Multi-Criteria Decision Support System for Predicting Financial Futures Using Ensemble of Deep Learning Algorithms with Heuristic Search Mechanisms

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Abstract

Financial markets are an intricate dynamic system. The difficulty comes from the contact among a market and its applicants, which means, the integrated consequence of the activities of whole applicants decides the market trend, while the market trend disturbs the actions of applicants. These linked interactions make financial markets keep developing. Financial markets are interchange financial instruments like savings certificates, bonds, stocks, and much more. Particularly in stocks, because variations in stock prices are inclined by numerous factors, with economic cycles, financial trends, financial structure, and other macro issues, as well as industry growth, listed businesses' financial quality. In the last few years, deep learning (DL) and machine learning (ML) techniques have been very effective in predicting financial futures. This study develops a Multi-Criteria Decision Support System for Predicting Financial Futures Using Ensemble of Deep Learning Algorithms with Heuristic Search Mechanisms (MDSSPFF-EDLAHS) model. The main intention of the MDSSPFF-EDLAHS method is to predict future of finances using advanced ensemble models. At first, the data normalization stage applies min-max normalization for transforming input data into a beneficial format. Besides, the ensemble of deep learning models namely variational auto encoder (VAE), bidirectional long short-term memory (Bi-LSTM) technique, and dueling double deep Q-network (DDQN) system have been executed for the prediction of financial futures. At last, the spider wasp optimization (SWO) algorithm adjusts the hyperparameter values of the ensemble models optimally and outcomes in greater prediction performance. The experimental evaluation of the MDSSPFF-EDLAHS is examined on a benchmark dataset. The extensive outcomes highlight the significant solution of the MDSSPFF-EDLAHS approach to the financial future predicting process

Keywords: Financial Futures; Ensemble of Deep Learning; Heuristic Search Mechanisms; Data Normalization; Spider Wasp Optimization

1. Introduction

As a vital part of the world economic markets, the economic futures market can have a substantial effect on the worldwide economy [1]. Stock index commodities that are effective economic derivatives for hedging trading hazards have become gradually more general among market participants, and multiple scientists have organized investigations on their price forecasts [2]. With the rapid growth of communication technology, the capability of investors to attain chances in a short period slowly rises. Afterward, there are multiplying individual counts and organized investors participating in HFT, and multiple investigators have aimed at the high-frequency price

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forecasting analysis [3]. Nevertheless, several experts argue that the conventional approaches are complex to attain a reasonable implementation because of the non-linear and indeterminate financial time series character. Stock market forecasts have a significant role, since they may substantially affect the worldwide economy [4]. Because of its functional significance, examining stock market instability became an innovative work problem in multiple fields, comprising statistics, mathematics, and finance. Nevertheless, most stock indexes perform likewise in a random walk, since the economic time series data is loud and non-stationary in nature [5]. Certainly, it is very complex to forecast the stock market, for the volatility is too extensive to be acquired in a paradigm. With latest improvements in computing technology, huge volumes of information and data are continually gathered.

Over recent decades, multiple techniques have been made to predict stock markets utilizing soft computing and statistical skills [6]. Most previous research is inclined to utilize statistical models, but these techniques have restrictions when utilized for complex real-time economic data, because of various statistical presumptions, like normality and linearity [7]. In recent times, Deep Learning (DL) has attracted a substantial amount of attention in several investigation domains. DL is a novel field of ML that has enhanced the capability of computers in regions of image classification and recognition, social network filtering, speech recognition, and Natural Language Processing (NLP) [8]. The DL framework is a multi-layer NN that employs multiple-layer cascades of non-linear processing units to transform and remove multiple aspects [9]. Its learning might be both unsupervised and supervised, and it builds a hierarchy of models by employing various depiction stages that compare with diverse abstraction levels [10].

This study develops a Multi-Criteria Decision Support System for Predicting Financial Futures Using Ensemble of Deep Learning Algorithms with Heuristic Search Mechanisms (MDSSPFF-EDLAHS) model. The main intention of the MDSSPFF-EDLAHS method is to predict future of finances using advanced ensemble models. At first, the data normalization stage applies min-max normalization for transforming input data into a beneficial format. Besides, the ensemble of deep learning models namely variational auto encoder (VAE), bidirectional LSTM (Bi-LSTM) technique, and dueling double deep Q-network (DDQN) system have been executed for the prediction of financial futures. At last, the spider wasp optimization (SWO) algorithm adjusts the hyperparameter values of the ensemble models optimally and outcomes in greater prediction performance. The extensive outcomes highlight the significant solution of the MDSSPFF-EDLAHS approach to the financial future predicting process.

