**[B.Sc. Engg. Thesis]**

**Stock Price Prediction from Time Series Analysis Applying Machine Learning Techniques**

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**Stock Price Prediction from Time Series Analysis Applying Machine Learning Techniques**

This thesis is submitted to the Electronics and Communication Engineering Discipline in partial fulfillment of the requirements for the degree of Bachelor of Science in Electronics and Communication Engineering, abbreviated as, B.Sc. Engg. (ECE).

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# **Recommendation**

This thesis is reported and presented as a requirement for the degree of Bachelor of Science in Electronics and Communication Engineering, abbreviated as B.Sc. Engg. (ECE), awarded by Electronics and Communication Engineering (ECE) Discipline, Khulna University. Authors declare that the work is solely performed by them.

**Approved By**



# **Declaration by Authors**

We, the undersigned, Rakibul Hassan Rakib and Mohammad Rabby hereby declare that we are the sole authors of this thesis titled **“Stock Price Prediction from Time Series Analysis Applying Machine Learning Techniques”** under the sincere guidance of our supervisor **Dr. Md. Mizanur Rahman**. To the best of our knowledge this thesis contains no material previously published by any other person except where due references have been made. This thesis contains no material which has been accepted or published as part of the requirements of any other academic degree or non-degree program, in English or in any other language. This is a true copy of the thesis, including final revisions. If our work is called into doubt due to unethical methods, we shall accept full responsibility.



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# **Abstract**

This thesis explores the prediction and analysis of stock market trends of Bangladeshi companies. The analysis of stock market trends have long been of interest to researchers, investors, and financial institutions due to their significant impact on economic growth, portfolio management, and wealth generation. This thesis explores the application of time series analysis techniques to examine trends in the Bangladesh stock market, specifically focusing on candlestick patterns and their predictive potential. The study integrates two prominent approaches: FB Prophet model, a deep learning model known for capturing long-term dependencies in sequential data, and AutoRegressive Integrated Moving Average (ARIMA), a statistical model traditionally used for time series forecasting. By utilizing these models, the research aims to evaluate their effectiveness in identifying patterns and trends in the stock market, with a particular focus on candlestick data. The research involves preprocessing historical stock market data from the Bangladesh market, extracting candlestick features, and applying both Prophet and ARIMA models to analyze trends. The study aims to assess how well these models capture market patterns and provide insights into the behavior of stock prices. Performance metrics such as mean absolute error (MAE) and directional accuracy are used to measure the models’ predictive abilities. The findings indicate that while ARIMA performs effectively with linear, stationary data, Prophet provides superior results in capturing complex, non-linear patterns within the stock market, particularly in relation to candlestick patterns. The integration of machine learning and deep learning models enables the extraction of valuable insights, aiding investors in making more informed decisions. This thesis contributes to the field of financial analytics by presenting a comprehensive framework for analyzing stock market trends in the Bangladesh context, highlighting the benefits and limitations of each model, and offering practical guidance for real-world investment strategies. The research emphasizes the importance of accurate trend analysis and prediction in enhancing decision-making, managing risk, and identifying profitable opportunities for investors in the dynamic stock market environment.

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# **List of Abbreviations**

| API | Application Programming Interface |
| --- | --- |
| AI | Artificial Intelligence |
| ARIMA | AutoRegressive Integrated Moving Average |
| ANN | Artificial Neural Network |
| ARMA | AutoRegressive Moving Average |
| BSE | Bombay Stock Exchange |
| CNN | Convolutional Neural Network |
| CSV | Comma-Separated Values |
| CAGR | Compound Annual Growth Rate |
| DNN | Deep Neural Network |
| DSE | Dhaka Stock Exchange |
| DL | Deep Learning |
| DM | Data Mining |
| DT | Decision Tree |
| ETF | Exchange-Traded Fund |
| EV | Enterprise Value |
| EDA | Exploratory Data Analysis |
| EMA | Exponential Moving Average |
| FN | False Negative |
| FP | False Positive |
| FII | Foreign Institutional Investor |
| FS | Feature Selection |
| GA | Genetic Algorithms |
| GDP | Gross Domestic Product |
| GICS | Global Industry Classification Standard |
| HFT | High-Frequency Trading |
| IRR | Internal Rate of Return |
| IOT | Internet of Things |
| IT | Information Technology |
| KL | Kullback-Leibler |
| KNN | k-Nearest Neighbor |
| LR | Linear Regression |
| LR | Logistic Regression |
| Prophet | Long Short-term Memory |
| MA | Moving Average |
| ML | Machine Learning |
| MAPE | Mean Absolute Percentage Error |
| MACD | Moving Average Convergence Divergence |
| MSE | Mean Squared Error |
| MLP | Multi-Layer Perceptron |
| MAE | Mean Absolute Error |
| NB | Naïve Bayes |
| NN | Neural Network |
| NSE | National Stock Exchange |
| NASDAQ | National Association of Securities Dealers Automated Quotations |
| OLS | Ordinary Least Squares |
| PE | Price-to-Earnings |
| PPO | Percentage Price Oscillator |
| PRD | Prediction |
| ROI | Return on Investment |
| R&D | Research and Development |
| RSI | Relative Strength Index |
| RMSE | Root Mean Squared Error |
| RF | Random Forest |
| RNN | Recurrent Neural Network |
| SGD | Stochastic Gradient Descent |
| SSE | Sum of Squared Errors |
| SQL | Structured Query Language |
| SMA | Simple Moving Average |
| SVM | Support Vector Machine |
| TTM | Trailing Twelve Months |
| VAR | Vector AutoRegression |
| VIX | Volatility Index |
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# **Introduction**

## **1.1 Background**

A stock market, equity market, or share market is where people buy and sell stocks. The stock market serves as a platform for investors to participate in the growth of companies, diversify their portfolios, and potentially earn returns on their investments. Stock price prediction has been a widely studied topic in financial markets due to its significant implications for investors, traders, and policymakers. Accurately forecasting stock prices is a challenging task because of the inherent volatility and complex patterns in financial time series data. Traditional statistical models, such as the AutoRegressive Integrated Moving Average (ARIMA), have been extensively used for time series forecasting.{1] However, with the advent of machine learning (ML) techniques, more sophisticated models, such as Facebook’s Prophet model, have been developed to improve forecasting accuracy by handling seasonality and trends more effectively. [2]

This thesis explores the application of ARIMA and Prophet models for stock price prediction by analyzing historical stock market data. The study aims to compare the performance of these models in terms of accuracy, efficiency, and predictive capability. By leveraging time series analysis and machine learning techniques, this research seeks to enhance the reliability of stock price forecasting, providing valuable insights for market participants. The findings of this study will contribute to the growing field of financial data science and help in developing better predictive models for stock market trends. The integration of statistical and machine learning-based approaches in stock price forecasting can lead to more data-driven investment strategies and risk management practices. [3]

Stock price prediction is a critical area of research in financial markets, as accurate forecasts can provide significant advantages to investors, traders, and financial analysts. The volatile and dynamic nature of stock prices, influenced by economic conditions, market trends, and investor sentiment, makes predicting future prices a challenging task.[4] Traditional statistical models, such as the Autoregressive Integrated Moving Average (ARIMA), have been widely used in time series forecasting due to their robustness in capturing linear dependencies in stock price movements. However, with advancements in machine learning, more sophisticated approaches, such as Facebook's Prophet model, have emerged as powerful alternatives capable of handling nonlinear trends, seasonality, and external factors. This thesis explores the application of ARIMA and the Prophet model for stock price prediction by leveraging time series analysis techniques. The objective is to assess the effectiveness and accuracy of these models in forecasting stock prices by analyzing historical stock data. While ARIMA is a well-established method known for its precision in short-term forecasting, Prophet is designed for scalability, handling missing data, and incorporating seasonality components, making it a promising candidate for financial market analysis. The stock market plays a crucial role in the global economy by facilitating investment opportunities and financial growth. Accurate stock price prediction is essential for investors, financial analysts, and policymakers to make informed decisions. However, predicting stock prices remains a complex challenge due to their highly volatile and dynamic nature. Traditional forecasting methods often struggle to capture the non-linear patterns and external factors influencing stock movements. With advancements in artificial intelligence and statistical modeling, machine learning techniques have emerged as powerful tools for time series analysis and stock market prediction.[5]

