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Exploring the Effectiveness of Machine Learning (ML) and Deep Learning (DL) Algorithms in Predicting Financial Asset Price

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ABSTRACT

It is a well-known fact in finance that the price of financial assets because of volatility are difficult to forecast. Although economists like to use models only few do the right modelling. Modern technology developments like Machine Learning (ML) and Deep Learning (DL) have opened exciting new possibilities for improving prediction accuracy in financial forecast. The broader objective of this research paper is to choose right model and predict right prices for the financial assets for investors and portfolio managers. In this context, this research paper highlights how the Decision Tree, Random Forest and Long Short-Term Memory (LSTM) algorithms help to forecast the stock price in case of NIFTY 50 index. To achieve the objective historical stock data from the years 2014 to 2024 is used and preprocess it with feature engineering, normalization, and the sliding window approach. For analysis, MSE, RMSE, MAE and R^2 are used to evaluate the performance. It tests hypothesis through (t-tests) and volatility-specific analysis to check robustness. The data shows that Random Forest has the best performance, but LSTM is more sensitive to volatility. This research is useful for investors and financial analyst who can use ML and DL for better decision-making regarding stock market forecasting..

1. INTRODUCTION

The financial market functioning is a complex issue because of a wide variety of contributing factors. These factors consists of the economic indicators, investor sentiment, global events, and market trends. The prediction of prices of any financial asset correctly is an important and difficult task for Investors, Portfolio Managers, and Financial Analysts. The traditional methods of predicting financial data are often made using ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) in time series [3]. However, predictions made by these models may not always be correct due to their linear assumptions. Because of this, predictions are not as good as expected and work badly in changing and unpredictable markets [6].

As artificial intelligence gets better, machine learning (ML) and deep learning (DL) models are seen as valuable substitutes for econometric models. Investors create models using data from previous financial events and adapt to changing conditions in market. Long Short-Term Memory (LSTM) networks, Random Forest, and Decision Tree have received significant attention for forecasting due to their power in uncovering hidden relationships in data and improving predictive accuracy for large datasets [10]. Random Forest uses several Decision Tree models to enhance prediction accuracy. They provide a simple yet interpretable approach to regression and classification. At the same time, LSTM, the special type of recurrent neural network (RNN), is suitable for the time-series forecasting because it captures long-term dependencies and patterns of stock price changes [5].

This paper attempts to use the ML and DL methods to predict stock prices of the NIFTY 50, the 50 best companies of India's stock market. For this purpose, the historical stock data from 2014 to 2024 is collected. Further they are pre-processed. The models' features were selected to be key financial indicators, namely open price, high price, low price, closing price, volume traded, and price to earning ie P/E ratio. To train and test the models, a sliding window approach is adopted so that the historical data trends are maintained. The research uses 80% of the information for training and the other 20% of the information for testing.

This research paper attempts to highlight how well a Decision Tree, Random Forest and LSTM predict a stock price. It compares the ability of all three predictive modelling techniques against performance metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and R square (R^2) values. Further, model robustness will be tested under varying market conditions. It conducts hypothesis testing by means of paired t-tests to see if these performance differences are statistically significant. To get a better understanding of how things varied with the high and low volatility period. Some volatility analysis has been done.

The paper sheds light on which ML and DL models perform best in predicting stock prices and returns, contributing to the field of forecasting stocks. By knowing the advantages and limitations of each model, one will be able to apply the same in real trading strategies. Also, the study points out how crucial it is to pick the right model, and treat the data, and validate statistically, to help a predictive model be reliable and generalisable to different market conditions. This research study highlights the use of artificial intelligence (AI) or the term “machine learning” (ML) in the financial markets using advanced ML and deep learning (DL) techniques along with a sound statistical evaluation.

