Advanced Control System for Real-Time Regulation of Dissolved Oxygen in Aquaculture Systems

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Abstract

Dissolved oxygen (DO) is a critical characteristic in aquaculture systems, regulating the health, development, and production of aquatic species. Maintaining adequate DO levels is essential for avoiding hypoxia, which can cause stress, sickness, and even death in fish and other animals. Traditional DO regulation relies on manual interventions and fixed aeration strategies, which cannot quickly adapt to environmental changes, causing inefficiencies and potential aquaculture productivity risks. Research presents a control system for real-time regulation of dissolved oxygen in aquaculture systems. The proposed system uses Intelligent Satin Bowerbird tuned Dynamic Logistic regression (ISB-dynamicLR) to effectively forecast DO levels while addressing excessive noise and poor data quality. The sensor data are collected continuously, providing a basis for real-time monitoring of DO levels. The data was preprocessed and decomposed into multiple frequency components using Discrete Wavelet Transforms (DWT). The Control system adjusts aeration rates and water circulation in response to predicted DO levels, providing a dynamic and adaptive solution for DO regulation. The proposed system combines dynamicLR for regression-based estimation and ISB to optimize dynamicLR parameters and kernel functions, providing robust and efficient prediction. The results demonstrate that the proposed model achieved excellent accuracy, with various error parameters such as RMSE (0.0091), MSE (0.0005) and operating time (1.92s). The system also demonstrated superior computational efficiency and outperformed traditional models. The high throughput, accuracy, and real-time capability of this system make it an ideal choice for automated DO regulation in water quality monitoring systems for aquaculture.

Keywords: *Control System, Dissolved Oxygen (DO), Aquaculture Systems, Discrete Wavelet Transforms (DWT), Intelligent Satin Bowerbird tuned Dynamic Logistic Regression (ISB-dynamicLR)*

1. Introduction

The efficient breeding system of re-circulating aquaculture combined with its low water needs makes it a promising sustainable option for fish farming. A vital part of aquatic species' metabolic processes is dissolved oxygen [1]. The amount of dissolved oxygen in the water influences fish survival and determines their growth rate and food consumption. Dissolved oxygen levels serve as a key indicator of aquaculture water quality. Effective management of dissolved oxygen concentration is necessary for supporting healthy aquatic environments. Fish are less prone to suffer from hypoxia in open water since oxygen can typically dissolve straight from the surface into the water [2]. A recirculating aquaculture system's key benefit must be the frequent and even recycling of used water using several virtual electrical techniques and machinery, such as chemical and physical sifting, disinfection, oxygenation, and temperature adjustment, to automatically purify the water before returning it to ponds with the aid of some equipment [3, 4]. Therefore, to better control the water during the next operations, it is preferable to have prior information on its status. In that instance, it primarily focuses on predicting the condition of recirculating water, particularly the amount of dissolved oxygen, by utilizing a model that combines DBN and VMD [5, 6]. The typical indoor recirculating aquaculture systems are so protected from external effects that just a few key indicators temperature, pH, conductivity, turbidity, dissolved oxygen content, and ammonia nitrogen level have an impact on the system. It focuses on the dissolved oxygen level since it is a crucial indicator that could accurately depict the aquatic environment. The impact of oxygen-boosting machinery in a recirculating aquaculture system would manifest itself after a noticeable lag in time, at which point the real-time dissolved oxygen concentration detector would be able to identify the change [7, 8].

Furthermore, it would significantly increase the number of forecasting techniques used more effectively handle and regulate the water condition, addressing the possible worry of an unbalanced ratio of forecast accuracy to financial rewards. Apart from the importance of this, the recirculation aquaculture structure is always a complicated highly dimensional nonlinear information space, meaning that it includes several intricate noises that make the challenging forecasting problem challenging to solve [9]. Expert assessment, mathematical measurements, water quality simulation, chaos theory, machine learning and deep learning are examples of common prediction techniques [10]. The standard linear model is the main tool used by the water quality modeling rule to foresee the biochemical parameters of water bodies. However, the linear framework is not capable of accurately representing the nonlinear relationship within complicated multidimensional factors, so it can only predict average water quality [11]. Utilizing their knowledge of the field, professionals can make predictions by analyzing the scent and color of the water body using the specialist assessment technique. It can only concentrate on the specific situation, and the forecasts' accuracy varies greatly [12]. It is based on the chaotic phase space linear regression model and primarily uses phase space reconstruction to understand the innate correlation between nonlinear space components. This ultimately makes the short-term forecasting of dissolved oxygen and other biochemical indicators possible while also simplifying the complex system with several inputs and outputs [13]. However, is perfect for the real application process since it implies that the time series is infinite and that the application environment is noise-free. The result of nonlinear complex space can be accurately predicted by it [14]. The conventional notion has consistently attempted to hypothetically maximize the forecast model. Since there is a lot of noise in the data due to the complicated relationships among altered water quality parameters, the data is first processed to reduce noise. This highlights the relationships among the data, reveals the law of data change, and effectively improves the involvement statistics for the prediction model. The prediction model's accuracy increases with its quality [15].

