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AGGREGATION AND HYBRID APPROACHES USING BPSO AND BGWO FOR FEATURE SELECTION FOR INDIAN STOCK INDEX PRICE PREDICTION USING GRU

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Abstract: **The stock exchange is a significant component of the economy, and forecasting its development is essential. Several deep-learning time series models based on RNN and its variants are used to forecast the stock market, but their accuracy still needs to be improved. Optimization strategies, such as GA, PSO, GWO, and others, have been used to enhance the reliability of these models. In this proposed paper, we have used the Binary GWO and Binary PSO algorithms to optimize the input characteristics of a two-layer GRU model for forecasting Indian stock index price. To increase the accuracy of these models, we have suggested two distinct approaches: Aggregation Method and the Hybrid method. In the 10-year time frame, the data indicated that the aggregation approach produced superior accuracy than standard Binary GWO and Binary PSO independently. Although the suggested hybrid method did not out perform individual Binary PSO methods in terms of accuracy, it performed better than the Binary GWO model in a 10-year time frame. Moreover, it showed promise for future improvement. The proposed approaches have the potential to make essential contributions to the index of stock price forecasting, particularly in the Indian market.**

Keywords: **Neural Network, LSTM, GRU, Binary PSO, Binary GWO**

I. INTRODUCTION

The stock exchange is one of the most significant areas in today's world, affecting practically everyone, from investors to industries, directly or indirectly. Therefore, it is critical to understand its movements and make correct predictions. Due to the unpredictable and nonlinear nature of the stock market, producing accurate predictions is a very complex and challenging task. Although we can now accurately anticipate stock market values thanks to the emergence and development of neural network models, it still needs to be improved as it also has a wide range of complexities. Determining the ideal approach within such a complicated environment is an optimization problem. If the problem is too complex or time-consuming to answer analytically, numerical approaches may be used, but they might only sometimes produce a globally optimized solution. Such numerical methods include meta-heuristic algorithms, which are often used to deal with a wide range of complicated challenges in various fields [1]. One such application of met heuristic algorithms is to be used as optimization algorithms for neural network models, notably to optimize the outputs of stock market prediction models [45].

In addition to developing a new meta-heuristic algorithm, another method known as hybridization can be used, which involves combining various algorithms to integrate their strengths and build a superior algorithm [2]. With the help of these hybrid techniques, we aim to predict stock market prices accurately. Since many variables might affect stock values, such as prevailing economic conditions, political policies, industry expansion, recent market developments, and environmental issues, it takes much work toget accurate predictions of stock prices [3,4].To overcome these challenges, the model employs another technique known as feature selection. Feature selection, a primary preprocessing step, aims to eliminate unnecessary and repetitive features from a particular dataset to enhance the prediction model's outcomes [38].

Along with the abovementioned techniques, many strategies and algorithms have been developed and used over the past decade to predict stock prices. These strategies include incorporating models like Recurrent Neural Networks (RNN) [5,6], Long-Short Term Memory (LSTM) [5,6,7], Gated Recurrent Units (GRU) [7,8], Support vector machines

(SVMs) [9, 10], and ARIMA [11,12] for predicting the stock market prices. Moreover, to improve these models' accuracy and to optimize them as well as to make them more stable various met heuristic algorithms like Genetic Algorithm(GA) [37], Particle swarm Optimisation (PSO) [13], Grey Wolf Optimisation (GWO) [14], Bee Colony Optimization (BCO) [16], Ant Colony Optimization (ACO) [15], Differential Evolution (DE) [42], etc., have been used.

Two of the most commonly used and deployed met heuristic algorithms used for optimization problems are GWO and PSO because of their ease of use and efficiency.PSO is a stochastic optimization technique introduced in 1995 in the works of Eberhart and Kennedy, which was encouraged by the collective behavior of various creatures asa group of birds, fishes, and insects [17, 18]. In PSO, a collection of particles (possible solutions) travels throughout a search area, altering its location to match its best and the best answer that all particles share. The particles interact with other particles and modify their positions to achieve the desired outcome. BPSO is a PSO variation utilized for the optimization of discrete binary variables. BPSO works similarly to PSO, except it alters particle paths so that each coordinate may only have two potential outcomes, 0 or 1. Because of this, BPSO is very beneficial when working with binary variables [17,18].

GWO is another met heuristic algorithm that imitates grey wolf hunting behavior for the most suitable solution. It uses three different sorts of wolves to symbolize the three best choices and adjusts the placements of the remaining wolves accordingly. Binary GWO is a variation of GWO that works with binary variables. It updates the binary string of the wolves rather than their location in the search space, making it suitable for binary optimization issues [19,20]. Both binary PSO and binary GWO offer advantages, including lower processing costs, parallel implementation, and effectiveness in high-dimensional search fields. As a result, in this work, we will solve the optimization problem using Binary PSO (BPSO) and Binary GWO (BGWO).

