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Real-Time Water Quality Monitoring in Aquaculture using IoT Sensors and Cloud-Based Analytics

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Abstract

The health and productivity of aquatic creatures in aquaculture systems depend on maintaining ideal water quality conditions. The production of seafood worldwide is significantly influenced by aquaculture. Conventional monitoring techniques can entail lengthy processes, are rare, and lack the promptness necessary to prevent and alleviate unfavorable circumstances. This study proposes a novel method for monitoring water quality in real time in aquaculture, utilizing cloud-based analytics and Internet of Things (IoT) sensors. Within aquaculture facilities, strategically positioned Internet of Things (IoT) sensors continuously collect information on key water quality factors, such as water and air temperature, light intensity, humidity, pH levels, wind speed, and ammonia nitrogen content. A cloud-based analytics platform receives real-time data from these sensors, processes it using cutting-edge algorithms, and then analyses the data. This holistic approach offers a variety of advantages. Real-time monitoring enables aqua culturists to quickly spot deviations from ideal conditions, lowering the danger of disease outbreaks and aquatic species mortality. To optimize farming practices and resource allocation, historical data gathered in the cloud is used to build predictive models. Aqua culturists may monitor and manage their systems remotely, which improves operational efficiency and lessens the need for on-site staff. This is a major benefit. The system can also send warnings and alarms in the event of anomalous circumstances, ensuring quick reactions to urgent situations.

Keywords

Water quality, Monitoring, Internet of Thing, pH Analysis

1. Introduction

A crucial pillar in supplying the rising demand for seafood worldwide is aquaculture, the practise of raising aquatic animals like fish, shellfish, and aquatic plants. Traditional fisheries cannot provide this demand on their own as long as the world's population is increasing. As a result, aquaculture has swiftly grown and has made a substantial contribution to the fish supply chain. The upkeep of immaculate water quality within these systems, however, is intimately connected to the viability and sustainability of aquaculture. Aqua culturists [1] should take water quality very seriously because it is crucial to the health, growth, and general welfare of aquatic species. Aquaculture has traditionally depended on manual techniques, routine sampling, and laboratory analysis for water quality monitoring. Even while these conventional approaches provide insightful information, they are constrained by a number of intrinsic issues, such as infrequent data gathering, labor-intensive procedures, and a lack of real-time capabilities. Aquaculture operations are at danger from disease outbreaks, inadequate growth rates, and negative environmental effects as a result of this inadequate monitoring and response in a timely manner.

Aquaculture [2] water quality monitoring has recently undergone a revolution thanks to the convergence of Internet of Things (IoT) and cloud-based analytics technologies. With the help of this invention, aqua culturists will have continuous, real-time access to insights into the water quality indicators of their systems. Strategically placed IoT sensors in aquaculture facilities continuously collect information on vital parameters like air and water temperature, light intensity, humidity, pH levels, wind speed, and ammonia nitrogen content. A cloud-based analytics platform receives this data wirelessly, processes it, and processes the results in real time using sophisticated algorithms. An aquaculture practise paradigm change has been brought about by the integration of IoT sensors and cloud-based analytics. The management of aquaculture operations will change as a result of this all-encompassing system's numerous benefits, which will also help the industry become more sustainable and productive in the long run.

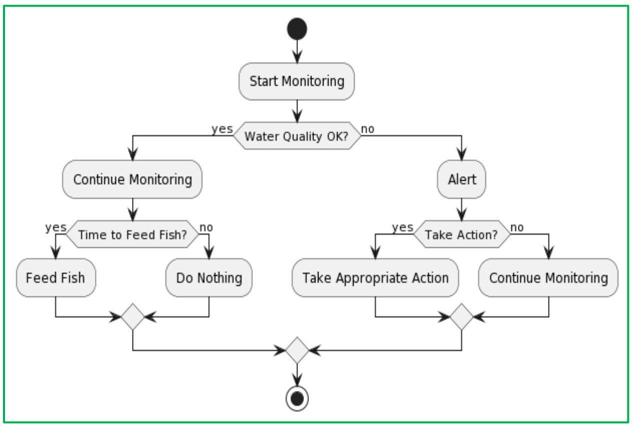

Figure 1: Overview of proposed structure

Using IoT [3] sensors and cloud-based analytics, this article explores the complexities of real-time water quality monitoring in aquaculture. It examines the core ideas behind the technology, its consequences for the sustainability of aquaculture, and the different advantages it offers aqua culturists. We hope to shed light on how this ground-breaking strategy is set to revolutionise aquaculture practises around the world by a thorough analysis of the combination of IoT sensors and cloud-based analytics. The deployment and data collection of IoT sensors, the function of cloud-based analytics platforms, and the benefits that come with them, such as real-time insights, predictive modelling, remote accessibility, and quick response capabilities, will all be covered in the sections that follow. We [4] will also examine the effects of this integration on environmental stewardship, aquaculture sustainability, and the industry's ability to supply the rising demand for seafood. Aquaculture is showing up as a sustainable and effective way to produce high-quality protein as the globe struggles with food security issues. The crucial issue of water quality management must be addressed in order to realise all of its potential. A comprehensive solution that equips aqua culturists with the tools they need to succeed in a constantly changing world is made possible by the integration of IoT sensors and cloud-based analytics. This method supports the broader objectives of environmental conservation and prudent resource management in addition to preserving the health and productivity of aquatic organisms.