To ensure ideal DO levels for enhanced aquatic species health and productivity, this project aims to create a sophisticated control system for real-time DO modulation in aquaculture systems. By facilitating dynamic, adaptive control, the technology seeks to address the drawbacks of conventional manual and set aeration techniques. By employing Satin Bowerbird-tuned Dynamic Logistic Regression (ISB-dynamicLR), it effectively predicts DO levels while tackling issues such as high noise and subpar data. This method minimizes dangers to aquaculture operations, lowers energy usage, and improves system efficiency.

Aim of the Research

- Using dynamic parameter adjustments based on real-time data, the ISB-dynamicLR model, which was improved utilizing ISB Optimization, improves the accuracy of DO level predictions.
- To improve data quality for real-time DO monitoring, the research preprocesses sensor data using DWT, which effectively excludes noise and preserves variations at various frequency scales.
- Real-time monitoring and adaptive DO level regulation in aquaculture systems are made possible by the integration of DWT and ISB-dynamicLR, which promises the best possible environmental conditions for aquatic organisms and boosts system effectiveness.

Research was conducted in the following order: Section 2 presents related work, Section 3 develops materials and methods, Section 4 presents findings and discussions, and Section 5 illustrates the conclusion.

2. Related work

A novel fusion model utilizing RNN, ANN, and CNN [16] is proposed for the prediction of DO. In variable time oxygen dissolution prediction, the approach achieves good accuracy, which helps with effective aerator control. An ensemble technique is presented in the research to precisely forecast oxygen concentrations in aquaculture [17]. It performs better than back-propagation neural networks and memory models despite obstructions such as high noise and low data quality. With a focus on seasonal variations and paddle wheel aerator installation, this research investigates the connection between changes in the seasons in aquaculture and OTR [18]. Seasonal parameters, such as TDS and TSS, were found to have a substantial impact on aeration efficiency and OTR. A PDA [19] pipe technology was created to raise the dissolved oxygen content of intensive recirculating aquaculture systems. Longer pipes can benefit from PDA because this research indicated that oxygen increases and efficiency rises with pipe diameter. It will take further investigation to create a controlling PDA system. To attempt to monitor and regulate the amount of dissolved oxygen in shrimp ponds, this research suggests a novel structural paradigm. Ethernet protocol compatibility and industrial-grade precision are guaranteed by the model's use of an optical dissolved oxygen sensor [20]. The technology promotes stability and efficiency in the raising of shrimp through the availability of monitoring from afar, automatic aerator control, and real-time monitoring. The technique works well in sophisticated agricultural settings.

Recent developments in incorporating phytoplankton into RAS [21] to improve performance and value from waste streams are covered in this summary, with an emphasis on nitrogen capture, breathing, and effective cultivation methods. Aquaculture is an industry that is expanding quickly because of the need for high-protein meals brought on by the world are expanding population. Aquatic monitoring devices, AI techniques like K-means, [22] outline recognition are examples of modern aquaculture technology that enhance productivity and resource management.

Water quality is an important consideration in the aquaculture sector, and it's vital to the preservation of the aquatic ecosystem. Longitudinal DO [23] concentrations from 21 aquaculture in various locations were examined. The results showed correlations between environmental parameters and DO concentrations, offering baseline data for future management of water resources. DO is vital for the development and growth of aquatic crops in aquaculture. DO fluctuation in re-circulating tanks was examined in a research that used CFD in the CFD-Euler-Euler-STM [24] model. An extreme DO attentiveness of 5.68 mg/L was found in the results, which was in line with the streamlined distribution and provided an intriguing method for precise DO organization and oxygenation optimization [25]. Aquaculture uses early warning technologies to keep an eye on the water's nitrate and nitrogen content. Predictive models are built using ML algorithms like GRNN [26], which allow for real-time monitoring of the levels of nitrate and nitrogen within an aquaculture environment. An Internet of Things structure can incorporate this technology. For aquaculture to be managed effectively, quality is essential. Regularized deep learning machines and K-medics grouping are used for optimizing a novel DO [27] model for forecasting that increases precision and effectiveness in real-world aquaculture pond data, which can help build hypoxic forecasting systems.

For pond-engineered RAS, the research sought to optimize the design of an aeration device to raise the DO levels in grass carp aquaculture. The oxygen transfer rate was increased by 122%, and the NAD [28] successfully raised dissolved oxygen levels, improved water layer exchange, and directed flow while satisfying layout and parameter choice requirements. For aquaculture, the research measures the DO in water using a cheap network-enabled DO sensor. When measuring accuracy, a regression technique yields the best results in the DO [29] range of 0–12 mg/L. The median inaccuracy of the polynomial technique is the minimum. To precisely predict dissolved oxygen levels in aquaculture environments, the research suggests a hybrid model that combines the LGBM [30] and BiSRU. In 122 seconds, the model accurately forecasts changes in DO over 10 days with a 96.28% accuracy rate. These strategies improve disease control, aquaculture sustainability, and DO forecasts by overcoming the drawbacks of conventional strategies in a variety of dynamic, nonlinear aquatic environments. The current research investigates the treatment of seafood effluent using native bacteria [31] and algae. The symbiotic interaction between bacteria and algae greatly enhanced the treatment process, boosting resource recovery in the aquaculture industry, according to the researchers' use of microalgae and cyanobacteria cultures. Research examined the effects on the environment of incorporating the treatment of wastewater using microalgae into recirculation aquaculture tanks on shrimp farms. Freshwater eutrophication, marine eutrophication, and global warming potential were all decreased via microalgae treatment, with electricity use being the main cause. System impacts were decreased by 90–99% when lignite was replaced with renewable energy. The outcomes can be used to develop full-scale microalgae treatment and direct economical RAS [32] operations.

