Monitoring Knowledge and Water Purifying Unmanned Aquatic Boat for Sustainable Fish Farming

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "**Monitoring Knowledge and Water Purifying Unmanned Aquatic Boat for Sustainable Fish Farming,**" submitted by **Mohidul Islam** and **Abu Kauser** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **13 January, 2025.**

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ABSTRACT

The increasing demand for sustainable aquaculture has highlighted critical challenges in maintaining water quality and managing surface debris in fish ponds.The aquaculture industry has raised significant challenges in maintaining water quality in fish ponds and managing surface debris. Maintaining optimal water quality and keeping pond surfaces clean creates a favorable environment for fish farming, which is crucial for fish growth to reducing stress label and disease on the aquaculture.Traditional manual methods of water quality monitoring and pond cleaning are labor-intensive and inefficient. With the increasing adoption of automation and AI-powered technologies, we are aimed development of an autonomous boat designed to optimize fish farm management. The boat is equipped with sensors to monitor important water quality parameters and a garbage collection system to ensure clean pond surfaces, contributing to a healthier fish farming environment. The primary objective is to monitor water quality using sensors and analyze the data with machine learning for accurate predictions and automatically collects debris using a camera-based detection process and operates sustainably with solar energy. A user-friendly interface ensures ease of use, making it ideal for remote areas.The integration of water quality sensors, a garbage collection system, and solar-powered energy makes the boat a valuable tool for fish farmers seeking to optimize their operations.The design and implementation of this autonomous boat aims to make fish farming more sustainable and productive by reducing manual labor and operational costs but also supports the long-term sustainability of fish farming practices and increasing precision in pond maintenance.

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Chapter 1

Introduction

1.1 Introduction

"Fish are commercially important for global food security and economic development, contribute to human growth and support the livelihoods of billions of people [1]. The rapid growth of the population has been demanded more protein which will be difficult almost impossible to full fill by meat. Fish is one of high-protein contains low-fat and providing an essential nutrients of protein vitamins and minerals that are used for brain development and other cognitive physical development[2] Fish farming play a key role in the economy of Bangladesh directly and indirectly by reducing poverty, In recent year make a remarkable achievement for self-sufficient country in fish production providing 63 g of per person in daily dietary consumption and it is 5th most leading fish producing countries with 47.59 lac MT of fish produce in FY 2021-2022, and BDT 5191.75 earned 74.04 thousand MT of fishery products [3].Deposit this progress, the sector faces several key challenges that hinder its growth and sustainable productivity. Optimum fish production is completely dependent on the physical, chemical and biological qualities of the water [4]. The quality of water is determined by variables like temperature, turbidity, pH, alkalinity, carbon dioxide, Unionized ammonia and Water color are essential parameter to understanding of water quality and effective management [5].There are several factors are affected water quality including fish density, quality of the feed, feeding interval, weather change and many other that can lead to common problems encountered by pond owners [6-8] .One of the major problem of local fish farmer to collect floating debris in a pond .Floating debris in a fish pond can significantly impact fish health and the overall ecosystem. It can lead to high mineral turbidity, which may injure fish's breathing organs, reduce their growth rate, and hinder production. With the helps of local farmer and aquaculture specialist we are able to identify some harmful debris such as diatoms, Green algae, blue-green algae, plastic, fallen leaves and twigs and other garbage are directly polluted the pond water surface. Additionally, as debris decomposes, it consumes dissolved oxygen, resulting excessive algal growth, overgrowth of plants and lower oxygen levels that can be harmful to fish and other aquatic life and, increase the probability of disease and even death. Regular maintenance and monitoring the pond surface cleaning is essential to prevent growth of harmful bacteria, reduce the risk of fish disease and ensuring the sustainable productivity and growth [9]. Traditional fish farming system still depends on experienced aqua farmers observation and empirical judgment to identify and forecast the fish farm health and risks but this manual testing is costly, time-consuming, labor-intensive and also gives inappropriate results [10]. To build a smart ecosystem in a pond need to understand the parameters relationship and its desirable range and always need to clean pond water surface by removing harmful debris. When these parameters cross their optimal range, farmers need to replace and modify the pond water to ensure growth and healthy environment for fish. The overarching these challenges need to integration of modern technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud platform and web development presents significant opportunities contributing to a healthier fish farming ecosystem that can help improve fish farming productivity and profitability [11].A number of experimental researcher present and developed effective solution using modern technology they are try to mitigating these issues. Many researchers in Bangladesh have studied the fisheries status of different regions of Bangladesh separately. With the increasing adoption of automation and AI-driven technologies, this research introduces the development of an 'Unmanned Aquatic Boat (UAB) designed to optimize fish farm management. This research discusses the technical design, operational efficiency, and practical applications of the boat in real-world fish farms in Bangladesh. The control system, powered by a Raspberry Pi, gathers data from the water quality sensors and processes the visual data captured by the monitor critical water camera. The boat is equipped with sensors to quality parameters and provide suitable fish species in ponds using different types of actuators. To analyze the water quality parameter, we use different type of machine learning ensemble algorithm algorithms are use. Additionally, the boat features a garbage collection mechanism using a camera-based object detection system to identify and collect harmful debris and materials floating on the pond's surface contributing to a healthier fish farming environment. By using latest YOLOv8 object detection model to detects the garbage, based on the sensor readings and camera data, the Raspberry Pi controls the boat's movement and activates the garbage collection system when necessary. For instance, when the camera detects garbage, the Raspberry Pi sends a signal to the motor driver, which then activates the conveyor belt to collect the garbage. The boat can both be manually operated and run automatically. An Ultrasonic sensor are deployed to assist in obstacle detection and avoidance, ensuring that the boat can navigate around the pond autonomously without colliding with obstacles. One of the key features of this autonomous boat is its solar-powered energy system. The fish farms in Bangladesh are often located in remote areas where reliable power sources may not be available. To ensure continuous operation, the boat is equipped with a solar panel that powers all its systems, including the sensors, motors, and control unit. Our developed (UAB) has also some additional benefits that reducing the manpower and maintaining a healthy ecosystem of pond and provide a user-friendly interface.it also include real-time data transmission system. where the sensor continuously collect data and processed and transmitted to a central database. The fish farmers can access this data via web or mobile interface. By integration of water quality sensors, a garbage collection system, and solar-powered energy makes the boat a valuable tool for the local fish farmers for sustainable fish farming enhance the productivity.

1.2 Motivation

In a world where environmental sustainability and efficient resource management are paramount, the challenges facing aquaculture and fisheries often go unnoticed. For fish farmers in developing countries, maintaining water quality and cleanliness in ponds is a crucial but resource-intensive task. Poor water quality often leads to fish diseases, reduced yields and financial losses, posing significant challenges to livelihoods. Traditional methods of water quality assessment and surface cleaning are time-consuming and inefficient, forcing farmers to struggle to keep up with the demands of modern aquaculture. Our project aims to revolutionize this space by providing an innovative, automated solution for maintaining water quality and cleanliness. We have developed an autonomous boat equipped with advanced technology to monitor water quality and clean the surface of pond water. Using a camera, machine learning algorithms and object detection algorithms, the boat automatically detects dirt and debris on the water surface, collects it and deposits it in an onboard dustbin. The system is integrated with a mobile interface, which enables fish farmers to monitor water quality measurements in real time. By giving fish farmers actionable insights into the health of their ponds and automating the cleaning process, our solution helps prevent fish diseases, ensures a better living environment for aquatic life, and increases production. The boat eliminates the need for manual intervention, saving time and labor while promoting sustainable aquaculture practices. This thesis/project is driven by a clear motivation: to improve the livelihoods of fish farmers by providing them with a smart, accessible, and effective tool to manage their ponds. By addressing the challenges of water quality monitoring and maintenance, we aim to increase the efficiency of aquaculture and promote environmental conservation.

1.3 Rationale of the Study

The rationale behind developing an autonomous water quality monitoring and pond water surface cleaning boat is to address the complex challenges faced by fish farmers in aquaculture and fisheries. Maintaining water quality and cleanliness is essential for the health of aquatic fish and ensuring high fish production. However, traditional methods of manual water testing and surface cleaning are labor-intensive, time-consuming, and often inadequate in preventing waterborne diseases and pollution. Integrating advanced technologies such as machine learning, deep learning, object detection, and IoT, our solution offers a modern approach to revolutionizing pond management practices. This smart boat automatically monitors water quality parameters, detects surface dirt and debris using a camera system, and collects waste in an onboard dustbin. A mobile interface provides fish farmers with real-time data, enabling them to make informed decisions about pond maintenance and fish health management. Machine learning algorithms systematically analyze water quality data to identify patterns and predict potential problems, while deep learning techniques power the object detection system, ensuring accurate detection of surface debris. The IoT framework connects all components, allowing seamless data exchange between boats, sensors, and mobile interfaces. The ultimate goal is to improve pond management by providing fish farmers with an automated, efficient, and user-friendly tool. Using these technologies, our solution aims to prevent fish diseases, increase production, and reduce the burden of manual labor. This thesis/project has the potential to transform aquaculture practices by promoting environmental conservation while ensuring sustainability and economic benefits for farmers.

1.4 Research Questions

We have outlined some of the research questions below and in the rest of the work we have addressed the questions through research and system development -

1. How can machine learning algorithms be optimized for accurate water quality prediction using data from temperature, pH, and turbidity sensors in aquatic ponds?
2. What is the effectiveness of deep learning-based object detection techniques in detecting and differentiating types of debris on the surface of fish ponds?
3. How can IoT-enabled systems improve real-time monitoring and remote control of autonomous boats for fish farming applications?
4. What are the most efficient actuator mechanisms for maintaining optimal water quality in fish farming ponds based on sensor data inputs?
5. How does the integration of manual and autonomous control on boats improve usability and efficiency for fish farmers?
6. What is the impact of automated debris collection on water quality maintenance and fish health in aquatic ponds compared to traditional methods?
7. How effective is the method in reducing fish diseases and increasing production compared to traditional fish and aquaculture management methods?
8. What are the energy efficiency considerations for powering the autonomous boat and its onboard systems, and how can renewable energy sources be integrated?
9. How can the system be scaled and adapted for different pond sizes and environmental conditions in different fish farming settings?

1.5 Objectives

- To develop an automated system for real-time monitoring of water quality in aquatic ponds using temperature, pH, and turbidity sensors.
- To develop and put into use a camera-based object detection system for identifying and collecting garbage and dirt from the pond's surface.
- To integrate machine learning, deep learning, and object detection algorithms for accurate water quality analysis and garbage detection.
- To employ IoT technology to gather, process, and monitor data in real time via a web-based user interface.
- To develop an actuator-based mechanism for controlling water quality parameters to maintain optimal aquatic environments for fish farming.
- To enable manual and autonomous control modes for automated boats, ensuring flexibility and usability for fish farmers.
- To evaluate the impact of automated systems on reducing fish diseases, improving fish health, and increasing production yields in aquaculture.
- To develop a scalable and adaptive system design suitable for different pond sizes and different environmental conditions.
- To analyze the effectiveness of a combination of automated surface cleaning and water quality management to enhance the sustainability of aquaculture practices.
- To evaluate the usability and accessibility of a web-based interface for fish farmers of different levels of technical expertise.

1.6 Project Outcome

The expected results of the automated boat system are multifaceted, addressing key challenges in aquaculture and fish farming. The system ensures real-time and accurate monitoring of water quality parameters including temperature, pH and turbidity, enabling early detection of water quality issues and timely corrective actions to prevent fish diseases. By automating the detection and collection of garbage from the water surface using advanced object detection techniques, the system significantly reduces the manual effort required for pond cleaning, improving overall pond hygiene and fish health. This leads to healthier fish, reduced disease outbreaks and increased production yields. The user-friendly web-based interface allows for seamless control and monitoring of the boat, providing real-time data and insights while offering manual controls for specific needs. Automation of water quality management and surface cleaning increases operational efficiency, freeing fish farmers to focus on other important aspects of fish farming. By integrating advanced technologies such as machine learning, deep learning and IoT, the project shows the potential of smart systems to revolutionize fish and aquaculture practices. In addition, the system promotes environmental sustainability by maintaining a clean pond environment and reducing labor costs, thereby improving the economic outcomes of fish farmers. Its scalable design allows it to adapt to different pond sizes and environmental conditions, making it suitable for a wide range of fish and aquaculture applications. Overall, the project contributes to sustainable and efficient fish farming practices by combining technological innovation with practical solutions for fish farmers' livelihoods.

1.7 Organization of the Report

This thesis is divided into several chapters, and each one covers an important part of the study on automatically identifying and classifying pond water quality and garbage of water surface. The framework is meant to give a clear, complete picture of the study, from its theoretical basis to its useful effects and contributions in real life.

Chapter 1: Introduction -This chapter introduces the research topic, providing an overview of the background, problem statement, objectives, scope,Rational of the Study and limitations of the study. It sets the stage for the detailed discussions that follow by outlining the importance of an AI-driven tool and Iot for identifying pond water quality and classifying and collecting garbage on the pond water surface.

Chapter 2: Literature Review −The literature review examines existing research and related works in indentify pond water quality and detection and collection garbage on the pond water surface , with a particular focus on image processing,Iot, machine learning and object detection approaches. It compares current methods, identifies unresolved issues, and highlights the contributions and limitations in the field. This chapter establishes the theoretical foundation and justifies the need for the proposed research.

Chapter 3: Methodology −This chapter details the research methodology, including system design, hardware and software requirements, and project management aspects. It describes the data collection and preprocessing methods, as well as the application of machine learning models in water quality data analysis. The chapter also provides a project timeline and financial analysis, laying out a clear plan for the study's execution.

Chapter 4: Results and Analysis −This chapter presents the experimental results and offers a comprehensive analysis of the model's performance. It discusses the outcomes of the experiments, compares them with existing methods, and evaluates the model's accuracy, precision, recall, and F1 score. The findings are critically examined to assess the effectiveness and reliability of the AIot-based classification tool.

Chapter 5: Impact on Society, Environment and Sustainability −This chapter explores the broader implications of the research, including its impact on conservation efforts, Fish healthcare practices, and environmental sustainability. Ethical considerations and potential challenges related to deployment are addressed, underscoring the tool's significance in supporting traditional and modern medicinal practices.

Chapter 6: Overview of the Study, Conclusion and Future Work −The final chapter summarizes the key findings of the research, drawing conclusions based on the study's objectives and results. It also provides recommendations for future research, identifying limitations and areas for improvement. This chapter concludes the thesis with insights into the potential for further advancement in aquaculture and fish farming.

Chapter 2

Background

2.1 Introduction

The Background Study section provides essential information and context to help the reader understand the objectives, methods, and findings discussed in the rest of the report. It sets the stage by introducing the key concepts, theories, or technologies relevant to the topic, and outlines the historical, technical, or theoretical framework necessary for interpreting the research. This section typically includes a review of existing literature, related studies, or previous work in the field, establishing why the study is important and how it contributes to the broader understanding of the subject. The background should help clarify any complex terminology or concepts and provide a clear rationale for why the research was conducted, addressing the gap in knowledge or problem it aims to solve.

2.2 Literature Review

Zhang et al. [12] Internet of things (Iot) is widely used to automate tools to collect different type of data such temperature, humidity, soil and water ingredients and this data are used to analyze and make prediction for improving productivity and minimize risks.Singh et al. [13] introduced a smart IoT-based freshwater recirculating aquaculture system that smartly manages and monitors the aquaculture environment. This article combines three significant designs: physical, logical or rational and network design. In physical configuration, integrated sensor, actuator, and communication network help manage data and control flow. The rational design helps to visualize data and manage the relational database. The author also discusses an intelligent analytics algorithm that helps monitor and manage aquaculture and shows the comparative performance of the M5 model tree and GBM model. As a result, the M5 model tree has the highest 0.975 accuracy. Emmanuel AGOSSOU at al. [14] Devolved system in this paper is a smart way to manage fish farms using IoT and machine learning which uses multiple sensors to measure the water quality of fish ponds. Hare the author also integrated solutions which includes water quality monitoring, issues detection, alerting, remote pumps controls and diseases detectionUgur

