International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8103
***Article Received:** 22 June 2023 **Revised:** 20 August 2023 **Accepted:** 04 September 2023*

Adaptive Grey Wolf Optimization Technique for Stock Index Price Prediction on Recurring Neural Network Variants

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Abstract— In this paper, we propose a Long short-term memory (LSTM) and Adaptive Grey Wolf Optimization (GWO)--based hybrid model for predicting the stock prices of the Major Indian stock indices, i.e., Sensex. The LSTM is an advanced neural network that handles uncertain, nonlinear, and sequential data. The challenges are its weight and bias optimization. The classical backpropagation has issues of dangling on local minima or overfitting the dataset. Thus, we propose a GWO-based hybrid approach to evolve the weights and biases of the LSTM and the dense layers. We have made the GWO more robust by introducing an approach to improve the best possible solution by using the optimal ranking of the wolves. The proposed model combines the GWO with Adam Optimizer to train the LSTM. Apart from the LSTM, we have also implemented the Adaptive GWO on other variants of Recurring Neural Networks (RNN) like LSTM, Bi-Directional LSTM, Gated Recurrent Units (GRU), and Bi-Directional GRU and computed the corresponding results. The Adaptive GWO here evolves the initial weights and biases of the above-discussed neural networks. In this research, we have also compared the forecasting efficiency of our proposed work with a particle-warm optimization (PSO) based hybrid LSTM model, simple Grey-wolf Optimization (GWO), and Adaptive PSO. According to the experimental findings, the suggested model has effectively used the best initial weights, and its results are the best overall.

Keywords- Optimization, Recurrent Neural Network, Grey Wolf Optimization.

I. INTRODUCTION

Stock price prediction is essential to many traders and the public. You can make or lose a lot of money by doing business. Algorithmic forecasting and models can be used to apply future predictions to historical data. Predicting the future is always difficult for many to learn about. This type of forecast is more attractive regarding risks such as economic and market sentiment. Researchers are investigating economic forecasting in many fields, including computer science and economics. Researchers have tried many methods to forecast the market, including different strategies, algorithms, and combinations of indicators. The qualifications required to build a forecasting model depend on what the market can trust. Short-term transformation (LSTM) is one of many RNN models. LSTM replaces traditional artefacts in the most valuable layers. With memory cells in place, the network can better correlate memory over time with long-term devices, so it pays to understand how to build robust information with strong predictive power. Every day, many types of research are carried out on stock price prediction using different data such as newspaper, Twitter data, Google, and Wikipedia data and different designs. All these external processes, together with the prices of the products and the products displayed, show that they impact the prices of the products. Improving the accuracy of commodity prices is an unresolved problem in today's society. Time series data is from behavior in social sciences, finance, physics, engineering, and economics. Such complexities make it very difficult to estimate costs. The primary purpose of estimating a time series is to simulate future results based on past results.

In most cases, the relationship between past and future knowledge could be more precise, equivalent to presenting a division of events by vision location. The combination of statistical models and learning has recently developed many machines and deep learning techniques, such as non-critical neural networks, regression trees based on gradients, support vector machines, and stochastic prediction models [1]. These algorithms can help understand complex nonlinear patterns and some relationships that are difficult to define with classical algorithms. The discussed algorithms have also proved their efficiency compared to the classical linear algorithms. Currently, many researchers are working on machine learning to use financial resources; some use tree models to predict profitable returns [2], and others use deep learning to create future value of financial assets.

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Additionally, some authors describe recovery estimation using the AdaBoost algorithm [3]. Others still use custom decision models to predict stock returns in day trading markets, and the authors have developed models that use the multivariate (MV) approach alongside the support vector machines (SVM) approach for selecting financial portfolios. Another article discusses some deep learning approaches for innovative measurement [4]. Additionally, many studies involve multiple models and machine learning techniques in finance; the literature reviewed in this article includes yield forecasting, ethics, deception, decision-making, linguistics, and dynamic analysis. This model is not based on the long run (transmission of data links), and in this case, the class of machine learning algorithms based on random connections has proven helpful in business finance and forecasting. An article compares the accuracy of the LSTM and the Autoregressive Integrated Moving Average (ARIMA) when used over time series data. This method was performed on financial data, showing that LSTM far exceeds ARIMA's performance [5]. Our article focuses on estimating the repair costs of real estate using LSTM RNN based on ML algorithms. Our goal is to find the most optimal algorithm for the prediction of stock prices. Since Adam does not converge locally, it is clear that the optimization of ANN weights and deviations depends on their initial values [6]. If the first value is in the local search area, the network will dangle around the local area. This problem is tackled using global search techniques for training neural networks. First, PSO is used to reduce the search space and find the optimal weights and bias of the hybrid neural network, and then use the weight and deviation as initial parameters of the LSTM neural network. In PSO, the inertia factor controls the balance between searching and using objects to prevent early interception [7]. In this study, [8] introduced a concept to improve the time-dependent coefficient of inertia to improve the search and development of PSO and achieve good results. They [9] proposed a modified PSO where different inertia coefficients are assigned to objects according to their class.

