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Research article

Smart aquaculture analytics: Enhancing shrimp farming in Bangladesh through real-time IoT monitoring and predictive machine learning analysis

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ABSTRACT

Water quality is a critical factor in shrimp farming, and the success of shrimp production is closely tied to the overall condition of the water. Challenges such as rapid population growth, environmental pollution, and global warming have led to a decline in fisheries production, particularly in the freshwater shrimp sector. This study addresses these challenges by monitoring multiple water parameters in shrimp farms, including pH, temperature, TDS, EC, and salinity. Traditional manual monitoring systems are known to be cumbersome, time-consuming, and lacking real-time capabilities. Consequently, a continuous and automated monitoring system becomes imperative for efficient and real-time metrics handling. This study introduces a real-time freshwater shrimp (locally named Galda, i.e., Macrobrachium Rosenbergii) farm monitoring system. The proposed system incorporates technologies such as microcontroller-based physical devices, IoT, cloud storage with service, machine learning models, and web applications. This integrated system enables users to remotely monitor shrimp farms and receive alerts when water parameters fall outside the optimal range. The physical implementation involves a set of sensors for collecting data on water metrics in shrimp farms. Regression analysis is employed for predicting next-day values, and a newly developed decision-based algorithm classifies shrimp production levels into low, medium, and maximum categories using six well-known classification algorithms. The system demonstrates a high success rate for next-day predictions (r^2 of 0.94) by multiple linear regression, and the accuracy in classifying shrimp production is 97.84 % by Random Forest. Additionally, a 'Smart Aquaculture Analytics' web application has been developed, offering features such as real-time dashboards, historical data visualization, prediction and classification tools, and automated notifications to farmers in Bangladesh.

1. Introduction

Aquaculture has become a crucial aspect of the world's food security; it offers a cost-effective and sustainable way to satisfy the growing interest in fish and seafood [1]. In Bangladesh's particular context, shrimp farming is a significant economic pillar that

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(a) Adult Galda (b) Shrimp farming

Fig. 1. The cultivation of (a) adult Galda in (b) a smart aqua method using Internet of Things (IoT) technology.

sustains livelihoods and makes a substantial contribution to export earnings [2]. Bangladesh is a small country, but it has a vast population. The amount of space is constantly decreasing due to the dense population. Over 69,000 ha of agricultural farmland are being lost to industrial development to fulfill the requirements of a growing population for employment opportunities [3]. Therefore, we must guarantee that every square inch of our farmland is utilized fully. The Bangladesh economy may greatly benefit from the fishing industry in such a situation. In addition to that, freshwater shrimp aquaculture is crucial to Bangladesh's economy [4]. This sector contributes significantly to the production of nutrition, the development of rural employment, the reduction of poverty, and the output of foreign exchange [5]. Although aquaculture represents a significant economic and nutritional asset, it has certain environmental restrictions and the effects of aquatic diseases. Aqua farm-generated aquatic commodities are significantly impacted by water quality [6].

Shrimp farming, known as shrimp aquaculture, involves raising shrimp in confined ponds, tanks, or other water bodies using modern system such as IoT (see Fig. 1) technology. Fig. 1(a) illustrates an adult Galda shrimp, while Fig. 1(b) showcases shrimp farming practices utilizing IoT technologies for enhanced monitoring and management. The techniques used in shrimp farming vary depending on the geographical region, the species being raised, and the level of technological development. Effective shrimp monitoring is essential for managing shrimp production efficiently. This leads to increased shrimp yields, which strengthens our national food supply and boosts the economy by meeting the growing global demand for shrimp exports and creating new opportunities [7]. The efficient production of shrimp depends on several environmental factors, including water temperature, turbidity, dissolved oxygen levels, water acidity and salinity stages, and others [8]. Most of the shrimp farms in Bangladesh are associated with seawater [9]. It has slightly more salinity than regular water. Several factors, including water quality, influence the cultivation of shrimp. Poor water quality causes different diseases to afflict shrimp farms, increasing the death rate of shrimp. As a result, farmers suffer financial losses and are progressively losing interest in shrimp farming. Firm water quality is a crucial factor in the growth of healthy shrimp. As a result, regular water quality monitoring is required. Temperature, pH level, dissolved oxygen concentration, salinity level, and turbidity of the water are some of the factors that serve as indicators of water quality [10]. In order to increase shrimp production under these conditions, it is necessary to check whether the water intensity is rising, whether the temperature is increasing or decreasing, and whether the pH level is correct.

The goal of this study is to develop a novel approach that enhances shrimp farming in Bangladesh by incorporating real-time IoT monitoring with predictive machine-learning techniques. The implemented model will monitor the pH, temperature (Temp), total dissolved solids (TDS), electricity conductivity (EC), and salinity of the shrimp farm. This approach also includes better environmental management, reduced damage from severe natural disasters, reduced production costs, and, most importantly, improved shrimp production quality. The physical device is developed with STM32 microcontrollers and intelligent web applications, which are this system's most critical technological improvements. Users or clients can remotely monitor the shrimp farm through the web application. Moreover, farmers can make choices based on information, increase productivity, lower production losses, and guarantee the industry's overall sustainability by integrating smart analytics and IoT technology.

2. Literature review

Numerous scholars, agro-data scientists, and industry professionals are actively engaged in advancing shrimp farming in Bangladesh by incorporating modern technology. However, progress in this sector is hindered by the prevalence of traditional farming practices, a shortage of technological infrastructure, and a delayed adoption of the fourth industrial revolution in the country. Consequently, implementing the IoT and machine learning in shrimp aquaculture in Bangladesh is limited. In contrast, several studies demonstrate the effectiveness of IoT-based systems in monitoring critical water parameters like temperature, pH, dissolved oxygen (DO), salinity, and turbidity. Salah Uddin et al. [5] suggested a real-time freshwater shrimp farm monitoring system. The proposed approach integrates technologies, including IoT, web applications, and physical devices with microcontrollers to enable users to monitor a shrimp farm remotely and receive notification when a water parameter (like temperature, pH, dissolved oxygen, salinity level, and water turbidity) is detected to be outside of the acceptable range. Tsai et al. [6] utilized an IoT-based smart aquaculture

Table 1
Key technologies for shrimp farming based on literature review.

Study	Microcontroller	Network	Cloud Storage	Predictive Analysis	ML/DL	Application
[5]	Arduino UNO	Wi-Fi	✓	×	×	Web & Mobile
[6]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[7]	Arduino UNO	GSMSIM900	✓	×	×	Mobile
[8]	Arduino UNO	Zigbee	✓	×	×	Web & Mobile
[10]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[11]	NodeMCU-ESP8266	Wi-Fi	✓	×	×	Web
[12]	Arduino Nano	Wi-Fi	✓	×	×	Mobile
[13]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[14]	Arduino UNO	Wi-Fi	✓	×	×	Web
[15]	Arduino Nano	Wi-Fi	✓	×	×	Mobile
[16]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[17]	×	×	×	✓	ML & DL	×
[18]	×	Wi-Fi	✓	✓	DL	Web & Mobile
[19]	Arduino UNO	Wi-Fi	×	×	×	Web
[20]	Arduino UNO	Wi-Fi	✓	×	×	×

system (ISAS) to monitor water quality in an aquafarm and automatically expand the water to improve fish and shrimp growth rates. This work uses temperature, pH level, dissolved oxygen content, and water hardness as the parameters analyzed to measure water quality. Goud et al. [7] illustrate a model for monitoring shrimp production conditions, including temperature, pH, DO, etc. This proposed concept will enhance traditional shrimp farming with a remote sensing monitoring system, significantly raising shrimp production. Encinas et al. [8] proposed IoT and wireless sensor network-based systems to analyze water quality. They built and implemented a method for maintaining aquaculture water's pH, temperature, and oxygen level. Wardhany et al. [10] proposed a model which consists of two parts. The sensors are attached to the Arduino board, and an Android application is used to monitor the shrimp ponds—the Arduino board is designed with the WeMos D1 mini-module. The module can link the Arduino board to the web server, send the data read from the temperature, pH, and salinity sensors, and then attach the Arduino board to the server. Again, the Android application monitors and reports the pH, salinity, and temperature. A notification will be sent to the smartphone if there are any changes to the water condition, and this application also offers a control mechanism to turn on and off the smart system. Darmalim et al. [11] suggested an IoT system to monitor environmental conditions automatically. The system used five sensors to measure each parameter. It is created with a web application and a Python framework to display data from the IoT device. Mahmud et al. [12] generated an IoT-based solution that links sensors and devices to gather data on shrimp farms before sending it to a remote server for analysis and decision-making. The system's major parts are three integrated sensors that measure temperature, turbidity, and light and how they affect water quality. The system also includes an Android-based mobile application that enables farmers to use remote monitoring capabilities to monitor sensor data, control the shrimp production cycle, and assess the health of shrimp from various farms.