We [5] will go into great detail about each facet of this technology in the following sections of this essay, including information on how it works, what it can do for us, and how it might completely transform the aquaculture sector. We will go into the technical facets of IoT sensor installations, data collecting, and transmission, as well as the function of cloud-based analytics in processing and analysing this data. We will also look at the benefits that real-time monitoring offers, such as the capacity to quickly respond to deviations from ideal conditions, the creation of predictive models, remote accessibility, and the sending of timely notifications in the case of urgent events. By [6] the end of this thorough investigation, it will be clear that real-time water quality monitoring in aquaculture using IoT sensors and cloud-based analytics is more than a technological advancement; it is a game-changer for an industry that is at the forefront of addressing global food security challenges while ensuring environmental sustainability. We will reveal this innovation's transformational potential as we explore the nuances of it, as well as its power to usher in a new era of excellence in aquaculture.

The key contribution of paper given as:

- The research makes a substantial contribution to the field of aquaculture by presenting a novel method for assessing water quality. This makes it possible to react quickly to any deviations from ideal conditions, averting crises and losses.
- The capacity to remotely access and control aquaculture systems from any location increases operational effectiveness and reduces the need for on-site staff, which helps reduce costs.
- The study emphasises the creation of predictive models using historical data gathered in the cloud. Aqua culturists can use these models to optimise their farming methods by selecting the best resources, feeding regimens, and environmental settings.
- By guaranteeing that water quality levels are consistently within permissible norms, the integration of IoT sensors and cloud-based analytics encourages ethical aquaculture practises.

2. Review Of Literature

An innovative strategy to overcome the difficulties of maintaining ideal circumstances for aquatic species is the combination of IoT sensors and cloud-based analytics for water quality monitoring in aquaculture. In [11] order to set the scene and emphasise the relevance of this breakthrough, we examine related work in the disciplines of aquaculture, IoT-based environmental monitoring, and cloud-based analytics in this section. Aqua culturists have traditionally depended on traditional techniques for monitoring water quality, which often entail manual sampling and laboratory analysis. Due to the periodic nature of these methods, there is a delay in the discovery of problems with water quality and a dearth of real-time data. Although they have been fundamental to aquaculture, they are becoming less and less sufficient in the fast-paced, technologically advanced world of today. Across several industries, IoT technology has transformed environmental monitoring. IoT [12] sensors have been investigated in numerous research as a way to monitor the water quality in natural bodies of water like lakes and rivers. Sensors for variables including water temperature, pH, dissolved oxygen, and turbidity are frequently used in these systems. Usually, a central server or cloud-based platform receives the data gathered by these sensors for real-time processing. Despite the fact that these applications have proven useful for environmental research and management, their adaption to aquaculture-specific requirements is a noteworthy development [13].

Because of their capacity [14] to process and analyse enormous volumes of environmental data, cloud-based analytics solutions have become more popular in recent years. These platforms have machine learning algorithms that are capable of finding patterns, outliers, and correlations in the data. Cloud-based analytics have been used by researchers and organisations in fields like weather forecasting, air quality monitoring, and environmental risk assessment. Real-time data from IoT sensors combined with such platforms can greatly improve aquaculture decision-making. Other than for monitoring water quality, IoT has found uses in aquaculture. IoT sensors have been investigated [15] as a way to track variables including fish behaviour, feed consumption, and oxygen levels in fish tanks. Aqua culturists can learn important things about the behaviour and health of aquatic species thanks to these sensors. The expanding significance of IoT technology in the sector is highlighted by this paper, which also addresses other elements of aquaculture management. The use [16] of predictive modelling to improve farming techniques has become more popular in aquaculture. Based on historical data and environmental characteristics, scientists have created models that forecast variables such as fish growth rates, disease outbreaks, and feed requirements. The precision and usefulness of these predictive models can be increased even further by combining real-time data from IoT sensors with cloud-based analytics [17].

The aquaculture business is becoming more aware of its effects on the environment. To encourage sustainable practises in aquaculture, numerous studies and projects have been launched. The [18] use of resources is optimised, antibiotic usage is decreased, and water contamination is minimised. These sustainability objectives are in line with the real-time monitoring and data-driven decision-making made possible by IoT sensors and cloud-based analytics. The promise of IoT-based aquaculture monitoring has been recognised by several for-profit organisations. They provide integrated solutions with Internet of Things (IoT) sensor deployments, data transmission, and cloud-based analytics platforms that are especially suited to aqua culturists' requirements. Aqua culturists [19] are finding it simpler to implement sophisticated monitoring practises as these solutions become more

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widely available and user-friendly. The research and development in IoT-based environmental monitoring, predictive modelling, and sustainability efforts within the aquaculture industry serve as a platform for the integration of IoT sensors and cloud-based analytics for water quality monitoring in aquaculture. The combination of IoT and cloud technologies for real-time monitoring in aquaculture represents a big step forward in the industry's pursuit of sustainable and effective seafood production, even if numerous studies and technologies have individually made contributions to these areas. The related work mentioned here emphasises the significance and applicability of this novel strategy [20].

