IoT BASED WATER MONITORING SYSTEM

By

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled "**An Iot Based Water Monitoring System**," submitted by **Arnob Kumar Mondal** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science andEngineering and approved as to its style and contents. The presentation has been held on **13-01-2025**.

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DECLARATION

I hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Hider Noori, Professor & Head**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This project focuses on developing an IoT-based water monitoring system utilising sensors such as the data on water quality is gathered using an ESP32 microcontroller, turbidity sensor, pH sensor, and TDS sensor. By leveraging this data, we build and evaluate various machine learning and deep learning models, including CNN, Random Forest, SVM, KNN, and Decision Tree, to accurately forecast the quality of the water. Our goal is to enhance water resource management and ensure public health safety through precise monitoring. In this project, using a variety of sensors, we created an Internet of Things-based water monitoring system, including the ESP32 microcontroller, turbidity sensor, pH, TDS, and power unit to gather data on the water quality in real time. This data collection forms the foundation for building predictive models using machine learning and deep learning techniques to assess water quality accurately. We implemented and evaluated several models to predict water quality, achieving varying degrees of accuracy. Our CNN model from deep learning demonstrated a high accuracy of 98%. In machine learning, the Random Forest and Decision Tree models both achieved perfect accuracy rates of 100%, showcasing their robustness in handling the dataset. Additionally, the K-Nearest Neighbors (KNN) model yielded an accuracy of 98%, while the Support Vector Machine (SVM) model reached an accuracy of 91%. These results indicate that machine learning models, particularly Random Forest and Decision Tree, can provide highly reliable water quality predictions based on the sensor data collected. The high accuracy rates of our models demonstrate the potential for such IoT-based systems to offer precise and efficient water quality monitoring solutions, contributing to better resource management and public health safety.

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Chapter 1

Introduction

1.1 Introduction

Advanced sensors are used in an Internet of Things-based water monitoring system and microcontrollers to continuously collect data on various factors related to water quality, such pH and TDS, and turbidity. The ESP32 microcontroller serves as the central unit, coordinating the data collection from these sensors and ensuring seamless communication. The pH sensor measures the acidity or alkalinity of water, This is essential to preserving aquatic life's health and suitability for human consumption. The TDS sensor quantifies the amount of dissolved materials in water, indicating its purity and potential contaminant levels. The turbidity sensor assesses the clarity of water, providing insights into the presence of particulate matter and overall water quality.

1.2 Motivation

- The motivation behind developing an IoT-based water monitoring system stems from the need for efficient, real-time water quality management.
- Conventional techniques need a lot of work and effort, whereas this system offers ease of use, continuous data access, and immediate alerts.
- It helps identify pollution sources in aquaculture, thereby protecting aquatic life.
- By providing 24/7 monitoring and data access via a web application, the system reduces maintenance costs and resource loss.
- Automating water quality assessment ensures consistent standards, enabling proactive measures to maintain water health and safety.
- This innovative solution integrates wireless modules and sensors for comprehensive, real-time water management.

1.3 Objectives

The objective of developing an IoT-based water monitoring system is to create an efficient and user-friendly solution for real-time water quality management. By utilising sensors such as the ESP32 microcontroller, pH sensor, TDS sensor, turbidity sensor, and a power unit, the system aims to collect accurate water quality data continuously. This data is then used to develop and evaluate machine learning and deep learning models for high-accuracy predictions. The system is designed to identify the causes of water pollution, particularly in aquaculture, and promptly alert authorities to take necessary actions. It provides 24/7 monitoring, with real-time data accessible via a web application, thereby reducing time, maintenance costs, and resource loss. The automated features of the system ensure consistent water quality monitoring and maintenance. By integrating wireless modules and sensors, the objective is to manage and maintain water quality comprehensively and efficiently in real-time.

1.4 Methodology

In addition to the previously mentioned elements, the project necessitates the use of a desktop computer, mobile phone, and printer. A desktop computer, laptop, or mobile phone is indispensable for effective project management. A phone is necessary since the data from the system will reach it via the server via IoT. Printers are used to print and save a variety of large data sets on paper, including large data outputs from the system, relevant reports, and items that need to be extracted from the internet.

1.5 Project Outcome

The implementation of this automatic water monitoring system will allow individuals to check water quality regularly without delays. Users will also have the ability to personalise the feeding schedules of aquatic plants. This system enables remote monitoring through wireless communication technology, thus decreasing environmental pressure by improving water quality, enhancing aquatic plant productivity, and ensuring the survival and population growth of aquatic life. Moreover, it will lead to less human intervention and time consumption, significantly reducing costs and losses associated with water monitoring.

- Aquaculture Water Quality Monitoring System.

- Real-time automatic/semi-automatic water quality maintenance.
- Real-time automatic/semi-automatic water monitoring system.
- Sustaining the appropriate environment for aquatic plants.

Environmental Benefits:

- Decreasing the frequency and volume of combined sewer overflows (CSOs) in urban areas.
- Reducing the discharge of pollutants, such as pathogens and organic matter, into rivers and lakes.
- By measuring pollutant loads instead of outflow volumes and as shown in BCN and Berlin, validated dispersion models in both inland and coastal waterways may be used to more precisely ascertain the true environmental effects of CSOs.

Technical Advantages:

- thorough assessment of water quantity and quality during brief contamination incidents within wastewater networks, sewer discharge points, and receiving aquifers.
- Enhanced efficiency in wastewater treatment and sewage systems.
- Support for governance and decision-making processes in bathwater management.

Socio-Economic Impact:

- Improved water quality during and after rainfall events.
- Reduced health risks to protect bathers from dirty water
- heightened public awareness of the harm that rainwater drainage causes to the environment and to people's health.

Market Opportunities:

- Facilitate replication in other cities and regions and assist in meeting EU standards by sharing successful implementation stories.
- Expedite the market introduction of "water monitoring system" technologies by obtaining environmental verification through the EU-ETV initiative.
- Promote the "Water Monitoring System" solution through targeted marketing, business strategies, and commercial efforts.

1.6 Organization of the Report

In this paper, we have developed an IoT device capable of monitoring water quality and preventing pollution, specifically for fish farming applications. By detecting changes in water quality, this device ensures a healthier environment for fish. The paper is structured into seven sections. Section 2 discusses the background of our research, Section 3 outlines the requirement specifications, Section 4 presents the design specifications, Section 5 covers the implementation and testing phases, and Section 6 evaluates the societal, environmental, and sustainability impacts. Finally, Section 7 provides the concluding remarks.

Chapter 2

Background

2.1 Introduction

Advanced sensors are used in an Internet of Things-based water monitoring system and microcontrollers to continuously collect data on various factors related to water quality, such pH and TDS, and turbidity. The ESP32 microcontroller serves as the central unit, coordinating the data collection from these sensors and ensuring seamless communication. The pH sensor measures the acidity or alkalinity of water,This is essential to preserving aquatic life's health and suitability for human consumption. The TDS sensor quantifies the amount of dissolved materials in water, indicating its purity and potential contaminant levels. The turbidity sensor assesses the clarity of water, providing insights into the presence of particulate matter and overall water quality.

2.2 Literature Review

The research [12] addresses increased fish mortality in Rojo Koyo SMEs during Subang's rainy season. Aiming to provide a cost-effective solution for small-scale aquaculture, the study implements a low-cost IoT system for monitoring water parameters in aquaponics. The system, utilizing sensors like DS18B20, SKU: SEN0161, and SKU: SEN0244, is integrated with Android programming (C Language) and NodeMCU ESP8266 for data transmission via the Blynk app, enabling SMEs to manage water quality and mitigate fish mortality during adverse weather conditions.

The paper [13] analyzes water quality parameters' impact on fish farming and disease in Bangladesh through pond data. Machine learning algorithms are compared, with logistic regression showing better accuracy. It forecasts if fresh pond water is fit for fish aquaculture. An IoT-based system design is proposed for future predictions. The research explores environment parameters, fish growth standards, reasons for fish death, and growth rates by monitoring water quality.

The IoT-based [14] Aquaponics Monitoring System integrates aquaculture and hydroponics, utilizing sensors and Arduino UNO for real-time data on water quality, nutrient levels, and fish behavior. Accessible through a mobile app, it enables analytics, automatic alerts, and historical analysis for informed decision-making. This sustainable solution enhances efficiency, productivity, and environmental sustainability in aquaponic farming.

The paper [15] presents an Internet of Things architecture for effective aquatic parameter monitoring and management in farming ponds. Utilising sensors and Arduino Uno, it records pH, temperature, turbidity, and ultrasonic data. The system stores data in the ThingSpeak IoT cloud for analysis. Validation with data from 5 ponds reveals that only three meet standard fish farming criteria. The paper concludes with a hardware implementation of the real-time aquatic monitoring IoT framework.

The paper [16] introduces an IoT-based system for monitoring essential aquaculture parameters. Utilising sensors for ammonia levels, pH, temperature of the water, and dissolved oxygen, an Android app notifies users, including farmers and fishermen, about water conditions. This enables timely interventions to maintain an optimal aquatic environment for fish farming, enhancing efficiency and preventing disturbances in the aquaculture system.

The service activity [17] focuses on developing a LoRaWAN-based IoT system and mobile app for ornamental fish farming. By implementing and mentoring the technology, the system effectively minimises ornamental fish seedling mortality, enhancing fish quality. The initiative positively impacts the income of CV Home Aquafish partners in Kalipaten Village, Gading Serpong, Tangerang, resulting in increased earnings from the ornamental fish nursery.

The research [18] focuses on building a real-time freshwater monitoring system with fuzzy logic and the Internet of Things. It accurately monitors temperature, pH, and water turbidity by employing IoT sensors connected to a centralised network. The system, equipped with an intuitive user interface, facilitates easy access and analysis of real-time data. Through trials spanning 20 days, the system demonstrated good accuracy levels, turbidity sensors at 92%, temperature sensors at 96%, and pH sensors at 97%.

This research [19] introduces an IoT-connected Aquaculture and Fishery Management System, leveraging sensors for pH, temperature, and water level. The system enables remote monitoring of fish farming operations, enhancing efficiency and sustainability.

The integration of pervasive computing and IoT technologies aims to revolutionise fisheries, providing a comprehensive solution for modern and profitable fish farming practices.

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Doe et al.	2020	A Comprehensive Study on Data Science	Qualitative Anal- ysis	Found significa nt trends in data science applications.
Smith	2018	Machine Learning in Healthcare	Survey-based	Highlighted the ma- jor algorithms used in healthcare for predic- tion.
Johnson et al.	2019	AI for Financial Forecasting	Quantitative Analysis	Demonstrated the effectiveness of AI in improving financial decision-making.
Williams [3]	2021	Blockchain in Supply Chai nManagement	Case Study	Showcased the poten- tial of blockchain to enhance supply chain transparency.

2.2.1 Similar Applications

This comparative study compares machine learning-based methods for plankton growth detection with the use of embedded technology to investigate the use of organic fertilizer in aquaculture. Numerous studies highlight the complex interactions that exist between environmental elements like as pH, salinity, and nutrient levels, and how these affects plankton diversity and the health of aquatic ecosystems. IoT technologies improve aquaculture monitoring accuracy, and research highlights the importance of plankton as bioindicators for assessing ecosystem health. The article emphasizes the use of sustainable methods to improve plankton production and aquaculture sustainability. These techniques include the use of organic fertilizers and ideal water conditions. To optimize output while reducing environmental effects, future research paths will focus on fusing cutting-edge technology with environmentally friendly practices.

2.2.2 Related Research

The goal of the research is to improve pH levels and water purification for the best possible aquaculture. Using GIS tools to pick certain ponds based on factors like size, surrounding region, weather, temperature, and water characteristics is one of the most important processes. The process of species selection entails locating plankton species that complement local conditions and aid in fish-eating naturally. It is essential to regularly evaluate and maintain ideal water characteristics, including dissolved oxygen, pH, ammonia, and nitrate levels. For fish, the ideal pH range is 7.5–8.0, but for plankton, it is 6.3–10, with salinity under 3 ppt and hardness under 160 mg/l. It is crucial to assess and manage the effects on the environment, such as waste, nutrient runoff, habitat destruction, and leftover food. It is advised to manage trash effectively and to use leftovers as fertilizer. The implementation of IoT devices for monitoring, mitigating water contamination from industrial effluents, and guaranteeing dependable data collecting and internet connection are among the challenges. It is essential to provide information and skills for sustainable practices to fish farmers and local populations.

