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Innovative Hybrid Model for Dissolved Oxygen Predictions to Optimize Water Quality in Intensive Aquaculture

[1] P Harika, *B.Tech Student, Department of CSE, DNR College of Engineering and Techonology,peruriharika12@gmail.com*
[2] Ch Revathi, *B.Tech Student, Department of CSE, DNR College of Engineering and Techonology,revathich2002@gmail.com*
[3] K Shanmukha S Chowdary, *B.Tech Student, Department of CSE, DNR College of Engineering and Techonology,shanmukh768@gmail.com*
[4] M Ruth Kumar, *B.Tech Student, Department of CSE, DNR College of Engineering and Techonology,ruthkumarm@gmail.com*
[5] Mr. K. Venkata Chandran, *M.Tech, Assistant Professor, Department of CSE, DNR College of Engineering and Techonology,chandran.kamani@gmail.com*

ABSTRACT: *This work suggests a hybrid model that combines Light Gradient Boosting Machine (LightGBM) and Bidirectional Simple Recurrent Unit (BiSRU) to effectively and correctly estimate dissolved oxygen (DO) levels in aquaculture settings. The significance of dissolved oxygen is determined and its levels in intensive aquaculture settings are predicted using the LightGBM algorithm after linear interpolation and smoothing methods are used to identify important parameters. To further improve BiSRU's predictive capabilities, an attention mechanism is used to provide different weights to its hidden states. Impressively, the model predicts changes in DO over a 10-day period with a stunning accuracy rate of 96.28% in only 122 seconds, showcasing its extraordinary ability. Because aquatic habitats are diverse, dynamic, and nonlinear, conventional techniques of estimating DO levels have their limitations. This methodology seeks to overcome these issues. Accurate DO prediction is crucial in aquaculture since optimum production is dependent on water quality maintenance. When it comes to improving the speed and accuracy of DO predictions, the suggested hybrid model is a great way to go. This will help with disease control and make aquaculture more financially sustainable. Non-linear, LightGBM, BiSRU, attention mechanism are terms used in the index.*

I. INTRODUCTION:

An important part of the world's food supply comes from aquaculture, or the growing of aquatic creatures. China is quickly becoming the leader in this field, producing more than 70% of the world's aquaculture output [1]. Dissolved oxygen (DO) is an important indication of water quality in aquaculture settings because of the vital role it plays in the metabolism and survival of aquatic species, which in turn affects the quality of aquatic commodities [2, 3].

It is crucial to keep DO levels at their ideal range to prevent stress, disease outbreaks, and mass death in farmed fish, shrimp, and other aquatic species. Failure to do so may result in significant economic losses [4, 5]. Therefore, for proactive control of water quality and sustainable growth of aquaculture, precise prediction of DO concentrations and trends is necessary [6].

As a result of heavy investment in research and the use of machine learning methods, dissolved oxygen prediction models have recently achieved remarkable strides forward. Many methods have been investigated, such as support vector regression, clustering techniques, extreme learning methods, wavelet transformations, deep belief networks, particle swarm optimization, principal component analysis, and grey correlation degree [7]-[13]. In order to help with well-informed decisions about aquaculture management techniques, these models try to improve the precision and effectiveness of DO prediction.

In order to help fish farmers, hatcheries, and researchers with water quality management, this project is concentrating on creating dissolved oxygen prediction models for intensive aquaculture settings. Improving forecasting accuracy, enabling real-time monitoring, and facilitating proactive intervention techniques to maintain ideal circumstances for aquatic species are all goals of the project, which aims to use deep learning and big dataset analysis. The research seeks to improve production efficiency, reduce risks, and encourage sustainable practices in aquaculture operations via precise DO forecast.

In summary, the introduction establishes the relevance of dissolved oxygen prediction in aquaculture, describes the current obstacles, and emphasizes the importance of this project in securing the sustainability of aquaculture systems and promoting efficient management techniques.

II. LITERATURE SURVEY

China accounts for more than 70% of the world's aquaculture production, a reflection of the rapid growth in the industry [1]. Because of their impact on the metabolism and survival of aquatic species, dissolved oxygen (DO) levels are an important measure of water quality in aquaculture [2]. For ideal circumstances and to avoid negative impacts on aquatic health and production, precise DO concentration prediction is necessary [3].

