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Predicting Aquatic Environment For Fish Species Survival Using IOT And ML

Capstone project

Students Details

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Abstract

This project presents an innovative approach to predicting aquatic environments conducive to fish species survival by integrating Internet of Things (IoT) and Machine Learning (ML) technologies. Utilizing a dataset from Kaggle containing pH, temperature, turbidity, and fish species, we developed a robust ML model in Google Colab. The dataset underwent balancing, and various classification models, including Decision Tree, KNeighborsClassifier, RandomForestClassifier, Support Vector, and GaussianNB, were trained and compared. The DecisionTreeClassifier demonstrated superior accuracy and was chosen for deployment. Comprehensive evaluation metrics such as Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient, and Kappa Statistic were employed to validate the model's performance. Our IoT hardware system, featuring an Arduino Uno with ethernet shield, pH, temperature, and turbidity sensors, collects real-time data and transmits it to a server via an API. The software architecture comprises a frontend developed using HTML, CSS, and JavaScript, and a backend built with FastAPI in Python. Data management is facilitated using a MySQL database hosted on a XAMPP local server. This project demonstrates the practical application of IoT and ML in aquaculture, providing a reliable tool for fish farmers to optimize water conditions for various fish species, thereby enhancing survival rates and productivity.

Acknowledgement

At the very beginning of this project, let us express our maximum gratitude towards our supervisor Suman Saha who has always been so kind to help us in every possible way for the successful completion of the project. Availing pertinent details concerning the degree of accomplishment of our assignments and pushing us to additional efforts. Special thanks to all members of the team for inputs, cooperation and the work done as the part of the project, towards delivering set objectives of the work. Many of these were successful and some were not, but all were done with each other and finally this project is Completed. Last but not the least, I want to express my gratitude to all the families, friends and other peers who have been willing to help to finish this project.

Table of Contents

List of Figure

List of Table

1 Introduction

Aquaculture, the practice of farming aquatic organisms such as fish, mollusks, crustaceans, and plants, has evolved significantly since its inception in China approximately 4,000 years ago. This practice involves the breeding, nurturing, and harvesting of these organisms in both freshwater and saltwater environments, and it plays a crucial role in global food production. Presently, aquaculture contributes more than half of the seafood consumed worldwide, a figure that continues to rise in tandem with the growing global population. According to the Food and Agricultural Organization (FAO), aquaculture production soared from 3 million tons in the 1970s to over 80 million tons in 2017.

Manual classification of fish species is a complex and labor-intensive task, often requiring expert knowledge. Accurate identification of fish species is essential for various industrial and agricultural applications, including food production. Traditional methods, such as classification trees, have been employed by marine biologists to categorize fish based on their characteristics, but these methods are time-consuming and lack efficiency. The advent of machine learning (ML) has revolutionized fish classification, offering significant improvements in speed, accuracy, and effort. Fish classification involves identifying species based on their physical traits or other distinguishing features. This process is vital for numerous reasons, including pattern and subsistence matching, feature extraction, and the identification of physical or behavioral characteristics. Effective fish classification aids in statistical control and quality assurance, which are crucial for the fishing industry and population assessments . Automating this process can further enhance classification speed and accuracy, reducing the dependency on manual efforts.

Various approaches have been proposed for automated fish species identification. This project leverages machine learning models, including Decision Tree, Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), to predict the survival of fish species in aquatic environments based on key environmental parameters: pH, temperature, and turbidity. Unlike traditional rule-based algorithms, ML models offer predictive capabilities for unknown datasets, as validated through the use of confusion matrices which provide comprehensive accuracy metrics.

Deep learning models, such as Convolutional Neural Networks (CNNs), although highly accurate, are computationally intensive and require substantial training time. Therefore, this project focuses on ML algorithms due to their lower computational complexity and efficient performance. Specifically, we propose a predictive model for fish survival in aquatic environments using the Decision Tree classifier, selected for its superior accuracy and performance.

The remaining of this paper is organized as follows: Section 2 reviews related literature; Section 3 discusses the proposed model; Section 4 describes the Methodology; Section 5 describes the

Experimental setup and analyzes the results; and Section 6 concludes with the findings and implications of this study.

1.1 Motivation

Aquaculture, the farming of aquatic organisms, is vital for global food security and economic growth. However, maintaining optimal water quality conditions is critical for fish species survival and health. Traditional methods of monitoring and managing aquaculture environments are often labor-intensive and prone to human error. By integrating IoT sensors with machine learning (ML) models, we aim to create an intelligent system that provides real-time insights and predictions to enhance fish farming efficiency and sustainability. This project addresses the need for innovative solutions to ensure optimal environmental conditions and reduce fish mortality rates.

1.2 Objectives

- Develop an Intelligent Monitoring System
- Predict Fish Species Survival using machine learning models
- Ensure High Model Accuracy and Reliability
- Facilitate User-Friendly Integration
- Promote Sustainable Aquaculture Practices

2 Literature review

Research in aquaculture is an input to sustain stabilized production because of its benefits in providing food and stimulating economic growth to the global community. Over the past decade, many scientists have embarked on efforts that finally offered new production technologies in the production farm. An example of a system that is demonstrated about the IoT devices for aqua culture is as discussed in [3] A. Ramya[4] have came up with an IoT solution for smart fish farming. Wen-Jiun Sung presented a framework for wireless sensor network for fish aquaculture monitoring. D. Prangchumpol [5] proposed the mobile application template for fish feeding. T Joseph et al [6] prescribes a holistic fish farming system that utilizes IoT gadgets. Authors [7] implemented an IoT system for Intelligent Fish Farming and Pond Management. A hazardous model of aquaculture is presented based on the IoT in authors [8]. . A regression model is utilized for predicting water quality of cultivating fish; however, they did not consider the prediction accuracy [10]. An automated strategy is developed for fish identification primarily based on the use of aid vector desktop and kmeans clustering algorithm [11]. A computerized robust Nile-Tilapia fish classification approach is proposed in [12], where the scale-invariant characteristics of fish's change are extracted. Then, these points are used to feed the support vector machine. All these authors do not develop any website for perception data using M-learning algorithms to remote monitoring. The main purpose of the system is to prevent dangers related to the fish farming system through the use of the above sensors to monitor the system remotely. With all these sensors, everything is done automatically and it will also be possible to monitor fish farming from other stations. The feasibility and capability of the proposed system are tested to analyze the performance and efficiency of the system. In this respect, it is a low-cost smart system that can help the users to monitor the water environment where the fishes are so that appropriate measures can be taken by the users whenever it is necessary.