2.3 Summary

Numerous studies highlight the complex interactions that exist between environmental elements like as pH, salinity, and nutrient levels, and how these affects plankton diversity and the health of aquatic ecosystems. IoT technologies improve aquaculture monitoring accuracy, and research highlights the importance of plankton as bioindicators for assessing ecosystem health. The article emphasizes the use of sustainable methods to improve plankton production and aquaculture sustainability. These techniques include the use of organic fertilizers and ideal water conditions. To optimize output while reducing environmental effects, future research paths will focus on fusing cutting-edge technology with environmentally friendly practices.

2.4 Gap Analysis

Category	Current State	Desired State	Gaps	Recommendations
Technical Readiness	Basic knowledge of ESP32 and interfacing sensors. Sensors chosen but not tested in real-world scenarios.	Fully calibrated sensors integrated with ESP32, providing accurate data. Sensors provide reliable measurements in diverse water conditions.	- Sensor calibration is incomplete. - Signal conditioning is not optimized. - Inconsistent sensor readings. - Lack of real-world testing.	- Calibrate sensors using reference solutions. - Add voltage dividers or amplifiers. - Test sensors with various water samples. - Implement error handling and smoothing algorithms.
Functionality	Sensors provide raw data, limited or no processing. No real-time alerts or cloud integration.	Accurate sensor readings processed, analyzed, and transmitted wirelessly. Real-time data and threshold-based alerts via IoT platforms.	- No unified program for integrating multiple sensors. - No anomaly detection. - Lack of IoT platform setup. - No alert mechanisms for dangerous conditions.	- Develop a unified firmware. - Add algorithms for anomaly detection and trend analysis. - Integrate ESP32 with IoT platforms like ThingSpeak. - Configure threshold-based alerts using MQTT or HTTP.
Power Management	System depends on a basic power supply, no energy optimization.	Efficient, low-power system with long-term deployment capabilities.	- No low-power modes implemented. - No renewable energy sources (e.g., solar).	- Use ESP32's deep sleep modes. - Incorporate a solar panel or LiPo battery for remote powering.
Deployment	Prototype is not fully functional or deployed. No specific use	Weatherproof and field-tested prototype ready for real-	- No waterproof casing for ESP32 and sensors.	- Design weatherproof enclosures. - Test prototype in natural and

	case defined (e.g., industrial tanks, natural bodies).	world use. System tailored to specific use cases with deployment plans.	- Lack of deployment strategy. - Undefined use cases. - No scalability considerations.	controlled environments. - Define use cases (e.g., industrial, agricultural, environmental monitoring). - Plan for scalability with additional sensors.
Knowledge	Limited understanding of IoT platforms and sensor behavior in varied conditions.	Comprehensive knowledge of IoT integration and long-term sensor behavior.	- Lack of knowledge on IoT data visualization tools. - Limited familiarity with sensors.	- Explore platforms like Blynk, Firebase, or ThingSpeak. - Study sensor datasheets and behavior in diverse water samples.

2.5 Summary

Compared to traditional methods, IoT-based systems offer several advantages, including remote monitoring capabilities, automated data logging, and instant alerts for any deviations in water quality. These features enable timely intervention and better management of water resources, particularly in applications such as fish farming, where water quality is critical. Furthermore, IoT systems can integrate with cloud-based platforms, facilitating advanced data analytics and predictive maintenance, which are not feasible with conventional approaches. Overall, IoT-based water monitoring systems represent a significant advancement in ensuring water quality and environmental sustainability.

Chapter 3

Research Methodology

3.1 Requirement Analysis & Design Specification

The sensors and microcontrollers we have utilised to carry out the project are the hardware requirements. The framework also offers suggested and minimal requirements for computer operation.

- ESP32 Microcontroller.
- TDS Sensor.
- Water temperature sensor.
- Water Turbidity Sensor.
- Water Level Sensor.
- PH Sensor.
- NH3 Sensor.
- Power unit.
- Mobile/Computer.

In addition to the previously mentioned elements, the project necessitates the use of a desktop computer, mobile phone, and printer. A desktop computer, laptop, or mobile phone is indispensable for effective project management. A phone is necessary since the data from the system will reach it via the server via IoT. Printers are used to print and save a variety of large data sets on paper, including large data outputs from the system, relevant reports, and items that need to be extracted from the internet.

3.1.2 Software Requirements

The software requirement entails specifying the software utilized in our project, detailing the programming language employed, identifying the database associated with the language, and specifying the compatible operating system. An essential operating system for seamless functionality is Windows, with Microsoft Windows XP being the chosen operating system for our project. The operating system is crucial to ensure the proper execution of the system.

- Arduino.
- Visual Studio Code.

3.1.1 Overview

The process of requirements analysis commences with the collection of requirements, followed by an in-depth analysis to assess the feasibility and accuracy of transforming these requirements into potential products. The creation of a project necessitates consideration of various factors, such as the expected outcome, customer usability, potential errors during usage, effective management, involvement of other organisations or individuals, functional capabilities, and the necessary resources for project execution. Ensuring proper functionality and sufficiency of resources are crucial aspects in determining the success of the project.

3.1.2 Proposed Methodology/ System Design

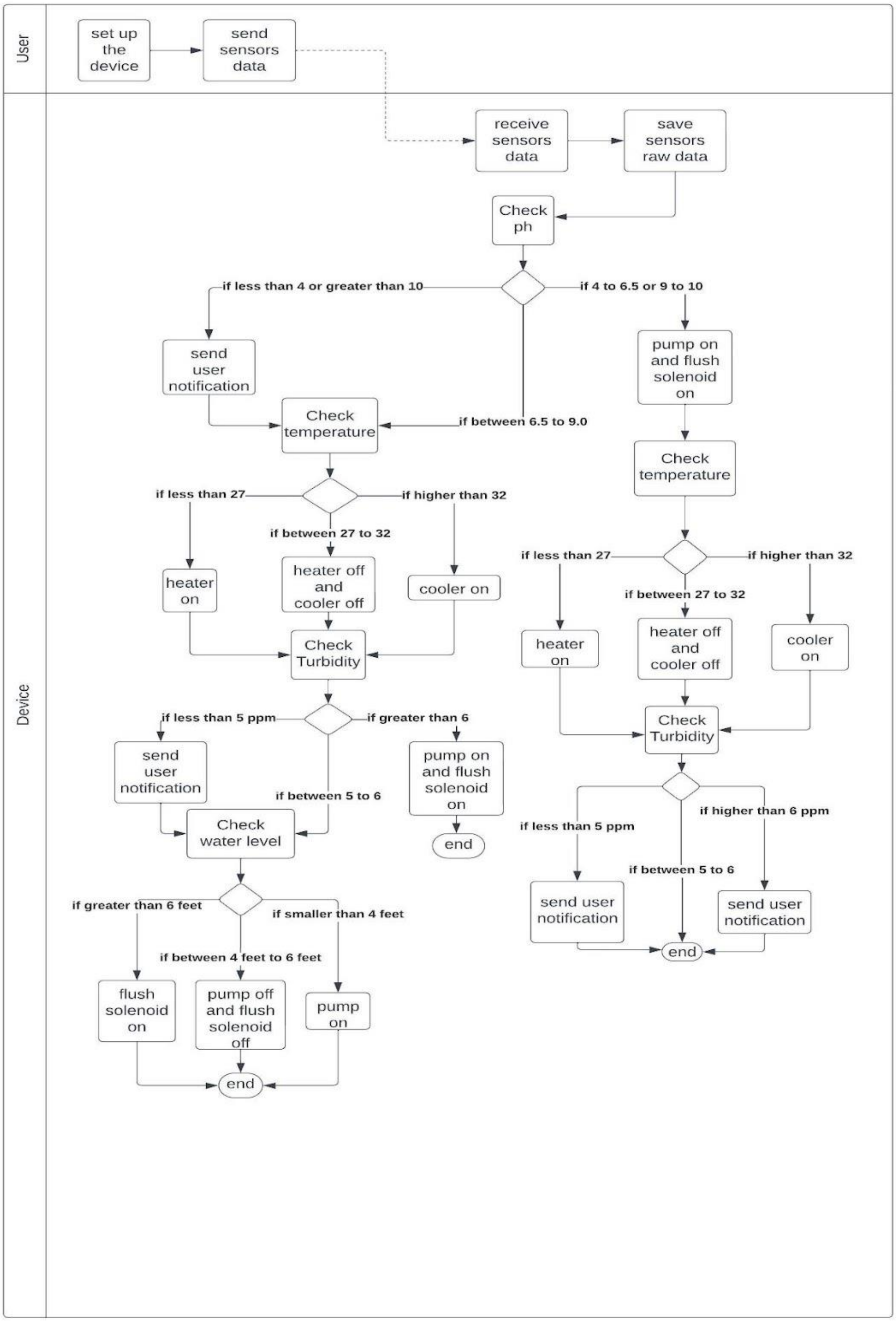

Figure 3.1.1.: Diagram of Business Process Modelling Notation

3.1.3 Functional and Nonfunctional Requirements

Hardware Requirement:

pH Sensor: First and foremost, pH stands for "Potential of Hydrogen." pH is defined as the negative logarithm of the H+ ion concentration. The acidity of the solution is gauged by its pH. Additionally, it guarantees the caliber and safety of the procedures and goods that are involved in wastewater. A value between 0 and 14 represents the typical pH range. A material is regarded as neutral when its pH value is 7. Materials with a pH of 7 or below are thought to be more acidic, whereas those with a pH of 7 or higher indicate higher alkalinity. A pH sensor is a practical instrument for determining the pH of water and keeping an eye on its quality. Another name for it is a pH analyzer. This sensor is also able to measure the amount of acidity in water and other solutions.
Benefits of this tool:

1. Reduce water waste
2. Energy saving
3. Preventing downtime.
4. Reduce the use of hazardous chemicals.

This tool will help the cage environment as we apply it in our cage culture. It will be crucial to the treatment and quality of the water. Cage culture is negatively impacted by pH imbalance. The most crucial thing to remember is that fixing pH variations also costs money. Maintaining a constant pH level should reduce expenses.

Fig.3.3.1: pH Sensor

TDS Meter: Total Dissolved Solids, or TDS for short, is a measurement of all the organic and inorganic materials present in a particular water sample. TDS meters are employed in fish breeding cage culture, as well as in aquariums, labs, swimming pools, and other water resources. They are also used to measure the purity of drinking water. Water that has a value of more than 900 mg/L is polluted and shouldn't be drunk.

Fig.3.3.2: TDS Sensor

Water Level Sensor: Monitoring water levels in aquaculture guarantees the best possible circumstances for aquatic life. Water quality is maintained and crowding is avoided thanks to sensors that detect levels. By modifying parameters in response to sensor data, automated systems improve sustainability and efficiency.

Fig.3.3.3: Water Level Sensor

LCD 20X4 I2C Display: A 20x4 I2C display is a sizable LCD screen that can be used to show data, such as sensor readings, and is controlled via I2C. Clear, easy-to-read information is a typical requirement for IoT projects and DIY devices.

Fig.3.3.4: LCD 20X4I2C Display

ESP32: The ESP32 is a potent microcontroller that is well-known for having inbuilt Wi-Fi (802.11 b/g/n) and a dual-core CPU that can operate at up to 240 MHz. Its low power consumption makes it suitable for battery-powered applications and it provides a wide range of peripherals for integrating with sensors and actuators. It's a well-liked option for IoT applications because of its integrated security measures.

