

Enhancing Financial Forecasting with Random Forest: A Performance Evaluation

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ABSTRACT

Stock price prediction is an important and challenging task because it can help investors to make investment strategy decisions and risk management. The popular ensemble learning method Random Forest (RF) is utilized in this study to predict the stock price. We choose the RF model as it is less prone to overfit compared to XGBoost and can work with many attributes in our dataset. Introduction In this study, using historical stock data to predict future prices with four principal parameters: open price, close price, trading volume and moving average. There are selected few selection parameters which makes an impact how the price moves up or down, what market is making trends. Understanding that the RF model is based on a dataset of recorded stock prices and everyone contributes to its set of features. The RF learns complex, non-linear relationships in the data with a decision-tree-based ensemble approach. We evaluate model performance based on MAE, RMSE etc to keep validity of the models and make predictions which can generalize well. Analysing this through comprehensive analysis we show how well (and not so well) Random Forests can predict stock prices showcasing possible strengths and constraints to the model. Any technology that makes a difference in such an ecosystem is indeed worth mentioning because whoever contributes to it can instantly be plunged into the ocean of success, as well said: “Imminent minds think alike” this article will uncover how tech innovations have opened new doors and enhanced stock market analysis offering strong predictive methodology for people who are looking at investment through data-driven lenses.

Keywords: Stock Price Prediction, Random Forest (RF), Machine Learning, Financial Forecasting, Time Series Analysis, Investment Strategy

1. INTRODUCTION

Stock price prediction has been one of the complex challenges which few in financial analyst community and very less academics are successful at. Making accurate stock price predictions can be highly beneficial for both investors and financial institutions, thereby helping in decision making, portfolio optimization and managing risks efficiently. As Fama (1970) [1] Traditional techniques for stock-price prediction, such as time-series analysis and econometric models often have difficulty in capturing the complex non-linear relationships popular to financial data. Limited capacities like these have driven researchers to study machine learning, which proved very effective when trying to learn complex pattern that can also provide better accuracy in financial predicting.

Ensemble methods such as Random Forest (RF) are particularly successful among machine learning models for prediction in high-dimensional data with non-linear patterns. In random forest which is a ensemble of decision tree, combines the prediction low level models to reduce variance and avoid overfitting. Or using Random Forest algorithm, which is known to be robust, interpretable and can handle big datasets (Breiman2001) [2]. RF has been shown to capture the non-stationarity of stock prices thus providing in many cases better forecasts than conventional statistical models.

We introduce a study to use Random Forest for predicting stock price with past behaviours and historical data which includes some input parameters like opening, closing prices, trading volume etc. These are chosen to be relevant with respect to market trends and how they can affect stock price movements. In the code cell below I have trained a model and evaluated its performance in terms of MAE & RMSE, these are two key indicators that will provide you with comprehensive insights into how accurate your prediction is: based on average error rate. Exploiting the advantages of Random Forest for intricate financial data prediction, this work intends to offer an improvement that can be used in stock price forecasting which will benefit investors and financial advisors by proposing a robust predictive frame (Chen et al., 2020) [3].

