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Theme

An Intelligent, Low-Cost IoT System for Real-Time Aquaculture Monitoring

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Abstract

Aquaculture plays a pivotal role in global food security, but its sustainability is challenged by the need for real-time monitoring and efficient resource management. This master thesis presents an intelligent IoT and AI-powered system designed for real-time, low-cost aquaculture monitoring. The proposed system integrates advanced sensors with AI-driven data processing to monitor key parameters such as Ph, Turbidity, Electrical conductivity, temperature, and dissolved oxygen. A robust anomaly detection module, leveraging deep learning algorithms, ensures early identification of irregularities, mitigating risks to aquatic life. In addition, the system incorporates predictive analytics to forecast environmental changes, enabling proactive decision making.

Keywords: IoT, Aquaculture Monitoring, Sensing, Anomaly detection, Machine learning.

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General introduction

The increasing global population, projected to reach nearly 10 billion by 2050, presents significant challenges for food security, particularly in the realm of protein sources. Aquaculture, the farming of aquatic organisms, has emerged as a vital solution to meet the growing demand for seafood while alleviating pressure on overexploited wild fish stocks. In Algeria, aquaculture holds immense potential to contribute to national food security and economic development. However, the sector faces numerous challenges, including inadequate infrastructure, limited access to financing, and insufficient technical expertise, which hinder its growth and sustainability. Historically, Algeria's aquaculture industry has struggled with underdevelopment, characterized by low production levels and a lack of modern technological integration. The establishment of the Ministry of Fisheries and Marine Resources in 1999 marked a significant step towards revitalizing the sector, yet production remains a fraction of its potential. The integration of modern technologies, particularly the Internet of Things (IoT) and artificial intelligence (AI), offers a promising pathway to overcome these challenges. By enabling real-time monitoring and management of aquatic environments, IoT technologies can enhance operational efficiency, improve resource management, and promote sustainable practices in aquaculture. The central problem addressed in this thesis is the absence of efficient and reliable methodologies for monitoring water quality within Algerian aquaculture farms. Traditional monitoring practices are frequently characterized by their labor-intensive nature, significant time requirements, and susceptibility to human error, factors that collectively lead to delayed responses when critical environmental changes occur. Consequently, this results in elevated fish mortality rates, diminished productivity levels, and unsustainable approaches to resource management. To effectively address this multifaceted problem, this thesis introduces the development of an intelligent, low-cost IoT system specifically engineered for real-time aquaculture monitoring. This innovative system integrates advanced sensor technologies with AI-driven data processing capabilities to meticulously monitor essential water quality parameters, including pH levels, turbidity, electrical conductivity, temperature, and dissolved oxygen concentrations. Furthermore, a robust anomaly detection module, leveraging sophisticated

machine learning algorithms, is incorporated to ensure the early identification of any irregularities, thereby proactively mitigating potential risks to aquatic life. Complementing these features, the system also employs predictive analytics to forecast environmental changes, empowering aquaculture farmers with the ability to make informed and proactive decisions.

Research Question

How can a low-cost, intelligent IoT system improve the real-time monitoring and sustainability of aquaculture practices in Algeria?

Hypothesis

Integrating IoT technologies and AI-based data analysis in water quality monitoring will significantly improve decision-making and operational outcomes in Algerian aquaculture.

Objectives

In response to the identified challenges, this research aims to:

- Develop a functional, intelligent, and cost-efficient IoT system for real-time water quality monitoring.
- Integrate advanced sensor technologies and machine learning algorithms to analyze key water parameters.
- Implement anomaly detection to enable early warning mechanisms for critical environmental changes.
- Provide predictive insights to support proactive decision-making by aquaculture farmers.
- Evaluate the system's performance and feasibility in the Algerian context.

This research also encounters several challenges, including limited access to real-world calibrated sensor data, difficulty in field testing, and technical integration constraints. Nonetheless, the development of a prototype using public datasets serves as a valuable proof of concept. In this context, and in response to the above-mentioned problem, this thesis is structured into five chapters, each addressing a key aspect of the research:

The first chapter provides a detailed overview of the aquaculture sector in Algeria, emphasizing its significance, inherent challenges, and potential opportunities. This chapter establishes the

foundational context for the research and underscores the critical need for innovative solutions aimed at enhancing both sustainability and productivity within the sector. The second chapter presents a comprehensive review of the existing literature pertaining to IoT-based water quality monitoring systems in aquaculture. This review examines the advancements achieved in real-time monitoring and data analysis, while also identifying gaps in the current body of knowledge, which subsequently informs the design and development of the proposed IoT system. Concurrently, the third chapter outlines the methodology employed in the design and implementation of the intelligent IoT system. This chapter details the system architecture, including the selection of appropriate sensors, microcontrollers, and communication modules, as well as the data acquisition process and the integration of machine learning algorithms for data analysis. Chapter Four presents the implementation and results of the intelligent IoT system, with a specific focus on the performance of various machine learning models applied to predict key water quality parameters. The chapter provides a comprehensive analysis of the results, highlighting the strengths and weaknesses of each model in the specific context of aquaculture monitoring. The last chapter emphasizes the technical and economic aspects of the proposed IoT system, outlining the project objectives, innovative features, and strategic market analysis. This chapter also discusses the production plan, organizational structure, and financial considerations necessary for the successful implementation of the proposed research project. Notably, the significance of this research extends beyond the technical aspects of system development; it addresses the broader implications for food security, economic growth, and environmental sustainability in Algeria. By providing aquaculture farmers with actionable insights derived from real-time data, the proposed IoT system aims to enhance productivity, reduce fish mortality rates, and ultimately contribute to the sustainable development of the aquaculture sector. Consequently, this thesis not only contributes to the existing body of knowledge in aquaculture monitoring but also serves as a foundation for future research and innovation in the field.

Chapter 1

Introduction

1.1 Introduction

The first chapter of this thesis provides a comprehensive overview of the background and importance of aquaculture, particularly in the context of Algeria. It outlines the historical development of the aquaculture sector, highlighting key milestones and challenges that have shaped its current state. The chapter emphasizes the critical role of aquaculture in ensuring food security and economic development, while also addressing the environmental concerns associated with traditional practices. By establishing a solid foundation for the research, this chapter sets the stage for the subsequent exploration of IoT technologies and their application in aquaculture monitoring.

1.2 Background of Aquaculture and its Importance

1.2.1 Background of Aquaculture in Algeria

Algeria's aquaculture history origins reach the late 19th century period when initial small-scale aquaculture units started to emerge. These initial programs confronted numerous barriers including inadequate backing which resulted in their ultimate downfall. The sector experienced prolonged underdevelopment across numerous years especially in coastal zones which demonstrate lower productivity compared to other Mediterranean areas. A few inland water bodies exist yet natural resource scarcity has kept overall yields low. [33] The Bou-Ismaïl station's founding in 1921 initiated the national oyster industry which concentrated on cultivating species including the Pacific oyster (*Crassostrea gigas*) and Mediterranean mussel (*Mytilus galloprovincialis*). The year 1937 saw the establishment of a freshwater fish breeding station designed to propagate largemouth bass (*Micropterus salmoides*) and rainbow trout (*Oncorhynchus mykiss*) for local water body stocking programs. The establishment of the Ministry of Fisheries and Marine Resources (MPRH) in 1999 represented a pivotal advancement for Algeria's aquaculture industry. Aquaculture production numbers have shown a slow upward trend reaching about 4,779 despite persistent difficulties in data collection and reporting. The recorded amount of 29 tonnes in 2021 stands as a minuscule fraction represented by 0. Africa's aquaculture output represents a mere 2% of its total potential production capacity while recording zero growth. 0044% of global aquaculture production. [56, 32]

1.2.2 Importance of Aquaculture in Algeria

In fact, aquaculture plays a crucial role in Algeria's economy and food security. Here are some key points highlighting its importance:

- **Food Security:** The population which numbered 44 million in 2020 is projected to reach 50 million by 2030 making aquaculture essential for maintaining a consistent supply of protein-rich food. The sector possesses the capability to address the growing need for fish and seafood which remains critical for nutritional requirements.
- **Economic Development:** Like any other industry, the aquaculture sector creates employment opportunities while bolstering local economies which in turn aids overall national growth. With an astonishing annual growth rate of 12.49%, this sector is likely to further aid in economic progression, especially considering that this percentage exceeds both regional as well as global averages.
- **Diversity of Production:** Economically important species include marine fish like the European seabass (*Dicentrarchus labrax*) and Gilthead seabream (*Sparus aurata*) which contribute substantially to aquaculture along the coastline. Common carp *Cyprinus carpio* as well as tilapia *Oreochromis* spp., also play an important role in aquaculture alongside freshwater regions.
- **Government Support:** In conjunction with the 2020-2025 Orientation Plan for the Development of Fisheries and Aquaculture Activities, the Algerian government has made efforts to increase funding and support for aquaculture development. Under this plan, Algeria aims to meet production goals of about 221,000 tons of marine captures and 53,000 tons from aquaculture by the year 2025. [82]

1.3 Introduction to IoT in Aquaculture

The Internet of Things (IoT) is revolutionizing various industries, including aquaculture, by enabling real-time monitoring and management of aquatic environments. In Algeria, the integration of IoT technology into aquaculture practices holds significant potential for enhancing productivity, sustainability, and operational efficiency.

1.3.1 Introduction to IoT

Internet of Things connects devices for data and information sharing over the internet. IoT devices and sensors that monitor temperature, salinity levels, water quality and fish behaviour

in aquaculture are also part of IoT. These devices enable automated data processing and collection, leading to prompt actions and decisions based on the results derived from the collected data. [42]

1.3.2 Relevance of IoT to Aquaculture in Algeria

Enhancing Operational Efficiency:

- **Real-Time Monitoring:** IoT devices are able to generate continuous environmental environment data, which allows farmers to keep the environmental conditions in an optimal state for the health and growth of the fish. For example, sensors can be used to track dissolved oxygen levels and activate aeration systems automatically when oxygen levels fall. [57]
- **Automated Feeding Systems:** IoT Enabled feeding systems can analyze data about fish feeding behavior and environmental conditions to optimize feeding schedules and feeding quantities. This minimizes waste and even makes certain that fish get sufficient fodder at the appropriate instances. [37]

1.4 Architecture of IoT in Aquaculture

The architecture of IoT systems in aquaculture typically involves several key components designed to monitor and manage aquaculture environments efficiently. Here's a breakdown of these components:

1. Sensors and Actuators:

- **Sensors:** These sensors are used for measuring the water quality parameters e.g. temperature, pH, Dissolved Oxygen (DO), and salinity. They are essential to keep conditions optimal for aquatic life.
- **Actuators:** Based on sets of sensors in the system, these devices can trigger air flow, water and feeding systems. [54]

2. Microcontrollers and Communication Modules:

- **Microcontrollers:** For processing the sensor data and controlling the actuators, devices like Arduino boards are employed. They handle the data flow to and from sensors and communications modules.

- **Communication Modules:** These modules, for instance, Wi-Fi modules, enable data to be transferred from the microcontroller to a cloud platform or server for analysis and monitoring in real time.

3. Gateway and Network:

- **Gateway:** Acts as a bridge between the outside world and the actuator/sensor network, facilitating data exchange.
- **Wireless Sensor Network (WSN):** Connects all the IoT devices, making it possible for them to share information with each other and the gateway. [30, 72]

4. Cloud Platform and User Interface:

- **Cloud Platform:** Acts as a bridge between the outside world and the actuator/sensor network, facilitating data exchange.
- **User Interface:** Offers a farmer's dashboard to look at information, get notified, and make remote adjustments. [7]

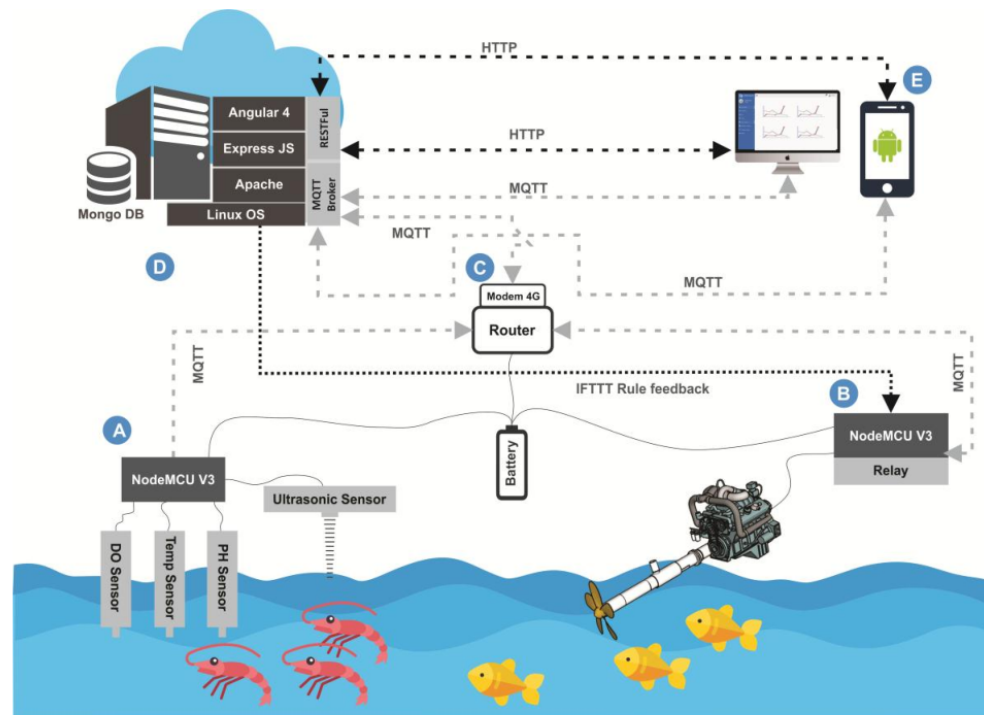


Figure 1.1: Architecture of IoT in aquaculture

1.5 Current challenges in aquaculture management

Despite its potential, Algeria's aquaculture sector faces challenges such as limited infrastructure, technical expertise, access to financing and several challenges hinder its development:

- **Data Collection Issues:** Poor national statistics system for aquaculture production is a reason why it is difficult to assess the sector's status accurately. The FAO has to often rely on alternative data sources and methods of estimation to estimate production levels. [34]
- **Infrastructure and Expertise:** Inadequate infrastructure and unavailability of skilled personnel are significant impediments to the aquaculture sector's growth. Greater research and development are required to enhance production techniques and sustainability. [82]
- **Environmental Concerns:** Aquaculture production contributes to environmental problems such as water contamination and habitat degradation. For this reason, sustainable methods are to be employed in order to offset these impacts. [32]
- **Market Demand and Consumer Preferences:** It is difficult to alter consumer attitudes since Algerians prefer wild-caught fish over farmed fish. This can be limiting in terms of market demand for aquaculture products. [56]

1.6 Objectives and significance of the research

1.6.1 Objectives

1. **Develop a Low-Cost IoT System:** Design and implement an affordable Internet of Things (IoT)-based system for real-time monitoring of critical water quality parameters in aquaculture, such as temperature, pH, and dissolved oxygen.
2. **Enhance Aquaculture Productivity:** Provide a robust system for best water quality conditions, thereby reducing fish mortality rates and increasing overall production. overall yield.
3. **Enable Data-Driven Decision Making:** Integrate the ability for real-time data capture and analysis to provide aquaculture farmers with actionable insights for efficient management.

4. **Promote Sustainability:** Minimize human interaction while maintaining environmental sustainability through effective utilization of resources and reduced operational costs.

1.6.2 Significance

1. **Economic Benefits:** By minimizing fish mortality and maximizing yield, the system enhances the economic growth of aquaculture farmers, particularly in limited-resource settings.
2. **Technological Advancement:** The research bridges the gap between traditional aquafarming methods and modern technological intervention by integrating IoT with low-cost sensors and communication modules.
3. **Environmental Impact:** Offers sustainable aquaculture practice through the control of optimal water conditions and wastage minimization.
4. **Global Food Security:** Helps to raise the demand for seafood by improving aquaculture efficiency to promote food sustainability worldwide.

1.7 Conclusion

In summary, Chapter one has laid the groundwork for understanding the significance of aquaculture in Algeria and the challenges it faces. The integration of IoT technologies presents a promising solution to enhance the sustainability and efficiency of aquaculture practices. This chapter's insights will inform the development of the intelligent monitoring system discussed in the following chapters, ultimately contributing to the overarching goal of improving aquaculture productivity and resource management.

Chapter 2

Literature Review

2.1 Introduction

The second delves into the literature surrounding IoT-based water quality monitoring systems in aquaculture. It reviews existing research and technologies, highlighting the advancements made in real-time monitoring and data analysis. The chapter also identifies gaps in the current literature, emphasizing the need for innovative solutions that can address the unique challenges faced by aquaculture in Algeria. By synthesizing relevant studies, this chapter provides a comprehensive understanding of the current state of knowledge in the field and informs the design of the proposed IoT system.

2.2 Overview of aquaculture monitoring systems

Algerian aquaculture monitoring systems continue to develop and enhance the governance and sustainability of fish farming practices. The systems apply a variety of technologies to monitor environmental status, improve operational efficiency, and ensure compliance with regulatory measures.

2.2.1 Current Monitoring Systems

1. **Vessel Monitoring Systems (VMS) and Automatic Identification Systems (AIS):** The Algerian government has initiated the installation of VMS and AIS technology as a strategy to improve fisheries control and surveillance. These technologies enable real-time tracking of fishing vessels to adhere to regulations and enhance management of marine resources. The European Fisheries Control Agency (EFCA) is supporting Algeria in the installation of these systems that are crucial for monitoring of fishing activities and prevention of illegal, unreported, and unregulated (IUU) fishing. [22, 21]
2. **IoT-Enabled Monitoring Solutions:** New technologies in IoT have brought about the establishment of new monitoring systems that are specifically designed for aquaculture in Algeria. The systems target real-time water quality parameters including temperature, pH, dissolved oxygen, and salinity within fish farms. Through the use of sensors that are internet-connected, aquaculture managers can obtain alerts and insights into data that enable timely intervention to ensure proper conditions for fish health. [83, 55]
3. **Decision Support Systems:** There are ongoing projects to develop decision

support systems for the monitoring of marine aquaculture in Algeria. The overall goal of the systems is the integration of heterogeneous data sources to deliver actionable insights to aquaculture stakeholders. For example, AquaFarm is under investigation as a means to improve decision-making processes associated with various aquaculture systems, thereby improving productivity and sustainability in general. [79]

4. **Research and Development Initiatives:** The National Centre for Research and Development of Fisheries and Aquaculture (CNRDPA) plays a fundamental role in advancing scientific knowledge and developing decision-making tools with a view to supporting sustainable aquaculture practices. The CNRDPA undertakes research on various aspects of aquaculture, including stock assessment and environmental monitoring, thus offering vital information that can inform management strategies. [16]

2.3 Existing IoT solutions in agriculture and aquaculture

In Algeria, a number of IoT solutions are being created and deployed to boost aquaculture operations, tackle the challenges faced by the sector, and augment productivity. Following is an outline of the current IoT solutions in aquaculture:

1. **Real-Time Aquaculture Monitoring Systems:** Most importantly, there are now IoT-enabled systems that are specifically designed to provide water quality monitoring in fish farms. These systems utilize several sensors to track important parameters such as temperature, pH, dissolved oxygen, and turbidity, providing real-time measurements that allow farmers to ensure the optimal environment for fish growth and health. [83]
2. **Aquasafe IoT Solutions:** Aquasafe introduced IoT-based products for aquaculture that facilitate real-time monitoring of environmental conditions. The products can be mounted at fish farms to provide visibility into water quality and other key parameters. There is a device fee and a monthly subscription fee for software services, which are reasonably priced for local farmers. [3]
3. **Farmonaut® AgTech Solutions:** Farmonaut has also expanded its list of agricultural technologies to include equipment applicable to aquaculture. The platform offers functionalities such as crop monitoring and irrigation management, which can be adapted for application in aquatic environments. Although agriculture is its core focus, the underlying technologies have the potential to benefit aquaculture by enhancing resource efficiency and productivity through data-driven analysis. [28]

4. **CNRDPA Initiatives:** The National Centre for Research and Development of Fisheries and Aquaculture (CNRDPA) is involved in researching IoT applications in aquaculture. It is founded on the creation of scientific information and decision-making tools incorporating IoT technologies to support sustainable aquaculture in Algeria. [16]
5. **Innovative Projects from Startups:** There are some startups being set up in Algeria's innovation ecosystem that are prioritizing the integration of IoT solutions into aquaculture. These ventures are more likely to emphasize sustainable approaches, for instance, using fish waste to produce organic fertilizers or employing smart cages for fish farming. Such projects are a growing trend towards using technology for driving efficiency and sustainability in aquaculture. [2]

2.4 Technologies in real-time data acquisition and analysis

In Algeria, various technologies are utilized in real-time data analysis and acquisition across a number of applications, including renewable energy and aquaculture. These technologies provide efficient process control, monitoring, and optimization. Below is a summary of recent technologies in real-time data acquisition and analysis in Algeria:

1. **Arduino-Based Systems:** Some Algerian projects with the use of Arduino microcontrollers have been employed to capture data in real time. For instance, the tracking of solar panels has been used to capture parameters such as voltage, current, and temperature. Such systems include sensors that convey data to the Arduino, which processes it and stores it on SD cards or onto LCD displays for instant inspection. [69, 70]
2. **LoRa Technology:** LoRa (Long Range) technology is utilized in a number of data acquisition systems because it consumes low power and has long-range communication capability. LoRa technology is used extensively in monitoring photovoltaic (PV) farms, where it connects multiple sensors with a master monitoring system. The utilization of LoRa facilitates effective transmission of data over extended distances, thereby ideal for use in remote monitoring applications.[49]
3. **DASYLab Software:** DASYLab is a general-purpose software package in Algeria that accommodates advanced real-time data acquisition and control scenarios. It offers the capability to create flowcharts that simulate the data flow within the system, with support for high-frequency real-time analysis (up to 800 kHz). DASYLab may be

applied to a broad array of applications, from environmental monitoring to industrial automation. [20]

