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LSTM based decision support system for swing trading in stock market

Shouvik Banik [a], Nonita Sharma [a], Monika Mangla [b], Sachi Nandan Mohanty [c,*], Shitharth S. [d]

[a] Department of Computer Science & Engineering, Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, India
[b] Department of Computer Engineering, Lokmanya Tilak College of Engineering, Navi Mumbai, India
[c] Department of Computer Science & Engineering, Vardhaman College of Engineering, Hyderabad, India
[d] Department of Computer Science & Engineering, Kebri Dehar University, Kebri Dehar, Ethiopia

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ABSTRACT

Due to the highly volatile and fluctuating nature of the Indian stock market which is influenced by a number of factors including government policies, release of a company's financial reports, investor's sentiment, geopolitical situation, and many others, the prediction of the stock market has been a daunting task for traders. In this study, a Long Short Term Memory enforced Decision Support System is developed for swing traders to accurately analyze and predict the future stock values. The Decision support system generates a report which incorporates the predicted values of the company stock for the next 30 days and other technical indicators like MFI, relative RSI, the Support and Resistance of the stock price, five Fibonacci retracement levels, and the MACD and SIGNAL LINE analysis of the company and NIFTY industry average stock price. The trader can use the investment success score calculated in the report to augment his investment decisions. The results achieved by the proposed model in terms of Root Mean Square Error, Mean absolute error, and Mean Absolute Percentage Error are 4.13, 3.24, and 1.21 % respectively which establishes the efficacy of the proposed technique compared with the state-of-art techniques.

1. Introduction

Indian stock market traders regularly face heavy challenges due to a number of reasons: Firstly, when compared to markets of other developed countries like the US, over the years Indian equities are more volatile with greater fluctuations in return. Dow Jones Index (DJI) volatility of 3.92% has been considerably lower than 5.06% of Bombay Stock Exchange (BSE) in the last ten years while DJI gave better returns than BSE in six of last ten years. Secondly Indian laws make it mandatory for a start-up to produce profits consecutively for three years before the companies can go public. This effectively eliminates interests from most traders to show confidence in the opportunities of new business models in spite of India having a thriving start-up ecosystem. Thirdly the Indian Rupee has consistently observed a decline in value. In this year alone the Indian Rupee fell 6% against US Dollar. This is a huge problem as due to this the value of investments shrinks overtime. And lastly unlike New York Stock Exchange or Tokyo Stock Exchange the National Stock Exchange of India does not provide global exposure which restricts the Indian traders in terms of diversification of their portfolio. When globally equities fell over 20%–30% due to the COVID-19 pandemic, diversification proved effective. S&P 500 recovered all losses from the pandemic by 8th June 2020 while SENSEX was still down 17% [1,2]. There is a distinct gap in the combined effort in usage of traditional technical analysis and algorithmic trading components. Such a need fuels this work to provide the swing traders with the kind of feedback which constitutes of a complete synopsis of the stock or the whole market in general. Additionally, there are various types of popular trading techniques widely used by investors currently like Scalp trading, Intraday trading, Swing trading and Long-term trading. In swing trading the trader holds the stock for a day to few weeks since alteration in corporate nucleus generally take time to produce sufficient price fluctuation and wait for the trade to develop [3].

Further, LSTM is a variant of Recurrent Neural Network (RNN) which is capable of dealing with long term patterns in the data by carefully appending or deleting information from the cell state [4]. Like all other RNNs there is a repeating module in LSTM, but there are four neural network layers instead of a traditional single neural network layer in each repeating module. Promising improvements is also seen with LSTM on further research like in Shi et al. [5] wherein a unique multi-step forecasting model is proposed which combines LSTM with Variational Mode

* Corresponding author.
E-mail addresses: shouvikbanik96@gmail.com (S. Banik), nonita@nitj.ac.in (N. Sharma), manglamona@gmail.com (M. Mangla), sachinandan09@gmail.com (S.N. Mohanty), shitharth.it@gmail.com (Shitharth S.).