In this study, we propose two distinct techniques to improve the accuracy of stock market prediction models. The two proposed methodologies, Aggregation and Hybrid, strive to improve our stock price prediction accuracy. In the Aggregation model, common traits were chosen from lists of features individually determined by the Binary PSO and Binary GWO algorithms for forecasting stock market values. For this purpose, we used a 2-layer GRU model. At the same time, the Hybrid model uses the features selected from Binary PSO as input features for Binary GWO. The final features selected by Binary GWO are then used over the 2-layer GRU model to predict stock prices. We employed the Nifty50 dataset along different hyper parameters and technical indicators to carry out this experiment.

The rest paper is organized as follows: Part 2 includes several relevant literary works referred to in the paper. Part 3 explains the employed optimization methods, and our proposed work is explained in Part 4 of the document. Part 5 consists of the results and analysis of the conducted study. Lastly, part 6 discusses the conclusion, and part 7 covers all the references of the proposed work.

II. LITERATURE REVIEW

Many valuable studies on optimization algorithms and their multiple uses in various sectors have been done, including stock market prediction. Some of them are briefly covered in this section.

In the works of S. Kumar Chandar, GWO is employed to enhance an Elman Neural Network (ENN) for forecasting the closing stock values of eight NASDAQ and NYSE businesses. The GWO-ENN model beats other models, including those optimized using bio-inspired algorithms like PSO and GA, in forecasting stock values one day in advance. The GWO algorithm optimizes ENN settings, saving time over trial-and-error approaches [21]. Researchers have also used PSO to predict the stock market. Lahmiri (2018) used time series data to estimate the stock price using support vector regression combined with PSO [22]. In order to optimize the structure of neural networks, In2004, the first discrete version of binary PSO was introduced by Jian et al. The particles employed binary strings to encode. The velocity was limited to a range of (0,1), and it was understood to represent "the change in probability" [23]. Veronica et al. employed a binary Grey wolf optimization-based TC method that minimizes active nodes to increase the lifespan of sensor nodes and the network while preserving coverage and connection. It decreases ANs and energy usage by 10% and 6.84%, respectively, and employs a fitness function to choose nodes with low residual energy. The results demonstrate a more minor standard deviation than other TC methods [24].

There have been several studies in which hybrid approaches have also been used. In another work, the GWO was used with SCA [25]. Ahmet et al. introduced a new hybrid method integrating PSO and GWO. The method is tested using five benchmark functions and three real-world issues. The hybrid technique outperforms traditional PSO and GWO algorithms and other hybrid approaches and converges to optimum solutions with fewer rounds [26]. In addition to using these optimization algorithms recently, researchers have paid close attention to optimization, particularly in hybrid algorithms [39]. For example, The authors suggested a PSO-GA hybrid model minimize a molecule's potential energy function [40].

Moreover, the authors have hybridized GWO with DE (differential evolution) on 3D stacked SoC(system-on-chip) [41]. PSO and GA are also hybridized to solve various optimization challenges [43]. Similarly,a hybrid of PSO and GWO is proposed by authors in order to reach the best characteristics of both types [44].Based on these concepts, two different optimization approaches have been proposed in this paper, which will be further detailed in later parts.

III. OPTIMIZATION ALGORITHMS

The optimization techniques employed in this study include BPSO and BGWO. These approaches are used to increase the accuracy of stock market prediction models. Binary PSO and binary GWO offer specific benefits over conventional optimization approaches, notably the capacity to handle binary-valued variables and the speed with which they converge. In the following sections of the article, we will go over these algorithms in further depth.

A. Binary Particle Swarm Optimization (BPSO)

BPSO is an advanced optimization technique created by Kennedy and Eberhart that has been frequently used to solve binary optimization problems. The technique is based on a colony of particles circulating and interacting in a search area to find the best solution. In BPSO, the search region is modeled as a hypercube, with the elements moving to closer and farther ends by switching multiple numbers of bits. The velocity movement can be expressed using variations in the probability of the bit being in any of two states. Each iteration modifies each particle's velocity and location (best, i, j) based on the most current best position (best, I j) and the best position established by informants. The following formula is used to modify each particle's location and velocity in the original continuous.

$$V_{i,j}(t+1) = W\,V_{i,j}(t) + C_1R_1(P_{best,i,j} - X_{i,j}(t) + C_2R_2(G_{best,i,j} - X_{i,j}(t)) \quad (1)$$

$$X_{i,j}(t+1) = X_{i,j}(t) + X_{i,j}(t+1) \quad (2)$$

Here, i represents the index of a particle in a swarm, j represents the particle's position at i index, T represents the iteration number, V represents the particle's velocity, and X represents the particle's location., R1 and R2 are random numbers, whereas C1 and C2 are acceleration coefficients that govern how the particle moves. Both the best answers identified personally and locally influence the current velocity vector. Moreover, W controls how much the past velocity influences the current velocity.

