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# Strategic Selection of Machine Learning Models for Short-Term Trading Optimization

**Suman Halder[1], Debjyoti Bagchi[2], Anirban Samanta[3], Debarghya Mondal[4], Subhradeep Samanta[5], Shreya Hati[6], Abhishek Kundu[7]**

[1,2]Assistant Professor, CSE Department, Calcutta Institute of Engineering and Management, Kolkata
[3,4,5,6,7]Final Year Student, CSE Department, Calcutta Institute of Engineering and Management, Kolkata

**Abstract**

Stock market prediction is a key aspect for a financial analyst and investor, as it facilitates better decisions and improved investment strategies. Towards this end, this project compares how machine learning (ML) models perform in predicting stock market prices with relatively small dataset sizes so as to get the best performing one. This study evaluates the efficiency and accuracy of artificial neural networks, support vector regression, LSTM and decision trees in capturing market trends and forecasting stock movements. The importance of our proposed paper lies in its potential to demystify the complexities of financial markets for students and new entrants in the field of finance. Participants can garner practical insights on how the stock market operates and the application of theoretical ML concepts to financial analytics by identifying the best-performing ML models with limited datasets, which is a common occurrence in real-life situations. This paper aims to analyse the commonly present machine learning models in stock market prediction and choose the most effective model depending upon their performance, which is achieved using limited information (short term data). This would provide an edge in taking small (less-risky) informed financial decisions without extensive study of the stock market.

**Keywords:** Stock Market, Machine Learning, Random Forest (RF), Support Vector Regression (SVR), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM).

## 1. Introduction

In today's financial markets, predicting stock movements is crucial for investors and analysts. For the students learning about finance, tapping into the potential of machine learning for stock market forecasting is not just a theoretical exercise but a valuable skill with real-world impact. This project delves into stock market prediction by comparing different machine learning models, offering guidance for students entering the field with advanced ML techniques. This project aims to explain the advantages of using predictive analytics in financial decision-making and how these skills can give a competitive advantage in the world of investments. For students, there are multiple benefits. First, learning about stock market prediction allows them to apply the theoretical knowledge they have gained in finance and machine learning courses in a practical way. This not only improves understanding but also helps them see how these subjects come together to produce valuable insights in real-world situations.

**Figure 1: Bull-Bear Stock Market**

Additionally, students can gain a better understanding of how the stock market operates by investing small amounts and earning returns without taking on too much risk. Understanding bull markets can aid in recognizing growth trends, whereas knowledge of bear markets can help in managing downturns effectively.

Furthermore, we investigate the diverse array of ML models employed for stock market prediction, offering a comprehensive comparison of their common features, strengths, and weaknesses. This project explores a range of approaches, from simple linear regression to advanced neural networks, to help identify the best model for different market conditions. By comparing machine learning models across various papers, the goal is to improve understanding of predictive algorithms and promote critical thinking in assessing their effectiveness. By analysing the performance of the models under various conditions, this paper serves as a guide for those looking to use machine learning in stock market prediction. It bridges the gap between theoretical knowledge and practical application, empowering aspiring financial analysts with the skills they need to interpret market patterns and confidently make informed financial decisions.

Till now, various work has been done related to the Stock Market Prediction. After analysing such papers available on the internet, we have selected some stock market prediction models along with two different papers that focus on reviewing the stock market prediction models that are present in the market. On analysing further, we found that:

With reference to Hiransha M. and team's paper [1][2][3] on Stock Market Prediction using different machine learning models, the study suggests the following advantages and disadvantages and can be concluded, i.e. CNN and other models performed better in capturing abrupt changes in stock prices. However, a probable disadvantage is the complexity and computational cost of the models, which are resource-intensive.

The subsequent paper by Kang Zang and team's paper [4][5][6] of Stock Market Prediction using a Generative Adversarial Network, when analysed, we concluded following advantage and disadvantage i.e. GANs perform better than other models (LSTM, ANN, SVR) in terms of MAE, RMSE, MAPE and AR and also provide better trend matching capability than other models but the problem that GANs have is that it generally need huge data to train and it also very difficult to interpret and understand due to adversarial nature and this makes it difficult to identify its potential bias and errors.

The paper by Mehar Vijh and her team [7][8][9] upon analysis we can draw the following advantages and disadvantages, Artificial Neural Network (ANN) show better performance in predicting the next day close price than random Forest in terms of RMSE (0.42), MAPE (0.77) and MBE (0.013) whereas Random Forest (RF) provides more advantages in terms of simplicity and interpretability, but the problem is that ANN is more complex, ANN requires a huge amount of data and RF has lower accuracy and limited flexibility.