The use of machine learning for DO prediction in water has been the subject of a great deal of research. For the purpose of predicting biofloc quantities and DO levels in shrimp culture systems, Jasmin et al. [2] presented a smart framework that makes use of machine learning approaches. In a similar vein, Ahmed and Lin [3] used quantile regression forest machine learning to forecast dissolved oxygen concentrations in flowing waterways subjected to varying land cover and usage.

For DO prediction, hybrid ML methods have also been explored. For the purpose of predicting the concentration of dissolved oxygen in flowing fluids, Dehghani et al. [4] used hybrid machine learning algorithms. A three-dimensional attention-GRU-GBRT-based approach for predicting dissolved oxygen in pond culture was developed by Cao et al. [5]. In their study, Li et al. [6] used a gated recurrent unit (GRU) to forecast DO in fisheries ponds.

On top of that, models using hybrid neural networks have been suggested by experts for DO forecasting. A hybrid neural network model for time-series forecasting of marine dissolved oxygen concentrations was reported by Liu et al. [7]. A deep belief network was investigated by Ren et al. [8] for the purpose of dissolved oxygen prediction in recirculating aquaculture systems.
In sum, the results show that machine learning methods are successful in predicting dissolved oxygen levels, which is crucial for aquaculture. Researchers are working to improve the accuracy of predictions, management practices in aquaculture, and the sustainability of aquatic habitats by using sophisticated algorithms and hybrid models.

III. METHODLOGY

a) Proposed work:

A new method for predicting dissolved oxygen levels in aquaculture settings utilizing a hybrid model is presented in the proposed study. Feature selection with LIGHTGBM, bidirectional training optimization with BI-SRU, and parameter modifications with Attention mechanism make up this model. The combination of these features is an attempt by the model to improve upon previous approaches, such as LightGBM-LSTM and LightGBM-GRU, in terms of predicted accuracy.

The accuracy of dissolved oxygen level predictions made using physical models, empirical formulae, and manual monitoring is limited. Unfortunately, the prediction accuracy is still inadequate even after using a number of algorithms such as XGBOOST, CNN, LSTM, SVM, Linear Regression, and Decision Trees. By using state-of-the-art methods and placing a premium on minimum Mean Squared Error (MSE), Mean Absolute Error (MAE), or Root Mean Squared Error (RMSE), the suggested hybrid model overcomes these shortcomings and improves the accuracy of dissolved oxygen level predictions.

b) System design: LightGBM dissolved oxygen level prediction in aquaculture settings entails a number of critical elements in the system design. Dataset factors including water temperature, pH, and turbidity are first entered. To make sure the data is good, the next step is to use data pretreatment methods including cleaning, normalizing, and dealing with missing information.

Data visualization tools like histograms, scatter plots, and box plots are used to understand the distribution and correlations between variables after preprocessing. The next step is to find the best characteristics for dissolved oxygen level prediction using feature extraction techniques.

To get a feel for how well the model performed, we divide the dataset into two parts: training and testing. The main method used for dissolved oxygen level prediction is LightGBM, a gradient boosting framework. Lastly, measurements like Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) are used to evaluate the efficacy of the LightGBM model in properly forecasting dissolved oxygen levels.

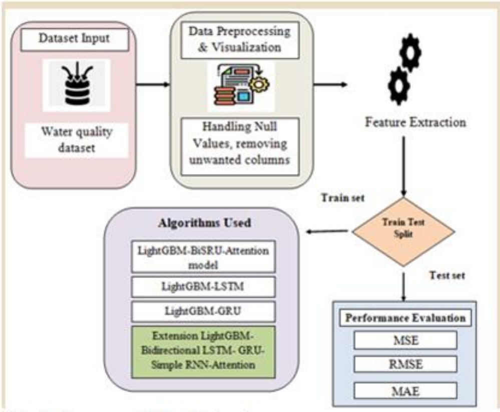


Fig 1 Proposed Architecture

b) Dataset collection:

Data on water quality samples were gathered for this study between December 7, 2020, and January 18, 2021. Five water quality indicators and sixty-five observation samples made up the dataset. This study's experiments and analyses were based on the data obtained.

