A COMPARATIVE ANALYSIS FOR STOCK PRICE PREDICTION USING IMPROVED EXPANSIVE DEEP LSTM MODEL

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Abstract

Due to a lack of clarity and flexibility, prediction leveraging ML models is not well fitted in many sections of commercial decision processes. Proposed model aim to employ deep learning strategy in the stock market pricing area to generate positive risk-adjusted price by analyzing previous transaction data and maintaining greater accuracy with a lower error rate. In this study, the deep learning approach is used, which is capable of handling time-series data. The results are obtained with evaluation of error rate metric MSE & RMSE which express how distant the data points are from the regression line. RMSE measures the dispersion of these residuals. It shows how concentrated the data is on the best fit line. This study compares a unique deep learning methodology with deep LSTM, GA and Harris Hawk optimization. As a part of this analysis results are observed and plotted for the various company stocks dataset, which clearly shows the effectiveness of proposed approach with reduced error rate.

***Keywords*: Stock market prediction; recurrent neural network; deep LSTM; DEEP RNN; Deep Learning.**

1. INTRODUCTION

Commodities and wealth may provide us with a pleasant and secure lifestyle. It's no wonder that the research and forecasting of potential financial market values and forecasts has received so much interest. A number of forecasting approaches have been suggested and put into practice. Each strategy has benefits and drawbacks of its own. Also with development of internet trading in recent years, the stock market became choice for novice investors to generate substantial gains. Therefore it’s highly appealing if system model could correctly foresee market behavior so that investors may take appropriate decision about investment. Developing such a forecasting model is a challenging issue owing to the considerable implied volatility rules driving price movement. Neural networks (NNs) have become a highly essential tool for stock price forecasts due to their capacity to cope with ambiguous, imprecise, or inadequate data that fluctuates frequently in very short times [Schoenberg (1990)]. The purpose of this study is to highlight the problems that have to be explored in future research as well as to outline the main advantages and limitations of previous methodologies in RNN applications for stock markets. Certain benefits and limits were discovered after a comparative review of earlier research's methodology in respect to issue domains, data models, and results criteria. The stock exchange may be affected by a wide range of intricate events, such as economic cycles, warning strategies, interest rates, political ideologies, etc. There are many forecasting patterns, however most of them have advantages and downsides of their own. The underlying seasonality, non-stationary and other factors are obliged to be accompanied by common mathematical approaches in particular [Tambi, (2005)].Moreover, use of normal statistical means beyond specialized knowledge becomes troublesome. Financial forecasting's fundamental objective is to identify leading lines on, allowing investors to must adhere to their investing plan unless confirmation reveals a deviation in the trend. The moving average and trading range break-out rules, two of the most fundamental and widely utilized trading principles, were first investigated in [W. Brock, (1992)]. Increasing forecasting accuracy, particularly for time series forecasts, is a crucial and challenging challenge for decision-makers in many fields. The attempt to improve the accuracy of forecasting models has never ended. Despite the large number of time series models that are currently accessible. Time series forecasting models find that, particularly when the models in the ensemble are very distinct, integrating forecasts from many models frequently results in increased performance [Hansen, (2002)]. Pattern recognition, classification, grouping, and forecasting with increased precision have all been successfully accomplished by artificial neural networks (ANNs) [Thangavel K. et.al. (2006), Thangavel K. et.al. (2005), Mehdi Khashei et.al. (2010)]. Forecasting is often regarded as hardest problem in time series prediction. The prognosis for the time series trend of the financial market is less accurate due to the noisy nature of the information utilize. The efficient market hypothesis (EMH) states that attempting to estimate future prices using the performance of financial assets will never result in excess returns. This is because a financial time series distribution function indicates a Brownian motion, which has features of an independent, random and Gaussian distribution. Some research conversely, they think that there is a repeated pattern that can assist predict future values and disagree with EMH. Applying ANN and SVM for financial time series prediction has increased over the past few decades [Apostolos, (1994)]. The accuracy of financial time series forecasting is increased by these uses of ML models. This study examines the prediction performance of an improved form of LSTM which work with recurrent neural network and focuses on the data preprocessing and data augmentation technique to make data more noise-free and consistent. Finally the findings for various time series data are obtained and evaluated by the Root Mean Square Error (RMSE) and MSE measure. The conclusion is obtain after analyzing the RMSE & MSE results of each dataset and analysis proves that proposed architecture is proven to be effective in reducing the error rate and forecasting the future price direction up to a year.

2. Literature Review

2.1. Approaches

The literature overview of conventional stock market forecasting methods is described in this part, along with discussions of their advantages and disadvantages. This information inspires researchers to develop a feasible stock market forecasting method.