2. Related Works

Zheng et al. [11] discovered the ML application in economic time-series investigation, aiming at forecasting tendencies in economic initiative stocks and financial data. It initiates by differentiating stocks from stocks and explains hazard organization approaches in the stock market. Conventional statistical models like exponential smoothing and ARIMA are deliberated regarding their limitations and advantages in economic prediction. Afterward, the efficiency of ML models, specifically CNN-BiLSTM and LSTM hybrid methods, in economic market forecast is described, emphasizing their ability to acquire non-linear models in dynamic markets. In [12], a forecast gold stock price model dependent on Bayesian network optimized LSTM (BO-LSTM) is projected. By developing a Bayesian network to enhance the LSTM hyper-parameters technique, forecasting the sturdiness and precision of methods are upgraded. The experimental findings demonstrate the BO-LSTM technique has a substantial benefit in the gold stock price forecast job that is better than the conventional LSTM and the benchmark techniques. Sui et al. [13] aimed to improve stock price prediction for retail stakeholders by enhancing progressive ML models on data from the stock exchange market. We employ an inclusive method that contains data preprocessing (DP) to manage missing outliers and values, cross-validation, parameter tuning, and feature engineering.

Maehara et al. [14] focus on this paper is dual, and depends on current information on demand for economic services and economic culture in the country: (I) To empirically examine how ML models, like RF, DT, XGBoost, SVM, and ANN might be a beneficial supplement to usual techniques that is generalized linear methods such as LR for evaluating economic integration in Peru, and (II) To recognize the most impactful socio-demographical features on economic inclusion evaluation in the country. In [15], a novel method for forecasting stock market prices (SMP) is developed, like stock market prediction depending on DL (SMP-DL). It is divided into dual levels that are (1) stock price prediction (SP2) and (2) DP. During the primary level, data are pre-processed to attain cleaned ones over multiple levels that are rejected and detect missing values, data normalization, and feature selection. Subsequently, in another level for instance SP2, the cleaned data will pass over the utilized forecast technique. During SP2, LSTM associated with Bi-GRU to forecast the stock market final price.

Balakrishnan et al. [16] aimed to provide a DL model that automatically mines the statistical material law and guides stock market processes utilizing empirical mode deconstruction and bottom neural network techniques. Prediction efficacy might be amplified by integrating exponential financial and non-stationary time series. If a particular level of trust is met, the DL forecast, which depends on the analysis of large quantities of economic trade

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data, can establish the upcoming trend and economic market pricing. Kalyani et al. [17] developed an innovative Jellyfish search optimizer-based ELM with AE (JSO-ELMAE) for return rate forecast of BC economic products. The JSO application aids in optimum parameter modification of ELMAE method for forecasting the return rate of bitcoin.

3. Proposed Methodology

In this study, we have developed a novel MDSSPFF-EDLAHS model. The main intention of the MDSSPFF-EDLAHS method is to predict future of finances using advanced ensemble models. It contains various kinds of procedures involved as data normalization, ensemble of prediction process, and parameter selection. Fig. 1 illustrates the workflow of the MDSSPFF-EDLAHS algorithm.

A. Data Normalization: Min-Max Normalization

At first, the data normalization stage applies min-max normalization for transforming input data into a beneficial format. Min-max normalization is a data pre-processing system, which is generally employed to measure financial data in ML techniques, particularly when forecasting financial futures [18]. It includes rescaling the data to a set range, usually [0, 1], by deducting the least value of the database and separating by the range (max-min). This confirms that every feature donates similarly to the system, averting any single feature from governing owing to variances in measure. In the context of forecasting financial markets, min-max normalization aids in enhancing the convergence and accuracy of methods like support vector machines or neural networks. It also improves the model's capability to simplify across dissimilar financial tools, making forecasts more trustworthy.

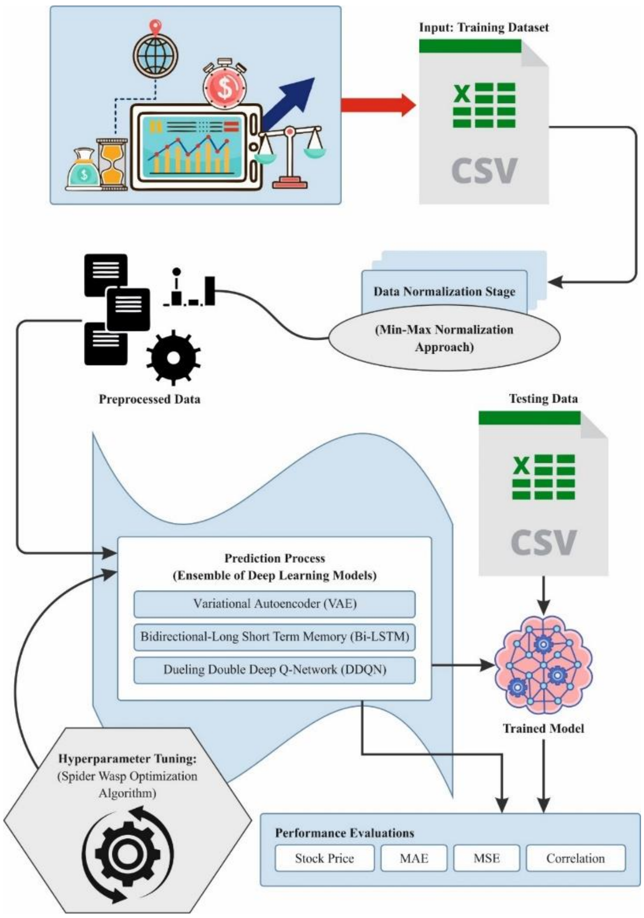

Figure 1. Workflow of MDSSPFF-EDLAHS method

B. Prediction Process: Three Ensemble Models

Besides, the ensemble of DL models namely VAE model, Bi-LSTM technique, and dueling DDQN system have been executed for the prediction of financial futures.