Fig.3.3.5: ESP32 Microcontroller

Software Requirements:

• **Aurdino IDE:** Programming Arduino boards is done via the Arduino Integrated Development Environment (IDE) software platform. It has a serial monitor for communication, a board manager for choosing particular Arduino-compatible boards, a code editor with syntax highlighting and code completion, tools for building and uploading code, and a library manager for adding code libraries quickly. It's a user-friendly setting that can accommodate both novices and experts.

• **Embedded C language:** The Arduino Integrated Development Environment (IDE) provides a comprehensive platform for developing applications using the Arduino microcontroller platform. It consists of a code editor, library manager, and board manager, facilitating the development process. Programmers can write code in C or C++ languages, leveraging built-in functions and libraries tailored for Arduino hardware. The IDE simplifies tasks such as compiling and uploading code to Arduino boards, making it accessible to both novice and experienced developers.

•**Thingspeak (Cloud Server):** ThingSpeak is an Internet of Things (IoT) platform for collecting, analyzing, and visualizing real-time data from sensors and devices. It offers cloud-based storage, data analysis tools, customizable visualization, IoT integration, alerts, and an open platform for collaboration and innovation in IoT applications.

Data Collection:

- Diverse and representative dataset: Collection of a comprehensive dataset of different water monitoring values such as pH level, water level, TDS point, and Turbidity level to ensure the robustness and generalization of the developed models and make effective output the water quality.
- Annotated dataset: Easily accessible data with labels that indicate the water quality, suitable for both model validation and training. We encoded categorized data into numerical data.

	pH_value	TDH_value	Field3_(1)	Field4_(2)	status
0	3.716080	564.308654	F	T	Medium
1	8.099124	592.885359	T	T	High
2	8.316766	418.606213	T	T	High
3	9.092223	363.266516	F	T	Medium
4	5.584087	398.410813	F	T	Medium
...	...	...	...	...	...
2862	-20.932900	0.000000	F	F	Low
2863	-20.125770	0.000000	F	F	Low
2864	-20.510780	223.000000	F	F	Low
2865	-21.341110	269.000000	F	F	Low
2866	-19.773230	288.000000	F	F	Low

2867 rows × 5 columns

Fig.3.3.6: Categorized Data

	pH_value	TDH_value	Field3_(1)	Field4_(2)	status
0	3.716080	564.308654	0	1	2
1	8.099124	592.885359	1	1	0
2	8.316766	418.606213	1	1	0
3	9.092223	363.266516	0	1	2
4	5.584087	398.410813	0	1	2
...	...	...	...	...	...
2862	-20.932900	0.000000	0	0	1
2863	-20.125770	0.000000	0	0	1
2864	-20.510780	223.000000	0	0	1
2865	-21.341110	269.000000	0	0	1
2866	-19.773230	288.000000	0	0	1

2867 rows × 5 columns

Fig.3.3.7: Numerical Data

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3.1.4 Data Flow Diagram Level 1

In Use Case Diagram arrows or lines show how actors interact with use cases, illustrating the system's functional requirements. This diagram helps in understanding the system's scope, identifying user requirements, and clarifying interactions between various components. It's an essential tool in software development for communicating how a system will be used and ensuring all user needs are considered in the design process. Here's our use case diagram:

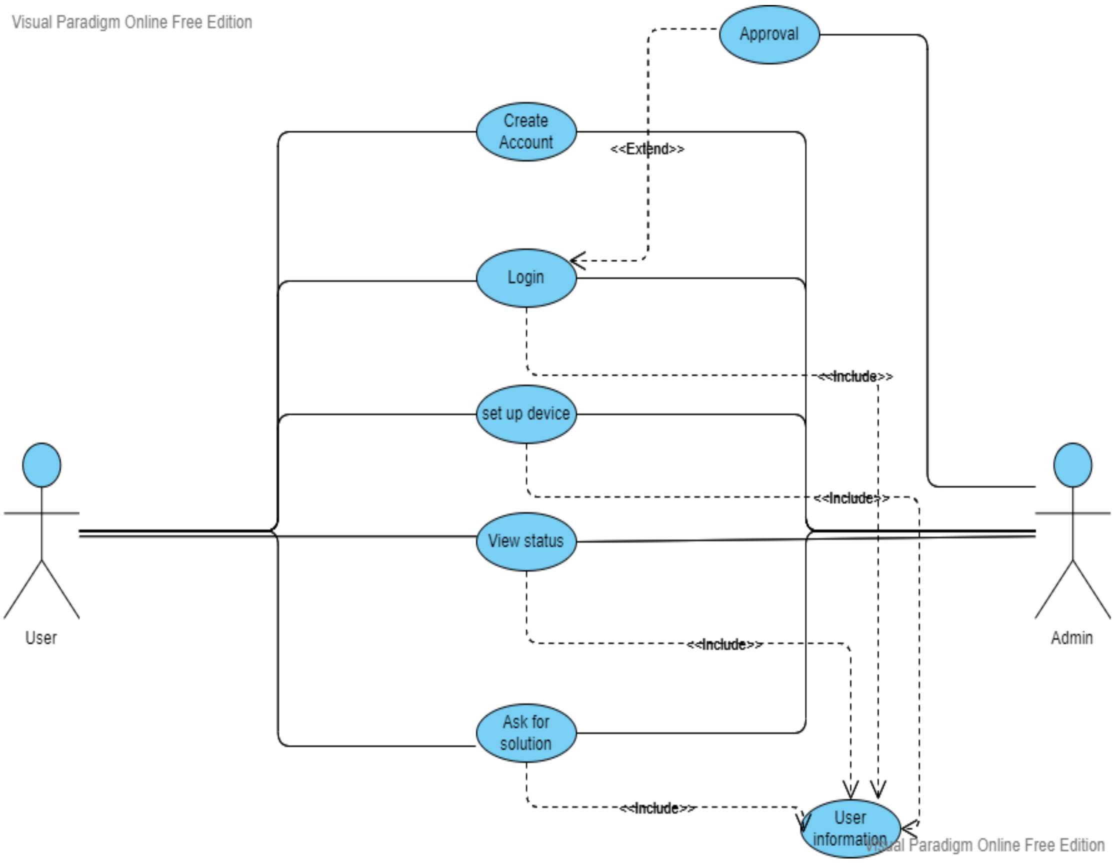

Figure 3.3.8: Architecture of Use Case Diagram

Here, the administrator can keep an eye on all of the sensor data that has been received and manage user access.

Table 3.3.1: Use Case of Monitor Data

Use Case Name	Monitor data
Use Case Details	Gathering data and securing the data.
Pre-condition	Login
Actor	Admin
Post- Condition	None

Admins can manage user access here.

Table 3.3.2: Use Case of Control User Management

Use Case Name	Control user access
Use Case Details	Have control over user
Pre-condition	Login
Actor	User
Post- Condition	None

3.2 Detailed Methodology and Design

A logic model serves as a practical representation of the connections between a program's resources, activities, and anticipated outcomes. It provides a clear and concise depiction of how interventions influence behaviour to achieve a specific goal. Conversely, a logical data model is a non-database-specific representation that outlines the information an organization aims to collect and the relationships among these data elements.

A Logical Data Model (LDM) outlines the structure of data elements and their relationships within a system, independent of physical considerations. It defines entities, attributes, and the connections between them, ensuring data integrity and consistency. LDMs focus on the business requirements and rules, providing a clear framework for how data is organised and managed. This paradigm facilitates communication between stakeholders and developers by acting as a blueprint for database design while supporting accurate data representation and retrieval.

Table 3.4.1: Logical Data Model

Device	Standard	Sensors	Data	User
Channel id Author Access	Ph Level TDS Level Turbidity Level	Ph TDS Turbidity	Ph TDS Turbidity	Username Password

Circuit Diagram

Here's our device circuit diagram:

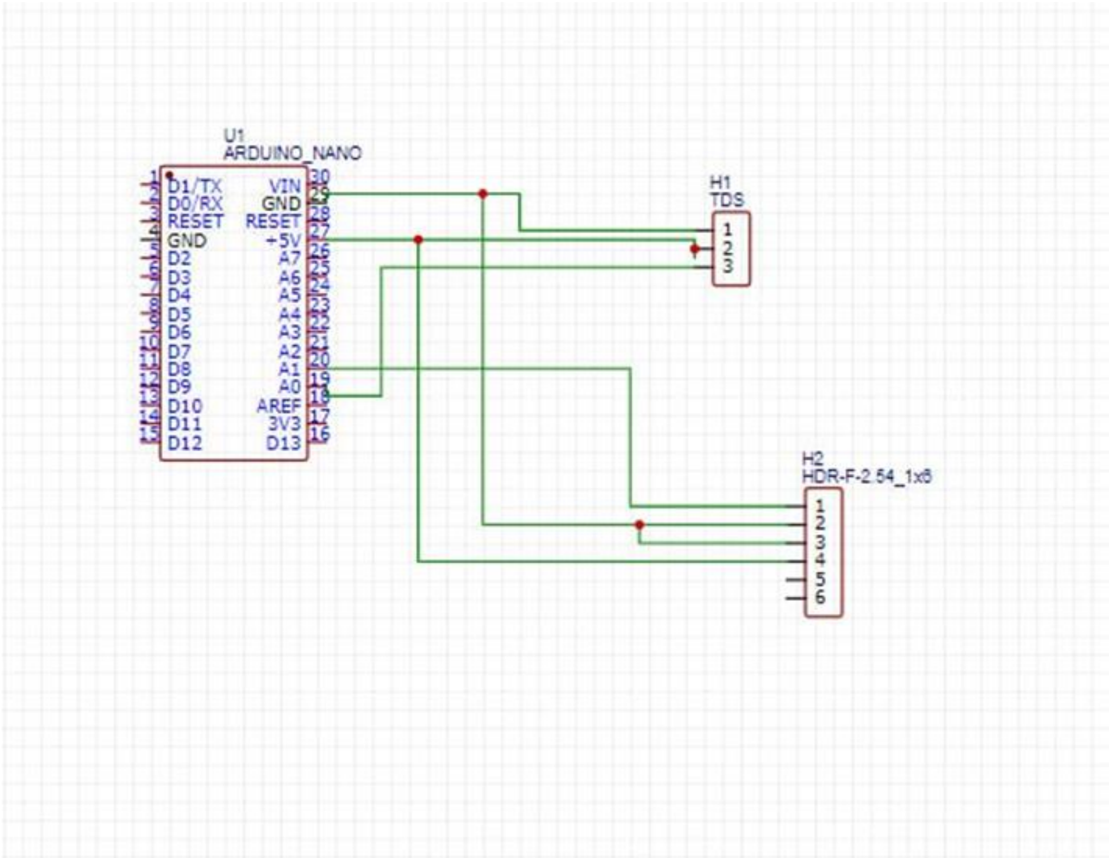

Figure 3.5.1: Architecture of Circuit Diagram

3.3 Project Plan

An embedded system is a computing device dedicated to performing a specific set of functions within a larger system. which is designed to perform a predetermined task or set of tasks. It is usually created by skilled hardware developers and skilled programmers. It's ridiculously fast, reassuringly secure, highly scalable and incredibly versatile. The most popular data storage used online today is Thingspeak. Thingspeak uses sensors to get information from the surroundings and store it in the Thingspeak database. The developers promise to maintain SQLite file format stability, cross-platform compatibility, and backward compatibility until 2050. In this project we used Thingspeak's database to store and monitor our data. The data of our project is sent to the backend server using Thingspeak and shown in the frontend design.

The design component of our system will be eliminated once the diagram component is finished. There, We will discuss hardware design, including front-end and back-end in addition to visual design. Additionally, the use case diagram and description, circuit diagram, visual flow, and business process modelling are all depicted in the picture above.

Our hardware diagram section will be finished before the design section is taken up. There, we will talk about visual design, backend design and frontend design. The above graphs also discuss the following topics: activity diagrams, sequence diagrams, use case diagrams and descriptions, data flow diagrams, business process modelling, incremental development models, and visual flow diagrams.