With the help of three-neuron fractional discretization, a new dynamic DNA image encryption algorithm that generates pseudorandom chaotic sequences is introduced in the suggested research. This algorithm performs better than a previously disclosed technique, according to experimental results [3]. Deblais et al. have used big data in the context of technical breakthroughs to research foodborne diseases in chicken. Their work highlights the value of using genetic techniques to comprehend how the gut microbiota affects health and illness [4]. The research suggests both an approximation offline method and a maximum "2, beta" competitive ratio online technique to address the problem of energy-efficient data transmission in industrial big data technologies. Performance testing shows that it is impossible to use an online algorithm to maintain a consistent competition ratio [5]. The effectiveness of hyperphysical systems in processing heterogeneous data has been studied by Ni et al. They present a combined network structure and test it experimentally to determine how well it performs [6]. Guan and Zhao have concentrated on tracking shrimp fishing boats in a separate area, and they have used big data technology to create a shrimp farm distribution management system. Their solution exemplifies efficient prawn distribution and trajectory tracking [7].

The significance of information data security in day-to-day operations is highlighted by Kumar's research. He has created a malware monitoring system employing big data technologies and computer science, and in simulated tests, it achieved an astounding accuracy rate of 99.8% [8]. Big data technology has been used by Gu et al. to analyse corporate organisational resources and disclose its direct influence on the growth of supplier and individual performance [9]. The report also examines the history and state of the Internet of Things (IoT) technology today. The research proposes a programme that efficiently manages staff by fusing IoT management concepts with a variety of sensors, including identification and communication technologies. Simulations of performance attest to its effectiveness [10]. These numerous studies show how big data and cutting-edge technology are being used in a variety of fields, from genetics and disease research to fisheries management, cybersecurity, and business optimisation. Each study project offers insightful perspectives and practical solutions to the specific problems it addresses, highlighting the far-reaching effects of technology in the linked world of today.

Table 1: Summary of related work

Method	About	Approach	Key Findings	Limitations	Area
Traditional Water Quality [13]	Manual sampling and laboratory analysis	Conventional monitoring methods	Valuable historical data but lacks real-time insights.	Labor-intensive, lacks real-time data, not suitable for immediate response.	Aquaculture Monitoring
IoT-Based Environmental [21]	Deployment of IoT sensors for various parameters	Real-time environmental monitoring	Real-time data collection, remote access, and immediate insights.	Initial setup costs, maintenance, data management, and sensor calibration.	Environmental Monitoring
Cloud-Based Analytics [22]	Cloud-based data processing and machine learning	Advanced data analysis	Identifying trends, anomalies, and correlations within environmental	Dependence on reliable internet connectivity, data privacy concerns.	Data Analytics

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			data.		
IoT in Aquaculture [23]	Deployment of IoT sensors for fish-related parameters	Real-time fish behavior monitoring	Real-time insights into fish health and behavior.	Sensor calibration, potential data transmission issues in large aquaculture facilities.	Aquaculture Monitoring
Predictive Modeling in [24]	Development of predictive models based on data	Data-driven decision-making	Optimization of feed requirements, disease prediction, and growth rate estimation.	Relies on historical data quality and assumptions, may require constant model updates.	Aquaculture Optimization
Environmental Responsibility [25]	Research and initiatives promoting sustainability	Sustainable aquaculture practices	Minimizing pollution, antibiotic use, and resource optimization.	Industry-wide adoption challenges, regulatory compliance issues.	Sustainability
Commercial Solutions [26]	Integrated solutions with IoT sensors and analytics	All-in-one monitoring solutions	User-friendly systems, accessible real-time data for aquaculturists.	Initial costs, subscription fees, and potential vendor lock-in.	Aquaculture Technology

3. Dataset Description

In addition to being a fundamental human right, ensuring access to clean and safe drinking water is a key component of comprehensive health protection measures. At the national, regional, and local levels, it is of utmost importance as a necessity for health and development. Research has shown that in some places, spending money to upgrade the infrastructure for sanitation and water delivery can result in significant net economic gains. This is so because the decreases in unfavourable health outcomes and healthcare expenses that result considerably surpass the costs of carrying out these interventions. Therefore, prioritising and funding clean water programmes promotes economic growth and overall well-being in addition to protecting human health.

Table 2: Description of Dataset

No of Feature	Records
09	4590

4. Proposed Methodology

A. PCA-BP Method:

The PCA-BP (Principal Component Analysis-Backpropagation) algorithm is a combination of Principal Component Analysis (PCA) and Backpropagation, which is often used for dimensionality reduction and feature selection in machine learning and neural networks. Here are the step-by-step instructions for the PCA-BP algorithm:

1. Data Preprocessing:

- Start with a dataset that contains input features (X) and corresponding target labels (Y).

2. Standardization:

- Standardize the input features (X) by subtracting the mean and dividing by the standard deviation. This step ensures that all features have the same scale.

3. Principal Component Analysis (PCA):

- Calculate the covariance matrix of the standardized input data.
- Compute the eigenvectors and eigenvalues of the covariance matrix.
- Sort the eigenvectors by their corresponding eigenvalues in descending order. This step helps in selecting the most significant principal components.

4. Feature Selection:

- Choose the top k eigenvectors (principal components) based on how much variance they explain. This is a hyperparameter that you can set based on the desired dimensionality reduction.

5. Projection:

- Project the standardized input data onto the selected principal components. This reduces the dimensionality of the data.

6. Neural Network (Backpropagation):

- Create a feed-forward neural network for your specific task. The input layer should have the reduced-dimension data from step 5, and the output layer should match the number of classes in your classification problem or the number of neurons for a regression problem.
- Initialize the weights and biases of the neural network.