II. LITERATURE REVIEW

Stock price time series prediction is a complex research area, as many unknown factors are associated with stock price movements. In recent years, machine learning ([10], [11]) and deep learning ([12], [13]) methods based on meta-heuristic optimization techniques ([14]) have gained popularity in the estimation and optimization of time series-based data. In research ([15]), a review of cognitive-based cost estimation models was done and examined whether neural network models were widely accepted. [16] Here, they performed a comprehensive analysis focusing on deep learning and analytics-based cost estimation models. They found that hybrid models based on LSTM are the most widely used models for time series estimation. [17] In research, the potential of LSTM for working on time-series-based data was reviewed. The researchers concluded that LSTM models are adequate for processing time tasks and suitable for problem-solving. A comprehensive review of hybrid models as an optimization method for tuning the hyper-parameters of various neural networks has been shown in a study [18]. They showed that the hybrid ANN model is flexible and effective in data analysis. In a recent study, [19] developed a new PSO named PSO of Gravity (PSOCoG) for selecting the optimal hyper-parameters for ANNs and evaluating the proposed cost estimation related to the COVID-19 outbreak [20] using the Convolutional Neural Network and LSTM, and one is a shallow neural network model. Multi-Person Perceptron and Random Forest to predict noticeable changes in the Closing Price of stock indexes. As expected, the experiment's results confirm that the deep learning model is more efficient and reach more accurate result than machine learning models. Here, they [21] developed a model with modified PSO in combination with LSTM. The modified PSO helped to optimize the LSTM hyper-parameters, thus creating a model for stock price prediction. The modified PSO was an improved PSO algorithm with improved inertia weights. The inertia weights are improved using nonlinear methods. Thus, the modified PSO was utilized to choose the optimal parameters like the number of epochs, hidden layers, etc. Here, the researchers [22] used the Fly Optimization Algorithm to select the optimal weights of LSTMs for time series-based data. The hyper-parameters considered here were batch size, window length, and number of hidden layers, epochs, and hidden neurons. A study [23] proposes a combination of variational mode decomposition, genetic algorithm, LSTM, and neural network based on backpropagation. Here, the time series is split based on long and short terms; after that, a genetic algorithm is used to reduce the loss, and the processed data is fed to LSTM for final prediction. [24] Here, they combined Empirical Wavelet Transform (EWT), Outlier Robust Extreme Learning Machine (ORELM), and deep learning-based models. The EWT and ORLEM were techniques used for the pre- and post-processing of economic time. The broadcast rule was used to improve the training process. PSO was used to determine the best hyper-parameters, like epochs and total hidden layers for the LSTM. In a study, the researchers [25] developed a deep learning method combining GA and LSTM networks to find the optimal window length for business forecast copy stock. They found that the proposed model is better than the standard model. In a study, the researchers [26] integrated theory and analysis and combined ABC with LSTM to develop a hybrid model for estimating time data. ABC is used to determine the optimal LSTM parameters like epochs, total hidden layers, and throughput rate and to estimate the truth. In a paper, researchers [27] reported a hybrid model to predict two major stocks by

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combining a machine learning environment (ELM) with advanced Harris hawk optimization (IHHO). This paper used IHHO for optimizing the ELM. [28] They use a hybrid method that includes ANNs and grey wolf optimization (GWO). Here, the researchers use GWO to correct the inaccuracy of the network to predict stock prices over time. Here, they [15] proposed an ANN model coupled with evolutionary algorithms combining PSO for optimization, principal component analysis for dimension reduction, and a feed-forward neural (FFNN) network to predict the closing value of the product market using various technical indicators. Here, PCA was used for reducing the size; The PSO was used to find the optimal weights and deviations for the FFNN, and the results were obtained.

III. METHODOLOGY

This paper will present a deep-learning model for stock index price prediction. The deep learning framework would have a four-phase development process to achieve a GWO-based hybrid deep learning model. Initially, we will discuss the technical indicators used for stock price prediction. We have to perform data normalization to narrow the technical indicators' range.

The second step is to use GWO to find the initial weights and biases of the LSTM and the FCL networks in the DNN. In the next step, we allocate the optimal weights and biases obtained from the above process to train an LSTM with an Adam optimizer. The final phase consists of evaluating the performance of the created model on four evaluation metrics and presenting the final results.

A. Technical Indicators and Pre-Processing.

The stock market has various measures to define a stock. The technical indicators are measures created using the daily Open, High, Low, and Close (OHLC) stock market data. The OHLC stock market data combines various data: open price, low price, high price, closing price, and volume. We have considered various technical indicators in the study of this paper from the research [15].