A method used in artificial intelligence called machine learning (ML) that enables a system to learn from experience and make predictions without the need for precise scripting [Ananthi,(2020)]. Several ML algorithms have already forecast the behavior of the market. Several researchers have applied neural network models extensively. The four main categories of contemporary stock analysis and forecasting techniques are sentiment analysis, machine learning (ML), pattern recognition, and statistical analysis. Market trends have also been predicted using time delay analysis. SVM, Bayesian belief networks, and evolutionary algorithms are a few examples of machine learning algorithms [A. Porshnev, (2013)]. Machine learning techniques like the k-NN regression model assert that it is more accurate than other regression methods like linear regression and SVM. Stock price forecasting has already been attempted, but only for financial advantage under the pretext of computer trading. Candlestick analysis is a common stock market pattern that predicts stock open and closing values based on preceding and historical data [Ananthi, (2020)]. In comparison to the quantity of literature based on daily close data, the authors Martinez et al. (2009) demonstrate that using an artificial neural network (ANN), they can estimate the lowest and highest stock prices of the current trading day of the two leading stocks on the Brazilian stock exchange [Martinez, (2009)]. [Mettenheim and Breitner (2012)] demonstrate that using ANN model predictions, it is able to correctly estimate the intraday dynamics of five liquid US equities [Mettenheim et.al. (2012), Adebiyi et al., (2014)] evaluate the predicting accuracy and comparison of the NYSE Exchange's multi-layer perceptron model's accuracy to an ARIMA model. They found that, in terms of mean squared error, the MLP model performed better than the ARIMA model. Owing to significant developments in deep learning techniques, in recent years, a number of applications including natural language processing, speech recognition, and computer vision have identified RNN as a viable model for managing linear data. Furthermore, several research demonstrated that RNN with LSTM cells is the most effective model for predicting financial time series. For example, [Chen et al., (2015)] proposed an LSTM-based stock price prediction model. Many fundamental stock variables are regarded as input characteristics. The model was evaluated on an additional 311361 samples after being trained on 900000 samples. They found that LSTM might do well in projecting changes in China's index prices. In prediction accuracy, the experimental findings showed that their approaches beat the regression model of ordinary least square. Although MLP may be used to predict time series models, multiple research have shown that it has certain limitations in learning patterns since stock data has a high dimension and a lot of noise. On outliers, MLP frequently demonstrates uneven and variable efficiency [Qiu M (2016)].

[J. Long et al. (2020)] evaluated a DNN framework employing open market data and transaction histories to evaluate price direction. Their final study revealed that bidirectional LSTM achieved the best outcome and could estimate the growth of the market for investors. [Rekha et al. (2019)] looked at how RNN and CNN algorithms were used and contrasted their accuracy with actual stock market data. To provide more precise stock market forecasts, [X. Pang et al. (2020)] merged LSTM with an automated encoder and LSTM with an integrated layer. According to basis of empirical evidence The Shanghai Composite Index was produced with 57.2 percent accuracy using LSTM with an integrated layer. Kelotra and Pandey used the deep convolutional LSTM technique to successfully anticipate changes in the stock market. RMSE and MSE were 2.6923 and 7.2487 respectively, using a Rider-based monarch butterfly optimization approach. In this study, comparison is carried out for the accuracy of three machine learning models (Harris Hawk optimization, GA and Deep LSTM) with proposed model in predicting stock price movement. Our model receives seven derived technical indicators as input. Model employ stock market data (open, close, high, low, and spread values). Data is augmented at the final stage of processing for input utilizing bootstrap approach. The data augmentation is used to minimize the over fitting issue and also enhances the generalization of systems. The bootstrap approach is used here as a kind of re-sampling technique. Based on the underlying characteristics of the market, each technical indicator has a distinct potential for upward or downward movement. The effectiveness of the cited models all experimental tests are performed using historical data from three market equities from various industries (FMCG, communications, and automobile) that encompass three, five, ten, and twenty years.

2.2. Challenges

Analysis and forecasting of the stock market remain complex and fascinating issues. Because more information becomes accessible, collecting and analyzing it to extract insights and assess market pricing presents new hurdles. Determine the performance criteria for erratic trend changes. The examination of all these techniques and performance provides even another issue since new learning models frequently enter the market. As these represent the prospective rate of returns, time series behavior of mispricing in the Indian market has to be studied. Literature also provides evidence of seasonal abnormalities in stock return series. It has to be investigated if shifting market circumstances and other variables affect the flow of knowledge.

It is necessary and overdue to examine the information flow between price and trading activity variables together since doing so would include a larger market and give a clearer picture of future price behavior. Scaling is required since the current system requires some sort of input interpretation. The prior findings suggest that when the conventional classifier is applied, the stock price is uncertain. Some neural network approaches have slow convergence rates a neural network takes longer to train because of its complexity. It is difficult to determine the global minimum and maximum because local neural minima and maxima networks, which rely on gradient descent approaches to discover local maxima, tend to get stuck on local minimum and maximum. Each machine learning method has its own advantages and disadvantages and is only useful under certain conditions. Although financial time series are not linear, a number of statistical assumptions, such as linearity and normality, have been made in the methodology. As a result, these strategies are ineffective for predicting stock prices. Fundamentals analysis performed automatically is not without flaws. First off, there is no assurance that there will be no disinformation, even if statements or reports are released by businesses, the media, or some other independent organization. It is unclear how much disclosure and stock price volatility are correlated.

Forecasting is a difficult task since stock time series data is dynamic and complicated. It is so challenging to use a range of deep learning algorithms for both sentiment feature engineering and stock movement prediction modelling. A variety of financial time series may be predicted using the hybrid forecasting paradigm. For accurate stock market forecasting, the forecasting findings may be integrated in effective stock market monitoring and financial data analysis [Liu (2020)]. Improved quality outcomes for forecasting will be obtained by using a more methodical approach to selecting stock-relevant keywords for social media and news monitoring [Khan (2020)].

3. Proposed Method

The purpose of the study is to evaluate and compare the performance of three existing methods Harris Hawk optimization, GA and deep LSTM with improved proposed framework improved recurrent rider deep LSTM (IRRLSTM). Here experiment is conducted without using any optimization techniques to train the proposed model. Step by step block diagram of experiment is shown as follows. Detail of procedure is discussed in further subsections.