3 Proposed Work

The proposed project aims to develop an advanced aquaculture monitoring system that leverages Internet of Things (IoT) technology and machine learning (ML) to optimize the survival and growth conditions for various fish species. The system will integrate environmental sensors to monitor key water quality parameters such as pH, temperature, and turbidity, which are critical for maintaining optimal fish health. The data collected by these sensors will be processed and analyzed using a Decision Tree Classifier, selected for its high accuracy in predicting suitable conditions for fish species.

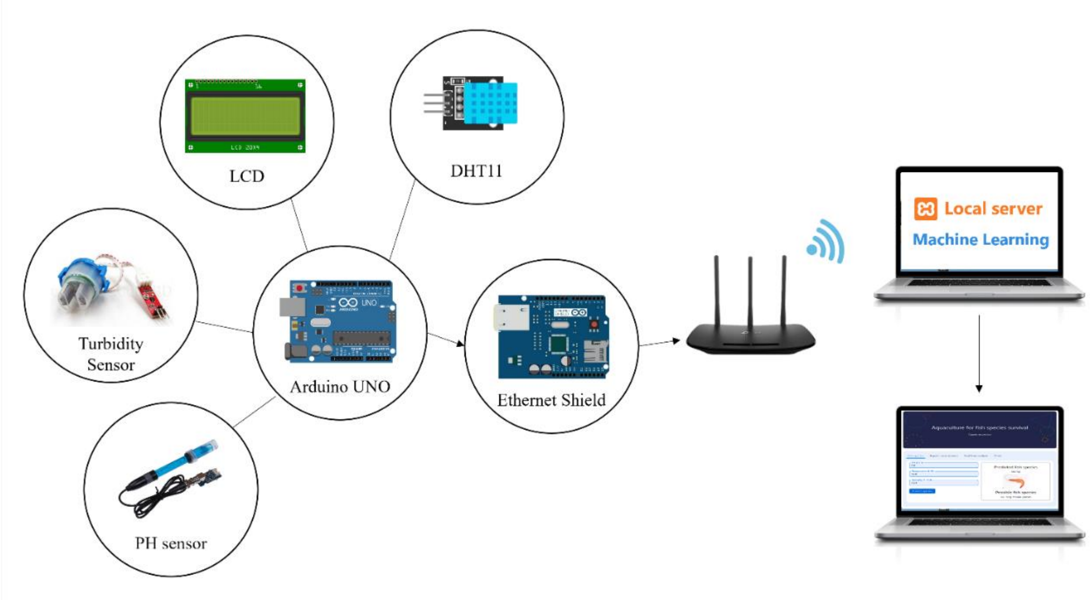

Figure 3.1 Send sensor data to server

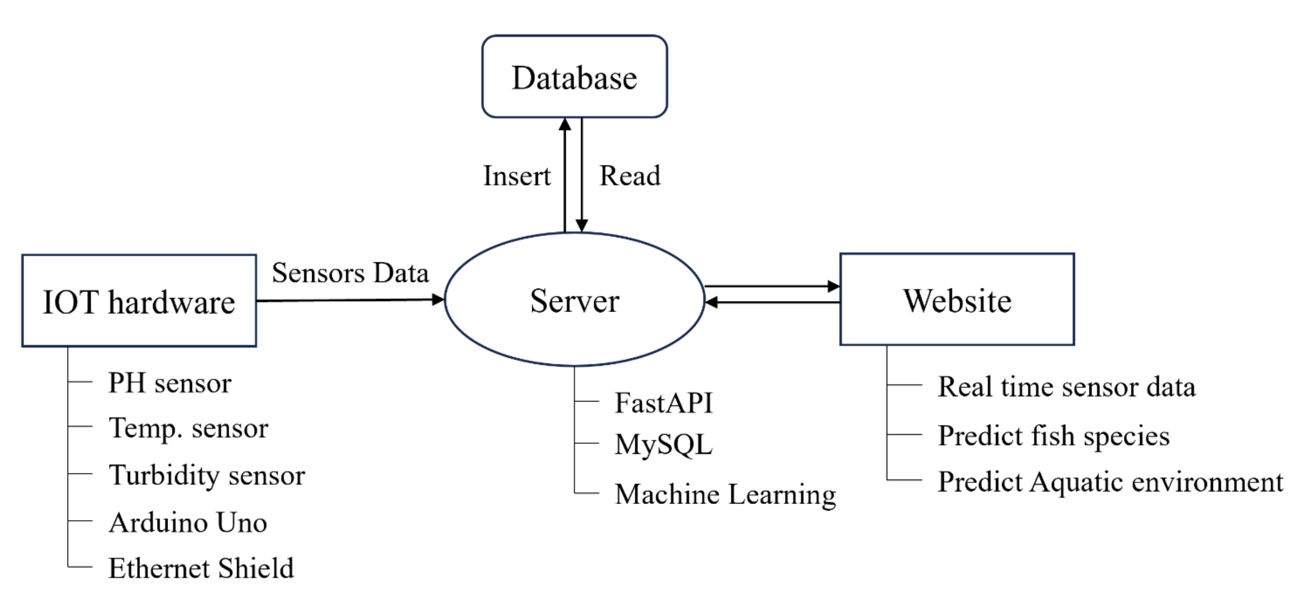

Figure 3.2 Block diagram of proposed system

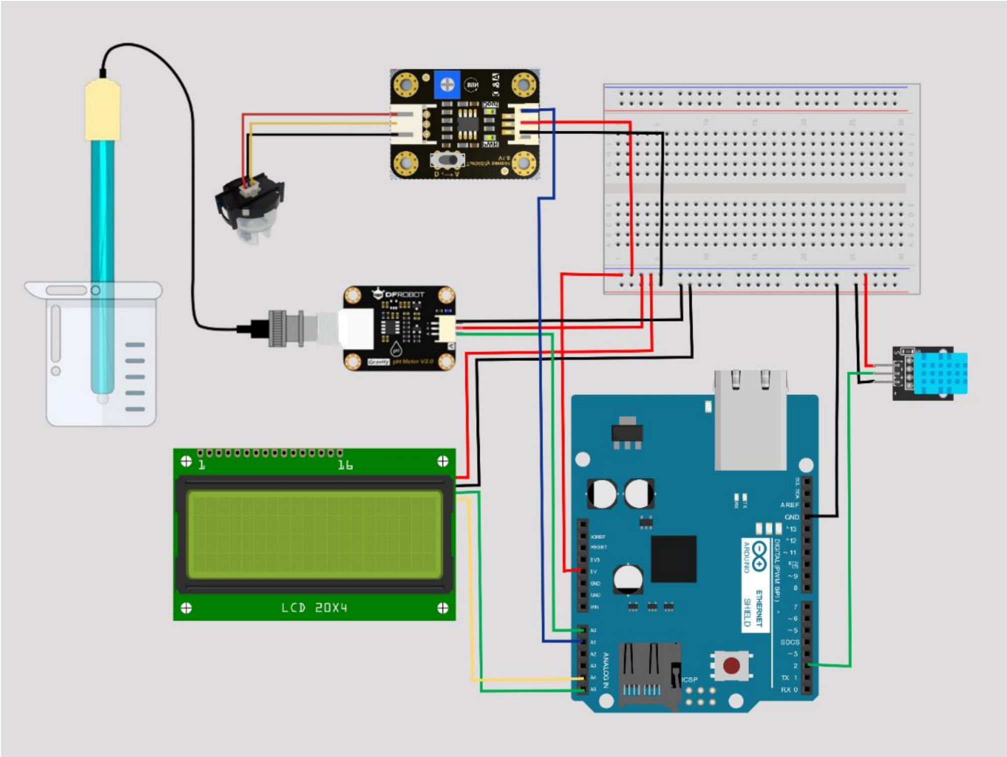

Figure 3.3 Circuit diagram of IOT hardware of my project

3.1 System Architecture and Components

3.1.1 Hardware Components

Sensors- pH sensor, temperature sensor, and turbidity sensor to measure water quality parameters.

Microcontroller0 Arduino Uno to interface with the sensors and collect data.

Communication Module- Ethernet shield to transmit data to a remote server using WiFi.

3.1.2 Software Components

Backend- Developed using FastAPI in Python, it will handle data processing, ML model integration, and API management.

Frontend- Created with HTML, CSS, and JavaScript, the user interface will provide real-time visualization and prediction functionalities.

Figure 3.4 Used technologies

HTML: HTML or HyperText Markup Language, is a crucial coding language used in web development. It serves as the standard markup language for creating and structuring web content. HTML employs a system of tags enclosed in angle brackets to define the structure and layout of web pages. These tags, such as html, body, p, a, and img are used to format text, create paragraphs, add links, and insert images, among other functions.

SCSS: The term SCSS is an acronym for Sassy Cascading Style Sheets. It is basically a more advanced and evolved variant of the CSS language. Natalie Weizenbaum and Chris Eppstein created it, and Hampton Catlin designed it. It comes with more advanced features- thus often called Sassy CSS.

