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NEWS BASED SENTIMENT ANALYSIS USING TANH GREY WOLF OPTIMIZER (TGWO) FOR STOCK PRICE PREDICTION

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Abstract - **Research on stock market forecasting has always been important to the financial sector. Shares price forecasting plays a significant role in raising investors' interest in an organization, which has a beneficial effect on the growth of shareholders in its stock. A substantial reward might have been available if the stock price had been correctly predicted. Due to advancements in science, technology, and the market economy, more elements today affect a company's price trend compared to the past. The traditional analytical technique cannot explain the fluctuations in stock price caused by important information hidden from view. Predicting these stock markets using confidential information can be achieved by several deep-learning time series models based on RNN and its derivatives, such as LSTM and GRU. However, their performance still needs to be improved. The use of optimization techniques like GWO, has improved the accuracy of these models, and to increase the reliability of the prediction, news sentiment has been used. The study comprised three phases. In the first phase, this study proposed a Tanh Grey Wolf Optimizer algorithm to increase the efficiency & accuracy of the model. Tanh is used to reduce the infinite search space to -1 and 1. Sigmoid and tanh are similar functions, but tanh has a more extensive range and is more symmetrical around the origin, resulting in results that are not biased. This property allows the potential for Tanh to have a superior gradient, which leads to more accuracy compared to the present basic GWO and binary GWO, which use sigmoid. In the second phase, News sentiment analysis used word embeddings to increase the predictions' reliability. In the last phase, these predictions are ensemble with news sentiment scores and classify the score into five classes, i.e., Strong Sell, Sell, Hold, Strong Buy, and Buy.**

Keywords: **Optimization, Gradient, Tanh, Sigmoid, GWO, binary GWO, LSTM.**

I. INTRODUCTION

Several behavioural finance studies have shown well-documented effects of investors' sentiment on the financial market [4]. Academics have worked hard to identify suitable and credible approximations to describe the underlying process of investor sentiment because it is an abstract term. These replacements for actual indicators of investor sentiment towards the financial market include mutual fund flows (MFF), closed-end fund pricing, news, and social media posts [7-9]. Due to the media's broad internet availability, news media has become an important source of knowledge for investors' investment decisions in recent years. News is constantly updating investors' knowledge of the market and comprehension, which affects investor sentiment [11][13][15]. The leading financial data providers, including Bloomberg and Thomson Reuters, now make news analytic tools nearly simultaneously available to traders and investors. Many recent types of research have concentrated on parsing news articles for assessing investor sentiment using text mining and NLP, according to the upgraded news feed delivery [11-12][14]. To get more reliable forecasting, it is necessary to not only classify article sentiment but also the words that need to be labeled. This can be done using word embeddings [16][19].

Due to the volatile nature of the stock trend, it takes work to get high accuracy. RNN& their variant can be used to store the movement in their memory & helps to get precise results [27]. To get more accurate results metaheuristics optimization algorithm can be used [21]. Metaheuristics algorithms also help in the feature selection process, which is essential for developing any model.

The proposed research has been separated into two sections. The first suggests the Tanh GWO algorithm to increase the stock prediction's accuracy by utilizing historical data and technical indicators. The second section uses news sentiment analysis to improve the reliability of forecasts. The stock forecast is then paired with the sentiment analysis data to categorize the outcome into five categories: Strong Buy, Buy, Hold, Sell, and Strong sell. The study proposes a system that uses NEWS & numerical data, i.e., historical data & technical indicators, to decide whether the investor has to "strong buy," "buy," "hold," "sell," and "strong sell" the stock. The system has 3 phases to predict the class. The first phase is news sentiment analysis, the second phase is to predict the growth or downfall of the stock price using historical data & technical data after the news arrived, and the third phase is to predict the class like strongly buy, buy, strongly sell, sell, or hold. To get better outcomes system uses a Tanh Grey Wolf optimization algorithm with a neural network model which analyses the news sentiment. The Tanh Grey Wolf optimizer has been used to optimize the result for the numerical data model. Then both neural models have been ensemble to predict the final trend.

