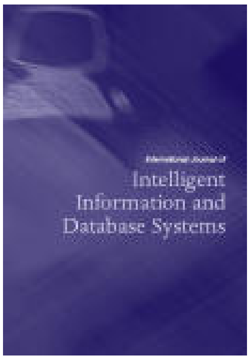


International Journal of Intelligent Information and Database Systems

ISSN online: 1751-5866 - ISSN print: 1751-5858
https://www.inderscience.com/ijiids

A novel heuristically adaptive dual attention-based long short-term memory for intelligent stock market trend prediction model

Anuja Jana Naik, Madanant Jana Naik

DOI: 10.1504/IJIIDS.2025.10068160

Article History:

Received:	18 November 2022
Last revised:	07 November 2023
Accepted:	15 December 2023
Published online:	23 December 2024

A novel heuristically adaptive dual attention-based long short-term memory for intelligent stock market trend prediction model

Anuja Jana Naik*

Department of Electronics and Computer Engineering,
Padre Conceicao College of Engineering,
Verna, Goa, India
Email: anuja2188@gmail.com
*Corresponding author

Madanant Jana Naik

Department of Commerce,
Goa Vidyaprasarak Mandal's Gopal Govind Poy
Raiturcar College of Commerce and Economics,
Farmagudi, Ponda Goa, India
Email: madanantnaik@gmail.com

Abstract: The deep learning method is designed for the stock market trend prediction through this paper. At first, stock market data are acquired from benchmark sources and are offered to the time series data formation phase. Deep convolutional temporal network (DCTN) is used here. Later, the attained features are provided to the prediction stage, and effective prediction is made by utilising adaptive dual attention-based long short-term memory (ADA-LSTM). Also, their parameters are tuned with the help of hybrid fruit fly spider monkey optimisation (HFF-SMO) by integrating fruit fly algorithm (FFO) and spider monkey algorithm (SMO) to attain an effective stock market trend prediction rate. Thus, the developed model secures effectively high accuracy rate in stock market trend prediction than existing approaches. Hence, the improved model obtained an effectively high accuracy rate in comparison with stock market trend prediction to existing approaches.

Keywords: stock market trend prediction; adaptive dual-based long-term memory; deep convolutional temporal networks; DCTNs; hybrid fruit fly monkey optimisation.

Reference to this paper should be made as follows: Naik, A.J. and Naik, M.J. (2025) 'A novel heuristically adaptive dual attention-based long short-term memory for intelligent stock market trend prediction model', *Int. J. Intelligent Information and Database Systems*, Vol. 17, No. 1, pp.57–91.

Biographical notes: Anuja Jana Naik is an Assistant Professor at, the Department of Electronics and Computer Engineering at Padre Conceicao College of Engineering, Verna, India. In 2022, she obtained her PhD in Computer Science and Engineering from Visvesvaraya Technological University, Karnataka, India. Her thesis concerned the precise violent activity recognition in video sequences. Her research interests include deep learning, machine learning, detection of activities in video, and object detection in video. She has authored many papers in reputed journals. She is a reviewer for prestigious international journals including conferences.

Madanant Jana Naik is presently working as an Assistant Professor of Commerce at Goa Vidyaprasarak Mandal's Gopal Govind Poy Raiturcar College of Commerce and Economics in Goa, India. With over eight years of teaching and research experience, he completed his PhD in Commerce from Goa University, India in 2018. His doctoral research focused on women's empowerment and human resource development through microfinance initiatives. His research interests include finance, stock pricing, marketing, and entrepreneurship. He has a significant number of published papers in reputed journals, contributing valuable insights and advancements in his fields of interest.

1 Introduction

One of the most vital things to make a robust economy for the country is the stock market. A company can increase the consequent amount of money for raising the business through initial public offering (IPO) (Liu and Wang, 2019). This is a good chance for investors to buy new stock and could be a stockholder, whom they can get additional gain for a trader, who can trade the stocks (Huang et al., 2022). The stock trader can get high gains when he can predict the current stock price accurately. Still, while the stock market is unstable, several customary conditions like improving political conditions, company activities, and other unpredictable situations can influence the stock prices in a good and bad way (Ishwarappa and Anuradha, 2021). From this, the investor cannot predict the stock prices perfectly but could forecast the upcoming short-term trends. Before deciding on buying the stock, they normally analyse the company's activities (Idrees et al., 2019). The analysing process includes the evaluation of a company's half-earnings report and paying attention to important news to avoid the purchase of overrated or high-risk stocks (Yuan et al., 2020). Yet, the daily news counting and the release speed have skyrocketed in previous years, and thus, it exceeds the investor's capacity to assess the high amount of data. Additionally, a decision support system is vital for predicting upcoming stock trends (Alsubaie et al., 2019; Bouktif et al., 2020) for automated analysing and getting the prediction outcomes.

On the financial side, the stock cost is unstable in time sequences. Stock costs are influenced by some causes like rate of interest, rate of exchange, investor's sentiment, monetary policy, etc. (Hou et al., 2021). It is a difficult thing for investors and researchers to model the relationship between the cost of stock and the stock cost trend prediction. There are two approaches from the previous survey: basic evaluation and technical analysis (Wang et al., 2019). The fundamental analysis uses the natural language processing (NLP) methods for analysing the financial statements and financial news from the institution and for predicting future stock trends (Gandhmal and Kumar, 2019). From the technical analysis, the mathematical property is highly utilised for either analysing the historical stock price pattern or predicting the upcoming stock prices (Hu et al., 2020). Some of the algorithms like multiple kernel learning, stepwise regression evaluation, deep learning, and so on are applied by the researchers (Ananthi and Vijayakumar, 2021).

To learn the correlation between the acquired features from news and stock trends, machine learning algorithms were implemented (Asghar et al., 2019). Deep neural networks (DNNs) have achieved achievements in numerous areas like speech recognition and computer vision in recent years. Most of the peak neural networks (NNs) are about image-based applications (Shen and Shafiq, 2020). But, 'residual neural network (RNN)' has flourishingly involved in the improvement of predicting the series of events in a vast field (Khan et al., 2020). The researcher has previously implemented some DNN figures on extracting features from acquired historical stock prices based on its efficiency (Khan et al., 2022). The extreme result is acquired by DNN in the speech and image recognition field (Jang et al., 1993). Various models such as 'convolutional neural network (CNN), RNN, long short-term memory (LSTM) and multi-layer perceptron' are utilised for predicting the price that is obtained from 'S&P 500 index', and the fast learning resources are included while utilising the higher order NNs. Those had powerful mapping, stronger approximation, and high fault tolerance. Thus, the deep learning-aided system is designed to identify the stock prices and promoted in this research work.

The major innovations considered in this research work are listed here:

- To predict the stock market using innovative techniques to get the chance of earning more money in a short time by investors helps in knowing the high interpretation of factors which influences the stock price, and extra advantages for new traders to reduce the mistakes and loss as they are new to the trading field.
- To present the prediction model with the incorporation of heuristic strategies along with deep convolutional temporal network (DCTN)-LSTM-based feature extraction or getting the precise outcomes to promote future forecasting in the real-time market field.
- To create a heuristic strategy named hybrid fruit fly spider monkey optimisation (HFF-SMO) for overcoming the challenges of existing DA-LSTM by tuning the parameters of this network to give precise final prediction outcomes with higher accuracy.
- To examine the effectiveness of the designed stock prediction system while estimating with conventional techniques owing to several performance metrics.

This work is developed as given, Section 2 represents a literature survey, Section 3 denotes stock market trend prediction utilising an adaptive extreme learning model, Section 4 represents deep feature extraction and deep learning prediction for stock market trend forecast, and Section 5 represents ADA-based LSTM for stock market trend prediction by the hybrid meta-heuristic algorithm. Section 6 presents the results and discussion. Finally, Section 7 concludes the study.

2 Literature survey

2.1 Related works

In 2019, Zhou et al. have been developed the 'empirical mode decomposition and factorisation machine-based neural network (EMD2FNN)' for predicting the stock market trend. For predicting the daily closing costs from, the Standard & Poor's 500 Composite Stock Price Index (S&P 500) and the Shanghai Stock Exchange Composite (SSEC) index, and the National Association of Securities Dealers Automated Quotations (NASDAQ) index, EMD2FNN was applied to illustrate the method. The comparison with results and the predictions acquired from the other methods has included the 'wavelet de-noising-based back propagation (WDBP)' NN model, the NN model, the EMD2NN model, and the factorisation machine-based neural network (FNN) model were held. According to the metrics of 'mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE)', the above-mentioned implemented techniques performed better than other techniques under the same condition.

In 2018, Minh et al. have been developed a new architecture for predicting the trend analysis of stock prices from both sentimental dictionary and news owing to financial status. Two important major experiments were held: the first one forecasted the 'S&P 500 index' stock cost by utilising the price of historical 'S&P 500' and articles crawled via Bloomberg and Reuters. The second one was to predict the cost trends of the VN-index. This system was efficient for the stock sector, from the results found.

In 2019, Chen et al. has been preferred the stock cost trend estimation based on an 'encoder-decoder framework', which predicted the movement of stock price and its time. The above-mentioned system has two phases; initially, the method of feature extraction was proposed to get more data from the market based on various times. This suggested model has applied the CNN and the PLR method to acquire the long-term temporal features and the short-term spatial features. After that, based on the dual attention process, the framework of encoder-decoder has been utilised for selecting and merging the appropriate features. For evaluating the improved TPM, acquired market data of high-frequency for 'stock indexes SSE 50, CSI300, CSI 500', and the performed execution were done based on three datasets. Results from the analysis have found that the suggested TPM has been implemented over state-of-art methods.

In 2021, Lin et al. have been proposed a new ensemble framework of machine learning for predicting the daily stock type that combined ancient candlestick procedure with recent artificial intelligence techniques. Based on the ensemble machine learning methods, the investment scheme was raised. From several measures like the elimination of abnormal data, feature standardisation, and big data, data noise could be efficiently solved. Based on their predicting framework, in either portfolio or an individual stock, an investment scheme was theoretically performed. Yet, the transaction price has a major effect on the stack. In major cases, technical indicators could improve prediction accuracy.

In 2019, Wen et al. have been preferred a new procedure for simplifying trend prediction. The analysis outcomes showed the suggested method efficiency in the feature learning outperformed in comparison to the frequency trading patterns. They have designed deep learning with a modelling approach for predicting the stock trend and outperformed the conventional processing techniques. In 2021, Ingle and Deshmukh has been suggested an ensemble deep learning model for the prediction of the next day's stock cost. To acquire various perfect outcomes, the dataset was executed by several deep learning methods. The suggested model had acquired perfect forecasts. By using high-frequency trading algorithms, the results could be developed further.

In 2022, Kanwal et al. have been stated a hybrid deep learning-based forecast model which had combined 'bidirectional Cuda deep neural network long short-term memory (BiCuDNNLSTM) and a one-dimensional CNN' for predicting the stock prices, efficiently. Comparing the suggested model BiCuDNNLSTM-1dCNN and the other hybrid DL-based models, their results were analysed, and it was found that the suggested hybrid model was effective for perfect forecasting of stock price. It was definitive to support investors in making their known financing resolutions. In 2021, Ishwarappa and

Anuradha have been suggested a deep CNN with reinforcement-LSTM model was suggested to forecast future stock prices based on major information. Then, to experiment with the efficacy of the suggested extreme CNN with the augmentation-LSTM model, four actual-time stock upcoming prices were utilised. Their performance was evaluated by conducting various tests such as one-week ahead, ‘one-day ahead and one-month ahead’. The suggested model provided good execution in various metrics in comparison with other actual methods.