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Decomposition (VMD) and Empirical Wavelet Transform (EWT) to obtain better results in terms of accuracy, and in Gao et al. (2022) an augmented LSTM is proposed which uses attention based mechanism and EWT to achieve more optimal MAR, RMSE and MAPE values [6].

This study aims to build a Decision Support System (DSS) which can accurately forecast future stock prices on the basis of previous stock prices using a LSTM model. Popular technical indicators like Money Flow Index (MFI), Relative Strength Index (RSI), Support and Resistance levels of the stock, 5 levels of Fibonacci Retracements and MACD & SIGNAL LINE analysis of the stock itself along with the NIFTY Industry Average are then evaluated over the forecasted values and a report is generated to assist the swing traders with the investment and significantly reduce the risk which accompanies any investment. A trader will be provided with an Investment Success Score which is used to understand how the trajectory of stock prices will react to current market conditions. The main contributions of this research work are:

- To build a Decision Support System for swing trading that accurately analyzes and forecasts future stock prices using LSTM model.
- A novel Investment Success Score evaluated by the proposed DSS based on technical indicators like MACD-Signal Line analysis, MFI, RSI.
- To generate an Investment Analysis Report based on the Investment Success Score to aid the swing traders for enhanced returns in short term as well as long term.

This paper is divided into five key segments with Introduction being the first one which describes the motivation of this research. It is then followed by Related Work where few significant advances in this field have been explored. It is then followed by Methodology which gives an architectural overview and details of all the computation and processes of the proposed system. It is then succeeded by experimental results which gives the details of how the model on which the DSS is built is performing in terms of an error metric. Also, how the LSTM performs with respect to similar models for the same purpose is explored. Finally, the conclusion caps off the work and the future scope of the research which states ways on how this work can be extended to provide a better solution for the problem taken into consideration.

2. Related work

Various research and experimental works have been conducted to predict stock prices. A brief overview of some notable recent developments in this area of research is given below. In [7] various methods are reviewed to analyze and understand the efficiency of the prediction performance. Methods like Back propagation Neural Network (BPNN), LSTM and Prophet are taken into consideration to predict the trend of the time series data of MSCI Taiwan Index. The LSTM performs with most accuracy and RMSE value of only 0.04464. Future work can be extended by developing a decision support system using LSTM for stock prediction integrated with real time data using market APIS. In [8] various machine learning techniques have been evaluated to select 10 of the best stocks from the CSI300 Index with the highest potential to exceed the median return. Random Forest, ANN and Logistic Regression are evaluated, and Random Forest achieved the highest test accuracy. Future work can be extended by developing a trading strategy on the basis of these selected stocks to maximize gain. In [9,10] the Bombay Stock Exchange (BSE) SENSEX is used to analyze the performance of various time series forecasting models such as Autoregressive Integrated Moving Average (ARIMA), BoxCox, Error Trend Seasonal (ETS), Meanf, Naïve, Snaive, and Neural Network. It is concluded that neural network and exponential smoothening gives less error persistently and the best performing model is linear regression with logarithmic Gross Domestic Product (GDP) values and open BSE values. In [11] a Relational Stock Ranking (RSR) deep learning model is proposed. The novelty of the proposed model is Temporal Graph Convolution component which is used to optimize the deep learning model for forecasting stock prices and time sensitive apprehension of stocks values. NYSE and NASDAQ stock data is used to validate the performance of this model and it is observed that RSR achieves an average return ratio of 98% and 78% in the respective datasets. In [12] the estimates of Random Forest ensemble of trees using LSBoost is combined (LS-RF) and compared with a standard model, Support Vector Regression (SVR). Statistical parameters are used to feed the Random Forest regression which forecasts future values and Least Square Boosting is being utilized for loss function training to enhance error estimates. CNX Nifty and S&P BSE SENSEX data is used for this comparison, and LS-RF is observed to perform significantly better than SVR. In [13] four market groups data from Tehran Stock Exchange is used to minimize the risk of forecasting stock market trend. Various machine learning models like Random Forest, Adaptive Boosting (AdaBoost), Decision Tree, Naïve Bayes, K-Nearest Neighbor (KNN), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Logistic Regression with Neural Network Models like Recurrent Neural Network (RNN), LSTM, and Artificial Neural Network (ANN) are compared using F1 score, accuracy, and ROC-AUC metrics. It was observed that using binary data as input parameters instead of continuous values showed significant improvement an RNN and LSTM had much better performance than other models. In [14] risks in parameter based supervised learning stock forecasting models are minimized by introducing a reinforcement learning ensemble which utilizes a Q-learning agent to maximize a return function. This model produces strong results, especially in Maximum Drawdown, Sortino Ratio and Equity curve metrics when compared to traditional buy and hold strategy. In [15] the S&P 500 stock prices from 1992 to 2015 are predicted using various methods namely Logistic Regression Classifier, LSTM, Deep Neural Network and Random Forest. LSTM model is observed to clearly outperform the other models that are taken into consideration. Deep Neural Network and Logistic Regression performed better than the Random Forest model. Only during a financial crisis, the Random Forest is observed to be performing comparatively better. In [16] LSTM, Wavelet Transforms and stacked autoencoders are integrated to predict stock prices. The stacked auto encoder is used to retrieve deep features. To eliminate noise, time series stock data is broken down using Wavelet Transformation. The stock prediction is done using the second autoencoder. The LSTM is used to forecast upcoming closing price of the equity by taking high level denoising features as input. Profitability and accurate prediction give this model higher competitive edge over other similar models. In [17] CSI300 data is used for stock market prediction. A LSTM is deployed which takes into account the sentiment of market investors. Naïve Bayes is used to retrieve sentiment from forum posts. A prediction accuracy of 87.86% is observed which outperforms other methods of stock prediction by 6%. Latest developments include isolating dynamic delays to recreate multivariate series for enhancing attention-based LSTM. For instance, In [18] authors have introduced a novel technique that separates the time-variant delays to recreate the data in order to improve the efficacy of the LSTM. Further, [5] proposed an ensemble technique uniting variational mode decomposition (VMD), empirical wavelet transform (EWT), and LSTM for multistep prediction. The novel work proposed by authors achieves the notable accuracy of 97.7%. Likewise, latest work of Peng