4. **Custom Data Logging Solutions:** Various research projects have been directed towards the development of customized data logging systems for specific applications. One example of a project on solar panels utilized a series of sensors and microcontrollers together to log data at predetermined time intervals (e.g., every 20 minutes). This allows for the detailed analysis of performance data over time, including details on optimal operating conditions.[70, 69]
5. **Environmental Monitoring Systems:** Environmental monitoring is also being addressed using data acquisition systems in Algeria. These systems acquire information about various environmental parameters, such as radiation levels or air quality indices. The obtained data can be analyzed in real-time to analyze environmental conditions and inform decision-making processes. [25]

2.5 Previews works

The collection of articles presents a comprehensive overview of advancements in water quality monitoring systems, particularly through the integration of Internet of Things (IoT) technologies and machine learning (ML) techniques. Varsha Lakshmikantha et al. (2021) [50] introduced a cost-effective IoT-based smart water quality monitoring system that continuously tracks water parameters such as pH, turbidity, and temperature. This system transmits data to a cloud server, emphasizing the need for real-time monitoring to combat water pollution and ensure safe drinking water. Their findings highlight the potential of IoT to provide timely alerts and facilitate proactive management of water quality. Similarly, Ismail Essamlali et al. (2024) [27] showcased the transformative potential of IoT and ML in water quality management. Their research illustrates how these technologies facilitate real-time data collection and predictive analytics, enhancing decision-making processes for water resource management. They emphasize the importance of integrating machine learning algorithms to predict water quality trends, which can significantly improve response strategies to pollution events. Allen T. Chafa et al. (2022) [4] further advanced this field by designing a real-time monitoring and control system specifically for water treatment plants. Their system utilizes fuzzy logic for autonomous control based on World Health Organization (WHO) standards, allowing for adaptive responses to varying water quality conditions. This approach not only improves operational efficiency but also ensures compliance with health standards. In

the realm of aquaculture, Adnan Sarwar et al. (2022) [1] proposed a health management system that monitors critical water quality metrics, such as dissolved oxygen and ammonia levels. This system enables aquafarmers to maintain optimal conditions for fish survival and productivity, thereby enhancing the sustainability of aquaculture practices. Their work underscores the importance of real-time monitoring in preventing fish mortality and optimizing growth conditions. Vaishnavi V. Daigavane and Dr. M.A. Gaikwad (2017) [18] contributed to this discourse by developing a low-cost system for real-time water quality monitoring, which is particularly beneficial for rural areas with limited resources. Their system employs various sensors to measure key parameters and transmits the data via Wi-Fi, making it accessible for local communities to monitor their water sources effectively. Abdul Azeem et al. (2024) [10] focused on a unified system for aquaculture that integrates multiple sensors for comprehensive monitoring. Their research highlights the significance of a multi-sensor approach in ensuring data accuracy and reliability, which is crucial for effective water quality management in aquaculture settings. This integration allows for a holistic view of water quality, enabling better management decisions. Other studies, such as those exploring e-aquaculture monitoring and AWS-based systems, underscore the growing reliance on IoT technologies for efficient data management and analysis. Collectively, these articles illustrate the significant strides made in leveraging IoT and ML for water quality monitoring, addressing challenges such as water scarcity and pollution, and promoting sustainable practices across various sectors. However, the discussions also reveal gaps in security and privacy considerations, indicating a need for further research to ensure robust and secure implementations of these technologies in real-world applications. As IoT systems become increasingly integrated into water quality management, addressing these concerns will be crucial for fostering trust and ensuring the long-term viability of these innovative solutions.

Study	Year	Applications	Key findings	Algorithm used	Low Cost	Anomaly detection
Advances in machine learning and IoT for water quality monitoring: A comprehensive review [27]	2024	Pond management and environmental conservation	Developed a system that monitors pH, turbidity, and TDS in ponds, with real-time data access via a mobile app	Not specified	Yes	Yes
Smart Aquaculture: IoT-Based Water Quality Monitoring System [10]	2024	Aquaculture management	Proposed a system that automates water quality monitoring and management in aquaculture	Not specified	Yes	Yes
IoT-Enabled Advanced Water Quality Monitoring System for Pond Management and Environmental Conservation [47]	2024	Monitoring water quality in various environments	Developed a system that uses IoT for real-time monitoring of water quality parameters	Not specified	Yes	Yes
SLOW-Cost Internet-of-Things Water-Quality Monitoring System for Rural Areas [12]	2023	Monitoring water quality in rural areas	Developed a low-cost system that measures various water quality parameters and reports them via a mobile app	Not specified	Yes	No
IoT-Based Underwater Robotics for Water Quality Monitoring in Aquaculture [80]	2023	Monitoring water quality in aquaculture using underwater robots	Focused on detecting radioactive contaminants using IoT-based underwater robots	Not specified	Yes	No

Design of a Real-Time Water Quality Monitoring and Control System Using IoT [4]	2022	Water treatment plant monitoring	Developed a system that detects deviations in water quality parameters and triggers control measures	Fuzzy logic for decision-making	Yes	Yes
IoT-Based Real-Time Aquaculture Health Monitoring System [1]	2022	Health monitoring in aquaculture	Developed a system that monitors water quality parameters to ensure fish health	Not specified	Yes	Yes
IoT Based Smart Water Quality Monitoring System [50]	2021	Real-time water quality monitoring	Developed a cost-effective IoT system that monitors pH, turbidity, and conductivity	Fast forest binary classifier for classification of water samples	Yes	Yes
Water Quality Monitoring System Based on IoT [18]	2017	Real-time monitoring of water quality parameters	Designed a low-cost system using various sensors to measure temperature, pH, and turbidity	Not specified	Yes	No
Smart Water Quality Monitoring System [64]	2016	Monitoring water quality in aquaculture	Proposed a system that uses IoT for real-time monitoring of water quality parameters	Not specified	Yes	Yes

Table 2.1: Review of Related Works

2.6 Smart Aquaculture Architecture:

Smart aquaculture systems often consist of four main layers: Physical Layer, Monitoring Layer, Virtual Layer, and Connection Protocol. Here is how these layers work together:

1. **Physical Layer (Sensors):** This layer consists of a series of sensors designed to monitor important water properties, which include temperature, pH, dissolved oxygen level, turbidity, and salinity. Key components of this system include sensors, such as pH and temperature sensors, microcontrollers like the Arduino Uno and the Arduino Mega2560 Pro Mini, and actuators such as water pumps and heaters. Envision a setup where these sensors are deployed in water, interfaced using microcontrollers such as Arduino boards, thus forming an effective monitoring system for aquatic environments.
2. **Monitoring Layer (Data Collection):** This layer has an interest in the gathering of sensor data, with the option of either processing the data locally or sending it to cloud-based systems for analysis. Framework fundamentals of this layer are microcontrollers, e.g., boards like Arduino, that interact with the sensors, and communication modules, e.g., the Wi-Fi ESP32 and ESP8266, that enable wireless transmission of data. Consider, for instance, a microcontroller gathering data from numerous sensors and transmitting the data wirelessly, hence enabling efficient monitoring and evaluation of environmental parameters.
3. **Connection Protocol (Communication):** This layer enables continuous communication between different devices and platforms, thus making real-time monitoring and management possible. It supports communication protocols such as MQTT and HTTP, uses Wi-Fi modules for creating internet connectivity, and incorporates mobile or web applications with user-friendly interfaces for interaction. Imagine a system in which several smart devices communicate via the internet, transmitting data to a cloud server that forwards the data to mobile apps or web portals so that users can monitor and manage their systems in real time.
4. **Virtual Layer (Data Processing):** This layer is particularly meant for analysis of data collected using algorithms or machine learning models to generate insights or enable automatic actions. Key components of this framework include cloud platforms such as ThingSpeak, machine learning algorithms, and fuzzy logic controllers. Think of a cloud server that analyzes incoming data and sends back commands to the system, hence

promoting informed decision-making and automatic responses based on the analyzed data.[71, 63, 11, 59]

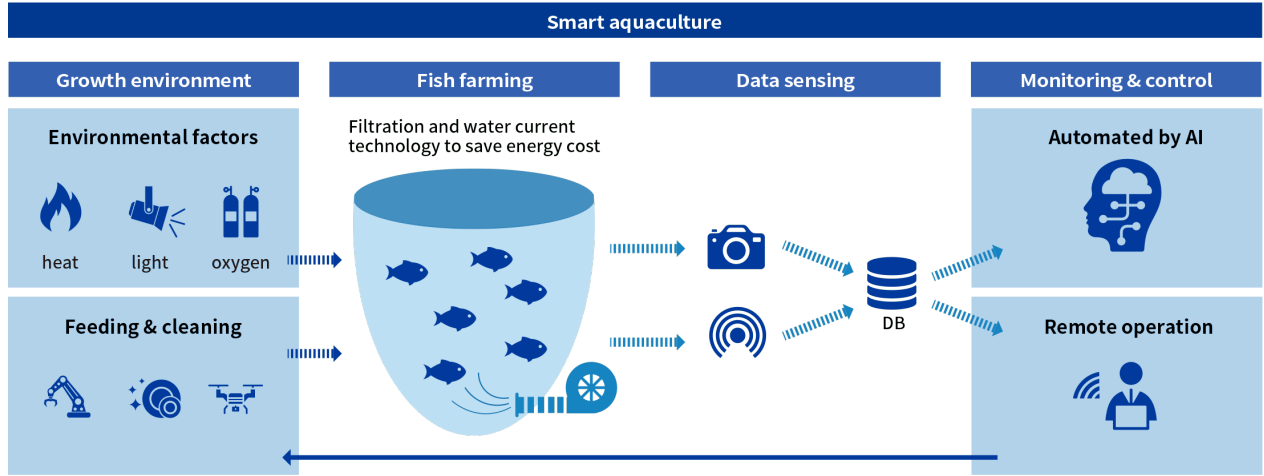


Figure 2.1: Smart aquaculture architecture [68]

2.7 Smart Aquaculture Applications:

Smart aquaculture applications are transforming the fish farming industry by integrating technologies like IoT, AI, and computer vision to enhance operational efficiency, sustainability, and productivity.

1. **Smart Feeding Systems:** They use IoT sensors and artificial intelligence to monitor fish behavior and schedule feeding to achieve optimal growth and reduce waste. Founded on technologies such as IoT sensors, underwater cameras, and machine learning algorithms, the systems optimize feed efficiency while, simultaneously, reducing environmental impact, leading to more sustainable aquaculture.
2. **Water Quality Management:** IoT sensors can constantly keep an eye on the important parameters of water like temperature, pH, and dissolved oxygen, so that real-time corrections can be made to provide an optimal environment for aquaculture setups. Using technologies such as IoT sensors and predictive analytics, these systems noticeably improve fish health and lower the mortality rates, thereby facilitating a more sustainable and efficient aquaculture business.
3. **Disease Detection and Prevention:** AI-driven biosensors and IoT tools facilitate the early detection of health issues in fish, which helps reduce mortality rates and

enhance overall fish health. By utilizing technologies such as AI algorithms and IoT sensors, these systems enable timely interventions that not only improve the well-being of the fish but also contribute to a reduction in antibiotic use, promoting a healthier aquaculture environment.

4. **Fish Biomass Estimation and Tracking:** Computer vision and acoustic analysis for fish counting and biomass estimation greatly improve yield prediction in aquaculture. Through technologies like acoustic sensors and computer vision, these techniques give precise information for inventory management, enabling close monitoring of fish populations. Consequently, the innovation assists in improved production scheduling and resource planning, thereby streamlining the overall activities of aquaculture.
5. **Automation and Robotics:** IoT and AI technologies enable automation of tasks such as feeding and water quality management in aquaculture and minimize human intervention by a great deal while optimizing operational efficiency at the same time. By utilizing IoT devices and AI algorithms, these kinds of systems enhance productivity levels while also lowering labor costs simultaneously, allowing aquaculture operations to run more smoothly and efficiently.
6. **Computer Vision in Fish Farming:** Computer vision is applied in fish species identification, counting, and behavior analysis to improve monitoring and management in aquaculture. Through the application of deep learning models and underwater cameras, these systems improve the ability to monitor fish populations and quantify their behavior, leading to better monitoring and ultimately promoting fish welfare in aquaculture plants. [26, 36, 84]

2.8 Technologies for Smart Aquaculture:

Smart aquaculture leverages a variety of cutting-edge technologies to enhance efficiency, sustainability, and productivity in fish farming.

1. **IoT Sensors:** IoT sensors constantly track water quality parameters like temperature, pH, dissolved oxygen, and salinity, enabling real-time adjustments to ensure optimal conditions in aquaculture. Such proactive monitoring results in better fish health and lower mortality rates, while also facilitating greater environmental sustainability by ensuring aquatic ecosystems are kept in a balanced and healthy condition.

2. **Artificial Intelligence (AI) and Machine Learning (ML):** Machine learning (ML) and artificial intelligence (AI) algorithms convert Internet of Things (IoT) sensor-collected data into the ability to predict future problems, optimize feeding procedures, and detect disease at early stages in aquaculture operations. Through predictive information derived from data on fish behavior, growth parameters, and environmental parameters, these algorithms make it possible to deliver accurate feeding quantities with less waste and generally better fish health. The integration of AI and ML in aquaculture enhances decision-making tremendously, as real-time data analysis offers actionable insights that enable farmers to make informed decisions regarding feeding and health management. Optimization leads to improved feed efficiency since algorithms dynamically adjust feeding schedules based on the specific needs of the fish and their conditions and offer improved growth rates. In addition, with precise predictions of nutritional needs, the unused feed is minimized, thereby not only reducing operational expenses but also evading the environmental cost of degrading excess feed. Overall, the intersection of artificial intelligence, machine learning, and Internet of Things technologies supports an efficient and sustainable aquaculture system. [87, 37, 62]
3. **Automation and Robotics:** Automated systems in aquaculture regulate essential processes like feeding, water flow, and environment control, largely eliminating the requirement for manpower but with optimal conditions being provided to aquatic animals. Utilization of these automated measures assists operations in attaining greater productivity as the activities are conducted uniformly and efficiently without the need for human involvement. The use of such automation contributes to not only reduced labor expenses but also to improved operational efficiency, thereby enabling aquaculture farms to give more attention to development and sustainability while adhering to high standards of care for aquatic animals that they raise. [87, 74]
4. **Computer Vision:** Computer vision technologies are being applied in aquaculture to count fish, estimate biomass, and track the behavior and health of fish. Computer vision delivers precise information for inventory management, resulting in more accurate yield forecasting and resource planning. Real-time fish behavior monitoring also improves fish welfare by enabling early intervention in the event of potential health problems, paving the way for a more sustainable aquaculture practice. [37, 67]

5. **Cloud Computing and Big Data Analytics:** Cloud platforms process huge volumes of data from IoT sensors, enabling real-time monitoring and predictive analytics for aquaculture. Scalability is achieved since data can be processed and analyzed easily regardless of the amount generated. Improved decision-making is facilitated by having access to in-depth insights, while greater operational efficiency is guaranteed by automating processes and optimizing resource utilization, culminating in improved aquaculture management. [74, 62]
6. **Digital Twins:** Digital twins in aquaculture systems benefit from several advantages including enhanced monitoring and predictive modeling for disease control, increased operational efficiency through real-time analysis of data, and the ability to test various scenarios for better decision-making. They also provide optimal feeding regimes and management of resources, and thereby improve fish farming productivity and sustainability. [74]
7. **Drones and Remote Sensing:** Aquaculture monitoring drones are highly necessary in fish health and water quality assessment. Drones monitor water parameters such as oxygen, salinity, and temperature and provide fish behavior and ecosystem condition in real-time, enhancing fish farming management practice. There are numerous advantages of drones in aquaculture that significantly enhance operating efficiency and sustainability. [67]
8. **Recirculating Aquaculture Systems (RAS):** Recirculating Aquaculture Systems (RAS) recycle water, significantly reducing water usage and waste and in most instances employing AI and IoT technologies for optimized functioning. RAS fosters sustainability through the reduction of the environmental impact of aquaculture activities. RAS also improves water quality control through round-the-clock monitoring and control, leading to healthier aquatic environments. As a result, the rate of fish growth is heightened, leading to more productive and efficient aquaculture activities. [23]

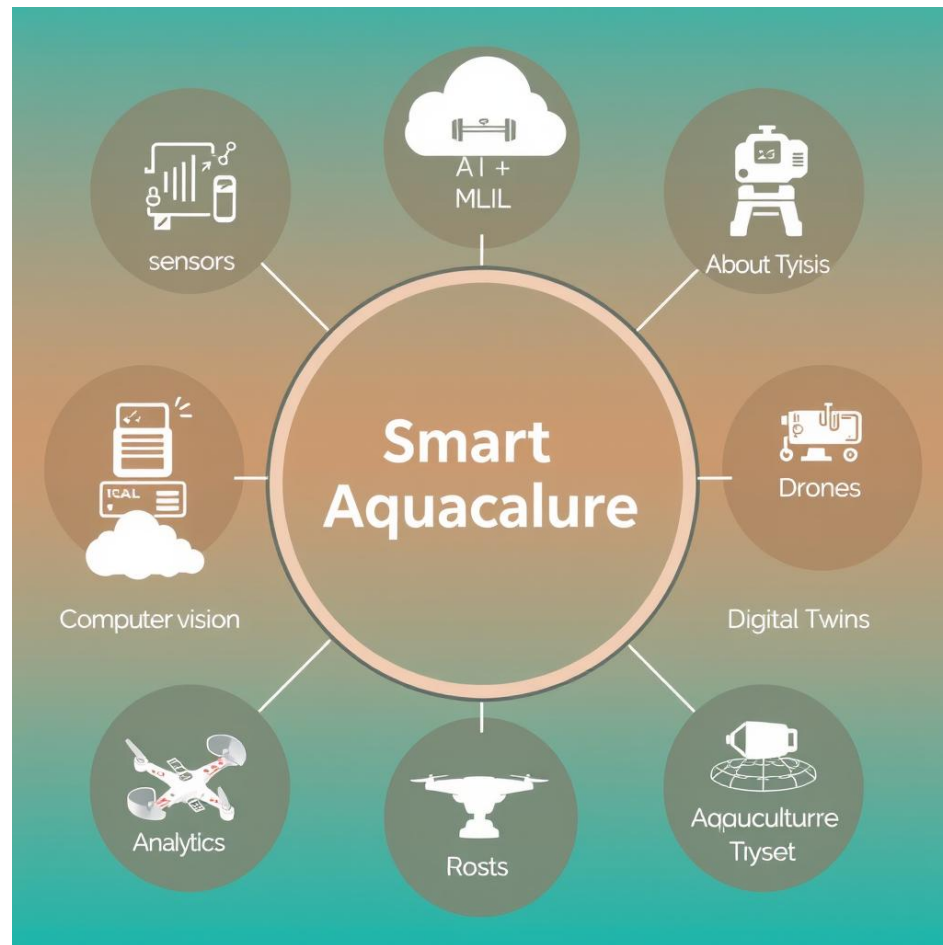


Figure 2.2: Technologies for Smart Aquaculture

Applications	Descriptions	Works
Fish Health Monitoring	AI is used for real-time monitoring and analysis of fish health, enabling early detection of diseases and timely intervention. Techniques include machine learning algorithms and image recognition to identify health issues and predict disease patterns	[15] emphasizes continuous monitoring for effective growth predictions, while [51] showcases automatic corrections to prevent fish kills. [48] illustrates the importance of immediate data access for timely interventions. [73] focuses on tracking key water quality metrics, and [24] aids in identifying harmful conditions. [58] stresses the need for safe water conditions, and [1] enables proactive management through forecasting.[61] underscores the role of real-time sensor data in maintaining optimal conditions for fish, reducing disease risks, and promoting sustainable aquaculture practices
Feed Optimization	AI optimizes feeding schedules by analyzing feeding patterns and environmental conditions, reducing waste and improving growth rates. Techniques include neural networks, fuzzy logic, and decision trees	[15] focuses on using IoT and AI to predict fish growth, which can inform better feeding strategies. [51] showcases how automatic monitoring of water quality can lead to reduced feed waste by optimizing feeding schedules.[48] highlights the role of real-time data in determining the appropriate amount of feed based on fish health and environmental conditions. [[73] emphasizes the analysis of feeding patterns in relation to water quality, ensuring that fish are fed optimally for growth. [1] illustrates how an intelligent control system can adjust feeding quantities based on water quality metrics, leading to improved feed efficiency and reduced waste

Water Quality Management	AI monitors and manages water quality by analyzing parameters like pH, temperature, and dissolved oxygen, ensuring optimal conditions for fish health. Techniques include expert systems and neural networks	[15] emphasizes the need for real-time monitoring to ensure optimal water conditions.[45] focuses on continuous tracking of essential parameters, while [51] showcases automatic corrections to prevent fish kills.[48] highlights the significance of immediate data access for timely interventions.[73] stresses the monitoring of key metrics for aquatic health, and [24] aids in identifying harmful conditions. [58] underscores the necessity of safe water conditions, while [1] enables proactive management through forecasting. [61] illustrates the role of real-time sensor data in ensuring optimal conditions for fish and promoting sustainable aquaculture practices
Environmental Monitoring	AI monitors environmental conditions such as temperature, turbidity, and carbon dioxide levels to ensure healthy aquatic environments. Techniques include IoT sensors and machine learning	[15] emphasizes the necessity of real-time monitoring to ensure optimal environmental conditions. [45] focuses on continuous tracking of essential parameters, while [51] showcases automatic adjustments to prevent adverse conditions for fish. [48] highlights the importance of immediate data access for timely interventions. [73] stresses the monitoring of key metrics for aquatic health, and [24] aids in identifying harmful environmental conditions. [58] underscores the necessity of safe environmental conditions, while [1] enables proactive management through forecasting

IoT Integration	AI integrates with IoT to automate tasks like water quality monitoring and feeding, enhancing efficiency and reducing labor costs. Techniques include smart sensors and cloud computing	[15] emphasizes the necessity of IoT for continuous monitoring to ensure optimal conditions. [45] focuses on the benefits of NB-IoT technology for tracking essential parameters,[51] showcases how IoT can automatically adjust conditions to prevent adverse effects on fish. [48] highlights the importance of immediate data access enabled by IoT for timely interventions. [24] aids in identifying harmful conditions through integrated IoT systems. [58] underscores the necessity of safe conditions maintained via IoT, [1] enables proactive management through IoT-based forecasting. [61] shows how real-time sensor data, facilitated by IoT integration, is vital for ensuring optimal conditions for fish
Sensor Calibration	AI ensures accurate sensor calibration to provide reliable data for decision-making. Techniques include machine learning algorithms for sensor data analysis	[15] emphasizes the necessity of calibrated sensors for continuous monitoring to ensure optimal conditions. [51] focuses on the importance of precise calibration to enable automatic corrections of water quality parameters. [48] highlights the significance of immediate access to accurate data made possible by well-calibrated sensors. [73] stresses the need for reliable readings in monitoring key health metrics, [24] aids in identifying harmful conditions through properly calibrated sensors. [58] underscores the necessity of safe conditions maintained via accurate sensor data, [1] enables proactive management through reliable forecasting based on calibrated measurements

Data Analysis	AI analyzes large datasets to identify patterns, detect anomalies, and predict outcomes, facilitating informed decision-making. Techniques include machine learning models and data analytics	[15] emphasizes the necessity of data analysis for continuous monitoring to ensure optimal conditions. [51] focuses on how data analysis enables automatic corrections of water quality parameters to enhance fish health. [48] highlights the importance of analyzing immediate data for timely interventions. [73] stresses the role of data analysis in monitoring key health metrics, while [24] aids in identifying harmful conditions through effective data interpretation. [58] underscores the necessity of safe conditions maintained via thorough data analysis, while [1] enables proactive management through forecasting based on analyzed data
Real-time Data Transmission	AI enables real-time data transmission from sensors and monitoring systems, allowing for immediate intervention when necessary. Techniques include cloud computing and IoT	[15] emphasizes the necessity of real-time transmission for continuous monitoring to ensure optimal conditions. [45] focuses on how NB-IoT technology facilitates the continuous transmission of essential parameters. [51] highlights the importance of real-time data transmission for automatic corrections of water quality issues. [48] stresses the role of immediate data access for timely interventions. [73] underscores the necessity of real-time transmission in monitoring key health metrics, while [24] aids in identifying harmful conditions through effective data transmission. [1] enables proactive management through forecasting based on real-time data

Table 2.2: AI Technologies of Smart Aquaculture

2.9 Datasets for Smart Aquaculture Research:

For smart aquaculture research, datasets are crucial for developing predictive models, optimizing operations, and enhancing sustainability.

