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Prediction Model for Stock Trading using Combined Long Short Term Memory and Neural Prophet with Regressors

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Abstract: The prediction of the stock market offers information for the business to increase the profit in the share market. The prediction of a stock's price is a challenging task because of the non-linearity, instability of time series information, and significant noise. In this research, an effective stock market prediction (SMP) is done by proposing the combination of long-short term memory (LSTM) and neural prophet (NP) namely the LSTMNP model. The interpretable features of NP are integrated with the LSTM to improve the prediction performances. On the other hand, the safety net incorporated in the LSTMNP is used to confirm the better prediction even if one of the models provides a lower performance. The main objective of this LSTMNP-SMP method is to improve the prediction with less errors. The LSTMNP-SMP method is analyzed using the parameters of mean absolute error (MAE), root-mean-square error (RMSE) and mean squared error (MSE). The existing approaches such as accelerated gradient-LSTM (AG-LSTM), support vector machine (SVM)-particle swarm optimization (PSO) and LSTM with artificial rabbits optimization (ARO) are used to compare the LSTMNP-SMP. The MSE of IBM for LSTMNP-SMP is 0.1110 which is less when compared to the AG-LSTM, SVM-PSO and LSTM-ARO.

Keywords: Long-short term memory, Neural prophet, Root-mean-square error, Safety net, Stock market prediction.

1. Introduction

A financial market is a market synchronized with the commodity market and labor market. The financial resource assignment and financial market development are an essential representation of the financial, institutional, and economic expansion of the country. Financial stock is an important factor in the economy [1, 2]. The economy is derived from the stock market which is a profitable investment for investors and firms. Initial public aids are profitable whereas the investor buys many shares and obtains the profit from the stockholder incentive plan of the corporation [3]. A huge stock exchange in the world is the New York stock exchange (NYSE) in 2018 February which has a market capitalization worth US$30.1 trillion. The stock market is an important field for earning money along with the debt markets. The stock interchange is extremely liquid which makes interested users easily sell and buy the securities [4]. Various reasons that create the fluctuations in stock price are immigration policies, public health conditions, natural disasters, variations in the unemployment rate, monetary policies influencing countries, and so on [5, 6]. Therefore, forecasting the stock value has become an important task in recent times. Forecasting defines the process of identifying the future value of any series using long historical data or earlier patterns [7-9].

Effective identification of stock prices offers beneficial assistance to shareholders in making appropriate decisions either purchasing or selling the shares. The behavior of predicting the stock's future value is represented as SMP [10, 11]. A precise identification of the stock is used to increase the profit. Hence, the development of an automatic approach for accurately identifying the market trends helps traders in maximizing profit which is important in the stock market. However, the identification of the stock market is a complex task, because of different

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factors such as company performance, economic variables, industry performance, investor sentiment, social media sentiment and company news [12]. A huge amount of noise is occurred in the financial time series information, because of the effect of different accidental parameters in the financial market. These noises frequently confuse the investors' decision on stock market trend and affects further investigation [13]. Specifically, the nonparametric, volatile, noisy and complex character creates difficulty while forecasting the stock market [14, 15].

The contributions are concise as follows:

- The interpretable features of NP are integrated with the LSTM for enhancing the prediction of stock price. The safety net incorporated in the LSTMNP is used to guarantee the prediction is not affected by the lower performance of any of the models.
- The developed LSTMNP is used to predict the stock's price using MCX Nickel Trade dataset.

The remaining paper is sorted as follows: Section 2 provides information about the recent research done for SMP. The forecasting of the stock market using LSTMNP is detailed in section 3 whereas the outcomes of LSTMNP-SMP are provided in section 4. Further, the overall work is concluded in section 5.

2. Related work

The information about the recent research done for stock market prediction is given in this section.

Deepika and Bhat [16] developed the Kalman filter SMP for improving the SMP. The stock market values were forecasted using the financial information from Yahoo and Twitter. The stock values were examined by obtaining the technical indices from the input data. The sentiment was investigated by extracting Twitter information related to the stock value of a company. Moreover, the errors from the data were minimized by the Kalman filter. Therefore, the classification using AG-LSTM was improved by avoiding unwanted features. The error value of AG-LSTM was high sometimes because of inappropriate information exists in the input data.

