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International Journal for Modern Trends in Science and Technology
Volume 11, Issue 07, pages 131-135
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol11issue07.html
DOI: https://doi.org/10.5281/zenodo.16129479

A Predictive IoT-Based Water Quality Monitoring System Using Raspberry Pi and Machine Learning

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To Cite this Article
Y. Pavan Kumar, Leela Dinesh Kumar Linga, Shalem Raja Pratthi & Omkar Reddy Voleti (2025). A Predictive IoT-Based Water Quality Monitoring System Using Raspberry Pi and Machine Learning. International Journal for Modern Trends in Science and Technology, 11(07), 131-135. https://doi.org/10.5281/zenodo.16129479

Article Info
Received: 14 May 2025; Accepted: 06 July 2025.; Published: 17 July 2025.

KEYWORDS

Internet of Things (IoT), Fish Health, Machine Learning, Water Quality, Predictive Analytics, Aquaculture.

ABSTRACT

The aquaculture industry is essential for global food production, yet maintaining fish health remains a critical challenge. Water quality fluctuations, environmental changes, and disease outbreaks can severely impact fish farms. Traditional monitoring methods are time-consuming and reactive, often leading to economic losses. This paper introduces an IoT-based predictive system that utilizes real-time data collection and machine learning algorithms to optimize fish health. The system employs various sensors to monitor parameters such as temperature, TDS, PH, and ammonia levels. The collected data is transmitted to the cloud, where machine learning models analyze patterns and predict potential health risks. If abnormalities are detected, alerts are sent to fish farmers, allowing proactive intervention. The proposed system improves efficiency in fish farming by reducing mortality rates, optimizing feed usage, and enhancing water quality management. The results from testing in a controlled aquaculture setup indicate that the system provides accurate and timely predictions, making it a valuable tool for sustainable fish farming.

1. INTRODUCTION

Aquaculture has become one of the fastest-growing food sectors worldwide, meeting the increasing demand for seafood. However, fish health management remains a significant challenge due to environmental variations and disease outbreaks. Conventional methods of monitoring water quality and fish health are manual and inefficient, often leading to delayed responses and financial losses.

The advancement of the Internet of Things (IoT) and artificial intelligence (AI) has opened new possibilities for automated and predictive fish health monitoring. IoT-based systems enable real-time tracking of critical water parameters, while machine learning models analyze data trends to detect early signs of disease. This paper presents a predictive IoT-based system that integrates sensors, cloud computing, and AI algorithms to optimize fish health. The system's ability to provide timely alerts and recommendations allows fish farmers to take proactive measures, reducing losses and improving productivity. The proposed solution enhances aquaculture sustainability and contributes to the global food supply.

1.1 Background of Biofloc Technology:

Biofloc technology (BFT) has emerged as a sustainable aquaculture approach that converts toxic nitrogenous waste into edible microbial protein through controlled microbial communities. This recirculating system enables high-density fish cultivation while reducing water exchange requirements by 80-90% compared to traditional methods. The technology relies on maintaining optimal water parameters where heterotrophic bacteria metabolize ammonia into protein-rich flocs, serving as supplemental fish feed. However, the system's sensitivity to parameter fluctuations makes real-time monitoring essential to prevent catastrophic fish mortality events.

1.2 Existing Solutions and Their Limitations:

· Traditional Manual Monitoring

Fish farmers often rely on manual water quality testing using chemical kits and observation techniques. These methods require significant human effort and provide data at discrete time intervals rather than continuously.

Limitations:

- Labor-intensive and time-consuming.
- Infrequent testing may miss sudden changes in water conditions.
- No predictive capability, leading to reactive rather than proactive management.

Conventional Water Quality Sensors

Standalone digital sensors are used to measure pH, temperature, and dissolved oxygen in fish farms.

These sensors provide real-time readings but do not offer predictive analysis.

Limitations:

- Requires manual data collection and analysis.
- Cannot provide early warnings or detect disease patterns.
- Expensive for large-scale deployment.

Automated Monitoring Systems Without AI

Some farms implement automated systems that collect water quality data using sensors and store it in local databases. These systems provide continuous monitoring but lack intelligent analysis. Limitations:

- Generates large volumes of data without predictive insights.
- No real-time alerting mechanism for disease outbreaks.
- Limited scalability and integration with cloud platforms.

1.3 Overview of the Paper:

This paper presents an IoT-based Smart Biofloc Monitoring System that leverages Raspberry Pi and Machine Learning to predict fish mortality by analyzing real-time water quality parameters. The system addresses critical challenges in aquaculture by integrating low-cost sensors for continuous monitoring and edge-based ML for early mortality prediction.