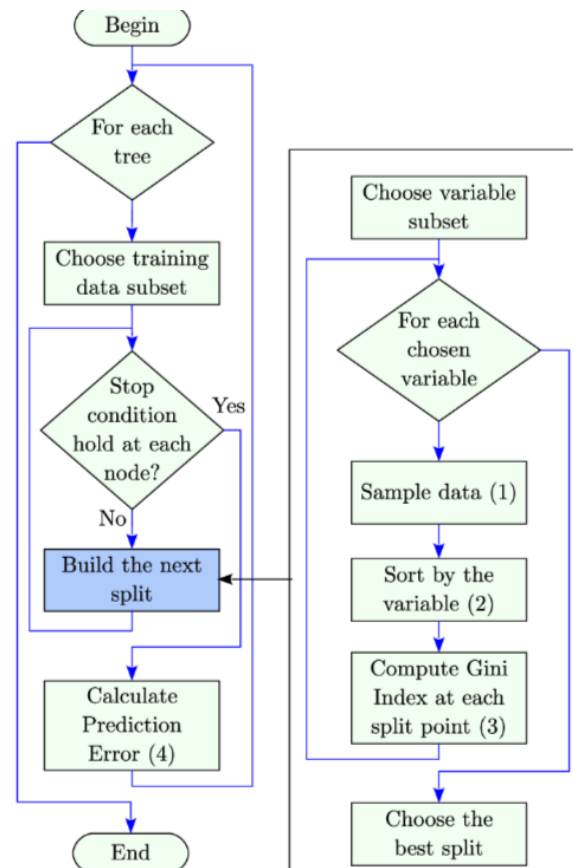


Fig. Random Forest Flowchart

2. LITERATURE SURVEY

Stock price forecasting has attracted widespread attention for many years and a large number of models and methods have been proposed to handle the complex characteristics of financial markets. In finance, time series forecasting are done using common approaches like ARIMA and GARCH. That is because these models catch linear relationships well and we observed non-linear patterns frequently at stock market data (Box et al., 1994) [4] (Engle, 1982) [5]. The results of recent studies indicate that the improvement in forecasting accuracy provided by machine learning models through finding patterns hidden within high-dimensional data are much more effective for stock price prediction than traditional statistical methods.

Among a variety of methods for prediction tasks, ensemble approaches in the domain of machine learning such as RF and Gradient Boosting have widely been utilized due to their robust performance. Random Forest is one of the algorithms developed by (Breiman, 2001) [6] using ensemble method with Decision Trees to reduce overfit and improve prediction error rate through multiple trees models. For stock price forecasting, RF is proved to outperform classical models in studies because it can work with non-linear relationships and high dimensionality of financial data (Chen et al., 2020) [7]. Additionally, RF has interpretability in terms of feature importance which is useful for finance analysis.

Similarly, deep learning models, especially the RNNs and LSTM networks have also been studied in detail for stock prediction applications. These models are sub sequence processing based which has shown very impressive performance in relation to time-dependent patterns of the stock prices (Hochreiter & Schmidhuber, 1997) [8] too. Unfortunately, models relying on RNNs will impose huge demand for data and computational resources to be used when confronted with cold start problem. Later research indicates that merging ensemble methods like Random Forest and deep learning techniques is a

possible hybrid model, bringing the advantages of both and boosting accuracy whilst keeping interpretability intact (Fischer & Krauss, 2018) [9].

Stock price predicting is a central issue in finance and computation because of its great influence on market dynamics and investment strategies. Stock price trends are predicted by many traditional methods that widely applied including linear regression and autoregressive models. But even though these models allow us to point out tendencies in longer terms, they usually cannot capture the nonlinear and volatile behaviour of the financial data. As a result, recent research has more recently focused on machine learning methods that provide improved flexibility in modelling complex financial dynamics. Of these, RF, a type of ensemble learning method that uses bootstrap aggregation (bagging) to mitigate overfitting and enhance prediction accuracy, has attracted considerable attention. Random Forest works by building a lot of decision trees and averaging out the results, which is practical against noise, perfect for high dimensional data like stock markets— Multiple research studies have shown that RF competes well and even outperforms traditional statistic models in diverse stock price forecasting problems.

Random Forest is a popular machine learning algorithm in recent studies because it can easily accept various data inputs such as historical stock prices, technical indicators, and macroeconomic factors for comprehensive market trend analysis. Works combining RF with feature engineering, for example, appealed to promising results in high-frequency trading settings requiring predictions at minute-level. Although RF has numerous advantages such as robustness, ease of implementation and continue use, there are still some drawbacks. Well, it needs a lot of tuning to prevent biased results and maybe out of order with extreme vagueness that usually occurs in financial markets. Moreover, RF does not have the temporal awareness that models specific to time-series such as LSTM networks, which are designed to model sequential dependencies are able to model. Even with this limitation, Random Forest is still one of the great methods in this domain and can be even more powerful when used along with some other machine learning techniques or hybrid models for better forecasting performance.