Dataset Format	Dataset Purpose	Source	Link
CSV	Real-time water quality monitoring for sustainable aquaculture	Kaggle	Dataset Link
CSV	real-time monitoring of water quality in five ponds, enabling data collection and analysis to assess aquatic environment health	Kaggle	Dataset Link
CSV	Monitoring the real-time aquatic environment using an IoT framework	Mendeley Data	Dataset Link
tar	Smart glass and computer vision technologies to improve decision making in farm management	CSIRO Data	Dataset Link
CSV	Aquaponic Fish Pond Water Quality Measurement	Mendeley Data	Dataset Link

Table 2.3: Datasets for Smart Aquaculture

2.10 Challenges in Implementing Smart Aquaculture

Implementing smart aquaculture systems faces several challenges that hinder the adoption and effectiveness of these technologies.

1. **Limited Connectivity and Infrastructure:** The majority of aquaculture farms are situated in remote areas with poor internet connectivity, causing enormous difficulties in

installing IoT systems that require continuous connections to give real-time information. To counter this, through the utilization of mobile networks such as 4G or 5G, and satellite connections, there can be more opportunities for connectivity. Nonetheless, it should be mentioned that they will be more expensive and might be less reliable than conventional broadband services. [42, 57]

2. **Data Security and Privacy:** Protection of sensitive data, including trade secrets and patented methods, is crucial to businesses, especially in environments where uncertainty regarding ownership of data and lawful use in public spaces makes it difficult. In order to overcome these weaknesses, the creation of robust data encryption and secure communication systems is necessary. These measures can help ensure the secrecy of sensitive data and prevent it from being accessed by unauthorized users, thereby enhancing the overall security of data in the aquaculture industry. [57]
3. **Integration with Existing Infrastructure:** The transition from traditional methods to IoT systems needs to be gradual and well-planned, particularly since the majority of operations continue to utilize non-digital machinery, thereby complicating the integration process. To facilitate this transition in a smoother manner, phased implementation approach, coupled with widespread training among farmers, can be extremely beneficial. This approach allows for the easier adoption of new technologies while empowering farmers with knowledge and skills to adapt to the evolving nature of aquaculture, thus efficiently enhancing productivity and efficiency. [57]
4. **Scarcity of Electricity:** In rural regions, the stability of the power supply may be a major issue, frequently impacting the functionality of IoT devices that are necessary for contemporary aquaculture. In order to solve this challenge, solar panels and photovoltaic batteries offer a sufficient solution by giving a renewable energy source. Through incorporating investments in renewable energy such as solar power, aquaculture activities can guarantee the continual operation of IoT devices, thus improving productivity and facilitating real-time farm operations monitoring and administration, even without a stable power supply. [42]
5. **Sensor Maintenance and Accuracy:** A water-immersed sensor may lose accuracy over time due to pollution and other environmental factors, thus regular cleaning or automatic cleaning mechanisms are needed to maintain sensor performance. As a solution to this challenge, sensor cleaning mechanisms are important to ensure that the collected data remains accurate and reliable. Though these CMOS sensor cleaning

solutions can enhance CMOS sensor functions, they can also increase operational costs. Striking a balance between more accurate monitoring and its cost will be essential for aquaculture enterprises seeking to optimize their surveillance. [42]

6. **Knowledge and Training Gaps:** The majority of aquaculture stakeholders lack the technical expertise and skills necessary for maximizing the use of AI and IoT technologies, an aspect that highly discourages adoption. To eliminate this barrier, providing adequate training and ongoing support is essential. Through it, equipping the stakeholders with necessary skills and competence enables them to understand and make maximum use of the advanced technologies, resulting in heightened operating efficiency and sectorial innovativeness. This approach not only facilitates the seamless integration of AI and IoT solutions but also allows stakeholders to make informed decisions in driving growth and sustainability. [35]
7. **High Initial Costs and Energy Consumption:** Implementing smart aquaculture systems such as Recirculating Aquaculture Systems (RAS) typically involves high initial costs and heavy energy requirements, which act as barriers to adoption for most operators. To counter this, offering financial incentives and subsidies can induce transition for aquaculture farms. Additionally, employing energy-efficient technologies can simplify operating costs in the long run and render RAS a more economically viable and environmentally friendly choice. Through the combination of these approaches, stakeholders can facilitate the adoption of high-tech aquaculture systems and environmental stewardship as well as long-term profitability. [35]
8. **Disease Management and Water Quality:** Maximum water quality and effective disease control are the most crucial components of intelligent aquaculture systems because variations in these areas can lead to reduced productivity and disease in aquatic animals. In order to combat these problems, the installation of advanced monitoring systems that can provide real-time information on water parameters is essential. Additionally, integrating comprehensive disease management programs can identify and combat potential outbreaks before they become more complicated. Through the combination of these approaches, aquaculture farms can be rendered more resilient, with improved conditions for aquatic life and consequently higher overall productivity and sustainability. [35]

2.11 Conclusion

In conclusion, Chapter two has provided a thorough examination of the existing literature on IoT solutions for aquaculture monitoring. The insights gained from this review underscore the potential of IoT technologies to revolutionize the aquaculture sector by enabling real-time data collection and analysis. The identified gaps in the literature further highlight the necessity for the development of a tailored IoT system that addresses the specific needs of aquaculture in Algeria, which will be explored in the subsequent chapters.

Chapter 3

Methodology

3.1 Introduction

The third chapter outlines the methodology employed in the design and implementation of the intelligent IoT system for aquaculture monitoring. It details the system architecture, including the selection of sensors, microcontrollers, and communication modules. The chapter also discusses the data acquisition process and the integration of machine learning algorithms for data analysis. By providing a clear and structured approach to the research, this chapter serves as a roadmap for the development of the proposed system.

3.2 System design and architecture

System design and architecture are fundamental aspects of building effective and stable systems. They provide a formal way of defining system components, their interactions, and the overall structure that enables functionality and performance. System architecture is a plan for how a system is built and how the components within it interact. It defines the overall structure, main guidelines, and design choices that influence how the system is made to behave, perform, and change.

1. **Sensors layer:** IoT system sensor layer for real-time aquaculture monitoring comprises several crucial sensors that offer vital information about the aquatic environment. The sensors are a temperature sensor, turbidity sensor, pH sensor, dissolved oxygen sensor, and electrical conductivity (EC) sensor. These sensors altogether facilitate comprehensive real-time monitoring to allow efficient management of aquaculture.
2. **Data acquisition layer:** In the Data Acquisition Layer of our IoT system, each sensor is associated with a microcontroller (Arduino MKR Wi-Fi 1010) that reads data from the sensors at regular intervals. The raw data is received by the microcontroller and processes it to make it ready for transmission.
3. **Communication layer:** In The Communication Layer, the microcontroller sends the collected data to a cloud server (Thingspeak) via wireless communication protocols which is Wi-Fi. This layer guarantees the secure and efficient transmission of the data.
4. **Data processing layer:** At the Data Processing and Analytics Layer, advanced data analysis and machine learning can be used on the collected data to create insights, predict trends, and offer recommendations for aquaculture management. The layer can also display data via dashboards.

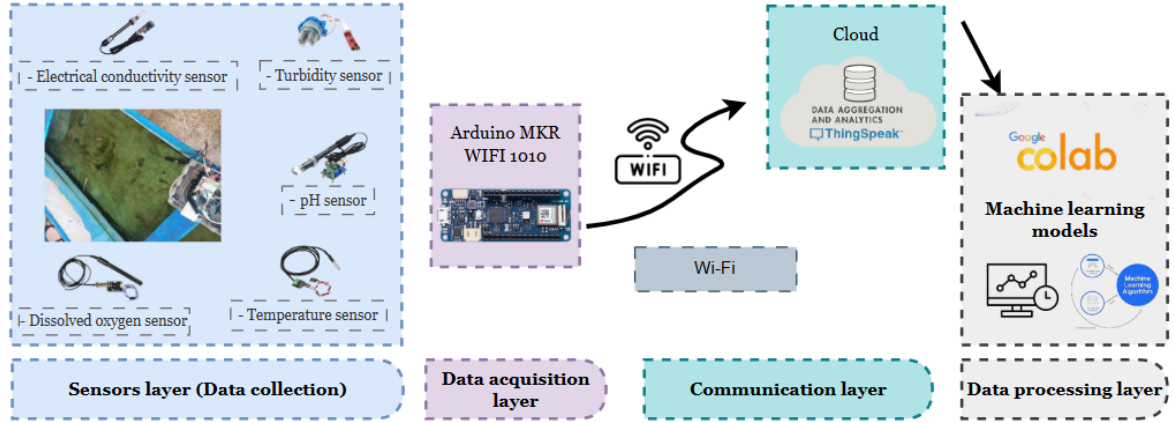


Figure 3.1: Global View of our proposed operational architecture

3.3 Selection of sensors and hardware components

3.3.1 Development tools

The development environment plays a crucial role in the successful implementation and implementation of deep learning models. The following tools and devices were used:

Hardware

- **Processor:** Intel(R) Core (TM) i7-7600U CPU @ 2.80GHz 2.90 GHz.
- **Installed RAM:** 8.00 GB.
- **System Type:** 64-bit Operating System, x64-based processor.
- **Operating System:** Windows 10 Professional.
- **System SKU:** LENOVO-MT-20JJ-BU-Think-FM-ThinkPad Yoga 370.
- **Computer Brand:** Lenovo ThinkPad Yoga 370.

Software

- **Google colab**

Google Colab (short for Collaboratory) is a free cloud-based development environment provided by Google that allows users to write and execute Python code through the browser. It is

especially popular in data science and machine learning due to its integration with Google Drive, access to GPUs, and collaborative features. [38]



Figure 3.2: Google colab

- **Arduino IDE**

Arduino IDE (Integrated Development Environment) is an open-source software platform used to write, compile, and upload code to Arduino microcontroller boards. It supports programming in C/C++ and provides a user-friendly interface, making it widely used for embedded systems, IoT projects, and rapid prototyping. [9]



Figure 3.3: Arduino IDE

- **Thingspeak**

ThingSpeak is an open-source IoT analytics platform developed by MathWorks that allows users to collect, analyze, and visualize sensor data in real time using the cloud. It supports MATLAB integration for advanced data processing and is commonly used in IoT and smart system projects. [52]



Figure 3.4: Thingspeak

3.3.2 Sensors

Sensors play a crucial role in monitoring water quality, In this thesis, I employed five specific sensors, namely:

pH meter:

The pH meter is employed to measure the alkalinity or acidity of water. It is typically a glass electrode and a reference electrode that generate a voltage proportional to the pH value. Accurate pH measurement is essential because most aquatic organisms are pH-sensitive, and pH change affects their survival as well as the quality of water for consumption. [14]

- **Calibration:** To ensure accurate measurements, it's important to calibrate the sensor using standard buffer solutions, specifically pH 4.0, 7.0, and 10.0. Start by rinsing the sensor with distilled water to remove any contaminants. Then, immerse it in the pH 7.0 solution and adjust the reading until it aligns perfectly. Next, repeat this process with the pH 4.0 and 10.0 solutions, making any necessary adjustments along the way. To maintain precision, be sure to calibrate regularly, especially if you notice any fluctuations in your readings. [31, 60]

Table 3.1: Measured and calculated pH values for different reference pH solutions

pHr	pHm	pHc	pHr	pHm	pHc	pHr	pHm	pHc
4	5.94	6.81682	7	7.56	8.36878	10	10.92	11.58766
4	5.75	6.6348	7	7.6	8.4071	10	11.08	11.74094
4	6.93	7.76524	7	7.58	8.38794	10	10.01	10.71588
4	4.4	5.3415	7	6.85	7.6886	10	11.94	12.56482
4	4.94	5.85882	7	8.46	9.23098	10	10.89	11.55892
4	4.64	5.57142	7	8.07	8.85736	10	10.55	11.2332
4	4.76	5.68638	7	7.62	8.42626	10	10.31	11.00328
4	4.91	5.83008	7	5.9	6.7785	10	11.46	12.10498
4	3.94	4.90082	7	7.87	8.66576	10	9.58	10.30394
4	5.07	5.98336	7	7.42	8.23466	10	12.02	12.64146

The table presents a comparison between reference pH values (pHr), the pH values measured by the sensor (pHm), and the calibrated or calculated pH values (pHc) obtained using a polynomial or linear correction model. The data is grouped by three reference points:

pH 4, pH 7, and pH 10, representing standard buffer solutions commonly used for calibration. This comparison illustrates the deviation of raw sensor readings from the actual values and highlights the effectiveness of the calibration method in improving measurement accuracy. The calibrated values (pH_c) show a more accurate alignment with the expected reference pH, confirming the reliability of the sensor after correction.



Figure 3.5: pH sensor calibration

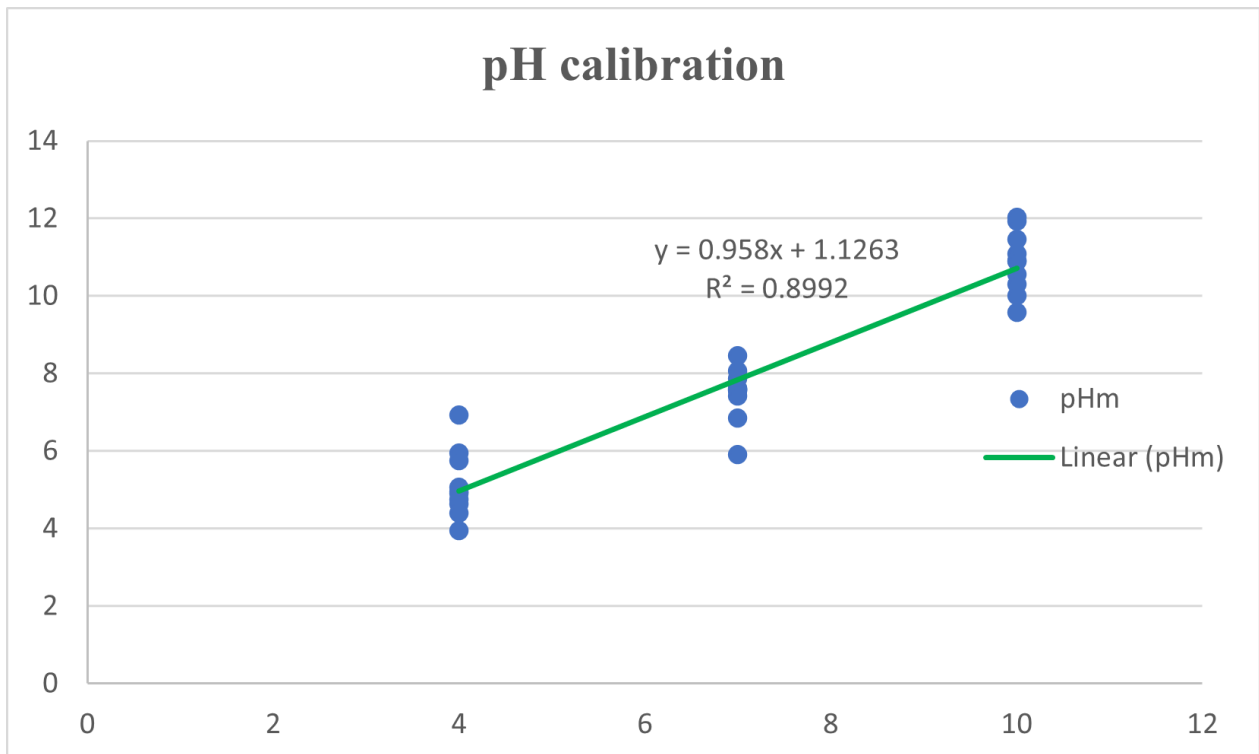


Figure 3.6: pH calibration graph



Figure 3.7: pH meter

Turbidity meter:

Turbidity meters measure cloudiness or haziness of water due to suspended particles. This is done by sending light through the water and measuring how much of the light is diffused by particles. High turbidity is at times an indicator of pollution or sedimentation, injuring aquatic life in addition to the effects on the treatment of water. [13, 66]

- **Calibration:** To ensure your turbidity measurements are accurate, start by using a standard turbidity solution, such as Formazin. Begin the calibration process by rinsing the sensor thoroughly, then immerse it in the standard solution. Adjust the sensor output until it matches the known turbidity level of the solution. It's important to calibrate frequently, especially when you're dealing with changing water conditions, to maintain reliable and precise readings. [31, 60]

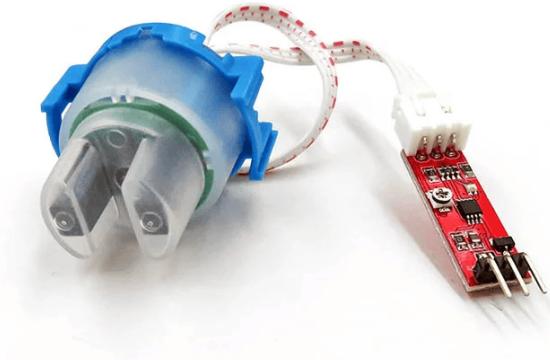


Figure 3.8: Turbidity meter

Electrical conductivity meter:

The EC meter measures the ability of the water to conduct an electric current, which is defined by the ion concentration in the water. This is one of the most important parameters employed in measuring salinity and overall water quality. Higher levels of conductivity might indicate higher dissolved salts or contaminants levels. [40, 29]

- **Calibration:** To ensure accurate conductivity measurements, start by using a standard conductivity solution, such as one with a value of 1413 $\mu\text{S}/\text{cm}$. Begin by rinsing the sensor with distilled water to eliminate any residues. Next, immerse the sensor in the standard solution and adjust the reading until it aligns perfectly with the known value. It's essential to calibrate regularly, particularly when measuring different types of water, to ensure your readings remain reliable and precise. [31, 60]



Figure 3.9: Electrical conductivity meter

Temperature sensor:

Temperature sensors are vital in measuring water temperature, which influences chemical and biological processes in aquatic ecosystems. Temperature determines gas solubility (such as oxygen) and organism metabolic rates and thus is an important parameter in water quality measurements. [40, 13]

- **Calibration:** To ensure your temperature measurements are accurate, use a reference thermometer for calibration. Start by placing both the reference thermometer and your temperature sensor in the same environment, whether it's a water bath or the air. Once they are both in place, compare the readings from each device and adjust the output of your temperature sensor if needed. It's a good practice to check the calibration periodically and especially after any significant temperature changes to maintain accuracy in your measurements. [31, 60]



Figure 3.10: Temperature sensor

Dissolved oxygen sensor:

Dissolved oxygen sensors measure the level of available oxygen in water, crucial to the existence of aquatic life. These sensors work based on an electrochemical process in measuring oxygen concentration, providing details on the well-being of aquatic ecosystems. [13, 14]

- **Calibration:** To ensure accurate measurements of dissolved oxygen (DO), use a calibration method involving saturated air and a known concentration solution. Start by placing the sensor in a water sample that is saturated with air. Then, adjust the sensor to match the known DO levels, such as 0 mg/L and the saturation point. It's important to perform this calibration regularly, especially after extended periods of use, to maintain the reliability and precision of your measurements. [31, 60]



Figure 3.11: Dissolved oxygen sensor

Arduino MKR WiFi 1010:

