Leveraging Stochastic Gradient Descent with Deep Learning Model for Financial Distress Prediction

Barbara Charchekhandra[*1], Rashel Abu Hakmeh[2], Murat Ozcek[3]
[1] Jadavpur University, Department Of Mathematics, Kolkata, India
[2] Faculty of Science, Mutah University, Jordan
[3] Gaziantep University, Department of Mathematics, Gaziantep, Turkey
Emails: Charchekhandrabar32@yahoo.com; Hakmehmath321@gmail.com; muratozcek.12@gmail.com

Abstract

Stock is a financial product considered by flexible trading, high risk, and high return that can preferred by several investors. Investors may get an abundance of returns through the accurate prediction of stock price trends. Nevertheless, the stock price can be influenced by certain factors including market conditions, companies' managerial decisions, macroeconomic situation, and investors' preferences for major economic and social events. Econometric and Statistical models are widely utilized in classical stock price prediction; however, these techniques could not handle the complex and dynamic environments of the stock market. Researchers have begun using deep learning (DL) and machine learning (ML) to estimate stock fluctuations and prices with the rapid evolution of artificial intelligence (AI), serving investors to define investment strategies to increase returns and decrease risk. Therefore, this manuscript presents a new dung beetle optimization with deep learning based stock price prediction (DBODL-SPP) methodology. The purpose of the DBODL-SPP algorithm is to predict the rise or fall of stock prices using the optimal DL model. In the DBODL-SPP technique, the min-max scalar can be deployed for pre-processing the input data. Besides, the DBODL-SPP approach applies the DBO algorithm for electing an optimal subset of features. The DBODL-SPP technique makes use of a multi-head attention long short-term memory (MHA-LSTM) model for the stock price prediction. Finally, by using the equilibrium optimizer (EO) algorithm, the parameter tuning of the MHA-LSTM algorithm can be carried out. A detailed set of experimentations has been applied to evaluate the enriched performance of the DBODL-SPP technique. The simulation values emphasized that the DBODL-SPP algorithm achieves better results than other techniques for stock price prediction

Keywords: Stock Price Prediction; Dung Beetle Optimization; Hyperparameter Tuning; Multi-Head Attention; Deep Learning

1. Introduction

The stock market is considered an unpredictable, non-linear, and dynamic feature naturally. Prediction of stock prices is a complex task because it relies on diverse conditions comprising however, not restricted to a corporation's financial statements and performances, world economy, political situations, and so on [1]. Accordingly, to decrease the losses and increase the profit, methods to estimate the values of the stock in advance by evaluating the trends in recent times, demonstrate the extremely beneficial to make the stock market activities [2]. Conventionally, two major techniques are developed for calculating the stock price of an organization. Technical analysis system employs the previous price of stocks such as opening and closing price, adjacent close values, the volume traded, and more. The stock is employed to predict the upcoming stock price [3]. Another category of analysis is qualitative which can be executed due to external factors namely market condition, company profile, financial and political aspects, textual data through social media, financial news articles, and even blogs by financial analysts [4]. Currently, advanced intelligent methods dependent upon both technological and basic analysis have been implemented to predict stock prices. Mainly, the data size must be non-linear and massive for analyzing the stock market [5]. In order to deal with numerous data effective system must be required to identify the hidden patterns and intricate relationships in these massive datasets. Machine learning (ML) methods in this domain are demonstrated to enhance effectiveness by 60-86 percent if related to the previous techniques [6].

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Continuous expansion in the AI domain causes the extensive usage of deep learning (DL) methods in several research domains and real-world conditions [7]. Applications comprise medical predictions, image recognition, natural language processing (NLP), etc. Neural networks (NNs) are implemented in such applications that can also emerge and be enhanced because of the increase in the DL. For instance, reinforcement learning (RL) achieved popularity after AlphaGo defeated the top chess player at that moment by employing it, and RL was applied to the financial prediction domain from that time. These technological breakthroughs have provided the stock and Forex prediction models a strong basis to begin and better opportunities for enhancement. An extremely difficult nonlinear correlation of DL will entirely define the intricate features of the manipulating factors [8]. DL is one of the ML techniques that can be newly developed. It is a subdivision of ML and artificial intelligence (AI) and a collection of methods, which can be attempted to model higher-level theoretical notions through learning in diverse layers and levels [9]. Several alternative domains have proved the accuracy of a DL method for prediction accuracy like gene analysis and image classification. Experimentation outcomes have been accomplished for time-series data analysis and prediction with a DL method; for instance, DL is employed for predicting offline store traffic [10]. Entire DL methods are exceedingly performed in alternative research domains.

This manuscript presents a novel dung beetle optimization with DL based stock price prediction (DBODL-SPP) algorithm. The purpose of the DBODL-SPP methodology is to forecast the rise or fall of stock prices using the optimal DL model. In the DBODL-SPP technique, a min-max scalar can be employed for pre-processing the input data. Besides, the DBODL-SPP methodology applies the DBO algorithm for optimum feature subset selections. Moreover, the DBODL-SPP algorithm uses a multi-head attention long short-term memory (MHA-LSTM) model for the prediction of stock prices. At last, the parameter tuning of the MHA-LSTM algorithm has been performed by the use of an equilibrium optimizer (EO) algorithm. The simulation values underlined that the DBODL-SPP approach obtains optimum performance with other methods on the prediction of stock prices.