Zaheer [17] presented the hybrid deep-learning approach for performing the model forecasting. Three models convolutional neural network (CNN), long-short term memory (LSTM) and single layer recurrent neural network (RNN) were considered to forecast the stock parameters by evaluating the time series data. From the CNN, LSTM and single-layer RNN, the best model was chosen according to the error rate. The developed hybrid deep-learning was failed to consider the risk factor which caused the impact during the SMP.

Kumar [18] developed the hybrid deep learning of LSTM with adaptive PSO to forecast the stock price. An LSTM and fully connected layer (FCL) weights were evolved using the adaptive PSO. The PSO's inertia coefficient was improved by introducing the adaptive approach. The incorporation of adaptive PSO in LSTM was used to handle the problem of vanishing and exploding gradient. The developed adaptive PSO with LSTM was weight sensitive while forecasting the stock market price.

Bazrkar and Hosseini [19] presented the machine learning (ML) technique namely SVM for predicting the stock price. The knowledge of the data was obtained by SVM which was effectively used for identifying the new stock data. Further, the PSO was used to identify the optimum parameters for SVM to avoid the over-fitting issue. In this work, an essential data about stock exchange organizations was not obtained because of lack of widespread assistance of stock exchange organizations.

Gülmez [20] presented the LSTM which was the type of artificial neural network (ANN) utilized in time series analysis. This LSTM effectively discovered the stock market prices by managing the numerous input and output time steps. Further, the ARO was used for hyper parameter optimization of LSTM for improving the accuracy. The developed LSTM-ARO does not considered the past trends and anticipated future moves while performing the SMP.

The limitations from the related work are given as follows: inappropriate information causes the error, failed to consider the required information such as risk factor, past trends & anticipated future moves and weight sensitive classifier. The aforementioned limitation affects the performance of SMP. In this research, the interpretable features of NP are combined with LSTM to enhance the stock price prediction. The prediction done by LSTMNP is guaranteed by using the safety net. Moreover, the incorporation of technical indicators is used to consider the past trends and anticipated future moves which additionally helps to enhance the prediction of LSTMNP.

3. Stock price prediction using LSTMNP

In this research, an effective stock price prediction is done using the improved deep learning architecture. The important processes are 1) Dataset acquisition from MCX dataset, 2) Technical indicators and pre-processing, 3) Classification using LSTMNP and 4) Performance analysis. An effective

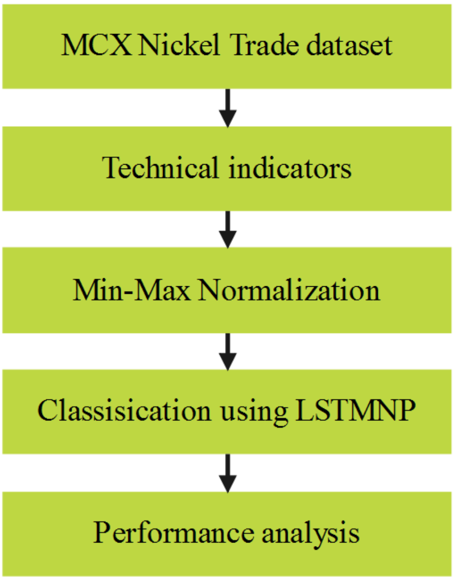

Figure. 1 Block diagram of the LSTMNP based SMP

interpretable feature of NP combined with the LSTM is used to enhance the classification of stock price prediction. Fig. 1 shows the block diagram of the LSTMNP based SMP.

3.1 MCX nickel trade dataset

This research considers the MCX nickel trade dataset which has the unpredictability of five metals such as gold, lead, nickel, tin, copper. The time-series data is used from 30th March 2006 to 20th March 2020 and comprises 3,575 data points for each metal. For all the metals, the spot market closing prices are gathered from the MCX website [21].

3.2 Technical indicators and pre-processing

The daily OHLC stock market data was used to create the pool of technical indicators [22] that comprises low (LO) price, high (HI) price, open (OP) price, closing (CL) price and volume (V). Next, the Min–Max normalization is applied for transforming the input in the short range by using the Eq. (1).

$$x = \frac{I - I_{min}}{I_{max} - I_{min}} (I'_{max} - I'_{min}) + I'_{min} \quad (1)$$

Where, I is the input; I_{min} and I_{max} are the minimum and maximum values of input data; I'_{min} and I'_{max} are the minimum and maximum values of new data, and x is pre-processed data.

3.3 Classification using LSTM with neural prophet (LSTMNP)

The preprocessed data from min–max normalization is given as input to the LSTMNP for predicting the stock price. In LSTMNP, the LSTM output is combined with the neural prophet via ANN. Fig. 2 shows the architecture of LSTMNP. In that, both the LSTM and NP are individually operated to generate the output features which are detailed in the following sections.

