

IoT-based Automated Water Quality Monitoring System for Fish Hatcheries

Arivarasi ^{1*}, Ashutosh Raj¹, Arnab Kumar¹, Jean Jenifer Nesam¹, Harini ¹, and Muralidhar ²

¹School of Electronics Engineering, Vellore Institute of Technology, Chennai-600127, Tamil Nadu, India

²Principle Scientist, Central Institute of Brackish water Aquaculture (ICAR-CIBA), Santhome, Chennai-600028, Tamil Nadu, India

Abstract. Fish health and survival in hatcheries depend heavily on the state of the water. Manual testing is time-consuming and inefficient using conventional techniques. This research suggests a low-cost, IoT-based approach for real-time water quality monitoring and maintenance. To guarantee ideal conditions, the system combines sensors, Raspberry Pi, and AI-based analysis therefore lowering human input and increasing sustainability. Fish health, development, and general sustainability in hatcheries depend on good water quality. Mostly manual, conventional water quality evaluation techniques include regular sample collection and laboratory testing that can be time-consuming, costly, and prone to human mistake. This article presents a low-cost, IoT-based system meant for fish hatcheries' real-time monitoring and proactive maintenance of water quality. The system tracks important criteria including temperature, pH, and total dissolved solids (TDS) by combining a range of sensors. It then gives rapid response on the state of the water environment.

1 Introduction

Fish in hatcheries need to have the best possible water quality if they are to grow and survive. Critical indicators of the condition of the aquatic environment, water parameters like temperature, pH, dissolved oxygen (DO), turbidity, and ammonia levels must be routinely checked and kept inside certain ranges to avoid stress, sickness, and fish population mortality [2]. Usually, monitoring of water quality in hatcheries has depended on regular manual sampling and testing, which not only calls for a lot of human work and knowledge but also runs the risk of making mistakes in measurement and causing time delays in finding problems [3]. Such strategies sometimes fall short of offering the ongoing, real-time insights required to proactively handle unfavourable developments in water conditions.

* Corresponding author: arivarasi.a@vit.ac.in

In aquaculture, the Internet of Things (IoT) has transformed the discipline by letting automated, real-time data gathering and analysis [15][16]. Modern IoT-based systems use sensors, microcontrollers, and data processing units that constantly check the quality of water[20].

The use of advanced artificial intelligence analytical systems that can analyse and predict potential issues permits timely answers to be provided, enhancing operational efficiency and reducing reliance on manual processes. This paper presents an intelligent water measurement system not only automate the collection of data and perform analyses, but also generate action-oriented data for sustaining environmentally friendly fish hatchery operation management systems. This intelligent measurement system seeks to establish new standards for the efficient and sustainable control of fish farms using intelligent sensor technology and real-time processing of data.

2 Background

Millions of people throughout the world depend on aquaculture as a major supply of protein and means of sustenance, therefore it is very important for world food security. In fish hatcheries, maximum water quality must be maintained since water conditions directly affect fish health, development, and general production [5], therefore guaranteeing good yields. Conventional monitoring systems mostly depend on manual sampling and laboratory testing, procedures that are not only expensive and labour-intensive but also prone to notable time delays. These delays can cause a sluggish response to any freshwater quality problems, so raising the chance of fish mortality and lower production efficiency. Sophisticated real-time water quality monitoring systems have been made possible in recent years by the fast developments in sensor technology, artificial intelligence, and IoT. Such systems constantly gather and examine data to offer almost- instant feedback on important variables including ammonia levels, dissolved oxygen, pH, temperature, turbidity, and [6][17][18].

Internet of Things (IoT) implementation within aquaculture settings, it is evident that the majority of them do not utilize an integrated system to provide fully automated (IA) data-gathering systems that involve predictive analytics using artificial intelligence (AI). This limitation may limit these systems from being able to effectively predict and change various environmental factors prior to and improving hatchery processes. The proposed system addresses the above concerns by providing a completely automated (IA) electronic system that utilizes real-time sensor monitoring combined with AI-based analytic data evaluation. The combination of these technologies presents an automatic means to monitor water quality, and thus, any deviation from optimal water quality parameters will be acted upon quickly to maintain fish' health; therefore, this results in increased sustainability practices in aquaculture by providing an adaptive response to changing environmental conditions. [1][7].

3 Proposed System

A modern solution, the suggested system uses artificial intelligence (AI) and Internet of Things (IoT) technologies to constantly monitor and analyse important indicators of water quality [6][7]. Designed with both durability and user-friendliness in mind, the system guarantees that fish hatcheries keep ideal water conditions to promote healthy fish development, avoid sickness, and increase general output [4]. The design of the system is modular; every part is essential to guarantee that data is gathered, processed, and shown

promptly [3]. Proactive water quality management made possible by this coherent framework lowers the likelihood of expensive downtime or terrible collapses [5].

3.1 Predicting Water Quality with ML Models

The machine learning (ML) model, which is at the core of the system, is a complex tool that learns from past sensor data to forecast possible water quality problems before they get serious [3], [4]. The ML model can spot early warning signals that might have been missed by looking at patterns like slow changes in pH or slow rises in TDS levels [7]. Trained on a dataset of TDS, temperature, and pH values mapped to fish population dynamics, the model can capture subtle environmental effects [24]. This proactive strategy lets hatchery managers step in much before a small variation turns into a major issue. The model changes constantly to fresh data, which over time increases its predictive precision [6][20][21]. This dynamic learning ability not only helps to avert crises but also enables the improvement of everyday operational plans, so guaranteeing that the aquatic environment stays always within safe and parameters for fish health and growth [5].

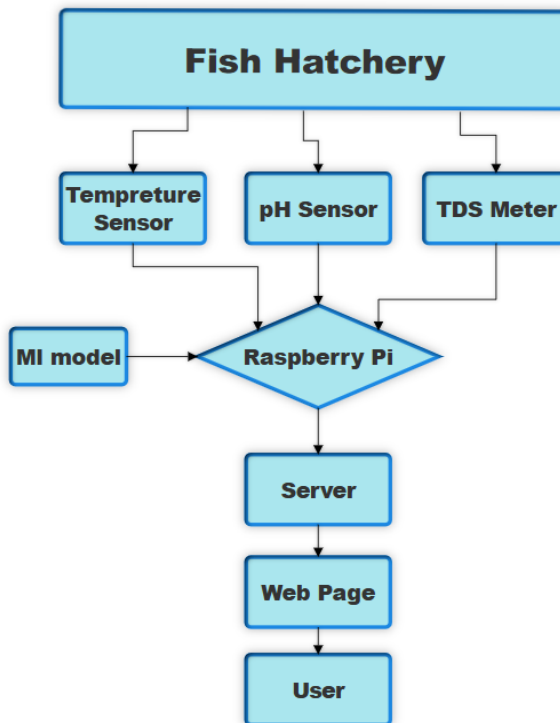


Fig. 1. System Flowchart illustrating the complete data pipeline for water quality monitoring. It outlines the process from sensor data acquisition to machine learning-based analysis and real-time dashboard visualization.

