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RESEARCH ARTICLE

A Novel Hybrid Model to Predict Dissolved Oxygen for Efficient Water Quality in Intensive Aquaculture

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ABSTRACT Dissolved oxygen content is a key indicator of water quality in aquaculture environment. Because of its nonlinearity, dynamics, and complexity, which makes traditional methods face challenges in the accuracy and speed of dissolved oxygen content prediction. As a solution to these issues, this study introduces a hybrid model consisting of the Light Gradient Boosting Machine (LightGBM) and the Bidirectional Simple Recurrent Unit (BiSRU). Firstly, Linear interpolation and smoothing were used to identify significant parameters. LightGBM algorithm then determines the significance of dissolved oxygen by eliminating irrelevant variables and predicting dissolved oxygen in intensive aquaculture. Finally, the attention method was implemented to map the weighting and learning parameter matrices, so enabling the BiSRU's hidden states to be assigned different weights. The findings shown that the presented prediction model can accurately anticipate the fluctuating trend of dissolved oxygen over a 10-day period in just 122 seconds, and the accuracy rate reached 96.28%. Comparing the model effects of LightGBM-BiSRU,

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LightGBM - GRU, LightGBM-LSTM, and BiSRU - Attention takes the least time. Its higher prediction accuracy can provide an essential reference for intensive aquaculture water quality regulation.

INDEX TERMS Non-linear, LightGBM, BiSRU, attention mechanism.

I. INTRODUCTION

In terms of aquaculture production, China dominates the global stage; the nation is responsible for over 70% of the world's total. In 2021, China's aquaculture output was 53.88 million tons, accounting for 80.50% of the total aquatic product [1]. Because aquatic organisms perform a range of physiological activities in water, such as respiration, feeding, excretion and reproduction, the quality and production of aquatic goods are directly influenced by the water quality of an aquatic environment [2]. Dissolved oxygen (DO) is a key indication of water quality since it is essential to the survival of aquatic animals and is used by their metabolism [3]. Excessive or insufficient DO can affect the healthy growth of farmed fish, shrimp, and other organisms, easily resulting in disease outbreaks and even mass mortality, which would result in significant economic losses for business [4], [5]. For this reason, predicting dissolved oxygen concentrations and their trends in advance, regulating dissolved oxygen concentrations in a timely manner and ensuring healthy growth of aquatic products in a comfortable environment are important for preventing water quality deterioration, reducing the risk of aquaculture and the healthy and sustainable development of intensive aquaculture [6].

Many findings have been made as a consequence of extensive study on dissolved oxygen prediction models utilizing machine learning conducted by academics both domestically and overseas. For example, Liu introduced a forecasting model that integrates grey correlation degree, empirical wavelet transformations, and the particle swarm optimization gravity search technique. Experiments show that this model can more accurately analyze the trend of dissolved oxygen [7]; Ren used Variational Mode Decomposition (VMD) to segregate and denoise the original data before feeding the decomposed data into a Deep Belief Network (DBN) for prediction [8]. Cao utilized principal component analysis (PCA) to filter the essential elements that would affect the dissolved oxygen, then K-means clustering and GRU were employed to create the dissolved oxygen prediction model [9]; Shi suggested a dissolved oxygen prediction model based on clustering and an enhanced extreme learning technique [10] and Huang proposed hybrid model based on CEEMDAN-LZC and GOBLPSO to improve efficiency [11]. A novel model based on feature extraction was proposed, which improved predictive performance and provide accurate predictions for dissolved oxygen levels [12]. Nong proposes a dissolved oxygen prediction model based on support vector regression combined with multi-feature engineering and optimisation methods, and the implementation shows that the model can effectively improve the accuracy of the prediction model [13]. Although the above-mentioned dissolved oxygen prediction models can predict dissolved oxygen content at future moments, they are still inadequate in terms of speed of computation and the capture of global contextual information, make it challenging to fulfill the demand of accurate and fruitful aquaculture production.

The Bidirectional Simple Recurrent Unit (BiSRU) is a two-layer network structure with reverse stacking, which can acquire the past and the future information but also has a highly parallelized architecture. This network is capable of not only sequence modeling, but also improves the gradient disappearance problem, making BiSRU widely used in many fields. For example, Jie used a prediction method based on BiSRU to achieve high accuracy prediction for intrusion detection of industrial control systems [14]. Ding et al. used an intrusion detection model combining CNN and BiSRU to achieve accurate prediction of network intrusion [15]. Ding proposed an effective model for network security protection using BiSRU in conjunction with feature reduction for identifying anomalous traffic [16].

In Machine learning, data is processed using attention mechanism, which is used to determine contribution size between input and out data, making it applicable to a variety of disciplines. For example, Jiang proposed a combined LSTM, transformer and attention mechanism for indoor temperature prediction model, which achieves accurate and efficient prediction of room temperature trends [17]. Zhang integrated transformer model and multiple attention mechanism to develop an attention network framework based on Transformer Encoder, which effectively achieved accurate prediction of stock trends [18]. Mei presented a hybrid model based on CNN, GRU and attention mechanisms, in which different neuron weights can be adjusted by the attention layer to achieve accurate prediction of water quality [19]. Li proposed a dissolved oxygen prediction model combining stack structure, multi-attention mechanism and TCN, which can effectively improve the prediction accuracy of water quality parameters in Marine pastures and bring positive influence to the development of Marine fisheries [20]. Duan achieved effective prediction of tool wear status using a hybrid attention based on parallel deep learning [21]. Therefore, the drawbacks of conventional approaches may be addressed by including an attention mechanism into the model to concentrate on data that is more important to the present job among the numerous inputs by adaptively learning the proportion of weights.