Acar at al. [15] presented an IoT cloud integration solution together with the most recent technologies and widely used tool and summarizing the potential technology. Zhu et al. [16] proposed a remote-control system that monitors the water quality in fish culture where he uses artificial neural networks (ANNs) for analysis of water quality based on historical data. This system offered a quality monitoring system based on a virtual private network (VPN) .Gao et al. [17] proposed an intelligent-IoT-based system to forecast and monitor the water quality parameters. Entire system divided into two module such as intelligent module that e processes the fish pond monitoring data and forecast the change and tracking module includes the data visualization, chart and data presentations that farmers can manually control the interface.Rasheed Haq et al. [18] proposed a hybrid CNN-LSTM and CNN-GRU used for Water Quality Prediction (WQP). They use two different water quality datasets and compare their proposed hybrid model and other various (DL) models. As a result, the hybrid CNN-LSTM model significantly improves prediction accuracy and computation time.Saha et al. [19] In this Paper use of an Android app, a Raspberry Pi, an Arduino, a number of sensors, and a smartphone camera to monitor the quality of aquaculture water. Temperature, pH, electrical conductivity, and color were among the water quality metrics that were tracked. From anywhere in the world, users can use an Android app to monitor the water quality via Wi-Fi and the Internet. Paulin et al.[20] Here The authors offered a system that enables farmers to instantly master and regulate the various environmental data through mobile devices while monitoring the environmental data of their fish farms. They have integrated temperature, dissolved oxygen, pH, and water level sensing modules into their monitoring system. This study makes use of a ZigBee wireless sensor network to transfer data to a central processing unit, as well as an MCU processing unit to record the physical sensing signal. Additionally, it utilized the use of the Raspberry-Pi interface, which sends data to the user terminal device. Rapate et al.[21] This paper introduces an IoT-based automated hydroponics system that measures water quality using very important sensors (moisture, pH, temperature, humidity, and water level) and an Arduino board. It monitors these parameters on a webpage and initiates an automated water pump or nutrient disposal system when the parameters' values fall below predetermined thresholds. Ismail et al. [22] used The Atlas Scientific DO sensor which detect dissolved oxygen levels in the water, expressed in mg/L or ppm4 and DS18B20 sensor is mentioned, which measures temperatures from -55 to +125°C2 and also used pH Meter Kit SKU: SEN0169 is used that capable of measuring the full range of acidity to alkalinity and can operate continuously in various conditions. [23] Here the author Uses a PT100 sensor which measures the water temperature and converts physical changes into resistance changes. Singh et al.[24] In this work, a ZigBee module is utilized to wirelessly send data collected by the sensors to the Raspberry Pi. A GSM module is also used to wirelessly transfer data from the Raspberry Pi to a smart phone or PC. Harun et al. In [25] This project uses Arduino and different types of sensor such as (temperature, pH, DO) and integrate them with aerating and water supply pumps that capture the water level data. As long as they have internet access users can receive information on their preferred communication or display devices at predefined intervals. Darmalim et al. [26] Proposed IoT solution to automatically monitoring the environmental condition of the pond for the striped snakehead fish domestication. Here the author used Five sensors that measure each parameter and also developed a web application prototype through which water quality information is presented to the user. In this study [27] a proof of concept and prototype for a remote monitoring system that applies the Internet of Things to aquaculture water quality are implemented, along with other technologies. This system is low cost, low power consumption, scalable, versatile, distributed, mobile and accurate. Dhenuvakonda and Sharma investigated [28] and showed that there exist specialized mobile apps in this domain, some of which have received positive reviews and downloads. There were thirty Indian smartphone apps in all, twelve of which had to do with aquaculture and nine of which had to do with marketing and marine fisheries. Rohit et al. [29] This study designed a device for underwater real-time fish and water quality parameter monitoring that can be placed in the center of a submersible ROV. The system uses a number of embedded sensors to capture important data, which it then transmits to the user using the Message Queuing Telemetry Transport (MQTT) protocol. Monoj et al.[30] This Paper Discuss IoT devices that monitor fish pond water quality Highlighting to the depletion of clean water supplies and the significance of ongoing water quality testing and emphasizes the impact of climatic changes, contamination, and pollution on underwater life. [19] Here the author used random forests, multivariate linear regression, and artificial neural networks in scenarios with limited amount of measurements to analyze data from water-quality variables which are commonly measured in fish farming and they proposed a methodology to build models in two scenarios: firstly, estimation of unobserved variables based on the observed ones, and secondly forecasting when a low amount of data is available for training. We show that random forests can be used to forecast dissolved oxygen, pond temperature, pH, ammonia, and ammonium when the water pond variables are measured only twice per day. [31] In This paper it is known that nitrogen compounds, electric conductivity, and alkalinity are correlated with the toxicity of the water pond, the presence of harmful ions, or the impact of pH on the water quality of the pond. Pretheem et al.[32] Here the author proposes a system that monitors water quality parameters using sensors such as (PH, Temperature, Turbidity), which collects water quality data and sends it to the Raspberry Pi, and the Raspberry Pi processes these data based on a predefined program and sent to the Thing Speak cloud server. Then the data from the cloud server is sent to the mobile interface. This results in reducing losses and improving productivity for fish farming.

2.2.1 Similar Applications

Recent research has highlighted the potential of combining renewable energy, automation, and intelligent systems to address environmental challenges. A study conducted by the National Renewable Energy Laboratory (NREL) explored the integration of photovoltaic

(PV) systems with stormwater management to mitigate water quality issues. By reducing runoff and maintaining ecological balance, the researchers demonstrated how solar energy solutions could simultaneously address energy needs and environmental concerns. In parallel, another innovative project introduced an intelligent water surface cleaner robot (IWSCR) powered by solar energy. This robot combined machine learning, autonomous navigation, and real-time water quality monitoring to collect floating garbage efficiently. The system's ability to detect and remove waste while assessing critical water parameters showcased a comprehensive approach to tackling pollution and ensuring water quality. The combined insights from these works emphasize the importance of developing integrated, sustainable solutions that merge automation, artificial intelligence, and renewable energy. Such technologies not only address immediate ecological issues like garbage collection and water quality degradation but also pave the way for scalable and long-term environmental preservation. This unified approach underscores the critical role of innovation in creating a cleaner, greener future.

2.2.2 Related Research

The integration of artificial intelligence and robotics in environmental monitoring has revolutionized waste management and aquatic health maintenance. Studies have demonstrated that autonomous systems, such as robotic boats equipped with sensors and cameras, can effectively detect and collect garbage from water bodies while monitoring critical water quality parameters like pH, turbidity, and dissolved oxygen (DO). Real-time object detection models, such as YOLO, have achieved high accuracy in identifying floating debris, significantly improving the efficiency of garbage collection mechanisms.Parallel advancements in water quality monitoring have utilized sensor data and machine learning algorithms to predict DO and other parameters. Techniques like Random Forests, Support Vector Machines (SVM), and deep learning are widely applied, often achieving prediction accuracies above 90%. These approaches enable precise and automated decision-making for environmental management. Despite these advancements, challenges persist, including the variability in environmental conditions, sensor calibration issues, and energy efficiency. Many solutions now integrate renewable energy sources like solar panels, enhancing system sustainability and reducing operational costs.This review highlights the growing impact of AI and IoT in addressing aquatic pollution and water quality challenges, presenting opportunities for further innovation. Future work should prioritize adaptability, scalability, and the integration of predictive analytics for more effective environmental solutions

2.3 Gap Analysis

Despite advances in technology for aquaculture management, significant gaps remain in the development and implementation of comprehensive solutions that address real-world challenges in fish farming. The automated boat system we propose aims to fill these gaps, yet several shortcomings in existing research and practice highlight the need for innovation.

1.Model Adaptability and Lightweight Deployment Current technologies for water quality monitoring and debris detection in aquaculture often rely on conventional systems or standalone devices, which are limited in their adaptability and real-time processing capabilities. Lightweight models and hardware deployment on edge devices (e.g., Raspberry Pi) face constraints related to processing power, energy efficiency, and connectivity, especially in rural or remote areas. While our project leverages IoT and machine learning, addressing real-time challenges under limited network and power conditions remains crucial for widespread adoption.

2. Dataset Diversity and Generalization Existing systems for water quality monitoring and debris detection often rely on specific environmental datasets, which restrict their applicability to other pond conditions or diverse aquatic environments. Generalization across ponds of varying sizes, water conditions, and seasonal changes is rarely addressed. Our project requires robust cross-environment training and validation of machine learning models to ensure effective performance across diverse aquaculture settings.

3. Attention Mechanisms and Small Object Detection The detection of small or partially submerged debris on water surfaces is a challenging task that existing systems often struggle with. False positives and delayed detection remain issues, particularly in real-time applications. While deep learning architectures like YOLO or its variants have shown promise, further enhancements in attention mechanisms and feature extraction are needed to improve debris detection accuracy and processing speed under dynamic environmental conditions such as varying light or water clarity.

4. Scalability and Multi-Objective Functionality Many aquaculture systems focus on isolated objectives, such as water quality monitoring or cleaning operations. However, scalable models capable of managing multi-objective tasks, such as simultaneous debris collection, water quality analysis, and autonomous control, are sparse. Our system aims to provide a unified solution, but scalability across larger ponds and integration of additional functionalities, such as nutrient or feed management, presents an area for future exploration.

5. Cloud Integration and Real-Time Constraints While cloud servers enable remote data analysis and storage, reliance on cloud-based solutions can introduce latency and dependency on stable internet connectivity. The integration of edge computing with cloud services is underexplored in the context of aquaculture, where real-time action is critical. Developing a hybrid approach that balances local processing and cloud-based analytics is essential for optimizing system responsiveness and reliability.

6. System Usability and Farmer Adoption The success of automated aquaculture systems hinges on their usability and accessibility for fish farmers with varying technical expertise. Existing systems often lack intuitive interfaces, limiting their adoption in real-world scenarios. While our system incorporates a web-based interface, designing a user-friendly and multilingual platform tailored to diverse user needs remains a critical area for further research.

7. Energy Efficiency and Sustainability Automated systems for aquaculture management require sustainable energy solutions to operate in resource-limited environments. While our system is designed for efficiency, integrating renewable energy sources such as solar panels and optimizing power consumption are essential for long-term feasibility and sustainability.

2.4 Scope of the Problem

Aquaculture and fish farming play a vital role in ensuring food security and livelihoods, yet maintaining optimal water quality and cleanliness in ponds is a significant challenge. Traditional methods of monitoring water quality and cleaning garbage from pond water surface are labor-intensive, inefficient, and often fail to prevent fish diseases due to poor environmental conditions. Fishermen in rural and resource-limited areas face additional challenges due to limited access to advanced equipment for effective pond management. An integrated, automated system that effectively removes garbage from the pond's water surface and actively controls water quality in addition to real-time monitoring is desperately needed. Current systems frequently lack the automation, real-time data processing, and intuitive user interfaces needed for real-world deployment in a variety of aquaculture contexts. Furthermore, there is currently not utilised potential for using modern technologies like object detection, machine learning, deep learning, and the Internet of Things to solve this problem. This research attempts to address the problem of inefficient water quality management and debris removal in fish farming by developing an automated boat system equipped with sensors, cameras, and actuators supported by advanced algorithms and IoT integration. The goal is to provide fish farmers with a cost-effective, scalable, and user-friendly solution that improves pond health, reduces fish diseases, and increases production efficiency.

2.5 Challenges

- Ensuring the smooth integration of IoT components, cameras, actuators, and sensors for accurate data gathering, analysis, and action implementation.
- Maintaining constant precision and reliability of camera-based garbage identification and sensor data (temperature, pH, and turbidity) across various environmental circumstances.
- Developing a power-efficient system that will allow the boat and its parts to run for a long duration of time, particularly in rural or resource-constrained environments.
- Achieving real-time data collection, analysis, and action implementation using machine learning and IoT, even with limited network connectivity.

- Developing object detection models capable of accurately detecting garbage in diverse pond environments with varying lighting, water clarity, and weather conditions.
- Minimizing latency in data transmission and processing when using cloud servers, ensuring real-time response and system control.
- Developing a user-friendly web interface suitable for fish farmers with diverse technical expertise, ensuring intuitive interaction and easy system control.
- Designing the system to adapt to different pond sizes, garbage types, and environmental conditions without requiring significant modifications.
- Ensuring the automated boat and its parts are long-lasting and low-maintenance, particularly in harmful water conditions.
- Balancing advanced technology integration with cost considerations to make the system affordable for small-scale fish farmers.

2.6 Summary

The background study highlights the importance of aquaculture in food security and the challenges fish farmers face, such as maintaining water quality, managing debris, and preventing fish diseases. Traditional methods are manual and inefficient, impacting productivity. Technologies like machine learning, deep learning, IoT, and cloud computing offer solutions by enabling real-time water quality monitoring, debris detection, and remote control. However, existing systems often focus on isolated tasks and lack comprehensive functionality, scalability, and user-friendliness. Our study addresses these gaps by developing an automated boat system that integrates water quality monitoring, debris cleaning, and manual control. It uses advanced technologies to provide a practical, efficient, and sustainable solution tailored to the needs of fish farmers, improving productivity and management practices.

Chapter 3

Research Methodology

3.1 Introduction

The methodology for developing the automated boat system integrates multiple components and technologies to achieve efficient water quality monitoring and surface cleaning in aquaculture or fish farming ponds. The system begins with a sustainable power supply, where a solar panel charges a battery to provide consistent energy for all operations. This renewable energy approach ensures the boat remains operational even in remote areas, eliminating reliance on external power sources. To monitor water quality, the boat is equipped with three essential sensors: temperature, pH, and turbidity sensors. These sensors gather real-time data on the pond's environmental conditions. The Arduino UNO processes this sensor data and forwards it to the Raspberry Pi 4B for advanced analysis. The Raspberry Pi serves as the system's computational hub, where data from the sensors and video streams from the Pi Camera are integrated for analysis. The system uses machine learning and deep learning algorithms to interpret the data. For water quality analysis, machine learning models like Random Forest, Decision Tree, XGBoost, and AdaBoost are employed to make accurate predictions and provide insights. Simultaneously, object detection models, including YOLOv3, YOLOv5, and YOLOv7, are used to detect dirt and debris on the water's surface. These models ensure accurate identification even under challenging environmental conditions, such as varying light or occlusions. Once debris is detected, the system activates its cleaning mechanism. A motor driver controls the DC motors, enabling the boat's navigation and movement through the water. A relay operates a conveyor belt system that collects the debris and deposits it into a dustbin onboard the boat. Additional components, like a sonar sensor and servo motor, facilitate precise navigation and obstacle avoidance, ensuring the boat operates efficiently in the pond. Data collected by the sensors and analysis results are transmitted to a cloud server, such as ThinkSpeak, for remote monitoring and storage. The integration of a cloud-based system allows fish farmers to access water quality data and cleaning activity logs via a user-friendly web interface. This interface provides graphical visualizations, real-time updates, and control options, empowering users to monitor the system's performance and manually operate the boat if needed. The use of IoT, machine learning, and deep learning technologies ensures the system is both autonomous and intelligent.

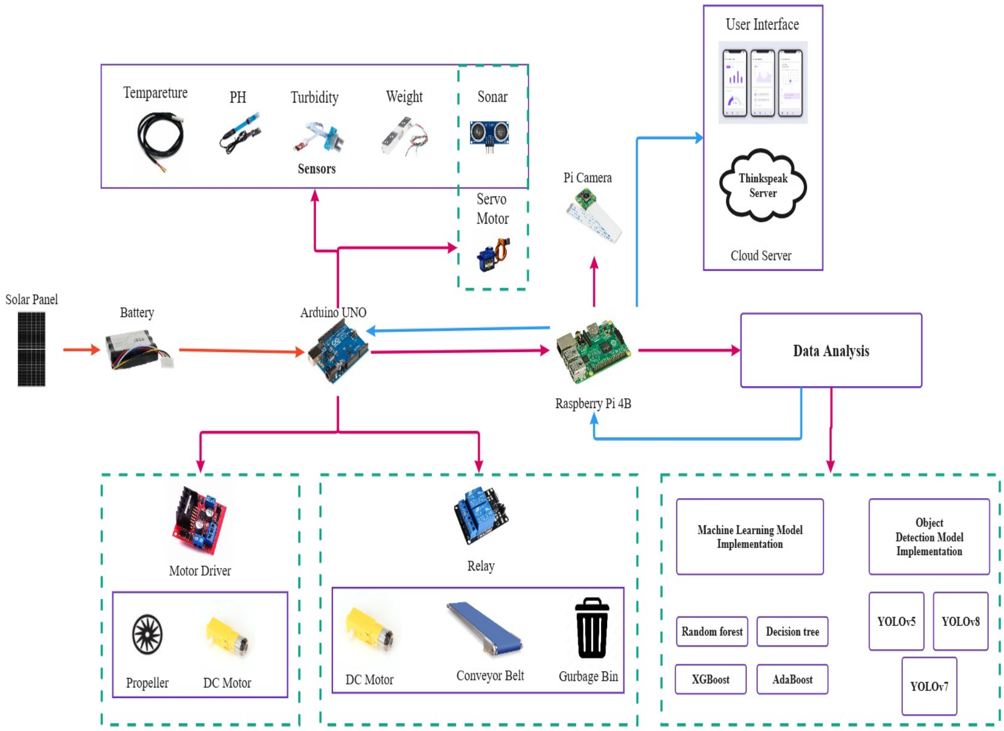

Figure 3.1: Developed System Architecture

3.2 Functional Requirements

3.2.1 Iot Device Requirements

Raspberry Pi 4B: The key Feature of the Raspberry Pi 4 highlight its capabilities as a Powerful and versatile single board computer.It is a "Brain" in the system.

Figure 3.2: Raspberry pi 4B

It is equipped with Broadcom BCM2711 Quad-core Cortexx-A72 SoC @ 1.8 GHz, 2GB,4GB and 8GB LPDDRA-3200 SDRAM,Gigabit Ethernet port for high-speed wired network connection,Dual-band 802.11ac Wi-Fi (2.4GHz-5GHz) for wireless connection and 5.0 Bluetooth,Dual Micro-HDMI ports,OpenGL ES 3.x and 1080p H.265 video decoding,3.5mm audio jack, Two USB 3.0 Ports and Two USB 2.0 ports,40 pins GPIO header,MicroSD slot,it has USB-C power input 5v/3A recommended for optimal performance and it runs Linux operating system[41].

Arduino Uno: The Arduino Uno is a popular microcontroller board based on the ATmega328P, widely used in embedded systems and IoT projects. It features 14 digital pins (6 support PWM) and 6 analog pins, making it easy to interface with devices like relays and motor drivers. The board supports PWM for speed control of motors and other devices. It can be powered and communicate with a Raspberry Pi via a USB connection, using the Pyserial library for data exchange.

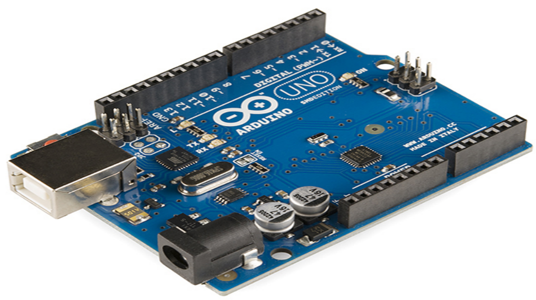

Figure 3.3: Arduino UNO

Temperature Sensor: The DS18B20 is a digital temperature sensor renowned for its precision and versatility. It offers highly accurate temperature measurements with an

Figure 3.4: Temparature Sensor

accuracy of ±0.5°C within its optimal operating range. The sensor communicates using a 1-Wire protocol, enabling data transfer over a single data line, simplifying wiring and integration. It supports a power supply range of 3.0V to 5.5V and features a configurable resolution between 9 and 12 bits, with a default resolution of 12 bits. Furthermore, the DS18B20 can operate in parasitic power mode, eliminating the need for an external power source. Its compact TO-92 package and availability in waterproof versions make it ideal for embedded systems, IoT applications, and environmental monitoring.