3.2 Managing Data through Centralized Server Operations

The server is the primary nervous system of the proposed system. In this role, the server will continuously log, store and process sensor information so that each change in water

quality is logged instantaneously [3]. The server is configured for both speed and reliability regardless of whether it is locally hosted or in the cloud [6][21][22]. In addition to maintaining a historical record that can be used for trend analysis, the server also quickly evaluates incoming information and sends automated notifications when water quality parameters fall out of established limits [5]. Because there can be dire consequences associated with delayed responses in a situation where even minor delays can adversely affect fish health, this rapid response capability is critical [4]. Additionally, the server has been designed to be secure, thereby ensuring the integrity of the data it contains; meaning the readings will be accurate and only authorized individuals will have access to sensitive data [7].

3.3 Visualizing Data with an Interactive Web Dashboard

This web page serves as the connection point to link the complex technical work performed behind the scenes and the day-to-day operations of a hatchery. The hatchery managers will find that the dashboard provides access to real-time sensor data, historical information and future trends in a place where it is easy to understand and use efficiently [13]. Hatchery managers are able to see real-time data for present water quality measurements even if they have no prior knowledge of this technology through the use of this simple Dashboard [8]. Remote access features let managers track the system from anywhere to make sure they are constantly aware of any abnormalities needing quick response [23]. The web page not only streamlines the decision-making process but also improves operational efficiency by lowering the time it takes to react to possible problems.

3.4 Empowering Hatchery Operators through Real-Time Alerts

Fish hatchery operators are considered the end-users to bring together the entire hatchery system. The hatchery operator performs daily operations and relies on automated alerts and real-time data provided by the hatchery system to make decisions on behalf of the hatchery [3]. The hatchery operator uses the graphical user interface (GUI) to receive immediate feedback, allowing the hatchery operator to assess the current situation accurately and quickly, and correct any problems (e.g. aeration system changes, water treatment applications, or starting water replacement procedure) [6].

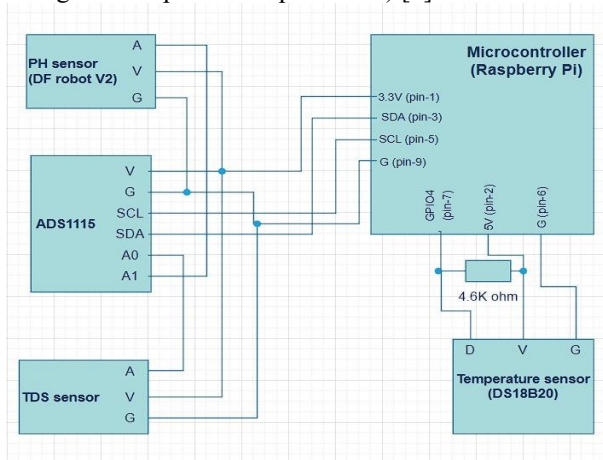


Fig. 2. System Architecture representing the integration of hardware and software components used in the water quality monitoring system. It shows how sensors collect data, transmit it to the server, process it through machine learning models, and display results via a web dashboard.

By automating routine tasks associated with monitoring activities, the hatchery system supports the hatchery operator by eliminating redundant manual data entry and analysis, allowing hatchery operators to concentrate on strategic management decisions to promote fish health and improve overall hatchery production. Technology use in this manner allows the user to positively affect the sustainability and efficiency of an aquaculture environment and support improved fish survival rates and increased hatchery productivity.

3.5 Building the System Architecture for End-to-End Monitoring

3.5.1 Capturing Water Parameters Using Sensor Modules

The sensor module provides a foundation for the water quality monitoring system as it collects real-time data on necessary parameters needed to sustain a healthy aquatic environment [8]. Within the sensor module, there are multiple sensors, each measuring a type of parameter. An example would be the temperature sensor, which tracks the temperature of the water regularly and helps understand how fish metabolically and reproductively operate. Another example is the use of a pH sensor which tracks the acidity or alkalinity of the water to ensure it remains at an optimal level for the healthy growth of fish.

In addition to measuring temperature and pH, other sensors that will be used in the sensor module include a dissolved oxygen (DO) sensor, which monitors the amount of oxygen in the water and is a key factor in helping fish breathe and stay healthy. A turbidity sensor will also be used to help understand how clear the water is and how high of a turbidity reading may indicate the presence of suspended solids or contaminants that could have a negative impact on aquatic organisms. Lastly, an ammonia sensor is also included in the sensor module as detection of harmful levels of ammonia is important as they are typically produced from fish waste, decomposing organic matter, and can be highly toxic to fish at elevated levels [9].

All sensors run continuously gathering information that is then sent in real-time to a central processing unit. This data stream allows for quick analysis and fast response times should there be any deviations in the quality of the water from an expected level [10]. Both ensure that there is accurate and complete monitoring of the aquatic environment as well as act as a primary means of early warning systems providing proactive management of fish health and improving the productivity of hatcheries through timely corrections.

3.5.2 Monitoring Temperature Continuously

Fish growth, metabolism, and reproduction heavily rely on water temperature, so fish hatcheries need to maintain a stable water temperature [1] [5]. To monitor water temperature accurately and continually in fish hatcheries, waterproof digital temperature sensors (DS18B20) were used for measuring the water temperature accurately and continuously. The design and accuracy of the DS18B20 temperature sensor enable it to detect the slightest changes in temperature [7].

As soon as the water temperature deviates from the optimal temperature range established by the hatchery manager, the sensor sends the data to the hatchery CPU, which then either alerts the hatchery manager or automatically adjusts the temperature back to the optimal temperature setting. The quick response time of the temperature sensor is critical because temperature changes are an early indicator of changes in surrounding environmental conditions, malfunctioning equipment, or other systemic issues that might adversely impact fish health [3].