B. Dataset and Data Normalization

In our research, we have used the Yahoo Finance Python library to download the BOMBAY STOCK EXCHANGE index data from 1 January 2013 to 1 January 2023.

The Python package used is ‘yfinance’.

We use the Min- Max normalization to convert the data values in a short range.

$$x^* = \left(\frac{x - X_{min}}{X_{max} - X_{min}}\right)(X^*_{max} - X^*_{min}) + X^*_{min}$$

x^* = The normalized value of x in a given range $[X^*_{min}, X^*_{max}]$ from a range $[X_{min}, X_{max}]$

x = The given value in a range $[X_{min}, X_{max}]$

X^*_{min} = Lower bound of the given range of values

X_{max} = Upper bound of the given range of values

X^*_{max} = Upper bound of the desired range of values

X^*_{min} = Lower bound of the desired range of values

C. Long Short Term Memory (LSTM) and Other RNN Variants

The LSTM neural network was developed by Hochreiter and Schmidhuber in 1997 [29]. LSTM is a variation of RNN with memory cells and gated units. The memory cells and gated units help LSTM capture the long-term dependencies in time-series-based sequential data [30]. Unlike the RNN network, LSTM networks can deal with vanishing gradient descent problems. The vanishing gradient prevents RNN from capturing the long-term dependencies in the sequential time series-based data [29]. The LSTM network can tackle the problem by selectively dealing with information, i.e., reading, writing, and forgetting the data so that only necessary information is stored in the memory cells.

The GRU is an improvement over the traditional RNN architecture, specifically designed to address the vanishing gradient problem, a common issue in training deep neural networks. In the vanishing gradient problem, the gradients used to update the network's parameters diminish exponentially over time, leading to slow or ineffective learning.

The GRU introduces the concept of "gates" to control the flow of information within the network. It consists of two main gates: the update and reset gates. The update gate determines how much of the previous hidden state should be retained and how much new information should be added to the current state. When computing the current state, the reset gate decides how much of the previous state should be forgotten.

D. Proposed Adaptive GWO-LSTM

In this work, we aim to optimize the weights and bias of LSTM and FCL by applying Adaptive Grey Wolf Optimization (GWO). Seyedali [31] introduced GWO, a meta-heuristic algorithm inspired by the social behavior of grey wolves. GWO stands for Grey Wolf Optimization. It is a meta-heuristic algorithm inspired by the social behavior of grey wolves. The GWO algorithm is based on the hunting behavior and hierarchical structure of grey wolves in the wild. It mimics the leadership hierarchy among the wolves, where an alpha wolf leads the pack, followed by beta, delta, and omega wolves. In

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the GWO algorithm, a population of candidate solutions, called a "pack," is initialized. The alpha, beta, delta, and omega wolves represent the best solutions in the search space.

During the optimization process, the wolves collaborate and communicate by sharing information about the best solutions discovered so far. This collaboration allows the algorithm to explore the search space efficiently and converge towards optimal or near-optimal solutions.

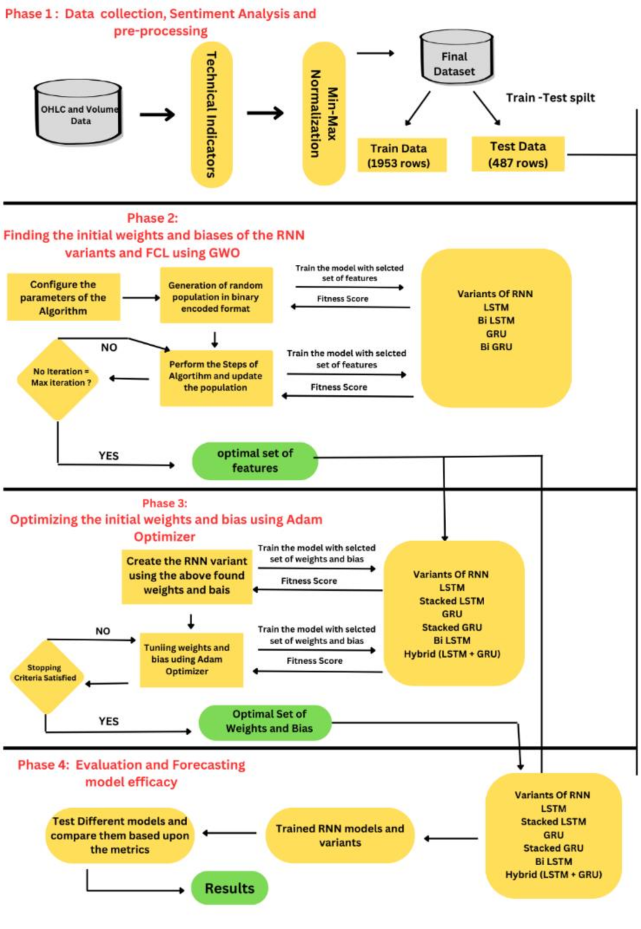

Fig. 1 – Flowchart of Research

In designing the LSTM, we can consider various hyper-parameters. Here, in our proposed model, we have used an LSTM network consisting of one hidden layer. The GWO here is used to find the initial weights and biases of the various LSTM parameters like the forget gate, solution vector, and the output gate of LSTM. We have also evolved the weights and biases of the FCL and output layer.

