-time Monitoring, pH, Turbidity, TDS (Total Dissolved Salts), Temperature, Ammonia, Dissolved Oxygen, Harmful Gases, Small-scale Farming, Mortality Rate, Fish Farming, Affordable, Prediction, Economy.*

Chapter 1
Introduction

1.1 Background

Aquaculture has become an essential pillar of global food security, contributing more than 50 percent of the world's fish supply. In India, aquaculture is not only a major contributor to the national GDP but also a primary livelihood for millions of rural families, especially in coastal regions like East Godavari, Andhra Pradesh. Despite its potential, the industry continues to suffer from preventable losses due to ineffective water quality management.

Small-scale fish farmers, who make up a significant portion of this sector, often lack access to the tools and knowledge necessary for scientific aquaculture practices. Water quality parameters such as pH, temperature, turbidity, total dissolved solids (TDS), dissolved oxygen (DO), and ammonia levels play a critical role in maintaining a healthy aquatic environment. Even minor deviations can stress fish, reduce growth rates, and cause diseases or mass mortality. These challenges are compounded by climate variability, pollution from nearby agricultural runoff, and inconsistent power supplies in rural areas.

Traditional monitoring techniques are largely manual and infrequent, offering no predictive capability and often identifying problems only after they've escalated. Moreover, the high cost and complexity of existing automated monitoring systems limit their adoption among small-scale farmers. This creates a technological gap where affordable, intelligent, and scalable systems are urgently needed.

With the rise of the Internet of Things (IoT) and Artificial Intelligence (AI), a new generation of smart aquaculture system is emerging. IoT allows the deployment of low-cost, energy-efficient sensors that can monitor water conditions in real-time, while AI (including machine learning algorithms) can process this data to detect patterns, predict risks, and even automate interventions like aeration or chemical dosing. These technologies offer the potential to shift aquaculture from reactive to proactive and predictive management.

This mini-project builds on this technological foundation by designing a cost-effective, IoT-integrated monitoring and controlling system tailored for commercial-scale aquaculture. The first phase focused on building a functional prototype capable of monitoring core parameters like pH, temperature, turbidity, and TDS. The current phase aims to:

- Integrate advanced sensors for ammonia and dissolved oxygen
- Improve real-time monitoring precision

- Enhance the system with machine learning-based predictive models
- Ensure data visualization and remote access through a web-based dashboard
- Design the architecture for scalability and deployment across multiple farms

In addition to solving technical challenges, the system is designed to address social and economic impacts. By reducing fish mortality and improving productivity, the solution can significantly enhance income stability for small-scale farmers. It also promotes sustainability by enabling data-driven decision-making, reducing waste of resources like feed and water, and encouraging environmentally responsible practices.
This project was conceptualized to address these issues by developing a low-cost, scalable, and easy-to-use IoT-based Sustainable Aquaculture Monitoring System. The goal is to bridge the gap between traditional farming methods and modern data-driven approaches. In its initial phase, the prototype focused on collecting and analyzing parameters such as pH, turbidity, temperature, and TDS. The second phase aims to refine and commercialize the system by adding support for more parameters (like ammonia and dissolved oxygen), integrating predictive analytics using machine learning, and automating control mechanisms like aeration and pH balancing.
By enabling continuous, real-time monitoring and predictive risk assessment, the system not only helps reduce fish mortality but also promotes sustainability, improves farm management efficiency, and supports the socio-economic development of rural communities.

1.1.1 The Importance of Water Quality Management

Water quality is a fundamental determinant of fish health, growth, and overall aquaculture productivity. Parameters such as pH, turbidity, total dissolved solids (TDS), temperature, air quality, dissolved oxygen and ammonia that must be maintained within optimal ranges to ensure a stable and healthy aquatic environment. Even slight fluctuations in these variables can stress fish, compromise their immune systems, and lead to reduced feeding efficiency, slower growth rates, disease outbreaks, or even mass mortality. The cumulative impact of poor water quality directly translates to financial losses, especially in intensive or commercial-scale aquaculture operations.
Despite the critical importance of maintaining water quality, many fish farmers—particularly small and medium-scale operators—continue to depend on outdated tools or manual testing methods. These traditional approaches are typically labor-intensive, time-consuming, and lack the precision and frequency required for effective risk prevention.

They provide only snapshot views of water conditions, missing dynamic fluctuations that can occur throughout the day. As a result, interventions are often reactive and implemented too late to prevent damage.

This pressing challenge highlights the need for modern, intelligent, and affordable water quality management systems. Leveraging technologies such as the Internet of Things (IoT), real-time sensors, and machine learning can provide continuous, accurate monitoring and early warning systems. Such solutions empower farmers to act proactively, reduce losses, and optimize production, all while promoting sustainability and responsible aquaculture practices. An integrated, technology-driven approach is no longer a luxury—it is an essential tool for the future of efficient and resilient fish farming.

1.2 Motivation and Inspiration

The primary motivation behind this project stems from the real-life challenges faced by small-scale fish farmers in regions like East Godavari, Andhra Pradesh. In these communities, aquaculture is not just a business—it's a lifeline. However, due to limited access to technology, poor infrastructure, and unpredictable water quality, farmers often face devastating fish losses, sometimes wiping out months of hard work and investment in a single day.

The team was inspired by firsthand accounts and field visits where farmers expressed frustration over their inability to detect water quality problems in time. Many rely on guesswork or delayed lab tests, which are neither practical nor reliable for daily operations. These experiences highlighted the urgent need for a smart, real-time, and affordable monitoring solution that could provide actionable data and help prevent losses before they occur.