2.2 Problem statement

Trend prediction in the stock market is an essential and complex work in the financial market. According to enhanced volatility in stock prices, traditional data mining approaches could not identify the critical and relevant market data for predicting stock price trends. The existing approaches are showcased in Table 1. EMD2FNN (Zhao et al., 2021) easily handles nonlinearity and time scales to select the accurate features, rapidly enhancing the accurate prediction rate, and they are cost-effective. But, they mostly presented non-stationary time series and did not consider quasi-stationary at the time of analysis. TGRU (Zhou et al., 2019) attained an enhanced robustness rate over volatility and has better adjusting capability. However, it required huge training data and also required more validation resources. CNN (Minh et al., 2018) can acquire the short as well as long-term temporal features from market data. Moreover, if a huge number of data is utilised, it lags in predicting the data accurately. Ensemble machine learning (Chen et al., 2019) effectively resolves the data noise issue in abnormal data, big data and feature standardisation. At the same time, it has very high transaction costs. CNN (Lin et al., 2021) is highly efficient concerning computational complexity. When the window size is too large, the validation time is also enhanced. TF-IDF (Wen et al., 2019) has a very low error rate when the prediction is performed. Still, it did not concentrate on high-frequency trading approaches to predict the data accurately. BiCuDNNLSTM-1dCNN (Ingle and Deshmukh, 2021) efficiently predicts the stock price more than conventional approaches and secures an accurate prediction rate. Moreover, it is highly complex when nonlinear data are utilised for prediction. Deep CNN (Kanwal et al., 2022) easily analyse the complex data attained in huge stock prices to achieve an effective accuracy rate. But, it is highly challenging to train the data to attain an effective prediction rate. Hence, it is important to develop an updated model for predicting stock market trends by utilising deep learning methods.

Table 1 Features and challenges of existing stock market trend prediction models

Author	*Methodology*	*Features*	*Challenges*
Zhou et al. (2019)	EMD2FNN	• It easily handles nonlinearity and time scales to select accurate features. • It rapidly enhances the accurate prediction rate, and they are cost-effective.	• They mostly presented non-stationary time series and did not consider quasi-stationary at the time of analysis.

Table 1 Features and challenges of existing stock market trend prediction models (continued)

Author	*Methodology*	*Features*	*Challenges*
Minh et al. (2018)	TGRU	• It attained an enhanced robustness rate over volatility and better adjusting capability.	• It required huge training data and also required more validation resources.
Chen et al. (2019)	CNN	• It can acquire the short as well as long-term temporal features from market data.	• If a huge number of data is utilised, then it gets lagged in predicting the data accurately.
Lin et al. (2021)	Ensemble machine learning	• It effectively resolves the data noise issue in abnormal data, big data and feature standardisation.	• It has very high transaction costs.
Wen et al. (2019)	CNN	• It is highly efficient concerning computational complexity.	• When the window size is too large, the validation time is also enhanced.
Ingle and Deshmukh (2021)	TF-IDF	• It has a very low error rate when the prediction is performed.	• It did not concentrate on high-frequency trading approaches to predict the data accurately.
Kanwal et al. (2022)	BiCuDNNLSTM-1dCNN	• It efficiently predicts the stock price more than conventional approaches and secures an accurate prediction rate.	• It is highly complex when nonlinear data are utilised for the prediction.
Ishwarappa and Anuradha (2021)	Deep CNN	• It easily analyses the complex data attained in huge stock prices to achieve an effective accuracy rate.	• It is challenging to train the data to attain an effective prediction rate.

3 Stock market trend prediction using an adaptive deep learning model

3.1 Developed stock market trend prediction framework

In the financial field, the stock price is an extremely unstable time sequence. Stock costs are influenced by monetary policy, exchange rates, interest rates, inflation, investor sentiment, etc. One of the difficult tasks for the researchers and investors is arranging the relationship between those above-mentioned factors with stock price prediction and their trends. The method used to predict the stock price is carried out by regression methods, ARIMA, exponential average, etc. Deep learning methods and machine learning have better nonlinear ability than statistical methods. For extracting the features and using those features for modelling and predicting the result, a particular amount of research is conducted. Yet, they omit the data fluctuations owing to the short-term continuity and data interaction. To violate this gap, they have proposed a feature extraction method based on single and multiple time points, which combine the temporal features of both short-term with long-term duration for improving the prediction accuracy. Thus, this research explores a new stock prediction module, and it is diagrammatically given in Figure 1.

Initially, the data as input is collected from standard benchmark sources and undergoes data formation. Collecting information in a measured and systematic manner helps for ensuring accuracy and facilitating data analysis, and then they are focused on estimating the time series data, and thus, the data formation phase is required. After that, the features are extracted using DCTN, which helps in decreasing the feature counts in a dataset by getting new features from the actual ones by using the HFF-SMO. Next, the adaptive dual attention-based long short-term memory (ADA-LSTM) algorithm undergoes stock trend forecasting. Later, the acquired features are provided to the prediction phase, and effective prediction is made by utilising ADA-LSTM, and also their parameters are tuned with the help of HFF-SMO by integrating fruit fly algorithm (FFO) and spider monkey algorithm (SMO) to attain an effective stock market trend prediction rate.

3.2 Stock market trend prediction dataset

This proposed stock market trend prediction framework collects the input data from Stock market data (NASDAQ, NYSE, S&P 500). It consists of daily stock market prices. It includes attributes of date, volume, high, low and closing price. It has four directories such as Forbes2000, NYSE, NASDAQ and SP500. There are 9,304 files and 29.7 K columns in stock market data.

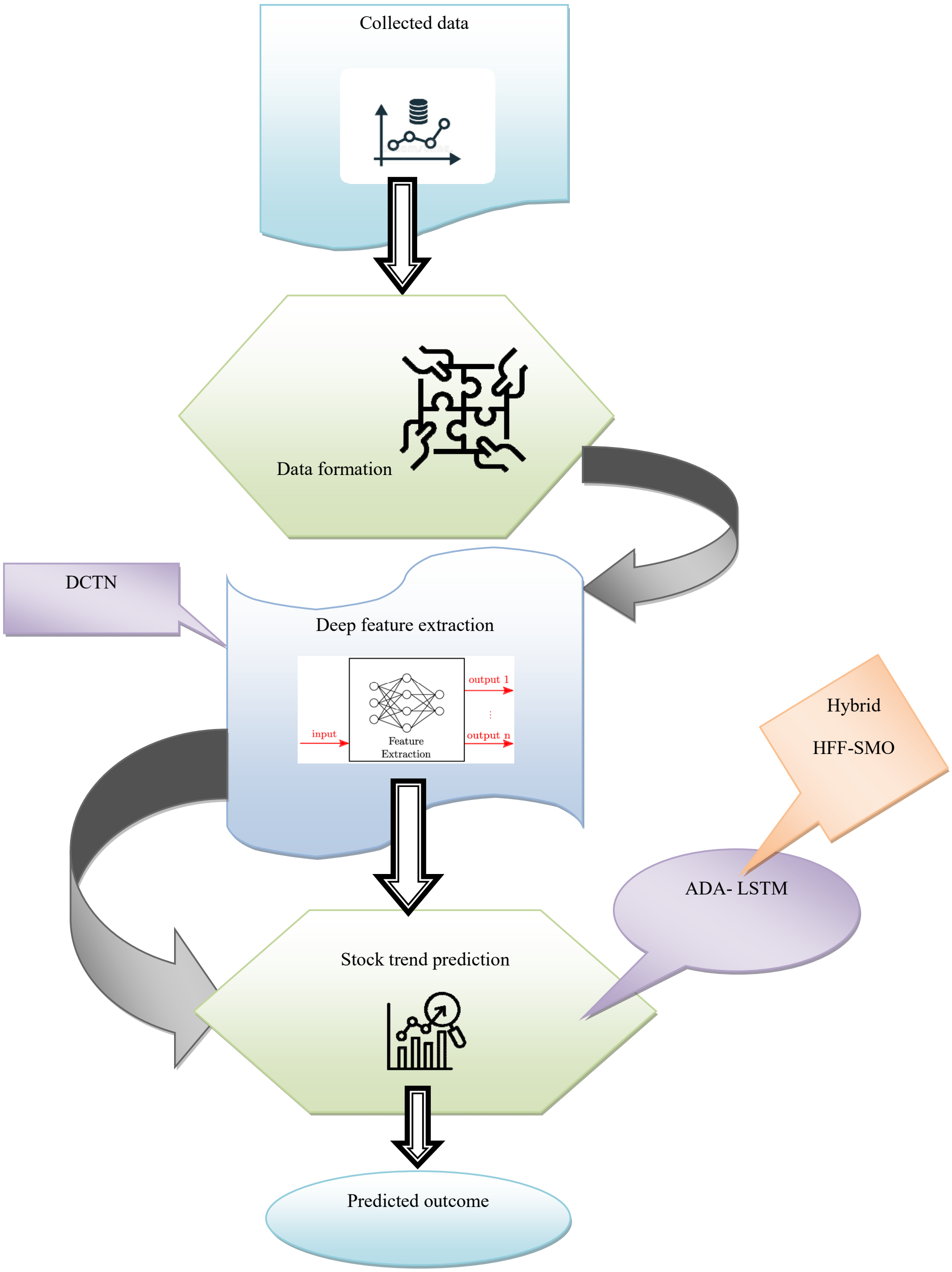
The stock data is collected from the external source 'https://unsplash.com/photos/amLfrL8LGls'.

Thus, the gathered data is known as P_n and the data series is represented by $P_n = P_1, P_2, P_3, \ldots, N$, where $n = 1, 2, 3, \ldots, N$ which N illustrate the total count of data in the database.

3.3 Data formation

The collected data P_n is formatted in the following way and undergoes processing. For ex., if there is a set of series data as 1, 2, 3, 4, 5, 6, 7, 8, and so on. The time series data from1 to 10 is considered training data, and the next one, 11, is considered a target. Similarly, the time series data from the 2nd to 11th data is considered training, the next one, 12, is considered a target, and so on. In comparison with normal data analysis and formatted data analysis, the formatted data analysis provides output in less time, and thus by we can save time. Then, it can provide output with higher data quality, high efficiency, reduced mistakes like retrieval times, missing values, faster queries, etc. Finally, the formatted data is known as P_n^{FR}.

Figure 1 New stock prediction module using improved deep learning methods (see online version for colours)



4 Deep feature extraction and deep learning prediction to predict the stock market trend

4.1 DCTN-based feature extraction

In this model, the formatted data P_n^{FR} is given to the DCTN (Zhang et al., 2018) to acquire the features from the data. In forecasting tasks, DCTNs are specialised models with advantages over recurrent networks. These are having the ability to extract long-term patterns by utilising residual blocks and dilated causal convolutions and also able to be more efficient in terms of computation time.

According to the previous s steps of the input data, prediction of the upcoming value $a(s + 1)$ with the time sequence $\{a\}$ of length L and the forecast model with η parameter is found, and the likelihood function could be expressed as given below in equation (1).

$$P(a \mid \eta) = \prod_{s=0}^{L-1} P\left(a(s+1)\right) \mid a(0), \ldots, a(s), \eta) \tag{1}$$

It uses two deep temporal CNN-based generative networks to learn the above-mentioned $P(.)$ forecast model. Especially, they have applied numerous variable time series that meant the input as P_n^{FR}.

4.1.1 Dilated casual temporal CNN

For making the temporal CNN, they have utilised dilated convolution kernel mechanism that can be defined as equation (2).

$$\left(K_{r*i}^{v} f^{v-1}\right)(v) = \sum_{e=\infty}^{\infty} \sum_{h=1}^{H_{t-1}} K_r^t(e, h) f^{v-1}(t-e, h) \tag{2}$$

Here $(K_{r*i}^{v} f^{v-1})(t)$ is the v^{th} convolution kernel feature mapping of the v^{th} layer. The weighted parameter is kr and i represents the number of cells and dilated coefficient, f^{v-1} which denotes the previous layer activation function. The recent computed data channel is h and H_{t-1} is the number of all the channels. The outputs as the features are denoted by A_x.

4.2 DA-LSTM-based prediction

DA-LSTM (Agrawal et al., 2018) is considered an extremely powerful algorithm for stock prediction, which takes the output as the features A_x. Because it remembers information over a long periods and makes them better suited for stock price prediction. This also captures historical trend patterns and for predicting highly accurate future values.

