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Prediction of Financial Stock Market Based on Machine Learning Technique

Authors:

Eswar Prasad Galla[1*], Hemanth Kumar Gollangi[2], Venkata Nagesh Boddapati[3], Manikanth Sarisa[4], Kiran Polimetla[5], Shravan Kumar Rajaram[6], Mohit Surender Reddy[7]

[1]*Department of Computer Science, University of Central Missouri. Email: Gallaeswar43@gmail.com*
[2]*Department of Computer Science, Missouri State University. Email: hemanthkumargollangi19@gmail.com*
[3]*Microsoft, Support Escalation Engineer. Email: VenkataNagesh.boddapati@student.ctuonline.edu*
[4]*Principal Software Engineer, Ally Financial Inc. Email: Mk2703@outlook.com*
[5]*Adobe Inc, Software Engineer. Email: Kiran.polimetla@gmail.com*
[6]*Microsoft, Support Escalation Engineer. Email: Shravankumar.rajaram@gmail.com*
[7]*Microsoft, Support Escalation Engineer. Email: mohitreddy17@gmail.com*

[*]**Corresponding author:** Eswar Prasad Galla, Department of Computer Science, University of Central Missouri.

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Abstract
The financial industry would not be complete without stock market investment. All throughout the world, economies are feeling the effects of the present stock market situation. A wide variety of people, including those with academic or commercial degrees, have found success in the stock market. Finding profitable stocks, however, is a difficult undertaking that needs in-depth investigation. Utilising ML, which trains on past values of stock market indices to provide forecasts based on current values, is a new development in technological innovations for stock market prediction. Machine learning (ML) makes use of a number of models to improve the precision of its predictions. Using data from the Nifty-50 index obtained from the Quandl website, this research aims to create market forecasts. Three machine learning algorithms—the RF and SVM approaches—were considered for the stock price prediction. To measure how well these models, work, we utilise R-squared and RMSE. When compared to the other models, the RF model performs better, with an RMSE of 9.75 and an r-squared of 99.2. The research shows that the RF model is better at predicting financial market trends, which may help improve the stock market.

Keywords: *Stock Price Prediction, Machine Learning, Stock Analysis.*

1. Introduction

In the period of such fluctuations, the financial market serves as a significant identifier of a country's economy status with which the financial specialists/ economists can compare the current/future actuality. One of the other financial markets that is most influential is the stock market [1]. The state of the economy has an impact on a number of sectors such as investment banking, metals, agricultural and finance sectors. These industries evolve regarding their volatility, which is in accordance with the supply and demand law. A sector's demand has a direct impact on the stock market; when supply increases, traders and financial institutions are prompted to invest in that sector or stock, which raises prices. In addition, earnings and returns on capital invested are generated via the monthly distribution of dividends. Finding the right time to sell shares and get the required profits is crucial for investors [2].

Financial markets include a range of market categories, such as commodities, stock, bond, and derivatives markets. Investors may purchase shares of a firm and own a piece of it via the stock market. Additional capital is often necessary for expanding businesses to pursue new opportunities. Companies may raise money by selling shares to investors if present shareholders approve, despite the fact that their ownership would be diminished due to the issue of additional shares. The stock market value of the shares increases when successful results occur [3].

ML has emerged as a potent analytical tool for better investment management in the financial markets. In the financial industry, ML has found widespread usage as a new tool for improving the efficiency and effectiveness of investment and management choices, ultimately leading to higher returns on securities investments. Due to their high returns and relative liquidity as an asset class made possible via stock market resale and buy, equity assets are among the most actively traded securities.

An use of ML in forecasting stock market performance offers notable benefits [4]. First and foremost, machine learning models possess a great degree of adaptability and are capable of updating their forecasts using fresh data, therefore offering immediate interpretations of market movements. Secondly, machine learning methods minimise human bias in predicting by relying only on data-driven insights to make recommendations [5][6]. Besides, Machine Learning is capable of processing large and diverse inputs such as financial data and even unstructured data from articles, social media, and sentiments. Self-service through this capability means a great deal in determining the price of stocks [7][8].