Objective:

- The broader objective of this study is about helping the investors and portfolio managers in choosing right model and predicting right prices for the financial assets with following sub objectives:
- To explore how stable ML and DL models are under different criteria or situations. Like during high volatility and low volatility situation.
- To use statistical hypothesis tests like paired T-test to figure out if differences in model performance are significant or just random variation

2. LITERATURE REVIEW

It has been a long-standing issue in finance to predict the financial asset prices. Conventional econometric models despite being useful, fail to handle the data complexities and non-linearities of the financial markets [1]. Different “machine learning” algorithms have been tested for the financial asset price forecasting, and all of them provided some degree of accuracy. One of the most effective techniques that have been employed in the prediction of Real Estate Investment Trust (REIT) prices is Support Vector Regression (SVR). In the study done by Fatim Z. Habbab and Michael Kampouridis [2], The findings of the study showed that the ML models outperformed the benchmark models with SVR providing the highest risk-adjusted returns for different time intervals. This is because ML can help in the optimization of mixed-asset portfolios through the provision of better price estimations as seen in [2].

Other study examined the application of ensemble methods. The researchers conducted a study to analyse different tree-based ensemble methods such as Random Forest, XGBoost, Bagging, AdaBoost among others [3]. The researchers utilized stock price data examined NYSE, NASDAQ, and NSE data and respectively found the ensemble model generally performs better than most of these models. This means that a collection of models is more effective at forecasting returns than just relying on a single model [3]. Support vector machines (SVM) has also been studied for stock price predictions effectiveness [4], [5]. M. Bhamare et al. [4] compared to the performance of SVM with RF and LSTM for predicting the closing stock prices of major Indian banks. The findings of their results say Random Forest model has better predictive accuracy as measured R-squared and Mean Absolute Percentage Error (MAPE) [4].

“Deep learning” (DL) algorithms are often used in forecasting financial data because they can learn complex non-linear relationships from large datasets [6]. RNNs, specifically LSTM networks, are often used because they are effective with sequential data like time series [7], [8], [9]. K. Akshitha et al. [7] reviewed the use of LSTM and its variants for predicting stock prices. They refer to the challenges posed by psychological, physical, rational, and irrational factors. Sidra Mehtab and Jaydip Sen applied LSTM networks for forecasting the NIFTY 50 index which exhibited good performance for univariate encoder-decoder LSTM model for the multi-step prediction [8].

Financial time series data applied to the CNN models are presented in [10], [11], [12]. Sidra Mehtab and Jaydip Sen used CNNs to predict NIFTY 50 index values, found them more accurate than traditional methods and any other ML approaches for shorter durations. M. Hiransha et al. A few different ML and DL architectures combine to suggest hybrid models [13], [14], [15]. A study proposed a hybrid DL framework (COVID19-HPSMP) for predicting the stock price movement, which integrates CNNs along the local/global attention modules and the BLSTM network, in response to the COVID-19 social media trend [13].

To discern how to assess them one should think about metrics to see how ML and DL models perform when used for financial prediction. Algorithms share some commonly used performance metrics. These include the MAE, the RMSE, the MAPE and the R-squared, as shown in [4], [5], [10], [15]. Moreover, explainability and interpretability of models are important to increase the faith and adoption of the financial sector. The longer the prediction horizon [16] and the stock markets [16], the less accurate the prediction can be. Examine the importance of features derived from limit order book data. Using features wisely through feature engineering, performance of deep learning models dealing with non-stationary data can be improved as shown by their work [17]. Jiwen Huang et al. combined numerical economic indicators, media information, and firm interaction data in the context of asset pricing.

The complexity of financial data and enhancement of vigorous feature engineering is one of the major challenges faced [7],[18]. Choosing what measurement to use depends on what you're predicting and what kind of the financial data it is. A lot of earlier studies use related techniques of cross-validation [19] ML and DL techniques are rapidly evolving with the improving quality of financial data [20].

3. METHODOLOGY

This research paper is based on exploratory and uses a quantitative method. It uses historical financial data for training and predicting models. Forecasting stock prices is a quite challenging task as they involve complex, non-linear relationship and trends in time-series data. This paper is based on secondary data and uses historical data of nifty 50 index. The sources of data like Yahoo Finance, Money Control and other financial platforms.