Table 1
Contribution of surveyed literature.

Author	Models employed	Contribution	Future scope
Carta et al. [14]	Reinforcement learning ensemble which utilizes a Q-learning agent to maximize a return function.	Risks are minimized and accurate results are observed in Maximum Drawdown, Sortino Ratio and Equity curve metrics when compared to traditional buy and hold strategy.	LSTM and other network architectures can be evaluated in search of better prediction accuracy.
Nabipour et al. [13]	Various Machine Learning and Deep Learning methods	Binary data as input parameters instead of continuous values showed significant improvement in RNN and LSTM had much better performance than other models.	The best performing model can be coupled with technical indicators to generate a decision
Fang et al. [7]	BPNN, LSTM, Prophet	LSTM performs with most accuracy and RMSE value of only 0.04464.	Stock prediction is not integrated with real time data.
Zhang and Bai [8]	Random Forest, ANN, Logistic Regression	Random Forest achieved the highest accuracy in selecting 10 of the best stocks from the CSI300 Index with the highest potential to exceed the median return.	No trading strategy was developed on the basis of the selected stocks to maximize gain.
Yadav and Sharma [9]	ARIMA, BoxCox, ETS, Meanf, Naïve, Snaive, and Neural Network	Neural network with exponential smoothening gives less error persistently and the best performing model is linear regression with logarithmic GDP values and open BSE values.	Investment Analysis Report was not suggested.
Feng et al. [11]	Relational Stock Ranking (RSR) deep learning model. Temporal Graph Convolution component is used in optimizing deep learning model.	RSR achieves an average return ratio of 98% and 78% in NYSE and NASDAQ.	The neural network can be used to build a recommender system.
Sharma and Juneja [12]	Random Forest estimates in ensemble of trees using LSBoost is combined (LS-RF). CNX Nifty and S&P BSE SENSEX data is used for this comparison	LS-RF perform significantly better than SVR.	The novel model proposed can be used for other fields such as weather forecasting, energy consumption forecasting and GDP forecasting.
Fischer and Krauss [15]	Logistic Regression Classifier, LSTM, Deep Neural Network and Random Forest are used to evaluate S&P 500 data.	LSTM model outperformed Only during a financial crisis the Random Forest is observed to be performing comparatively better	The model can be coupled with technical indicators to generate a decision
Bao et al. [16]	LSTM, Wavelet Transforms and stacked autoencoders are integrated to predict stock prices.	Profitability and accurate prediction give this model higher competitive edge over other similar models.	A more advanced hyper-parameters selection scheme might be embedded in the system to further optimize the proposed deep learning framework.
Li et al. [17]	Naïve Bayes is used to retrieve sentiment from forum posts for CSI 300 data.	A prediction accuracy of 87.86% is observed which outperforms other methods of stock prediction by 6%.	Forum posts can also consist of speculative rumors so further classification of the type of post is required before building a model.