In intensive aquaculture, there are complex biochemical reactions in the water column and complex mechanisms

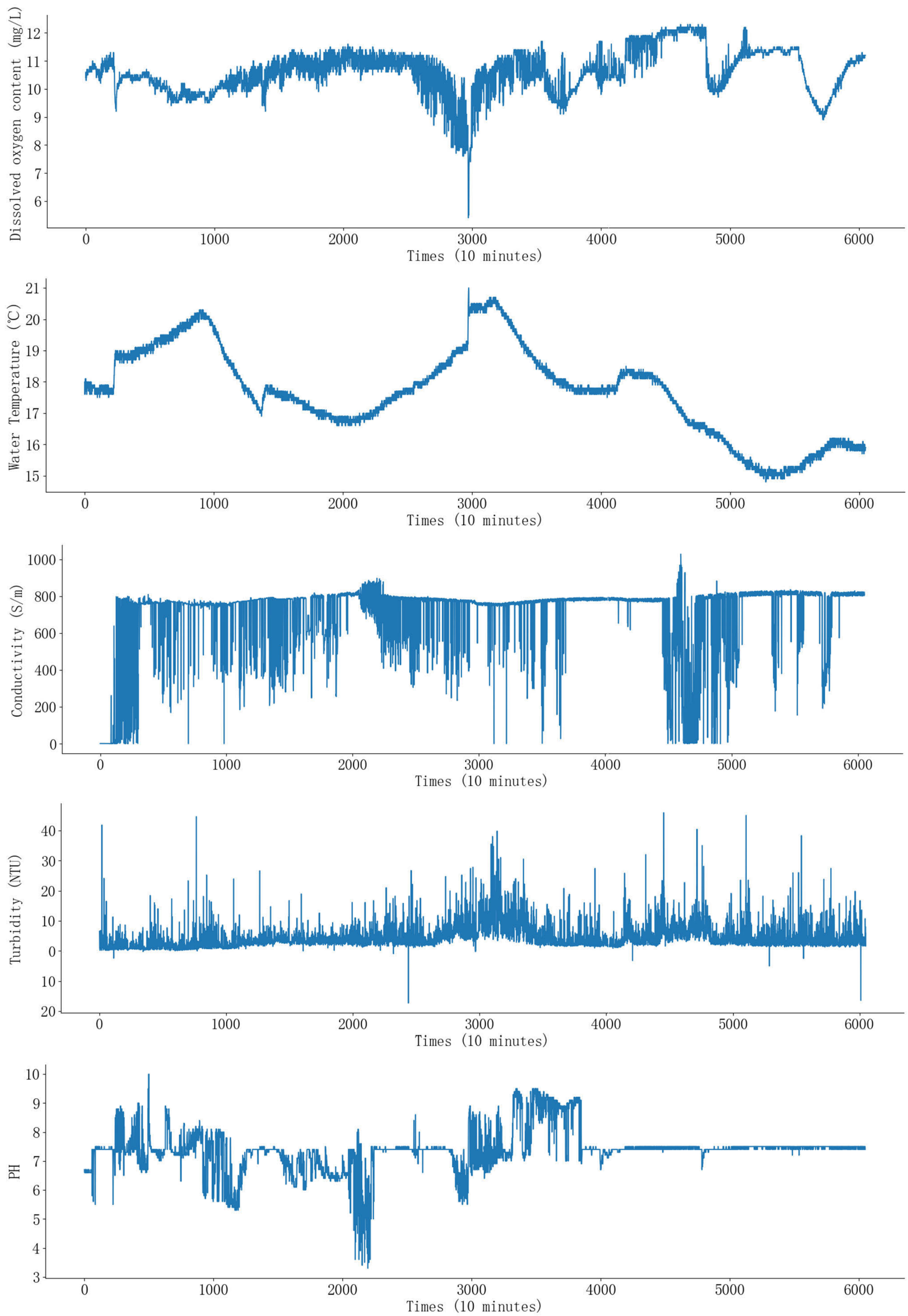

FIGURE 1. Raw data of water quality parameters of intensive aquaculture.

of action between the factors. The accuracy and computational complexity of dissolved oxygen prediction for water quality parameters in intensive aquaculture suffer by feeding the all factors into the dissolved oxygen prediction model,