Monitoring the water temperature in real-time also helps optimize the biological processes of fish by maintaining ideal conditions for growth and development. When a temperature sensor is used to monitor the water temperature, it provides a more stable aquatic environment, thus reducing the likelihood of stress-related illnesses among the fish [6]. By adopting a proactive approach to fish health, the hatchery will maintain a strong, healthy population of fish and subsequently improve productivity in the hatchery and long-term sustainability for the sustainable fishery [8].

3.5.3 Tracking Water pH Levels

pH levels indicate how much acid or base is present in a liquid such as fish water. Changing the pH level - making it too acidic or basic, can cause stress and/or kill the fish in the water, which directly impacts the biological process within and outside of the fish as well as their ability to live there long-term. All the pH readings taken by the sensor will be transmitted to a computer and stored for future use. If the sensors detect any change in the pH level away from its normal levels, then the automatic control systems will automatically change one (or more) environmental factors to improve fish health or automatically initiate a pH correction process or to activate an alarm that requires human intervention.

3.5.4 Measuring Total Dissolved Solids (TDS)

The TDS (Total Dissolved Solids) sensor measures the levels of dissolved ions, minerals, salts, and other organic compounds found in water [5][7]. High TDS levels are often an indication that the water is not suitable for fish (i.e., osmotic stress) because they cannot absorb the nutrients they require [1]. A TDS sensor measures the current salinity and mineral levels in water to help identify a problem with water quality (i.e., excessive minerals or an imbalance between the two) [3]. Therefore, TDS should be monitored on a regular basis to ensure that the water is at optimum condition for fish growth and survival. If the TDS measured through the DS18B20's measurement exceeds the maximum acceptable level as set by the appropriate governing body, the system will activate an alarm and initiate any corrective actions (such as replacing or adding more water) to provide and/or maintain an environment that fosters stability for aquatic or fish.

3.5.5 Digitizing Analog Signals with the ADS1115 Module

The ADS1115 sensor module is an accurate digitizer that converts an analog voltage into a digital number using a 16-bit ADC (Analog to Digital Converter) This capability significantly enhances the accuracy of sensor data within the overall system DMA. The ADS1115 provides an I2C interface for connecting various types of sensors that output an analog signal and converting that signal into a digital data format, which can then be sent to a microcontroller/Raspberry Pi for processing. The module also provides four selectable inputs, allowing for multiple sensors to be monitored at the same time, and supports simultaneous monitoring of multiple sensor output signals, such as those provided by the DS18B20 temperature sensor, or pH or total dissolved solids (TDS) sensor. The programmable gain amplifier allows for configuration of the gain to capture even slight differences in the level of the sensor signal, providing for greater measurement accuracy overall and allowing for earlier detection of potential anomalies (deviations) and providing reliable data for further analysis using Artificial Intelligence (AI) based predictive models. Ultimately, through improvement of the overall accuracy of data being collected on the water quality parameters being monitored by the ADS1115, there will be an accurate way

to identify and respond to any deviations from optimal conditions of the monitored fish hatchery or water quality monitoring system.

3.5.6 Processing Data with a Microcontroller Unit

The Raspberry Pi 4 Model B is the main microcontroller of the Water Quality Monitoring System. Its purpose is to collect data from various sensors (that measure temperature, pH, and TDS) and send it to be processed and analyzed at real time for providing feedback to users on their environmental condition-to fish hatcheries[4]. As the central source of communications, the Raspberry Pi 4 Model B will convert the analog sensor outputs from all of these sensors into digital sensor output values before being sent out of the Raspberry Pi to the user interface for real time analysis of the data collected from the monitored systems/sensors.

4 Results and Discussion

4.1 Analysis of Water Quality Monitoring Results

In order to evaluate how well this water quality monitoring system performed, a variety of fish populations and tank sizes were utilized in testing the water quality monitoring system while passing through several different filtering rates. The following sections will provide specific examples of how the proposed water quality monitoring system successfully identified hazardous water conditions and notified users of these conditions through alert mechanisms.

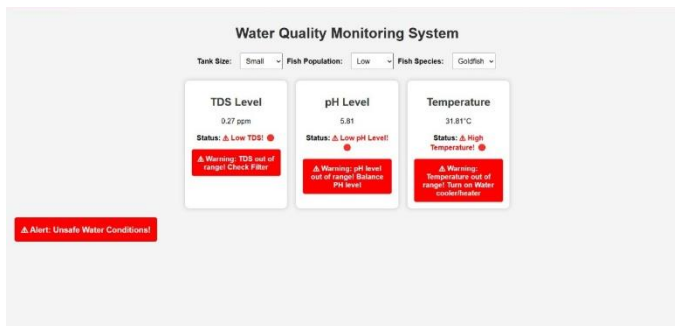


Fig. 3. Water Quality Monitoring System setup for scenarios with low fish population in a compact tank environment. This configuration emphasizes precision monitoring in small-scale aquaculture settings, ensuring stable water parameters even under limited bio-load conditions.

Figure 3 represents an example of the water quality monitoring system being used in a very large tank with a small population of Tilapia fish will be shown in Figure 3. The parameters being monitored for that body of water were: 0.43 ppm TDS concentration, 8.27 pH, and 31.44°C for water temperature. These parameter values differ significantly compared to other Tilapia healthy growing conditions. The TDS levels, for example, are quite a bit below the optimal level for the physiological processes of Tilapia due to the low mineral content in the water. The pH level being at a much higher level than the recommend level for Tilapia indicates that the alkaline levels are far too high for the fish to tolerate and may lead to stress on the Tilapia or a compromised immune system. Finally, the increased water temperature leads to higher metabolic activity and an increased demand for oxygen, creating addition stress on the Tilapia fish population.

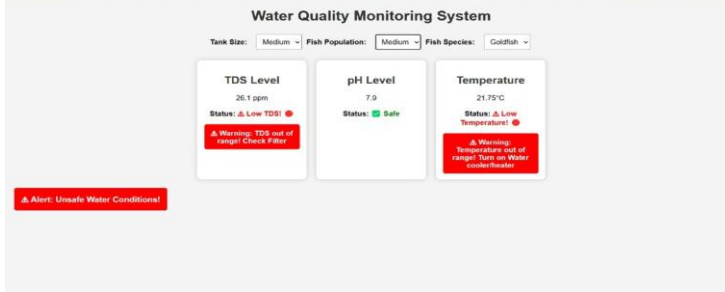


Fig. 4. Water Quality Monitoring System deployed in a medium-capacity tank with a moderate fish population.