et al. [6] emphasizes the application of LSTM for achieving better prediction results. Here, authors have utilized the attention method for analyzing the impact of influencing factors and performed the multifactor prediction analysis for optimal energy consumption. The technique was applied on real life scenario and yielded remarkable results with MAPE below 6%. Furthermore, authors in [19] proposed a novel FOA-LSTM that employs fruit fly optimization algorithm (FOA) with LSTM to solve time series problems. In order to summarize the latest work on the stock market analysis, a brief comparative evaluation of the state of art techniques is given in Table 1.

3. Methodology

The proposed method of forecasting stock market is given in the below Fig. 1 along with its description in the following subsection.

The stock price of ICICI Bank and NIFTY-Banking Sector is taken into account from National Stock Exchange of India data in Kaggle [20]. The data is taken over a large period of trading (1st Jan 2020 to 31st July 2020). Key features which will be used in the analysis is extracted and taken into consideration like Opening & Closing Price, Highest & Lowest Price in a day and volume traded in a day.

The candlestick chart of closing price of the stock and industry average is given in the Figs. 2 and 3.

The values of volume traded in a day, closing price, opening price, highest price in a day and the lowest price in a day of the equity taken into consideration and the closing price of the NIFTY industry average closing price is forecasted using the LSTM Neural Network by at first scaling the data from 0 to 1 using the Min–Max Scaler and then fitting a sequential model which compiles using the Adam optimizer and mean squared error as loss. Hyper-parameter tuning is done on each of these models with appropriate epochs and batch size to enhance their performance. Optimal batch size and epochs is found out by consecutively mapping the output of RMSE values from multiple runs and selecting the configuration with least RMSE. Appropriate learning rate is generated by cosine annealing learning rate scheduler with restart intervals using keras callback repository which has 1e-5 to 1e-2 range for min and max learning rate.

However, a swing trader needs much more depth in analysis than just forecasted stock prices and volume traded before investing. This is where the novel idea of generating technical indicators from the predicted prices and volume comes into play.