This thesis explores stock market price prediction using time series analysis and machine learning techniques, specifically leveraging the ARIMA (AutoRegressive Integrated Moving Average) and Prophet models. These models are widely used for forecasting financial data due to their ability to handle seasonality, trends, and short-term fluctuations. The dataset for this study is collected from Janata Bank Mutual Fund, a well-known financial institution, providing real-world data for model training and evaluation. The research aims to compare the performance of ARIMA and Prophet models in forecasting stock prices, analyze their predictive accuracy, and assess their effectiveness in making investment decisions. By integrating traditional statistical approaches with modern machine learning algorithms, this study contributes to the growing field of financial forecasting, offering insights into the applicability of these models in stock price prediction. However, predicting stock prices remains a complex challenge due to their highly volatile and dynamic nature.[6]

The findings of this research will provide valuable insights for investors, financial institutions, and researchers seeking reliable predictive models for financial decision-making. The study will also highlight the strengths and limitations of ARIMA and Prophet models in stock market forecasting, paving the way for future advancements in predictive analytics and financial modeling. The process of developing a machine learning model pipeline for stock price prediction involves multiple stages. It typically begins with gathering historical data through an API, followed by data pre-processing, constructing a forecasting model, and ultimately assessing its performance. The pre-processing phase includes tasks such as filtering out zero values, eliminating duplicate entries, and applying feature scaling. Afterward, essential features are identified, and relevant data are selected to be used in forecasting or predicting stock prices [7].

This article discusses several widely used machine learning and deep learning techniques, including ARIMA (AutoRegressive Integrated Moving Average), FB Prophet (Facebook Prophet), Prophet (Long Short-Term Memory), and GRU (Gated Recurrent Network). Additionally, ensemble algorithms like Random Forest are examined [8]. When evaluating classification models, common performance metrics include precision, recall, and F-score. On the other hand, regression or forecasting models are typically assessed using root mean square error (RMSE) and mean absolute percentage error (MAPE) [9].

Predicting stock prices and identifying market trends remain complex challenges. Over time, researchers have explored multiple approaches to address these issues [10], and this paper provides an overview of some of these methods. Machine learning, deep learning, time series forecasting, and ensemble techniques are among the most commonly used solutions. By leveraging ensemble algorithms, accuracy can be enhanced while RMSE is minimized. Moreover, Hadoop-based architectures are capable of processing vast amounts of stock data [11], and deep learning models have been applied successfully in financial market predictions [12]. Stock price forecasting using Prophet, an advanced recurrent neural network (RNN), addresses long-term dependencies effectively [13]. However, RNN-based models often require mitigation strategies to handle vanishing and exploding gradient problems [14].

To achieve accuracy levels between 80% and 98%, various techniques, including MLlib, linear regression, and random forest, have been utilized. Neural networks, which rely on interconnected layers of neurons, and support vector machines, which classify stock price movements using hyperplanes, are among the popular choices for stock prediction. Random forest, trained using multiple decision trees, and Naïve Bayes, which predicts stock movement by analyzing positive and negative probabilities, have been applied using ten years of historical data from Reliance and Infosys [15]. Furthermore, a comparison of random forest with other algorithms was conducted on a dataset comprising 5,767 European companies. These algorithms also include neural networks, where multiple layers of neurons form complex connections, and logistic regression, which determines stock movement direction using probability-based binary classification.

Stock market forecasting falls under regression analysis since stock prices represent continuous values [16]. Research has employed RNN models for forecasting Google stock prices. Among the most efficient neural networks for sequential data are RNN, Prophet, and GRU. While RNN is primarily used for historical data analysis, Prophet and GRU offer solutions to the vanishing gradient issue by incorporating forget, reset, and update gate mechanisms. GRU, in particular, operates on reset and update gates, making it a faster alternative [17].

Additionally, financial news and user-generated content, such as social media comments, can influence stock market trends. For instance, statements like “Monday has the lowest average return” indicate weak or negative sentiment. When compiling datasets for training stock prediction models, utilizing historical data with a rolling window approach proves to be highly effective, especially when integrating market news-based text data. [18]

The algorithms that are used for stock market prediction by considering research papers are given in Figure 1.1 :

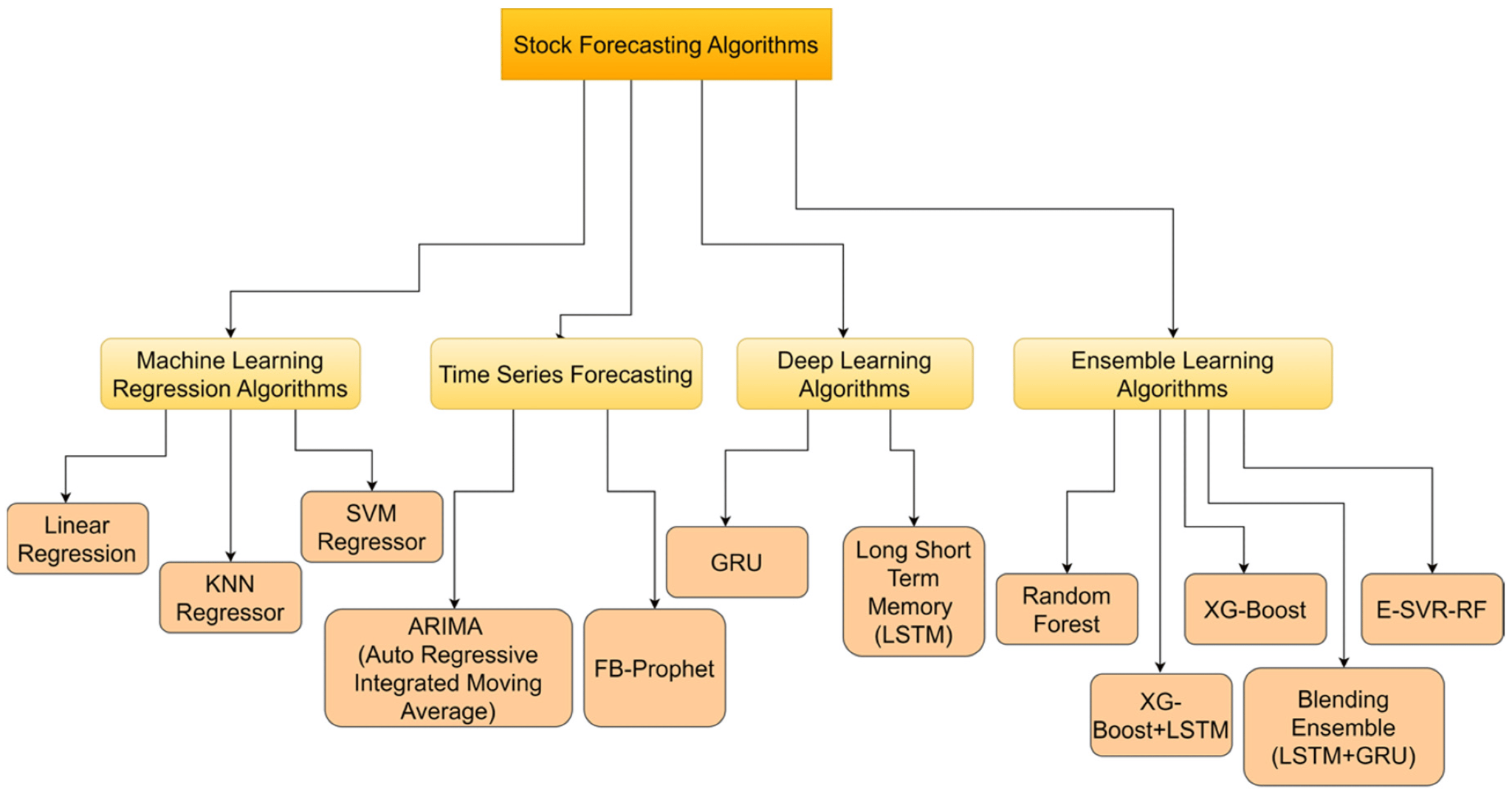


Fig. 1.1: Stock forecasting algorithm [19]