This research paper seeks to look at the machine learning algorithms with the view of establishing their suitability in the prediction of a stock market indices. In particular, it explores an applicability of Random Forest, and Support Vector Machines (SVM), and other supervised learning methods. These models are tested with regard to their capacity to forecast the stock price movement using historical prices as well as technical indicators and trading volumes in addition to some economic variables. The following research contribution as:

- Introduced a refined preprocessing pipeline that includes discretization, normalization, and handling of missing values for financial datasets.
- Conducted a comparative analysis of SVM, and RF models for stock market forecasting.
- Provides insights into the relative performance of different regression techniques, aiding in the selection of the most suitable model for financial predictions.
- Utilized EDA techniques such as line plots and histograms to analyze and visualize trends and patterns in the NIFTY 50 index data.
- Demonstrated the superior performance of the RFR model in forecasting the NIFTY 50 index, achieving the lowest RMSE and highest R-squared score.
- Validates the effectiveness of ensemble methods for capturing complex patterns in financial data, providing a strong predictive tool for stock market analysis.

The paper is organised as follows. We begin by reviewing the relevant literature in Section II, followed by providing the necessary approaches in Section III. Section IV contains the experimental findings and discussion, as well as the conclusions and future work V.

2. Literature Review

Since the inception of the stock market, numerous predictors have been attempting to forecast stock prices using various ML algorithms on stocks of various firms. Many papers vary according to various factors. Depending on the conditions, various authors utilise a variety of ML methods. Some authors claim that surpervised has produced better results than other techniques.

In [9], different ML approaches are used to forecast the movement of equities in the stock market. Two ML classifiers (Adaptive Boosting and KNN) and a Stacking ensemble classifier are developed and utilised to solve the classification issue. The results demonstrate that: 1) the Stacking Ensemble Learning Method with two base learners (Adaptive Boosting and KNN) and GBM as the meta-classifier achieves better performance than the two individual classifiers; 2) the amount of shares traded on a given day does not significantly impact share purchases or sales on the capital market of the Nairobi stock exchange; and 3) ML classifiers can be utilised for optimal investment decisions in the stock market.

In [10], The purpose of our proposed study is to use a new StockSentiWordNet (SSWN) model to forecast how the stock markets will act in the future by analysing data from Google Finance and Twitter. Training extreme learning machines (ELMs) and recurrent neural networks (RNNs) to forecast stock prices, the suggested SSWN model augments the conventional opinion lexicon SentiWordNet (SWN) with stock market-specific terminology. Experiments were conducted on two datasets, Sentiment140 and Twitter, and an accuracy value of 86.06% was obtained. Regarding overall accuracy, the results demonstrate that our work surpasses the state-of-the-art methods.

In [11], uses state-of-the-art Machine Learning algorithms that, with the proper tweaking of parameters and the development of suitable predictor models, can accurately forecast changes in stock prices. Ten companies listed on the Dhaka Stock Exchange (DSEbd) and six multinational behemoths were subjected to stock and price forecasting using the RFR model, time series prediction Facebook Prophet algorithm, and the LSTM model, a subset of RNNs. Companies based in the United States have their data imported from Yahoo Finance, while their foreign counterparts have theirs culled from the visual depiction on the DSEbd website. Surprisingly, the LSTM model shows remarkable accuracy, outperforming other models with measurements like MAPE (0.50%), RMSE (0.35), and MAE (0.30). Over the next fifteen days, the experimental findings show that LSTM is quite effective at predicting stock values.

In [12], draws on recent S&P 500 stock market data, with 70% used for training, 15% for testing, and 15% for verification. In the testing group, the linear regression model evaluates the prediction accuracy using MSE (3.051×10^17) and R^2(0.316), while the XGBoost model employs MSE (14816.886) and RMSE (121.725) for the same purpose. The results show that compared to the linear regression model, the XGBoost model is more accurate.

