NNAR AS A RELIABLE TOOL FOR PREDICTING VOLUME-WEIGHTED AVERAGE PRICE BEHAVIOUR

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1 Abstract

In this competitive era of financial expertise predicting stock behavior has become significant because it facilitates data-driven decisions that help traders design their investment strategy which impacts their portfolios. This research aims to use Neural Network Auto-regressive models to analyze Volume- weighted average prices and make predictions. By examining data and interrelated financial variables the project aims to provide forecasts that reveal trends and risks involved in investment decisions. Utilizing NNAR models will help the understanding of the future ahead of us which gives insights in decision-making. This study not only contributes to the field of analytics but also has practical applications that contribute to investment strategies, risk management, and policy development. The NNAR model is an integration of a feedforward neural network with lagged inputs and a single hidden layer with non-linear functions it is said to be one of the best tools for analyzing time-series data.

2 Introduction

The Stock market is a place that experiences constant fluctuations with numerous changes happening at a time that determines the future of a particular company. The markets by design are made by complicated and interconnected forces that are influenced by economic policies and geopolitical events that affect a trader's sentiment. Understanding the behavior of a stock is not only a fundamental aspect of financial management but also able to predict the future which determines a trader's future course of action. This quest of predicting stock market benchmarks has attracted countless traders and analysts who have been doing intense research for many years. This search for precise and comprehensive tools that help us in forecasting has increased exponentially over the years where data-driven decisions are required. This is the challenge we are trying to solve with this project, we aim to unravel the reliability of the NNAR model in predicting volume- weighted average price which can possibly unravel the complexities in the stock market movements.

The stock market is defined by its complicated nature and being volatile makes it difficult to predict the market trends. Few traditional methods can be used to make certain predictions but they are proved to be primitive when put into practice along with modern machine learning models. It will be very tedious to find interdependence between financial variables when we use traditional methods, machine learning models such as NNAR makes it easier to predict. The NNAR model offers a multivariate time-series approach that can determine the relationships between variables allowing us to give a more accurate and comprehensive analysis of how economic factors impact the financial variables.

Buying a stock has become one of the frequent ways for an insightful investor in the current year, be it the Mutual fund or securities or buying a stock directly. The volatile nature of the stock market offers a platform to generate high returns whether it is a short-term or a long term investment.

The underlying statement is that traders in the current time need a sophisticated tool that makes predictions faster with small data provided and which can be relied upon to take calculated risks.

There is as much a downside as there is an upside, which means the price can rise or drop at any point given. At times geopolitical events that concern one country can determine the events happening in the stock market of another country. For instance, the Russia-Ukraine war has affected the stock market in India for a week at least. Another instance is the Taliban takeover of Afghanistan. One might argue that there can be better chances in the long-term investment whereas the fact is that there is an equal amount of risk involved in the long-term investment as it is in the short-term investment.

In this project, we concentrate on the benchmark VWAP(Volume-weighted average price), it is a combined indicator for representing average price of a security based on price and volume. It helps the traders in determining the entry and exit points of a particular stock. VWAP is widely used by traders and analysts to make informed decisions because it provides better and more accurate representation of a company's true average price over a stipulated time. VWAP can also be used to determine if a company is undervalued or overvalued when we compare it with the current price. The direction of VWAP indicates the trends in the market, mastering the interpretation of VWAP can be very useful in enhancing trading strategies.

In today's world traders face one common problem on a daily basis, which is to what to do with the money they have. The traders and other participants actively look to make informed decisions rather than depending on sheer luck or chance. The ability to predict stock behavior is not just something nice to have it is also something that helps everyone to make smart choices, know the risks involved and achieve financial goals.

3 Literature survey

Many researchers have approached this problem of predicting stock market with different approaches of both Statistical and Machine learning methods on time-series data, some of them have even tried combining two models to give a new model. All these researchers are unique in their own way, we cannot classify any results as significant results keeping the dynamic nature of our dataset in mind. In our previous research where we found out that the NNAR model is a better performing model than the VAR model to make predictions on VWAP.

