IoT-driven Water Quality Monitoring and Classification System for Biofloc Aquaculture using Machine Learning

A Research Project Report submitted to the
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B.Sc. in Computer Science and Engineering

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DECLARATION

We hereby declare that this research work entitled "IoT-driven Water Quality Monitoring and Classification System for Biofloc Aquaculture using Machine Learning" is the result of our own work. Materials of work found by other researcher are mentioned by reference.

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

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APPROVAL

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ABSTRACT

Biofloc aquaculture can be challenging and intricate for farmers to manage, but it can be highly efficient and lucrative when done correctly. This project presents a real-time Internet of Things (IoT)-driven water quality monitoring and classification system for biofloc aquaculture using machine learning. The system aims to provide a reliable and efficient method for monitoring water quality parameters in biofloc aquaculture and to classify the water quality based on machine learning algorithms. It consists of a set of sensors that continuously monitor the water quality parameters such as pH, TDS, temperature, and ammonia concentration, and transmit the data to a cloud server through a wireless network. Machine learning algorithms are then used to classify the water quality based on the collected data. The system's performance was evaluated using a biofloc aquaculture setup, and the results showed that the system was able to accurately monitor and classify the water quality parameters in real time. This system can be used as a tool for farmers to improve their biofloc aquaculture practices, and can also be extended to other aquaculture systems for efficient water quality monitoring and management.

Keywords: Internet of Things (IoT), Machine Learning (ML), Biofloc Technology (BFT).

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CHAPTER 1
INTRODUCTION

1.1 Overview

Biofloc Technology (BFT), an innovative and sustainable method to aquaculture, shows significant potential for intensive fish farming systems. By exploiting the symbiotic link between bacteria and other microorganisms, it produces a self-sustaining ecosystem [1] that improves the quality of water management, waste treatment, and the prevention of disease.

However, the use of IoT technology and machine learning (ML) to BFT may bring about a paradigm change in aquaculture efficiency and cost-effectiveness. This cutting-edge integration may automate numerous procedures, save labor expenditures, and help fish farmers to optimize nitrogen and carbon amounts in their tanks, thereby raising production levels and decreasing human interference.

The suggested IoT-based biofloc automation system, an imaginative and inexpensive solution for fish farming, especially in Bangladesh, may greatly help in catering to the rising need for aquatic food [2]. By integrating sophisticated technologies, such as IoT and ML, this system can accurately monitor water quality, offer real-time data analysis and forecasts, and allow farmers to make well-informed choices. With conclusion, the combination of IoT and ML with biofloc technology presents an amazing possibility for sustainable and lucrative aquaculture. By applying this technology, fish farmers may enhance efficiency, cut expenses, boost profitability, and contribute to a more sustainable and prosperous future for everybody.

1.2 Background Study

Dr. Yoram Avnimelech first introduced the idea of Biofloc technology in the 1970s [3]. However, an American scientist named Dr. Craig Browdy invented the word "Biofloc" in the early 2000s to refer to the microbial communities that emerge in industrial shrimp production systems. Early in the new millennium, Biofloc gained popularity in the Southeast, most notably in the shrimp farming sector. Research is still being done to determine whether BFT has the potential to increase aquaculture productivity, profitability, and sustainability. BFT is currently seen as an environmentally friendly alternative to conventional aquaculture methods.

A few works based on biofloc with IoT and Machine Learning have investigated many elements of this sustainable aquaculture approach, including its microbial ecology, nutrient dynamics, and aquaculture performance, despite the fact that many works have been conducted for aquaculture. According to studies in microbial ecology, BFT systems encourage the development of bacteria, fungus, protozoa, and microalgae, which produce complex bioflocs that supply nutrients to the cultured organisms. Studies on nutrient dynamics have looked at the intake and cycling of nitrogen, phosphorous, and carbon in BFT systems.

The use of IoT in aquaculture allows for the monitoring of environmental factors like water quality. In the tanks or ponds, sensors can be installed to monitor variables including temperature, dissolved oxygen (DO) levels, total dissolved solids (TDS), and pH levels [4]. The information can then be used for analysis to spot potential issues and implement solutions, such altering the water's temperature or adding nutrients. The use of IoT in conjunction with biofloc has the potential to boost productivity, cut costs, and enhance the industry's overall sustainability.

A supervised machine learning approach called classification asks the model to estimate the proper label for particular input data. The user may rapidly classify the biofloc tanks using this technique.

1.3 Biofloc Technology

Biofloc Technology (BFT) is a fish farming alternative in which waste materials are reprocessed and reused as fish food. BFT's main approach is to dig appropriate microorganisms alongside aquatic fish to manage a sustainable ecosystem that benefits from little or no water interchange. The technique focuses on:

1. Manage water quality by destroying harmful nitrogenous components to create microbial protein.
2. Increase feed conversion ratio while lowering total farming costs.
3. Enhances nutrient utilization and reduces environmental pollution.
4. Improves water resource utilization and reduces the risk of water scarcity.

1.3.1 How Biofloc Technology works

Biofloc Technology is a biotic approach combining restricted aquatic fleshly, heterotrophic microbes, and other microorganisms in a Biofloc tank. Biofloc shortage also results in nutritious food for farmed fish species. This suggests BT is a potential choice for easy and efficient fish rearing.

Figure 1.1 Biofloc tank.

Behold, a technology of unrestrained effectiveness, aiming at ameliorating water quality, includes the amalgamation of supplementary external carbon sources with abundant aeration, causing the profuse multiplication of microbiological bacterial floc inside aquaculture systems. In this strategy, preserving a carbon-to-nitrogen ratio higher than 10 is critical, which may be done by adding carbon-rich organic compounds like molasses, grain flour, or starches. Alternatively, lowering the protein level of the meal might also improve the functioning of heterotrophic microbes [5]. Assuming the availability of organic carbon sources, the trapping of ammonia by heterotrophic bacteria transpires swiftly inside the bio floc, manifesting in a couple of hours or days [6].

This method operates based on the idea of flocculation or co-culture of heterotrophic bacteria and algae inside the system. This is mentioned that biological contact may take place between certain groups of microorganisms in systems like bacteria. Some bacteria may have a favorable influence on the growth of pelagic species like microalgae.

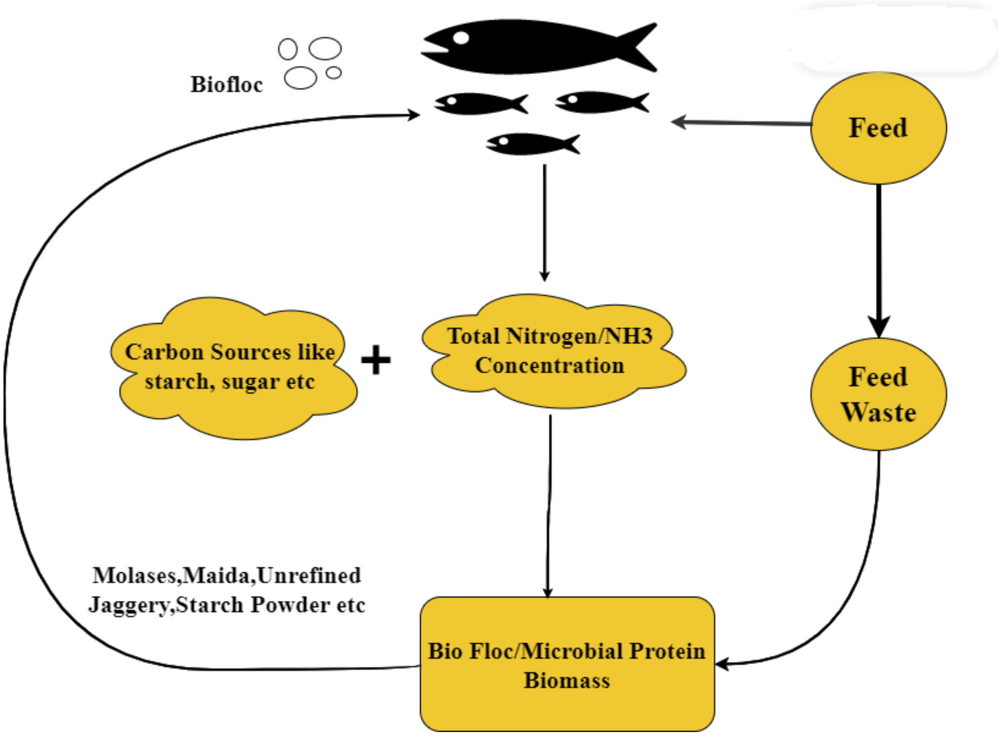

Figure 1.2 Schematic diagram of biofloc implementation in aquaculture systems.