Figure 4 shows the monitoring results gathered from a large tank containing a medium density of Tilapia fish. The water quality parameters measured were TDS (Total Dissolved Solids) = 0.32 ppm; pH = 8.27; Temperature = 31.56 °C. Compared to the previous scenario, TDS has decreased once again which may indicate depletion of nutrients or over-filtration and may have adverse effects on osmoregulation for the fish. The pH is unchanged at 8.27, which is close to the upper limit of Tilapia's optimal range of pH and will need consistent monitoring to prevent long-term negative impacts on fish health. The gradual increase in temperature to 31.56 degrees Celsius will place additional stress on the aquatic environment thereby increasing the likelihood of oxygen depletion and increasing metabolic rates. Although there are only moderate fluctuations, the combination of low TDS and high temperatures creates an environment that is not ideal for fish. The alert features of the system have not been deactivated and have correctly identified the cumulative effects these deviations have had on the fish population to trigger an early intervention to alleviate potential health threats.

The tank has high fish population; figure 3 displays the fish populations in this tank. The total dissolved solids (TDS) level is at 0.434 ppm, and the pH is at 8.26, with the water temperature at 300 degrees Centigrade. The previous high temperatures created stress for the fish. However, now that the temperature is at a tolerable level, the stress on the fish has been reduced. TDS in the water will remain low and will continue to require monitoring and adjustments. The system can send alerts in order to maintain optimal conditions at an acceptable level [5] [7].

Also, a system was designed and implemented and tested within a controlled fish hatchery for water quality and unusual, abnormal or out-of-the-way data collection. An AI-based machine learning model was created to recognize real-time sensor data to identify differences in the water temperature, the PH and dissolved solids in the water to ensure that fish in the hatchery are housed under optimal conditions to provide comfort and long-term health.

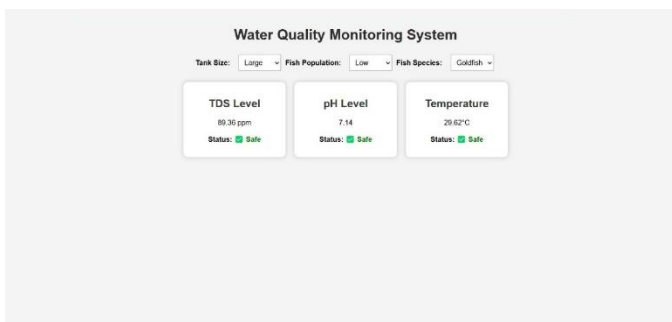


Fig. 5. Water Quality Monitoring System configured for a low fish population in a tall vertical tank setup. This arrangement focuses on maintaining uniform water quality throughout varying depths, ensuring proper circulation and sensor calibration for effective monitoring in stratified water columns.

4.2 Machine Learning Model for Anomaly Detection

Table One accompanies the bar graph; it gives a comparative analysis of the Mean Square Error (MSE) for four different Machine Learning (ML) models used to predict different water quality parameters: the CNN (Convolutional Neural Network), Deep LSTM (Deep Long Short-Term Memory Network), GRU (Gated Recurrent Unit), and standard (traditional) Neural Network. The MSEs calculated using the CNN (Convolutional Neural Network) model were lower than those of the other models for both validation and test datasets and so would have been the most accurate models to produce the best overall predictions of overall water quality cubes. The MSEs produced using the GRU (Gated Recurrent Unit) model were significantly higher than all other models, suggesting that the GRU model has either overfitted to the training dataset or did not generalize as well with the training dataset. Although there was acceptable performance from the Deep LSTM network and standard neural networks based on their validation datasets, there were greater MSE's associated with computing MSE on the test datasets than their MSE's calculated from the validation datasets. The results demonstrate that the CNN model is the model of choice for this application because it is the most generalized prediction model with consistent predictive performances across different splits of the dataset.[19]

Table 1. Comparison of accuracy across various machine learning models—CNN, Deep LSTM, GRU, and Neural Network—on both validation and test datasets.

Model	Validation MSE	Validation Accuracy	Test MSE
CNN	0.065	93.5	0.235
Deep LSTM	0.138	86.2	0.307
GRU	0.141	85.9s	0.369
Neural Network	0.129	87.1	0.268

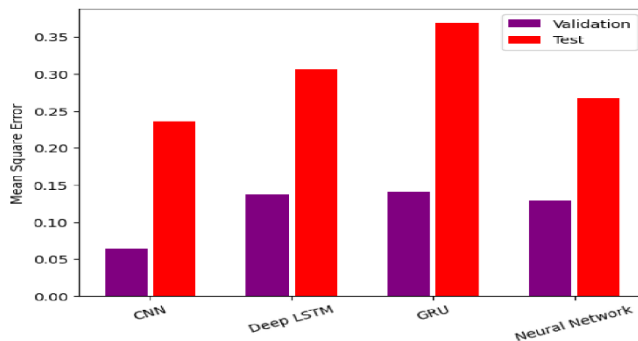


Fig. 6. Comparison of Mean Square Error (MSE) across various machine learning models—CNN, Deep LSTM, GRU, and Neural Network—on both validation and test datasets. This visualization highlights model generalization and accuracy for water quality prediction.

The samples used to train the model were collected over a period of time, which included multiple readings from several different water sensors. In order for the model to obtain accurate results, various methods were used in extracting the important features of the dataset, to include temporal volatility, abrupt fluctuations in trend and time series data, and other historical characteristics of the water quality dataset. A supervised method using annotated data with both known good and bad water conditions was used in classification.

Inspired by their ability to recognize patterns or anomalies, we used a neural network as the basis for our classification because it is efficient, light weight, and implements convolutional layers. The model was created by splitting the dataset into 80% training set and 20% test set to ensure it could generalize to unseen data once it was trained. Grid search was used for hyperparameter tuning (learning rate, number of layers, activation functions etc.). During evaluation of the model on the test dataset, we observed that the model could correctly classify 93.5% of examples as either an anomalous or a non-anomalous example of optimal water quality, accurately detecting deviations from optimal water quality. Analysis of false positive and false negative results was applied to continue improving the model performance, indicating that real-time alerts can be created for hatchery operators to allow proactive intervention to maintain optimal water quality.