3.3.1. LSTM

LSTM is a category of RNN model that solves the short term dependence issue by observing the parameters of long-term dependencies. Fig. 3 shows the architecture of LSTM cell which comprises four critical layers such as input gate, output gate, forget gate and memory cell layer. Eqs. (2)-(7) are used to provide the gate layer.

$$f_t = \sigma(h_{t-1} W^f + x_t U^f) \quad (2)$$

$$i_t = \sigma(h_{t-1} W^i + x_t U^f) \quad (3)$$

$$\hat{C}_t = tanh(h_{t-1} W^g + x_t U^g) \quad (4)$$

$$C_t = \sigma(f_t \times C_{t-1} + i_t \times \hat{C}_t) \quad (5)$$

$$o_t = \sigma(h_{t-1} W^0 + x_t U^0) \quad (6)$$

$$h_t = o_t \times tanh(C_t) \quad (7)$$

where, the input is denoted as x which is pre-processed data; the forget layer cell is denoted as f; the hidden layer is denoted as h; the candidate hidden state is $\hat{C}_t$; internal memory unit is C; output is denoted as o_t; input gate is denoted as i_t; log-sigmoid and hyperbolic tangent activation function are denoted as σ and $tanh$ respectively; the weight matrix that links the input and hidden layer is denoted as U, and the connection between the current and previous hidden layer is denoted as W.

3.3.2. Neural prophet (NP)

The pre-processed data is given as input to the NP which is an improved version of FbProphet. This NP integrated the deep learning terms for enhancing the prediction. NP has various elements such as seasonality, trend, auto-regression, extra regressors, and so on. The three important components of a prophet are holidays, trend and seasonality. The aforementioned components are integrated with the Eq. (8).

$$NP(t) = TMF(t) + SF(t) + HF(t) + EV(t) \quad (8)$$

Where, the trend-modeling function is denoted as

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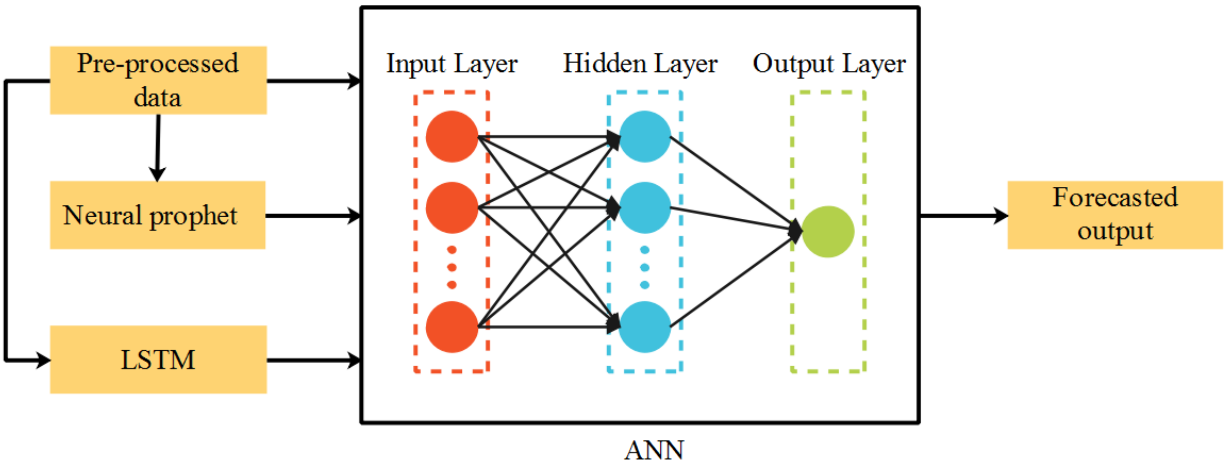