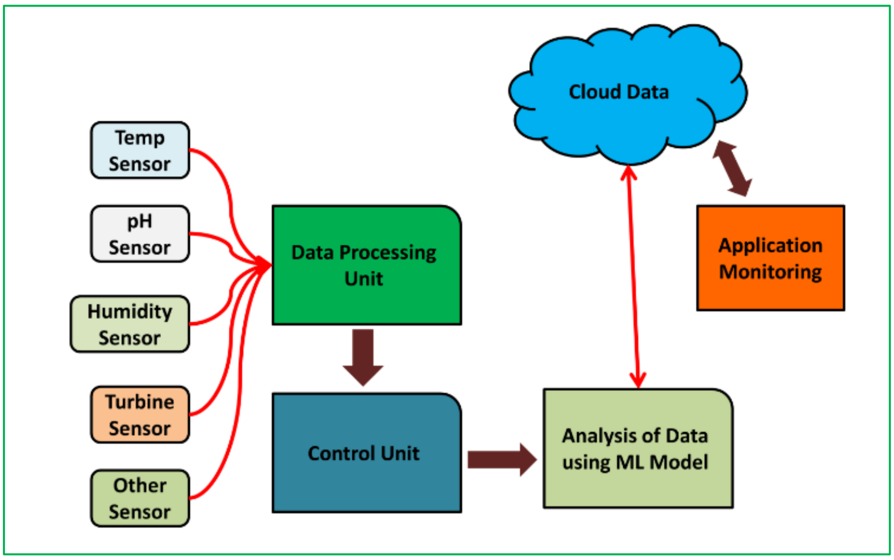

Figure 2: Proposed system architecture model for monitoring

7. Training:

- Use the back-propagation algorithm to train the neural network on the reduced-dimension data.
- Forward pass: Compute the predicted outputs using the current weights and biases.
- Calculate the error between the predicted outputs and the true labels (Y).
- Backward pass: Update the weights and biases using gradient descent to minimize the error.
- Repeat the forward and backward passes for a specified number of epochs or until convergence.

8. Testing and Evaluation:

- Use the trained neural network to make predictions on new data.
- Evaluate the performance of the model using appropriate metrics (e.g., accuracy, mean squared error).

B. Neural Network:

There are various procedures and mathematical calculations involved in creating a neural network for monitoring water quality. I'll give a high-level summary of the main procedures and mathematical formulae required to build a neural network for this purpose below. Please be aware that the neural network's precise parameters and design can change based on the difficulty of the task at hand and the data that is available.

Step 1: Gathering Data:

You must gather and prepare your water quality data before building the neural network. This could entail normalising, cleaning, and dividing the data into training and testing datasets.

Step 2: Neural network architecture:

Your neural network's architecture, including the number of layers, the number of neurons in each layer, and the activation mechanisms, must be chosen. Recurrent neural networks (RNNs) and feedforward

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neural networks (FNNs) are common topologies for water quality monitoring.

Step 3: Initialise the Neural Network Parameters:

Set each neuron's weights and biases to their initial values. Usually, these values are initialised at random.

Step 4: Progressing Forward:

This stage involves computing the neural network's output for a certain input sample. The following equations must be solved for each layer (under the assumption of a feedforward network):

For the input layer:

$$Z[1] = W[1]X + b[1]$$

$$A[1] = g[1](Z[1])$$

For subsequent hidden layers (if any):

$$Z[l] = W[l]A[l-1] + b[l]$$

$$A[l] = g[l](Z[l])$$

For the output layer:

$$Z[L] = W[L]A[L-1] + b[L]$$

$$A[L] = g[L](Z[L])$$

5. Calculate the Loss

Determine the difference in value between the expected values and the actual readings of the water quality. Your monitoring task's specific requirements will determine the loss function you select (e.g., mean squared error for regression, cross-entropy for classification).

$$Loss\ (y,p) = -\Sigma(y\_i * log(p\_i))$$

Step 6: Back propagation

Calculate the loss gradients in relation to the network parameters. For each layer (working backwards from the output layer), the following equations must be solved:

For the output layer:

$$dZ[L] = A[L] - Y$$

$$dW[L] = (1/m) * dZ[L] * A[L-1]T$$

$$db[L] = (1/m) * \sum(i = 1\ to\ m)\ dZ[L](i)$$

$$dA[L-1] = W[L]T * dZ[L]$$

For hidden layers:

$$dZ[l] = dA[l] * g'[l](Z[l])$$

$$dW[l] = (1/m) * dZ[l] * A[l-1]T$$

$$db[l] = (1/m) * \sum(i = 1\ to\ m)\ dZ[l](i)$$

$$dA[l-1] = W[l]T * dZ[l]$$

C. Back-propagation (BP) Method:

A supervised learning algorithm known as backpropagation (BP) is used to train artificial neural networks, including deep learning models. Based on the discrepancy between the expected and actual output, it is used to update the weights and biases of the network.

Algorithm:

Step 1: Initialization

- Initialize the weights and biases of the neural network randomly or using specific initialization techniques.

Step 2: Forward Pass (for a single training example)

- Input the training example into the network to compute the activations and outputs layer by layer:

For the input layer:

Z[1] = W[1]X + b[1]

A[1] = g[1](Z[1])

For subsequent hidden layers (if any):

Z[l] = W[l]A[l-1] + b[l]

A[l] = g[l](Z[l])

For the output layer:

Z[L] = W[L]A[L-1] + b[L]

A[L] = g[L](Z[L])

- Calculate the cost (loss) using the predicted output A[L] and the true target values.