As a result, a particle travels in a space confined to one of two values (0 or 1) on each dimension, with each vid representing the probability that xi is set to 1. Thus, p_{id} and x_{id} are integers in the range [0, 1], and v_{id}, as it is the probability, must be restricted to the range [0.0, 1.0]. The position will be updated following equation (4) by creating $S(v_{id})$ in equation (3). Algorithm 1 is the pseudo code of Binary PSO [17,27].

$$S(v_{id}) = \frac{1}{1+e^{-v_{id}}} \quad (3)$$

If rand() < $S(v_{id}(t+1))$ then $x_{id}(t+1) = 1$ (4)

else$x_{id}(t+1) = 0$

Here,

$S(v_{id})$ = Sigmoid Limiting Transformation

rand() = a quasi-random number selected from an even distribute range of [0.1, 1.0]

$V_{id}$is limited in [$-v_{max}$, $+v_{max}$]

Algorithm 1

Binary Particle Swarm Optimisation (BPSO)		
Start		
1	:	Initialize the related parameter of BPSO
2	:	Randomly generate the position for the particles
3	:	Assigning 0 and 1 values to Particles based on eq 2
4	:	**for** each iteration, T ranges from (1, Max_iter)
5	:	**for** each population, N ranges from (1, Total Population)
6	:	Calculate Fitness Value using all particles which equals 1
7	:	Update the Pbest
8	:	**End For**
9	:	Update the position and velocity using eq. 1 and 2
10	:	Repeat step 3
11	:	Update the Gbest
12	:	**End for**
13	:	Output →Selected Features
End		

B. Binary Grey Wolf Optimisation (BGWO)

The BGWO is a binary optimization technique replicating grey wolf social structure and hunting behaviors. The system simulates three sorts of wolves - alpha (α), beta(β), and delta (δ) - as alternative solutions to locate the optimal solution, which is the prey. The omega (ω) group consists of the remaining candidate solutions that change their places dependent on the hierarchical placements of α, β and δ. The search space in BGWO is specified as a hypercube in which wolves can only occupy places with binary values of 0 or 1.

The wolves change their places within the hypercube by changing particular values to get closer or farther away from the optimal solution. The optimal values of α, β, and δ can be determined as follows [28]

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \quad (1)$$

$$\vec{B} = 2\vec{r_2} \quad (2)$$

$$\vec{D_\alpha} = \left|\vec{B}.\vec{X}_\alpha - \vec{X}_\imath\right| \;,\; \vec{D_\beta} = \left|\vec{B}.\vec{X}_\beta - \vec{X}_\imath\right| \;,\; \vec{D_\delta} = \left|\vec{B}.\vec{X}_\delta - \vec{X}_\imath\right| \quad (3)$$

$$a = 2 - t\frac{2}{\mathrm{MaxIter}} \quad (4)$$

Where Xi, $\vec{X_\alpha}$, $\vec{X_\beta}$, and $\vec{X_\delta}$ represent position vectors of I, α, β, and δ, respectively

$\vec{D_\alpha}$, $\vec{D_\beta}$, and $\vec{D_\delta}$ denote the distance vectors between α, β δ, and I, respectively

$\vec{r_1}$and$\vec{r_2}$ are random vectors in the range [0,1]

$\vec{A}$ and $\vec{B}$represent coefficient vectors

ais a parameter that governs the balance between exploration and exploitation, which gets updated linearly in the range from 2 to 0 for every iteration.

tdenotes the number of iterations

MaxIteris the maximum number of optimization iterations permitted

Now, by using the Sigmoid function (S_1) values of s_1, s_2 and s_3 can be calculated using these equations

$$s_1^d = 1/(1 + e^{-10(A^d.D_\alpha^d - 0.5)}) \quad (5)$$

$$s_2^d = 1/(1 + e^{-10(A^d.D_\beta^d - 0.5)}) \quad (6)$$

$$s_3^d = 1/(1 + e^{-10(A^d.D_\delta^d - 0.5)}) \quad (7)$$

Where d = d^{th} dimension of a wolf

The values of $bstep_1$, $bstep_2$, and $bstep_3$are calculated as follows.

$$bstep_1^d = \begin{cases} 1, & if\,(s_1^d \geq \text{ randn }) \\ 0, & else \end{cases} \quad (8)$$

$$bstep_2^d = \begin{cases} 1, & if\,(s_2^d \geq \text{ randn }) \\ 0, & else \end{cases} \quad (9)$$

$$\mathrm{bstep}_3^d = \begin{cases} 1, & \text{if}(s_3^d \geq \text{ randn }) \\ 0, & \text{else} \end{cases} \quad (10)$$

Where bstep_1, bstep_2, and bstep_3 are the lengths I can cover about α, β, and δ.

Brandon is an arbitrary number that lies in [0, 1].

Once optimization is completed, the output will be binary rather than continuous. The binary data will get transformed using equations (5)-(7), and values of 0 and 1 are needed to compare it with random numbers.