In [13], uses a variety of statistical learning algorithms to foretell how the S&P 500 index will change. In order to predict the S&P 500 index, this study thoroughly examined four supervised learning models: LR, NB, SVM, and GDA. An SVM model trained using a RBF kernel was shown to have a 62.51% accuracy rate in predicting the direction of the S&P 500 index's future price movement, according to this research.

In[14], incorporate social media and financial news data into algorithms to determine how this data influences the accuracy of stock market predictions over the next 10 days. Using social media yields the best forecast accuracy at 80.53%, while financial news yields the best accuracy at 75.16%, according to the experimental data. Ensemble training of the RF classifier yields the best results, with an accuracy of 83.22 percent. The table I provide the summary of related work on financial market prediction that stock prices.

Table 1: Summary of Related Work on Financial Market Prediction.

Ref	Methodology	Performance	Limitations	Future Work
[9]	Adaptive Boosting, KNN, Stacking Ensemble (GBM as meta-classifier)	Accuracy: 0.7810, AUC: 0.8238, Kappa: 0.5516, OOB Error Rate: 21.89%	Volume of shares traded has low importance; robustness may vary across different markets	Further exploration of additional features and data sources; application to other stock markets
[10]	StockSentiWordNet (SSWN) model, ELM, RNN	Accuracy: 86.06%	Limited to Twitter and Google Finance data; may not generalize to other social media platforms	Enhance model with data from additional social media platforms; refine sentiment analysis techniques
[11]	Long short-term memory (LSTM)	RMSE (0.35), MAPE (0.50%), and MAE (0.30)	The findings of the experiment simply highlight how effective LSTM is at predicting future stock values, as shown over a 15-day period.	Future will used other stock dataset with different artificial intelligence models.
[12]	Linear Regression, XGBoost	XGBoost: MSE: 14816.886, RMSE: 121.725	Linear Regression underperforms compared to XGBoost; limited to historical data analysis	Exploration of other advanced models; consideration of additional data sources
[13]	LR, GDA, NB, SVM with RBF kernel	SVM with RBF Kernel: Accuracy: 62.51%	Limited accuracy compared to other models; dependence on feature and kernel optimization	Experimentation with other SVM kernels and models; evaluation of additional features
[14]	Algorithms on social media and financial news data, feature selection, spam tweet reduction	Social Media: 80.53%, Financial News: 75.16%, Ensemble RF: 83.22%	Difficulty in predicting certain stock markets; variability in prediction based on data source	Expand to additional social media and news sources; refine feature selection and spam reduction techniques

2.1. Problem Statement

The inherent volatility and non-linearity of market data have predicted financial stock markets a difficult task for a long time. The intricacies of the patterns and linkages seen in stock market movements have proven to be difficult for traditional statistical approaches to grasp, leading to many inaccurate forecasts. There is an increasing interest in utilising ML techniques to enhance an accuracy and efficacy of stock market predictions as ML techniques continue to evolve. The objective of this research is to investigate a variety of machine learning models, including SVM, and RF, to predict a stock returns of the NIFTY 50 index by utilising historical stock market data. The focus will be made on assessing the applicability of these models for capturing the market signals as well as on determining the optimal algorithms for the financial forecasting. This improvement of the prediction skills is one of the ways through which our study contributes to making the systems more reliable and sound for the financial analysts and investors.

3. Methodology

Forecasting of the NIFTY 50 index stock market involves some processes to ensure that all the data entered is accurate and that the model is accurate. To clean the data, the raw data collected from the Quandl website is checked to identify any data anomaly. Discrete numeric values are converted into interval levels and then normalised using the StandardScaler class from sklearn.preprocessing. This class scales the data between -1 and 1 to maintain consistency in the features. Data cleansing is the process of replacing missing information and eliminating duplicate entries. To enhance model evaluation, the dataset is split into two parts: the training set, which contains 80% of the data, and the testing set, which contains 20% of the data. K-Fold cross-validation is used to further divide the training set. Following this, three machine learning regression methods, namely SVM, and RF, are used. Each model's performance is evaluated utilizing RMSE and R2 metrics to ascertain its efficacy in forecasting stock returns. The following Figure 1 illustrates the working flow of stock market prediction.