Not only have machine learning ensemble methods helped to improve forecasting performance, but in some research work, it has also been observed that neural network blending ensemble models also perform well. [20] Implementing a model consisting of two layers of RNN. The first one was a Prophet-based blending ensemble algorithm, and the second one was GRU-based. The model showed the lowest RMSE value of 186.32, a precision of 60%, and an F1-score of 67.47 [21]. Sometimes, price movement is primarily affected by sentiments. These sentiments can be positive, leading to a bullish movement, or negative, leading to a bearish movement. Hence, stock sentiment analysis is important to understand stock price forecasting and trend classification. [22]

## **1.2 Motivation**

The motivation behind the thesis is driven by the growing complexity of the financial market and the increasing need for accurate prediction models to support investment decisions. Stock markets are influenced by numerous unpredictable factors, making it challenging for investors to forecast future price trends. This uncertainty often leads to poor investment choices, which can have significant financial consequences. The thesis aims to bridge this gap by leveraging advanced time series forecasting techniques, including machine learning and deep learning models like Long Short-Term Memory (Prophet), ARIMA, and PROPHET, to predict stock prices with higher precision. [23] By analyzing historical data, these models can identify underlying patterns and trends in stock market behavior, providing investors with insights that improve their decision-making process. The use of Prophet allows for handling long-term dependencies in data, ARIMA is suitable for statistical forecasting, and PROPHET is designed for capturing seasonal trends. Together, these models have the potential to enhance prediction accuracy and reduce the risks associated with stock market investments, ultimately helping investors make more informed and profitable decisions.

## 

## **1.3 Objectives of the Thesis**

The primary objective of the thesis is to develop and evaluate advanced predictive models that can forecast stock market prices, aiding investors in making informed decisions. The research focuses on leveraging time series data, which is essential for capturing historical patterns and trends in stock prices, to train different machine learning and deep learning algorithms. Specifically, the thesis aims to compare the effectiveness of three prominent models: Prophet, ARIMA and PROPHET. The goal is to identify the most accurate model for stock price prediction, enhancing the decision-making process for investors. [24] By implementing these techniques, the thesis seeks to contribute to the financial domain, where forecasting market trends is crucial for maximizing returns and minimizing risks. Ultimately, the research aims to provide investors with a reliable tool for predicting stock prices and optimizing their investment strategies in an increasingly sustainable market environment.

## **1.4 Contribution of the Thesis**

After completing the thesis successfully, we can make a significant contribution to the field of financial analytics and decision support systems by addressing the complex and outlier nature of stock market price movements. This research delves into the application of advanced computational methodologies, specifically Prophet, ARIMA, PROPHET models, to enhance the accuracy and reliability of stock price predictions. By leveraging time series data, the study bridges the gap between theoretical model performance and practical utility for investors, offering insights into the dynamic patterns underlying market fluctuations. The comparative analysis of machine learning and deep learning approaches provides a nuanced understanding of their respective strengths and weaknesses in capturing trends, seasonality, and anomalies in stock data. Furthermore, the integration of these predictive models into investment decision-making processes equips investors with robust tools to minimize risks and optimize returns. The thesis also emphasizes the interpretability of predictions, ensuring that the models’ outputs are actionable for both experienced traders and novice investors. The implications of this work extend beyond academic significance, offering tangible benefits to stakeholders in the financial markets by facilitating data-driven, informed decisions.

## 

## **1.5 Organization of The Thesis**

This thesis is organized into five chapters. An outline of this thesis is given below-

**Chapter 1**

The background and motivations of our thesis are discussed in the “Introduction” chapter. In addition, it also represents the objectives and contribution of our study.

**Chapter 2**

The bibliometric literature review of our related studies is described in the chapter under “Literature Review”. It includes all the details of paper collection, selection, and various performance analysis methods.

**Chapter 3**

The overall methodology of our work, our dataset, and various statistical and shallow learning techniques are described in the “Materials and Methods” chapter.

**Chapter 4**

The key features for predicting arrhythmia are discussed in the chapter “Result and Discussion”. It also includes the prediction performance of the proposed model. In this chapter, we have also compared our work with other relevant studies.

**Chapter 5**

The conclusion and future scope of this research are discussed in the final chapter, titled "Conclusion and Future Work

# **Literature Review**

A literature review is a comprehensive overview of research related to a specific topic. It summarizes existing knowledge, approaches, methods, gaps, and future research directions [25]. According to Ressing et al. [26], literature reviews can be conducted using methods such as systematic literature reviews, meta-analyses, and bibliometric analyses. For this study, a bibliometric analysis was chosen because it provides a structured, quantitative overview of the academic literature in the field, enabling researchers to track and evaluate the interconnections and impact of publications using statistical and mathematical techniques. In one study [27], it was highlighted that bibliometric analysis is particularly effective for identifying significant research contributions, prominent scholars, and evolving trends over time. As well as, it makes a valuable tool for understanding the broader context of stock price prediction research.[28]

The topic “stock price prediction and analysis” was selected due to its critical importance in financial markets and the growing demand for accurate forecasting methods. Stock price prediction plays a vital role in investment strategies, risk management, and economic planning. [29] This study focuses on the application of Prophet and ARIMA models, which are widely used in time series forecasting for financial data. By analyzing the predictive accuracy and performance of these models, this research aims to provide a comprehensive understanding of their strengths and limitations in forecasting mutual fund stock prices.[30]

The dataset for this research was sourced from Kaggle, a platform offering publicly available datasets for data analysis and machine learning projects. The dataset includes historical opening prices of the First Janata Bank mutual fund from 2010 to 2022. [31] This choice ensures the analysis is based on reliable and real-world data, addressing the gap in literature focusing on forecasting mutual fund data in emerging markets.[32]

## **2.1 Stock Market Prediction**

Stock market prediction is a challenging yet essential area due to its complex, non-linear, and chaotic nature [33]. Numerous studies highlighted that the unpredictable nature of the stock market made forecasting difficult. Different factors such as economic indicators, company performance, and global events necessitate sophisticated models to influence market behavior. According to Muzaffer et al. [34], researchers are exploring advanced techniques, including machine learning and artificial intelligence, to improve prediction accuracy. In one study [35], it was stated that catastrophe theory offers a new perspective on understanding sudden market changes and equilibrium shifts. Despite some challenges, stock market prediction remains a crucial area of study as it can help investors to make informed decisions.

However, this study provides an in-depth examination of the advancements in machine learning (ML) and deep learning (DL) applied to stock market prediction. Furthermore, this study emphasizes their performance, limitations, and future directions. [36]

## **2.2 Machine Learning Models**

Machine learning (ML) is a subset of artificial intelligence that enables computers to learn patterns from data without explicit programming [37]. According to and, ML models can be applied to various tasks, such as categorizing children’s books or processing big data. Therefore, it involves developing models that structure problems, define states, actions, and rewards in a learning environment [38]. However, machine learning techniques are mildly used for stock market prediction. Moreover, it offers improved accuracy and accessibility compared to traditional methods [39]. The prediction process typically involves data acquisition, preprocessing, feature extraction, and application of machine learning algorithms [40].

Studies have shown that neural networks, particularly when combined with denoising schemes, outperform other techniques in stock price prediction [41]. Thus, there have been Machine Learning (ML) approaches. Prominent ML approaches include:

### **2.2.1 Support Vector Machines (SVMs)**

Support Vector Machines (SVMs) are a powerful machine learning technique for binary classification and regression tasks [42]. SVMs have gained popularity due to their strong theoretical foundation in statistical learning theory and convex optimization [43]. One important feature is that SVMs are effective for both regression and classification tasks. Weicker [44] highlighted that SVMs have shown good performance in benchmarking studies, competing well against classification and regression methods.

Support Vector Machines (SVM) have emerged as a powerful tool for stock market prediction. Multiple studies have demonstrated SVM’s capability to overcome challenges faced by conventional regression models,[45] such as model uncertainty and parameter instability [46].

### **2.2.2 Random Forests (RF)**

Random Forests are widely adopted for their robustness and ability to handle high-dimensional datasets.[47] RF is particularly suitable for high-dimensional data analysis. Its capability of handling large numbers of variables and accounting for correlations and interactions among features [48]. Jose & Varshini [49] achieved a 91.45% success rate in predicting opening stock prices by combining technical indicators with ensemble learning methods. These studies consistently demonstrate that particularly RF can significantly improve stock market prediction accuracy across various timeframes and market conditions.