4.2.1 Dual attention-based LSTM

There are two types of stages in the encoder-decoder framework. During the initial phase, CNN processes the input and obtains the short-term market spatial features. Further, the input data is processed into an LSTM encoder based on the attention mechanism, which is the apt short-term feature, and then it is converted into vectors. In the second stage, long-term temporal features and the abovementioned encoded vectors are extracted by an input. Then, the LSTM decoder decodes the actual vectors for predicting the stock price trend.

4.2.2 Attention-based short-term feature encoder

Here, the features of the short-term spatial market $p_{Market} = (P_1, P_2, \ldots, P_{T-1})$, which is obtained by the CNN and at every time point t, the mapping relationship between the hidden state A_t and the input feature P_t that is learned by the encoder is given in equation (3).

$$A_t = fen\left(P_t, A_{t-1}; \mu_{en}\right) \tag{3}$$

Here, the encoder's hidden state at duration t the $A_t \in N^k$ in which the hidden state size represents the nonlinear function, and the encoder parameters are μ_{en}. Output and the state upgrade by an output gate ε_3, input gate ε_2, and a forget gate ε_1 and the expression are followed in the following equation (4)–equation (9), respectively.

$$f_t = \varepsilon_1\left(P_f\left[A_{t=1}; A_t\right] + b_f\right) \tag{4}$$

$$i_t = \varepsilon_2\left(P_i\left[A_{t-1}; P_t\right]\right) + b_i \tag{5}$$

$$\overline{€}_t = \tan A\left(P_c\left[A_{t-1}; P_t\right] + b_c\right) \tag{6}$$

$$o_t = \varepsilon_3 P_o A_{t-1}; P_t + b_o \tag{7}$$

$$€_t = f_t * €_{t-1} + i_t * \overline{€}_t \tag{8}$$

$$A_t = o_t * \tan A\left(€_t\right) \tag{9}$$

Here, the input at the time point t is P_t, A_{t-1} represents the hidden state of the previous time point $t - 1$, and the element-wise operator is $*$, and ε_1, ε_2 and ε_3 are the three sigmoid functions.

There, they have introduced the attention mechanism where the input feature division P_{Market} into $P_1, P_2, \ldots, P_m$ based on a feature position, where $P_d = (P_{d,1}, P_{d,2}, \ldots, P_{d,T-1})$ be the d^{th} position feature at every time point. At the time $t - 1$, the cell state $€_{t-1}$ and the hidden state P_{t-1} is calculated in equation (10).

$$\beta_{p,t} = va \tan AP_a\left[A_{t-1}; C_{t-1}\right] + U_a P_a \tag{10}$$

$$\alpha_{d,t} = \frac{\exp \beta_{d,t}}{\sum_{d=1}^{m} \exp\left(\beta_{d,t}()\right)} \tag{11}$$

$$F_t = \alpha_{1,t}, P_1, t, \alpha_{1,t}, P_2, t, \ldots, \alpha_{m,t}, P_m, t \tag{12}$$

Here, the term α_m is a softmax function, parameters are devised as $V_a \in T - 1$, $P_a \in N(T - 1) \times 2k$ and $U_a \in N(T - 1) \times (T - 1)$, then, the hidden set of time points is given in equation (13).

$$A_t = fen\left(F_t, A_{t-1}; \theta_{en}\right) \tag{13}$$

At every time t, they can select the proper position of spatial features via the above steps.

4.2.3 Attention-based long-term feature decoder

Through the PLR method, 'long-term temporal feature' $Y_{T-1} = (Q_1, Q_2, \ldots, Q_{T-1})$ is extracted, where the sequence of length is $T - 1$, and at the point t, the long-term temporal features are $Q_t = (s_t, j_t)$. The mapping relationship between the hidden state A_t' and the long-term feature Q_t is given in equation (14).

$$A_t' = f_{je}\left(Q_t, P_t, A_{t-1}'; \theta_{je}\right) \tag{14}$$

Then, the 'hidden state of the decoder' at duration t is $A_t' \in N^g$, the decoder parameters are je, and the nonlinear function is specified as $f_{je}(.)$. The significance of the 'hidden state' ω_i in the i^{th} encoder at the time t is acquired by equation (15).

$$v_{i,t} + u_b \tan a\left(P_b\left[A_{t-1}'; C_{t-1}'\right] + U_b A_i\right) \tag{15}$$

$$\omega_{i,t} = \frac{\exp\left(v_{i,t}\right)}{\sum_{f=1}^{T-1} \exp\left(v_{i,f}\right)} \tag{16}$$

After that, the context vector via all the hidden states of the encoder $(A_1, A_2, \ldots, A_k)$ is given by equation (17).

$$C_t' = \sum_{i=1}^{T-1} \omega_{i,t} A_i \tag{17}$$

Then, the mixed feature Y_t is obtained as in equation (18).

$$Y_t = P_C^t\left[Q'; C_t'\right] + b_c \tag{18}$$

Further, they got the decoder hidden state A' instead of the feature y_t given in equation (19).

$$A_t' = f_{je}\left[y_t, A_{t-1}'; \mu_{je}\right] \tag{19}$$

At the time point t, the stock prediction $\hat{y}_t = (S_t, J_t)$ is given below in equation (20).

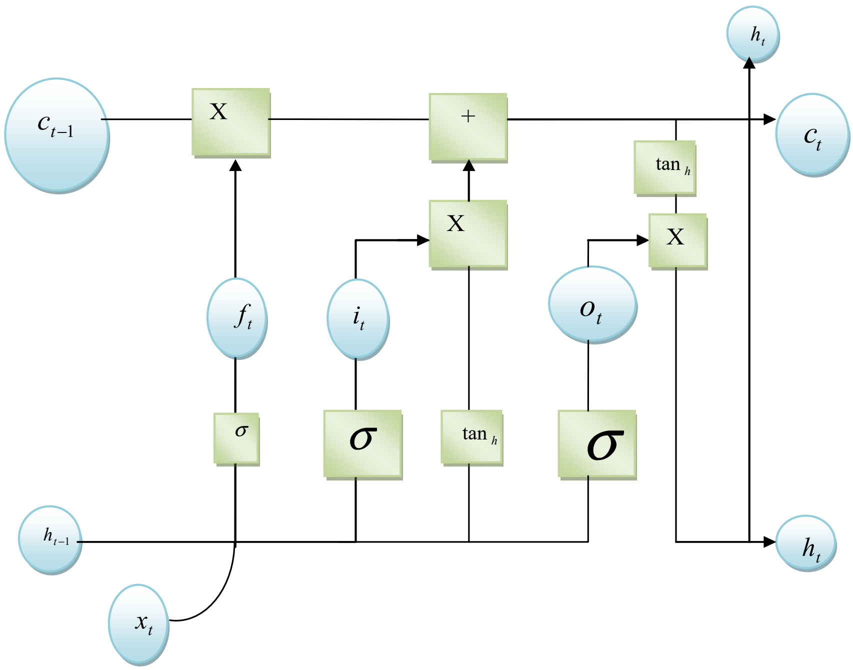
$$\hat{y}_t = F\left(z_{t-1}, s_{t-1}\right) = u_j^t\left(P_j\left[H_{t-1}'; c_{t-1}'\right] + b_j\right) + b_j' \tag{20}$$

Here, H'_{t-1} and c'_{t-1} denotes the 'hidden state and the decoder content vector at time point'. The loss function is given in equation (21).

$$(P, b) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_t^i - y_t^i\right)^2 + \omega[[P]]_2 \tag{21}$$

Here, P and b denotes the weights and bias and n the counting of training samples. The illustration of the DA-LSTM is given in Figure 2.

Figure 2 Representation of DA-LSTM for stock prediction (see online version for colours)



5 ADA-LSTM for stock market trend prediction using the hybrid meta-heuristic algorithm

5.1 Proposed HFF-SMO

The proposed HFF-SMO is used in the newly designed deep learning-based stock market prediction by ADA-LSTM and HFF-SMO to get higher accuracy. By using the HFF-SMO, the given below variables are optimised; epochs in DA-LSTM, hidden neuron count in DA-LSTM, and learning rate in DA-LSTM. Such an optimisation algorithm has features like converting to programme code, simple computational process, understanding, etc. But, the recent algorithm proposed by the FOA for this survey may not be enough. Hence, it was expected that more researchers could participate in the promotion and test. SMO is one of the algorithms inspired by spider monkeys' (SMs) intelligent behaviour. The SMs utilise a different type of communication tricks that is unsimulated by the suggested series. Hence, they suggest the HFF-SMO algorithm due based on its efficiency.

Let us find the mean value for the two positions $Position_1$ and $Position_2$. X_{SMO} comes from the SMO (Wu et al., 2019) algorithm. Similarly, X_{FF} comes from the FF algorithm. The mean value equation is expressed by equation (22).

$$X_{new} = \frac{Mean(X_{SMO}, X_{FF}) + STD(X_{SMO}, X_{FF})}{2} \tag{22}$$

This is a current algorithm for finding the global optimisation based on fruit flies' food-finding behaviour. In sensing and perception, the fruit fly was superior to other species. The fruit fly's aphaeresis organs can find all kinds of scents that float in the air; this can even smell the food sources from 40 km away.

- *Start the problem and algorithm parameters:* This optimisation problem can be expressed below equation (23).

  $$\text{MIN}\, f(X) \text{ s.t.: } X_b \in [LB_b - UB_b]\, b = 1, 2, \ldots, n \tag{23}$$

  Here, the objective function $f(X)$, $X = (X_1, X_2, \ldots, X_n)$ is the decision variables set, n the number of decision variables, LB_b and UB_b the upper and lower bounds for the decision variable X_b.

  The FFO (Johari et al., 2013) algorithm parameters are (PS) the maximum number of iterations ($Itermax$). A good set of parameters can improve the ability of the algorithm to find near optimum region or global optimum with a maximum convergence value.

- *Start the fruit fly swarm position:* The dimension of the fruit fly swarm $\Delta = (\delta_1, \delta_2, \ldots, \delta_n)$ is started in the search space as in equation (24),

  $$\delta_b = LB_b + (UB_b - UB_b) \times rand(\,),\, b = 1, 2, \ldots, n \tag{24}$$

  Here, $rand(\,)$ is a function that returns a value that comes from a uniform distribution interval of [0, 1].

- *Osphresis for the aging stage:* In the osphresis for the aging stage, PS food population sources are obtained around the dimension of the current fruit fly swarm Δ in the osphresis for the aging stage. Assume that $X_1, X_2, \ldots, X_n$ denotes the food sources generated. Here, $X_a = (X_{a,1}, X_{a,2}, \ldots, X_{a,n})$, $a = 1, 2, \ldots, n$. The PS is yielded as equation (25).

  $$X_{a,b} = \delta_b \pm rand(\,),\, b = 1, 2, \ldots, n \tag{25}$$

- *Vision foraging stage:* Here, a greedy selection procedure is carried out by FFO. The lowest fitness with good food source $X_{best} = \arg(\text{Min}_{a=1,2,\ldots,ps} F(X_a))$ is found. While X_{best} it is better to the actual fruit fly swarm dimension D, the swarm location will be replaced and then become a new one in the next iteration, Z that is $\Delta = X_{best}$, whether it satisfies the condition $F(X_{best}) \angle F(\Delta)$.

5.1.1 Major steps of SMO algorithm

This algorithm is an error and trial-based collaborative, iterative process like the other population-based algorithms. The process has six stages: 'global leader learning (GLL) phase, local leader phase, local leader decision phase, GLL phase, local leader decision phase and global leader phase (GLP)'. The location upgrade process in the global leader stage is inspired by the G_{best}-guided ABC and the modified version of ABC. Information on every step of SMO execution is illustrated below.