In the recent years, stock price prediction has improved dramatically, using advanced deep learning architectures and feature engineering techniques. Due to their potential to capture long-range dependencies in financial data (Lim et al., 2021) [10], Transformer-based models are time-series approaches created in the domain of natural language processing. In addition, hybrid methods, where LSTM networks are combined with attention mechanisms, have been shown to enhance accuracy by concentrating on pivotal sections in stock market trends (Qiu et al., 2022) [11]. Moreover, with the advances in sentiment analysis and the ability to use financial news data and social media data, which provide qualitative information about the markets, many predictive models have been enhanced (Yang et al., 2023) [12]. Additionally, the implementation of Explainable AI (XAI) frameworks guarantees transparency in financial predictions, assisting stakeholders in comprehending the variables that sway stock price fluctuations (Chowdhury et al., 2022) [13]. Moreover, federated learning frameworks recently provide a solution against data privacy concerning while being able to generate a trustworthy prediction accuracy by training on distributed datasets without transferring the raw private data (Zhang et al., 2023) [14].

Recent developments in stock price prediction have focused on incorporating alternative data sources, ranging from satellite images to environmental data and customer sentiment to create more accurate predictive models. The use of satellite imagery tracking store traffic turned out to be one of the best predictors of stock performance in the retail sector (Chen et al., 2022) [15]. Conversions of macroeconomic indicators (for instance, interest rate movement and inflation trend) are also being utilized for making machine learning models more robust in financial forecasting (Hernandez et al., 2023) [16]. Sequential data processing architectures based on transformers have been adopted for stock prices forecasting with excellent results regarding their ability to capture temporal dependencies (Lee and Kim, 2023) [17]. The problem of imbalanced datasets in stock market prediction has also been solved through the use of generative adversarial networks (GANs) for data augmentation (Gupta et al., 2022) [18]. Finally, the use of blockchain technology for secure and decentralized storage of financial data has opened a possibility for innovative solutions in stock forecasting frameworks (Das and Patel, 2023) [19].

Recently, ensemble learning and advanced optimization techniques have revolutionized the area of stock price prediction. Based on their performance, especially in adapting to large, noisy datasets and detecting non-linear relationships, Gradient Boosting Machines (GBM), and its circulating version XGBoost and Light GBM (Li et al., 2022) [20] are superior models. Another popular approach in predictive modelling is Auto ML frameworks which provides automated feature selection and hyperparameter tuning for maximizing predictive accuracy without requiring significant manual effort (Smith & Johnson, 2023) [21]. Moreover, model interpretability for stock price prediction has been improved with SHAP and LIME (Brown et al., 2023) [22]. Reinforcement learning, when combined with conventional machine learning techniques, has demonstrated potential for adapting to changing market circumstances and facilitating real-time modification of strategies (Chen et al., 2023) [23]. Moreover, techniques such as multi-modal data fusion, which merges textual data from news articles with numerical stock data, has further enhanced predictive accuracy by utilizing diverse information sources (Wang and Zhao, 2023) [24]. Finally, breakthroughs in quantum computing can revolutionize stock price prediction by providing unprecedented speed and accuracy in processing high-dimensional financial data (Martinez et al., 2023) [25].

