Intervention Analysis for Predicting Stock Market using Deep Learning Algorithms and Time Series Analysis

Krish Valecha
Dept. of Computer Science and Engineering (Data Science)
Dwarkadas J. Sanghvi College of Engineering
Mumbai, India
saumyakrish123@gmail.com

Yash Pandloskar
Dept. of Computer Science and Engineering (Data Science)
Dwarkadas J. Sanghvi College of Engineering
Mumbai, India
pandloskaryash@gmail.com

Sowmya Dadheech
Dept. of Computer Science and Engineering (Data Science)
Dwarkadas J. Sanghvi College of Engineering
Mumbai, India
dadheechsowmya@gmail.com

Pradnya Saval
Dept. of Computer Science and Engineering (Data Science)
Dwarkadas J. Sanghvi College of Engineering
Mumbai, India
pradnya.saval@djsce.ac.in

***Abstract*—Stock market being intricate and volatile pose challenges for classical Time Series Analysis techniques in terms of generalization and computation on real-world data. In order to improve prediction capacities, new methods like intervention analysis and Deep Learning (DL) are required. The research seeks to unravel the complexities of stock price prediction modelling by comparing Time Series Analysis with Deep Learning augmented by intervention analysis. Upon evaluation on different datasets, the Deep Learning models, specifically the Recurrent Neural Network (RNN) performed better than the other models considered. RNN outperformed other models on Mean Squared Error (MSE) for Tesla and IBM data, with values 3.874 before intervention and 3.593 after intervention and 46.52 before intervention and 42.97 after intervention respectively, thus highlighting the advantages of Deep Learning models for predictions. The goal of investigating intervention analysis methods incorporated into predictive models is to create processes that can predict overall market trends and efficiently identify and address sudden deviations.**

***Index Terms*—stock market, intervention analysis, Time Series, Deep Learning**

I. Introduction

Accurate anticipation of stock prices is still a challenging process affected by a number of factors, some visible and invisible. Precise value estimates require the understanding of stock values in terms of movements that are derived from historical data. Similarly, in the stock market, different economic aspects can influence groupings and movements like political changes, general economic environment, price index for commodities, investors waiting other markets to move before they do, investor sentiment concerning good or bad news about earnings announcements and dividends as well as others. Predicting stock prices is a difficult endeavour because the markets are unpredictable. These limitations have turned attention towards newly developed methodologies such as Intervention Analysis (IA) and Deep Learning (DL). They may be able to incorporate intervention analysis into predictive frameworks that will help in adaptation to volatile market situations like sudden shifts or unexpected market disruptions. By integrating intervention analysis techniques into their predictive models; financial institutions and investors can be better placed to manage their risk exposure. This research aims at assessing the complexities faced during developing models for forecasting stock prices using traditional Time Series Analysis combined with DL via intervention analysis for comparison purposes. There is a constant effort to make sure the truthfulness and toughness of the prediction of stock prices improve against unanticipated market activities, which provides impetus for the study. With the assistance of Intervention analysis, predictive models can respond accordingly in relation to ever changing market situations by capturing and adding to their predictions, the impacts of external interventions.

II. Literature Survey

A. Analyzing and Predicting Stock Market

Many attempts have been made to use Time Series Analysis and Deep Learning (DL) to anticipate stock market patterns [1], [2], [3], [10]. For instance, Daiyou Xiao et al. [1] created a hybrid model of Autoregressive Integrated Moving Average - Long Short Term Memory (ARIMA-LSTM) where prediction of non-linear trends takes place by LSTM recursive neural networks and the linearity in the data is removed using ARIMA modeling. Ping Hu et al. [2] uses a novel model, Time Series Relational Model (TSRM) for predicting the stock prices which enhances prediction by incorporating relationships between stocks using Graph Convolution Network (GCN) and temporal information about stock prices that it records using Long Short Term Memory (LSTM).