1.4 Internet of Things (IoT)

The Internet of Things is a revolutionary paradigm change in the IT sector. The term "Internet of Things," also commonly abbreviated as IoT, is derived from two words: "Internet" and "Things". The availability of devices in the house, health care, factories, and other locations in technological advancement is bringing together their all-encompassing manner in daily life [7].

This is a network-based method that connects these objects without requiring human-to-human interaction. The IoT is a natural progression of inspection control, process control, and data collection from remote locations to regulate equipment and provisions. The Internet of Things has already altered how we live and work, primarily by reciprocating the world. IoT naturalizes connectivity letting people naturally collaborate because Wi-Fi capabilities and the Internet are now available practically everywhere in a wide range of gadgets.

The Internet of Things entails extending connection via conventional machines to any variety of subsequent low-level devices and everyday things. These objects can interact and communicate through the web with the help of technology and can be monitored and controlled from a distance. In recent years, the IoT's key important bias has been the explosive expansion of items networking and connecting via the web. Because of the wide range of IoT applications, there are common traits that most objects have, but they might vary from one device to the next.

1.4.1 How IoT Works

A physical layer, networking, data transfer, and user applications comprise an IoT system. Sensors are devices, modules, or subsystems. The purpose of a sensor is to detect events or changes in its surroundings and relay the information to other equipment. First, sensors or devices collect data from their surroundings. Individual computers, mobile devices, terminals, and local area networks link to the global Internet. Second, the data is delivered to storage (fog or cloud) via a variety of techniques, including Zig Bee, RFID, Bluetooth, or direct ethernet connection to the Internet [7]. Data processing means the process of obtaining meaningful information from data that has been acquired and manipulated.

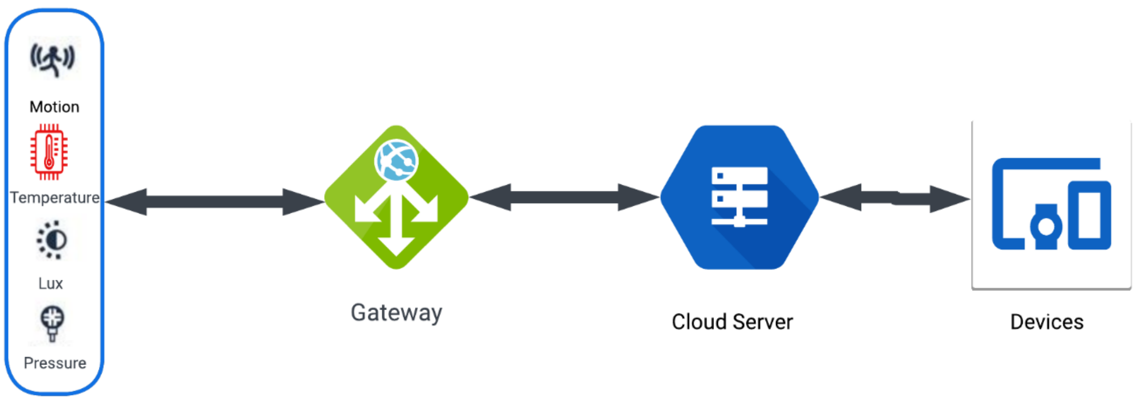

Figure 1.3 Working process of IoT.

After delivering data to storage, software redacts some operations on the data in order to process the data. The field of human-technical or computing device interaction is known as user interface. Finally, information is ripped useful to end-users via email, SMS, notification, and so on.

1.5 Motivation

On the same land, Biofloc can generate many times more fish. IoT and machine learning combined with biofloc could revolutionize the fish sector in Bangladesh. The following list of reasons is why this research was conducted:

- The current system continues to have a number of problems.
- There aren't many projects involving biofloc with IoT and machine learning.

- Since Bangladesh is an agricultural nation, this may benefit large-scale farmers that work with the fish business.
- This model can be improved upon and more machine learning techniques used.
- It is possible to suggest a better database administration system. Majority of systems are incapable of controlling ammonia.
- This will show the tank's exact ammonia level. Bangladeshi farmers are less familiar with biofloc. They can obtain accurate information so they can use this technique.
- A biofloc system cannot be implemented without heterotrophic bacteria. However, no work has yet included a floc management method.

These issues motivated me to make a contribution in this sector. The implemented system will perform better than existing systems.

1.6 Problem Statement

Pond Systems are frequently used by farmers to raise fish. People require a small tank or pond where fish can grow in this method. Because the water containing fish waste is utilized to feed the agricultural land, it is one of the most advantageous fish farming methods. As a result of the close proximity and selective breeding of the fish, there may be more infections in this system. Moreover, fish may be given pellets manufactured from less desirable species, which would lower the amount of food available to other fish. A small number of farmers started using Bifloc technology to solve these issues.

Water quality must be adequately maintained because the Biofloc fish farming technology depends on continuous water quality monitoring. Yet, the farmer is not entirely aware of the information that lowers the quality of the water. The Internet of Things (IoT) has the potential to be a key factor in fostering progress. It is necessary to measure everything accurately, including the pH value, water temperature, total dissolved solids (TDS), dissolve oxygen (DO), flock counts, and ammonia levels. More advanced methods are required in order to measure those aspects. Only a select handful, nevertheless, can perform expensive stream or real-time predictive analytics.

In order to introduce themselves with the necessary IoT devices and how they can measure the parameters using the sensors and classify the water quality in an accurate manner, Biofloc uses IoT and Machine Learning (ML) in this article. On a dataset of implemented models, this model will be evaluated and validated, and it will be compared to the standard measurement of variables like pH, ammonia, and TDS, among others. Also, this model will undergo testing in several biofloc tanks to show that it is accurate.

1.7 Objective of the Work

The purposes of this project are following:

- Applying IoT (Internet of Thing) and Machine Learning with existing biofloc technology.
- To measure and track the factors that affects biofloc technology.
- To reduce the human effort.
- To reduce the production cost.
- To make a classification system that could able to classify the tanks according to their quality.
- To develop an automated model for measuring environmental factors.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

This chapter offers a concise overview of the main components covered in the researchers' past endeavors on the subject, along with addressing the potential directions for future work.

In order to meet the rising global demand for aquatic food supply, aquaculture is crucial. The viability and multiplication of aquatic species, however, depend critically on maintaining ideal water quality in aquaculture systems. For the real-time monitoring and analysis of water quality in biofloc aquaculture systems, the combination of Internet of Things (IoT) technology and machine learning algorithms offers advantageous options.

With a focus on biofloc aquaculture and the application of machine learning algorithms, this literature review offers a thorough overview of current research, methodology, and breakthroughs in IoT-based water quality monitoring and analysis. Future study areas will be identified as we examine the advantages and difficulties of using these technologies to biofloc aquaculture.

2.2 Integration of IoT and Machine Learning for Biofloc Aquaculture

The seamless integration of IoT-based water quality monitoring with machine learning algorithms engenders advanced analysis and informed decision-making within biofloc aquaculture systems. The confluence of real-time data acquisition facilitated by IoT devices and the analytical capabilities of machine learning models furnishes profound insights into the intricate interrelationships between water quality parameters, microbial dynamics, feed management, and growth rates. Such integration allows for the optimization of feed strategies, water treatment protocols, and environmental condition, thereby enhancing overall efficiency and sustainability of biofloc aquaculture operations. This not only enhances the efficiency and sustainability of the operation, but it can also lead to improved animal welfare and increased profitability.

In short, the integration of IoT-based monitoring and machine learning is a game-changer for the aquaculture industry.

2.3 Optimal Water Quality Parameters for Biofloc Aquaculture

The acceptable range of water parameters for the majority of fish species is provided below:

- pH (Potential of Hydrogen) – (6.5 – 8.5).
- TDS (Total dissolved solids) 1500-2000 ppm salinity.
- Temperature (28-32 $°C$).
- DO (Dissolved Oxygen) – (5.5mlg – 8.5mlg) [8].
- If the pH and temperature increase, the level of ammonia also increases.
- Keeping snails in the system can be beneficial for maintaining optimal pH and temperature levels. They also eat algae, phytoplankton, and zooplankton, which helps to create and sustain the flocs in the system[8].

Table 2.1 Effects of pH on biofloc tank.

pH	**Effects**
4 or lower	Acid death point
4-5	No breeding
5-6.5	Slow growth of fish
6.5-9.0	acceptable range for fish
9.0-10	Slow growth
11 or upper	Alkaline death point

2.4 Related Works

A few studies in literature review focus on how aquatic life will be impacted by improvements in water quality metrics [9] and how IoT is used to resolve the problem. Since IoT has recently gained traction with its use by agriculturists, a lot of research has been done to address these kinds of problems [10], [11].