In parallel, the growing field of IoT (Internet of Things) and machine learning has opened exciting new possibilities for low-cost innovation in agriculture and aquaculture. We were inspired by how simple sensors and intelligent software could transform traditional practices, making high-tech solutions accessible even in remote or low-income areas. The idea of using cutting-edge technology not just for industrial automation, but to solve grassroots problems, was a major driving force behind the project.

Another key inspiration came from sustainability goals. Fish farming, when done right, is one of the most environmentally friendly ways to produce protein. However, poor management can lead to overuse of antibiotics, water pollution, and high mortality—all of which harm both the environment and farmer livelihoods. Our project aims to promote sustainable aquaculture practices by enabling better control, transparency, and ecological balance.

Lastly, this project is driven by the belief that engineering should serve society. By combining electronics, coding, data analysis, and real-world problem-solving, this work reflects the essence of engineering education: creating technology that is useful, impactful, and inclusive.

1.3 Objectives

This study aims to develop and implement a technology-driven solution to revolutionize water quality management in fish aquaculture. The specific objectives include:

1. Development of an IoT-based monitoring system: Designing a low-cost and reliable sensor network to collect real-time data on key water parameters such as pH, temperature, turbidity, TDS, ammonia, and dissolved oxygen.

2. Integration of machine learning algorithms: Utilizing predictive analytics to detect early signs of unfavorable water conditions or potential fish mortality risks, enabling timely and data-driven interventions.

3. Web application for monitoring and control: Building a web-based platform for remote visualization of sensor data, generating real-time alerts, and enabling control of automated devices like aerators and chemical dosers.

4. User-centric and scalable system design: Creating an intuitive and accessible system suitable for small- to medium-scale farmers, with architecture that supports expansion across multiple tanks or farm sites.

5. Promoting sustainability and productivity: Supporting environmentally responsible aquaculture by reducing manual errors, resource wastage, and fish losses, thereby enhancing long-term productivity and profitability.

1.4 Scope

The scope of this project involves the development and deployment of an IoT-based, real-time aquaculture monitoring and controlling system tailored for small- to medium-scale fish farms. It includes the integration of low-cost sensors to monitor critical water quality parameters such as pH, temperature, turbidity, TDS, ammonia, and dissolved oxygen. The system continuously collects and transmits data using an ESP32 microcontroller and presents it through a user-friendly web interface. Machine learning algorithms are incorporated to analyze historical and real-time data, enabling the prediction of unfavorable water conditions and fish mortality risks. Designed with scalability and affordability in mind, the system can be expanded to support multiple tanks or farms, making it suitable for commercial-scale deployment. The solution aims to empower farmers with timely insights, reduce losses, and promote sustainable aquaculture practices, particularly in rural regions with limited resources.

1.5 Thesis Organization

This thesis is structured into five chapters, each addressing a key aspect of the project. A summary of the chapters is provided below:

Chapter 1 – Introduction This chapter presents the motivation, background, and objectives of the study. It highlights the challenges faced by small-scale fish farmers due to poor water quality monitoring and introduces the proposed IoT-based solution aimed at reducing fish mortality and enhancing sustainability in aquaculture.

Chapter 2 – Literature Review This chapter reviews existing research on IoT and machine learning applications in aquaculture. It identifies the limitations of current systems, particularly in terms of cost, scalability, and usability, and establishes the research gap that this project seeks to address.

Chapter 3 – System Design and Methodology This chapter details the design and implementation of the IoT-based monitoring system. It explains the selection of sensors, system architecture, data acquisition methods, preprocessing techniques, and the development of machine learning models used for predicting water quality risks.

Chapter 4 – Results and Discussion This chapter presents the results from system testing and field trials. It evaluates the performance of the system in terms of accuracy, responsiveness, and practicality. The discussion highlights how real-time monitoring and predictive analytics contributed to improved decision-making and reduced fish mortality.

Chapter 5 – Conclusion and Future Work This chapter summarizes the key outcomes of the project and its contributions to sustainable aquaculture practices. It also outlines directions for future enhancements, including multi-species monitoring, integration of solar power, improved automation, and more sophisticated AI-based analytics.

Chapter 2
Literature Review

[1] **Detection Methods of Ammonia Nitrogen in Water (2020)** This review paper analyzes over 100 studies on various techniques used to detect ammonia nitrogen in water, including ion-selective electrodes, colorimetry, spectrophotometry, and biosensors. It provides a comparative overview of sensitivity, cost, and applicability of each method under different conditions. However, the paper does not present a real-world implementation plan or guidance for sensor selection in field-deployable IoT systems, limiting its direct application in practical aquaculture settings.

[2] **Development of Smart Aquaculture Farm Management System Using IoT and AI-Based Surrogate Models (2022)** This study presents a machine learning-based aquaculture management system using Random Forest and Artificial Neural Networks to predict dissolved oxygen and biofloc levels. It leverages data collected from shrimp aquaculture environments and integrates it with surrogate models to optimize farm operations. While effective in shrimp environments, the study does not model ammonia, which limits its usefulness in comprehensive water quality monitoring systems for fish farming.

[3] **IoT-Based Water Quality Monitoring System (2021)** The paper focuses on developing a low-cost IoT-based monitoring system using NodeMCU, pH, turbidity, and dissolved oxygen sensors. Data is uploaded to a cloud platform for visualization and alerts. The study demonstrates functional monitoring under lab conditions but lacks advanced machine learning or prediction capabilities. Its application is limited to simple threshold-based alert systems without predictive insights.

[4] **Application of Machine Learning in Intelligent Fish Aquaculture (2022)** This study explores the integration of real-time sensor data with machine learning pipelines for fish health prediction. It uses field test data and cloud dashboards to assess water quality and forecast potential threats. Parameters like DO, pH, ammonia, and turbidity are analyzed using AI models. However, the system remains in early development stages with limited validation on large-scale datasets, affecting its immediate scalability and reliability.