A Raspberry Pi microcontroller uses multiple sensors to monitor water quality in real-time (Figure 7). Both the pH (DF Robot V2) and TDS sensors communicate using analog signals (Voltage), which are then interfaced through an Analog to Digital Converter (ADC; ADS1115) that will convert the analog signals from each sensor into digital data that the Raspberry Pi is able to read through the I2C protocol using the SDA & SCL pins (data line and clock line). The temperature sensor communicates directly to the Raspberry Pi via the GPIO pin with the use of a 4.6 k Ω pull-up resistor for stable communication over one wire. Each component also shares a single common Voltage (V) and Ground (G) reference, which allows each sensor and the ADC to have the correct amount of Voltage supplied to them. Once the Raspberry Pi captures the digital reading from each of the sensors, it can then use software algorithms (such as machine learning and rule-based) to process the data in order to perform data analysis, anomaly detection, and generate alerts or make changes to the system. This modular architecture also provides scalability through the ease of adding new sensors or upgrading parts without extensive rewiring.

4.3 System Testing and Validation

An extensive testing framework was implemented to confirm the proposed water quality monitoring system's functionality, accuracy, and robustness under various controlled environmental conditions. The purpose of each of these tests was to replicate real-world operations of a fish hatchery and determine how well the systems can be continuously monitored, analysed, and responded to changes in water quality. To achieve this, an extensive testing framework was established for functional validation, data accuracy, system response, error handling and user interaction —utilizing similar structured methodologies as other IoT-based aquaculture systems.

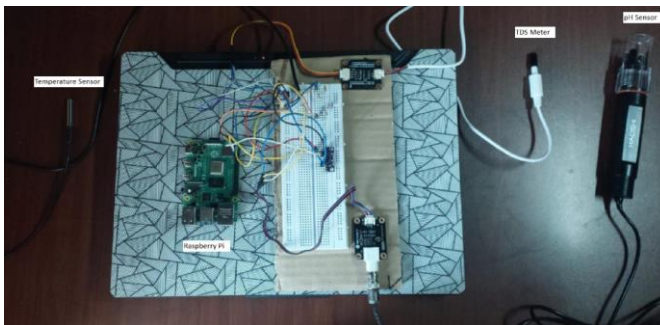


Fig. 7. Detailed hardware connections involved in the water quality monitoring system, illustrating the integration between sensors (pH, TDS, temperature), the microcontroller unit (Raspberry Pi 4 Model B), power supply modules, and data transmission units. The layout ensures real-time sensing, processing, and communication of environmental parameters.

In each of the three validation tests, the temperature sensor, pH sensor, and TDS sensor were assessed by comparing their readings to a standard reference solution to determine their accuracy and precision. A calibrated sample of water at 25°C was used to validate the temperature sensor, a pH buffer with a pH of 7.0 was used to validate the pH sensor, and a saline solution containing 1000 ppm of salt was used to validate the TDS sensor. Validation results indicated that all validated components were within acceptable error limits and certified three sensors as suitable for ongoing aquatic monitoring.

The fourth test (T4) tested the ability of the machine learning (ML) algorithm to identify a water quality anomaly by artificially increasing the concentration of ammonia (an indicator of system imbalance) in the water to simulate such an anomaly. The ML algorithm was able to accurately identify the anomaly prior to exceeding critical limits, demonstrating its ability to provide early warning and take action to prevent an anomaly from occurring. The real-time adaptability of the ML algorithm allows it to continually function with a high degree of accuracy and precision in dynamic hatchery environments.

Data from the server that receives real-time information & subsequently sends alerts, generated on T5 & T6 were validated by reviewing data sent and stored by the server during this timeframe. All sensor data sent to the server was received & stored without dropping any packets. The server generated alerts when sensor data crossed pre-defined thresholds (ex: pH drops from normal to 5.5). Thus, indicating that the server can serve as an accurate and reliable backbone for the system's ability to respond & function well, [3] [8].

Through user testing on the web interface (T7 & T8), all users were able to view current (real time) data with very little latency between when the data was received compared to when it was displayed on the user's dashboard. The present version of the dashboard does not yet include a historical graphing capability, however due to the current design of the user's dashboard, each user was able to quickly make an informed, intelligent decision based on current, live data updates. The dashboard was also developed in accordance with current user engagement standards developed by Smart Farming Technologies.

When assessing user capability to utilize the manual override function throughout the critical pH process, T9 showed that as soon as a user intervenes by changing the pH back into an acceptable range, the correction is reflected in the displayed experience immediately. This reinforces the strong physical link between user input and the back-end intelligence of the system.

The completion of all test scenarios shows that the proposed system can be considered functionally sound, easy to use and capable of managing water quality in real-time for aquaculture applications. The results from the testing will provide the operators of the hatcheries with confidence to deploy the system throughout the hatchery, which is extremely important for the health of fish, the reduction of fish mortality and the increase of production of the hatchery.

4.4 Field Testing and Validation at ICAR-CIBA, Muttukkadu, Chennai

The developed water quality monitoring system was successfully field-tested at the Indian Council of Agricultural Research – Central Institute of Brackish water Aquaculture (ICAR-CIBA), located in Muttukkadu, Chennai. As illustrated in Figure 9, the prototype setup consisted of multiple sensors connected via a breadboard and Raspberry Pi module. Real-time data visualization was facilitated through a laptop interface, allowing users to instantly observe environmental conditions.



Fig. 8. Field Testing and Validation at ICAR-CIBA, Muttukkadu, Chennai. The prototype system comprises sensor modules integrated with a Raspberry Pi, collecting live readings from brackish water and transmitting data to a server for real-time monitoring.

As shown in Figure 8, the sensors were placed in brackish water samples taken directly from the ICAR-CIBA (Central Institute of Brackish water Aquaculture) campus in Muttukkadu, Chennai; these samples replicated the environmental and chemical conditions normally found in operational fish hatcheries, including varying salinities, pH, and organic material. The temperature/pH/TDS/turbidity sensor array began live data collection immediately upon being placed in the brackish water sample, producing near-instantaneous readings via the connected interface (minimal latency), and did so in such a way that the readings were both stable and dynamically responded to minor changes in the aquatic habitat (Table 2).