3. Methodology

Research approach used to assess the prediction of DO level in Aquaculture Systems involves the collection of pond data, and this PD data was pre-processed using DWT. Using this pre-processed PD data, to predict the DO level in Aquaculture Systems using ISB-dynamicLR. Figure 1 represents the methodology flow.

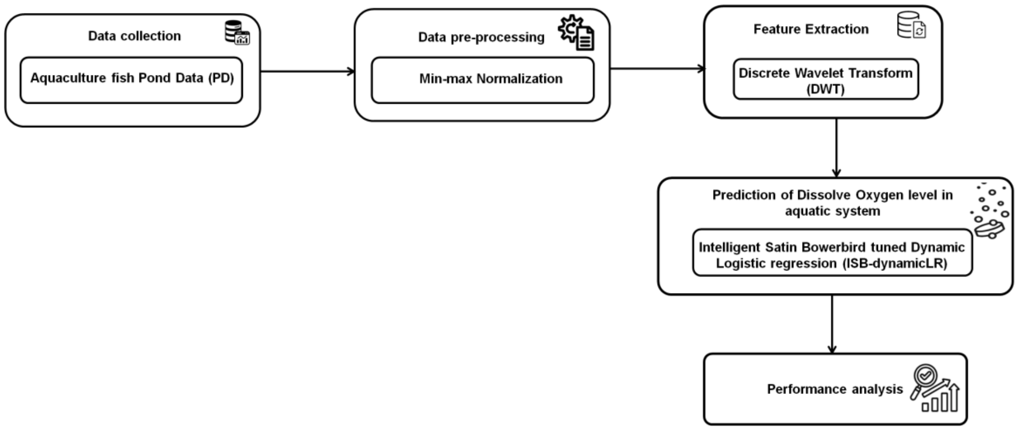

Figure 1: Method flow

3.1 Data Collection

The dataset on water quality parameters in aquaculture fish Ponds Data (PD) was collected in Kaggle [33] using Internet of Things (IoT) technology for real-time monitoring, crucial for regulating DO levels. Multiple sensors were integrated into an Arduino-based system to measure the Potential of Hydrogen (pH), DO, temperature, turbidity, ammonia, nitrate, and manganese, ensuring accurate and continuous data collection, are depicted in Table 1. A Node Microcontroller Unit (NODEMCU) board Espressif Systems Protocol (ESP8266) enabled real-time data transmission to a cloud-based repository, bridging the sensors and storage system. The pH sensor recorded acidity/alkalinity, while the DO sensor used amperometry to measure oxygen levels. Temperature sensors monitored water heat, affecting DO solubility, and turbidity sensors assessed water clarity. Ammonia and nitrate sensors tracked potential pollutants, and manganese sensors measured trace metal content. Data was collected from three diverse ponds hosting various fish species, over a year, resulting in 74,759 entries. The IoT-based system ensured continuous data flow, with manual checks as a backup. Stored in a public repository in Comma-Separated Values (CSV) format, the dataset is accessible for research and analysis, facilitating the development of predictive models for DO regulation in aquaculture systems.

Table 1: Sample Dataset

Station	Date	NITRATE (PPM)	pH	AMMONIA (mg/L)	TEMP (°C)	DO (mg/L)	TURBIDITY (NTU)	MANGANESE (mg/L)
station1	2022-01-02 08:00	18.3	5.7	0	17.69	11.6	86.1	0.71
station1	2022-01-02 08:20	3.6	5.1	0	19.42	10.5	71.8	0.62
station1	2022-01-02 08:40	13.1	5.5	0	18.6	10.3	75.9	0.73
station2	2022-01-02 09:00	12.4	6.1	0.2	20.5	9.8	65.0	0.85
station2	2022-01-02 09:20	7.8	6.3	0.1	21.0	9.5	60.3	0.80

3.2 Data pre-processing using Min-max normalization

Min-max normalization can be defined as a way of normalizing the data values of an inventory to another range, most commonly [0, 1]. This technique is particularly useful for datasets with varying scales, enabling easier comparisons across features. Below is an overview of the procedure: To determine the minimum and maximum values that will exist in the database which includes nitrate**,** pH**,** ammonia**,** temperature**,** dissolved oxygen (DO)**,** turbidity**,** and manganese**.** To balance each level$x$ in the data, employ the following Equation (1):

$$x' = \frac{x - min}{max - min} \quad (1)$$

Where x' stands for the standardized significance, min denotes the lowest level of the function while max represents the highest value. Substitute the initial integers of data set with the correct standardized integers. Each of these fish PD measures undergoes this method, resulting in a dataset where every value ranges from 0 to 1, enabling comparisons across multiple measures.