Initialisation of the population

Initially, SMO obtained a uniformly separated starting population of N SMs where every monkey $X_z(I = 1, 2, \ldots\ldots, Q)$ is the W-dimensional vector. There, W represents the variables count in the optimisation issue and the z^{th} SM in the population AH_z. Each AH_z is started as in equation (26).

$$X_{zy} = X_{\min y} + L(0, 1) \times \left(AH_{\max y} - AH_{\min y}\right) \tag{26}$$

Here, $AH_{\min y}$ and $AH_{\max y}$ are the bounds of AH_z in the y^{th} direction and $L(0, 1)$ is evenly 'distributed random number in the range [0, 1]'.

Local leader stage

Through the local leader phase, every SM has changed its current position based on the local leader and group member experience. The acquired new position fitness value is calculated. The upgrade equation for i^{th} X that stage is stated in equation (27).

$$X_{newzy} = X_{zy} + L(0,1) \times \left(Nk_y - X_{zy}\right) + L(-1, 1) \times \left(X_{fy} - X_{zy}\right) \tag{27}$$

Here, X_z represents the z^{th} dimension of the zX, NN_{by} be the y^{th} location of the k^{th} local group leader position. The term AH_{fy} is "the dimension of f^tX, which is chosen randomly within b^{th} a group such that $f = z$, $L(0, 1)$ is an evenly distributed random number between (0, 1)."

Global leader phase

The GLP is initiated when the LLP stage is completed. All the SMs are updated their position. The updated equation for the GLP stage is given below equation (28).

$$X_{newzy} = X_{zy} + L(0,1) \times \left(CN_y - SM_{zy}\right) + L(-1, 1) \times \left(X_{fy} - X_{zg}\right) \tag{28}$$

Here, y^{th} the 'dimension of the global leader position $y \in \{1, 2, \ldots, W\}$ represented the randomly chosen index'. Here, X_z 'positions of SMs are updated based on probabilities' $prob_z$ that are calculated by utilising their fitness, and it can be valued by utilising the given equation (29).

$$prob_z = 0.9 \times \frac{fitness_z}{\max\_fitness} + 0.1 \tag{29}$$

Here, $fitness_z$ the z^{th} SM fitness value and the 'maximum fitness in the group' represents the $fitness_{\max}$.

GLL stage

From the application of 'greedy selection in the population', the position of the GL is upgraded. Then, whether the global leadership position is updated or not is checked. If it is not updated, then the 'global limit count (GLC)' by one is done.

Local leader learning stage

Through the application of 'greedy selection' in that group, the location of the local leader is updated in this stage. After that, the comparison between the executed position of the local leader and the old one is made. When the local leader is not upgraded, an increment of 'local limit count' by one is done.

Local leader decision stage

When the update of any local leader position is not done, then all the group members will upgrade their positions via GL combined information and LL from equation (30).

$$X_{newzy} = X_{zy} + L(0,1)\times\left(CN_y - X_{zy}\right) + L(0,1)\times\left(X_{zy} - NN_{f,y}\right) \tag{30}$$

Via equation (5), it is found that the upgraded SM position is attracted to the 'global leader and repelled through the LL'.

Global leader decision (GLD) stage

There, the dimension of GL is screened. If it is not get updated, then the GL separates the 'group into smaller groups'. Initially, the population is separated into two classes, three, and so on, until the 'maximum number' reaches. The LLL process is started for electing the local leader in the recently developing classes. In this, the higher count of the class is developed. If the dimension of GL is not updated, it combines all the classes to get a single class.

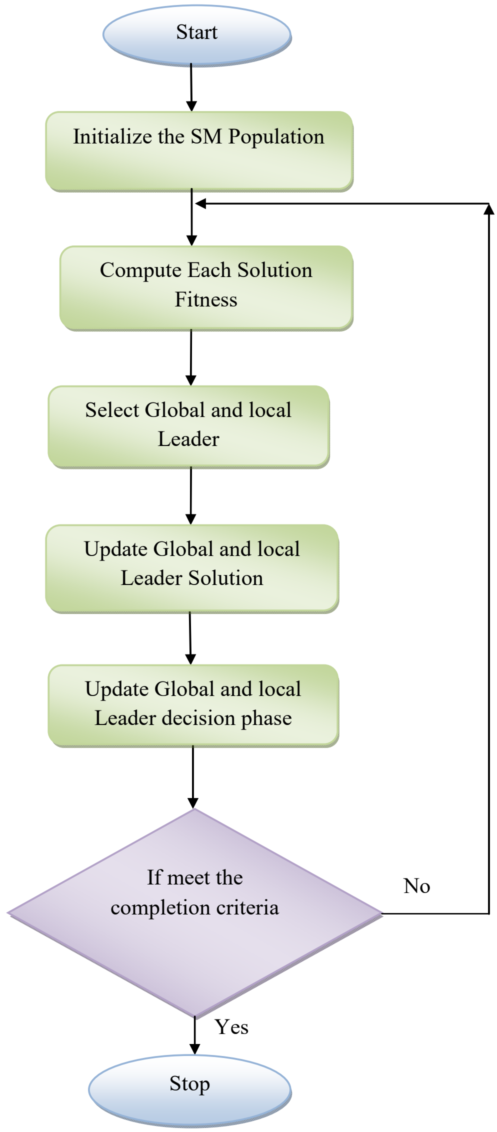
- *Check to stop criteria:* The computation is terminated when the stopping criteria are satisfied, or the osphresis foraging and vision foraging stages are repeated. The proposed SMO-HHF algorithm 'pseudo-code is given in Algorithm 1'.

Algorithm 1 Suggested SMO-HFF

```
Start the random population
Adjust the random parameters
While Z < Zmax
    For Z = 1 to n
        Upgrade the SMO position using equation (24)
        Upgrade the FFO position utilising equation (27)
        Define the mean among
        Define the standard deviation among
    Upgrade the solution by utilising equation (22)
    Stop for
Stop while
Stop
Return the best solution
```

The designed HFF-SMO algorithm flow diagram is given in Figure 3.

Figure 3 Flowchart of the designed HFF-SMO algorithm (see online version for colours)



5.2 Developed ADA-LSTM-based prediction

It is especially designed for forecasting each training sample separately and for integrating the forecast results of DA-LSTM predictors for generating the outcomes. Variables of DA-LSTM are optimised using the HFF-SMO algorithm that is epochs *Ep* in DA-LSTM range from [50–100] hidden neuron count *HC* in DA-LSTM [10–256] and learning rate *LR* in DA-LSTM. The objective function of the developed ADA-LSTM for the stock prediction model is indicated in equation (31).

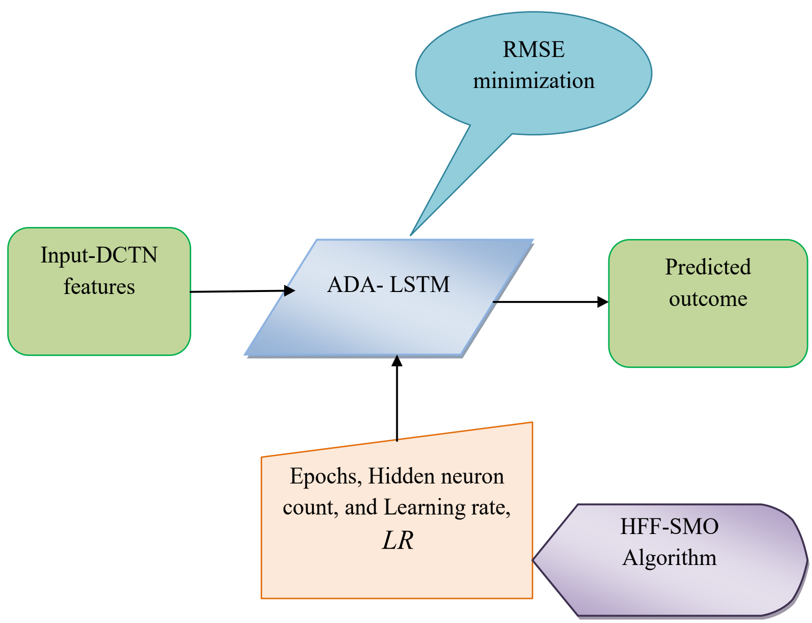
$$\beta F = \underset{\{Ep, HC, LR\}}{\arg\min}\,(RMSE) \tag{31}$$

RMSE: 'It is a frequently used measure of the differences between values predicted by a model or an estimator and the values observed' and thus obtained in equation (32).

$$RMSE = \sqrt{\frac{\sum_{bz=1}^{by}\left(ud_{bz2} - ud_{bz1}\right)^2}{by}} \tag{32}$$

Here, *bz* represents the computation value 'included for every fitted point', *by* denotes the 'fitted points counts', *uh* describes the 'actual value', and *ud* represents the predicted value. The designed ADA-LSTM-based prediction model ensures the final stock trend forecasting with the least error rates via analysing the ADA-LSTM-based prediction results. In Figure 4, ADA-LSTM-based stock prediction is represented.

Figure 4 Developed ADA-LSTM-based prediction for stock trends (see online version for colours)



6 Results and discussion

6.1 *Experimental setup*

The stock market trend predictions were executed in python, and the performance evaluations were done. Here, the performances of the suggested models were evaluated with the conventional techniques in terms of various error surveys. The classifiers are CNN (Minh et al., 2018), random forest (RF) (Hussain et al., 2022), RNN (Shukla et al., 2019), LSTM (Bashar et al., 2020) and DA-LSTM (Agrawal et al., 2018). Similarly, the algorithms are squirrel search algorithm (SSA) (Zheng and Luo, 2019), 'deer hunting optimisation algorithm (DHOA)' (Brammya et al., 2019), FFO (Johari et al., 2013) and SMO (Wu et al., 2019).

6.2 Performance measures

Some standard measures used for the analysis are given here:

a SMAPE: SMAPE is an accuracy measure based on percentage errors.

$$SMAPE = \frac{100\%}{by} \sum_{bz=1}^{by} \frac{|ud - uh|}{\frac{(uh + ud)}{2}} \tag{33}$$

b 'MASE: It is the MAE of the forecast values, divided by the MAE of the in-sample one-step naive forecast' which is represented in equation (34).

$$MASE = mean\left(\frac{|ud|}{\frac{1}{by-1} \sum_{bz=1}^{by} \left| uh_{bz} - uh_{bz-1} \right|} \right) \tag{34}$$

c 'MAE: It is a measure of the difference between two continuous variables', which is derived in equation (35).

$$MAE = \frac{\sum_{bz=1}^{by} \left| Fv_{bz} - uh_{bz} \right|}{bz}. \tag{35}$$

6.3 Analysis of heuristic algorithms

The below-given line graph for two datasets differing the learning percentages are depicted in Figure 5 and Figure 6, and Figure 7 and Figure 8 illustrate the analysis of prediction month variation, which represents the technique-based performance evaluation on stock trend prediction. In Figure 5(a), the process takes place from MAE to the prediction level per month. In month 2, the error is at the rate of 56; then, in the 4th month, the error rate decreases to 44, and then it gradually decreases to 25 in the 12th month. Thus, it achieves a good prediction rate with lower error rates. Similarly, the error rate gradually decreased, and the prediction level increased in the MAE, RMSE, MASE and SMAPE. In MASE and SMAPE, the learning percentages of errors from SSA-ADA-LSTM, DHOA-ADA-LSTM, SMO-ADA-LSTM, and FFO-ADA-LSTM gradually decrease from 58% to 32%, respectively.