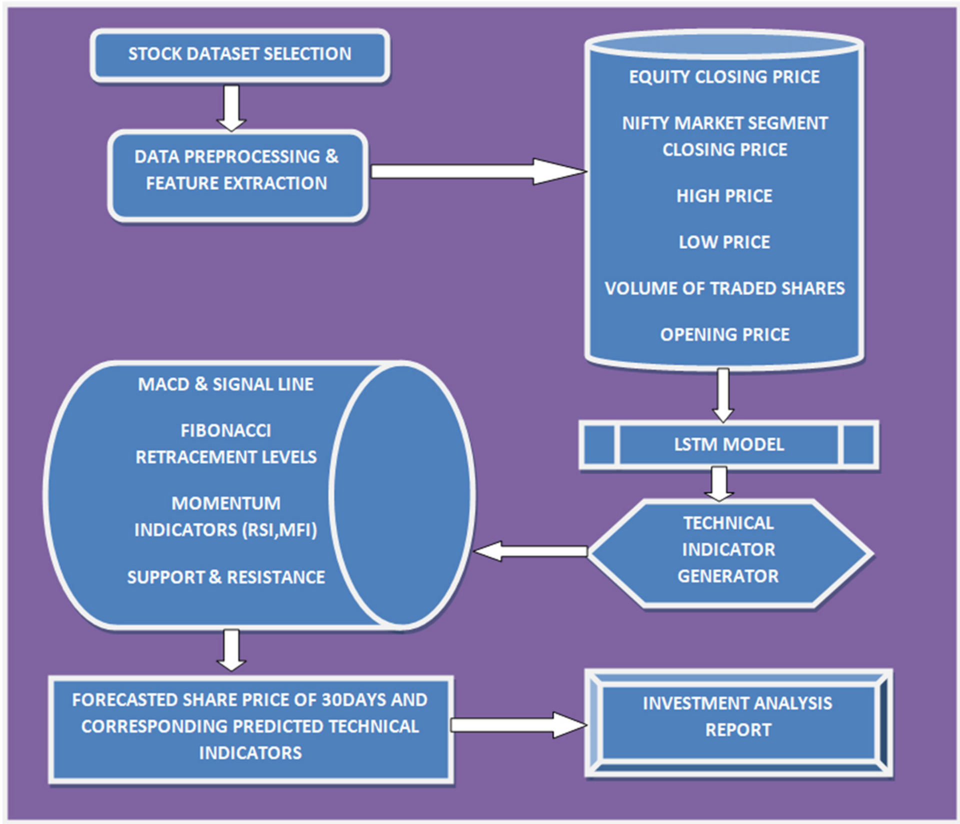

Fig. 1. Proposed method for stock market forecasting DSS functioning.

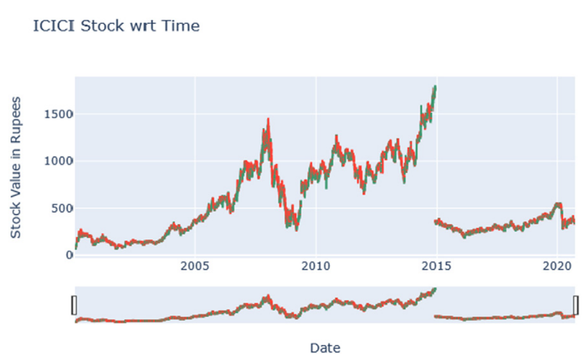

Fig. 2. ICICI stock w.r.t time.

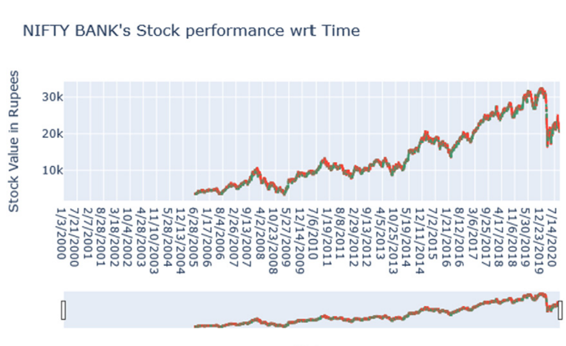

Fig. 3. NIFTY BANK's stock w.r.t time.

Instead of directly forecasting the technical indicators, they are generated from the forecasted stock performance parameters because these parameters have a high correlation with the stock parameter values and have little significance on their own. The Money Flow Index (MFI) is a technical indicator whose value fluctuates between zero to hundred. The MFI gives us an idea about the stock being overbought (MFI>80) or oversold (MFI<20). The MFI takes the predicted high, low, volume and closing price into account. The MFI is calculated by the Money Flow Ratio (MFR) which is the ratio of positive and negative typical price multiplied by the traded volume. The typical price is generated by calculating the average of high low and closing price of the equity. The RSI is also a similar momentum indicator where RSI>70 is considered as overbought stock and RSI<30 is considered oversold stock. The main difference between these two is that MFI takes both volume and price as parameters while RSI takes only the price into consideration. The RSI is calculated by using the ratio of the summation of current gain and previous thirteen period average gains with the summation of current loss and previous thirteen period average gains. The support and resistance are also key technical indicators where support indicates the price level floor from where the stock is expected to bounce back and the resistance act as a ceiling threshold value which the stock is not expected to cross. The support and resistance are then used to generate the Fibonacci retracement levels (FIBRL) which give a fair idea about where the prices are expected to oscillate between. The FIBRL analyses trends like an initial wave and a completed wave to offer insights in stock movements. The stock Moving Average Convergence Divergence (MACD) is calculated by comparing exponential moving averages of different time periods and the MACD is then observed with respect to signal line. Analyzing the point of intersection of signal line and MACD helps in better understanding of the market whether it is bullish or bearish in nature.