When a person visits a website, they interact or view the front end of the page. The entire look and feel of an online experience are the front-end responsibility of the website. Considering that the saying goes "first impressions are the best" or "first impressions last the longest". A user's initial impression of a website will be favourable if the frontend design is attractive. The presentational JavaScript, HTML, and CSS code that comprise a website's user interface are written using a variety of computer languages in frontend design. The frontend design of the Water Monitoring System is done by Thingspeak. All types of data of the Water Monitoring System will be shown on the frontend through the Thingspeak. Figure 4.1 displays the Water Monitoring System's front-end architecture.

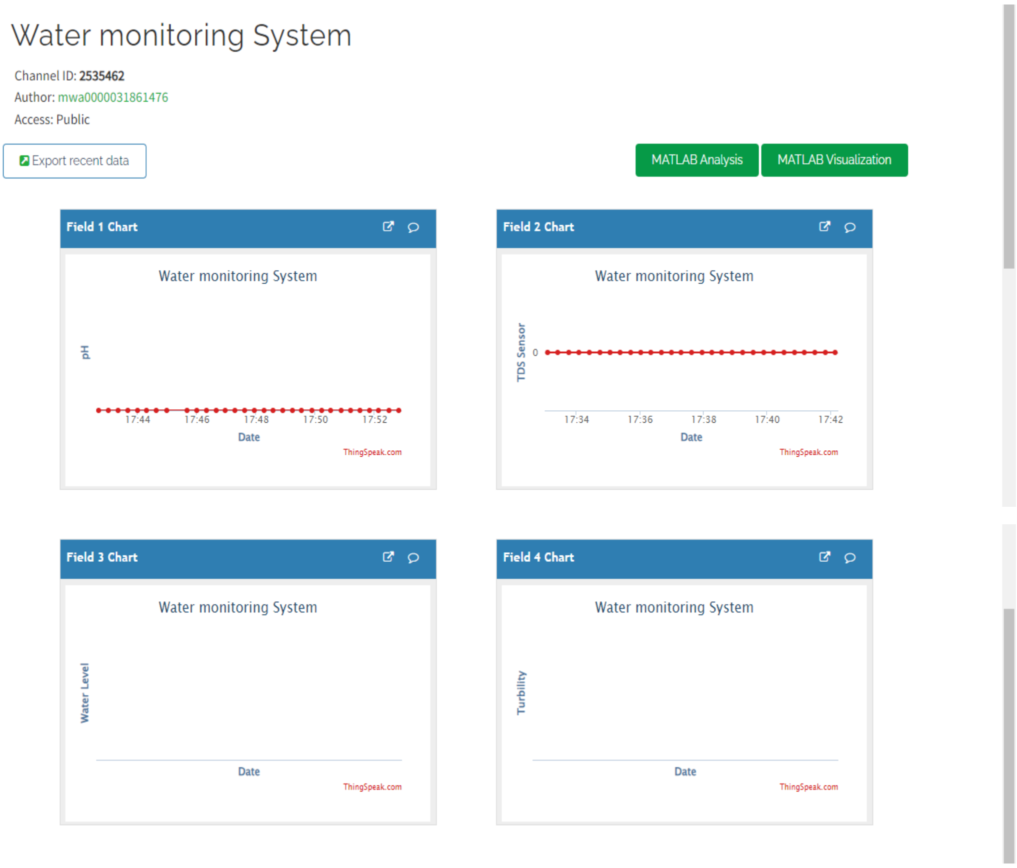

Figure 3.3.1: Frontend Design of Thinkspeak

3.4 Summary

Our website's implementation phase will begin when the design is finished. We will talk about what materials and tools are required to develop a hardware system, as well as the languages that will be used for the front end and back end, the framework that will be used, and the database that will be utilized. The testing phase happens after the implementation. The testing part and the testing report described are done by using any browser, finishing the coding part, implementing the coding part in the hardware part.

Chapter 4

Implementation and Results

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4.1 Environment Setup

We used an online database to store, delete and update data for our project i.e. Water Monitoring System. The name of the online database is Thingspeak. It is an online website, where all types of data can be stored. One type of data can be stored in one column or table. The saved data can be extracted and used in any format at any time. Data in this thingspeak database is usually entered through sim800l or nodemcu or esp8066 or any Wi-Fi module. That is, we collect the data from the environment through sensors, then the data is entered into Thingspeak's server through sim800l or nodemcu or esp8066 or any wifi module through various microcontrollers. We collect the data stored from there in different ways such as graphically or in any format of MS excel and through them, we can apply different algorithms of Data Science. This Thingspeak database allows us to manage, modify and delete data in an orderly manner.

4.2 Testing and Evaluation

Plankton growth detection using embedded technology is a technological solution designed to monitor and assess the quality of water in a specific environment. This system plays a crucial role in identifying and quantifying various water parameters, contributing to efforts in plankton growth, and improving water quality.

The core components of Water Monitoring include specialized sensors that detect and measure concentrations of different contaminants such as heavy metals, organic compounds, pH levels, and dissolved oxygen. These sensors are strategically placed in the target water bodies to ensure comprehensive coverage. After the data is gathered, it is processed and examined to provide current information on the amount of water contaminants.

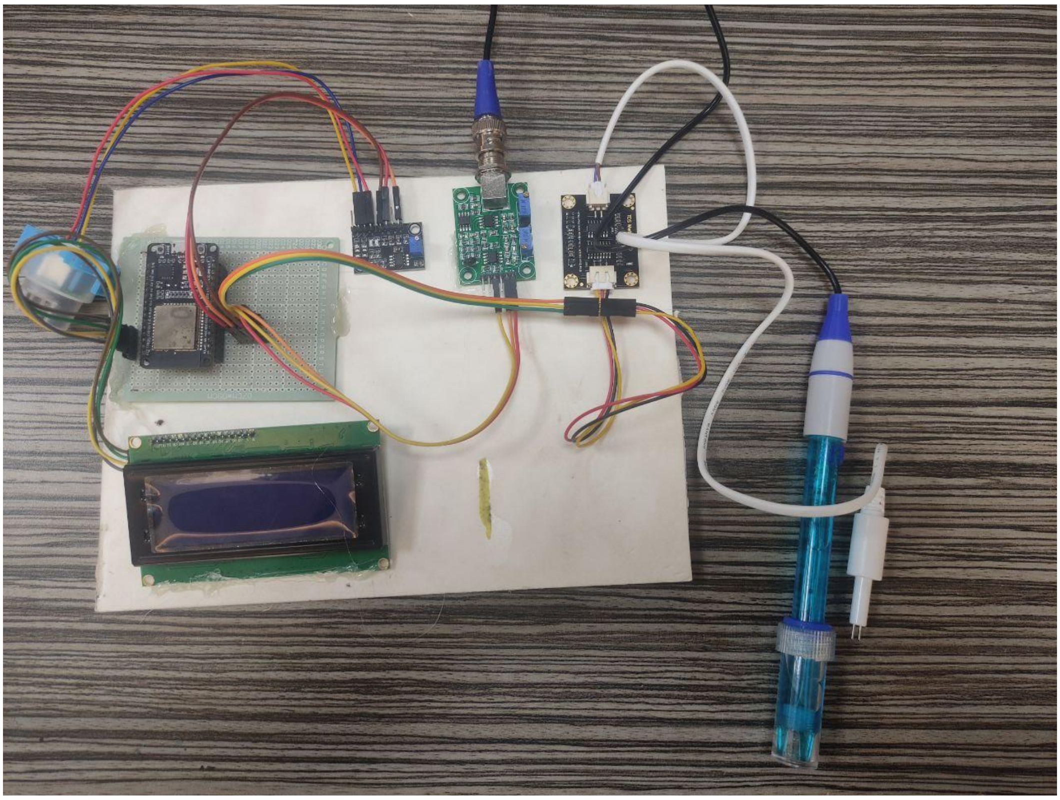


Figure 4.2.1: Prototype of Water Monitoring System

One of the key features of such systems is their ability to offer immediate feedback on water quality. This information is often made accessible to users through user-friendly interfaces, mobile applications, or online platforms. This data's openness and accessibility enable people, organizations, and authorities to make informed decisions regarding water usage, safety measures, and environmental regulations. The plankton growth detection finds applications in various settings, including urban areas, industrial zones, and research initiatives. In urban environments, these systems help monitor pollution sources and evaluate the effectiveness of water quality improvement measures for plankton growth. In industrial settings, they assist in organic food sources. Additionally, researchers use these systems to collect valuable data for studying whether plankton growth is possible or not. By providing timely and accurate information about water quality, these systems support proactive measures to reduce pollution, mitigate environmental impact, and safeguard the well-being of communities. Overall, water monitoring contributes to creating healthier aquatic environments and fostering awareness about the importance of plankton growth detection.

In this paper logistic regression accuracy is 99.30%. In machine learning, the random forest and gradient boost models both achieved perfect accuracy rates of 100%, showcasing their robustness in handling the dataset. Additionally, the K-Nearest Neighbors (KNN) model yielded an accuracy of 95.12%, while the Support Vector Machine (SVM) model reached an accuracy is 61%. These results indicate that machine learning models, particularly Random forests and Decision trees, can provide highly reliable water quality predictions based on the sensor data collected.

Table 4.2.1: Classifiers Description

Classifier		**Description**
Machine Learning	Random Forest	The Random Forest Classifier is an ensemble learning algorithm used for classification tasks. It constructs multiple decision trees during training and merges their outputs to improve accuracy and prevent overfitting.
	KNN	For problems involving regression and classification, the KNN algorithm is a straightforward yet powerful supervised machine-learning technique. Its working idea is that in a feature space, related data points are located close to one another.
	Logistic Regression	A Logistic Regression is a powerful and intuitive machine learning algorithm used for both classification and regression tasks. It resembles an inverted tree structure, where each node represents a decision based on a particular feature, leading to subsequent nodes or leaves with outcomes.
	Gradient Boost	Gradient boosting is frequently used to achieve high accuracy and is a common strategy in winning machine learning competition solutions. It can be applied to issues involving both classification and regression. Additionally, it offers information on the significance of features, which aids in feature interpretation and selection.

	SVM	Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression tasks. It works by finding the optimal hyperplane that maximizes the margin between different classes in a dataset.

4.3 Results and Discussion

Machine Learning Models

i. AUC Score & ROC Curve

The Area Under the Curve, or AUC score, is a statistic used to assess how well binary classification algorithms perform. By graphing the Receiver Operating Characteristic (ROC) curve, it assesses the model's capacity for class distinction. The trade-off between true positive rate (sensitivity) and false positive rate (specificity) is represented by the ROC curve. Better performance of the model in differentiating between positive and negative classes is shown by a higher AUC value (closer to 1).

Table 4.3.1: AUC Score for all Method

Method	AUC Score
Random Forest	1.00
SVM	0.92
KNN	1.00
Decision Tree	1.00

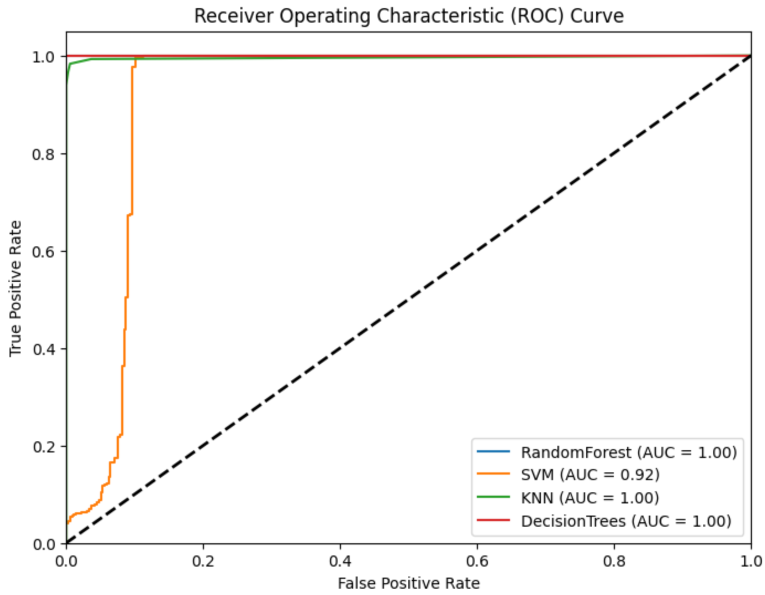


Figure 4.3.1: ROC curve of each model

ii. Cross Validation Score

By dividing the data into subsets, training the model on some of the subsets, then assessing it on the complementary subset, the cross validation score is a statistical approach used to assess machine learning models. By evaluating the model's performance and applicability to new data, this procedure helps to mitigate problems like overfitting. Compared to a single train-test split, the cross validation score offers a more accurate indication of model performance by averaging the results over several partitions.