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1. VAE Model

VAE is a type of ANNs applied mainly to decompress and compress the data sets [19]. Therefore based on images, the VAE may condense the images into the additionally condensed latent variable area and then uncompressed it revert to reconstructed images. The traditional structure of a VAE contains 3 modules: decoder, latent space, and encoder. The encoding element normally maps input data points that are characterized like vector $x = \{x_1, x_2, \dots x_n\}$ (for example: image pixel intensity) of length n within the new variable area $\mathbb{R}^n$, to other vector, z, of dimensions $m(m < n)$ in the latent variable area $\mathbb{R}^m$

$$z = e(x) \tag{1}$$

e in such a case characterizes the mapping function of the encoder.

Once the input is encoded as a multiple-variable likelihood distribution above the latent area and z is selected from these distributions, a probability-based model is applied in the VAE field:

$$z \sim p(z|x) \tag{2}$$

Now, specified the code (or the new) variable, p refers to conditional probability distribution of the encoding variable (z). A multiple-variable Gaussian distribution is normally applied; so, the formulation is inscribed as shown:

$$z = g(x) + \zeta h(x) \tag{3}$$

Rebuilding the unique is attained by mapping the vector, z, from R^m get back to the new area R^n utilizing the decoder:

$$\hat{x} = d(z) \tag{4}$$

As the above-mentioned equations, the probability-based model is stated as shown:

$$\hat{x} = p(x|z) \tag{5}$$

Error of reconstruction, or RE, that is the average squared change among x and X is computed as shown:

$$RE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{6}$$

As the VAE basis is a probability-based method, it is important to consider either the reconstruction error itself or some possible changes. One way to calculate this change is by using the KullbackLeibler (KL) divergence.

$$Loss = RE + \beta KL \tag{7}$$

β in such a case represents the term of regularization. VAE training intentions to decrease the complete loss are essentially possible. Fig. 2 depicts the framework of VAE.

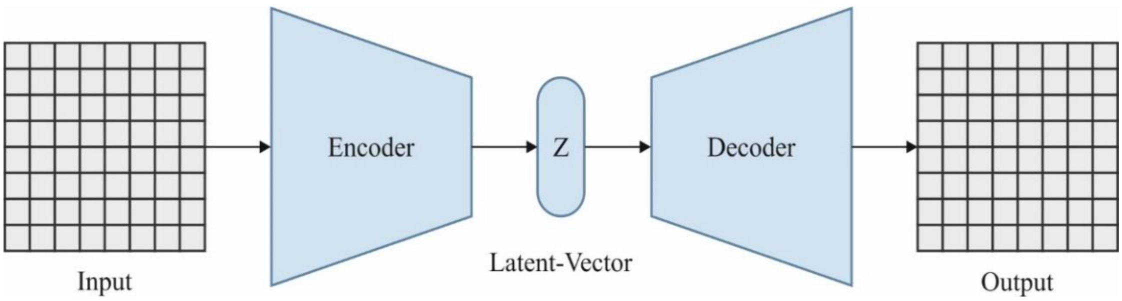

Figure 2. Framework of VAE

2. BiLSTM Technique

It can be observed that the Bi-LSTM method is assembled from a group of LSTM methods with backward and forward phases [20]. Complete, the Bi-LSTM architecture is created from famous gates: a memory cell, an input, an output, and a forget gate. The result to reserve the information from the preceding previous computation is specified by the $forget\ gate$, whereas the $input\ gate$ is applied to update the offered information, lastly, the tanh layer is applied to generate novel information. From the mathematical viewpoint, the input variable (x) is applied and incorporated to offer the $hidden\ state$ (h_t) that transfers straightforwardly to the fully connected

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(FC) layer to provide the last reply utilizing the activation function of the sigmoid. The forward and backward phases are expressed as shown:

$$\vec{h}_t = LSTM_f(x_t, \vec{h}_{t-1}) \quad (8)$$

$$\vec{h}_t = LSTM_b(x_t, \vec{h}_{t-1}) \quad (9)$$

Whereas the $LSTM_f$ and $LSTM_b$ characterize the forward and backward LSTM layers; $\vec{h}_t(i = t-1, t)$ and $\vec{h}_t(j = t, t+1)$ indicate the hidden layer output for the forward and for the backward LSTM layers, correspondingly.