Equations (11)-(13) are then used to determine the X1, X2, and X3 values.

$$X_1^d = \begin{cases} 1, & \text{if}(X_\alpha^d + \mathrm{bstep}_1^d \geq 1\,) \\ 0, & \text{else} \end{cases} \quad (11)$$

$$X_2^d = \begin{cases} 1, & \text{if}(X_\beta^d + \mathrm{bstep}_2^d \geq 1\,) \\ 0, & \text{else} \end{cases} \quad (12)$$

$$X_3^d = \begin{cases} 1, & \text{if}(X_\delta^d + \mathrm{bstep}_3^d \geq 1\,) \\ 0, & \text{else} \end{cases} \quad (13)$$

Finally, as indicated in Eq. (14), the location of $X_i$will be updated in the next iteration as follows:

$$X_i^d(nt) = \begin{cases} X_1^d & \text{if}\left(\text{rand} < \frac{1}{3}\right) \\ X_2^d & \text{elseif}\left(\frac{1}{3} \leq \text{rand} < \frac{2}{3}\right) \\ X_3^d & \text{else} \end{cases} \quad (14)$$

Where nt denotes the next iteration

Algorithm 2 outlines the working of Binary Gray Wolf Optimization (BGWO). It is worth noting that the mathematical formulae used in this section were taken from [28] and [36].

Algorithm 2

Binary Grey Wolf Optimizer (BGWO)		
Start		
1	:	Initialize the related parameter of BGWO
2	:	Randomly generate the positions of the wolves
3	:	Compute the fitness of each wolf
4	:	Find X_α, X_β, and X_δ
5	:	**for**i=1: MAX_IT **do**
6	:	Using Eqs (1)(2) (4), update a, A, and C
7	:	Compute the positions of each wolf by Eqs (5) – (14)
8	:	Compute the fitness of each wolf
9	:	Update X_α, X_β, and X_δ
10	:	**end for**
11	:	Output → X_α
End		

IV. PROPOSED WORK

In the suggested paper, two different approaches to optimize the accuracy of our stock market prediction model are used in which we experiment with two optimization techniques: aggregation and the Hybrid method. To implement these methods, we used two advanced optimization algorithms, Binary PSO) and Binary GWO. A detailed explanation of both methods is explained in the subsequent sections. It should be emphasized that the two suggested approaches are not mathematical integrations of Binary PSO and Binary GWO but rather integrations of features selected by both algorithms in various combinations.

A. Aggregation Method

The concept of aggregation is combining information from multiple sources to arrive at a single, coherent result. Therefore, we apply this concept to optimize the performance of our stock prediction model in our research. Following this concept, we propose the Aggregation method, which involves selecting the best features from two optimization algorithms, Binary PSO and Binary GWO. To implement the Aggregation technique, we independently perform feature selection (from a pool of 22 features) using the Binary PSO and Binary GWO algorithms. Then, we choose the standard features discovered by both optimization techniques. These selected features are then used as input features to train our two-layered GRU model, which is then used for forecasting stock prices. The related hyper parameters, like the number of epochs, choice of the optimizer, batch size, and time step, are likewise appropriately described [34, 35].

Lastly, we calculated the correctness of our model to verify the results, for Binary PSO number of iterations used is 10, while only 1 iteration was used for Binary GWO.

Both models will run independently based on their notions, as mentioned in section 3, and we will only utilize the final feature chosen by both of them. The Aggregation method's goal is to combine the capabilities of both optimization techniques by selecting standard features. We expect to enhance our model's prediction accuracy and acquire more trustworthy and accurate outcomes by doing so. The Aggregation method is algorithmically shown below.

Algorithm 3

Aggregation Method		
Start		
1	:	Initialize the related parameter of BPSO
2	:	Initialize Algorithm 1
3	:	Create array 1 of output/selected features from Algorithm 1
4	:	Initialize the related parameter of BGWO
5	:	Initialize Algorithm 2
6	:	Create array 2 of output/selected features from Algorithm 2
7	:	Create array three consisting of standard output/selected features from Algorithm 1 and Algorithm 2
8	:	Initialize related parameters of the Stock price prediction model
9	:	Train the model using array three as input parameters
10	:	Evaluate the R2 score (Model Accuracy) of the Model
11	:	Output → Accuracy of the Aggregation method
End		

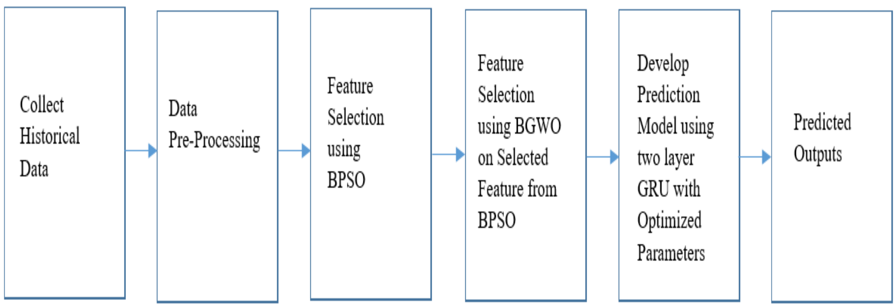

Figure 1: Block diagram of aggregation using BPSO and BGWO for feature selection for stock price prediction using GRU

B. Hybrid Method

In the Hybrid approach, we integrate the findings of two optimization techniques, Binary PSO and Binary GWO, to improve our stock market prediction model results. Initially, we used the Binary PSO algorithm to choose the most optimal features from a pool of 22 features. After this, we ran Binary GWO to further select the features from the pool of features chosen by Binary PSO. Binary GWO's final selected features were then used as input features for our Stock price prediction model, a 2-layer GRU model in which hyper parameters are predefined [35]. Finally, we assessed the model's accuracy to assess the hybridization technique's performance. In the hybrid model, we have also used ten iterations for Binary PSO and only 1 for Binary GWO.