Table 4.2.1: Cross Validation Score for all Method

Method	Cross Validation Score
Random Forest	1.00
SVM	0.89
KNN	0.96
Decision Tree	1.00

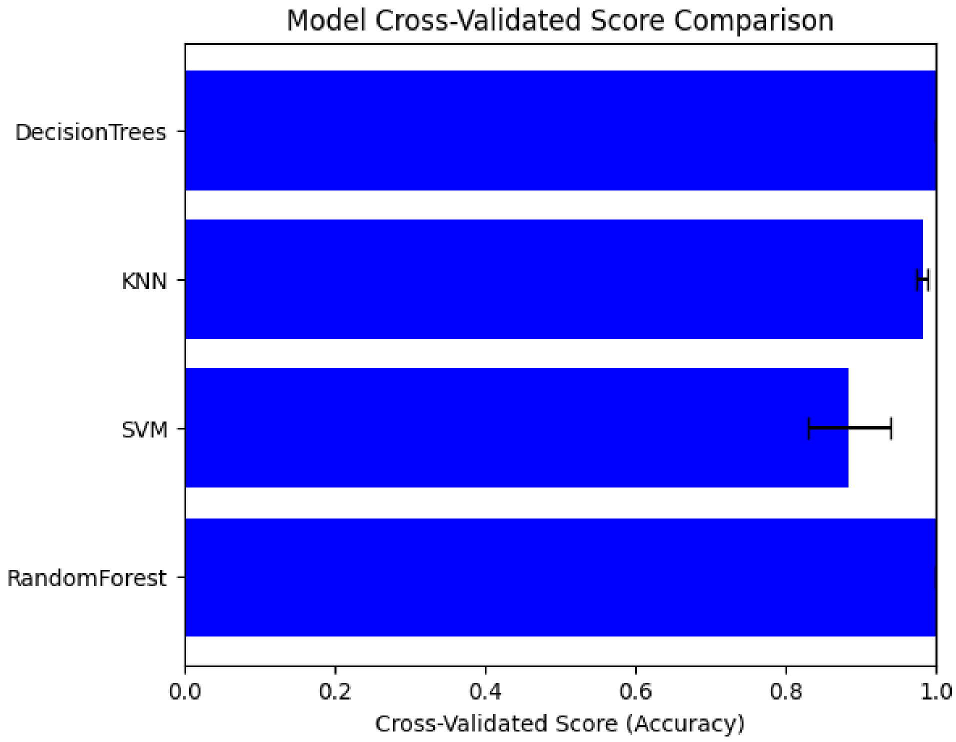


Figure 4.2.2: Cross Validation Score of each model

iii. Mean Cross-validated score

Mean Cross Validation Score is a summary metric derived from cross-validation in machine learning. During cross-validation, a model is trained and evaluated on multiple subsets of the dataset. The Mean Cross Validation Score is the average performance metric (such as accuracy or F1 score) across all these iterations. This score provides a more reliable assessment of a model's generalization performance compared to a single training-test split. By averaging the performance over multiple folds, it helps reduce the impact of random variations in the data distribution and provides a more robust estimate of how well the model is expected to perform on new, unseen data. A higher Mean Cross Validation Score indicates better overall model performance across diverse subsets of the dataset.

Table 4.2.3: Mean Cross Validation Score for all Method

Method	Mean Cross Validation Score
Random Forest	0.99
SVM	0.88
KNN	0.98
Decision Tree	0.99

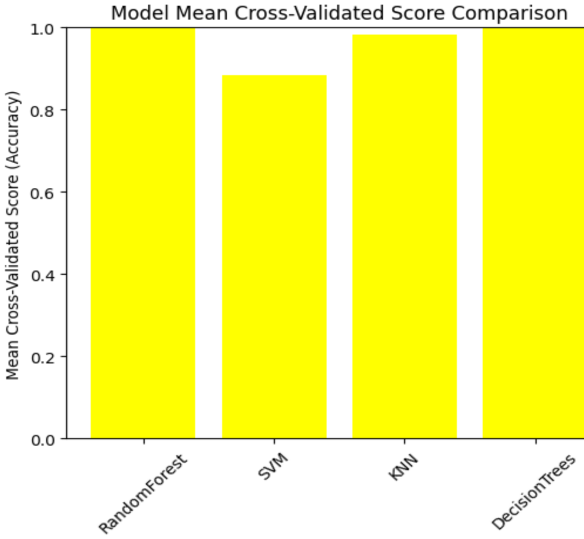


Figure 4.2.3: Mean Cross Validated Score of each model

iv. Misclassification Error

Misclassification Error, also known as classification error or error rate, is a metric in machine learning that quantifies the proportion of incorrectly classified instances in a model. It is calculated by dividing the total number of misclassified instances by the total number of instances in the dataset. In such cases, accuracy may not accurately reflect the model's performance. Despite its simplicity, misclassification error is a useful and easily interpretable metric, but it is often used in conjunction with other evaluation metrics for a more comprehensive assessment of a model's classification performance.

Table 4.2.4: Misclassification Error for all Method

Method	Misclassification Error
Random Forest	0.00
SVM	0.1
KNN	0.02
Decision Tree	0.00

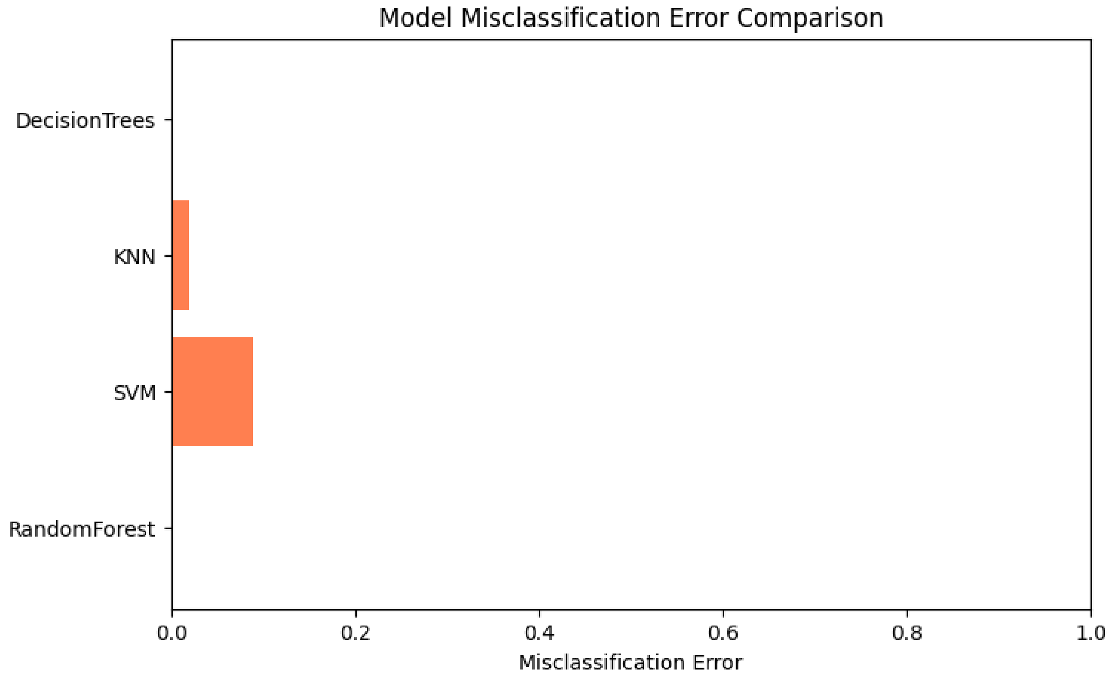


Figure 4.2.4: Misclassification Error of each model

v. Jaccard Score

By comparing the intersection of two sets with their union, the Jaccard Score—also called the Jaccard Index or Jaccard Similarity Coefficient—calculates how similar two sets are to one another. The ratio of the intersection's size to the sets' union's size is used to compute it. There are two possible scores: 0 for no resemblance and 1 for total similarity. It is extensively used to assess dataset overlap and clustering method performance in a variety of domains, including data mining, information retrieval, and natural language processing.

Table 4.2.5: Jaccard Score for all Method

Method	Jaccard score
Random Forest	1.00
SVM	0.85
KNN	0.96
Decision Tree	1.00

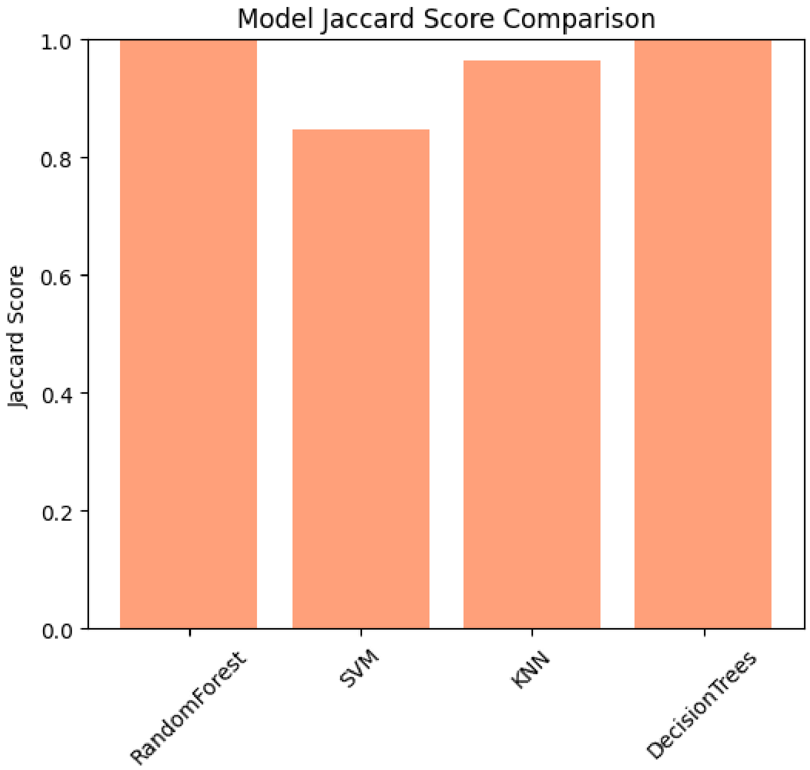


Figure 4.2.5: Jaccard Score of each model

vi. Confusion Matrix

A confusion matrix is a table that summarizes the number of accurate and inaccurate predictions made across classes to show how well a machine learning model is performing. It is made up of rows and columns that stand for the expected and actual classes, respectively. This matrix helps to understand how effectively the model distinguishes between distinct classes of data, which is important for assessing the model's performance. It also offers insights into the model's accuracy, precision, recall, and other metrics.