JavaScript: JavaScript (JS) is a versatile and widely-used programming language primarily employed in web development. It enables the creation of interactive and dynamic content on websites. Unlike HTML and CSS, which focus on structure and design, JavaScript is responsible for adding behavior and functionality to web pages. It can be used to respond to user actions, manipulate the Document Object Model (DOM), and make web applications more engaging and responsive.

Python: Python is a high-level, general-purpose programming language. Its design philosophy emphasizes code readability with the use of significant indentation. Python is dynamically typed and garbage-collected. It supports multiple programming paradigms, including structured, object-oriented and functional programming

FastAPI: FastAPI is a modern, fast (high-performance), web framework for building APIs with Python based on standard Python type hints. The key features are: Fast: Very high performance, on par with NodeJS and Go (thanks to Starlette and Pydantic). One of the fastest Python frameworks available.

3.1.3 Database

MySQL: Used to store sensor data and prediction results, hosted on a XAMPP local server.

3.1.4 Functionality

Real-Time Monitoring- The system will continuously monitor water quality parameters and display the data on a user-friendly dashboard. Fish Species Prediction- Users can input water quality parameters (pH, temperature, turbidity) into the system, and the ML model will predict the most suitable fish species for the given conditions. Optimal Environment Prediction- Users can input a specific fish species, and the system will provide the optimal pH, temperature, and turbidity values for that species, aiding in better management of aquaculture environments.

3.1.5 Machine Learning Model

The Decision Tree Classifier, trained on a dataset from Kaggle, is used due to its interpretability and accuracy. The model is capable of predicting both fish species based on water parameters and optimal water conditions based on the fish species.