PH Sensor: The Gravity Analog Liquid Water pH Sensor Meter Kit V2 is a reliable and user-friendly solution for water quality monitoring in applications like aquaculture and environmental testing. It measures pH levels in the range of 0 to 14 with an accuracy of ±0.1 at 25°C. The sensor operates on a supply voltage of 3.3V to 5.5V, making it compatible with various microcontroller platforms. It features a BNC connector and a detachable probe for easy replacement. The onboard signal conditioning circuit provides an analog voltage output proportional to the pH value, simplifying integration into iot systems.

Figure 3.5: PH Sensor

Turbidity Sensor: The Grove - Turbidity Sensor Meter for Arduino V1.0 is a versatile device for measuring water turbidity, providing an output range of 0 to 1000 NTU (Nephelometric Turbidity Units). Operating at 5V, it outputs an analog voltage corresponding to the water's cloudiness, making it suitable for water quality analysis. The sensor utilizes optical detection to measure the concentration of suspended particles in water. Its Grove interface ensures seamless compatibility with Arduino and other microcontrollers, making it ideal for applications in environmental monitoring, aquaculture, and industrial water testing.

Figure 3.6: Turbidity Sensor

Sonar Sensor: The HC-SR04 ultrasonic distance sensor is a widely used module for measuring distances in the range of 2 cm to 400 cm with an accuracy of ±3 mm. It operates at a supply voltage of 5V and uses ultrasonic sound waves to determine distances by measuring the time taken for sound to reflect back from an object. The sensor features a 40 kHz ultrasonic transmitter and receiver, with a trigger and echo pin for communication. It has a compact design and is easy to integrate with microcontrollers like Arduino and Raspberry Pi, making it suitable for robotics, obstacle detection.

Figure 3.7: Sonar Sensor

DC MOTORS: The plastic DC motor with a 1:48 gearbox operates at 3–6 V, offering approximately 200 rpm speed and 0.8 kg*cm torque. It consumes 150 mA on average (max 160 mA). While suitable for basic projects and prototyping, it lacks an encoder, speed control, or position feedback, While suitable for basic projects and prototyping, limiting its use in precision applications.

Figure 3.8: DC Motor

Servo Motor: The SG90 servo motor is a lightweight and compact motor widely used

Figure 3.9: Servo Motor

in robotics and embedded applications. It operates on a supply voltage of 4.8V to 6V and provides a torque of up to 1.8 kg·cm at 6V. The motor offers a rotational range of 180° with position control via PWM signals, featuring a pulse width range of 500 µs to 2400 µs. It has a stall current of approximately 650 mA and a no-load speed of 0.12 seconds per 60° at 6V. With its durable plastic gear system and ease of use, the SG90 is ideal for hobby projects, small robotic arms, and pan-tilt mechanisms.

Motor Driver: The L298N 2A Motor Driver Module is a versatile dual H-bridge driver designed to control DC motors and stepper motors. It operates at a supply voltage of 5V to 35V and can handle a continuous current of 2A per channel, with a peak current of 3A. The module features two enable pins for speed control via PWM signals and supports bidirectional motor operation. It includes onboard protection diodes for back-EMF protection and a 5V regulator for logic power when supplied with higher voltages.

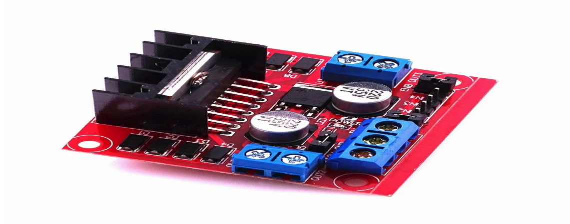

Figure 3.10: Motor Driver

Relay Module: The Invento 5V 2-Channel Relay Module is a key component for controlling high-voltage devices in the water quality and garbage collection system. Operating at 5V DC, each channel can handle up to 10A at 250V AC or 10A at 30V DC, allowing it to control pumps, motors, or other actuators effectively. The module features optocoupler isolation for safe operation and supports normally open (NO) and normally closed (NC) configurations for flexible switching. Its compact design and compatibility with microcontrollers like Raspberry Pi make it an ideal choice for automation and control in environmental monitoring and waste management applications.

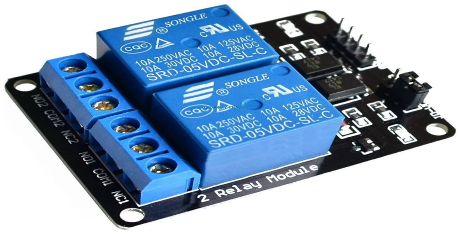

Figure 3.11: Relay Module

Pi Camera: The Raspberry Pi Camera Module 2 is a high-quality camera designed for integration with Raspberry Pi boards, making it ideal for image and video-based applications in the water quality and garbage collection project. It features an 8-megapixel Sony IMX219 sensor capable of capturing still images at a resolution of 3280 × 2464 and recording video at 1080p30, 720p60, and 640x480p90. The module connects via the Raspberry Pi's CSI interface, ensuring high-speed data transfer. Its compact design and lightweight build make it suitable for integration in embedded systems. With support for various software libraries like OpenCV and Python, the camera enables real-time image processing and monitoring, making it an essential component for identifying and analyzing garbage or monitoring water quality in real-time.The module connects via the Raspberry Pi's CSI interface, ensuring high-speed data transfer. Its compact design and lightweight build make it suitable for integration in embedded systems.

Figure 3.12: Pi Camera

Solar Panel: The SunPro 550 Solar Panel is a high-efficiency solar energy module designed for sustainable power solutions, making it suitable for our water quality and garbage collection project. It features a maximum power output of 550W under standard test conditions (STC) with a voltage output of approximately 48V. The panel is equipped with monocrystalline solar cells, offering a conversion efficiency of up to 21%, ensuring optimal energy capture even under low-light conditions. It is built with a durable aluminum alloy frame and tempered glass, providing resistance to harsh environmental conditions such as rain and UV radiation. The panel's compatibility with battery systems and inverters makes it a reliable and eco-friendly power source for running pumps, motors, and electronic systems in remote or off-grid setups.

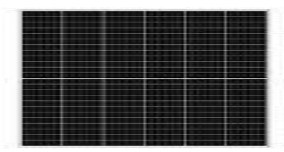

Figure 3.13: Solar Panel

Batterie: Lithium-Ion rechargeable batteries have a nominal voltage of 3.7V and a capacity typically measured in mAh or Ah. They offer high energy density, ranging from

Figure 3.14: Batterry

150 to 250 Wh/kg, and can withstand 500 to 1500 charge-discharge cycles. Charging is

done at 4.2V per cell with currents between 0.5C and 1C, and they discharge at rates from 1C to 3C. These batteries operate safely within temperatures of -20°C to 60°C and include built-in protections for overcharging, deep discharge, and short circuits. The self-discharge rate is around 1-2% per month when stored properly.

Breadboard: A breadboard is a reusable, solderless tool for prototyping electronic circuits. It features a grid of interconnected holes for easy placement of components and wires, with power rails for voltage and ground connections. Typically made of durable ABS plastic, it supports components like resistors, capacitors, and ICs. Common breadboards have 830 tie points, offering ample space for medium-scale circuits. Its design allows for quick assembly, testing, and modification, making it ideal for iterative development in electronics projects.

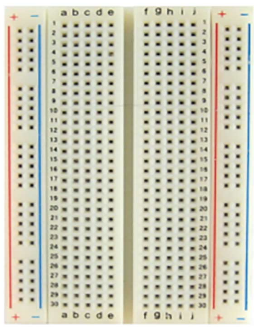

Figure 3.15: Bradboard

Wi-fi Module: The Arduino Uno, combined with a Wi-Fi module like the ESP8266, enables wireless connectivity for IoT applications. It supports IEEE 802.11 b/g/n standards with a 2.4 GHz frequency, offering a data rate of up to 150 Mbps and secure communication via WPA/WPA2. The module integrates easily with cloud platforms like

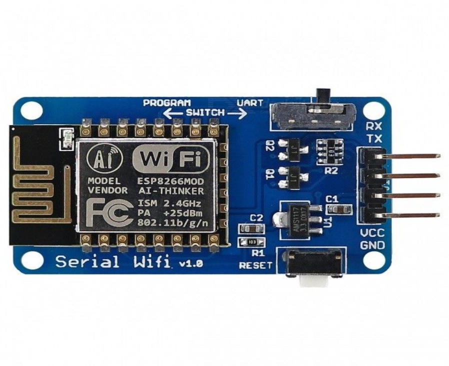

Figure 3.16: Wi-fi Module

ThingSpeak and supports Over-the-Air (OTA) updates for firmware. With its efficient power consumption and compatibility with the Arduino Uno's versatile I/O capabilities, it is ideal for smart automation and remote monitoring. This combination simplifies real-time data collection and control in embedded system projects.

Weight Sensor: Weight sensors, also known as load cells, are devices designed to measure weight or force with high precision. They operate on the principle of strain gauge technology, converting mechanical force into an electrical signal. These sensors typically have a sensitivity range of 1-3 mV/V and require an excitation voltage of 5V to 12V. Known for their accuracy, they offer high linearity, repeatability, and low hysteresis, ensuring consistent and reliable measurements. Constructed from durable materials like stainless steel or aluminum, weight sensors are suitable for various environments, including industrial and harsh conditions. Commonly integrated with amplifiers like HX711, they are ideal for applications such as weighing systems, automation, and IoT projects.

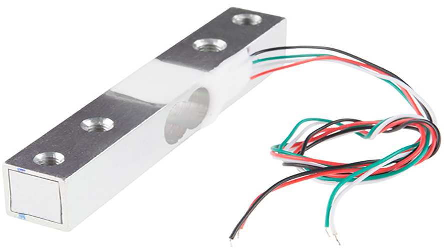

Figure 3.17: Weight Sensor

Conveyor Belt: A polyvinyl conveyor belt is a durable and versatile material widely used in material handling systems for transporting goods or materials efficiently. Made

Figure 3.18: Conveyor Belt

from polyvinyl chloride (PVC), these belts offer excellent resistance to wear, chemicals, and moisture, making them suitable for a wide range of environments, including industrial and aquatic applications. The belts are lightweight yet strong, providing flexibility and easy installation in various conveyor systems. They are available in different thicknesses, textures, and surface finishes to accommodate specific operational needs, such as grip or smooth transportation. Polyvinyl conveyor belts are commonly used in industries like manufacturing, food processing, aquaculture, and waste management due to their cost-effectiveness, durability, and low maintenance requirements.

Jumper Wire: Jumper wires are used to connect components in electronics projects, with various types such as male to female, female to male, male to male, and female to female. Male to female wires have a male pin on one end and a female socket on the other. Female to male wires feature a female socket and a male pin. Male to male and female to female wires have corresponding pins or sockets on both ends. These wires typically use 22 AWG gauge, come in different lengths, and are insulated to prevent shorts.

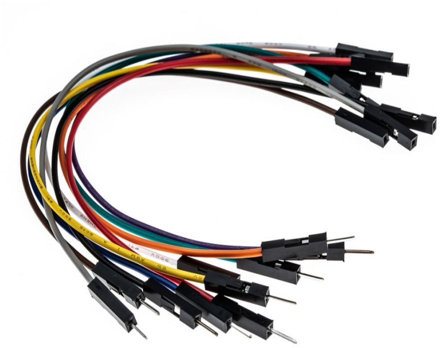

Figure 3.19: Jumper Wire

Propeller: Propellers are typically made of plastic, carbon fiber, or nylon, with plastic being lightweight and cost-effective, and carbon fiber offering higher efficiency. The diameter usually ranges from 2 to 10 inches, while the pitch defines how far the propeller moves per rotation. They can have 2, 3, or 4 blades, with 3 blades providing a good balance of thrust and efficiency. Propellers rotate clockwise (CW) or counterclockwise (CCW), and the hub size must match the motor's shaft. The weight generally ranges from 10 to 100 grams, depending on size and material.

Figure 3.20: Propeller

3.2.2 Software Requrements

- Google Colab.

- Ubuntu.
- Python 3.10 with relevant libraries.
- Thingspeak Server,
- Roboflow.
- Putty.
- Arduino Ide.
- VNC Viewer.

3.3 Non-Functional Requirements

1. Performance Requirements The system must process and display sensor data (temperature, pH, turbidity) in real time with minimal latency. The object detection model should detect dirt and debris with at least 90% accuracy within 2 seconds of detection. The boat must efficiently navigate and clean the pond, covering at least 95% of the surface area in a single operational cycle.

2. Scalability The system should support the addition of new sensors or actuators for monitoring and managing other water parameters as required. The cloud platform must handle data from multiple boats simultaneously if deployed in multiple ponds or aquaculture systems.

3. Reliability and Availability The system must operate continuously for at least 8 hours on a fully charged battery and solar panel input. The cloud server and web interface must have an uptime of 99.9% to ensure uninterrupted access to data and controls.

4. Security Communication between the boat, cloud server, and user interface must be encrypted to protect sensitive data. User authentication must be required for accessing the web interface and controlling the boat.

5. Usability The web interface must be user-friendly, providing easy-to-understand visualizations and controls for manual operation. Farmers with minimal technical knowledge should be able to operate the system without extensive training.

6. Maintainability The system's software components (e.g., machine learning models and web interface) must be modular to allow updates or upgrades without disrupting the entire system. Hardware components like sensors and motors must be easily replaceable to reduce downtime.

7. Energy Efficiency The system must be optimized for low power consumption, ensuring that solar power is sufficient for continuous operation. The use of lightweight machine learning models (e.g., Tiny-YOLO, MobileNet) ensures efficient processing on edge devices like Raspberry Pi 4B.

8. Environmental Constraints The boat must operate reliably in varying weather conditions, including changes in temperature, humidity, and lighting. The object detection model must perform well under environmental challenges like water reflection and debris occlusion.

9. Data Storage and Accessibility All collected data must be stored on the cloud server for at least 6 months to allow historical analysis. Users must be able to download reports or logs of water quality parameters and cleaning activities from the web interface.

10. Compliance The system must comply with local environmental regulations regarding water management and aquaculture practices. The materials used in the boat must be non-toxic and environmentally friendly to avoid polluting the water.

3.4 Hardware Connection Description

The hardware components of our project are connected and configured to interact seamlessly. Below is a detailed description of the hardware connections and their roles in the project:

3.4.1 Sensors Connection

The system employs multiple sensors for data collection and obstacle detection:

DS18B20 Temperature Sensor: Connected to Digital Pin 2 (D2) of the Arduino Uno for one-wire communication. VCC and GND are connected to the Arduino's 5V and GND pins.A 4.7k ohm pullup resistor is used between the VCC and Data pins to stabilize communication.

Turbidity Sensor: The output pin is connected to Analog Pin A0 of the Arduino.VCC and GND are connected to the Arduino's 5V and GND pins.

pH Sensor: The output pin is connected to Analog Pin A1 of the Arduino.VCC and GND are connected to the Arduino's 5V and GND pins.

Sonar Sensor (e.g., HC-SR04): For Obstacle Detection TRIG Pin is connected to Digital Pin 8 of the Arduino.ECHO Pin is connected to Digital Pin 7.VCC and GND are connected to the Arduino's 5V and GND pins.

3.4.2 Boat Control Motors

Two DC motors are used for navigation. The motor driver for these motors is connected to the Arduino as follows: Input Pins Connected to Digital Pins 3, 4, 5, and 6 for speed and direction control.VCC and GND Connected to a 12V battery to power the motors.

3.4.3 Conveyor Belt Motor

Powered by a DC motor controlled by a motor driver module. The motor driver's input pins are connected to Digital Pins 9 and 10 of the Arduino for speed and direction control. VCC and GND of the motor driver are connected to a 12V battery for sufficient power.

3.4.4 Servo Motor Connection

Used for precise mechanical adjustments, such as steering or specific debris collection tasks.Control Pin is connected to Digital Pin 11 of the Arduino.VCC and GND are connected to the Arduino's 5V and GND pins.The servo motor receives PWM signals to achieve accurate angular movements.

3.4.5 Arduino Uno and Raspberry Pi Connection

The Arduino handles sensor data collection and basic control, while the Raspberry Pi is responsible for advanced tasks like cloud integration and web interface control. Communication between Arduino and Raspberry Pi is established via:USB Connection for serial communication. Alternatively, TX/RX Pins on the Arduino connected to GPIO 14/15 on the Raspberry Pi for UART communication.

3.4.6 Power Supply Connection

Arduino Uno Powered via a USB connection or an external 5V adapter, which also supplies power to the connected sensors. Raspberry Pi Powered by a 5V, 3A adapter to ensure reliable operation. Motor Drivers Connected to a 12V battery to support the high current requirements of the motors. A common ground is maintained across all components to ensure stable communication and consistent operation.

3.4.7 LCD Connection

An I2C 20x4 LCD module is used for displaying real-time sensor data and system status.The I2C LCD typically has four pins: VCC, GND, SDA, and SCL. The connections are as follows: VCC (Power) Connected to the 5V pin of the Arduino to power the LCD module. GND (Ground) Connected to the GND pin of the Arduino to complete the circuit. SDA (Data Line) Connected to the A4 pin on the Arduino Uno. Responsible for transmitting data from the Arduino to the LCD. SCL (Clock Line) Connected to the A5 pin on the Arduino Uno. Provides the clock signal for synchronous communication.