3. Dueling DDQN Method

Dueling DDQN is an additional development upon DDQN, joining the Dueling Networking Structure with the selected action and assessment separation method of DDQN [21]. The basic notion of Dueling Networking Structure is for decomposing the Q-value into dual modules; this can be presented in Eq. (10).

$$Q(S_t, A_t) = V(s) + A(s, a) \quad (10)$$

The last state-action $Q(s, a|\theta)$ in Dueling $DDQN$ is stated as presented in Eq. (11):

$$Q(s, a|\theta) = V(s|\theta, \alpha) + \left(A(s, a|\theta, \lambda) - \frac{1}{|A|}\sum_{a'} A\,(s, a'|\theta, \lambda)\right) \quad (11)$$

Whereas $V(s|\theta, \alpha)$ characterizes the value of the state, $A(s, a|\theta, \lambda)$ signifies the benefit functions, θ embodies the hidden layer (HL) networking parameters, $|A|$ symbolizes the action counts, α denotes the value of the state networking parameters, and λ exemplifies the action benefit networking parameters.

C. Parameter Selection: SWO

At last, the SWO algorithm adjusts the hyperparameter values of the ensemble models optimally and outcomes in greater prediction performance. It presented a novel bio-inspired meta-heuristics based approach, the SWO model that is stimulated by the nesting, mating, and hunting behaviors of female SW naturally, and contains a range of single upgrading tactics for a range of $NP\text{-}hard$ issues [22]. The SW model mimics the natural behavior of SW and is encapsulated in 4 portions:

(1) Search behavior.

The search behavior determines the model to search for prey at the beginning of optimization, searching for spiders that are appropriate for larval development.

$$\overrightarrow{SW_i}^{t+1} = \overrightarrow{SW_i}^{t} + \mu_1 \times \left(\overrightarrow{SW_a}^{t} - \overrightarrow{SW_b}^{t}\right) \quad (12)$$

$$\mu_1 = |rn| \times r_1 \quad (13)$$

Whereas a and b are dual arbitrary individuals within the population; μ_1 signifies a significant step size; r_1 denotes randomly generated number among (0,1); and $|rn|$ denotes randomly generated number, which imitates standard distributions. Female wasps might occasionally fail to discover a spider, which had dropped from the web of the spider, thus the model permits female wasps to hunt the region closer to the fallen point of the spider.

$$\begin{cases} \overrightarrow{SW_i}^{t+1} = \overrightarrow{SW_c}^{t} + \mu_2 \times \left(\vec{L} + \vec{r_2} \times (\rightarrow -\vec{L})\right) \\ \mu_2 = B \times \cos(2\pi l) \\ B = \frac{1}{1+e^l} \end{cases} \quad (14)$$

Whereas c signifies an arbitrarily chosen female wasp inside the population; l refers to randomly generated numbers amongst -2 and 1. By randomization either Eqs. (12) or (14) hunts, the female wasp transfers near the promising position of the spider r_3 and r_4 are either two random numbers:

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Equation\ (12) r_3 < r_4 \\ Equation\ (14) otherwise \end{cases} \quad (15)$$

(2) Escaping and Following behavior.

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After identifying their spiders/prey, they might attempt to escape. Then, female SW follows their victim, dragging and paralyzing the appropriate one. C signifies the controller feature for the female bees' speed that decays from 2 to 0.

$$\begin{cases} \overrightarrow{SW_i}^{t+1} = \overrightarrow{SW_i}^{t} + C \times |2 \times \overrightarrow{r_5} \times \overrightarrow{SW} - \overrightarrow{SW}| \\ C = (2 - 2 \times (\frac{t}{t_{\max}})) \times r_6 \end{cases} \tag{16}$$

Whereas a denotes arbitrarily chosen individuals from the population, t and $t_{\max}$ represent the present iteration amount and the maximal iteration amount, correspondingly; $\overrightarrow{r_5}$ denotes randomly generated vector within the range [0,1]; and r_6 signifies randomly generated numbers within the range [0,1]. After distance improves, the exploitation stage moves to the exploration stage.

$$\begin{cases} \overrightarrow{SW_i}^{t+1} = \overrightarrow{SW_i}^{t} \times \overrightarrow{vc} \\ k = 1 - \left(\frac{t}{t_{\max}}\right) \end{cases} \tag{17}$$

Whereas $\overrightarrow{vc}$ denotes vector amongst k and $-k$ based on the standard distribution. The exchange among the above dual tendencies is understood stochastically by Eq. (18):

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Equation\ (16) r_3 < r_4 \\ Equation\ (17) otherwise \end{cases} \tag{18}$$

To pursue globally, the authors utilize the follow-and-avoid method for optimizer from the probability of determining the optimum solution area and preventing dropping into the local minimum, and fine-tune the search and emulates method by the succeeding equation:

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Equation\ (15) p < k \\ Equation\ (18) otherwise \end{cases} \tag{19}$$

(3) Nesting behavior.