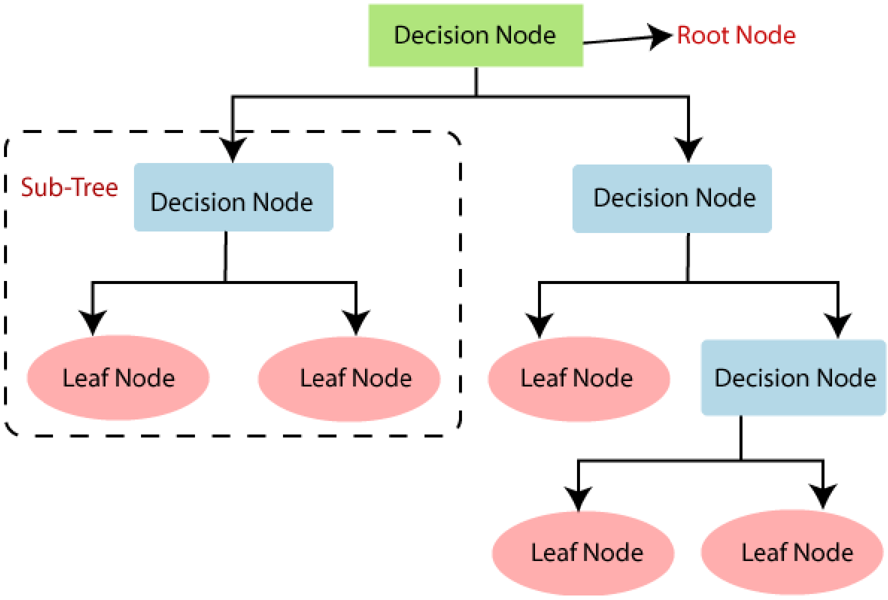

Figure 3.5 Decision Tree Classification Algorithm

3.1.6 Description of dataset

I collect dataset from kaggle named "Realtime pond water dataset for fish farming". The dataset is divided into two parts: one containing information about the aquatic environment, and the other focusing on fish species. The target attribute consists of 11 different fish species, including katla, shing, prawn, rui, koi, pangas, tilapia, silver carp, karpio, magur, and shrimp. Regarding the aquatic environment characteristics, we specifically consider pH, temperature, and turbidity as the key parameters of interest.

pH: pH is necessary for aquaculture as a measure of the acidity of the water or soil. The optimal pH for fish is between 6.5 and 9. Fish will grow poorly, and reproduction will be affected at consistently greater or lower pH tiers. The pH level for warm-water pond fish is 4 for acid death point, 4 to 5 for no reproduction, 5 to 6.5 for slow growth, 6.5 to 8.5 for desirable ranges, 9 to 10 for slow growth, and 11 for alkaline death point.

Temperature: The increase and endeavor of the fish rely on their physique temperature. The body temperature of the fish is about the same as the water temperature and varies with it. Each fish species is tailored to develop and reproduce inside well-defined stages of water temperatures, but the most useful boom and replica take area within narrower tiers of temperature. It is important, therefore, to understand the water temperatures reachable at your fish farm nicely to pick out the right species of fish and to graph its management as a result.

Turbidity: The ability of water to transmit the light that restricts light penetration and limit photosynthesis is termed as turbidity and is the resultant impact of several elements such as suspended clay particles, dispersion of plankton organisms, particulate natural things and also the pigments caused with the aid of the decomposition of organic matter. Acceptable turbidity varies from 30-80 cm is properly for fish health.

Fish species: In our dataset, we utilized a total of 11 fish species as the target variable. The fish species in our dataset are presented in figure 3.6;

All the parameter are described that are essential for better aquatic environment like PH, temparature, turbidity. And also In figure 3.6 all the fish that are used in our project are shown by image. There are 11 species fish and all the fish species image is shown together and labeled.

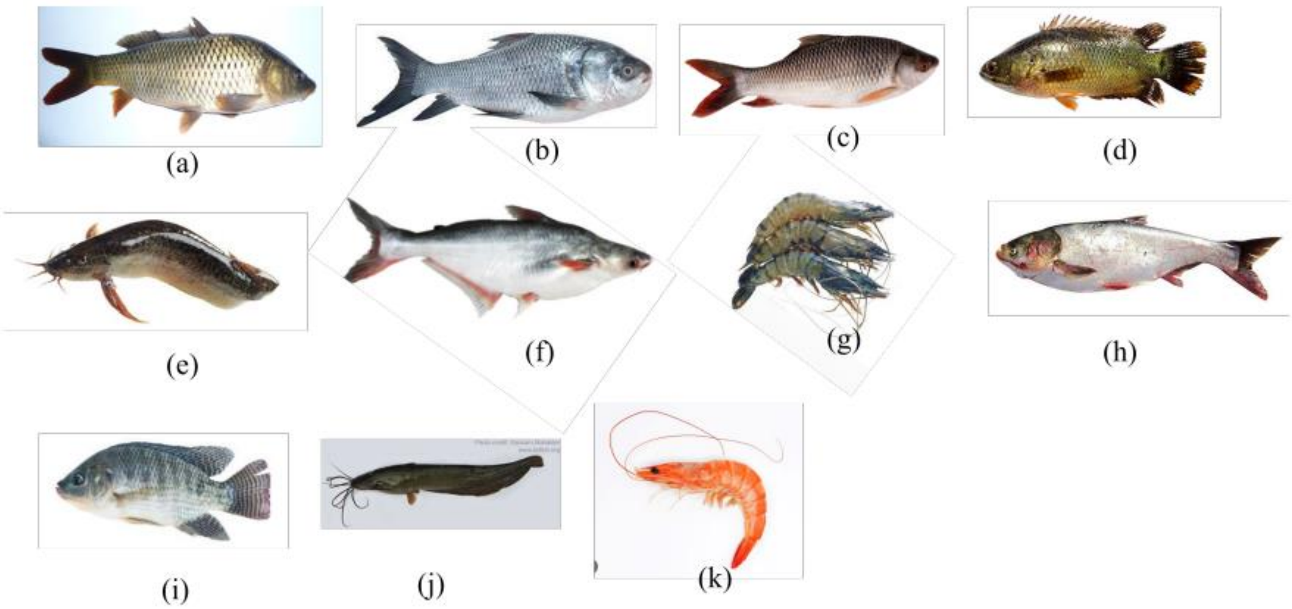

Figure 3.6 Sample fishes: (a) carpio fish, (b) katla fish, (c) rui fish, (d) koi fish, (e) magur fish, (f) pangas fish, (g) prawn fish, (h) silver carp fish, (i) tilapia fish, (j) shing fish and (k) shrimp fish