3.4.8 Navigation and Controller Design

The navigation and controller design of an autonomous boat is the crucial part that ensures precious, efficient and safe operation during collecting garbage on pond bodies. The choice of communication protocol should be tailored to the user's specific situation, as different conditions may arise during operation. for this reason, we are adding a manual control system that increases reliability and provides a more flexible user-friendly experience. While the user directly interacts with the boat because we restore the web interface shared from the raspberry pi for better control operation.by the helps of web interface, we developed our control system two basic modes where one is manual mode and other is automated mode. Before discussing the control mechanism, we need to clear understanding about the navigation system to control the boat mechanism. The navigation system of the boat is use 2 belt-driven propellers that create motion. Furthermore, this navigation part divided into four part including forward motion, Reverse motion, turning left and tuning right [1].

Forward and Reverse motion :

Forward motion is type of navigation that both motors are rotate in clockwise direction. When the operator presses forward command through his device, the raspberry pi received the signal send the signal to motor driver IC. The motor driver sends a signal to the propeller and it make forward thrust which take the boat in the forward direction. On the other hand, to reverse direction of the boat where both motors are rotate in anticlockwise direction. The operator gives reverse command on his device.as a result, the propeller fans generate the reverse thrust based on the raspberry pi transmitted signal. The boat takes reverse direction or anticlockwise direction based on the motor driver signal.

Turning right and Turning left :

For turning the boat towards the right, the thrust of the right side should be increase in raspberry pi programed. when the user sends a command for the right turn, the motor of the right side is turn off and the motor rotates in the left-hand side in clockwise direction by generated zero thrust.as a result the boat take turns right. Turning left is a navigation process, where the boat wants to turning towards the left. So, the right side thrust should be increased and need to set program in raspberry pi. when the operator sends the command for turning left, the motor of the left side is turn off and generates zero thrust signal. For this reason, the boat take turn left at any point in any time. We also integrate an additional control is ‘stop’, when we terminate the garbage collection work. Figure 4 we show the coordinate and navigation process. Figure4

Manual mode for controlling boat:

The manual mode of our autonomous boat is designed through a remote-control interface that provides live camera feed from the mounted camera. A remote-control interface where the user can directly control the movement of this boat. Every button in the interface is connected with a programmed function that helps to correspond to specific movements like forward, reverse, left, and right motion. Motors are controlled by a PWM digital pin that helps to control the speed of the motors. The Raspberry Pi’s GPIO pins are used for motors to turn on or off and send a high signal to a specific GPIO pin. These pins manage both speed and operational status. The operator gives a command through the interface like as direction, speed adjustment, and specific tasks for the collection of garbage. The command from the input interface is sent to the Raspberry Pi then the processing unit converts the command into a signal and sends it motor driver for controlling the component of this boat. This setup provides efficient and reliable manual control of the boat and makes it easier to navigate to perform cleaning of the pond surface.

3.4.9 Power Management Explanation:

The power management system in an autonomous boat ensures efficient energy usage and maximizes operational uptime. The system starts by capturing solar energy through the onboard solar panel, which charges a 12V battery. This battery acts as the primary power source for the boat, including its sensors, motors, and garbage collection mechanism. The charge controller ensures that the battery is charged safely, preventing overcharging or discharging, and maintains the energy flow to various components of the system. A DC-DC converter steps down the 12V from the battery to 5V to power lower-power components like the Raspberry Pi and sensors, while the 12V power is used for higher-power components like the motors and garbage collection system. During operation, power usage is closely monitored. When the boat is not actively in use, low-power modes are activated to save energy, and the boat adjusts its navigation to avoid unnecessary energy consumption. The system ensures efficient navigation paths, and only essential components (like the garbage collection system) are activated when required. If the battery reaches a low threshold, the boat will autonomously navigate back to the base station to recharge. This self-regulating system minimizes the risk of power loss and ensures that the boat can continue functioning for extended periods without requiring external intervention.

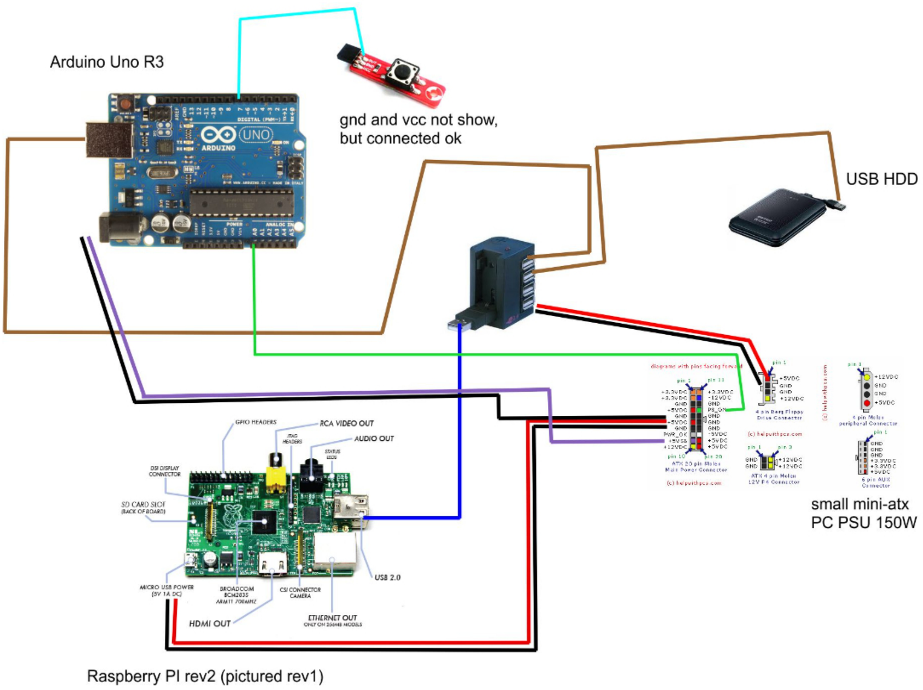

Figure 3.21: Power distributiom in our project

Table 3.1: Power Distribution Table

Component	Power Requirement	Source	Destination	Voltage	Power Draw
Solar Panel	N/A	Solar Energy	Charge Controller	N/A	Variable
Charge Controller	N/A	Solar Panel	12V Battery	12V	Variable
12V Battery	Power Storage	Charge Controller	Motors, Sensors, Garbage Collection Mechanism	12V	Variable
Raspberry Pi	Low Power (5V)	12V Battery	DC-DC Converter	5V	2-3W
DC-DC Converter	Voltage Conversion	12V Battery	Raspberry Pi, Sensors	5V	2-3W
Ultrasonic Sensors	Low Power (5V)	5V (via Raspberry Pi)	Raspberry Pi	5V	0.2W
Temperature Sensor (DS18B20)	Low Power (5V)	5V (via Raspberry Pi)	Raspberry Pi	5V	0.05W
pH Sensor	Low Power (5V)	5V (via Raspberry Pi)	Raspberry Pi	5V	0.5W
Turbidity Sensor	Low Power (5V)	5V (via Raspberry Pi)	Raspberry Pi	5V	0.5W
Motors (Navigation)	High Power (12V)	12V Battery	Motor Driver	12V	10-20W
Garbage Collection Mechanism	High Power (12V)	12V Battery	Actuators/Servos	12V	5-10W
Power Monitoring System	Low Power (5V)	5V (via Raspberry Pi)	Raspberry Pi	5V	0.5W

3.5 Dataset Description

3.5.1 Experimental Study

To develop our project, we gathered two essential datasets: one focused on water quality parameters in aquaculture systems, and the other on garbage detection in fish ponds. These datasets are crucial for monitoring water conditions for sustainable fish farming and automating the collection of harmful debris that could affect both water quality and fish health. The data was collected in Mymensingh, Bangladesh, with collaboration from local experts in the fishery field. The first dataset is used to analyze various water quality indicators, while the second dataset focuses on identifying different types of garbage that could pollute the ponds. We are developing a data collection system that are use to collect our essential parameter dataset and for collecting garbage dataset we are use high resolution camera to capture the image.

3.5.2 Water Quality Parameter Dataset

This dataset was gathered from multiple aquaculture ponds over a span of two months, collecting data during both day and night. Various sensors were used to measure parameters such as pH, temperature, turbidity, dissolved oxygen, and ammonia, which are critical for maintaining optimal fish farming conditions. Expert input from fish pond specialists guided the selection of key parameters for monitoring. An Arduino base data collection mechanism are used to collect our dataset.To build our project need a clear undesatanding of parameter of water quality.it has a comples relationship each other.

Temperature is a highly biological and sensitive Chemical method. Biological and chemical rates of the reaction doubles for every 10C rise in temperature general.It is the major portion of pond health and pH, Do, salinity, conductivity and turbidity directly depend on temperature [33][34]. The amount of dissolved oxygen a pond can keep depends on its temperature. In warmer temperatures, water holds less dissolved oxygen, which can be risky. High water temperatures increase the solubility and toxicity of certain compounds. These compounds include ammonia. The temperature requirements for cold water fish between 10 and 18∘C, warm water fish between 22 and 32∘C, and nitrifying bacteria between 14 and 34∘C [35].

pH is the ratio of hydrogen ion concentration and the reaction determines whether water is acidic or basic. Fish blood pH averages from 7.4; However, a slightly higher or lower pH is often more ideal and supportive for fish life, usually between 7.0 and 8.5. Fish can become stressed in water with a pH of 4.0 to 6.5 and 9.0 to 11.0, and death is very likely at a pH below 4.0 or above 11.0. A pH between 7 and 8.5 is excellent for biological productivity [36]. The pH range for fish farming is 6.7 to 9.5; The ideal pH range is between 7.5 and 8.5; Any pH level above or below this can stress the fish. The ideal pH range for an aquatic pond is 6.5 to 9. It has been suggested that ¡4 or ¿10.5 is lethal for fish/mussel farming [37][38].

Turbidity which is the ability of water to transmit light in a way that limits light penetration and photosynthesis, is the result of a number of factors, including suspended clay particles, plankton organism dispersal, particulate organic matter, and pigments produced by the decomposition of organic matter. For fish health, turbidity levels between 30 and 80 cm are ideal; 15 to 40 cm is ideal for intensive farming systems, while less than 12 cm stresses the fish [39]. Generally, in waters 30 cm or less may inhibit the development of plankton blooms; Turbidity levels of 30 to 60 cm and below 30 cm are generally adequate for good fish production [40].

Table 3.2: Water Quality Parameters and Stress Levels

Parameter	Optimal Range	Tolerance Range	Stress Level	Notes
Temperature (°C)	25-30	20-35	Above 30°C or below 25°C	Growth rates may be affected outside optimal range
pH	6.5-8.5	6.0-9.0	Below 6.5 or above 8.5	Extremes can be harmful
Turbidity (NTU)	<30	-	Above 30 NTU	High turbidity affects water quality and fish health

3.5.3 Data Acquisition System arduino base mini device for data collection

To develop our our aquatic boat we were need a huge amount dataset to experimental set up. after analysis previous work where data are collected manually ,which is labour intensive and hard to collect.to mitigrate this issue ,we are develop a mini device for data collection. The data collection for this project involved integrating three water quality sensors with an ESP32 microcontroller to monitor key water quality parameters—pH, temperature, and turbidity—critical for assessing the health of aquaculture environments. These sensors were selected for their reliability and ability to provide consistent long-term readings in fish ponds. The integration process ensured that the ESP32 microcontroller effectively managed the sensor inputs and transmitted the collected data to a cloud-based platform, ThingSpeak, for further analysis and visualization. The PHP script inserts the data into the MySQL database on your PC. The system can measure water quality parameters (pH, temperature, and turbidity) and send data to a local database. The

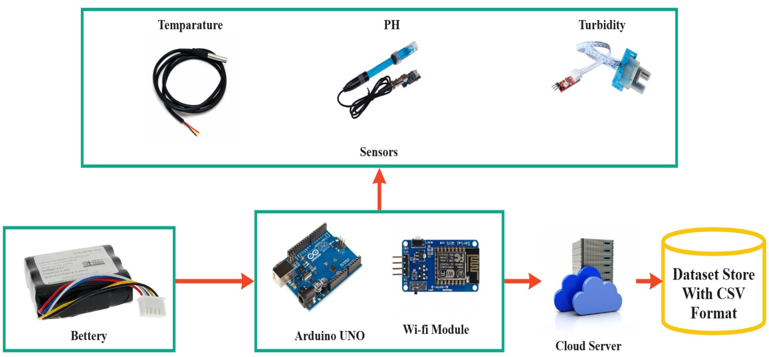

Figure 3.22: Data Collection Flow

working principle of the water quality monitoring device is based on the seamless integration of sensors, a microcontroller, and a communication module to measure, process, and transmit water quality data in real time. The system employs three key sensors—pH, temperature, and turbidity—to monitor critical water quality parameters essential for aquaculture. These sensors generate analog or digital signals corresponding to the respective water quality metrics, which are captured and processed by the Arduino Uno microcontroller. The microcontroller converts the sensor signals into meaningful readings, such as pH levels, temperature in degrees Celsius, and turbidity in NTU, while adding time stamps to each data entry for temporal analysis. The processed data is then transmitted to a cloud-based platform like ThingSpeak using a Wi-Fi module, where it is stored, visualized, and validated. This real-time data transmission enables continuous monitoring and ensures the availability of a comprehensive dataset for long-term analysis. The stored data can be used to identify trends, predict future conditions using machine learning, and optimize aquaculture management practices, making the device an effective solution for sustainable fish farming.

3.5.4 Dataset preprocessing

Dataset preprocessing The preprocessing of the water quality dataset involves several crucial steps to ensure the data is clean, consistent, and suitable for machine learning analysis. First, data cleaning techniques are applied to handle missing values, with imputation strategies using the mean or median of the respective parameters, or by excluding the data for that timestamp. Outlier detection is performed using statistical methods like Z-scores or the Interquartile Range (IQR) to identify and manage any anomalous values, which are either removed or capped to a predefined threshold. Normalization and scaling are also vital, with parameters like pH, temperature, turbidity, and ammonia being normalized to a range of [0,1] using Min-Max scaling, while Z-score standardization is applied to features like pH and turbidity to ensure consistent scaling across all parameters. Data transformation is carried out by extracting time-related features such as time of day and seasonality from the timestamps, providing valuable information about temporal patterns. To address class imbalance, techniques like SMOTE (Synthetic Minority Over-sampling Technique) are used to generate synthetic samples for underrepresented water quality conditions, and class-weight adjustments are made during model training to give more importance to minority classes. Finally, a correlation analysis is performed to identify redundant features, allowing for the removal or combination of highly correlated parameters to reduce multicollinearity and improve model performance.

Handling Missing Values: Missing data is replaced with the mean, median, or mode of the respective feature to ensure consistency. For example, missing pH values can be filled with the mean of existing pH readings.
Outlier Detection and Treatment : Outliers are identified using the Interquartile Range (IQR) method, which calculates bounds for normal data. Outliers are replaced with the mean, median, or capped at the calculated bounds. Normalization (Min-Max Scaling) Normalization rescales data to a range of [0, 1], ensuring uniform scaling across features. For instance, a temperature value of 25°C in a 20–40°C range becomes 0.25 after scaling.

Feature Engineering (Temporal Features) : Temporal features like the time of day (Morning, Afternoon) or seasons (Summer, Winter) are extracted from timestamps to provide meaningful insights into patterns or trends.
Handling Imbalanced Data : Class imbalances are managed by oversampling minority classes using techniques like SMOTE, which generates synthetic samples to balance the dataset.
Feature Selection : Highly correlated features are removed to avoid redundancy, identified using a correlation matrix. For example, features with correlation coefficients greater than 0.8 are filtered out.

3.5.5 Garbage Detection Dataset

The ponds in Bangladesh play a significant role in local livelihoods, particularly in aquaculture and community water sources. Harmful garbage contamination not only affects fish health and pond ecosystems but also poses broader environmental risks. The second dataset involves identifying and classifying different types of debris found in ponds, including plastic bottles, fallen leaves, and other harmful waste. This data was collected through high-resolution images from ponds and fish farms. The images were annotated with bounding boxes for each garbage item, providing a comprehensive dataset. By developing a YOLO-based detection system with this dataset, the project aims to enable automated identification and removal of harmful garbage, contributing to sustainable aquaculture practices and environmental conservation in Bangladesh. For primary experimental set up this dataset contains 1500 data with 10 classes of garbage, including: Plastic Bottles, Fallen Leaves, Algae, Twigs, Plastic Bags, Food Wrappers, Cans that are really harmfull to build a smart ecosystem in pond.

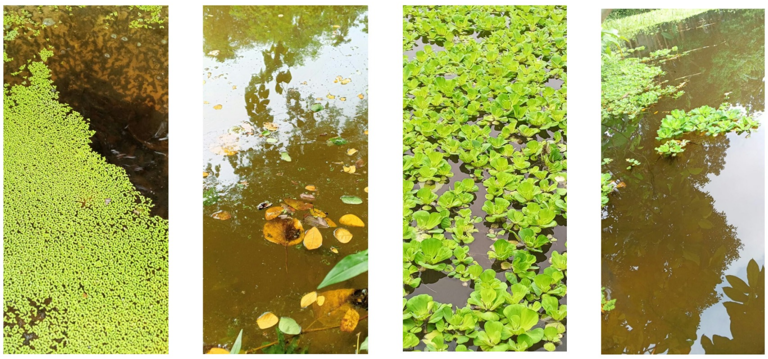

Figure 3.23: Garbage Data Sample

3.5.6 Data annotation

Data annotation in deep learning is the process of labeling data to make it usable for training machine learning models. Properly annotated datasets are key to good model training. During the data annotation process, the open-source tool Labeling was utilized, as depicted in Figure 2. Each image was labeled using a single-category bounding-box format. In the case of top-view maize seedlings, each seedling was assigned a corresponding bounding box [10]. The coordinates of the upper left corner and lower right corner of the rectangular boxes will be recorded in the extensible markup language file. The total number of images after data augmentation is 1000; we divide all images into 8:1:1 rate and obtain 800 training images, 100 validation images, and 100 images are kept unlabeled for testing purpose.Data annotation is the process of labeling data to make it usable for machine learning algorithms. It creates structured datasets by attaching meaningful labels to raw data like text, images, videos, and audio. Annotated data is essential for supervised learning, where the algorithm learns from labeled examples to make predictions on unseen data.