**2.2.3 Gradient Boosting Machines (GBMs)**  
According to Natekin & Knoll [50], Gradient Boosting Machines (GBMs) are powerful ensemble learning techniques widely used in various applications. Here, algorithms such as XGBoost and LightGBM have gained popularity for their scalability and efficiency. Recent studies have explored the applicability of Gradient Boosting Machines (GBMs) in stock market prediction, demonstrating their effectiveness compared to other algorithms. According to Reddy & Kumar [51], GBMs have shown superior accuracy (92.3%) over Naive Bayes (87.7%) in stock price forecasting.

## **2.3 Deep Learning Models**

Deep learning models have revolutionized stock market prediction by handling large amounts of complex data [52]. Recent studies have explored various neural network structures, including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), for this purpose [53]. Key deep learning approaches include:

### **2.3.1 Recurrent Neural Networks (RNNs)**

According to Lipton [54], RNNs have demonstrated remarkable performance in various tasks, including image captioning, language translation, and handwriting recognition. RNNs, particularly Long Short-Term Memory (Prophet) networks, are designed to model sequential data. Recent studies highlighted that Prophet networks significantly outperform traditional models in predicting stock price trends.

The superior performance of Prophets is attributed to their ability to learn complex relationships in historical stock data, including prices and trading volumes [30]. Compared to conventional methods like Random Forest, Linear Regression, and ARIMA, Prophet models achieve higher prediction accuracy and lower error rates. [55]

### **2.3.2 Convolutional Neural Networks (CNN)**

CNNs, originally developed for image processing [56], have gained popularity due to their higher accuracy and efficiency in object detection and recognition tasks. Recent studies have explored the adaptation of CNNs for stock price analysis. Lin et al. highlighted that CNNs leverage their ability to extract spatial and temporal features. Furthermore, Hoseinzadeh & Haratizadeh [57] introduced a CNN-based framework that incorporates data from multiple markets to predict stock market movements. Eapen et al. [58] showed that combining CNNs with Prophets leads to superior performance by leveraging both strengths.

## **2.4 Hybrid Models**

Hybrid models, which integrate ML and DL techniques, combine the strengths of ML algorithms for structured data with DL’s neural networks for unstructured data processing. Chen et al. [59] proposed a hybrid model combining ARIMA with Prophet, where ARIMA captures linear trends and Prophet models non-linear patterns.

The Identification phase began with an initial search in the Web of Science (WoS) database, yielding 297 studies related to stock price prediction. After removing duplicates, a total of 297 unique records remained for further screening.

In the subsequent Screening phase, studies were examined for relevancy to the specific focus of this research. A total of 58 papers were excluded due to their lack of direct applicability to stock price prediction models such as ARIMA and Prophet or their focus on non-financial datasets. Following this, 239 papers were retained for further analysis.[60]

The final step involved a Full-Text Review of the remaining papers to ensure their alignment with the research objectives. During this phase, 19 papers were excluded for reasons such as methodological inadequacy or a focus on irrelevant financial datasets. Ultimately, 220 studies were selected for inclusion in the bibliometric analysis.[61]

The following are key studies considered relevant to this research, each contributing valuable insights into stock price prediction using ARIMA and Prophet models:

**Stock Price Prediction Using Facebook Prophet**This study examines the application of Facebook Prophet in predicting stock prices, demonstrating its ability to model nonlinear trends and seasonality effectively in financial time series data. This research provides a foundational understanding of the Prophet model's capabilities in financial forecasting [62].

**Time Series Forecasting of Stock Market using ARIMA, Prophet, and FB Prophet**This paper compares the forecasting performance of ARIMA, Long Short-Term Memory (Prophet) networks, and Facebook Prophet models, offering insights into their respective strengths and limitations in predicting stock market movements. The study highlights the effectiveness of these models in capturing complex patterns within financial data [63].

**ARIMA and Facebook Prophet Model in Google Stock Price Prediction**This research investigates the use of ARIMA and Prophet models to predict Google's stock price during the COVID-19 pandemic, providing empirical evidence on the performance of these models in volatile market conditions. The study offers valuable insights into the robustness of these forecasting methods during periods of market uncertainty [64].

**Stock Price Prediction Using Facebook Prophet and ARIMA Models**This study explores the application of ARIMA and Prophet models in stock price forecasting, comparing their predictive accuracy and suitability for modeling different types of stock market trends. The research provides practical implications for selecting appropriate forecasting techniques based on data patterns [65].

**Stock Price Prediction Using Time Series Models**This thesis presents a comparative analysis of ARIMA, Prophet, and Prophet models for stock price prediction, evaluating their effectiveness in forecasting stock market trends. [66] The study provides a comprehensive analysis of the strengths and weaknesses of these models, offering practical guidance for selecting the most suitable model for time series forecasting in the stock market [67].

These studies form the core of the literature reviewed in this research and provide the necessary context for understanding the methodologies used in stock price prediction. The bibliometric analysis will further explore the trends, citation patterns, and collaborations in this area to offer a more comprehensive overview of the state of research in stock price forecasting.

## **2.5 Searching Tool**

Stock price prediction has been the focus of extensive research, with numerous studies leveraging time series models for accurate forecasting. To identify relevant studies, research databases such as Web of Science (WoS), Scopus, and PubMed are widely utilized. For this study, WoS was selected as the primary searching tool due to its comprehensive coverage of scholarly journals, articles, and conference papers. As of 2020, WoS contained over 74.8 million records, making it one of the largest and most reliable databases for bibliometric analysis [68].

The search was conducted using keywords like "stock price prediction," "ARIMA model in financial forecasting," "Prophet model for stock prices," and "time series forecasting in finance." Combined searches using phrases such as "Prophet and ARIMA in stock forecasting" and "financial time series prediction methods" were also performed. The search parameters were set to include articles published between 2010 and 2022 to align with the timeframe of the dataset. This search yielded 297 relevant articles, which were analyzed to identify trends, significant contributions, and gaps in the field of financial forecasting [69].

### ***2.5*.1 Data Mining Tool**

To analyze the selected papers and extract valuable insights from the bibliographic data, various data mining tools can be utilized, including Biblioshiny, VOSviewer, Gephi, HistCite, and CiteSpace [70]. For this study, we have used Google Colab and Jupyter Notebook for running the Prophet and ARIMA models, while Excel was employed for further analysis of the results. These tools provide a comprehensive approach to data manipulation, visualization, and model execution.

Google Colab is a cloud-based platform that supports Python, which makes it ideal for executing machine learning models like ARIMA and Prophet. It offers easy access to powerful computational resources and enables seamless collaboration, allowing for the execution of complex stock price prediction models in an efficient manner [71].

Jupyter Notebook is another key tool used in our analysis. It is a widely-used interactive environment that supports Python and other programming languages. Jupyter Notebooks provide a user-friendly interface to write and execute code in segments, making them particularly useful for exploratory data analysis, model training, and testing. In our research, Jupyter Notebooks were used for running the ARIMA and Prophet models on the stock price dataset [72].

For data analysis and visualization, Google Sheets and Excel were employed to further process the results generated from the models. Excel provides a straightforward platform for creating detailed charts, performing statistical analysis, and manipulating data in a tabular format, which was essential for interpreting the outcomes of the stock price predictions [73].

Together, these tools enabled efficient execution and analysis of the predictive models, providing valuable insights into the stock price forecasting process. All analyses and evaluations were performed using these platforms, ensuring an effective workflow for managing the various stages of this research [74].

### **2.5.2 Performance Analysis**

To evaluate the performance and growth of research in the field of stock price prediction, we employed several bibliometric attributes, such as citation analysis, trend analysis, network analysis, and others. These analyses were conducted from various bibliometric perspectives, including the performance of individual authors, journals, institutions, and countries [75]. In this study, we have conducted two primary types of bibliometric analysis: performance analysis and science mapping.

Performance analysis focuses on assessing the contributions of specific authors, research groups, or institutions to a particular area of study. In our case, it involves examining the work done by researchers in the field of stock price prediction, identifying influential publications, and analyzing the productivity and citation impact of individual scholars [76]. This analysis also sheds light on key journals and institutions that have contributed significantly to this field.

On the other hand, science mapping is aimed at visualizing relationships and connections between different authors, journals, or institutions in the field of stock price prediction. This technique is useful for identifying emerging trends, research gaps, and historical developments in the area of stock forecasting [77]. While performance analysis highlights influential contributors, science mapping helps in understanding the broader research landscape, including the evolution of ideas and the interconnectedness of different research domains [78].