The paper by M. Nabipour and his team [10][11][12] upon analysis we can draw the following advantage and disadvantage, Ensemble methods like Bagging, Random Forest, AdaBoost, etc. generally outperform

Decision Tree and give faster prediction times compared to neural network, whereas LSTM or RNN generally achieve better predictions than this model.

In the paper by Xiao Zhong and his team [13][14][15] upon analysis we can draw the following advantages and disadvantages, Deep Neural Network (DNN)-based classifiers achieve higher accuracy than Principal Component Analysis (PCA), but DNN with an increased number of hidden layers and neurons can significantly increase computation time. In cases of limited data, DNN is not the best choice rather, PCA or ANN can be used to get good accuracy.

Achyut Ghosh and his team [16][17][18] explored the application of Long short-term memory (LSTM) on the Indian Share market and upon further examination, we found out that LSTM has the capability to learn or capture long term dependencies in time series data, which makes it suitable for analysing stock market data, and it can outperform other models, including CNN and other classical linear models. However, LSTM model performance is more effective in long term dependencies, but it may encounter challenges in small term fluctuation and sudden market change due to natural occurrences such as market rumours and external economic factors.

In the paper authored by Bruno Miranda Henrique and his team [19][20][21], our analysis indicates that Support Vector Regression (SVR) using both linear and radial kernels can outperform random walk models in daily price predictions, and the errors encountered by the SVR model can be used for risk management strategies, such as setting an exposure limit. Though SVR is sensitive to data quality issues like missing data and outlier, which may hamper its performance. Also, it should be noted that SVR only considers limited data periods.

In the following research paper, led by Suryoday Basak and his team [22][23][24], we found out upon further analysis that the use of random forests and gradient boosted decision tree allows for more accurate predictions of stock prices compared to existing methods. The authors adopted the problem as a direction-predicting problem, i.e. focusing on gains and losses rather than predicting a specific price value.

Issac Kofi Nti and his teammates [25][26][27] evaluated the stock market prediction by using ensemble learning, we found out that ensemble techniques like stacking, blending, DT ensemble classifiers, etc. demonstrate superior accuracy in prediction for, e.g. DT ensemble classifiers by boosting (DTBotc) and bagging (DTBagc) obtain an accuracy of 99.98% with (10-200) estimators over the GSE, BSE, and NYSE datasets. But these are often computationally expensive due to prolonged training and testing.

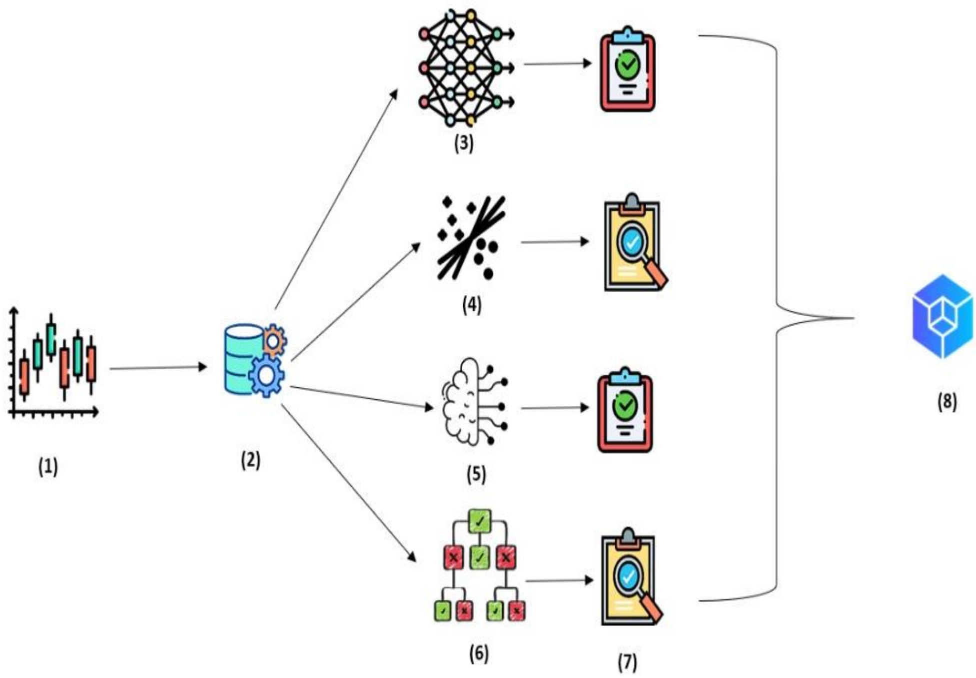
The paper by Sikkisetti Jyothirmayee and his teammates [28][29][30], upon analysis, found out that they used a supervised classification methodology with 80% data for training and the remaining 20% for testing. They utilized algorithms such as Support Vector Classification (SVC), K-Nearest Neighbours (KNN), Bernoulli Naïve Bayes and Random Forest (RF). They used different methods to calculate different parameters, such as F1 score, Precision etc. Among all other models used in this paper, SVC performed with higher accuracy.