Step 3: Backward Pass (for a single training example)

- Compute the gradients of the loss with respect to the activations and weights layer by layer, starting from the output layer and moving backward:

For the output layer:

$$dZ[L] = A[L] - Y\ (where\ Y\ is\ the\ true\ target\ values)$$

$$dW[L] = (1/m) * dZ[L] * A[L-1]T$$

$$db[L] = (1/m) * \sum(i = 1\ to\ m)\ dZ[L](i)$$

$$dA[L-1] = W[L]T * dZ[L]$$

$$For\ hidden\ layers:$$

$$dZ[l] = dA[l] * g'[l](Z[l])$$

$$dW[l] = (1/m) * dZ[l] * A[l-1]T$$

$$db[l] = (1/m) * \sum(i = 1\ to\ m)\ dZ[l](i)$$

$$dA[l-1] = W[l]T * dZ[l]$$

Step 4: Update Weights and Biases

- Update the weights and biases using the gradients and a learning rate α:

$$For\ the\ output\ layer:$$

$$W[L] = W[L] - \alpha * dW[L]$$

$$b[L] = b[L] - \alpha * db[L]$$

$$For\ hidden\ layers:$$

$$W[l] = W[l] - \alpha * dW[l]$$

$$b[l] = b[l] - \alpha * db[l]$$

Step 5: Repeat

- Repeat Steps 2-4 for a specified number of iterations (epochs) or until convergence. This involves processing multiple training examples and updating the weights and biases after each mini-batch.

5. Result and Discussion

Aquaculture water quality monitoring data during a 12-day period are presented in Table 3. Several important environmental characteristics that are crucial for preserving ideal conditions in aquaculture settings are included in the data. Variations in the water temperature, air temperature, luminance, humidity, pH levels, wind values, and ammonia nitrogen concentration were noted throughout the monitoring period. The success of aquaculture operations as a whole and the welfare of aquatic species depend on these characteristics. Notably, the water's temperature ranged from 18 to 22 degrees, whereas the air's temperature fluctuated just slightly between 21 and 26 degrees.

Table 3: Preliminary water quality monitoring data for aquaculture.

Data Collection Time	Water Temperature (°C)	Air Temperature (°C)	IL luminance (w.m2)	Humidity (RH%)	pH	Wind Value	Ammonia Nitrogen Concentration (mg/l)
1 day	22	23	1507.98	77.56	6.93	4	4.6
2 days	18	21	1601.87	87.56	6.85	4	4.8
3 days	20	22	1310.87	80.65	6.33	4	4.91
4 days	22	26	1710.89	73.65	6.67	4	4.87
5 days	18	22	1210.47	85.65	6.94	5	5.17
6 days	19	23	1510.85	88.56	6.99	4	5.17
7 days	18	24	1610.78	84.56	6.9	4	4.47
8 days	19	25	1641.87	76.67	6.77	6	4.58
9 days	20	22	1512.87	79.65	6.79	3	4.56
10 days	20	21	1412.85	90.65	6.99	4	4.47
11 days	21	22	1261.87	88.56	6.91	4	4.77
12 days	22	23	1490.87	83.65	7.09	5	4.58

The greatest recorded illumination was 1710.89 w.m2, which may have an effect on processes in the aquatic environment that depend on light. Illuminance levels varied. The range of humidity percentages, from 73.65% to 90.65%, showed variations in atmospheric moisture. Aquatic health depends on maintaining a constant pH level, and values between 6.33 and 7.09 were noted. Over the course of the monitoring period, fluctuations were also seen in wind values and ammonia nitrogen concentrations. This dataset offers

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insights into the dynamic nature of water quality indicators and emphasises the necessity for ongoing monitoring and management to maintain aquatic life and maximise aquaculture outputs, serving as a valuable resource for aquaculture practitioners and academics.