The research by Sadia et al[1] (2022) aims to draw a performance evaluation of three models TBATS, NNAR, and ARIMA on similar datasets which is the dataset of Blockchain-based Cryptocurrencies. The research extends from statistics to quantitative finance by using machine learning. Sadia et al chose RMSE and MAPE as the metrics to evaluate the models. In conclusion, they said the NNAR and TBATS models are better at predictions on time series data than the other models.

Avramov et al [2] (2019) explored the profitability of investments based on deep learning signals in the context of difficult-to-arbitrage stocks and high limitsto-arbitrage market states. They explored two different approaches, the first is a fee-forward neural network with three hidden layers and the second approach combines four neural networks including recurrent neural network and feed-forward neural network with LSTM cells and forming a generative adversarial network (GAN). The GAN approach incorporates an adversarial process where one player aims to choose the best-performing model while the other player selects conditions leading to the worst performance, aligning with the findings of previous studies by Hansen and Richard (1987). They aimed to explore profitability, downside risk, and the ability to use the considered methods to identify mispriced stocks rather than relying on accuracy as a performance metric. Avramov et al stated the economic significance of machine learning algorithms in predicting stock returns, they showcased that these methods can generate economically interpretable trading strategies given prior knowledge.

Toharudin et al[3] (2021) discussed the impact of larger-scale social restrictions on COVID-19 cases in Jakarta and West Java, Indonesia. They used neural network methods to predict future movement of COVID-19 cases. They followed NNAR, MLP, and ELM approaches to assess the historical data of confirmed, recovered, and death cases of COVID-19. These models were used to forecast the movements of COVID-19 cases by using different metrics like Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Scaled Error (MASE). Their study found that the government’s measures including Large Scale

Social Restrictions (PSBB) and the transition to the "new normal," had a significant impact on the number of COVID-19 cases in both regions. They also concluded that after the introduction of the new normal phase, both the regions saw a significant increase in the number of cases. This rise was said to be caused by people not following the health protocols and underestimating the risk of COVID-19 transmission.

J S Vaiz et al[4] (2017) used the capabilities of SVM and ANN to predict stock market trends, they made a hybrid model by taking advantage of both models. SVM offers feature selection by which they have cleared the noise and irrelevant features from the dataset and ANN was trained on that modified data. The performance metrics followed were Accuracy, Precision, and Specificity. J S Vaiz et al showed that ANN has predicted better over the hybrid model rather than ANN predicting over data alone. They have achieved an accuracy of 83 to 90 percent with their hybrid model.

Aydin et al[5] (2015) did a comparative analysis of Neural Networks and Machine learning models. The analysis includes the utilization of Artificial neural networks(ANN) and Vector Auto regression(VAR) models on different variables that are volatile and similar to the stock exchange data. The variables that were considered are the USD/TRY exchange rate, gold prices, and the BIST 100 index. Aydin et al found that the ANN approach has given superior prediction capabilities when compared to VAR. They further discussed the VAR model being less capable with low data and finding it difficult to make predictions over time series data than ANN can.

Almarashi et al[6] (2024) have studied and tried to enhance the accuracy of predicting player standings in future matches by using time as a factor in the analysis specifically by comparing the non-linear NNAR with ARIMA and TBATS. The study evaluates the findings by calculating Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). They were able to exhibit 95 percent confidence intervals.

Benrhmach et al[7] (2020) discussed the application of a Nonlinear Autoregressive Neural network and used the Extended Kalman Filter for predicting financial time series. They used mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination as their performance evaluation metrics. The study demonstrated the superiority of their proposed NAREKF model over existing prediction models

Mohamad As'ad et al[8] (2020) aimed to address the uncertainty in the gold price to help investors seeking profit from their investments. They have employed the NNAR method to make predictions on the historical data available. NNAR(25,13) is the model that Mohamad As'ad et al found most accurate for their study, it involves one hidden layer in the Neural network structure. They have used mean absolute percentage error (MAPE), mean absolute square error (MASE), and root mean square error (RMSE) as their performance evaluation metrics. The researchers found that NNAR relatively offers a promising approach and can be implemented using open- source software. Mohamad As'ad et al[11] 2020 aimed to address the uncertainty in the gold price to help investors seeking profit from their investments. They have employed the NNAR method to make predictions on the historical data available. NNAR(25,13) is the model that Mohamad As'ad et al found most accurate for their study, it involves one hidden layer in the Neural network structure. They have used mean absolute percentage error (MAPE), mean absolute square error (MASE), and root mean square error (RMSE) as their performance evaluation metrics. The researchers found that NNAR relatively offers a promising approach and can be implemented using open- source software.