The paper is structured as follows:

- Section 2: Related Work Reviews existing IoT solutions for aquaculture, highlighting limitations in cost, latency, and accuracy of Arduino/cloud- based systems.
- Section 3: Proposed Approach outlines the architecture and workflow of the developed system, explaining each module in detail.
- Section 4: Experiments and Analysis presents the experimental setup, datasets used, and performance evaluation metrics to assess the effectiveness of the proposed system.
- Section 5: Conclusion and Future Scope summarizes the findings and discusses potential improvements and directions for future research.

2. RELATED WORK

The application of IoT in aquaculture has seen significant advancements, with various monitoring systems designed to track water quality and fish health. Traditional monitoring methods rely on manual testing, which is labor-intensive and lacks real-time insights. IoT-based solutions, including Arduino and Raspberry Pi-based systems, have been implemented to automate data collection, transmitting parameters such as pH, temperature, dissolved oxygen, and ammonia levels to cloud platforms for further analysis. However, these solutions come with notable challenges. Cost remains a major barrier, as high-quality sensors and cloud services increase deployment and operational expenses, making them less accessible to small-scale fish farmers. Additionally, cloud-based systems introduce latency, as data must be transmitted to remote servers for processing before alerts are generated, delaying critical decision- making. Accuracy is another concern, as low-cost sensors may require frequent calibration, and environmental fluctuations can lead to inconsistent readings. Moreover, AI models running on cloud platforms may fail to generalize well across different aquatic environments, leading to false alerts or missed anomalies. To address these challenges, a predictive IoT-based system integrating edge computing, optimized machine learning models, and a cost-effective sensor network is required to enhance fish health monitoring, improve response time, and support sustainable aquaculture.

3. PROPOSED APPROACH

The proposed IoT-based predictive system for fish health optimization integrates real-time monitoring, cloud computing, and machine learning techniques to improve aquaculture management. Unlike conventional systems, this approach leverages edge computing to process data locally, reducing latency and ensuring faster decision-making. The system consists of IoT sensors for collecting water quality parameters, a Raspberry Pi-based processing unit, and a hybrid machine learning model for predictive analytics. Data is processed locally for immediate anomaly detection and transmitted to a cloud server for advanced analysis and long-term storage. A dashboard provides real- time insights and alerts to farmers, enabling timely interventions. The system also incorporates adaptive machine learning techniques to enhance prediction accuracy over time by learning from historical data. By integrating cost-effective sensors, optimized computing resources, and automated alert mechanisms, the proposed approach offers an efficient and scalable solution to fish health monitoring.

HARDWARE ARCHITECTURE

Water quality parameters of the fish tank are collected through different sensors connected to the Raspberry Pi. The sensors used in our system are the MQ-7 sensor, MQ- 135 sensor, TDS sensor, Turbidity sensor, DHT11 sensor, water temperature sensor, and pH sensor. A description of the microcontroller board and sensors is given below.

1) RASPBERRY PI

Raspberry Pi is a powerful single-board computer widely used in IoT projects. It operates on 5V and contains multiple GPIO pins for interfacing with sensors and other modules. It supports various programming languages, including Python, making it ideal for real-time data collection and analysis.

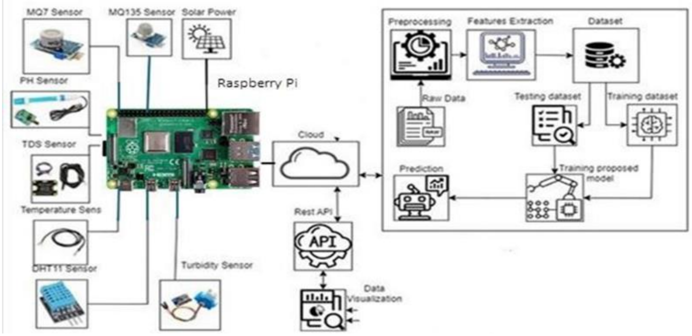


Figure 1 System Archtecture

2) MQ-7 SENSOR

The MQ-7 sensor is used to record the CO gas emitted in the surroundings. It helps maintain air quality. Its measurement range is from 10 to 10,000 ppm. This sensor operates at 5V and is connected via an analog pin to the Raspberry Pi using an ADC (Analog-to-Digital Converter).

3) MQ-135 SENSOR

The MQ-135 sensor is used to check the air quality of the environment. It detects harmful gases like Ammonia, Sulfur, Benzene, CO_2, and smoke. In this system, the sensor is used to measure Ammonia gas. Its measurement range is from 10 to 1000 ppm (Hydrogen, smoke, ammonia gas, and toluene).