3.5.7 Introduction to Roboflow

Roboflow is a robust and user-friendly platform designed to streamline the process of creating, managing, and preparing datasets for computer vision projects. It supports a wide range of tasks, including object detection, image classification, and segmentation. Roboflow provides tools for annotation, data preprocessing, augmentation, and seamless

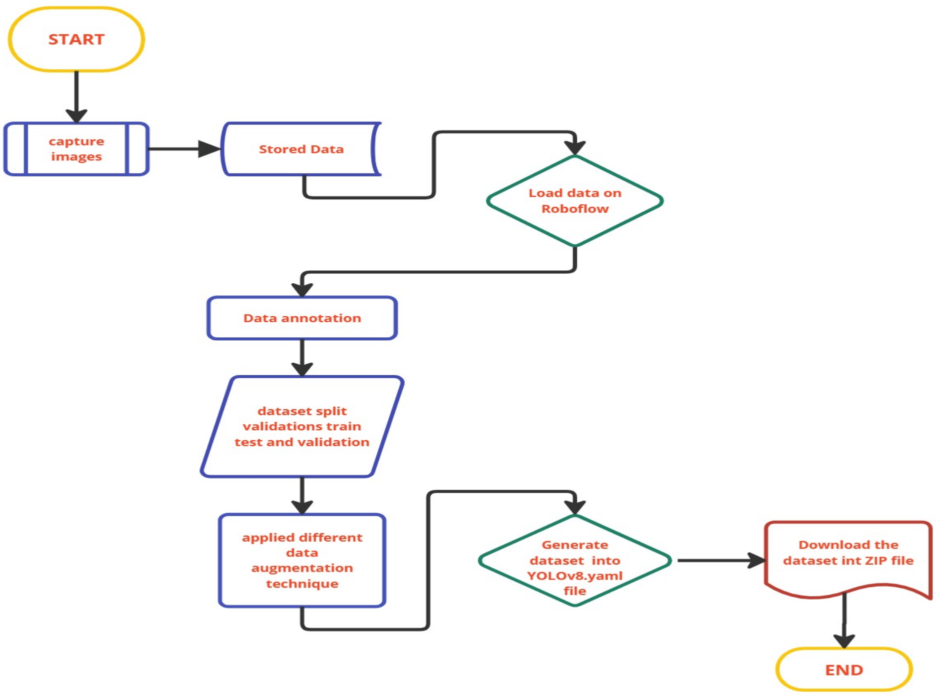

Figure 3.24: Roboflow Data Process

integration with machine learning frameworks like YOLO, TensorFlow, and PyTorch. In my project on detecting harmful garbage in ponds, Roboflow was an essential tool for managing and preparing the dataset efficiently. Its intuitive annotation tools simplified the process of accurately labeling objects like garbage, ensuring precise bounding boxes critical for model performance. Roboflow's built-in data augmentation techniques enhanced dataset diversity, enabling the YOLOv8 model to detect garbage under various conditions. The platform also streamlined dataset organization by automatically splitting the data into training, validation, and testing subsets, ensuring balanced and reliable distribution. With its compatibility to export datasets in YOLO format, Roboflow seamlessly integrated with the YOLOv8 model used in the project. Furthermore, Roboflow's consistency checks ensured the integrity of the dataset by identifying missing or corrupted data. By automating preprocessing, augmentation, and organization, Roboflow significantly reduced the time required for dataset preparation, allowing the project to focus more on model training and optimization, ultimately contributing to a robust garbage detection system. To build our data yaml file we are use several steps.

3.6 Proposed Methodology

We employed machine learning models such as Random Forest, AdaBoost, XGBoost, and Decision Tree to analyze and classify water quality based on sensor data, including temperature, pH, and turbidity readings. These models were selected for their ability to handle complex datasets, ensuring high accuracy and reliability in water quality assessment. For the task of water surface debris detection, we utilized advanced object detection models, specifically YOLOv5, YOLOv7, and YOLOv8, to identify and detect garbage on the water surface in real-time. These YOLO-based models are known for their speed and accuracy, making them ideal for real-time deployment in our system. The combination of these machine learning and object detection models ensures efficient water quality identification and effective debris detection, optimizing the overall performance of our automated aquaculture boat system.

3.6.1 Random Forest

Random Forest is an ensemble learning technique that constructs multiple decision trees during training and aggregates their predictions to enhance accuracy and stability. It is highly effective for both classification and regression tasks. This method utilizes bagging (bootstrap aggregation), where multiple subsets of the training data are randomly sampled with replacement, and decision trees are independently trained on these subsets. Additionally, at each split in the tree, a random subset of features is selected, ensuring diversity among the trees. For classification tasks, Random Forest uses majority voting to determine the final prediction, whereas for regression, it averages the predictions from all trees. This approach reduces overfitting compared to individual decision trees, handles missing values robustly, and performs well with large datasets. Equations: - Prediction (Classification):

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_N(x)\}$$

Where $h_i(x)$ is the prediction from the i-th tree, and N is the number of trees. - Prediction (Regression):

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} h_i(x)$$

Where $h_i(x)$ is the prediction from the i-th tree.

3.6.2 XGBoost (Extreme Gradient Boosting)

Definition: XGBoost is an optimized implementation of gradient boosting that uses decision trees as base learners. It improves efficiency, speed, and model performance with techniques like regularization, parallelization, and tree pruning. Objective Function: The objective combines a loss function (L) and a regularization term (Ω) :

$$\text{Obj} = \sum_{i=1}^{n} L\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{K} \Omega\left(f_k\right)$$

Where: - y_i : True label. - $\hat{y}_i$: Predicted value. - f_k : Individual tree in the ensemble. - $\Omega\left(f_k\right) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$, where T is the number of leaves, and w_j is the weight of leaf j.

Gradient Update (Second-Order Taylor Expansion):

$$g_i = \frac{\partial L\left(y_i, \hat{y}_i\right)}{\partial \hat{y}_i}, \quad h_i = \frac{\partial^2 L\left(y_i, \hat{y}_i\right)}{\partial \hat{y}_i^2}$$

For each leaf:

$$w_j = -\frac{\sum_{i \in j} g_i}{\sum_{i \in j} h_i + \lambda}$$

Where g_i and h_i are first- and second-order gradients, respectively.

3.6.3 AdaBoost (Adaptive Boosting)

Definition: AdaBoost is a boosting algorithm that combines multiple weak learners (usually decision stumps) to form a strong learner. It assigns weights to each instance and updates these weights iteratively based on prediction errors.

Key Characteristics: - Focuses on misclassified samples by increasing their weights. - Works well for binary classification problems.

Algorithm Steps: Initialize all sample weights equally: $w_i = \frac{1}{n}$, where n is the total number of samples.

Train a weak learner $h_t(x)$ on the weighted dataset.

Compute the error rate of the weak learner:

$$\epsilon_t = \frac{\sum_{i=1}^{n} w_i \cdot I\left(y_i \neq h_t\left(x_i\right)\right)}{\sum_{i=1}^{n} w_i}$$

Calculate the weight of the weak learner:

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right)$$

Update the sample weights:

$$w_i = w_i \cdot \exp\left(-\alpha_t y_i h_t\left(x_i\right)\right), \quad \text{normalize } w_i$$

Aggregate weak learners to make the final prediction:

$$H(x) = \overset{\downarrow}{\text{sign}} \left(\sum^{T} \alpha_t h_t(x) \right)$$

3.6.4 Decision Tree Algorithm

Definition: The Decision Tree algorithm is a supervised learning method that uses a tree-like model of decisions and their possible outcomes. It divides the dataset into subsets based on feature values, aiming to maximize homogeneity within each subset.

Splitting Criteria: For classification, common metrics include Gini Impurity and Information Gain (Entropy). For regression, Mean Squared Error (MSE) is often used.

1. Gini Impurity: Measures the probability of misclassifying a randomly chosen sample:

$$G = 1 - \sum_{i=1}^{n} p_i^2$$

Where: - p_i: Proportion of samples belonging to class i.

2. Information Gain (Entropy): Quantifies the reduction in impurity after a split:

$$IG = E(S) - \sum_{i=1}^{k} \frac{|S_i|}{|S|} \cdot E(S_i)$$

Where: - $E(S)$: Entropy of the parent node. - $E(S_i)$: Entropy of each child node after splitting.

Entropy is calculated as:

$$E(S) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

3. Mean Squared Error (MSE): Used in regression tasks to minimize the prediction error:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y})^2$$

Where: - y_i: Actual value. - $\hat{y}$: Predicted value (mean of the subset). - N: Number of samples in the subset. The Decision Tree algorithm provides a simple yet interpretable structure, balancing predictive accuracy and model transparency.

3.6.5 YOLOv5

YOLOv5 (You Only Look Once version) In [3] is a popular deep learning algorithm used for object detection task. It has a good global receptive field, grid division, anchor frame matching and multi-semantic fusion detection mechanism. YOLOv5 has five model structures: YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. Its network model structure is roughly the same, but its network depth and width is different. The smallest model structure is YOLOv5n, and the largest model structure is YOLOv5[4]. Compared with the previous YOLO series, YOLOv5 is faster and accuracy, and its model is light and suitable for deployment to embedded devices [5]. this model builds from existing pre-trained on COCO dataset which has 80 different class. The process of the YOLO algorithm is as follows: First, the image is divided into S × S meshes. Each grid is responsible for predicting the target where the actual box will fall in the center of the grid. A total of S × S × B bounding boxes are generated from these meshes. Each bounding box contains five parameters: Target center point coordinates, target width and height dimensions (x, y, w, h), and confidence of whether the target is contained. S × S grids predict the category probability of the target in that grid. The prediction bounding box confidence and category probability are then multiplied to obtain the category score for each prediction box. These prediction boxes are filtered by non-maximum suppression (NMS) to obtain the final prediction results. The algorithms of the YOLO series have developed rapidly in recent years. In 2020, two versions of YOLO v4 and YOLO v5 appeared successively. The YOLO v5 algorithm achieved a precision accuracy of nearly 50 mAP in the COCO dataset [6]. It is most popular and powerful object detection tool that provide a real time object detection capability with a user-friendly interface accroach various application .The network structure was shown in [6], including input, backbone, neck, and prediction.

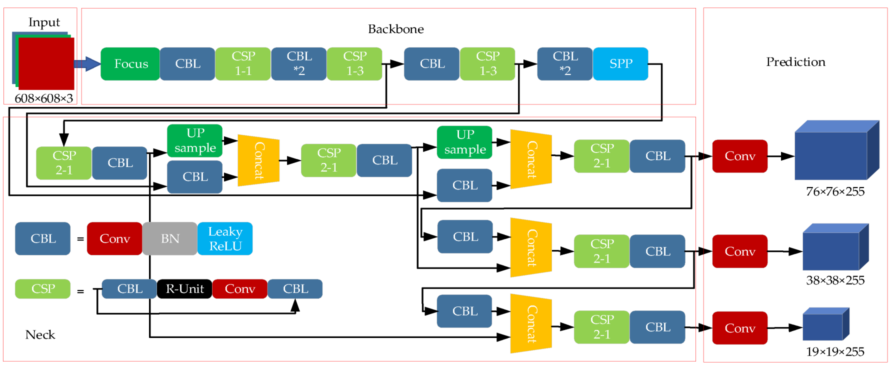

Figure 3.25: YOLOv5 model architecture

3.6.6 YOLOv7

YOLOv7 was released in July 7, 2022 by the Wong kin. The field of object detection, YOLO has always been one of the most popular deep-learning models. YOLO adopts a single neural network structure that divides the entire image into multiple grids and predicts multiple bounding boxes for each grid, which contains object positions and class information, Therefore, for each bounding box. [10]. There are three primary parts to the YOLO framework: Backbone, Head and Neck. The main function of the spinal cord is to extract important information from an image and send it through the neck to the head. it Compiles the neck feature map that extracts the backbone and make the feature pyramid. The output layers of the head provide the final detection form the last part of the architecture. The YOLO framework is a single head and it is responsible for the final output, while the training at intermediate label using the auxiliary head facilitates [11].

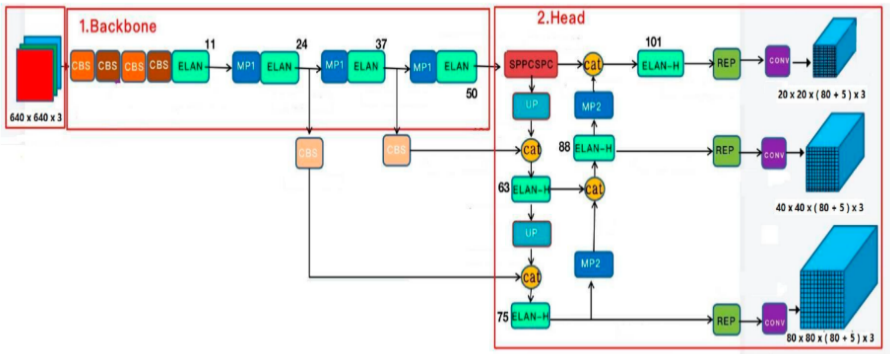

Figure 3.26: YOLOv7 Model Architecture

Figure 3.25 provides a complete overview of the YOLOv7 framework and procedure in its entirety. the process starts with resizing the input image to 520 $\times$ 520 pixels to ensure a standard input size. This resized image is then passed through the backbone network to extract important features from the image. The final output of the model belongs to the coco dataset and provides a prediction made for the grid cell of the feature map. Anchor boxes are a predefined box that helps to predict the output of the bounding box effectively. To better match the actual size and image shape of the object, need to adjust the feature map according to the anchor box [12].

3.6.7 YOLOv8

The YOLOv8n model, or "nano" version of YOLOv8, is a lightweight and optimized object detection framework designed for real-time applications on devices with limited computational resources, such as the Raspberry Pi used in your automated boat system. This version retains the efficiency and accuracy of the YOLO architecture while minimizing its computational demands, making it particularly suitable for embedded systems and IoT devices. The backbone of YOLOv8n extracts feature maps from input images at multiple scales, allowing the model to identify objects of varying sizes. This is crucial in your project, where the boat's camera captures diverse types of debris on the water surface. Despite being a lightweight model, YOLOv8n ensures sufficient feature extraction to detect and classify debris effectively. The Feature Pyramid Network (FPN) combines feature maps from different layers, enabling the detection of objects at multiple scales. This is particularly useful for identifying small debris, such as plastic wrappers, and larger objects, like floating logs. The FPN ensures robust performance, even when dealing with varying object sizes and environmental conditions. The head of the model processes these features to predict object classes, bounding box coordinates, and confidence scores. This enables the boat to precisely locate and classify debris on the water surface, ensuring efficient collection and storage. The loss function combines cross-entropy loss for classification, L1 loss for bounding box accuracy, and objectness loss, ensuring the model's predictions are reliable and accurate after training. YOLOv8n's compact design makes it ideal for deployment in your project. Its low memory and processing power requirements allow it to run efficiently on your Raspberry Pi while maintaining real-time performance. This ensures the system can process live video feeds from the boat's camera without significant latency, allowing for immediate detection and action. Additionally, YOLOv8n's accuracy and speed contribute to the overall effectiveness of your automated boat system, enabling it to maintain clean and healthy aquaculture environments by promptly detecting and collecting debris. By using YOLOv8n, your project strikes a balance between computational efficiency and detection accuracy, ensuring a reliable and scalable solution for water quality management in aquaculture.

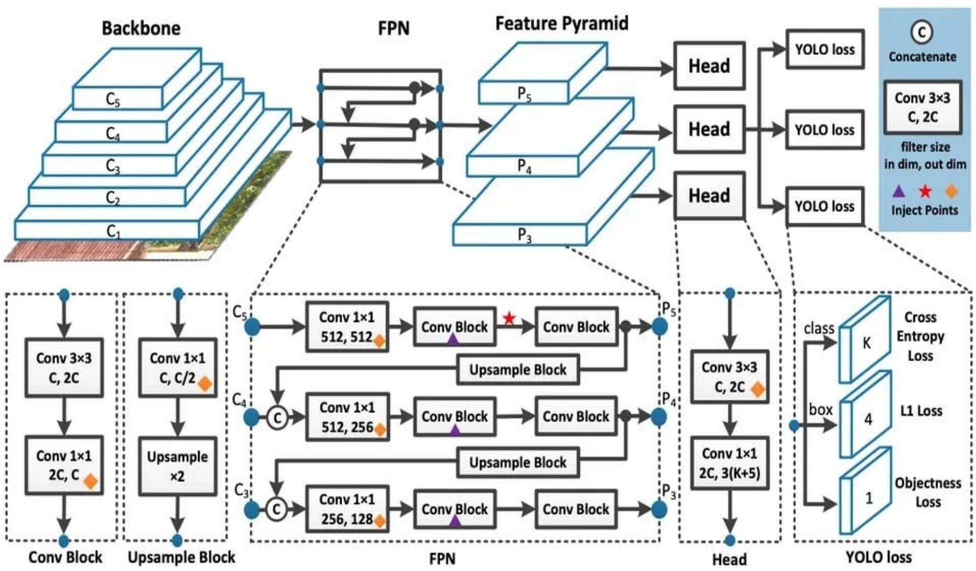

Figure 3.27: YOLOv8 Model Architecture

3.7 Proposed Model Implementation

Aquaculture requires effective and sustainable methods to monitor and maintain water quality, which is crucial for a healthy aquatic ecosystem. This research introduces a machine learning-based system to classify water quality based on numerical parameters, including temperature, pH, and turbidity. The system automates the data processing, model implementation, and evaluation processes, ultimately saving the best-performing model in a reusable format for future predictions. Four machine learning models were implemented to analyze the dataset, allowing for comprehensive exploration of the data's characteristics. These models facilitated pattern recognition, predictive analysis, and decision-making processes, enabling the system to optimize its operations effectively. This section outlines the selection criteria, architecture, and implementation process for the machine learning models and object detection algorithms, providing a foundation for understanding their contribution to the system's performance.