The Arduino MKR WiFi 1010 is a compact and powerful microcontroller board developed by Arduino. It is designed for IoT (Internet of Things) applications, combining a SAMD21 Cortex-M0+ 32-bit low-power ARM MCU with a u-blox NINA-W102 Wi-Fi module, which supports Wi-Fi and BLE (Bluetooth Low Energy). The board provides a simple and accessible platform for connecting smart devices to the internet, offering secure communication and efficient power usage. It's part of the MKR family, which prioritizes small form factor and low power consumption. [19]

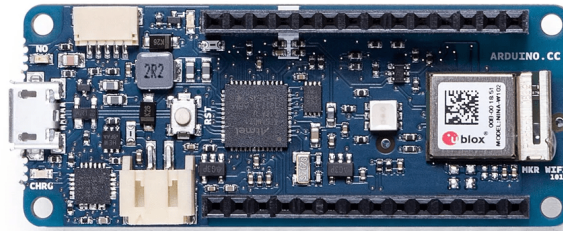


Figure 3.12: Arduino MKR WiFi 1010 card

Key Features:

- **Microcontroller:** SAMD21 Cortex-M0+ 32-bit ARM MCU
- **Operating Voltage:** 3.3V
- **Input Voltage (recommended):** 5V via USB or 3.7V Li-Po battery
- **Wi-Fi/BLE Module:** u-blox NINA-W102
- **Flash Memory:** 256 KB
- **SRAM:** 32 KB
- **Digital I/O Pins:** 8 (12 with analog capability)
- **Analog Input Pins:** 7
- **Analog Output Pins:** 1 (DAC)

- **Interfaces:** UART, SPI, I2C
- **Secure Crypto Chip:** Microchip ECC508 for hardware-based security
- **USB:** Micro USB connector for programming and power
- **Dimensions:** 61.5mm x 25mm [19]

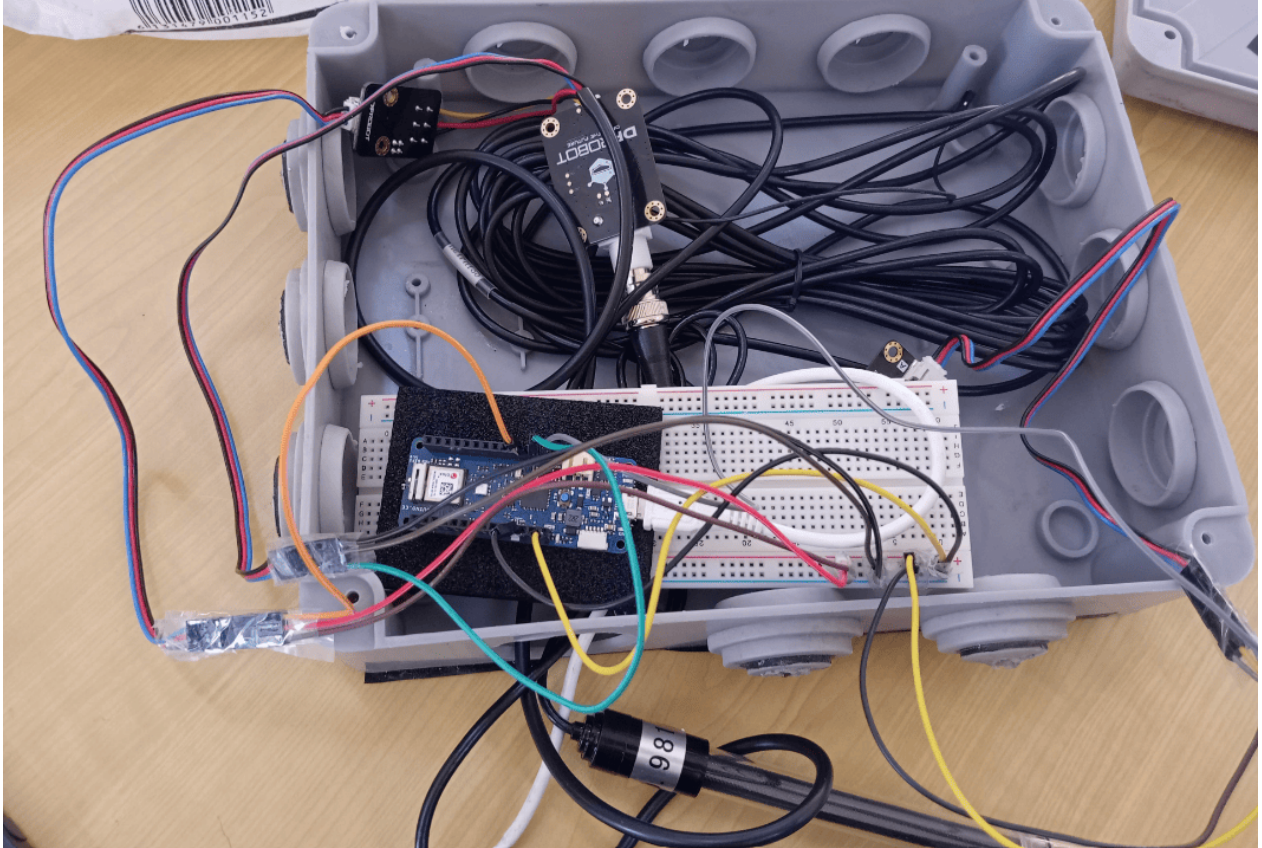


Figure 3.13: Arduino MKR WiFi 1010 card in protocol

3.4 Assembly of the Experimental Kit:

In this kit, I used a variety of tools and components essential for the development of the system. These include a breadboard (also known as a prototyping board), Energizer batteries as the power source, jumper wires for electrical connections, and the Arduino MKR WiFi 1010 board as the main microcontroller. Of course, sensors were integrated into the setup, including a temperature sensor, a pH sensor, an electrical conductivity (EC) sensor, and a turbidity sensor. All components were housed in a protective enclosure to ensure organization and safety. In addition, my laptop was used to program, upload code via the Arduino IDE, and monitor the data.

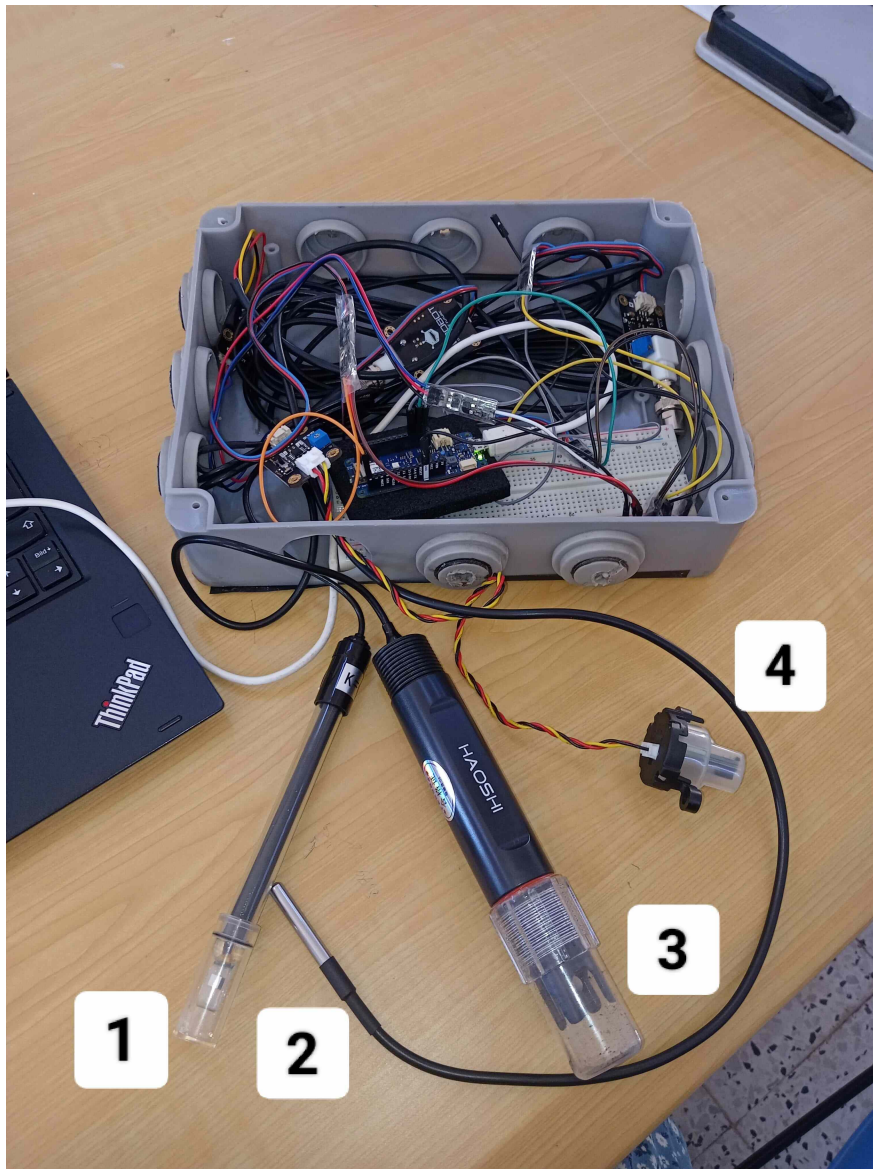


Figure 3.14: Assembly of the experimental Kit

1. Electrical conductivity sensor
2. Temperature sensor
3. pH sensor
4. Turbidity sensor

To operate the system, I developed a code — with the assistance of ChatGPT — that enables the acquisition of sensor data every 3 seconds. This data, which includes values from the temperature, pH, EC, and turbidity sensors, is transmitted to the ThingSpeak cloud platform

using the built-in WiFi functionality of the Arduino MKR WiFi 1010 board. The connection is established via the ThingSpeak API key, ensuring secure and direct communication between the device and the online server, where the data can be stored, monitored, and visualized in real time.

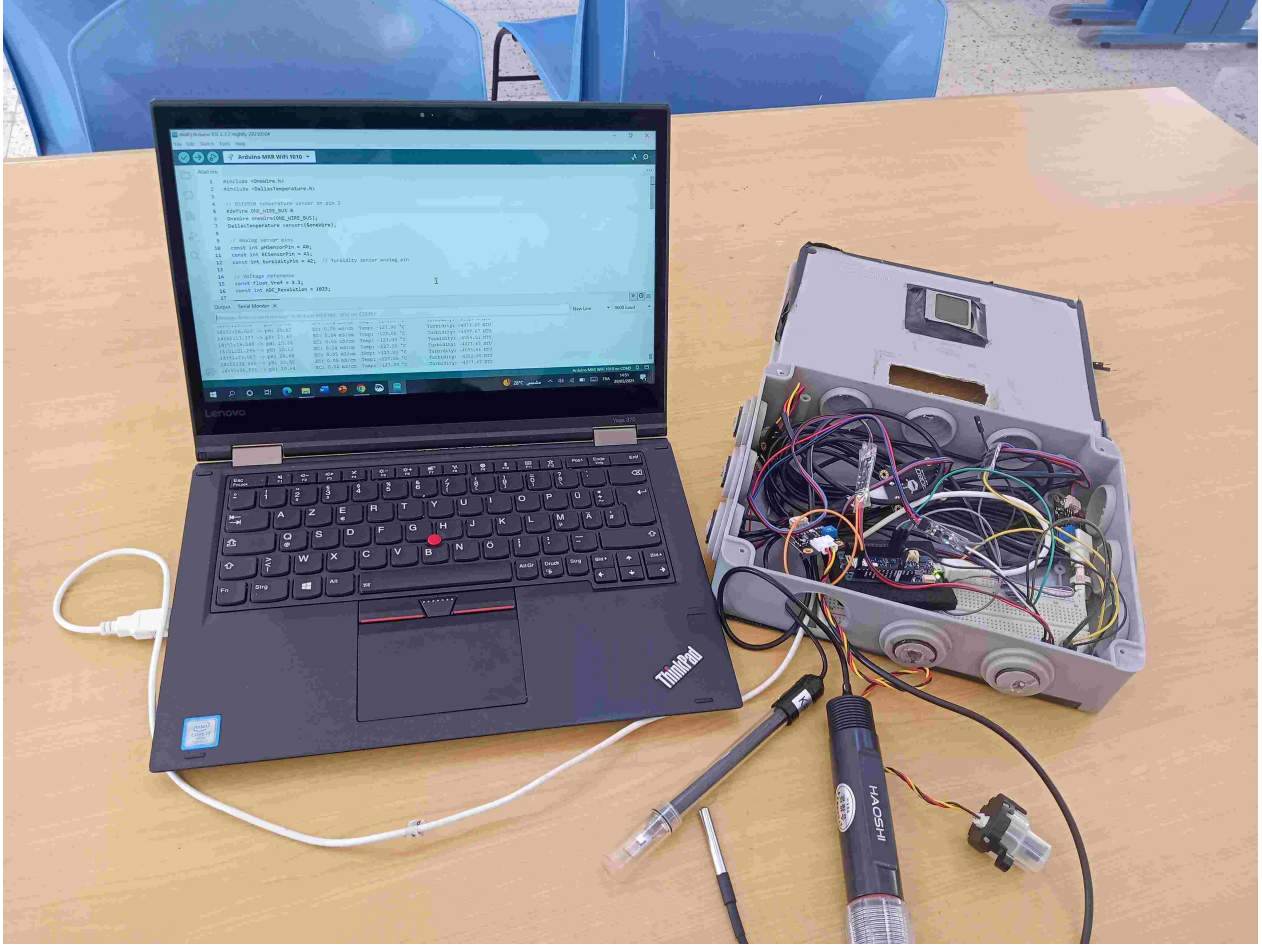


Figure 3.15: Data acquisition using Arduino IDE

3.5 Field Visit to ITPA

As part of my project, I visited the Institute of Fisheries and Aquaculture Technology (ITPA), which houses a tilapia aquaculture basin. The purpose of the visit was to test the IoT monitoring kit and begin gathering real-world data. However, due to the sensors not being properly calibrated at the time, the measurements collected during the visit were not reliable enough to be used in the analysis. As a result, I had to rely on a publicly available dataset to proceed with the development and testing of the system. Nevertheless, the visit was valuable, as it allowed me to gain a practical understanding of the aquaculture environment and better

connect theoretical concepts with real-world conditions relevant to my project theme.

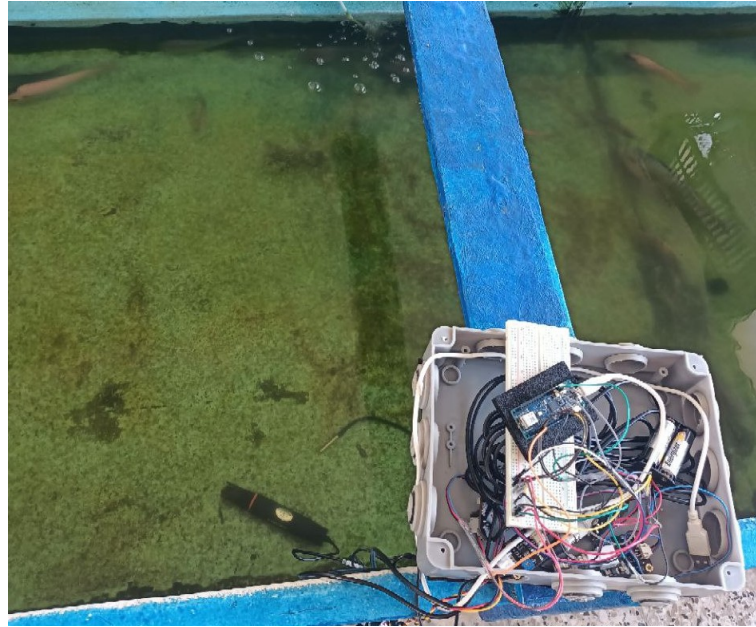


Figure 3.16: Kit in the Tilapia Aquaculture System 1

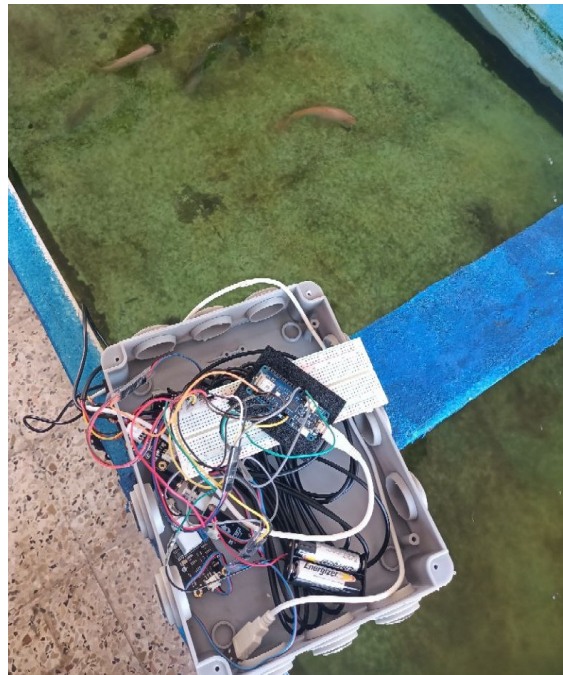


Figure 3.17: Kit in the Tilapia Aquaculture System 2



Figure 3.18: Kit Deployment



Figure 3.19: Waterborne sensors

3.6 Conclusion

In summary, Chapter three has detailed the methodology used to develop the intelligent IoT system for aquaculture monitoring. The systematic approach outlined in this chapter ensures that the system is designed to meet the specific needs of aquaculture farmers while leveraging advanced technologies for optimal performance. The insights gained from this methodology will be critical in evaluating the effectiveness of the system in the subsequent chapters.

Chapter 4

Implementation and Results

4.1 Introduction

The fourth chapter presents the implementation and results of the intelligent IoT system for aquaculture monitoring. It discusses the performance of various machine learning models applied to predict key water quality parameters, including pH, dissolved oxygen, temperature, turbidity, electrical conductivity, ammonia, manganese, and nitrate. The chapter provides a comprehensive analysis of the results, highlighting the strengths and weaknesses of each model in the context of aquaculture monitoring.

4.2 Introduction to Machine Learning

Machine learning (ML) is a branch of artificial intelligence that allows systems to recognize patterns within data and make decisions or predictions on their own without being explicitly programmed. ML algorithms are categorized into three general types: supervised, unsupervised, and reinforcement learning. Supervised learning is the focal point of this study, more precisely regression problems where the objective is to forecast continuous values.

4.2.1 Supervised Learning for Regression

Supervised learning uses labeled data to train predictive models. For regression problems, the output variable is continuous. In this work, we use regression techniques to forecast future values based on historical data. This is crucial in various domains such as finance, weather prediction, and energy consumption forecasting.

4.2.2 Applied Regression Models

To evaluate the performance of different regression approaches, we implemented the following models:

1. Linear Regression (LR):

It is a fundamental statistical and machine learning technique used to model and analyze the relationship between a dependent variable (also called the response or target) and one or more independent variables (predictors or features). The primary goal is to find the best-fitting straight line (or hyperplane in higher dimensions) that predicts the value of the dependent variable based on the independent variables. [86, 53]

Linear Regression

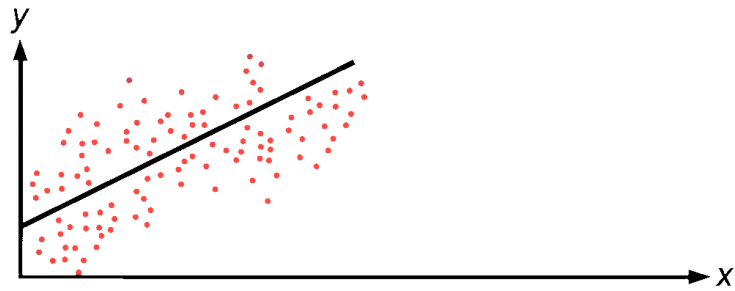


Figure 4.1: Linear Regression

2. Ridge Regression:

is a type of linear regression that addresses the problem of multicollinearity-when independent variables in a regression model are highly correlated-by introducing a regularization (penalty) term to the cost function. This penalty term shrinks the regression coefficients towards zero, helping to stabilize the estimates and prevent overfitting, especially in models with many predictors or when the number of predictors exceeds the number of observations. [76, 81]

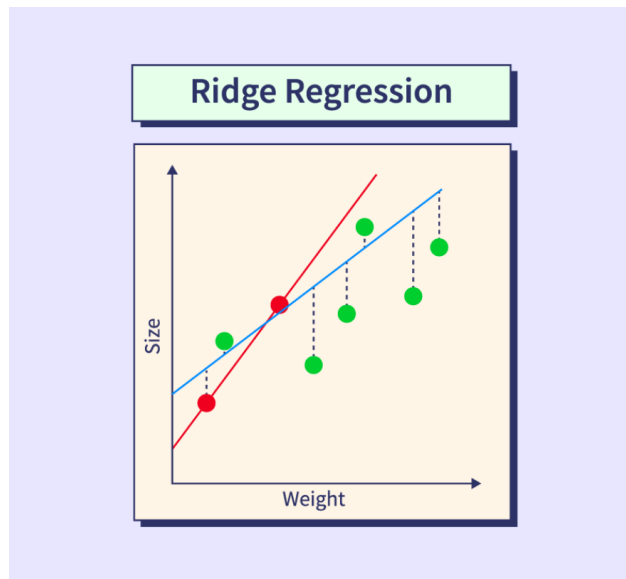


Figure 4.2: Ridge Regression

3. Random Forest Regressor (RF):

is a supervised machine learning algorithm used for regression tasks that builds an ensemble of decision trees to predict continuous target variables. It operates by constructing many decision trees during training, each built on different random subsets of the data and features (a technique known as bagging), and then averages their predictions to produce a final output. This ensemble approach reduces variance and overfitting compared to individual decision trees, improving predictive accuracy and model robustness. [6, 78]