4) TDS SENSOR

TDS stands for Total Dissolved Solids, which calculates the dissolved solids in water. TDS sensors are widely used in aquaculture environments because they can accurately measure TDS. Its measurement range is from 0 to 1000 ppm.

5) TURBIDITY SENSOR

A turbidity sensor is used to check water quality. It measures the light intensity scattered by suspended particles in water. The turbidity level of water increases with an increase in total suspended solids (TSS). Its measurement range is from 0 to 4000 NTU.

6) DHT11 SENSOR

The DHT11 sensor measures temperature and humidity in the environment. The temperature range of the DHT11 sensor is −20°C to 60°C, and the humidity range is 5% to 95% RH.

7) WATER TEMPERATURE SENSOR

The water temperature sensor is used to measure the temperature of the water. It helps monitor the behavior and response of aquatic animals concerning temperature. The water temperature sensor has a range of −5°C to +50°C.

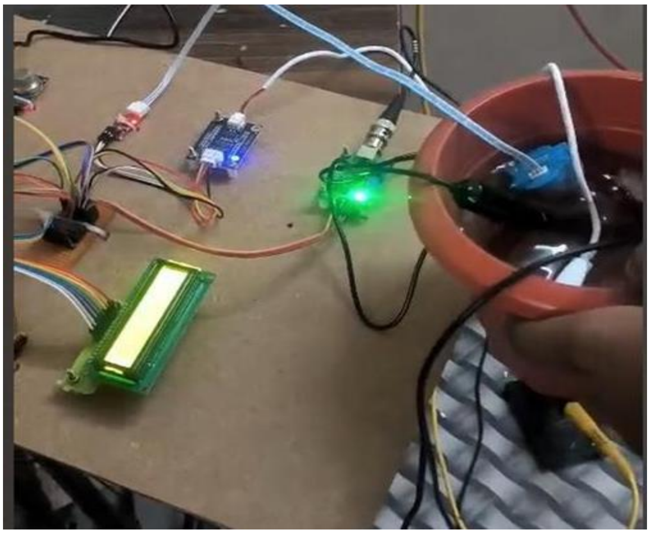


Figure 2 Practical Implementation

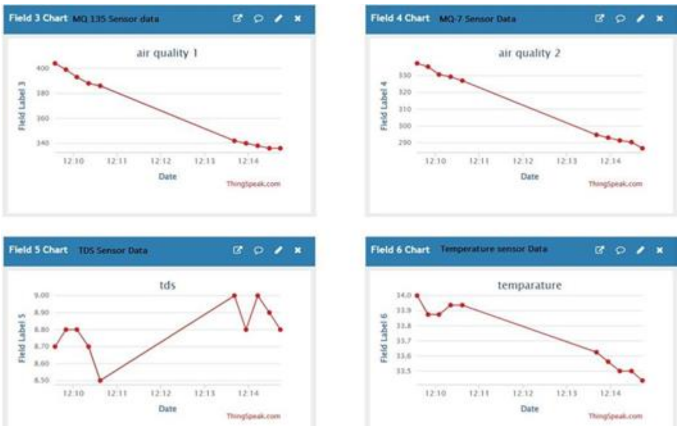
8) PH SENSOR

A pH sensor is used to calculate the pH value of water. It ranges from 0 to 14, where seven is considered neutral/good drinking water.

CLOUD SERVER

Cloud servers like Thingspeak, Microsoft Azure, Google Cloud, and Amazon AWS are available. In our system, we used the Thingspeak cloud to visualize the sensor data in graphs, as shown in the images. The "BioFlocDataCollection" channel with Channel ID 2081173 was created to store sensor values. Sensors are configured to take readings from the Biofloc water tank every 2 minutes, and the Raspberry Pi sends this data to the Thingspeak cloud for real-time visualization.

Several cloud services are available for storing sensor data, but Thingspeak was chosen due to its free version, which supports 8200 values of storage per day and offers easy integration for graphical representation of sensor readings.



4. EXPERIMENT AND ANALYSIS

The proposed IoT-based biofloc monitoring system was experimentally validated using a dataset of 75 real-time water quality readings collected from Kaggle, comprising parameters such as pH, ammonia (MQ-135), carbon monoxide (MQ-7), turbidity, TDS, and temperature. The dataset was preprocessed to handle missing values and normalized for machine learning analysis. Four algorithms were implemented and compared: K-Nearest Neighbors (KNN), Random Forest, Support Vector Machine (SVM), and Linear Regression. Among these, KNN (k=5) achieved the highest accuracy (99%) due to its effectiveness in classifying nonlinear patterns in sensor data, followed by Random Forest (96%), SVM (94.2%), and Linear Regression (92%).