II. LITERATURE SURVEY

Recently, many researchers have researched stock market forecasting using historical data on the stock market & news related to it. Because of the exponential growth of different social media platforms nowadays, news sentiment analysis plays important for predicting stock prices [17-18]. With the development of technology & high availability of the internet, the use of news sentiments becomes necessary to forecast financial trends & markets more precisely [5-6].
On the other hand, to increase the accuracy of stock prediction, many researchers have worked on time series forecasting with the help of metaheuristics algorithms. These algorithms help to find the optimal solution more accurately and precisely [26]. These algorithms have gained popularity at an exponential rate in the last decade. Some of these metaheuristics algorithms are Particle swarm optimization, also known as PSO [29-30]; Swarm intelligence [28]; Ant Colony Optimization, also known as ACO [31-34]; and Grey Wolf Optimization, also known as GWO [21-23]. These metaheuristics algorithms are highly inspired by nature and hence are also known as nature-driven algorithms [36]. These algorithms are highly adaptable to a large variety of problems, making them a hot topic to research for computer scientists & researchers.
Xu et al. [1] developed a model to predict stock prices using historical data & financial news. The model was created by combining information from two sources and then analyzed to study the impact of economic news on stock prices to increase accuracy. Using sentiment analysis, Ho et al. [2] developed an ANN model to predict stock prices. Researchers have developed trading rules for the up & down movement of the stock price. Li et al. [3] researched the relationship between technical indicators & news sentiments by using text news & articles. The first step of this study was to extract technical indicators using historical data, evaluate sentiment scores of news articles, and finally create a snapshot series & build an LSTM model to predict prices. Song et al. [4] applied a learning-to-rank algorithm to analyze the sentiment of investors & impact of it on the stock price. Researchers used technical indicators with investor sentiment to develop prediction rules with the help of ListNet and RankNet.
Jin et al. [37] proposed a model to predict stock prices using sentiment analysis & LSTM. Researchers used empirical modal decomposition to counter the complex time series pattern to get better results. With the LSTM, they had incorporated an attention mechanism. Ma et al. [20] used aspect-based sentiment analysis with the LSTM attention mechanism to predict stock prices. Researchers also proposed Sentic and H-Sentic LSTM to improve the model's performance. Li et al. [18] proposed a market Style analysis to predict the complex behavior of the stock market. Researchers have also used technical indicators to study critical patterns. Also, two sentiment dictionaries have been used. These are SentiNet 5 and Loughram-McDonald financial dictionary. Kurani et al. [35] used ANN and SVM to predict stock prices. Researchers have proposed hybrid models like ANN-MLP and GARCH-MLP to predict the price.

III. METHODOLOGY

3.1 GWO

In recent years, multiple researchers have worked on stock market forecasting using historical data on the stock market & news related to it. Due to the exponential rise of different social media platforms nowadays, news sentiment analysis is essential for predicting stock prices [17-18]. With the development of technology & high availability of the internet, the use of news sentiments becomes necessary to forecast financial trends & markets more precisely [5-6].
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developed trading rules for the up & down movement of the stock price. Li et al. [3] researched the relationship between technical indicators & news sentiments by using text news & articles. The preparatory step of this study was to extract technical indicators using historical data, evaluate sentiment scores of news articles, and finally create a snapshot series & build an LSTM model to predict prices. Song et al. [4] applied a learning-to-rank algorithm to analyze the sentiment of investors & impact of it on the stock price. Researchers used technical indicators with investor sentiment to develop prediction rules with the help of ListNet and RankNet.

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$\vec{X}_{(t+1)} = \vec{X}_{p(t)} + \vec{A}.\vec{D}$ (1)

Here, $\vec{D}$ in equation (2) is defined as,

$\vec{D} = |\vec{C}.\vec{X}_{p(t)} - \vec{X}_{(t)}|$ (2)

Here,

$\vec{A}$and$\vec{C}$ are vectors of the coefficient, $\vec{X}_p$defines the position of the prey, $\vec{X}$ defines the position of the grey wolf, and t is the iteration number.

Calculations for coefficient vectors $\vec{A}$ and C have been discussed in equations (3) and (4).