Using the K-means approach, the model automates the segregation of stocks based on transactional data and discover the links between stocks. M Nabipour et al. [3] contributed in forecasting of the immediate performance of the newly established Tehran Market using data spanning one year. This was done so using several tree- based techniques which include random forests, bagging and boosting and decision trees. Neural Networks such as Artificial Neural Networks (ANN), RNN and LSTM were used for prediction. LSTM produced the most accurate findings out of the rest in their study. Mahantesh Angad et al. [10]employs the ARIMA model for prediction of stock market price. The system involved collection of data, Data pre-processing and Data Wrangling, Training the model, Forecasting the results, Plot visualization. The study's main goal was to determine the parameters for the ARIMA model, which is used to predict stock price indices in the short run, and to evaluate the model's performance. Pin Lv et al. in [9] offer a hybrid model for stock index prediction that combines CEEMDAN decomposition and ARMA/LSTM models. It solves the limits of traditional methods, integrates linear and non-linear methodologies. Yuyu Yuan et al. in [11] introduce Data Augmented Reinforcement Learning (DARL), a framework that employs minute-candle data to train RL agents for daily trading, thus increasing training data volume. It concludes that the Proximal Policy Optimisation (PPO) method is the most effective, outperforming Deep Q-learning (DQN) and Soft Actor Critic (SAC). Mugdha Kulkarni et al. in [12] compare Simple Moving Average (SMA), ARIMA and Holt-Winters models for forecasting Bombay Stock Exchange (BSE) stock prices and finding Simple Moving Average (SMA) most effective for short-term forecasts. Andrew Brim et al. in [13] investigate the application of deep reinforcement learning, specifically a Double Deep Q-Network (DDQN), to forecast stock market behaviour using feature maps and neuron activity in response to candlestick images. Zheng Tan et al. in [14] assess the efficacy of a random forest model in stock selection in the Chinese market, utilising fundamental and momentum feature spaces to forecast price trends and create excess returns. Soni Payal et al. in [15] provide a comprehensive evaluation of machine learning approaches for stock price prediction, examining classical techniques, deep learning methods, time series analysis, and graph-based ways to effectively anticipate stock values.

B. Intervention Analysis

A statistical method called intervention analysis is used to evaluate how treatments, interventions, or outside variables affect a system or procedure. It entails examining time series data to identify shifts in the behavior or pattern of a relevant variable following the implementation of an intervention. Hendri Prabowo et al.[7] provide a thorough examination of the COVID-19 pandemic's impact on stock market conditions in China, the United States, South Korea, and Indonesia. The study analyzes composite and individual stock price data using Deep Learning Neural Netowrks (DLNN) which is a machine learning technique and intervention analysis. The results show a widespread fall in stock prices following the COVID-19 outbreak, with differing effects in different nations.The study shows important insights into the dynamics of stock price variations throughout the pandemic and focuses on the importance of statistical and machine learning methodologies in understanding the effects of global crises on financial markets. Chinese stock price forecasting and analysis using ARIMA - intervention analysis is investigated by Jeffrey E. Jarrett et al. [8]. The aim of the study is to comprehend the nature of the Chinese equity markets that are predictable, especially in times of economic turbulence. Through the application of intervention analysis within the ARIMA framework, the researchers hope to evaluate how outside events—like the 2008 global financial crisis—affect stock prices. The study's models include transfer function models to examine the impact of exogenous time series on stock prices and ARIMA modeling with intervention, which incorporates intervention variables to account for unusual events affecting the output variable. By using these approaches, the researchers want to shed light on how Chinese stock prices behave and how macroeconomic variables affect them. This will ultimately improve their power to forecast and analyze data in the context of the volatile Chinese market.