Figure. 2 Architecture of LSTMNP

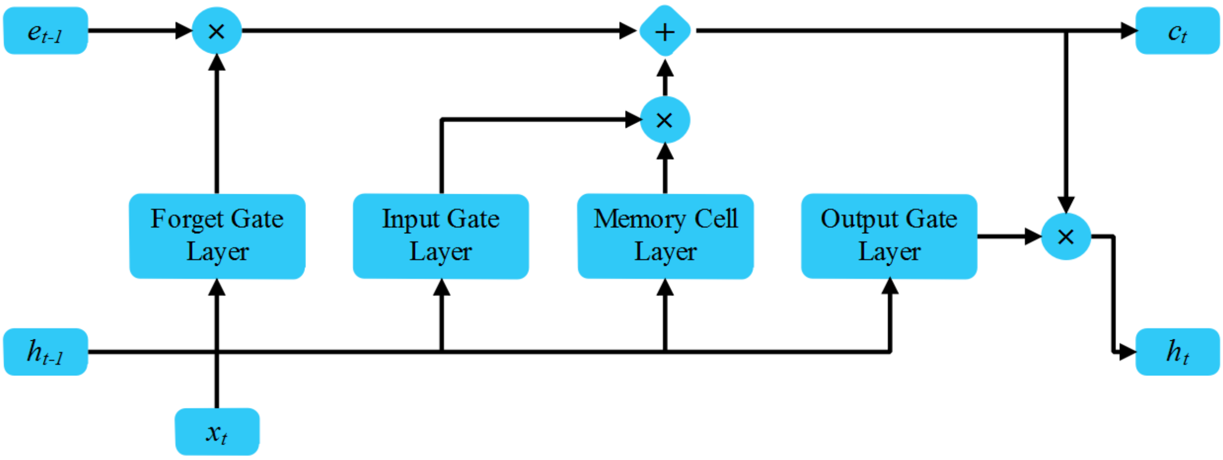

Figure. 3 LSTM cell architecture

$TMF(t)$; seasonality function is denoted as $SF(t)$; holiday function is denoted as $HF(t)$ and error variation is denoted as $EV(t)$. Fig. 4 shows the forecasting process of NP. In that, the Fourier series are utilized for modelling the time series seasonality component whereas the time series holidays component is described by using the additive models. Generally, the Fourier series is a mathematical tool which used to describe the periodic functions that utilized for modelling the seasonality component. Eq. (9) expresses the fourier series which is denoted as sum of sines and cosines.

$$SF(t) = a_0 + \sum_{k=1}^{n} \left(a_k cos \frac{2\pi kt}{T} + b_k sin \frac{2\pi kt}{T} \right) \quad (9)$$

Where, the data point time is denoted as t; the time series period is denoted as T; the number of terms in the series is denoted as n; time series average is denoted as a_0; and sines and cosines coefficients defined by Fourier analysis are denoted as a_k and b_k respectively.

The generative additive model (GAM) is used to model the holidays component and this GAM allows to insertion of extra elements for influencing the time series. The GAM is a reliable and non-parametric regression model utilized for matching complex data patterns. This matching is ensured by denoting the connection between the response variable and predictor variables. The GAM utilized by NP is denoted as shown in Eq. (10).

$$HF(t) = g_1(t) + g_2(t) + \cdots + g_k(t) + \epsilon(t) \quad (10)$$

Where smooth function which modeled the ith predictor variable is denoted as $g_i(t)$ and error term which denotes the variation/ random noise in the data is denoted as $\epsilon(t)$.

The estimation of $g_i(t)$ is used for predicting future values by fitting the GAM to the data. This GAM generates the time series forecast and uncertainty intervals for assessing the reliability of the prediction.

The deep learning terms are integrated on the lagged information whereas the hyper parameters are automatically tuned for enhancing the prediction. The

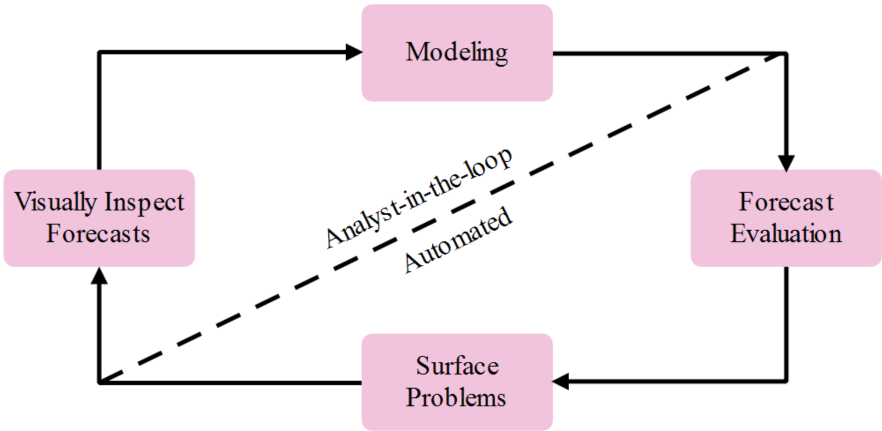

Figure. 4 Forecasting process of NP

Table 1. Analysis of LSTMNP for MCX dataset

Classifiers	MAE	MSE	RMSE
Fbprophet	9.3192	7.5219	2.7426
NP	8.0033	5.9001	2.4290
LSTM	7.3942	5.3309	2.3089
LSTMNP	5.0039	3.1674	1.7797