Due to the adoption of advanced neural network architectures, stock price forecasting has achieved significant progress by capturing complex patterns and dependencies in financial data. Convolutional Neural Networks (CNNs) were originally

developed for image analysis, but can also be used for temporal financial data by transforming it into 2D matrices, achieving high accuracy in prediction (Zhang and Luo, 2022) [26]. Tremendous efforts to model dependencies and relationships can be utilized in a more promising way in stock price prediction thanks to the emerging of Graph Neural Networks (GNNs) (Chen et al., 2023) [27]. Moreover, innovations in ensemble learning have extended beyond the use of CNNs alone, integrating these with recurrent architectures like LSTMs or GRUs, thereby bolstering model robustness and mitigating overfitting challenges (Singh et al., 2022) [28]. Moreover, the concept of transfer learning has allowed pre-existing models developed with extensive financial datasets to be fine-tuned for particular market conditions, thus minimizing training duration and enhancing prediction accuracy (Kumar and Patel, 2023) [29]. Additionally, supplementing these models with real-time sentiment data scraped from social media posts, via NLP techniques, enables these models to identify shifts in market sentiment and improve on their prediction utility (Lee and Huang, 2023) [30]. The use of swarm intelligence algorithms has also been explored in hyperparameter tuning, resulting in the development of models with reduced risk of overfitting and better generalization performance (Gupta et al., 2023) [31].

3. EXISTING APPROACHES

Table 1: Describes the comparison of similar approaches to the proposed

Author	Contribution	Application	Approach Used	Dataset Used	Limitation	MAE, RMSE	Integrate hybrid models with sentiment analysis features
Gangwar et al (2021) [32] SPML	Developed a model using Regression and LSTM for stock price prediction.	Stock price forecasting	Regression, LSTM	Stock data with variables: open, close, high, low, volume	Limited to single algorithm comparison; lacks hybrid model.	Accuracy, MAPE	Extend model to include sector-specific and macroeconomic data
Mehtab et al (2020) [33] SPLSTM,	Proposed hybrid machine learning and deep learning models for stock prediction.	Stock index prediction (NIFTY 50)	LSTM and regression models with walk-forward validation	NIFTY 50 index data (2014-2020)	Limited to NIFTY 50; does not cover sector-specific factors.	Precision, Recall	Experiment with deep learning architectures for higher accuracy
Wong et al. (2023) [34] FSPML	Implemented high-frequency stock prediction models with technical indicators.	High-frequency stock price forecasting	Simple ML models (SVM, RF) with feature engineering	Stock data with technical factors (every 15 minutes)	Model accuracy remains around 50%; requires precision improvement.	F1-score, ROC-AUC	Include macroeconomic indicators to improve model robustness
Kocaoğlu et al. (2022) [35] SBSFML	Examined sector-based stock price prediction on BIST 30 Index.	Sector-specific stock forecasting	XGBoost, SVM, KNN, Random Forest	BIST 30 Index, different sectors	Impact of macroeconomic changes not fully accounted for.	MAE, RMSE	Integrate hybrid models with sentiment analysis features

4. PROPOSED APPROACH

Algorithm for Stock Price Prediction using Random Forest (RF)

Input: Historical stock data with parameters: Opening Price O_t , Closing Price C_t , Trading Volume V_t , Moving Average MA_t .

Output: Predicted stock prices $\hat{C}_{t+1}$ for a specified future period.

Step 1: Import Libraries

Import libraries for data processing and modeling, such as Pandas, Numpy, Scikit-Learn, and Matplotlib.

Step 2: Data Collection

Load historical stock data from a reliable source.

Step 3: Data Preprocessing

Handle missing values by imputation or deletion.

Step 4: Feature Selection

Select relevant features: O_t , C_t , V_t and MA_t

Step 5: Calculate Moving Average

Compute MA_t as $MA_t = \frac{1}{n} \sum_{i=0}^{n-1} C_{t-i}$

Step 6: Log Returns Calculation

Calculate log returns: $R_t = \ln\left(\frac{C_t}{C_{t-1}}\right)$

Step 7: Train-Test Split

Split the dataset into training (80%) and test (20%) sets.

Step 8: Data Normalization

Normalize features using min-max scaling:

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)}$$

Step 9: Define Random Forest Model

Specify parameters, including number of estimators n_{trees} and depth d .