C. Research Gaps

In the comprehensive literature survey that was conducted, the meticulous examination involves several different studies in the domain of stock price prediction. While reviewing these papers, a common gap emerged—most of the existing studies have not integrated intervention analysis into their predictive models. Intervention analysis involves accounting for unexpected events and external factors that can significantly impact stock prices over time. In the identified gap, the majority of prior research appears to overlook the dynamic nature of financial markets, where unforeseen events, market shocks, or external influences can trigger abrupt changes in stock prices. The absence of intervention analysis in the existing literature implies a potential limitation in the predictive accuracy of these models, as they may not adequately capture the real-world complexities associated with unexpected market dynamics. Among the other gaps present, a gap in [9] is that the study could focus on improving temporal modelling and making the framework more generalizable to other markets. Adopting advanced recurrent neural network topologies, such as long short-term memory (LSTM) networks, can improve temporal modelling by excelling at learning sequential input and its relationships over time. Secondly, if the framework is not generalizable to other markets, its utility and practical applicability would be severely limited. Without generalizability, the framework would struggle to provide meaningful insights or predictions in markets beyond those for which it was specifically designed. This limitation could hinder its adoption by practitioners and researchers seeking versatile tools for market analysis and forecasting.

Even if intervention analysis is used in the studies that were researched, it came with certain drawbacks. For example, in

[7] and [8], intervention analysis is performed only on the ARIMA model due to which, it is unknown how other models would have performed in the same condition and if they would have actually given a better output or not.

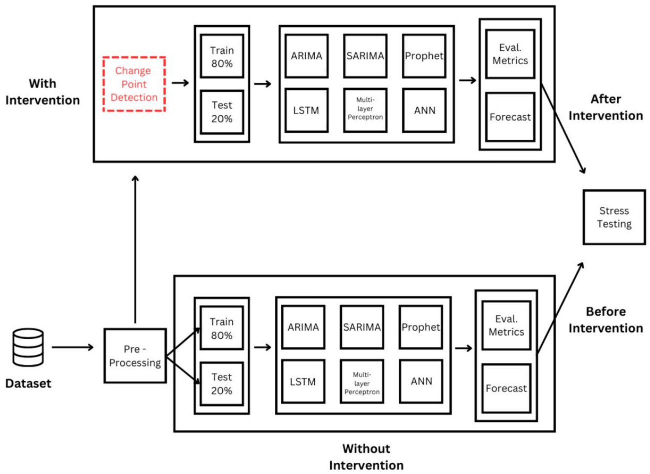

Fig. 1. A graphical representation of the approach

III. Proposed Approach

Fig.1 represents an overview of the proposed approach towards the problem statement. The approach uses 6 different models on a dataset of Tesla and IBM stocks along with intervention analysis to see which model gives the most accurate output before and after an intervention point. The evaluation metrics used to determine the best model are Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

A. Data Collection and Preprocessing

The dataset of Tesla and IBM stocks was collected from a legitimate source. The dataset includes multiple features, which are the Open, Low, High, Close, Adj Close, Date and Volume. The 'Date' column was formatted to achieve uniformity. . The data was divided into training and testing groups using an 80/20 split for model fitting.

B. Model Development

The model development phase involved the integration of intervention analysis into traditional Time Series Analysis and Deep Learning methodologies. The models that are used in our approach are :

1) ARIMA with intervention variables: The equation for the ARIMA model before intervention is given as,

$$X_t = c + \alpha_p X_{t-p} + \beta_q \epsilon_{t-q} + \epsilon_t \tag{1}$$

and the equation for the ARIMA model after intervention is given as,

$$X_t = c + \alpha_p X_{t-p} + \beta_q \epsilon_{t-q} + \delta D_t + \epsilon_t \tag{2}$$

Where,

X_t represents the element at time t,
$\alpha_1, \alpha_2, ..., \alpha_n$ represent autoregressive parameters,
$\beta_1, \beta_2, ..., \beta_n$ represent moving average parameters,
ϵ_t represents the error term at time t,
c represents the constant term,
δ represents the intervention effect and,
D_t represents the intervention variable at time t.