The method depends on dual equations, which mimic exhausted prey to the neighborhood of nest of proper prey and size of the egg. The initial formula can be defined mathematically as shown:

$$\overrightarrow{SW_i}^{t+1} = \overrightarrow{SW}^{*} + \cos(2\pi l) \times \left(\overrightarrow{SW}^{*} - \overrightarrow{SW_i}^{t}\right) \tag{20}$$

Whereas $\overrightarrow{SW}^{*}$ signifies the optimal outcome at the present phase. The next equation will arbitrarily choose female wasps in the population and shell at their position, preventing numerous nesting at a similar position by an added step size:

$$\overrightarrow{SW_i}^{t+1} = \overrightarrow{SW_a}^{t} + r_3 \times |\gamma| \times \left(\overrightarrow{SW_a}^{t} - \overrightarrow{SW_i}^{t}\right) + (1 - r_3) \times \vec{U} \left(\overrightarrow{SW_a}^{t} - \overrightarrow{SW_c}^{t}\right) \tag{21}$$

Whereas γ denotes value made from lévy flight; b, and c are 3 individual female bees arbitrarily chosen; U denotes binary vector applied to define after a phase is utilized to evade nesting numerous times at a similar position, and U is allocated the succeeding equation:

$$\vec{U} = \begin{cases} 1 & \overrightarrow{r_4} > \overrightarrow{r_5} \\ 0 & otherwise \end{cases} \tag{22}$$

The dual processes are arbitrarily exchanged by the succeeding equation:

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Equation\ (20) & r_3 < r_4 \\ Equation\ (21) & otherwise \end{cases} \tag{23}$$

Lastly, the switch among nesting and hunting behavior is completed through Eq. (24). Every female wasp will look for the equivalent spiders at the start of the optimization procedure and push them to an appropriate position for nesting:

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Equation\ (19) & i < N \times k \\ Equation\ (23) & otherwise \end{cases} \tag{24}$$

(4) Mating behavior

The simulation produced eggs by utilizing a similar uniform boundary process amongst male SWs S_m^t and female SWs S_i^t, while males produce positions over females:

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$$\overrightarrow{SW_i}^{t+1} = Crossover(SW_i^t, SW_m^t, CR) \tag{25}$$

$$\overrightarrow{SW_m}^{t+1} = \overrightarrow{SW_i}^t + e^l|\beta|\overrightarrow{v_1} + (1 - e^l)|\beta_1|\overrightarrow{v_2} \tag{26}$$

The above-mentioned equations β and β_1 are dual randomly generated numbers based on the standard distribution, e denotes exponential constant, and vectors $\overrightarrow{v_1}$ and $\overrightarrow{v_2}$ are produced by the succeeding Eqs. (27) and (28):

$$\overrightarrow{v_1} = \begin{cases} \overrightarrow{x_a} - \overrightarrow{x_i} & f(\overrightarrow{x_a}) < f(\overrightarrow{x_i}) \\ \overrightarrow{x_i} - \overrightarrow{x_a} & otherwise \end{cases} \tag{27}$$

$$\overrightarrow{v_2} = \begin{cases} \overrightarrow{x_b} - \overrightarrow{x_c} & f(\overrightarrow{x_b}) < f(\overrightarrow{x_c}) \\ \overrightarrow{x_c} - \overrightarrow{x_b} & otherwise \end{cases} \tag{28}$$

Once a female wasp ends the shell later finishes egg laying, it represents the female should not endure taking part in following optimizer.

$$N = N_{\min} + (N - N_{\min}) \times k \tag{29}$$

Whereas $N_{\min}$ signifies the minimal population counts set to prevent dropping into local minima. Here, the SWO is applied to determine the hyperparameter intricate in the ensemble DL models. The MSE is measured as an objective function and is expressed below.

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \tag{30}$$

While M and L signify the resultant value of layer and data respectively, y_j^i and d_j^i means an achieved and suitable magnitudes for jth unit from the resultant layer in tth time respectively.

4. Experimental Validation

In this segment, the prediction results of the MDSSPFF-EDLAHS model can be studied using NIFTY-50 Stock Market Data [23].

In Table 1 and Fig. 3, the stock price prediction (SPP) outcome of the MDSSPFF-EDLAHS algorithm using the Axis Bank database. The testing outcomes designate that the MDSSPFF-EDLAHS algorithm properly forecasts the SMPs but the difference among the predicted and actual SP can be predicted as decreased. Using 50 times and an actual SP of 54.19, the MDSSPFF-EDLAHS model forecasts an SP of 77.57. Following, using 300-time intervals and actual SP of 124.56, the MDSSPFF-EDLAHS system calculates an SP of 130.48.