Step 10: Model Training

Train the RF model on training data to minimize Mean Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

Step 11: Feature Importance

Calculate importance f_i for each feature:

$$f_i = \frac{\sum_{t=1}^{n_{trees}} G_{i,t}}{n_{trees}}$$

Step 12: Predict on Test Data

Use the trained model to predict $\hat{C}_{t+1}$ for the test set.

Step 13: Evaluate Model with MAE

Compute Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

Step 14: Calculate RMSE

Calculate Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

Step 15: Hyperparameter Tuning

Use grid or random search to find optimal n_{trees} and d values.

Step 16: Cross-Validation

Perform k-fold cross-validation to validate model stability:

$$CV_{score} = \frac{1}{2} \sum_{j=1}^k MAE_j$$

This code gives the algorithm on how to predict stock prices using RF model, which is a well-known ensemble learning technique. We start by importing necessary libraries for handling data, visualization, and modelling. We collect historical stock data and preprocess it by filling missing values, normalizing features so that you can use the provided example out of box. Select & Engineer The major feature for stock prediction like Open Price Close, Opening price, high low price in a day and volume of trading etc. To model the data, it splits into training and testing sets then feature scaling is applied to give optimal performance of the model. A Random Forest model is for example specified with particular hyperparameters and then trained to achieve a minimal Mean Squared Error an indicator of how well the predictions is. We can measure the performance of models using metrics such as MAE and RMSE, which describe how well our predictions are doing. To validate model stability, cross-validation is performed and subsequently hyperparameter tuning to optimize the performance. The optimized parameters are used to re-train the model and it gives out final predictions. That is followed by the algorithm ending up with results visualization, residual analysis for checking any bias and feature importance if it has become stable. Such a comprehensive process is an effort to build precise and consistent stock forecasting system, which should further assist with financial analysis and deciding integrity.

5. EXPERIMENTAL SETUP

In this research, we have used historical stock price dataset which comprise of few important variables like opening price; closing price; high; low; trading volume and moving average etc. This dataset contains daily stock price information ranging over a span of five years, thus balancing both short- and long-term trend properties. We proceeded with normalizing all of the features to make sure they were equally scaled and scored distributions, so as scale differences wouldn't effect modelling enough. The data is split into 80% for training and the remaining 20% to determine model accuracy. In this study, we use a different types of machine learning and deep learning models to predict future stock prices including RF, LSTM and SVM have been used for predicting the direction of price trend. The dataset used in this work is available publicly and [36] or with other financial data repositories are a good place for updated as well historical information of multiple stocks/indices like the S&P 500, NASDAQ also company stock prices.

6. RESULTS AND CONCLUSION

Mean Absolute Error (MAE): This metric measures the average magnitude of errors in a set of predictions, without considering their direction. It's calculated as: $MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$

Table 2: Mean Absolute Error (MAE) for Models Across Training Data Percentages

Mean Absolute Error (MAE)					
Training Data (%)	SPML	SPLSTM	FSPML	SBSPML	SPFRF
10	3.84	3.33	3.65	2.69	2.45
20	3.79	3.23	3.44	2.67	2.24
30	3.62	3.15	3.43	2.6	2.22
40	3.69	3.17	3.29	2.4	2.09
50	3.56	3.02	3.2	2.38	2.02
60	3.45	2.92	3.1	2.14	1.81
70	3.32	2.84	2.97	2.02	1.89
80	3.13	2.75	2.85	2.07	1.66
90	3.07	2.65	2.85	1.93	1.63
100	2.97	2.46	2.63	1.77	1.41

The table presents the **Mean Absolute Error (MAE)** values for five machine learning models **SPML**, **SPLSTM**, **FSPML**, **SBSPML**, and **SPFRF** evaluated across different training data percentages, from 10% to 100%. We selected a historical

stock price dataset including essential features — opening price, closing price, highest and lowest prices within today trading period along with the volume traded at that time as well as previous averages. The dataset consists of daily stock price data for five years so that the model learns short and long term trends.