The suggested hybridization strategy tries to improve the feature selection process by combining the advantages of both optimization algorithms and the stock market prediction model's accuracy. Algorithm 4 depicts the pseudo code of the Hybrid approach.

Algorithm 4

Hybrid Method

Start

: Initialize the related parameter of BPSO
: Initialize Algorithm 1
: Create array 1 of output/selected features from Algorithm 1
: Initialize the related parameter of BGWO
: Use output/selected features of Algorithm 1 as input parameters for BGWO
: Initialize Algorithm 2
: Create array 2 of output/selected features from Algorithm 2
: Initialize related parameters of the Stock price prediction model
: Train Model using array two as its input parameters
: Evaluate R2 score (Model Accuracy)
: Output → Accuracy of the Hybrid method

End

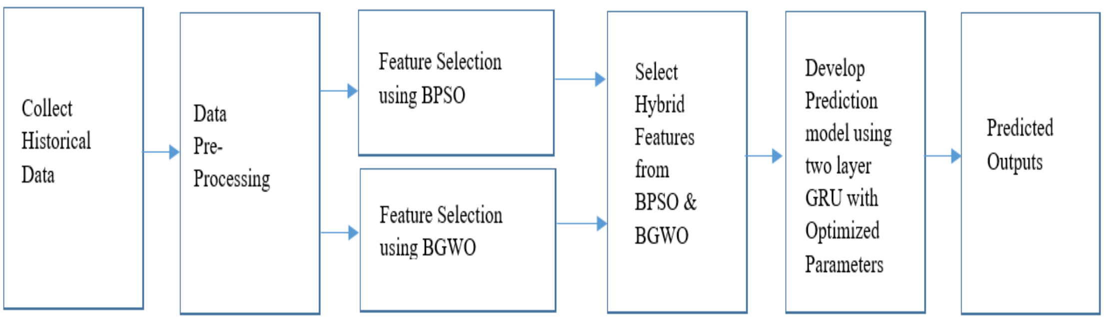

Figure 2: Block diagram of hybrid method for feature selection using BPSO and BGWO for stock price prediction using GRU

C. Dataset

The Nifty50 dataset of the Indian stock market is used for the study; this dataset is freely available via several sources like Yahoo Finance. The dataset is selected in two-time frames to examine the effectiveness of the methods. The first dataset spans ten years from 01/01/2013 to 31/12/2022, while the second dataset covers five years from 01/01/2018 to 31/12/2022. The dataset was partitioned in an 80:20 ratio for training and testing purposes.

The input parameters taken into account for the analysis include high, low, open, close, adj close, and volume, along with a number of technical indicators including SMA20, SMA50, EMA20, EMA50, EMA200, UpperBB, LowerBB, RSI, MFI, ATR, Force_Index, MACD, MACD_SL, ADX, OBV, and OBV_EMA [29,30,31]. A total of 22 features have been considered for analysis.

D. Model Architecture and Hyper parameters

A two-layer GRU model is used to evaluate our proposed approaches to optimize stock market prediction results. R2 score has been used as a metric for assessing the model's degree of accuracy. The hyper parameters implemented for the model are listed in the table below [32,33].

Table 1. Hyper parameters Table

Hyper parameters	
Number of epochs	10
Loss Function	MSE
Metrics	MAE
Time steps	50
Optimizer	Adam
Batch Size	32
Dense layer	1

V. RESULT AND ANALYSIS

Based on the study, the findings are described in this section. In Table 2, the accuracy, as well as the feature selected by Binary GWO and Binary PSO on GRU 2-layer model in two different time frames, is shown.

Table 2. Accuracy of Binary GWO and Binary PSO

Model	GRU 2 Layer		GRU 2 Layer	
Algorithm	Binary PSO		Binary GWO	
Timeframe	Ten years	Five years	Ten years	Five years
Accuracy	0.974209	0.941323	0.961595	0.930535
Features Selected	Low, Close, EMA20, EMA50, EMA200, LowerBB, RSI, Force_Index, ADX	Low, Close, Adj Close, UpperBB, RSI, Force_Index, OBV	Low, Volume, SMA20, SMA50, EMA20, EMA200, MFI, Force_Index, MACD, OBV	Open, High, Low, EMA50, EMA200, UpperBB, MFI, MACD, OBV, OBV_EMA

E. Aggregation Method

Table 3 shows the outcomes of the aggregate method. According to the results, the aggregation method outperforms Binary GWO and Binary PSO optimization algorithms in the 10-year timeframe. However, during the five years, the aggregation approach did not beat the Binary PSO algorithm but exceeded the Binary GWO algorithm. The suggested aggregation approach can potentially improve prediction accuracy.