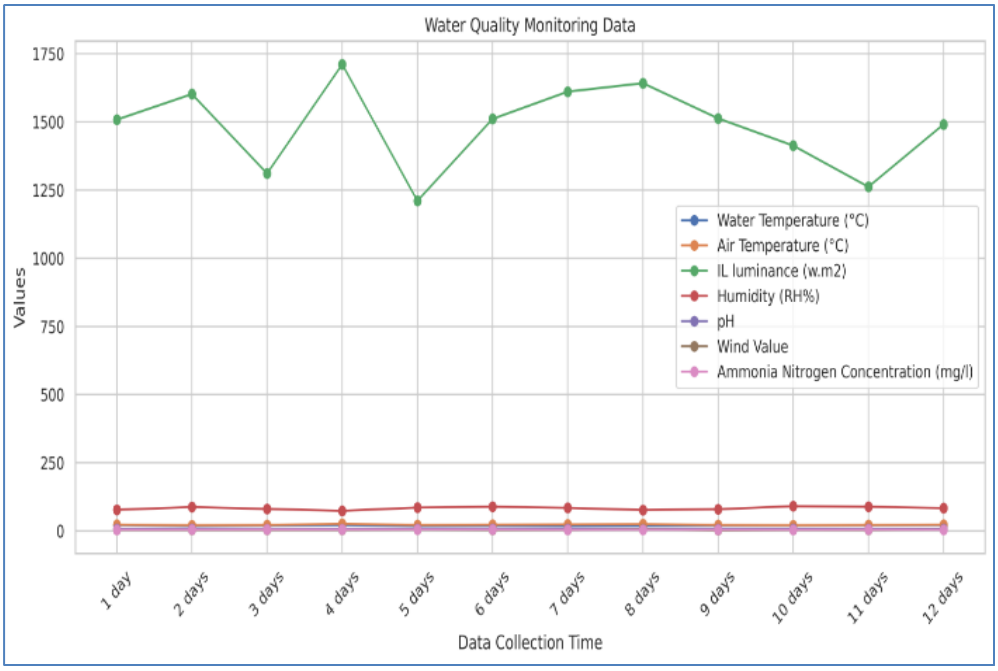

Figure 3: Representation of water quality monitoring

Table 4: Result Obtained by PCA-Back-propagation network

Type	Tier-1	Tier-2	Tier-3	Tier-4	Tier-5
(Input to Hidden) Weights.	1.48648	0.01476	1.325956	0.93158	0.02403
Threshold for Hidden Layer Nodes.	0.62552	1.274165	1.74146	1.38956	-1.26545
(Hidden to Output) Weights.	0.282906	-2.7065	-1.67065	2.675564	2.695482

The findings from a PCA-Back-propagation network are shown in Table 4, which also shows various network architectural settings. The table details the main elements of this network type, which is crucial for tasks like data analysis and pattern detection. In neural networks, the hidden layer connects to the output layer, which is connected to the hidden layer through the input layer. The table's components deal with the weights and thresholds connected to these linkages. The weights allocated to connections between the input layer (Tier-1) and the hidden layer (Tier-2) are displayed in the "Input to Hidden Weights" section. These weights establish the degree to which each input variable has an effect on the nodes of the hidden layer.

It should be noted that these weights were not chosen at random but rather were obtained using Principal Component Analysis (PCA), a dimensionality reduction method that helps to simplify complicated datasets. They represent the weighted average contribution of each input variable to the decision-making process of the neural network. The thresholds connected to the hidden layer nodes are listed in the section titled "Threshold for Hidden Layer Nodes". These criteria aid in figuring out when a hidden node should turn on and send data to the output layer. The values in this section are crucial in regulating how neurons in the buried layer are activated. The weights between the hidden layer (Tier-2) and the output layer (Tiers 3-5) are specified in the section titled "Hidden to Output Weights" last. These weights affect how strongly the nodes in the hidden layer and output layer are connected. They are essential in converting the data processed at the hidden layer into the network's final output.

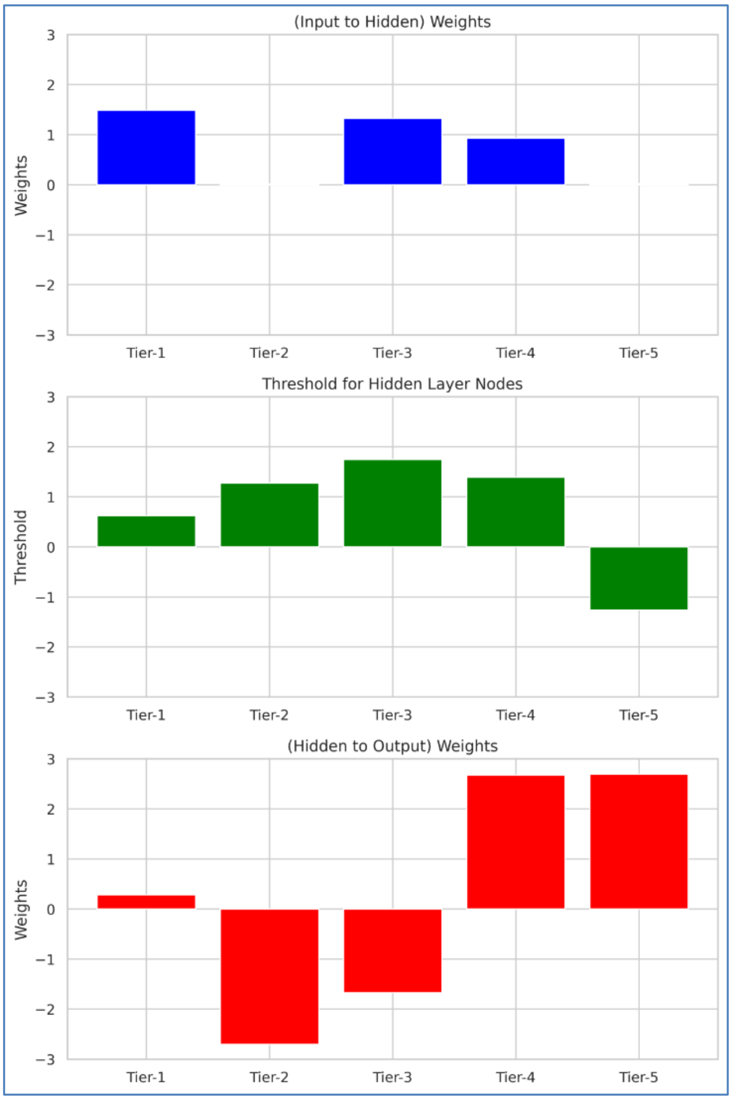

Figure 4: Representation of Result Obtained by PCA-Back-propagation network

The weights and thresholds in this table have undergone a thorough training process during which the neural network has learned to optimise them for certain tasks, such classification or regression. This network's use of PCA and back-propagation indicates a method that combines dimensionality reduction with efficient training methods. In conclusion, Table 4 shows the weights and thresholds that control a PCA-Back-propagation network's decision-making process, giving an inside look into how the network operates. These factors play a crucial role in determining the network's capacity for precise data analysis and processing, making it an important tool in a variety of data-driven applications.