2. Literature Review

Patil et al. [11] developed an effectual plan named the Deep Recurrent Rider LSTM method. Dual classifiers like Rider Deep LSTM and Deep RNN techniques are employed. The Rider Deep LSTM is a result of the incorporation of the Rider idea with Deep LSTM, while the Deep RNN has been trained to utilize the developed Shuffled Crow Search Optimizer (SCSO) method. Furthermore, the SCSO was a result of the combination of SSO and CSA models. Tao et al. [12] project a novel knowledge graph and DL model integrated with a stock price forecast system. The knowledge graph was employed over the ConvLSTM network. Afterward, the technique builds the mutation point space weight matrix and gets the mutation point data features over the GCN. Lastly, mutation point data, the features of market data, and the target stock price were merged. In [13], a clustering-enhanced DL framework is presented with 3 DL techniques namely LSTM, RNN, and GRU. The method projects a novel resemblance measure, named Logistic Weighted Dynamic Time Warping (LWDTW), by spreading a Weighted Dynamic Time Warping (WDTW) technique. Particularly, the cost weight function of WDTW is adapted with the logistic possibility density distribution function. Furthermore, the clustering-based predicting structure is executed with the above 3 DL methods.

Das et al. [14] present dual novel hybrid DL-based methods named "En-Tweet-Hib-SMF" and "En-Tweet-Deep-SMF". These plans include improving scores of Twitter sentiment utilizing an improved method and potent practical indicators. The "En-Tweet-Deep-SMF" technique utilizes a GRU, whereas the "En-Tweet-Hib-SMF" method employs the CNN-BLSTM hybrid DL-based technique. Moreover, kernel principal component study is employed. In [15], a novel framework structure is projected, which merges CNN and LSTM, which is called stock sequence array convolution LSTM (SACLSTM). It forms a series array of past data and its foremost indicators employs the array as an input image and removes definite feature vectors over the convolution and pooling layers. Das et al. [16] offer a new technique by uniting ensemble CNN, ensemble empirical mode decomposition (EEMD), and X (Twitter) sentiment scores dependent upon past stock data. This method uses EEMD. Then, an ensemble CNN is made, including parallel sub-networks. This ensemble CNN contains manifold parallel sub-networks; every learning has different IMF representations. The scores of X sentiment are combined over a distinct CNN that examines sentiment.

In [17], a DL structure is offered by utilizing Generative Adversarial Networks (GAN). A generic method containing a Phase-space Reconstruction (PSR) model which is projected for rebuilding price series and GAN which is a mixture of dual neural networks such as CNN as a Discriminative model and LSTM as a Generative model. Mu et al. [18] integrate the multi-source data affecting stock values and relate the SI algorithm, sentiment analysis, and DL to construct the MS-SSA-LSTM technique. Initially, crawling is completed to compute the index of sentiment. Then, the SSA enhances the LSTM hyperparameter. Lastly, the vital trading data and sentiment index are united, and LSTM was employed in order to estimate stock values in the prospect.

3. The Proposed Method

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In this article, we have introduced a new DBODL-SPP methodology. The purpose of the DBODL-SPP approach is to forecast the increase or fall of stock prices using the optimal DL model. It encompasses four different kinds of processes involving data normalization, DBO-based feature selection, MHA-LSTM-based price prediction, and EO-based hyperparameter tuning process. Fig. 1 represents the entire flow of the DBODL-SPP technique.

A. Min-Max Normalization

At the primary level, the DBODL-SPP technique undergoes a min-max scalar to preprocess the input data. The previously trained method pre-processes the input data by normalizing it utilizing the MinMaxScaler [19]. This stage is essential because it makes sure that every input feature is on a similar scale and prevents the model from being biased by nearby features with superior values. Normalized also supports the model to converge quicker and enhances its entire solution. This ensures that every value is among zero and one, which is essential for learning efficiently.

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

whereas x refers to the new data, $x_{\min}$, and $x_{\max}$ denote the minimal and maximal rates from the data, correspondingly, and x_{norm} signifies the normalization data.