Sensor aging or surface contamination are two examples of environmental conditions that might have introduced noise interference into the obtained data during data collection. As a result, the initial signal from the water quality monitoring data was subjected to noise reduction processing in order to extract the true signal. Equation 1 shows the procedure for filling out out-of-the-ordinary data points using the mean smoothing approach. This made sure that the data set wasn't contaminated with irrelevant information and that it fairly reflected the water quality metrics being studied.

	Sample ID	pH	Temperature (°C)	Turbidity (NTU)	Dissolved Oxygen (mg/L)	Conductivity (µS/cm)
0	1	7.25	23.1	4.5	7.8	342
1	2	7.11	22.3	5.1	6.2	335
2	3	7.03	21.5	3.9	8.3	356
3	4	7.38	22.9	3.2	9.5	327
4	5	7.45	20.7	3.8	8.1	352
...	...	...	...	...	...	...
495	496	7.01	20.8	4.6	7.1	327
496	497	7.31	22.5	3.8	9.4	361
497	498	7.02	21.2	4.7	7.5	334
498	499	7.25	23.0	3.9	8.7	359
499	500	7.12	20.9	4.4	8.2	339

Fig 2 Data Set

IV. DATA PROCESSING

The study's data processing step included identifying and removing unnecessary columns from the dataset in order to make the data more manageable for further analysis. In this stage, we looked at each column individually to see whether it had any bearing on our ability to forecast dissolved oxygen levels in highly controlled aquariums. In order to eliminate unnecessary information and concentrate on the most important aspects, we removed columns from the dataset that were not relevant to the prediction job.

Data preparation involves removing unnecessary columns to make analysis and model training more efficient. The predictive models are able to better grasp the data's underlying patterns and correlations when superfluous variables are removed, making the dataset more focused and succinct. More precise and trustworthy estimates of dissolved oxygen levels in intensive aquaculture settings may be made as a result of this.

f) Selecting Features

Finding the most important factors that affect the prediction of dissolved oxygen levels in intensive aquaculture settings was the goal of the study's feature selection phase, which included a rigorous approach. To do this, we had to look at how each attribute related to the target variable and how important it was for making predictions. Features with high predictive potential and relevance to aquaculture water quality management were prioritized using a variety of methods, including feature priority ranking, correlation analysis, and domain knowledge. Excluded from the modeling procedure were features that were determined to have poor correlation with the target variable or were determined to be unrelated to the prediction goal.

Improved accuracy and efficiency in forecasting dissolved oxygen levels in intensive aquaculture systems may be achieved by narrowing the predictive model's emphasis to the most important and useful elements. This allows the model to capture the fundamental patterns and correlations in the data.

section f) testing and training

A training set and a testing set were created from the dataset at random throughout the testing and training stages. The hybrid model was trained using historical observations of dissolved oxygen levels and accompanying feature values from the training set, which makes about 80% of the total data. Learning the underlying data patterns and improving the model parameters were part of this approach.

After the training was complete, the trained model was tested using the testing set, which included the remaining 20% of the data. The testing set was used to evaluate the model's generalizability and its capacity to correctly forecast dissolved oxygen levels in unseen data. It was an independent dataset.

One way to objectively assess the hybrid model's performance is to divide the dataset into training and testing subsets. This will allow us to see how well the model predicts dissolved oxygen levels and how well intensive aquaculture operations control water quality.

LightGBM-LSTM is one of the algorithms.

A hybrid model called LightGBM-LSTM combines the feature selection method LightGBM with the sequential data processing capabilities of the Long Short-Term Memory (LSTM) [17] neural network. It takes use of the best features of both algorithms to make better predictions. Dissolved oxygen level prediction in intensive aquaculture systems is achieved in this study by use of LightGBM-LSTM. A network trained to recognize temporal correlations in data is LSTM[17], whereas the LightGBM method chooses useful features from the dataset. The model's ability to include these two approaches allows it to catch intricate patterns in dissolved oxygen levels over time, which aids in the efficient control of water quality in aquaculture operations.