The population-based metaheuristic algorithm known as Grey Wolf Optimization (GWO) was motivated by the natural hunting methods of grey wolves. It was proposed in 2014[31]. GWO solves optimization problems by simulating grey wolves' social hierarchy and hunting patterns. The Fig 2 is a clear depiction of the grey wolf optimization. Here is a detailed description of the Grey Wolf Optimization algorithm, along with the steps involved:

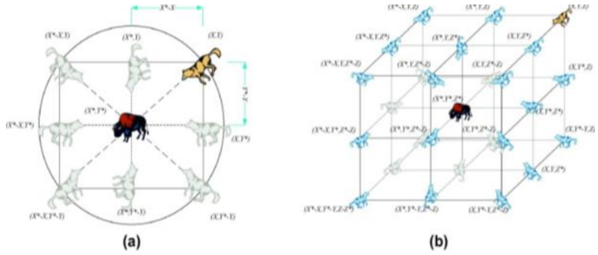

Fig 2 – Grey Wolf Optimization [31]

Step 1: Initialization

- Define the population size (number of wolves) and the maximum number of iterations.
- Generate an initial population of grey wolves randomly within the search space.
- Each wolf's position represents a candidate solution to the optimization problem.

Step 2: Fitness Evaluation

- Evaluate the fitness of each wolf in the population using the objective function.
- The objective function represents the optimized problem and assigns a numerical value to each candidate solution based on quality.

Step 3: Dominance Ranking

- Rank the wolves based on their fitness values in ascending order.
- Assign the alpha, beta, and delta positions to the top three wolves, representing the pack's leaders.
- Alpha: The best wolf with the highest fitness value.
- Beta: The second-best wolf.
- Delta: The third-best wolf.

Step 4: Update the Positions of the Wolves

- Update the positions of all the wolves in the population using the following formulas:

  For each dimension d of a wolf's position:

- Update the position of the alpha wolf:

$$X\_alpha(d) = X\_alpha(d) - A * D\_alpha(d)$$

- Update the position of the beta wolf:

$$X\_beta(d) = X\_beta(d) - A * D\_beta(d)$$

- Update the position of the delta wolf:

$$X\_delta(d) = X\_delta(d) - A * D\_delt\ a(d)$$

- Update the position of the rest of the wolves:

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$$X\_i(d) = (X\_alpha(d) + X\_beta(d) + X\_delta(d)) / 3 - A * D\_i(d)$$

In the above formulas, X represents the position of a wolf, A is a coefficient controlling the step size, and D represents the distance vectors between a wolf and the alpha(α), beta(β), or delta(δ) wolves.

Step 5: Boundary Handling

- Check if any wolves have moved outside the search space boundaries.
- If a wolf is out of bounds, bring it back within the valid range by adjusting its position or applying suitable boundary-handling techniques.

Step 6: Fitness Re-evaluation

- Evaluate the fitness of the updated positions for all wolves.

Step 7: Dominance Ranking and Leader Update

- Perform dominance ranking again to determine the new alpha(α), beta(β), and delta(δ) wolves according to their updated fitness values.
- Update the alpha(α), beta(β), and delta(δ) positions accordingly.

Step 8: Stopping Criterion

- Check whether the total iteration equals the defined max iterations or satisfies a termination condition.
- If the stopping criterion is met, terminate the algorithm; otherwise, go back to Step 4.

Step 9: Output

- The best solution, represented by the alpha wolf's position, is considered the final solution to the optimization problem.

Grey Wolf Optimization iteratively improves the candidate solutions by simulating the hunting behavior of wolves, where the alpha, beta, and delta wolves guide the pack's other members toward better solutions. By updating the positions of the wolves based on the fitness values and distances to the leaders, GWO explores the search space to find optimal or near-optimal solutions.