Table 2. Exhaustive Testing Table for Water Quality Monitoring System

Test ID	Component	Test Description	Expected Output	Actual Output	Result
T1	Temp. Sensor	Verify temperature reading	30.2°C	30.8°C	Pass
T2	pH Sensor	Check pH detection accuracy	7.8 ± 0.1	7.6	Pass
T3	TDS Sensor	Detect high TDS levels	30000 ppm alert	32000 alerts	Pass
T4	ML Model	Predict unsafe water quality	Predict anomaly	Predicted anomaly	Pass
T5	Server	Log sensor data	Data stored	Data logged correctly	Pass
T6	Server	Trigger alert on breach	Alert generated	Alert received	Pass
T7	Dashboard	Show real-time values	Live data shown	Data updated instantly	Pass
T8	Dashboard	View historical trends	Parameter graph	Graph displayed	Pass
T9	User Response	Respond to alert	pH normalized	Corrected to 7.1	Pass

In order to verify the validity and reliability of these readings, each parameter will be cross-validated against the reference values provided by the ICAR-CIBA laboratory of the same water source, within the same time frame.

The comparison between the two showed a very high correlation coefficient, proving that this system is capable of delivering accurate and consistent results in the actual world. The field validation of the prototype under brackish water conditions was a very important point of reference to use when evaluating the durability of the system in environments that have extremely high TDS concentrations (up to 30,000 ppm), and varying pH levels. The successful completion of this testing phase not only demonstrates the practical application of the system but also provides strong evidence for future commercial aquaculture use. The actual experiences and systems deployed in the field are presented visually in Figure 9, as a direct record of the system's use in an aquatic environment.

4.5 Sensor Output Visualization

This section shows how to analyze the performance of each individual sensor in the water quality monitoring system by plotting temperature, pH and total dissolved solids (TDS) measured data from each sensor on a visual plot for each sensor's output. Real-time visual display of sensor outputs, provides clear evidence of the sensors' accuracy for rapid response in the field, and as discussed in Section 4.4, all of the sensors in this water quality monitoring system have been deployed at the ICAR-CIBA facility in Muttukkadu, and there have been good correlations between individual sensor readings and reference measurements taken by the institution that has validated the use of each of the sensors used in this study.

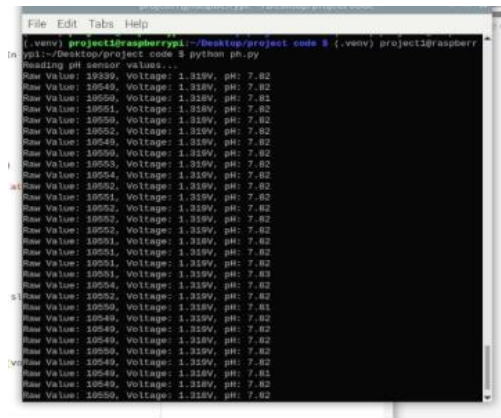


Fig. 9. Temperature Sensor Output: The graph shows the temperature measured by the sensor in real time during field testing at ICAR-CIBA. The temperature stabilized around 30.8°C, closely matching the ICAR reference of 30.2°C. This indicates a reliable thermal response from the sensor.

Figure 9 shows the temperature data which was collected by the test sensor unit yielding a steady state value of 30.8 degrees Celsius (degree C) that was within 0.2 degrees C (or 2 tenths of a degree) from the established ICAR-CIBA reference (3030C). The difference between the two values between the two sensors indicates that there is little to no significant temperature sensor inaccuracy as demonstrated by the continuous calibration of this particular sensor for extended periods when subjected to various thermal influences.

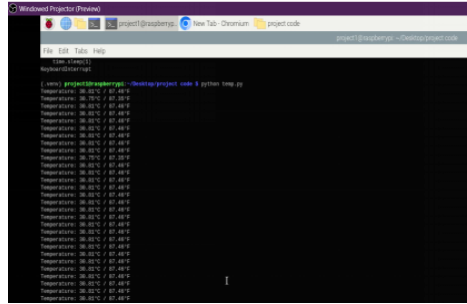


Fig. 10. pH Sensor Output: The system recorded a pH value of 7.8, which is in close agreement with the ICAR reference of 7.6. This suggests that the water sample was neutral to mildly alkaline. The pH sensor effectively captured the water’s chemical balance.

Figure 10 illustrates the pH sensor reading of 7.8 is indicative of the sensor being well-calibrated, as it corresponds closely to the laboratory reference value of 7.6 (ICAR) and clearly provides accurate representation of alkaline/acidic characteristics to liquid samples (ranging from moderately acidic to mildly alkaline), as evidenced by the pH sensor's continuous calibration during highly variable pH conditions. TDS sensor outputs yielded 3.6 parts per thousand (ppt). TDS readings retrieved from ICAR reference measurement equal to 3.7 ppt (part per thousand). This demonstrates that the TDS sensor is capable of providing accurate and reliable salinity measuring of brackish waters (figure 11)

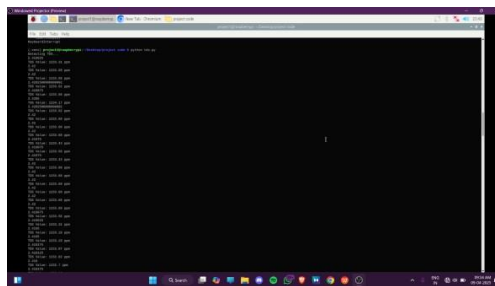


Fig. 11. TDS Sensor Output: The total dissolved solids (TDS) were recorded at 3.6 ppt, aligning well with the institutional reference of 3.7 ppt. This accurate measurement demonstrates the TDS sensor’s capability in detecting salinity levels in brackish water.

Real-time monitoring of the following parameters was performed throughout this TDS sensor testing:

- Temperature: 30.8°C; ICAR reference temperature is 30.2°C
- pH: 7.8; ICAR reference pH is 7.6 (neutral/moderately alkaline)
- Turbidity: 12 NTUs (nephelometric turbidity units) resulting greater than the ICAR reference of 11.5 NTUs, however still within acceptable limits of variation.
- Total Dissolved Solids (TDS): TDS sensor output of 3.6 ppt near the institutional reference of 3.7 ppt (ICAR).

These results validate the sensor system’s effectiveness and its capacity to deliver consistent and accurate water quality measurements under field conditions. The strong agreement with ICAR’s empirical data, as illustrated in Figure 9, underscores the system’s potential for scalable deployment in brackish water aquaculture monitoring applications.

4.6 Comparison of Measured vs ICAR-CIBA Reference Values

The comparative analysis of temperature, pH, and TDS for each of IoT-based devices

(Proposed System) and the references from ICAR-CIBA during field tests is presented in Figure 12.