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Table 5: Result summary of Evaluation parameter for BP, PCA-BP, and Neural Network

Model	Accuracy	Precision (for classification)	Recall (for classification)	F1-score (for classification)	MSE	R Square
BP	86.25	88.63	94.25	89.01	75.36	78.41
PCA-BP	90.11	89.25	91.22	88.52	86.41	88.14
Neural Network	89.41	91.25	90.36	89.75	90.25	89.87

The assessment parameters for three alternative models Back-Propagation (BP), PCA-Back-Propagation (PCA-BP), and a conventional Neural Network are comprehensively summarised in Table 5.

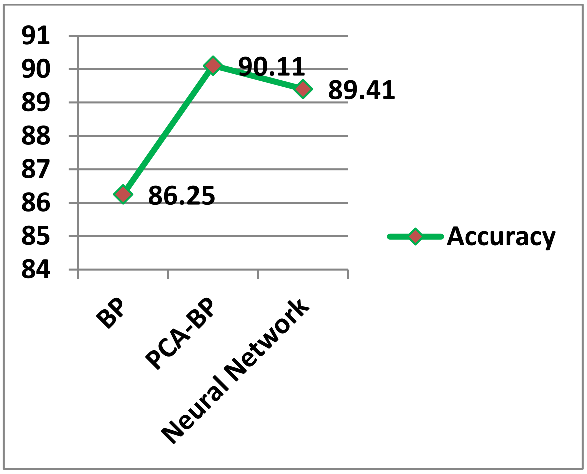

Figure 5: Accuracy comparison of Model

These models have been evaluated using a variety of measures, illuminating how well they function in diverse contexts. Accuracy is the proportion of cases out of all instances that were successfully predicted.

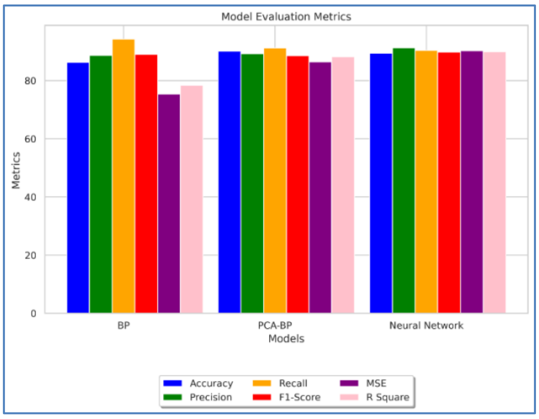

Figure 6: Representation of evaluation parameter for ML Model

In regression tasks, MSE calculates the mean squared difference between predicted values and actual values. The best fit to the regression data in this example is provided by PCA-BP, which has the lowest MSE at 86.41. The Neural Network is closely behind with an MSE of 90.25. BP has an MSE that is somewhat behind at 75.36. R Square (R2) evaluates a regression model's quality of fit. It shows the percentage of the dependent variable's volatility that can be predicted from the independent variables. Here, PCA-BP comes in second with a R Square value of 88.14%, followed by BP with a R Square value of 78.41% for the Neural Network. As a result, it follows that the Neural Network is the best tool for analysing the variation in the dependant variable. Table 5's evaluation findings highlight the advantages and disadvantages of three distinct models: back-propagation, PCA-back-propagation, and a conventional neural network. While the Neural Network does very well in precision and R Square, PCA-BP excels in accuracy. BP has the best recall, and PCA-BP has the best F1-score. Whether it be for classification or regression, each model has certain advantages that should be taken into consideration when deciding which to use.