A large number of studies focus on specific sensors such as DO, pH and turbidity [12]–[14] and so on, as well as solutions to those problems. Regardless, optimal fish production is absolutely dependent on numerous chemical, physical, and biological characteristics of water to a large extent. Thus, effective pond management necessitates an understanding of water quality. Water quality is determined by a variety of factors, including temperature, turbidity, transparency, color, pH, carbon dioxide, alkalinity, hardness, dissolved oxygen (DO), conductivity, salinity, TDS, unionized ammonia, nitrate, nitrite, primary productivity, plankton population, BOD, and others [15].

The "Knowledge-Based Real Time Monitoring System for Aquaculture Using IoT" was developed by G. Harish Kumar Varma and K. Raghu Sita Rama Raju in 2017. The system uses a variety of sensors, including those that measure pH, temperature, ammonia, dissolved oxygen, salt, nitrate, and carbonates [16]. However, maintaining a large number of sensors can be costly and time-consuming. As a result, a system that is both reasonably priced and capable of accurately determining the quality of water should be developed. This idea serves as the cornerstone of our investigation.

After extensive research, we have come to the conclusion that not all metrics require monitoring. We can infer the condition of other parameters from the quantity of some parameters since some parameters can induce the imbalances of other parameters. We have selected temperature, pH, ammonia, TDS and water color as working factors, respectively. We'll now go over the causes of this.

The effects of temperature on biological and chemical processes are significant. Each 10 °C increase in temperature doubles the rates of biological and chemical reactions. Chemical treatments are highly impacted by temperature. Fish are not very resilient to abrupt temperature fluctuations. Fish are frequently stressed or even killed when temperature changes occur quickly, even by as little as 5°C [17]. Temperature directly affects factors including pH, DO, conductivity, salinity, and more [15], [17]–[19]. Therefore, before checking other parameters, the temperature should be within the expected range. The typical threshold temperature range is 21°C to 33°C [16], which is simple to maintain. We use temperature as our first working parameter for these reasons.

The concentration of hydrogen ions influences the pH of water, which defines whether it is acidic or basic. Aquatic plants send oxygen into the water during photosynthesis, which can increase pH. Due to a variety of factors, including temperature and light intensity, the pH of water can naturally change throughout the course of a day. Prior to daybreak, the pH range for waters with low aggregate alkalinity is typically 6 to 7.5, but at night when phytoplankton development is intense, pH values may increase to 10 or even much higher [17]. So, pH values might change depending on the unique features of the water body. The pH of natural waterways can be affected by the amount of carbon dioxide, an acidic gas [15]. The pH of pond water can fluctuate as a result of interactions between carbon dioxide and other ions [15].

The total concentration of electrically charged ions (anions – $SO4^-$, $HCO3^-$, Cl^-, $CO3^-$; cations – Na^+, Mg^{2+}, K^+, Ca^{2+} and other constituents such as $NO3^-$, $NH4^+$, and $PO4^-$) is what defines salinity [15]. Salinity is a significant factor that affects the population density and growth of aquatic organisms [15]. Rarely is it possible to measure the concentration of all ions in water over time. There is a link between conductivity and TDS, and a conductivity sensor can be used to measure conductivity, determine the approximate salinity, and quantify conductivity [17]. Water's conductivity depends on the types of dissolved solids it contains and how its ions are fixed. Therefore, it is sufficient to measure conductivity alone rather than TDS and other ions separately. Salinity is the third factor we are taking into account.

The turbidity level of the water can be determined by its color. If it is dark, clay is frequently to blame [18], but if it is greenish, plankton is to blame. Clear water denotes low biological production; it is insufficiently fertile and will not support the growth of fish. Because the clay particles in murky water can obstruct fish's gills and cause death, murky water is not good for fish culture. Dark green water indicates excessive plankton growth, which is used as fish food but results from the addition of excess composts, manure, or nutrient-rich nutrients to a pond. The water's slightly green color (Brownish/bluish green) suggests a healthy plankton population, which is excellent for fish health [15].

One of the most significant aspects of aquaculture is DO. However, we are not measuring this because DO fluctuates with temperature, salinity, and conductivity, decreasing with higher temperatures and increasing with lower salinities. Once more, it varies in a manner akin to pH level [18], [19]. Therefore, we can anticipate that if temperature, pH, and conductivity are all balanced, so will DO. The condition of DO in water can then be inferred once more from its color. For example, greenish water suggests that DO levels are appropriate because a suitable amount of DO generates phytoplankton, which turns the water green.

Diverse water quality management systems and control techniques have been proposed by researchers for aquaculture; however, they focused on a small number of sensor types, such as pH, temperature, and water level sensors, while omitting water regulating actuators. Low-cost Internet of Things (IoT) solutions were created by Zougmorc [20] for African agricultural fish producers, however the system is missing an automated actuator that controls water parameters.

A ZigBee-based wireless sensor network for aquaculture systems that featured a temperature sensor, a pH sensor, and a dissolved oxygen sensor was demonstrated by Encinas [21]. However, this location does not also manage the water parameters. Recirculating Aquaculture System (RAS) was employed by Liu to experiment on "Ras Carpio" [22]. In 2011, pond-based aquaculture was outperformed by RAS. Continuously monitored water parameters resulted in automated water recirculation if a parameter's value exceeded predetermined limits.

Watt Sensolyt, Watt TriO Matic, and Watt Tri oxyTherm type sensors were used to measure temperature, dissolved oxygen, and pH.. The technique offered a number of benefits, but it also had certain shortcomings that led to it being swiftly replaced by a standard aquaculture system. It necessitates water exchange, a pricey and time-consuming process. Based on the IFTTT design, Dzulqornain created a unique Internet of Things system [23]. They took measurements of the water's temperature, PH level, and dissolved oxygen concentrations.

The water level was determined by sensors, and the system was controlled by an aerator system. A propeller, a relay, a power source, and a microprocessor were all integrated into the aerator system. The customer could view the sensor data from anywhere thanks to the transfer of the data to the web. A real-time management system for fish ponds was suggested by Teja [24] using the ESP 32 development board, the AWS cloud, and sensor technologies. This system uses a pH sensor, an ultrasonic sensor, and a DHT 11 sensor to assess the water's purity. The suggested system's flaw is that actuator control of water quality parameters was not carried out, despite the fact that this system monitored sensors.

In order to maximize productivity, people must observe the ethical standards for fish farming and pay attention to the following water quality indicators. A key element that significantly affects fish farming is water temperature. Larvae of fish can survive in a range of temperatures. Fish have a low tolerance for abrupt temperature fluctuations. Due to the fact that zooplankton and algae are also temperature-sensitive, the temperature has additional negative effects. Both directly and indirectly, it regulates salinity, pH, oxygen levels, and other temperature-dependent water properties. Due to the lack of oxygen in hot water, dissolved oxygen levels decrease as the temperature rises and more carbon dioxide is produced in the water [25], [26].

The ideal water temperature for the well-being and growth of fish in a tank is between 24 and 30 degrees Celsius [15]. It is important to consider the pH level, which indicates the solution's acidity or alkalinity, along with the temperature as it can have an impact on the fish. The water in the tank can have an acidic pH of 7.0 or an alkaline pH greater than 7.0. A reduction in the pH level can result in a chemical reaction between ammonia ions (NH_3) and hydroxyl ions (OH^-) and ammonium ions (NH_4^+) in the water [27]. In contrast, an increase in pH levels can lead to the combination of carbon dioxide (CO_2) with water to produce toxic ammonia ions (NH_3), which can have harmful effects on the fish, including death [15].

2.5 Benefits of IoT-based Biofloc Water Quality Monitoring System

IoT-based water quality monitoring combined with machine learning-based analysis brings several advantages to biofloc aquaculture.

Through IoT-based water quality monitoring, water quality parameters can be monitored in real-time. This allows for the timely detection of changes in water quality and the identification of potential issues before they escalate. Real-time monitoring of water quality parameters enables precise management of biofloc systems. This facilitates the optimization of water quality parameters, leading to increased productivity and reduced operational costs.

Leveraging machine learning algorithms, historical data can be analyzed to predict potential issues. This proactive approach to managing biofloc systems helps prevent problems before they occur. Poor water quality can trigger disease outbreaks in biofloc systems. By employing real-time monitoring and proactive management of water quality parameters, the risk of disease outbreaks can be reduced, thereby improving the overall health of the fish.