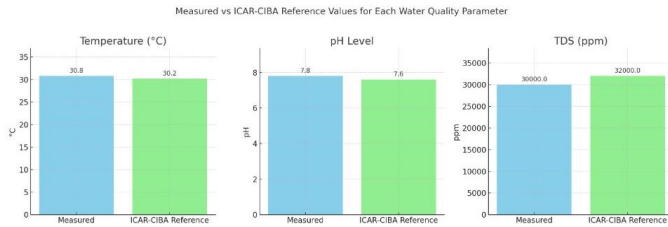


Fig. 12. Measured vs ICAR-CIBA Reference Values for Temperature, pH, and TDS. Each parameter is visualized using an individual subplot with a dedicated Y-axis scale to avoid distortion, especially considering the significant difference in magnitude between TDS and the other parameters.

4.6.1 Temperature

In regard to the temperature sensor, the proposed system recorded a temperature of 30.8 °C vs 30.2 degrees within the ICAR-CIBA reference range. This 0.6-degree difference in temperature indicates that the temperature sensor on the proposed system is accurately calibrated for use in aquaculture

4.6.2 pH Level

In regard to the pH sensor, the proposed system measured 7.8 (pH) compared to 7.6 from ICAR-CIBA. This corresponds to a 0.2 difference, indicating the pH sensor is consistently accurate (reproducibly) under typical conditions and has stable buffering capacity.

4.6.3 Total Dissolved Solids (TDS)

As for TDS measurement, the proposed device measured TDS as 30,000 ppm compared to ICAR-CIBA's reported TDS of 32,000 ppm (20+% high concentrations of salinity), indicating that the device will be sufficiently robust to report accurate salinity readings even at high concentrations.

4.6.4 Conclusion

The visual representation of the comparative data gathered in this experiment supports that this water quality monitoring system provides real time, accurate readings on the water quality in a field setting. In fact, across all measured water quality parameters, the sensor integrated water quality system showed minimal deviation from the reference values obtained from the ICAR-CIBA in all cases, which supports the reliability of the sensors and corroborates that the monitoring system is well suited to monitor the water quality on a larger scale in aquaculture systems.

The results from laboratory and field tests show that the proposed water quality monitoring system has multiple unique features. The system utilizes low-cost, integrated sensors to monitor water quality in real-time (temperature, pH, TDS) unlike traditional methods that rely on manual sampling with a delayed analysis phase [1][3][4]. The system received high accuracy ratings in actual aquaculture conditions during testing at the ICAR-CIBA, with sensor readings being very close to those of the control sample. The use of machine learning on an easily accessible local Raspberry Pi 4 Model B enabled the system to perform anomaly detection early in the cycle (before cloud services or high bandwidth

was needed). An additional feature that adds to the uniqueness of the system is its ability to work accurately in water with salinity levels up to 30,000 ppm, proving that it can be used in brackish water applications. In addition, the system provides web-based dashboards for instant alerting and live data visualization, enabling hatchery managers to act immediately upon receiving alerts. These characteristics combine to make this system a completely new solution for the smart aquaculture industry based on having been validated in both the laboratory and field, low-cost deployment, and the use of predictive intelligence [4].

5 Conclusion

The purpose of this research is to develop an improved Internet of Things (IoT) based automated system for monitoring the quality of water specifically for aquaculture operations. The goal of this project is to allow for the creation of optimal water conditions for raising fish while reducing the amount of manual labor required, thus minimizing the number of mistakes made by humans. Conventional monitoring of water quality is mostly done through manual sampling performed at random intervals, leading to long delays between sampling events and an increased likelihood of making mistakes due to inconsistencies or lack of proper maintenance throughout the monitoring process [4]. This is typically combined with the use of various automated sensor technologies, Cloud Computing, and AI Analytics that can automatically provide near real time measurements of numerous water quality parameters on an ongoing basis to aquaculture facilities.

The system consists of an array of precision sensors capable of measuring ambient temperature, pH, Total Dissolved Solids (TDS), as well as many other parameters related to water quality. The sensors' outputs are fed directly into a central processing Unit (CPU) where an AI-Based Predictive Modelling System can analyze trends, deviations or anomalies within the data to predict future issues based on previously observed patterns or anomalies with the respective data sets. By identifying potential issues before they occur, operators can intervene early enough to prevent damage to fish populations or disruptions to production at hatchery [5]. By storing this data on a Cloud Computing platform, all entities are able to access live data regarding the current state of their water environment from anywhere at any time; thus, improving their ability to make informed operational decisions and increasing flexibility in their operations.

This technology will lower human involvement but continue to provide accurate and dependable results. Providing a web-based user interface allows hatchery operators to easily understand the water quality data provided, be alerted in real time and implement corrective actions as need arises. Furthermore, due to the automation of this technology, there will be a significant reduction in labor expenses thereby providing an economically feasible solution for all sizes of aquaculture enterprises (large and small).

Technology not only provides immediate benefit to producers but will also have long-term impacts on the way aquaculture is operated in a sustainable manner. Technology will support the health of fish by improving their environment through optimized water quality (i.e. maintaining a safe environment for fish), reducing the rate of fish deaths and improving the overall yield of fish. Additionally, by combining artificial intelligence-powered anomaly detection and predictive maintenance, the hatchery environments will be maintained as stable, thereby reducing the probability of water pollution and fluctuations in environmental conditions. In the future, the system will be improved through the addition of more sensors (e.g. nitrate and phosphate sensors) to provide a more comprehensive understanding of the dynamics of water quality. Additionally, improved use of machine learning techniques to refine AI models will provide increasingly accurate predictions, allowing for increasingly precise monitoring and automated responses. Furthermore, future developments may include implementing blockchain-based security protocols to guarantee

the integrity and authenticity of the water quality data, thereby providing producers with compliance to both industry regulations and standards for sustainable operations.

The research has established a revolutionary movement towards the transformation of aquaculture management, through developing and implementing an IOT-driven water quality monitoring solution that will improve both productivity and sustainability at fish hatcheries [1]. The water quality monitoring system is cost-effective, scalable and highly efficient at enabling the sustainable development of aquaculture by integrating Internet of Things (IOT), Artificial Intelligence (AI) and cloud-based computing technologies into the fish hatchery management process. Additionally, this project has created a solid foundation upon which to build future advancements in fish hatchery automation.