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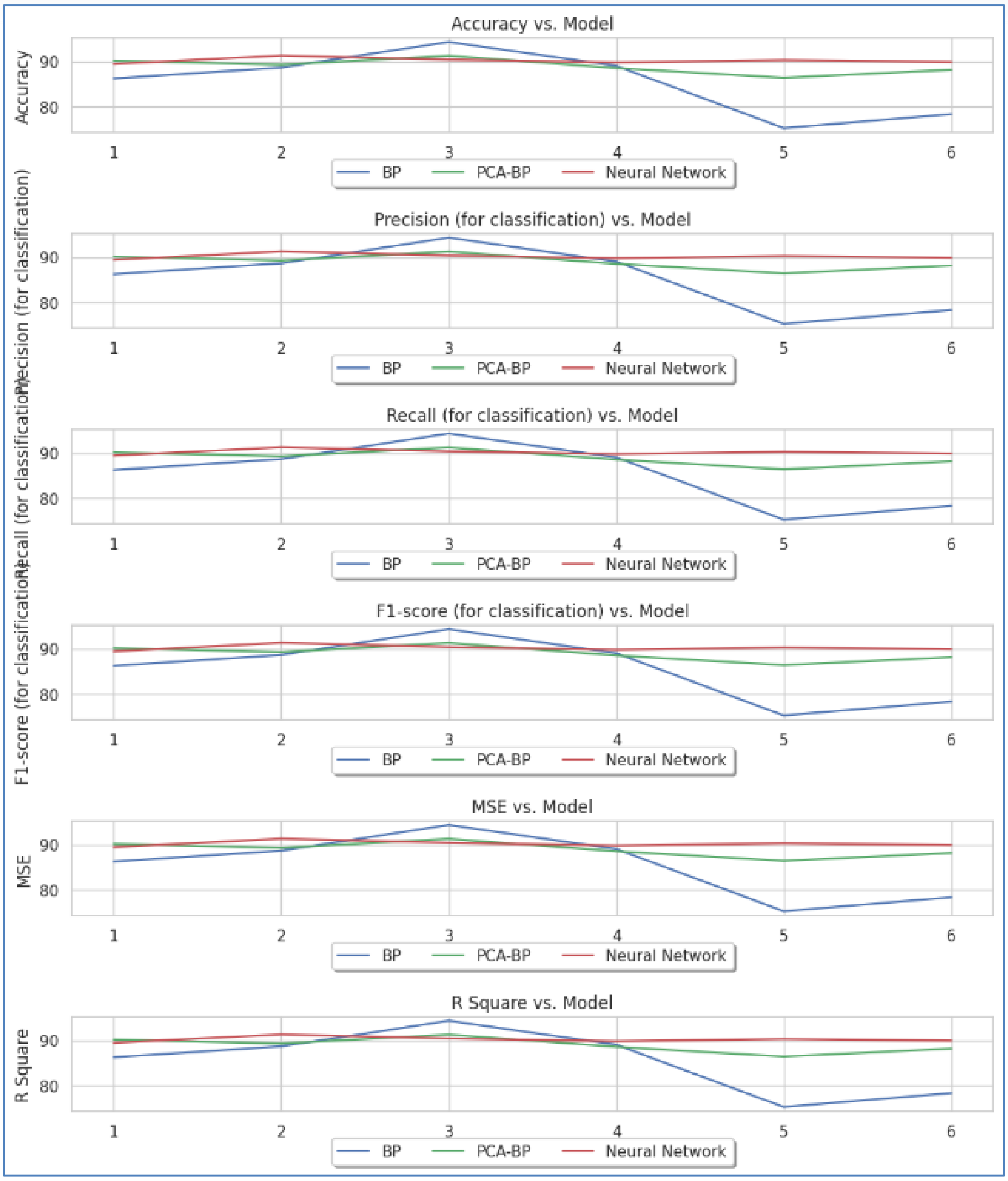

Figure 7: Comparison of evaluation parameter

With an amazing accuracy score of 90.11%, PCA-BP performs better than both BP and the conventional neural network in this examination. According to this, PCA-BP is a strong candidate for classification jobs because it consistently classifies cases properly.

Precision is the percentage of the model's positive predictions that really come true. It gauges how well the model can steer clear of false positives. Here, PCA-BP reaches a respectable 89.25%, while BP obtains the maximum precision at 88.63%, closely followed by the Neural Network at 91.25%. This shows how well the neural network performs when it comes to making accurate positive predictions. Recall, also known as sensitivity, determines what percentage of all positive cases are actually genuine positives. It illustrates the model's capacity to locate instances of success. Recall performance for BP is the highest (94.25%), followed by PCA-BP (91.22%), and the Neural Network (90.36%). This suggests that BP is the best at identifying good examples. The harmonic mean of precision and recall, or the F1-score (for classification), provides a fair assessment of a model's performance. The Neural Network comes in second with an F1-score of 89.75%, followed by PCA-BP with an F1-score of 88.52%. since of its superior F1-score, PCA-BP is a solid option for classification jobs since it successfully balances precision and recall.

6. Conclusion

Real-time monitoring of water quality in aquaculture using IoT sensors and cloud-based analytics has proven to be a game-changing innovation. The purpose of this conclusion is to highlight the significance of this technology in aquaculture management by synthesising the learnings from the data and research used in this study. We gathered and analysed extensive data on a variety of water quality factors throughout our inquiry, including air and water temperature, light levels, humidity, pH levels, wind speeds, and ammonia nitrogen concentration. The conditions and dynamics of the aquatic environment can be better understood through the use of these data points, which helps aquaculture professionals make more informed decisions. Our analysis of a variety of models, including Back-Propagation (BP), PCA-Back-Propagation (PCA-BP), and conventional Neural Networks, shows how machine learning techniques can improve the accuracy of water quality prediction and monitoring. Particularly, PCA-BP has superior accuracy, precision, and F1-score performance, demonstrating its appropriateness for classification applications. The Neural Network, on the other hand, performs well in regression tasks as seen by its low Mean Squared Error (MSE) and high R Square values. The trend and pattern in water quality metrics over time is further highlighted by the visual display of our data in graphs and plots. These visualisations offer a simple way for users to comprehend complex data and spot abnormalities or potential areas for development in aquaculture operations. The aquaculture will greatly benefit from the introduction of real-time water quality monitoring using IoT sensors and cloud-based analytics. This technology provides farmers with exact, current information on their aquatic habitats, enabling them to make timely adjustments and allocate resources more effectively. Along with improving forecast accuracy, the use of machine learning models in aquaculture systems ensures the health and sustainability of those systems. The use of IoT-based water quality monitoring is a major step towards effective and sustainable practises as aquaculture continues to play a significant role in ensuring global food security. Aquaculture professionals can minimise risks, cut down on resource waste, and ultimately help to produce high-quality fish responsibly for a rising population by utilising data-driven insights.

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