$\vec{A} = 2a.\vec{r_1} - a$ (3)

$\vec{C} = 2\vec{r_2}$ (4)

Here are random vectors. These vectors' range is [0, 1] and linearly decreases from 2 to 0 throughout each iteration.

The alpha usually takes the lead in hunts. The beta and delta ought to rarely hunt prey. The alpha candidate solution is the best and most successful candidate for numerically simulating the grey wolf's hunting habits. When choosing a model to have more information about the likely location of prey, the delta is considered the third-best option, with the beta being regarded as the second-best. The remaining search agents, including the omegas, realign their positions to coincide with those of the most successful searchers due to the available top three candidate solutions. Equation (5) has been modified as a consequence to account for the position of the wolves.

$\vec{X}_{(t+1)} = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3}$ (5)

Where equations (6), (7), and (8) are used to define$\vec{X_1}$ X2 and X_3severally,

$\vec{X_1} = |\vec{X}_\alpha - \vec{A_1}.\vec{D_\alpha}|$ (6)

$\vec{X_2} = |\vec{X}_\beta - \vec{A_2}.\vec{D_\beta}|$ (7)

$\vec{X_3} = |\vec{X}_\delta - \vec{A_3}.\vec{D_\delta}|$ (8)

here, at any given iteration, t, $\vec{X}_\alpha$, $\vec{X}_\beta$, $\vec{X}_\delta$are the first three best solutions.

Equation (3) is used to define $\vec{A_1}$, $\vec{A_2}$, and A3, and equations (9), (10), and (11) are used to define $\vec{D}_\alpha$, $\vec{D}_\beta$, and Dδ, serially

$\vec{D_\alpha} = |\vec{C_1}.\vec{X}_\alpha - \vec{X}|$ (9)

$\vec{D_\beta} = |\vec{C_2}.\vec{X}_\beta - \vec{X}|$ (10)

$\vec{D_\delta} = |\vec{C_3}.\vec{X}_\delta - \vec{X}|$ (11)

Where equation (4) is used to define $\vec{C_1}$, $\vec{C_2}$, and $\vec{C_3}$.

The last point regarding GWO is the parameter update, which governs the relationship between exploration and exploitation. According to equation (12), each iteration linearly decreases from 2 to 0.

$a = 2 - t\frac{2}{MaxIter}$ (12)

Where is the maximum number of optimization iterations permitted, and what is the iteration number? The continuous or basic grey wolf optimization (CGWO) technique is described in Algorithm 1.

Algorithm 1	:	**Basic Grey Wolf Optimizer**
Start		
1	:	Initialize the related parameter of Basic GWO
2	:	Randomly generate the positions of the wolves
3	:	Compute each wolf's level of fitness
4	:	Find X_α, X_β, and X_δ
5	:	**for** i=1: MAX_IT **do**
6	:	Update a, A, and C by using Equations (3), (4), and (12)
7	:	Compute the positions of each wolf by Equations (5) – (11)
8	:	Compute each wolf's level of fitness

9	:	Update $X_\alpha, X_\beta, and\ X_\delta$
10	:	**end for**
11	:	Output X_α
End		

Binary GWO We can find the positions of GWO everywhere throughout the endless, continuous space. Therefore, using the updating equations is straightforward. The BGWO considers the hypercube-shaped search space, where we can see only wolf positions in the ranges of 0 or 1. The hypercube cannot be updated using similar equations, not even with the help of the sigmoid function, because the wolves alter some variables to approach nearer or farther from it.

3.2 Proposed Work

The proposed work has been divided into two parts, first proposed Tanh GWO algorithm to improve the accuracy of the stock prediction using historical data and technical indicators. In the second part, news sentiment analysis increases the reliability of forecasts. After that, these sentiment analysis results are combined with stock prediction & classify the outcome into five classes, i.e., Strong Buy, Buy, Hold, Sell, and Strong sell.

Motivation to develop novel Tanh GWO Algorithm:

The problem of the wolves continuously shifting their positions in the infinite search space to improve results is resolved in the binary GWO algorithm, but this constrains the wolf's space in {0,1}, which limits its ability to improve accuracy and results when used with RNN to predict time series data.