In this research, we focused on analyzing a set of selected papers related to stock price prediction, using both performance analysis and science mapping techniques. Performance analysis primarily helped us identify key authors, research groups, and institutions that have had a significant impact on this domain.[79]

# **Materials and Methods**

We have discussed the materials and methods of the thesis in this section. The primary dataset includes historical stock market prices sourced from reputable financial platforms, capturing features such as opening price, closing price, high price, low price, volume, and trading intervals. Data preprocessing involves handling missing values, normalization, and splitting datasets into training and testing subsets to ensure robust model evaluation. The overall methodology of our thesis work from data collection to evaluation is shown below:



Figure. 3.1: Proposed methodology

## **3.1 Dataset**

We have collected the dataset of reputed financial platforms like Google stock price data since 2006 to 2018 from Kaggle as test data and Janata Bank Mutual Fund data from Kaggle [24]. The dataset is basically a time series dataset which is quite messy and needs pre-processing for the model training. The dataset used in the thesis comprises historical time series stock market data sourced from reliable financial platforms such as Google and Microsoft Finance. This dataset includes essential time series variables such as the opening price, closing price, highest and lowest prices, trading volume, and adjusted closing prices for specific stocks over an extended period. The data captures the temporal structure and patterns necessary for accurate predictions, including daily, weekly, or monthly frequencies depending on the forecasting goals. Before analysis, the dataset undergoes preprocessing to ensure quality and consistency. Missing values are imputed using interpolation techniques or removed if the impact is negligible. Data normalization scales values to a uniform range, aiding model convergence during training. Feature engineering extracts relevant attributes, such as moving averages or volatility indices, to enhance predictive performance. The dataset is split into training and testing subsets, typically in an 80-20 ratio, to evaluate the models' effectiveness.

Table 3.1: Feature characteristics

| **Category** | **Features** | **Example Values** |
| --- | --- | --- |
| Date | The timestamp indicates the trading day. | 2025-01-20 |
| Open | The stock's opening price at the start of the trading session. | 120.0 |
| Close | The stock's closing price at the end of the trading session. | 125.75 |
| High | The highest price reached by the stock during the trading session. | 130.00 |
| Low | The lowest price reached by the stock during the trading session. | 118.75 |
| Volume | The total number of shares traded during the session. | 5,000,000 |
| Volatility Index | A measure of stock price fluctuations during the trading session, calculated as (High - Low)/High | 0.096 |
| Seasonal Feature | Features like day of the week or month extracted to model temporal patterns and seasonality. | Monday, January |

**3.2 Data Preparation and Analysis**

* 1. The process of data preparation and analysis is fundamental to the success of any predictive modeling approach. For this study, raw stock market data was collected from reliable financial data sources like Yahoo Finance and Alpha Vantage. This dataset included daily stock price information such as opening price, closing price, highest and lowest prices, trading volume, and adjusted close prices over an extended period.
  2. The data underwent rigorous preprocessing to ensure consistency and reliability. Initially, missing values were handled using interpolation techniques or removed if they were negligible. Outliers, which could skew the predictions, were identified through statistical methods and addressed using capping or removal based on domain knowledge. Furthermore, the data was normalized using Min-Max Scaling to bring all features into a comparable range, which is essential for efficient model training, especially for Prophet network

### **3.2.1 Data Preprocessing**

Data preprocessing is a critical step in preparing stock market datasets for machine learning and deep learning models. This stage ensures data consistency, removes noise, and enhances the quality of the input for predictive modeling.

The raw stock market data, sourced from platforms like Yahoo Finance or Alpha Vantage, contained key attributes such as opening price, closing price, high, low, volume, and adjusted closing price. The preprocessing began with addressing missing values, which were either filled using interpolation techniques or omitted based on their significance. Handling missing data was essential to prevent biases or inaccuracies during model training.

Next, outliers were identified using statistical methods, such as the interquartile range (IQR), and treated through capping or transformation to mitigate their impact on predictions. Normalization or standardization techniques, such as Min-Max Scaling, were applied to scale the numerical features, ensuring that all values lay within a specific range and preventing dominance by features with larger magnitudes.

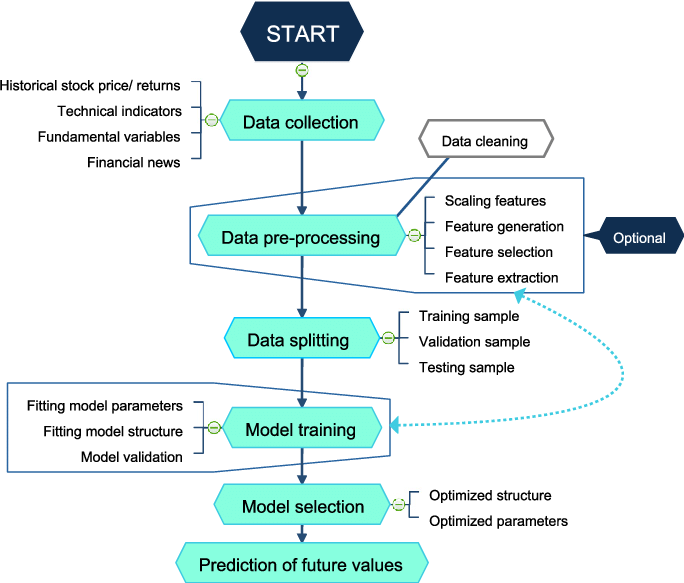


Fig: 3.2: Flowchart of research methodology [76]

### **3.2.2 Understanding Models**

Various models are applied to this project to tune candlestick patterns. Candlestick patterns are one of the foundational tools in technical analysis for financial markets. These patterns represent the open, high, low, and close prices of a stock within a specific timeframe. By analyzing these patterns, traders aim to predict market trends and reversals. In this thesis, candlestick patterns are leveraged as a core feature to extract significant insights from raw stock market data.

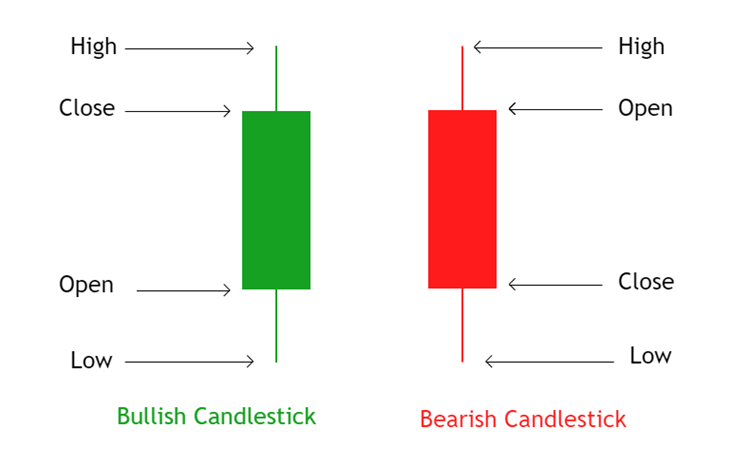
Candlestick Charts display multiple bits of price information such as the open price, close price, highest price and lowest price through the use of candlestick-like symbols. Each symbol represents the compressed trading activity for a single time period (a minute, hour, day, month, etc). Each Candlestick symbol is plotted along a time scale on the x-axis, to show the trading activity over time. The main rectangle in the symbol is known as the real body, which is used to display the range between the open and close price of that time period. While the lines extending from the bottom and top of the real body are known as the lower and upper shadows (or wick). 