Table 3. Accuracy of Aggregation Method

Model	GRU 2 Layer	
Algorithm	Common features selected from the best results of the Bi_GWO run and Bi_PSO run	Standard features selected from the best results of the Bi_GWO run and Bi_PSO run
Timeframe	Ten years	5 years
Accuracy	0.978895	0.932399
Common Features Selected	Low, EMA20, EMA200, Force_Index	Low, UpperBB, OBV

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5.2 Hybrid Method

Table 4 summarizes the findings of the hybrid method, which failed to beat the individual Binary PSO results in any period but outperformed Binary GWO in the 10-year time frame. One probable explanation for such results is that the features chosen by Binary PSO are already limited in number. As a result, the number of features reduces even further after getting selected by Binary GWO. This results in relatively few input characteristics for our model, resulting inless accurate results.

Table 4. Accuracy of Hybrid Method

Model	GRU 2 Layer	
Algorithm	Features selected from Bi_GWO then put into Bi_PSO	
Timeframe	Ten years	Five years
Accuracy	0.971221	0.921983
Features Selected by Bi_GWO	Open, High, Close, Adj Close, Volume, SMA20, EMA50, EMA200, MFI, MACD_SL, ADX	Open, High, Low, Adj Close, SMA20, UpperBB, MACD, MACD_SL, OBV, OBV_EMA
Final Features Selected by Bi_PSO	Close, Volume, EMA50, MACD_SL	Adj Close, UpperBB

5.3 Model performance under various metrics

Table 5. Various performance metrics results in 10 years timeframe

Algorithms	**MAE**	**MSE**	**RMSE**	**MAPE**	MdAPE
Binary PSO	0.010711	0.000194	0.013954	0.89 %	0.70 %
Binary GWO	0.013921	0.000308	0.017571	1.14 %	0.94 %
Aggregate	0.010411	0.000187	0.013698	0.86 %	0.67 %
Hybrid	0.011958	0.000231	0.015210	0.98 %	0.79 %

Table 6. Various performance metrics results in 5 years timeframe

Algorithms	**MAE**	**MSE**	**RMSE**	**MAPE**	**MdAPE**
Binary PSO	0.013548	0.000296	0.017213	0.95 %	0.66 %
Binary GWO	0.015991	0.000398	0.019963	1.05 %	0.89 %
Aggregate	0.015271	0.000386	0.019659	1.01 %	0.77 %
Hybrid	0.016486	0.000434	0.020834	1.08 %	0.98 %

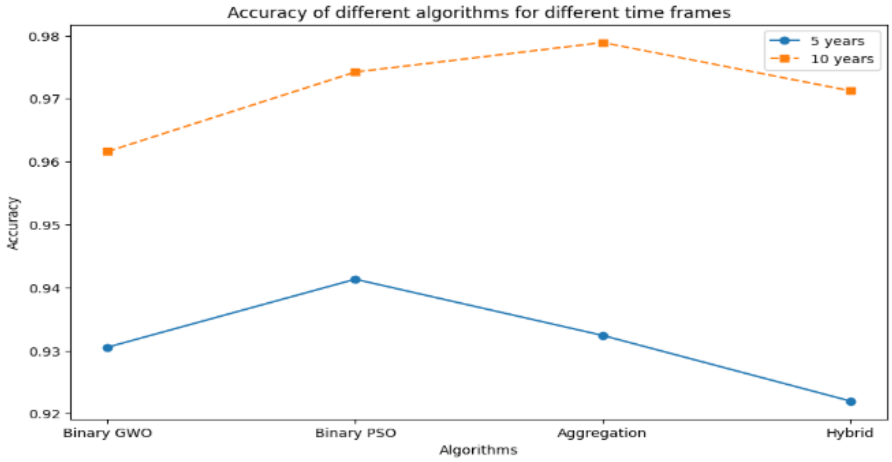

Figure 3: Accuracy graph

VI. CONCLUSION

The stock exchange is critical to the global financial system, and precisely forecasting its performance is essential. Even though deep learning time series models are frequently used for stock market prediction, their accuracy remains a challenge. We used the Binary GWO and Binary PSO optimization algorithms to solve this. We proposed two approaches for improving the performance of these models: the Aggregation Method and the Hybrid Method, and applied optimized parameters to the two-layer GRU model. Our findings reveal that the aggregation method can successfully integrate the pluses of both optimization algorithms and select the best features common to both algorithms. However, also more modifications are required for the hybrid model to produce better outcomes. Overall, our findings are significant as they show the effectiveness of the presented aggregation model in stock price prediction. In the future, we can try different optimization methods as well as different neural network models to improve accuracy and minimize the time and space complexity.