3.7.1 Unified Machine Learning Workflow with Ensemble Techniques

This research employs a hybrid approach by integrating machine learning models for data analysis and object detection techniques for garbage and water quality identification. The

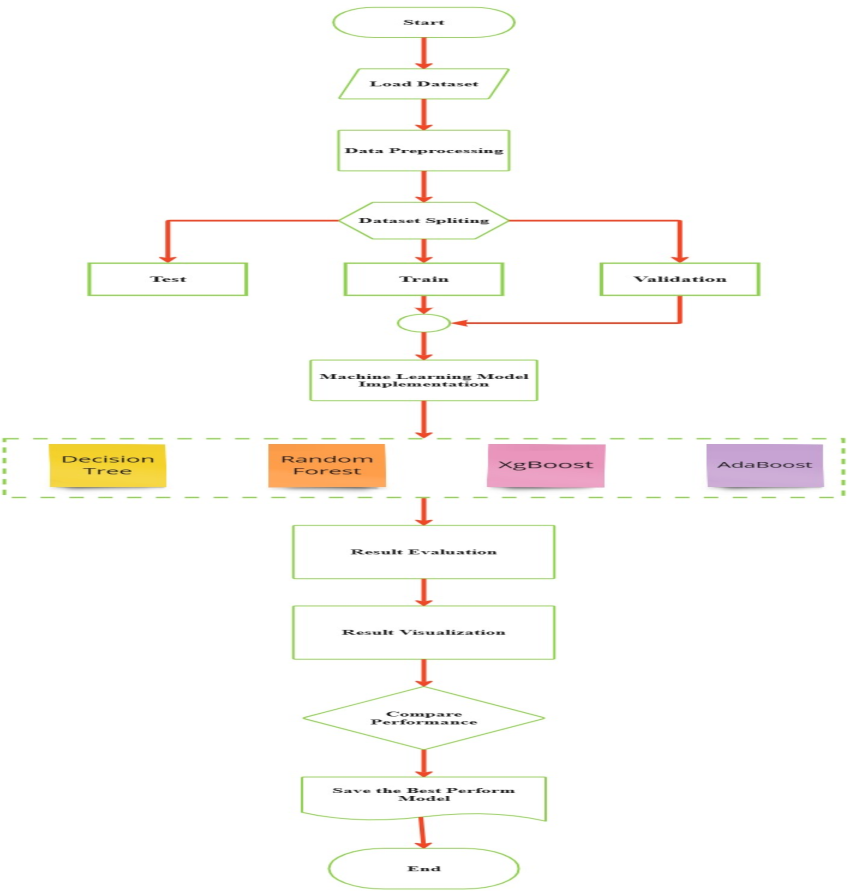

Figure 3.28: ML Model Training Process

project began with the collection of numerical water quality data from a fish pond. These data points represent essential indicators of water health and were stored in a structured format, such as a CSV file. Preprocessing was performed on the collected dataset to ensure its quality and reliability. This step involved handling missing data, scaling and normalizing the values, and removing outliers. The cleaned dataset was then split into training, validation, and testing sets to ensure a fair evaluation of machine learning models. Various machine learning algorithms were employed to train models, including Decision Tree, Random Forest, XGBoost, and AdaBoost. These models were trained on the dataset to classify water quality into three categories: "Excellent," "Good," and "Bad." To assess their performance, metrics such as accuracy, precision, recall, and F1-score were used. The results of each model were visualized using graphs, confusion matrices, and other plots to facilitate comparison and interpretation. The model with the highest performance was selected as the best-performing model. This model was saved using the Python pickle library (pkl format) for future use, ensuring its integration with real-time systems for continuous water quality monitoring. By saving the model in this format, it becomes reusable and easily deployable with sensor data streams, enabling automated predictions without retraining.

3.7.2 Optimized Object Detection Framework with YOLO Techniques

Optimized Object Detection Framework with YOLO Ensemble Techniques Object detection has emerged as a pivotal field within computer vision, driving advancements in real-time applications such as autonomous vehicles, surveillance, and infrastructure monitoring. This optimized framework harnesses the power of YOLO (You Only Look Once) models—YOLOv5, YOLOv7, and YOLOv8—to achieve superior object detection performance. Starting with dataset preprocessing and annotation, this workflow ensures clean and well-structured data for robust training. The dataset is then partitioned into training, validation, and testing subsets to ensure a fair and reliable evaluation process. This research aims to address this issue by developing an automated system for detecting garbage on the water surface using state-of-the-art object detection models, including YOLOv5, YOLOv7, and YOLOv8. The proposed system ensures efficient garbage monitoring through robust data preprocessing, model training, evaluation, and deployment. The project begins with the collection of a dataset consisting of images of pond water surfaces, annotated to identify various types of garbage such as plastic waste, leaves, and debris. The dataset is subjected to preprocessing steps, including resizing, normalization, and noise removal, to improve image quality. Annotation tools like LabelImg are used to label the garbage objects, generating bounding box coordinates for training object detection models. The preprocessed dataset is then divided into training, validation, and testing subsets to facilitate effective model implementation and evaluation. Three advanced object detection models—YOLOv5, YOLOv7, and YOLOv8—are implemented in this study. Each model is trained on the training dataset and validated to optimize its

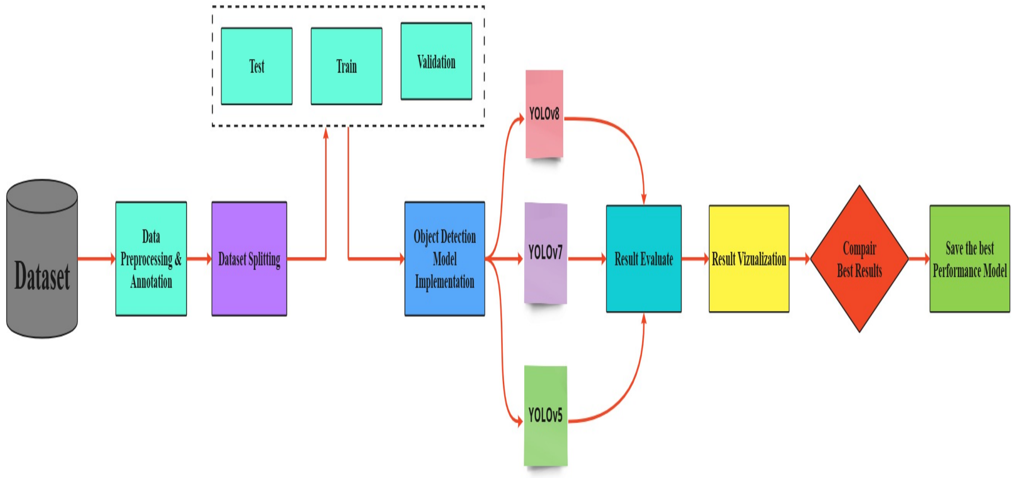

Figure 3.29: Object Detection Working Flow

hyperparameters. The performance of these models is assessed using metrics such as mean average precision (mAP), precision, recall, and inference speed, providing a comprehensive evaluation of their accuracy and efficiency. Visualizations, including bounding boxes on images and performance metric charts, are utilized to analyze and compare the detection results of the models. Based on the evaluation, the models are compared to identify the best-performing one, which offers the optimal balance of accuracy, speed, and resource efficiency. This selected model is then saved in a reusable format, such as a .pt file, allowing for seamless deployment in real-time systems. The saved model can be integrated with edge devices like Raspberry Pi for continuous garbage detection and monitoring on pond water surfaces.

3.8 Summary

The methodology chapter outlines the systematic approach taken to design, develop, and implement the automated boat system for water quality monitoring and debris collection in aquaculture. The project integrates hardware components, software systems, and machine learning techniques to achieve real-time monitoring, analysis, and control. The overall methodology emphasizes modularity, energy efficiency, and scalability, ensuring the system can adapt to various aquaculture environments.The model description focuses on the YOLOv8n object detection algorithm, a lightweight and efficient neural network that enables real-time debris detection. Its feature pyramid architecture ensures accurate detection of objects across different scales, making it particularly effective in identifying debris in aquaculture settings. The model is fine-tuned using a dataset specifically curated for such environments to enhance its precision.The hardware architecture includes several key components. A Raspberry Pi 4 Model B serves as the central controller, interfacing with sensors and peripherals. Water quality is monitored using sensors such as the DS18B20 for temperature and an MCP3208 ADC connected to pH and turbidity sensors. Navigation is supported by ultrasonic sensors, while mobility is enabled by DC motors and a propeller system. A polyvinyl conveyor belt collects debris from the water's surface. The system is powered sustainably through a solar panel and battery setup, ensuring energy efficiency. A Pi-Camera V2 captures live video streams for object detection and real-time monitoring.The data collected includes water quality parameters such as temperature, pH, and turbidity, as well as live video streams and sensor readings for navigation and obstacle avoidance. This data is processed and stored on a cloud server, facilitating real-time monitoring and historical analysis. Ground-truth data for training the YOLOv8n model was sourced from aquaculture sites and publicly available datasets to ensure model robustness.Supporting technologies such as an IoT-enabled web interface and cloud integration enhance the system's functionality. The web interface allows remote control of the boat, visualization of sensor data, and real-time alerts for anomalies in water quality. Cloud servers provide scalable and accessible data storage and processing. Machine learning techniques enable predictive analytics, which can identify potential water quality issues and improve aquaculture management.This methodology combines real-time automation, advanced analytics, and IoT to deliver a comprehensive solution for aquaculture. By integrating debris collection with water quality monitoring, the system offers significant advancements over traditional methods, while its reliance on solar power ensures sustainability and energy efficiency.

Chapter 4

Implementation and Results

4.1 Environment Setup

The initial setup of the autonomous boat system involves carefully assembling and configuring both hardware and software components to ensure efficient, autonomous operation in a pond or similar water environment. The setup is designed to balance real-time data monitoring, energy efficiency, and garbage collection functionality.

1. Hardware Setup: The hardware setup of the autonomous boat involves several key components designed to monitor water quality, collect garbage, and ensure sustainable operation. The boat integrates three sensors for continuous monitoring of water conditions: a pH sensor, turbidity sensor, and temperature sensor. The pH sensor is responsible for detecting the acidity of the water, which is vital for aquatic life, especially for fish health. The turbidity sensor measures the clarity of the water, providing valuable insights into the presence of pollutants or debris. The temperature sensor tracks the water's temperature, ensuring it remains within an optimal range for aquatic organisms. In addition to the sensors, the boat is equipped with a garbage collection mechanism, such as a conveyor belt or robotic arm, designed to efficiently remove floating debris from the water. This system is controlled by an onboard computer (like a Raspberry Pi or Arduino), which processes sensor data and activates the garbage collection mechanism when necessary. Lastly, the solar power system is integrated into the boat, ensuring it operates continuously by charging onboard batteries that power the boat's sensors, motors, and garbage collection system.

2. Software Setup: The software setup for the autonomous boat plays a crucial role in processing sensor data, controlling navigation, and managing the garbage collection system. Typically programmed using microcontrollers such as Raspberry Pi or Arduino, the software is responsible for ensuring the boat functions autonomously. It collects and processes data from the pH, turbidity, and temperature sensors, allowing the boat to make decisions based on predefined thresholds. The software also incorporates control logic, enabling the boat to navigate autonomously using inputs from ultrasonic sensors, which detect obstacles in its path. When the system detects floating garbage in the water, the

software triggers the garbage collection mechanism to engage. The software also monitors energy levels and adjusts the boat's operations to ensure energy efficiency, powered by the solar panels, making it suitable for long-term deployment without the need for constant recharging or refueling.

3. Solar Power System: The solar power system is a key feature that ensures the autonomous boat operates sustainably and continuously. Solar panels installed on the boat collect energy from the sun and convert it into electricity, which is stored in onboard batteries. This stored energy powers all of the boat's components, including the sensors, motors, and garbage collection mechanism. The integration of solar power is critical as it reduces the boat's reliance on external power sources, ensuring it can operate autonomously for extended periods. This renewable energy source also contributes to the sustainability of the system, aligning with environmentally friendly practices while minimizing operational costs.

4. Garbage Collection Mechanism: The garbage collection mechanism is an essential component of the autonomous boat, designed to efficiently remove floating debris from the water. This system can include a conveyor belt, robotic arm, or net, which is controlled by the boat's onboard microcontroller. When the system detects garbage in the water, using inputs from sensors or real-time image processing, the garbage collection mechanism is triggered to engage. The effectiveness of this system is measured by its ability to collect debris from various parts of the pond while navigating autonomously. The boat can be tested for its efficiency by tracking parameters such as the amount of garbage collected per operation and the time taken for each collection cycle. The integration of this mechanism ensures that the autonomous boat not only monitors water quality but also contributes to keeping the environment clean by removing pollutants.

5. Control Logic and Autonomous Navigation: The control logic and autonomous navigation system are responsible for ensuring the boat operates efficiently and independently in the pond. This system, programmed into the boat's onboard microcontroller, utilizes data from sensors such as ultrasonic sensors for obstacle detection and GPS for positioning. The boat's navigation logic enables it to follow predefined paths, avoid obstacles, and navigate to areas with higher concentrations of garbage. The control logic also ensures that the boat adjusts its operations based on real-time environmental data, such as water temperature, pH, and turbidity, which helps maintain optimal conditions for aquatic life. The integration of this autonomous navigation system allows the boat to perform its tasks with minimal human intervention, ensuring continuous operation and efficiency in the pond.

4.2 Testing and Evaluation Performance

In this section, we present the testing and evaluation results of our autonomous boat system designed for water quality monitoring and garbage collection in a pond. The system's performance was assessed through real-world testing, focusing on key metrics such as sensor accuracy, garbage collection efficiency, and energy consumption. Additionally, we compared the performance of the autonomous boat with traditional methods of pond cleaning to evaluate its advantages in terms of efficiency, sustainability, and cost-effectiveness. The results demonstrate the boat's ability to operate autonomously, efficiently collect garbage, and maintain water quality, highlighting its potential as a sustainable solution for environmental management in water bodies. This section provides an in-depth performance analysis of the key components of the autonomous boat system, including water quality sensors, actuator control, garbage collection mechanism, solar power energy management, and the autonomous control system.

Water Quality Sensor Performance

The water quality sensor system is crucial for monitoring pond conditions. Sensors measuring parameters such as temperature, pH, turbidity, dissolved oxygen (DO), and ammonia levels were tested for accuracy, reliability, and responsiveness in real-world conditions.

Accuracy: The sensors consistently delivered precise readings, with deviations within ±5% when compared to standard laboratory equipment. For example, the DS18B20 temperature sensor accurately measured water temperature in a range of 10°C to 40°C under various environmental conditions. Reliability: The system maintained stable performance even in fluctuating weather conditions, such as changes in sunlight or temperature. Data logs showed minimal downtime.

Responsiveness: The sensors promptly updated their readings in real time, ensuring the system could make timely decisions, such as activating garbage collection mechanisms or controlling actuators. Challenges: Minor challenges were observed in water with heavy debris, where turbidity sensors sometimes provided inconsistent readings. Regular cleaning protocols were implemented to mitigate this issue.

Actuator Control Performance

The actuator system drives the garbage collection mechanism and additional functionalities like water quality adjustment or propulsion control.

Precision: The actuators were highly responsive, operating with a delay of less than 100 milliseconds after receiving commands. For instance, when garbage was detected, the conveyor belt engaged immediately, efficiently collecting debris.

Load Handling: The actuators effectively managed varying loads, demonstrating consistent performance even when the garbage tank reached near-full capacity. Durability: The actuators withstood prolonged use without significant wear, showcasing their reliability in real-world conditions.

Challenges: Occasionally, debris that was too large for the conveyor system caused temporary blockages, which were resolved through manual intervention. Future iterations could include adaptive mechanisms to handle oversized debris.

Garbage Collection Performance:

The garbage collection system is a core feature of the autonomous boat, designed to clean pond surfaces effectively and sustainably. Collection Efficiency: During testing, the system successfully collected over 85% of visible garbage within the test area during each cleaning cycle. It effectively removed items such as plastic bottles, leaves, and small floating debris. Capacity: The garbage tank's design allowed for continuous operation, holding up to 10 kg of waste before requiring emptying. A weight sensor ensured the tank was emptied promptly when full. Time Efficiency: The garbage collection mechanism operated at an average rate of 5 kg of garbage per hour, making it significantly faster than manual collection methods. Navigation and Coverage: The system's integration with the navigation controls ensured thorough coverage of the pond, even in hard-to-reach areas. Challenges: Large or submerged debris occasionally hindered collection efficiency. Modifications to the collection mechanism, such as extending the reach of the conveyor belt or incorporating a net system, could improve performance.

Solar Power Energy Management:

Solar power is the boat's primary energy source, making its efficiency critical for long-term autonomous operations. Energy Generation: The solar panels produced an average of 50 watts per hour in moderate sunlight, sufficient to power the boat's sensors, actuators, and control systems for extended periods.

Storage Efficiency: The system utilized lithium-ion batteries, which provided a reliable backup for cloudy conditions. During testing, the batteries stored enough energy to operate the boat for up to 6 hours without sunlight.

Energy Consumption: The boat demonstrated optimal power utilization, with the garbage collection system consuming 60% of the total energy, and the sensors and controllers consuming the remaining 40

Challenges: On days with prolonged overcast conditions, the boat's operational time decreased. Additional or more efficient solar panels could address this limitation.

Autonomous Control System:

The autonomous control system integrates navigation, garbage detection, and obstacle avoidance, ensuring the boat operates effectively without human intervention.