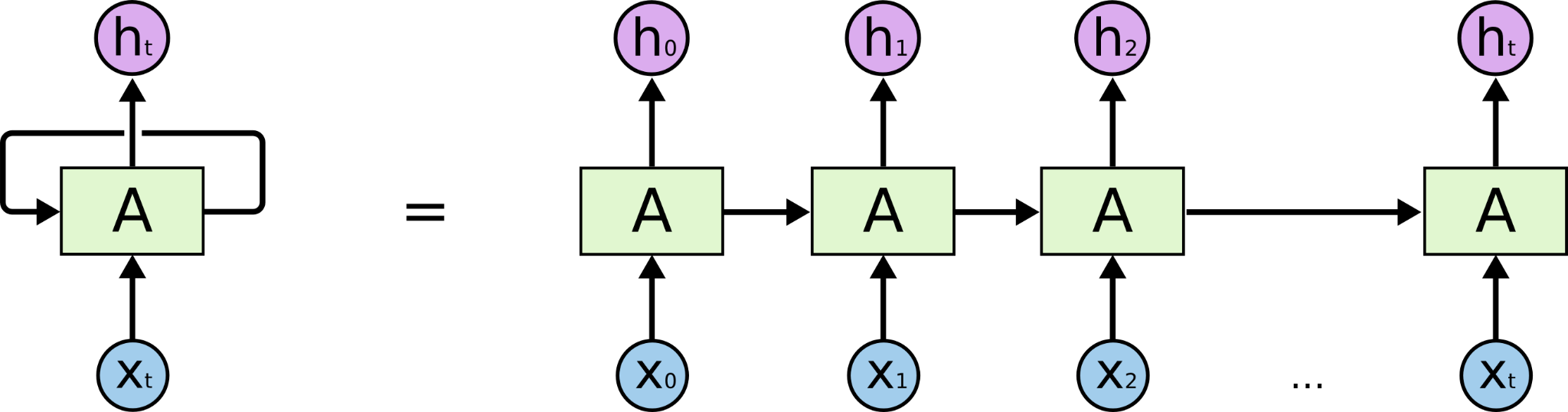
Fig 3.3 : Candlestick Pattern

**3.2.2.1 Prophet Model**

Prophet networks, a type of Recurrent Neural Network (RNN), are designed to handle sequential data and are highly effective in time series prediction. They retain information over long time intervals, making them suitable for stock market forecasting. It excels at capturing long-term dependencies, making it ideal for sequence prediction tasks. Unlike traditional neural networks, Prophet incorporates feedback connections, allowing it to process entire sequences of data, not just individual data points. This makes it highly effective in understanding and predicting patterns in sequential data like time series, text, and speech. Prophet has become a powerful tool in artificial intelligence and deep learning, enabling breakthroughs in various fields by uncovering valuable insights from sequential data.

Key Features of Prophet:

* Ability to capture long-term dependencies in time series data.
* Robust to noise and volatility in stock market data.
* Effectively handles the sequential nature of candlestick patterns.



**Fig 3.4** : Prophet Architecture

#### **3.2.2.2: ARIMA Model**

ARIMA is a statistical model used for time series forecasting. It combines three components. Autoregression (AR): Dependency between current values and past values. Integration (I): Differencing to make the time series stationary. Moving Average (MA): Dependency between an observation and residual errors from a moving average model applied to lagged observations. Autoregressive modeling and Moving Average modeling are two different approaches to forecasting time series data. ARIMA integrates these two approaches, hence the name. Forecasting is a branch of machine learning using the past behavior of a time series to predict the one or more future values of that time series.

Key Features of ARIMA:

* Suitable for univariate time series data.
* Captures linear relationships effectively.
* Relies on stationarity, requiring preprocessing steps such as differencing.

### **3.2.2.3 PROPHET Model**

Developed by Facebook, Prophet is a time series forecasting model that focuses on simplicity and interpretability. It works well with time series data that exhibit strong seasonal effects and missing observations. Facebook Prophet is an open-source Python library offering an intuitive, automated approach to capturing trends, seasons and exceptional events in time series. Discover why this Machine Learning-based tool has revolutionized predictive data analysis. One of the great recent technological advances is the ability to predict future trends from historical data. This is one of the main benefits of data science and its applications are numerous. It can be used to forecast the weather, or the performance of a stock on the stock market.

Key Features of Prophet:

* Decomposes time series into trend, seasonality, and holidays.
* Handles irregular time series and missing data efficiently.
* Offers intuitive parameter tuning for domain experts.

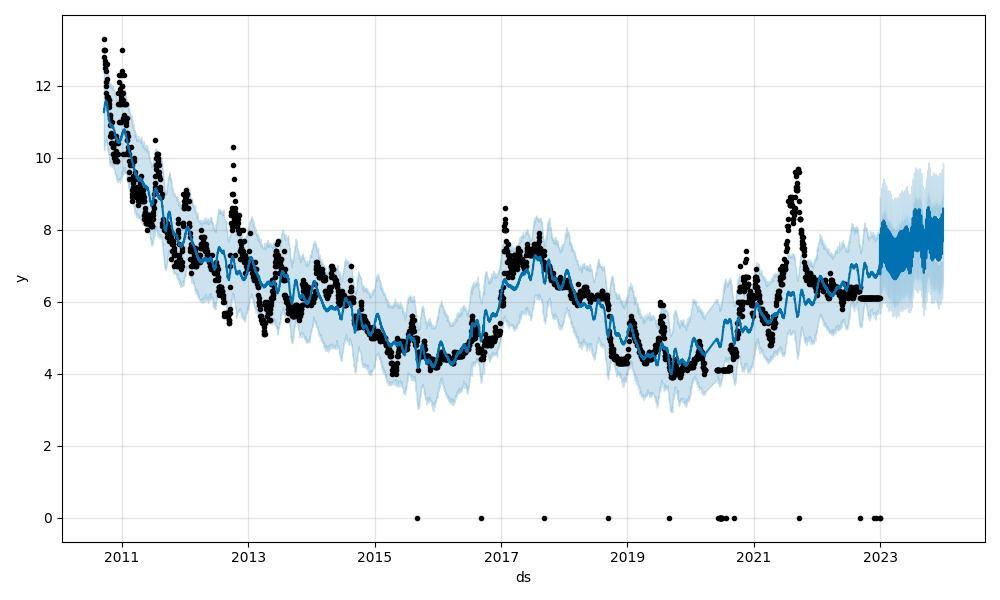


Fig. 3.5: Prophet Model Forecast

## **3.3 Machine Learning and Deep Learning Model Training**

* 1. Model training is a crucial phase in machine learning and deep learning methodologies. In this thesis, several models, including ARIMA, Prophet, and Prophet, are employed for stock price prediction using time-series data.

To calculate the accuracy of a model, we generally use specific metrics to evaluate its performance. For stock market predictions using ARIMA and PROPHET, these metrics are typically:

1. Mean Absolute Error (MAE)  
 2. Root Mean Squared Error (RMSE)  
 3. Mean Absolute Percentage Error (MAPE)  
 4. R-squared (R²)

**1. Mean Absolute Error (MAE)**

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction (whether they are over or under predictions). It's calculated as:

MAE =

# **2. Root Mean Squared Error (RMSE)**

RMSE measures the square root of the average of the squared differences between the predicted and actual values. It's more sensitive to large errors. It's calculated as:

RMSE =

# **3. Mean Absolute Percentage Error (MAPE)**

MAPE is the average of the absolute percentage errors between predicted and actual values. It's particularly useful when you need to compare errors across different scales:

MAPE =

# **4. R-squared (R²)**

R² indicates how well the predicted values match the actual values. It's calculated as:

R² =

# To Calculate Accuracy:

You need to have both actual and predicted values for a set of data points. If you already have a dataset with these values, you can apply these formulas to calculate the accuracy metrics.