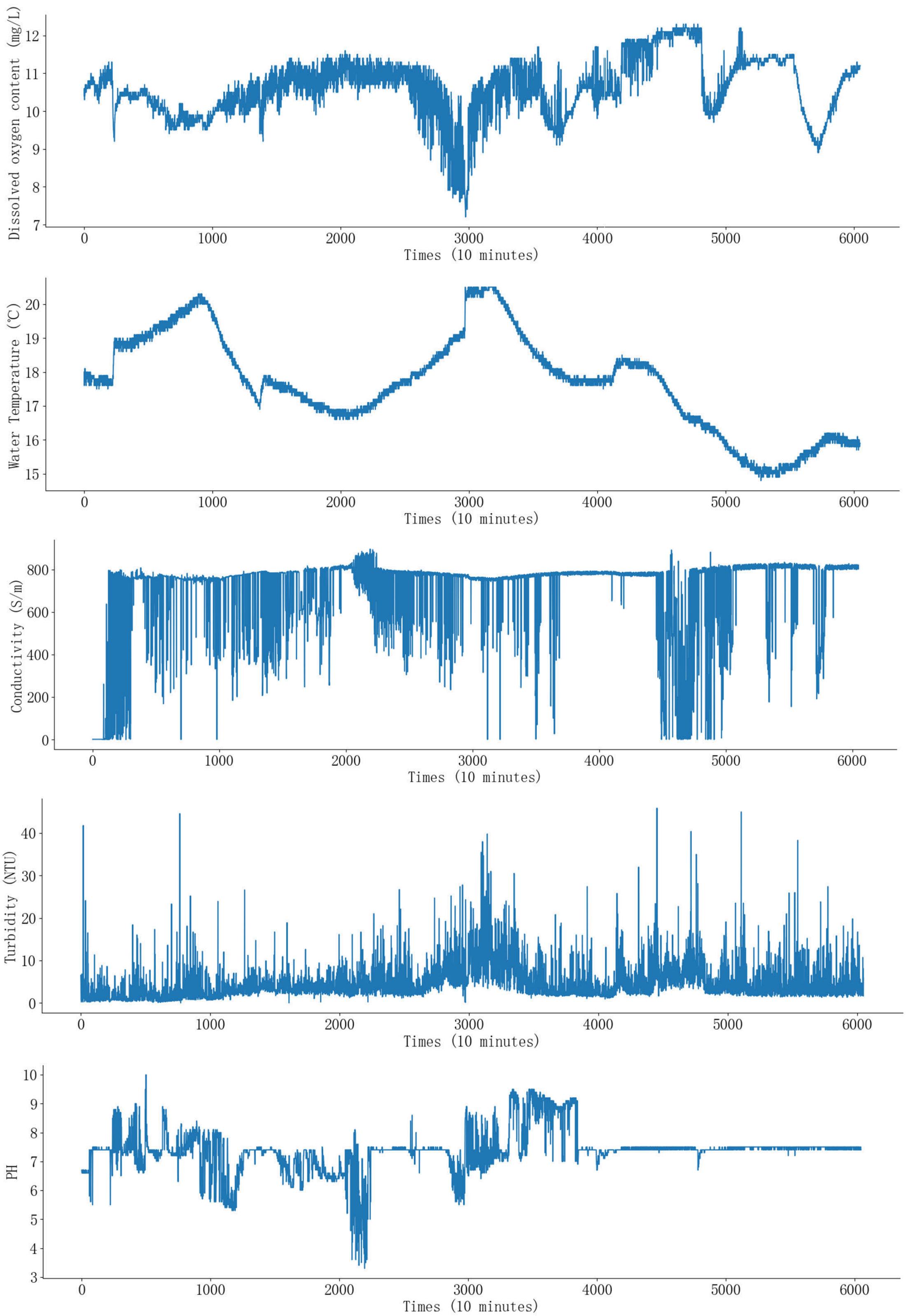

FIGURE 2. Raw data of water quality parameters of intensive aquaculture.

which leads to a complex prediction model network structure and redundancy or overlapping information. LightGBM is a tree-based boosting algorithm that can not only process data efficiently but also reduce memory consumption and

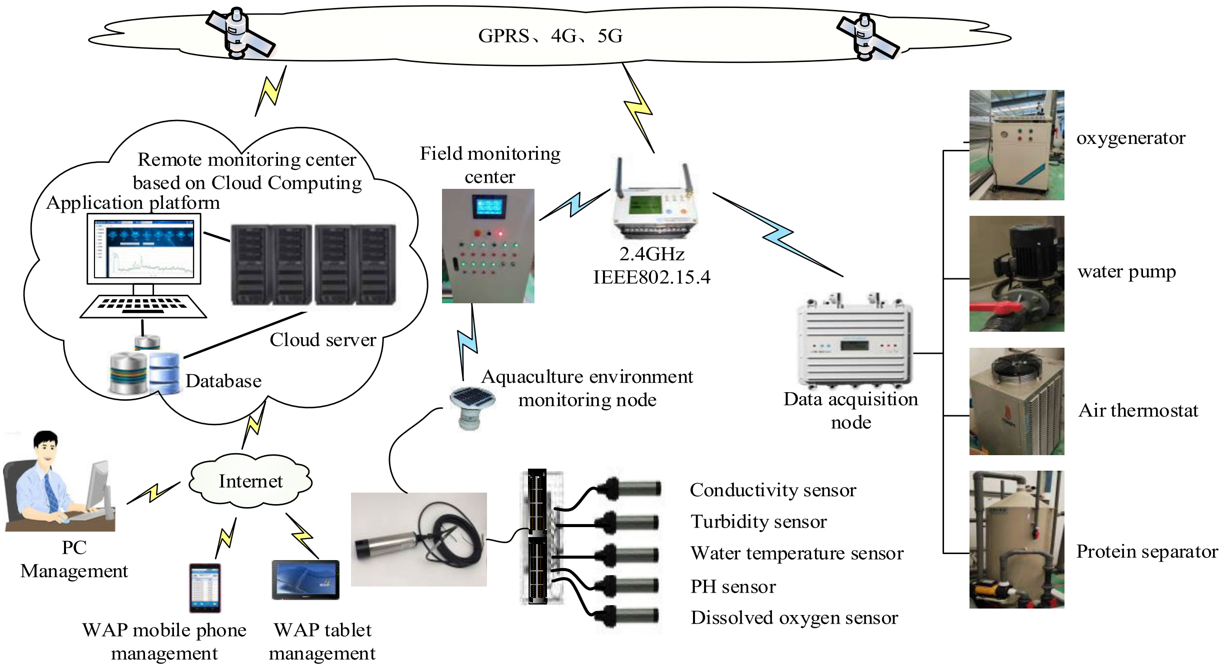

FIGURE 3. Internet of Things based real time monitoring system.

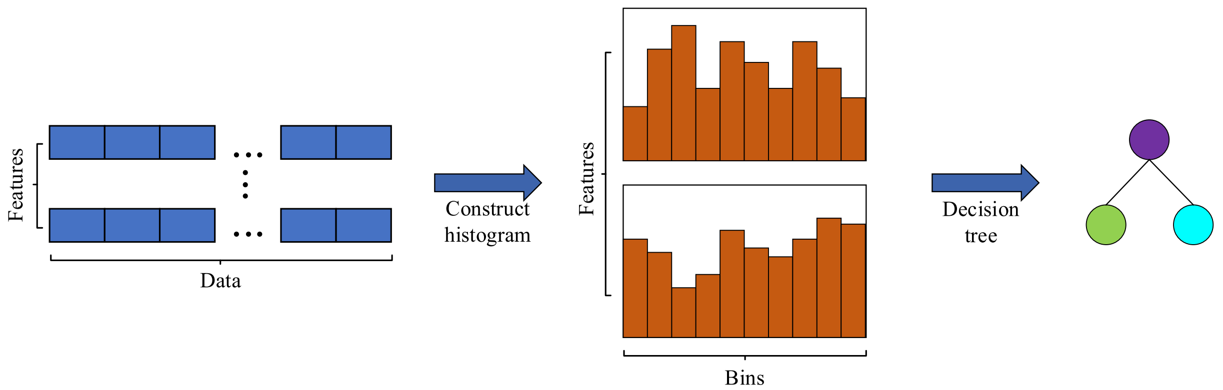

FIGURE 4. Histogram algorithm.