[5] **Artificial Intelligence-Based Aquaculture System for Optimizing the Quality of Water (2023)** This research implements an AI-driven system for monitoring and optimizing water quality in aquaculture. Real-time sensor data is analyzed using predictive models to maintain optimal conditions for fish health. Key parameters include DO, pH, ammonia, and turbidity. Although promising, the system has not been validated on a wide scale, and its effectiveness under diverse environmental conditions remains untested.

[6] **Acute and Chronic Toxicity of Ammonia to Marine Fish and a Mysid (1990)** This foundational toxicological study evaluates the impact of ammonia on marine species through laboratory bioassays. It determines the acute and chronic toxicity levels of ammonia exposure in fish and mysid crustaceans. While the findings are critical for understanding safe ammonia limits, the study is not intended for real-time or IoT-based implementation and does not consider freshwater species commonly used in inland fish farming.

[7] **Intelligent framework for prediction and forecasting of DO and biofloc in shrimp culture (2022)** This study proposes a machine learning-based system to predict and forecast dissolved oxygen (DO) levels and biofloc amounts in shrimp aquaculture. Using models such as Random Forest, Artificial Neural Networks (ANN), and regression techniques, the system analyzes sensor data collected from shrimp ponds, including parameters like DO, temperature, biofloc, and turbidity. The framework aims to help farmers make proactive decisions to improve shrimp health and yield. However, the system is focused specifically on shrimp farming and does not include ammonia modeling, limiting its direct applicability to broader aquaculture systems involving fish.

[8] **Optimizing Brackishwater Shrimp Farming with IoT-Enabled Water Quality Monitoring and Decision Support System(2021)** This study proposes a machine learning-based system to predict and forecast dissolved oxygen (DO) levels and biofloc amounts in shrimp aquaculture. Using models such as Random Forest, Artificial Neural Networks (ANN), and regression techniques, the system analyzes sensor data collected from shrimp ponds, including parameters like DO, temperature, biofloc, and turbidity. The framework aims to help farmers make proactive decisions to improve shrimp health and yield. However, the system is focused specifically on shrimp farming and does not include ammonia modeling, limiting its direct applicability to broader aquaculture systems involving fish.

Title/Year	Objectives	Methods	Datasets	Parametrs	Limitations
Detection methods of ammonia nitrogen in water: A review (2020)	Review and compare ammonia detection techniques.	Literature survey.	100+ articles reviewed.	Ammonia-N, nitrate, pH, temperature.	No implementation or sensor selection guide for field deployment.
Development of smart aquaculture farm management system using IoT and AI-based surrogate models(2022)	Predict DO and biofloc using ML.	Random Forest, ANN, regression.	Shrimp aquaculture sensor data.	DO, temperature, biofloc, turbidity	Focused on shrimp; no ammonia modeling.
IoT-based Water Quality Monitoring System(2021)	Build a real-time water quality monitoring system.	IoT (NodeMCU + sensors), cloud interface.	Prototype and lab measurements.	pH, DO, turbidity, temperature.	No ML integration, limited to basic threshold alerts.
Application of machine learning in intelligent fish aquaculture (2022)	Combine IoT data and ML for fish health predictions.	Real-time ML pipelines, cloud dashboard.	Field test pond datasets.	DO, pH, ammonia, turbidity.	Early-stage system, no large-scale validation.
Artificial Intelligence-Based Aquaculture System for Optimizing the Quality of Water(2023)	Combine IoT data and ML for fish health predictions.	Real-time ML pipelines, cloud dashboard.	Field test pond datasets.	DO, pH, ammonia, turbidity.	Early-stage system, no large-scale validation.
Acute and chronic toxicity of ammonia to marine fish and a mysid (1990)	Examine toxicity limits in marine species.	Lab-based bioassays.	Fish and mysid test species.	Ammonia, exposure time.	Not designed for freshwater species or real-time integration
Intelligent framework for prediction and forecasting of DO and biofloc in shrimp culture (2022)	Predict DO and biofloc using ML.	Random Forest, ANN, regression.	Shrimp aquaculture sensor data.	DO, temperature, biofloc, turbidity.	Focused on shrimp; no ammonia modeling.
Optimizing Brackishwater Shrimp Farming with IoT-Enabled Water Quality Monitoring and Decision Support System (2021)	Develop a decision support system leveraging IoT sensors and data analytics to promote sustainable aquaculture practices.	Implementation of an IoT-based Analytical Hierarchy Process Decision Support System (AHP-DSS) for water quality monitoring in brackishwater shrimp farming.	Data collected from shrimp ponds using sensors measuring pH, DO, temperature, turbidity, and salinity.	shrimp ponds using sensors measuring pH, DO, temperature, turbidity, and salinity. pH, DO, temperature, turbidity, salinity.	High initial cost of sensor deployment and the need for regular maintenance to ensure data accuracy.

Table 2.1: Literature Review

Chapter 3
Proposed Approach

To address the critical issue of high fish mortality in aquaculture, particularly among small-scale farmers in regions like East Godavari, Andhra Pradesh, this project employs an integrated technological approach. By combining Internet of Things (IoT) devices with machine learning algorithms, the system is designed to continuously monitor essential water quality parameters such as pH, temperature, turbidity, TDS, ammonia, and dissolved oxygen. The methodology focuses on building a robust, real-time monitoring and control system that not only provides timely alerts but also automates necessary interventions to maintain optimal conditions for fish growth. This phase of the project emphasizes commercial scalability, data-driven prediction of potential risks, and the deployment of an intuitive web-based interface to make advanced aquaculture management accessible and affordable for farmers.