Based on the sensor readings, the authors of [13] introduced a smart aquaculture system that tracks the pH and salinity measurements. The sensor sends data on pH and salinity, which the monitoring and control system subsequently records and hosts in a database. They claimed that if the pH is between 6.5 and 7.5, a harmful salt content would be worth less than 160 and more than 210. Kiruthika et al. [14] presented an automated fish farming monitoring system to help aqua farmers save time, money, and electricity. Several sensors, including pH, temperature, and water level sensors, are utilized in raising fish. All the work will be automated using these sensors, making monitoring the fish farming remotely from any location simple. Faruq et al. [15] proposed a system for water quality monitoring based on temperature, water salinity, pH, and water level. In this system, pH level is determined by the SEN0161 sensor, salt content by the conductivity sensor, temperature by the DS18B20 sensor, and water level by the HC-SR04 ultrasonic sensor. The Arduino Uno microcontroller controls the system, which is attached to the Raspberry Pi 3 as its primary component. Lim et al. [16] developed a wireless IoT solution for remote aquaculture farming monitoring. This model introduced an Android application for water monitoring systems for aquaculture farming—a cloud-based database system for water quality and the environment. Data collection and transmission tools include the Arduino Uno, humidity, waterproof temperature, and ultrasonic sensors. Through a wireless internet connection, the data will be sent to a cloud platform to be accessed on an Android-based smartphone. Following the advancement of machine learning and deep learning, Prema et al. [17] recommended an IoT-enabled real-time vision-based support system for detecting shrimp freshness, applying a highly effective deep learning framework based on convolutional neural networks (CNN) and Support Vector Machine (SVM). The suggested model was evaluated using precision, accuracy, and F1 score measures and compared to the conventional approach (CNN with SoftMax). The authors of [18] suggested a model that references deep learning and the Long-Short Term Memory (LSTM) algorithm for forecasting water quality evaluations. They describe the structure for IoT systems that will be attempted to predict and monitor water quality, including (indicators of salinity, temperature, pH, and dissolved oxygen - DO) in aquatic farming. Zainuddin et al. [19] presents a wireless sensor network-based model for monitoring the factors that influence pond water quality. The system comprises numerous transmitter units that each include three sensor parameters—a pH sensor, a temperature sensor, and a turbidity sensor—that are utilized to collect data on the water in shrimp ponds and then process that data using Arduino devices. Data processed by Arduino is delivered to the Xbee device, which receives it and displays it on an LED. In [20], Arduino is used to measure the water, temperature, pH, and DO levels and combine them with aerating and water supply pumps. The user might receive information on their favorite medium at predetermined intervals. The authors investigated temperature, pH, and

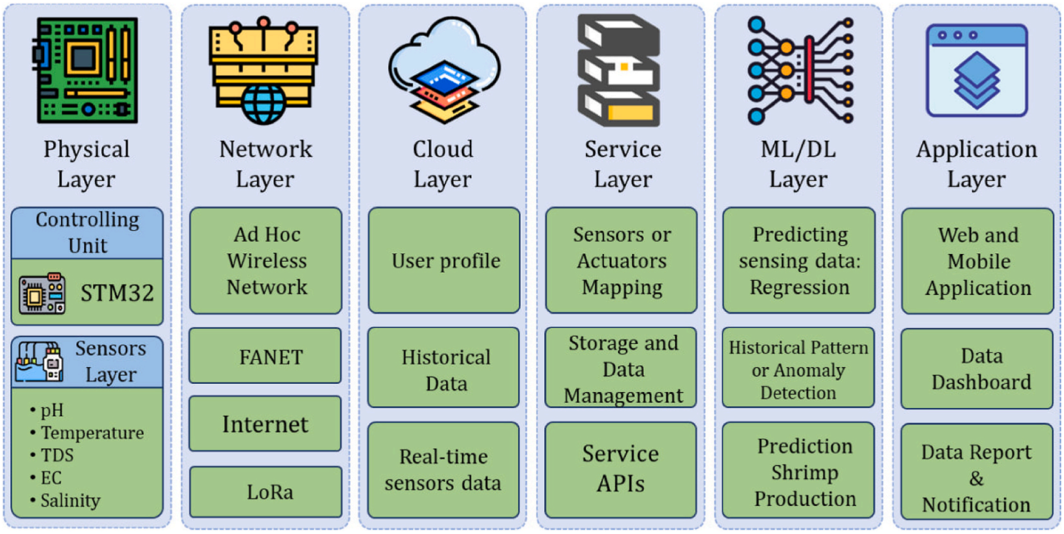


Fig. 2. The diagram of an overview of developing a smart aquaculture system.

DO levels on a sample of two consecutive days. Results indicate that this integrated system will allow farmers to reduce operational expenses and increase efficiency by removing the requirement for workers on their property.

A comprehensive review of smart shrimp aquaculture technologies (see Table 1) highlights several limitations that must be addressed for successful implementation in Bangladesh. While the reviewed studies demonstrate the effectiveness of Arduino microcontrollers and Wi-Fi for data collection and cloud storage, a significant gap exists in utilizing advanced analytics. Only two studies explored predictive analysis using machine learning to develop expert systems, indicating a promising but underutilized approach. Moreover, the literature review reveals a critical limitation specific to Bangladesh. Very few studies directly address the needs of Bangladeshi shrimp farmers, suggesting that the advanced technological infrastructure successfully employed in other countries has not yet been widely adopted in Bangladesh. This disparity underscores the urgent need for focused research and development efforts to bridge this gap and support Bangladeshi shrimp farmers. Real-time shrimp monitoring and advanced devices for accurate water quality sensing are essential to a modern shrimp farming system. An IoT-based intelligent system that incorporates predictive analytics and machine learning, along with an intelligent notification system through mobile/web applications, can significantly enhance the efficiency and productivity of shrimp farming in Bangladesh.

3. Research method

This research study aims to develop an effective and efficient smart aquaculture system for shrimp farmers in Bangladesh. The project is based on IoT technology, coupled with predictive analysis using machine learning, and involves several stages. These stages include designing and developing the IoT device, integrating the IoT device with the system, collecting data, processing data, conducting analysis and decision-making, and finally, developing an application for the user group. To achieve this objective, the proposed smart aquaculture system comprises several layers, including a physical (hardware) layer, a network layer, a cloud layer, a service layer, a machine learning (ML) layer, and an application layer. This multi-layered approach offers a highly effective and advanced solution for modern shrimp farming [21,22]. Therefore, the proposed IoT-based intelligent system, with its advanced monitoring, predictive analytics, and smart notification capabilities, offers a superior solution compared to many other studies [5,17,23,24]. It addresses the crucial need for accurate water quality sensing and real-time data analysis, thereby enhancing the productivity and sustainability of shrimp farming in Bangladesh. The proposed system architecture of the working process is presented in Fig. 2.

3.1. Physical layer

The physical layer serves as the hardware layer, incorporating sensors and a microcontroller. In this study, a hardware device is designed, featuring five sensors (pH, temperature, TDS, EC, and salinity) alongside an STM32 microcontroller functioning as the controlling unit. This setup is utilized to monitor shrimp farms and collect relevant data. The subsequent section provides a detailed description of the controlling unit and the incorporated sensor specifications.