IV. IMPLEMENTATION OF FORECASTING MODEL AND EVALUATING METRIC.

A. Evaluation measures

We have used four evaluation measures, namely Mean Squared Error (MSE) [32], Root-Mean-Squared Error (RMSE)[33], Mean Absolute Error (MAE)[34], and Symmetric Mean Absolute Percentage Error (SMAPE)[35] to compare the model's accuracy. The mathematical formula associated with the above metrics is given below:

$$\textbf{MSE} = \frac{1}{N}\sum_{k=1}^{N}(a_i - p_i)^2$$

$$\textbf{MAE} = \frac{1}{N}\sum_{k=1}^{N}(a_i - p_i)$$

$$\textbf{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(a_i - p)^2}$$

$$\textbf{SMAPE} = 100 \times \frac{1}{N}\sum_{k=1}^{N}\frac{mod(a_i - p_i)}{\{mod(a_i) + mod(p_i)\}/2}$$

Here, a_i is the actual value of the stock price, and p_i is the value that our proposed model derives. "i" here refers to the ith observation from the dataset of sample size N.

B. Results

In the experiments, we evaluated the performance of each model using GWO and adaptive GWO on the LSTM Models. Initially, we calculated the results for each model without applying any optimization techniques for feature selection. The graphical representations of the results for each model are displayed below

Table 1- Adaptive-LSTM-GWO Results Comparison

Model	Training Evaluation				Testing Evaluation			
	MSE	MAE	RMSE	SMAPE	MSE	MAE	RMSE	SMAPE
LSTM-GWO	0.00020	0.01050	0.04009	5.95956	0.00160	0.03051	0.04009	8.21578
ADAPTIVE GWO	**0.00016**	**0.00910**	**0.039095**	**4.66298**	**0.00152**	**0.02980**	**0.03909**	**7.90581**
LSTM-PSO	0.00030	0.01355	0.042000	6.37779	0.00176	0.03163	0.04200	7.90385
ADAPTIVE PSO	0.00019	0.00987	0.04008	4.77385	0.00160	0.03066	0.04008	7.9991

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Table 2- Adaptive-GRU-GWO Results Comparison

Model	Training Evaluation				Testing Evaluation			
	MSE	MAE	RMSE	SMAPE	MSE	MAE	RMSE	SMAPE
GRU-GWO	0.00020	0.01095	0.03738	5.67011	0.00139	0.02887	0.03738	7.62149
ADAPTIVE-GWO	0.00016	0.00910	0.039095	4.66298	0.00152	0.02980	0.03909	7.90581
GRU-PSO	0.00018	0.00973	0.03650	5.34064	0.00133	0.02770	0.03650	7.21488
ADAPTIVE PSO	0.00019	0.00987	0.04008	4.77385	0.00160	0.03066	0.04008	7.9991
ADAPTIVE-GWO-GRU	**0.00014**	**0.00823**	**0.03596**	**4.25753**	**0.00129**	**0.02753**	**0.03596**	**7.20230**

Table 3- Adaptive-Bi-LSTM-GWO Results Comparison

Model	Training Evaluation				Testing Evaluation			
	MSE	MAE	RMSE	SMAPE	MSE	MAE	RMSE	SMAPE
Bi-LSTM-GWO	0.00016	0.00921	0.03874	4.70573	0.00150	0.03030	0.03874	8.05805
ADAPTIVE-GWO	0.00016	0.00910	0.039095	4.66298	0.00152	**0.02980**	**0.03909**	**7.90581**
Bi-LSTM-PSO	0.00041	0.01702	0.04647	8.42974	0.00215	0.03662	0.04647	9.56225
ADAPTIVE PSO	0.00019	0.00987	0.04008	4.77385	0.00160	0.03066	0.04008	7.9991
ADAPTIVE-GWO-Bi-LSTM	**0.00016**	**0.00876**	**0.03871**	**4.09723**	**0.00149**	0.03024	**0.03871**	**7.91452**

Table 4- Adaptive-Bi-GRU-GWO Results Comparison

Model	Training Evaluation				Testing Evaluation			
	MSE	MAE	RMSE	SMAPE	MSE	MAE	RMSE	SMAPE
Bi-GRU-GWO	**0.00015**	0.00856	**0.03613**	4.27941	**0.00130**	**0.02773**	**0.03613**	**7.24805**
ADAPTIVE-GWO	0.00016	0.00910	0.039095	4.66298	0.00152	0.02980	0.03909	7.90581
Bi-GRU-PSO	0.00017	0.00973	0.03691	4.69529	0.00136	0.02864	0.03691	7.37117
ADAPTIVE PSO	0.00019	0.00987	0.04008	4.77385	0.00160	0.03066	0.04008	7.9991
ADAPTIVE-GWO-Bi-GRU	**0.00015**	**0.00822**	0.03656	**3.91402**	0.00133	0.02831	0.03656	7.39305