The utilization of IoT-based water quality monitoring and machine learning-based analysis contributes to the sustainability of biofloc aquaculture. Optimizing water quality parameters not only enhances productivity but also reduces operational costs, resulting in a more environmentally friendly and sustainable approach to aquaculture.

2.6 Conclusion

This chapter gives a general overview of how IoT technology and machine learning algorithms can be used to analyze and monitor water quality in biofloc aquaculture systems in real time. Informed decision-making and advanced analysis are made possible by the integration of these technologies, allowing biofloc aquaculture enterprises to operate more efficiently and sustainably by optimizing feed plans, water treatment procedures, and environmental factors. Along with the impact of temperature and pH on water quality, the allowable range of water parameters for various fish species in biofloc systems is also covered. The chapter emphasizes the value of maintaining close watch on multiple indicators of water quality and presents a practical method for choosing parameters based on the interdependencies of these indicators.

CHAPTER 3
CASE STUDY

To gain a deeper understanding of how biofloc works in real life and how biofloc owners handle the related tasks, we visited Kaichabari, Pallibiddut, Savar, Dhaka and met with a personal biofloc project owner named Mr. Remon. His project is called "RSL High Tech Biofloc Fisheries and Hatchery".

Mr. Remon and his mother provided us with a wealth of information about their project, including how they maintain the biofloc water and how they manually monitor the water quality. They also shared the difficulties they have faced in maintaining water quality. Based on their information, we conducted further studies and developed a problem statement along with a solution that could promote their project.

Figure 3.1 RSL biofloc tank.

Figure 3.2 Fish from RSL biofloc.

Firstly, they use a pH meter to measure the pH of the water. This is done once a day. They use a TDS meter which also can measure temperature. This is also done once a day.

Figure 3.3 Manual pH meter.

Figure 3.4 Manual TDS meter.

To measure ammonia levels, they use an ammonia color test kit. They add 1 and 2 drops of chemicals from two different bottles to a test tube filled with water from the biofloc system and then compare the resulting color to a chart. The middle 3 colors indicate that the ammonia levels are within acceptable limits for fish, but the colors on the right and left sides of the chart indicate that the ammonia levels are too high or too low, which is harmful to the fish.

Figure 3.5 Ammonia test kit.

Figure 3.6 Dissolved oxygen test kit.

Dissolved oxygen levels are also measured using a similar method. Chemicals are added to a water sample from the biofloc system in a test tube, and the resulting color is compared to a chart to determine the dissolved oxygen concentration. They perform ammonia and dissolved oxygen measurements once a week.

Figure 3.7 Flocs inside imhoff cone.

The last step in keeping an eye on the biofloc system is to count the floc, and this is done using a Imhoff cone. The cone is filled with water from the biofloc system, and after a few minutes, the floc settles at the bottom of the cone. The height of the floc is then measured and recorded. This process is repeated several times a day to monitor the growth and health of the biofloc. By keeping track of the floc, the biofloc owner can adjust the feed and oxygen levels to maintain a healthy environment for the fish.

In conclusion, Mr. Remon's “RSL High Tech Biofloc Fisheries and Hatchery” project gave us significant insight into the practical issues of operating a biofloc system. The use of manual water quality testing equipment and regular monitoring of the floc levels allowed Mr. Remon and his team to maintain water quality for their fish. However, they also faced difficulties in maintaining water quality, which highlighted the need for a more efficient and automated monitoring system. Our team has developed a solution that could address these challenges and potentially promote the success of the project. Overall, this case study highlights the importance of proper monitoring and management in maintaining the health of biofloc systems and the success of aquaculture projects.

CHAPTER 4
BACKGROUND TOOLS AND STRATEGIES

4.1 Overview

As this project is based on IoT, so different types of sensors have been used to continuously monitor water quality parameters such as temperature, pH, dissolved oxygen, and ammonia levels etc. and get real time data from those. This chapter gives an overview of the IoT sensors used in building of the Bio floc model and some machine learning libraries associated with the model.

4.2 IoT Sensor and Device

Several sensors and NodeMCU board were used to implement the models, and some of them are mentioned in the following section.

4.2.1 Microprocessor

In this work, the microprocessor is used to collect sensory information, make real-time decisions, take action & dispatch information to the cloud. We have recommended a microprocessor for the ESP 32 NodeMCU.

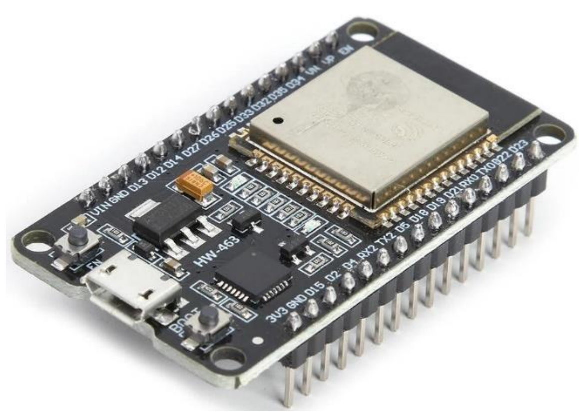

Figure 4.1 ESP 32 model NOD-50032.

Espressif Systems developed the ESP32 using a number of inexpensive, low power SoC (System on a Chip) and modules [28]. This new ESP32 is the replacement for the well-known ESP8266, which gained a lot of popularity due to its built-in WiFi. In addition to WiFi, ESP32 also includes Bluetooth and Bluetooth Low Energy built in. It is an all-purpose MCU module with Wi-Fi, BT, and BLE.ESP-WROOM-32s Wi-Fi, Bluetooth low energy, and conventional Bluetooth are all integrated inside the Module.

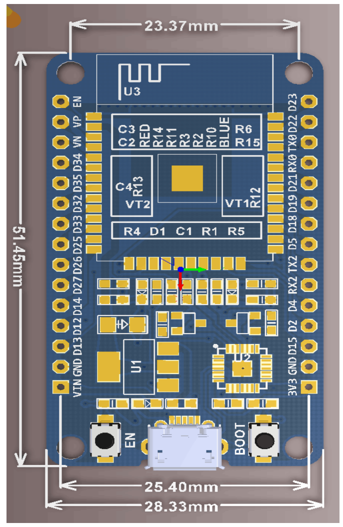

Figure 4.2 Schematic diagram of ESP 32.

A variety of uses Bluetooth enables users to connect to a mobile phone or broadcast a BLE Beacon for signal identification, while Wi-Fi supports a wide variety of communication links as well as a direct connection to the Internet via a router. This ESP32 Development Board available today is the 30-pin which consists of ESP-WROOM-32 as the baseboard and additionally few pins and components to easily interact with ESP32 [29].

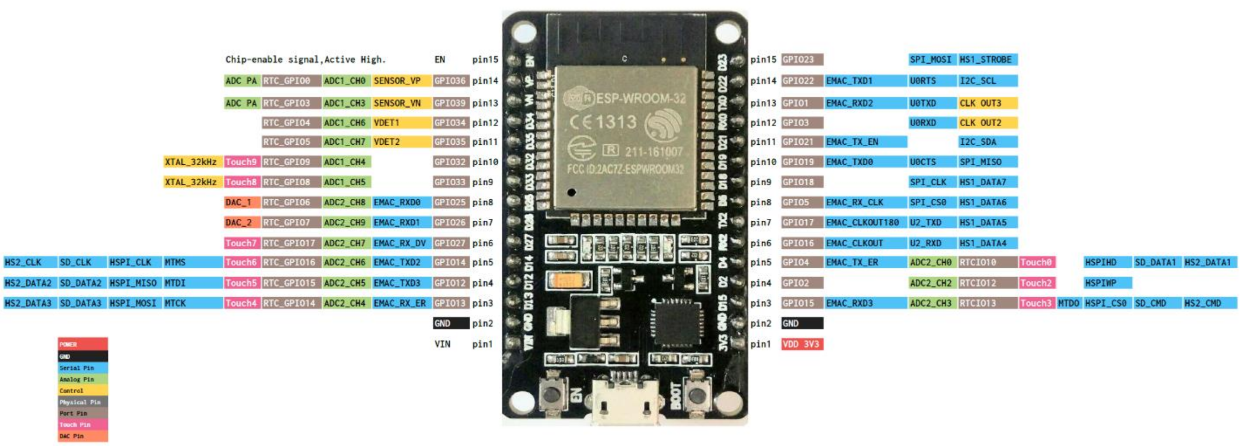

Figure 4.3 Pin diagram of ESP-32.

