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Stock Price Prediction Using Facebook Prophet

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***Abstract** - Guessing the stock market is a challenging task as it requires in-depth information to exclude news events, analyze historical data, and the impact of news events on stock price trends. The challenge is exacerbated by the volatile nature of stock prices. The prophecy of equating sales leads to a fair cost in the stock market. In Stock Price Prediction, the purpose is to predict the future value of a company's financial stock. The latest trend in stock market forecasting technology is the use of Machine Learning that makes predictions based on current stock market indicators by training in their previous values. Machine learning itself uses different models to make predictions easier and more realistic. In this case, Facebook Prophet is used to predict future stock market ratings used to analyze future stock market prices and how they differ from previous stock markets. With state-of-the-art design and consideration of preconceived notions and prior data processing techniques, this effort commits itself to analyzing the sales rate.*

***Keywords** - Stocks prediction, Facebook Prophet, Time Series Variation, Machine Learning, ANN*

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I. INTRODUCTION

Productive market speculation suggests that stock investments tolerate a lot of erudition without rational speculation and that recently disclosed information about the business environment is an immediate update on existing stock counts. Thus, stock market fluctuations predict further propaganda. There are many factors involved in predicting future price prices such as rational factors, tangible features, unrealistic factors. All of these ideas include designing rising and growing stock prices in terms of the best level of efficiency. Traditionally in addition to analyzing the emergence of stores, traders were used to assess price estimates and stock ratios in improving the recognition associated with those stocks. Commercial real estate is a complex and sophisticated system in which the public can trade in money, property, assets in addition to working principles sponsored by third parties. The stock market allows traders to go to the natural category of civil society organizations over the same trade in exchange or for conflicting information. The retail market is ownership of the important provinces to which traders are committed, so the continuation of the retail market examination is an ongoing matter for commercial and professional domain investigators. These stores have told shareholders the opportunity to earn money and a life of wealth by investing in a financial saurian accompanied by a reduction in threats before fearing a collapse of the current business. The formal prediction of stock market yields is a very difficult responsibility due to the flexibility and negative aspect of stock trading. During the illumination of the Time series and the improved trend for ciphering, beget-targeting strategies have been shown to be more productive in stock forecasts.

II. LITERATURE REVIEW

The stock price may depend on a number of factors determining the level of the current market and the stock market. There are two main features which are:

1. The authority of stock prices on additional companies alike is how the accumulation of stocks of additional companies affects the stock price of a particular company.
2. Past production and documentation relating to company stock price forecasts.

Here, various strategies are used to develop the historical pattern of the stock market and to predict future results accordingly. The stock market is classified as dynamic, invisible, and indirect.

Although a well-organized advocacy firm believes that it is impossible to accurately predict stock market prices, but the analysis of the stock forecast time series using mathematical methods and methods based on machine learning has been accepted for many years. Both methods have limitations and their strengths. Initially, researchers adopted statistical approaches like authors in [1] identified the financial movement direction of the NIKKEI 225 index by using different techniques. The use of Dynamic Mode Decomposition (DMD)-based trading strategies is recommended in the literature by many researchers to identify evolutionary patterns from stock price data [2]. [3] Extract price prediction from daily stock price data using DMD method. [4] Proposed a new SVM method for Financial Distress Prediction (FDP). Comparisons show that ANN achieves better results as compared to SVM [5]. Here, we implement Facebook prophet toproject the behavior of future stocks that examines the pattern of stocks.

III. DATA SET

Here, the data set covers 1 year of data from 2020-2021. The data set consists of 249 complete rows and 7 columns. The columns are: Date, Open, Up, Down, Close, Adj Close, Volume.
Date- This is an Index feature.
High- Indicates the maximum amount of stock per day.
Low - Lowest stock price for that day. Open - Opening price for that day.

Close - Closing price for that day.
Adj Close- Specifies the nearest fixed value.Volume - The amount of stock sold that day.
Here, we will consider the 'Close' price for each stock as an attribute for each item in our stock. The structure of data including sample rows is as follows:

TABLE I. DATA SET

Date	Open	High
2020-11-03	52.70	53.84
2020-11-04	53.25	53.95

TABLE II. DATA SET

Low	Close	Volume
50.97	52.59	11671919.0
51.08	53.45	13555398.0

This is specimen data. Before performing any algorithm commentary on the data, we necessitate doing fascinating pre-processing measures.