The sampling of this paper encompasses a portion of the NIFTY 50 index which are selected based on market capitalization and their trading activity, hence, this paper is based on purposive sampling, The historical data of stock price for previous 10 years is covered. The accuracy of different ML and DL model is applied to check how accurate decision trees and random forest, ML models are. For deep learning, this study will consider "Long Short-Term Memory" (LSTM) networks. Both ML and DL model are compared, with the ML model serving as a benchmark at the very least. This paper applies Hypothesis Testing using (t-tests) and Bootstrapping for accuracy of results

Hypothesis:

1. Null hypothesis (H0): There is no difference in performance between the models
2. Alternative hypothesis (H1): There is a significant difference.

Analysis & Findings:

The paper attempts to test the accuracy of the three models, with the help of different metrics. For instance, MSE, MAE, and RMSE. Also, the R-squared (R2) is examined. The measures provide a numeric measure to indicate how accurate the models are and how well the models capture the patterns. As per Table 1, different models have different performance measures.

Table 1: Model Performance Metrics

Model	MSE	MAE	RMSE	R2
Decision Tree	[15583897.566]	[3177.8523]	[3947.644]	[-1.39930]
Random Forest	[14958804.824]	[3069.3841]	[3867.661]	[-1.30306]
LSTM	[1081085.753]	[874.0000]	[1039.752]	[0.83355]

The predictive capacity of the models is illustrated through the outcomes that are visually represented. Figure 1 shows the predicted and actual prices of stocks for all models. Figure 2 has a bar graph comparing the models based on RMSE, MSE, MAE, and R2 for a better understanding of the models. According to Figure 3, a model's predictive ability depends upon market volatility and here the models' RMSE is checked during the high and low volatility of the market.