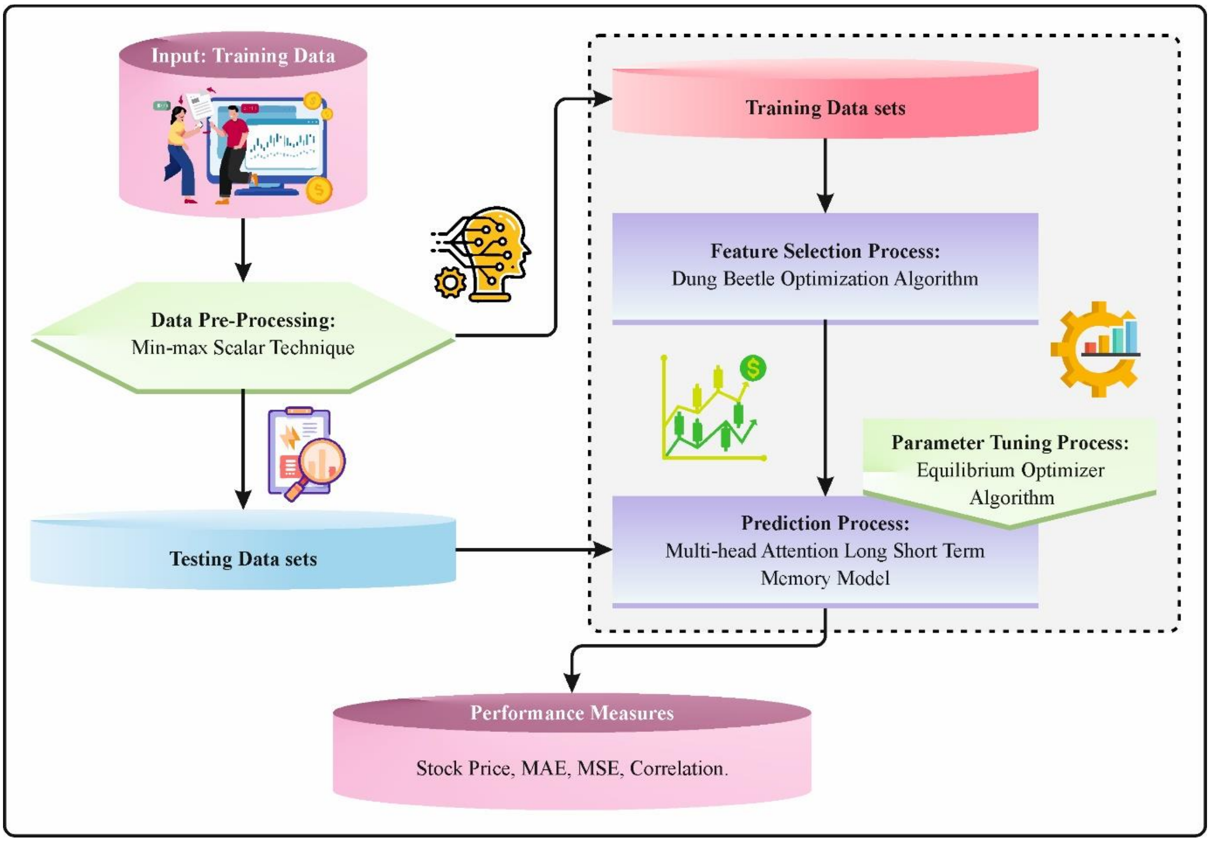

Figure 1: Overall flow of DBODL-SPP technique

B. DBO-based Feature Subset Selection

In this work, the DBODL-SPP technique applies the DBO algorithm for electing an optimal subset of features. Xue and Shen recently proposed the DBO algorithm based on the dung beetle's behavior [20]. DBO is better than other optimization techniques on test functions. This emerges from the impact of global best and worst individuals. In this proposed model, the individual is considered a dung beetle in a multi-dimensional search range, and every individual is a promising solution to the optimizer problems. The DBO technique includes 5 steps.

1) Initialization

Assume that n agents in the d-dimension space, followed by the X population formulated by:

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$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d} \end{bmatrix} \quad (2)$$

Each individual must be distributed over the solution space to prevent the optimum solution.

2) Calculate Fitness Value

During this phase, the fitness value of each agent is evaluated. Therefore, the global optimum individuals correspond to the lowest fitness values, and the fitness function (FF) relies on the problems to be resolved.

3) Upgrade Locations

Every individual is split into rolling dung beetles, brood ball beetles, small dung beetles, and thieves, increasing the diversity of new locations. Assume that the amount of initial population is 30, amongst them, six are brood balls, seven are small dung beetles, six are ball-rolling dung beetles, and the residual are thieves. All the types upgrade their location based on the formula.

a: Ball-Rolling Dung Beetle

The ball-rolling dung beetle rolls the ball and updates the position using the subsequent equation:

$$x_i(t+1) = x_i(t) + \alpha \times k \times x_i(t-1) + b \times \triangle x \quad (3)$$

$$\triangle x = |x_i(t) - X^w| \quad (4)$$

Now, X^w indicates the location of global worse dung beetles up to the prior iteration. α is allocated 1 or -1. The constants k and b values range between [0,0.2] and [0,1], correspondingly. The location of i^{th} dung beetles at iteration $tX(t)$.

The 10% probability that they will dance and update the location:

$$x_i(t+1) = x_i(t) + \tan(\theta)|x_i(t) - x_i(t-1)| \quad (5)$$

Here, θ is a uniform distribution randomly value within $[0, \pi]$, demonstrating the angle of defection.

b: Brood Ball

The brood ball dung beetles update the location using the subsequent equation:

$$x_i(t+1) = X^* + b_1 \times (x_i(t) - Lb^*) + b_2 \times (x_i(t) - Ub^*) \quad (6)$$

In Eq. (6), the best position (local best location) amongst n dung beetles at the existing iteration is represented as X^*. The spawning region is constrained within $[Lb^*, Ub^*]$. b_1 and b_2 are random vectors of $1 \times d$ size, uniform distribution within [0,1].

c: Small Dung Beetle

The small dung beetle updates the location using Eq. (7):

$$x_i(t+1) = x_i(t) + C_1 \times (x_i(t) - Lb^b) + C_2 \times (x_i(t) - Ub^b) \quad (7)$$

Here C_1 denotes the random value following a Gaussian distribution, C_2 is a random number within [0,1], and the optimum foraging region is constrained within $[Lb^b, Ub^b]$.

d: Thief

The thieves updated the location based on Eq. (8),

$$x_i(t+1) = X^b + S \times g \times (|x_i(t) - X^*| + |x_i(t) - X^b|) \quad (8)$$

In Eq. (8), X^b symbolizes the optimum location of dung beetles. S shows the constant values, and g refers to the random vector generated from the Gaussian distribution with 1xd dimensional.

4) Judge if out of Boundary

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Every individual updated to the novel place. Nevertheless, any agents might be outside the boundary of the solution space. In such cases, this agent will set the boundary value.

5) Loop or Terminate

Repeating step 2 still the terminating criteria is satisfied.

The FF undertakes the classifier accurateness and FS counts. It enhances the classifier accuracy and decreases the fixed dimension of FS. Accordingly, the resulting FF has been deployed for evaluating individual results as defined in Eq. (9).

$$Fitness = \alpha * ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \tag{9}$$

whereas $ErrorRate$ denotes the classifier error values employing the FS. $\#SF$ stands for the count of elected features and $\#All\_F$ implies the entire count of attributes from the new database. $ErrorRate$ represents the considered as the percentage of inappropriate classified to the amount of classifiers made, defined as a rate among zero and one. α is deployed to manage the significance of classifier quality and subset length.