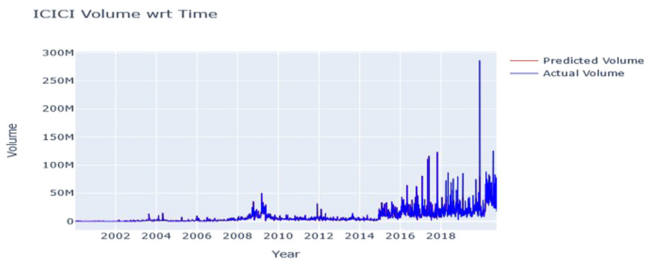

Fig. 4. Predicted volume vs. actual volume w.r.t time.

Fig. 5. Predicted open vs. actual open w.r.t time.

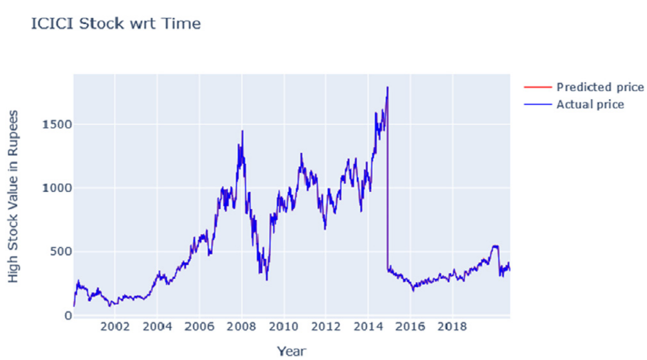

Fig. 6. Predicted high vs. actual high w.r.t time.

Fig. 7. Predicted low vs. actual low w.r.t time.

Fig. 8. ICICI predicted vs. actual closing price .

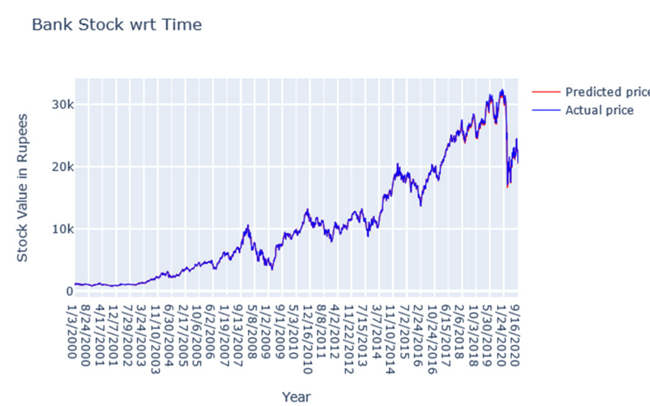

Fig. 9. NIFTY Industry average predicted vs. actual closing price.

An investment success score is generated in the report by giving these technical parameters individual weights which indicates the chances of the investment to be successful in making profit. 10% weight is given to MFI and RSI each while the industry signal line-MACD analysis and the predicted price of future closing stock prices enjoy 20% weightage. The equity signal line-MACD analysis is assigned the most weight of 40%. This added up calculated score along with the Fibonacci retracement, support and resistance levels and most importantly the thirty-day stock value forecast provides a swing trader with enough insight to contribute in his investment decision making.

4. Experimental results

The following results are observed in our predicted model. Graphically the performance of the LSTM model is visualized by comparing the forecasted prices and volume of the equity and the forecasted prices of the market segment with the actual values.

