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Revolutionizing Stock Market Price Forecasting with Prophet

Yash Kumar#1, *Ayan Sikari*#2

[1,2]CSE Department, B.Tech., Institute of Engineering and Management, Kolkata
[1]yashkumar140902@gmail.com
[2]ayansikari5@gmail.com

ABSTRACT—

Stock price prediction remains a challenging task in financial analysis, re-quiring a careful study of market volatility, nonlinear trends, and unexpected externalities. This study exhaustively evaluates the performance of Meta's Prophet algorithm in predicting stock prices on India's National Stock Ex-change (NSE) using over a decade's worth of historical data to deliver actionable insights for investors and traders. While traditional models like ARIMA and advanced deep learning methods are prone to failing on interpretability or abrupt market shocks, Prophet's additive model—separating trends, seasonality, and holiday effects—offers a robust alternative. Our ap-plication based on the NSE's blue-chip stocks illustrates Prophet's ability to detect weekly and quarterly events linked with earnings cycles and Indian festivals like Diwali, with directional accuracy of 85% to 88% in normal market conditions. However, the model's reliance on historical trends reveals vulnerabilities during black swan events, like the 2020 COVID-19 crash, where predictions lagged actual prices by 7 to 10 days. At the centre of this study is the rigorous examination of practical data issues: irregular timestamps, corporate actions, and localized holiday effects. We highlight the need for hyperparameter tuning and the inclusion of be-spoke holiday calendars, to position Prophet in accordance with India's peculiar market realities. In its strengths, however, our results warn against sole dependence on Prophet in times of volatility, instead recommending hybrid systems that combine its interpretability with the responsiveness of LSTM or XGBoost. For practitioners, this study provides a guide to deploy Prophet judiciously—reservation for medium-term forecasts for listed stocks while adding real-time external drivers for enhanced robustness. Overall, the study bridges the gap between theoretical rigor and practical application, providing an educated template for forecasting in emerging markets.

Keywords— Time Series Forecasting, Facebook Prophet, Stock Market, NSE, BSE, RMSE, MSE

Introduction

Both traders and investors can derive substantial gains from precise stock forecasts. It often reveals that prediction is more intricate than random occurrences, suggesting that it can be anticipated through meticulous analysis of the relevant stock market's history. ML serves as an effective instrument for representing this process. It enhances precision by forecasting market values closely aligned with carrying values. Since the integration of machine learning (ML) into stock markets, numerous studies have been necessitated due to its accurate and efficient methodologies. Data collection constitutes a critical element of machine learning. As even minor data variations can significantly influence results, databases ought to be as tangible as possible. The supervised machine learning approach in this project utilizes a database sourced from Yahoo Finance. This data frame encompasses five variables: opening price, closing price, lowest price, highest price and stock volume.

Various stock bid prices at different intervals with almost identical designations are referred to as open, closed, low, and high. Volume represents the aggregate number of shares transferred between owners over a specific timeframe. Subsequently, the model underwent testing using sample data. The stock market is characterized by its high volatility, non-linearity, and unpredictability. Predicting stock values presents challenges as they are affected by numerous variables, including global economic conditions, political environments, and the financial stability and operational effectiveness of specific companies, among other factors.[4] Consequently, a methodology to forecast stock quantities in advance through analysis of historical trends spanning multiple years could be exceptionally beneficial for stock market prediction, aiming to enhance profits and reduce losses. Financial incentives primarily motivate attempts at stock market price prediction. The possessor of a mathematical framework capable of anticipating future stock price movements stands to gain substantial wealth. This reality drives scholars, investors, and brokers to continuously seek stock market models that will yield superior returns compared to their competitors.