DATA VISUALIZATION:

One of the best predominant actions while dispensing with data is data visualization, we can visualize data with the help of different graphs using Plotly library in python which gives us a bigger and picture of data that we are dealing with.
Decentralizing data furnishes a more immeasurable perception of data. If in case data consist of large numbers of columns and rows it is difficult to analyze and plot for everydistinctive parameter distinctly. To overcome this, PlotlyExpress is used. This comprises gatherings that can generatean entire figure at once.
The X-axis is Date, Y-axis is columns in data.

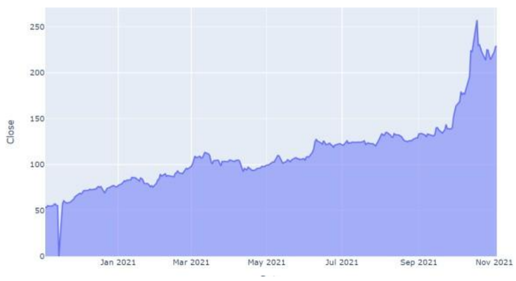

Fig. 1. Area Graph Close vs Date

The above graph is an Area Graph of Close value vs Dateof the TATAPOWER stock.

Fig. 2. Line Graph Close vs Date

Above is the line graph of Close value Vs Date for thesame stock.

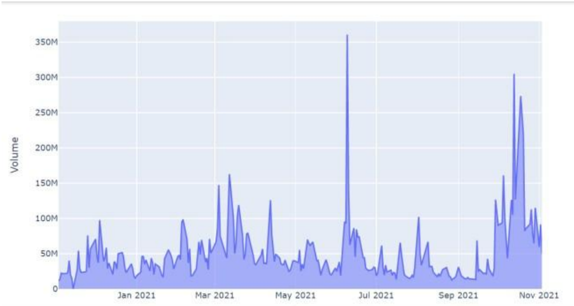

Fig. 3. Area Graph Volume Vs Date

The above graph tells us about the amount of stocks sold /exchanged on different dates.

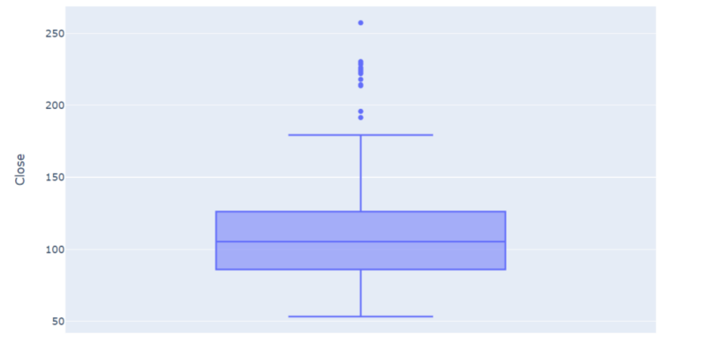

Fig. 4. Box Plot

The above graph is a Box Plot which tells us about theoutliers in the dataset.

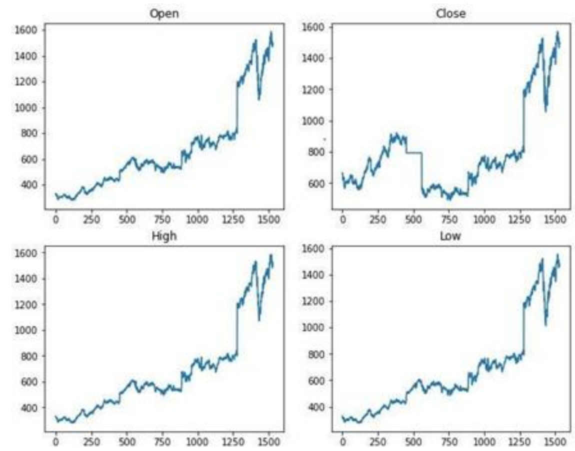

Fig. 5. Subplots of data

These are subplots of data that shows a trend or pattern of data for every column.

IV. METHODOLOGY

To get more reliable performance of ultimate forecasts of data some techniques and algorithms are used. Data can be better analyzed by using correlation plots, Moving averages, RMSE. Before performing the algorithm, techniques data must be checked for stationary test whether data is stationaryor Non-stationary.

Correlation Plot:

Used to review the data interdependence between variousvariables. Helps us to recognize how each variable is conditioned on the other.

Heatmap for Correlation:

Symbol representation of data where values are displayed in color. It is obvious to visualize complex data as well.

Indicates how each variable is associated with each variable. If the Correlation value is high between the two variables, it means that the 2 variables are highly correlated.

