Performance Evaluation of Machine Learning Algorithms for Stock Market Price Forecasting

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***Abstract*— Stocks market is a complex and volatile nature and hence, effective financial decision making relies on proper stock price forecasting. With an increasing amount of historical market data, machine learning and deep learning algorithms have proven to be a powerful tool of analysis that can be applied to the historical price movement to reveal the latent patterns and forecast the future price movement. The paper will be a comparison of deep learning applications in predicting the stock prices of the large banking companies which are listed in the NIFTY 50 index. In the discussion, five leading Indian banks are used and they include State Bank of India, HDFC Bank, Axis Bank, ICICI Bank and IndusInd Bank. Historical closing price data of the yahoo finance between January 2020 and February 2026 were obtained using the yahoo finance API. The study presents a comparison between Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Stacked LSTM neural networks that are particularly most suitable to time-series forecasting since they can model the time-based relationships. The inspection of quality and optimization of the results of the model were performed prior to the model training, through the use of large data preprocessing and feature engineering techniques. To calculate the efficacy of the models and give a stringent portable appraisal, the standard evaluation measures such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the coefficient of determination (R 2) were used to assess the efficacy of the models. The results of the experiment indicate that deep learning models may be employed to make efficient and reliable predictions in the selected stocks.**

Keywords: Stock Price Prediction, Machine Learning, Deep Learning, LSTM, RNN, Stacked LSTM, Time Series Forecasting, Nifty 50, Financial Analytics.

I. Introduction

Stock market is an important part of the global economy as it helps in the formation of capital and creation of wealth. Nevertheless, the price trends of stocks are affected by many factors which encompass market sentiment, macro-economic factors, political factors and the behavior of investors and hence price fluctuations are very dynamic and hard to forecast. Developing efficient and precise predictions of stock prices has become a major challenge to investors, financial analysts and institutions wishing to make sound decisions whilst dealing with risks at the same time. The traditional methods used in forecasting like fundamental analysis and technical analysis are mainly based on past trends and financial indicators which are not able to capture sudden changes in the market and non-linear trends.

As the amount of data increases exponentially, and computation capabilities have improved, data-driven approaches have become the focus of interest in financial forecasting. These strategies use past market data to discover the concealed trends, and intricate associations that could be not easily identified through the traditional methods. More sophisticated predictive models have the ability to evolve with changing market situations and also enhance forecast accuracy with time by learning directly through past patterns of movement of the prices. This paradigm shift has broadened the sources of researching the intricate market forces and facilitating more credible decision making.

The banking sector is very crucial to the economic growth and financial stability in the emerging economies like India. The shares of big banking organizations as the representatives of the major indexes are usually characterized by high volume of trading and often mirror the tendencies in the whole market, which is why they are easy targets in predictive analysis. The analysis conducted on such stocks is very informative to the market processes and it also holds some practical importance to the institutional and retail investor.

The proposed study is aimed at predicting the stock prices based on the past closing price of the major banking stocks in the Indian stock market. Through time-series data (a multi-year) analysis, the study determines the efficiency of data-driven forecasting techniques in reflecting on the critical market trends and price patterns. The comparative structure that is undertaken in the current research allows to make an objective evaluation of the predictive performance of various modeling strategies. These results are likely to be useful in making informed investment choices, enhanced risk management, and the accumulating literature on the smart use of data in making decisions about the stock market.

II. Related work

In the financial decision-making and risk management, the prediction of stock price has drawn a great deal of research interest. According to the latest research, there has been an increasing use of data-driven and learning-based methods to address the shortcomings of the traditional forecasting methods. The initial studies point out that more traditional statistical models do not tend to capture the nonlinear relationships and abrupt shifts in the market, which makes it possible to apply advanced computational models to achieve a higher quality of the prediction [1], [2].

A number of studies involve an assessment of deep learning models in predicting stock prices in the future. Such publications indicate that sequence-based models are especially useful in understanding temporal relationships between historical price data, which results in a reduced prediction error in various market environments [3], [4]. The comparative studies of several stocks and indices also suggest that the model performance changes depending on the datasets which again proves that a proper choice of the forecasting methods depends on the specific market features which are not identical [5], [6].

In recent studies, the hybrid and ensemble frameworks that mix various learning methods have also been investigated to gain robustness and stability in predictions. The purpose of such structures is to combine the strengths of various models that are complementary to each other, which leads to higher forecasting accuracy and less sensitivity to noises [7], [8] Furthermore, backs in the literature involving sentiment data and outside sources of information, which include financial news, show that contextual data can have a tremendous effect on price dynamics and enhance predictive performances when used together with past price patterns [9], [10].