Murthy et al[9] (2023) focused on predicting BSE Sensex, which is the stock market index of India using Machine learning techniques. They aimed to forecast the BSE Sensex accurately to help the analysts make informed decisions. The study also focused on the preprocessing of historical data, feature selection was applied to prepare it as an input for the Machine Learning models. They have employed the NNAR model to generate accurate forecasts. With the help of NNAR, they tried to capture the sequential dependencies and patterns. The research highlights that the daily price of gold is significantly influenced by the gold price from the previous day up to 24 periods ago when using the NNAR (25,13) model.

Saadon et al[10] (2024) studied to determine the behavior of Nonlinear multi- dependent variables with the help of the Neural Network AutoRegressive exogenous (NNARX) model. The study was conducted on the nonlinear behavior of riverbank erosion rates of the Sg. Bernam River in Malaysia. The the model had 5 independent variables and 10 hidden layers and was stated to be the most accurate predictor for this dataset. They have considered Mean Square Error (MSE), Root Mean Square Error (RMSE), and Discrepancy Ratio (DR) to evaluate the model.

Almarashi et al focussed[11] (2024) on modeling the Gross Domestic Product(GDP) of Saudi Arabia using both linear and non-linear time series models, by using the NNAR model. They aimed to provide efficient and accurate forecasting of the GDP annual growth rate. The findings have shown the lowest values of Mean Absolute error(MAE) and Root Mean Squared error(RMSE), with that they have concluded that NNAR(5,3) is the optimal model over the other models. The model predicted the growth to be 1.3% which is closely aligned with the projection of the International Monetary Fund benchmark of the year 2023.

P.V. Thayyib et al[12] (2023) focused on the forecasting of Indian Goods and Service tax(GST) revenue using various time series models such as TBATS, ETS, ANN, ARIMA, NNAR, and also a hybrid time series model. All these models were trained with the historical data and a comparative analysis was drawn to identify the most accurate and effective model for forecasting monthly GST revenue. The hybrid models include ARIMA-NNAR, ARIMAANN, Theta-NNAR, and Theta-TBATS. They tried minimizing Mean Absolute error(MAE) and Root Mean Squared error(RMSE) which are used to evaluate the models. They have concluded that the hybrid mode Theta-TBATS has performed better than the other models in making accurate predictions.

Jan Rindell[13] (2023) focused on Nonlinear Auto-regressive Neural Network(NARNN), for forecasting exchange rate movements in foreign markets. This study compared the performance of ARIMA and NARNN using historical data of EUR/USD and EUR/GBP currency pairs from 2013 to 2022. The performance

metrics used were MSE, RMSE, R-Value, Akaike's Information Criteria (AIC), and Bayesian Information Criteria (BIC). The study aimed to provide insights into the application of Neural Networks in predicting currency exchange rate movements and to assess their performance compared to traditional statistical models in the context of the forex market.

R Gautham Goud and M. Krishna Reddy[14](2024) focused on the application of advanced predictive modeling techniques, particularly neural networks in their study. They aimed to predict the Price-to-Earning ratio for the Indian Equity market stock index NIFTY 50. This research explored various methods like ARIMA, NNAR, and MLP. They concluded that neural network models specifically NNAR(2,5) and MLP(2:5:1) have performed better than the ARIMA(1,1,1) model in their field of study.