This problem has been addressed using the novel Tanh Grey Wolf algorithm. Tanh GWO uses the Tanh function because it has a better gradient than the sigmoid and a more extensive output range than the sigmoid, both producing superior outcomes [40-41]. Tanh is a function similar to the sigmoid but with a more extensive range and symmetrical origin. Tanh has been chosen as an alternative to the sigmoid function because it is zero-centered, balance-centered, and contains gradients that are unrestricted in their ability to oscillate in one direction.

The gradient of the tanh function is quadruple that of the sigmoid. This suggests that using the tanh activation function causes the gradient values to be maintained during training to be larger, which in turn causes the network's weights to shift by higher amounts [38-40]. The sigmoid function, which produces a value between 0 and 1, is used for all three gates (in, out, and forget) in the LSTM as a gating mechanism since it may permit no flow or complete transmission of information across the gates. Researchers require a function whose second derivative can endure across a wide range before decreasing at 0 to address the vanishing gradient problem. Tanh is a helpful function having the qualities shown above.

3.1 Proposed Algorithm

In The Proposed algorithm, the wolves α, β & δ positions, i.e., $\overrightarrow{D_\alpha}$, $\overrightarrow{D_\beta}$, and $\overrightarrow{D_\delta}$, can be calculated using the equations (9) to (11). Then after, it obtains t_1, t_2, and t_3 by using the tanh function (Called T_1), as follows.

$$y_\alpha = -10(A^d.D_\alpha^d - 0.5) \quad (13)$$
$$y_\beta = -10(A^d.D_\beta^d - 0.5) \quad (14)$$
$$y_\delta = -10(A^d.D_\delta^d - 0.5) \quad (15)$$
$$t_1^d = (e^{y_\alpha} - e^{-y_\alpha})/(e^{y_\alpha} + e^{-y_\alpha}) \quad (16)$$
$$t_2^d = (e^{y_\beta} - e^{-y_\beta})/(e^{y_\beta} + e^{-y_\beta}) \quad (17)$$
$$t_3^d = (e^{y_\delta} - e^{-y_\delta})/(e^{y_\delta} + e^{-y_\delta}) \quad (18)$$

Where d is the d^{th} dimension of a wolf.

Eqs. (19) – (21) have been used to calculate the Value of $cstep_1$, $cstep_2$, and $cstep_3$.

After completing this step, the result will no longer be continuous but a value of -1 or 1. As seen in Equations (16) – (18), it switches using the transfer function. To compare with random numbers, the integers -1 and 1 are needed.

$$cstep_1^d = \begin{cases} 1, & if(t_1^d \geq \text{randn}) \\ -1, & else \end{cases} \quad (19)$$
$$cstep_2^d = \begin{cases} 1, & if(t_2^d \geq \text{randn}) \\ -1, & else \end{cases} \quad (20)$$
$$cstep_3^d = \begin{cases} 1, & if(t_3^d \geq \text{randn}) \\ -1, & else \end{cases} \quad (21)$$

Where "and" is a random number between [-1, 1]. The distances are $cstep_1$, $cstep_2$, and $cstep_3$ so that it will change relative to α, β, and δ. Next, the following equations are used to calculate X_1, X_2, and X_3.

$$X_1^d = \begin{cases} 1, & if(X_\alpha^d + \text{cstep}_1^d \geq 1) \\ -1, & \text{else} \end{cases} \quad (22)$$
$$X_2^d = \begin{cases} 1, & \text{if}(X_\beta^d + \text{cstep}_2^d \geq 1) \\ -1, & \text{else} \end{cases} \quad (23)$$
$$X_3^d = \begin{cases} 1, & \text{if}(X_\delta^d + \text{cstep}_3^d \geq 1) \\ -1, & \text{else} \end{cases} \quad (24)$$

The last stage uses a straightforward stochastic crossover, as given in Eq. (25), to update the location in the following iteration.

$$X_i^d(nt) = \begin{cases} X_1^d & \text{if}\left(\text{rand} < -\frac{1}{3}\right) \\ X_2^d & \text{elseif}\left(-\frac{1}{3} \leq \text{rand} < \frac{1}{3}\right) \\ X_3^d & \text{else} \end{cases} \quad (25)$$

Tanh GWO's pseudo code is described in Algorithm 2.