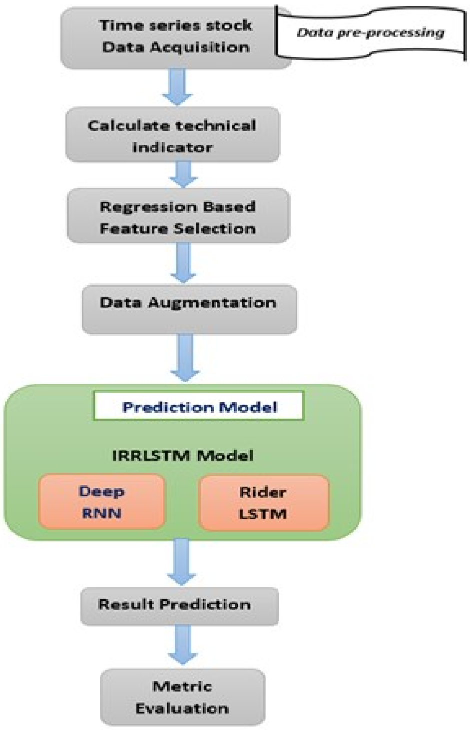

Fig. 1. Block Diagram of Proposed Method

3.1 Acquisition of Input data

This study will be based on historical time series data that spans three stock market sectors (FMCG, communications, and car) throughout periods of three, five, ten, and twenty years from 2010 to 2020. Seven technical indicators are chosen for this study in order to save calculation time. There are several technical indicators available for forecasting stock market movement, and each has a distinct ability to predict future market moves. Technical indicators including the Average True Range (ATR), Triple Exponential Average (TRIX), Rate of Change, Relative Strength Index, Average Directional Movement Index, and William's Percent Money Flow Index are utilized in this model to extract the features. Then, using a regression-based feature selection wrapper approach, the feature vector acquired from the feature extraction phase is put through the feature selection process. Additionally, the chosen feature is fed into the stage of data augmentation using the Bootstrap approach. Finally, an enhanced Recurrent Rider LSTM is suggested and used to identify stock market activity. However, the suggested enhanced Recurrent Rider LSTM is created by fusing Deep RNN and Rider Deep LSTM.

3.2 Data Preprocessing

As the time series data is obtained from online web resource, gathered data consist of some irrelevant and noisy values which need to be preprocessed before using as an input to the proposed framework. Real-world data typically includes noise, missing values, and may be in an undesirable format, making it impossible to build machine learning models on it directly. Pre-processing data is required to clean it and prepare it for a machine learning model, which also improves the model's performance and robustness. In this research, the mean values of the property are used to replace NULL and missing values.

3.3 Feature Extraction

To extract pertinent and desirable features, the input was exert for the feature extraction process. The process of constructing a new feature space, known as feature extraction, is regarded as a crucial component for classification and analysis purposes. It is necessary identify independent, fundamental, technical, and macroeconomic elements for forecasting stock. Model basically attempt to extract fundamental variables like open, close, High, Low, Volume, etc. A crucial role in distinguishing the features from a given dataset is played by the technical indicators. It was able to make effective predictions as a consequence. Seven technical indicators are used in this model to extract the characteristics, which are described below.

(1) Average True Range (ATR)

The volatility is assessed using the ATR, or average true range. Additionally, it is used to assess the length of time.

$$f_1 = a\left(f_{1_{ran}}, n\right) \quad (1)$$

Where, a denotes ATR, and $f_{1_{ran}}$ specifies the true range.

(2) Rate of Change (ROC)

The momentum indicator is another name for the ROC indicator. It is used to calculate the current and historical prices for specific time intervals.

$$f_2 = \frac{I(k)}{I(k-n)} * 100 \quad (2)$$

Where, $I(k)$ implies the latest price and value of a limited number of period is signified as $I(k-n)$.

(3) Relative Strength Index (RSI)

The RSI is a momentum oscillator used in order to ascertain whether a product is overbought or oversold.

$$f_3 = \frac{A_v(P_u)}{(A_v(P_u) + A_v(P_d))} * 100 \quad (3)$$

Where,

$$\begin{cases} P_u(k) = 1*(P(k) - P(k-1)), \; for \, P(k) - P(k-1) > 0 \\ P_d(k) = 1*(P(k-1) - P(k)), \; for \, P(k) - P(k-1) < 0 \end{cases} \quad (4)$$

Where, $A_v(P_u)$ indicates the average of price up value and mean of price down value is specified as $A_v(P_d)$.

(4) Average Directional Movement Index (ADMI)

The Average Directional Movement Index (ADMI) measures the strength of a trend, which is determined over past 10 days corresponding to the input window length. It also indicates about the trending and non-trending condition of a market.

$$f_4 = 100 * \frac{(DI^+ - DI^-)}{(DI^+ + DI^-)} \quad (5)$$

(5) William's % R

In addition to being an inverse of the Fast Stochastic Oscillator, an indication of momentum is William's percent R. The ratio of the change in the difference between the highest and nearest price to the change in the difference between the highest and least price is known as William's percent R.

$$f_5 = \left[\frac{(H_p - C_p)}{(H_p - L_p)}\right] * 100 \quad (6)$$

Where, H_p and L_p denotes the highest and lowest price, respectively. The closest price of the current day is represented as C_p.

(6) Money Flow Index (MFI)

The level of the money supply is assessed by the Money Flow Index and establishes the selling and purchasing pressure using both price and volume.

$$f_6 = \left(100 - \frac{100}{(1 + M_r)}\right) \tag{7}$$

Where, M_r denotes the Money ratio.

(7) Triple Exponential Average (TRIX)

The triple exponential moving average is a tool for facilitating insignificant fluctuations. The TRIX indicator is notated as f_7 .