Figure 5 Analysis of the stock trend prediction model over the heuristic methods for dataset 1 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)

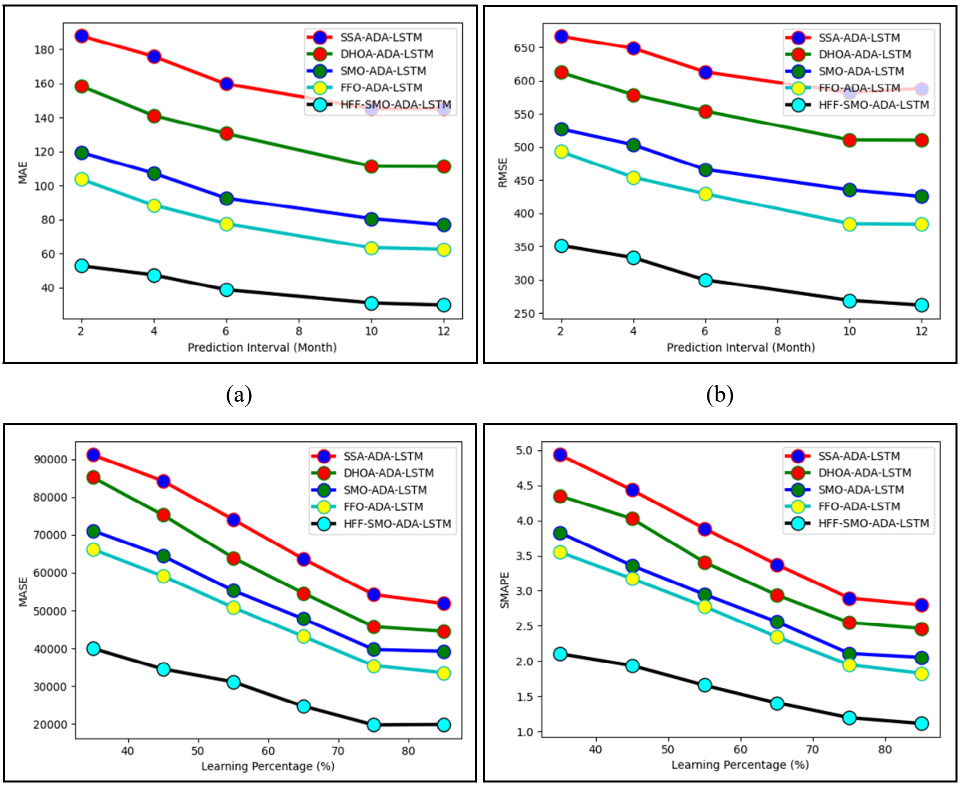
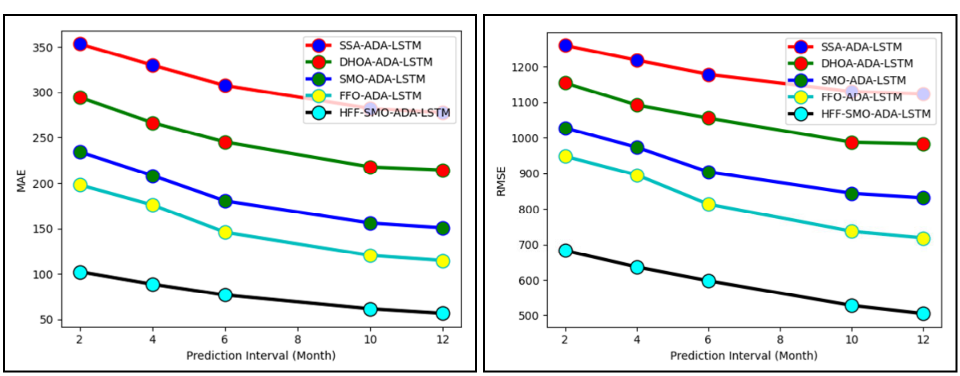
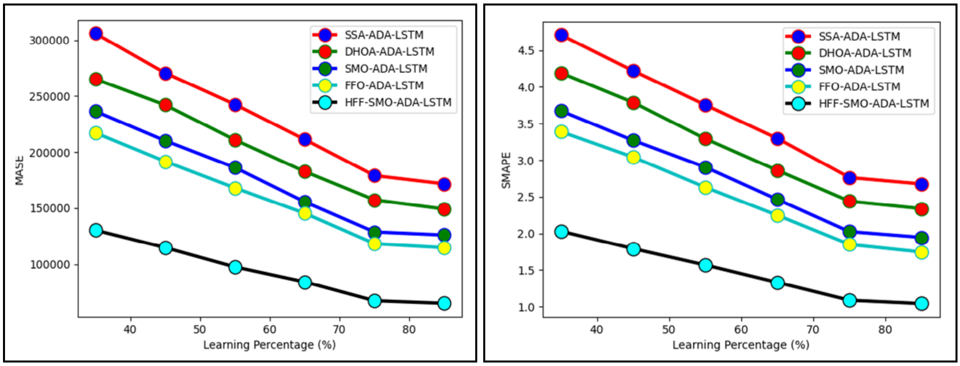


Figure 6 Analysis of the stock trend prediction model over the heuristic approaches for dataset 2 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)



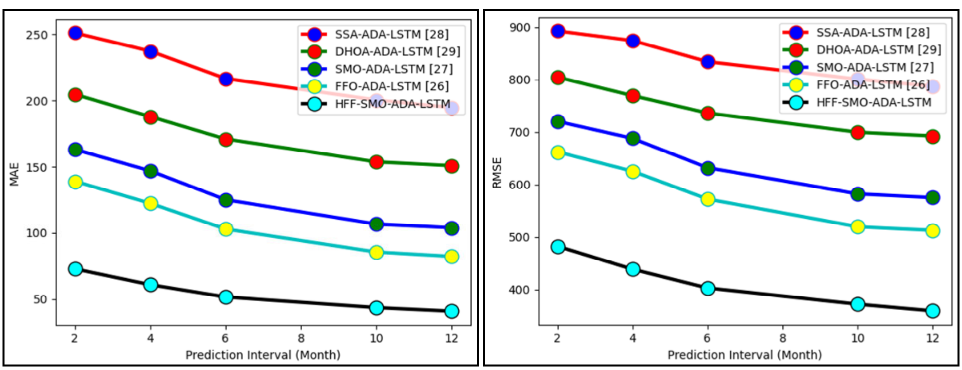
(a) (b)

Figure 6 Analysis of the stock trend prediction model over the heuristic approaches for dataset 2 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (continued) (see online version for colours)

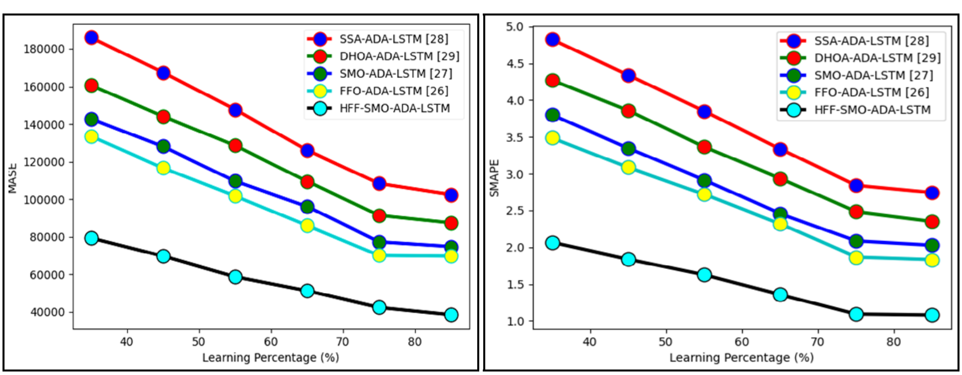


(c) (d)

Figure 7 Analysis of the stock trend prediction model over the heuristic approaches for dataset 3 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)

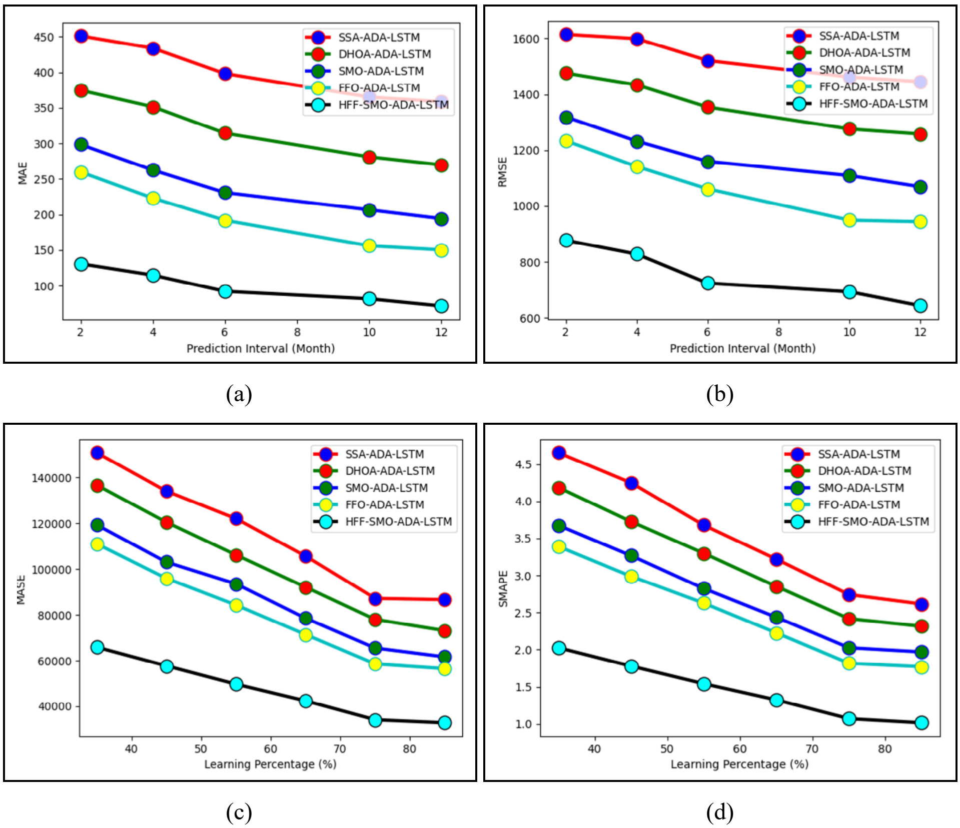


(a) (b)



(c) (d)

Figure 8 Analysis of the stock trend prediction model over the heuristic approaches for dataset 4 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)



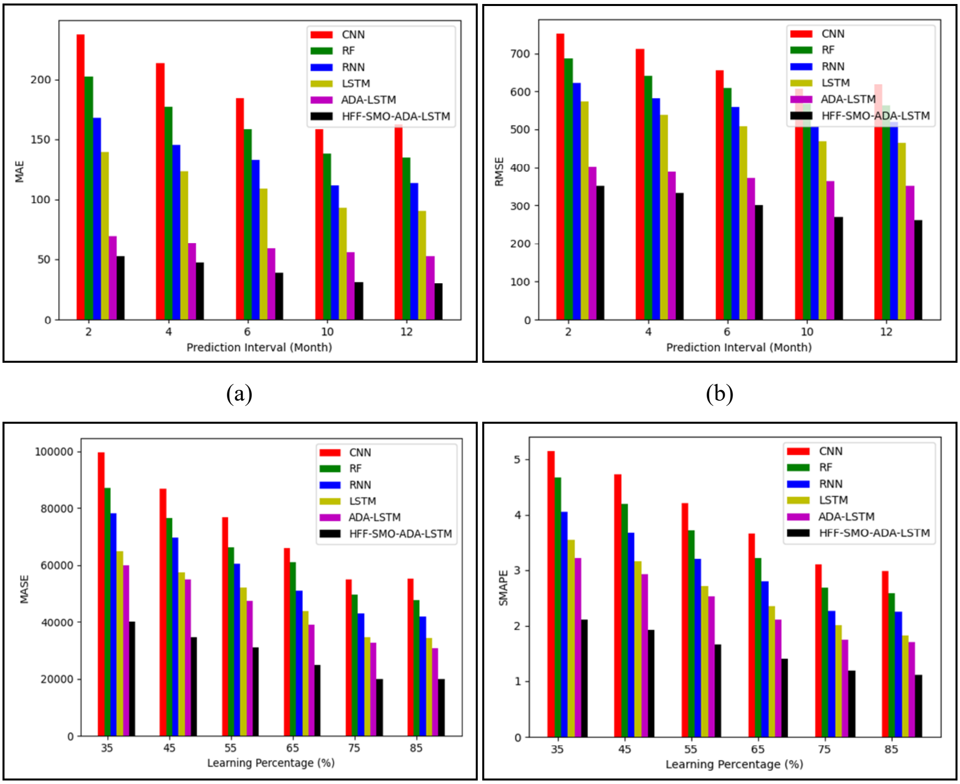
6.4 *Analysis of classifiers*

The given bar graphs represent the classifier-based performance evaluation represented in Figure 9, Figure 10, Figure 11 and Figure 12. Here, CNN, RF, RNN, LSTM, and ADA-LSTM are the existing models, whereas the HFF-SMO-ADA-LSTM is the developed algorithm. In this graphical representation, the error rate gradually decreases, and the learning percentage of SMAPE is 62.9%, 60%, 50%, 47.3% and 44.4%, respectively, superior to CNN, RF, RNN, LSTM and DA-LSTM.