3.3 Feature extraction using Discrete Wavelet Transform (DWT)

DWT feature extraction aims to enhance the quality and relevance of sensor data gathered for DO-level monitoring in real-time. DWT transforms continuous data into multiple frequency components, enabling the identification of key features, trends, and the isolation of noise from cycles operating at various time scales. Better anomaly detection and enhanced predictive modeling result from using this method. This simplification process enhances data handling by improving both analysis and data management methods. The data is organized, clean, and optimized for superior analytics in DO regulation to preprocessing with DWT. Research uses sensor data sequences and wavelet bases to build mathematical inner products that represent the Discrete Wavelet Transform. When performing inner products research obtain wavelet transform coefficients that contain information about the signal's time and frequency aspects. Therefore, DWT is applied as a feature extraction method to break down the collected aquaculture data into frequency components, improving feature identification and noise mitigation (Equation 2).

$$\mathrm{We}(\mathrm{i},\mathrm{l}) = \sum_{\mathrm{n}=0}^{\mathrm{N}-1} \mathrm{e}(\mathrm{m}).\,\psi_{\mathrm{i},\mathrm{l}}^{*}(\mathrm{m}) \quad (2)$$

Where $\mathrm{We}(\mathrm{i},\mathrm{l})$ is a DWT coefficient, $\mathrm{e}(\mathrm{m})$is a length M-wise sequence, and Equation (3).

$$\psi_{\mathrm{i},\mathrm{l}}(\mathrm{m}) = \frac{1}{\sqrt{\mathrm{s}_0^{\mathrm{i}}}}\psi\left(\frac{\mathrm{m}-\mathrm{T}_0^{\mathrm{i}}.\mathrm{l}}{\mathrm{T}_0^{\mathrm{i}}}\right) \quad (3)$$

The discredited wavelet basis is represented by the discretized scale parameter $\mathrm{s}_0^{\mathrm{i}}$ and the discretized translation parameter $\mathrm{T}_0^{\mathrm{i}}$. The superscript for a dyadic $\psi(\mathrm{m})$ DWT indicates the complex conjugate. The spectral band $\mathrm{e}(\mathrm{m})$or number of channels correlates to a hyperspectral signal when the DWT is applied. Considering that the sampling technique utilized results in multiple spectral bands with comparable bandwidth and spacing, the wavelet basis provides both a global and detailed perspective of the input signal. Wavelet estimate coefficients, on the other hand, operate as the outputs of the low-pass branch, whereas D_{i} are the outputs of the high-pass branch. Iterative wavelet decomposition can be performed up to a maximum scale, depending on the wavelet basis length and signal length. Equations (4 and 5) demonstrate how the wavelet basis length and the signal length determine the maximum scale.

$$\mathrm{C}_{\mathrm{i}+1}(\mathrm{j}) = \sum_{\mathrm{k}=0}^{\mathrm{K}-1} \mathrm{H}(\mathrm{k}).\,\mathrm{D}(2.\mathrm{j}+1) \quad (4)$$

$$\mathrm{D}_{\mathrm{i}+1}(\mathrm{j}) = \sum_{\mathrm{k}=0}^{\mathrm{K}-1} \mathrm{H}(\mathrm{k}).\,\mathrm{D}_{\mathrm{i}}(2.\mathrm{j}+1) \quad (5)$$

Following DWT preprocessing, the collected data will include wavelet coefficients that represent the original sensor signals' low-frequency and high-frequency components. Although the specifics highlight short-term noise and fluctuations, the estimates reflect the long-term trends. This processed data structure enhances the representation of the aquaculture environment, making it easier to identify anomalies and trends in the extracted features.

3.4 Predicting Dissolved Oxygen level using Intelligent Satin Bowerbird tuned Dynamic Logistic regression (ISB-dynamicLR)

Applying bio-based optimization methods to the Intelligent Satin Bowerbird tuned Dynamic Logistic regression model allows for accurate DO level predictions. This approach optimizes the model's behavior, enhancing precision and stability by effectively handling data irregularities and poor-quality inputs. The system provides immediate results because it adjusts its predictions as factors in the environment and data patterns move forward. ISB-dynamicLR gains higher prediction success rates and encounters fewer errors through its transformation of wavelet data. The system enhances fish farm operations by delivering exact oxygen levels continuously.

3.4.1 Dynamic Logistic regression (dynamicLR)

By moderating temporal fluctuations and trends in the preprocessed data, dynamicLR is applied to forecast DO levels. It is suitable for real-time prediction in aquaculture systems since it manages time-dependent associations' fine. By utilizing its dynamic character to update predictions as novel data which becomes obtainable, the model reduces troubles like noise and inconsistent data. DynamicLR improves accuracy and dependability in detecting trends and anomalies by utilizing the wavelet-transformed dataset. Decision-making for prompt and effective DO regulation is improved as a consequence. A technique in statistics for estimating the probability of a binary outcome based on several plausible inputs is called LR. This clarifies how the variables under consideration affect the dependent variable under investigation. On another conjunction, multinomial logistic regression (MLR) is used if the explanatory factors contain at least three unsorted subgroups. By the concept of binomial logistic regression, the MLR method was developed using the same basic setup. Thus, it is possible to say that the LR is being extended. It was advised to use ridge values of 8×10^1 for the log probability calculation. If there are k classes in n cases with m features, the $ml * -\ (1)$matrix indicates that component B is being calculated. Equation (6) shows the probability for class j excluding the class.