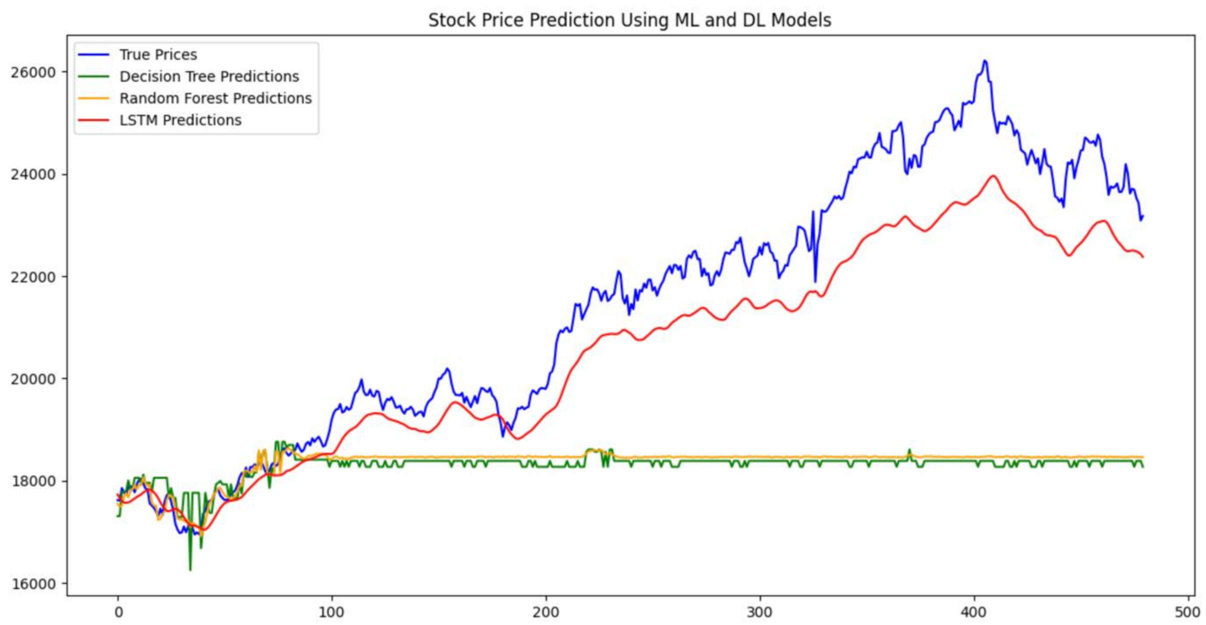
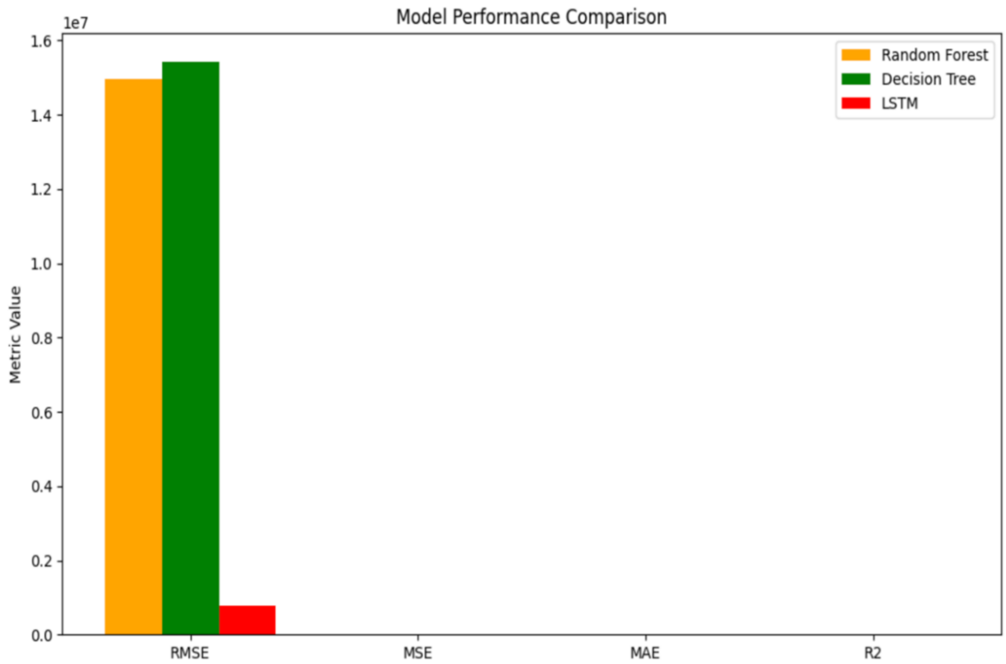


Figure. 1



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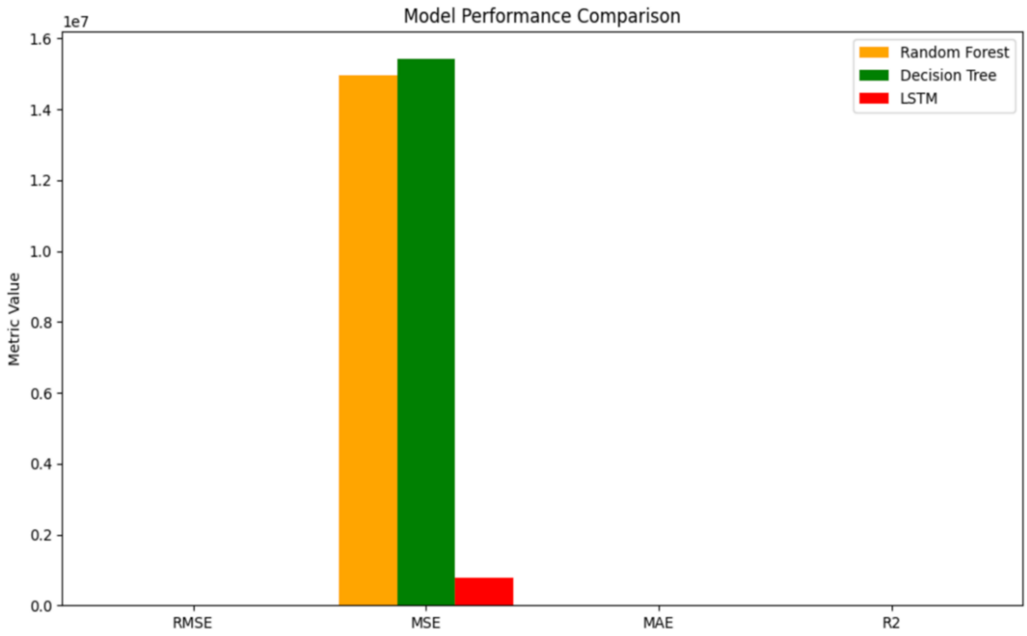