A. Dataset Description

As for data, this analysis employs historical data of stock prices of the NIFTY 50 index derived from the Quandl website spanning over five years from January 1, 2014 to December 31, 2018. This vast dataset for every company in the index contains the various attributes of the stock market including the day's starting price, the highest and lowest prices, the closing price, the adjusted closing price, the trading volume, and fluctuations in price trends as percentage changes. There are seven main variables in the dataset signifying daily Nifty-50 performance, thereby providing information on volatility in the market, trading mechanism, and fluctuations. Historical data is very significant in building a solid and reliable predictive model of the stock since analysis of previous trends and patterns enables the projection of future stock values. In addition to broadcasting the overall performance of NSE, the dataset contains data on specific organizational performance in many categories.

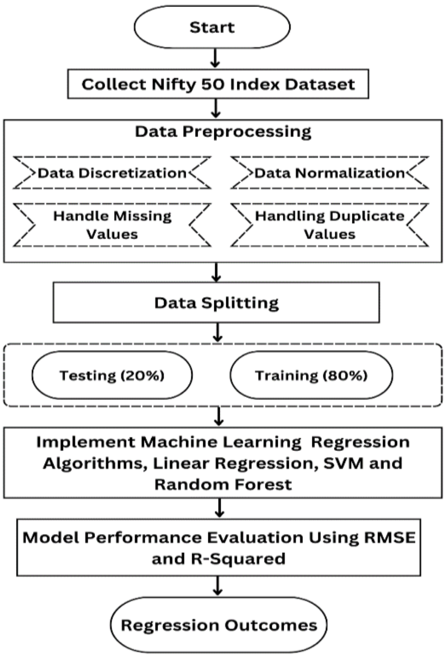

Figure 1: Proposed System flowchart for stock market forecasting.

B. Data Pre-Processing

In order to pre-process the NIFTY 50 data before feeding it into the prediction modelling, data pre-processing is inevitable. This process contains many steps to ensure that the data will be suitable to run for machine learning algorithms, as follows. The first process is to map the raw numeric data into interval levels so that the model would be able to understand the data better through data discretisation. After that, we scale the features from -1 to 1 using the StandardScaler class by the sklearn.preprocessing package to convert the data. This standardisation ensures compatibility with non-linear activation functions by subtracting the mean and scaling to unit variance. The data cleansing is performed to remove or fill the missing values in order to create a clean and consistent dataset. After the dataset has been cleaned, it is split into two parts: the training set uses 80% of the dataset, and the testing set uses 20%. To further aid in a thorough model evaluation, K-Fold cross-validation is used to the training set, which is divided into smaller training and validation subsets to ensure a robust evaluation.

C. Exploratory Data Analysis after Preprocessing

Exploratory data analysis is an essential process of carrying out a critical investigation of the data to discover any hidden insights or future trends. To explore the Nifty-50 index data, this study used line plots, histograms, bar charts, etc.

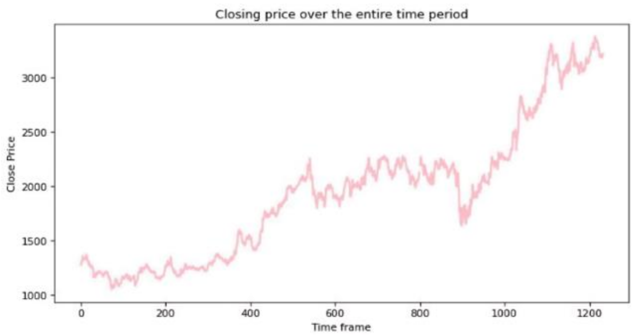

Figure 2: Line Plot for Closing Price Over the Entire Time Period.