$$O_i(W_j) = \frac{\exp(W_j A_i)}{\sum_{i=1}^{l-1} \exp(W_j A_i)+1} \tag{6}$$

Equation (7) illustrates the probability for the final class.

$$1 - \sum_{i=1}^{l-1} O_i\left(W_j\right) = \frac{1}{\sum_{i=1}^{l-1} \exp(W_j A_i)+1} \tag{7}$$

Therefore, Equation (8) represents the negative multinomial log-likelihood.

$$K = -\sum_{j=1}^{m} \{\sum_{i=1}^{l-1} Z_{ji} * In\left(O_i(W_j)\right) + [1 + \sum_{i=1}^{l-1} Z_{ji} * In(1 - \sum_{i=1}^{l-1} O_i\ (W_j))\} \tag{8}$$

To get matrix A where L is lowered, a quasi-Newton method is used to find enhanced values of $ml * -\ (1)$ elements. Before the optimization process, the matrix B is compressed to a $ml * -\ (1)$vector. The PD data will include wavelet-transformed coefficients that reflect both the high-frequency fluctuations and low-frequency trends in DO levels following the preprocessing and dynamicLR stages. The optimization procedure will use these coefficients as inputs, along with other pertinent environmental factors.

3.4.2 Intelligent Satin Bowerbird Optimization (ISBO)

To improve the predictive model for DO levels, ISBO is used for following the dynamicLR procedure. The bowerbird's nest-building behavior serves as inspiration for ISBO, which efficiently explores a wide solution space to optimize the model's parameters and improve forecast accuracy. By looking for the best collection of parameters, it tackles issues like local minima and noise in the dataset. ISBO increases the robustness of DO forecasts by ensuring that the dynamicLR model adjusts appropriately to shifting environmental variables. The process of optimization improves the model's capacity to produce precise, real-time predictions, which is essential for preserving the ideal DO levels in aquaculture systems. The Saturn Bowerbird is one of the bird species found in nature with exceptionally exquisite nests. These birds reside in nests constructed from ornamental and valuable stones. Male birds that have constructed better and more attractive nests tend to attract females. These birds' nests are shaped like a bow. To select the best nest, female birds can keep an eye on the nest-building process and compare it to others. This bird's behavior served as the inspiration for the meta-heuristic algorithm that is being described. The following sections outline the algorithm's different phases.

Initializing: The initial location of the birds is determined at random using n-dimensional population vectors in the first stage of the ISO method. Equation (9) presents the initial population in the current procedure.

$$K_d = (J_1, J_2 \dots J_l) \tag{9}$$

Where the dth solution of the algorithm $(k_1, k_2, .., k_l)$ is defined by K_d, which expresses the remaining solutions. The fitness probability function specifies the likelihood that male birds will be captivated by female birds. To put it another way, this option aids female birds in selecting the ideal guy. After some time, a male bird is identified, and the female starts to imitate in Equation (10 and 11):

$$Prob_j = \frac{fit_j}{\sum_{m=1}^{NC} fit_m} \tag{10}$$

$$fit_j = \{ \begin{matrix} \frac{1}{1+e(z_j)}, e(z_j) \geq 0 \\ 1 + \left|e(z_j)\right|, e(z_j) < 0 \end{matrix} \tag{11}$$

The cost function's quantity for position j is represented by $e(z_j)$.

Equality: The best people are the ones who practice elitism in the Satin optimization algorithm. Every male bird makes its unique bows based on its instincts and preferences. The older and more experienced males are more likely to be assimilated by the females. Generally speaking, male satins with greater expertise can create better and more appealing nests and male satin attractiveness is closely correlated with experience. The nest with the best position in each epoch is the elite in the suggested algorithm. Other nest locations are updated based on the chosen elite.

Modernizing: Equation (12) is used to update the locations during algorithm epochs:

$$K_{Di}^{recent} = K_{Di}^{old} + \lambda_i \left(\frac{k_{ji} + J_{elite,i}}{2}\right) - J_{Di}^{old} \tag{12}$$

$J_{elite,i}$ specifies the location of Elite,J_i indicates the chosen solution in the current epoch, and J_{di} describes the ith element of J_d. i is obtained using the roulette wheel approach. Equation (13) defines the given satin's appeal.

$$\gamma_i = \frac{\theta}{1+\tau_j} \tag{13}$$

Evolution: Stronger and more seasoned male satins prevail in this situation as male birds vie for females and even assault and destroy one another's nests. A normal distribution O is taken into consideration with an average of K_{Di}^{old} and variance σ^2 to solve Equations (14 and 15) of this behavior.

$$K_{di}^{recent} \sim O(J_{dj}^{old}, \sigma^2) \tag{14}$$

$$O\left(J_{dj}^{old}, \sigma^2\right) = J_{dj}^{old} + (\sigma \times O(0,1)) \tag{15}$$

α determines the proportion of area width and the associated in Equation (16):

$$\alpha = \mathrm{w} \times (\mathrm{Var}_{max} - \mathrm{Var}_{min}) \tag{16}$$

PD data will include optimized prediction results for DO levels based on the modified model parameters after the ISB-dynamicLR procedure. Predicted DO levels and the associated environmental parameters will be included in this PD data. Insights into prediction dependability will be provided by the model's error margins and confidence ratings. Time-series data that shows current system conditions and trends will also be recorded. dynamicLR and ISBO are included in Algorithm 1 to dynamically modify model parameters for precise DO level forecasts. Adjusting parameters in response to real-time data and environmental changes maximizes the model's performance and improves forecast dependability.