Sestanovic[15] (2024) discussed a comprehensive approach to Bitcoin forecasting using neural networks. These neural networks include autoregression, Jordan neural network, ARIMA, and GARCH models. The conclusions emphasized the potential of neural networks in Bitcoin forecasting while considering the challenges posed by external factors.

4 Research Gaps

- Model Comparison and Evaluation: Many studies have compared different predictive models such as TBATS, NNAR, ARIMA, and ANN. Some of these studies have used metrics like RMSE and MAPE while some of the other studies have used accuracy, reliability, and economic significance. Standardization of the evaluation metrics would facilitate a transparent understanding of the users. Developing one such metric can be a challenging task because different researchers and different readers have different tastes in looking at evaluations. A technical expert may be looking for a minimum RMSE whereas a general investor might look for a better accuracy. Moreover, when evaluating one model alone we cannot depend on multiple metrics like RMSE, MAPE, and MAE. We can take MAPE and aim to minimize it.

- Feature Selection and Model Performance: Several studies have stated the importance of feature selection in improving the predictive capabilities of Machine learning models. However, there is a need to study those specific features that can be relevant for most predictive tasks. Because after all, it is the characteristic of the stock market to be volatile and show abnormalities in the data. There is a need to capture and understand these abnormalities.

- Data for training: While taking training data many researchers have taken historical data for more than 5 years and some have considered it for more than 20 years which may take time for the Machine learning algorithms to read and capture the patterns. Moreover especially in stock market data, and historical data for more than 8 previous quarters the predictions may be misleading in a few cases. That is because there will be a change in dividend to price ratio over time which affects the volume of the shares purchased, these metrics are not reflected in the price of the stock.

- Interpretation and Transparency: While Machine learning models often offer high accuracy in predictions few of them lack interpretation which makes it tough for the stakeholders to understand the factors driving the predictions. There is a need for robust techniques of interpretation especially in the field of finance.

- Long-term Predictive Modeling: Many researchers have focused on Long-term predictive modeling rather than short to medium predictions for stock market benchmarks. By the nature of the stock market we never know what will happen soon, so predicting for a longer period is risking the accuracy of the prediction. Moreover, most traders look at a picture of 2 to 3 months to determine their entry and exit at a stock.

- Dynamic Model Adaption: Existing predictive models often assume stationary data distributions and have fixed the model parameters over time. However, the financial systems are inherently dynamic and subject to changes, and external shocks. There is a need for research on adaptive predictive modeling techniques that can adjust the model parameters dynamically and structures in response to market conditions.

- Expectations from the results: Predicting the right value at one particular time should not be the goal of a predictive model. When it comes to the prediction of stock market benchmarks the model should be able to deliver the Strength, Momentum, and Direction of the stock.

5 Proposed system

This system aims to utilize Neural Network Auto-regression (NNAR) models for the time series analysis to forecast and explain stock market benchmark VWAP's behavior. The mission is to offer valuable insights to traders into dynamic market trends and empower them with clear actionable information. The wishes to encompass comprehensive data processing using the NNAR with transparent data visualization. In the present day understanding the market is the ultimate goal, this system aims to shed light on intricate market patterns and aid data-driven decision-making.

5.1 Data Collection and Preprocessing

The foundation of the system begins with the collection of historical data for selected stock market benchmarks. These benchmarks may include indices, opening and closing prices, and other financial indicators. In this case, the benchmark is Volume-weighted Average Price (VWAP). It is calculated by the summation of the rupees traded for every transaction (price multiplied