4 Methodology

The methodology of this project involves a systematic approach to designing, developing, and implementing an IoT and ML-based aquaculture monitoring system. This section outlines the steps taken to achieve the project objectives, including data collection, model development, system integration, and evaluation.

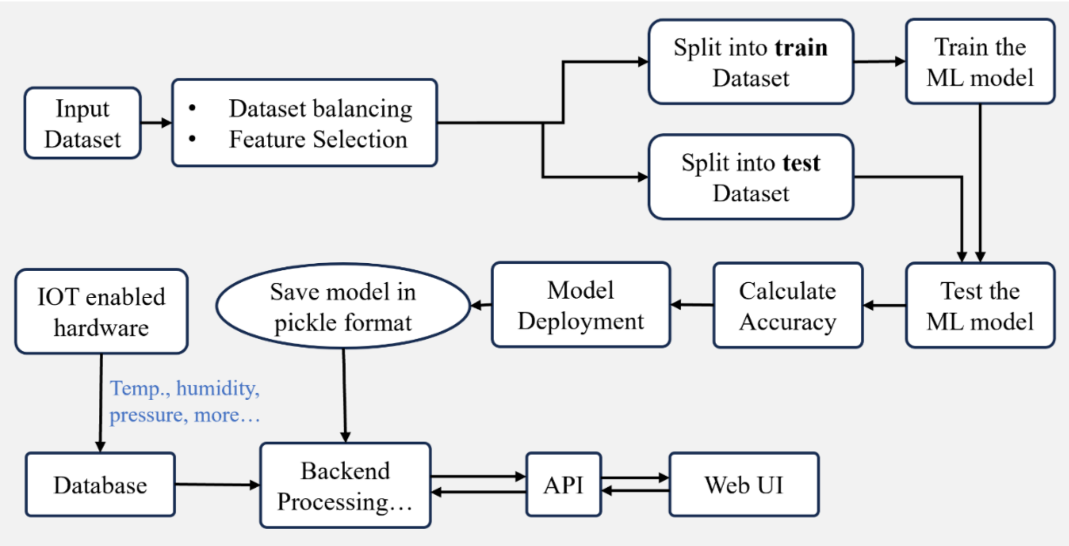

Figure 4.1 Overall workflow diagram

4.1 Data Collection

Dataset Acquisition: A comprehensive dataset was sourced from Kaggle, containing critical water quality parameters: pH, temperature, turbidity, and fish species. Sensor Deployment: pH, temperature, and turbidity sensors are deployed in the aquaculture environment to collect real-time data. Data Transmission: Sensor data is transmitted to a server using an Arduino Uno microcontroller and a Wi-Fi module.

4.2 Machine Learning Model Development

Model Selection: Several machine learning models are considered, including Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine, and GaussianNB. Training and Validation: Models are trained using the preprocessed dataset and validated using cross-validation techniques. Model Comparison: Models are evaluated based on accuracy, precision, recall, F1-Score. Model Selection: The Decision Tree Classifier is selected for its superior performance.

4.3 System Integration

In backend development, FastAPI is used to develop the backend, handling data processing, ML model integration, and API management. In fontend development, HTML, CSS, and JavaScript are used to create a user-friendly interface, allowing users to input parameters and receive predictions. A MySQL database is implemented to store sensor data and prediction results, hosted on a XAMPP local server.

4.4 Prediction Functionality

The IOT hardware able to send data to server in each second. The frontend displays real-time sensor data in graphical form, allowing users to monitor water quality. By using this real time data user can predict proper fish species for their aquaculture. In the other hand, users can also manually input water quality parameters to predict the most suitable fish species. Users input a fish species to receive optimal water quality parameters for that species.

4.5 Evaluation and Testing

The ML model is tested in a controlled environment to ensure accurate predictions. To get a proper machine learning model we train various model using our dataset to get a proper machine learning model. This machine learning models performance is evaluated using confusion matrices and other statistical measures. The user interface is tested for usability and functionality.

4.6 Deployment and Maintenance

The system is suitable for deployment in a real-world aquaculture environment for continuous monitoring and prediction. This system requires regular maintenance to ensure sensor accuracy, data integrity, and system reliability.

5 Experimental setup and result analysis

In this section hardware setup, model training, accuracy information, output, web application interface etc are described. Figure 5.1 shows the circuit implementation of IoT related devices. This hardware system contains Arduino Uno, Ethernet shield attached with Arduino Uno, Temperature measuring sensor, PH sensor, turbidity sensor. There are also a LCD by which we can see values of sensor. This hardware system also able to send data to server using WiFi.