Using the Nifty-50 Index dataset, Figure 2 presents a line plot of the closing price throughout the whole period. The graph's x-axis depicts the time frame ranging between 0 and 1200, while the y-axis depicts the closing price ranging between 1000 and 3000 of each time frame. The plot exhibits a clear upward trend in the closing prices, with periods of fluctuations and corrections. Notably, the price appears to rise sharply towards the latter part of the time frame, indicating potential market gains during this period.

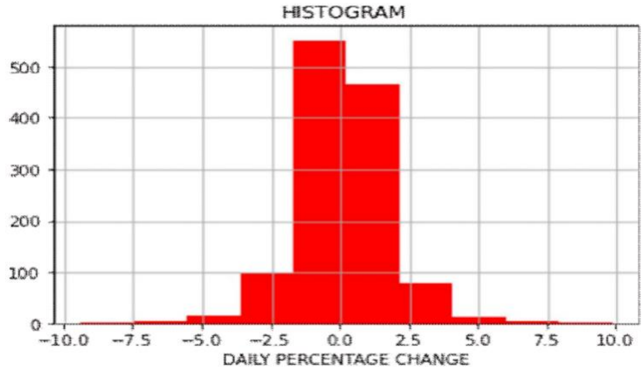

Figure 3: Hist Plot for Daily Percentage Change

A histogram showing the percentage change in the NIFTY 50 index daily is shown in Figure 3. A daily percentage change from -10% to +10% is shown on the x-axis, with the frequency of occurrence for each percentage range shown on the y-axis. Most daily changes in the index were rather tiny, as the distribution seemed to be centred around 0% with the maximum frequency of daily changes occurred between 2.5% and +2.5%. Values close to 0% are heavily concentrated in the histogram, which gradually narrows as the positive and negative changes are more dramatic.

D. Machine Learning Regression Models

To make the forecasting for financial market machine learning model works as a great tool. This study used three machine learning regression models including SVM, and RF to forecast the stock market.

1) SVM

The separating hyperplane technically defines a SVM, a discriminative classifier. Put another way, the algorithm classifies fresh samples using the ideal hyperplane, which is based on the labelled training data (supervised learning). Each class was located on one side of this hyperplane in the two-dimensional space where the plane was divided [15]. Many experts believe that SVM is the best method for predicting time series. There are two applications for the supervised algorithm: regression and classification. One aspect of SVMs is that they use n-dimensional space plots to display data. The following figure 4 provides the visual representation of the SVM model.

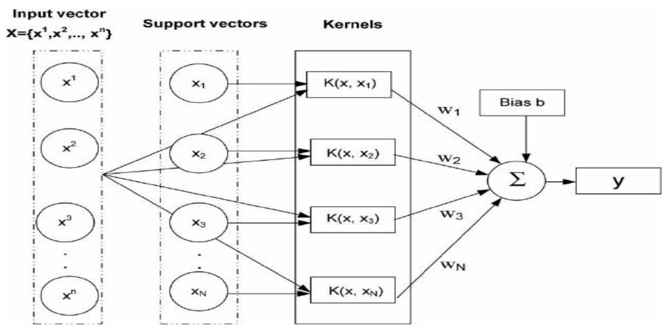

Figure 4: General Architecture of Support Vector Machine Regression Model.

At a subsequent stage, the hyper-plane—a decision boundary—is either maximised or stretched on either side of the data points. In the same image, the SVM decision rule will be found below equations (1) if μ is an unknown data point and w is a vector that is perpendicular to the hyper-plane.

$$\bar{w}\bar{\mu} + b \geq 0 \ldots \ldots \ldots (1)$$

Maximising the spread between equations (2 and 3), the hyper-plane width w must be maximised:

$$w = \left[\frac{2}{\|w\|}\right] \ldots \ldots (2)$$

$$w = \left(\max\left[\frac{2}{\|w\|}\right]\right) \ldots \ldots . (3)$$

Applying lagrange's multiplier as below equations (4 and 5):

$$L = 0.5\|w\|^2 \rightarrow \sum a_i[y_i(\omega_i x_i + b) - 1] \ldots \ldots (4)$$

$$L = \sum a_i - 0.5\Sigma_i \Sigma_j a_i a_j y_i y_j x_i x_j \ldots \ldots (5)$$