Table 1: SPP outcome of MDSSPFF-EDLAHS method with Axis Bank database

SPP - Axis Bank Database		
Time	Actual SP	Predicted SP
0	57.12	947.14
50	54.19	77.57
100	68.82	86.43
150	74.61	95.28
200	101.17	115.73
250	115.73	133.47
300	124.56	130.48

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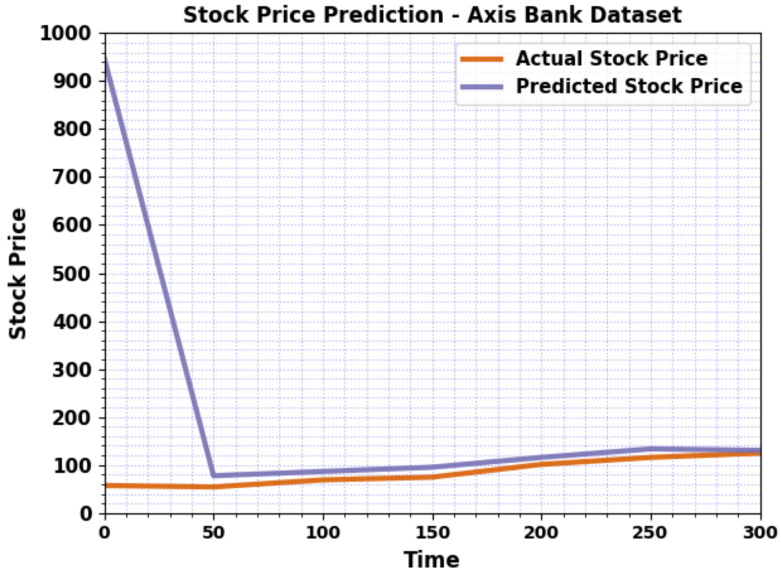

Figure 3. SPP of MDSSPFF-EDLAHS technique with Axis Bank database

In Fig. 4, the SPP outcome of the MDSSPFF-EDLAHS method using the BHEL database. The testing results represent that the MDSSPFF-EDLAHS approach properly forecasts the SMPs but the modification among the predictive and actual SP can be assessed as diminished. Using 100-time periods and an actual SP of 69.63, the MDSSPFF-EDLAHS method forecasts an SP of 78.50. Afterward, using 800-time intervals and an actual SP of 190.87, the MDSSPFF-EDLAHS forecasts an SP of 179.02.

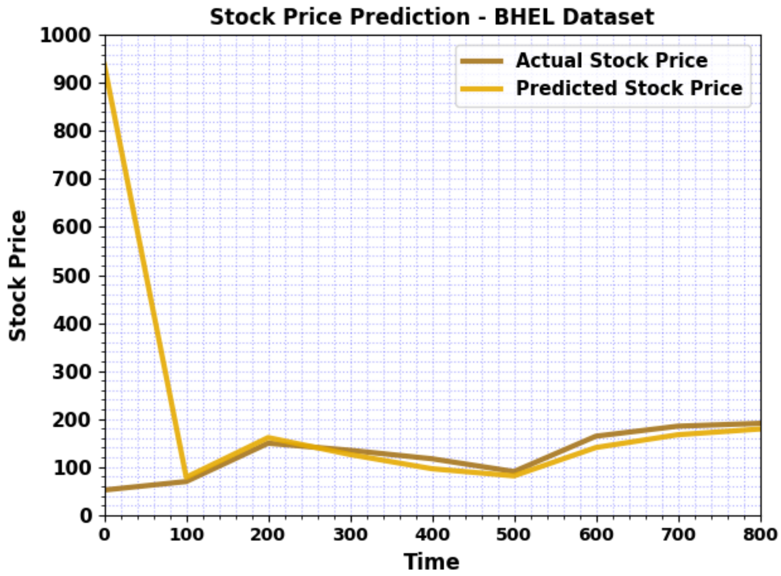

Figure 4. SPP of MDSSPFF-EDLAHS algorithm with BHEL database

In Fig. 5, the SPP outcome of the MDSSPFF-EDLAHS algorithm with the Maruti database. The investigation analysis signifies that the MDSSPFF-EDLAHS system properly forecasts the SMPs where the divergence among the predictive and actual SP are calculated as diminished. Using 20 times and actual SP of 59.66, the MDSSPFF-EDLAHS methodology forecasts an SP of 71.98. Next, with 120 times and an actual SP of 69.04, the MDSSPFF-EDLAHS approach forecasts a SP of 75.13.

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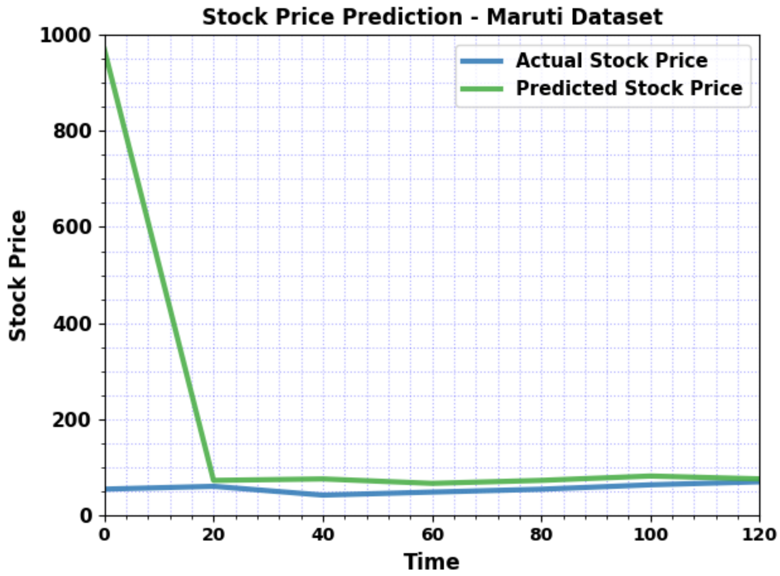