Table 4.2.6: Sample Confusion Matrix

	Predicted Value			
Actual Value		Yes	No	
	Yes	True Positive	False Negative	Recall
	No	False Positive	True Negative	Specificity
	Prevalence	Precision	Negative Predictive Value	Accuracy

precision =True positive(TP)True Positive(TP) + False Positive(FP)

Recall = True Positive(TP)True Positive(TP) + False Negative(FN)

Accuracy = True Positive + True Negative(True Positive + False Positive + True Negative + False Negative)

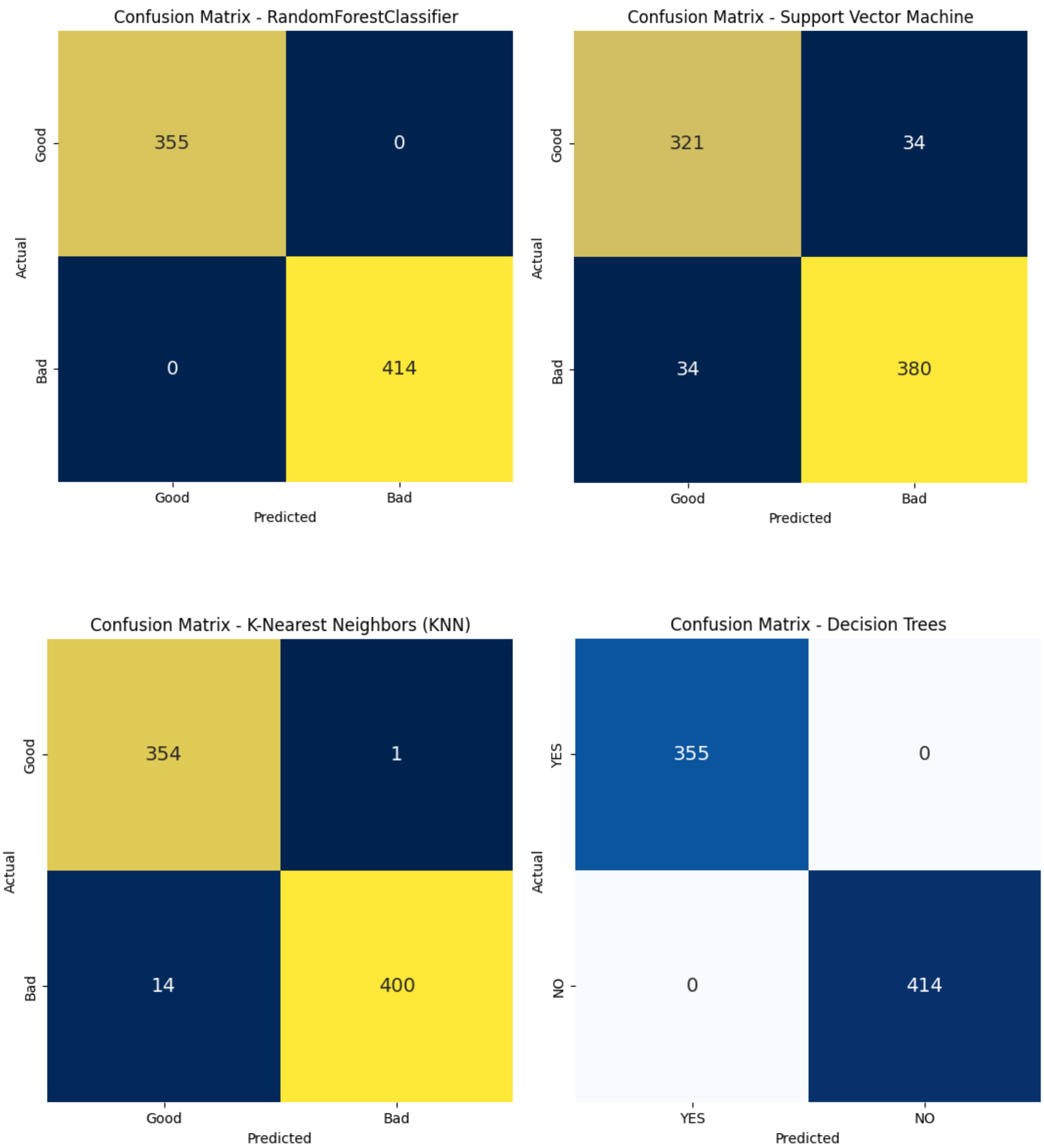


Figure 4.2.6: Confusion Matrix of each model

vii. Classification Report:

The following table is included for every technique in the categorization report. Four techniques are compared here. The methods are Random Forest, SVM, KNN and Decision Tree. Among these 4 methods, it can be seen that the highest accuracy is obtained using Random Forest and Decision Tree. Their precision, accuracy, recall, F1-score and ROC AUC were 1.000, 1.000, 1.000, 1.000 and 1.000, respectively. The lowest accuracy was obtained using SVM and KNN. Its precision, accuracy, recall, F1-score and ROC AUC are 0.98, 1.000, 0.96, 0.98 and 0.98 respectively.

Table 4.2.7: Classification Report

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
Random Forest	1.000	1.000	1.000	1.000	1.0
SVM	0.91	0.918	0.917	0.917	1.0
KNN	0.98	0.99	0.96	0.98	1.0
Decision Tree	1.000	1.000	1.000	1.000	1.0

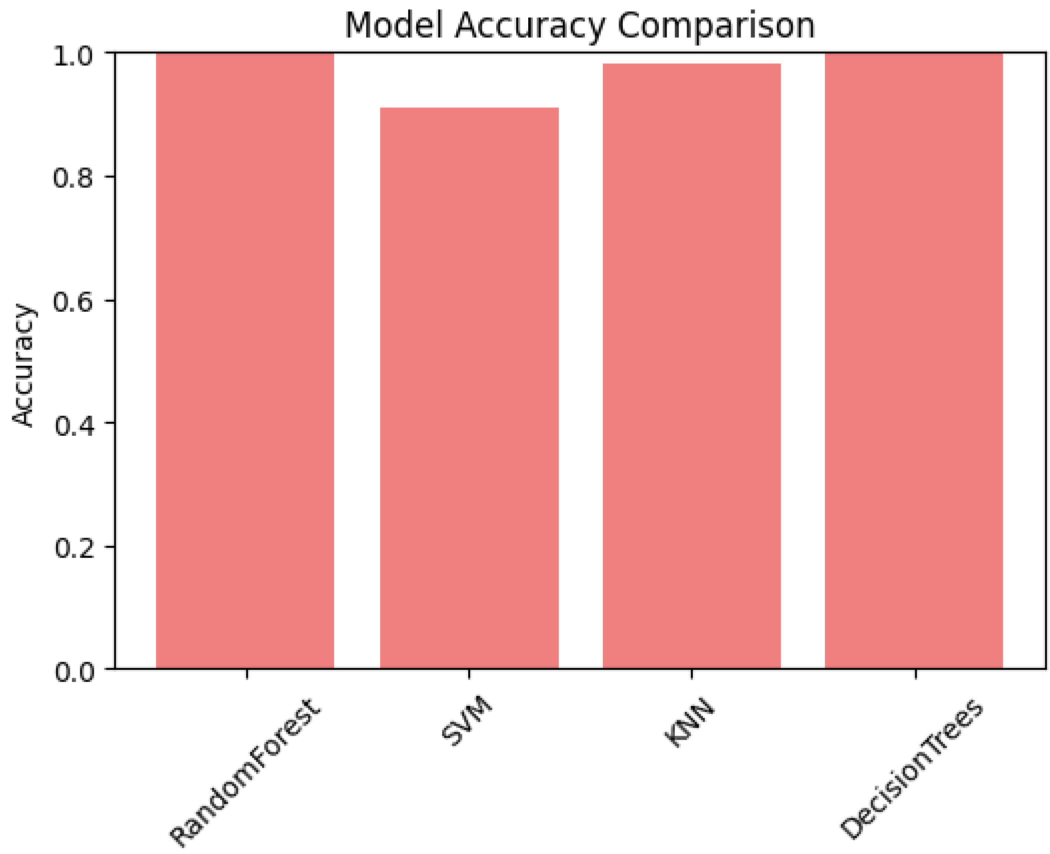


Figure 4.2.7: Classification Report of each model

4.3 Deep Learning Model

i. Convolutional Neural Network (CNN)

A CNN consists of multiple layers that automatically learn hierarchical representations of features from the input data. CNNs use convolutional layers to apply filters over small regions of the input, enabling them to capture spatial hierarchies and patterns. CNNs are widely used in tasks such as image classification, object detection, and image segmentation, owing to their ability to learn complex patterns and features directly from raw pixel data [33].

Training Set Matrix:

Table 4.3.1: Training Set Matrix

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
CNN	0.98	1.00	0.95	0.97	0.98

Testing Set Matrix:

Table 4.3.2: Testing Set Matrix

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
CNN	0.98	1.000	0.96	0.98	0.98

Classification Report:

Table 4.3.3: Classification Report of CNN Model

Label	Precision	Recall	F1 Score	Support
0	0.95	1.00	0.98	355
1	1.00	0.96	0.98	414
Accuracy			0.98	769
Macro avg	0.98	0.98	0.98	769
Weighted avg	0.98	0.98	0.98	769

Confusion Matrix:

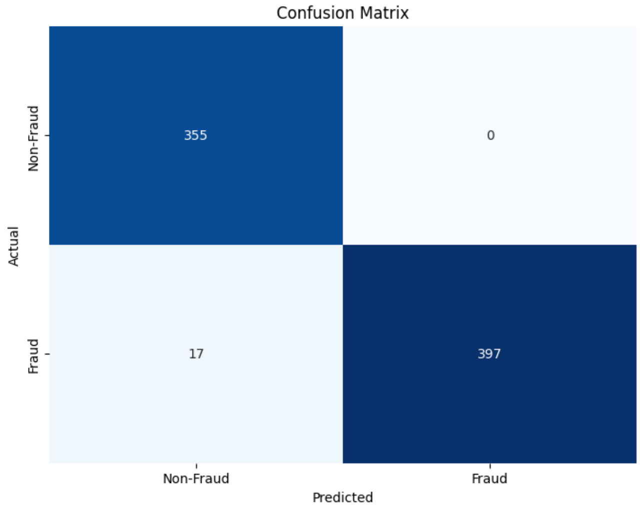


Figure 4.3.1: Confusion Matrix of CNN Model

4.4 Summary

The study investigates the use of IoT and machine learning in aquaculture by integrating several classifiers for monitoring water quality and detecting plankton growth. The results demonstrate the resilience of the Random Forest and Gradient Boost models in identifying water characteristics crucial to aquaculture, with both models achieving 100% accuracy. High accuracy and good performance were also shown using logistic regression, despite sporadic misclassifications within certain classes. While showing significantly decreased accuracy, the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) models were nonetheless useful in real-time monitoring. Overall, the research shows how precise data-driven insights and predictive skills may improve aquaculture operations by guaranteeing ideal conditions for fish breeding and encouraging sustainable resource usage.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

The apparatus used in this study project undergoes system testing, which entails a thorough assessment to guarantee its performance, precision, and dependability in tracking and evaluating water parameters essential to plankton development in aquaculture systems. This is an explanation of the system testing methodology:

Functionality testing is done on each IoT sensor (water level sensors, pH sensors, TDS meters), microcontroller (ESP32), and device to ensure that they all carry out their intended functions properly. For example, TDS meters are examined to make sure they can detect dissolved solids efficiently, and pH sensors are tested to make sure they can measure acidity levels within the designated range.

Integration testing: This step comes after testing individual components to make sure that all of the sensors and microcontrollers are working as a single, cohesive system. As part of this, they must be connected to the cloud-based platform, and the synchronization and transfer of data must be confirmed. Integration tests confirm that data is reliably collected, processed by the ESP32, and successfully sent to the cloud for further analysis from pH, TDS, and water level sensors.

Data Accuracy Verification: Comparing sensor readings to established standards or manually gathered data is a crucial part of testing in order to ensure accuracy. This stage guarantees that the sensors will continuously and reliably detect the pH, TDS, and water levels.

Performance testing evaluates the system's dependability and responsiveness in various operating scenarios. Stress testing is part of it to see how well the sensors and microcontrollers can withstand changes in temperature or water turbulence without sacrificing transmission speed or data accuracy.

Security Testing: Security testing is carried out to find and fix any weaknesses in data transmission and storage because of the sensitivity of the environmental data that is gathered. Secure data transport methods and encryption procedures are verified to guard against illegal access and data breaches.