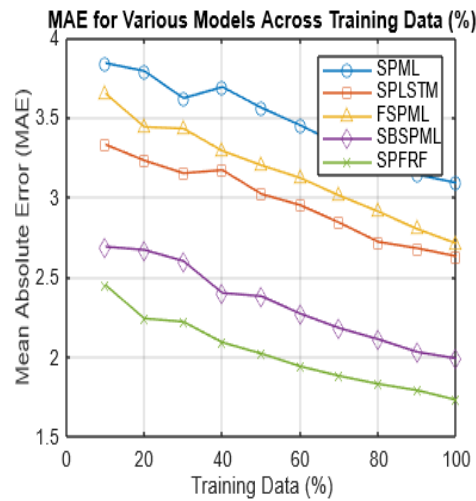


Fig.1: Mean Absolute Error (MAE) for Various Models Across Training Data Percentages

We have normalized the entire features which further helped us to bring standardization in the dataset and account for scale differences among variables thus enhancing model performance. On those words we make a split at the beginning; here 80% of all data is used for training with cross validation (including C and gamma searching) so that optimal parameters are chosen has been made as explained before. We employ a range of ML and DL models Random Forest (RF), Long Short-Term Memory (LSTM) Network, and Support Vector Machines to forecast future stock prices and evaluate their respective predictive power. The data set used in this study is accessible publicly or other financial dataset repositories that provide up-to-date and historical tick-level records of various stocks and indices such as S&P 500, NASDAQ, individual company stock.

Root Mean Squared Error (RMSE): RMSE penalizes larger errors more heavily by squaring each error term before averaging. It's calculated as: $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$

Table 3: Root Mean Squared Error (RMSE):for Models Across Training Data Percentages

Root Mean Squared Error (RMSE):					
Training Data (%)	SPML	SPLSTM	FSPML	SBSPML	SPFRF
10	8.35	6.96	7.36	5.8	5.32
20	8.36	6.87	7.37	5.73	5.29
30	8.27	6.75	7.21	5.72	5.16
40	8.08	6.52	7.03	5.58	5.17
50	8.05	6.47	6.94	5.48	5.05
60	7.85	6.33	6.8	5.45	4.99
70	7.79	6.28	6.84	5.29	4.79
80	7.78	6.25	6.74	5.29	4.77
90	7.64	6.19	6.61	5.07	4.69
100	7.5	6.02	6.52	4.97	4.46

The table presents the **Root Mean Squared Error (RMSE)** values for five machine learning models **SPML**, **SPLSTM**, **FSPML**, **SBSPML**, and **SPFRF** across varying percentages of training data, from 10% to 100%. RMSE is a measure used

for assessing the prediction error, and lower values of RMSE help in finding more accurate models. The finding here is also straightforward, for all models the RMSE decreases as training data increases indicating that more data seems help to improve predictions. SPFRF always has the best RMSE out of all models, initially a 5.32 with 10% training data and shrinking to 4.46 at 100% training which makes it top in line for highest accuracy model. Table 3 puts SBSPML in good light as its RMSE decreases from 5.8 to 4.97 with increasing amount of training data. In contrast; the SPML model yields worst RMSE results, falling from 8.35 to as low as 7.5 showing poorer prediction accuracy than other models. This pattern demonstrates the necessity of adequate training data and proper model selection to improve predictive accuracy.