Upon analysis of these papers, we identified various models that are used for different purposes and predictions that have been mentioned till now. In our further study, we have narrowed down the models that were frequently used in this paper for further analysis and study. These models are –

1. Random Forest (RF)
2. Support Vector Regression (SVR)
3. Artificial Neural Network (ANN)
4. Long Short-Term Memory (LSTM)

While there are existing review papers that analyse prediction models, this particular review paper focuses on commonly used machine learning stock predictions from those papers. The goal is to examine, analyses, and compare the accuracy of these models to determine which one performs better in the current market conditions. In this review paper, we analyse the effectiveness of machine learning models in predicting stock market trends. We discuss different ML techniques, such as neural networks, support vector machines, decision trees, and ensemble methods. By comparing and categorizing existing research, we evaluate the predictive capabilities of each model and examine their strengths and weaknesses. While neural networks are great predictors, they need a lot of data and can overfit. Support vector machines are excellent for high-dimensional data. Decision trees are easy to understand but not very complex to implement due to the large number of possible parameters. Ensemble methods improve accuracy but can be computationally expensive. This analysis compares different machine learning approaches for stock market prediction, providing valuable insights for researchers and practitioners.

**Figure 2: Comparative Analysis of Stock Market Prediction Models**

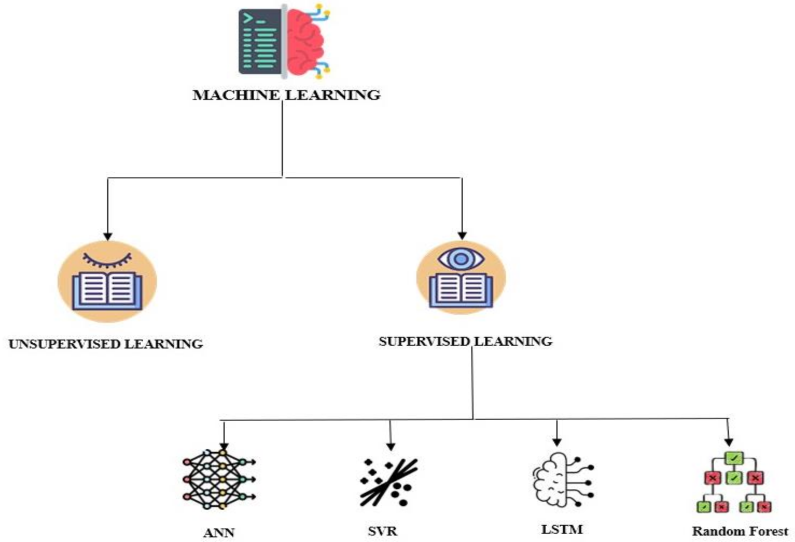



(1): Share/Stock Market Data (2): Data Collection (3): ANN (4): SVR (5): LSTM (6): Random Forest (7): Different Outputs from Different Model (8): Selected Model out of four

## 2. Methodology

Machine learning is a branch of artificial intelligence that enables systems to learn from data and enhance their performance without the need for explicit programming. It works by using algorithms to recognize patterns and connections in data in order to make predictions or decisions. There are three main types of machine learning techniques: supervised learning, unsupervised learning, and reinforcement learning.

**Figure 3: Machine Learning**




Supervised learning is when the algorithm learns from data that has been labelled, meaning each input is matched with a specific output. This type of learning is crucial for predicting stock market trends, as it allows models to analyse historical data with known results to identify patterns and connections between different market indicators and upcoming price changes. By examining factors such as previous stock prices, trading volumes, economic indicators, and sentiment analysis, supervised machine learning algorithms can be programmed to forecast future stock prices.