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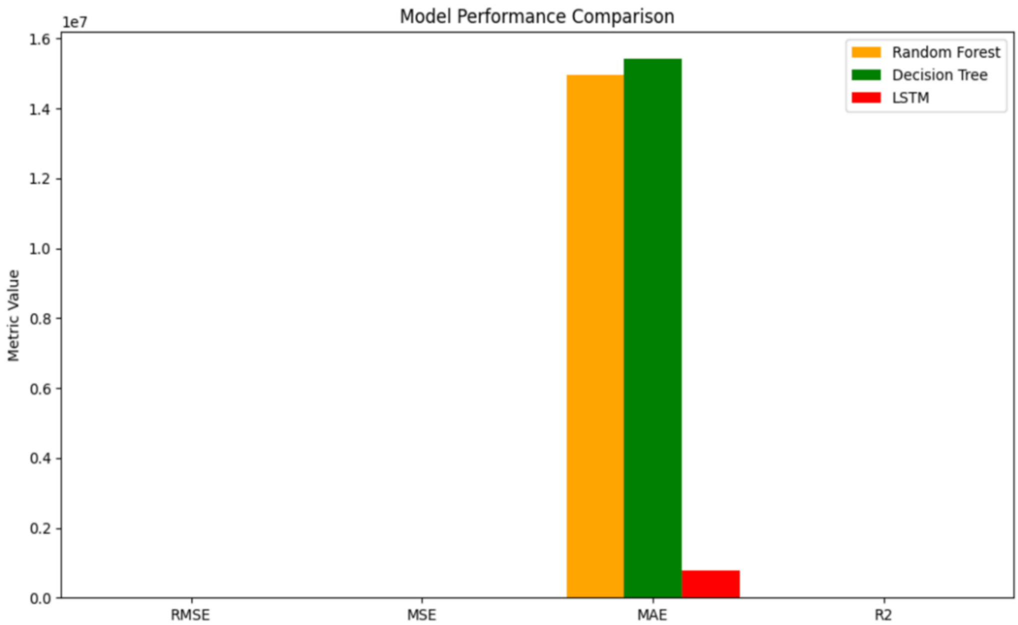

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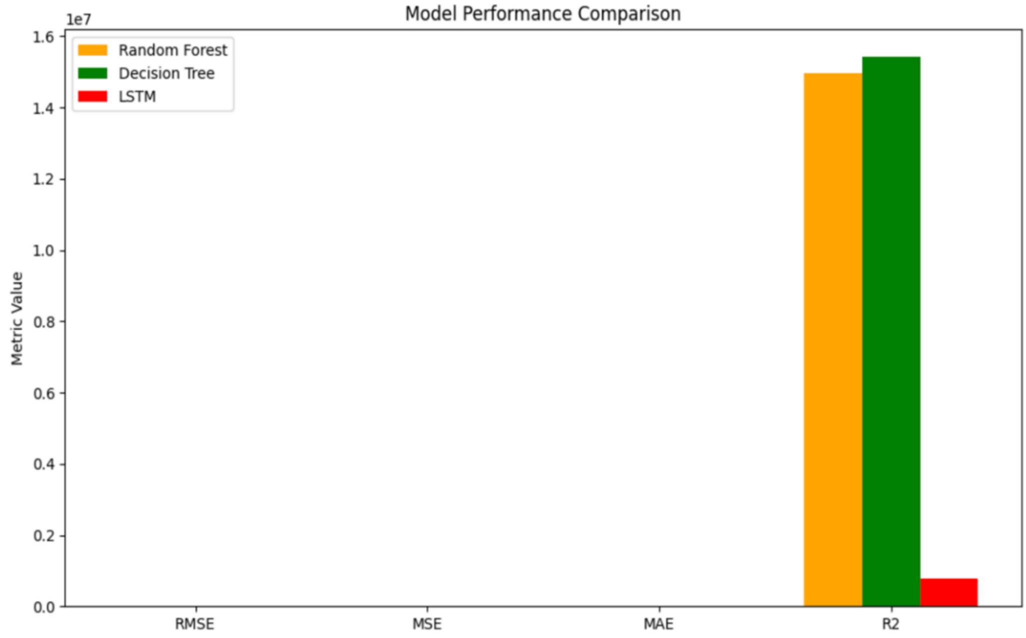