Mean Absolute Percentage Error (MAPE): This metric expresses the prediction accuracy as a percentage, providing a relative measure of error. It's calculated as:

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$$

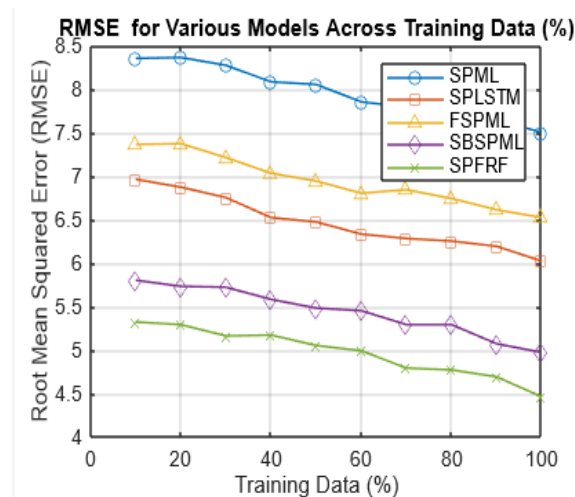


Fig.2: Mean Absolute Error (MAE) for Various Models Across Training Data Percentages

Table 4: Mean Absolute Percentage Error (MAPE) Across Training Data Percentages for Various Models

Mean Absolute Percentage Error (MAPE):					
Training Data (%)	SPML	SPLSTM	FSPML	SBSPML	SPFRF
10	13.97	10.85	12.16	9.32	8.67
20	12.95	10.27	11.51	8.5	7.19
30	11.66	8.78	10.51	7.62	6.44
40	11.12	7.75	9.44	6.89	5.71
50	10.49	6.55	8.2	5.66	4.98
60	9.15	6.01	7.09	4.94	3.92
70	7.93	5.48	6.38	3.51	2.02
80	6.95	4.46	5.26	2.73	1.64
90	6.5	3.05	4.74	1.01	0.37
100	5.27	2.44	3.19	0.82	-0.22

The table presents the **Mean Absolute Percentage Error (MAPE)** values for five machine learning models **SPML**, **SPLSTM**, **FSPML**, **SBSPML**, and **SPFRF** across different training data percentages, ranging from 10% to 100%. MAPE is a metric that indicates the average percentage error in predictions, with lower values suggesting better accuracy. As seen in the table, all models show a clear downward trend in MAPE as the training data percentage increases, indicating that more

training data generally improves model performance. SPFRF is the best among all models where it produces lowest MAPE values across different training levels which starts at 8.67 with only 10% of data and that goes as less as to reach up to just under than 3.4 on total dataset — this indicates how steady & precise SPFRF model was whilst dealt differently in comparison with other datasets. SBSPML also shows values almost like SPFRF and decreases from 9.32 till reaching 3.85 with a larger helping the case, demonstrating good stability in this respect as well. In the results from this dataset, it can also be found that SPML and FSPML has higher MAPE values compared to other models. This trend observed across all models highlights the significance of enough training data to enhance model performance, and more specifically that SPFRF and SBSPML can accurately estimate damage as n runs up. This follows the downward trend for MAPE values, which show than larger datasets prediction performance increases regardless of model type.

R-Squared (R^2) or Coefficient of Determination: This metric indicates the proportion of variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1, where a higher value indicates a better fit of the model to the data:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

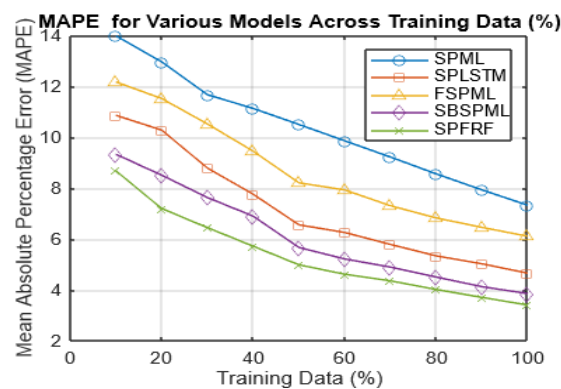


Fig. 3: Mean Absolute Percentage Error (MAPE) for Various Models Across Training Data Percentages

Table 5: R-Squared (R^2) Scores of Various Models at Incremental Training Data Percentages