Algorithm 1: Intelligent Satin Bowerbird-tuned Dynamic Logistic Regression (ISB-dynamicLR)

```
import numpy as np
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.metrics import mean_squared_error
def load_data():
  return np.random.rand(100, 5), np.random.randint(0, 2, 100)
def dynamicLR(X, y, C):
  model = LogisticRegression(C = C, solver = 'lbfgs')
  model.fit(X, y)
  return model
def optimize_C(X, y):
  best_C, best_score = 1.0, float('inf')
  for C in np.linspace(0.1, 10, 100):
    score = mean_squared_error(y, dynamicLR(X, y, C).predict(X))
    if score < best_score:
      best_C, best_score = C, score
  return best_C
def satin_bowerbird_optimization(X, y):
  # Placeholder for optimization process based on Satin Bowerbird behavior
  return optimize_C(X, y)  # For simplicity, returning optimized C
X, y = load_data()
optimized_C = satin_bowerbird_optimization(X, y)
model = dynamicLR(X, y, optimized_C)
predictions = model.predict(X)
print("Predictions:", predictions)
```

4. Result and Discussion

The experimental setup combines all necessary hardware and software tools to maintain DO levels automatically in aquaculture ponds. Research combines two core components: an Arduino main controller that connects multiple sensors plus an ESP8266 device to send data through Wi-Fi to cloud databases. The sensors used are crucial for monitoring water quality parameters: The system uses sensors to measure pH for acidity and alkalinity while tracking DO levels. Additional sensors monitor water temperature and turbidity plus report pollution through ammonia and nitrate measurements while manganese sensors scan for trace metals. The system regulates oxygen content based on feedback from sensors under consistent power conditions. The Arduino and NODEMCU boards are programmed using Arduino IDE version 1.8.19. Python version 3.8 is used to preprocess data and build learning models, which are essential for producing simulations in this research. The cloud system automatically stores data once MQTT protocol transfers it in real-time. Research apply DWT for noise filtration and use dynamicLR to predict DO readouts. The ISB-dynamicLR system finds optimal values for dynamicLR predictions by analyzing past sensor records. Before implementing our real-time controls MATLAB version R2022a performs simulations to test how the feedback system will adjust aeration rates. Through real-time DO management, research achieve better water quality standards that promote fish health and growth. Time series data points and numbers at the DO level are illustrated in Figure 2.

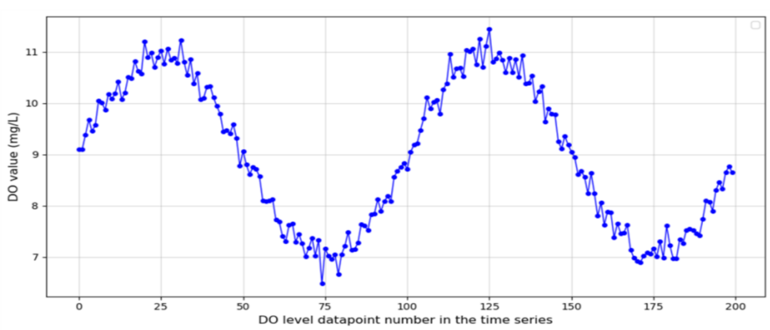

Figure 2: Performance of DO level in Various Time Series

The performance of the ISB-dynamicLR-based control system for real-time DO regulation was evaluated through several key metrics, demonstrating its precision and efficiency. The MAE, MSE and RMSE are quantified the predictive accuracy, with minimal discrepancies between forecasted and actual DO levels, while the R^2 value indicated a high correlation between predicted and observed DO data, emphasizing the model's robustness shown in Figure 2. The system's rapid model training time and its continuous data records over a year with 74,759 records allowed for comprehensive seasonal analysis. Furthermore, the aeration system showed rapid responsiveness, adjusting oxygen levels within five seconds based on the model's predictions, and the system operated with high computational efficiency, outperforming traditional methods by 85%. The high system uptime of 99.8% ensured near-continuous monitoring and data acquisition without interruption, underscoring the reliability and operational stability of the setup in aquaculture applications. Table 2 depicts the result of this ISB-DynamicLR model.