Utilizing supervised machine learning (ML) in stock market prediction is valuable because it can adapt to unfamiliar data and provide precise forecasts for upcoming stock prices. Through supervised ML's training on categorized data, it can identify intricate connections and trends within the market. This enables investors and financial experts to discover potential market patterns and make well-informed investment choices. This feature is essential in the fast-changing and unpredictable setting of financial markets, where precise predictions can result in substantial financial profits or losses.

### 2.1 Explanations of models

Random forest is a type of machine learning model that creates several decision trees and then merges their predictions to achieve more precise and reliable results. To build each decision tree, a random subset of the training data and features is used. The final prediction is determined by averaging or voting on the predictions made by each tree. This approach helps prevent overfitting and enhances the model's accuracy. Random forests have several benefits. They are good at dealing with big datasets that have many variables. They are also less likely to overfit and can give insight into which features are most important. However, there are drawbacks. They can be hard to interpret because of the many trees involved, and training them can be computationally intensive.

### 2.2 Random Forest

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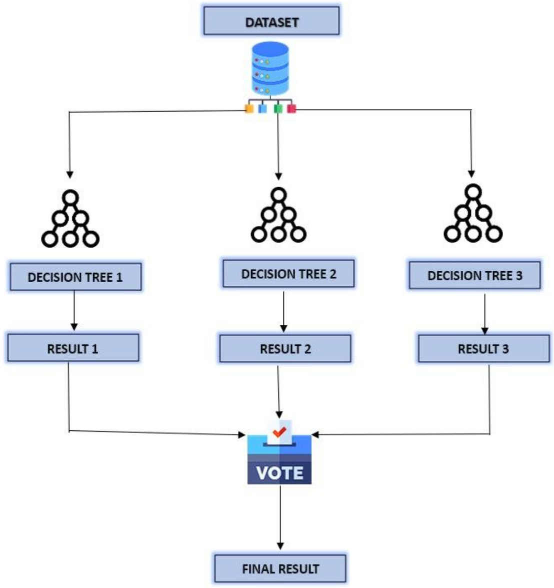
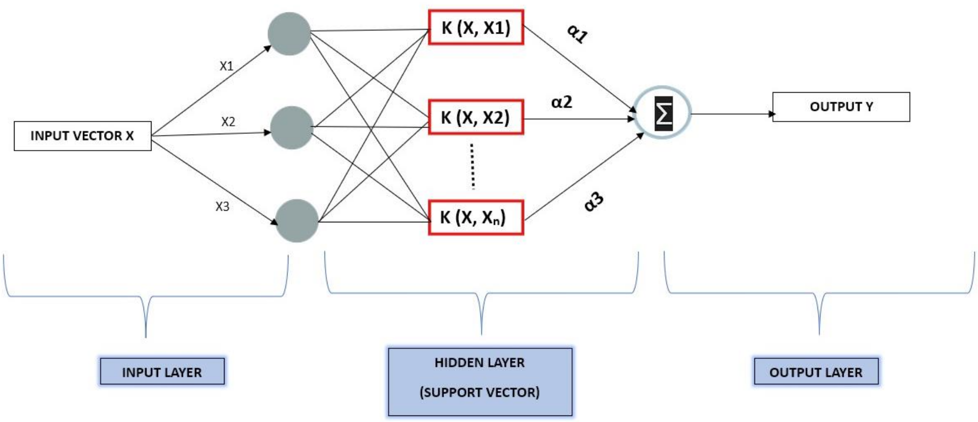
**Figure 4: Random Forest Model**




### 2.3 Support Vector Regression (SVR)

Support Vector Regression (SVR) is a machine learning tool that is commonly used for regression tasks, with the objective of predicting continuous outcomes. SVR operates by identifying the best hyperplane that can effectively fit the given data points while reducing errors. In contrast to standard regression methods, SVR places emphasis on identifying a margin around the hyperplane where errors are allowed, treating data points outside of this margin as support vectors. Support Vector Regression (SVR) has several benefits. It can handle non-linear relationships using kernel functions and is effective in high-dimensional spaces. SVR is also robust to outliers because it focuses on support vectors. On the other hand, there are drawbacks to consider. Tuning parameters like the regularization parameter and kernel parameters is necessary and can affect the model's performance. Additionally, dealing with large datasets can lead to computational complexity.