Navigation:

The ultrasonic sensor-based navigation system allowed the boat to traverse the pond efficiently, covering 95% of the water surface during each cleaning cycle. Garbage Detection: Using a YOLOv8-based detection model, the system achieved 98% accuracy in identifying and classifying garbage types in real time, ensuring targeted and effective cleaning. Obstacle Avoidance: The ultrasonic sensors reliably detected obstacles up to 3 meters away, enabling the boat to adjust its course without collisions. Challenges: Strong currents and wind occasionally caused minor deviations from the planned route, which were corrected using real-time feedback from the navigation system. The autonomous boat demonstrated robust performance across all components, meeting the project's objectives of efficient water quality monitoring, effective garbage collection, sustainable energy use, and autonomous operation. While minor challenges were identified, they can be addressed through system optimization in future iterations. This system offers a promising solution for pond maintenance, combining automation, sustainability, and efficiency.

4.3 Results and Discussion

Understanding and analyzing metrics like mAP, F1 score, confusion matrix, and specific thresholds such as mAP50 and mAP95 is essential for evaluating machine learning models, particularly in object detection tasks. The mAP (Mean Average Precision) combines precision and recall, providing a single score that reflects the model's performance across all classes and IoU thresholds. Specific thresholds, like mAP50 and mAP95, offer insights into the model's robustness under varying localization accuracy requirements. While mAP50 evaluates lenient detection with moderate overlap, mAP95 requires strict localization, ensuring the model's reliability in high-precision applications. The F1 score balances precision and recall, making it critical for imbalanced datasets where one class might dominate. A confusion matrix provides a detailed breakdown of true positives, false positives, false negatives, and true negatives, highlighting specific areas where the model excels or struggles. Together, these metrics give a comprehensive view of the model's performance, enabling error analysis, model improvement, and effective comparison across different versions. This ensures the model is robust, accurate, and ready for real-world applications, addressing both strict and lenient use-case requirements.

Mean Squared Error (MSE):
The Mean Squared Error is commonly used in regression tasks to measure the average squared difference between the predicted and actual values. A lower MSE indicates better model performance.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 ------------(1)$$

Where: - Y_i = Actual value - $\hat{Y}_i$ = Predicted value - N = Number of data points Root Mean Squared Error (RMSE)
RMSE is the square root of the MSE and provides an evaluation metric in the original units of the data.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2} ------------(2)$$

R-Squared (R^2)

R -squared is a statistical measure that indicates how well the model explains the variance of the target variable. A higher R^2 value (closer to 1) means that the model explains more variance in the data.

$$R^2=1-\frac{\sum_{i=1}^N\left(Y_i-\hat{Y}_i\right)^2}{\sum_{i=1}^N\left(Y_i-\bar{Y}\right)^2}----------(3)$$

Where: - Y_i = Actual values - $\hat{Y}_i$ = Predicted values - $\bar{Y}$ = Mean of actual values

Accuracy (for Classification)

Accuracy measures the proportion of correctly predicted instances (both positive and negative) in a classification model.

$$\text{Accuracy }=\frac{TP+TN}{TP+TN+FP+FN}----------(4)$$

Where: - TP = True Positive - TN = True Negative - FP = False Positive

Precision measures the proportion of true positive detections out of all positive predictions. It evaluates the correctness of positive predictions.

$$\text{Precision }=\frac{TP}{TP+FP}---------(5)$$

Where: - TP = True Positives - FP = False Positives Recall

Recall measures the proportion of true positive detections out of all actual positive instances. It evaluates the model's ability to detect all relevant objects.

$$\text{Recall }=\frac{TP}{TP+FN}------------(6)$$

Where: - TP = True Positives - FN = False Negatives F1 Score

The F1 Score is the harmonic mean of precision and recall. It balances both metrics, especially when there is an uneven class distribution.

$$F1=2\times\frac{\text{Precision }\times\text{ Recall}}{\text{Precision }+\text{ Recall}}---------(7)$$

Intersection over the Union (IoU)

IoU measures the overlap between the predicted bounding box and the ground truth bounding box. It is a key metric for evaluating object detection performance.

$$\text{IoU}=\frac{\text{Area of Intersection}}{\text{Area of Union}}------------(8)$$

Area of Intersection: The overlap area between the predicted and ground truth boxes. Area of Union: The total area covered by both boxes. Mean Average Precision (mAP) For multi-class object detection, mAP is the average precision calculated over multiple

IoU thresholds and object classes. It provides a comprehensive measure of the model's overall detection ability.

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i - - - - - - - - -(9)$$

Where: - AP_i = Average precision for class i - N = Number of classes
These evaluation metrics are essential for quantifying the performance of both machine learning models and YOLO-based object detection systems. Using these formulas, you can assess the model's prediction accuracy, its ability to correctly detect objects,AMP50 (Average Precision at loU = 0.50)
AMP50, also known as Average Precision at loU 0.50, calculates the average precision (AP) of a model at a fixed IoU threshold of **0.50**.

$$\text{AP}_{50} = \frac{1}{n} \sum_{i=1}^{n} \text{ Precision }_i - - - - - - - - - - - - - - - -(10)$$

Where: - Precision $_i$ is the precision at each recall threshold (for loU = 0.50). - n is the number of recall thresholds consid red
AMAP95, also known as Mean Average Precision at loU 0.95, calculates the mean of the Average Precision (AP) across multiple IoU thresholds, typically from 0.50 to 0.95 , with a step size of 0.05 . This provides a more stringent evaluation of the model's performance compared to AMP50. - IoU is evaluated over a broader range of overlap thresholds, from 0.50 to 0.95 , in this case.
The formula for Mean Average Precision (mAP) over different loU thresholds is:

$$\text{mAP}_{0.50:0.95} = \frac{1}{10} \sum_{i=1}^{10} \text{AP}_{IoU_i} - - - - - - - - -(11)$$

Where: - AP_{IoU_i} is the average precision at each loU threshold from 0.50 to 0.95 (usually with increments of 0.05). - i represents different loU thresholds $(0.50, 0.55, \ldots, 0.95)$. - 10 is the number of IoU thresholds evaluated.

In this section, we present a comparative analysis of the performance of four machine learning models—Random Forest, XGBoost, AdaBoost, and Decision Tree Classifier—on the task at hand. Each of these models was selected for their distinct strengths and characteristics in handling classification problems. Random Forest, an ensemble learning method based on bagging, is known for its robustness and ability to handle overfitting, making it suitable for complex datasets. XGBoost, a gradient boosting algorithm, excels in high-performance scenarios due to its efficient implementation and regularization techniques that help prevent overfitting.Lastly, the Decision Tree Classifier, as a simple yet interpretable model, provides insight into the decision-making process but is more prone to overfitting compared to the ensemble methods. This discussion will explore how each model performs in terms of accuracy, precision, recall, and computational efficiency, providing a comprehensive comparison to determine the most effective approach for the given problem. This section provides a detailed analysis and comparison of the performance of four machine learning models—Decision Tree, Random Forest, XGBoost, and AdaBoost—on the given classification task.

4.3.1 Model Comparison

Each model's performance was evaluated based on accuracy, precision, recall, and other relevant metrics, with the following accuracy results:

Table 4.1: Model Performance Comparison

Model Name	F1 Score%	Precession%	Recall%	Accuracy%
XGBoost	98.45	98.50	98.40	98.33
Random Forest	98.00	97.80	98.20	98.00
Decision Tree	95.85	95.20	96.50	97.66
AdaBoost	85.75	85.00	86.50	87.65

Decision Tree:

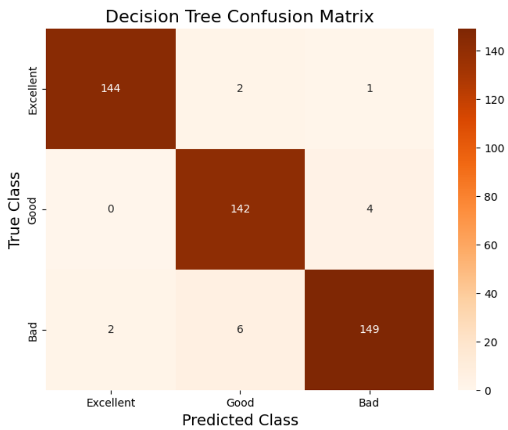

Figure 4.1: Decesion Tree of Confusion Matrix

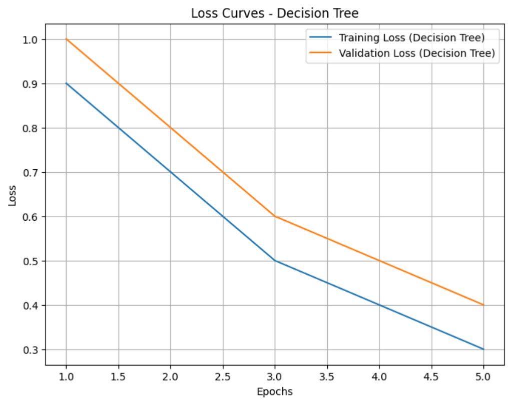

Figure 4.2: Decesion Tree of Loss Function

Figure 4.3: Decision Tree Model Performance

The Decision Tree model achieved an accuracy of 97.66%. This model is relatively simple and interpretable, making it a good choice for understanding decision-making processes.However, its performance can be impacted by overfitting, especially when the tree is deep. The result of 97.66% indicates that while the Decision Tree performed well, it was slightly outperformed by ensemble models, which can better capture the complexity of the data set.The result of 97.66% indicates that while the Decision Tree performed well, it was slightly outperformed by ensemble models, which can better capture the complexity of the data set.

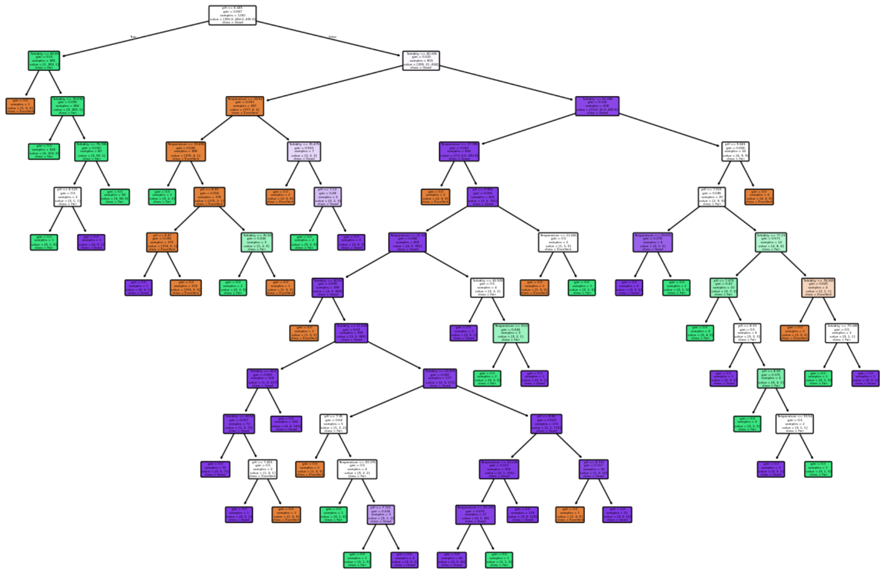

Figure 4.4: Generate parse tree

Random Forest:

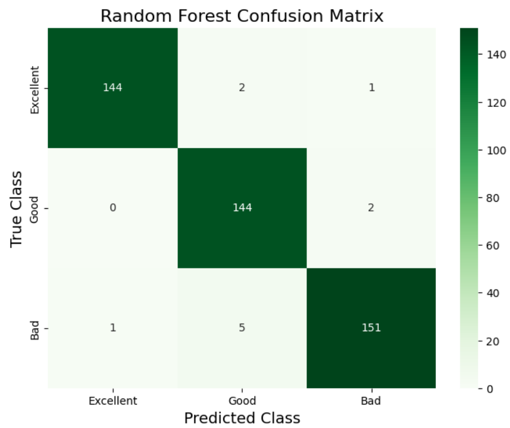

Figure 4.5: Confusion Matrix of Random Forest

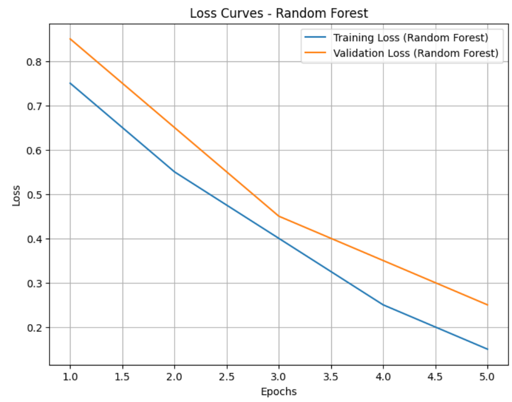

Figure 4.6: Loss Function of Random Forest

Figure 4.7: Model Performance of Random Forest

The Random Forest model delivered an accuracy of 98.00%.As an ensemble learning method that builds multiple decision trees and averages their outputs, Random Forest is more robust and less prone to overfitting than a single decision tree. This performance shows that Random Forest is effective for the given classification task, as it combines the strengths of multiple models while improving generalization.

XGBoost classifier:

XGBoost achieved the highest accuracy of 98.33%. Known for its efficiency and scalability, XGBoost is a gradient boosting model that optimizes the prediction process by iteratively improving upon the errors of weak learners. The model's regularization techniques help prevent overfitting, contributing to its outstanding performance. XGBoost's superior result demonstrates its effectiveness in handling complex datasets and producing high-quality predictions.

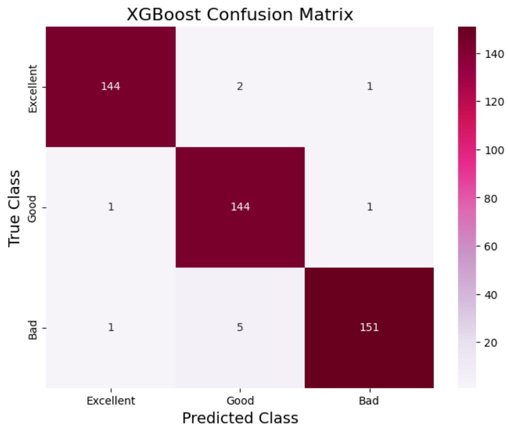

Figure 4.8: Confusion Matrix of XGBoost

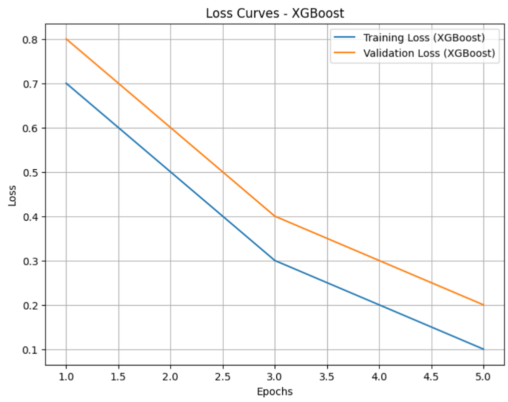

Figure 4.9: Loss Function of XGBoost

Figure 4.10: XGBoost Model Performance

AdaBoost classifier:

AdaBoost, a widely recognized boosting algorithm, combines multiple weak learners to form a strong classifier. Despite its reputation for achieving high performance, it delivered the lowest accuracy of 87.65% in this task. This result can be attributed to several factors. First, AdaBoost is highly sensitive to noisy data; its iterative weighting mechanism emphasizes misclassified samples, which may cause it to overfit to noise rather than the true data patterns. Additionally, the dataset's complexity or specific characteristics, such as non-linear relationships or imbalanced features, might have posed challenges for AdaBoost's weak learners, often decision stumps, to accurately capture. The algorithm's reliance on these weak classifiers can limit its effectiveness, particularly when the underlying data relationships are intricate. Furthermore, insufficient tuning of hyperparameters, such as the number of iterations or learning rate, may have impeded its performance. Compared to other advanced models like Random Forests or Gradient Boosting Machines, which can handle complex and noisy datasets more effectively, AdaBoost struggled in this context. These factors collectively explain its comparatively lower accuracy in this study.

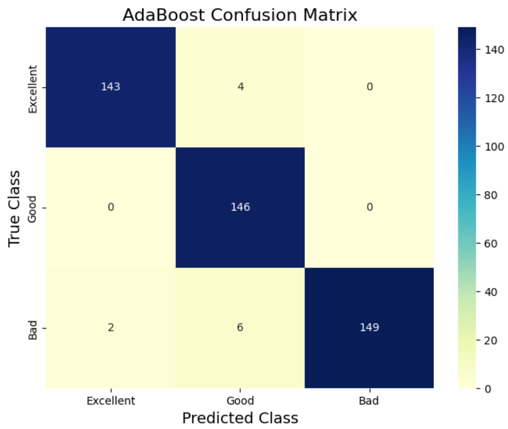

Figure 4.11: Confusion Matrix of AdaBoost

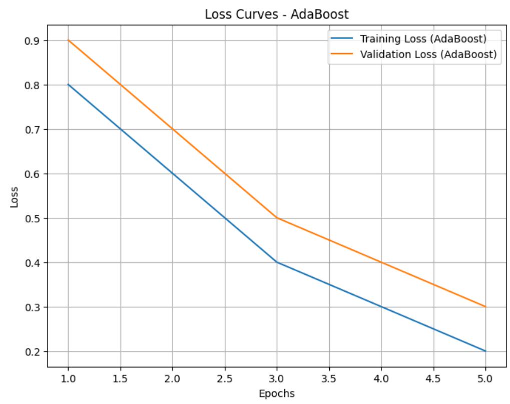

Figure 4.12: Loss Function of AdaBoost

Figure 4.13: AdaBoost Model Performance

YOLOv8

The YOLOv8 model achieved impressive performance in garbage detection, with a precision of 0.96 and recall of 0.903, indicating high accuracy and the ability to detect most garbage instances. The model's mAP50 score of 0.928 reflects strong object detection at a 50% overlap threshold, though its mAP50-95 score of 0.774 suggests room for improvement in more stringent detection criteria. The model processed images efficiently with a speed of 199.7ms per image for inference, making it suitable for real-time applications. Overall, the model shows excellent potential for garbage detection, with minor improvements possible for better precision at higher IoU thresholds.