From the Figs. 4, 5, 6, 7, 8 and 9 it is clearly observed that our model has shown promising results in each of the parameters where the actual values and the predicted values are compared. Root Mean Squared Error (RMSE) penalizes large errors values. Mean Absolute Error (MAE) is more effective when the increase in error actually corresponds proportionally to the overall impact. Mean absolute Percent Error (MAPE) is also a very useful measure to understand the performance of forecasted values. Hence, we use the RMSE, MAE and MAPE metrics to analyze the performance of each of the given parameters which are used to generate the future values of technical indexes.

Table 2 shows promising results put forward by LSTM. Using these metrics to compare the performance of LSTM with other models using the closing price parameter we observe striking differences. In the below table the RMSE and MAE values of LSTM is compared with a few other prominent models. The underlying differences in the error metric values observed in Table 3 show that LSTM shows significant improvement in terms of stock price forecasting capability.

Table 2
RMSE values of Various features.

Parameters	RMSE	MAE	MAPE
Opening price of stock	7.90	6.90	1.88
Closing price of stock	**4.13**	**3.24**	**1.21**
Highest price of stock	8.89	6.94	5.53
Lowest price of stock	8.72	6.53	2.68
Volume of stock traded	16.04	11.66	5.47
Closing price of NIFTY -Industry Average	50.39	38.17	1.29

Table 3
RMSE values using various models.

Models	RMSE	MAE
Linear Regression	7.53	5.42
Moving Average	146.51	121.03
XGBR	103.62	87.44
SVR	60.15	52.87
ARIMA	57.41	46.47
SNaive	82.83	65.57
ETS	57.54	46.31
Naive	76.07	58.98
Meanf	57.54	46.31
BoxCox	54.93	43.68
LSTM	**4.13**	**3.24**

Fig. 10. Stock closing price w.r.t. support and resistance.

Fig. 11. Stock closing price w.r.t. FIBRL.

The stock support and resistance values, MACD and signal line, Fibonacci retracement levels (FIBRL) and the NIFTY Industry (Banking) average MACD and signal line is plotted corresponding to the predicted closing price and the following graphs are generated. It is observed in Fig. 10 how the support and resistance levels boxes in the closing price. In Fig. 11 the stock price can be seen oscillating between the different Fibonacci retracement levels which act as trend indicators.

In Fig. 12 it is observed that whenever an intersection occurs between the signal line and MACD, it is acting as an indicator for the change in curve for the closing price. Similar observation can be made in the NIFTY stock market segment (Banking) closing price values (see Fig. 13).

Fig. 12. Stock closing price w.r.t. MACD and signal line.

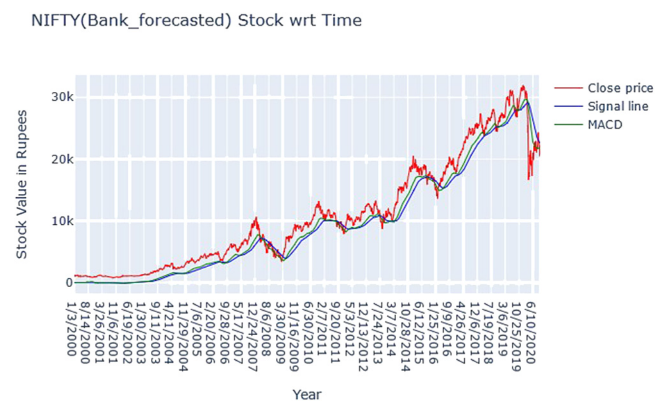

Fig. 13. NIFTY Banking closing price with MACD and signal line.

Table 4
Execution time for various parameters.

Parameters	Execution time	Computing specification
Opening price of stock	5 h 23 min	10th Generation Intel® Core™ i3-1005G1 Processor (4 MB Cache, up to 3.4 GHz) with Intel® UHD Graphics with shared graphics memory
Closing price of stock	5 h 18 min	
Highest price of stock	5 h 27 min	
Lowest price of stock	5 h 11 min	
Volume of stock traded	5 h 48 min	
Closing price of NIFTY -Industry Average	5 h 16 min	

Finally, these technical indicators are used to generate the Investment Success Score using appropriate weightage assigned to each of them. The user of the Decision Support System is provided with thirty days closing stock price forecast along with the technical indicators generated from the forecasted prices. Market segment and equity market sentiment analysis and most importantly the investment success score is also presented in the investment analysis report as observed in Fig. 14.