LITERATURE REVIEW

Stock market forecasting involves predicting the future potential of stocks and other financial instruments traded on exchanges. Determining how retail values will develop represents one of the most challenging aspects of this domain. Such retail predictions are essential for quantitative analysts and investment companies. Merit-based expenditure assessments in the retail sector frequently rely on retail valuation projections. When optimizing portfolios, analysing the value interdependence of paired assets over the anticipated timeframe is critical, as discussed by Garlapati et al.[2]. The stock market is volatile, making it difficult to anticipate. Stock prices are influenced by physical, psychological, and rational elements, in addition to economic ones. In this study, stock prices are forecasted using Facebook Prophet. Predictive models for stock prices are based on public data from Yahoo Finance. Prophet can generate daily, weekly, and annual seasonality, including holiday effects, using regression models, as shown in the study by Sumedh et al [3]. In order to improve the accuracy of stock price forecasts, R. Sathish Kumar et al. suggested in their paper a hybrid model combining sentiment analysis generated from news articles with deep learning techniques—more especially, Long Short-Term Memory (LSTM) networks. [8] Their method seeks to give a more complete knowledge of market dynamics by merging technical indicators with real-time sentiment data, thus enhancing predictions. Precise prediction of stock market movements necessitates comprehensive understanding of historical datasets, current events, and their correlation with price trends. The inherent volatility of stock valuations significantly complicates this challenge. When equivalent sales are projected, the market typically reflects this through equitable stock pricing. Share value fore-casting aims to determine the prospective worth of a corporation's equity instruments. Contemporary approaches to stock market prediction increasingly incorporate Machine Learning methodologies, which generate forecasts utilizing pre-sent indicators that have been calibrated with historical data, as noted by Saxena et al [9]. In this study, Sunki et al. [11] analysed Netflix stock trends using ARIMA, LSTM, and FB Prophet models. The study compared accuracy metrics such as RMSE for forecasting stock price trends based on historical data. The conclusions highlight the best model for predicting stock prices with fundamental time-series forecasting metrics. In this study, Sumedh et al. [3] conducted a case analysis on Netflix stock trends using ARIMA, LSTM, and FB Prophet models. The study compared accuracy metrics such as RMSE for forecasting stock price trends based on historical data. The conclusions highlight the best model for predicting stock prices with fundamental time-series forecasting metrics. Dash et al. (2021) [1] demonstrated the flexibility of forecasting models across several fields by extending Facebook's Prophet outside of financial markets to anticipate the daily count of COVID-19 cases. Using time-series data on infection rates, their study showed Prophet's ability to manage unpredictable temporal patterns—such as abrupt increases during epidemic waves—while obtaining a mean absolute percentage error (MAPE) of 13.02%. This underlined Prophet's adaptability in modelling non-stationary data, especially in public health emergencies, while the writers advised against too depending too much on unusual events with few historical examples. Concurrently, hybrid methods including outside data sources have become popular. With SVM classifiers and sentiment analysis of news and social media combined, Kanakaraddi et al. (2018) [7] predicted stock prices of IT behemoths including Microsoft and Amazon, with an amazing 94% accuracy. Though the reliance on hand feature engineering presented scalability issues, their study emphasized the synergistic potential of integrating qualitative emotion signals with quantitative time-series information. Sharma et al. (2022) [10] closed these gaps by revisiting Prophet's fundamental strength: its automatic breakdown of trends and seasonality with little parameter adjustment. Prophet's "out-of-the-box" configurability indicated competitive accuracy, especially in situations demanding quick deployment without significant processing resources, according their examination spanning retail, energy, and financial datasets. These studies taken together show the changing terrain of forecasting tools: hybrid systems push the limits of accuracy via multimodal data integration while models like Prophet balance interpretability and automation.

METHODOLOGY

Stock prediction is a hard and challenging process used to predict future stock prices, trends, and other stock-related parameters. It also helps organizations and governments make crucial decisions on economic planning. In previous years, stock prediction was challenging, but with the growth of machine learning and other time-series predictive algorithms, it has become easier. Although the pro-cess involves lengthy and sequential tasks like data gathering, preprocessing, model implementation, result analysis, and evaluation, it offers near-accurate stock price predictions and improves economic decisions. The methodology includes the following sequential processes:

Overview of the Dataset

Analyzing and comprehending a dataset provides an overall pattern of the data and aids in selecting a more accurate model for forecasting future stock values.