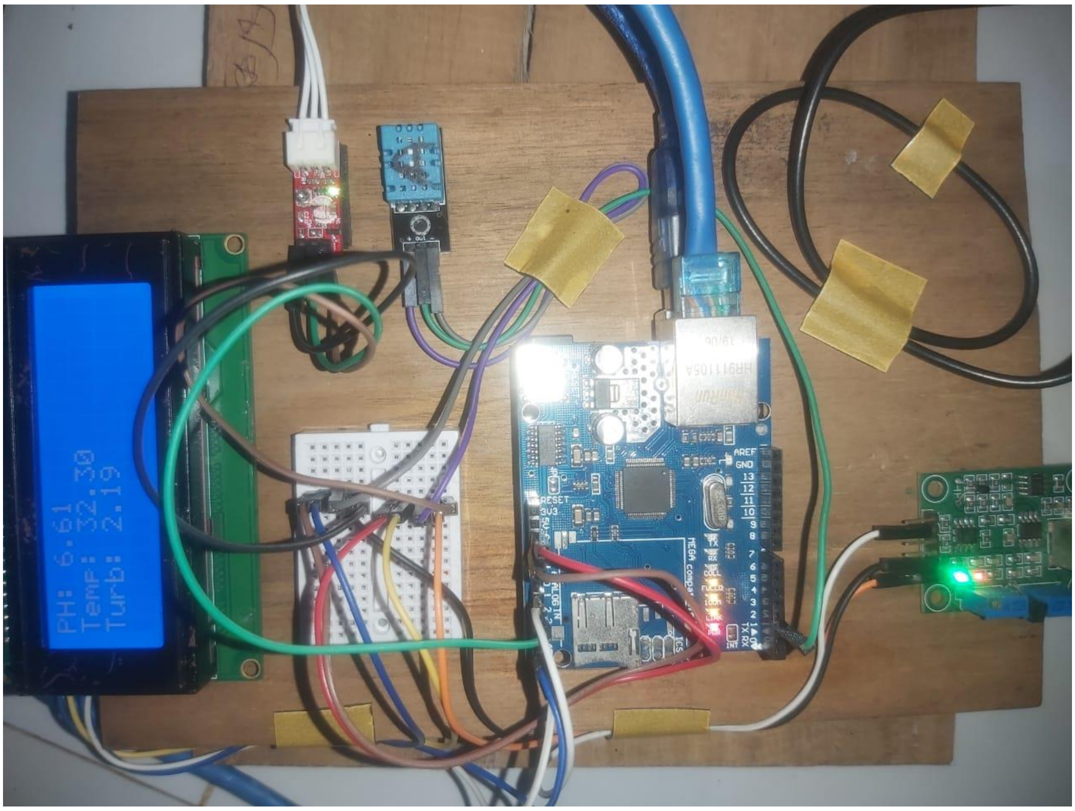

Figure 5.1 IoT hardware

Model	Accuracy
Decision Tree Classifier	0.82
KNeighbors Classifier	0.68
Random Forest Classifier	0.83
Support Vector	0.39
GaussianNB	0.39

Table 5.1 Accuracy for unbalanced dataset

Model	Accuracy
Decision Tree Classifier	0.98
KNeighbors Classifier	0.90
Random Forest Classifier	0.97
Support Vector	0.49
GaussianNB	0.51

Table 5.2 Accuracy for balanced dataset

The table 5.1 and 5.2 compares the accuracy of various machine learning models on balanced and unbalanced datasets. In table 5.2, which depicts the accuracy for the balanced dataset, the Decision Tree Classifier achieved the highest accuracy (98.24%), followed by KNeighborsClassifier (98.05%) and RandomForestClassifier (97.54%). Conversely, Support Vector and GaussianNB performed poorly with accuracies of 49.65% and 51.76%, respectively.

In table 5.1, for the unbalanced dataset, the accuracies drop significantly across all models, with the Decision Tree Classifier and RandomForestClassifier maintaining relatively better performance at 82.35% and 83.19%, respectively. KNeighborsClassifier, Support Vector, and GaussianNB show notably reduced accuracies of 68.07%, 39.45%, and 39.50%, respectively. This comparison highlights the importance of data balancing in achieving higher model accuracy.
The image presents two classification reports comparing the performance of a machine learning model on unbalanced and balanced datasets.

Fish Species	Precision	Recall	F1-Score	Support
karpio	0.75	0.75	0.75	4
katla	0.63	0.92	0.75	13
koi	0	0	0	4
magur	0.5	0.5	0.5	2
pangas	0.86	0.92	0.89	13
prawn	0	0	0	1
rui	1	0.82	0.9	17
shrimp	1	1	1	24
silverCup	0.91	1	0.95	10
sing	0.67	0.67	0.67	9
tilapia	1	0.82	0.9	33
Accuracy			0.82	119
Macro Avg	0.66	0.67	0.66	119
Weighted Avg	0.85	0.82	0.83	119

Table 5.3 Classification report for unbalanced dataset

Table 5.3, Classification Report for unbalanced Dataset: The overall accuracy is 82%, with a macro average precision, recall, and F1-score of 0.66, 0.67, and 0.66, respectively. Precision, recall, and F1-scores vary significantly across classes, indicating poor performance for some species (e.g., koi, prawn).

Fish Species	Precision	Recall	F1-Score	Support
karpio	1	1	1	28
katla	0.92	0.96	0.94	24
koi	0.94	1	0.97	17
magur	1	1	1	25
pangas	1	0.94	0.97	31
prawn	0.94	1	0.97	32
rui	1	1	1	23
shrimp	1	1	1	24
silverCup	1	1	1	26
sing	1	0.97	0.98	32
tilapia	1	0.95	0.98	22
Accuracy			0.98	284
Macro Avg	0.98	0.98	0.98	284
Weighted Avg	0.98	0.98	0.98	284

Table 5.4 Classification report for balanced dataset

Table 5.4, Classification Report for balanced Dataset: The overall accuracy improves to 98%, with macro average precision, recall, and F1-score all at 0.98. Performance metrics are consistently high across all classes, reflecting better model reliability and effectiveness when trained on a balanced dataset. These reports underscore the importance of dataset balancing in enhancing model accuracy and ensuring consistent performance across different classes.