4.3 Sensing Unit

In this work, different kinds of sensors that would be placed within a fish tank were presented. These will measure a few important parameters before sending data to ESP 32.

4.3.1 Temperature Sensor

The temperature is one of the essential Parameter for better production.SO temperature management should be precise. That’s why we use the DS18B20 sensor for temperature measurement. The DS18B20 sensor is pre-wired and waterproof in this variant. Handy for measuring things from a distance or in damp situations. The cable is PVC-coated, therefore even if the sensor is good up to 125°C, we advise keeping it under 100°C. It can measure a wide range of temperature from -55°C to +125° with a decent accuracy of ±5° C [30]. Even over vast distances, there is no signal deterioration because they are digital! The onboard digital-to-analog converter of these 1-wire digital temperature sensors may provide up to 12 bits of precision. Using a single microcontroller, they operate flawlessly.

Figure 4.4 Waterproof DS18B20 digital thermal sensor.

4.3.2 pH Sensor

The sound potential of hydrogen (PH) in water is a must for fish’s health and proper growth. In this (SEN-50201) sensor there are an electrode, a pH meter measuring sensor for determining the concentration of an aqueous solution of H (pH value), is constructed of a pH glass electrode and a reference electrode combined composite electrode. It is extensively used in this model to determine pH [31].

Figure 4.5 PH sensor module.

4.3.3 Ammonia Detection Sensor

Water pollution is one of the major problems of biofloc system. Ammonia is one of the leading water Pollutant for the ground and surface water [32]. Since ammonia is toxic to fish, its presence in the aquarium has an impact on fish growth. Ammonia is present because to fish discharge from its gills [33]. So, the amount of ammonia presents in the system have to measure precisely. For this we have used MQ137 ammonia Detection Sensor (Model – SEN 15137).

Figure 4.6 MQ-137 Ammonia gas sensor.

4.3.4 TDS Sensor

The term TDS (Total Dissolved Solids) describes the amount of soluble solids that have dissolved in one liter of water. In general, the more soluble solids that are dissolved in water and the higher the TDS value, the less pure the water is. As a result, one reference for indicating the purity of water is the TDS value. So, this is an important parameter for a good quality water management in aquaculture. The sources published the water quality parameters standard stated that the standard amount of Total Dissolve Solid (TDS) is 400mg/l. If this exceeds limits, water quality is not suitable for fish health. This sensor calculates the amount of soluble solids are dissolved in milligrams per liter [34].

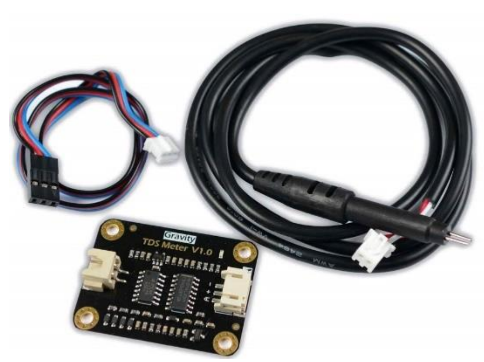

Figure 4.7 TDS sensor.

4.4 Machine Learning Libraries

Several libraries were used to implement the models and some of them are mentioned in the following section.

4.4.1 NumPy

For executing operations on multi-dimensional arrays, many programmers use the core open-source Python module known as Numpy. To facilitate complex computations, it contains a variety of mathematical functions for linear algebra procedures, random number generation, matrices, and more. The performance of Numpy on contemporary CPU architectures has been enhanced.

4.4.2 Pandas

Python's Pandas package is mostly used for analyzing and manipulating data. It offers methods and data structures for effectively handling and modifying numerical tables. Pandas can import data from a variety of file types, including CSV, Microsoft Excel, SQL databases, and JSON. A wide variety of data manipulation activities, including as choosing, reshaping, merging, data cleansing, and wrangling, are supported by the library**.**

4.4.3 Scikit-Learn

Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. SVM, K-Means Clustering, Random Forests, and gradient boosting are just a few of the classification, clustering, and regression algorithms supported by Scikit-learn, a potent machine learning toolkit for Python. It makes use of.High-performance array and linear algebra computations are frequently performed with NumPy. Additionally, Scikit-learn can be combined with other Python libraries to increase its functionality, including Pandas for SciPyss, Matplotlib and Plotly for visualization, and more.

4.4.4 Keras

Keras is a popular high-level neural network library written in Python. This provides abstract building blocks for constructing deep learning networks with great power. These building blocks are constructed using TensorFlow or Theano, which enable easy derivation of gradients and building of computational graphs [35]. Keras can be used for both CPU and GPU computation and is an excellent tool for rapidly prototyping ideas. Due to its flexibility and simplicity, it is an ideal choice for developers who need to construct deep learning models quickly and efficiently. Keras enables you to build sequential models and incorporate a variety of layers with unique features like convolution, max pooling, activation, dropout, and batch normalization[36].

4.5 Models Related to Our Work

There are some classification models that are related to our work. They can provide similar output that we want. The models are explained below.

4.5.1 Support Vector Machine (SVM)

For classification and regression analysis, Support Vector Machines (SVM), a supervised learning technique, is used. The SVM looks for a hyperplane or line that, with the greatest possible separation or margin, splits the data points into two groups [37]. The margin is the distance between the hyperplane and the nearest data points from each class. The kernel trick is a technique that SVM uses to handle non-linear data. With this technique, the data is transformed into a higher-dimensional space that enables linear data separation. The most often used kernels in SVM are linear, radial basis function (RBF), and polynomial. By use of kernel function mapping technique, SVMs can achieve good ability of classification generalization through small data learning [37].

4.5.2 K-Nearest Neighbor (KNN)

A simple but effective machine learning algorithm for regression and classification is K-Nearest Neighbors (KNN). It makes no assumptions about the fundamental distribution of the data because it is non-parametric. It predicts whether a particular data point belongs to a particular class or the other based on the calculated distance between the particular data point and the other points [38]. KNN works by finding the k nearest neighbors to a given data point in the training set, where k is a user-defined parameter. The new data point's class or value is then determined using the majority class or of its k nearest neighbors. Euclidean distance is widely used to determine the distance between data points while classifying data. The absolute difference between the input feature values or the squared difference are usually used to determine regression distance [38].

4.5.3 Decision Tree

A decision tree is a supervised learning technique that is ideal for classification issues since it can organize classes precisely. It functions similarly to a flow chart, splitting data points into two related categories at a time, from the "tree trunk" through "branches," to "leaves," where the categories become more finitely similar [39]. The primary objective of using DT is to create a training model that can predict the class or value of the target variable by learning simple decision rules based on prior data. This develops subcategories, allowing for organic classification with minimal human supervision.

4.5.4 Naïve Bayes

Naive Bayes calculates the possibility of whether a data point belongs within a certain category or does not. The particular data point pertains to that class whose data points are nearest to it. Naïve Bayes (NB) classification algorithm is a probabilistic classifier. It is based on probability models that incorporate strong independence assumptions [40].

4.5.5 Random Forest

Random Forest is a supervised ML algorithm used for classification and regression problems [41]. It is an extension of Decision Tree in that we first build a large number of decision trees with training data, then fit our fresh data into one of the trees as a "random forest" [41]. It effectively averages our data in order to connect it to the closest tree on the data scale.

4.6 Conclusion

This chapter demonstrates how the IoT sensors like pH, TDS sensor, Ammonia sensor etc. has been used alongside with some machine learning libraries like Numpy, Sci-kit Learn, Keras etc. and some classification algorithms. The chapter also gives an overview of the IoT sensors used in building of the Bio floc model and some machine learning algorithm associated with the model.

CHAPTER 5
METHODOLOGY

5.1 Overview

This chapter will provide comprehensive coverage of the working flow, design, proposed system model, implementation, and the final system prototype.

5.2 System Working Flow

To ensure that our project is developed systematically and effectively, we are adhering to the flowchart shown below. This flowchart provides a clear and concise visual representation of the development process, outlining the various stages and tasks involved in the project's implementation.

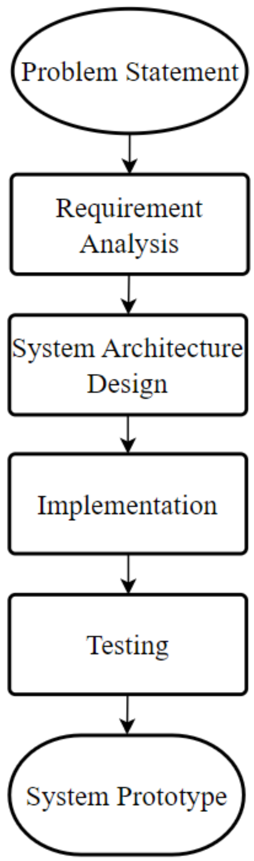

Figure 5.1 Working flowchart.