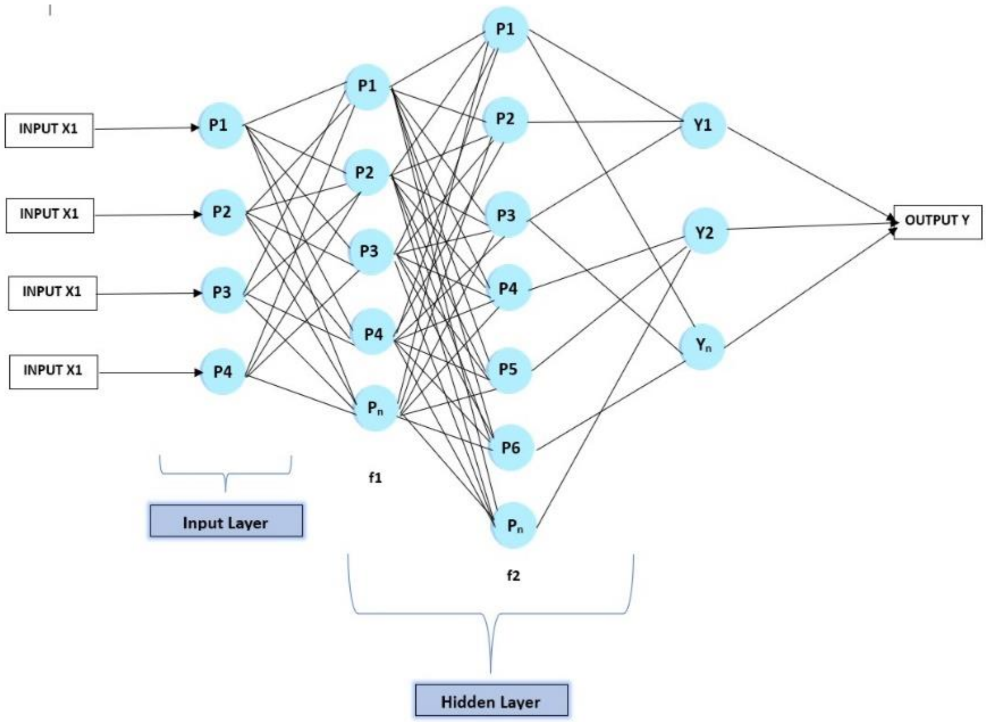
**Figure 5: Support Vector Regression (SVR) Model**




### 2.4 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are a type of machine learning model that takes inspiration from the way the human brain works. ANN is made up of interconnected nodes, called neurons, that are arranged in layers, including input, hidden, and output layers. These neurons communicate with each other by sending information back and forth, with each neuron receiving input, processing it, and then passing it along to the next layer. By undergoing a training process, ANN is able to modify the connections between neurons in order to improve the accuracy of its predictions. ANNs have several benefits, such as being able to understand intricate patterns in data, manage vast sets of data, and adapt effectively to unfamiliar information. On the downside, they require substantial data for training, run the risk of overfitting, and present challenges in deciphering the connections between inputs and outputs. Moreover, training ANNs can be costly in terms of computing power and hardware resources.

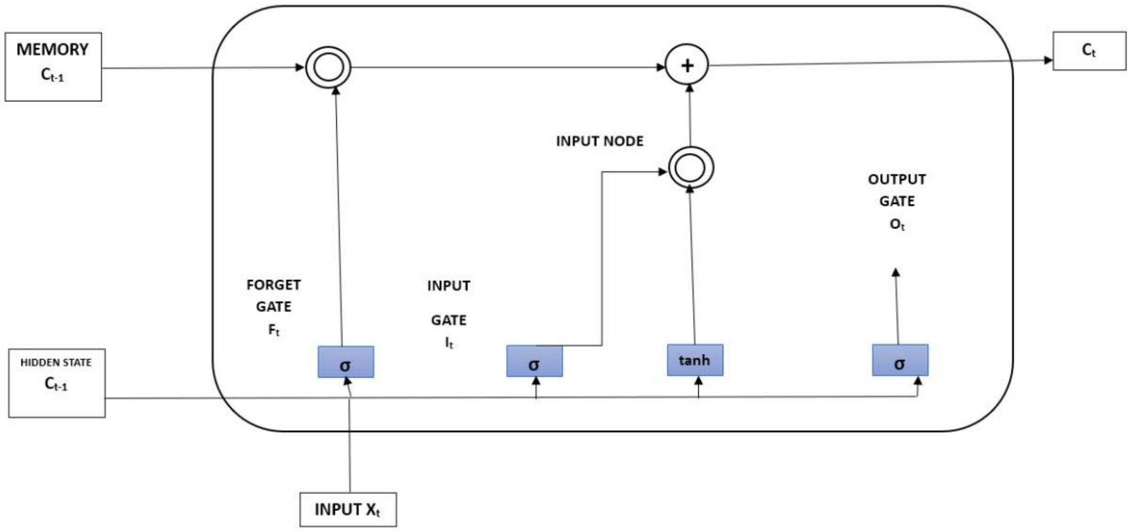
**Figure 6: Artificial Neural Network (ANN) Model**