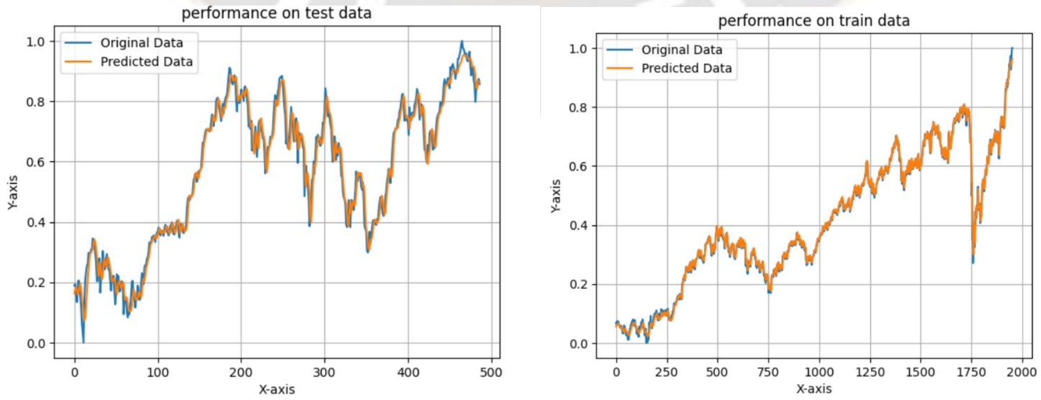

Fig 3 - Adaptive - GWO Results

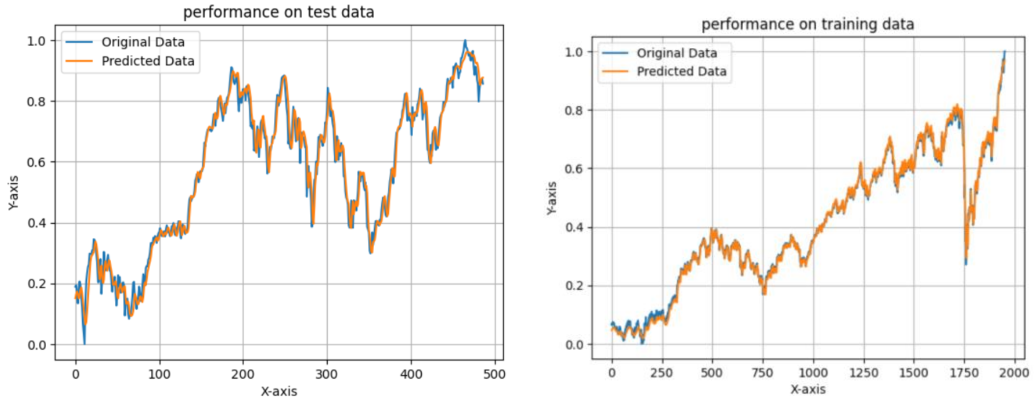

Fig 4 - LSTM-GWO Results

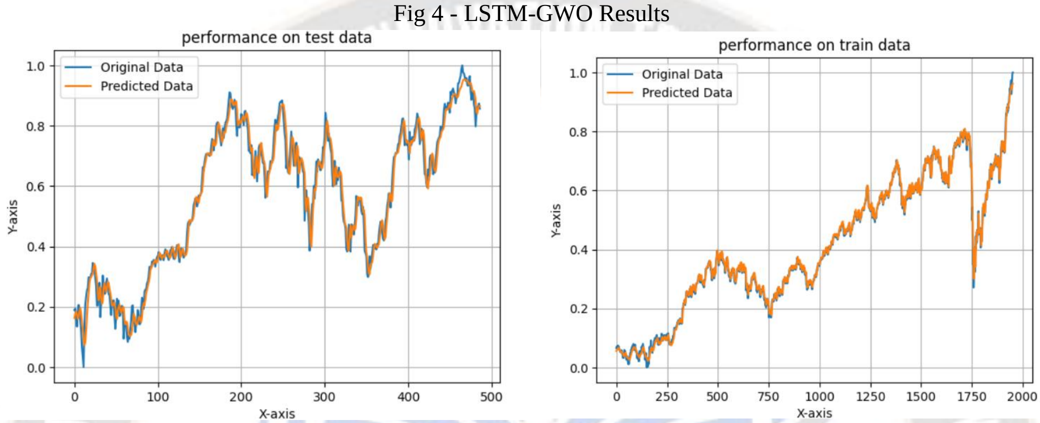

Fig 5 - Adaptive-GRU-GWO Results