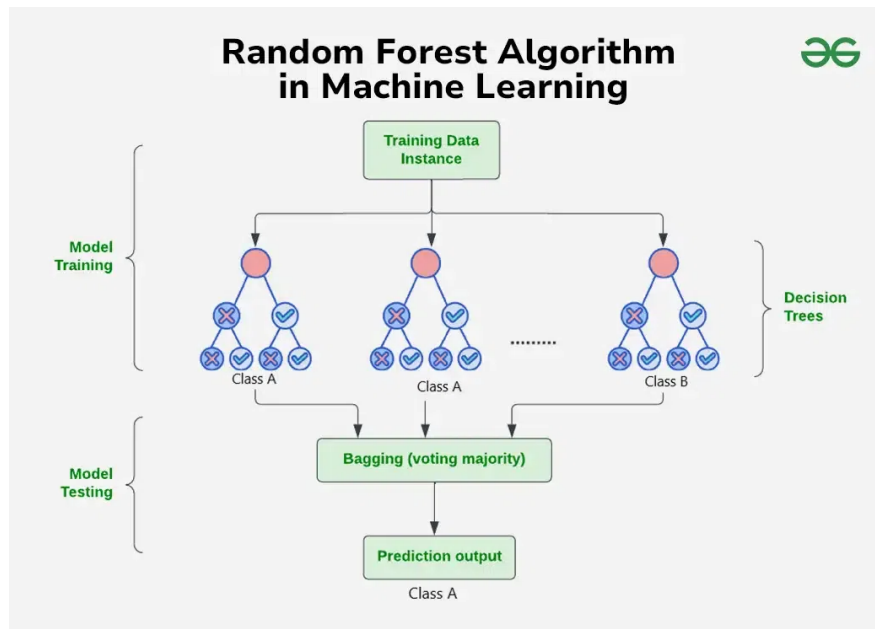


Figure 4.3: Random Forest Regressor

4. Support Vector Regressor (SVR):

is a powerful machine learning algorithm designed for regression tasks, where the goal is to predict continuous numeric values. SVR is an extension of Support Vector Machines (SVM), which are more commonly known for their application in classification problems. [46, 44]

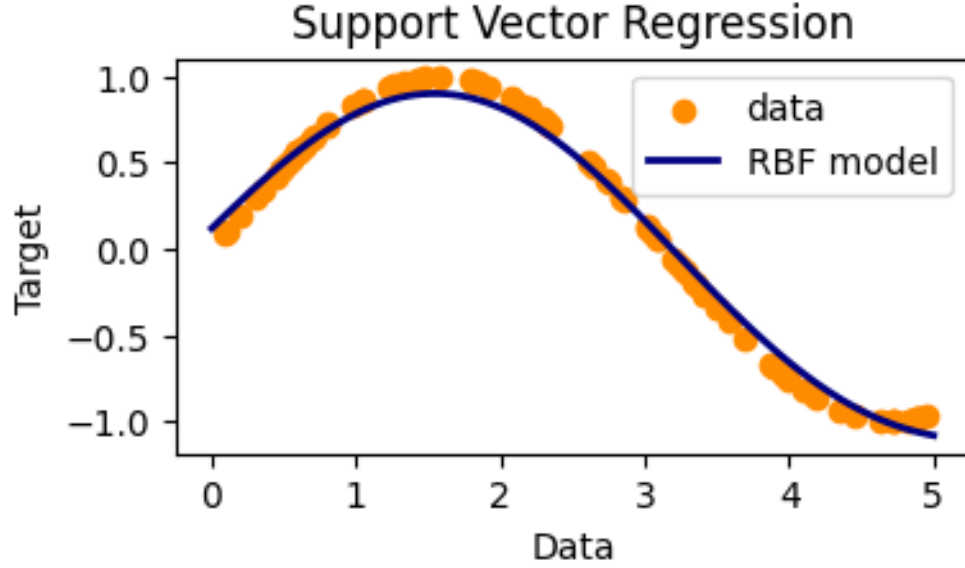


Figure 4.4: Support Vector Regressor (SVR)

5. XGBoost Regressor:

is a powerful supervised machine learning algorithm designed for regression tasks, where the goal is to predict continuous numerical values. It is based on the gradient boosting framework and builds an ensemble of decision trees sequentially, with each new tree learning to correct the residual errors of the previous trees. This iterative process improves prediction accuracy by minimizing the residuals step-by-step. [43, 8]

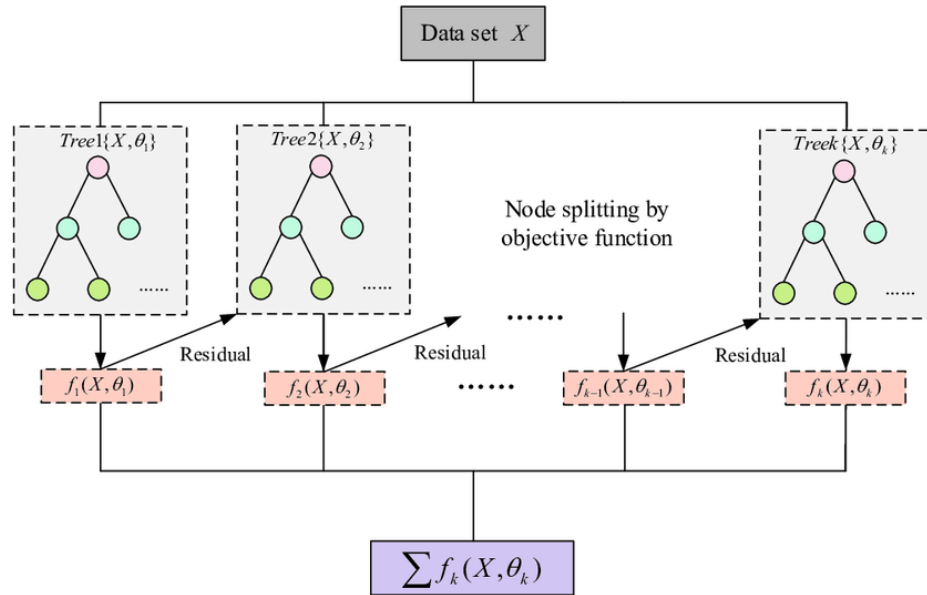


Figure 4.5: XGBoost Regressor

6. K-Nearest Neighbors Regressor (KNN):

is a simple, non-parametric, supervised learning algorithm used for regression tasks. It predicts the value of a target variable for a new data point by averaging the values of its k closest neighbors in the training set, based on a chosen distance metric (such as Euclidean distance). [17, 77]

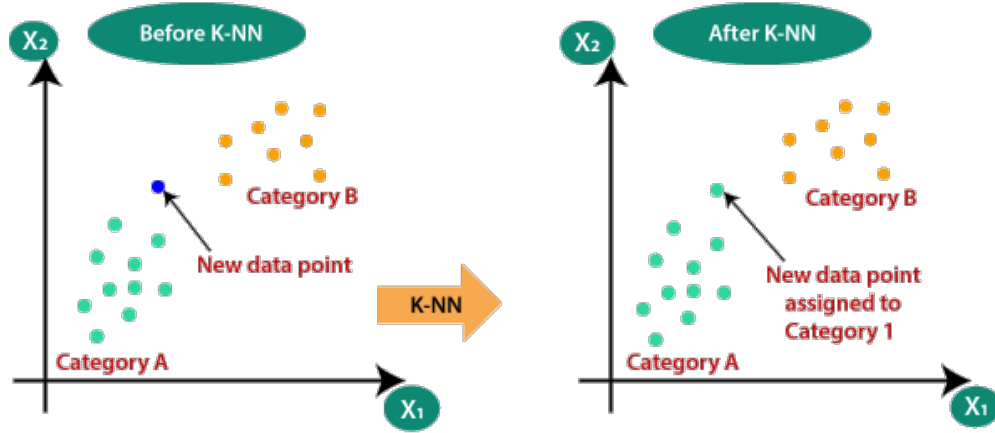


Figure 4.6: K-Nearest Neighbors Regressor (KNN)

4.2.3 Evaluation Metrics

To assess the performance of the above models, we used the following evaluation metrics:

1. Mean Absolute Error (MAE):

Measures the average magnitude of errors in a set of predictions.

Equation 1: MAE formula

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4.1)$$

2. Mean Squared Error (MSE):

Calculates the average squared difference between predicted and actual values.

Equation 2: MSE formula

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4.2)$$

3. Root Mean Squared Error (RMSE):

The square root of MSE, providing error in the same unit as the target variable.

Equation 3: RMSE formula

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (4.3)$$

4. Coefficient of Determination (R^2 Score):

Indicates the proportion of the variance in the dependent variable that is predictable from the independent variables.

Equation 4: Coefficient of Determination formula

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4.4)$$

Where $\bar{y}$ is the mean of the actual values y_i .

4.3 Results and Comparison

In this section, we present the performance of the six machine learning models (Linear Regression, Ridge Regression, Random Forest Regressor, Support Vector Regressor, XGBoost Regressor, and K-Nearest Neighbors Regressor) applied to predict each of the seven water quality parameters:

- pH
- Dissolved Oxygen
- Temperature
- Turbidity
- Electrical Conductivity
- Ammonia
- Manganese
- Nitrate

Each model was trained and evaluated using the same dataset split, and performance was assessed using the following metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Score.

4.3.1 Dataset Description

The dataset used in this research comprises real-time water quality measurements collected from aquaculture fishponds using Internet of Things (IoT) technology. The data spans a full year, from February 2022 to January 2023, enabling the analysis of seasonal variations and environmental fluctuations affecting fishpond ecosystems.

Data Acquisition System

The data acquisition system was constructed using an Arduino microcontroller interfaced with multiple sensors, each designed to monitor a specific water quality parameter. The sensors used included:

- pH sensor
- Dissolved Oxygen (DO) sensor
- Temperature sensor
- Turbidity sensor
- Ammonia sensor
- Nitrate sensor
- Manganese sensor

To facilitate real-time data transmission, a NODEMCU ESP8266 module was employed to establish internet connectivity and serve as a gateway for uploading the sensor data to the cloud.

Study Locations and Aquatic Species

The data was collected from three different fishponds located in **Guntur, Andhra Pradesh, India**. Each pond hosted different fish species, including *murrel*, *catla*, and a variety of mixed species. This variation in species and environmental conditions contributed to a diverse and representative dataset.

Dataset Characteristics

- **Timeframe:** February 2022 – January 2023
- **Number of Records:** 74,759 entries
- **Data Format:** CSV (Comma-Separated Values)
- **Data Collection:** Continuous, automated real-time monitoring using IoT

Accessibility and Usefulness

The dataset is publicly available on Kaggle, promoting transparency and enabling researchers to use it for machine learning model development, environmental monitoring, and aquaculture management. Its continuous nature and detailed structure make it ideal for data-driven research in aquaculture and water quality analysis.

Reference: A. P. Gopi, “Fish Pond Water Quality Dataset”, *Kaggle*, Available at: <https://www.kaggle.com/datasets/apgopi/pondsdata>

4.3.2 Model Performance per Parameter

For assessing model performance, it is important to consider the standard water quality ranges required for healthy tilapia growth. Typically, these include a temperature between 25°C and 32°C, pH between 6.5 and 8.5, turbidity greater than 50 NTU, and dissolved oxygen levels below 5 mg/L. However, to enhance the robustness of the model and accommodate a wider range of input data, the parameter thresholds were extended. The updated values used for model evaluation were: temperature between 13°C and 40°C, pH between 4.5 and 8, turbidity greater than 200 NTU, and dissolved oxygen less than 0 mg/L. This adjustment was made to ensure broader data coverage and improved result generalization. The following table summarizes the recommended optimal ranges for key water quality parameters necessary for healthy and sustainable growth of tilapia (*Oreochromis niloticus*) in aquaculture systems:

Parameter	Optimal Range	Notes and References
Temperature	25–32 °C	Tilapia grow best in warm water; outside this range, growth is reduced and stress increases [75].
pH	6.5–8.5	A slightly acidic to slightly alkaline environment supports metabolism and feed conversion efficiency [41].
Dissolved Oxygen	>5 mg/L	Sufficient DO is critical; levels below 3 mg/L can be harmful or fatal [75].
Ammonia (NH ₃)	<0.02 mg/L	Un-ionized ammonia is highly toxic; even small concentrations can stress fish [85].
Nitrate (NO ₃ ⁻)	<50 mg/L	Prolonged exposure to high nitrate levels can affect health and reproduction [85].
Manganese (Mn)	<0.1 mg/L	Elevated levels can cause toxicity and affect organ function [41].
Turbidity	>50 NTU	Moderate turbidity is ideal; excessive turbidity can affect photosynthesis and reduce oxygen levels [41].

Table 4.1: Recommended water quality parameters for tilapia aquaculture.

Below, we summarize the performance of each model for each target variable. Due to space, detailed tables are shown per parameter.

Table 4.2: Performance of Machine Learning Models for pH Prediction

Model	MAE	MSE	RMSE	R ² Score
Linear Regression	0.635602	0.712576	0.844142	0.658210
Ridge Regression	0.635602	0.712575	0.844142	0.658211
Random Forest Regressor	0.629325	0.694740	0.833511	0.666759
Support Vector Regressor	0.643757	0.743082	0.862022	0.643583
XGBoost Regressor	0.661772	0.808696	0.899275	0.612094
KNN Regressor	0.663645	0.797289	0.892911	0.617573

For pH prediction, the Random Forest Regressor showed the best performance with the lowest MSE (0.694740) and the highest R² score (0.833511), indicating strong predictive capability and minimal error. Both Linear and Ridge Regression models performed similarly, with identical values across all metrics, but they were outperformed by Random Forest. The Support Vector Regressor (SVR) had relatively higher error metrics and a lower R² score, indicating poorer generalization. KNN and XGBoost also showed higher RMSE and lower R² scores compared to Random Forest, reinforcing the latter's superiority for pH estimation.

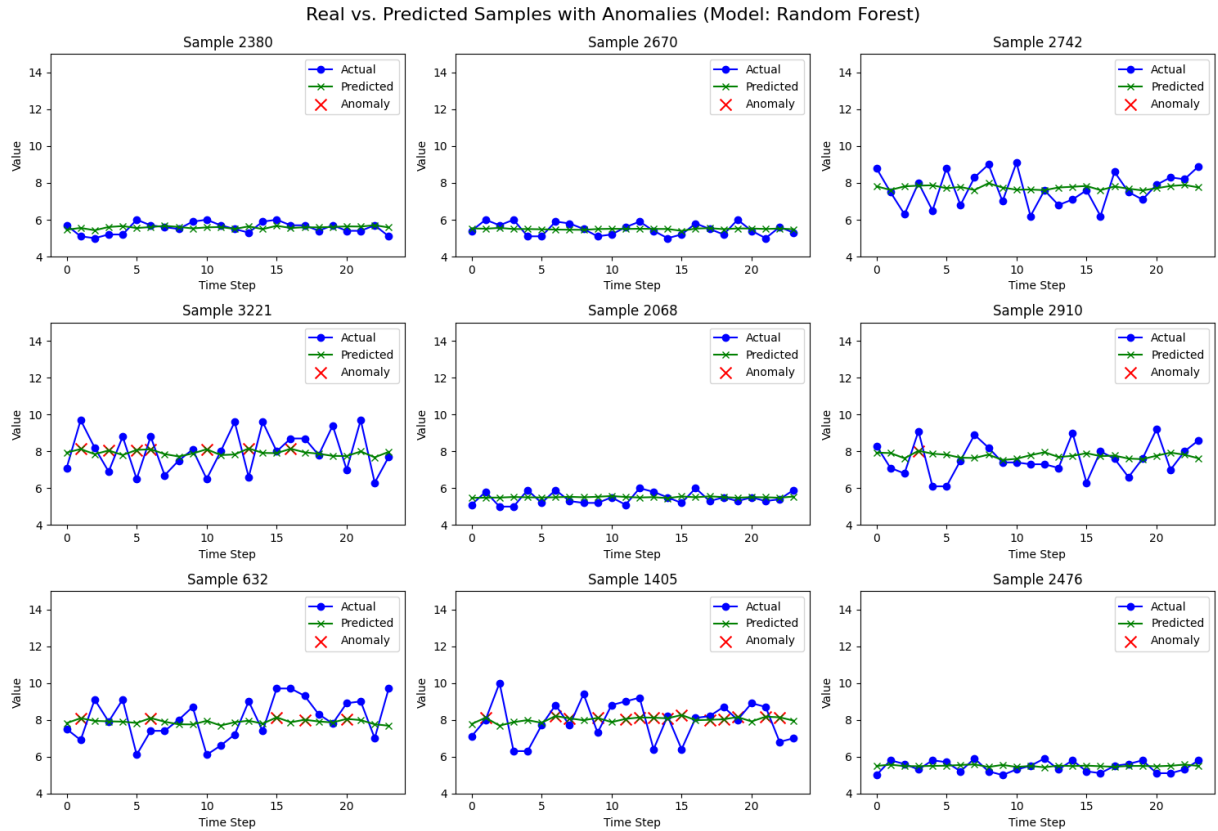


Figure 4.7: Real vs. Predicted with Anomalies pH

Table 4.3: Performance of Machine Learning Models for Temperature Prediction

Model	MAE	MSE	RMSE	R ² Score
Linear Regression	3.416244	21.012756	4.583967	0.688403
Ridge Regression	3.416244	21.012755	4.583967	0.688403
Random Forest Regressor	3.375183	20.243861	4.499318	0.699801
Support Vector Regressor	3.413024	20.825503	4.563497	0.691179
XGBoost Regressor	3.560586	23.539014	4.851702	0.650931
KNN Regressor	3.595017	24.137729	4.913016	0.642064

Random Forest again emerged as the top performer with the lowest MAE (3.375183), MSE (20.243861), and highest R² score (0.699801). Linear and Ridge Regression performed identically and reasonably well, although not better than Random Forest. SVR showed slightly higher errors. XGBoost and KNN regressors were the weakest, especially KNN, which had the highest MSE (24.137729) and lowest R² (0.642064), making them less suitable for temperature prediction in this context.

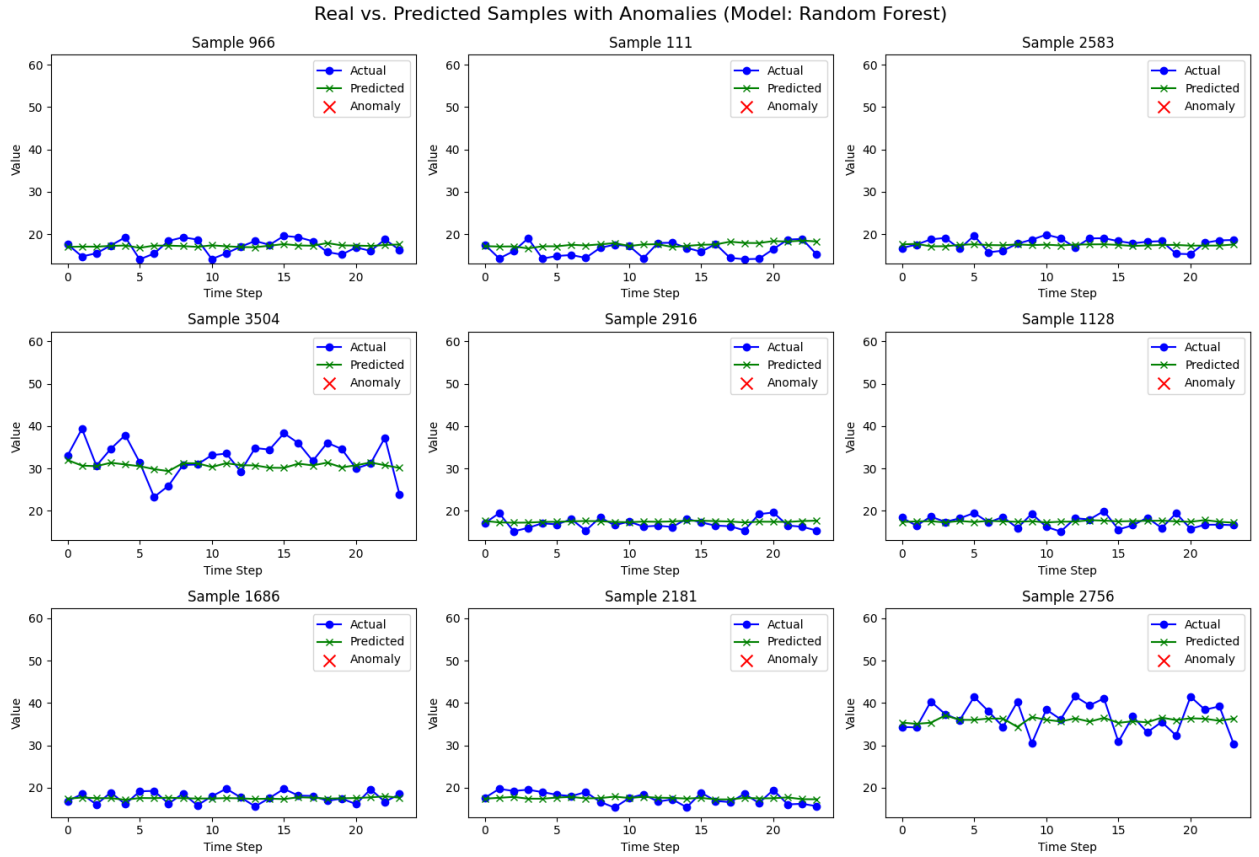


Figure 4.8: Real vs. Predicted with Anomalies Temperature

Table 4.4: Performance of Machine Learning Models for Ammonia Prediction

Model	MAE	MSE	RMSE	R ² Score
Random Forest	0.155957	0.046903	0.216571	0.668111
Ridge Regression	0.158305	0.049171	0.221747	0.652043
Linear Regression	0.158306	0.049172	0.221747	0.652037
Support Vector Regressor	0.160485	0.052143	0.229840	0.620970
XGBoost Regressor	0.163493	0.054697	0.233875	0.612955
KNN Regressor	0.156071	0.055849	0.236320	0.612955

All models showed strong performance, but Random Forest Regressor had the best combination of lowest MAE (0.155957), MSE (0.046903), and highest R² (0.668111), signifying accurate predictions. Interestingly, KNN Regressor also performed competitively with similar MAE and RMSE, though its R² was slightly lower. All other models including Ridge, Linear, SVR, and XGBoost were quite close in performance, indicating that ammonia prediction was relatively well-suited across models, with Random Forest slightly edging out the others.