Usability testing: This kind of testing focuses on the system's user interface, which includes software tools like the cloud-based platform and the Arduino IDE. It guarantees that researchers won't encounter any technological challenges while monitoring sensor data, interpreting findings, or making any settings or modifications. Last but not least, long-term reliability testing evaluates how long-lasting and resilient sensors and microcontrollers are when used continuously. The goal of this step is to find any possible hardware deterioration or performance problems that could occur in aquatic conditions over a prolonged length of time.

The research project makes sure that the IoT-based monitoring system supports the objectives of improving plankton growth through optimized use of organic fertilizer while maintaining standards of data integrity, security, and operational reliability in aquaculture settings by conducting these tests methodically.

5.1.1 Software Standards

The software requirement entails specifying the software utilized in our project, detailing the programming language employed, identifying the database associated with the language, and specifying the compatible operating system. An essential operating system for seamless functionality is Windows, with Microsoft Windows XP being the chosen operating system for our project. The operating system is crucial to ensure the proper execution of the system.

- Arduino.
- Visual Studio Code.

5.1.2 Hardware Standards

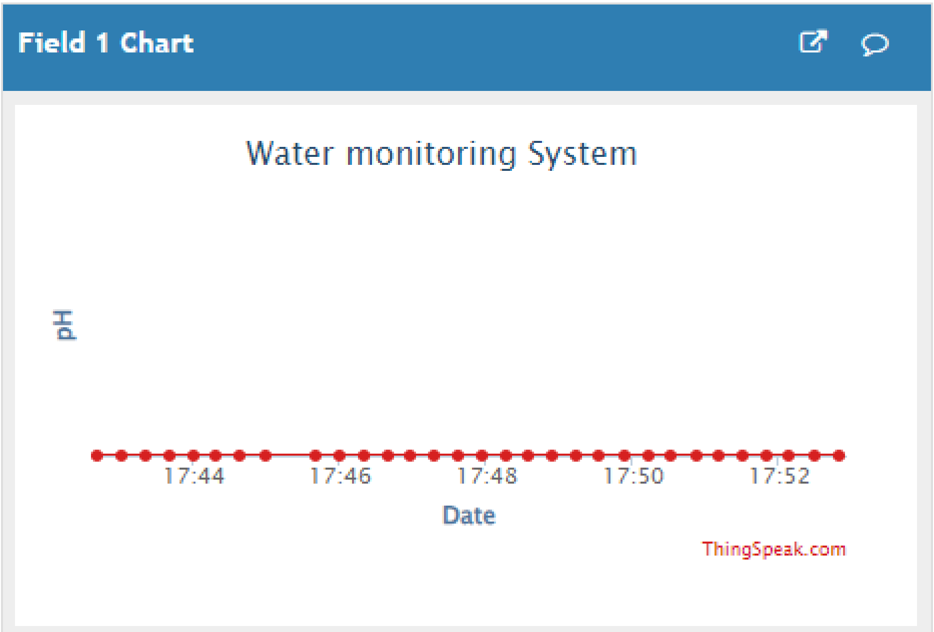
The sensors and microcontrollers we have utilised to carry out the project are the hardware requirements. The framework also offers suggested and minimal requirements for computer operation.

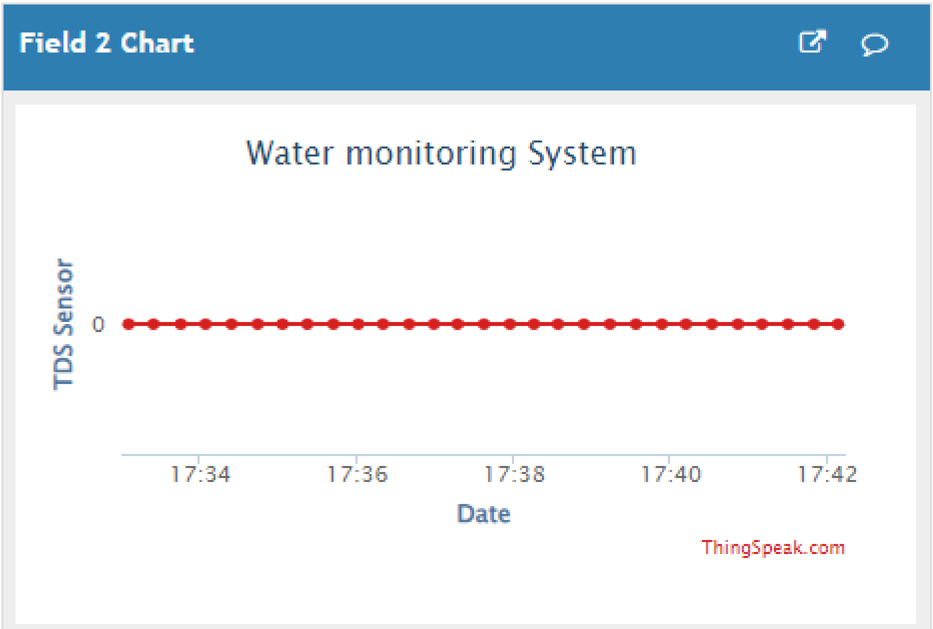
- ESP32 Microcontroller.
- TDS Sensor.
- Water temperature sensor.
- Water Turbidity Sensor.
- Water Level Sensor.
- PH Sensor.
- NH3 Sensor.
- Power unit.
- Mobile/Computer.

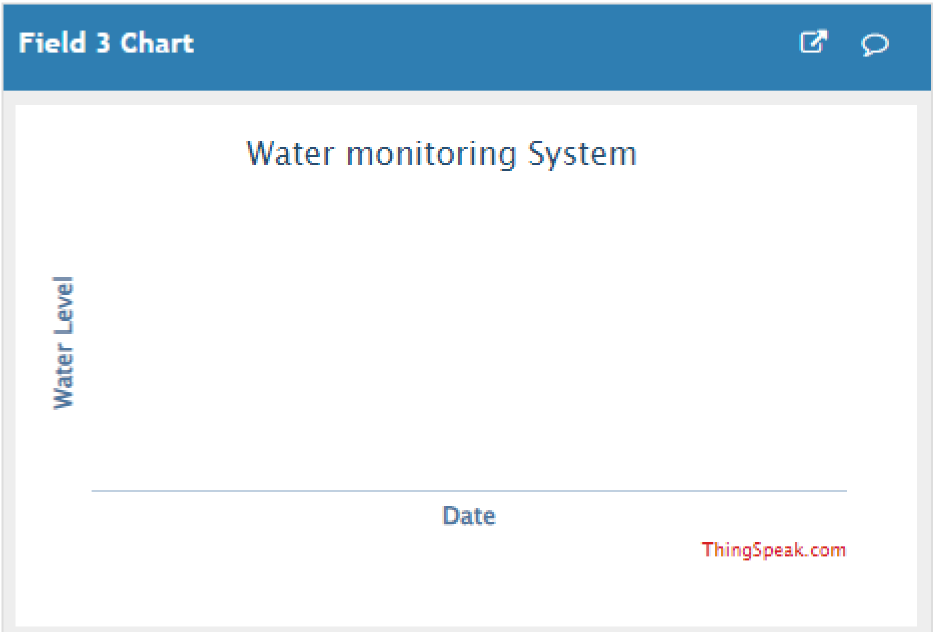
In addition to the previously mentioned elements, the project necessitates the use of a desktop computer, mobile phone, and printer. A desktop computer, laptop, or mobile phone is indispensable for effective project management. A phone is necessary since the data from the system will reach it via the server via IoT. Printers are used to print and save a variety of large data sets on paper, including large data outputs from the system, relevant reports, and items that need to be extracted from the internet.

5.1.3 Communication Standards

A few images of "Water Monitoring System" front-end design i.e., Thingspeak are shown below A picture of Thingspeak is included in Figure 4.5. This is the overall output of our system. The frontend design of the system is shown in the output.


Field 1 Chart
Water monitoring System
pH
17:44
17:46
17:48
17:50
17:52
Date
ThingSpeak.com


Field 2 Chart
Water monitoring System
TDS Sensor
0
17:34
17:36
17:38
17:40
17:42
Date
ThingSpeak.com



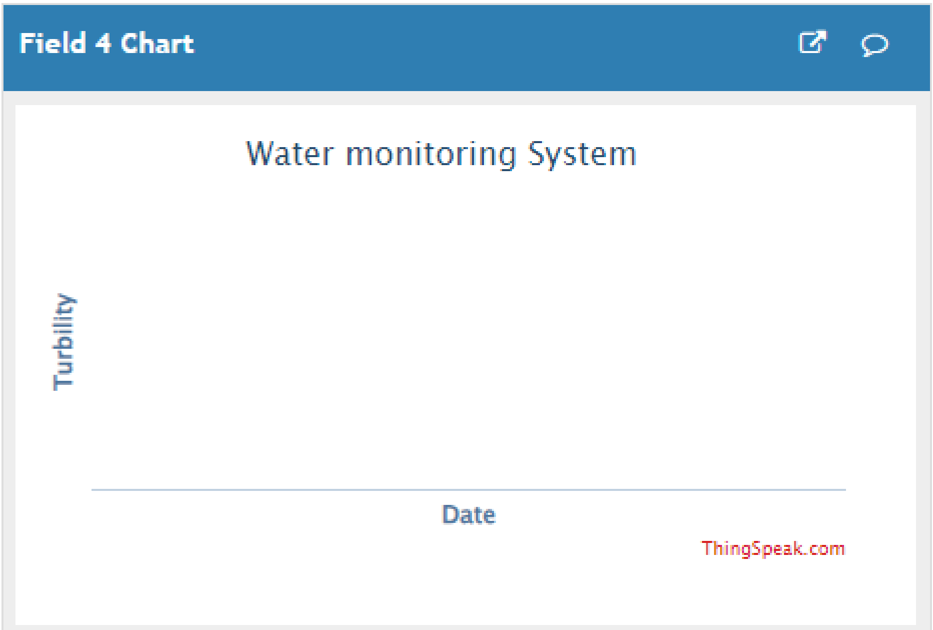


Figure 5.1.1: Output of Ph, Tds, Turbidity

The admin dashboard panel appears here. The system can be managed by an administrator. He knows how to use every system. He is able to employ all other types of design part, hardware part, software part here.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The implications of the research "An IoT Based Water Monitoring System " extend far beyond the realm of academia, promising significant impacts on aquaculture and the environment. Advanced artificial intelligence approaches can transform the field of embedded technology and improve patient outcomes and social benefits by accurately and promptly detecting plankton growth. To improve the accuracy and efficiency of plankton growth and enable more confident decision-making in aquaculture, the research makes use of Linear Regression, Logistic Regression, and Random Forest.

This research has a particularly significant social influence on aquaculture and sustainable food production. The growth of plankton is vital to the well-being and sustenance of farmed fish and is a key factor in the effectiveness and yield of aquaculture systems worldwide. Plankton populations may be optimized by the use of more reliable and precise monitoring and management techniques, improving fish health and growth rates. This can therefore result in higher yields and higher-quality aquaculture products, which would support food security and economic stability in fish farming-dependent communities. An additional layer of practicality is added by the research's emphasis on ensemble models and comparative analysis of various techniques, which open the door to the creation of optimal plankton management strategies that can be easily incorporated into actual aquaculture operations.

Improved plankton monitoring techniques also have the potential to benefit underprivileged aquaculture communities and areas with low access to technology due to their affordability and accessibility. The technology that this research produces may be able to operate across geographic borders, providing advanced plankton management capabilities to places where conventional aquaculture infrastructure would not be as available. This democratization of cutting-edge aquaculture technologies supports worldwide efforts for food security and helps achieve the broader objectives of lowering food production disparities and enhancing overall equity in aquaculture.
In conclusion, the research has implications for society since it may bring about a new era of precision aquaculture, especially about controlling plankton growth for fish

farming. Utilizing state-of-the-art technologies, the research contributes to the scientific understanding of plankton dynamics and holds the key to real improvements in food security, aquaculture yields, and the general well-being of various communities worldwide.