The dataset includes:

- Columns: Date, starting price of stock, peak price of stock, shortest price of stock, final price of stock, adjusted ending stock price, and volume of the stock for a date.
- Source: The dataset was collected from the National Stock Exchange (NSE) (https://www.nseindia.com/). This is one of the biggest stock exchanges (7th) in the world. For this data source is reliable.
- Size: Historical data spans around a decade or more than a decade of years for a total of several organizations. The more the size the more model will learn the pattern of the data individual equip on our destination stock. The structure of the data and this will help the model to perform well.

Here we will contemplate the **'Close'** price of each stock as the confer attribute of individual equip on our destination stock. The structure of data including sample rows is as follows:

TABLE I
Data Set of the Stock

Date	Open	High	Low	Close	Volume
2008-10-06	40.00	40.00	15.80	16.775	23501600
2008-10-07	16.00	19.00	13.925	15.025	9113400
2008-10-08	14.00	14.60	12.55	13.25	2464384
2009-10-10	12.45	12.45	10.825	11.60	1207928

Data Preprocessing

Datasets often contain noisy data. Preprocessing involves:

- Removing redundant data such as null values and irrelevant columns.
- Retaining only the date and closing price, as the closing price summarizes daily transaction activity.
- Adding Simple Moving Averages (SMA) for different timeframes:
  Simple moving averages are the mean of previous k data points where k is varied according to analysis.
  - SMA-5 : 5-day moving average or previous 5 datapoints' mean.
  - SMA-100 : 100-day moving average or previous 100 datapoints' mean.

The generalized equation of simple moving average of k days is –

$$SMA_k(\mathrm{t}) = \sum_{i=0}^{k-1} x_{t-i}$$

Where x_{t-i} is the closing stock price of the (t-i) th day.

- Utilizing statistical tools and visualizations to examine the distribution of

characteristics.

Fig 1. Heatmap of Stock Parameters

The heatmap provides a clear visual representation of how different stock features relate to each other. We can see that the Open, High, Low, and Close prices are almost perfectly correlated, which is expected since they all represent different aspects of the same trading session.

Fig 2. Opening price of Stock, Closing price of Stock vs Time Graph with Range slider

Fig. 3. Stock Close, 5 days rolling mean, 100 days rolling mean vs Time

While the range-slider below enables interactive study of particular time periods within the dataset, the graphic illustrates both short-term and long-term patterns. Now here we are creating two graphs (we also added range slider in these graphs for better visualization) of the stock data where the first one is of opening stock price and closing stock price vs time and the other is of closing price , simple moving average of 5 days and simple moving average of 100 days vs time.