C. Stock Price Prediction using MHA-LSTM

The DBODL-SPP technique uses the MHA-LSTM model for the prediction of stock prices. The applications of LSTM to time series predictive problems are where they truly shine [21]. Although LSTM is specially designed to alleviate these problems, Backpropagation in RNN is plagued by exploding and disappearing gradient problems. LSTM is a variant of RNN with the memory unit in all the neurons; hence, the network might either discard or retain historical information. LSTM consists of three gates: an input gate that defines what amount of information from the prior layer is to be saved from the cell; an output gate that defines what the next layer learns about the existing cell layer and a forget gate that defines how the information from the existing layer of memory unit is forgotten. Like RNN, the overall structure of LSTM is the same, the cell was differently constructed. In the training process of RNN, the gradient explosion and disappearance problems might be well solved using the novel structure of LSTM. The forget gate layer is accountable for discarding irrelevant information from the cell state.

$$f_f = \sigma\left[w_f(h_{t-1}, x_t) + b_f\right] \tag{10}$$

In Eq. (10), x_i is the new input, w_f denotes the weight, h_{t-1} refers to the output from the prior time step, and b_f is the bias. The input gate layer is accountable for updating and determining the original data that would be stored from the cell layer. Next, the $tanh$ layer produces the vector of possible new layer values.

$$i_t = \sigma[w_i(h_{t-1}, x_t) + b_i] \tag{11}$$

$$\hat{c}_i = tanh[w_c(h_{t-1}, x_t) + b_i] \tag{12}$$

The c_{t-1} cell state can be updated to the c_t state. f_t intensifies the prior condition. Then $i_t * \hat{C}_t$ element is added. This produces the new candidate value based on what extent the state value has been modified.

$$c_t = f_t * c_{t-1} + i_t * \hat{c}_t \tag{13}$$

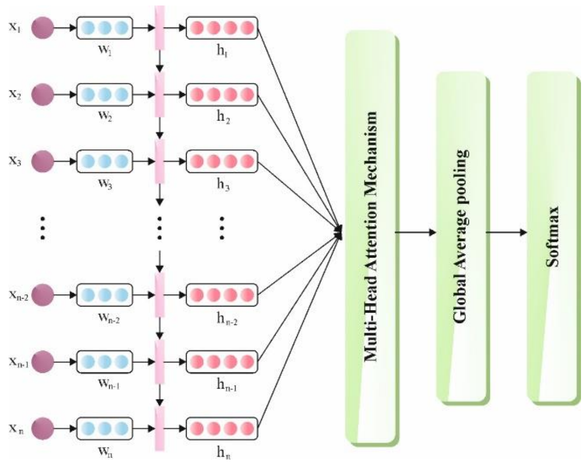

Figure 2: Architecture of MHA-LSTM Model

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The cellular state is processed by means of the sigmoid layer to define which section would be the outcome. The sigmoid output gate is multiplied by the cell layer (to force the value to be within [-1, 1]).

$$\hat{o}_i = tanh[w_0(h_{t-1}, x_t) + b_i] \tag{14}$$

Like the attention mechanism, a multi-head attention (MHA) model similarly seeks to consolidate valuable information from word features but permits several convex integrations for attention under distinct words [22]. During this method, it can execute an attention model with the next transitions:

$$d_i^{(j)} = w_2^{(j)} \tanh\left(W_1^{(j)} h_i + b_1^{(j)}\right) + b^{(j)} \tag{15}$$

$$a_i^{(j)} = \frac{\exp(d_i^{(j)}}{\sum_l \exp(d_l^{(j)}} \tag{16}$$

$$m^{(j)} = \sum_i a_i^{(j)} h_i \tag{17}$$

$$r = m^{(1)} \| m^{(2)} \| \ldots . \| m^{(K)} \| \tag{18}$$

whereas h_i refers to the representation of the word w_i , $a_i^{(j)}$ is its equivalent attention weighted for the j^{th} head, $m^{(j)}$ implies the aggregation solution for the j^{th} head, and r represents the aggregation solution for every head. || stands for the concatenation function and $W_1^{(j)} \in R^{2Lx2L}$, $b_1^{(j)} \in R^{2L}$, $w_2^{(j)} \in R^{2L}, b^{(j)} \in R$ implies the weight parameters, with L indicating the size of LSTM hidden layer and K demonstrates the amount of heads. Fig. 2 represents the infrastructure of MHA-LSTM.

D. Hyperparameter Tuning Process

Eventually, the hyperparameter tuning of the MHA-LSTM algorithm was executed by the use of the EO technique. EO uses a certain population during the optimization process, and each is considered a feasible solution to the problems [23]. The following main steps of EO are given:

1. Initialization

Initially, EO needs an arbitrary solution set to begin its optimizer algorithm. A primary set is generated according to the highest and lowest boundary of the solution:

$$E_m = E_m^{lst} + RND \times (E_m^{hst} - E_m^{lst})\ with\ m = 1, \ldots, N_{Po} \tag{19}$$

2. Solution update procedure

The update process for the new solution is performed after the initialization is completed. After each iteration, the update process enhances the quality of existing solutions. The mathematical model to find a new solution is given below:

$$E_m^{new} = E_{ref} + \left(E_m - E_{ref}\right) \times EM + \frac{GP}{RP \times V} \times (1 - EM) \tag{20}$$

Where, GP, E_{ref}, and EM denote the generating proportion, reference solution, and exponential multiplier. RP refers to the return proportion from the volume (V) and can evaluated by the fraction of rated flow (RF) by the model and V. E_{MB} is a center attained solution, $E_{ref1}, E_{ref2}, E_{ref3}$, and E_{ref4} are the 4 prominent solutions with the smaller FF values from the existing population.

$$E_{ref} \in \left[E_{ref1}, E_{ref2}, E_{refs}, E_{ref4}, E_{MB}\right] \tag{21}$$

$$E_{MB} = \frac{E_{ref1} + E_{ref2} + E_{ref3} + E_{ref4}}{4} \tag{22}$$

The computation of EM: In metaheuristic approach, EM is considered as a scale factor to generate jumping steps among new and old solutions. Usually, the factor is an arbitrary integer in a specific range. But this factor considerably balances the exploitation and exploration in the optimizer algorithm.

$$EM = 2 \times sign(\gamma - 0.5) \times [e^{-tv} - 1] \tag{23}$$

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Where tv denotes the time variation:

$$tv = \left(1 - \frac{CI}{MI}\right)^{\frac{CI}{MI}} \tag{24}$$

The computation of GP: It enhances the balance between the exploitation and the exploration capabilities.