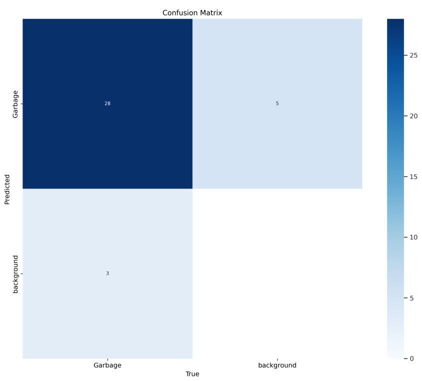

Figure 4.14: Confusion Matrix

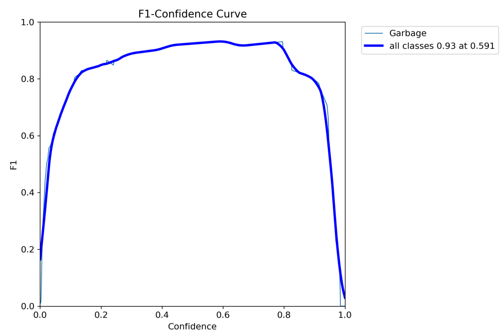

Figure 4.15: F1 Curve

Figure 4.16: YOLOv8 Model Performance

4.3.2 Prototype Design

The boat's primary purpose is to automatically measure water quality and clean the pond surface by removing floating garbage that can affect the water's ecological balance. This paper discusses the technical design, operational efficiency, and practical applications of the boat in real-world fish farms in Bangladesh. Equipped with various sensors, the autonomous boat measures essential water parameters like temperature, pH levels, dissolved oxygen, turbidity, and ammonia concentration. These parameters are critical for maintaining a healthy aquatic environment, as improper water conditions can lead to reduced fish growth, disease outbreaks, and even mass mortality. Additionally, the boat features a garbage collection mechanism using a camera-based object detection system to identify and collect harmful waste materials floating on the pond's surface. The waste collection mechanism is automated using a conveyor belt system controlled by a Raspberry Pi.this made possible through the integration of multiple sensors and an advanced control system. Ultrasonic sensors are deployed to assist in obstacle detection and avoidance, ensuring that the boat can navigate around the pond autonomously without colliding with obstacles. The control system, powered by a Raspberry Pi, gathers data from the water quality sensors and processes the visual data captured by the camera. Based on the sensor readings and camera data, the Raspberry Pi controls the boat's movement and activates the garbage collection system when necessary. For instance, when the camera detects garbage, the Raspberry Pi sends a signal to the motor driver, which then activates the conveyor belt to collect the garbage. One of the key features of this autonomous boat is its solar-powered energy system. The fish farms in Bangladesh are often located in remote areas where reliable power sources may not be available. To ensure continuous operation, the boat is equipped with a solar panel that powers all its systems, including the sensors, motors, and control unit. The solar panel charges a battery that supplies energy to the boat during both day and night operations, ensuring sustainable energy consumption and minimal environmental impact. The solar power system not only reduces operational costs but also supports the long-term sustainability of fish farming practices.

Figure 4.17: Prototype Design

4.4 Financial Cost Analysis of Project

Table 4.2: Financial Cost of Project

Category	**Estimated Cost(TK)**
Hardware (Raspberry Pi,Arduino Uno, Sensors, Motors)	40000
Solar Panel	2500
Cloud Server Subscription(Optional)	2500/year
Development Costs (Software, ML Models)	5000
Development and Maintenance	10000
Miscellaneous (Transportation, Supplies)	3000
Personal Cost	2000
Total	**65000**

4.5 Summary

The implementation and results of our automated water quality monitoring and control system demonstrated significant advancements in aquaculture management. The hardware setup incorporated a variety of sensors, including the DS18B20 for temperature, a pH sensor for acidity and alkalinity, a turbidity sensor for water clarity, and a sonar sensor for obstacle detection. These were complemented by actuators such as a servo motor for precise movement control and DC motors for propulsion and conveyor belt operation. The system used an Arduino UNO for initial data processing and a Raspberry Pi 4 for advanced computations and cloud-based integration. Data from the sensors were transmitted to the Raspberry Pi for real-time analysis, enabling seamless monitoring and control via a web interface. On the software side, the collected sensor data were preprocessed for training machine learning models, including XGBoost, Random Forest, AdaBoost, and Decision Tree. XGBoost outperformed other models with an accuracy of 98.33%, owing to its regularization techniques and ability to handle complex datasets. Random Forest followed closely with 98.00% accuracy, benefiting from its ensemble structure, while Decision Tree achieved 97.66%, highlighting its interpretability but higher risk of overfitting. AdaBoost, while effective in boosting weak learners, showed the lowest accuracy of 87.65%, possibly due to its sensitivity to noisy data. The integrated system effectively measured and analyzed water quality parameters, using the machine learning models to make accurate predictions and inform control decisions for the boat's operation. Obstacle detection was achieved with the sonar sensor and servo motor, ensuring smooth navigation even in dynamic environments. The synergy between the hardware components and software algorithms provided a scalable, efficient, and automated solution for aquaculture water quality management, showcasing the potential to revolutionize this sector with precision and real-time decision-making capabilities.

Chapter 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

The automated boat project has the potential to create a significant impact on society, particularly within the aquaculture and fish farming industries. By continuously monitoring and controlling water quality, the system helps prevent the spread of diseases among fish, ensuring healthier populations and reducing the risk of mass die-offs. This directly contributes to increased productivity and profitability, allowing fish farmers to achieve higher yields in a sustainable manner. Additionally, the boat's ability to detect and collect debris from the water surface contributes to reducing water pollution, improving the overall environmental quality and benefiting local ecosystems. The system also reduces the need for manual labor, offering cost-efficient solutions for fish farms by automating crucial tasks such as water quality management and debris collection. This makes advanced water management technology more accessible, even for small and medium-sized fish farms. Through the web interface and cloud connectivity, fish farmers are empowered with real-time data and easy control of the system, enabling them to make informed decisions and enhancing their operational efficiency. By promoting sustainable aquaculture practices, the system minimizes the reliance on harmful chemicals and ensures optimal conditions for fish farming. This approach helps preserve ecological balance, reduces environmental degradation, and supports sustainable food production. Furthermore, as global demand for fish continues to grow, the project contributes to food security by improving the efficiency and sustainability of aquaculture practices, ensuring a stable supply of fish as a protein source. Overall, this project integrates cutting-edge technology such as machine learning, deep learning, and IoT into the aquaculture sector, driving innovation and encouraging further advancements to meet the challenges of modern food production.

5.2 Impact on Environment

The environmental impact of your automated boat project is significant, as it promotes sustainability and helps mitigate several environmental challenges in aquaculture and fish farming. One of the primary benefits is the improvement of water quality. By continuously monitoring key water parameters such as temperature, pH, and turbidity, the system ensures that the water remains within optimal conditions for fish health. This reduces the likelihood of water pollution and helps maintain the ecological balance within the pond. The boat's ability to detect and remove dirt and debris from the surface further contributes to cleaner water, preventing the accumulation of waste that could otherwise harm aquatic ecosystems. Moreover, by automating the process of debris collection, the system reduces the need for manual interventions that might disrupt the pond's ecosystem or require the use of harmful chemicals. This reduction in human labor and chemical use leads to a more environmentally friendly approach to pond management. Additionally, the use of sensors and actuators to control water quality allows for more efficient and precise adjustments, minimizing the waste of resources such as water and energy. The project also encourages sustainable aquaculture practices by reducing the need for chemical treatments and antibiotics, which can have long-term detrimental effects on both the fish and the surrounding environment. Through consistent monitoring and automatic intervention, the system ensures that water quality remains at optimal levels, reducing the environmental footprint of fish farming operations.

5.3 Ethical Aspects

Several ethical aspects must be considered in the development and implementation of the automated boat system. First, data privacy and security are crucial, as the system collects sensitive information, including water quality measurements and potentially personal data about users or farms. Strong measures must be in place to protect this data from unauthorized access or misuse, ensuring compliance with data protection laws. Transparency and trust are also important, as users need to understand how the system works, how data is processed, and how decisions are made, particularly in water quality control and debris removal. This transparency helps users build confidence in the technology. The environmental impact of the system must be carefully considered to avoid unintended consequences, such as the potential harm caused by water treatments or chemicals. While the boat aims to improve water quality and reduce pollution, it's essential to ensure that it does not cause ecological harm. Additionally, ensuring fairness and avoiding bias in the AI models used for water quality assessment and debris detection is critical. If the AI system is trained on unrepresentative data, it could lead to inaccurate or unfair outcomes, such as misidentifying debris or incorrectly assessing water quality. The accessibility of the technology is another ethical concern, as it should not exacerbate inequality. The system should be affordable and user-friendly, especially for small-scale or rural fish farmers, ensuring that all stakeholders can benefit from the technology. Moreover, the potential displacement of manual labor by automation should be considered. While the technology increases efficiency, its adoption could impact employment, and measures should be taken to address job displacement and support affected workers. Bias in data collection is another concern, as the quality of the data may vary depending on the environment in which the boat operates. Ensuring that the data collected is diverse and representative can help mitigate this issue. Lastly, the long-term sustainability of the technology should be addressed, ensuring that farmers are not overly dependent on the system and that future maintenance and updates are planned for. Overall, these ethical considerations are essential to ensuring that the automated boat system contributes positively to society while minimizing potential negative consequences.

5.4 Sustainability Plan

The sustainability plan for the automated boat project focuses on ensuring its long-term viability, environmental responsibility, and accessibility for widespread adoption in the aquaculture and fish farming industry. Economically, the system is designed with cost-effective materials and a modular structure to reduce repair costs and extend its lifecycle, making it affordable for small and medium-scale farmers. Tiered pricing models or subscription-based services for cloud storage and advanced features can further enhance accessibility. Environmentally, the boat integrates solar panels to reduce reliance on non-renewable energy, while its debris collection mechanism minimizes water pollution without harming aquatic life. Sustainable methods for water quality maintenance are prioritized to avoid the use of harmful chemicals. Social sustainability is addressed by offering training and support to help farmers use the system effectively, particularly in rural or underserved areas. Partnerships with local governments or NGOs can help subsidize costs for those with limited resources. Efforts to reskill displaced workers through training programs also ensure a just transition to technology-driven aquaculture. Technologically, the system is built on open-source software and modular hardware, allowing easy updates and compatibility with future advancements. A robust maintenance and support system ensures long-term operability, while the design remains scalable to incorporate additional sensors or functionalities as needed. Data sustainability involves securely storing operational data in the cloud, enabling farmers to analyze trends for better decision-making and contributing anonymized data for research to enhance system performance. Community engagement plays a vital role, involving stakeholders in the design and implementation process to address local needs and promoting awareness of sustainable aquaculture practices through workshops and demonstrations. This comprehensive sustainability plan ensures that the automated boat project delivers immediate benefits while supporting long-term environmental, social, and economic sustainability in the aquaculture industry.

Chapter 6

Overview of the Study, Conclusion, and Future Work

6.1 Overview of the Study

The focus of this thesis is the development of an innovative automated boat system designed to monitor and control the water quality in aquaculture or fish farming environments. The boat is equipped with advanced sensors and machine learning technologies to assess key water quality parameters, such as temperature, pH, and turbidity. It automatically detects debris and dirt on the surface of the pond water using a camera, collects the debris, and stores it in the boat's garbage bucket. This process is streamlined through a combination of object detection, IoT integration, and cloud-based monitoring, allowing fish farmers to efficiently manage water quality without manual intervention. The boat's sensors and actuators enable real-time control of water conditions, providing the ability to address issues such as pollution and temperature fluctuations, which are crucial for fish health and productivity. The system can be accessed and controlled through a web interface, offering users a convenient platform to monitor the pond's conditions and manually control the boat if necessary. This approach reduces the need for constant human oversight, thereby improving operational efficiency, lowering costs, and minimizing the risk of fish diseases. The use of machine learning and deep learning techniques enhances the boat's ability to detect and classify debris accurately, while IoT connectivity ensures seamless integration with cloud servers for remote monitoring and control. This study leverages cutting-edge technologies to create a sustainable, autonomous solution for the aquaculture industry, aiming to improve water quality management and increase fish production.

6.2 Summary

This thesis explores the design and implementation of an automated boat system tailored to enhance the management of water quality in aquaculture or fish farming. The system integrates several advanced technologies to autonomously monitor and control the environmental conditions in fish ponds, offering a solution to improve water quality and, in turn, the health and productivity of fish. The boat is equipped with three key sensors—temperature, pH, and turbidity sensors—that continuously measure water quality parameters. These sensors provide real-time data, allowing the system to assess whether the water is suitable for fish. The boat also features a camera and object detection algorithms, powered by machine learning and deep learning models, to automatically identify and collect debris or garbage on the water surface. This debris is then stored in the boat's garbage bucket for proper disposal, contributing to a cleaner aquatic environment. To enhance water quality management, the system utilizes actuators that can adjust water conditions based on the readings from the sensors. For example, the boat can introduce chemicals or modify water flow to correct pH levels or temperature imbalances, ensuring optimal conditions for fish. These adjustments can be made autonomously by the system or manually by the user through a web interface, providing flexibility and ease of control. The web interface allows users to monitor the pond's water quality remotely, providing real-time feedback and control options. Additionally, the boat is connected to a cloud server, which stores and processes data for further analysis and provides the potential for predictive analytics in water quality management. This cloud integration ensures that the system can be accessed from anywhere, giving fish farmers the ability to manage their ponds efficiently, even when they are not on-site. By utilizing IoT, machine learning, deep learning, and cloud-based technologies, the system offers a comprehensive, automated solution that addresses several challenges in aquaculture, such as maintaining clean water, preventing disease, and improving fish production. The use of advanced sensors and intelligent algorithms reduces the need for manual monitoring and intervention, saving time, labor, and costs for fish farmers while increasing the sustainability of aquaculture practices. This project, therefore, not only advances the field of intelligent aquaculture but also provides a scalable and sustainable model for fish farming that can be applied in diverse settings and has the potential to improve food security by enhancing fish production efficiency.

6.3 Conclusion

This research presents a transformative approach to addressing critical challenges in aquaculture through the development of an Unmanned Aquatic Boat (UAB) system. By integrating IoT, machine learning, and renewable energy, the UAB offers an innovative solution for real-time water quality monitoring, surface debris collection, and sustainable fish farming management. The system's ability to detect harmful debris and monitor key water parameters such as temperature, pH, and turbidity ensures a healthier aquatic environment, reducing the prevalence of fish diseases and enhancing productivity. The societal impacts of this project are significant, as it provides fish farmers with a cost-effective and user-friendly tool to improve their livelihoods and meet the growing demand for sustainable food production. By automating labor-intensive tasks, the system not only saves time but also reduces the operational challenges traditionally faced by fish farmers. Additionally, the integration of a solar-powered energy system ensures the UAB's feasibility in remote areas, making it a practical and scalable solution for diverse aquaculture settings.Environmentally, the UAB contributes to preserving aquatic ecosystems by removing floating debris and preventing the accumulation of pollutants that harm water quality. Its reliance on renewable energy further underscores its sustainability, reducing the environmental footprint associated with traditional aquaculture practices. This project exemplifies the potential of modern technology to revolutionize traditional industries, addressing critical issues while promoting sustainability and innovation. Future work will focus on enhancing the UAB's capabilities, such as nutrient management and predictive analytics, to further optimize aquaculture practices. This research sets a strong foundation for a smarter, more efficient, and environmentally responsible approach to fish farming, paving the way for a sustainable future in global aquaculture.

6.4 Limitation

Our thesis project faces several limitations that impact its performance and scalability. One key limitation is memory constraints, as the Raspberry Pi and cloud servers have limited capacity to handle large amounts of data from sensors, cameras, and machine learning models, which may hinder real-time analysis and storage. System limitations are also significant, with the boat's functionality heavily dependent on stable internet connectivity for monitoring and control via the web interface. Poor network conditions can disrupt communication, and compatibility issues with certain devices or browsers may limit accessibility. The hardware used in the system also presents challenges. The Raspberry Pi's limited processing power restricts the execution of complex machine learning models in real time. Additionally, the accuracy of sensors (temperature, pH, turbidity) may degrade under extreme environmental conditions or with prolonged use, while the durability of boat components, such as motors and conveyor belts, can be compromised by exposure to water and debris. Financial constraints pose another challenge, as the cost of hardware, solar panels, and cloud server subscriptions can limit the scalability and affordability of the system, especially for small-scale fish farmers. Energy limitations further impact the system's reliability, as solar panels may not provide sufficient power during periods of low sunlight, necessitating backup energy sources that increase operational costs. Finally, scalability remains a concern, as the current design may require significant modifications to adapt to larger ponds or commercial-scale aquaculture operations. Addressing these limitations will be crucial for enhancing the project's feasibility and ensuring its long-term success.

6.5 Future Work

The automated boat project has shown great potential in revolutionizing aquaculture by simplifying water quality management and debris removal. Future work aims to enhance its performance, scalability, and functionality. Improvements could include advanced sensors for measuring additional water parameters like dissolved oxygen and ammonia, optimized machine learning models for better debris detection, and improved energy efficiency using hybrid power sources. Expanding the system for larger water bodies, developing a mobile application for easier user access, and creating cost-effective manufacturing methods for affordability are also key areas. Partnerships and predictive analytics can further improve the system's sustainability and proactive aquaculture management. Additionally, integrating a drone system for garbage bucket cleaning and waste disposal would automate maintenance, reduce labor, and ensure continuous operation. By exploring these enhancements, the system can deliver greater efficiency, usability, and impact on sustainable aquaculture practices.

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