Algorithm 2	**:**	**Tanh Grey Wolf Optimizer**
Start		
1	**:**	Initialize the related parameter of tanh GWO
2	**:**	Randomly generate the positions of the wolves
3	**:**	Compute each wolf's level of fitness
4	**:**	Find X_α, X_β, and X_δ
5	**:**	**for** i=1: MAX_IT **do**
6	**:**	Update a, A, and C by using Equations (3), (4), and (12)
7	**:**	Compute the positions of each wolf by using Equations (13) – (25)
8	**:**	Compute each wolf's level of fitness
9	**:**	Update X_α, X_β, and X_δ
10	**:**	**end for**
11	**:**	Output X_α
End		

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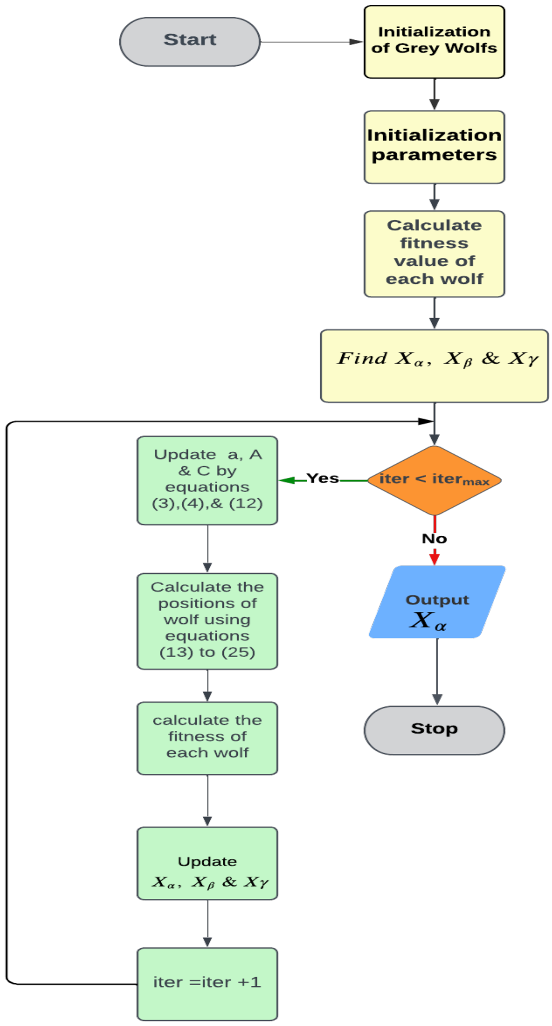

Figure 1: Algorithm 2 flowchart

Figure 1 shows the flowchart representation of Algorithm 2, i.e., Tanh Grey Wolf Optimizer.

3.4 Rules for trend classes

For example: If news arrives at time hh: mm has the sentiment "S" and the stock price at that time is "P" and the prediction of 5 minutes after the stock price is "Q," then the percentage change in stock price is X then:
If X>30, then Strong Buy, and if S > 0.5, then Strong Buy, so the final verdict will be Strong Buy.
Here S is in the range of -1 to 1. Similarly, depending on the cases, the result will be classified into Strong Buy, Buy, Hold, Sell, and Strong Sell.

3.5 Dataset

In the proposed study, minute-by-minute data from the Indian market Nifty50 has been used, which is open-source & can be extracted from yahoo finance. The dataset used to make the model is from 19 April 2023 to 4 May 2023, i.e., 15 days.
For training and testing, the dataset has been partitioned into 80:20 ratios. Parameters taken for the analysis are Low, Open, Close, Hig, Adj Close & technical indicators such as SMA20, SMA50, EMA20, EMA50, EMA200, UpperBB, LowerBB, RSI, ATR, MACD, MACD_SL, ADX. In Total, 17 features have been considered.