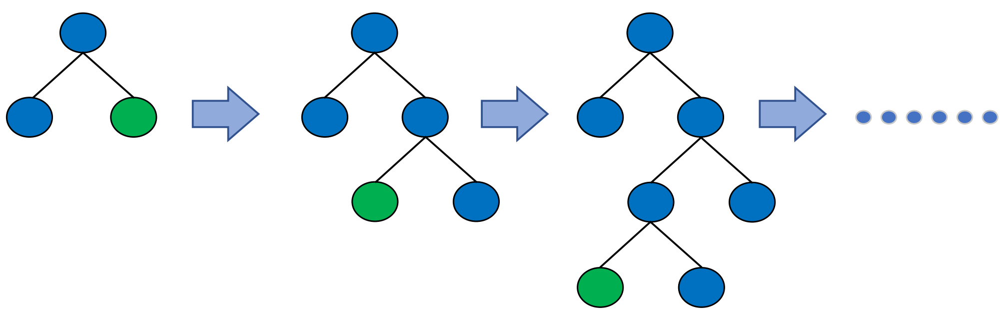

FIGURE 5. Growth of leaf-wise tree-based decision tree learning process.

significantly improve the speed of the algorithm in large sample applications. Wang et al. constructed LightGBM model for corporate financing risk prediction, which can effectively improve the accuracy of risk prediction [22]. Sun et al.

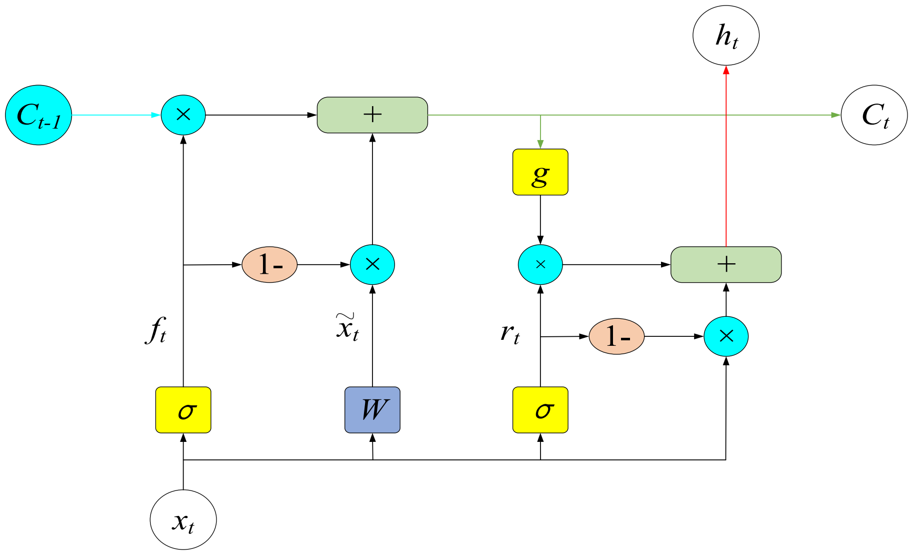

FIGURE 6. Detailed structure of SRU hidden layer.

adopted LightGBM to build a cryptocurrency price trend prediction model, effectively providing decision support for investors to invest in cryptocurrency [23]. Ren constructed a CNN-LSTM-LightGBM based attention mechanism for short-term wind power forecasting model, which achieves the accurate prediction [24].

This study proposed a hybrid model consist of a LightGBM (Light Gradient Boosting Machine), Bidirectional Simple Recurrent Unit (BiSRU), and Attention mechanism to overcome the limitations of traditional approaches for dissolved oxygen prediction. The LightGBM was used to identify the significant parameters affecting the dissolved oxygen concentration in intensive aquaculture. A nonlinear hybrid model was proposed by simplifying the network architecture using a bidirectional simple loop unit and an attention mechanism to predict of dissolved oxygen. The experimental results showed that the forecasting results of this model can provide technical support for the accurate control of water quality parameters in intensive aquaculture.

II. MATERIALS AND METHODS

A. DATASET AND PRE-PROCESSING

From December 7, 2020 to January 18, 2021, water quality sample data were collected for this research, which comprised five water quality indicators and a total of 6050 observation samples. Testing and training and testing dataset curve can be seen in Figure 1.

As a consequence of environmental factors during the data collection process, such as sensor aging or surface contamination, there is noise interference in the acquired data. Noise reduction processing must be applied to the original signal of the monitored water quality data in order to reduce noise and recover the actual signal as show in Figure 2. In the process of noise reduction, the abnormal data is filled with the mean smoothing method as shown in eq 1

$$x_m = \frac{x_{m-1} + x_{m+1}}{2} \tag{1}$$

where x_{m-1} and x_{m+1} are value at the $m-1$ and $m+1$ times, respectively, and x_m is the abnormal data at the m-th time.

Figures 1 and 2 demonstrate noise reduction is decreased successfully monitoring data for intensive aquaculture.

B. EXPERIMENTAL SETUP

The experimental environment include: processor i7-11800H, CPU frequency 2.3GHz, memory 16.0GB, Windows 10 (64-bit), python3.8 (64-bit), integrated development environment Anaconda3.

LightGBM initial parameters are: num_leaves are 1000, learning_rate is 0.2, feature_fraction is 0.8, bagging_fraction is 0.8, max-bin is 800, and boosting_type is gbdt.