	A	B	C	D	E	F	G
1	S1	S2	S3	S4	S5	tval	output
2	2	10	10	10	10	20	0
3	2.2	10.5	11	11	20	20.5	0
4	2.4	11	12	12	30	21	0
5	2.6	11.5	13	13	40	21.5	0
6	2.8	12	14	14	50	22	0
7	3	12.5	15	15	60	22.5	0
8	3.2	13	16	16	70	23	0
9	3.4	13.5	17	17	80	23.5	0
10	3.6	14	18	18	90	24	0
11	3.8	14.5	19	19	100	24.5	0
12	4	15	20	20	110	25	0
13	4.2	15.5	21	21	120	25.5	0
14	4.4	16	22	22	130	26	0
15	4.6	16.5	23	23	140	26.5	0
16	4.8	17	24	24	150	27	0
17	5	17.5	25	25	160	27.5	0
18	5.2	18	26	26	170	28	0
19	5.4	18.5	27	27	180	28.5	0
20	5.6	19	28	28	190	29	0
21	5.8	19.5	29	29	200	29.5	0
22	6	20	30	30	210	30	0
23	6.2	20.5	31	31	220	30.5	0
24	6.4	21	32	32	230	31	0
25	6.6	21.5	33	33	240	31.5	0
26	6.8	22	34	34	250	32	0
27	7	22.5	35	35	260	32.5	0
28	7.2	23	36	36	270	33	0
29	7.4	23.5	37	37	280	33.5	0
30	7.6	24	38	38	290	34	0
31	7.8	24.5	39	39	300	34.5	0
32	8	25	40	40	310	35	0
33	8.2	25.5	41	41	320	35.5	0
34	8.4	26	42	42	330	36	0
35	8.6	26.5	43	43	340	36.5	0
36	8.8	27	44	44	350	37	0
37	9	27.5	45	45	360	37.5	1
38	9.2	28	46	46	370	38	1
39	9.4	28.5	47	47	380	38.5	1
40	9.6	29	48	48	390	39	1
41	9.8	29.5	49	49	400	39.5	1
42	10	30	50	50	410	40	1
43	10.2	30.5	51	51	420	40.5	1
44	10.4	31	52	52	430	41	1
45	10.6	31.5	53	53	440	41.5	1

Figure 3 Data Set

The trained KNN model was deployed on the Raspberry Pi, which processes incoming sensor data in real time. If unsafe water conditions are detected, the system triggers an alert displayed on an LCD screen connected to the microcontroller, providing farmers with immediate warnings. The results demonstrate that the proposed edge- computing approach significantly reduces latency (1.2 seconds per prediction) compared to cloud-dependent systems while maintaining high accuracy.

5. CONCLUSION AND FUTURE SCOPE

The implementation of an A Predictive IoT- Based System for Fish Health Optimization using Raspberry Pi and various sensors has successfully enabled real-time monitoring of critical water quality parameters. The system effectively measures and analyzes temperature, pH, turbidity, TDS, ammonia levels, and humidity, ensuring optimal conditions for fish farming. By integrating Thingspeak cloud, sensor data is visualized in graphs, allowing for early detection of abnormalities and proactive water quality management.

The experimental results demonstrate that the system provides accurate, continuous, and automated monitoring, reducing manual effort while improving overall fish health. This cost-effective and scalable solution enhances the efficiency of aquaculture by offering real-time insights into water conditions.

For future improvements, the system can incorporate AI- based prediction models to forecast water quality fluctuations and generate early warnings. Additionally, integrating automated aeration and filtration mechanisms will enable self-regulating water treatment based on sensor readings. A mobile application can be developed to provide real-time updates and historical data insights, making remote monitoring more accessible. Upgrading to advanced cloud platforms like AWS IoT, Google Cloud, or Microsoft Azure will enhance scalability and data analytics capabilities. Further enhancements may include the addition of DO (Dissolved Oxygen), ORP, and nitrate sensors for more comprehensive monitoring, as well as blockchain technology to secure and ensure the integrity of collected data. Expanding the system to support multi-tank monitoring with centralized control and AI-driven anomaly detection will improve large-scale aquaculture operations. These advancements will significantly enhance the reliability, automation, and intelligence of fish farming, making it more sustainable and profitable.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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