$$GP = EM \times CP\left(E_{ref} - tv \times E_m\right) \tag{25}$$

$$CP = \begin{cases} \frac{\varepsilon_1}{2}, & if\ \varepsilon_2 \geq 0.5 \\ 0, & otherwise \end{cases} \tag{26}$$

3. Correction of new solutions

The limitation of the solution is used to correct and check the new ones after finding a new solution attained by Eq. (20):

$$E_m^{new} = \begin{cases} E_m^{lst}\ if\ E_m^{new} < E_m^{lst} \\ E_m^{hsT}\ if\ E_m^{new} > E_m^{hsT} \\ E_m^{new}\ otherwise \end{cases} \tag{27}$$

4. Selection procedure

The primary objective is to abandon the poor-quality solution and save the maximum-quality solution for the following iteration. The selection process is performed by comparing the fitness value going to the new and the old performances:

$$Ft_m = \begin{cases} Ft_m^{new}\ if\ Ft_m \geq Ft_m^{new} \\ Ft_m, \quad otherwise \end{cases} \tag{28}$$

$$E_m = \begin{cases} E_m^{new}\ if\ Ft_m \geq Ft_m^{new} \\ E_m, \quad otherwise \end{cases} \tag{29}$$

In Eqs. (28) and (29), Ft_m and Ft_m^{new} are the existing and new fitness values of the solution m, correspondingly.

The EO algorithm develops an FF to attain greater classifier efficiency. It resolves a positive integer to exemplify the good efficiency of the candidate outcomes. During this case, the minimizing of the classifier error value can be assumed that the FF, as defined in Eq. (30).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{Misclassified\ instance\ counts}{Total\ instance\ counts} * 100 \tag{30}$$

4. Performance Validation

In this section, the prediction results of the DBODL-SPP methodology can be investigated. For simulation result analysis, Stock databases [24] for different stock tickers namely BHEL, TCS, Tata Steel, Axis Bank, Wipro, and Maruti are used.

In Table 1 and Fig. 3, the SPP outcomes of the DBODL-SPP system are tested on the Axis Bank dataset. The outcomes are inspected under varying time intervals. It is observed that the DBODL-SPP technique reaches effectual prediction of the stock prices to actual stock prices. With a time interval of 50s, the DBODL-SPP technique predicted a stock price of 78.86 with the original stock price of 55.30. Also, with a time interval of 150s, the DBODL-SPP approach predicted a stock price of 96.53 with the original stock price of 75.81. Additionally, with a time interval of 300s, the DBODL-SPP system predicted a stock price of 131.75 with the original stock price of 125.85.

Table 1: SPP outcome of DBODL-SPP technique with various time intervals on Axis Bank dataset

Stock Price Prediction - Axis Bank Dataset

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Time	Actual Stock Price	Predicted Stock Price
0	58.10	948.34
50	55.30	78.86
100	69.91	87.46
150	75.81	96.53
200	102.16	116.82
250	117.03	134.72
300	125.85	131.75

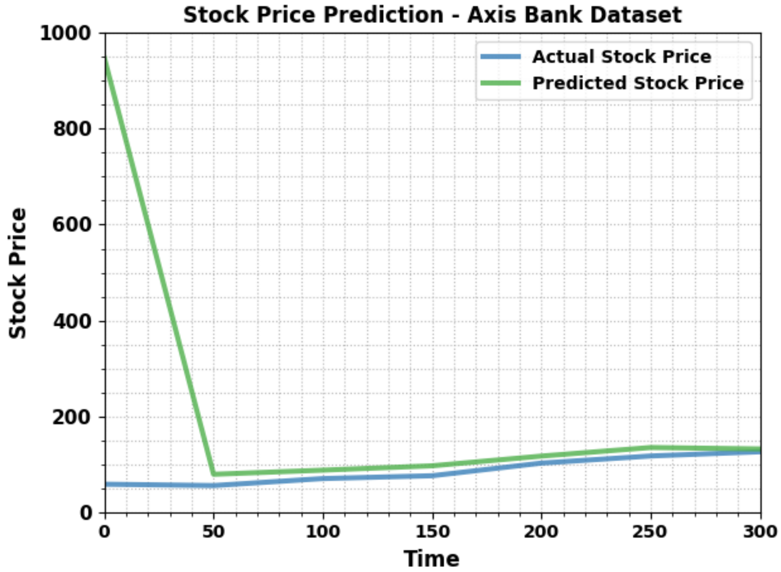

Figure 3: SPP outcome of DBODL-SPP technique on Axis Bank dataset

In Table 2 and Fig. 4, the SPP outcome of the DBODL-SPP methodology can tested on the BHEL dataset. The outcomes are examined under varying time intervals. It is clear that the DBODL-SPP system attains effective prediction of the stock prices to actual stock prices. With a time interval of 100s, the DBODL-SPP methodology predicted a stock price of 81.09 with the original stock price of 75.25. In addition, with a time interval of 500s, the DBODL-SPP approach predicted a stock price of 83.59 with the original stock price of 92.84. Furthermore, with a time interval of 800s, the DBODL-SPP methodology predicted the stock price of 181.38 with the original stock price of 193.37.