With regards to the emerging markets, several studies have noted that the stock behavior is complex and volatile especially in industries like banking and finance. The studies devoted to Indian stock market show that the model of learning is capable of capturing the sector-specific trends and market dynamics, and the model will be very informative to investors and analysts [11], [12]. These results confirm the increasing topicality of intelligent forecasting systems in the emerging economies.

The methodologies of evaluation have also changed and the recent literature shows the tendency of using various metrics of performance so that a model becomes fully evaluated. Mean Square error, mean absolute error, root mean square error and R square score are very common measures of predictive power and descriptive power [13], [14]. This standardized analysis allows a reasonable comparison between models and datasets.

Moreover, recent review studies summarize existing literature and arrive at a conclusion that advanced learning-based methods are always better in stock price prediction tasks, compared to traditional methods [15]. Nevertheless, they also observe issues with the interpretability of the models, dependency on data and generalizability even in divergent market circumstances. All in all, the literature highlights the imperative of comparative studies to establish the best forecasting methods and thus inform future studies and practical applications in financial market forecasts.

III. Proposed methodology

In this section the systematic approach followed to come up with, establish and assess the predictive models to forecast stock prices will be described. The methodology is organized into three distinct stages: data acquisition and preparation, model building and its performance.

A) Data Collection and Preprocessing.

The data of this research is a set of historical stock market data of five listed major banking stocks under the index Nifty 50: SBI, HDFC bank, Axis Bank, ICICI bank, and Indus Ind Bank. The information was obtained with the help of the Yahoo Finance API and covers the time frame between January 2019 and September 2024. The analysis is limited to the daily closing prices only as they indicate the market-wide agreement at the end of a trading day and are commonly applied in the financial analysis and forecasting.

Preprocessing of data is very important in enhancing model performance. First, there were missing values, inconsistencies, and outliers in the dataset that were checked. Any of the missing values were managed through proper imputation methods to ensure that there was continuity of data. As the data available on the stock prices is chronological in nature, the records were marked in order to maintain the time dependencies. Scaling techniques were used to normalize the closing prices to make them numerically stable and converge faster in the course of training. The data was further converted into supervised learning format through the development of input output sequences; past values of prices were used to predict future price. The obtained processed data was further divided into training and testing as the past data were utilized in training and the latest data was kept in evaluation.

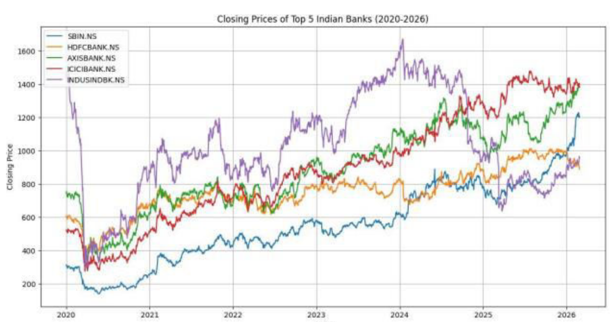

Figure 1 Closing Price Trend Of Top 5 Indian Banks

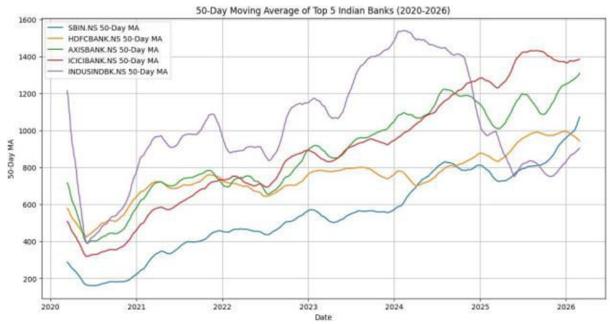

Figure 2 Day Moving Average Trend Of Top 5 Indian Banks

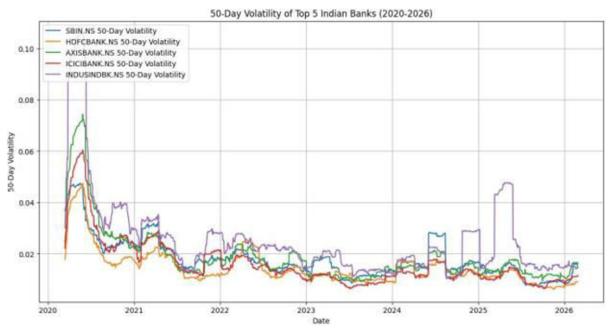

Figure 3 Day Volatility Trend of Top 5 Indian Banks

Figure 4 Correlation Matrix

B) Model Development and Training.