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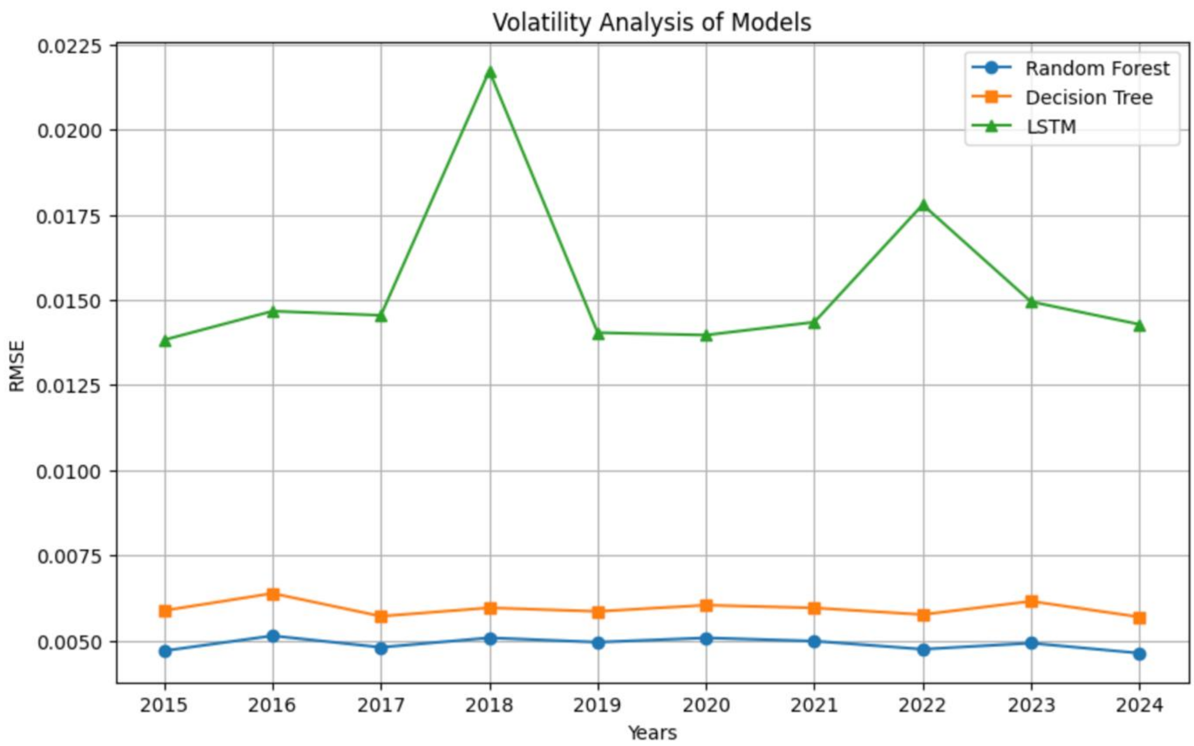

Figure. 6

4. DISCUSSION

Based on the extensive review of performance metrics, visualizations, and statistical tests, findings are given below:

- The Random Forest scored better than the Decision Tree and LSTM models on all performance metrics chosen. The model with lower values for MSE, MAE and RMSE is accurate. It shows that the model captures a complex relationship with the data to make predictions. According to Figure 2-5, Random Forest has the lowest values for the four metrics, confirming its superior performance.