The aforementioned seven feature vector is produced by combining features, and the extracted feature is shown as,

$$f = \{f_1, f_2, f_3, f_4, f_5, f_6, f_7\} \tag{8}$$

3.4 Feature Selection

A fundamental stage in the realm of stock market forecasting is feature selection in which pertinent variables are chosen in accordance with their importance. It is also more beneficial in lowering the dimension size of the datasets to increase the precision and effectiveness of prediction systems. Characteristics that are unimportant or just marginally significant might harm a model's performance. Regression-based feature selection is used in the experiment. In this wrapper strategy, the evaluation function is the classifier error rate. To identify all the feature subsets, the classifier is wrapped in the wrapper technique. By learning the error rate and classification accuracy, the machine learning algorithms simplify the wrapping method to feature selection. Based on learning algorithms, it fine-tunes the prediction system. The wrapper approach's key contribution is to lower classification error and improve classification performance.

3.5 Data Augmentation

The technique of enhancing data by producing additional data that corresponds to the original data is known as data augmentation. Here, data augmentation is employed to improve system generalization and reduce the problem of over fitting. The bootstrap method is a type of resampling strategy used to sample a database using replacement and get statistics like mean or standard deviation. It is mostly used to assess the capabilities of machine learning models while generating predictions based on training data.

3.6 Proposed improved Recurrent Rider LSTM

Incorporating Rider Deep LSTM with Deep Recurrent Neural Network results in the proposed Recurrent Rider LSTM. In the part that follows, the structures of the Rider Deep LSTM network and Deep Recurrent Neural Network are briefly explained.

(1) Rider Deep LSTM network

Rider Deep LSTM operates on time series data (P. Suman , 2015). The Rider Deep LSTM's main contribution is the function of memory gates and forget gates, which are used to manage information in order to rebuild appropriate information at all times. The core of the network's four levels are input layer, fully connected layer, LSTM layer, and output layer for regression. The Rider Deep-LSTM updates the trained network up until the previous step while making predictions about the values at each step and being aware of data trends. Finally, the fault values are predicted using the trained network. Rider Deep-structure LSTM's is as per shown in Figure 2.

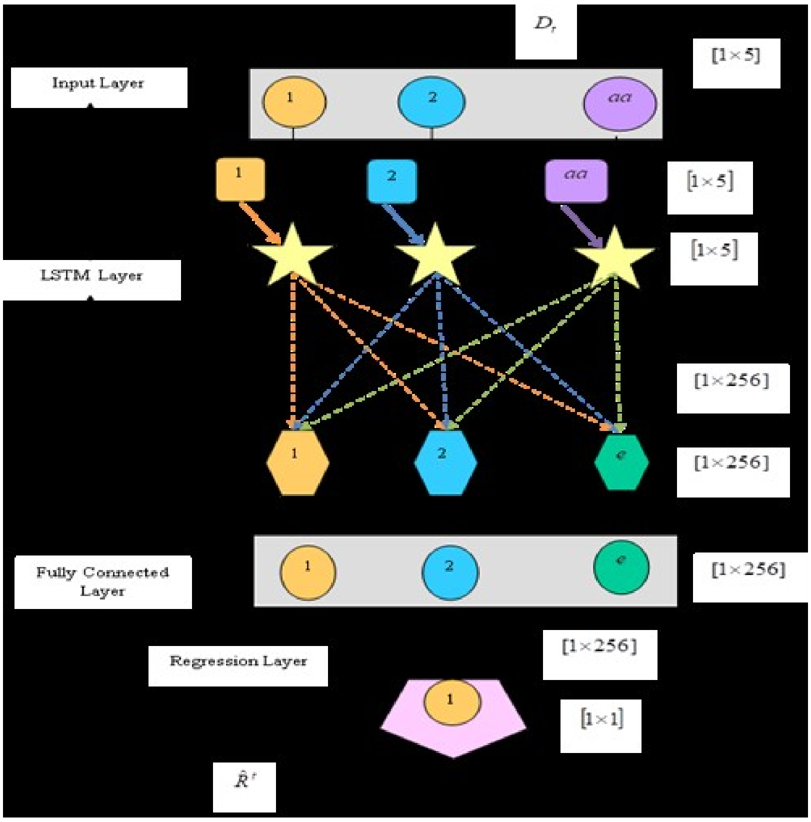

Fig. 2. Rider Deep LSTM

(b) Deep RNN

RNN is a popular learning method that is also employed as an estimator and is very practical when dealing with time-series data. Large networks' handling of temporal movement during the training phase is implemented by the RNN. RNN is a high throughput network structure that preserves the unprocessed sensor input without removing the feature and also offers high detection rates with quick sequential processing. An Elman-type network with a number of layers, such as the Deep RNN network, is one in which the internal layers are completely linked at the same network based on time direction. The Deep RNN network's structure is shown in Figure 3.

The input vector of g^{th} layer at time period x is given by,

$$S^{(g),x} = \left[S_1^{(g),x}, S_2^{(g),x}, \ldots S_y^{(g),x}, \ldots S_o^{(g),x}\right] \tag{9}$$

And the output vector of the layer at time x is expressed as,

$$T^{(g),x} = \left[T_1^{(g),x}, T_2^{(g),x}, \ldots T_y^{(g),x}, \ldots T_o^{(g),x}\right] \tag{10}$$

Here, y is an arbitrary unit number of g^{th} layer and o represents the total count of units.