The LightGBM-GRU

Feature selection in LightGBM and sequence modeling in Gated Recurrent Unit (GRU) [9] come together in LightGBM-GRU, a hybrid model. Utilizing LightGBM, it chooses relevant features and uses GRU to capture temporal relationships in sequential data. The goal of this study is to forecast the amount of dissolved oxygen in systems that use intensive aquaculture by using LightGBM-GRU [9]. LightGBM aids in feature extraction from the dataset, while GRU handles the data's sequential nature. Improved forecasts and efficient water quality management in aquaculture settings are achieved by the model's integration of these two methodologies, which successfully capture temporal trends in dissolved oxygen levels.

Attention, LightGBM-BISRU

For the purpose of forecasting dissolved oxygen levels in intensive aquaculture situations, LightGBM-BISRU-Attention is a hybrid model. It blends LightGBM for feature selection, Attention mechanism for parameter changes, and Bidirectional Simple Recurrent Unit (BISRU) for bidirectional training optimization. The Attention mechanism makes real-time adjustments to the parameters, LightGBM finds the important features, and BISRU[25] improves bidirectional training to capture temporal relationships. This model is used in the project to improve the accuracy of dissolved oxygen forecasts. It does this by making good use of feature selection, bidirectional training, and parameter modifications. As a result, aquaculture systems may regulate water quality more efficiently.

Simple LightGBM-Bidirectional LSTM-GRU Reinforcement Learning with Attention

One all-inclusive hybrid model for predicting dissolved oxygen levels in intensive aquaculture is the LightGBM-Bidirectional LSTM-GRU-Simple RNN-Attention method. It uses LightGBM to pick features, Bidirectional LSTM and GRU layers to capture temporal dependencies in both directions, Simple RNN to model sequentially, and an attention technique to dynamically modify parameters. By using dynamic parameter modifications, bidirectional and sequential modeling, and feature selection, this model provides improved accuracy in dissolved oxygen prediction. In this research, it is used to better understand the dynamics of dissolved oxygen in aquaculture systems, which helps with managing water quality better and getting the most out of productivity.

V. EXPERIMENTAL RESULTS

MSE

The average squared difference between the actual values in a dataset and the projected values is measured by Mean Squared Error (MSE), a statistical metric. Averaging the squared differences between each actual value and its matching anticipated value yields this calculation. With lower numbers indicating higher performance, MSE gives a quantifiable assessment of a predictive model's overall accuracy. Regression analysis and machine learning rely on it heavily for evaluating model goodness-of-fit and comparing models' performance in terms of prediction accuracy.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

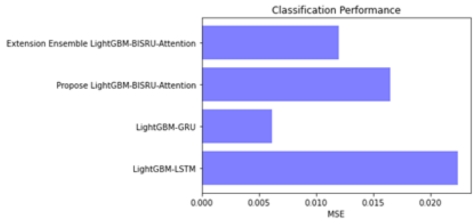


Fig 3 COMPARISON GRAPHS

RMSE

As a statistical metric, Root Mean Squared Error (RMSE) quantifies the typical size of discrepancies between a dataset's expected and observed values. To determine it, one must take the square root of the average of the squared discrepancies between the expected and observed values. RMSE is a more interpretable metric for predictive model accuracy than MSE as it is expressed in the same unit as the target variable. Regression analysis and machine learning often use RMSE as a measure of model performance; lower values imply improved predicted accuracy.

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}}$$

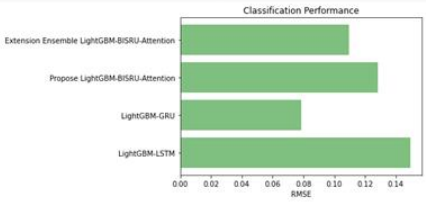
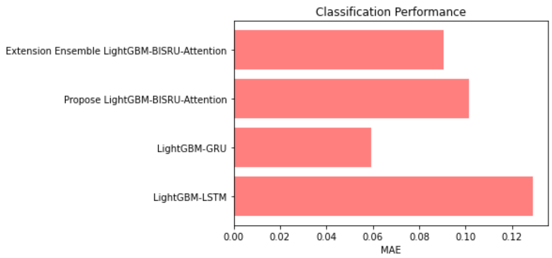


FIG 4 COMPARISON GRAPHS

MAE

One way to quantify the average size of discrepancies between expected and observed values in a dataset is by calculating the Mean Absolute Error (MAE). To determine it, we average the absolute discrepancies between the expected and actual values. By calculating the average absolute deviation of forecasts from the real values, MAE offers a simple way to evaluate a predictive model's accuracy. Although it does not square the errors, MAE is less affected by outliers than MSE and RMSE, two other error measures. Regression analysis and machine learning often use it to evaluate model performance; lower MAE values signify improved predicted accuracy.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$