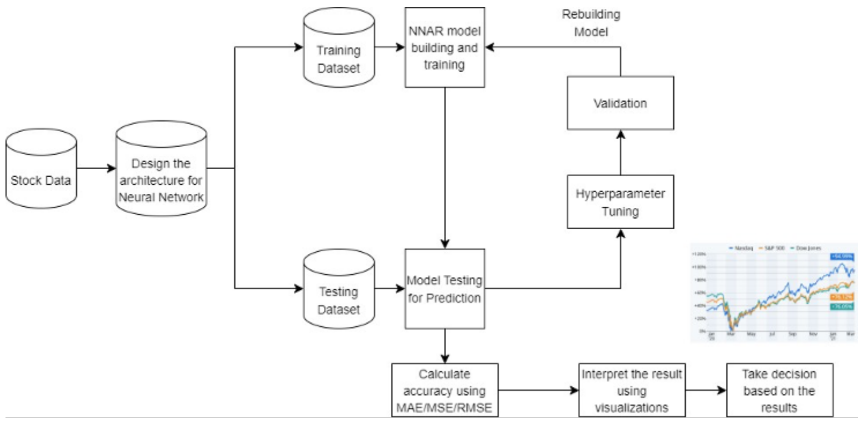


Figure 1: NNAR modelling

by the number of shares traded at an instance) and then divided by the total shares traded for the day. It is a good indicator because it incorporates both the price of the stock and the volume traded into consideration by providing a comprehensive view of the market activity.

$$VWAP = \frac{\sum Price \times VolumeofPrice}{\sum TotalVolume}$$

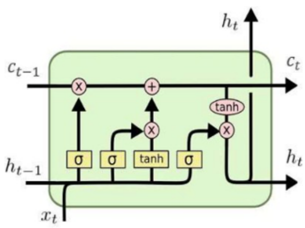
The foundation of the system begins with the collection of historical data for selected stock market benchmarks. These benchmarks may include stock indices, individual stocks, or other relevant financial indicators. Data sources can encompass public financial databases, market exchanges, or other reliable sources.

5.2 Neural Network Auto-regression (NNAR) Implementation

The core of this system leverages the implementation of Neural Network Auto-regression (NNAR) models. NNAR models are dynamic and adaptable tools for time series analysis, designed to capture intricate dependencies and patterns within different stock market benchmarks.

1. Network Architecture Design: The configuration of a Neural network is an important part of building the model because it involves in determining the number of hidden layers and the number of neurons in each layer. These choices affect the model's ability to make predictions.

2. Training and Learning: The NNAR model's training process is the process of making the model study the time series it uses optimization techniques like stochastic gradient descent(SGD). The model learns from the historical data and identifies the patterns and relationships that are used in making predictions.



LSTM
(Long-Short Term Memory)

3. Hyperparameter Tuning: Fine-tuning of hyperparameters such as learning rates, batch sizes, and regularization terms are required to get optimal performance. These adjustments are important in NNAR's predictive accuracy.

4. Time Lag Consideration: Similar to VAR, the NNAR approach also takes time lags into account. It involves selecting an optimal number of lag terms to capture short-term dependencies within the time series data.

5.3 NNAR model in detail

- The NNAR model architecture consists of two LSTM layers followed by a Dense layer.

- Long Short-Term Memory(LSTM) units are a type of recurrent neural network(RNN) that captures long-term dependencies in sequential data. Each LSTM unit performs operations involving input, output, and forget gates to control the flow of information through the steps.

- This model is compiled using Adam optimizer and mean squared error loss function. Adam optimizer adjusts the learning rate adaptively during training, and MSE loss measures the difference between predicted and actual VWAP values.

- The mathematical operations involve matrix multiplication, activation functions tanh within the LSTM units, and optimization techniques during model training.

$$\boldsymbol{y}_{t-1} = (y_{t-1}, y_{t-2}, \dots, y_{t-10})'$$

Figure 2: NNAR vector equation

$$y^*_{T+1} = f(\boldsymbol{y}_T) + \varepsilon^*_{T+1}$$

Figure 3: NNAR vector equation with Error series

Figure 2 is a vector containing lagged values of the series, and f is a neural network with 6 hidden nodes in a single layer. The error series

$$\epsilon_t$$

is assumed to be homoscedastic (and possibly also normally distributed) We can simulate future sample paths of this model iteratively, by randomly generating a value for

$$\epsilon_T$$

either from a normal distribution or by resampling from the historical values. So if