VII. REFERENCES

[1]. Christensen J, Bastien C (2016). Chapter—seven-heuristic and meta-heuristic optimization algorithms. In: Christensen J, Bastien C (eds) Nonlinear optimization of vehicle safety structures. Butterworth-Heinemann, Oxford, pp 277–314

[2]. Hopper, E. B. C. H., and Brian CH Turton. "An empirical investigation of meta-heuristic and heuristic algorithms for a 2D packing problem." European Journal of Operational Research 128, no. 1 (2001): 34–57.

[3]. Guresen, G. Kayakutlu, T.U. Using artificial neural network models in stock market index prediction, Daim, Expert Syst. Appl. 38 (8) (2011) 89–97. [3] T. Lee, C. Chiu, Neural network forecasting of an opening cash price index, Int. J. Syst. Sci. 33 (3) (2002) 29–37 .

[4]. T. Lee, C. Chiu, Neural network forecasting of an opening cash price index, Int. J. Syst. Sci. 33 (3) (2002) 29–37.

[5]. Pawar, Kriti, Raj SrujanJalem, and Vivek Tiwari. "Stock market price prediction using LSTM RNN." In Emerging Trends in Expert Applications and Security: Proceedings of ICETEAS 2018, pp. 493-503. Springer Singapore, 2019.

[6]. Roondiwala, Murtaza, Harshal Patel, and ShraddhaVarma. "Predicting stock prices using LSTM." International Journal of Science and Research (IJSR) 6, no. 4 (2017): 1754-1756.

[7]. Gao, Ya, Rong Wang, and Enmin Zhou. "Stock prediction based on optimized LSTM and GRU models." Scientific Programming 2021 (2021): 1–8.

[8]. Li, Chengyu, and GuoqiQian. "Stock Price Prediction Using a Frequency Decomposition Based GRU Transformer Neural Network." Applied Sciences 13, no. 1 (2022): 222.

[9]. Heo, Junyoung, and Jin Yong Yang. "Stock price prediction based on financial statements using SVM." International Journal of Hybrid Information Technology 9, no. 2 (2016): 57-66.

[10]. Ince, Huseyin, and Theodore B. Trafalis. "Short-term forecasting with support vector machines and application to stock price prediction." International Journal of General Systems 37, no. 6 (2008): 677–687.

[11]. Mondal, Prapanna, Labani Shit, and SaptarsiGoswami. "Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices." International Journal of Computer Science, Engineering and Applications 4, no. 2 (2014): 13.

[12]. Poongodi, M., V. Vijayakumar, and Naveen Chilamkurti. "Bitcoin price prediction using ARIMA

model." International Journal of Internet Technology and Secured Transactions 10, no. 4 (2020): 396–406.

[13]. Thakkar, Ankit, and KinjalChaudhari. "A comprehensive survey on portfolio optimization, stock price and trend prediction using particle swarm optimization." Archives of Computational Methods in Engineering 28 (2021): 2133-2164.

[14]. Kumar Chandar, S. "Grey Wolf optimization-Elman neural network model for stock price prediction." Soft Computing 25 (2021): 649–658.

[15]. Mavrovouniotis, Michalis, and Shengxiang Yang. "Training neural networks with ant colony optimization algorithms for pattern classification." Soft Computing 19 (2015): 1511–1522.

[16]. Ghaleini, EbrahimNoroozi, MohammadrezaKoopialipoor, MohammadrezaMomenzadeh, Mehdi EsfandiSarafraz, EdyTonnizamMohamad, and BehrouzGordan. "A combination of an artificial bee colony and neural network for approximating the safety factor of retaining walls." Engineering with Computers 35 (2019): 647-658.

[17]. Kennedy, James, and Russell C. Eberhart. "A discrete binary version of the particle swarm algorithm." In 1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational cybernetics and simulation, vol. 5, pp. 4104-4108. IEEE, 1997.

[18]. Wang, Dongshu, Dapei Tan, and Lei Liu. "Particle swarm optimization algorithm: an overview." Soft computing 22 (2018): 387-408.

[19]. Mirjalili, Seyedali, Seyed Mohammad Mirjalili, and Andrew Lewis. "Grey wolf optimizer." Advances in engineering software 69 (2014): 46–61.

[20]. Hu, Pei, Jeng-Shyang Pan, and Shu-Chuan Chu. "Improved binary grey wolf optimizer and its application for feature selection." Knowledge-Based Systems 195 (2020): 105746.

[21]. Kumar Chandar, S. "Grey Wolf optimization-Elman neural network model for stock price prediction." Soft Computing 25 (2021): 649–658.

[22]. Lahmiri, Salim. "Minute-ahead stock price forecasting based on singular spectrum analysis and support vector regression." Applied Mathematics and Computation 320 (2018): 444–451.

[23]. Jian W, Xue Y, Qian J (2004). An improved particle swarm optimization algorithm with neighborhoods topologies. In: Proceedings of 2004 international conference on machine learning and Cybernetics, pp 2332–2337, Shanghai, China, August 26–29, 2004

[24]. Ghorpade, Sheetal N., Marco Zennaro, and Bharat S. Chaudhari. "Binary grey wolf optimization-based topology control for WSNs." IET Wireless Sensor Systems 9, no. 6 (2019): 333–339.