forecasting design flow of NP is shown in Fig. 4. The time series data forecasting is developed by specifications and parameters which have direct interpretation of human. Next, the performance of forecasting is examined in the NP. The NP informs the human analyst to interfere, when the issue occurs i.e., poor performance. Accordingly, the NP is adjusted depending on the feedback.

3.3.3. Integration of LSTM with NP

The LSTM and NP are utilized individually for generating the output features of o_t and NP along with time series data. Next, the generated outputs are given to the ANN for obtaining the final forecasting of stock price. On the other hand, the time series data and statistical values from the historical load are given as additional regressors for enhancing the forecasting of LSTMNP. A safety net is incorporated into this LSTMNP model to ensure the accuracy is not affected by other models. If any one model provides lower performances, then the respective model is eliminated from the prediction.

4. Results and discussion

The simulation of the LSTMNP for SMP is done in anaconda navigator 3.5.2.0 with Python 3.7. The system configuration used for this work is a Windows 10 operating system, Intel Core i9 processor and 128 GB RAM. The MCX dataset used in this work is divided as 20% for testing and 80% for training. The parameters of MAE, MSE and RMSE expressed in Eqs. (11) to (13) are used to analyze the LSTMNP-SMP. In that, the MSE is the value of variation among the identified and the actual values; RMSE evaluates the identified values from the model with actual values. MAE is another parameter for identifying the variation among identified and actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2 \tag{11}$$

$$RMSE = \sqrt{MSE} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - A_i| \tag{13}$$

Where, A_i and P_i are actual and predicted values and the total number of records or samples is denoted as n.

4.1 Performance analysis

The LSTMNP-SMP is developed for identifying the stock price using the dataset of MCX dataset. However, this MCX dataset is not used in much recent research, therefore one more dataset namely the Yahoo finance dataset is also considered for analyzing the LSTMNP-SMP. From the Yahoo finance dataset, the stock values related to Amazon and IBM are taken for analysis. In this analysis, different classifiers namely Fbprophet, NP and LSTM are considered for analyzing the performance of the LSTMNP. Tables 1 and 2 show the performance analysis for different classifiers of MCX and Yahoo finance datasets respectively. Further, Fig. 5 shows the graphical comparison for MCX whereas Figs. 6 & 7 show the comparison of Yahoo finance datasets. This analysis shows that the LSTMNP provides better performance than the Fbprophet, NP and LSTM. For example, the MSE of LSTMNP for MCX dataset is 3.1674, whereas Fbprophet obtains 7.5219, NP obtains 5.9001 and LSTM obtains 5.3309.

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Table 2. Analysis of LSTMNP for Yahoo finance dataset

Classifiers	Company name	MAE	MSE	RMSE
Fbprophet	**Amazon**	0.3300	0.2601	0.0510
	IBM	0.3573	0.2637	0.0513
NP	**Amazon**	0.2911	0.2344	0.0484
	IBM	0.3408	0.2039	0.0451
LSTM	**Amazon**	0.2507	0.1833	0.0428
	IBM	0.2808	0.1704	0.0412
LSTMNP	**Amazon**	0.2114	0.1103	0.0252
	IBM	0.2343	0.1110	0.0121