6.5 *Predicted vs. actual prices on analysis*

Figure 13 denotes the analysis of stock price prediction over predicted vs. actual prices. Here, we try to match the actual value to the predicted value. In this, we have almost matched the above-mentioned performance. Thus, stock price prediction is a little bit easier by the proposed model than the others.

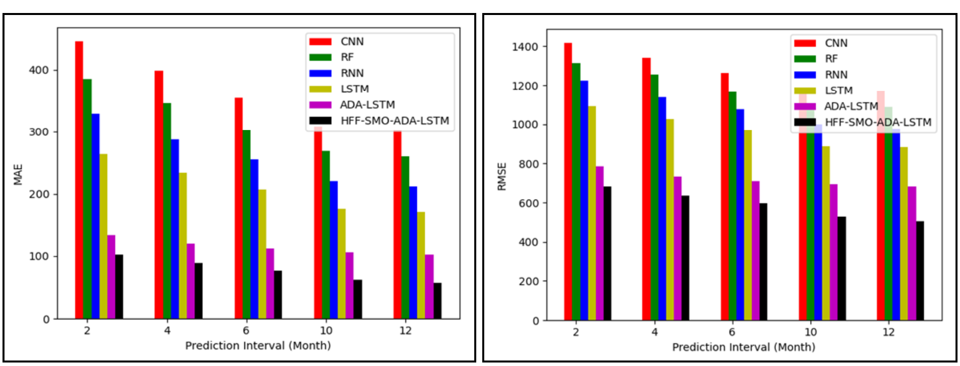
Figure 9 Analysis of the stock trend prediction model over the classifier approaches for dataset 1 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)



(a) (b)

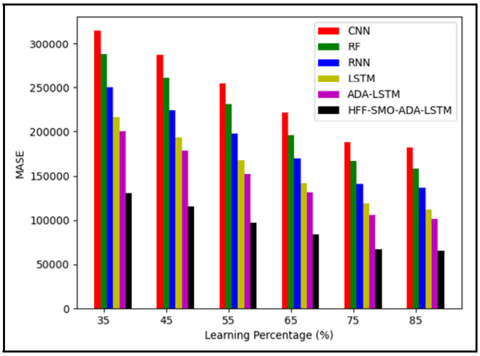
(c) (d)

Figure 10 Analysis of the stock trend prediction model over the classifier approaches for dataset 2 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)

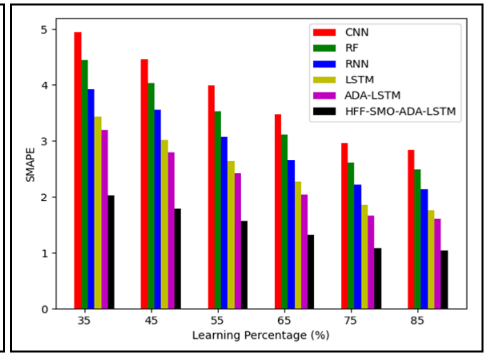


(a) (b)

Figure 10 Analysis of the stock trend prediction model over the classifier approaches for dataset 2 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (continued) (see online version for colours)

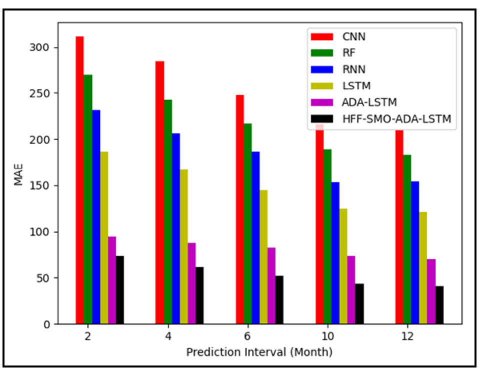


(c)

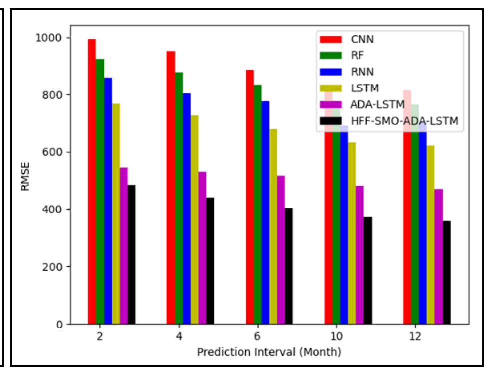


(d)

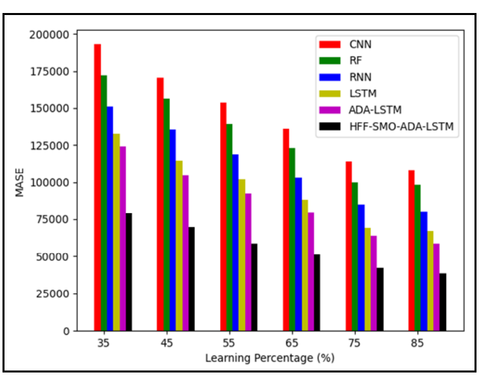
Figure 11 Analysis of the stock trend prediction model over the classifier approaches for dataset 3 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)



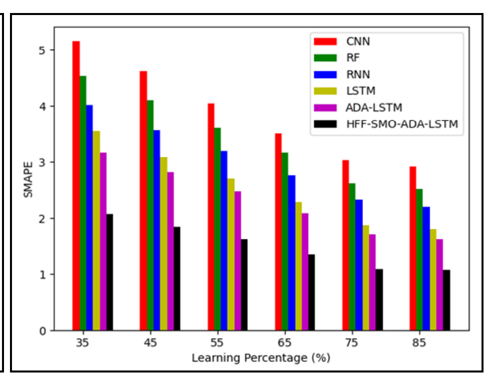
(a)



(b)

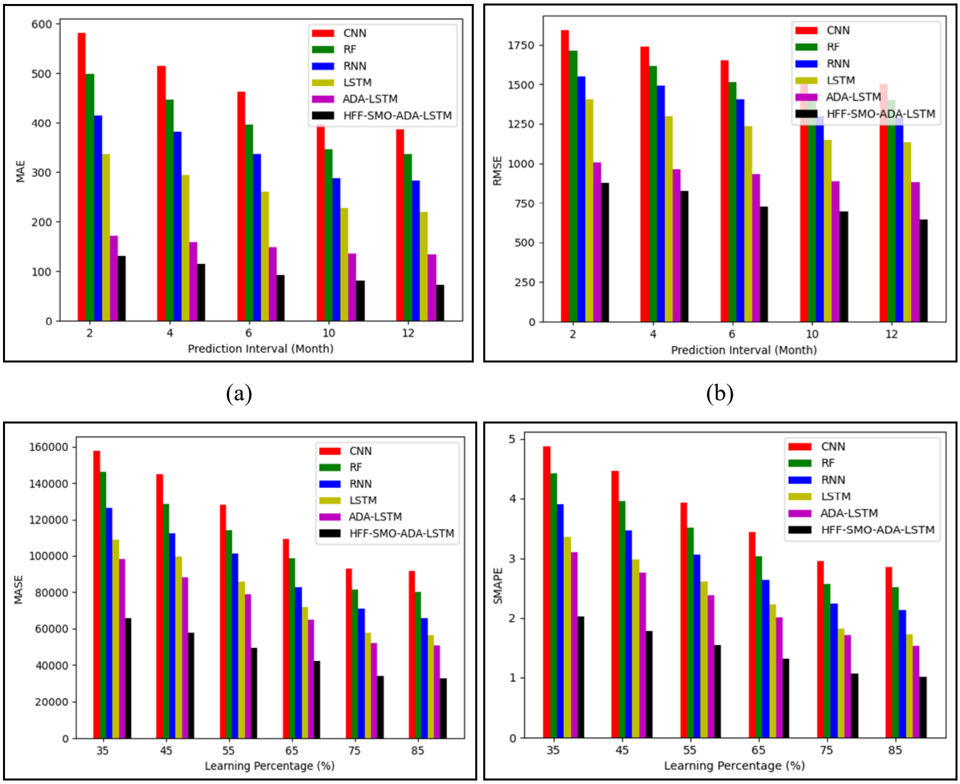


(c)



(d)

Figure 12 Analysis of the stock trend prediction model over the classifier approaches for dataset 4 owing to (a) MAE, (b) RMSE, (c) MASE and (d) SMAPE (see online version for colours)



(a) (b)

(c) (d)

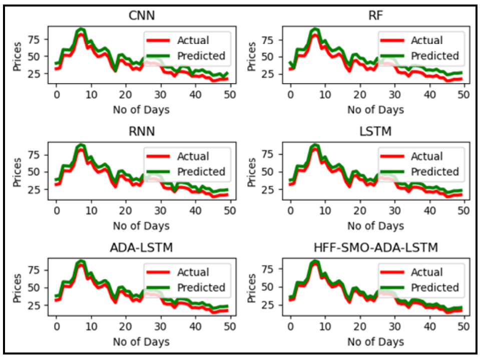
6.6 Comparative analysis over heuristic algorithms

Here, the comparative analysis is carried out based on the learning percentage over existing approaches that are given in Table 2 and Table 3. The percentage value for MEP from the algorithms SSA, DHOA, SMO, and FFO with the proposed model is 59.5%, 55.2%, 46.4%, and 40.4% superior to SSA, DHOA, SMO and FFO, respectively.

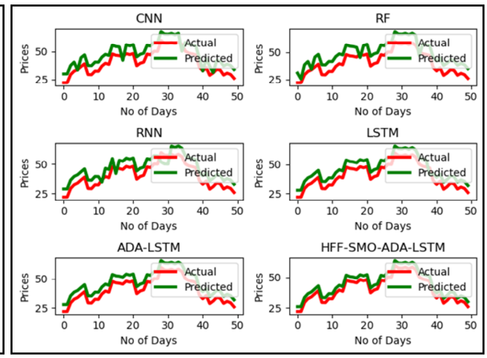
6.7 Analysis of classifiers

The analysis of existing classifiers is listed in Table 4 and Table 5. Here, the percentage values are 69.4%, 47.6%, 56%, 57.6%, and 35.2% in SMAPE with the proposed model and the classifiers.