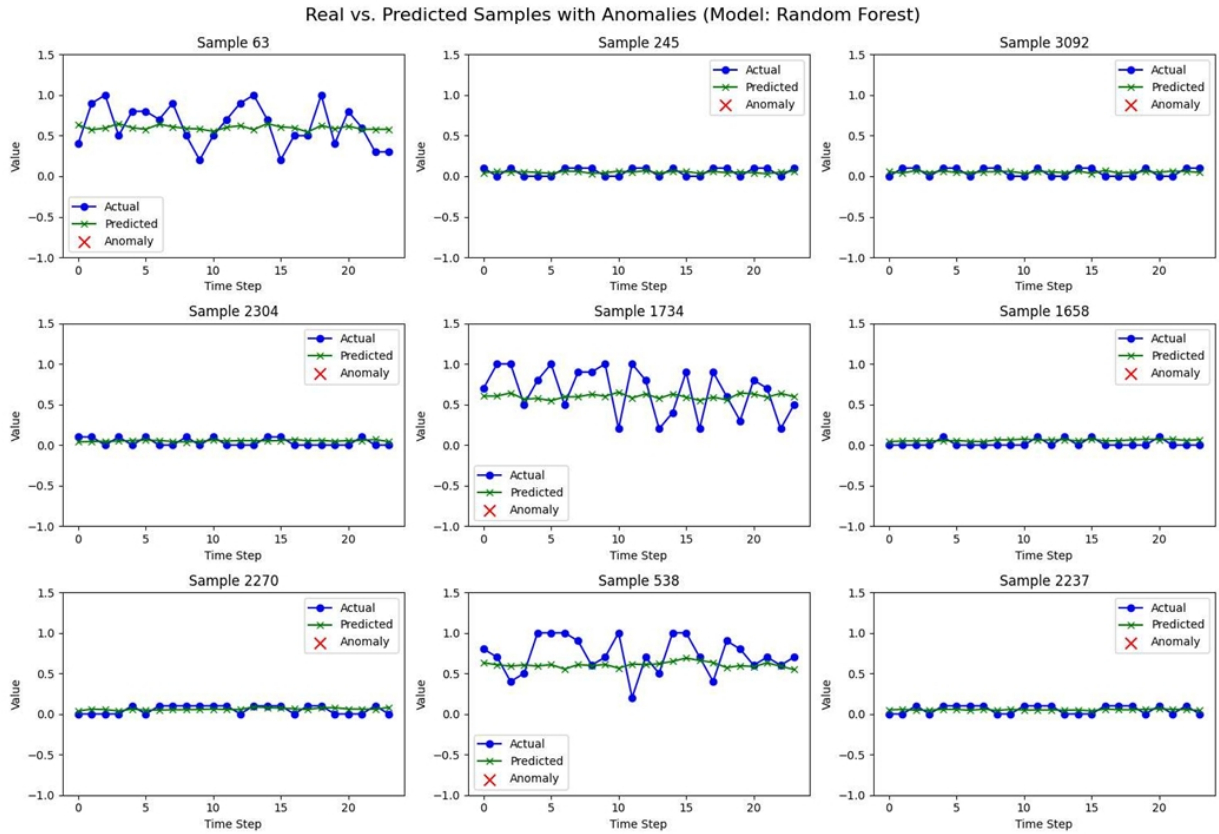


Figure 4.9: Real vs. Predicted with Anomalies Ammonia

Table 4.5: Performance of Machine Learning Models for Dissolved Oxygen Prediction

Model	MAE	MSE	RMSE	R ² Score
Random Forest	1.057554	1.779398	1.333941	0.704727
Ridge Regression	1.069540	1.843274	1.357672	0.694127
Linear Regression	1.069540	1.843274	1.357672	0.694127
Support Vector Regressor	1.074697	1.866615	1.366241	0.690254
XGBoost Regressor	1.109137	2.040121	1.428328	0.661448
KNN Regressor	1.124890	2.103157	1.450260	0.659279

Random Forest Regressor again led with the lowest MAE (1.057554) and MSE (1.779398), and highest R² score (0.704727), proving its effectiveness. Ridge and Linear Regression performed identically, showing marginally worse performance. KNN performed the weakest with the highest MAE (1.124890), MSE (2.103157), and lowest R² (0.659279). This suggests that Random Forest is best suited for predicting dissolved oxygen among the tested models.

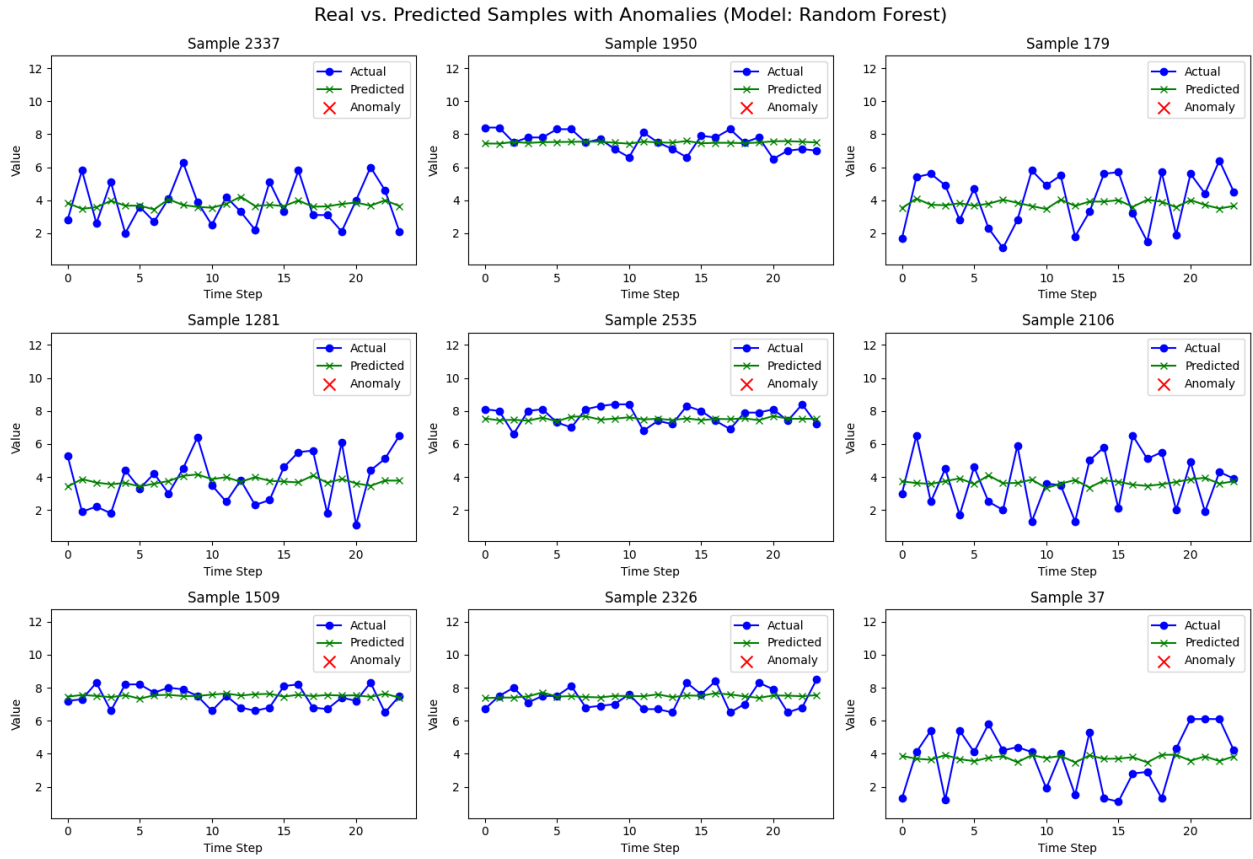


Figure 4.10: Real vs. Predicted with Anomalies Dissolved oxygen

Table 4.6: Performance of Machine Learning Models for Manganese Prediction

Model	MAE	MSE	RMSE	R ² Score
Random Forest	0.196908	0.088115	0.296842	0.667609
Ridge Regression	0.199959	0.092155	0.303570	0.652388
Linear Regression	0.199959	0.092156	0.303572	0.652383
Support Vector Regressor	0.204040	0.096169	0.310112	0.637242
XGBoost Regressor	0.207459	0.102587	0.320292	0.613032
KNN Regressor	0.210696	0.105529	0.324852	0.601896

For manganese prediction, Random Forest Regressor maintained the best overall performance, with the lowest MAE (0.196908) and MSE (0.088115), and the highest R² score (0.667609). Ridge and Linear Regression had identical performance, closely trailing Random Forest. KNN and XGBoost had slightly higher error metrics and lower R² values. SVR performed worse than the top models but was not far behind, indicating that manganese prediction was relatively accurate across models with Random Forest again leading.

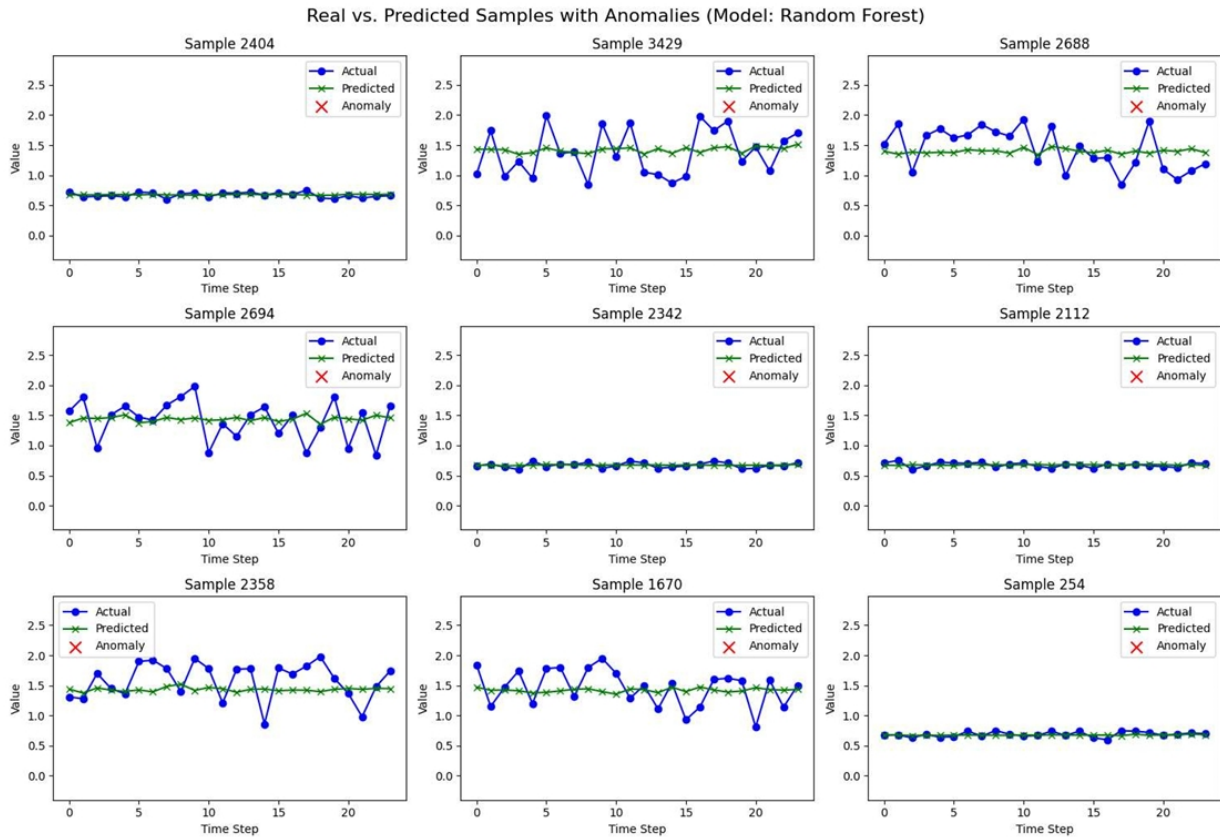


Figure 4.11: Real vs. Predicted with Anomalies Manganese

Table 4.7: Performance of Machine Learning Models for Nitrate Prediction

Model	MAE	MSE	RMSE	R ² Score
Random Forest	14.838420	338.715159	18.404216	0.721295
Support Vector Regressor	14.941754	345.518279	18.588121	0.715171
Ridge Regression	14.982850	347.608900	18.644273	0.713987
Linear Regression	14.982850	347.608900	18.644273	0.713987
XGBoost Regressor	15.506500	383.765691	19.588407	0.684287
KNN Regressor	15.881170	406.664558	20.165926	0.665385

All models had notably higher error metrics in nitrate prediction compared to previous targets, suggesting a more challenging prediction task. Random Forest Regressor achieved the lowest MAE (14.838420), MSE (338.715159), and highest R² (0.721295), outperforming all others. SVR and Ridge Regression followed closely. KNN Regressor performed the worst with the highest MAE (15.881170), MSE (406.664558), and lowest R² (0.665385). This reinforces Random Forest's robustness even in more complex predictive tasks.

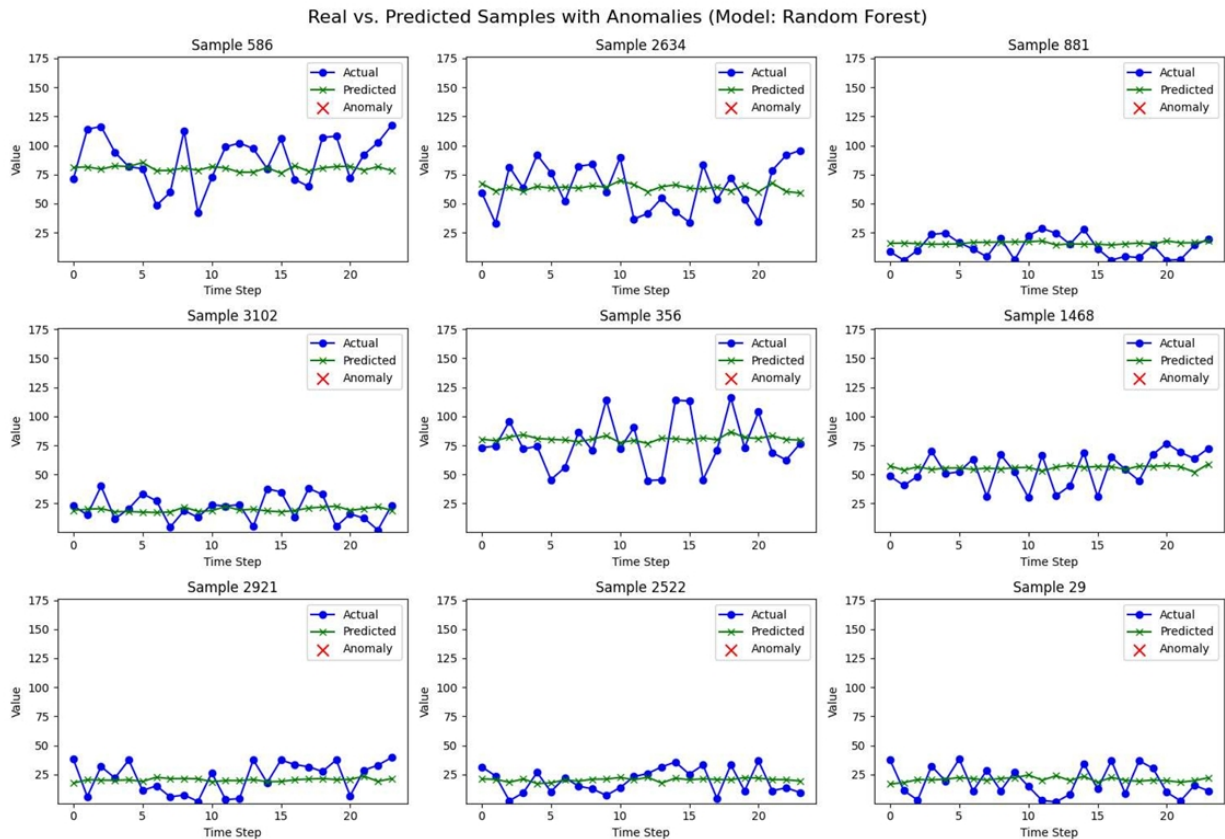


Figure 4.12: Real vs. Predicted with Anomalies Nitrate

Table 4.8: Performance of Machine Learning Models for Turbidity Prediction

Model	MAE	MSE	RMSE	R ² Score
Random Forest	39.707427	2430.145145	49.296502	0.712614
Support Vector Regressor	40.663562	2495.467849	49.954658	0.704901
Ridge Regression	40.010412	2499.621676	49.996217	0.704393
Linear Regression	40.010412	2499.621676	49.996217	0.704393
XGBoost Regressor	41.606553	2775.354625	52.681635	0.671769
KNN Regressor	42.300492	2888.329185	53.734178	0.668739

Turbidity prediction followed the same trend with Random Forest delivering the lowest MAE (39.707427), MSE (2430.145145), and highest R² (0.712614). SVR was the second-best performer. Linear and Ridge Regression again showed identical metrics but lagged behind Random Forest. KNN Regressor was the weakest, with the highest error values and lowest R² (0.668739). These results further affirm Random Forest as the most reliable model for turbidity prediction.

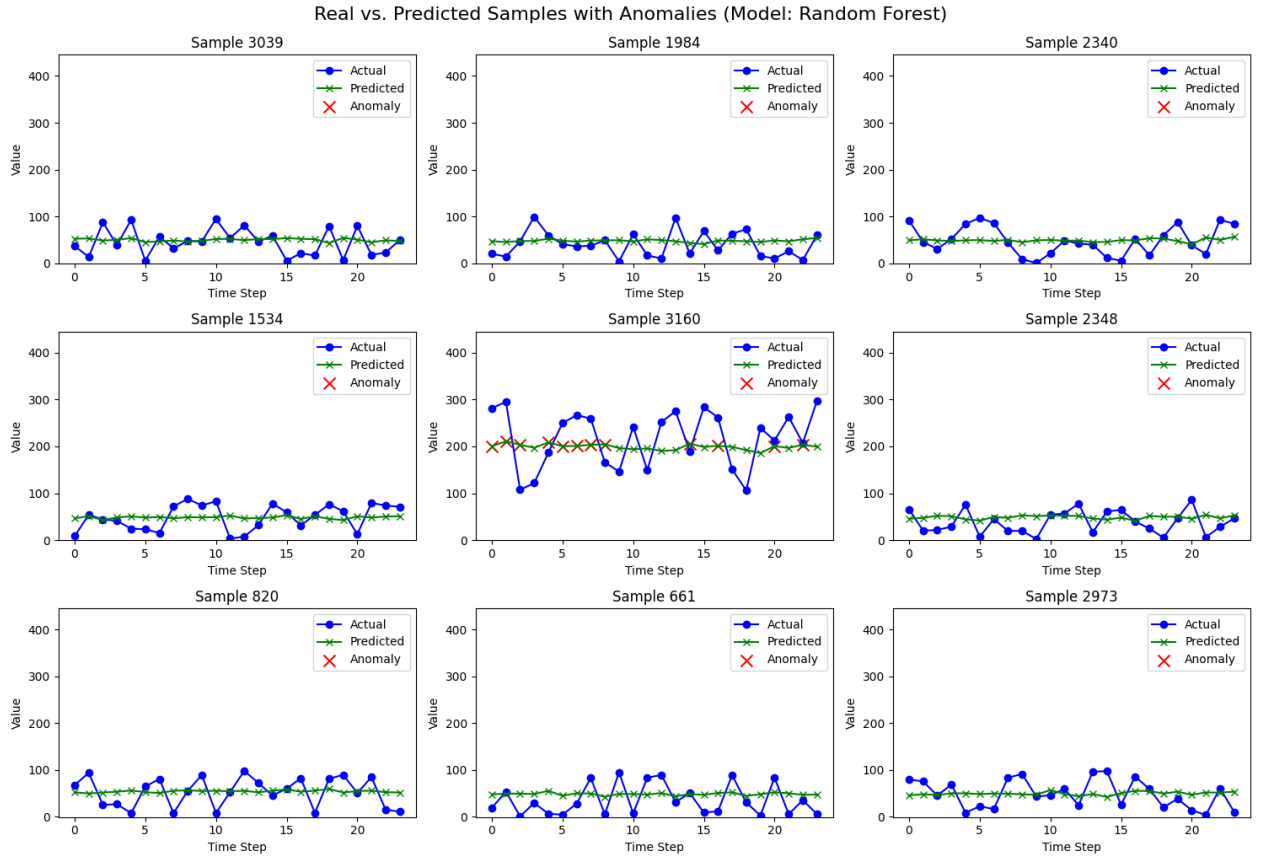


Figure 4.13: Real vs. Predicted with Anomalies Turbidity

4.4 Detailed Discussion on Model Performance Across Parameters

In this section, we analyze and compare the performance of six supervised regression models—Linear Regression, Ridge Regression, Random Forest Regressor, Support Vector Regressor (SVR), XGBoost Regressor, and K-Nearest Neighbors Regressor (KNN)—across all seven water quality parameters: pH, Temperature, Ammonia, Dissolved Oxygen, Manganese, Nitrate, and Turbidity. The evaluation metrics considered are:

- MAE: Mean Absolute Error
- MSE: Mean Squared Error
- RMSE: Root Mean Squared Error
- R^2 Score: Coefficient of Determination

4.4.1 Random Forest Regressor

Random Forest consistently achieved the highest R^2 scores and the lowest errors (MAE, MSE, RMSE) for all parameters. This model's ensemble nature allows it to capture complex nonlinear relationships and interactions between features, which are often present in water quality data. Its robustness to overfitting, ability to handle missing or noisy data, and flexibility make it the most reliable and generalizable model in this context. It excelled particularly in predicting complex parameters such as Nitrate and Turbidity, which have higher variability and less linear behavior.