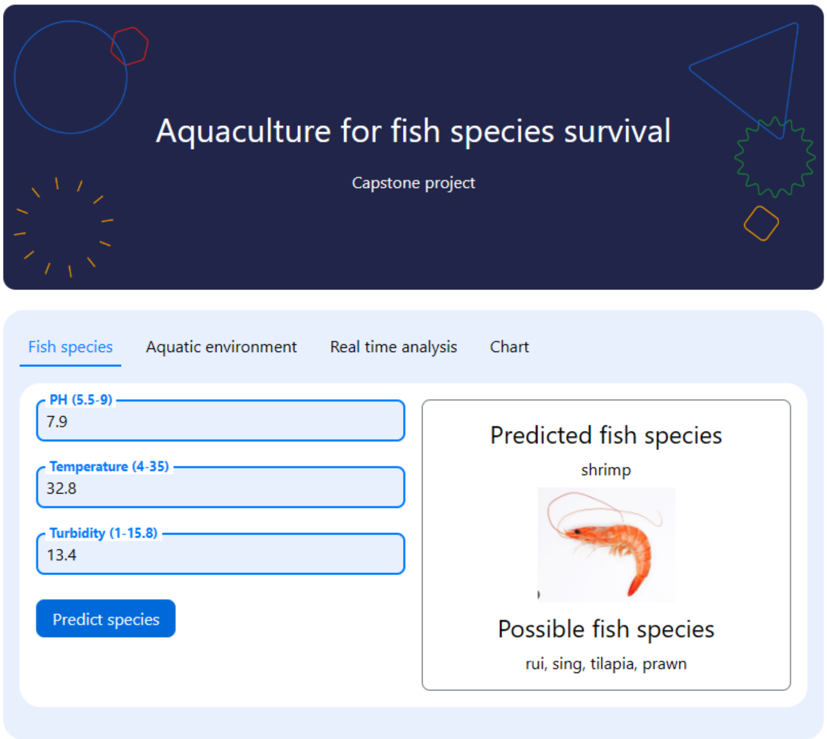

Figure 5.2 Fish prediction based on given parameter

Figure 5.4 illustrates the web interface designed for users to input values for pH, temperature, and turbidity. This interface allows users to determine the appropriate fish species for their aquaculture system based on the given parameters. By entering these environmental conditions, the user can instantly identify which fish species are most suitable for cultivation, thereby optimizing their aquaculture setup.

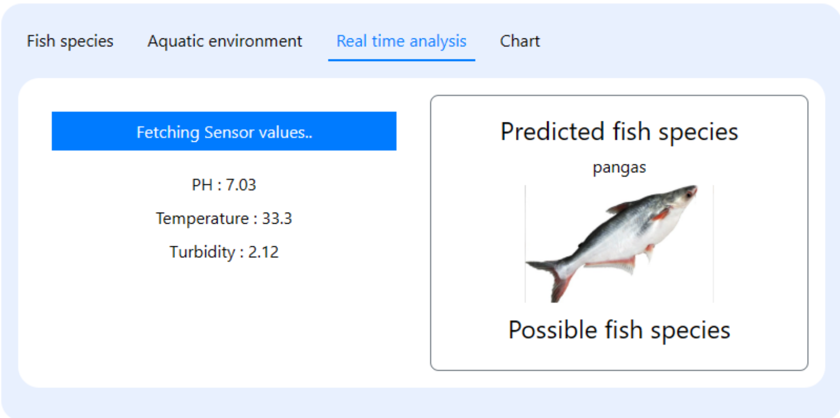

Figure 5.3 Fish prediction based on real time sensor data

Figure 5.5 demonstrates the real-time fish species prediction system. In this setup, data on pH, temperature, and turbidity are continuously gathered from an IoT hardware system. These values are updated every second in the database, reflecting the most current environmental conditions. A machine learning model operates in the backend, analyzing the real-time data to predict the most suitable fish species. This dynamic system provides users with continuous, up-to-date information, ensuring that their aquaculture operations are always aligned with the optimal conditions for fish health and growth.

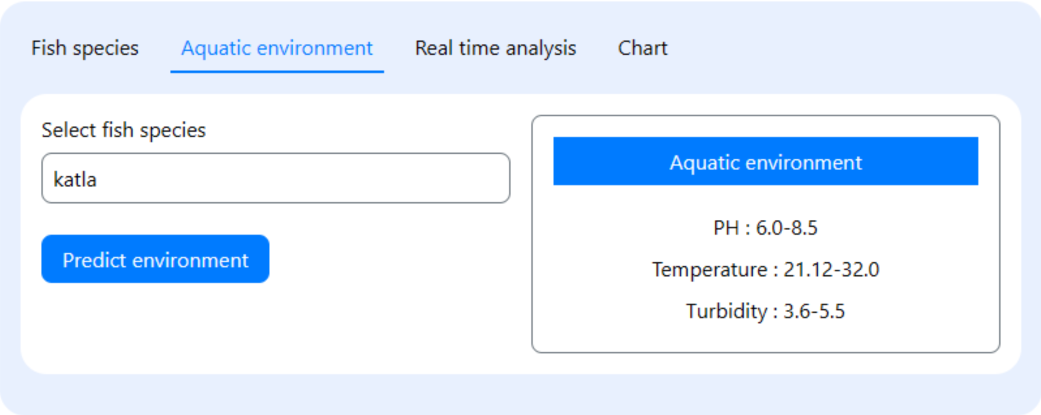

Figure 5.4 Aquatic environment prediction based on Fish species

Figure 5.6 highlights a feature that allows users to learn about the optimal environmental parameters for specific fish species. Users can input the name of a fish species and receive information on the ideal pH, temperature, and turbidity values required for its aquaculture. This functionality is particularly useful for aquaculturists who are looking to introduce new species or refine their existing aquaculture practices based on precise environmental needs.