## 2.5 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a special type of recurrent neural network (RNN) that was created to solve the problem of the vanishing gradient, a challenge that commonly occurs with traditional RNNs. LSTMs have a distinctive structure that consists of memory cells and gates that help manage the flow of information. These memory cells enable LSTMs to store data over extended sequences and selectively retain or discard information based on its importance. The benefits of using LSTMs include their capability to comprehend long-term relationships in sequential data, like time series or natural language, and their efficiency in handling the issue of vanishing gradients during the training process. AI models like this one can handle input sequences of different lengths and are resistant to overfitting. However, drawbacks include the need for complex hyperparameter tuning, higher computational complexity, and a risk of overfitting if not properly regulated or trained on enough data.

**Figure 7: Long Short-Term Memory (LSTM) Model**




## 2.6 Data Collection

To assess the effectiveness of prediction models, we gathered historical stock market data for the Nifty Fifty index from trustworthy financial databases and sources. This dataset consisted of daily or interval-based records of stock prices, such as the opening, closing, high, and low prices for the Nifty-fifty Index on the NSE in the Indian market.

## 2.7 Preprocessing

The collected raw data underwent comprehensive preprocessing steps to ensure its quality and suitability for modelling.

## 2.8 Model Selection

In order to compare the accuracy of the aforesaid stock predictions, four different machine learning models were selected to ensure coverage of a broad range of modelling techniques and capabilities. The Random Forest model, known for its strong ensemble method, was chosen for its power and capability to handle high-dimensional data. We also included the Support Vector Machine (SVM) model, a versatile classifier that excels at capturing complex relationships and handling non-linear data. The Long Short-Term Memory (LSTM) neural network, famous for its ability to model sequential data and capture long-term dependencies, was added to address the time-series nature of stock market data. Additionally, the Artificial Neural Network (ANN) was integrated for its adaptability in learning intricate patterns and relationships in data, making it ideal for capturing the nuances of stock market dynamics and trends.

## 2.9 Data Splitting

In order to guarantee a fair assessment of the model's performance, we divided the dataset into two parts: 80% for training and 20% for testing. The training portion was used to teach the models, and the testing portion was kept aside to evaluate how well the models could predict and generalize with new data.

## 2.10 Model Implementation

The chosen models were created using widely-used machine learning tools like scikit-learn for Random Forest and SVM, and TensorFlow/Keras for LSTM. Adjusting hyperparameters was a crucial part of implementing these models, with methods like grid search or random search used to improve performance. The emphasis was placed on balancing model intricacy, regularization, and optimization techniques to avoid overfitting and boost overall effectiveness.

### 2.11 Model Training

The models were trained on a dataset using suitable algorithms and techniques. Throughout training, the models continually adjusted their parameters to reduce a predefined loss function, with the goal of accurately predicting stock market trends and fluctuations.

### 2.12 Model Evaluation

The models underwent thorough evaluation using a separate test dataset to measure their accuracy in predicting stock market behaviour. Performance metrics such as accuracy, precision, recall, F1-score, and mean squared error were calculated to evaluate the models' predictive abilities and effectiveness.