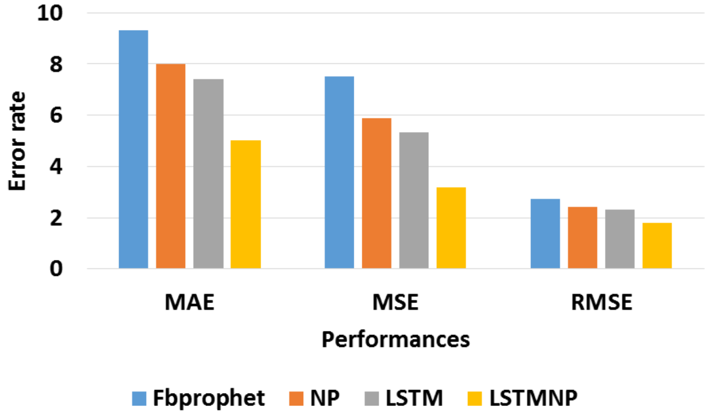

Figure. 5 Graph of LSTMNP comparison for MCX dataset

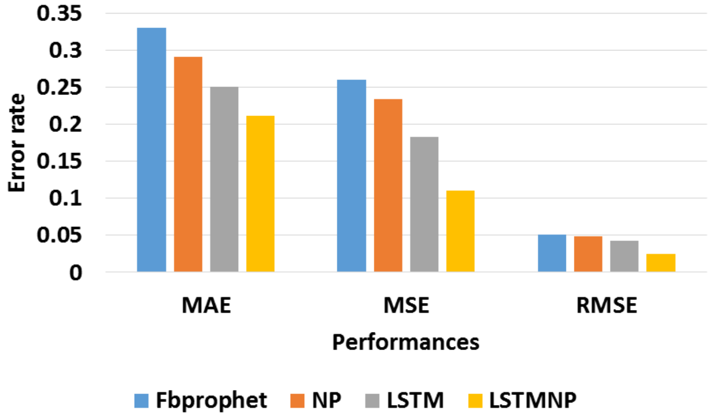

Figure. 6 Graph of LSTMNP comparison for Amazon Yahoo finance dataset

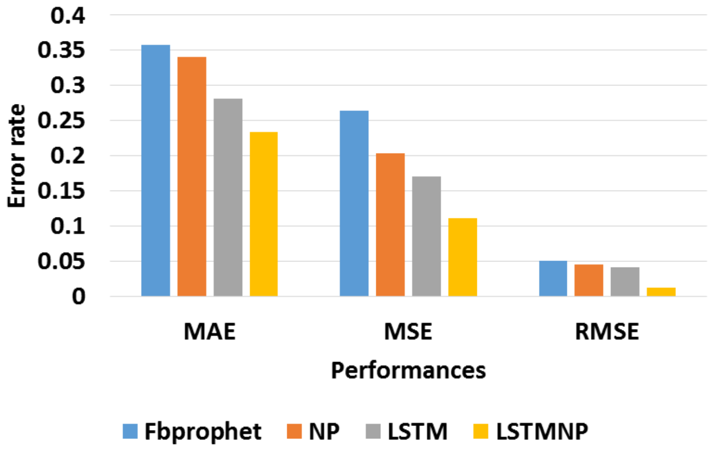

Figure. 7 Graph of LSTMNP comparison for IBM Yahoo Finance dataset

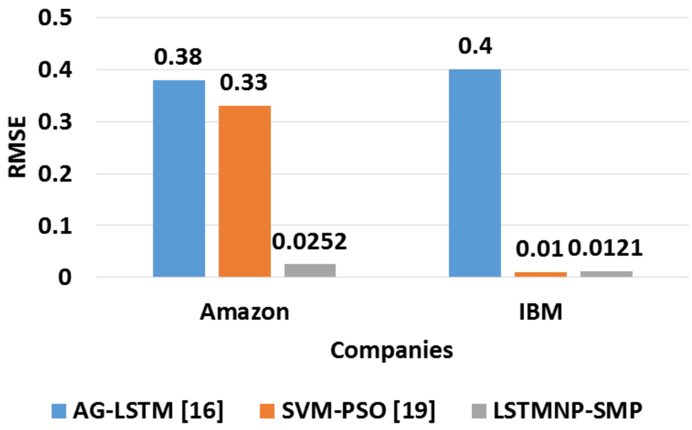

Figure. 8 Graph for RMSE comparison

Table 3. Comparative analysis for LSTMNP-SMP

Performances	Company name	AG-LSTM [16]	SVM-PSO [19]	LSTM-ARO [20]	LSTMNP-SMP
MAE	**Amazon**	0.24	NA	NA	0.2114
	IBM	0.31	NA	2.113	0.2343
MSE	**Amazon**	0.15	NA	NA	0.1103
	IBM	0.16	NA	7.333	0.1110
RMSE	**Amazon**	0.38	0.33	NA	0.0252
	IBM	0.4	0.01	NA	0.0121

The following strategies of LSTMNP are used to improve the prediction performances: 1) Interpretable feature of NP combined with the LSTM is used for enhancing the prediction; and 2) The incorporated safety net is used to ensure the accuracy isn't affected by other models.