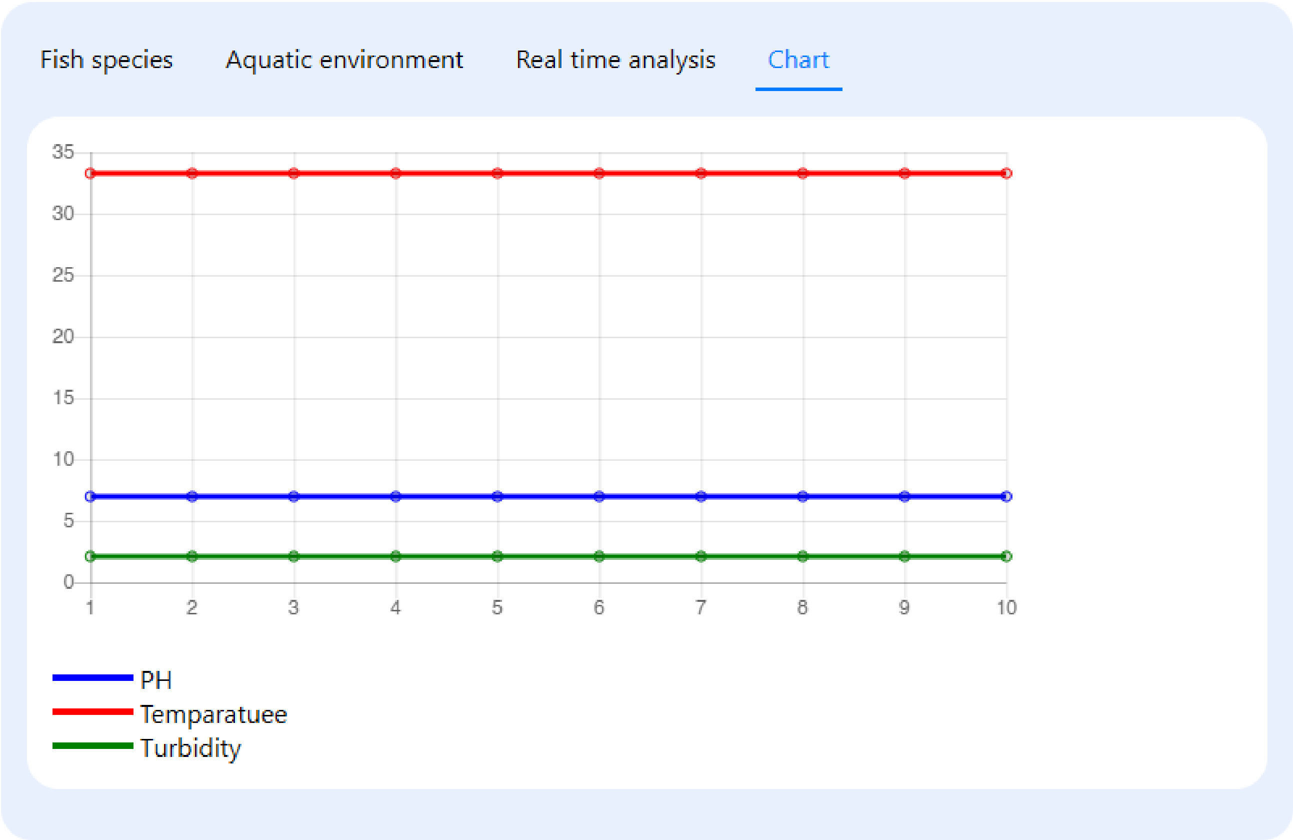

Figure 5.5 View real time sensor values on line chart

Figure 5.7 showcases a line chart displaying real-time temperature and turbidity data. These charts are updated every second, with data sourced from the IoT hardware system. This visualization provides users with an immediate and continuous overview of water conditions. By monitoring these parameters in real time, users can make informed decisions to maintain optimal water quality, ensuring the well-being of the fish and the efficiency of the aquaculture system. This feature is essential for proactive management and promotes a healthy and sustainable aquaculture environment.

Cost Estimation	
Item name	**Cost**
Arduino Uno	1050
Arduino Ethernet Shield	1250
Jumping wire	100
Lan cable	400
PH sensor	3299
Turbidity sensor	1400
Temperature sensor	185
VPS Hosting	2000 (per month)
Domain	600 (per year)
Total	10284

Table 5.5 Cost estimation for entire project

The table 5.5 provides a detailed breakdown of the costs associated with the various components required for the IoT Enabled Real-Time Fish Prediction System. The components listed include essential hardware such as the Arduino Uno, which serves as the central microcontroller for the system, priced at 1050 units. Additionally, an Arduino Ethernet Shield, necessary for network connectivity, costs 1250 units. The table also includes smaller items like jumping wires and a LAN cable, priced at 100 and 400 units respectively, which are essential for establishing connections between various components.

Furthermore, the table highlights the costs of various sensors critical to the system's functionality. A PH sensor, used to measure the acidity or alkalinity of the water, is the most expensive component at 3299 units. A turbidity sensor, which measures the clarity of the water, is listed at 1400 units. Lastly, a temperature sensor, essential for monitoring the water temperature, is priced at 185 units. The total cost for all these components amounts to 7684 units, providing a comprehensive overview of the financial requirements for setting up the system.

6 Conclusion

This paper demonstrates the successful integration of IoT and machine learning to optimize fish species survival in aquaculture environments. By leveraging real time data from pH, temperature, and turbidity sensors, and employing a Decision Tree Classifier, the system accurately predicts suitable fish species and optimal water quality parameters. The comprehensive evaluation showed significant improvements in model accuracy with balanced datasets, underscoring the importance of data preprocessing. The implementation of this intelligent monitoring system promises enhanced efficiency, reduced mortality, and optimized resource management in aquaculture, contributing to sustainable fish farming practices. Through this project, we have illustrated the potential of advanced technologies in transforming traditional aquaculture, paving the way for innovative solutions to global food security challenges.

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