The predictive modelling step consisted in developing a series of deep learning models of forecasting that could be used on time-series data. The models were created to be learning the temporal pattern and trends with respect to historical stock prices. The individual stocks of the banks were trained on each model to identify stock behavior and price dynamics.

The training process was to input sequential price information in the models and to continuously solve the model parameters to achieve the minimal prediction error. Early stopping and validation-based monitoring were also used to enhance the efficiency of learning and to remove overfitting. Hyperparameter tuning was done to determine the best settings, such as learning rate, batch size, number of hidden units, and training epochs. This process of tuning was done so that each of the models would work within its optimum performance parameters where a fair and accurate comparison could be made.

The historical data until the year-end 2023 was used to train the models whereas 2024 was used solely in testing. This design replicates the conditions of actual forecasting and further, this design guarantees that the models are tested on unexplored data hence, increasing the validity of the results.

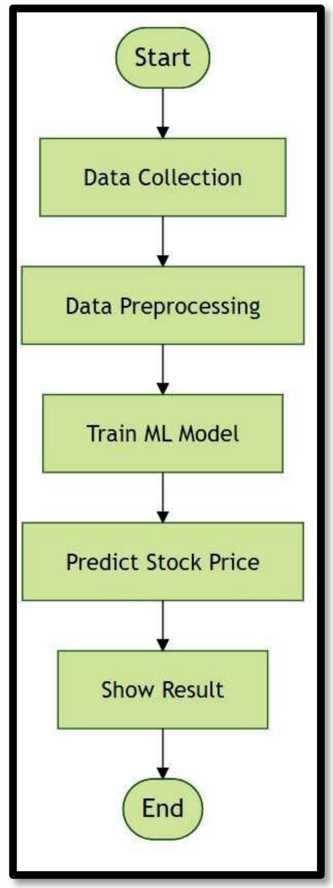

Figure 5 Project Flow Diagram

C) Comparison and Performance evaluation.

To determine the utility of the forecasting models, some evaluation measures were adopted. The size of prediction errors was assessed using Mean Squared error and root mean squared error but the mean absolute error provided a measure that is easy to interpret of the average deviation of actual prices. The quality of the explanatory factors was taken to be the score of R-Squared that was used to approximate the variability of the stock prices by the models.

Each banking stock was considered independently in terms of its performance to determine the differences in model conduct in diverse market circumstances. Comparative analysis was done thereafter in order to establish the most reliable and precise forecasting method. This assessment system offers practical information to investors and financial analysts by identifying strengths, weaknesses and applicability of model to particular stock, and eventually aiding decision making and mitigating risks in the financial markets.

IV. ARCHITECTURE DETAILS

A) Repetitive Neural Network Framework.

Information memory to the past time instances is used to process the sequential data in the model. It does not work out individual data points but takes a chain structure where past predictions influence the current one. This skill helps the model to establish the short-term trends and patterns of the stock prices. The present input is processed along with the contextual data of the last step and this enables the learning in a temporal nature.

The structure is not efficient in long sequence information maintenance despite the fact that it is efficient in simple tasks that have time-series. The longer the data length, the more chances of missing out critical data in the past hence affecting the accuracy of prediction. Despite this limitation, it is computationally accurate and easy to execute, and, therefore, it can be utilized as a benchmarking forecasting model. This architecture is a good introduction to a sequential learning to the novice, the way the history information of the prices could influence the future value of the stock.

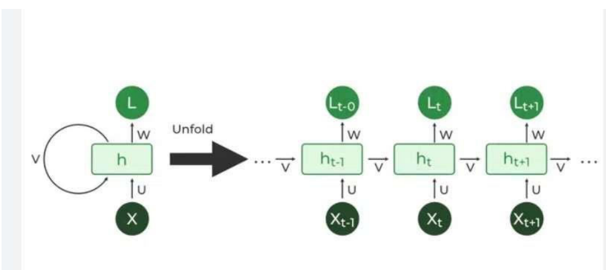

Figure 6 RNN Model

B) Long Short-Memory Architecture.

This architecture facilitates sequential learning having internal memory system that governs the circulation of information over the course of time. It has control mechanisms which determine information that must be stored, updated or discarded. The design enables the model to permit long-run dependence and multifaceted patterns of past stock price information.