3.1.1. Controlling unit

The STM32 [25] microcontroller is employed as the controlling unit in this study. A series of 32-bit integrated circuit microcontrollers produced by STMicroelectronics is known as STM32 and uses the STM32F1 series. The STM32F1 is designed to collect sensor sensory data, process it, and transmit it to the cloud layer. It acts as a mediator between the sensors and the cloud layer. Every

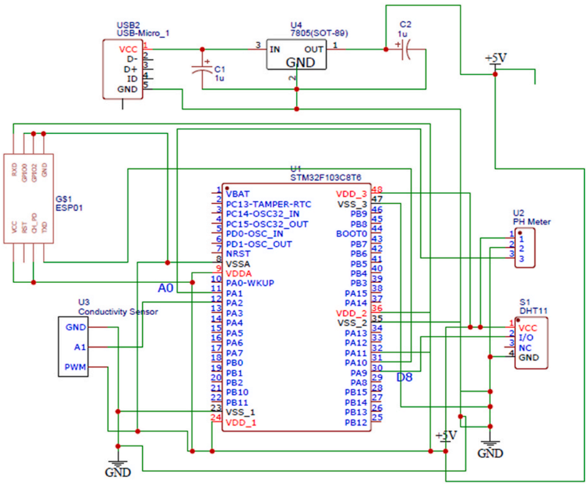


Fig. 3. The pin-out diagram of the proposed IoT device for shrimp farming monitoring.

sensor directly connects to the STM32F board via input or output pins. Sensor data is collected using the STM32F1 board's input and output ports. The STM board sends the gathered data to the cloud layer through Internet connectivity. After the STM32F1 board uploads the data to the cloud, it becomes available for the application layer. The STM32F103C8T6 features 37 digital I/O pins and 10 analog inputs, with a working voltage of 3.3V, a microSD card slot, a USB-A port, Ethernet capability for the built-in WiFi, and a micro-USB connection.

3.1.2. Sensors layers

1. **pH Sensor:** pH is a crucial tool to estimate the quality of water [26]The pH scale, which ranges from 0 to 14, determines a solution's acidity or alkalinity. pH indicates the level of hydrogen ions in a given solution. A range of 0–7 indicates acidic, and 7 is neutral. Above 7 to 14 indicates alkalinity. The optimal pH range is 6.5–9.5.
2. **Temperature Sensor:** A temperature sensor is used for maintaining and monitoring temperature [27]. Typically, it is defined as Celsius (°C). The water's temperature is measured using a waterproof liquid temperature sensor. The optimal range of temperature is 6.5–9.5.
3. **TDS Sensor:** TDS defines Total Dissolved Solids (TDS). TDS sensors are used for measuring the total amount of dissolved solids in a liquid, including minerals, salts, organic matter, and even some gases [24]. To evaluate electrical conductivity, which is inversely correlated to the level of TDS, a current is usually passed through the liquid to measure its resistance. Usually, it is declared as parts per million (ppm).
4. **EC Sensor:** The electrical conductivity sensor, often known as an EC sensor, is used to measure the electrical conductivity of solutions, typically in the context of water quality assessment and aquaculture [28].
5. **Salinity Sensor:** The amount of dissolved salt in water is measured as salinity [29]. A salinity sensor measures water's salinity in ppm (parts per million) using electrical conductivity characteristics.

An IoT-based device is developed to integrate control unit and sensor layers. The pin-out diagram of the developed device is presented in Fig. 3.

3.2. Network layer

The network layer serves as an intermediary between the physical and cloud layers. Through this layer, we transmit data into the cloud. In the network layer, there are four communication protocols proposed in this research, and these are: Ad-Hoc Wireless Network [30], FANET [31], Internet, and LoRa. In this study, the internet network is used as a network layer. Wi-Fi connections are required through the Internet to pass data between two layers. The physical layer collects data via different sensors like pH, temperature, TDS, and EC sensors, and with the help of the internet, this data passes into the cloud layer.

3.3. Cloud layer and service layer

The cloud layer plays a crucial role in the overall architecture of the farm monitoring system, encompassing data storage, manipulation, and service provision. The collected data from various sensors is stored within this layer, including user profiles, representations of historical information, and real-time sensor data. In addition to data storage, the cloud layer interfaces with the service layer, where sensors and actuators are mapped. This layer manages data storage and facilitates service APIs for seamless

Table 2
The description of Regression and classification model.

Model	Description
Regression Model	
Multivariate Linear Regression	Multivariate linear regression [33] is a statistical method used to model the relationship between multiple independent variables and a dependent variable. In the context of sensing values, it helps predict the outcome based on several input features. The general equation for multivariate linear regression is as follows, $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon$ (1) Where, Y is the dependent variable, β_0 is the intercept, $\beta_1, \beta_2, .., \beta_n$ are coefficients, $X_1, X_2, .., X_n$ are the independent variables, and ϵ is the error.
Classification Model	
Logistic Regression	Logistic regression [34] is a classifier that models the association between predictors and a binary result. It assigns class inputs based on a decision threshold and predicts probabilities using a sigmoid function. The sigmoid function has an S-shaped curve, smoothly transitioning from 0 to 1. This makes it suitable for models where we need a gradual change in the output rather than a step function. The equation for logistic regression, $f(z) = \frac{1}{1+e^{-z}}$ (2) Where, $f(z)$ is the sigmoid function, and e is the Euler's number.
Decision Tree	A decision tree [35] is a versatile and widely used machine learning algorithm for classification and regression tasks. It works by recursively partitioning the data into subsets based on the values of input features. The decision tree model made the decision based on the entropy function. The entropy function is used in decision trees to quantify the impurity of a node and guide the tree-building process by selecting the splits that produce the most homogeneous child nodes, thereby creating a more effective model $Entropy = \sum_{i=1}^{c} -P_i \times log_2(P_i)$ (3) Where, c is the number of classes, and P_i is the probability of class i.
Random Forest	Random Forest is an ensemble learning technique that constructs multiple decision trees during training. Each tree uses a random subset of the data (bootstrapped samples) and a subset of features at each node [36]. The predictions of individual trees are combined through averaging voting for classification to produce the final prediction. The process involves calculating the entropy or Gini impurity at each node to determine the best split, typically using information gain or reduction in impurity. $RF(x) = Ensemble(f_1(x), f_2(x), \ldots, f_M(x))$ (4) Where, M is the total number of trees in the Random Forest. $f_i(x)$ is the prediction of the i^{th} decision tree.
Multilayer Perceptron	Multi-layer perceptron [37] is an artificial neural network that is made up of multiple layers of interconnected neurons. A feed-forward network can be applied to classify the depression-level data using gradient-based training techniques like backpropagation to minimize the error between predicted and target outputs. The prediction equation is expressed as, $\hat{y} = \sigma\left(W^L \sigma\left(W^{L-1} \ldots \sigma\left(W^1 x + b^1\right) + b^{L-1}\right) + b^L\right)$ (5) Where, x is the input feature vector, $W^{(L)}$ is the weight for layer l, $b^{(L)}$ is the bias vector for layer l, and σ is the activation function.
AdaBoost	AdaBoost (Adaptive Boosting) [38] is an ensemble learning method that combines the predictions from multiple weak learners to create a robust predictive model. A weak learner is a model that performs slightly better than random chance. AdaBoost, short for Adaptive Boosting, is a popular ensemble learning technique primarily used for binary classification tasks, although it can be extended to regression problems as well. It combines multiple weak learners (typically decision trees) to create a strong learner. AdaBoost assigns weights to the training instances and focuses on the misclassified ones, enabling subsequent weak learners to emphasize these instances during their training. $Final\ Prediction = sign\left(\sum_{t=1}^{T} \propto_t \times h_t(x)\right)$ (6) Where, T is the number of weak learners, $\propto_t$ is the weight of the weak learner, and $h_t(x)$ is the prediction of the weak learner.
eXtreme Gradient Boosting	eXtreme gradient boosting (XGBoost) [36] is a popular and powerful gradient-boosting algorithm designed for speed and performance. It belongs to the family of ensemble learning methods and is particularly effective for a wide range of machine learning tasks, including classification, regression, and ranking. $Final\ Prediction = \sum_{t=1}^{T} Weight_k \times f_k(x)$ (7) Where, $f_k(x)$ is the prediction rate, $Weight_k$ is its associated weight.

interaction with the shrimp farm monitoring system. The services offered by the cloud layer include:

A Report Generation Services
B. Quality Level Assurance
C. Real-time Sensor Data Visualization
D. Historical Data Visualization
E. Push Notification-Based Messaging
F. User Authentication and Validation

Integrated with the cloud layer, the service layer is crucial in mapping sensors and actuators, managing data storage, and offering service APIs. This collaborative approach enhances the functionality and efficiency of the farm monitoring system, providing users with a comprehensive and responsive shrimp farm monitoring and management system in Bangladesh.

3.4. ML/DL layer

The predictive layer in our system combines both Machine Learning (ML) and Deep Learning (DL) methodologies to forecast shrimp production based on sensing data. Initially, a multivariate linear regression (multi-variate LR) model is employed to predict the next-

Table 3
Parameter grid and optimal parameters for machine learning models.