2) LSTM with Intervention Analysis: LSTM networks often have numerous gates that manages the information flow throughout the network. The formulae for these gates before intervention are:

$$a_t = \sigma(V_i.h_{t-1} + V_i.x_t + b_i) \tag{3}$$

$$b_t = \sigma(V_f.h_{t-1} + V_f.x_t + b_f) \tag{4}$$

$$c_t = \sigma(V_o.h_{t-1} + V_o.x_t + b_o) \tag{5}$$

and the equations after intervention will be,

$$a_t = \sigma(V_i.h_{t-1} + V_i.x_t + V_i.D_t + b_i) \tag{6}$$

$$b_t = \sigma(V_f.h_{t-1} + V_f.x_t + V_f.D_t + b_f) \tag{7}$$

$$c_t = \sigma(V_o.h_{t-1} + V_o.x_t + V_o.D_t + b_o \tag{8}$$

Where,

a_t is the input gate,
b_t is the forget gate,
c_t is the output gate,
σ is the sigmoid activation function,
V_i, V_f, V_o represent the weight matrices,
b_i, b_f, b_o represent the bias vectors,
h_{t-1} represents the previous hidden state,

3) PROPHET with intervention analysis: The equation of PROPHET before intervention is,

$$y_t = g_t + s_t + h_t + \epsilon_t \tag{9}$$

and the equation for PROPHET after intervention is,

$$y_t = g_t + s_t + h_t + \delta I_t \epsilon_t \tag{10}$$

Where,

y_t is the value observed at time t,
g_t is the trend component or the 'growth term',
s_t is the seasonal component,
h_t captures the holiday effect,
δI_t represents the intervention term representing the effect of the intervention at time t.

4) SARIMA with Intervention Analysis: The equation for the SARIMA model before intervention is,

$$Y_t = c + \gamma_1 X_{1,t} + \gamma_2 X_{2,t} + \cdots + \gamma_k X_{k,t} + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + b_1 \epsilon_{t-1} + \cdots + b_q \epsilon_{t-q} + \epsilon_t \quad (11)$$

The equation after intervention for the SARIMA model is,

$$Y_t = c + \gamma_1 X_{1,t} + \gamma_2 X_{2,t} + \cdots + \gamma_k X_{k,t} + \delta D_t + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + b_1 \epsilon_{t-1} + \cdots + b_q \epsilon_{t-q} + \epsilon_t \quad (12)$$

Where,
$\gamma_1, \gamma_2, \ldots, \gamma_k$ are coefficients of external intervention variables.

5) RNN with Intervention Analysis: The equations used for the RNN model before intervention are,

$$u_t = tanh(W_{hx}.x_t + W_{hu}.u_{t-1} + b_u) \quad (13)$$

$$y_t = W_{yh}.u_t + b_y \quad (14)$$

and the equations after intervention will be,

$$u_t = tanh(W_{hx}.x_t + W_{hu}.u_{t-1} + \delta I_t + b_u) \quad (15)$$

$$y_t = W_{yh}.u_t + b_y \quad (16)$$

Where,
u_t is the hidden state at time t,
$tanh$ is the activation function used,
W_{hx}, W_{hu} are the weight matrices for input and hidden states respectively,
b_u is the bias for hidden states,
W_{yh} is the weight matrix for output state,
b_y is the bias vector for output.

6) MLP with Intervention Analysis: Implementing Q Network (Q Net) with intervention-awareness to capture sudden changes influenced by external factors.