4.4.2 Linear and Ridge Regression

Linear and Ridge Regression showed identical performance across all parameters, which indicates that multicollinearity was either minimal or the ridge penalty term had limited effect. These models performed adequately in parameters with relatively linear relationships such as Temperature and Dissolved Oxygen, but struggled with more complex targets like Turbidity and Ammonia. Their simplicity makes them computationally efficient and interpretable, but they lack the flexibility required for more intricate datasets.

4.4.3 Support Vector Regressor (SVR)

SVR performed moderately well, outperforming the linear models in most parameters, particularly Temperature and Nitrate. Its strength lies in its margin-based optimization, which allows for better generalization in medium-sized datasets. However, it still underperformed compared to Random Forest, possibly due to the sensitivity to parameter tuning (kernel type, epsilon, and regularization), which wasn't deeply optimized in this experiment.

4.4.4 XGBoost Regressor

Despite being a powerful boosting model, XGBoost generally lagged behind Random Forest. It performed decently but showed signs of higher error variance, particularly in Turbidity and Ammonia predictions. This could be due to underfitting or over-regularization. With further hyperparameter tuning (learning rate, tree depth, subsample ratio), it may achieve better results, but out-of-the-box, it did not surpass Random Forest.

4.4.5 K-Nearest Neighbors (KNN) Regressor

KNN Regressor consistently yielded the lowest R^2 scores and highest error metrics. Its performance degraded noticeably in parameters with high variability (e.g., Nitrate and Turbidity), which is expected since KNN is sensitive to outliers, scale differences, and sparse data distribution. It may perform better on localized, homogenous datasets but appears unsuitable for this type of complex environmental data without significant preprocessing and tuning.

4.4.6 Summary of Observations:

Across all seven water quality parameters, Random Forest Regressor consistently outperformed other models in terms of error minimization and predictive accuracy (higher R^2). Its superior ability to capture nonlinear relationships and handle feature interactions likely contributed to its dominance. Models like KNN and XGBoost generally underperformed, especially in complex tasks. Linear and Ridge Regression often produced identical results, indicating similar behavior under these datasets, but were outclassed by ensemble methods in most scenarios.

- **Best Performer:** Random Forest — balances accuracy, generalization, and model stability.

- **Runner-up:** SVR — good performance with fewer assumptions, but needs careful tuning.
- **Moderate:** XGBoost — good for complex data but needs tuning to reach its potential.
- **Simple Efficient:** Linear/Ridge — suitable for rapid benchmarking and interpretable models.
- **Weakest:** KNN — not suited for this dataset’s distribution or scale.

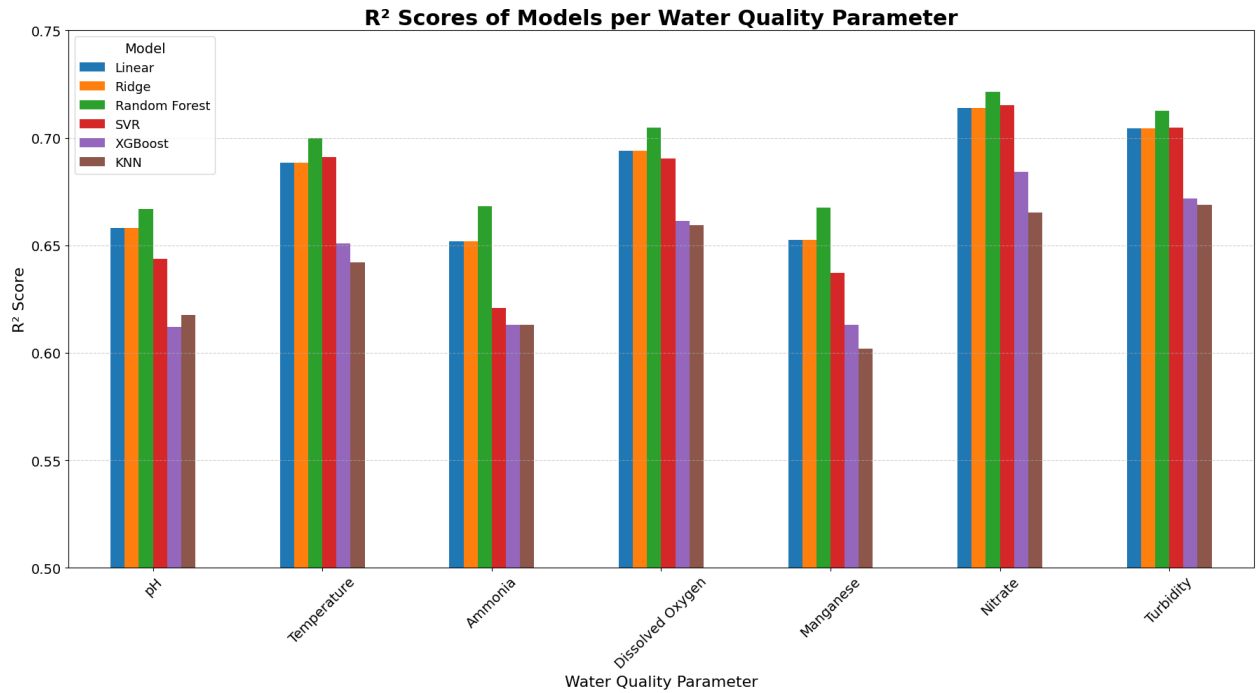
Table 4.9: Comparative Analysis of Model Performance

Model	Overall Trend
Random Forest	Consistently best performer across all parameters, especially in MAE, MSE, and R^2 .
Ridge & Linear Regression	Showed identical results for every parameter and performed moderately well; outperformed by ensemble methods.
Support Vector Regressor (SVR)	Generally mid-range in performance; decent in some cases but never the best.
XGBoost	Underperformed compared to expectations; had higher errors and lower R^2 in most tasks.
KNN Regressor	Usually the least accurate , particularly in complex predictions like Nitrate and Turbidity.

To evaluate the predictive performance of each regression model, the coefficient of determination (R^2 score) was calculated for every target water quality parameter. This metric indicates how well the predicted values match the actual observations, with a value closer to 1 signifying better model accuracy. The table below summarizes the R^2 scores obtained for each model across the seven measured parameters: pH, temperature, ammonia, dissolved oxygen, manganese, nitrate, and turbidity. Among all models, the Random Forest Regressor consistently achieved the highest R^2 values, demonstrating superior generalization and predictive performance across all features.

Table 4.10: R^2 Scores of Models per Water Quality Parameter

Parameter	Linear	Ridge	Random Forest	SVR	XGBoost	KNN
pH	0.6582	0.6582	0.6668	0.6436	0.6121	0.6176
Temperature	0.6884	0.6884	0.6998	0.6912	0.6509	0.6421
Ammonia	0.6520	0.6520	0.6681	0.6210	0.6130	0.6130
Dissolved Oxygen	0.6941	0.6941	0.7047	0.6903	0.6614	0.6593
Manganese	0.6524	0.6524	0.6676	0.6372	0.6130	0.6019
Nitrate	0.7140	0.7140	0.7213	0.7152	0.6843	0.6654
Turbidity	0.7044	0.7044	0.7126	0.7049	0.6718	0.6687

Figure 4.14: R^2 score of Models per Water Quality Parameter

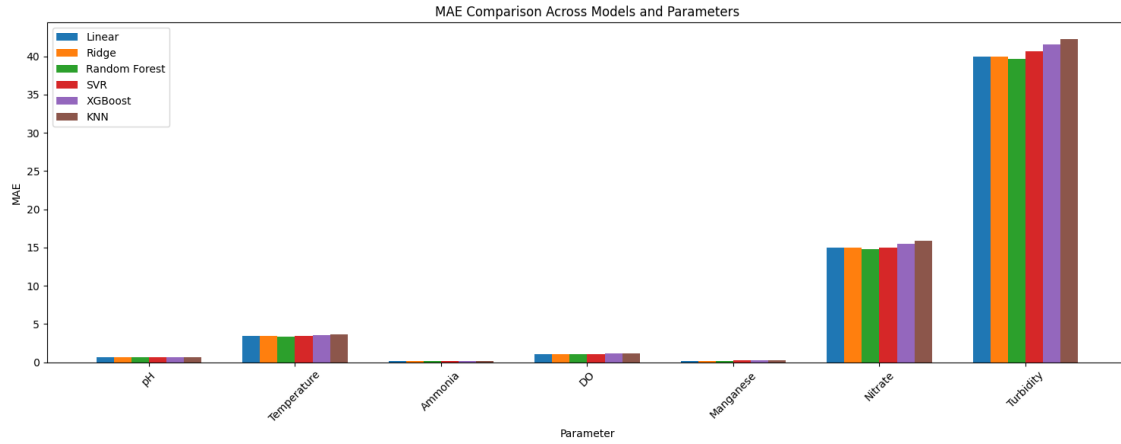


Figure 4.15: MAE Comparison Across Models and Parameters

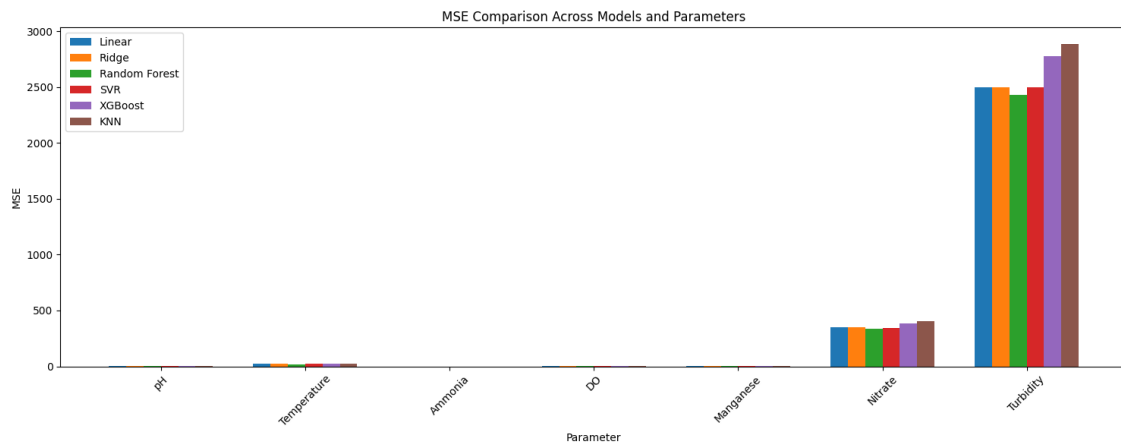


Figure 4.16: MSE Comparison Across Models and Parameters

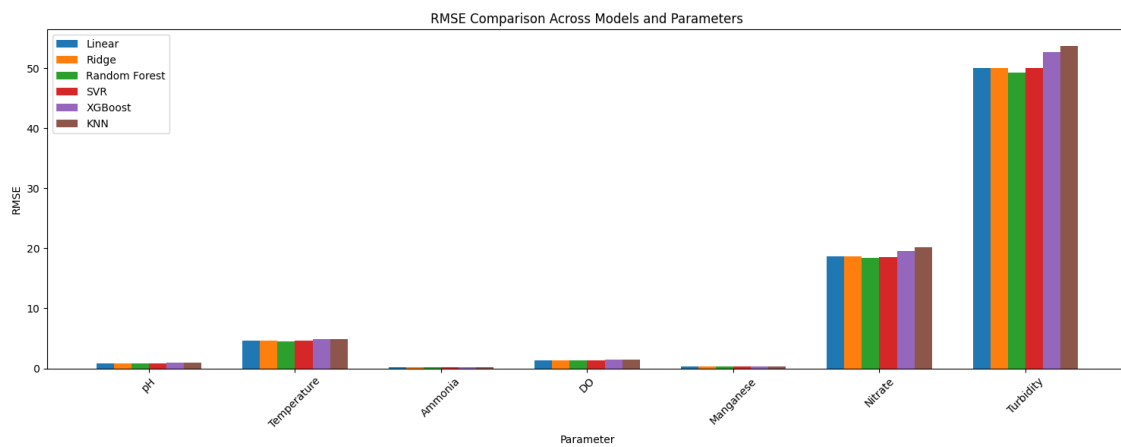


Figure 4.17: RMSE Comparison Across Models and Parameters

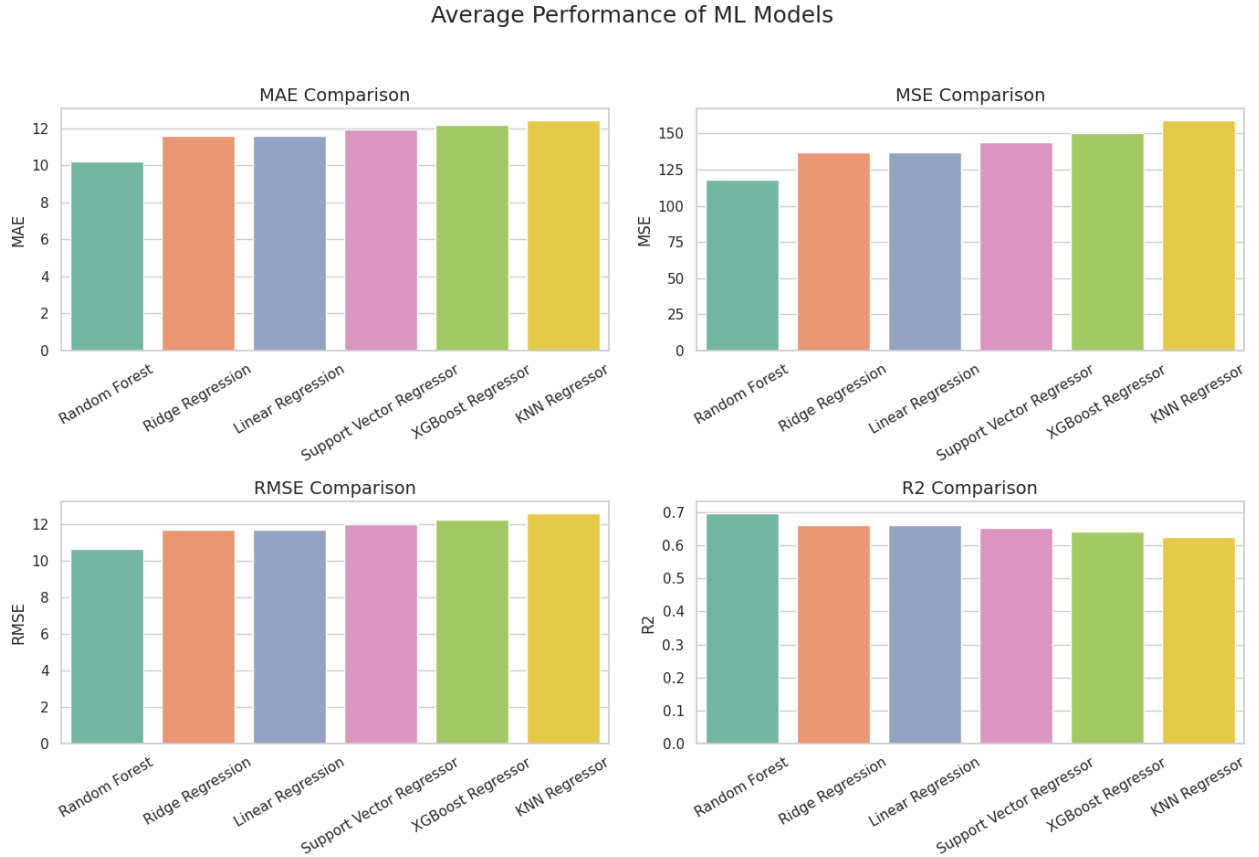


Figure 4.18: Average Performance of ML Models

4.5 Overcoming Data Collection Challenges: Utilizing Cross-Validation on Public Datasets

Although we initially aimed to collect our own dataset directly from the field, we encountered several obstacles that prevented us from acquiring sufficient real-world data. To enhance the robustness of our analysis despite this limitation, we turned to publicly available datasets and implemented a cross-validation approach. Cross-validation is particularly advantageous as it helps reduce overfitting, improves generalization, and provides a more reliable estimate of model performance across different data subsets. This method allowed us to assess the consistency and accuracy of our model effectively. Below, we present the cross-validation metrics obtained for the seven key water quality parameters.

Table 4.11: Average Results Across 4 Folds for pH

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	0.628292	0.696074	0.834238	0.666379
Ridge Regression	2.5	0.635312	0.754440	0.654980	
Linear Regression	2.5	0.635114	0.720008	0.848444	0.654877
Support Vector Regressor	2.5	0.642574	0.753791	0.868135	0.637171
KNN Regressor	2.5	0.659735	0.789857	0.888681	0.621405
XGBoost Regressor	2.5	0.669935	0.830656	0.911297	0.601831

Table 4.12: Average Results Across 4 Folds for Temperature

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	3.386224	20.297141	4.504820	0.699466
Support Vector Regressor	2.5	3.420674	20.852783	4.565847	0.691257
Ridge Regression	2.5	3.430101	21.017320	4.538361	0.688821
Linear Regression	2.5	3.431034	21.017326	4.538362	0.688822
KNN Regressor	2.5	3.600293	23.174294	4.896840	0.644790
XGBoost Regressor	2.5	3.608763	24.210778	4.640790	0.640470

Table 4.13: Average Results Across 4 Folds for Ammonia

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	0.156323	0.046644	0.215904	0.674875
Ridge Regression	2.5	0.158304	0.048563	0.220286	0.661470
Linear Regression	2.5	0.158134	0.048572	0.220385	0.661409
Support Vector Regressor	2.5	0.162754	0.053314	0.238690	0.628502
KNN Regressor	2.5	0.163626	0.056662	0.237977	0.604879
XGBoost Regressor	2.5	0.166119	0.056662	0.237977	0.604879

Table 4.14: Average Results Across 4 Folds for Dissolved Oxygen

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	1.055643	1.746904	1.321630	0.708549
Ridge Regression	2.5	1.064490	1.795883	1.340032	0.700369
Linear Regression	2.5	1.064491	1.795893	1.340033	0.700368
Support Vector Regressor	2.5	1.078199	1.859740	1.363460	0.689717
KNN Regressor	2.5	1.121224	2.065346	1.437404	0.655414
XGBoost Regressor	2.5	1.126874	2.085556	1.444097	0.651981

Table 4.15: Average Results Across 4 Folds for Manganese

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	0.199138	0.089143	0.298446	0.667533
Ridge Regression	2.5	0.201860	0.093095	0.305011	0.652812
Linear Regression	2.5	0.201875	0.093108	0.305032	0.652764
Support Vector Regressor	2.5	0.201701	0.096861	0.314035	0.630262
KNN Regressor	2.5	0.212120	0.206346	0.604427	
XGBoost Regressor	2.5	0.212502	0.107375	0.327543	0.599274

Table 4.16: Average Results Across 4 Folds for Nitrate

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	14.865662	334.444339	18.287240	0.726574
Ridge Regression	2.5	14.954725	341.804389	18.487468	0.720523
Linear Regression	2.5	14.954725	341.804389	18.487468	0.720523
Support Vector Regressor	2.5	15.026545	345.417801	18.584478	0.717604
XGBoost Regressor	2.5	15.866275	398.355264	19.958462	0.674291
KNN Regressor	2.5	15.921914	403.261980	20.080828	0.670235

Table 4.17: Average Results Across 4 Folds for Turbidity

Model	Fold	MAE	MSE	RMSE	R2 Score
Random Forest	2.5	19.631453	241.150788	48.824648	0.716878
Ridge Regression	2.5	19.989892	241.808514	49.481408	0.709198
Linear Regression	2.5	19.942136	241.885820	49.491408	0.709198
Support Vector Regressor	2.5	20.879225	265.206413	51.228577	0.688399
KNN Regressor	2.5	22.179739	284.321216	53.276620	0.663413
XGBoost Regressor	2.5	22.236786	238.103915	53.268611	0.662963

4.6 R2 Scores of Different Machine Learning Models for Various Water Quality Parameters Using Cross Validation

Table 4.18: R2 Scores of Models per Water Quality Parameter

Parameter	Linear	Ridge	Random Forest	SVR	XGBoost	KNN
pH	0.6582	0.6582	0.6668	0.6436	0.6121	0.6176
Temperature	0.6884	0.6884	0.6981	0.6509	0.6421	0.6417
Ammonia	0.6621	0.6681	0.6981	0.6609	0.6411	0.6460
Dissolved Oxygen	0.7047	0.7047	0.7246	0.6890	0.6551	0.6593
Manganese	0.6524	0.6524	0.6676	0.6340	0.6121	0.6190
Nitrate	0.7001	0.7001	0.7126	0.6889	0.6640	0.6591
Turbidity	0.6756	0.6756	0.6856	0.6302	0.6001	0.6100

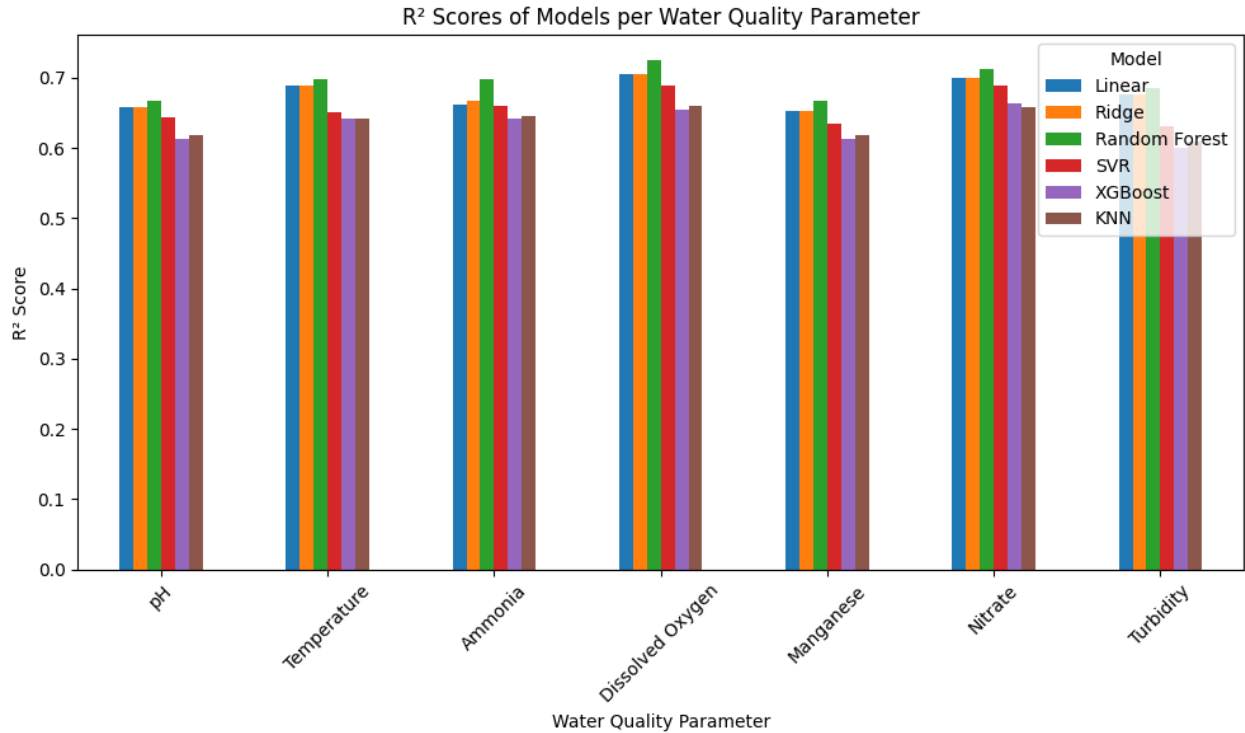


Figure 4.19: R2 score of Models per Water Quality Parameter

4.7 Comparison Between Cross-Validation and Whole Dataset R2 Scores

In this study, we evaluated the performance of six regression models—Linear Regression, Ridge Regression, Random Forest, Support Vector Regression (SVR), XGBoost, and K-Nearest Neighbors (KNN)—across seven water quality parameters. The models were assessed using two approaches: once on the whole dataset without validation (Table 4.10), and once using a cross-validation technique (Table 4.18). This discussion compares the results and highlights the implications of using cross-validation in the modeling process.