Model	Parameter Grid	Optimal parameter
MLR	{fit_intercept: 'True', 'False', n_jobs: default}	fit_intercept = True
LR	{'C': [0.1, 1.0, 10.0], 'penalty': ['l1', 'l2']}	C = 1.0, penalty = l1
DT	{'max_depth': [5, 10, 20], 'min_samples_split': [2, 4, 6, 10]}	max_depth = 10, min_samples_split = 4
RF	{'n_estimators': [100, 200, 300], 'max_depth': [5, 10, 20], 'min_samples_split': [2, 4, 6, 10]}	n_estimators = 100, max_depth = 10, min_samples_split = 6
MLP	{'hidden_layer_sizes': [(50), (100), (50, 50)], 'activation': ['relu', 'tanh'], 'alpha': [0.0001, 0.001, 0.01]}	hidden_layer_sizes = 100, activation = relu, alpha = 0.001
AdaBoost	{'n_estimators': [50, 100, 200], 'learning_rate': [0.1, 0.5, 1.0]}	n_estimators = 50, learning rate = 0.1
XGB	{'n_estimators': [100, 200, 300], 'max_depth': [3, 5, 7], 'learning_rate': [0.1, 0.01, 0.001]}	n_estimators = 100, max_depth = 5, learning rate = 0.01

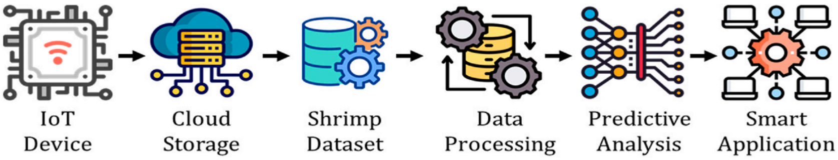


Fig. 4. Overview of the working step of the proposed system to develop a smart application for shrimp farming.

Table 4
The measurable schedule of shrimp data collection.

Water Parameters (Sensors)	1st Measurement (hours)	2nd Measurement (hours)	3rd Measurement (hours)
pH	6.00 a.m.–9.00 a.m.	13.00 p.m.–15.00 p.m.	18.00 p.m.–19.00 p.m.
Temperature	6.00 a.m.–9.00 a.m.	13.00 p.m.–15.00 p.m.	18.00 p.m.–19.00 p.m.
TDS	6.00 a.m.–9.00 a.m.	13.00 p.m.–15.00 p.m.	18.00 p.m.–19.00 p.m.
EC	6.00 a.m.–9.00 a.m.	13.00 p.m.–15.00 p.m.	18.00 p.m.–19.00 p.m.
Salt	6.00 a.m.–9.00 a.m.	13.00 p.m.–15.00 p.m.	18.00 p.m.–19.00 p.m.

day results for five sensing values. This regression model aims to provide continuous predictions for these values. Following the classification, six machine learning classification approaches — Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Multilayer Perceptron (MLP), AdaBoost, and eXtreme Gradient Boosting (XGB) — are implemented to predict shrimp production levels as low, medium, and maximum. During the implementation of the model, a specific set of parameters is considered to configure the machine learning model to optimize its performance. The 'GridSearchCV' [32] technique is then applied to determine the best or optimal parameters for machine learning algorithms except MLR. Table 2 provides a description of the model, while Table 3 presents the configured model along with its optimal parameters.

3.5. Application layer

The application layer seamlessly integrates the web and mobile applications, data dashboards, and report generation services, enabling users to access comprehensive monitoring services. Farmers can view real-time data through the web application, offering additional daily functionalities such as generating reports. Moreover, the application facilitates setting sensor threshold levels, allowing users to configure notifications based on these thresholds. The graphical visualization of water quality enhances the user experience, clearly representing the data. Additionally, the application layer is designed to send notifications to farmers, ensuring timely and relevant information is delivered.

3.6. Details of the proposed system

The integrated system for effective shrimp farm monitoring and production enhancement involves several layers for specific functionalities. The process begins with deploying IoT devices in the shrimp farm, which collects real-time sensing data. This data is then transmitted over the internet to be stored in a cloud storage system. The next layer involves retrieving the shrimp dataset from the cloud storage, followed by a preprocessing step to clean and organize the data for analysis (see Fig. 4). The preprocessed dataset is then implemented to implement a smart application incorporating predictive analysis capabilities.

To illustrate the practical application of this system, real-time sensing data is collected from the shrimp farm three times a day, spanning the duration from June 08, 2023 to 09/09/2023, and able to collect 3240 data. The specific schedule for shrimp data collection is outlined in Table 4. For reference, a sample dataset derived from the sensors layer is presented in Table 5. This dataset serves as a foundation for further analysis and decision-making within the smart application, contributing to the overall efficiency and

Table 5
Sample data of water quality parameter shrimp farm.

DateTime	pH	Temp	TDS	EC	Salinity
14/8/2023 13:30	10.3	27.34	11287	21010	16831
14/8/2023 18:15	8.26	33.08	10832	14889	16877
15/8/2023 6:15	9.87	37.1	11616	20232	15983
15/8/2023 13:30	8.78	29.25	12614	25276	11778
15/8/2023 18:15	10.37	41.55	14228	16541	19132

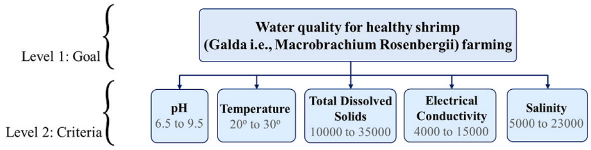


Fig. 5. The analytic hierarchy for freshwater shrimp farm monitoring system.

Table 6
The pairwise comparison matrix with normalized value and rank by priority weightage of criteria.

Criteria	Pairwise comparison matrix					Normalized matrix					Priority Weightage	Rank	Consistency Ratio
	pH	Temp	TDS	EC	Salinity	pH	Temp	TDS	EC	Salinity			
pH	1	1/2	3	4	1/3	0.203	0.057	0.243	0.527	0.068	0.220	2	−0.716
Temp	3	1	4	2	3	0.610	0.114	0.324	0.264	0.610	0.385	1	
TDS	1/4	1/4	1	1/4	1/4	0.051	0.029	0.081	0.033	0.051	0.049	5	
EC	1/3	3	4	1	1/3	0.068	0.343	0.324	0.132	0.068	0.187	3	
Salinity	1/3	4	1/3	1/3	1	0.068	0.457	0.027	0.044	0.203	0.160	4	

productivity of the shrimp farming operation.

During the data collection and extraction process from cloud storage, it was noted that specific data was missing, potentially due to network issues or sensor malfunctions. To address these missing values, a 'forward fill' [39] technique is implemented. This technique involves propagating the last observed value forward in time to fill the gaps caused by missing data. After completing the data pre-processing and predictive analysis, the results are divided into two parts. Firstly, a forecast is generated for the next day's values of five sensing indicators. Secondly, shrimp production is predicted by incorporating a decision-based technique, such as the Analytic Hierarchy Process (AHP) [40], used to rank the five water quality indicators. This ranking is then used to design an algorithm that classifies the production into different categories. The AHP structures the problem as a hierarchy. Fig. 5 illustrates the decision hierarchy for healthy shrimp production.