[25]. Singh, Narinder, and S. B. Singh. "A novel hybrid GWO-SCA approach for optimization problems." Engineering Science and Technology, an International Journal 20, no. 6 (2017): 1586-1601.

[26]. Şenel, FatihAhmet, FatihGökçe, AsımSinanYüksel, and TuncayYiğit. "A novel hybrid PSO–GWO algorithm for optimization problems." Engineering with Computers 35 (2019): 1359-1373.

[27]. Nezamabadi-pour, Hossein, Majid Rostami-Shahrbabaki, and MaliheMaghfoori-Farsangi. "Binary particle swarm optimization: challenges and new solutions." CSI J ComputSciEng 6, no. 1 (2008): 21-32.

[28]. Hu, Pei, Jeng-Shyang Pan, and Shu-Chuan Chu. "Improved binary grey wolf optimizer and its application for feature selection." Knowledge-Based Systems 195 (2020): 105746.

[29]. Yao, Jingtao, Chew Lim Tan, and Hean-Lee Poh. "Neural networks for technical analysis: a study on KLCI." International journal of theoretical and applied finance 2, no. 02 (1999): 221–241.

[30]. De Oliveira, Fagner A., Cristiane N. Nobre, and Luis E. Zárate. "Applying Artificial Neural Networks to the Prediction of stock price and Improvement of the directional prediction index–A case study of PETR4, Petrobras, Brazil." Expert systems with applications 40, no. 18 (2013): 7596-7606.

[31]. Shakeri, Behnoush, MH FazelZarandi, MosaharTarimoradi, and I. B. Turksan. "Fuzzy clustering rule-based expert system for stock price movement prediction." The 2015 Annual Conference of the North American Fuzzy Information Processing Society (NAFIPS) was jointly held with the 2015 5th World Conference on Soft Computing (WConSC), pp. 1–6. IEEE, 2015.

[32]. Gao, Penglei, Rui Zhang, and Xi Yang. "The application of stock index price prediction with a neural network." Mathematical and Computational Applications 25, no. 3 (2020): 53.

[33]. Althelaya, Khaled A., El-Sayed M. El-Alfy, and Salahadin Mohammed. "Stock market forecast using multivariate analysis with bidirectional and stacked (LSTM, GRU)." In 2018 21st Saudi Computer Society National Computer Conference (NCC), pp. 1–7. IEEE, 2018.

[34]. Saud, Arjun Singh, and SubarnaShakya. "Analysis of gradient descent optimization techniques with the recurrent gated unit for stock price prediction: A case study on banking sector of Nepal stock exchange." Journal of Institute of Science and Technology 24, no. 2 (2019): 17-21.

[35]. Bhandari, Hum Nath, BinodRimal, Nawa Raj Pokhrel, RamchandraRimal, Keshab R. Dahal, and Rajendra KC Khatri. "Predicting stock market index

using LSTM." Machine Learning with Applications 9 (2022): 100320.

[36]. Emary, Eid, Hossam M. Zawbaa, and Aboul Ella Hassanien. "Binary grey wolf optimization approaches for feature selection." Neurocomputing 172 (2016): 371-381.

[37]. M. M. Kabir, M. Shahjahan, and K. Murase, “A new local search based hybrid genetic algorithm for feature selection,” Neurocomputing, vol. 74, no. 17, pp. 2914–2928, 2011.

[38]. Dash, Manoranjan, and Huan Liu. "Feature selection for classification." Intelligent data analysis 1, no. 1-4 (1997): 131-156.

[39]. Talbi, El-Ghazali. Metaheuristics: from design to implementation. John Wiley & Sons, 2009.

[40]. Tawhid, Mohamed A., and Ahmed F. Ali. "A hybrid grey wolf optimizer and genetic algorithm for minimizing a potential energy function." Memetic Computing 9 (2017): 347–359.

[41]. Zhu, Aijun, ChuanpeiXu, Zhi Li, Jun Wu, and Zhenbing Liu. "Hybridizing grey wolf optimization with differential evolution for global optimization and test scheduling for 3D stacked SoC." Journal of Systems Engineering and Electronics 26, no. 2 (2015): 317-328.

[42]. Zorarpacı, Ezgi, and Selma Ayşe Özel. "A hybrid approach of differential evolution and artificial bee colony for feature selection." Expert Systems with Applications 62 (2016): 91-103.

[43]. Premalatha, K., and A. M. Natarajan. "Hybrid PSO and GA for global maximization." Int. J. Open Problems Compt. Math 2, no. 4 (2009): 597-608.

[44]. Singh, Narinder, and S. B. Singh. "Hybrid algorithm of particle swarm optimization and grey wolf optimizer for improving convergence performance." Journal of Applied Mathematics 2017 (2017).

[45]. Ghasemiyeh, Rahim, Reza Moghdani, and ShibSankar Sana. "A hybrid artificial neural network with metaheuristic algorithms for predicting stock price." Cybernetics and Systems 48, no. 4 (2017): 365-392.