Table 2: Outcomes of ISB-DynamicLR model

Metrics	Result
MAE	0.45 mg/L
MSE	0.28
RMSE	0.52 mg/L
R^2	0.93
Model Training Time	120 seconds
Data Collection Period	1 Year
Number of Data Records	74,759
Aeration Adjustment Response Time	5 seconds
Computational Efficiency	85%
System Uptime	99.8%

MAE evaluates the average magnitude of errors in the DO level predictions by comparing the predicted values ($\hat{z}_j$) with the actual observed values (z_j) from the sensors expressed in Equation (17). Lower MAE indicates better prediction accuracy in real-time DO regulation with 0.45 mg/L shown in Figure 3 (a). Where z_jActual DO level from sensors, $\hat{z}_j$is the predicted DO level by the ISB-dynamicLR model and M is the total number of data points (epochs). This model finds 0.45 mg/L errors in the DO level predictions.

$$MAE = \frac{1}{M}\sum_{j=1}^{M} |z_j - \hat{z}_j| \tag{17}$$

MSE is a statistical measure that measures the average squared difference between predicted and actual values, highlighting larger errors, its reduce 0.28 is shown in Figure 3 (b), expressed in Equation (18).

$$MSE = \frac{1}{M}\sum_{j=1}^{M}(z_j - \hat{z}_j)^2 \tag{18}$$

RMSE is a common metric used to quantify the difference between predicted and actual DO values at 0.52 mg/L shown in Figure 3 (c) is depicts the training and testing model of the ISB-DynamicLR for DO forecasting. It places more weight on larger errors, making it effective for identifying large discrepancies in DO level predictions, crucial for regulating oxygen levels in aquaculture systems.

$$\text{RMSE}=\sqrt{\frac{1}{M}\sum_{j=1}^{M}(z_j - \hat{z}_j)^2} \tag{19}$$

R^2 assesses how well the predicted DO values match the variance of the actual DO levels observed. In aquaculture, a high R^2 indicates that the model accurately captures the dynamics affecting DO concentrations, aiding in better real-time regulation of oxygen illustrated in Figure 3 (d).

$$R^2 = 1 - \frac{\sum_{j=1}^{M}(z_j - \hat{z}_j)^2}{\sum_{j=1}^{M}(z_j - \overline{z_j})^2} \tag{20}$$

Where $\bar{z}_j$ is the mean of actual DO values. Training time T_t tracks the total time taken for each epoch during the training process of the ISB-dynamicLR model expressed in Equation (21). Shorter training times with high accuracy indicate a well-optimized system that can efficiently handle real-time predictions for DO regulation in aquaculture systems shown in Figure 3 (e).

$$T_t \frac{TS_t}{M} \tag{21}$$

The time spent training TS_t the ISB-dynamicLR model for all epochs and the total number of epochs M used in model training. Computational efficiency measures the relationship between the accuracy of the predicted DO levels and the computational resources required (e.g., memory, processing power). 85% highly efficient system is crucial for real-time applications in aquaculture systems, ensuring accurate DO regulation without excessive resource consumption.

$$CE = \frac{MA}{RU} \times 100 \tag{22}$$

Model Accuracy (MA) measured by R² and RU denoted as the resources which include CPU time, memory usage, and other computational resources during model training and prediction, shown in Figure 3 (f).