The previous hidden layer's output is given as input for the next hidden layer, which produces an output with a dimension of $[1 \times 8]$. Additionally, the output layer is sent to the output layer from the hidden layer, which creates a final output with a dimension of $[1 \times 1]$

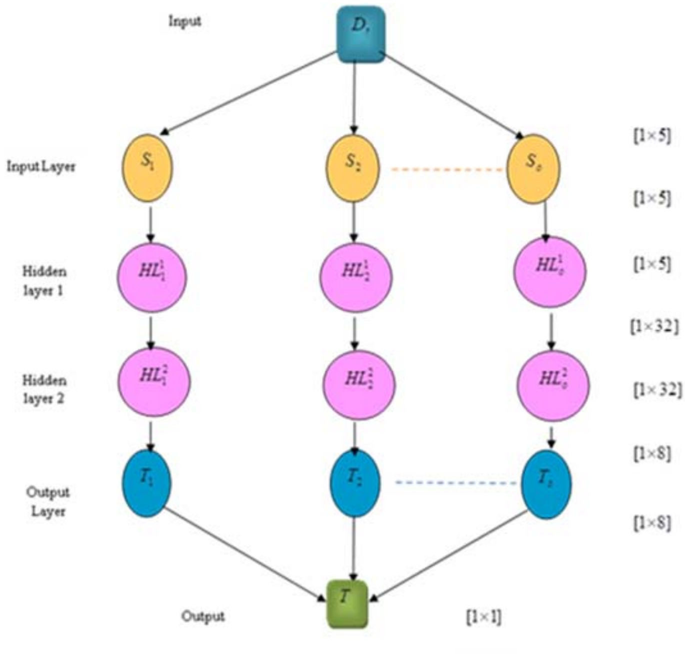

Fig. 3. Deep RNN

4. Results & Discussion

Three stocks from the NSE of the Indian stock market—Asian Paints, Bajaj Auto, and Bharati Airtel are used as a dataset for testing and analyzing the proposed enhanced recurrent rider LSTM and existing approaches. The dataset attributes includes open, high, low, close, volume, and other technical indicators. MSE shows the root of the average squared difference between the actual values and projected values in a dataset, whereas the average squared difference between the actual values and expected values in a dataset is shown by RMSE.MSE and RMSE are regarded as assessment metrics. If a model has a lower RMSE value, it will be more accurate. To evaluate the consistency and effectiveness of the model, result graphs for MSE and RMSE are displayed for the three stock datasets over periods of three, five, ten, and twenty years of time series. Results for MSE of all three datasets are displayed in Table 1, Table 2 & Table 3 and results for RMSE are displayed in Table 4. Table 5 & Table 6. Empirical analysis of MSE results for the Asian Paints, Bajaj Auto, and Bharati Airtel is shown by Figure 4, Figure 5 & Figure 6. Also analysis of RMSE for the Asian Paints, Bajaj Auto, and Bharati Airtel is shown by Figure 7, Figure 8 & Figure 9.As shown in Figure 4 results for the MSE of Asian paints for four methods, proposed model shows lowest MSE level of 0.062, Figure 5 shows results for the MSE of Bajaj auto for four methods, proposed model shows lowest MSE level of 0.06. Figure 6 shows results for the MSE of Bharti Airtel for four methods, proposed model shows MSE level of 0.08 which is lowest. Similarly as shown in Figure 7 results for the RMSE of Asian paints for four methods, proposed model shows lowest RMSE level of 0.24, Figure 5 shows results for the RMSE of Bajaj auto for four methods, proposed model shows lowest RMSE level of 0.248. Figure 6 shows results for the RMSE of Bharti Airtel for four methods, proposed model shows RMSE level of 0.29 to 0.31. In order to study the effectiveness of proposed LSTM model with respect to deep LSTM, results are plotted and observed in Figure 10 & Figure 11 for MSE & RMSE. Collective results of all dataset for all-time series duration are plotted in Figure 12 & Figure 13, which concludes that proposed approach is proved to be effective as compare to existing HHO, GA & deep LSTM methods.

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Asian Paints	20	MSE	0.611	0.598	0.514	0.067
Asian Paints	10	MSE	0.597	0.572	0.559	0.064
Asian Paints	5	MSE	0.619	0.598	0.504	0.066
Asian Paints	3	MSE	0.614	0.563	0.550	0.062

Table 1. MSE Results of Asian Paints

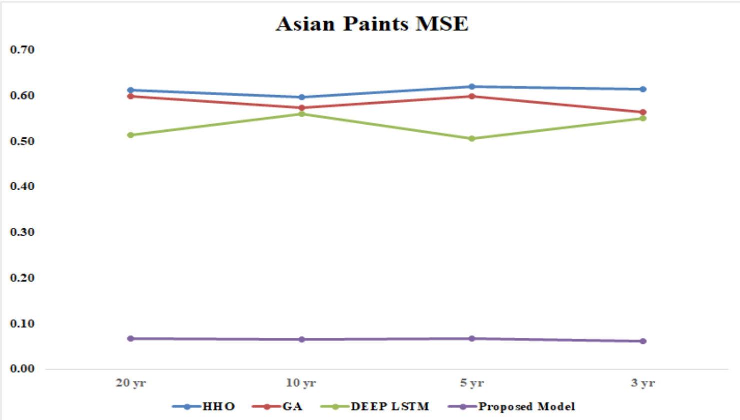

Fig. 4. MSE of Asian Paints

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Bajaj Auto	20	MSE	0.602	0.579	0.546	0.06
Bajaj Auto	10	MSE	0.583	0.577	0.568	0.06
Bajaj Auto	5	MSE	0.582	0.581	0.565	0.06
Bajaj Auto	3	MSE	0.585	0.573	0.570	0.06