C. MODEL PERFORMANCE METRICS

To evaluate the performance of the dissolved oxygen forecast model for intensive aquaculture water quality parameters, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Square Error (MSE) were selected as error evaluation indicators. The higher the value of these indicators converges to zero, the higher the prediction accuracy. The higher the value of the coefficient of determination R^2, the better the model fits the data. The specific formulae are shown in equations (2)-(5).

$$E_{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \sqrt{\hat{y}_i}\right)^2} \tag{2}$$

$$E_{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{3}$$

$$E_{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \tag{4}$$

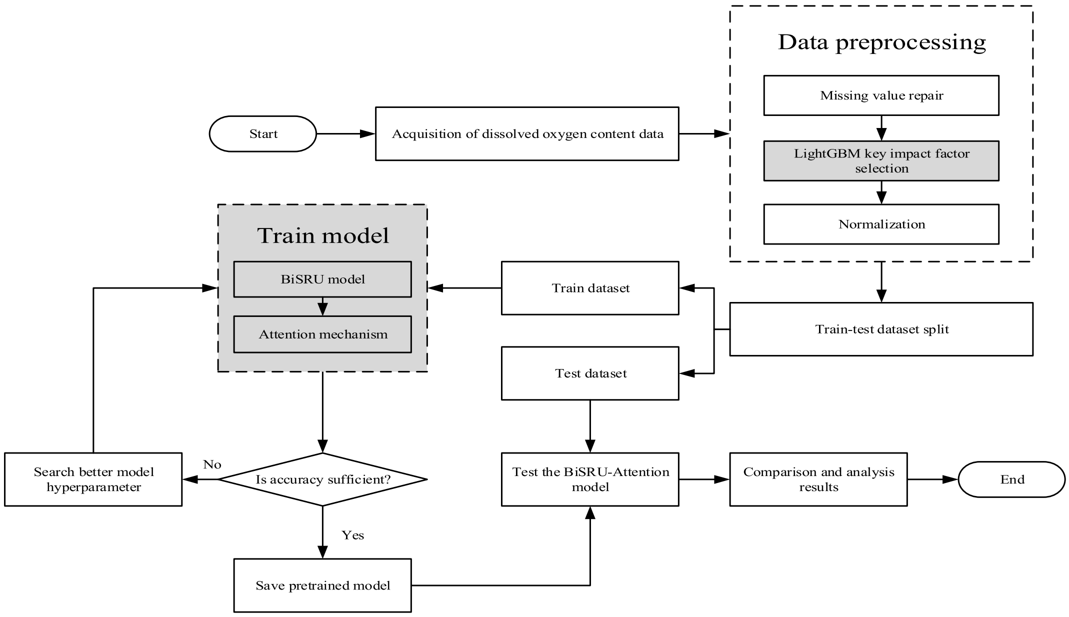

FIGURE 7. Structure of LightGBM-BiSRU-Attention network model.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}_i\right)^2} \quad (5)$$

where: is y_i the true value $\bar{y}$ of sample i ; is the mean value of the sequence of true values; is $\hat{y}_i$ the model predicted value of sample i ; N is the number of test sample sets.

D. DATA ACQUISITION

In this paper, a pond with a depth of 1.5 m and an area of 200 m^2 was selected in an aquaculture Dongchong Town, Nansha District, Guangzhou in China. The pond equipped modern aquaculture IOT based system for real time monitoring and data collection which includes: temperature, dissolved oxygen, ammonia nitrogen oxygen sensors, ultraviolet filters, aerators, and biological towers as shown in Figure 3. Data was collected after every 10 minutes and store it on the server for real-time viewing on the terminal through the IoT architecture.

E. LIGHT GRADIENT BOOSTING MACHINE (LIGHTGBM)

LightGBM uses a histogram-based algorithm and a leaf-by-leaf tree structure, which can effectively improve computational efficiency and reduce memory consumption [25] as show in in Figure 4. In XGBoost, the tree is grown using the level-wise growth strategy, and the level-wise algorithm searches and splits the leaves at each level, which has the problem of extra consumption and leads to inefficiency. For this reason, LightGBM is optimized with a leaf-wise algorithm that performs a deep leaf-by-leaf search and split, as shown in Figure 5. The depth-based leaf-wise algorithm can efficiently find nodes with small information gain and exclude them from selection, avoiding significant additional memory consumption [26].

TABLE 1. Feature importance of water quality parameters.

Name	Feature importance
PH	25.030687
Conductivity(S/m)	17.479757
Turbidity (NTU)	11.006372
Water Temperature (℃)	0.000000

F. SIMPLE RECURRENT UNIT (SRU)

Lei proposed Simple Recurrent Unit (SRU) to simplify parameters, parallel processing and increase the speed of model runs, and has been widely used in many fields [27]. When compared to conventional recurrent and acyclic designs, the SRU performs better since its gate computations are not dependent on those of prior time steps. The SRU architecture is shown in Figure 6.

Both the “forget gate” and the “memory unit” are essential components of the SRU. In order to fine-tune the memory device, forget gate was employed, which symbolizes for the significance of the preceding step to the current state. The memory component unit performs the calculations necessary to determine the final output state. In general, the parameter formulation of a single-layer SRU model is as follows:

$$\tilde{x}_t = W x x_t \quad (6)$$

TABLE 2. Error comparison of models.

Model	MSE	MAE	RMSE	R^2	T(s)
LightGBM-GRU	0.0033	0.0498	0.0578	0.7726	359
LightGBM-LSTM	0.0052	0.0633	0.0722	0.6348	824
BiSRU-Attention	0.0010	0.0238	0.0323	0.9359	277
LightGBM-BiSRU	0.0011	0.0244	0.0333	0.9352	102
LightGBM-BiSRU-Attention	0.0008	0.0199	0.0285	0.9628	122

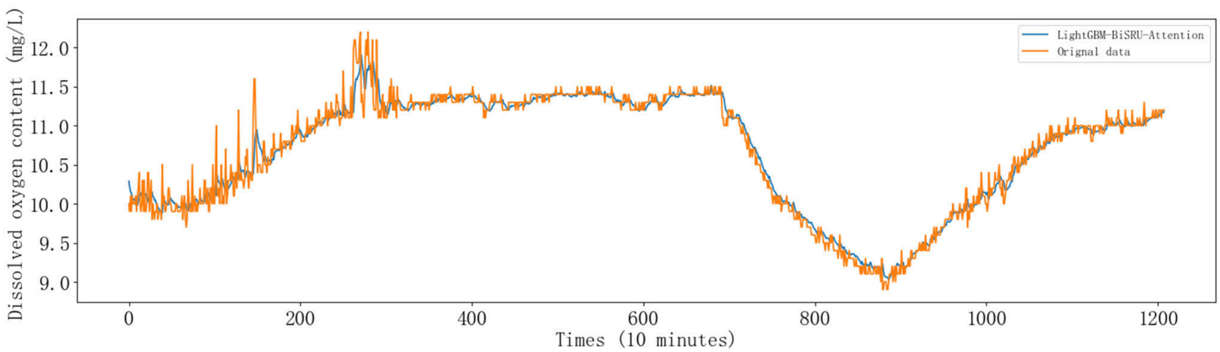

FIGURE 8. Proposed LightGBM-BiSRU-Attention model-based DO prediction.