$$\epsilon_T + 1^*$$

is a random draw from the distribution of errors at time T + 1, then

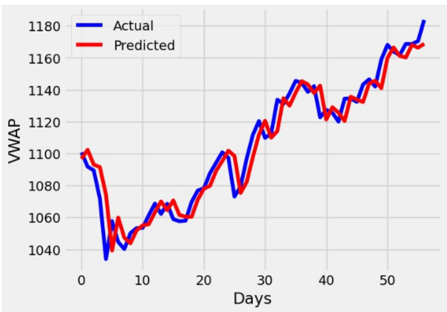
5.4 NNAR in Forecasting

NNAR models have emerged as powerful tools in the world of forecasting, particularly in predicting financial variables. The NNAR model can become one of the vital tools in risk management thus helping users to build a better portfolio. Notable researchers have highlighted the significance of NNAR modeling on quantitative risk evaluation and defining entry and exit points in stock. Studies have mentioned how NNAR models provide insights to make data-driven decisions. Multiple pieces of evidence suggest that NNAR models can significantly impact the accuracy of forecasting and aid in building robust portfolios.

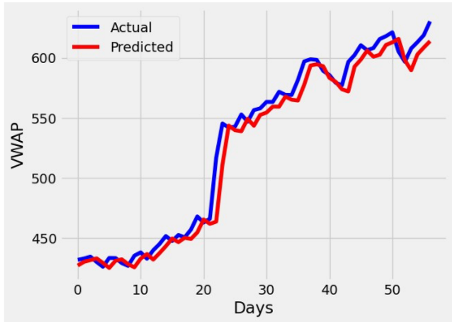
6 Results

We have taken one fiscal year's(1st April 2022 to 31st March 2023) data for each stock to train the models, i.e. data from the previous four quarters. The models were individually tuned to give better predictions and tested the results with the upcoming quarter(1st April 2023 to June 30th 2023). We have conducted experiments on 25 companies across 5 sectors by at least considering 4 companies per sector. Below are some of the results from the experiments which will give an overall insight into the results.

6.1 Performance Evaluation of Models with IT Sector



(a) Results on HCLTECH



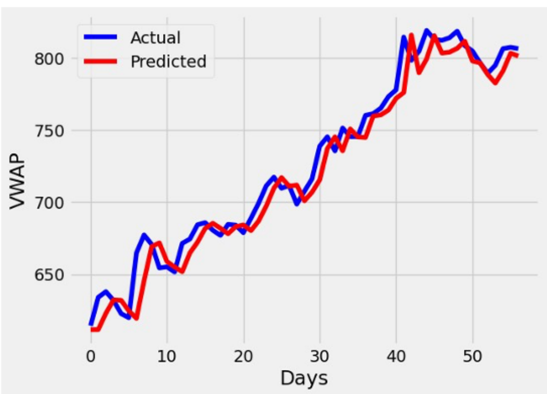
(b) Results on INTELLECT

The above two are a few of the results that give an overall insight into the analysis of the IT sector. HCL Technologies Ltd (HCLTECH)'s predictions

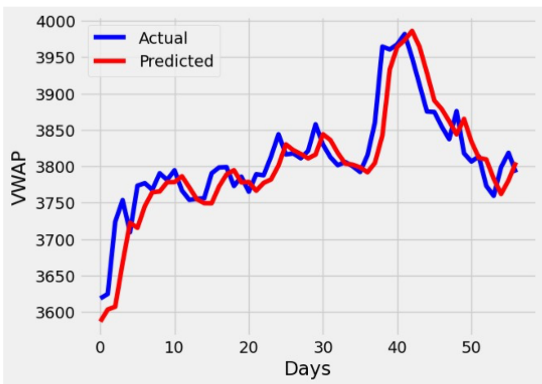
have given a MAPE of 4.05270510374. Intellect Design Arena(INTELLECT)'spredictions have given a MAPE of 15.6340588783. The predictions have provided great

insights into the overall momentum of the stock and can be said reliable in terms of the direction and strength of the predictions.