	ML Model	MSE	RMSE	MAE
0	LightGBM-LSTM	0.022421	0.149737	0.129270
1	LightGBM-GRU	0.006148	0.078412	0.059561
2	Propose LightGBM-BISRU-Attention	0.016512	0.128499	0.101702
3	**Extension LightGBM- Bidirectional LSTM- GRU-Simple RNN-Attention**	**0.011986**	**0.109481**	**0.090655**

FIG 6 PERFORMANCE EVALUATION TABLE

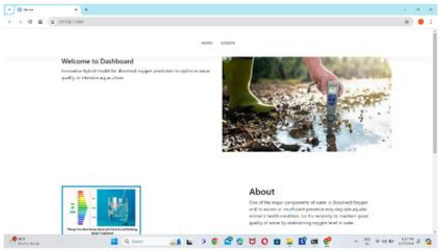


FIG 7 HOME PAGE

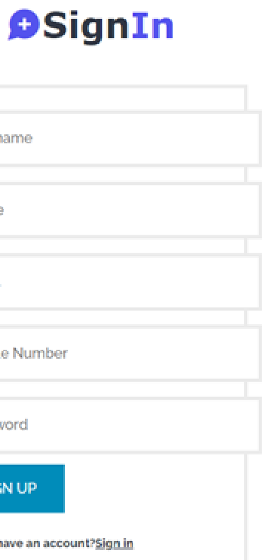


FIG 8 Sign Up

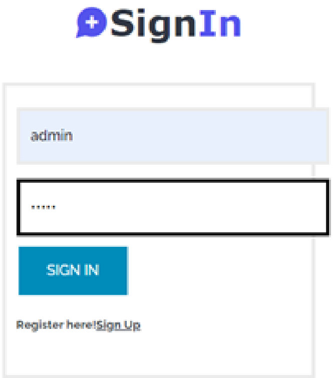


Fig 9 SIGN IN

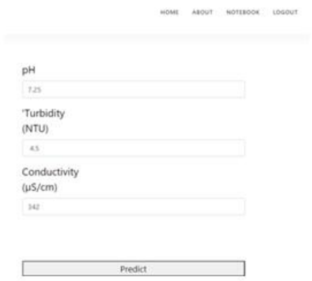


Fig 10 Upload Input Data

Fig 11 Predicted Result

VI. CONCLUSION

Finally, for very intense aquaculture systems, the suggested LightGBM-BISRU-Attention model is a huge step forward in terms of water quality prediction. The model improves the accuracy of dissolved oxygen predictions significantly by combining function updates with feature selection using Bidirectional Simple RNN and Attention. The hybrid technique is more accurate and efficient than variations like LightGBM+LSTM and LightGBM+GRU, according to the comparison. The effectiveness of ensemble approaches is further shown by the Ensemble model, which combines many algorithms to improve forecast accuracy. Flask with SQLite provides an intuitive testing interface for models, making it useful for academics, environmental organizations, and aquaculture businesses. Sustainable aquaculture techniques and environmental conservation efforts are bolstered by precise dissolved oxygen prediction. This, in turn, benefits populations that rely on aquatic food exports.

VII. FUTURE SCOPE

Numerous opportunities exist for further research and development in the field of dissolved oxygen prediction for effective control of water quality in intensive aquaculture. First, deep learning structures like transformers or attention mechanisms, together with other sophisticated machine learning approaches, might improve the efficiency and accuracy of predictions even more. Secondly, aquaculture systems can be better managed and monitored in real-time using data from internet of things (IoT) devices. This allows for more response to changing environmental circumstances. The model may be even more useful for holistic aquaculture management if it could anticipate not just dissolved oxygen but also pH, ammonia levels, and temperature, among other important water quality characteristics. To make sure the model works in different aquaculture environments, it's a good idea to work with environmental authorities and industry partners to come up with customized solutions and strategies for implementation. All things considered, intense aquaculture techniques may be made more effective and environmentally friendly with the help of ongoing research and new developments.

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