$$z_t^{(1)} = \sigma\left(W^{(1)} \cdot x_t + b^{(1)}\right)$$

$$z_t^{(2)} = \sigma\left(W^{(2)} \cdot z_t^{(1)} + b^{(2)}\right)$$

$$y_t = \sigma\left(W^{(L)} \cdot z_t^{(L-1)} + b^{(L)}\right)$$

And the equations after intervention will be,

$$z_t^{(1)} = \sigma\left(W^{(1)} \cdot x_t + b^{(1)}\right)$$

$$z_t^{(2)} = \sigma\left(W^{(2)} \cdot z_t^{(1)} + \delta I + b^{(2)}\right)$$

$$y_t = \sigma\left(W^{(L)} \cdot z_t^{(L-1)} + b^{(L)}\right)$$

C. Evaluation Metrics and Forecasting

To assess the models' performance, after training and testing, evaluation metrics was calculated. The evaluation metrics included Root Mean Square Error(RMSE), Mean Absolute Error(MAE), Mean Squared Error(MSE). Future values were predicted using the trained models. The models' ability to forecast future values was assessed by comparing anticipated and actual values.

D. Intervention Analysis

The basic idea behind intervention analysis is to examine how a particular event (intervention) affects the behavior of a system over time. For intervention, the time series data will be recursively divided into segments until a change point is detected in each segment. Detection of change point is done using the method of sliding window. Evaluation metrics was calculated for the data before and after intervention using the specified models and then analyze to draw conclusions.

The detection of the intervention point and segmentation of the data was done in a set of steps where a fit term is calculated to determine the influence of an intervention on time series data. After the fit term was calculated, the next step was the calculation of the cost function where a penalty term was added to the fit term after which, optimal segmentation was done where the algorithm finds an intervention point with minimum cost.

The formulae for these steps are,

$$F_k(S_i, S_j) = \exp\left(-\frac{1}{2\gamma^2}\left|x_i - x_j\right|^2\right)$$

Where,

- F_k is the fit term,
- S_i, S_j are two segments in the time series data,
- x_i, x_j are two data points in the segments S_i, S_j respectively,
- $|x_i - x_j|^2$ is the squared Euclidean Distance,
- γ^2 is the bandwidth parameter which controls the smoothness of the cost function.

After obtaining a value using the above formula, a penalty term is added to it.

$$C_k = F_k + P_k$$

Where,

- C_k is the total cost for segmenting data into k segments,
- F_k is the fit term which measures how well the data fits the model,
- P_k is the penalty term.

After calculating the cost function for several data points, optimal segmentation with minimum cost was selected.

$$\hat{k} = \arg\min(C_k)$$

E. Test Cases

Visualizations were generated based on the calculated metrics. The visualizations compared the original stock prices of the dataset and the predicted ones. These comparisons were the test cases for us which includes the graphs showing true vs predicted values before as well as after intervention.

IV. RESULTS

A. Testing on IBM dataset

The data for IBM spans from April 27, 2020, to April 22, 2022. The data is partitioned into train and test set comprising 80/20 split. The six models were applied to predict IBM's stock price movements before and after intervention. The RNN model outperformed the other models, as indicated by decreased RMSE, MSE, and MAE. Since the RNN models effectively captures the complex patterns and dependencies, it provides more accurate predictions

TABLE I
EVALUATION METRICS FOR IBM DATASET BEFORE INTERVENTION

Model	MSE	RMSE	MAE
Prophet	171.22	13.08	11.923
ARIMA	135.663	11.647	10.462
SARIMA	206.914	14.384	13.32
RNN	3.874	1.968	1.324
MLP	4.122	2.03	1.39
LSTM	8.858	2.976	2.132

TABLE II
EVALUATION METRICS FOR IBM DATASET AFTER INTERVENTION

Model	MSE	RMSE	MAE
Prophet	163.88	12.8	11.614
ARIMA	124.243	11.146	9.81
SARIMA	206.914	14.384	13.32
RNN	3.593	1.895	1.324
MLP	3.853	1.963	1.442
LSTM	8.293	2.879	2.21

Upon the observations done with respect to the evaluation metrics calculated in Table I and Table II for the IBM Dataset, it is discernible that the RNN model performs the better performing model among all other models used.

Fig. 2 and Fig. 3 shows how the model (RNN) has performed in predicting the future values of the IBM stock price before and after intervention respectively, in the form of a graph.