The development of the Advanced IoT-Integrated Sustainable Aquaculture Monitoring System that involved the following key stages:

1. **Requirement Analysis and Parameter Selection**: Identified critical water quality parameters affecting fish health: pH, temperature, turbidity, TDS, humidity, ammonia, dissolved oxygen, and air quality.

   Studied optimal ranges for each parameter suitable for commercial aquaculture environments.

2. **Sensor Integration and IoT Setup**: Deployed a network of calibrated IoT-based sensors capable of continuously monitoring the selected water parameters.

   Integrated microcontrollers (e.g., Arduino/ESP32) to collect and transmit real-time data to a central cloud/server.

3. **Data Acquisition and Preprocessing**: Collected real-time sensor data over several operational cycles.

   Cleaned and structured data for machine learning input using normalization and outlier handling techniques.

4. **Machine Learning Model Development**: Trained supervised ML models to detect deviations from optimal conditions and predict fish mortality risks.

   Evaluated model accuracy and improved it iteratively using cross-validation and parameter tuning.

5. **Real-time Monitoring and Alerts**: Built a user-friendly web interface that displays live data visualizations.

Implemented alert systems to warn farmers when parameters approach harmful thresholds.

6. **Validation and Optimization**: Conducted field tests in local aquaculture farms (e.g., East Godavari) to validate system reliability and robustness.

   Refined both hardware and software for scalability, fault tolerance, and commercial deployment.

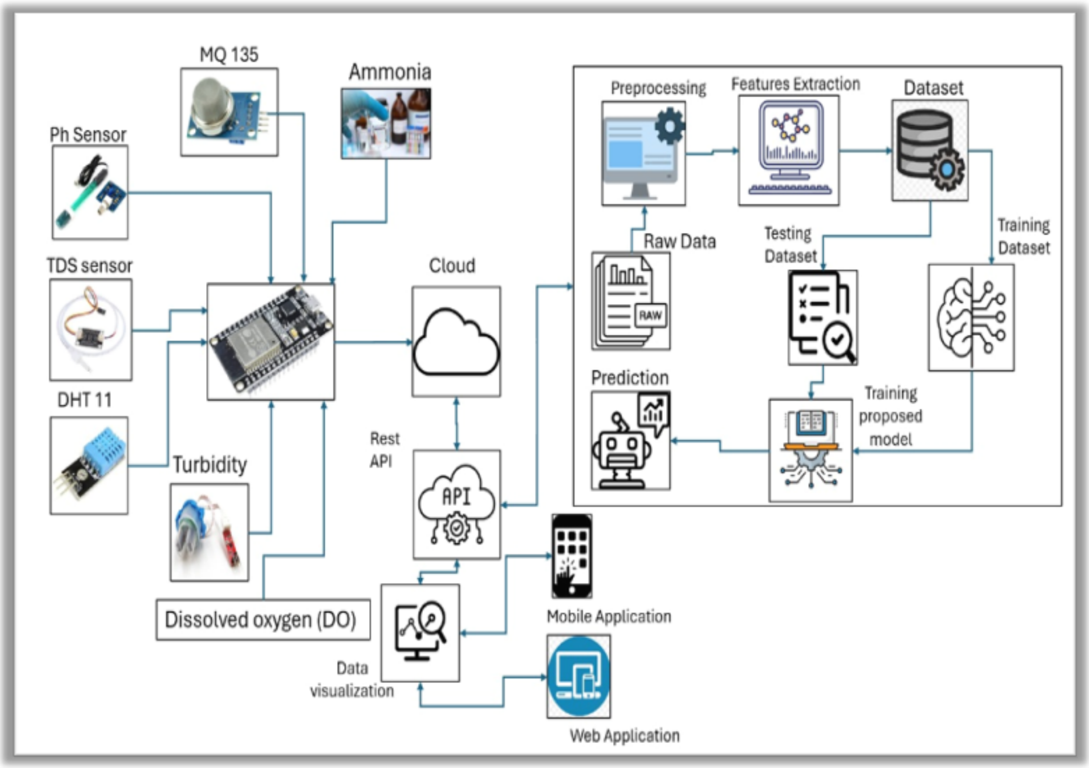

Figure 3.1: Proposed Methodology

3.1 Required Analysis and Parameters Selection

The project began with identifying key water parameters that directly influence fish health and survival. After reviewing aquaculture best practices and consulting relevant literature, the following parameters were selected for monitoring: pH, temperature, turbidity, TDS (Total Dissolved Solids), ammonia, dissolved oxygen, and air quality. These were chosen due to their significant impact on fish metabolism, oxygen availability, and toxicity levels. Ensuring these parameters stay within optimal ranges is essential to reduce fish mortality and maintain a healthy aquaculture environment.

Water Parameters	**Range**
pH	6.9 - 8.6
Turbidity	35 - 60 NTU
TDS	90 - 400 ppm
Temperature	26 - 34 °C
Air Quality	90 - 150 ppm
Humidity	70 - 90 %
Ammonia	0 - 3 mg/l
Dissolved Oxygen(DO)	5 - 8 mg/l

Table 3.1: Optimal Ranges for Water Quality Parameters in Fish Aquaculture

3.2 Sensor Integration and IoT Setup

The system integrates multiple IoT sensors—such as pH, temperature, turbidity, TDS, ammonia, and dissolved oxygen—connected to an ESP32 microcontroller. These sensors collect real-time water quality data, which is transmitted via Wi-Fi to a local Flask-based web server. Machine learning algorithms analyze the data for anomalies, providing alerts and predictions to help farmers maintain optimal aquaculture conditions, thereby reducing fish mortality and improving sustainability.