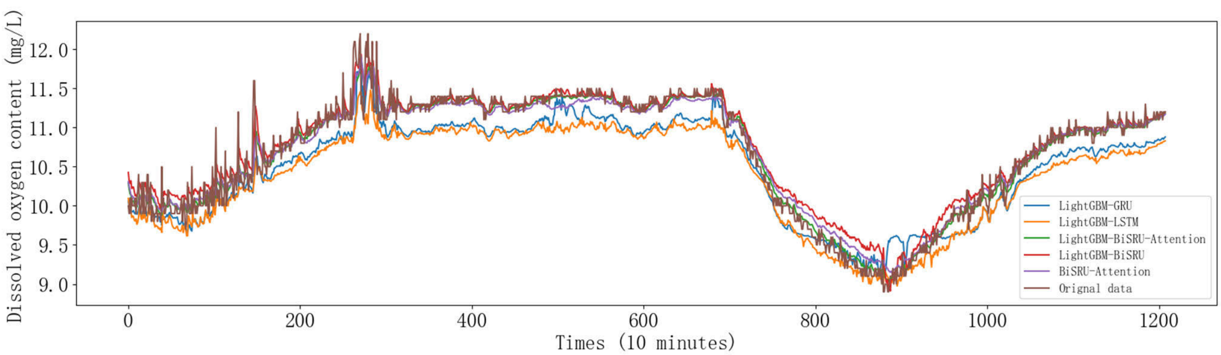

FIGURE 9. Proposed LightGBM-BiSRU-Attention model comparison.

$$f_t = \sigma\left(W_f x x_t + b_f\right) \tag{7}$$
$$r_t = \sigma\left(W_r x x_t + b_r\right) \tag{8}$$
$$C_t = f_t x C_{t-1} + \left(1 - f_t\right) x \tilde{x}_t \tag{9}$$
$$h_t = r_t x g\left(C_t\right) + \left(1 - r_t\right) x x_t \tag{10}$$

x_t is current moment input; $\tilde{x}_t$ is linear transformation at the current moment, f_t is the forget gate, r_t is the reset gate, c_t and h_t are memory unit and hidden layer state. w_r and w_f are reset and forget gate, respectively.

G. BIDIRECTIONAL SIMPLE RECURRENT UNIT (BISRU)

The BiSRU model improves on the standard time series model. The main concept is that the traditional model processes the actual sequence front to back rather than superimposing a forward and reverse SRU on the input signal and connecting the two SRUs toward an output unit. The traditional time series model is prone to problems such as gradient disappearance and poor training effectiveness [28]. Ling proposed a detection approach based on BiSRU to successfully address the aforementioned issues [29]. This model uses parallel computing to speed up model training, makes each time step independent of the one before it, employs skip connections to solve the gradient disappearance problem, and improves information capture about the time series' characteristics with respect to its positive and negative bi-directional structure. BiSRU is an improved version of

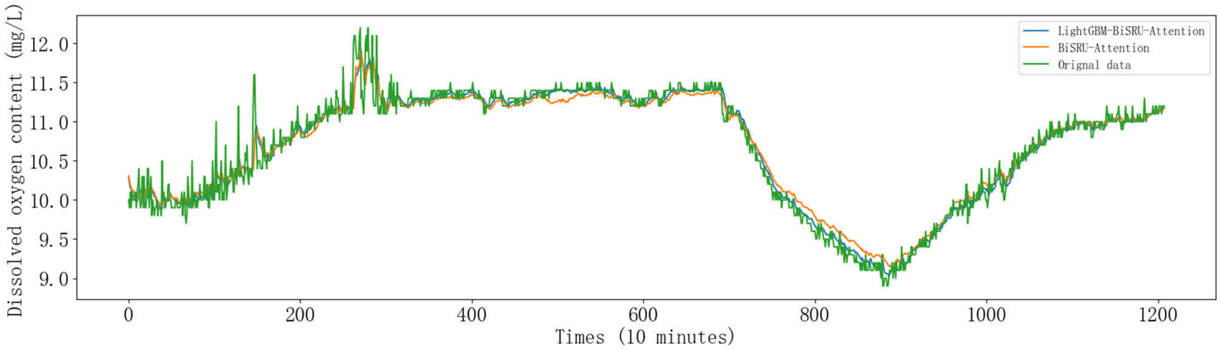

FIGURE 10. Comparison of BiSRU-Attention and LightGBM-BiSRU-Attention models.

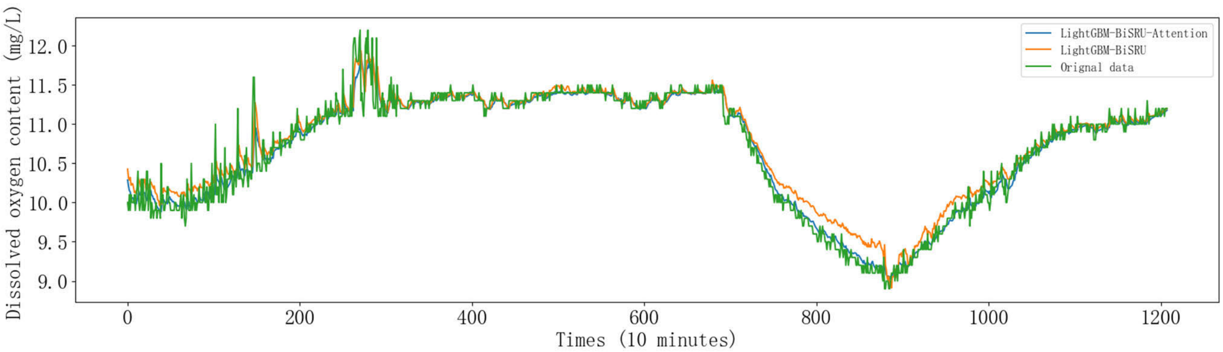

FIGURE 11. Comparison of LightGBM-BiSRUand LightGBM-BiSRU-Attention models.