The first level of the hierarchy represents the overall goal of ensuring healthy shrimp production. The second level consists of the criteria in this study: pH, Temperature, TDS, EC, and Salinity. The second step in the AHP process is determining these criteria' relative priorities (weights). These relative priorities are derived using pair-wise comparison matrices. The mathematical formula for generating the pairwise comparison matrix is provided below.

$$\boldsymbol{A} = [P_{rc}] \tag{8}$$

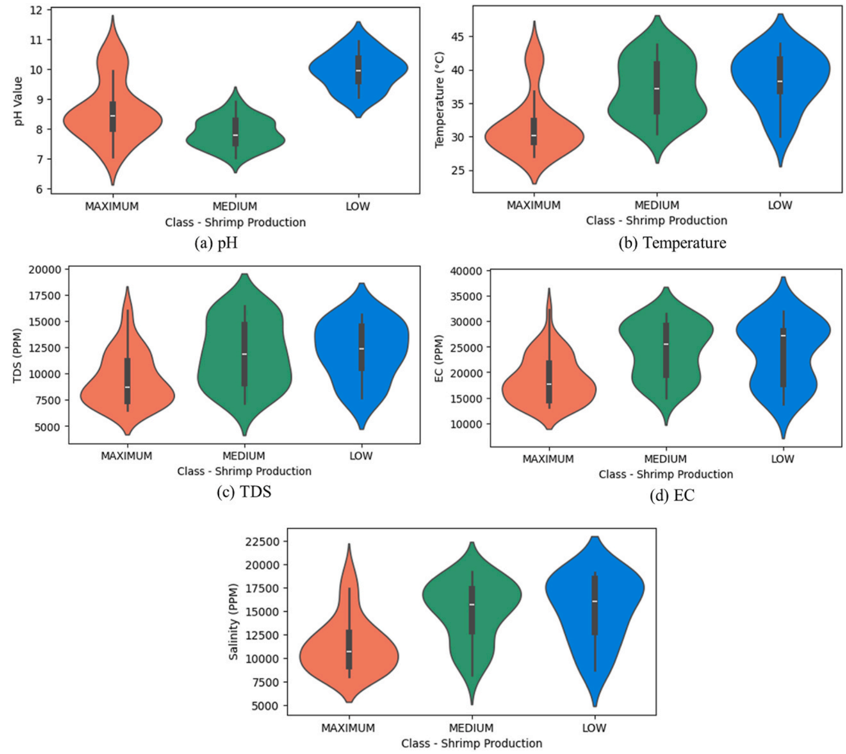
Where, $\boldsymbol{P_{rc}}$ is the pair-wise comparison matrix for criteria-1, r and criteria-2, c. Using Saaty's nine-point rating scale [5,40], a pair-wise comparison matrix is prepared, and the following normalized matrix is presented in Table 5. Normalization is achieved by dividing each cell value by the sum of the corresponding column values (for example, for the *pH* column, the column sum is 4.916; dividing the first cell of the temperature column by 4.916 gives 0.203). The priority weight of each criterion is then computed from the normalized matrix based on the average value of each row. The criteria are ranked based on the priority weights (see Table 6). The pair-wise comparison matrix was found to be consistent (i.e., consistency ratio, CR < 0.1), validating the results of the AHP [41]. The final mathematical equation for determining the water quality score, based on the decision matrix, is provided in "(9)".

$$Water_{Quality\ score} = Water_{pH} \times 0.22 + Water_{Temp} \times 0.385 + Water_{TDS} \times 0.049 + Water_{EC} \times 0.187 + Water_{Salinity} \times 0.16 \tag{9}$$

To determine the shrimp production class, an algorithm is developed that considers the optimal values of water quality, as outlined in Table 7. This algorithm classifies shrimp production as low, medium, and maximum based on the water quality parameter. The following is a demonstration of the algorithm:

Table 7
Water quality monitoring parameters with their optimal value of operation.

Water Parameters (Sensors)	Optimal Range	Unit
pH	6.5 to 9.5	pH unit
Temperature	20 to 30	Celsius
TDS	4000 to 15000	PPM
EC	10000 to 35000	PPM
Salt	5000 to 23000	PPM



(a) pH (b) Temperature (c) TDS (d) EC (e) Salinity

Fig. 6. Class-wise data distribution for each parameter (a–e) of water quality in the shrimp farm.

Table 8
Sample data of timeframe, water quality indicators, and defined shrimp production classes based on the developed algorithm.

DateTime	pH	Temp	TDS	EC	Salinity	Class
14/8/2023 13:30	10.3	27.34	11287	21010	16831	Maximum
14/8/2023 18:15	8.26	33.08	10832	14889	16877	Medium
15/8/2023 6:15	9.87	37.1	11616	20232	15983	Low
15/8/2023 13:30	8.78	29.25	12614	25276	11778	Maximum
15/8/2023 18:15	10.37	41.55	14228	16541	19132	Low

Algorithm 1. Shrimp Production Classification

1. Consider, water quality = [pH, Temp, TDS, EC, Salt], optical range = [6.5 to 9.5, 20 to 30, 4000 to 15000, 10000 to 35000, 5000 to 23000], and rank [1–5]
2. **if** water quality meets the optimal values for all parameters and rank
3. ***Then***, set 'Maximum'
4. ***elseif*** water quality is within an acceptable range but not optimal and rank
5. ***Then***, set 'Medium'
6. **else** water quality falls below the acceptable range
7. ***Then***, set 'Low'
8. **End**

Following the application of the developed algorithm to classify shrimp production based on water quality parameters with score, a structured framework for decision-making in shrimp farming production is developed. The data distribution for each class is represented in Fig. 6. From Fig. 6, it illustrates the distribution of water quality indicators— Fig. 6(a) pH, Fig. 6(b) Temperature, Fig. 6(c) TDS, Fig. 6(d) EC, and Fig. 6(e) Salinity—across different shrimp production levels, highlighting the maximum, median, and minimum value ranges. Then the class imbalance is solved using SMOTE [42]. The results of the algorithm are organized and presented in Table 8, providing a tabulated representation of the categorized classes for further analysis.

3.7. Performance evaluation

A comprehensive set of performance metrics is utilized to gauge the efficacy of the advanced predictive analysis incorporating a multivariate regression model for forecasting next-day parameter values and predicting shrimp production based on water quality parameters. Regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared are utilized to assess accuracy and precision. MAE measures average error magnitude, MSE measures squared error averages, RMSE represents MSE's square root, and R-squared indicates variance proportion predictable by independent variables, ranging from 0 to 1.

For classification evaluation, metrics include accuracy, error rate, True Positive Rate (TPR), False Negative Rate (FNR), False Positive Rate (FPR), True Negative Rate (TNR), Precision, and F1 Score. Accuracy measures correctly classified instances proportion, TPR identifies correctly identified actual positives, FNR identifies actual positives incorrectly predicted as negative, FPR identifies actual negatives incorrectly predicted as positive, TNR identifies correctly identified actual negatives, Precision measures true positives proportion among all positive predictions, and F_1 Score balances precision and recall (TPR) as a harmonic mean, ranging from 0 to 1. Their mathematical equations are given below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \widehat{Y}_i| \tag{10}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2 \tag{11}$$

$$RMSE = \sqrt{MSE} \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \overline{Y}_i)^2} \tag{13}$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ no.\ of\ sample} \times 100\% \tag{14}$$

$$TPR = \frac{True\ Positive}{True\ Positive + False\ Negative} \times 100\% \tag{15}$$

$$FNR = \frac{False\ Negative}{True\ Positive + False\ Negative} \times 100\% \tag{16}$$

$$FPR = \frac{False\ Positive}{False\ Positive + True\ Negative} \times 100\% \tag{17}$$

$$TNR = \frac{True\ Negative}{False\ Positive + True\ Negative} \times 100\% \tag{18}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \times 100\% \tag{19}$$

$$F_1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \tag{20}$$

$$Error\ Rate = \frac{False\ Negative + False\ Positive}{Total\ no.\ of\ samples} \times 100\% \tag{21}$$

4. Results and discussions

After comprehensively integrating all proposed system layers, a robust smart aquaculture System has been developed, providing farmers with advanced monitoring capabilities for shrimp farms. This system encompasses predictive functionalities, including the forecasting of next-day values for crucial parameters such as pH, Temperature, Total Dissolved Solids (TDS), Electrical Conductivity

Table 9
Performance metrics for multivariate linear regression model.

Model	Parameter	MAE	MSE	RMSE	R-Square
Multivariate Linear Regression	pH	1.08	1.63	1.28	0.89
	Temperature	4.48	31.2	5.59	0.91
	TDS	1857	5427849	2329.77	0.83
	EC	4776.08	31379938.30	5601.78	0.94
	Salinity	3012.27	13228260.60	3637.08	0.91

Table 10
Confusion matrix for six machine learning classifiers.

Model	Class	3 × 3 Confusion Matrix			2 × 2 Confusion Matrix			
		Low	Medium	Maximum	TP	FN	FP	TN
LR	Low	225	27	11	225	38	16	369
	Medium	16	154	5	154	21	43	430
	Maximum	0	16	192	192	16	16	424
DT	Low	247	5	11	247	16	77	308
	Medium	44	132	0	132	44	5	467
	Maximum	33	0	176	176	33	11	428
RF	Low	231	11	0	131	11	10	496
	Medium	5	192	0	192	5	11	440
	Maximum	5	0	203	203	5	0	440
MLP	Low	220	0	16	220	16	16	396
	Medium	11	192	0	192	11	5	440
	Maximum	5	5	198	198	10	16	424
AdaBoost	Low	231	16	16	231	32	16	369
	Medium	11	165	0	165	11	16	456
	Maximum	5	0	203	203	5	16	424
XGB	Low	236	5	22	236	27	28	357
	Medium	22	154	0	154	22	5	467
	Maximum	6	0	192	192	6	22	428

Table 11
Performance metrics for six machine learning classifiers.