Table 4 portrays the execution time for computing forecasted values of various parameters. This is to be noted that this execution time will vary greatly with the performance capability of the executing system

5. Conclusion and future scope

In this work a DSS is introduced for Indian swing traders to predict the stock market. Novel ideas presented in this research

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Date: 2018-08-20
Close: 316.8392639160156
MFI: 59.82500374962388
RSI: 48.87284373262177
Stock is bullish according to MACD & SIGNAL LINE ANALYSIS
Support: 257.85
Resistance: 365.11846923828125
Fibonacci Retracement Level 1 304.26586923828125
Fibonacci Retracement Level 2 266.61976923828126
Fibonacci Retracement Level 3 236.19346923828124
Fibonacci Retracement Level 4 205.76716923828124
Fibonacci Retracement Level 5: 162.44836923828123
Predicted closing price of next 30 days:
320.8860778808594
322.68548583984375
324.848876953125
327.0403137207031
330.3155822753906
332.68475341796875
334.3632507324219
334.9763488769531
333.60540771484375
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339.03533935546875
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338.7176208496094
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333.06610107421875
332.0414733886719
329.8035888671875
328.9736022949219
328.2012939453125
326.2591857910156
324.86810302734375
323.0341796875
319.8556823730469
317.59814453125
316.55938720703125
NIFTY-BANK is indifferent according to MACD & SIGNAL LINE ANALYSIS
Investment success score: 60
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Fig. 14. Investment analysis report.

including the Investment Success Score and amalgamation of technical indicators on LSTM model predicted parameters provide a trader with a clear insight of the equity taken into consideration for investment. The results demonstrated in the research work assists in concluding that the LSTM model performs significantly better than other comparable models with the least tolerance for error. MACD-Signal Line analysis of the stock clearly portrays strong indicative points to buy or sell a stock. Other technical indicators like MFI, RSI helps the trader to understand how the stock is selling and the Support-Resistance curves identify crucial thresholds that the stock can reach. In a world of algorithmic trading common margins in which the stock is expected to bounce between is explored using the Fibonacci retracement levels. This insight can help the swing trader not only in the short term but also if he wants to hold the stock in long term for more returns. The industry MACD-Signal line average also plays a low-key factor in the stock prices as the stock prices generally have a positive correlation with the segment of market the stock belongs to. An investor can have high confidence in the intent of buying or selling the stock when his hunches are backed by the Investment Success Score developed by the DSS.

This methodology presents its own disadvantage. The computation of entire history of stock data in LSTM before forecasting future parameters is time consuming as noted in Table 4 when a system of low compute power is used it is rendered unusable for Scalp Trading. However, this can be mitigated by using high performance computers with dedicated GPUs and good multithread benchmark scores to be used for Scalp Trading also.

Work in a similar direction can be extended by analyzing the results with theoretical aspect. Assigning weights using neural networks to the parameters involved in the investment analysis report might generate a better profitability. Also, there is room for improvement in generating a better model for predicting the NIFTY industry average stock price and especially the volume of stock traded. Models like Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors (SARIMAX) and Prophet can be explored for better performance. Automation of similar report generation for all the stocks enlisted in NIFTY or other indexes can give a trader unparalleled edge in gaining huge profits in the stock market.

CRediT authorship contribution statement

Shouvik Banik: Idea conceptualization, Data collection, Framework, Implementation, Visualization, Writing – original draft preparation. **Nonita Sharma:** Literature review, Analysis of results, Reviewing and supervision. **Monika Mangla:** Writing – reviewing & editing. **Sachi Nandan Mohanty:** Results verification, Validation, Manuscript-Proof reading. **Shitharth S.:** Software analysis and reporting, Detailed discussion of the results, Visulaization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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