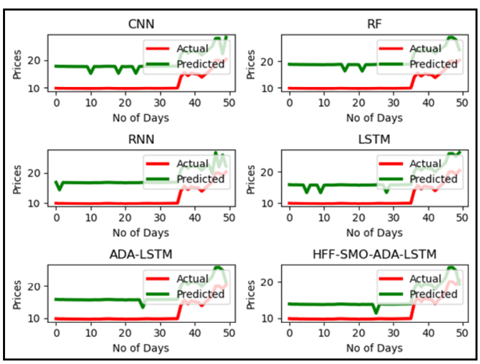
Figure 13 Analysis of predicted vs. actual prices owing to the classifiers for stock trend prediction model of four datasets owing to (a) dataset 1, (b) dataset 2, (c) dataset 3 and (d) dataset 4 (see online version for colours)



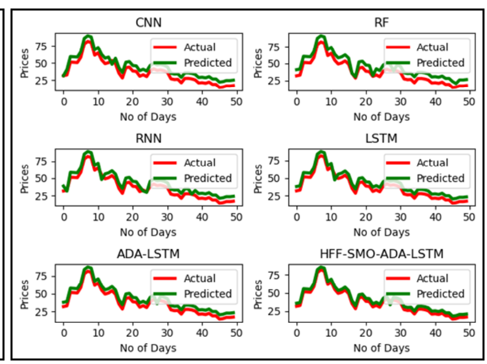
(a)



(b)



(c)



(d)

Table 2 Comparative analysis of stock trend prediction model for four datasets in terms of learning percentage owing to four datasets

Measures	*SSA-ADA-LSTM (Wu et al., 2019)*	*DHOA-ADA-LSTM (Johari et al., 2013)*	*SMO-ADA-LSTM (Agrawal et al., 2018)*	*FFO-ADA-LSTM (Johari et al., 2013)*	*HFF-SMO-ADA-LSTM*
			Dataset 1		
MEP	2.47142	2.157337	1.801691	1.655903	0.984097
SMAPE	0.028947	0.025465	0.021085	0.019456	0.01192
MASE	541.7891	456.9363	397.0551	354.2696	197.5397
MAE	1.660133	1.398867	1.2312	1.091333	0.611533
RMSE	6.239241	5.680557	5.399111	5.076928	3.738993
One-norm	24,902	20,983	18,468	16,370	9,173
Two-norm	764.1479	695.7234	661.2534	621.7942	457.9312
Infinity-norm	495.97	489.46	467.97	430.98	402.98

Table 2 Comparative analysis of stock trend prediction model for four datasets in terms of learning percentage owing to four datasets (continued)

Measures	*SSA-ADA-LSTM (Wu et al., 2019)*	*DHOA-ADA-LSTM (Johari et al., 2013)*	*SMO-ADA-LSTM (Agrawal et al., 2018)*	*FFO-ADA-LSTM (Johari et al., 2013)*	*HFF-SMO-ADA-LSTM*
			Dataset 2		
MEP	2.389034	2.091165	1.742834	1.590296	0.935086
SMAPE	0.027623	0.024388	0.020231	0.018491	0.010866
MASE	1,790.907	1,574.031	1,287.553	1,183.413	674.4536
MAE	3.18422	2.7729	2.28762	2.10468	1.20028
RMSE	12.04888	11.23217	10.17388	9.808046	7.320085
One-norm	159,211	138,645	114,381	105,234	60,014
Two-norm	2,694.211	2,511.59	2,274.948	2,193.146	1,636.821
Infinity-norm	497.98	490.54	488.95	470.12	457.87
			Dataset 3		
MEP	2.428669	2.113484	1.781765	1.603749	0.940658
SMAPE	0.028422	0.024821	0.02085	0.018681	0.010902
MASE	1,082.59	913.4543	773.0903	700.3832	423.82
MAE	2.243	1.903433	1.6116	1.4513	0.8842
RMSE	8.457596	7.75132	7.105022	6.739622	5.325004
One-norm	67,290	57,103	48,348	43,539	26,526
Two-norm	1,464.899	1,342.568	1,230.626	1,167.337	922.3177
Infinity-norm	48.98	46.98	40.98	60.97	388.97
			Dataset 4		
MEP	2.377626	2.079577	1.750659	1.574757	0.925835
SMAPE	0.027423	0.024175	0.02026	0.018165	0.010706
MASE	871.6051	779.751	654.7583	585.5783	341.5754
MAE	4.01932	3.56416	2.98792	2.69992	1.58072
RMSE	15.34464	14.48655	13.21954	12.56085	9.594815
One-norm	100,483	89,104	74,698	67,498	39,518
Two-norm	2,426.2	2,290.524	2,090.192	1,986.044	1,517.073
Infinity-norm	88.76	88.35	84.90	81.65	75.90

Table 3 Comparative analysis of stock trend prediction model in terms of the month variation for four datasets owing to four datasets

Measures	*SSA-ADA-LSTM (Wu et al., 2019)*	*DHOA-ADA-LSTM (Johari et al., 2013)*	*SMO-ADA-LSTM (Agrawal et al., 2018)*	*FFO-ADA-LSTM (Johari et al., 2013)*	*HFF-SMO-ADA-LSTM*
			Dataset 1		
MEP	2.193102	1.685417	1.165853	0.918259	0.450422
SMAPE	0.026096	0.019897	0.013699	0.010915	0.005199
MASE	476.6138	365.8747	251.419	201.0925	96.48541
MAE	1.452867	1.112533	0.769	0.6244	0.2978

Table 3 Comparative analysis of stock trend prediction model in terms of the month variation for four datasets owing to four datasets (continued)

Measures	*SSA-ADA-LSTM (Wu et al., 2019)*	*DHOA-ADA-LSTM (Johari et al., 2013)*	*SMO-ADA-LSTM (Agrawal et al., 2018)*	*FFO-ADA-LSTM (Johari et al., 2013)*	*HFF-SMO-ADA-LSTM*
			Dataset 1		
RMSE	5.877919	5.09983	4.254088	3.833414	2.616524
One-norm	21,793	16,688	11,535	9,366	4,467
Two-norm	719.8951	624.5991	521.0173	469.4955	320.4575
Infinity-norm	35.65	35.96	33.90	39.07	31.89
			Dataset 2		
MEP	2.104575	1.61754	1.126823	0.879396	0.447679
SMAPE	0.024376	0.018764	0.013106	0.010238	0.005205
MASE	1,562.04	1,209.528	847.8745	643.6158	317.3046
MAE	2.77594	2.1436	1.50706	1.14812	0.5668
RMSE	11.23981	9.826088	8.309285	7.18166	5.046452
One-norm	138,797	107,180	75,353	57,406	28,340
Two-norm	2,513.297	2,197.18	1,858.013	1,605.868	1,128.421
Infinity-norm	468.24	469.06	561.89	521.98	468
			Dataset 3		
MEP	2.142026	1.632652	1.142283	0.896797	0.444556
SMAPE	0.025015	0.018987	0.01327	0.010525	0.005128
MASE	935.6208	722.6063	498.1294	394.4622	195.5765
MAE	1.948167	1.508733	1.039833	0.8225	0.4086
RMSE	7.874188	6.923756	5.75204	5.128408	3.592251
One-norm	58,445	45,262	31,195	24,675	12,258
Two-norm	1,363.849	1,199.23	996.2826	888.2663	622.1961
Infinity-norm	448.09	498.45	588.45	474.35	429.23
			Dataset 4		
MEP	2.089337	1.616063	1.123265	0.872611	0.440837
SMAPE	0.024249	0.018764	0.013029	0.01009	0.005158
MASE	775.7708	581.9882	422.1662	323.3373	153.3532
MAE	3.587	2.69776	1.94204	1.50268	0.71292
RMSE	14.44824	12.57814	10.68974	9.436785	6.429896
One-norm	89,675	67,444	48,551	37,567	17,823
Two-norm	2,284.468	1,988.779	1,690.197	1,492.087	1,016.656
Infinity-norm	823.09	878.976	863.65	856.09	778.98

Table 4 Analysis of stock trend prediction model over classifiers for four datasets by varying learning percentages owing to four datasets

Terms	*CNN (Ishwarappa and Anuradha, 2021)*	*RF (Hussain et al., 2022)*	*RNN (Shukla et al., 2019)*	*LSTM (Bashar et al., 2020)*	*ADA-LSTM (Zheng and Luo, 2019)*	*HFF-SMO-ADA-LSTM*
			Dataset 1			
MEP	2.626158	2.298866	1.950096	1.678065	1.4787	0.984097
SMAPE	0.031086	0.026851	0.022705	0.020076	0.017454	0.01192
MASE	550.077	497.0593	430.3255	345.9776	325.8118	197.5397
MAE	1.682067	1.524267	1.326533	1.065467	0.985667	0.611533
RMSE	6.208988	5.936733	5.605307	4.948441	4.81515	3.738993
One-norm	25,231	22,864	19,898	15,982	14,785	9,173
Two-norm	760.4426	727.0983	686.5071	606.0578	589.733	457.9312
Infinity-norm	35.67	35.09	32.33	32.29	31.23	29.65
			Dataset 2			
MEP	2.552137	2.242077	1.909501	1.596821	1.428843	0.935086
SMAPE	0.029675	0.026079	0.022146	0.018532	0.016576	0.010866
MASE	1,887.684	1,669.983	1,407.414	1,185.629	1,057.974	674.4536
MAE	3.3289	2.95692	2.49908	2.11074	1.88348	1.20028
RMSE	12.2271	11.57929	10.61652	9.789522	9.22028	7.320085
One-norm	166,445	147,846	124,954	105,537	94,174	60,014
Two-norm	2,734.063	2,589.208	2,373.927	2,189.004	2,061.717	1,636.821
Infinity-norm	685.33	68.43	62.23	66.44	61.23	59.43
			Dataset 3			
MEP	2.585953	2.256035	1.970079	1.608009	1.45597	0.940658
SMAPE	0.030256	0.026268	0.023178	0.018766	0.017047	0.010902
MASE	1,140.674	998.7799	852.5022	690.9997	637.1165	423.82
MAE	2.378067	2.0647	1.780267	1.441367	1.3223	0.8842
RMSE	8.728264	8.076251	7.538766	6.732565	6.505252	5.325004
One-norm	71,342	61,941	53,408	43,241	39,669	26,526
Two-norm	1,511.78	1,398.848	1,305.753	1,166.114	1,126.743	922.3177
Infinity-norm	488.09	412.89	479.08	482.98	489.79	411.01
			Dataset 4			
MEP	2.552382	2.218365	1.920613	1.576482	1.449604	0.925835
SMAPE	0.029537	0.025684	0.022321	0.018187	0.017127	0.010706
MASE	931.1514	813.7053	712.4827	577.7058	522.6396	341.5754
MAE	4.29084	3.73984	3.31644	2.65852	2.42804	1.58072
RMSE	15.8274	14.70116	14.01464	12.34511	11.92387	9.594815
One-norm	107,271	93,496	82,911	66,463	60,701	39,518
Two-norm	2,502.531	2,324.458	2,215.909	1,951.933	1,885.33	1,517.073
Infinity-norm	499.80	455.89	456.90	478.09	490.97	402.98

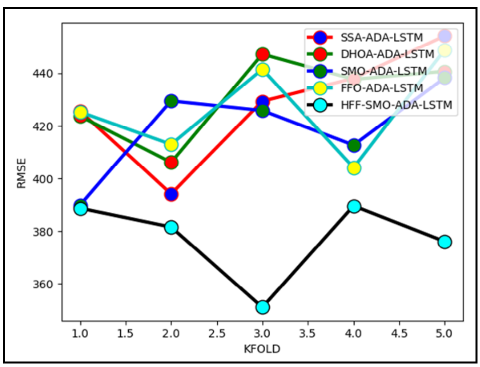
Table 5 Analysis of stock trend prediction model over classifiers for four datasets by varying the months owing to four datasets