Table 2: SPP outcome of DBODL-SPP technique with various time intervals on BHEL dataset

Stock Price Prediction - BHEL Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	54.33	940.50
100	72.25	81.09
200	151.83	163.46
300	137.02	128.25
400	119.39	98.58
500	92.84	83.59

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600	166.39	142.88
700	187.39	169.71
800	193.37	181.38

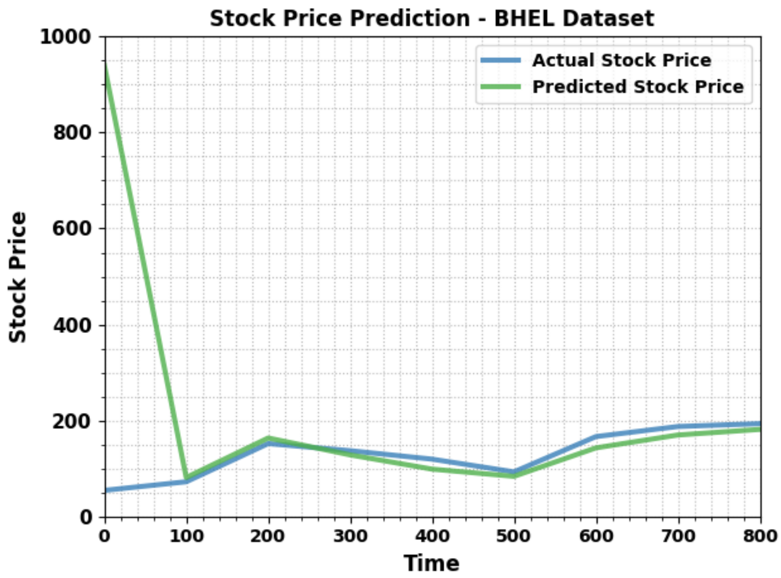

Figure 4: SPP outcome of DBODL-SPP technique on BHEL dataset

In Table 3 and Fig. 5, the SPP examination of the DBODL-SPP methodology is tested on the Maruti database. The experimental values are inspected under varying time intervals. It is noticed that the DBODL-SPP system obtains effective prediction of the stock prices to actual stock prices.

Table 3: SPP outcome of DBODL-SPP technique with various time intervals on the Maruti dataset

Stock Price Prediction - Maruti Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	54.49	971.30
20	60.67	72.92
40	42.20	75.81
60	48.28	66.69
80	54.37	72.70
100	63.77	82.07
120	69.82	75.76

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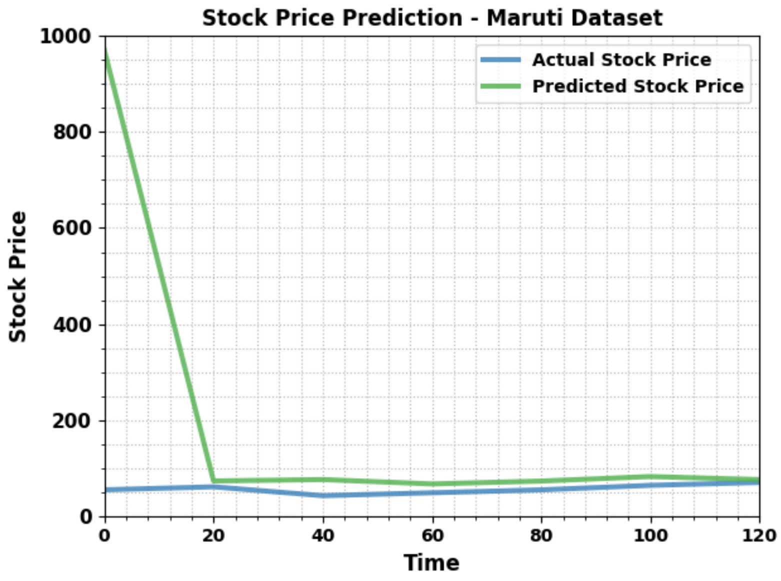

Figure 5: SPP outcome of DBODL-SPP technique on Maruti dataset

With a time interval of 20s, the DBODL-SPP methodology predicted a stock price of 72.92 with the original stock price of 60.67. Followed by, with a time interval of 80s, the DBODL-SPP algorithm predicted the stock price of 72.70 with the original stock price of 54.37. Finally, with a time interval of 120s, the DBODL-SPP system predicted a stock price of 75.76 with the original stock price of 69.82.

In Table 4 and Fig. 6, the SPP outcome of the DBODL-SPP methodology is tested on the Tata Steel database. The outcomes are inspected under varying time intervals. It is obvious that the DBODL-SPP algorithm attains effectual prediction of the stock prices to actual stock prices. With a time interval of 100s, the DBODL-SPP system predicted the stock price of 297.04 with the original stock price of 291.23. Likewise, with a time interval of 500s, the DBODL-SPP approach predicted a stock price of 88.29 with the original stock price of 76.78. Eventually, with a time interval of 800s, the DBODL-SPP technique predicted a stock price of 394.32 with the original stock price of 379.96.

Table 4: SPP outcome of DBODL-SPP technique with various time intervals on Tata Steel dataset

Stock Price Prediction - Tata Steel Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	202.70	943.65
100	291.23	297.04
200	468.68	471.49
300	603.29	597.60
400	577.57	574.76
500	76.78	88.29
600	148.38	154.01
700	305.48	305.69
800	379.96	394.32

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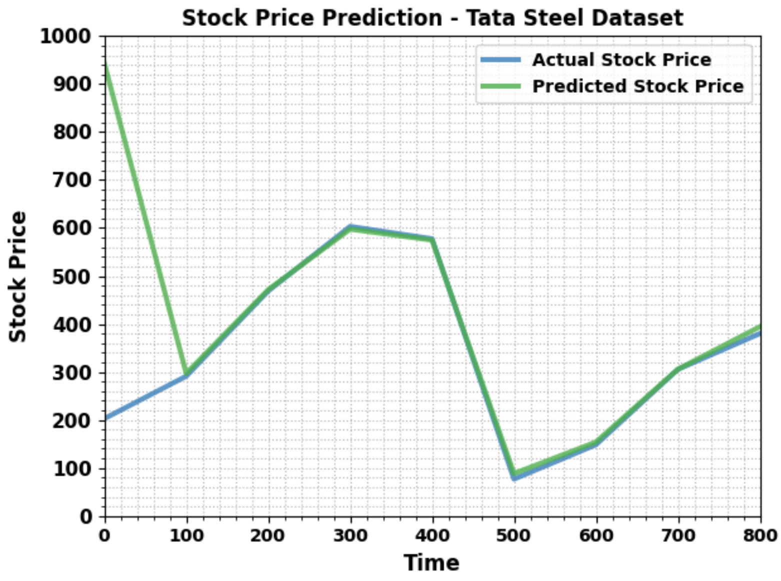