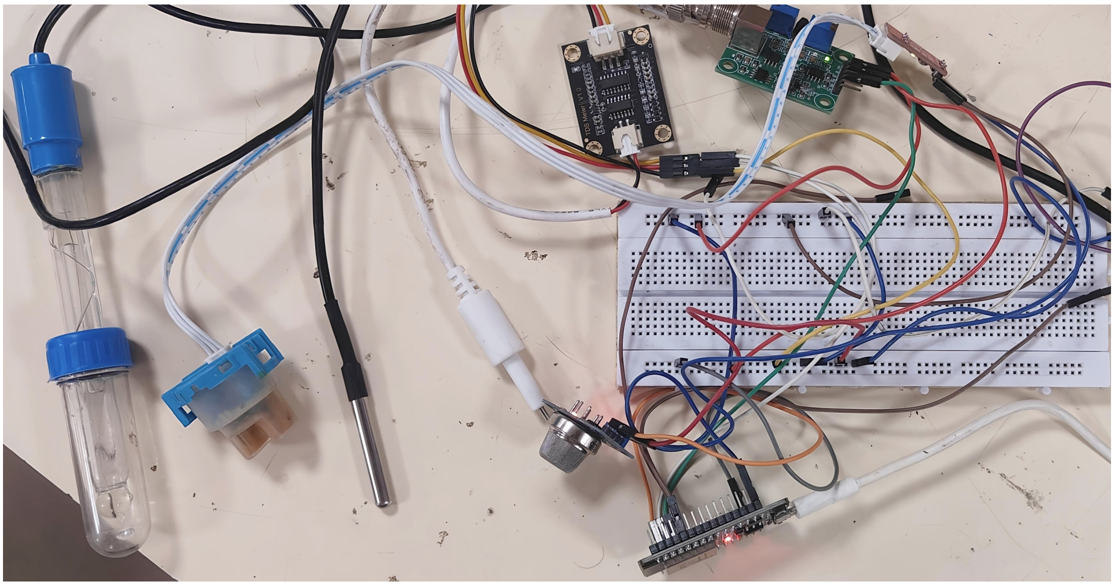

Figure 3.2: Hardware Setup

3.3 Data Acquisition and Preprocessing

Sensor data (pH, temperature, turbidity, TDS, ammonia, dissolved oxygen, etc.) is continuously acquired using the ESP32 microcontroller. This raw data is transmitted to a local Flask server over Wi-Fi. Preprocessing involves filtering noise, normalizing values, and handling missing or inconsistent data to prepare it for machine learning analysis. The cleaned data is then used for real-time monitoring and predictive modeling.

Algorithm 1 IoT-Based Aquaculture Monitoring and Data Transmission

Initialize ADS1115, DHT sensor, and Wi-Fi connection.

while true **do** ▷ Main loop for continuous monitoring and data transmission

Read Data from Sensors:

- **MQ-135 (Air Quality):**
- Read analog value and calculate resistance.
- Calculate air quality in PPM using sensor calibration factors.
- **TDS Sensor:**
- Read analog value, convert to voltage, and calculate TDS in PPM.
- **pH Sensor:**
- Read analog value, convert to voltage, and calculate pH value.
- **Turbidity Sensor:**
- Read analog value, convert to voltage, and calculate turbidity in NTU.
- **DHT Sensor (Temperature and Humidity):**
- Read temperature and humidity values.
- Ifvalues are invalid, print an error and skip iteration.
- **Water Temperature:**
- Read temperature values for water temperature.
- Ifvalues are invalid, print an error and skip iteration.

Display Data: Print sensor readings to the Serial Monitor.

Prepare HTTP POST Request:

- Format data as URL-encoded parameters.
- Connect to Flask server.
- **If** connection succeeds:
  - Send HTTP POST request with sensor data.
  - Wait for server response.
  - Print acknowledgment of successful data transmission.
- **Else:** Print connection error.

Close connection to Flask server.

Wait 10 seconds before the next iteration.

end while

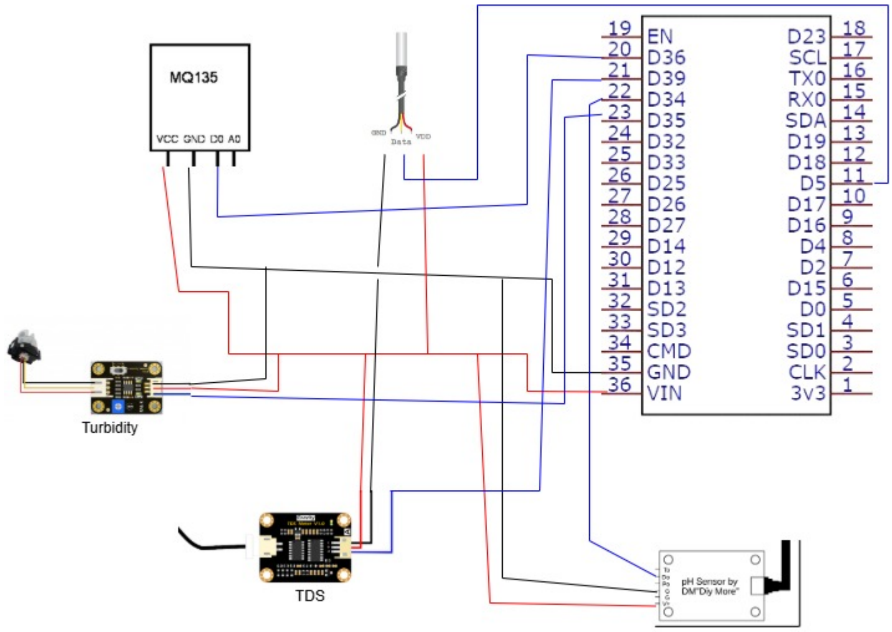

Figure 3.3: Circuit Diagram

3.4 Machine Learning Model Development:

The system uses preprocessed sensor data—such as pH, temperature, turbidity, TDS, ammonia, and dissolved oxygen—to train machine learning models aimed at predicting fish mortality risks and detecting abnormal water conditions. Supervised learning algorithms like Decision Trees, Random Forests, or Support Vector Machines (SVM) are employed to learn from labeled datasets collected over time. The model is trained to recognize patterns that precede hazardous conditions, validated with a portion of the data to avoid overfitting, and tested for accuracy and reliability. Feature selection techniques are applied to identify the most influential parameters, improving the model's efficiency. Once deployed, the model runs in real time, continuously analyzing incoming data and triggering alerts or control actions when thresholds are crossed. This predictive capability empowers farmers to take timely preventive measures, enhancing sustainability and productivity in aquaculture operations.