Table 2. MSE Results of Bajaj Auto

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Bharti Airtel	20	MSE	0.62	0.60	0.47	0.08
Bharti Airtel	10	MSE	0.79	0.54	0.25	0.10
Bharti Airtel	5	MSE	0.77	0.54	0.31	0.08
Bharti Airtel	3	MSE	0.70	0.61	0.33	0.09

Table 3. MSE Results of Bharti Airtel

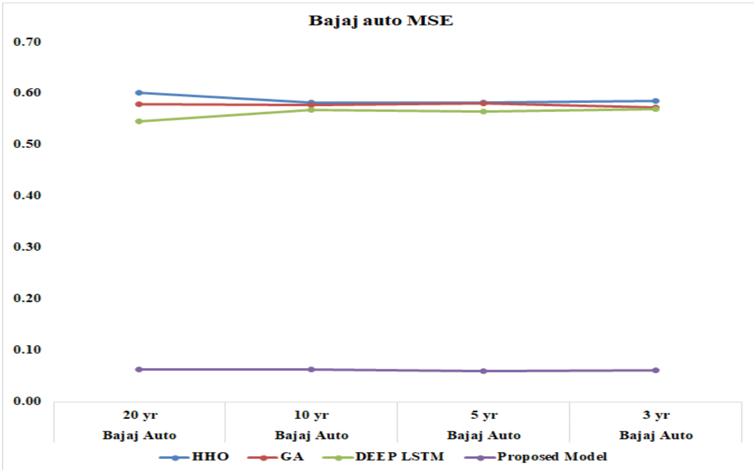

Fig. 5. MSE of Bajaj Auto

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Bharti Airtel	20	MSE	0.62	0.60	0.47	0.08
Bharti Airtel	10	MSE	0.79	0.54	0.25	0.10
Bharti Airtel	5	MSE	0.77	0.54	0.31	0.08
Bharti Airtel	3	MSE	0.70	0.61	0.33	0.09

Table 3. MSE Results of Bharti Airtel

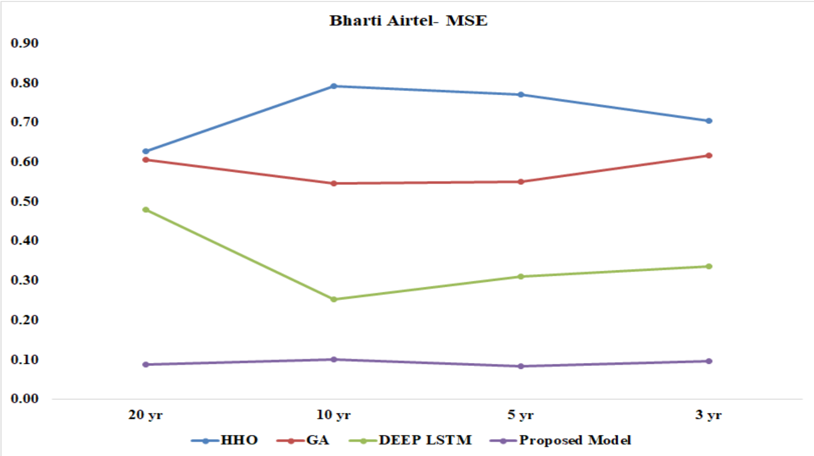

Fig. 6. MSE of Bharti Airtel

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Asian Paints	20	RMSE	0.782	0.773	0.717	0.259
Asian Paints	10	RMSE	0.772	0.757	0.747	0.253
Asian Paints	5	RMSE	0.787	0.773	0.710	0.258
Asian Paints	3	RMSE	0.784	0.750	0.742	0.248

Table 4. RMSE Results of Asian Paints

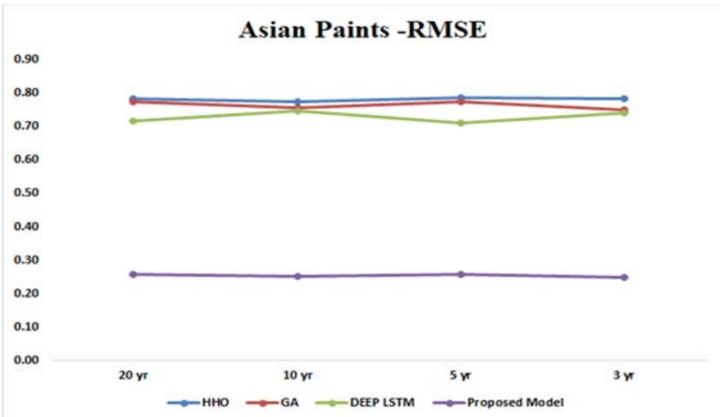

Fig. 7 RMSE of Asian Paints

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Bajaj Auto	20	RMSE	0.77	0.76	0.73	0.25
Bajaj Auto	10	RMSE	0.76	0.76	0.75	0.25
Bajaj Auto	5	RMSE	0.76	0.76	0.75	0.24
Bajaj Auto	3	RMSE	0.76	0.75	0.75	0.24