Figure 6: SPP outcome of DBODL-SPP technique on Tata Steel dataset

In Table 5 and Fig. 7, the SPP investigation of the DBODL-SPP system is tested on the TCS database. The experimental values are examined at various time intervals. It is noticed that the DBODL-SPP methodology gains effectual prediction of the stock prices to actual stock prices. With a time interval of 100s, the DBODL-SPP methodology predicted a stock price of 205.57 with the original stock price of 208.78. Besides, with a time interval of 500s, the DBODL-SPP algorithm predicted a stock price of 121.41 with the original stock price of 105.80. Moreover, with a time interval of 800s, the DBODL-SPP methodology predicted a stock price of 324.28 with the original stock price of 333.87.

Table 5: SPP outcome of DBODL-SPP technique with various time intervals on TCS dataset

Price Prediction - TCS Dataset		
Time	Actual Stock Price	Predicted Stock Price
0	218.18	967.75
100	208.78	205.57
200	186.85	174.46
300	165.27	149.66
400	161.95	152.63
500	105.80	121.41
600	155.87	149.45
700	249.52	233.78
800	333.87	324.28

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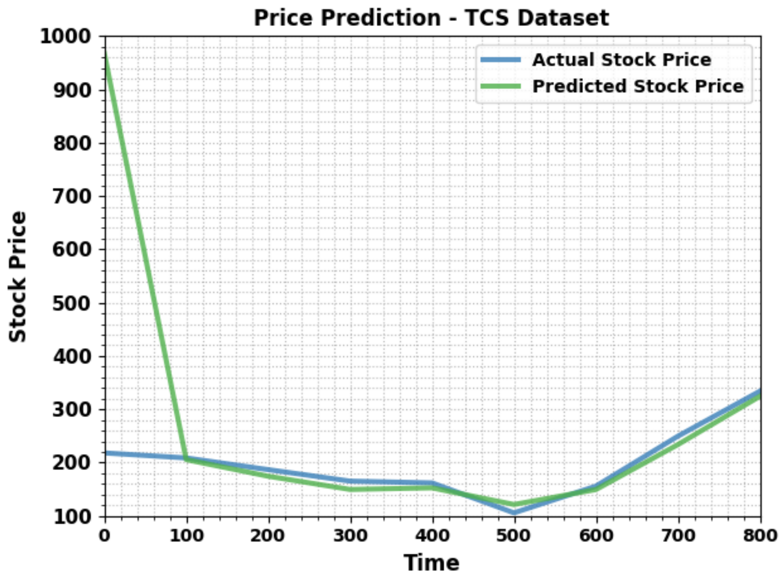

Figure 7: SPP outcome of DBODL-SPP technique on TCS dataset

Table 6 and Fig. 8 present a comparative MAE outcome of the DBODL-SPP algorithm with recent models under varying stock tickers [25]. The simulation values implied that the MM-HPA and GAN-HPA systems have reported worse MAE values. Along with that, the MMGAN-HPA model has accomplished slightly reduced MAE values. Nevertheless, the DBODL-SPP technique gains better performance with the least MAE of 0.0019, 0.0020, 0.0021, 0.0022, 0.0020, and 0.0038 under TCS, BHEL, WIPRO, Axis Bank, Maruti, and Tata Steel, correspondingly.

Table 6: MAE analysis of DBODL-SPP technique with other models under various datasets

MAE				
Stock Ticker	MM-HPA	GAN-HPA	MMGAN-HPA	DBODL-SPP
TCS	0.0031	0.0031	0.0026	0.0019
BHEL	0.0034	0.0028	0.0025	0.0020
WIPRO	0.0030	0.0028	0.0028	0.0021
AXISBANK	0.0035	0.0029	0.0028	0.0022
MARUTI	0.0027	0.0025	0.0026	0.0020
TATASTEEL	0.0054	0.0048	0.0043	0.0038

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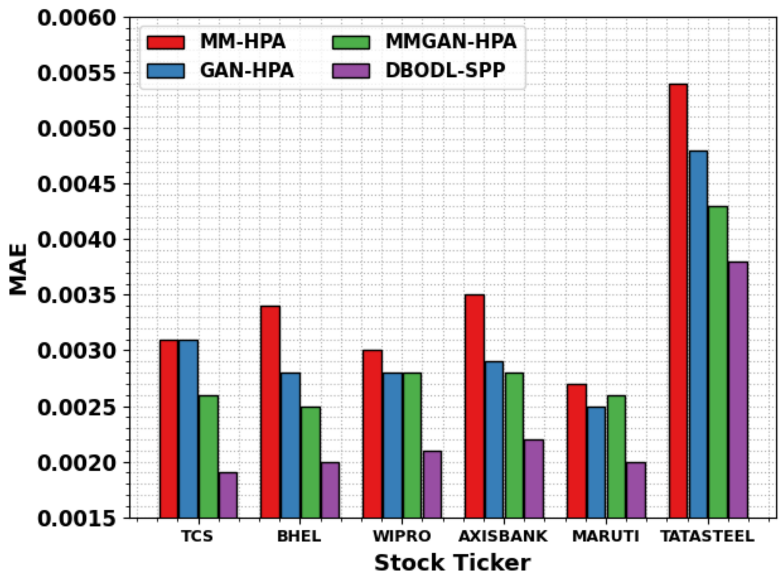

Figure 8. MAE analysis of DBODL-SPP technique under various datasets

Table 7 and Fig. 9 define a comparative MAE analysis of the DBODL-SPP technique with recent algorithms under various stock tickers. The experimental values referred that the MM-HPA and GAN-HPA approaches have reported worse MAE values. Besides, the MMGAN-HPA approach has accomplished somewhat reduced MAE values. But, the DBODL-SPP methodology achieves higher performance with minimal MAE of 0.000024, 0.000019, 0.000022, 0.000025, 0.000018, and 0.000060 under TCS, BHEL, WIPRO, Axis Bank, Maruti, and Tata Steel, correspondingly.