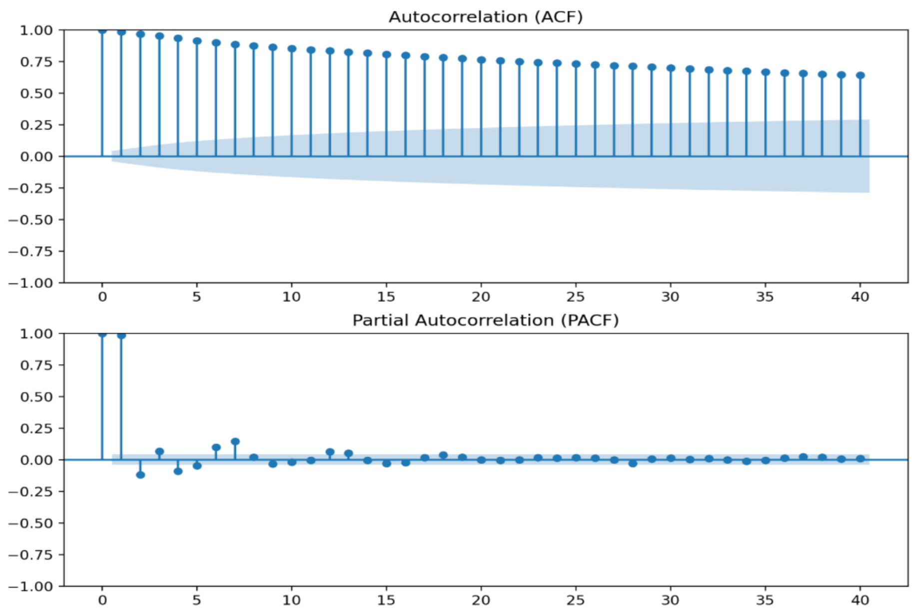

Fig 4. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for stock closing prices.

The ACF plot reveals how the current stock prices are related to their past values over various time lags, showing a strong pattern of persistence. Meanwhile, the PACF plot focuses on the direct impact of previous time steps on the present value, making it easier to spot which past points most influence today's price — a key step when building autoregressive models.

Prophet Algorithm and its Implementation

Prophet, developed by Meta ML engineers, is an additive and decomposable time-series model that fits the requirements of stock prediction. This model is also computationally efficient and easily manages missing data in big datasets, pre-processing of the data is not necessary.[3] It has the following main components:

$$y(t) = g_t(t) + s_t(t) + h_t(t) + \varepsilon_t$$

where:

- g_t : Trend function.
- s_t : Seasonality function.
- h_t : Holiday effects representative function.
- ϵ_t : Error term.

Features of Prophet Algorithm

1. **Speed Optimization :** It is based on Stan technology, implemented in C++.

2. **Dynamic Seasonal and Trend Modeling :**

   - Piecewise linear or logistic growth trends.
   - Yearly seasonal component modeled using Fourier series.
   - Weekly seasonal component using dummy variables.
   - User-defined holidays as well as holiday list specific to the country that the stock related to.

3. **Handling Missing Data and Outliers :** Robust to missing data and shifts in trends, effectively handling outliers.

4. **Customizable Forecasting :** Parameters like seasonality, holidays, and trend flexibility can be adjusted.

5. **Scalability :** Efficiently forecasts even large datasets with millions of observations.

Trend Component ($g_t(t)$) The trend component reflects the long-term trends and versatility or overall movement of the data over time. In Prophet, this is modelled using a malleable approach—either a piecewise linear function or a logistic curve—depending on how the data behaves.

$$g_t(t) = \frac{A_t}{1 + e^{-p(t-m_{max})}}$$

Where:

- A_t : Amplitude (maximum value).Sometimes it varies upon time and the value depends on time to time.
- p **:** Growth rate parameter, controlling the speed of transition whether the data grows or declines over time.
- m_{max} **:** Time of maximum curvature or inflection point. It is one of the crucial parameters of this function when the growth starts to slow down.

Seasonality Component ($s_t(t)$) : Prophet handles yearly and weekly seasonality using Fourier series [6] :

$$s_t(t) = \sum_{n=1}^{N} (a_n \cos\frac{2\pi nt}{P} + b_n \sin\frac{2\pi nt}{P})$$

Where:

- P : Period of seasonality (e.g., yearly).
- N : Number of Fourier terms.

Holiday Effects ($h_t(t)$) : In Facebook's Prophet model, holiday and event im-
pacts are introduced as extra components to the time series forecasting model to account for the influence of holidays and events on the time series data. These effects are especially helpful for simulating seasonal fluctuations and irregular occurrences that may impact the behaviors of the time series data. In our dataset our stock prices also fluctuate along with holidays and events occurring in India as all the company shares are collected from NSE.