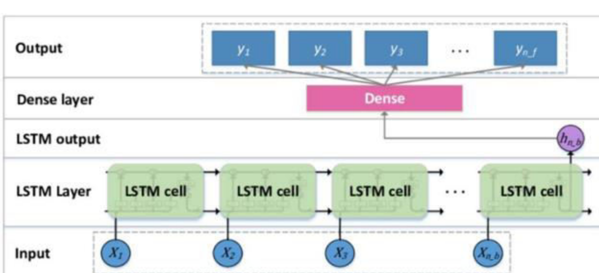

Figure 7 LSTM Model

This model can learn trends, cycles and variation of the price much more effectively by storing information that can be useful with longer durations. It is best applicable in situations where past of the market behavior plays a significant role on future prices. It is more stable and predictive and requires more computation needs but is more complicated and unpredictable. This model can be viewed as a clever mechanism to an introvert that selectively retrieves important information of the past and therefore, it is appropriate in forecasting financial time-series.

C) Stacked Architecture

It is a sequence learning architecture which constructs sequence learning in multiple steps. Each of the different layers receives different sets of information regarding the input data. Lower layers are informed about trivial price variation but higher levels are informed about abstract and long-term trends. This hierarchy of learning model enhances the ability of this model to comprehend complex behavior of stock markets.

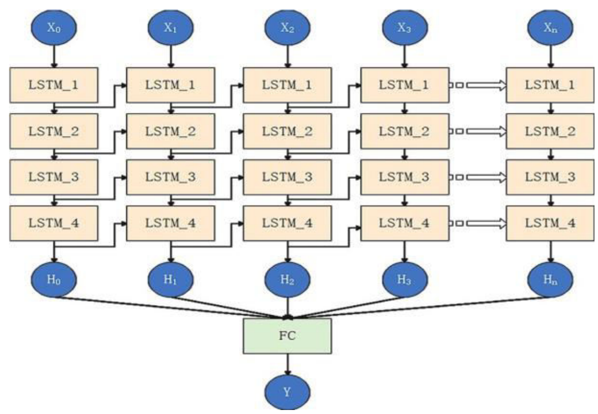

Figure 8 Stacked LSTM Model

The improved design adds representational power and, in most instances, results in a higher accuracy in prediction. However, it complicates training as well and may lead to overfitting when not properly addressed. The techniques that will be required to ensure that it is stable will include validation monitoring and regularization. This approach would look like a multi-level learning system in its simplistic version where the level of information will be refined and hence more specific and accurate price forecasts of the stock price.

D) The Gated Recurrent Unit Architecture.

The reason behind this is to make sure that it is efficient and performs well, and is a simplified counterpart of memory-based sequence models. It makes use of gating processes to decide how much past information is to be stored or revised at any one step. It is simple since it introduces the memory control as a smaller number of components and also, it can capture meaningful patterns over time.

This model is also simplified and thus is known to train at a higher rate, and at the same time less computational resources are used compared to its more complex architecture counterparts. It operates with time-series data when the medium- and long-term dependence is present. It is effective and thus can be used in big data and real time forecasting programs. To the layperson, this architecture can be viewed as an architecture of a small and lean sequence learner that offers good quality performance but is not overworked with excessive operationalization.

V. Results and Discussion

Table 1 Arima Model Results

Stock Symbol	MSE	RMSE	MAE	R^2 Score
SBIN.NS	123.23	11.10	7.77	0.9919
HDFCBANK.NS	82.01	9.06	6.89	0.9761
AXISBANK.NS	255.78	15.99	11.23	0.9773
ICICIBANK.NS	204.72	14.31	10.43	0.9606
INDUSINDBK.NS	424.23	20.60	12.36	0.9546

Table 2 Lstm Model Results

Stock Symbol	MSE	RMSE	MAE	R^2 Score
SBIN.NS	540.29	23.24	17.04	0.9656
HDFCBANK.NS	339.02	18.41	14.81	0.9036
AXISBANK.NS	1501.56	38.75	30.75	0.8708
ICICIBANK.NS	945.14	30.74	25.53	0.8204
INDUSINDBK.NS	2034.92	45.11	26.59	0.7761

Table 3 Stacked Lstm Model Results

Stock Symbol	MSE	RMSE	MAE	R^2 Score
SBIN.NS	556.83	23.60	17.09	0.9646
HDFCBANK.NS	706.45	26.58	23.05	0.7991
AXISBANK.NS	782.12	27.97	20.90	0.9327
ICICIBANK.NS	1376.10	37.10	29.14	0.7385