6 Future Work

While the current system provides real-time monitoring and automated response, there are several areas for further improvement:

6.1 Cloud Storage and Processing

In the cloud-computing-enabled proposed system, the use of cloud storage provides seamless management of water quality data, scalability for managing large data sets and the ability to access real-time information about critical water quality parameters [1]. For example, data continuously collected by sensors that monitor key water quality parameters (e.g., temperature, pH, total dissolved solids (TDS), dissolved oxygen) will automatically transmit to a cloud-based system for securely storing, processing and accessing data remotely [2].

One of the biggest advantages of using cloud storage is its ability to accommodate large amounts of data without needing a local infrastructure; cloud-based solutions are much more cost effective than traditional on-site server-based systems. On-site servers are costly to maintain and typically have many limitations (e.g., the potential for hardware failure, loss of data and limited space available to store data); therefore, using cloud computing in the proposed system addresses all of these shortcomings and creates a reliable and scalable solution to store multiple years of water quality data without the potential for degradation or risk of loss [4].

In addition to storing vast amounts of information, the ability to process data in the cloud has enabled more sophisticated ways to process, analyze and aid in the determination of decision-making regarding water quality. The cloud's infrastructure provides high performance computing resources that can perform analysis on historical and real-time data about water quality [5]. Machine learning methods in the cloud not only allow processing of the data from the machine learning perspective; they also allow the identification of patterns, prediction of outcomes, and generation of proactive notifications to operators of hatcheries [6]. This enables operators of hatcheries to detect slight shifts in the water conditions in real-time so that they can take immediate action to correct them, even if the changes may not otherwise be observed.

Another advantage of cloud-based processing is the ability of the operator to access water quality data remotely. By using either, a web-based dashboard or a mobile application, stakeholders and hatchery operators have access to the water quality data from any place [7]. As a result, on-site monitoring is not required on an unending basis, and they have greater flexibility to respond to conditions. In addition, the cloud allows multiple users to access the same information and work together in real-time [8].

In addition to the other benefits associated with working in the cloud, cloud integration enables automated backup of critical data and disaster recovery mechanisms [9]. In the

event of a cyber-attack or system failure, all critical data is protected and can be easily restored, allowing business operations to continue [10]. In addition, the cloud provides encryption of sensitive data and access control for the entire data set, protecting water quality data from unauthorized use/ access [11].

In general, the implementation of cloud storage and processing greatly increases the reliability, efficiency, and intelligence of the proposed system. By converting the unprocessed sensor data into actionable insights, ensuring security of the data produced by the sensors, and providing hatchery operators with real-time access to the important information needed to make better decisions about their business operations and implement sustainable practices in aquaculture, cloud-based storage and processing will greatly enhance aquaculture operations.

As technologies continue to evolve, many opportunities exist to further enhance the proposed water quality assessment solution to improve efficiency, accuracy, and responsiveness. Two focus areas for future enhancement will include improving the AI algorithms used for detecting anomalies in waters' quality and adding more sensors to broaden the monitoring capability of the waters' quality.

6.2 Enhancing AI Algorithms for Improved Anomaly Detection

To be classified as an intelligent monitoring system, it must have the ability to track and monitor anomalous conditions in real-time, generating predictions about future conditions using historical data as the basis for those predictions [14]. The current state of AI is that it has enabled operators to identify unsafe conditions earlier than ever before by allowing them to review and analyze aggregated historical data for various trends and relationship patterns within the various water quality parameters.

While these types of data will still continue to assist Operators with useful insight, there remains an opportunity to improve the ability to accurately predict future events by using more advanced deep learning technologies (i.e. Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs)) to enhance the capability of the system to process large amounts of sensor data and to develop new complex patterns associated with water quality from diverse sensor data sets [3]. The utilization of sensor information received from the Operations Manager will provide a basis for the system to evaluate whether or not there have been any environmental impacts to water quality resulting from natural occurrences or through negative effects thereby allowing for the reduction of false positive alerts while still being able to identify significant incidents [4].

In addition, using reinforcement learning as part of the AI model will enable the development of an optimal behavior pattern under certain conditions for the automated response to specific scenarios. As a result, the required repair work can be performed more quickly to bring the water back to an acceptable level. The proposed solution may also include incorporating external variable influences to enhance the prediction accuracy of identifying anomalous conditions within the Ai model, which would include weather variations and seasonal patterns, as well as biological data related to specific hatcheries [5]. In summary, adding external data sources into the AI model will enable hatchery managers to have a higher level of predictability and assurance, allowing them to take action to prevent major declines in water quality prior to any significant loss occurring.

6.3 Integrating Additional Sensors for Comprehensive Monitoring

The existing water quality sensors that measure important parameters like temperature, pH, total dissolved solids (TDS), are able to control the waterway for healthy fish production. To enhance the water quality of the system, adding more sensors that monitor additional

water quality parameters will improve the way in which the system is able to monitor the waterway for healthy fish [9]. Two additional water quality parameters that could be added to the existing system include nitrate level and phosphate level [12].

Nitrate and phosphate concentrations are highly significant indicators of the water quality of an aquatic environment. In aquaculture, excessive nutrient build-up will produce harmful algae and reduce the oxygen in the waterways [11]. High levels of nitrate from fish waste and uneaten feed can become toxic to fish, and the elevated levels of phosphates will pose a challenge to an aquatic environment trying to keep the ecological system balanced [10]. By implementing sensors to measure the nitrate and phosphate levels of the waterway, the existing water quality measurement system will provide a comprehensive assessment of the existing water quality, allowing hatchery personnel to make timely decisions, such as modifying feed ratios, improving filtration, or employing water treatment systems.

The real-time monitoring of phosphates and nitrates, in addition, assists aquaculture operations in preventing ecological disaster by timely compliance with environmental laws within the hatchery [14]. The combination of water quality monitoring with artificial intelligence predictive analytics will assist hatchery in improving hatchery operations by predicting potential water quality concerns before they escalate [8].

This research aims to create an enhanced learning process for the AI software, along with different types of sensors to identify various environmental variations in aquaculture conditions. Through ongoing updates of both the AI software and the number of sensors, the potential exists for the aquaculture management system to develop into a much smarter system compared to conventional aquaculture management systems. The end result is that fish populations will be in better health with more productive rates, while at the same time making substantial contributions toward bettering the environmental aspects of and sustainability of aquaculture.

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