3.6 Neural Network Model Architecture & Hyperparameters

Hyperparameters	
Number of epochs	20

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Optimizer	Adam
Loss Function	MAE
Timesteps	25
Batch Size	16
Dense Layers	5 & 1

Table 1: Hyperparameters table

3.7 Evaluation Metrics

Various metrics have been used to evaluate the model's effectiveness and determine the market price prediction's accuracy.

RMSE (Root Mean Squared Error)

The ratio of 'n' observations to the square root of the sum of observed and valid deviations. It serves as a scale for the divergence between actual and anticipated values. The lower the Value hence more accurate it is [42].

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

Here, n represents total observations, and y_i and $\hat{y}_i$ represent actual and anticipated values, respectively.

MAE (Mean Absolute Error)

There must be an absolute difference between the actual and anticipated values. Using fundamental difference, the result's negative sign is discarded. The above error's average across all examples in a dataset is what MAE returns as its output. The lower the Value hence more accurate it is [42].

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

Where n represents the total number of observations and the actual and predicted values, respectively.

MAPE (Mean Absolute Percentage Error)

The MAPE can be viewed as a loss function that describes the error referenced by the model assessment. The MAPE enables us to determine accuracy by measuring the deviations between the actual and predicted figures. MAPE can be stated as a percentage as well. Better model fit is indicated by a lower MAPE [42].

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

Here, n represents total observations, and y_i and $\hat{y}_i$ represent actual and predicted values, respectively.

MdAPE (Median Absolute Percentage Error)

An error statistic called median absolute percentage error (MDAPE) assesses how well regression models perform. It represents the average of all determined absolute percentage differences between predicted and actual matching values, where the model is more accurate when the percentage is lower.

$$\mathrm{MDAPE} = \mathrm{median}\left(\frac{|\hat{y}_i - y_i|}{y_i}\right) * 100$$

Where y_i and $\hat{y}_i$ represent the actual and predicted values, respectively.

Accuracy

We have used the "r2 score" to find the accuracy. The r2 score is also called the coefficient of determination. It has also pronounced as R squared. The R2 is calculated by subtracting the outcome from 1 and dividing the total squared amount of deviations from the average model by the total squared amount of residuals from the regression model [42].

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}$$

Here y_i, $\hat{y}_i$, and $\bar{y}$ represent actual Value, predicted Value, and mean of actual values, respectively. The requirements for an excellent R-Squared reading can be very high, like 0.9 or more.

Section 4: RESULT

	Accuracy	MAE	MAPE	MDAPE	RMSE
Without GWO	63.2987	0.03	0.09	0.07	0.0853
With GWO	91.8971	0.02	0.05	0.05	0.0840
Sigmoid GWO	92.7923	0.01	0.05	0.04	0.0836
Proposed GWO	**94.1963**	**0.01**	**0.04**	**0.04**	**0.0818**

Table 2: Numerical Data

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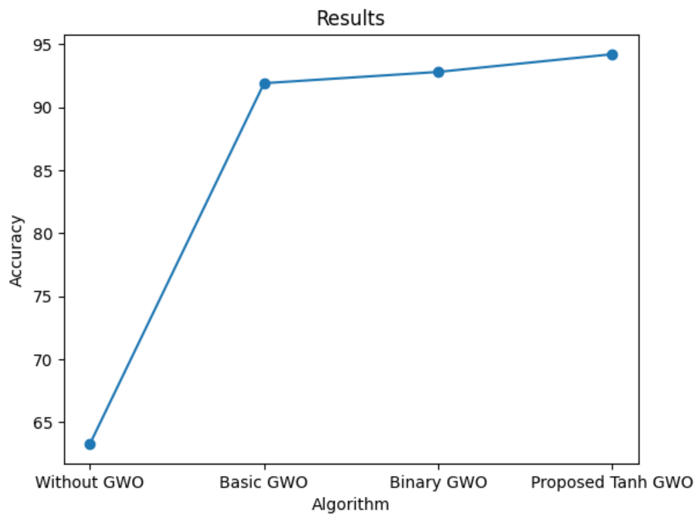

Fig 2: Accuracy Graph

From the result of Table 2 and Figure 2 and Figure 3 graph, it can infer that the accuracy of the proposed Tanh GWO is far better than others. The RMSE value of Tan GWO is lesser than that of others, indicating less error because the lesser the error better the algorithm is, and the greater the accuracy better the algorithm. This concludes that the Proposed Tanh GWO outperforms others.