Terms	*CNN (Ishwarappa and Anuradha, 2021)*	*RF (Hussain et al., 2022)*	*RNN (Shukla et al., 2019)*	*LSTM (Bashar et al., 2020)*	*ADA-LSTM (Zheng and Luo, 2019)*	*HFF-SMO-ADA-LSTM*
			Dataset 1			
MEP	2.341231	2.006244	1.674722	1.346734	0.821407	0.450422
SMAPE	0.027339	0.023616	0.019665	0.015976	0.009808	0.005199
MASE	530.5497	440.8423	368.7937	292.9287	172.5292	96.48541
MAE	1.623067	1.353067	1.138667	0.9038	0.527133	0.2978
RMSE	6.192113	5.642068	5.209952	4.653479	3.524098	2.616524
One-norm	24,346	20,296	17,080	13,557	7,907	4,467
Two-norm	758.3759	691.0094	638.0862	569.9325	431.6121	320.4575
Infinity-norm	37.90	39.07	35.90	37.90	38.93	31.56
			Dataset 2			
MEP	2.298553	1.963301	1.642046	1.30057	0.778596	0.447679
SMAPE	0.026787	0.022767	0.019134	0.015162	0.009005	0.005205
MASE	1,698.706	1,466.518	1,192.297	963.0941	573.7273	317.3046
MAE	3.02084	2.60572	2.12356	1.7107	1.0258	0.5668
RMSE	11.69825	10.88109	9.774139	8.820965	6.819868	5.046452
One-norm	151,042	130,286	106,178	85,535	51,290	28,340
Two-norm	2,615.808	2,433.085	2,185.564	1,972.428	1,524.969	1,128.421
Infinity-norm	68.97	64.89	63.89	68.99	64.90	56.90
			Dataset 3			
MEP	2.315033	2.000561	1.658999	1.315356	0.788211	0.444556
SMAPE	0.027038	0.023437	0.01936	0.015349	0.009216	0.005128
MASE	1,008.971	882.2031	740.1403	578.5775	334.6899	195.5765
MAE	2.093533	1.832033	1.540967	1.2073	0.695533	0.4086
RMSE	8.132224	7.652766	7.033347	6.21345	4.682976	3.592251
One-norm	62,806	54,961	46,229	36,219	20,866	12,258
Two-norm	1,408.543	1,325.498	1,218.211	1,076.201	811.1153	622.1961
Infinity-norm	49.78	48.09	43.90	41.08	45.56	38.22
			Dataset 4			
MEP	2.256478	1.94408	1.625732	1.303724	0.77793	0.440837
SMAPE	0.026092	0.022466	0.018823	0.015161	0.009102	0.005158
MASE	843.6661	733.1389	610.9613	474.9626	287.354	153.3532
MAE	3.86816	3.36636	2.82268	2.19964	1.33452	0.71292
RMSE	15.00203	13.9991	12.89742	11.34147	8.814645	6.429896
One-norm	96,704	84,159	70,567	54,991	33,363	17,823
Two-norm	2,372.03	2,213.451	2,039.262	1,793.244	1,393.718	1,016.656
Infinity-norm	88.56	83.76	89.87	78.65	86.87	67.89

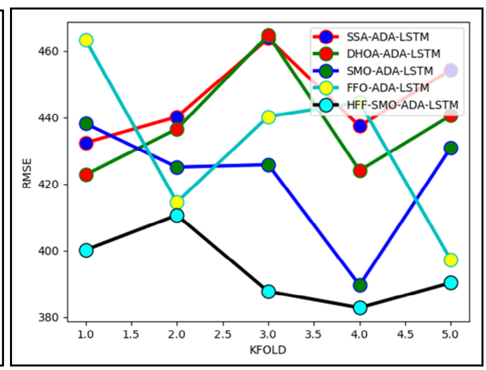
6.8 K-fold analysis of stock prediction using various conventional methods

The k-fold analysis of the stock trend prediction model with different algorithms and classifiers is shown in Figure 14 and Figure 15. The RMSE of the designed HFF-SMO-ADA-LSTM method attains 1.9%, 2.4%, 2.7%, and 3.6%, superior to SSA, DHOA, SMO and FFO. Here, the graph analysis shows the equivalence performance. The FFO holds the second better performance. Throughout the analysis, the suggested HFF-SMO-ADA-LSTM model has attained enriched performance while combining with the other baseline approaches.

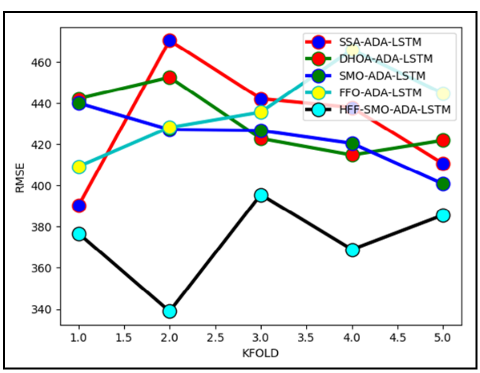
Figure 14 K-fold analysis of developed stock prediction model using different algorithms (see online version for colours)



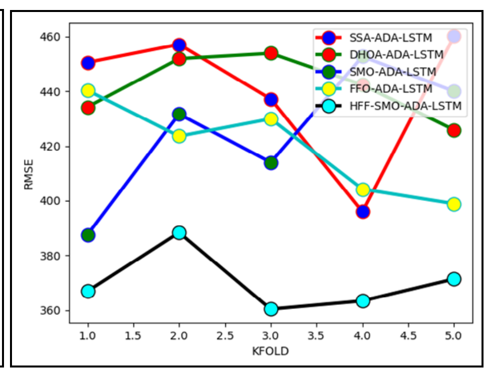
(a)



(b)



(c)

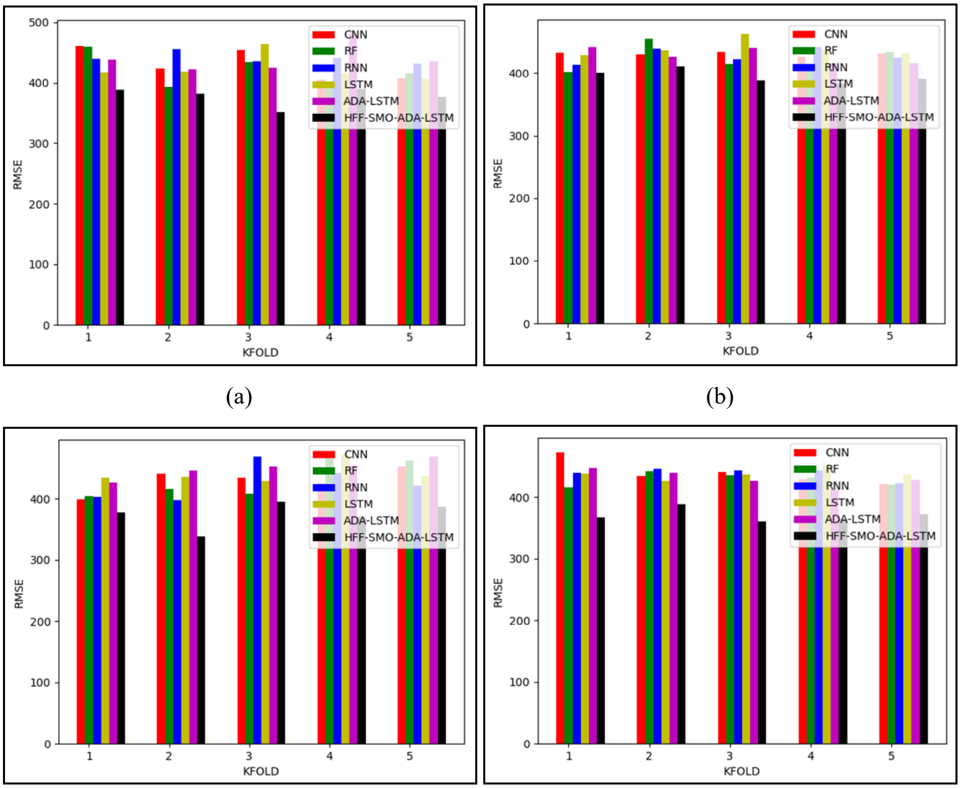


(d)

6.9 Statistical analysis of designed stock trend prediction model using various algorithms

The statistical analysis for predicting the stock trend model with several algorithms is given in Table 6. Thus, the simulation analysis has proved that the designed HFF-SMO-ADA-LSTM method has attained better performance when compared with the other existing algorithms.

Figure 15 K-fold analysis of developed stock prediction model using various classifiers (see online version for colours)



(a) (b)

(c) (d)

Table 6 Statistical analysis of the developed model using different algorithms

Terms	*SSA (Wu et al., 2019)*	*DHOA (Johari et al., 2013)*	*SMO (Agrawal et al., 2018)*	*FFO (Zhang et al., 2018)*	*HFF-SMO-ADA-LSTM*
			Dataset 1		
Worst	2.563473	1.747222	2.536691	2.289102	5.257633
Best	0.710571	0.418302	0.898356	0.403662	0.419769
Mean	1.153153	0.992884	1.306121	0.90236	0.647832
Median	0.816455	0.462211	1.518766	0.995559	0.419769
Standard deviation	0.705971	0.627488	0.377651	0.366322	0.956046
			Dataset 2		
Worst	4.115324	5.006683	3.831396	2.964352	6.849525
Best	0.818402	0.372238	0.494742	0.721121	0.375477
Mean	1.634887	1.552188	1.282258	0.90058	0.634438
Median	0.818402	1.73029	1.4186	0.721121	0.375477
Standard deviation	1.210027	1.474806	0.868638	0.608573	1.268649

Table 6 Statistical analysis of the developed model using different algorithms (continued)

Terms	*SSA (Wu et al., 2019)*	*DHOA (Johari et al., 2013)*	*SMO (Agrawal et al., 2018)*	*FFO (Zhang et al., 2018)*	*HFF-SMO-ADA-LSTM*
			Dataset 3		
Worst	3.733655	3.513489	5.083076	7.142733	0.732269
Best	0.722723	0.455965	0.462226	0.478703	0.373489
Mean	1.213389	1.532904	1.032201	1.029416	0.494853
Median	0.722723	0.455965	0.530314	0.574102	0.569264
Standard deviation	1.100794	1.25637	1.127566	1.550467	0.126684
			Dataset 4		
Worst	3.197385	1.216006	5.11383	5.856054	2.596612
Best	0.422678	1.103293	0.421347	0.501935	0.375271
Mean	0.913826	0.343059	1.009541	1.057744	0.656475
Median	0.906089	1.430924	0.421347	0.501935	0.375271
Standard deviation	0.74659	0.067566	1.255906	1.245836	0.592613

6.10 Computational analysis of the designed method in the stock prediction model

The computational analysis of the proposed HFF-SMO-ADA-LSTM model with various existing algorithms is shown in Table 7. Thus, the simulation outcome has revealed that the designed HFF-SMO-ADA-LSTM method has attained higher performance while combined with the other existing algorithms.

Table 7 Computational analysis of stock prediction model with various existing algorithms

Methods	*Time (sec)*
SSA (Wu et al., 2019)	4.96064
DHOA (Johari et al., 2013)	3.503054
SMO (Agrawal et al., 2018)	2.43272
FFO (Zhang et al., 2018)	1.90432
HFF-SMO-ADA-LSTM	1.890324

6.11 Discussion

Some of the challenges of the existing works are shown here. In SSA, the forecasting of the stock market was become challenging due to the irregular and noisy behaviour in the examined data. Additionally, the accurate prediction of the stock market was a complex task. The time series problems were not solved by the DHOA. However, in price prediction, the noise cannot be extracted effectively from the stock market. It does not have the capability to deal with a large number of complex data. Due to the complex market behaviour, the price movement could not predict the stock market price in SMO. To overcome these challenges, an effective deep-learning approach was utilised to predict the stock market. Moreover, the parameters of FFO and SMO were tuned with the help of

HFF-SMO to achieve an effective forecasting rate in the stock market. The proposed HFF-SMO method can minimise the errors regarding MAE and RMSE.

7 Conclusions

Here, it has implemented a novel deep-learning approach that was tried for predicting the trend in the stock market. Initially, data was collected from standard benchmark sources, and they were given to do the data formation phase on the time series data. Then, the acquired data from data formation was subjected to a deep feature acquisition stage, and the features were extracted by DCTN. Later the attained features were provided to the prediction phase, and the effective prediction was performed using ADA-LSTM. Also, their parameters were tuned using HFF-SMO by FFO and SMO to attain an effective stock market trend forecasting rate. Thus, the developed model has effectively secured a lower error rate in stock market trend prediction than existing approaches. The proposed HFF-SMO-ADA-LSTM was 80.5%, 77.9%, 72.2%, 66.4%, and 48.2% over other models.

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