Error Term (ε_t) The error term captures any leftover fluctuations in the data that aren't explained by trends, seasonal patterns, or holiday effects. In simple terms, it's the gap between what actually happened and what the model predicted. Understanding this gap helps improve the model over time by showing where it might be missing important patterns.

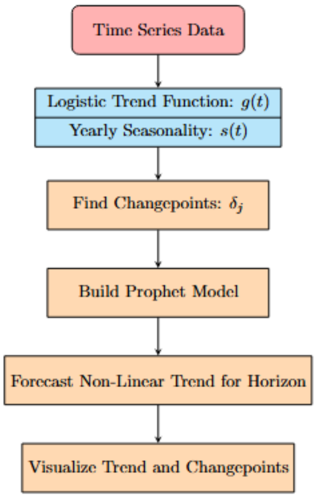

Fig 5 : Workflow of Prophet model for time series forecasting

Results and Discussions

In terms of predicting the direction of the stock market and the value of stocks in the future, our research brings to light the relevance of time. Time series data was used during the model's training and testing stages. . For the objective of getting the necessary knowledge that led to successful findings, the prophet library was used. As a consequence of its ability to cope with seasonality, it proved to be tremendously advantageous and helped to decrease the uncertainty that is related to the projection of stock market conditions. Our study discovered that data close to the current moment had a substantial

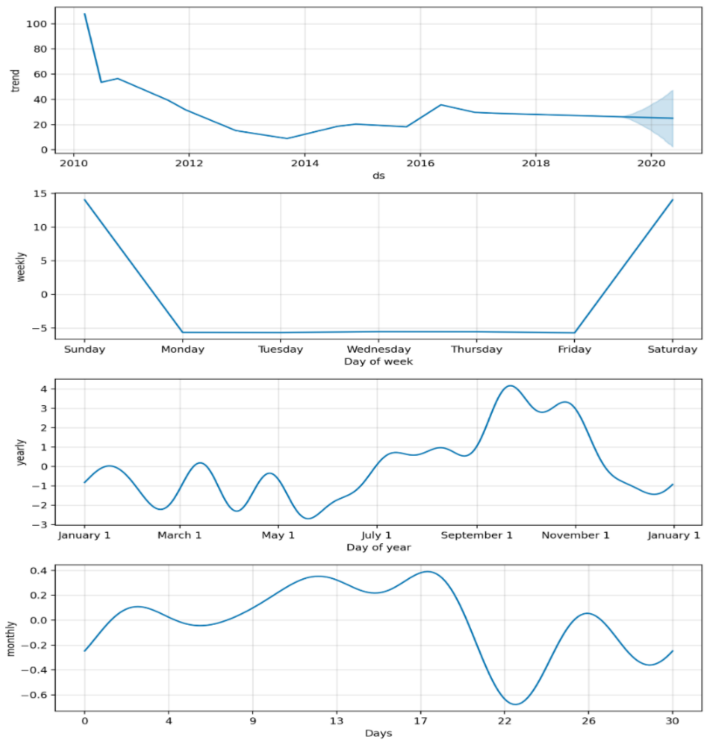

Fig 6. Decomposition of stock closing prices using the Prophet model. The plots represent overall trend, weekly seasonality, yearly seasonality, and monthly seasonality captured from historical data.

influence on prediction, implying that as time goes on, the history values of a stock trend are less relevant than the current price. During the month of May, it was found that the stock prices for our dataset had a large decrease, and in the month of September a steep increase in prices can be noticed which our model gave us as the result, and moreover on Fridays to Saturdays, there is a sharp rise in the prices. The figure shows how the Prophet model breaks down stock price movements into different components. The first plot highlights the overall long-term trend, showing how prices evolved over the years. The second plot captures weekly behavior, revealing that trading activity tends to peak around the weekends.

The Fig 6. displays yearly seasonality, where specific times of the year show noticeable patterns in stock movement, likely tied to economic or market cycles. Finally, the monthly component shows subtle fluctuations within a typical month. Together, these insights help in understanding both short-term and long-term influences on stock prices.