Model	Class	Accuracy	TPR	FNR	FPR	TNR	Precision	F1 Score	Error Rate
LR	Low	91.67	85.55	14.45	4.16	95.84	93.36	89.29	8.33
	Medium	90.12	88.00	12.00	9.09	90.91	78.17	82.80	9.88
	Maximum	95.06	92.31	7.69	3.64	96.36	92.31	92.31	4.94
DT	Low	85.65	93.92	6.08	20.0	80.00	76.23	84.16	14.35
	Medium	92.44	75.00	25.0	1.06	98.94	96.35	84.35	7.56
	Maximum	93.21	84.21	15.79	2.51	97.49	94.12	88.89	6.79
RF	Low	96.76	92.25	7.75	1.98	98.02	92.91	92.58	3.24
	Medium	97.53	97.46	2.54	2.44	97.56	94.58	96.00	2.47
	Maximum	99.23	97.60	2.40	0.00	100.0	100.0	98.78	0.77
MLP	Low	95.06	93.22	6.78	3.88	96.12	93.22	93.22	4.94
	Medium	97.53	94.58	5.42	1.12	98.88	97.46	96.00	2.47
	Maximum	95.99	95.19	4.81	3.64	96.36	92.52	93.84	4.01
AdaBoost	Low	92.59	87.83	12.17	4.16	95.84	93.52	90.59	7.41
	Medium	95.83	93.75	6.25	3.39	96.61	91.16	92.44	4.17
	Maximum	96.76	97.60	2.40	3.64	96.36	92.69	95.08	3.24
XGB	Low	91.51	89.73	10.27	7.27	92.73	89.39	89.56	8.49
	Medium	95.83	87.50	12.50	1.06	98.94	96.86	91.94	4.17
	Maximum	95.68	96.97	3.03	4.89	95.11	89.72	93.20	4.32

(EC), and Salinity [43]. Subsequently, six machine learning classification models—Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Multilayer Perceptron (MLP), AdaBoost, and eXtreme Gradient Boosting (XGB)—are implemented to predict shrimp production levels as low, medium, and maximum. The system's performance is evaluated in various ways, and the results are presented sequentially.

4.1. Performance of regression analysis

Each parameter relies on the values of the preceding 10 days to predict the next day's water quality parameters. The model's performance is assessed using MAE, MSE, RMSE, and R-square. Notably, the regression model exhibits optimal performance in

Fig. 7. The home page of the smart aquaculture web application for shrimp farm monitoring.

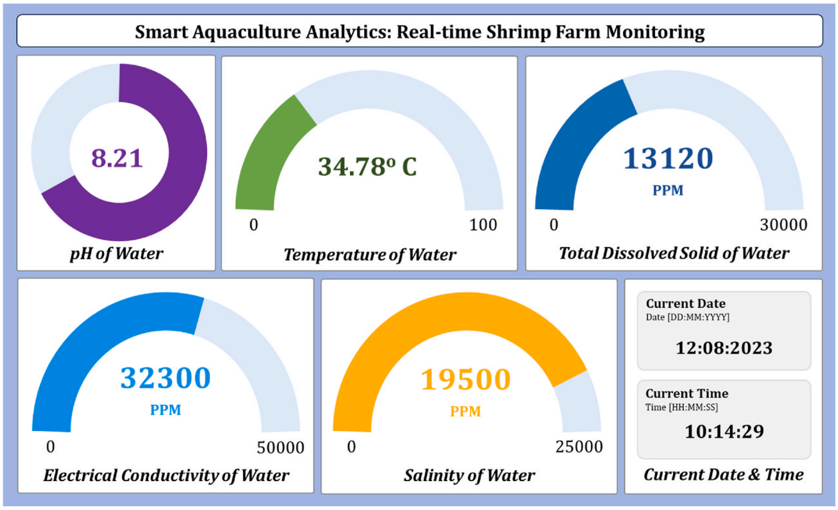


Fig. 8. The home page of the smart aquaculture web application for shrimp farm monitoring.

Electrical Conductivity (EC) prediction, achieving a substantial 0.94 while providing satisfactory R-square values of 0.91 for both pH and salinity predictions. The comprehensive performance metrics for the multivariate linear regression model are presented in Table 9.

4.2. Performance of prediction shrimp production level

To evaluate the six machine learning models in the classification task, a confusion matrix is generated to quantify accuracy, error rate, TPR, FNR, FPR, TNR, precision, and F1-score. Shrimp production levels—maximum, medium, and low—are designated classes, resulting in a 3 × 3 confusion matrix. The 3 × 3 confusion matrix is transformed into a 2 × 2 matrix to facilitate computation. The confusion matrices for each of the six classifiers are presented in Table 10.

Table 11 reveals notable distinctions in class-wise accuracy among the classifiers. Random Forest (RF) stands out by attaining the highest accuracy of 99.15 % in predicting the 'maximum' class, contributing to an outstanding overall accuracy of 97.84 %. Conversely, the Decision Tree (DT) exhibits the lowest accuracy at 90.43 %, although this is still a commendable performance in shrimp prediction. Examining precision, RF demonstrates stability with a consistent 95.83 %, showcasing its ability to make correct predictions consistently. Additionally, RF proves effective in mitigating false positive rates, a critical factor in classification tasks. In terms of F1 score, RF excels with a score of 95.79 %, while DT follows with a respectable score of 85.80 %. The class-wise performance of the six classifiers is comprehensively detailed in Table 11, shedding light on their respective strengths and weaknesses in predicting shrimp production levels.

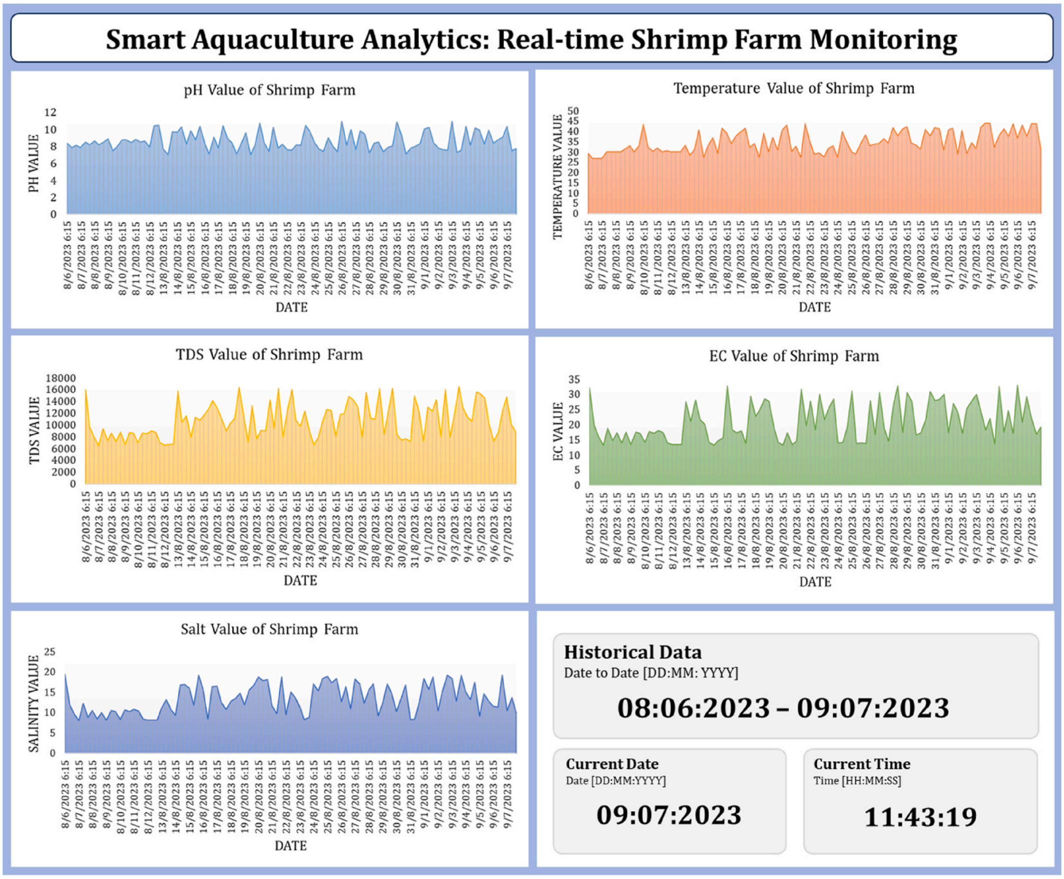


Fig. 9. Historical data visualization based on a range of data.