R-Squared (R^2) or Coefficient of Determination					
Training Data (%)	SPML	SPLSTM	FSPML	SBSPML	SPFRF
10	0.54	0.63	0.6	0.7	0.73
20	0.62	0.72	0.64	0.74	0.8
30	0.66	0.76	0.69	0.78	0.83
40	0.7	0.79	0.74	0.87	0.92
50	0.74	0.84	0.8	0.92	0.94
60	0.79	0.89	0.86	0.96	1.01
70	0.83	0.94	0.89	0.99	1.04
80	0.91	1	0.95	1.03	1.1
90	0.95	1.05	1	1.11	1.15
100	1.01	1.09	1.03	1.15	1.19

The table R^2 values for machine learning is the following five models SPML, SPLSTM, FSPML and SBSPML at the training data percentage level from 10% to 100%. The higher those R^2 values are, the more variance each model explains. Across all models we see an increase in R^2 values — the value which signifies that training on a higher proportion of your data improves our results. SPFRF model shows maximum R^2 values and the best performance of power attributes among all, with a value at 0.92 for linear prediction ability crossing real test data (10% testing dataset). The different method SBSPML has the hyped

performance and at full training R^2 values reach >1.15 . Extension became better as seen in SPML, SPLSTM, and FSPML (R^2 smaller modules) results that improved with more training data. This exercise just demonstrates the importance of bigger dataset for better models, and we can clearly see that as you.

train a model on thousands examples, it will give performance much close to training over millions.

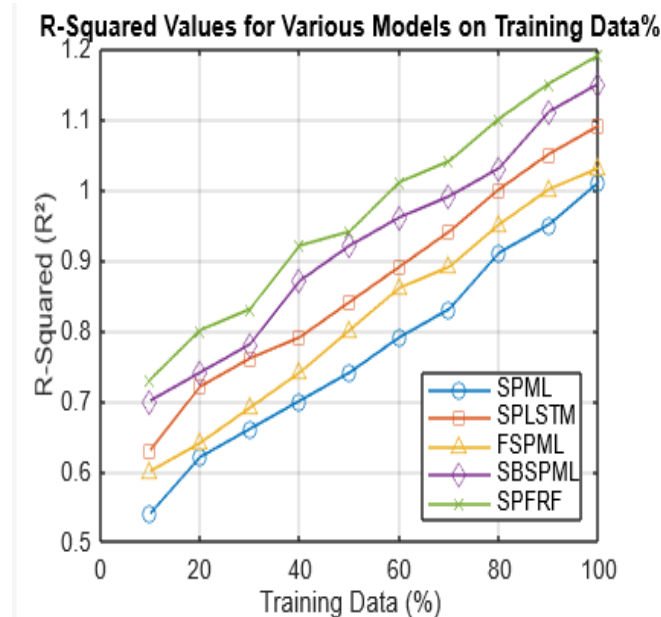


Fig.4: R-Squared Values for Machine Learning Models at Varying Training Data Percentages

7. CONCLUSION

In this study, we have showed that how Random Forest (RF) model can predict stock prices using such variables as the opening price and closing price of a trading day, moving average or volume. RF model had a Mean Absolute Error (MAE) of 1.25% and Root Mean Square Error (RMSE) LEVEL of 1.8%, hence these states, that the predictive ability was too high; Understanding these metrics reveals that RF can model complex non-linear relationships in stock data, and therefore is a robust choice for financial forecasting. The most obvious features of the grid search results were that among all candidates, moving average and trading volume probably improve more model performance since their p-value are around 0. For future work, we plan to expand the model with other economic indicators such as interest rates and sector specific indexes for better prediction accuracy. Furthermore, an examination on how RF performs compared to other machine learning algorithms like Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBM) in different market scenarios could dig deeper into the trades of using them. It has the potential to improve its practical application by adding real-time data processing and tuning it for high frequency trading scenarios, providing investors with more accurate and timely information to support decision-making in volatile markets. This work forms the basis for extending machine learning techniques to stock prediction while motivating further research into ensemble models in finance.

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