4.2 Comparative analysis

The existing research such as AG-LSTM [16], SVM-PSO [19] and LSTM-ARO [20] are used to compare the efficiency of LSTMNP-SMP. The comparative analysis for LSTMNP-SMP with AG-LSTM [16], SVM-PSO [19] and LSTM-ARO [20] is shown in Table 3, where the NA represents the values are Not Available in the respective researches. For comparison, the stock values related to Amazon and IBM are taken from the Yahoo finance dataset. Further, the RMSE comparison of LSTMNP-SMP with AG-LSTM [16] and SVM-PSO [19] is shown in Fig. 8. The MSE of IBM for LSTMNP-SMP is 0.1110 which is less when compared to the AG-LSTM [16], SVM-PSO [19] and LSTM-ARO [20]. This analysis shows that the LSTMNP-SMP has better performance than the AG-LSTM [16], SVM-PSO [19] and LSTM-ARO [20]. The interpretable features of NP and safety net incorporation of LSTMNP are used to achieve a better prediction of stock price. The past trends and anticipated future moves are considered by using the technical indicators that additionally helps to enhance the prediction of LSTMNP.

5. Conclusion

In this research, an effective forecasting of stock price is done using the LSTMNP model. Initially, the technical indicators and pre-processing are done to normalize the data for ease of training during the prediction. The integrated interpretable features of NP with LSTM are used to enhance the forecasting performances. The NP has three important components such as holidays, trends and seasonality for enhancing the forecasting process. In that, the trend denotes the decrease or increase over the long term in the stock market and the seasonality denotes the repeating pattern of a stock price in a fixed period. The holiday component of NP is important because it accomplishes a huge amount of pre market changes i.e., the decisions to sell or buy before opening the market. The holiday component is one of the important factors in regressor because it has a huge impact on decision making to sell or buy stocks, when there is festive period or sudden holiday or long holiday. Further, the incorporated safety in the LSTMNP guarantees enhanced prediction even if one of the models provides lower performance. Therefore, the developed LSTMNP-SMP provides a better prediction of stock price. From the results, it is concluded that the LSTMNP-SMP outperforms well than the AG-LSTM, SVM-PSO and LSTM-ARO. The MSE of IBM for LSTMNP-SMP is 0.1110 which is less when compared to the AG-LSTM, SVM-PSO and LSTM-ARO. In the future, the stock market movement patterns are additionally considered as features for improving the stock price prediction.

Notation

Parameter	Description
I	Input
I_{min}	Minimum values of input data
I_{max}	Maximum values of input data
I'_{min}	Minimum values of new data
I'_{max}	Maximum values of new data
x	Pre-processed data
f	Forget layer cell
h	Hidden layer
$\hat{C}_t$	Candidate hidden state
C	Internal memory unit
o_t	Output
i_t	Input gate
σ	Log-sigmoid activation function
$tanh$	Hyperbolic tangent activation function
U	Weight matrix that links the input and hidden layer
W	Connection between the current and previous hidden layer
NP	Neural prophet
$TMF(t)$	Trend-modeling function
$SF(t)$	Seasonality function
$HF(t)$	Holiday function
$EV(t)$	Error variation
t	Data point time
T	Time series period
n	Number of terms in the series
a_0	Time series average
a_k	Sine coefficients defined by Fourier analysis
b_k	Cosine coefficients defined by Fourier analysis
$g_i(t)$	Smooth function
$\epsilon(t)$	Error term
A_i	Actual values
P_i	Predicted values
MAE	Mean absolute error
$RMSE$	Root-mean-square error
MSE	Mean squared error

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

References

[1] M. Sharaf, E. E. D. Hemdan, A. E. Sayed, and N. A. E. Bahnasawy, "StockPred: a framework for stock Price prediction", *Multimedia Tools and Applications*, Vol. 80, No. 12, pp. 17923-17954, 2021.

[2] T. I. Theodorou, A. Zamichos, M. Skoumperdis, A. Kougioumtzidou, K. Tsolaki, D. Papadopoulos, T. Patsios, G. Papanikolaou, A. Konstantinidis, A. Drosou, and D. Tzovaras, "An AI-Enabled Stock Prediction Platform Combining News and Social Sensing with Financial Statements", *Future Internet*, Vol. 13, No. 6, p. 138, 2021.

[3] K. Venkateswararao and B. V. R. Reddy, "LT-SMF: long term stock market price trend prediction using optimal hybrid machine learning technique", *Artificial Intelligence Review*, Vol. 56, No. 6, pp. 5365-5402, 2023.