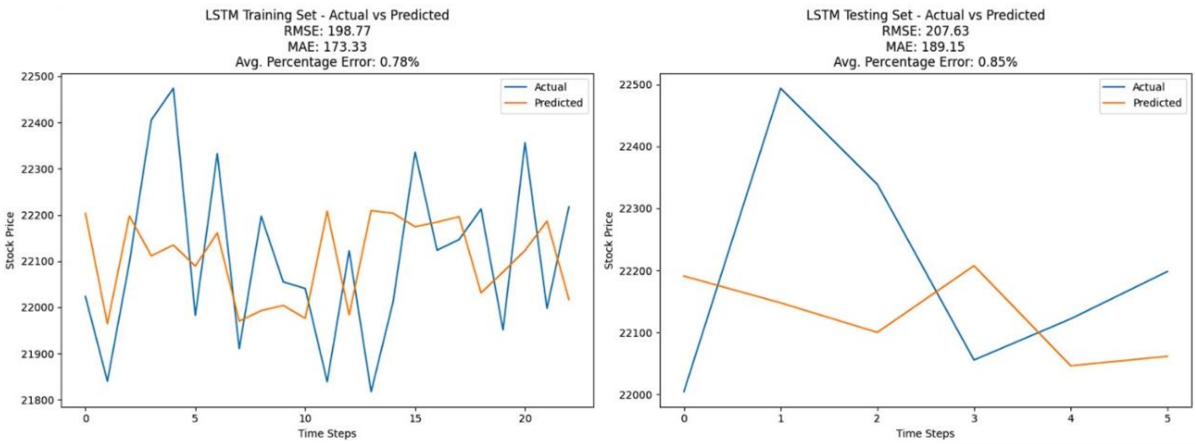
### 2.13 Comparative Analysis

We conducted a thorough analysis to compare the performance of three different models. We used statistical tests or visualizations like confusion matrices, ROC curves, and precision-recall curves to interpret the variations in model performance based on different metrics.

## 3. Result and Conclusion

We examined four well-known machine learning models: Long Short-Term Memory (LSTM), Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Decision Trees in our project using Nifty-Fifty dataset within a short period of three months. Each model was measured by how well it predicted stock market directions, thus providing an insight into how they performed with limited information.

**Figure 8: Behaviour of (LSTM) Model**




One of the most appropriate models for processing sequences is an LSTM, a type of recurrent neural network that has been proven to understand temporal dynamics effectively. But it was not among the best models in this case, despite its high-quality outputs.

On the other hand, Artificial Neural Networks are good at learning non-linear interactions between inputs and outputs, they managed high performance only because they trained on them in less time than is required for understanding markets' structure completely.