The first stage of the flowchart is the problem statement, which involves clearly defining the problem or challenge that our project aims to solve. The next stage is the design phase, where we develop a detailed plan for the project, including architecture, components, and technologies that will be used.

The implementation stage involves actualizing the plan developed during the design phase, putting the hardware and software in place, and building the system. Once the implementation is complete, we move on to the testing phase, where we ensure that the system is functioning correctly and meets the project's requirements. Finally, the last stage is the system prototype, where we present the final product, including the physical device and software applications.

By following this flowchart, we can ensure that we are meeting the project requirements, delivering a high-quality product, and addressing any issues or challenges that may arise during the development process. It provides a clear roadmap for our team to follow, ensuring that we are working collaboratively and efficiently to meet our project goals.

5.3 Proposed System Architecture

The system depicted in Figure 1 illustrates the architecture of our IoT-based biofloc water quality monitoring system. Through the use of an ESP32 development kit module and cloud infrastructure, the system continuously monitors water quality and sends data to the cloud and visualize the data using GUI, allowing users to access real-time data remotely. The main objective of this project is to analyze pH, temperature, ammonia level and total dissolved solids (TDS) of the water. Additionally, machine learning techniques (supervised learning) were applied to a dataset of biofloc to train and classify water quality in the container. Real-time measurements from the system's sensors are used to generate output, which is analyzed alongside the training data. The system monitors water quality, evaluates the situation, and automatically adjusts actuators to maintain a specified level of water quality. An accompanying app notifies the user of the results and options, providing real-time water metrics.

Temperature, pH, ammonia and TDS sensors are connected with ESP32 and the ESP32 is connected with a power unit. We chose not to employ a DO sensor in the implementation because it is correlated with pH and temperature. As a result, the DO level can be determined by measuring other parameters, which is a more cost-effective solution since DO sensors are expensive. We have used BlynkIoT platform for the interfacing. Sensor data acquisition is performed by Arduino program.

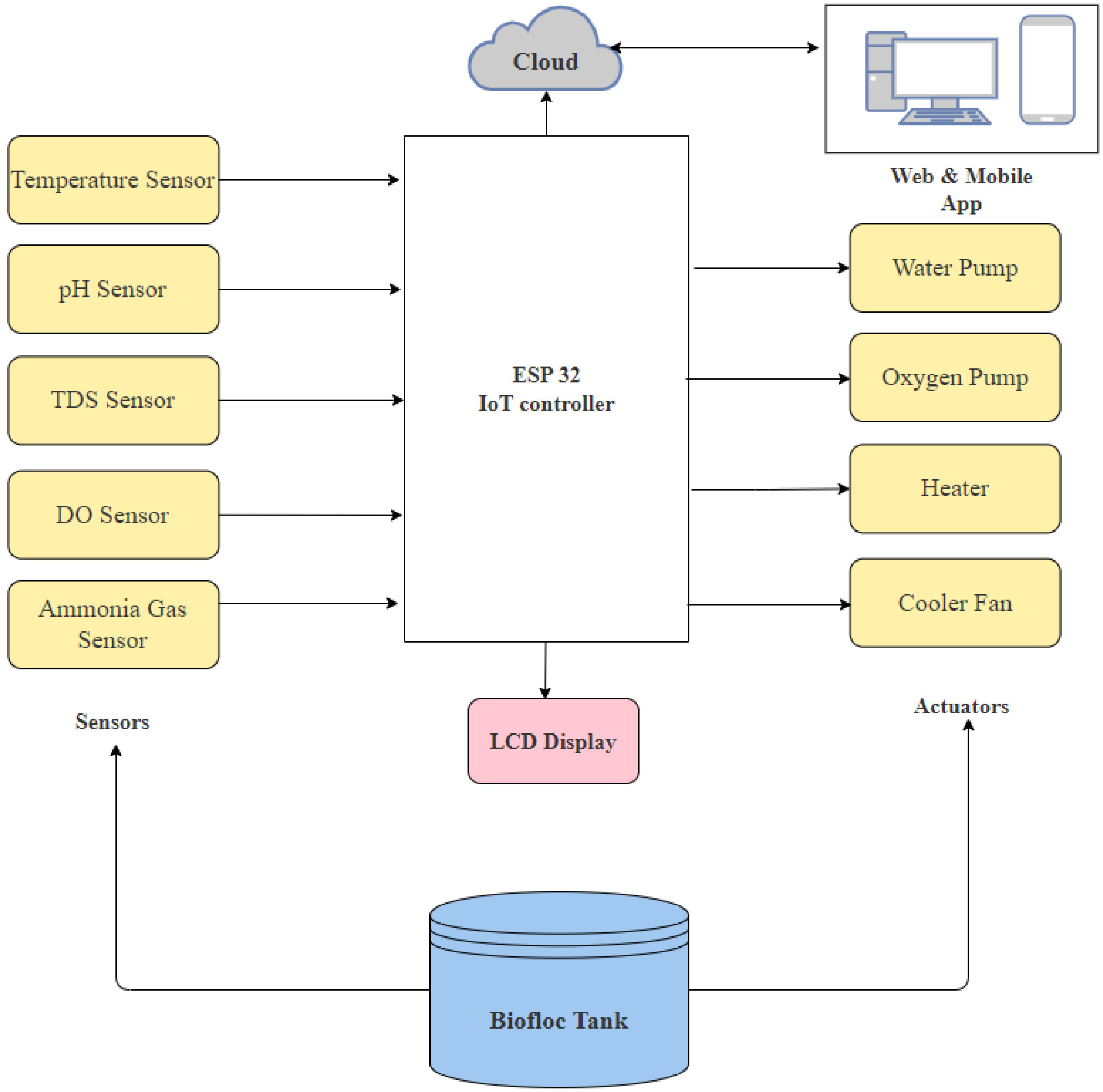

Figure 5.2 System architecture.

The Arduino program integrates with the IoT platform. In IoT the protocol we have used is MQTT (Message Queuing Telemetry Transport). MQTT is a lightweight messaging protocol designed for IoT and other resource-constrained environments. It uses publish-subscribe messaging model and supports various QoS levels. MQTT is widely used in remote monitoring and control, telemetry, and sensor data collection applications.

5.4 Circuit Diagram

The given circuit diagram illustrates the connection between the sensor and ESP32 NodeMCU. It indicates the pins of the sensors that are linked with the pins of the ESP32. The pH sensor value is read through the D35 pin of the ESP32, the ammonia sensor (MQ-137) is connected through D34, and the temperature is measured using the DS18B20 sensor through the D13 pin. In addition, two 4.7k resistors have been used with the ammonia and temperature sensor in this setup.

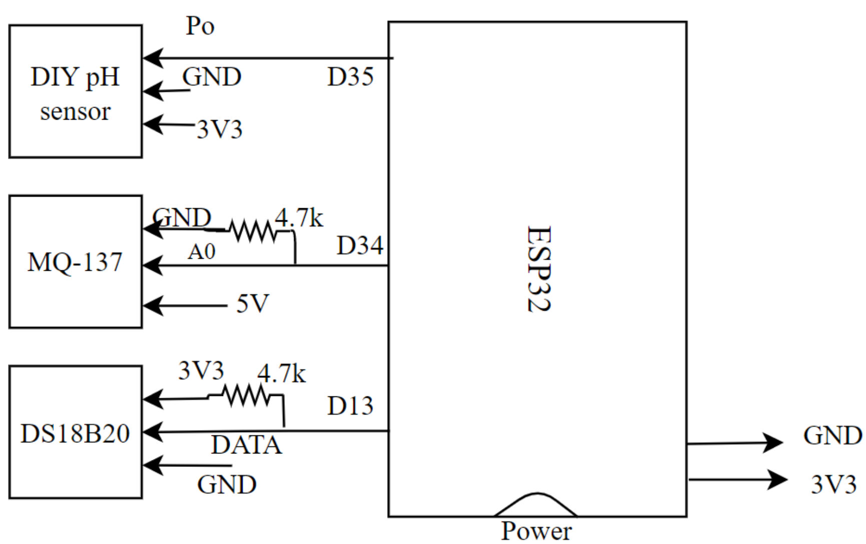

Figure 5.3 Circuit diagram.

5.5 Classification using Machine Learning

Our study involved the implementation of six different supervised classification algorithms and compared their performance to determine which one was most suitable for classifying our model. The dataset used in our analysis was obtained from our implemented IoT project and was suitably structured for classification purposes. To prepare the dataset for analysis, we split it into training and testing data.