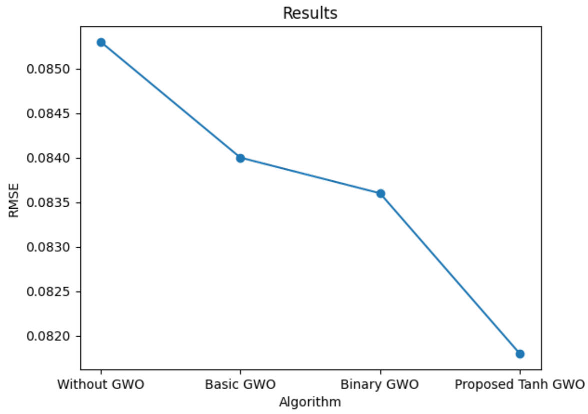

Fig 3: RMSE Graph

Algorithm	Training Accuracy	Testing Accuracy	Precision	Recall
Text Vectorization + LSTM	**0.971**	**0.771**	0.761	0.733
Tf-idf vectorizer + Naïve Bayes	0.795	0.754	0.781	0.647
Count vectorizer + Naïve Bayes	0.794	0.760	0.758	0.703

Table 3: News sentiment analysis result table

From the result in Table 3 and Figure 4 graph, it can infer that the accuracy of LSTM with text vectorization is better than the Naïve Bayes algorithm when used with Count vectorization & also with Tf-idf vectorization. The training & testing accuracy value of LSTM is greater than that of others, which indicates that the efficiency of the LSTM neural network is better than the Naïve Bayes.

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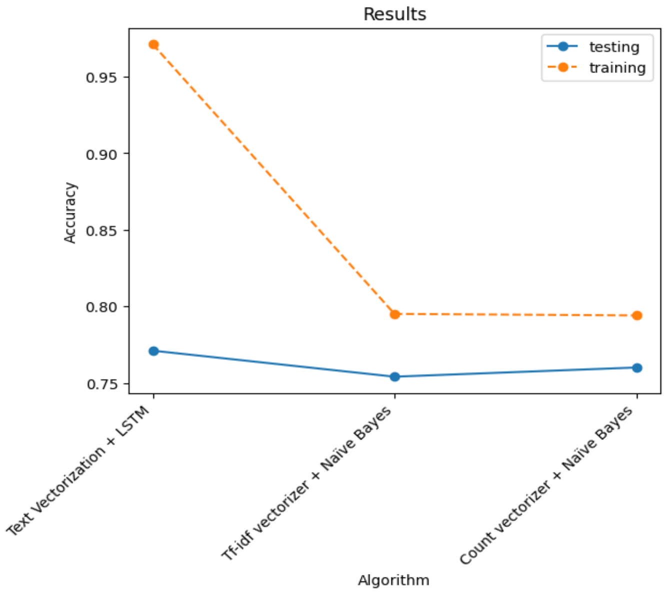

Figure 4: News sentiment analysis result graph

IV. CONCLUSION

In concluding the study, we were made up of three phases. In its initial stage, this study suggested a unique Tanh Grey Wolf Optimizer method to boost the neural model's effectiveness and accuracy. Tanh narrows the infinite search space down to -1 and 1. The functions sigmoid and tanh are comparable, but tanh has a broader range and is more symmetrical around the origin, producing results that are not biased. This feature gives Tanh the potential to have a better gradient than the current basic GWO and binary GWO, which employ sigmoid, leading to greater accuracy. The results inferred from the table & graph support the statement; hence, Tanh GWO outperforms the other algorithms. Word embeddings were used in the second phase of the research to perform sentiment analysis on news articles, improving the reliability of the predictions. These forecasts are combined with the news sentiment score in the last step, which divides the result into five categories: Strong Sell, Sell, Hold, Strong Buy, and Buy.

V. REFERENCES

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