Figure 5. SPP of MDSSPFF-EDLAHS model with Maruti database

In Table 2 and Fig. 6, the SPP outcome of the MDSSPFF-EDLAHS model with the Tata Steel database. The testing results suggest that the MDSSPFF-EDLAHS algorithm suitably forecasts the SMPs but the adjustment among the predictive and actual SP can be calculated as decreased. Using 100-time periods and an actual SP of 290.70, the MDSSPFF-EDLAHS method forecasts an SP of 296.43. Then, using 800 times and actual SP of 379.33, the MDSSPFF-EDLAHS system forecasts an SP of 393.72.

Table 2: SPP outcome of MDSSPFF-EDLAHS technique with Tata Steel database

SPP - Tata Steel Database		
Time	Actual SP	Predicted SP
0	201.93	943.00
100	290.70	296.43
200	468.17	470.90
300	602.51	596.87
400	576.87	574.11
500	76.13	87.43
600	147.62	153.23
700	305.08	304.95
800	379.33	393.72

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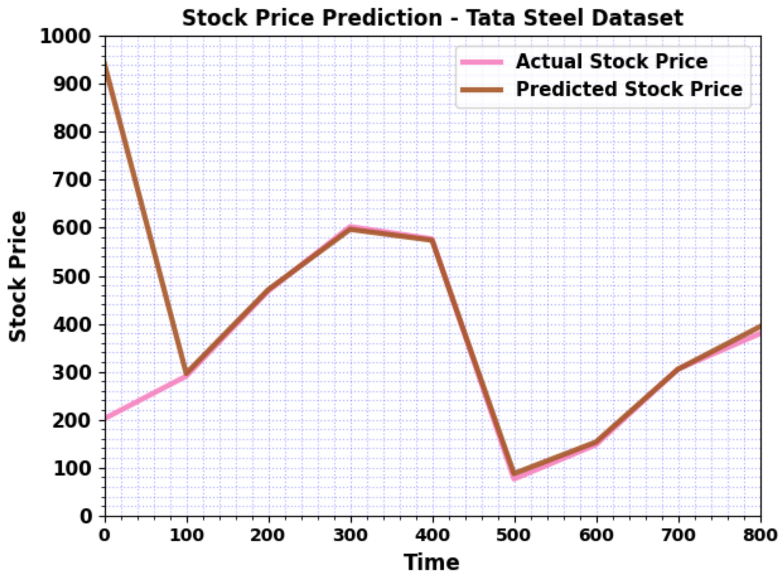

Figure 6. SPP of MDSSPFF-EDLAHS method with Tata Steel database

In Fig. 7, the SPP outcome of the MDSSPFF-EDLAHS approach with the TCS database. The testing results imply that the MDSSPFF-EDLAHS algorithm properly forecasts the SMPs where the difference among the predictive and actual SP are projected as diminished. Using 100-time periods and an actual SP of 207.88, the MDSSPFF-EDLAHS system forecasts an SP of 204.74. Afterward, using 600 times and actual SP of 154.70, the MDSSPFF-EDLAHS model forecasts a SP of 148.47.