We then applied the six classification algorithms-

1. KNN
2. SVM
3. Decision Tree
4. Random Forest
5. ANN
6. Naïve Bayes

Python programming language. To facilitate the implementation of these algorithms, we utilized several Python libraries, such as pandas for reading the dataset in CSV format, Scikit-learn, and Keras for classification. Moreover, we performed accuracy measurements on all six algorithms to evaluate their performance. By comparing the results of each algorithm, we were able to determine the best performing classification method for our model.

For the purpose of training classification model, we have prepared a dataset of 5000 samples. To assess the water quality of the biofloc system, we examined three essential parameters: temperature, PH, and ammonia. We have also established a cutoff point for important parameters that indicate a healthy environment, including temperature (24–30), PH (6–8.5), and ammonia (1–4). We classify the data as representing poor water quality if any of the corresponding parameter values exceed the threshold.

Table 5.1 Sample dataset for classification.

Temperature (°C)	**pH**	**NH3(ppm)**	**Condition**
22.41	6.45	2.66	Bad
22.62	6.99	0.74	Bad
27.93	6.97	3.97	Good
26.28	6.02	1.39	Good
24.33	8.57	3.07	Bad
27.7	5.33	3.22	Bad
34.78	7.09	4.11	Bad
34.63	7.71	5.65	Bad
33.32	8.61	4.61	Bad
24.57	8.21	1.99	Good
33.1	6.82	2.36	Bad
27.97	5.59	1.66	Bad
23.7	5.8	0.19	Bad
24.27	7.96	3.88	Good
24.12	8.53	5.49	Bad
28.49	8.11	3.52	Good
26.81	7.47	4.73	Good
29.37	6.25	5.88	Bad
29.75	5.79	0.46	Bad
29.44	6.27	2.13	Good

CHAPTER 6
IMPLEMENTATION AND EVALUATION

We have completed the setup of the hardware part first and then coding part of the project.

6.1 Hardware Setup

To calibrate the pH sensor, we went to the chemistry laboratory and used a manual pH meter along with high-purity water. We tested the sensor several times to ensure accurate calibration. In addition to the implementation process, we also conducted testing of the system. We initially tested the system using drinking water. For ammonia testing, we mixed glass cleaner with water.

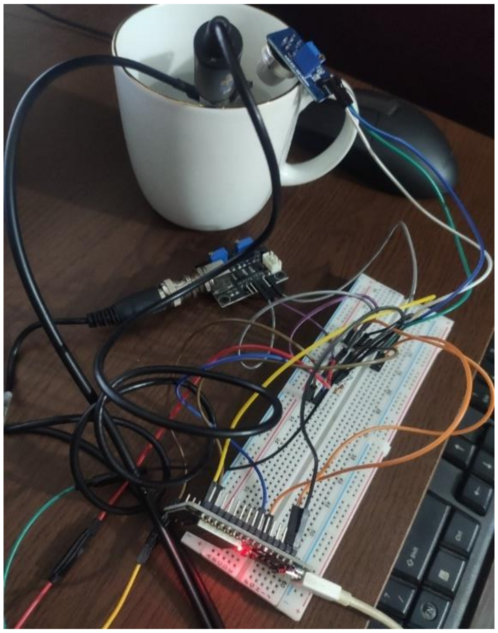

Figure 6.1 Hardware setup during implementation.

6.2 C++ Coding for IoT

To develop the software for our IoT project, we used the Arduino IDE. We wrote code in the C++ programming language, using various libraries to simplify the process. Some of the libraries we used included Dallas Temperature, One Wire, and Simple Timer.

The Dallas Temperature library allowed us to interface with the DS18B20 temperature sensor, reading the temperature data and sending it to the ESP32 microcontroller. The One Wire library provided communication between the DS18B20 sensor and the ESP32. The Simple Timer library helped us to set up timed events and delay functions, ensuring that the program ran smoothly and efficiently.

After we finished writing the code, we uploaded it to the ESP32 microcontroller, which served as the main hardware component of our project. The ESP32 collected data from the sensors and transmitted it wirelessly to the Blynk IoT platform. The Blynk platform allowed us to visualize the data in real-time and provided an interface to control the system.

Overall, by using these software tools and libraries, we were able to build a robust and functional IoT system that could monitor the water quality parameters in a biofloc system. The code we wrote was optimized for efficiency and accuracy, ensuring that the system could provide reliable data for analysis and decision-making.

6.3 Python Coding for Classification

The project was created using Python 3.10 and IDLE. Scikit-learn, NumPy, Pandas and Keras were the main libraries used. This code was organized as follows:

Data loading and any necessary cleaning and normalization were done as part of the data preprocessing step. A variety of features in the dataset used for this project needed to be preprocessed before being fed into the classification models. The data was initially separated into input features and target labels after being loaded from a CSV file.

The KNN, ANN, Naive Bayes, SVM, random forest, and decision tree classification models were all generated separately using independent programs. Every algorithm received as input the preprocessed data and outputs the expected labels.

Another function was developed to assess the effectiveness of each model using accuracy. Using a 70:30 ratio, the dataset was divided into a training set and a test set. The hyperparameters of each model were adjusted using cross-validation on the training set to make sure they weren't overfitting. The test set was used to assess each model's performance.

6.4 System Prototype

This is the final demo of the hardware implementation. We have merged all the hardware inside a box to keep it safe and good looking.

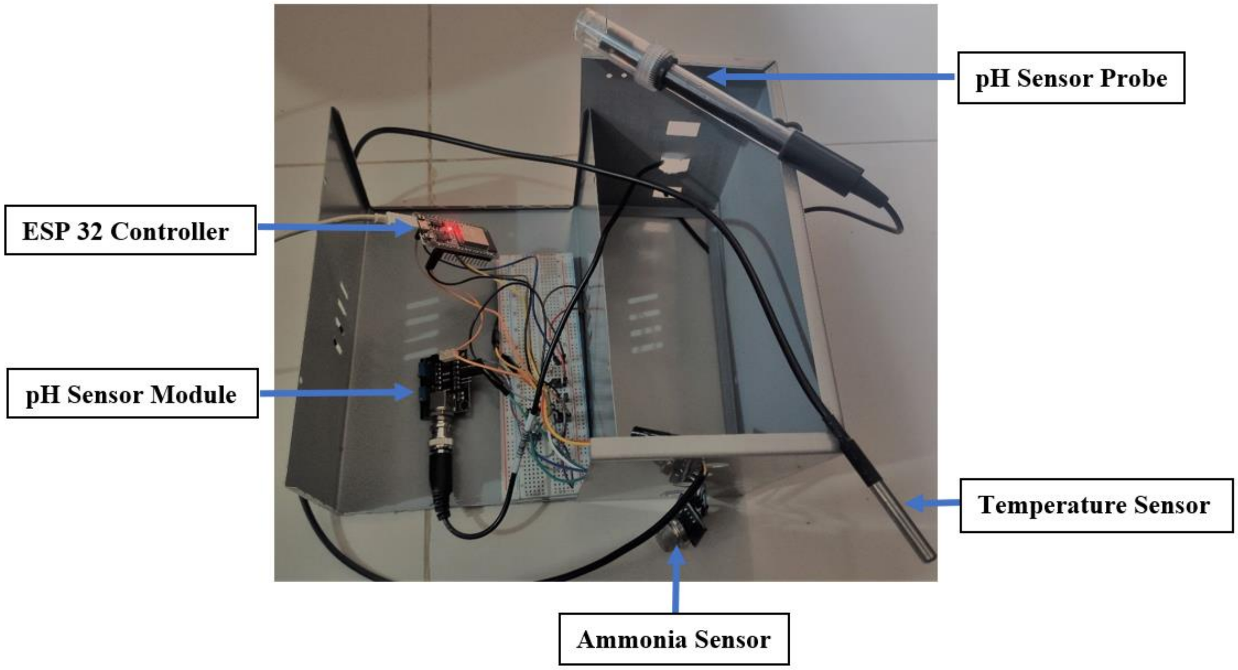

Figure 6.2 System prototype.

6.5 Web view of data monitoring

The system enables users to monitor water parameters in real-time, with the ability to view temperature, pH, and NH3 values through a gauge display. Additionally, pH and temperature can be viewed on a live chart, allowing users to interpret the data in different ways. The live chart view enables users to spot patterns and changes in the data over time, while the gauge view offers a simple way to determine whether a parameter falls inside a given range.