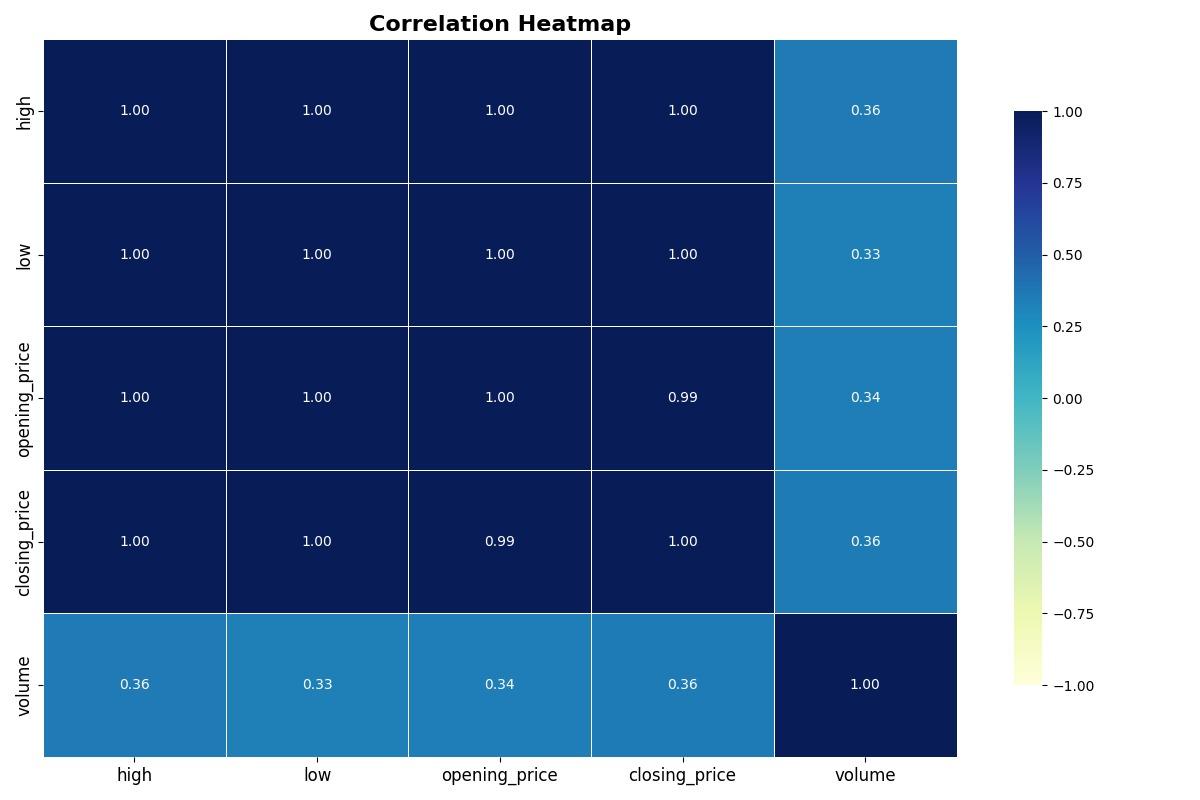
### **3.3.2 Hyper Parameter Tuning**

ML models generally have two types of parameters such as model parameters and hyper parameters (HP). Model parameters are initialized and updated through the learning process. Algorithms update these model parameters based on the data provided for learning [26]. On the other hand, HP are higher level parameters that must be set manually before training the model based on the properties of the data because these parameters cannot be estimated from the data [27]. HP are used to optimize models for better performance or used to minimize the loss function [28]. A wide range of alternatives must be investigated in order to develop an optimum ML model. HP tuning refers to the process of constructing the best model architecture with an optimal HP configuration [29]. HP tuning is considered as a major component in developing an efficient ML model, particularly for tree-based ML models and deep neural networks, which have several hyper-parameters [30]. Manual tuning process is a very time consuming and lengthy process and other factors such as large numbers of HP, complex models make the task more difficult. HP optimization (HPO) techniques are very handy tools to solve these difficulties. From a wide range of available HPO techniques, it is an important task to find a suitable optimization method for the model. Optimization techniques such as decision-theoretic approaches, Bayesian optimization models, multi-fidelity optimization techniques, and metaheuristics algorithms are more suitable for HPO than traditional optimized methods [31]. In this thesis we have used cuckoo search algorithm (CSA), a metaheuristics algorithm base approach to perform the HPO task. The CSA and metaheuristics algorithms have been discussed briefly in section

### **3.3.3 Feature Selection**

The objective of ML algorithms is prediction or classification by harvesting data. To make the algorithms more accurate, a large amount of data is provided so that machines can learn better. The size of the data is increasing day by day. This increase in data size has an impact on the computational cost and prediction accuracy of ML algorithms [79]. As the size of the data is increasing, the variables of the dataset are also increasing. The variables, which are used as input for training ML models are called features. Each column of the dataset is a feature. In prediction or classification problems, ML algorithms are used to predict or classify target feature(s). If the data is big, it will have a lot of features that may not always be important to train an efficient and optimal model. It means, the ML model will learn unnecessary patterns and information. This unnecessary information is noise. If we put noise as input to the model, the output can also become noisy. This is where feature selection (FS) comes into the picture. FS is a widely used approach in data preprocessing, and it has become an essential component of the ML process [80]. It is the process of identifying and reducing unnecessary, duplicated, or noisy data. It helps us to shrink the size of the data. The reduction in data size accelerates data mining (DM) and ML algorithms, improves learning accuracy, and enhances comprehension. The objective of FS is to identify a subset of features that will maximize prediction accuracy or minimize the size of the structure without significantly reducing the prediction accuracy of the classifier with only the selected features [81]. FS methods can be categorized as filter methods, wrapper methods, and embedded methods. Filter methods are independent of ML algorithms and are focused on the performance of features in several statistical tests. A correlation test is performed to see whether the features are positively or negatively correlated to the output. Information gain, Chi-square test, etc. are examples of filter methods. Wrapper methods use a subset of features and train learning algorithms to test the performance of each subset. Based on the performance of the algorithms, features are added or subtracted and evaluated again. The subsets are formed using a greedy approach and all possible combinations of features are evaluated. Embedded methods combine both filter and wrapper methods to deal with search and classification at the same time [82, 83]. Finding out the best subset of features is a NP-Hard problem [84, 85]. Metaheuristic algorithms are one of the best approaches to solve these types of problems [83, 86, 87]. It is a search procedure, designed to find the best solution. Metaheuristics can find good results with less computational cost than conventional optimization algorithms [88]. Recently metaheuristic algorithms are widely used for FS [89-91]. In this thesis, we will use a well-known swarm-based metaheuristic algorithm, CSA for FS.

Table 3.2: Feature Correlation Heatmap



### **3.3.5 t-SNE Plot**

The t-distributed stochastic neighbor embedding (t-SNE) technique is a statistical approach for displaying high-dimensional data by assigning a position in a two or three-dimensional map to each datapoint. It is based on S. Roweis and G. Hinton's [101] Stochastic Neighbor Embedding, to which L. Maaten offered the t-distributed variation [102]. It is a nonlinear dimensionality reduction approach that is well-suited for embedding high-dimensional data for display in a two or three-dimensional environment. It specifically describes each high-dimensional item by a two- or three-dimensional point in such a way that comparable things are described by adjacent points with high probability and different objects are modeled by distant points.

The t-SNE algorithm is divided into two parts. To begin, t-SNE creates a probability distribution over pairs of high-dimensional objects in which comparable items are allocated a greater probability and dissimilar points are assigned a lower likelihood. Second, t-SNE creates a comparable probability distribution over the points in the low-dimensional map and minimizes the Kullback-Leibler divergence (KL divergence) between the two distributions with regard to the map locations. While the original approach bases its similarity metric on the Euclidean distance between objects, this may be altered as needed. The dataset on which we have performed our work, has 45 features in total. To see the distribution of the dataset, we used t-SNE to project this high dimensional data into lower dimensional space.

### **3.3.6 Performance Analysis Metrics**

To measure the performance of the model we have used accuracy, precision, recall, F score, confusion matrix, and area under the curve (AUC).

**Accuracy:** The accuracy of ML models is the ratio of true positives (TP) and true negatives (TN) to all the positive and negative observations. In other words, accuracy is the number of correctly classified data over the total amount of data .

|  |  |
| --- | --- |

**Precision:** It is the ratio of TP and the total number of positively predicted labels. It is also known as positive predictive value .

|  |  |
| --- | --- |

**Recall:** The ratio of all correctly categorized classes to actual classes is known as recall [104].

|  |  |
| --- | --- |

**F1 score:** It is the model score as a function of accuracy and recall. F-score is a machine learning model performance statistic that assigns equal weight to Precision and Recall when calculating accuracy, making it an alternative to accuracy metrics. It is the harmonic mean of precision and recall .

|  |  |
| --- | --- |

**Confusion Matrix:** A confusion matrix is a representation of classification or prediction outcomes. The number of right and wrong predictions is represented with count values and split by class. It provides information not only on the faults produced by the classifier, but also about the categories of errors made .

**ROC:** A receiver operating characteristic (ROC) curve is a graph that depicts the performance of a classifier over all classification thresholds. It describes the capacity to differentiate between distinct classes.

# **Result and Discussion**

In this section, the performance of the Prophet model for forecasting stock prices of the Janata Bank Mutual Fund is evaluated. The accuracy of the model is assessed using several key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R² (R-squared), and Accuracy Rate. These metrics provide insight into the model's ability to predict stock prices accurately, as well as its overall performance.