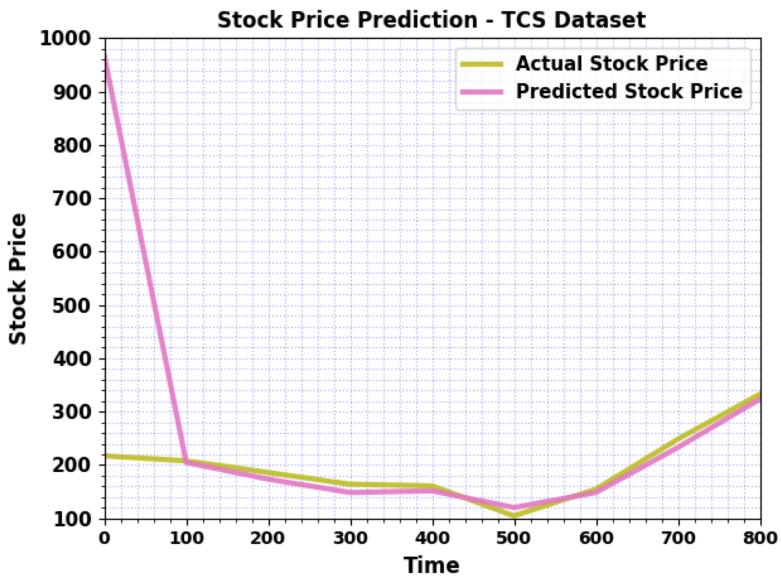

Figure 7. SPP of MDSSPFF-EDLAHS model with TCS database

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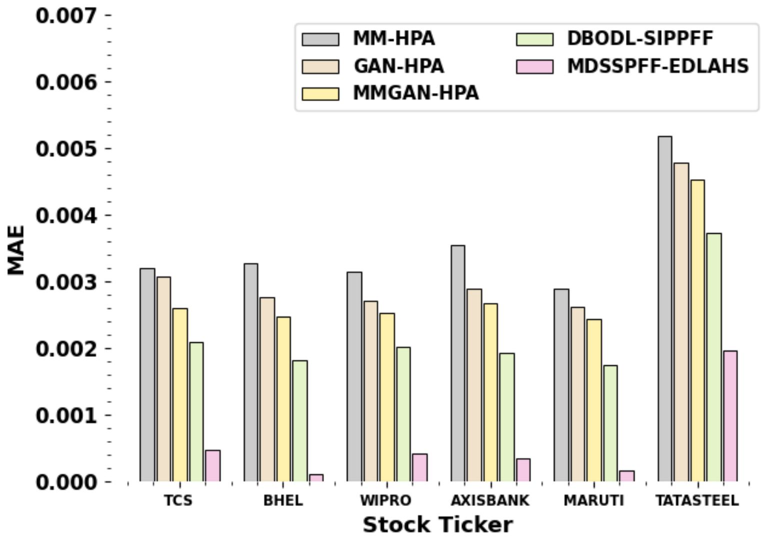

Figure 8. MAE outcome of MDSSPFF-EDLAHS algorithm under various stock tickers

In Fig. 8, the proportional MAE calculation of the MDSSPFF-EDLAHS model has been stated in several databases [24]. These testing result values specified that the MM-HPA and GAN-HPA methods are exemplified minimal outcomes through the maximum MAE values. Simultaneously, the MMGAN-HPA and DBODL-SIPPFF approaches provide reasonable performances. However, the MDSSPFF-EDLAHS algorithm gets ultimate solutions with decreased MAE values of 0.00047, 0.00011, 0.00042, 0.00034, 0.00016, and 0.00197 below TCS, BHEL, WIPRO, AXISBANK, MARUTI, and TATASTEEL databases respectively.

The MSE efficacy of the MDSSPFF-EDLAHS algorithm can be related to current models on dissimilar databases in Fig. 9. These obtained result values show the enhanced forecasting analysis of the MDSSPFF-EDLAHS system with lesser MSE values. According to TCS database, the MDSSPFF-EDLAHS method delivers a decreased MSE of 0.000041 while the MM-HPA approach, GAN-HPA model, MMGAN-HPA system, and DBODL-SIPPFF approach offer maximum MSE of 0.000098, 0.000082, 0.000092, and 0.000077, correspondingly. Moreover, with the TATASTEEL database, the MDSSPFF-EDLAHS model gained a decreased MSE of 0.000082 but the MM-HPA approach, GAN-HPA model, MMGAN-HPA system, and DBODL-SIPPFF approach give greater MSE of 0.000127, 0.000134, 0.000123, and 0.000117.

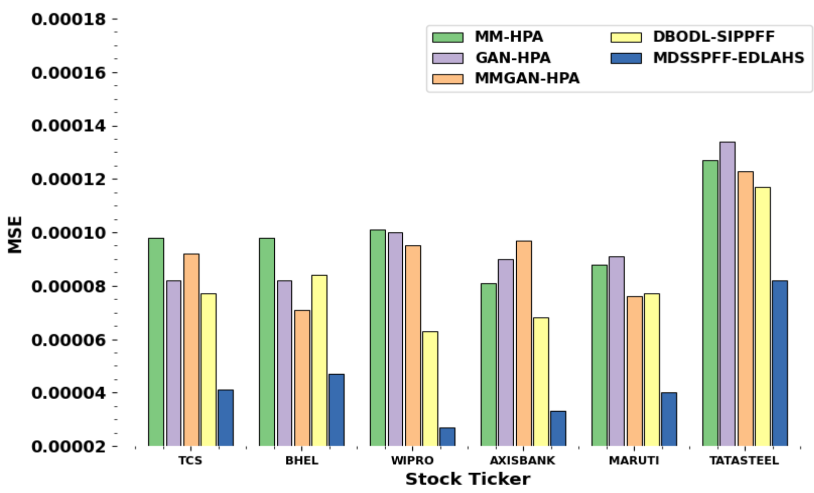

Figure 9. MSE outcome of MDSSPFF-EDLAHS algorithm under various stock tickers

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5. Conclusion

In this study, we have developed a novel MDSSPFF-EDLAHS model. The main intention of the MDSSPFF-EDLAHS method is to predict future of financials using advanced ensemble models. At first, the data normalization stage applies min-max normalization for transforming input data into a beneficial format. Besides, the ensemble of DL models namely VAE model, Bi-LSTM technique, and dueling DDQN system have been executed for the prediction of financial futures. At last, the SWO algorithm adjusts the hyperparameter values of the ensemble models optimally and outcomes in greater prediction performance. The experimental evaluation of the MDSSPFF-EDLAHS are tested on a benchmark dataset. The extensive outcomes highlight the significant solution of the MDSSPFF-EDLAHS approach to the financial future predicting process.

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