4.3. *Smart aquaculture analytics*

The proposed smart aquaculture system for shrimp farmers is developed based on regression analysis, classification analysis, and web-based application to boost shrimp farming in Bangladesh. The screenshot of the web application with its numerous features is shown in Figs. 7–11.

Fig. 7 illustrates the main page of the ‘Smart Aquaculture Analytics’ web application, serving as the gateway for farmers to sign up and sign in to access the system. Upon logging in, farmers can navigate to the dashboard, providing real-time monitoring of shrimp farming with detailed information on the five water quality parameters. In Fig. 8, the real-time monitoring values of these parameters are depicted alongside the current date and time, offering farmers a comprehensive overview of shrimp farming conditions. Additionally, farmers can retrieve historical data by specifying a date range, as demonstrated in Fig. 9. This historical data dashboard allows users to plot each water quality parameter over time. Utilizing patterns identified in historical data, farmers can predict the next day’s values based on the preceding 10 days, as depicted in Fig. 10. The graph compares actual and predicted values for the last 10 data points, ultimately forecasting the 11th datapoint and indicating the expected shrimp production level. Fig. 11 showcases a notification system where farmers receive SMS alerts on their mobile phones to ensure timely awareness. This integrated feature enhances the system’s user-friendliness and enables proactive decision-making for efficient shrimp farming management.

4.4. *Feedback from farmers*

Farmer feedback is critical for enhancing user satisfaction and the system’s overall effectiveness. This feedback drives continuous improvement and innovation in aquaculture technology. During the experiments, interviews were conducted with three shrimp farmers to understand the effectiveness of the proposed system and to identify their actual needs. The feedback from these three farmers has been summarized in Table 12, categorized into positive aspects, challenges, and future scope.

User feedback from shrimp farmers highlights the system’s strengths in providing real-time data, improving farm management, and promoting sustainable practices. However, affordability for smaller farms, data security in remote areas, and the need for more advanced features (disease identification, data analysis tools, API integration) are identified as limitations. Addressing these concerns through cost-effective solutions, local data storage options, and functionalities tailored to diverse farm sizes will be crucial for broader

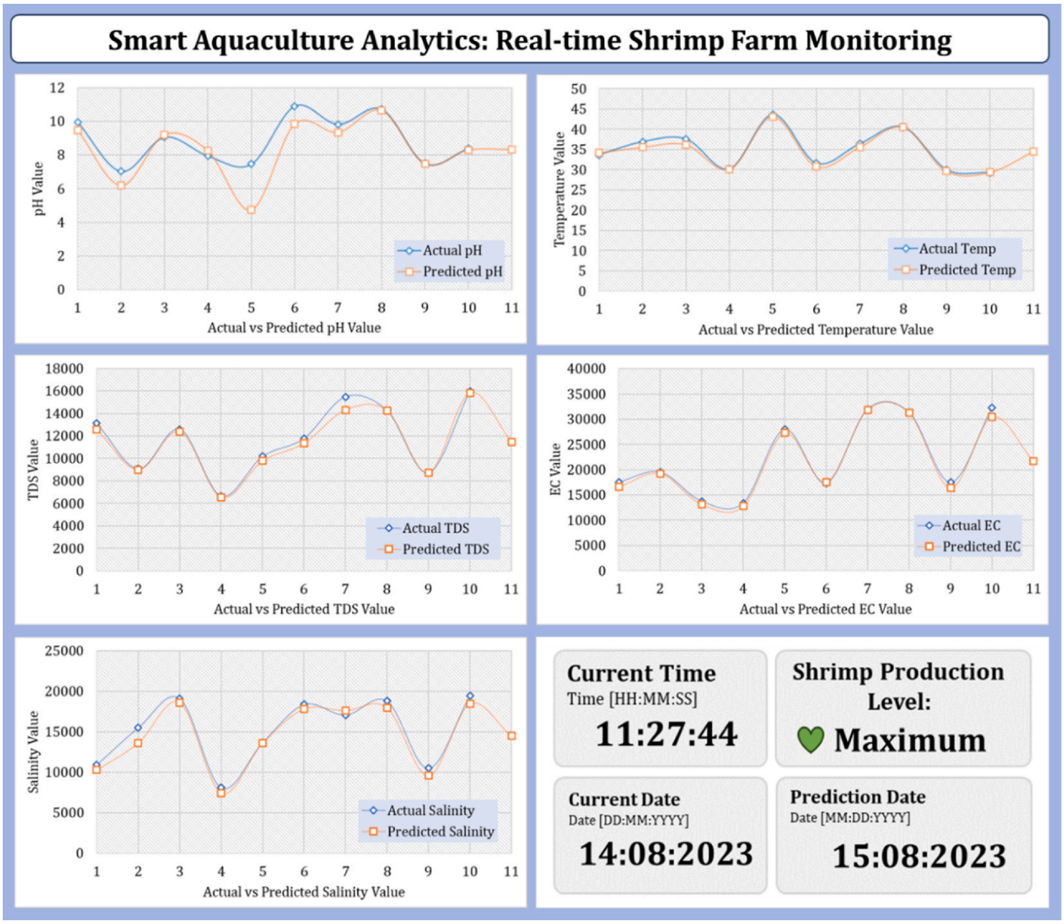


Fig. 10. Forecasting five parameters of water quality the next day and prediction of shrimp production based on the previous 10 days.

adoption and maximizing the system's impact on Bangladesh's shrimp farming industry.

4.5. Discussions and recommendations

The physical device has been successfully deployed in a shrimp gher/lake owned by a private company situated in Kaligang Upazila, Satkhira, Bangladesh. The generated data from this system is stored in a cloud database, accumulating a dataset spanning 90 days during the testing phase. This dataset comprises 3240 examples, capturing estimations of various parameters, including pH, temperature, total dissolved solids, electrical conductivity, and salinity levels of water. The data is collected during three distinct periods: 6:00 to 9:00, 13:00 to 15:00, and 18:00 to 19:00. These time slots were chosen strategically, aligning with the essential times for monitoring shrimp culture lakes/ghers to ensure optimal water quality [31]. The collected sensing data is stored in cloud storage via the internet and extracted using Python libraries for subsequent analysis. From this dataset, 648 examples are selected to test the developed regression model and the six machine-learning classifier models utilized to predict shrimp production levels. The practical performance of the proposed study is comprehensively presented in Figs. 7–11.

In the context of comparative analysis and aligning with the current state of the art, Table 13 provides a comparison with prior work on shrimp farming utilizing IoT technologies [44–51]. Notably, many researchers have employed Arduino microcontrollers as their control units, whereas this study implemented the more modern and powerful STM32 microcontroller. Existing research on shrimp farming technologies often lacks comprehensive real-time monitoring systems, focusing primarily on limited water quality parameters or relying on manual monitoring methods with basic sensing devices. Additionally, the application of predictive analytics and machine learning in shrimp farming is scarce, particularly in countries like Bangladesh. This study distinguishes itself by incorporating advanced predictive analysis using regression and classifier models, providing more accurate and actionable insights for shrimp farm management. Moreover, the integration of a web application and smart mobile SMS notifications significantly enhances the overall effectiveness and user accessibility of the proposed solution. By addressing these gaps, the study advances the technological framework for shrimp farming and offers a robust and scalable system tailored to the specific needs of shrimp farmers in Bangladesh.