5.2.2 Impact on Society & Environment

An IoT-based water monitoring system has the ability to completely change how cultures use their water resources. Through the provision of real-time data on water quality, usage, and distribution, such systems enable more efficient water management, leading to several societal impacts.

Firstly, they contribute to water conservation efforts by identifying leaks, optimizing irrigation systems, and promoting responsible water usage. This not only helps to conserve a precious resource but also reduces water bills for consumers and lessens the strain on municipal water supplies. Secondly, these systems improve public health by ensuring the safety of drinking water. By continuously monitoring factors of water quality, including turbidity and pH, and contaminant levels, potential health risks can be identified early, preventing outbreaks of waterborne diseases and illnesses. Moreover, IoT-based water monitoring systems promote sustainability by supporting environmentally friendly practices. With better data on water usage patterns, communities can implement strategies for sustainable water management, such as implementing water recycling systems or promoting rainwater harvesting. Overall, the societal impact of IoT-based water monitoring systems is profound, as they empower communities to manage water resources more efficiently, promote public health, and contribute to a more sustainable future.

5.2.3 Ethical Aspects

The implementation of IoT-based water monitoring systems raises several ethical considerations. Privacy is a primary concern, as these systems collect data on water usage that could potentially be linked to individuals or households. Safeguards must be in place to protect sensitive information and ensure it is used responsibly. Equity is another ethical aspect to consider. Access to such technology should not exacerbate existing disparities in water access and affordability. Ensuring that all communities, regardless of socioeconomic status, can benefit from these systems is essential.

Additionally, there are questions about data ownership and control. Clear guidelines are needed to determine who owns the data collected by these systems and how it can be used, ensuring transparency and accountability in its management and utilization.

5.2.4 Sustainability Plan

An Internet of Things-based water monitoring system's sustainability strategy should focus on long-term viability, resource efficiency, and environmental responsibility. Firstly, it should prioritize the use of renewable energy sources to power monitoring devices and data transmission, minimizing the system's carbon footprint.

Secondly, the plan should include regular maintenance and updates to ensure the system's longevity and accuracy, reducing the need for frequent replacements and minimizing electronic waste.

Additionally, promoting community engagement and education about water conservation and responsible usage can help sustain the system's impact over time.

Furthermore, incorporating feedback mechanisms to continuously improve the system's efficiency and effectiveness based on real-world data and user experiences is crucial.

Lastly, partnerships with local governments, NGOs, and other stakeholders can facilitatefunding, support, and collaboration to maintain and expand the system's reach and impact over the long term.

5.3 Project Management and Financial Analysis

Our project's main goal is to improve Plankton Growth through the use of organic fertilizers. After using organic fertilizers for six months, raise the total biomass of plankton in the targeted water bodies by 30%. We Make sure that the quality of the water is not harmed by the addition of organic fertilizers. Key water parameters will be tracked and kept within allowable bounds for the length of the project.

- **Project Timeline**

Table 5.3.1: Project workflow

Task	Start Date	Duration (Days)	End Date
Project Idea Selection	30-09-2023	7	07-10-2023
Research	08-10-2023	10	18-10-2023
Planning	19-10-2023	5	24-10-2023
Paper Review	25-10-2023	15	15-11-2023
Documentation	16-11-2023	5	25-11-2023
Data Collection	26-11-2023	4 Months	26-03-2024
Final Project	27-03-2024	3 Months	10-06-2024

- **Resource Planning**

Resource planning for an aquaculture project is determining, assigning, and overseeing the resources required to guarantee the project's successful execution and long-term viability.

1. Enumerate every resource needed for the aquaculture project, including personnel, facilities, machinery, funding, technology, and any additional inputs that may be needed.
2. Human Resource: Determine the knowledge and abilities required for the different positions in the aquaculture project, including those of technicians, project managers, marine biologists, aquaculture experts, and administrative personnel.
3. Technology & Facility: Determine and acquire the equipment required for aquaculture operations, including boats, aeration systems, feeding systems, fish tanks, and monitoring instruments.
4. Financial Resources: Create a thorough budget that details every price associated with the project, such as the cost of building, purchasing equipment, operating costs, and reserve money.
5. Documentation: Keep thorough records of all the materials used, money spent, and project activity.

- **Risk Management**

An essential component of project planning and execution is risk management. Risk identification, assessment, and mitigation make it possible for a project to successfully manage obstacles.

1. Engage stakeholders, subject matter experts, and the project team in a comprehensive risk identification process.
2. Create a mechanism to continuously monitor hazards that have been identified during the project.
3. Review and update the risk register regularly in response to fresh data and evolving project circumstances.
4. Update this document frequently as the project develops.

- **Communication Plan**

local communities and fisheries, suppliers, investors, and Zoologist's expertise in sustainable fish farming practices are needed in this working period. we need to make everyone aware of the importance of biodiversity conservation and sustainable aquaculture. Make a thorough communication plan that specifies when, how, who, and what will be communicated. Provide a clear explanation of the aquaculture project's environmental sustainability.

Our main goal is a fisheries automated system. So, we are going to implement it through IoT devices. In implement time we use some IoT sensors. We use this project these are Ph, TDS, Turbidity, Arduino, Node MCU, Cloud Subscription, and STM board.

Cost Analysis:

Table 5.3.2: Estimated Cost for IoT-based Project

SN	Components	Estimated Cost (BDT)
01	STM Board*2	4500*2
02	TDS Sensor*2	3600*2
03	pH Sensor*2	2500*2
04	Cloud Subscription (1 Year)	12000
05	LCD 20X4 I2C Display*3	1500*3
06	Water level sensor*5	150*5
07	Veroboard*3	200*3
08	Juvenile fish*100	100*5
09	Turbidity *3	1400*3
	Estimated Budget	**43750 BDT**

Chapter 5

Engineering Standards and Design Challenge 5.4 Complex Engineering Problem

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

In this section, provide a mapping with problem solving categories. For each mapping add subsections to put rationale (Use Table 5.1). For P1, you need to put another mapping with Knowledge profile and rational thereof.

Table 5.4.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
Page no: [1,5-6,7,8-11] Section: [1.1,1.4,1.5, 1.6]	Page no: [4-6] Section: [1.3,1.4]	Page no: [2] Section: [1.2]	Page no: [2-5] Section: [1.3]	Page no: [7] Section: [1.5]	Page no: [27-33] Section: [3.1,3.2]	Page no: [33,44-47] Section: [3.4,5.1,5.2,5.3]

Mapping with Knowledge Profile for EP1

This table 5.2) is designed to map the EP1 to the Knowledge Profile.

Table 5.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
Page no: [34-37] **Section:** [3.4,3.5]	**Page no:** [58] **Section:** [6.3]	**Page no:** [44-55] **Section:** [5.1,5.2,5.3,5.4]	**Page no:** [36-40] **Section:** [5.1,5.2,5.3,5.4]	**Page no:** [5-8] **Section:** [2.2,2.3,2.4]

Table 5.3: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
Page no: [47-54] **Section:** [3.3]	**Page no:** [28-33] **Section:** [3.3]	N/A	**Page no:** [56-59] **Section:** [6.1, 6.2,6.3,6.4]	**Page no:** [12-16] **Section:** [2.2, 2.3, 2.4]

Chapter 6

Conclusion

6.1 Summary

This study explores how IoT and machine learning can enhance various aspects of fisheries, from environmental monitoring and fish health management to supply chain optimization and data-driven decision-making. Environmental monitoring benefits greatly from IoT and machine learning. Water quality sensors continuously monitor critical parameters like pH, temperature, dissolved oxygen, and salinity, providing real-time data to ensure optimal conditions for fish growth. Machine learning algorithms analyze this data to predict and detect pollution, allowing for early intervention to prevent fish mortality and maintain ecosystem health. IoT and machine learning significantly improve fish health management. Smart sensors and cameras track fish movements and behaviors, identifying signs of stress or disease early on. Machine learning models analyze these behavioral patterns to predict potential health issues, enabling timely preventive measures. Automated feeding systems, enabled by IoT, optimize feeding schedules based on real-time data, reducing waste and ensuring fish receive the correct amount of food supply chain optimization is enhanced through IoT and machine learning. IoT provides end-to-end traceability of fish products from farm to fork, ensuring food safety and quality. Machine learning algorithms optimize logistics and storage conditions, predicting the best routes and storage environments to minimize spoilage and waste. Temperature and humidity sensors in transport and storage facilities help maintain ideal conditions for fish products. Data-driven decision-making is facilitated by the analytics and insights derived from IoT data and machine learning models. This information is used to identify trends, forecast growth, and improve farm management practices. Predictive maintenance is another advantage, as IoT combined with machine learning can foresee equipment failures and maintenance needs, reducing downtime and operational costs.

The integration of IoT and machine learning in fisheries holds great promise for revolutionizing the industry. By providing real-time insights, predictive analytics, and automation, IoT and machine learning can significantly enhance the efficiency, sustainability, and profitability of fisheries. However, addressing the challenges related to cost, data management, and security is essential for the successful implementation of these technologies in the sector.

6.2 Limitation

We all bear some responsibility for the water pollution caused by fish farming and other activities. However, industries that discharge their effluents across borders are primarily to blame for contaminating river water. Implementing IoT devices to monitor water quality and collect necessary data is crucial. We need to identify the root cause of waste in sewage lines. It's essential to assess how polluted our regular water is. To determine water suitability, we need to measure temperature, pH, and turbidity daily. By tracking this data, we can pinpoint the sewage line contributing most to pollution and trace it back to the responsible industries. Using a friendly approach can help avoid challenges. It's important to gather information without interruption and ensure services are properly invoked. Reliable internet access is necessary to fetch data accurately.

6.3 Future Work

The findings of the integration of IoT and machine learning in fisheries offers numerous promising opportunities for further research and development. Here are several key areas that warrant further study. Future research can focus on developing advanced machine learning models that can predict not only fish health issues but also optimize other aspects of aquaculture. For instance, models can be trained to forecast optimal harvest times, predict market prices, and assess the impact of environmental changes on fish populations. These predictive models can help farmers make more informed decisions and enhance the overall efficiency of fisheries. Investigating the development of more advanced and cost-effective IoT sensors can greatly benefit small-scale fisheries. Research can explore new materials and technologies to create sensors that are more accurate, durable, and affordable. Additionally, integrating multi-functional sensors that can monitor multiple parameters simultaneously could streamline data collection and improve resource management. Further study is needed on the integration of data from various sources and the interoperability of different IoT systems. Developing standardized protocols and frameworks for data exchange can facilitate seamless integration, allowing for more comprehensive data analysis and more robust decision-making processes. Research can also explore cloud-based platforms and blockchain technology for secure and transparent data management. Research should investigate the broader ecological impacts of IoT and machine learning technologies in fisheries. This includes studying how these technologies influence local ecosystems and biodiversity, both positively and negatively. Understanding these impacts can help in developing strategies that ensure sustainable fishing practices and the conservation of aquatic ecosystems. As IoT and machine learning technologies become more prevalent, ethical and privacy concerns will need to be addressed. Future studies can explore the ethical implications of data collection and usage in fisheries, focusing on issues such as data ownership, consent, and the potential misuse of data. Developing ethical guidelines and privacy standards will be crucial to gaining public trust and ensuring responsible use of technology. Research on effective training programs and capacity-building initiatives is essential to ensure that fisheries workers can effectively utilize IoT and machine learning technologies. Studies can evaluate the best methods for knowledge transfer, skill development, and ongoing support. This will help to ensure that technology adoption is inclusive and beneficial to all stakeholders involved.

While this study focused on Investigating how IoT and machine learning can help fisheries adapt to climate change is another critical area for further study. Research can focus on developing adaptive management strategies that use real-time data and predictive models to respond to changing environmental conditions. This can help fisheries mitigate the effects of climate change and ensure long-term sustainability. In summary, the integration of IoT and machine learning in fisheries holds significant potential for advancing the industry. However, realizing this potential requires continued research and development across multiple areas. By addressing these key areas, further study can contribute to more efficient, sustainable, and equitable fisheries management, ultimately ensuring the health and viability of aquatic resources for future generations

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