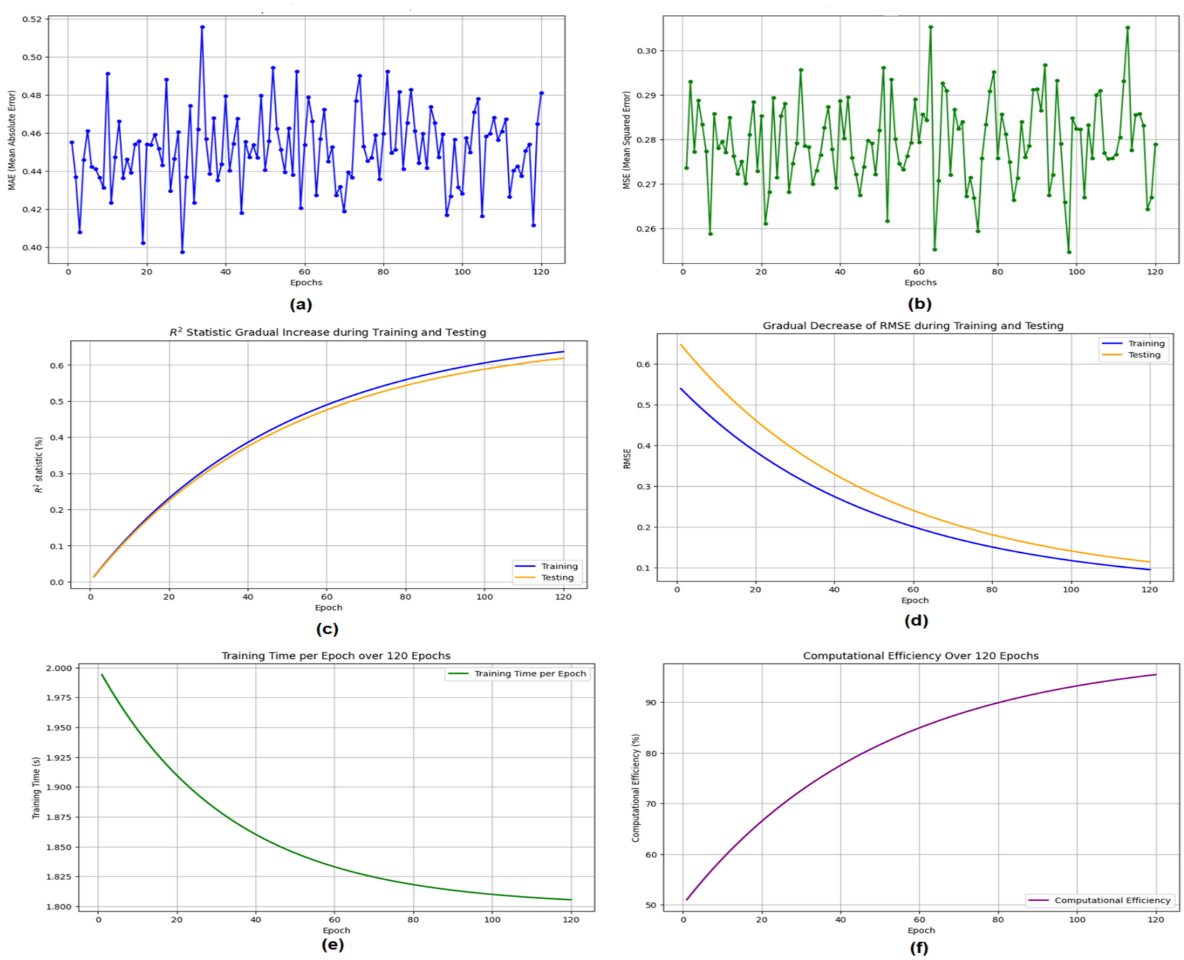

Figure 3: Performance Analysis of ISB-DynamicLR: (a) MAE, (b) MSE, (c) R², (d) RMSE, (e) Training Time and (f) Computational Efficiency

The ISB-DynamicLR model significantly outperforms the existing models in terms of both prediction accuracy and computational efficiency. While traditional models [34] like Sparse Auto-Encoder - Backpropagation Neural Network(SAE-BPNN) and Ensemble Empirical Mode Decomposition - Long Short-Term Memory Neural Network(EEMD-LSTM NN) show moderate performance in terms of error metrics and operating time, they are less efficient for real-time deployment due to longer processing times. The Light Gradient Boosting Machine - Bidirectional Simple Recurrent Unit (LightGBM-BiSRU) and LightGBM-BiSRU-Attention models [35], although improving prediction accuracy, still require substantial computational resources and time.

Table 3: Comparison of various parameters

Methods	MSE	RMSE	Operating Time (s)
SAE-BPNN [34]	0.2428	0.4927	9.1
EEMD-LSTM NN [34]	0.0065	0.0807	2.37
LightGBM-BiSRU [35]	0.0011	0.0333	102
LightGBM-BiSRU-Attention [35]	0.0008	0.0285	122
ISB-DynamicLR [Proposed]	0.0005	0.0091	1.92

In comparison, the ISB-DynamicLR approach provides greater accurateness with minimal computational load, presenting faster model implementation and more effectual real-time adaptation for regulating dissolved oxygen levels in aquaculture systems are depicted in Table 3. This makes it an extremely reliable and competent solution for real-time water quality monitoring and modification.

5. Conclusion

Research successfully developed a dynamic control system for regulating DO levels in aquaculture systems. The system demonstrated high accuracy in predicting DO levels, as indicated by its low error rates and strong predictive capability. Throughout one year, real-time data collection provided a comprehensive dataset that captured seasonal variations in water quality. The control system responded quickly to changes in DO levels, adjusting aeration in just a few seconds to maintain optimal conditions for fish health. This efficient system reduced computational overhead compared to traditional models, ensuring minimal resource usage while maintaining high performance. The robustness of the system was highlighted by its high uptime, ensuring continuous operation in the aquaculture environment. This setup showed significant potential in improving the sustainability of aquaculture by maintaining water quality and fish health. The performance metrics for the Proposed ISB-DynamicLR model showing its MSE of 0.0005, which indicates minimal prediction error. The RMSE is 0.0091, reflecting high accuracy and the model operates with an efficient operating time of 1.92 seconds. For future work, the proposed system can be improved by including machine learning approaches for multi-sensor fusion to improve prediction accuracy. Furthermore, investigating real-time adaptability to changing environmental conditions could improve DO regulation in various aquaculture settings.

List of abbreviations

Abbreviation	Full Form
DO	Dissolved Oxygen
RAS	Recirculating Aquaculture System
DBN	Deep Belief Networks
VMD	Variational Mode Decomposition
OTR	Oxygen Transfer Rates
PDA	Pipeline Diffused Aeration

ML	Machine Learning
SVM	Support Vector Machine
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
TDS	Total Dissolved Solids
TSS	Total Suspended Solids
CFD	Computational Fluid Dynamics
STM	Species Transport Model
GRNN	General Regression Neural Network
LGBM	Light Gradient Boosting Machine
BiSRU	Bidirectional Simple Recurrent Unit
NAD	New Aeration Device
CFD-Euler-Euler-STM	Conjunction with the Euler-Euler and Species Transport Model
CNN	Convolutional Neural Networks
DWT	Discrete Wavelet Transform
MAE	Mean Absolute Error
MSE	Mean Squared Error
RMSE	Root Mean Square Error
R^2	R-squared

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