There were a total of three intervention points detected by the algorithm in the IBM Dataset.

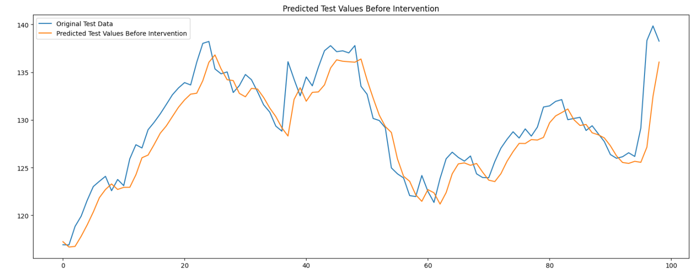

Fig. 2. Graph denoting forecasting before intervention

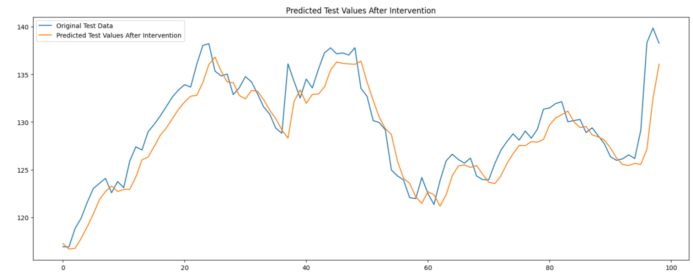

Fig. 3. Graph denoting forecasting after intervention

1) 25/03/2021: On March 25, 2021, there were a few significant events that might have affected IBM's stock price such as the announcement of IBM's accession of Taos, a cloud consulting and engineering company. This acquisition was seen as a strategic move by IBM to strengthen its cloud capabilities and expand its hybrid cloud services. The news might have had been beneficial for IBM's stock price.

2) 20/10/2021: IBM released its third-quarter financial report on October 20, 2021, revealing a revenue shortfall and unsatisfactory outcomes in its consulting division. It's possible that this revelation played a role in the day's stock price intervention for IBM. The stock price may have also been impacted by rumors that IBM was planning to pay $6.4 billion to acquire cloud software startup Hashi Corp at the same time. It's probable that the prices of dropped as a result of the market's unfavorable reaction to the purchase announcement.

3) 16/12/2021: IBM's (International Business Machines Corp.) third-quarter earnings, released on December 16, 2021, showed a revenue gap and unsatisfactory results in its consulting division. IBM reported an increase in revenue by 1% to $14.5 billion and maintained its free cash flow estimate of $12 billion for the fiscal year ending in December. Nonetheless, IBM's $6.4 billion acquisition of software company Hashi Corp Inc. was eclipsed by the unimpressive consulting unit sales. IBM made its largest acquisition since purchasing software company Red Hat for $31.8 billion in 2019. The market might have reacted negatively to the acquisition news, causing the stock price to decline.

B. Testing on Tesla dataset

The Tesla dataset, spanning 2023-2024, is divided into two sets: the training set with 80% of the data and the test set with the remaining 20%.The evaluation metrics given in the Table

III and Table IV show that the RNN model has outperformed other models in the contexts to the prediction of Tesla's stock price before and after intervention.

TABLE III
EVALUATION METRICS FOR TESLA DATASET BEFORE INTERVENTION

Model	MSE	RMSE	MAE
Prophet	1748.05	41.80	33.55
ARIMA	1356.76	36.83	30.15
SARIMA	1506.99	38.81	31.40
RNN	46.52	6.82	5.1
MLP	49.23	7.01	5.24
LSTM	139.38	11.80	9.10

TABLE IV
EVALUATION METRICS FOR TESLA DATASET AFTER INTERVENTION

Model	MSE	RMSE	MAE
Prophet	2064.05	45.43	36.27
ARIMA	1003.16	31.67	26.11
SARIMA	1506.15	38.80	31.39
RNN	42.97	6.55	4.90
MLP	70.69	8.40	6.74
LSTM	84.62	9.20	7.09

The predictions of Tesla's stock market prices, before and after intervention, done by RNN model were plotted in fig. 4 and fig. 5 respectively.