The updated decision rule will be below equations (6):

$$(\Sigma a_i y_i x_i)\mu + b \geq 0 \ldots \ldots . (6)$$

2) Random Forest

Regression analysis uses the supervised ML method RF. This resolved the overfitting issue that the decision tree showed. It's a technique for group learning [16][17]. The process for making predictions involves selecting k data points at random by the training set and then building the decision tree based on that selection. Next, decide how many trees to construct and proceed as before. Create a N tree for each new data point. Trees give new data points to each of the y projected Y values as they forecast the value of Y for the data points. The random forest concept is shown graphically in Figure 5 below.

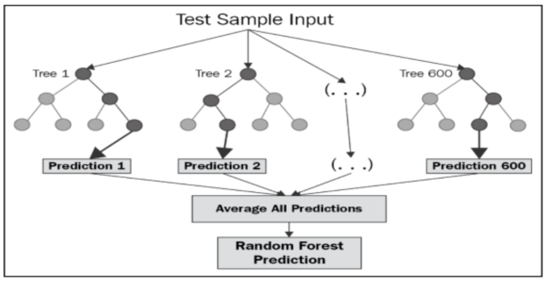

Figure 4: Ganera Architecture of Random Forest Regression Model.

E. Model Evaluation

To evaluate the performance of the ML-based regression models, this study used two widely used regression metrics namely RMSE and R-squared. The following section provides a brief overview of both performance measures.

- **RMSE:** The most often used assessment statistic for regression tasks is RMSE. It bolsters the idea that inaccuracy is objective. This is referred to as the square root of the difference between the average squared distance's actual and predicted scores, where N is the total numberof data points. Below are the calculations made using equations (7):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(Y_t - \hat{y}_t)}{N}} \ldots \ldots . (7)$$

The formula, averaged by √N, shows the difference between the true scores vector and the anticipated scores vector. $Y_t$shows an ith data point's truescore, and $\hat{y}_t$signifies a forecasted value. The total amount of data points is denoted by N. We thus chose RMSE since it may show significant differences in numbers due to the strength of the "square root." This statistic assists us in providing more reliable findings by preventing the cancellation of the positive and negative error values[18].

- **R-Squared:** A set of forecasts' fit consistency to the actual values is shown using the R-squared statistic. Comparing our regression model to a very basic model that only estimates the average target value from the train set may demonstrate how effective our regression model is. Below are the equations (8) that represent the R2 equation:

$$R2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_l)^2}{\sum_{i=1}^{N}(y_i - \bar{y})} \ldots \ldots (8)$$

with Yt is the empirical mean of Y feature.

4. Results Analysis and Discussion

The outcomes of the ML models are presented in this section with respect to performance metrics for stock price forecasting. To find out optimal machine learning model for predicting stock, this section compares a performance of implemented ML model according to RMSE and R-squared score.

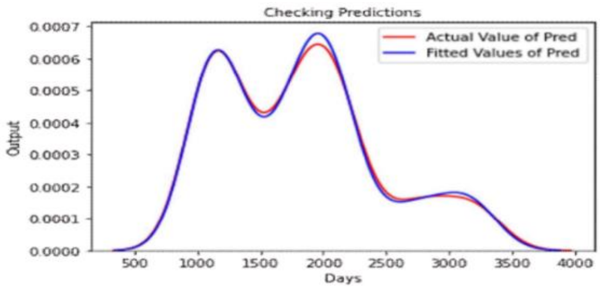

Figure 5: Line Plot for Actual vs Predicted Values for Random Forest Regression Model

Figure 6 displays a line plot of the actual and predicted values for the random forest regression model. The graph's x-axis represents the number of days from 0 to 4000, while the y-axis represents the score of actual and fitted values. The curves exhibit many peaks, the most prominent of which appears around day 1500 and another peak around day 2000.