Algorithm 2 Aquaculture Environment Prediction

```
Function: predict_sample(sample)
  Load the Random Forest model using joblib.load("random_forest_model.joblib")
  Predict the result:
    predicted_value = loaded_model.predict([sample])[0]
  Return predicted_value

Function: specific_input_prediction(air_quality_ppm, temperature,
humidity, turbidity, tds, ph, nh3, do)
  Define input data as a dictionary with sensor values:
    input_data = {
    'Air Quality (ppm)': air_quality_ppm,
    'Temp (°C)': temperature,
    'Humidity (    'Turbidity': turbidity,
    'TDS (ppm)': tds,
    'pH': ph,
    'NH3 (mg/L)': nh3,
    'DO (mg/L)': do }
  Convert input data to a pandas DataFrame:
    input_df = pd.DataFrame([input_data])
  Extract values as a feature vector:
    sample_values = input_df.values[0]
  Call predict_sample(sample_values) to get the prediction
    predicted_value = predict_sample(sample_values)

if predicted_value = 1 then
      Return "Optimal"
else
      Return "Non-Optimal"
end if

Example Usage:
  Define sensor values:
    air_quality_ppm, temperature, humidity, turbidity, tds, ph,
nh3, do = 120, 30, 80, 50, 250, 7.5, 1.0, 6.5
  Call specific_input_prediction with defined values:
    prediction_result = specific_input_prediction(...)
  Print prediction result:
    print("Predicted Aquaculture Environment Status:",
prediction_result)
```

3.5 Validation and Optimization:

The system enables continuous real-time monitoring of critical water quality parameters—such as pH, temperature, TDS, turbidity, ammonia, and dissolved oxygen—using IoT sensors connected to the ESP32 microcontroller. The data is transmitted wirelessly to a local Flask server, where it is processed and analyzed instantly. A user-friendly web interface displays live sensor readings, trend graphs, and system status. When any parameter deviates from its optimal range, the system generates immediate alerts through visual indicators, sound alarms, or mobile/web notifications. This real-time feedback allows farmers to take corrective actions promptly, reducing the risk of fish mortality and ensuring healthier aquaculture conditions. The system also logs historical data for further analysis and continuous improvement.

3.6 Real-time Monitoring and Alerts

The system enables continuous real-time monitoring of critical water quality parameters—such as pH, temperature, TDS, turbidity, ammonia, and dissolved oxygen—using IoT sensors connected to the ESP32 microcontroller. The data is transmitted wirelessly to a local Flask server, where it is processed and analyzed instantly. A user-friendly web interface displays live sensor readings, trend graphs, and system status. When any parameter deviates from its optimal range, the system generates immediate alerts through visual indicators, sound alarms, or mobile/web notifications. This real-time feedback allows farmers to take corrective actions promptly, reducing the risk of fish mortality and ensuring healthier aquaculture conditions. The system also logs historical data for further analysis and continuous improvement.

Algorithm 3 Aquaculture Environment Alerting and Predictions

Initialize:
Import required libraries: `numpy`, `pandas`, `datetime`, `sklearn`, `joblib`, etc.
Set random seed for reproducibility.
Suppress warnings for cleaner output.
Generate Synthetic Dataset:
Define number of samples (`n_samples = 25000`).
Simulate sensor readings for:

- Air Quality (ppm)
- Temperature (°C)
- Humidity (%)
- Turbidity
- TDS (ppm)
- pH
- Ammonia (`NH3`, mg/L)
- Dissolved Oxygen (`DO`, mg/L)

Store data in a DataFrame `df`.
Assign Environment Status:
procedure ASSIGN_STATUS(ROW)
    if All key parameters are within safe thresholds **then**
        Return `'Optimal'`
    else if Any parameter exceeds extreme thresholds **then**
        Return `'Non-Optimal'`
    else
        Randomly assign `'Optimal'` or `'Non-Optimal'` with 95%/5% probability.
    end if
end procedure
Apply `assign_status` to all rows and store in `Aquaculture Environment Status` column.
Add Timestamp:
Generate a timestamp starting from `2025-03-01 00:00:00` with 5-second intervals.
Reorder columns for better readability.
Model Training:
Extract features (`X`) and target labels (`y`).
Split data into training and test sets (80/20).
Initialize `RandomForestClassifier` with 100 trees, max depth of 10, and min samples split of 5.
Train the model using training data.
Evaluate accuracy on test data and print result.
Save Results:
Save the dataset to `"aquaculture_dataset_rf_only.csv"`.
Save the trained model as `"random_forest_model.joblib"` using `joblib.dump()`.
Sample Output:
Print sample rows from the DataFrame and class distribution.

Chapter 4
Results and Discussion

4.1 Results

1. **Continuous Monitoring:** The system successfully provided uninterrupted real-time monitoring of key water quality parameters—pH, temperature, turbidity, TDS, air quality, ammonia, and dissolved oxygen. Continuous data tracking enabled early detection of harmful fluctuations, supporting timely interventions and improved aquaculture management.