6.2 Performance Evaluation of Models with Pharma Sector



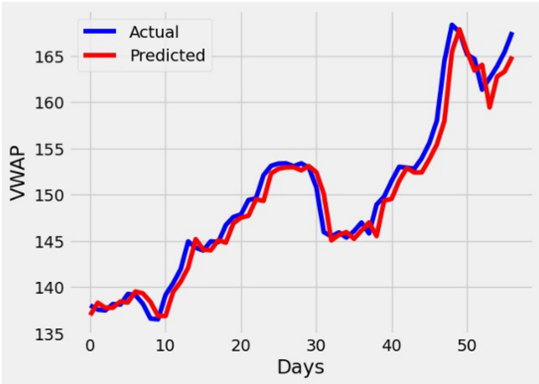
(a) Results on CAPLIPOINT



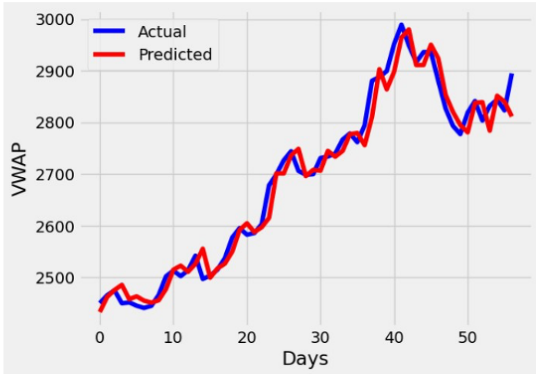
(b) Results on PFIZER

The above two are a few of the results that give an overall insight into the analysis of the Pharma Sector. Caplin Point Laboratories Ltd(CAPLIPOINT)'s predictions have given a MAPE of 9.95087110753 and Pfizer Ltd(PFIZER)'s predictions have given a MAPE of 2.03782920255. These predictions got the direction of the stock right through the period and have given accurate values in terms of strength and overall momentum.

6.3 Performance Evaluation of Models with Automobile sector



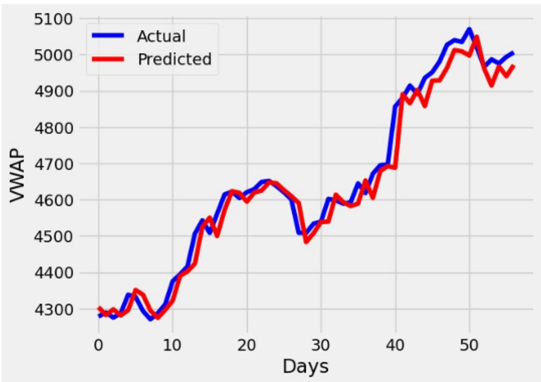
(a) Results on ASHOKLEY



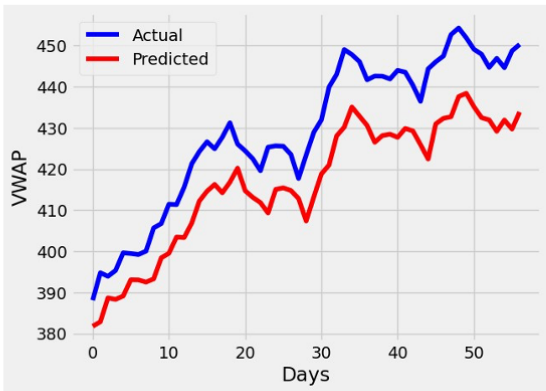
(b) Results on HEROMOTOCO

The above two are a few of the results that give an overall insight into the analysis of the Automobile sector. Ashok Leyland Ltd(ASHOKLEY) has given a MAPE of 6.51914255199 with its predictions and Hero Motocorp Ltd(HEROMOTOCO) has given a MAPE of 7.10930934319 with its predictions. Both of the above graphs have given clear insights into the overall momentum, direction, and strength of the stock movement.