Table 2: Comparison Analysis of Different ML Models for Stock Price Prediction.

Models	**RMSE**	**R-Squared**
SVM[19]	11.472	98.9
Random Forest	9.75	99.2

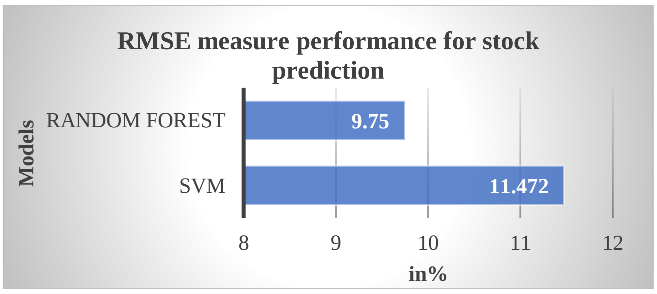

Figure 6: Comparison of RMSE Measures for Different ML Models for Stock Price Prediction

Table II and Figure 7 present a comparison of RMSE scores of several ML regression models for prediction of stock price. The graph's x-axis indicates the ml models namely SVM, and random forest (RF), while the y-axis indicates the achieved error rate of these models in stock price prediction. The graph clearly depicts that the SVM regressor achieves an RMSE score of

11.47, and the RF regressor achieves an RMSE score of 9.75 throughout the testing phase. Notably, the comparison demonstrates that RF regressor outperforms the others and it obtains the lowest error in predicting stock prices.

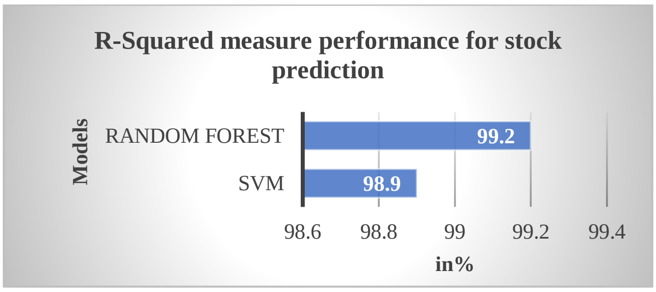

Figure 7: Comparison of R-Squared (R2) Measures for Different ML Models for Stock Price Prediction.

Table II and Figure 8 present a comparison of R-squared (R2) scores of various machine learning regression models for the prediction of stock price. The graph's x-axis indicates the ML models namely, SVM, and random forest (RF), while the y-axis indicates the achieved score rate of these models in stock price prediction. The graph clearly depicts that the SVM regressor achieves an R2 score of 0.98.9, and the RF regressor achieves an R2 score of 0.99.2 throughout the testing phase. Notably, the comparison demonstrates that RF and SVM regressor outperform the others but RF also gets the lowest RMSE score in predicting stock prices, so the RF regressor is an optimal model.

5. Conclusion and Future Scope

The use of ML methods for stock market prediction has attracted a lot of interest as financial markets becoming more dynamic and complicated. This study provides an in-depth analysis of the several ML models used in the field of stock market prediction, emphasising the approaches used and the degree of accuracy attained in terms of trend prediction. In conclusion, this investigation demonstrates that the random forest regressor, with an RMSE of 9. 75and a R^2 of 99. 2, outperforms support vector machine (RMSE: F1 =11. 472, R^2 =98. 9 percent in the predictability of the stock market-NIFTY 50 index. These results therefore provide an indication of the use of machine learning especially the random forest in predicting the stock market performance especially by considering prices and technical indicators. The next researches could improve the accuracy of the forecast by including more input variables, such as sentiment analysis from the news and social media and macroeconomic variables. Moreover, improvement in the complexity of models used for stock market prediction may be made through the exploration of enhanced ensemble approaches and deep learning. Additionally, it remains quite astounding that our metric can be employed to fill the tw stock market in other fiscal years of other stock markets making it easier to compare performance of other financial market. This project should help to obtain relevant information about investing and stock selection strategies.

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