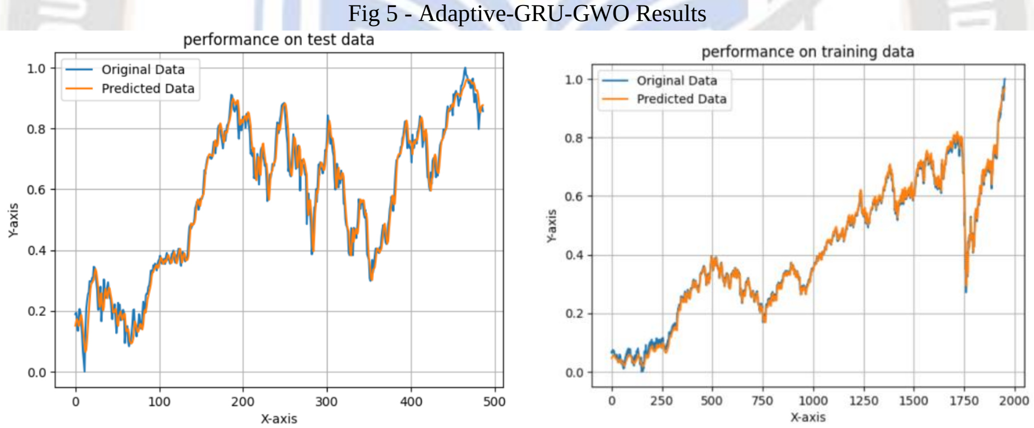

Fig 6 - GRU-GWO Results

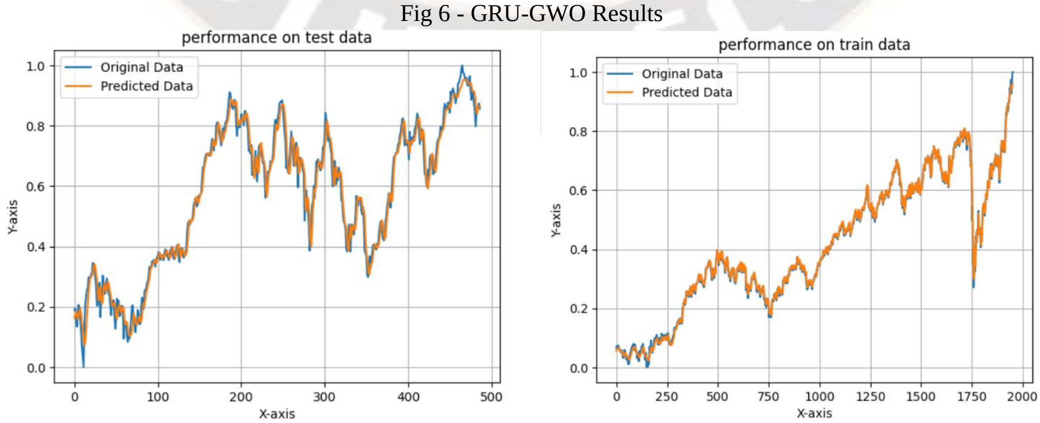

Fig 7 - Adaptive – Bi-GRU-GWO Results

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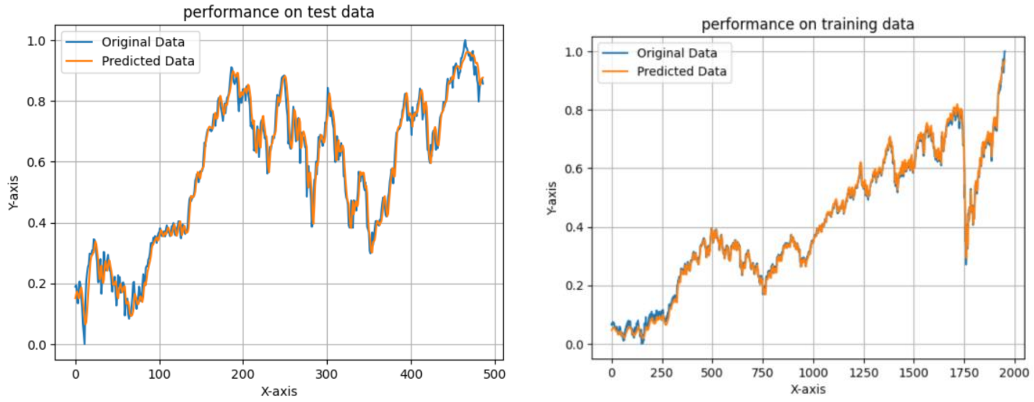