6.4 Performance Evaluation of Models with FMCG Sector



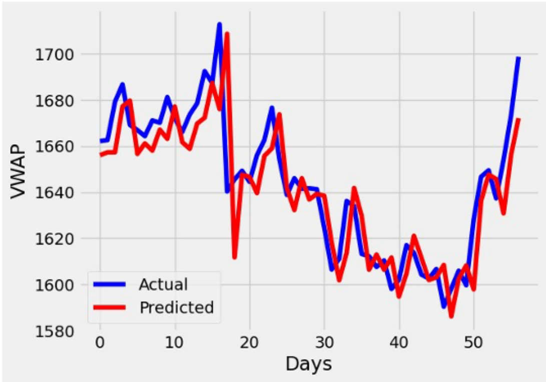
(a) Results on BRITANNIA



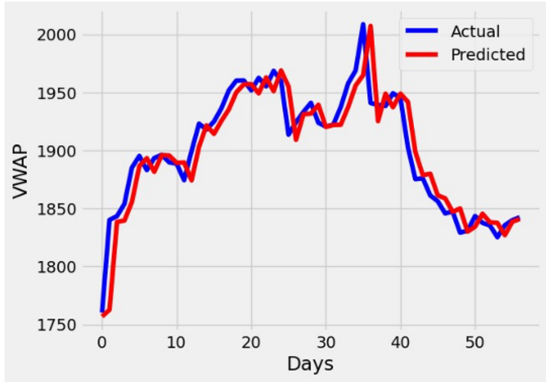
(b) Results on ITC

The above two are a few of the results that give an overall insight into the analysis of the FMCG sector. Britannia Industries Ltd(BRITANNIA) has given predictions with a MAPE of 5.82882499553 and ITC Ltd(ITC) has given predictions with a MAPE of 5.1189680698. Both the predictions were successful in providing the overall momentum, strength, and direction of the stock movement.

6.5 Performance Evaluation of Models with Banking Sector



(a) Results on HDFCBANK



(b) Results on KOTAKBANK

The above two are a few of the results that give an overall insight into the analysis of the Banking sector. HDFC Bank Ltd(HDFCBANK) has given a MAPE of 2.03819824016 with its predictions and Kotak Mahindra Bank Ltd Fully Paid Ord. Shrs(KOTAKBANK) has given a MAPE of 3.03932818354 with the predictions made. Both predictions can be said reliable in terms of Momentum, direction, and strength of the stock movement.

7 Conclusions

When it comes to the predictions three important abstract aspects attract the traders and build their trust in the predictive model, they are Direction, Momentum, and Strength. To put these terms in context

- Direction: A predictive model should determine the direction of the stock from a particular point to another point between any two given points of the graph that match the observed values.

- Momentum: A predictive model should determine the overall movement of the stock, be it upward or downward correctly.

- Strength: A predictive model is said to have good strength when the values predicted by the model are very near to the values observed.

From the observed results we can confidently say that the NNAR model was successful in predicting the behavior of VWAP and can be said to be a reliable tool that can make predictions that traders can trust by scrutinizing the above three factors.

A predictive model's ultimate goal should be serving its stakeholders right. Here in our research, we wish to empower traders with data-driven decisions who can determine their entry and exit from a stock to maximize their profit. Usually, most traders look at a picture for a month or two in our results we have given our best to produce reliable predictions for a quarter that is three months which is a huge window. Another aspect is that traders need to make decisions faster, comparatively the NNAR model is a faster model to execute than the other Bootstrapping and Bagging algorithms in machine learning.

The benchmark VWAP is chosen in our project to predict the stock market because this particular benchmark is a combined metric of several factors. Let us say there is an important decision that was taken and has been announced to the market, it is not the price that is affected immediately after the announcement it is the volume. The volume transacted and the price at which the volume was transacted determines the behavior of the stock. Since

VWAP is a combined metric of volume and price, the predicted fluctuations in VWAP can be mapped to the fluctuations of the observed prices. The financial decision that was taken cannot be fed into the model but we can feed the effect of that decision by considering VWAP. When we take the price of the stock as our variable to predict we can only determine the price volatility but when we consider VWAP we can determine price volatility and also the volume volatility.

Predictions are said to be reliable in the financial sector when an interested trader can use a particular set of predictions to determine when to buy a stock and when to sell it. A model is said to be robust when it generates predictions that can be used to make informed decisions on when to enter and when to exit.

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