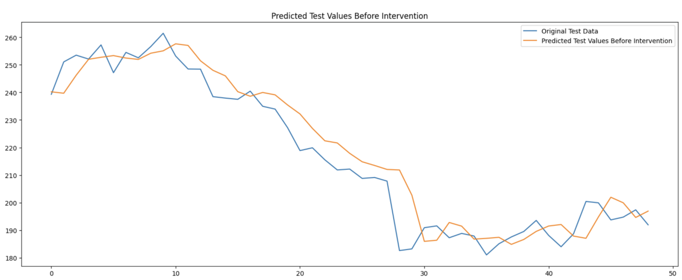

Fig. 4. Graph denoting forecasting before intervention

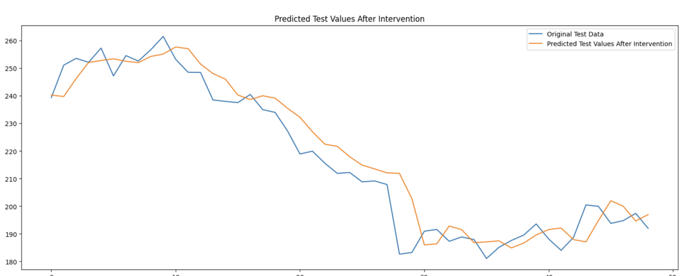

Fig. 5. Graph denoting forecasting after intervention

There were two intervention points detected by the algorithm in the Tesla dataset.

1) 06/06/2023: According to SP Global Market Intelligence statistics, Tesla (TSLA 0.65%) increased its share price by 28.3% in June. While the rebound in technological stocks was undoubtedly a factor, the electric car maker acquired further momentum and experienced repeated growth spikes over the last month, propelling the stock higher. The tidal wave of carmakers adopting Tesla's North American Charging Standard (NACS) charging port and joining Tesla's Supercharger Network was likely the most significant driver of Tesla's stock gain in June. Tesla also stated that all Model 3 and Model Y vehicles would be qualified for the full $7,500 federal tax credit under the new EV criteria.

2) 18/01/2024: Tesla, Inc. (TSLA) Shares dipped 2% after the company cut prices for its model Y automobiles in Germany, following a previous price cut for some models in China. The company's revenue and earnings missed market expectations, with automotive revenue rising just 1year-on-year.

CONCLUSION

From the above conducted study, the study concludes that the RNN(Recurrent Neural Network) consistently outperforms other models like ARIMA, SARIMA, PROPHET, MLP and LSTM to predict stock values with utmost accuracy. The RNN model proves to be effective due to its ability to consistently produce low values of MSE, MAE and RMSE. The improvement in performance can be contributed to the distinct features of the RNN model. The main feature being the model architecture which is excellent in identifying consecutive patterns in the provided stock price data which allows for accurate predictions while also leveraging historical trends. Furthermore, RNN has inherent capabilities to handle non-linear dynamics making RNN better equipped to handle data with correlations. RNN also has the capabilities to quickly modify estimates due to external events. This is due to RNN's responsiveness to intervention analysis. RNN model also improves its recognition of intricate patterns and linkages by expertly using the input data. These combined advantages allow RNN to predict stock values expertly and reliably over a wide range of market conditions

FUTURE SCOPE

Though our proposed study produced a satisfactory result, this research has more potential for future research. By integrating machine learning algorithms to dynamically adjust portfolio allocations based on sentiment analysis and intervention points recognized through historical data. This could lead to more adaptive and responsive investment strategies that capitalize on market sentiment shifts and regulatory interventions. Furthermore, using advanced NLP algorithms to news, social media posts, and other sentiment data may improve the model's prediction power.

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