**Figure 9: Behaviour of ANN Model**

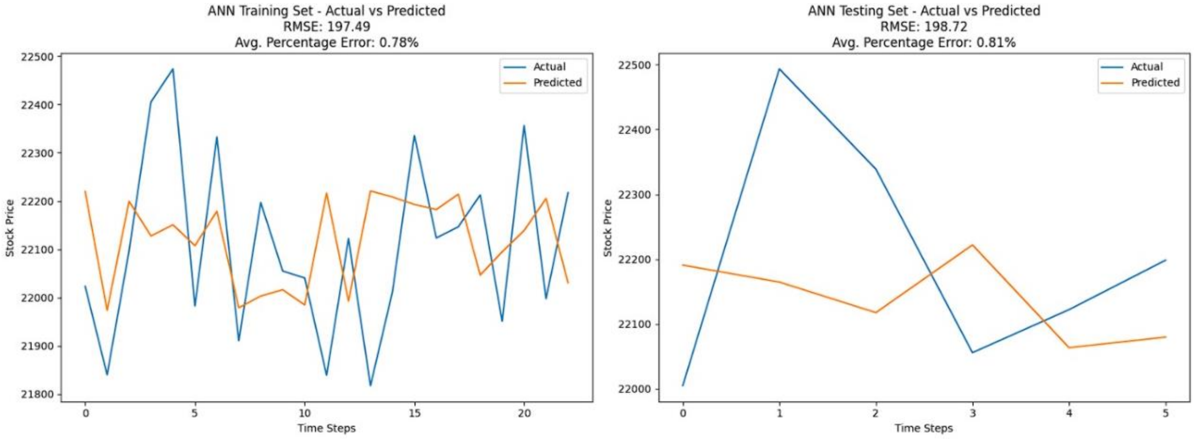
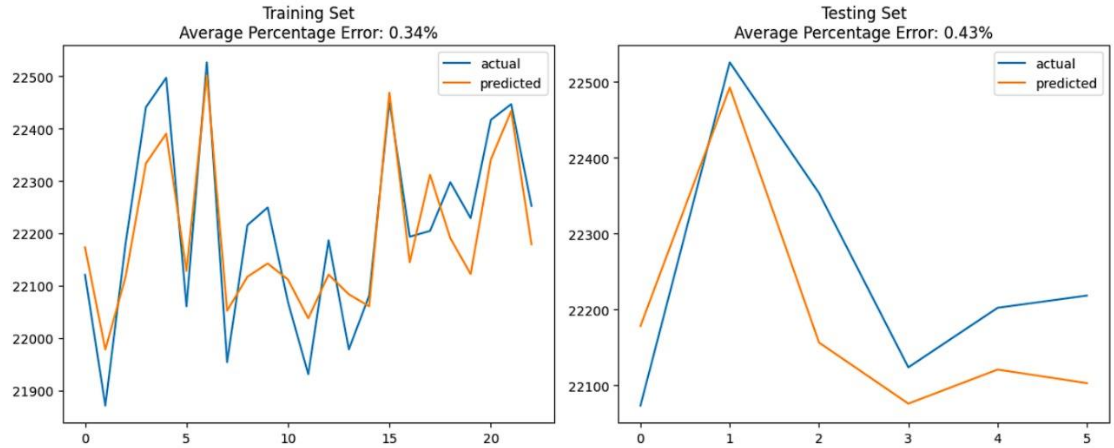
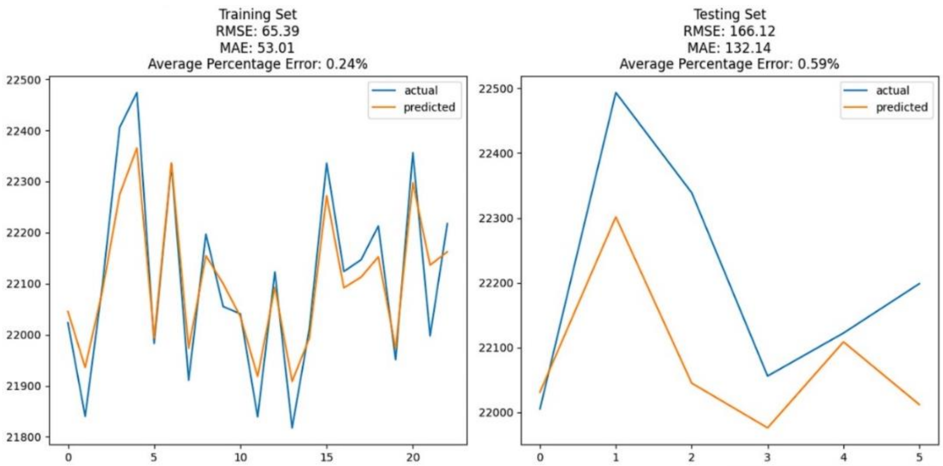



**Figure 10: Behaviour of Random Forest Model**




A hyperplane in a high-dimensional space that best fits the data is easily discovered by Support Vector Regression, which according to our results performed better than other methods tried. Due to its capability of modelling nonlinear relationships and handling regression tasks perfectly, it is so effective in terms of stock market predictions if one uses short-term data. In this scenario, however, the SVR had better generalizability properties for small sample sizes hence; we have concluded that it is the best predictive model among all.

**Figure 11: Behaviour of SRV Model**



The Decision Tree model, although easy to understand and implement, showed the least favourable results due to its propensity for overfitting, particularly with smaller datasets.

Through meticulous interpretation of the results, it became clear that SVR outperformed the other models in accuracy and reliability in capturing market trends from the short-term dataset.

The analysis doesn't only bring to light what is good and bad about each model, but it also serves as a compass for people who select and use them in the future according to how data around them. For analysts who wish to predict the stock market accurately through machine learning this comparison provides valuable information.

According to a comparison analysis performed on the Nifty Fifty dataset, SVR is considered the best model to forecast short term stock exchange developments. Therefore, SVRs have been positioned at a strategic place in financial analytics due to their remarkable consequences. In this regard, they have an upper hand in terms of prognostication accuracy than any other model, hence placing them at a focal point where investors as well as appraisers can make improved decisions on how much risk should be taken and what type of assets in their portfolio should be bought or sold.

Leveraging the insights obtained from the SVR model, financial professionals can now select their investments more wisely, henceforth having the ability to proactively manage the possibility of risk occurrence and then allocating resources in such a way that they yield maximum profits, thus achieving investment portfolios that are more resilient and profitable. Through the use of advanced machine learning techniques such as SVR, this research points out the critical part played by this transformation of financial practices influenced by technology for investment managers who wish to succeed within the industry.

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