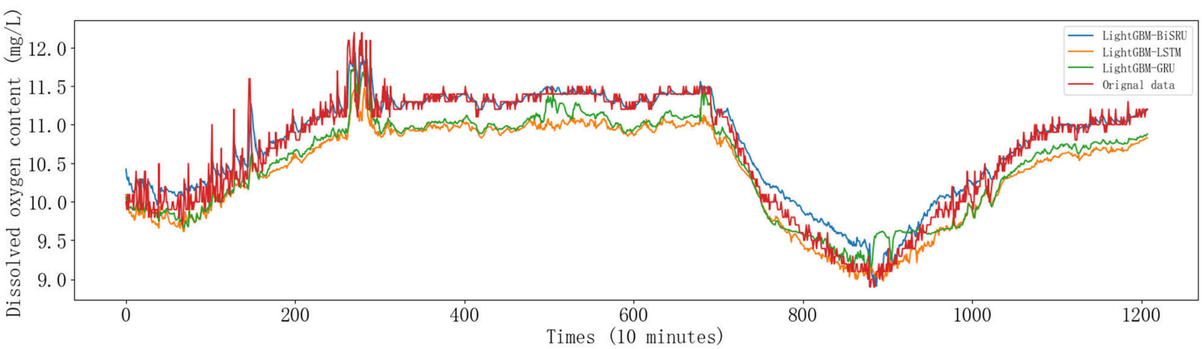

FIGURE 12. Comparison of LightGBM-BiSRU, LightGBM-LSTM and LightGBM-GRU models.

BiGRU that retains the modeling capabilities while using less computation (and hyperparameters) [30].

H. ATTENTION MECHANISM

Bahdanau et al. presented the Attention mechanism to overcome the issue that input data information cannot be completely collected, which simulates the resource allocation mechanism of human brain attention [31]. Attention, ignoring irrelevant information while amplifying desired information [32]. Exceptional achievements have been obtained in the domains of machine translation [33] and voice recognition [34] using attention mechanism. By calculating the correlation between the data, the attention mechanism gives different weights to different feature data. This makes it easier to find useful information in the input data and the target output than in the original data, brings out the most important features related to the prediction, and improves the quality of the output.

In the attention mechanism structure, X_t ($t \in [1, n]$) is the input to the BiSRU network, h_t ($t \in [1, n]$) represents to the hidden layer output obtained from each input BiSRU, and α_t ($t \in [1, n]$) is the attention probability distribution value of

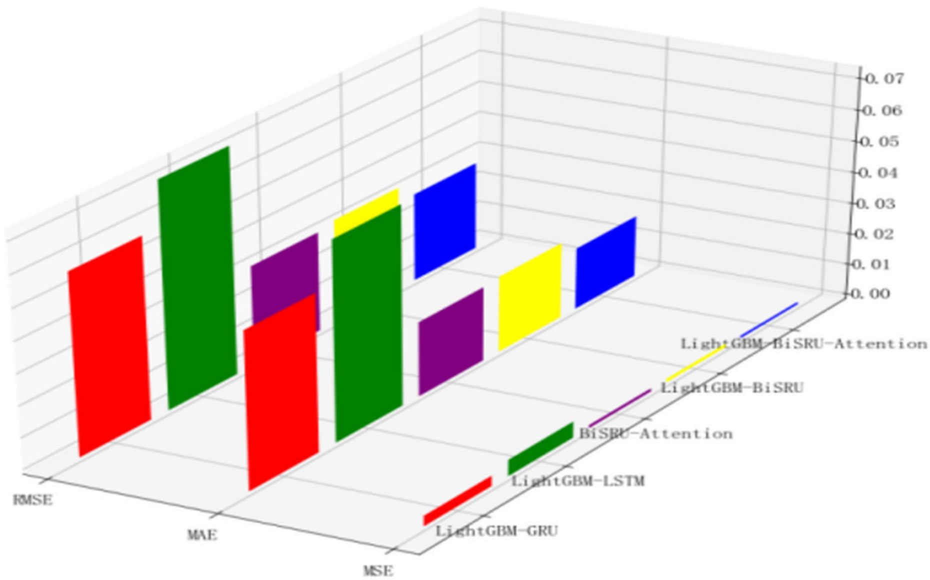

FIGURE 13. **Critical indexes-based model comparison.**

the BiSRU hidden layer output by the Attention mechanism, and y is the final output value of the Attention mechanism.

I. THE HYBRID FORECASTING MODEL BASED ON LIGHTGBM - BISRU - ATTENTION

LightGBM-BiSRU-Attention are organically integrated to construct a non-linear dissolved oxygen model for intensive aquaculture, which improves the performance of the dissolved oxygen prediction model. The basic ideas are: firstly, the dissolved oxygen data of intensive aquaculture are preprocessed, secondly, the structure of the BiSRU prediction model was simplified by using LightGBM to screen for key influences on water quality parameters dissolved oxygen. Subsequently, the prediction model of BiSRU-Attention was trained and predicted to obtain the final prediction results, which effectively improved the prediction accuracy of the combined model. Proposed non-linear hybrid prediction model is shown in Figure 7, and the specific steps are as follows.

Step 1: Collect water quality parameter dissolved oxygen time series data online through the Intensive Aquaculture Internet of Things (IoT) cloud platform and pre-process them.

Step 2: Screen of key influences on dissolved oxygen for water quality parameters in intensive aquaculture using LightGBM, eliminating multivariate redundant information and streamlining the prediction model structure.

Step 3: The split samples are the training and test datasets, and the best BiSRU-Attention prediction model is obtained by feeding the training dataset.

Step 4: Testing BiSRU-Attention and proposed LighGM-BISRU-Attention on data set by comparing the result to verify the result for proposed model prediction.