Table 5. RMSE Results of Bajaj Auto

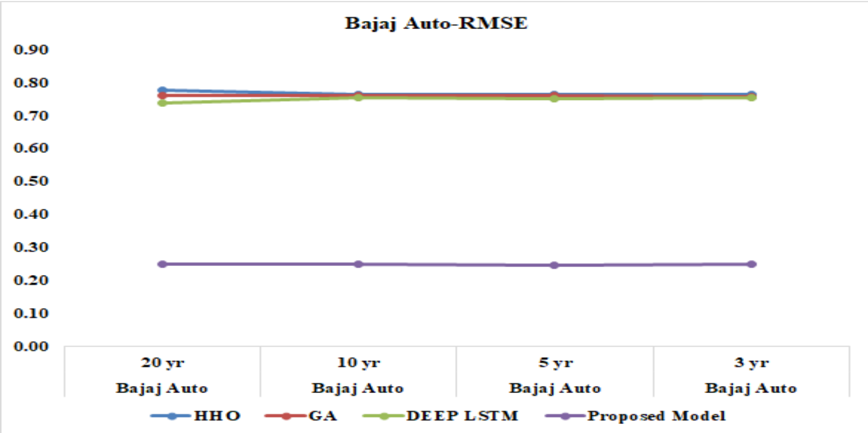

Fig. 8 RMSE of Bajaj Auto

STOCK	Historical data duration (In Years)	Metric	HHO	GA	DEEP LSTM	Proposed Model IRRLSTM
Bharti Airtel	20	RMSE	0.79	0.77	0.69	0.29
Bharti Airtel	10	RMSE	0.89	0.89	0.50	0.31
Bharti Airtel	5	RMSE	0.87	0.74	0.55	0.29
Bharti Airtel	3	RMSE	0.83	0.78	0.58	0.31