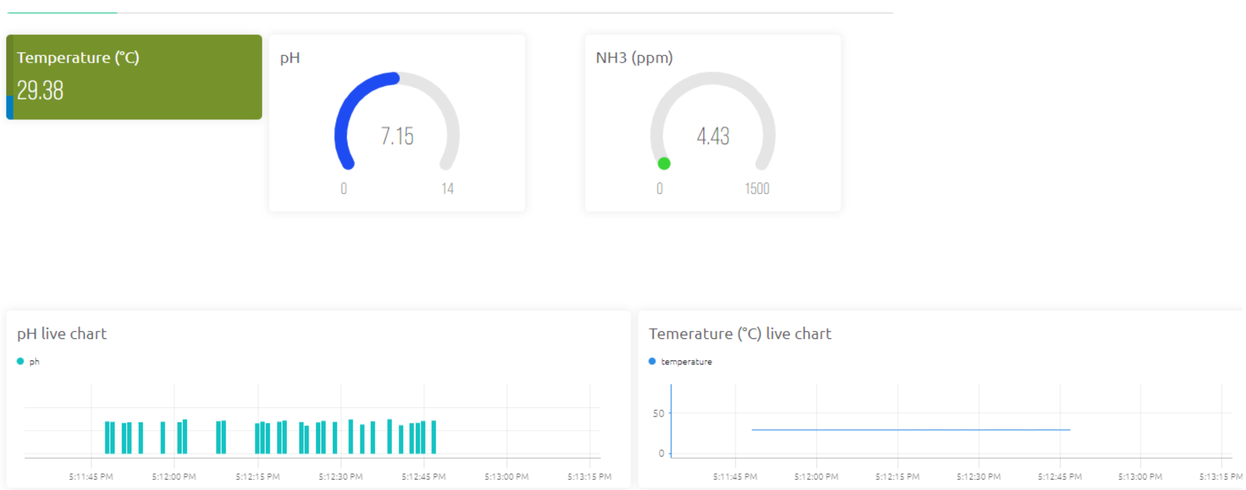

Figure 6.3 Website UI.

6.6 Mobile view of data monitoring

In addition to the website view, users can also monitor the water parameters using a mobile phone. The mobile view allows users to see temperature, pH, and NH3 levels in a gauge view, as well as a live chart view of the pH level. This provides users with the flexibility to monitor the water parameters on-the-go and ensures that they have access to the data anytime and anywhere.

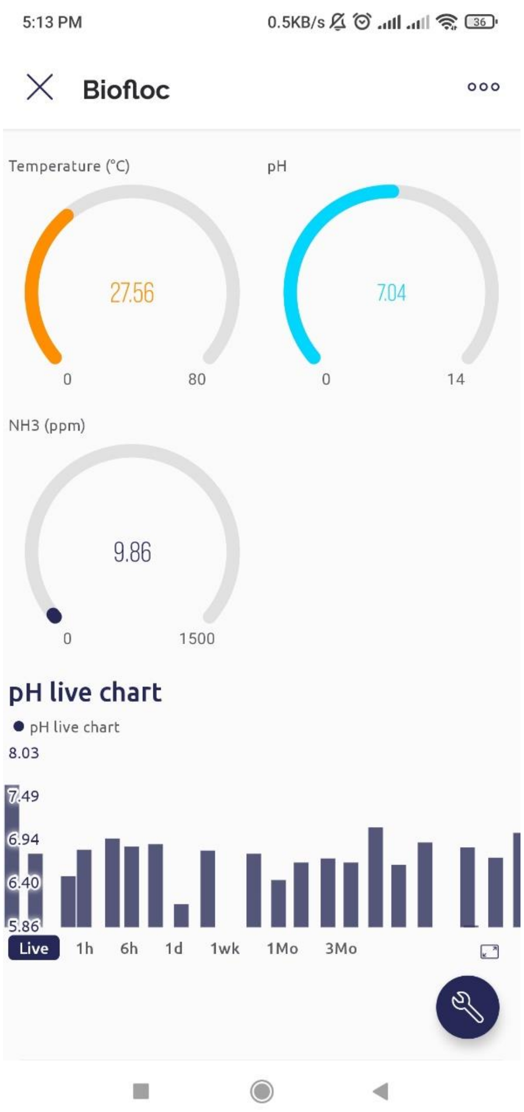

Figure 6.4 Mobile UI.

6.7 Classification Analysis

The data shown in table 6-1 displays several sensor measurements that were taken throughout the course of a day using the biofloc device. The water temperature was found to be significantly lower in the morning and evening and higher in the middle of the day, which had an impact on PH. On the other hand, the gas level stayed the consistent all day.

Table 6.1 Real-time data using system prototype.

Time	**Temperature (°C)**	**pH**	**NH3(ppm)**
6:00 AM	24.41	6.45	5.14
6:30 AM	24.62	6.99	5.32
7:00 AM	24.93	6.97	5.97
7:30 AM	25.28	6.02	5.39
8:00 AM	25.33	8.57	5.07
8:30 AM	25.7	5.33	5.22
9:00 AM	25.78	7.09	5.11
9:30 AM	25.93	7.71	5.65
10:00 AM	26.32	8.61	5.61
10:30 AM	26.57	8.21	5.99
11:00 AM	27.11	6.82	5.36
11:30 AM	27.97	5.59	5.66
12:00 PM	28.23	5.8	5.19
12:30 PM	28.27	7.96	4.88
1:00 PM	28.92	8.53	6.12
1:30 PM	29.49	8.11	6.22
2:00 PM	29.81	7.47	6.13
2:30 PM	30.37	6.25	5.87
3:00 PM	30.75	5.79	5.46

We conducted a comparison of six different classification on our dataset. We highlighted the method's precision, recall and accuracy and F1 score. We have seen that the highest accuracy is 91% of Random Forest with precision 0.9, F1 Score 0.94, and recall 0.83 which is good.

Table 6.2 Algorithms comparison.

Classification Algorithm	Accuracy	Precision	Recall	F1 Score
KNN	82%	0.70	0.86	0.77
ANN	81.84%	0.73	0.696	0.71
Naïve Bayes	69%	0.56	0.58	0.57
SVM	59%	0.44	0.58	0.50
Decision tree	86%	0.77	0.86	0.81
Random forest	91%	0.90	0.83	0.94

6.8 Project Cost Analysis

This is the cost estimation for our project indicates that excluding the DO sensor, which costs 18400/- BDT, makes it a more cost-effective option.

Table 6.3 Project cost estimation.

Sensors and Device	Price
ESP 32 NodeMCU Development Board	650/-
DS18B20 Waterproof temperature Sensor	170/-
PH sensor Module + Probe BNC	4,500/-
MQ137 Ammonia Detection Sensor	3,500/-
LCD2004 20*4 character	390/-
Others (resistors, jumper wires, Breadboard etc.)	2,000/-

Total - 11,220/-

CHAPTER 7
CONCLUSION AND FUTURE WORKS

Since a farmer may grow highly dense fish populations with almost no food or water waste, biofloc farms have the potential to transform Bangladesh's fish sector for the better [42].

Fish farming has been successful for many years despite financial constraints, rising costs, and even a lack of labor. This is partly attributable to consistent water management and the ability of the sector to adjust to sharp spikes in pollution. This project, A smart system that monitors water conditions in real-time has been implemented, which has further decreased production costs, boosted productivity, decreased reliance on humans, and ensured socioeconomic sustainability. The suggested method continuously monitors the quality of the water. The use of a machine learning technique (Supervised Algorithms) was made to maintain sustainable water conditions.

By incorporating cutting-edge technology, such as IoT and machine learning, we can optimize fish farming processes and ensure the efficient use of resources. Moreover, the potential of biofloc technology to revolutionize the industry is significant, particularly in a country like Bangladesh where fish farming is a crucial source of income and food security.

The proposed IoT system underwent testing to validate it, and the results showed a highly accuracy rate. The accuracy of the model will be enhanced going future, and its performance in terms of fish development in the biofloc will be evaluated.

7.1 Limitations

In this project we have some limitations too.

1. We were unable to use the TDS sensor because it was not available in the shop.
2. The NH3 level measurement was found to be less accurate and prone to sudden fluctuations.
3. We utilized the Blynk IoT platform, but a raw implementation may also be viable.

7.2 Future Works

We’ve the following plans to do in future in the project:

1. First of all, we will focus to the raw development of IoT platform using MQTT protocol.
2. We will use TDS sensor.
3. Further we’ve planning to add more features like email notification, emergency alarm due to bad condition of water to make the system more useful.

4. We are planning to include a controlling system that can manage components like water pumps, air pumps, and so on.

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