This study outlines the pathway for scaling and commercially deploying its findings in shrimp farming based on promising results

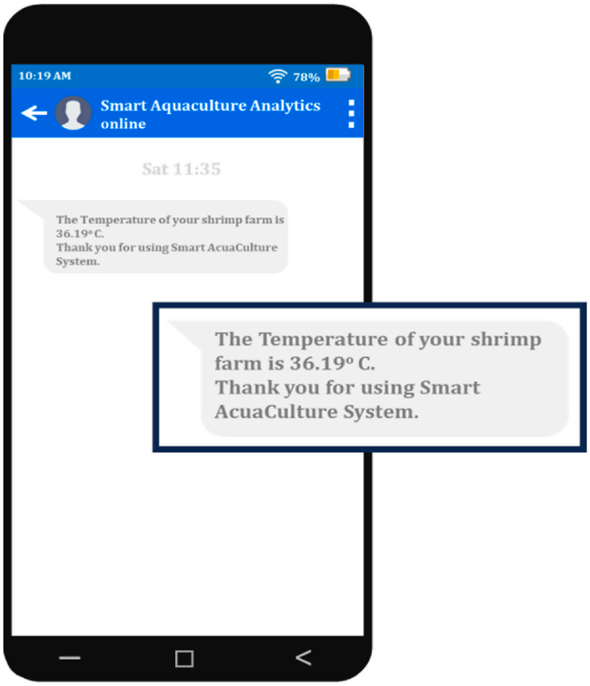


Fig. 11. Smart notification service to farmers from Smart Aquaculture Analytics system.

Table 12
Summary of Shrimp farmers' feedback.

Farmer	Positive Aspects	Challenges	Future Scope
1	The system was easy to set up and use. The app notifications helped me stay informed about water quality changes.	The initial cost of the system was a bit high for my small farm. I'd like to see more affordable options available	Adding features for basic disease identification within the app would be incredibly helpful.
2	The real-time data and alerts allowed me to optimize feeding schedules and save on feed costs, improving shrimp health significantly.	Sometimes the internet connectivity in my area was unreliable, causing data gaps. A backup system for local data storage would be beneficial.	Integrating the system with automated feeding systems could further streamline operations and improve efficiency.
3	The system's scalability was excellent. We easily integrated additional sensors to monitor specific parameters across our multiple ponds.	The user interface could be more customizable for complex farm management needs. Additional features for data analysis and trend identification would be valuable	Developing an API for integration with existing farm management software would be a game-changer for large-scale operations.

under controlled experimental conditions. To effectively implement this study on a larger scale or for commercial use in Bangladesh, the hardware infrastructure is designed to be modular and expandable, facilitating the integration of additional sensors as necessary. For example, salty water shrimp farming requires parameters like Dissolved Oxygen (DO) and Ammonia (NH3/NH4+) [52], which can be added easily. Then, the cloud infrastructure is scalable, handling increased data loads efficiently [53]. The selected robust, weather-resistant hardware ensures reliable performance in fluctuating temperatures, humidity, and salinity ranges. Robust data transmissions technologies such as LoRaWAN or cellular networks ensure reliable connectivity across multiple farm locations, bolstered by scalable cloud infrastructure capable of efficiently managing increased data loads [54]. Distributed computing frameworks enable effective real-time data processing and analysis [55]. The web application's user interface is designed to support varying levels of complexity, offering customizable dashboards and reporting tools that cater to the specific needs of different farm sizes and types [56]. Implementing role-based access control ensures that users can manage and monitor their farms effectively, regardless of scale [57,58].

IoT devices and sensors used for real-time monitoring can consume significant energy, especially when deployed in large numbers across extensive shrimp farms [59]. Energy-efficient hardware is selected, and power management techniques like duty cycling and low-power modes are employed to reduce consumption [44]. Utilizing renewable energy sources like solar or wind to power IoT devices and network infrastructure can further enhance sustainability [60,61]. Addressing the long-term impact of the system on shrimp farming practices and its potential environmental footprint is crucial for sustainability [62]. Adopting energy-efficient technologies (E.g., smart grid), optimizing data transmission intervals, and leveraging renewable energy sources can minimize these impacts [63,64]. The system's ability to optimize resource use, enhance the decision-support model (i.e., AHP) through machine learning models, and reduce manual intervention may lead to more sustainable farming practices [65–67]. Cultivating freshwater

Table 13
Comparison with earlier studies on shrimp farm monitoring systems.

Study	Microcontroller	Network	Cloud Storage	Predictive Analysis	ML/DL	Application
[5]	Arduino UNO	Wi-Fi	✓	×	×	Web & Mobile
[6]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[7]	Arduino UNO	GSMSIM900	✓	×	×	Mobile
[8]	Arduino UNO	Zigbee	✓	×	×	Web & Mobile
[10]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[11]	NodeMCU-ESP8266	Wi-Fi	✓	×	×	Web
[12]	Arduino Nano	Wi-Fi	✓	×	×	Mobile
[13]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[14]	Arduino UNO	Wi-Fi	✓	×	×	Web
[15]	Arduino Nano	Wi-Fi	✓	×	×	Mobile
[16]	Arduino UNO	Wi-Fi	✓	×	×	Mobile
[17]	×	×	×	✓	ML & DL	×
[18]	×	Wi-Fi	✓	✓	DL	Web & Mobile
[19]	Arduino UNO	Wi-Fi	×	×	×	Web
[20]	Arduino UNO	Wi-Fi	✓	×	×	×
[44]	Electronic Circuit	Wi-Fi & GPRS	✓	×	×	Mobile
[45]	XBee & ATMega328p	Wi-Fi	✓	×	×	Mobile
[46]	AVR Microcontroller	Wi-Fi	✓	×	×	Mobile
[47]	Arduino Yun	Wi-Fi	✓	×	×	Mobile
[48]	Raspberry Pi	GSM	✓	×	×	Mobile
[49]	Arduino UNO	LoRa	✓	×	×	×
[50]	Arduino Yun	ESP32, Wi-Fi & LoRa	✓	×	×	Mobile
[51]	Raspberry Pi	Wi-Fi	✓	×	×	Mobile
This study	STM32	Wi-Fi	✓	✓	✓	Web & SMS Notification

shrimp alongside other fish species in polyculture systems can have several impacts, including recourse competition, environmental stress, and disease transmission. Integrated multi-trophic aquaculture (IMTA) practices can be employed to minimize these potential impacts in shrimp farming. IMTA involves cultivating different species (e.g., shrimp and fish) together to maximize resource utilization and reduce environmental impact [68,69].

Moreover, addressing environmental impacts involves monitoring and minimizing ecological risks associated with traditional farming methods. Policy adaptation should prioritize environmental sustainability, aligning with Bangladesh's agricultural policies to ensure long-term benefits for farmers and the ecosystem. Overall, integrating these strategies ensures that the system enhances productivity and profitability and fosters responsible environmental stewardship in Bangladesh's shrimp farming industry.

5. Conclusion

In conclusion, integrating IoT and machine learning has brought about a transformative revolution in the aquaculture of shrimp in Bangladesh. The combination of predictive machine learning and real-time IoT monitoring is a promising approach to enhancing shrimp aquaculture processes in the country. The critical aspect of water quality observation in shrimp farming is effectively addressed through the proposed system, allowing farmers to monitor crucial water quality parameters in real-time. The analysis of various machine learning approaches for predicting the next day's value with 0.94 (max) r-squared value by multivariate linear regression and shrimp production reveals the effectiveness of Random Forest, achieving an impressive accuracy of 97.84 %. The proposed system, tailored specifically for Bangladeshi shrimp farms, emphasizes the centrality of IoT. All key productivity metrics for shrimp farming have been considered in the development process, resulting in a system architecture encompassing six layers: the hardware/physical layer, the network layer, the cloud layer, the service layer, the ML/DL layer, and the application layer. The physical layer incorporates sensors and a handling unit, such as STM32, serving as the infrastructure that relays information to the online database in the cloud layer. The cloud layer functions as the primary data-handling unit, offering features such as report generation, real-time data visualization, threshold level estimation, and alert notifications. The application layer provides a user-friendly interface for farmers to interact with the system, accessing real-time data and analytical insights. Based on farmer feedback, the proposed system shows potential for further automation, including disease identification, advanced data analysis tools, and API integration. Integrating computer vision can revolutionize monitoring practices by automating the detection of shrimp health indicators such as shrimp counting, growth patterns, behavioral anomalies, and disease symptoms directly from video feeds. This capability offers real-time insights into individual shrimp and overall farm conditions, facilitating proactive management and timely interventions. This research introduces a robust solution for shrimp farm management in Bangladesh and lays the groundwork for future advancements in aquaculture technology.

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Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Fizar Ahmed: Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Md Hasan Imam Bijoy:** Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Habibur Rahman Hemal:** Writing – original draft, Methodology, Formal analysis. **Sheak Rashed Haider Noori:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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