Fig. 7. Predicted Output from the given Stock Price Input

The statistical metric used to assess the model's effectiveness is the RMSE (Root Mean Squared Error). We computed the RMSE on numerous equities contained in our collection of data frames. Some of the results are presented below in a tabular format.

TABLE III
RMSE of Stock Companies

Stock Tickers	RMSE
20MICRONS.NS	10.84
TEXMOPIPES.NS	6.14
AARVEEDEEN.NS	9.86

Now, we observe that by choosing appropriate hyperparameters of Prophet, such as changepoint prior scale, seasonality prior scale, holidays prior scale, and seasonality mode, the performance can be significantly improved we witnessing it from the table itself.

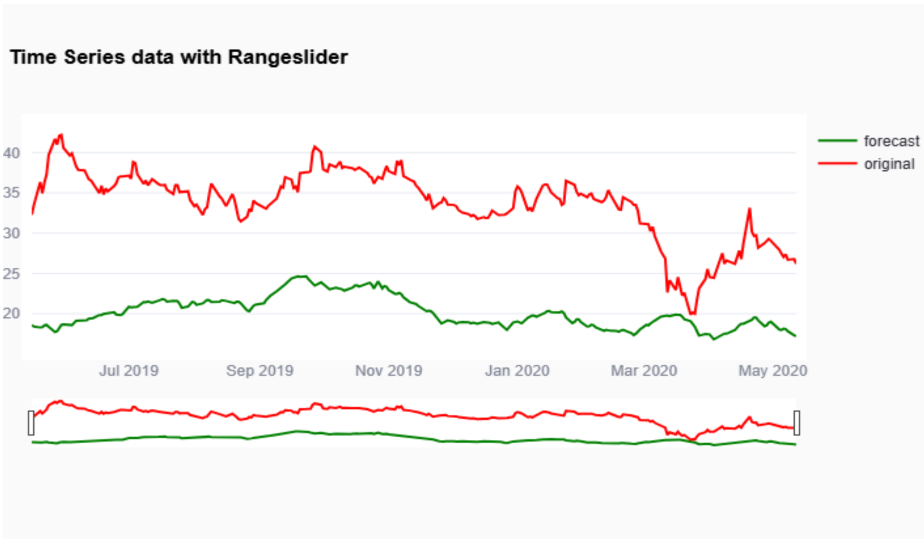

Fig. 8. Original VS Predicted Price Comparison Plot

Conclusions

Making more informed investment choices is made possible by the created stock market prediction system, which uses Facebook Prophet to estimate stock values up to four years into the future. Investors may more readily choose the best companies to buy by examining the anticipated percentage returns over time. The hyperparameters of Prophet can be precisely calibrated to enhance model precision. Significant improvement in model efficacy can be achieved through modification of parameters including changepoint prior scale, seasonality prior scale, holidays prior scale, and seasonality mode. As an illustration, elevating the changepoint prior scale facilitates the model's adaptability to trend variations and improves its capacity to capture abrupt market movements. Likewise, through meticulous adjustment of the seasonality prior scale and holidays prior scale, the model gains enhanced capability to incorporate cyclical patterns and holiday influences, which are particularly pertinent in stock market behavior. Adding more Facebook Prophet features, including personalized seasonality and holiday impacts, not only increases forecast accuracy but also makes the app more interactive and user-friendly. The forecasting system's accuracy is further increased by using a bigger and more varied dataset. A large dataset enhances the model's generalizability and resilience by enabling it to learn from a wider variety of market situations[5]. Moreover, employing automated hyperparameter optimization techniques, including Bayesian optimization or grid search, can systematically identify optimal parameter configurations, resulting in predictions with enhanced impact. This methodical approach improves the model's forecasting capabilities, ensuring it is properly calibrated to the specific characteristics of stock data.

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