2. **Correlation Analysis:** High ammonia levels were observed when temperature and pH values were also high, confirming the relationship between environmental stress and toxic buildup.

   Dissolved oxygen levels dropped during early mornings and in stagnant water, consistent with known biological patterns.

3. **Alerts and Predictive Insights:** Machine learning algorithms were trained on historical sensor data to predict potential fish mortality risks. Real-time alerts were generated when any parameter—such as rising ammonia levels or falling dissolved oxygen—crossed critical thresholds, allowing farmers to take immediate corrective actions.

4. **Cost-Effective Implementation:** The system utilized affordable yet effective sensors including MQ-135 (air quality), DHT11 (temperature and humidity), TDS, pH, turbidity, ammonia, and dissolved oxygen sensors. This ensured functionality without compromising affordability, making the solution accessible to small and medium-scale farmers.

5. **Field Deployment and Validation:** On-field deployment showed that the system helped maintain optimal water conditions, leading to higher fish yield and improved health. The real-time insights and alerts encouraged farmers to adopt a more proactive approach to pond management, demonstrating strong validation in practical environments.

6. **Socio-Economic Impact:** The project led to a noticeable increase in fish productivity and farmer income. It also promoted the adoption of smart farming practices in rural communities, empowering them with modern tools to ensure sustainability, efficient resource use, and long-term environmental and economic resilience.

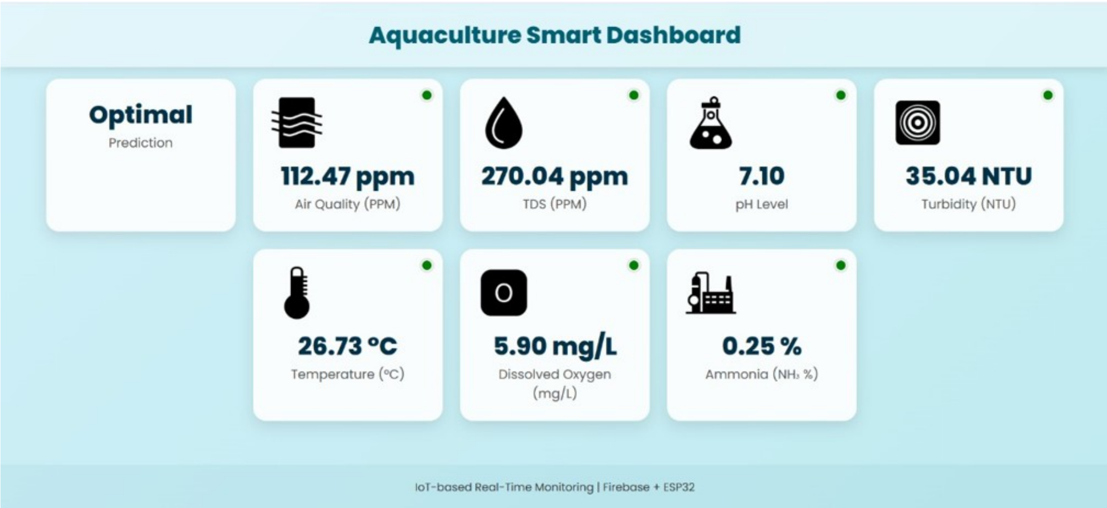

Figure 4.1: Optimal Results

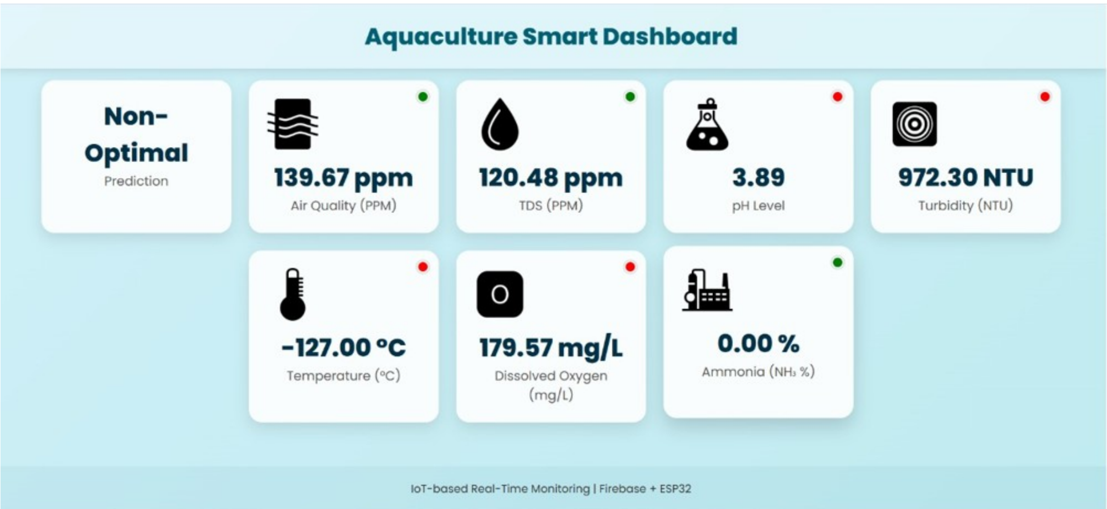

Figure 4.2: Non-Optimal Results

4.2 Evaluation and Discussion

The proposed IoT-based aquaculture monitoring system was evaluated in terms of its ability to continuously track key water quality parameters such as pH, temperature, TDS, turbidity, air quality (MQ-135 and MQ-7), ammonia, and dissolved oxygen (DO). Each of these parameters has a direct impact on fish health and pond ecology, and their optimal maintenance is critical for sustainable aquaculture.