Table 7: MAE analysis of DBODL-SPP algorithm with other models under various datasets

MSE				
Stock Ticker	MM-HPA	GAN-HPA	MMGAN-HPA	DBODL-SPP
TCS	0.000042	0.000038	0.000034	0.000024
BHEL	0.000029	0.000029	0.000027	0.000019
WIPRO	0.000030	0.000028	0.000026	0.000022
AXISBANK	0.000037	0.000032	0.000032	0.000025
MARUTI	0.000029	0.000025	0.000025	0.000018
TATASTEEL	0.000073	0.000071	0.000068	0.000060

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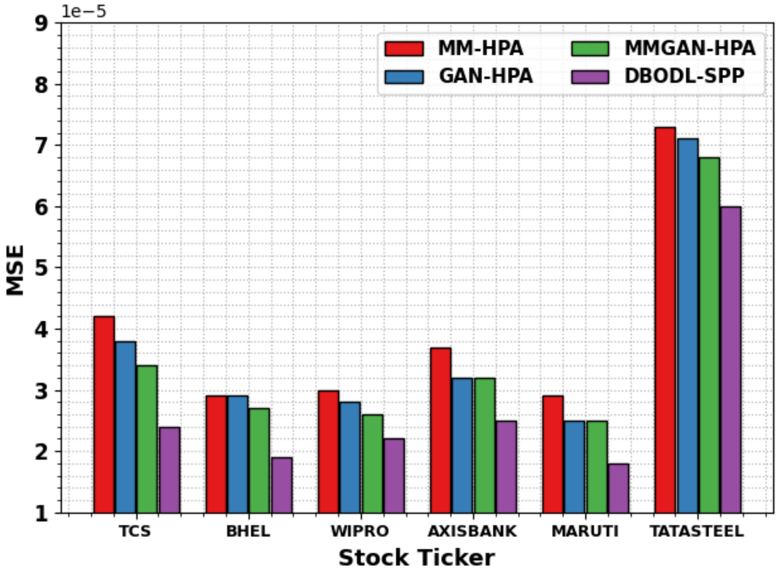

Figure 9: MSE analysis of DBODL-SPP technique under various datasets

Table 8 and Fig. 10 demonstrate a comparative CORR outcome of the DBODL-SPP algorithm with recent techniques under various stock tickers. The simulation values inferred that the MM-HPA and GAN-HPA algorithms have reported the worst CORR values. Along with that, the MMGAN-HPA approach has proficiently slightly increased CORR values. Nevertheless, the DBODL-SPP technique gains optimum solution with improved CORR of 0.9978, 0.9987, 0.9990, 0.9999, 0.9990, and 0.9992 under TCS, BHEL, WIPRO, Axis Bank, Maruti, and Tata Steel, correspondingly.

Table 8: CORR analysis of DBODL-SPP technique with other models under various datasets

CORRELATION				
Stock Ticker	MM-HPA	GAN-HPA	MMGAN-HPA	DBODL-SPP
TCS	0.9964	0.9967	0.9968	0.9978
BHEL	0.9973	0.9974	0.9976	0.9987
WIPRO	0.9977	0.9980	0.9980	0.9990
AXISBANK	0.9988	0.9989	0.9992	0.9999
MARUTI	0.9978	0.9979	0.9980	0.9990
TATASTEEL	0.9977	0.9979	0.9982	0.9992

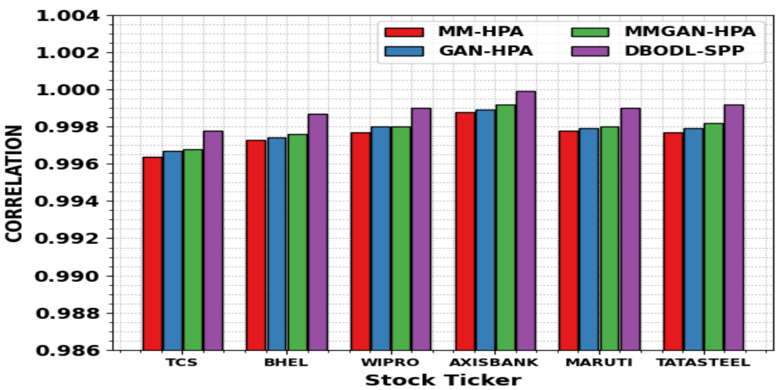

Figure 10: CORR analysis of DBODL-SPP technique under various datasets

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Thus, the DBODL-SPP technique can be applied to predict stock prices proficiently.

5. Conclusion

In this manuscript, we have introduced a new DBODL-SPP technique. The drive of the DBODL-SPP technique is to forecast the rise or fall of stock prices using the optimal DL model. It encompasses four different kinds of processes involving data normalization, DBO-based feature selection, MHA-LSTM-based price prediction, and EO-based hyperparameter tuning. At the primary level, the DBODL-SPP technique undergoes a min-max scalar that has been deployed for pre-processing the input data. Besides, the DBODL-SPP system applies the DBO algorithm for electing an optimal subset of features. For the prediction of stock prices, the DBODL-SPP technique uses the MHA-LSTM algorithm. At last, the parameter tuning of the MHA-LSTM methodology was performed by the use of the EO algorithm. To evaluate the improved performance of the DBODL-SPP system, a wide range of experiments are made. The simulation outcomes underlined that the DBODL-SPP algorithms obtain optimum performance with other approaches to the prediction of stock prices..

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