Fig 8 - Bi-GRU-GWO Results

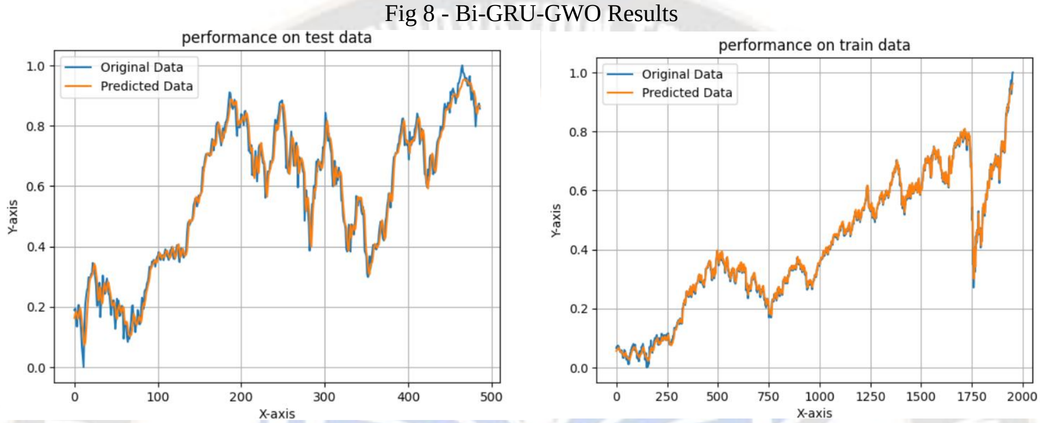

Fig 9 - Adaptive – Bi-LSTM-GWO Results

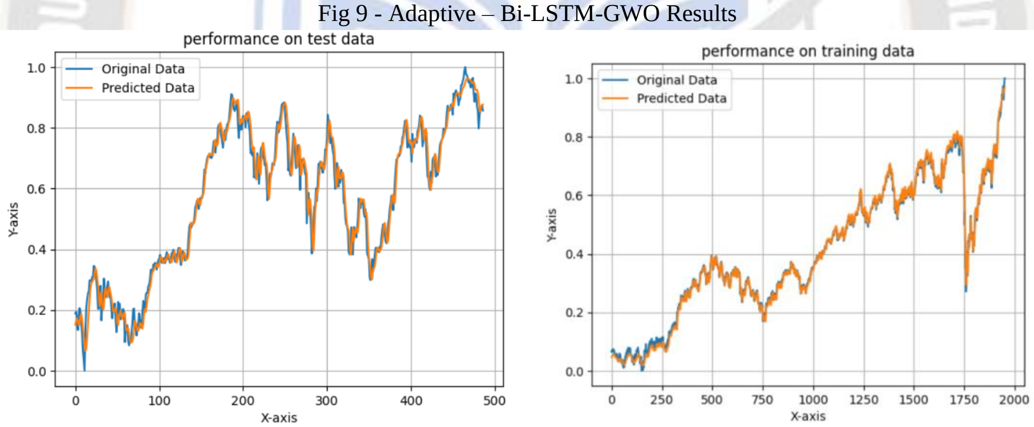

Fig 10 - Bi-LSTM-GWO Results

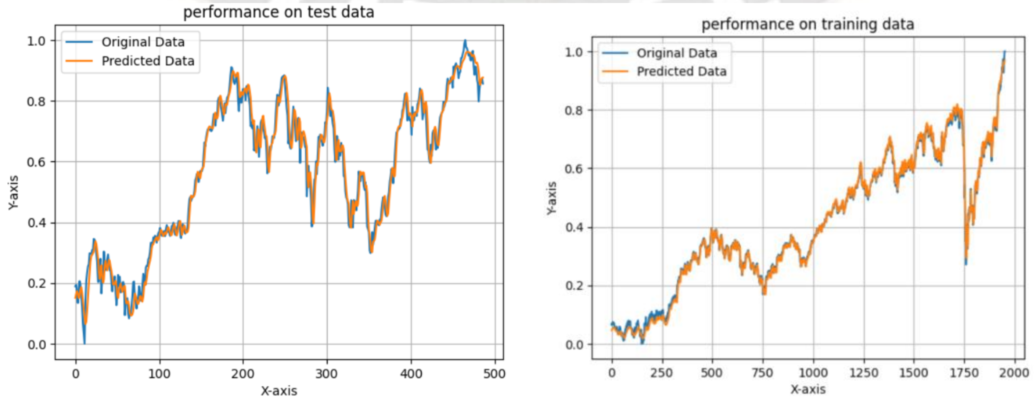

Fig 11 - Adaptive – PSO Results

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V. CONCLUSION AND FUTURE WORK

We worked on combining nature-inspired optimization algorithms with a deep-learning model. Adaptive GWO is a combination of one such algorithm with many neural networks. The proposed Adaptive GWO searches the optimal weights and biases for the neural networks. We evaluated the model on the SENSEX data and compared the efficacy with other models.

The findings of the study can be summarized as:

1. The model can find the optimal weights and biases for different neural networks.
2. The Proposed model suggests the usage of a combination of GWO and Adam optimizer, which combines the potential of global search of GWO along with the local search potential of Adam optimizer, making the proposed model more robust.

We can extend the above work for future work by considering the other hyper-parameters associated with the RNN and its variants. These can be learning rate, count of hidden layers, window size, epochs, etc. We suggest improving the given model's hyper-parameter, and we can work on some new and advanced nature-inspired computation techniques and achieve more optimal results.

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ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8103
***Article Received:** 22 June 2023 **Revised:** 20 August 2023 **Accepted:** 04 September 2023*

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