Table 6. RMSE Results of Bharti Airtel

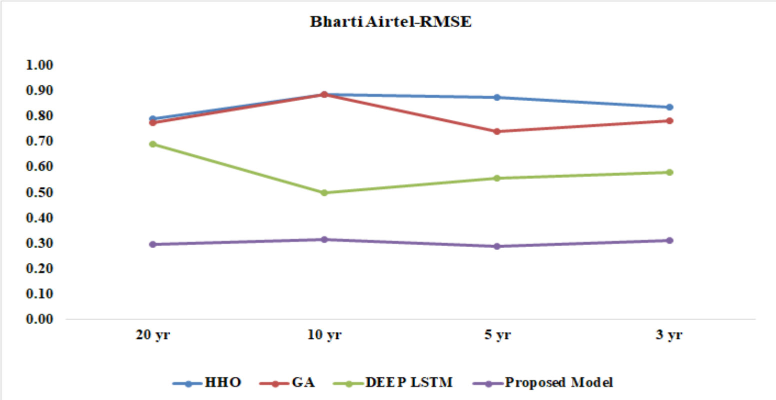

Fig. 9 RMSE of Bharti Airtel

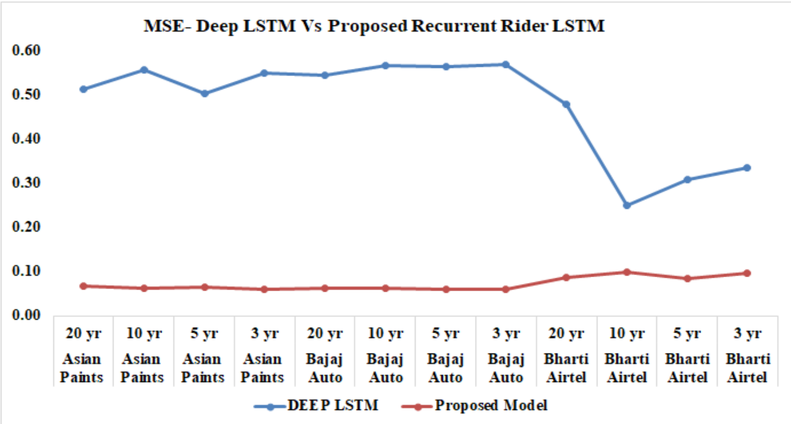

Fig. 10 MSE of Deep LSTM vs. Proposed Recurrent Rider LSTM

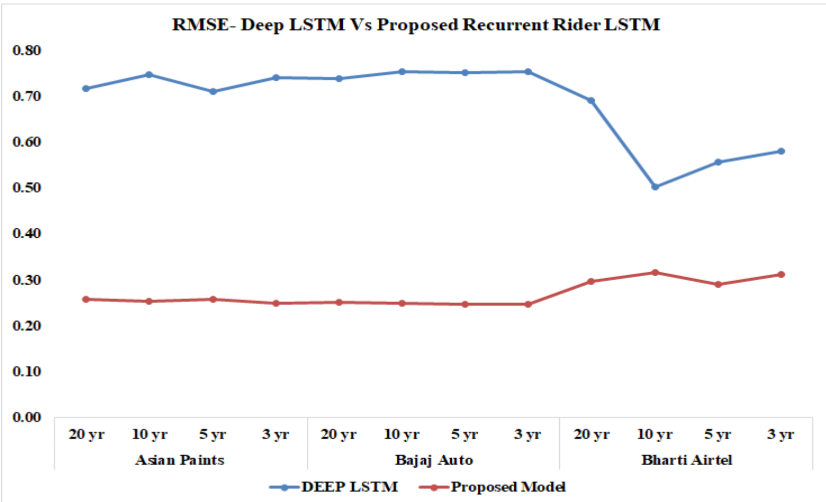

Fig. 11. RMSE of Deep LSTM vs. Proposed Recurrent Rider LSTM

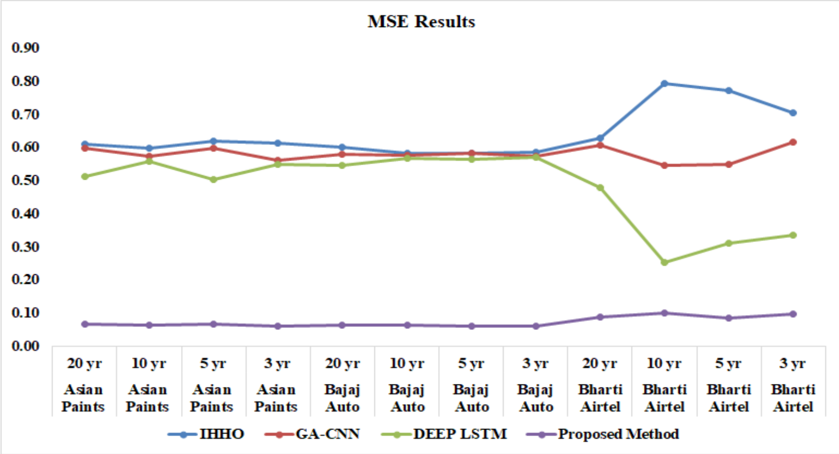

Fig. 12 Empirical MSE Results

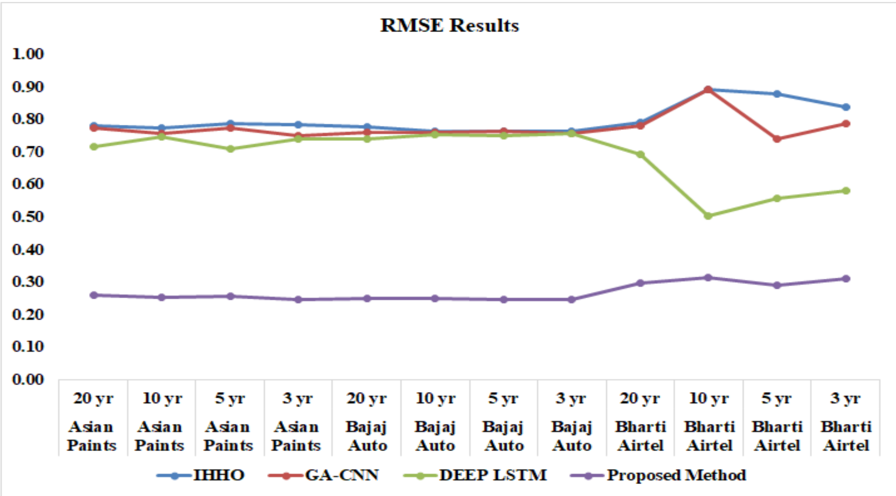

Fig. 13 Empirical RMSE Results

Table 1, Table 2, Table 3 & Table 4, Table 5, Table 6 values indicates the residuals' standard deviation (prediction errors). It shows how closely the data are grouped around the line of best fit. Better fit is shown by lower MSE and RMSE values. A decent indicator of how effectively the model was used to determine the reaction is the RMSE. If the primary goal of the model is prediction, then this fit criteria is crucial.

4.1. Comparative Analysis

In this subsection, three datasets are used to compare the proposed Deep Recurrent Rider LSTM with existing approaches in terms of the assessment criteria. The analysis of developed model with respect to MSE is presented in Figure 4. When the delay is 5000, the MSE achieved by developed improved Recurrent Rider LSTM is 0.067, 0.063, and 0.088 for the three twenty year time series dataset of Asian Paints, Bajaj Auto, and Bharati Airtel respectively. Similarly for the ten, five and three year time series dataset of stocks as shown in Figure 4, Figure 5, Figure 6, it obtained MSE of 0.064,0.063 , 0.100 and 0.066, 0.061, 0.084 and 0.062,0.061,0.097 respectively. The analysis of results of MSE conclude that the more time series data is helpful in reducing the error rate. Similarly the analysis of developed model with respect to RMSE is depicted in figure 4. When the delay is 5000, the RMSE achieved by developed improved Recurrent Rider LSTM is 0.259, 0.250, and 0.297 for the three twenty year time series dataset of Asian Paints, Bajaj Auto, and Bharati Airtel respectively. Similarly for the ten, five and three year time series dataset of stocks as shown in Figure 7, Figure 8, Figure 9, model obtained RMSE of 0.253,0.250,0.316 and 0.258,0.246,0.290 and 0.248,0.248, 0.311 respectively. Here also observation of results of RMSE depict that the large time series data is providing reduce error rate. Study and results of normal deep LSTM and proposed improved recurrent rider long short term memory model from Figure 10 & Figure 11, proposed LSTM outperforms in terms of MSE & RMSE. Here no kind of optimization training is provided to the proposed RNN LSTM model. Further scope of study and experiment of optimization approaches is to be studied.

5. Conclusion

The price of stocks fluctuates over time on the stock market. In reality, along with its non-linearity, dynamic nature, and complexity, stock market prediction continues to be a significant challenge. The researchers' primary focus in the previously published publications was empirical methods. Financial time series data is not a typical use for deep learning. The deep learning model, which also has the capabilities to accommodate the time-series data well, is used in this analysis. In this paper, an effective stock market prediction method with reduced error rate called improved Recurrent Rider LSTM is suggested. Study and analysis of the results in the research depict the effectiveness of LSTM in processing the time series data. Overall evaluation metric results observed that proposed LSTM proved to be outperforming as compare to earlier methods such as deep LSTM, HHM & GA method. Here LSTM operates without the aid of an optimization training method to best suit the answer, but future research may examine LSTM performance in conjunction with more complex optimization techniques.

Conflict of interest

"The authors have no conflict of interest to declare"

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