Table 4 GRU Model Results

Stock Symbol	MSE	RMSE	MAE	R^2 Score
SBIN.NS	205.07	14.32	10.32	0.9869
HDFCBANK.NS	127.60	11.30	9.00	0.9637
AXISBANK.NS	317.35	17.81	13.02	0.9727
ICICIBANK.NS	263.68	16.24	12.02	0.9499
INDUSINDBK.NS	774.18	27.82	16.42	0.9148

This section demonstrates the performance of the ARIMA, LSTM, Stacked LSTM, and GRU models in terms of their performance in stock price prediction of the large Indian banking stocks that include, SBIN.NS (State Bank of India), HDFCBANK.NS (HDFC Bank), AXISBANK.NS (Axis Bank), ICICI Bank (ICICI Bank) and INDUSINDBK.NS (IndusInd Bank). To determine the performance of the model, the means squared error (MSE), the root mean squared error (RMSE), the mean absolute error (MAE) and the R 2 score were used to compare the results.

According to Table 1, the ARIMA model performed best in the overall performance of the majority of stocks. SBIN.NS had the best MSE (123.23), RMSE (11.10), and MAE, (7.77) and a high R2 value of 0.9919 which shows that it has a good goodness-of-fit. Likewise, HDFCBANK.NS and AXISBANK.NS had high predictive accuracy with R 2 values of greater than 0.97. Conversely, as indicated in Table 2, the simple LSTM model had greater error measures in all stocks. Despite the comparatively high R 2 value of SBIN.NS, 0.9656, the values of MSE and RMSE were much bigger than that of ARIMA, which implies that it was less precise in prediction. The Stacked LSTM results are given in table 3. Although the AXISBANK.NS had been relatively high R 2 of 0.9327, generally, the performance of HDFCBANK.NS and ICICIBank.NS decreased, indicating that the models may be overfitting or getting more complex without corresponding performance improvement.

GRU model as it can be observed in Table 4 proved to be competitive, with most cases proving to be better than the LSTM and Stacked LSTM. In the case of SBIN.NS, the GRU model had an R 2 value of .9869 and lower error measures than LSTM models. Nevertheless, ARIMA was the most constant and precise model in general.

These findings suggest that classical time-series models like ARIMA could be more successful at short term forecasting of stock prices than deep learning models in structured financial data.

VI. CONCLUSION

The paper has provided a comparison of state of art machine learning and deep learning models in stock price prediction in the Indian banking industry. This particular paper tested the ability of the sequential learning methods to learn time dependence and market trends with regard to the historical closing prices of five large banking stocks, namely, State Bank of India, HDFC Bank, Axis Bank, ICICI Bank, and IndusInd Bank. Several measures of evaluation were used to make sure that a stringent judgement of predictive power and power of explanation was performed. The experiment findings indicate that deep learning models have high predictive potentials on diverse stocks and they are effective in modeling nonlinear trends and time-related configurations of financial data. Nonetheless, the models have not performed equally: some strategies have been found to be more effective in reducing forecast errors, whereas others demonstrated high capability to explain price variations. This difference reveals that stock-specific traits and market dynamics have an effect on model performance and it is imperative that a comparative analysis is done instead of concentrating on a single forecast method.The research will be useful in enhancing the development of smart forecasting tools in financial analytics, especially in one of the vital industries of a developing market. The results are useful to investors and financial analysts as they can be used to make informed decisions, risk better analysis, and gain a more in-depth insight into the behavior of the stock prices. In general, this study confirms the applicability of more sophisticated analytical models in financial time-series projections and provides a strong base on which future studies in data-driven stock market forecasting may be conducted.

VII. Future Scope

Although the results of this study are promising there are still a number of avenues in which the research can be enhanced. Further studies can include other explanatory factors including trading volume, technical indicators and macroeconomic factors, which may further enhance predictive performance. There is also a possibility of integrating other data sources such as financial news and market sentiment indicators that would also contribute to modeling real-world events and their impact on stock price changes. The scope of analysis may be broadened by including stocks from diverse industrial sectors or extending the framework to international markets, thereby improving the generalizability of the findings. The deployment of trained models within real-time trading environments represents another important direction, facilitating the development of practical, real-time forecasting systems. Furthermore, hybrid and ensemble approaches may be explored to combine the strengths of multiple models, thereby improving robustness, stability, and overall predictive reliability. Increasing model understandability is also a work that is of paramount importance to do in the future because clear and transparent predictions are the only way to become an investor. Based on these research direction refinements, more trustworthy and scalable and practically feasible stock forecasting systems can be developed to enable informed decision making in the changing financial markets.

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