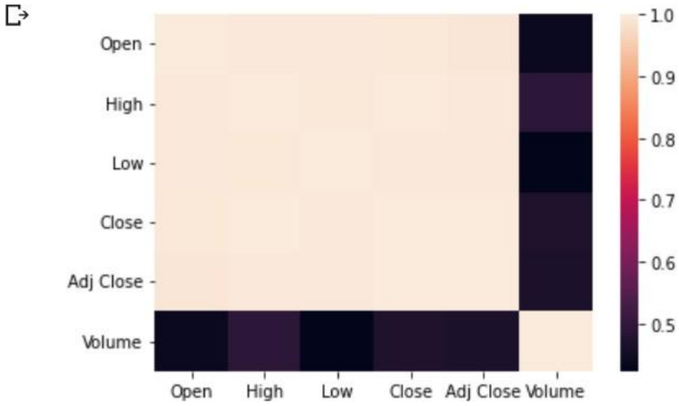

Fig. 6. Heatmap for correlated values.

Here, the above Figure6 says that almost all values are correlated with each other.

Moving Averages:

These are simple and common examples of slides used in time series analysis. It involves designing a new series where the values are combined with the sum of the immature values in the first-time series. These are the basic ideas for the timeline. This forms the basic model for analyzing time series. One of the main areas of moving averages is the time series and has a slightly different meaning. If data has a lot of flexibility it has a fixed meaning and medium movement may not be the best wayto predict. If the data has a fixed rate, the data is stationary and the moving average can be used. It can be used to prepare data, feature engineering, and predictive guides. Listed below are the types of moving averages.

Simple Moving Average (SMA):

It measures the average area of the last 'n' data points. It is an effective measure that can help determine if the value of the asset will continue or decrease the trend.

SMA: (t + (t-1) + (t-2) +…. (T-n)) / n

Determines the fraction of the selected different prices, the closing prices on a regular basis, by the number of times in that range.

Weighted Moving Average (WMA):

Provides a weighted point of the last n 'data point where the weight is assigned. It is a special indicator that attaches great weight to many modern data points, as well as light weight to data points in the past.

WMA: (t * weighting factor) + ((t-1) * 1 factor)

+…. + ((t-n) * weight factor-n) / n

It is won by multiplying the whole number in the data set by the preset weight and by adding the resulting values.

Exponential Moving Average (EMA):

It compares to a weighted scale but we do not share weights here. It takes longer to calculate EMA and takes EMA as thenext input rather than t-1 and t-2. A special chart indicator that follows the cost price over time.

EMA: (Close - previous EMA) * (2 / (span + 1)) + Previous EMA

Accept changes to data points immediately. Here, Span is thelength of time we want to calculate.

Exponential Smoothing:
Expected another parameter called 'α'. α is a slippery slope. A large number of α means that the model keeps paying attention to the most recent data points. A little α means to count history.
Yt + 1: α [Y t + (1-α) Yt-1 + (1-α2) Yt-2 + (1-α3) Yt-3
+…]
It is a precept of the precept process of smoothing outtime-series data using an interpreter window function.

RMSE:
If RMSE is less then, the Error is less. Here, RMSE is adopted to estimate which moving average is best for data. Here, we examine the ‘Close’ column and applying RMSE for that.

RMSE: $\hat{G}\sum_{i=1}^{n}(($ Y^i – y i)2)/2

TABLE IV. RMSE RESULTS FOR MOVING AVERAGES

Moving Average	21.519
Weighted moving average	19.750
Exponentially weighted average	20.075
Exponential smoothing	17.664

From TABLE4 it shows that the Exponential smoothingaverage is the best moving average for this data set.

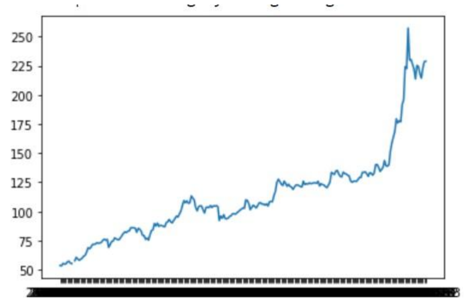

Fig. 7. Moving averages graph for Close column.

The above Figure7 shows which moving average is best.