III. RESULTS AND DISCUSSION

Dissolved oxygen is influenced by various factors and has a complex mechanism of action. Suppose all parameters are directly input into the prediction model. In that case, it will easily lead to a complex model network structure and high computational complexity. Therefore, it is necessary to eliminate the multiple covariances, extract influencing key factors, and optimize the prediction model network structure to improve the prediction performance. LightGBM has an ability to screening key influencing factors. Therefore, this paper selected LightGBM to screen the key influencing factors of dissolved oxygen and obtained the contribution of each feature, as shown in Table 1. Among them, the first three influencing factors have a greater impact on dissolved oxygen, so the study screened the key influencing factors are acidity, conductivity, and turbidity, which were also unanimously approved by experts in the field of aquaculture, to construct the training and testing data set for dissolved oxygen prediction model.

The results of Proposed LightGBM-BiSRU-Attention model are shown in figure 8. The proposed LightGBM-BiSRU-Attention hybrid model is an innovative and useful technique for dissolved oxygen prediction, since it has a robust learning capacity and achieves high generalization performance.

The conventional LightGBM-GRU, LightGBM-LSTM, BiSRU-Attention, and LightGBM-BiSRU were chosen for comparison analysis based on the identical original data to analyze the performance of the LightGBM-BiSRU-Attention. Figure 9 and Table 2 respectively provide the fitting curve comparison graphs and the prediction performance comparison data of their five models.

The non-linear hybrid LightGBM-BiSRU-Attention model proposed in this paper was compared with the standard LightGBM-GRU model, LightGBM-LSTM model, BiSRU-Attentionmodel and LightGBM-BiSRU model, which shows the better prediction effect.

Figure 10 illustrates the BiSRU-Attention model's prediction findings, which were obtained without applying the key factor screening method and trained using data on intensive aquaculture water quality, had anticipated values that differed considerably from the actual measured values. Table 2 shows that when comparing LightGBM-BiSRU-Attention with BiSRU-Attention under the identical circumstances, the evaluation metrics MSE, MAE, and RMSE dropped by 0.02%, 0.39%, and 0.38%. While R^2 rose 2.69%. It is confirmed that the underlying model's performance and prediction accuracy can be significantly enhanced by the LightGBM approach employed in this article.

Figure 11 shows that the LightGBM-BiSRU-Attention model provides a better match than the LightGBM-BiSRU model when comparing anticipated outcomes. Table 2 shows that when comparing LightGBM-BiSRU-Attention to LightGBM-BiSRU, the evaluation metrics MSE,MAE, and RMSE all improve by 0.03%, 0.45%, and 0.48%, respectively, while R^2 improves by 2.76%. This exemplifies how incorporating an attention mechanism into a model may improve its output quality and boost its overall performance, bringing with it time and cost savings. The model is slower than the LightGBM-BiSRU model but quicker than the comparative models because of the attention mechanism's inclusion in the whole.

In Figure 12, we can see that the LightGBM-BiSRU-based model provides the best fit, while the LightGBM-LSTM-based model deviates the most from the actual value. Table 2 shows that both LightGBM-GRU and LightGBM-LSTM improved upon the baseline in terms of MSE (0.19%), MAE (1.35%), RMSE (1.44%), and T (465.0 s), whereas R^2 (13.78%) was higher in both cases. Based on these results, it seems that GRU is superior than LSTM in terms of prediction accuracy even when using a smaller sample size. Due to the fact that LSTM has three distinct gate structures whereas GRU only contains two, LightGBM-LSTM has extra gate than the LightGBM-GRU, along with a more complicated structure and additional parameters. Therefore, the LightGBM-GRU-based prediction model outperforms the LSTM-based in terms of accuracy and processing speed. The error indicators as: MSE, MAE, RMSE, and time to complete a task are all improved by 0.22%, 2.54%, 2.45%, and 257 seconds, respectively, using lightGBM-BiSRU, while R^2 is increased by 16.26%. BiSRU's improved performance in dissolved oxygen prediction may be attributed to its bidirectional structure, which collects all relevant data, as well as its greater memory capacity and enhanced time series prediction capabilities when compared to GRU.

The proposed model has the minimum error, as seen more clearly in Figure 13's three-dimensional representation of the assessment metrics for the prediction models. As a whole, the LightGBM-BiSRU-Attention model, which incorporates all of the components of LightGBM, BiSRU, and Attention, is superior for serial prediction of the water quality parameter dissolved oxygen in high-density aquaculture.

IV. CONCLUSION AND FUTURE WORK

This study contributes as follows:

1. The data is preprocessed and filled using linear interpolation, and smoothing corrects anomalous data to improve prediction accuracy.
2. LightGBM was used to assess the degree of other water quality parameters on dissolved oxygen, taking into consideration their correlation strength.
3. A hybrid dissolved oxygen prediction model (LightGBM - BiSRU - Attention) is proposed. The bidirectional structure (BiSRU bidirectional simple recurrent unit) is used to transform the upcoming information into current time point prediction, select the key points via the attention mechanism which enables accurate prediction of dissolved oxygen.

A new hybrid model (LightGBM-BiSRU-Attention) is proposed in this paper to address the issues of slow operation speed, complex network structure, and insufficient capture of global contextual information for dissolved oxygen prediction of non-linear and non-smooth intensive aquaculture water quality parameters directly by traditional dissolved oxygen prediction methods. The LightGBM-BiSRU-Attention model was constructed by integrating the three LightGBM, BiSRU, and Attention approaches. The results clearly show that when RMSE, MAE, MSE, and R^2 are used, the proposed method outperforms LightGBM-GRU, LightGBM-LSTM, BiSRU-Attention, and LightGBM-BiSRU. In current intensive aquaculture, the hybrid technique of LightGBM-BiSRU-Attention has higher predictive performance and is an excellent predictive method for predicting dissolved oxygen time series.

This study has certain limitations and requires more investigation. In the future, it is planned to investigate advanced algorithms such as: the bat algorithm, particle swarm optimization algorithm, and swarm spider optimization, can be combined with BiSRU for more accurate and efficient prediction of dissolved oxygen levels and further improve prediction capability. All figures and tables should be cited in the main text as Figure 3, Table 1, etc.

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