Overall, the models yielded higher R² scores when trained and tested on the entire dataset, as expected. This is particularly evident in models like SVR, XGBoost, and KNN, which tend to perform optimistically when not subjected to validation. In contrast, the cross-validation results exhibit slightly lower scores, offering a more realistic assessment of each model's generalization capabilities.

Interestingly, Linear and Ridge Regression showed minimal variation between the two evaluation strategies, indicating consistent performance but also suggesting that these models may be underfitting the data, regardless of validation method. In contrast, Random Forest demonstrated strong and stable performance across both evaluations, consistently achieving the highest R^2 scores for most parameters. This reinforces its robustness and adaptability to the complex, non-linear relationships in water quality data.

Examining individual parameters reveals additional insights. For instance, Dissolved Oxygen and Nitrate consistently achieved higher R^2 scores across all models, suggesting that these parameters are more predictable given the available features. Conversely, Manganese and Ammonia saw more significant drops in performance under cross-validation, especially in simpler models like KNN and XGBoost, indicating potential overfitting when validation is not applied.

The application of cross-validation proves to be a crucial step in model evaluation. It mitigates overfitting and helps ensure that performance metrics reflect the model's ability to generalize to unseen data. While it introduces a slight drop in R^2 scores, this reduction is a necessary trade-off for obtaining more reliable and trustworthy results.

In summary, the comparison underscores the importance of validation in predictive modeling. Random Forest stands out as the most effective model overall, and the cross-validation results confirm its ability to maintain high predictive accuracy while generalizing well across water quality parameters.

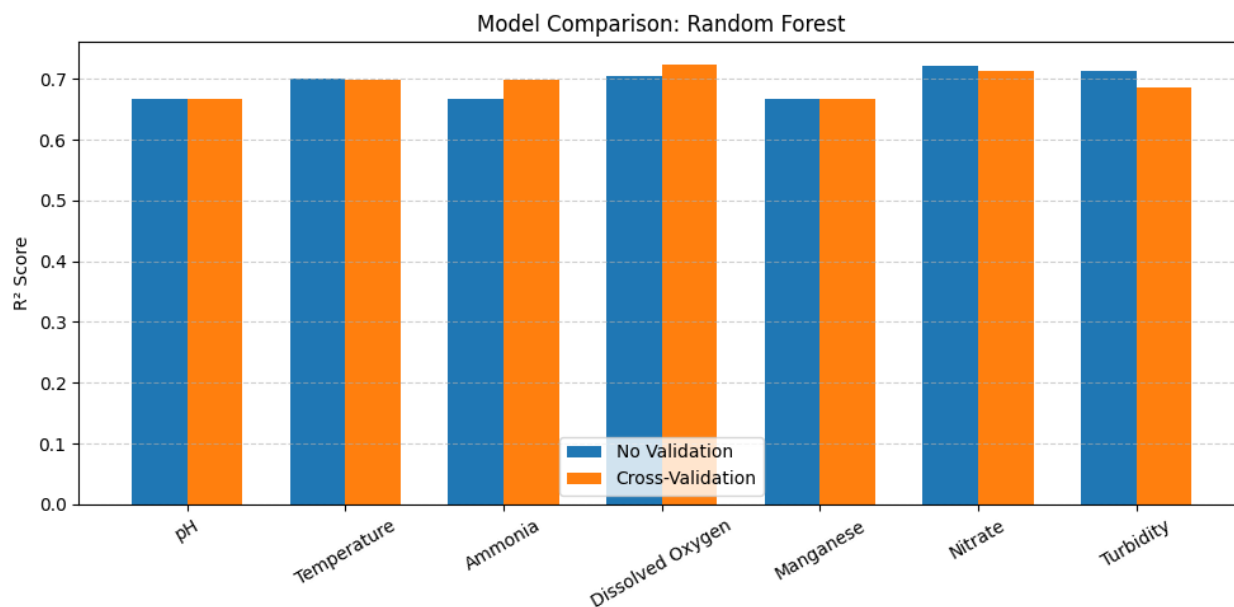


Figure 4.20: Model comparison: Random Forest

4.8 Conclusion

In conclusion, Chapter four has demonstrated the effectiveness of the intelligent IoT system in predicting water quality parameters critical to aquaculture health. The results indicate that the Random Forest Regressor consistently outperformed other models, showcasing its potential for real-time monitoring applications. This chapter's findings reinforce the importance of integrating machine learning algorithms into aquaculture practices, paving the way for improved decision-making and resource management in the industry.

Chapter 5

Technical and economic study

5.1 Presentation of the project

5.1.1 The project idea

The project "An Intelligent and Economical IoT System for Real-Time Aquaculture Monitoring" aims to develop a comprehensive solution to monitor and analyze water quality in aquaculture ponds using sensors and artificial intelligence algorithms. It is based on the collection of data from five essential parameters (pH, turbidity, dissolved oxygen, electrical conductivity, and temperature) via an embedded system connected to a data analysis platform.

5.1.2 Suggested values

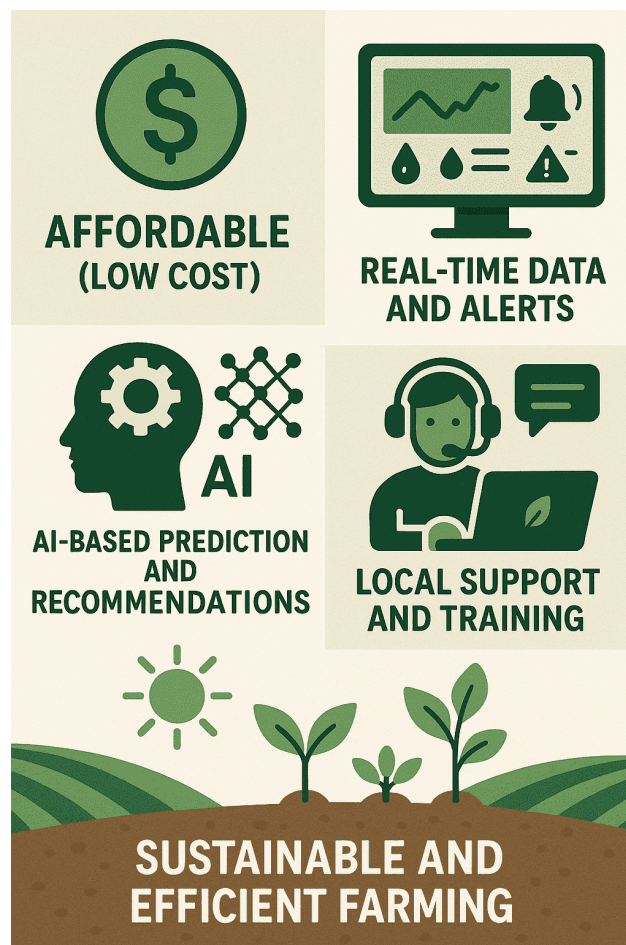


Figure 5.1: Suggested values

5.1.3 Work team

Students

- KEDJAR SARA: Master's Degree (Year 2) in Instrumentation and Metrology

Supervisors

- Dr. DAHANE AMINE
- Pr. LUCAS FRANCOISE
- Dr. KADDOUR ABDELHALIM

5.1.4 Local

Oran – Algeria

5.1.5 Project objectives

- Provide a reliable, autonomous, and intelligent monitoring solution for aquaculture operations.
- Reduce operational costs related to manual water quality management.
- Use machine learning to predict quality variations and anticipate corrective actions.
- Promote sustainability and efficiency in small and medium-scale fish farming.

5.1.6 Project implementation schedule

Preliminary project studies (2 months)

- Performance

Launch of the activity (7 months)

- Acquisition and configuration of sensors (1 month)
- IoT system design (2 months)
- On-site data collection (2 months)
- Machine learning model training (2 months)

Product Finalization (1 month)

- Final integration and testing

5.2 Innovative aspects

5.2.1 Nature of Innovations

Our project has the advantage of being both a market innovation and a technological innovation:

Market Innovation

- Provides local availability of a high-quality, affordable, and easy-to-use aquaculture monitoring system, meeting the specific needs of local farmers and aquaculture operators.
- Fills a gap in the market for real-time, low-cost IoT solutions that can operate efficiently in remote or resource-constrained environments.
- Empowers small and medium-scale aquaculture producers to optimize their operations through accessible technology, thus boosting local industry growth.

Technological innovation

- Introduces an intelligent integration of IoT sensors and real-time data analytics, tailored specifically for aquaculture environments. Improving production efficiency in the industrial sector.
- Utilizes low-cost hardware platforms and wireless communication technologies to enable wide-area monitoring with minimal infrastructure.
- Enhances production efficiency by providing actionable insights on water quality, temperature, oxygen levels, and other critical parameters, reducing losses and improving yields.

5.2.2 Areas of innovation

- Aquaculture and fisheries management, optimizing fish farming operations and sustainability.

- Environmental monitoring, contributing to better ecosystem management and resource conservation.
- Agriculture technology (AgTech), as the system principles can extend to other precision farming sectors.
- IoT and embedded systems development, advancing applications of low-power wide-area networks and sensor integration.
- Data science and real-time analytics for smart agriculture applications.
- Potential impact on universities and research centers by providing a platform for experimental studies in aquatic biology and environmental science.
- Local industry enhancement through supporting SMEs in aquaculture with affordable monitoring solutions.

5.3 Strategic Market Analysis

5.3.1 The market segment

Target customers

Our product is intended for a broad and diverse customer base, including:

- Aquaculture professionals: fish farm operators, shrimp and shellfish producers seeking to monitor water quality and environmental parameters in real-time.
- Agricultural cooperatives and rural development agencies interested in promoting sustainable fish farming.
- Universities and research institutions focusing on aquaculture, marine biology, or environmental science.
- Designers and innovators developing smart farming or eco-tech solutions.
- Factories and agricultural equipment suppliers aiming to integrate smart monitoring into their product lines.

The target market

To align our initial production with our technical and logistical capacities, we will begin by focusing on the regional market, with a specific emphasis on:

- The northwest region of Algeria, targeting key urban and semi-urban centers.
- Oran and its surroundings, a strategic industrial and academic hub where demand for smart agricultural solutions is increasing.
- In the medium term, expansion will aim to further serve other Algerian regions and North African markets with similar challenges and conditions in aquaculture.

5.3.2 Measuring the intensity of competition

- Direct competitors are currently limited, as very few local companies offer integrated real-time IoT systems specifically tailored for aquaculture.
- Indirect competitors include suppliers of generic IoT devices or imported monitoring equipment not adapted to local conditions (cost, environment, connectivity).
- Our competitive edge lies in:
 1. Compact design and modularity, making our system easy to deploy and maintain.
 2. Use of durable materials such as aluminum, increasing lifespan and performance.
 3. High measurement precision and data reliability.
 4. Award-winning innovation that recognizes the system's value and potential.
 5. Mobility and adaptability, allowing use in various aquatic environments with minimal setup.

5.3.3 Marketing strategy

Our marketing efforts will be focused and strategic to maximize visibility and adoption:

- Social media marketing and sponsorships to raise awareness, targeting platforms popular among tech-savvy professionals, students, and aquaculture businesses.
- Collaboration with universities and training centers to promote the educational and research potential of our product.

- Building strategic partnerships with aquaculture cooperatives, NGOs, and local governments to accelerate deployment and adoption.
- Participation in national trade fairs and innovation exhibitions, especially those focused on agriculture, technology, and environmental solutions.

5.4 Production plan and organization

5.4.1 Production Process

The production of our intelligent low-cost IoT system for real-time aquaculture monitoring follows a structured, quality-oriented process:

- Initial design of the device and test stand.
- Reception and inspection of raw materials and electronic components from verified suppliers. Each item is validated to meet the required technical and quality standards.
- Integration of structural components with the electronic subsystems, including sensors, control boards, and communication modules.
- Rigorous testing is conducted to ensure system stability, sensor accuracy, and real-time data transmission performance.
- After passing quality assurance, the units are securely packaged, with manuals and documentation included.
- Packaged units are dispatched to clients or local distribution hubs, with transportation optimized to ensure safe and timely delivery.

5.4.2 Procurement

To guarantee reliable quality and availability of components, procurement is handled through established foreign suppliers experienced in dealing with the Algerian market. We maintain a close communication loop with our suppliers to ensure component compatibility, stock availability, and after-sales support.

5.4.3 The workforce

Given our initial low-scale production approach, the team is intentionally kept compact yet fully functional, composed of:

- Engineer (hardware and firmware)
- Administrator (operations/logistics)
- Accountant (finance and purchases)
- 2 Technicians (assembly/testing)

5.4.4 Key partners

Strategic partnerships play a vital role in the development and sustainability of our project. We carefully select partners based on:

- Manufacturing capability.
- Supplier reliability.
- Trade and industrial organizations.
- Academic institutions.

5.5 Financial Plan

5.5.1 Costs and charges

Variable Loads

	Gross product	Overall quantity	Unit	Value of Gross Product (DA)	Unit quantity (for 1 unit)	Unit	Unit cost (DA)
Raw materials	capteur de température DS18B20	50	Room	13 154.40	1	Room	263.09
	carte Arduino MKR WiFi 1010	50	Room	238 914.33	1	Room	4 778.29
	Les câbles	5 000	m	15 000.00	10	m	30.00
	kits turbidity	50		37 552.22	1	Room	751.04
	PH metre	50	Room	348 688.55	1	Room	6 973.77
	Conductivity Sensor	50	Room	176 792.43	1	Room	3 535.85
	SEN0189 DFRobot	50	Room	78 256.19	1	Room	1 565.12
	boite	100	Room	10 000.00	1	Room	100.00
	piles	200	Room	57 865.16	1	Room	289.33
Total variable expenses				2 466 645.07	///		18 286.49

Table 5.1: Variable Loads

Equipment

Equipment	Designation	Unit Value (DA)	Quantity	Total Value (DA)
	PC	70 000	2	140 000
	Multifunction Laser Printer	40 000	2	80 000
	Modem Wifi	3 000	1	3 000
Total			5	223 000
Depreciation (5 yrs)				44 600

Table 5.2: List of Equipment and Depreciation

Organization/Workforce

Organization/Workforce	Post	Number	Monthly Salary (DA)	Gross Salary (DA/year)
	Engineer	1	50 000	600 000
	Administrator	1	35 000	420 000
	Accountant	1	50 000	600 000
	IT Specialist	1	45 000	540 000
	Technician	1	35 000	420 000
Total payroll		5	215 000	2 580 000

Table 5.3: Organization/Workforce

Fresh and ServedThese Drivers

Category	Service	Number	Monthly Amount (DA)	Annual Amount (DA)
	Internet subscription	1	2 000	24 000
	Electricity subscription	1	3 000	36 000
Miscellaneous Fees & Services	Cleaning	1	2 500	30 000
	Water subscription	1	2 000	24 000
	Antivirus Software License (5 pc)	1	700	8 400
	Rental Fees	1	30 000	360 000
Total Services		6	51 700	482 400
Total Fixed Costs (DA)				3 062 400

Table 5.4: Fees and Services Drivers

Investment costs

Designation	Value (DA)
Paint	15 000
Decoration	10 000
Miscellaneous work	2 500
Furniture	100 000
Total	127 500
Allocation to investments (Over 10 years)	12 750

Table 5.5: Investment Fees

Marketing

Month	1	2	3	4	5	6	7	8	9	10	11	12	Total
Monthly Budget ($\times 1000$ DA)	20	20	20	20	20	20	20	20	20	20	20	20	240

Table 5.6: Marketing

5.5.2 Turnover

Product Sales

Goods / Services	1	2	3	4	5	6	7	8	9	10	11	12	Total
Product/Service 1 — Units Sold	2	6	10	15	15	15	20	10	10	30	40	30	203
Sale Price ($\times 1000$ DA)	80	80	80	80	80	80	80	80	80	80	80	80	///
Turnover ($\times 1000$ DA)	160	480	800	1200	1200	1200	1600	800	800	2400	3200	2400	16 240

Table 5.7: Product Sales

5.5.3 Final assessment

Description	Formula	Amount (DA)
Initial Unit Cost (AIR)		18 286,49
Unit Fixed Costs (DA)		15 085,71
Unit Depreciation Expense (Over 5 years)		219,70
Unit Investment Allocation (Over 10 years)		62,81
Final Unit Cost (DA)	$A + B + C + D$	33 654,71
Production Capacity (units/year)		203
Marketing Budget (DA/year)		240 000,00
Annual Project Cost (AIR)	$(E \times F) + G$	7 071 907,10
Annual Turnover (AD)		16 240 000,00
Annual Profit (AIR)	$I - H$	9 168 092,90
Profit Margin (%)	$(J \times 100) / I$	56,45 %

Table 5.8: Final assessment

5.5.4 Business Model Canvas

Business Model Canvas		
Key Partners	Key Activities	Value Propositions
Sensor & Electronics Suppliers Agricultural Incubators & Accelerators Tech Partners (Cloud providers, PCB companies)	Product Design & Development Sensor Data Collection & Calibration Machine Learning Modeling	Affordable (Low cost) Real-Time Data and Alerts AI-Based Prediction and Recommendations Local Support and Training Sustainable and Efficient Farming
Customer Relationships	Customer Segments	Key Resources
Personal Assistance (Sales & Setup) Online Support & Troubleshooting Training and Education Automated Monitoring & Notifications	Aquaculture Farmers Aquaculture Research Centers Engineering/IoT Solution Providers	Hardware Components Software & Platform (ML models) Electronics, ML Engineer Software Developer
Channels	Cost Structure	Revenue Streams
Direct Sales Online Presence (website, social media) Institutional Partnerships	Hardware Costs Software Development Testing & Calibration Cloud & Hosting Marketing, Logistics Annual: 7071907,10 DZD Fixed: 15085,71 DZD Variable: 18286,49 DZD	Device Sales Software Subscriptions Installation & Training Services Maintenance Contracts Grants, B2B Deals

Table 5.9: Business Model Canvas

5.6 Experimental prototype



Figure 5.2: Prototype final

General conclusion

In conclusion, this thesis has demonstrated the feasibility and effectiveness of an intelligent, low-cost IoT system for real-time aquaculture monitoring. The integration of advanced sensor technologies and machine learning algorithms has proven to be a powerful approach to enhancing the sustainability and efficiency of aquaculture practices. The findings of this research highlight the critical role that technology can play in addressing the challenges faced by the aquaculture sector in Algeria, including data collection issues, environmental concerns, and the need for improved decision-making processes. The results indicate that the proposed IoT system not only facilitates real-time monitoring of key water quality parameters but also empowers aquaculture farmers to make informed decisions that can significantly improve fish health and productivity. The Random Forest Regressor emerged as the most effective machine learning model for predicting water quality parameters, showcasing its potential for real-time applications in aquaculture. This research underscores the importance of leveraging technology to bridge the gap between traditional aquafarming methods and modern practices, ultimately promoting a more sustainable and resilient aquaculture industry. Moreover, the implications of this research extend beyond the immediate context of aquaculture in Algeria. The insights gained from this study can inform policy decisions, guide investments in technology, and inspire further research in the field of aquaculture monitoring. As the global demand for seafood continues to rise, the integration of IoT and AI technologies into aquaculture practices will be essential for ensuring food security and promoting sustainable development worldwide. In light of the findings presented in this thesis, it is clear that the future of aquaculture in Algeria and potentially in other developing regions lies in the adoption of innovative technologies that enhance operational efficiency and sustainability. The proposed IoT system serves as a model for future developments in aquaculture monitoring, paving the way for a more productive and environmentally responsible industry. In truth, to achieve a better level of aquaculture, constant research and collaboration among stakeholders will be crucial in realizing the full potential of aquaculture as a sustainable source of food and economic growth.

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