FACEBOOK PROPHET:
It is an algorithm developed by Facebook's Core Data Science team that is used in various time series forecasting systems. It is widely used when there is a chance for seasonal results.
The Prophet was first established to produce high-quality sales forecasts. This is trying to get points like: Changes in trend due to different brands. Outliers Seasonal results such as weekly, monthly, annual cycles. y (t): g (t) + s (t) + h (t) + ε * t
y (t) - Reversal model to add g (t) - trends (t) - season
ε * t – Error

There are many strategies for predicting time series. MAPE can be used for accurate prediction. This equips us with the ability to make timetable predictions with good accuracy using natural parameters and there is an arrangement for capturing the view of the season and holiday heritage.
Facebook Prophet seeks to equate with various consecutive and indirect time activities such as objects. Modeling the season as part of an add-on is the same strategy taken by the exponential smoothness. This library isso important that it has the ability to stand within data and season-related features.

But Facebook Prophet has some limitations like it presumesto be input columns with names ‘ds’ and ‘y’ where ‘ds’ is Date and ‘y’ is the target variable. Here, a trend can either be positive or negative and may be increasing or decreasing. The sample of this data is as follows:

TABLE VII. FACEBOOK PROPHET SAMPLE DATA

	ds	Y
0	2021-01-03	54.590
1	2021-01-04	58.450
2	2021-01-05	55.210

Here, ds is the Day column and Y is the target column. This is what the Facebook Prophet needs to be in order to install ds and y. It does not take any other variables except these two. Then, the model is ready to match the train data. After the data is ready for training future forecasts are made on the data.
Data for future forecasting is as follows:

TABLE VIII. FUTURE DATA FRAME

ds	Y hat	Y hat_ lower	Y hat_ upper
2020-12-26	52.352	50.036	55.649
2020-12-27	51.407	50.644	53.335
2020-12-28	50.271	49.401	52.738

This is sample data for future predictions. Y hat- Predicted value
Y hat_ upper – upper confidence interval Y hat_ lower – lower confidence interval

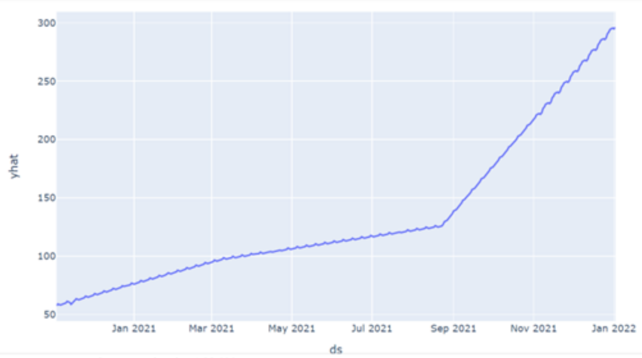

Fig. 10. Forecasting of future predictions

From Figure 10, the y-hat is obtained based on y years ago. Here, y is a real prediction of data, and y-hat is a prediction of the future based on previous data. Our model has probably seen good performance in predicting future stock prices.

We can see it better by using a prediction strategy using the confidence interval as well.
There is a parameter called interval _ width if that is set to 0.95 which indicates setting the confidence level to 95%.

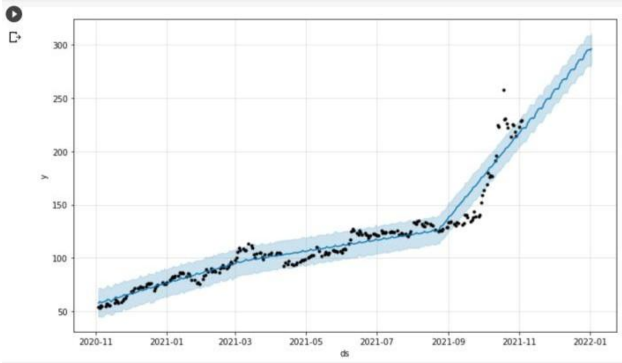

Fig. 8. Forecast future predictions

Here, X-axis is the Date and Y-axis is the target variable that is the Close column variable. Here, **Black** points indicate original data, **Blue** indicates Predicted values and **Light blue** indicates Confidence interval. Our model

has done a good performance in the prediction of future stocks.
And this Figure8 can be more clearly shown by using change points.

Change Points:
These are unexpected fluctuations in time series data. Such modifications may render developments intervening variables. Detection of these change pointsis useful in modeling and predicting time series.

V. CONCLUSION

In this paper, we have discussed stock market trends and analyzed various data patterns, and performed analysis to predict stock prices in the future. For this analysis and foresight FACEBOOK PROPHET is used. To construct these models, data are taken from stock price estimates from 2012-2020.
This analysis has the potential for further investigation.
The FACEBOOK PROPHET here is used to show future stock prices.

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