[4] P. Chhajer, M. Shah, and A. Kshirsagar, "The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction", *Decision Analytics Journal*, Vol. 2, p. 100015, 2022.

[5] H. N. Bhandari, B. Rimal, N. R. Pokhrel, R. Rimal, K. R. Dahal, and R. K. C. Khatri, "Predicting stock market index using LSTM", *Machine Learning with Applications*, Vol. 9, p. 100320, 2022.

[6] P. N. Achyutha, S. Chaudhury, S. C. Bose, R. Kler, J. Surve, and K. Kaliyaperumal, "User Classification and Stock Market-Based Recommendation Engine Based on Machine Learning and Twitter Analysis", *Mathematical Problems in Engineering*, Vol. 2022, p. 4644855, 2022.

[7] K. Yadav, M. Yadav, and S. Saini, "Stock values predictions using deep learning based hybrid models", *CAAI Transactions on Intelligence Technology*, Vol. 7, No. 1, pp. 107-116, 2022.

[8] S. Wu, Y. Liu, Z. Zou, and T. H. Weng, "S_I_LSTM: stock price prediction based on multiple data sources and sentiment analysis", *Connection Science*, Vol. 34, No. 1, pp. 44-62, 2022.

[9] S. R. Velu, V. Ravi, and K. Tabianan, "Multi-Lexicon Classification and Valence-Based Sentiment Analysis as Features for Deep Neural Stock Price Prediction", *Sci*, Vol. 5, No. 1, p. 8, 2023.

[10] P. Koukaras, C. Nousi, and C. Tjortjis, "Stock

Market Prediction Using Microblogging Sentiment Analysis and Machine Learning", *Telecom*, Vol. 3, No. 2, pp. 358-378, 2022.
[11] J. M. T. Wu, Z. Li, N. Herencsar, B. Vo, and J. C. W. Lin, "A graph-based convolutional neural network stock price prediction with leading indicators", *Software: Practice and Experience*, Vol. 29, No. 3, pp. 1751-1770, 2023.
[12] T. T. Ho and Y. Huang, "Stock price movement prediction using sentiment analysis and CandleStick chart representation", *Sensors*, Vol. 21, No. 23, p. 7957, 2021.
[13] D. Wu, X. Wang, and S. Wu, "A hybrid framework based on extreme learning machine, discrete wavelet transform, and autoencoder with feature penalty for stock prediction", *Expert Systems with Applications*, Vol. 207, p. 118006, 2022.
[14] N. Das, B. Sadhukhan, T. Chatterjee, and S. Chakrabarti, "Effect of public sentiment on stock market movement prediction during the COVID-19 outbreak", *Social Network Analysis and Mining*, Vol. 12, No. 1, p. 92, 2022.
[15] Y. Shi, Y. Zheng, K. Guo, and X. Ren, "Stock movement prediction with sentiment analysis based on deep learning networks", *Concurrency and Computation: Practice and Experience*, Vol. 33, No. 6, p. e6076, 2021.
[16] N. Deepika and M. N. Bhat, "An efficient stock market prediction method based on Kalman Filter", *Journal of The Institution of Engineers (India): Series B*, Vol. 102, No. 4, pp. 629-644, 2021.
[17] S. Zaheer, N. Anjum, S. Hussain, A. D. Algarni, J. Iqbal, S. Bourouis, and S. S. Ullah, "A Multi Parameter Forecasting for Stock Time Series Data Using LSTM and Deep Learning Model", *Mathematics*, Vol. 11, No. 3, p. 590, 2023.
[18] G. Kumar, U. P. Singh, and S. Jain, "An adaptive particle swarm optimization-based hybrid long short-term memory model for stock price time series forecasting", *Soft Computing*, Vol. 26, No. 22, pp. 12115-12135, 2022.
[19] M. J. Bazrkar and S. Hosseini, "Predict stock prices using supervised learning algorithms and particle swarm optimization algorithm", *Computational Economics*, Vol. 62, No. 1, pp. 165-186, 2023.
[20] B. Gülmez, "Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm", *Expert Systems with Applications*, Vol. 227, p. 120346, 2023.
[21] MCX dataset: https://www.mcxindia.com/
[22] G. Kumar, S. Jain, and U. P. Singh, "Neuro-Fuzzy and Particle Swarm optimization based Hybrid Approach for Stock Price Forecasting", In: *Proc. of 2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Pune, India, pp. 753-758, 2021.