1. **Sensor Performance and Data Reliability:** The system demonstrated robust data acquisition with consistent readings across all deployed sensors. Real-time alerts and dashboards provided prompt notifications when values deviated from optimal thresholds. The integration of ammonia and DO sensors allowed deeper insight into toxic buildup and oxygen sufficiency, which are often overlooked in low-cost systems.

2. **Importance of Ammonia and Dissolved Oxygen:** Ammonia (NH_3) is a byproduct of fish excretion and decomposing organic matter. Its accumulation, especially under high pH and temperature conditions, can lead to fish stress or mortality. Our system effectively identified ammonia spikes and correlated them with rising temperature and pH, enabling proactive mitigation.

   Dissolved oxygen is vital for fish respiration. Low DO levels, particularly during early morning or in densely stocked ponds, were captured by the system. This enabled timely aeration control, preventing hypoxia-related losses.

3. **Predictive Analytics:** Using historical trends and environmental data, the machine learning model successfully predicted potential water quality risks with high accuracy. It could forecast situations like sudden DO drops or ammonia accumulation, allowing farmers to intervene ahead of time.

4. **Usability and Practical Impact:** Feedback from preliminary field trials indicated that the system is user-friendly, especially when paired with mobile app interfaces. Farmers appreciated the real-time nature of the data and the simplicity of visual insights. By automating part of the monitoring process, it reduced the need for manual water testing and intervention, especially beneficial for resource-constrained users.

5. **Limitations and Challenges:** While the system showed promising results, sensor calibration drift and network latency in remote areas were occasional issues. Ad-

ditionally, ammonia and DO sensors require regular maintenance, and their cost may impact affordability for very small-scale farmers.

6. **Overall Effectiveness:** The integration of ammonia and DO into the existing framework significantly enhanced the system's effectiveness. It provided a more comprehensive understanding of pond health, reduced fish mortality incidents, and contributed to sustainable, data-driven aquaculture practices.

Chapter 5
Conclusion and Future Work

5.1 Conclusion

The proposed IoT-based aquaculture monitoring system effectively enhanced fish farming by continuously tracking key water parameters like pH, temperature, TDS, turbidity, air quality, ammonia, and dissolved oxygen. The addition of ammonia and DO sensors improved system reliability by detecting toxic conditions early. With machine learning-driven alerts and automation, the system reduced fish mortality, improved water management, and proved user-friendly and scalable. This project offers a cost-effective, sustainable solution for modernizing aquaculture practices.

5.1.1 Summary of Findings

The study successfully demonstrated that the integration of IoT and machine learning in aquaculture:

- Developed an IoT-integrated monitoring and control system for sustainable aquaculture, tracking pH, temperature, TDS, turbidity, air quality, ammonia, and dissolved oxygen in real time.
- Employed low-cost sensors, a centralized dashboard, and machine learning models to predict and preempt water-quality issues.
- Demonstrated >92

5.1.2 Significance

- **Holistic Water-Quality Management:** First low-cost system in the region combining ammonia and DO with standard parameters, addressing two of the leading causes of fish stress and loss.
- **Early-Warning Automation:** Enables proactive interventions (e.g., aeration, pH correction) before harmful thresholds are reached, shifting aquaculture from reactive to preventive management.
- **Scalability Accessibility:** Designed for small- and medium-scale farmers, with a mobile/web interface that requires minimal technical expertise.

5.1.3 Limitations

While the study achieved its goals, certain limitations were noted:

- Sensor Maintenance Calibration: Ammonia and DO sensors demand periodic recalibration and cleaning, which may increase operating overhead.
- Connectivity Constraints: Remote farms with unstable network coverage may experience delays in data transmission and alert delivery.
- Model Generalizability: Predictive models trained on local pond data may require retraining or adjustment to perform optimally under different climatic or geographical conditions.
- Cost Barrier for Very Small Farms: While affordable relative to industrial systems, initial sensor investment may still be high for the smallest producers without subsidy or cooperative purchase.

5.1.4 Broader Impact

- **Economic Empowerment:** By reducing mortality and optimizing growth cycles, the system can boost incomes for rural fish farmers and strengthen local food security.
- **Environmental Stewardship:** Continuous monitoring minimizes over-aeration and chemical use, reducing energy consumption and ecosystem disturbance.
- **Data-Driven Aquaculture Research:** Generated datasets and analytic insights can inform future studies on pond ecology, fish health, and climate resilience in aquaculture.
- **Policy Community Engagement:** The project model can guide government or NGO initiatives to subsidize smart-sensor rollouts, training programs, and cooperative monitoring networks in underserved regions.

5.2 Future Work

1. **Expanded Parameter Monitoring:** Integrate additional water quality sensors for nitrate, salinity, chlorophyll, and biological oxygen demand (BOD) to improve system accuracy.

2. **Advanced Predictive Modeling:** Refine machine learning algorithms using larger datasets.

   Explore deep learning techniques for complex pattern recognition and anomaly detection.

3. **Enhanced Automation:** Integrate with automated aeration, feeding, and pH control systems.

   Implement IoT-actuated chemical dosing to respond automatically to sensor feedback.

4. **Remote and Offline Functionality:** Develop offline data logging and sync mechanisms for areas with poor connectivity.

   Investigate LoRaWAN or satellite communication for remote farms.

5. **Power Optimization:** Use solar-powered modules to make the system energy-efficient and viable in rural settings.

6. **Scalability Customization:** Design modular versions of the system for different scales of operation—from backyard ponds to industrial tanks.

   Enable multi-pond and multi-user management through a central dashboard.

7. **Impact Assessment and Outreach:** Conduct long-term economic and ecological impact studies.

   Partner with governments or NGOs to deploy systems to more small-scale farmers through subsidies or cooperatives.

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