- The LSTM model managed to capture long-term trends remarkably well. However, it was heavily influenced by market volatility. Figure 6 shows that the LSTM has a high RMSE during volatile periods of the comparison period. As we can see, the LSTM model may lack the robustness associated with the market's busy hours to accurately predict prices. The significant increase in RMSE indicates its susceptibility to market fluctuations.
- The Decision Tree approach was used as a baseline model in the experiment and moderately performed. However, it was consistently outperformed by Random Forest and LSTM. With the larger error metrics and a low R2 value, it may not be able to predict the stock market data effectively.

As illustrated in Figure 6, the model performance varies based on different market volatility The line graph shows the RMSE of all models during high volatilities and low volatilities. This analysis leads to the following observations.

- The Random Forest did not show much difference during high volatility and low volatility. Its RMSE did not change significantly and remained low throughout the study. The finding shows that the Random Forest can adjust to different types of market conditions while remaining accurate.
- During low periods of volatility, the working of the LSTM model is good. However, during high volatility periods, there is a major spike in the RMSE of the LSTM model. This means that the performance of the LSTM model is more sensitive to market turmoil and that it may not accurately predict prices during periods of intense market activity.
- Decision Tree RMSE Sensitivity is Moderate. The Decision Tree increased RMSE moderately during a high-volatility period as opposed to a low-volatility period. This indicates that the Decision Tree model is influenced to a certain degree by changes in the market, but not as much as LSTM.

To validate the differences in performance, bootstrapping and hypothesis testing (t-test) are used, with alpha 0.05. The results reveal:

- The performance of Random Forest which is significantly superior to Decision Tree and LSTM as can be seen from the p-values obtained from the results of t-tests which are less than alpha. The finding strongly suggests that the Random Forest model fits the data much better than the other models.
- The t-test that compared Decision Tree and LSTM did not give a p-value that was less than alpha. The Decision Tree and LSTM have no significant difference. This suggests the performance of the two models is comparable.

This paper attempts to assess the effectiveness of three predictive models – Decision Tree, Random Forest and LSTM, in forecasting closing price of NIFTY 50 (NSEI) with the stock price data. The results show that Random Forest has the lowest error metrics (MSE, MAE, RMSE) and highest R2 value as compared to all the other models. The working of the LSTM model was affected by volatilities in the stock market as the model showed good results in long-term trends. But is not very accurate during these volatile situations due to increased errors. Unlike the other models, the Random Forest model performed robustly across varying levels of volatility, highlighting its accuracy. The Decision Tree, which is used as a baseline, performed moderately but consistently worse than Random Forest and LSTM. Statistical tests confirmed that Random Forest's better performance over the other models is indeed significant. This paper attempts to offer useful insights that could be employed to develop a sophisticated tool for stock market forecasting as well as enhance investment decisions.

5. CONCLUSION

After performing a performance metric analysis, visualization and statistical testing, it can be concluded that the "Random Forest" is the best model for forecasting the NIFTY 50 closing price. The stock market prediction is a powerful tool that adapts well to different volatility levels and shows superior accuracy. It is statistically significant too. The results indicate that ensemble algorithms, such as Random Forest, can effectively detect non-linear relationships in financial data, offering valuable insights to investors and traders. Therefore, the Random Forest model's proven effectiveness in forecasting share prices creates new means to develop advancements in trading strategies. Also, the information gained from volatility analysis can help investors and traders understand different market conditions and make more informed investment decisions.

Although there are some techniques presented in this research work to predict stock prices using various ML and DL models, however, it has limited scope of data as only NIFTY 50 index (NSEI) and its past data is used. This output may not apply to any other stock market share or stock

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