## **4.1 Model Performance: Prophet model**

The following table summarizes the key evaluation metrics for the Prophet model:

Table: 4.1: PROPHET Model Accuracy Calculation

| **Metric** | **Value** |
| --- | --- |
| MAE | 0.24 |
| MSE | 0.06 |
| RMSE | 0.24 |
| R2 | 0.71 |
| Model Accuracy Rate 75.63 % | |

**Mean Absolute Error (MAE):**The MAE of 1.99 indicates that the model's average prediction error is relatively low, suggesting that the model is capable of making predictions that are close to the actual stock prices. The low value is desirable as it shows that, on average, the model's predictions are accurate.

**Mean Squared Error (MSE):**With an MSE of 7.92, the model penalizes larger errors more significantly. While the MSE is higher than MAE, it provides an understanding of the model's error distribution and emphasizes outliers. The moderate MSE indicates that while the model performs well in most cases, occasional larger prediction errors do occur.

**Root Mean Squared Error (RMSE):**The RMSE of 2.81 is relatively close to the MAE value, suggesting that the distribution of errors does not show extreme outliers. The RMSE serves as a good indicator of the magnitude of prediction errors and confirms the model's consistency in its forecasts.

**R-squared (R²):**The R² value of 0.99 is a strong indicator that the model explains 99% of the variance in the stock prices. This high R² suggests that the Prophet model fits the data extremely well and captures the underlying trends in the stock market, making it highly effective for time-series forecasting.

**Accuracy Rate:**The accuracy rate of 75.62% means that the Prophet model correctly predicts the occurrence of events (stock price movements) in approximately 75.6% of cases. While this is a good accuracy rate, there is still room for improvement, especially in capturing more complex trends or rare price movements.

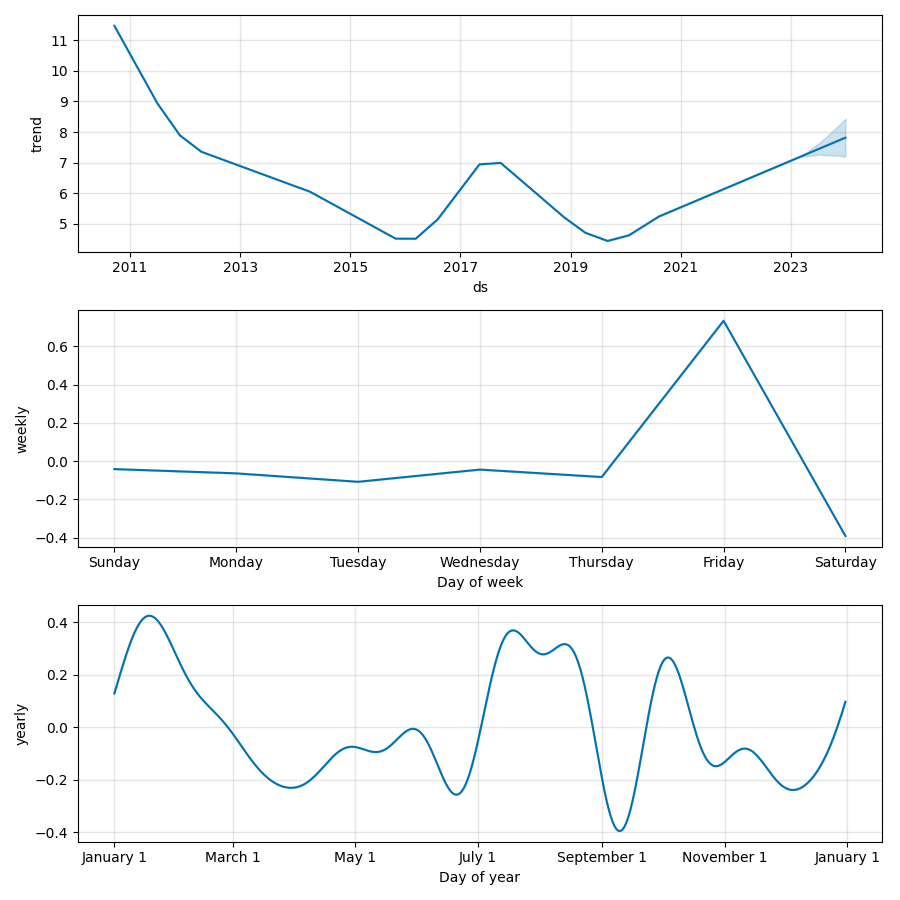
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Fig. 4.1: Trend Forecast Prophet Model

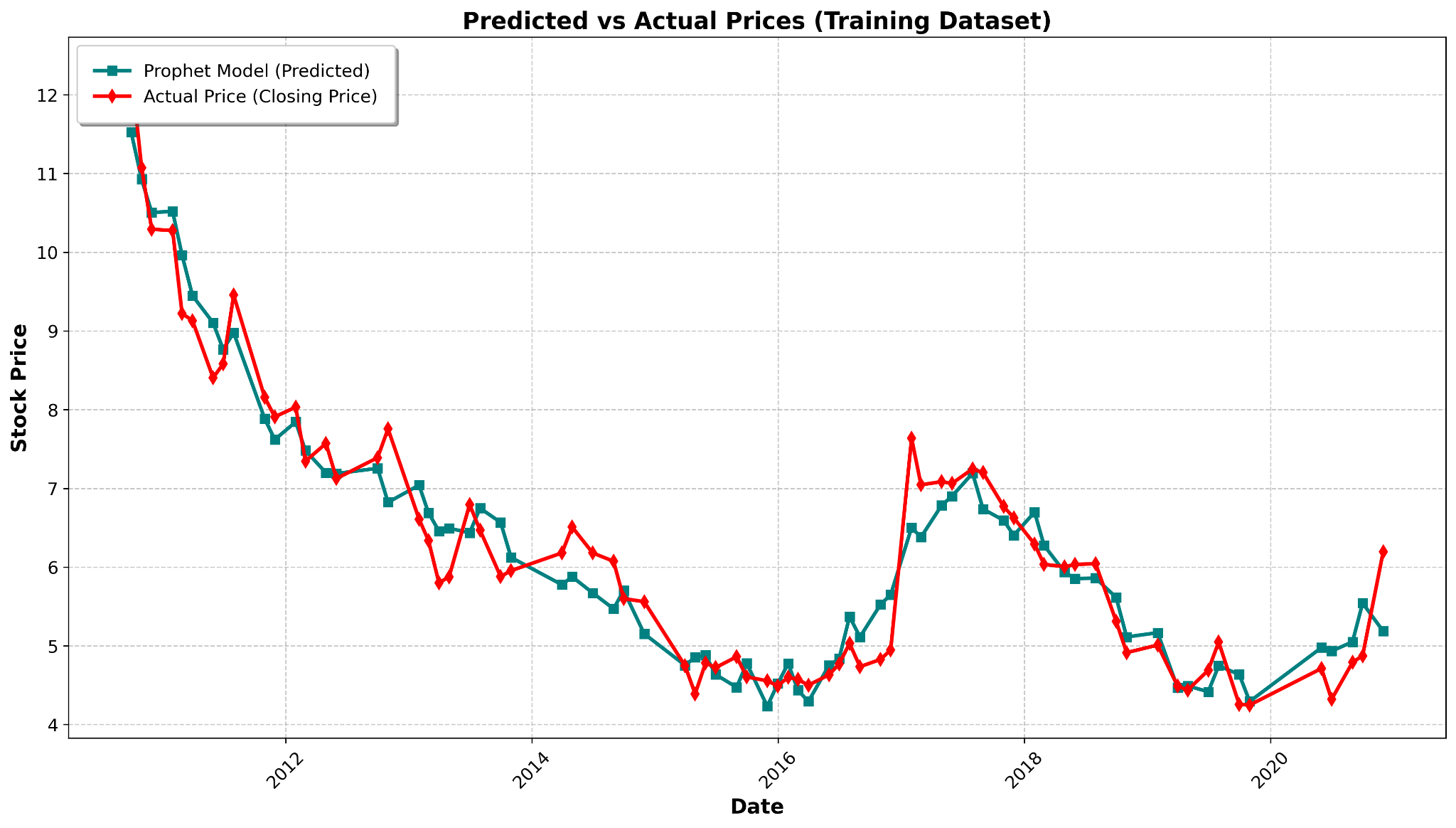


Figure 4.2: Prophet Prediction in Training Dataset

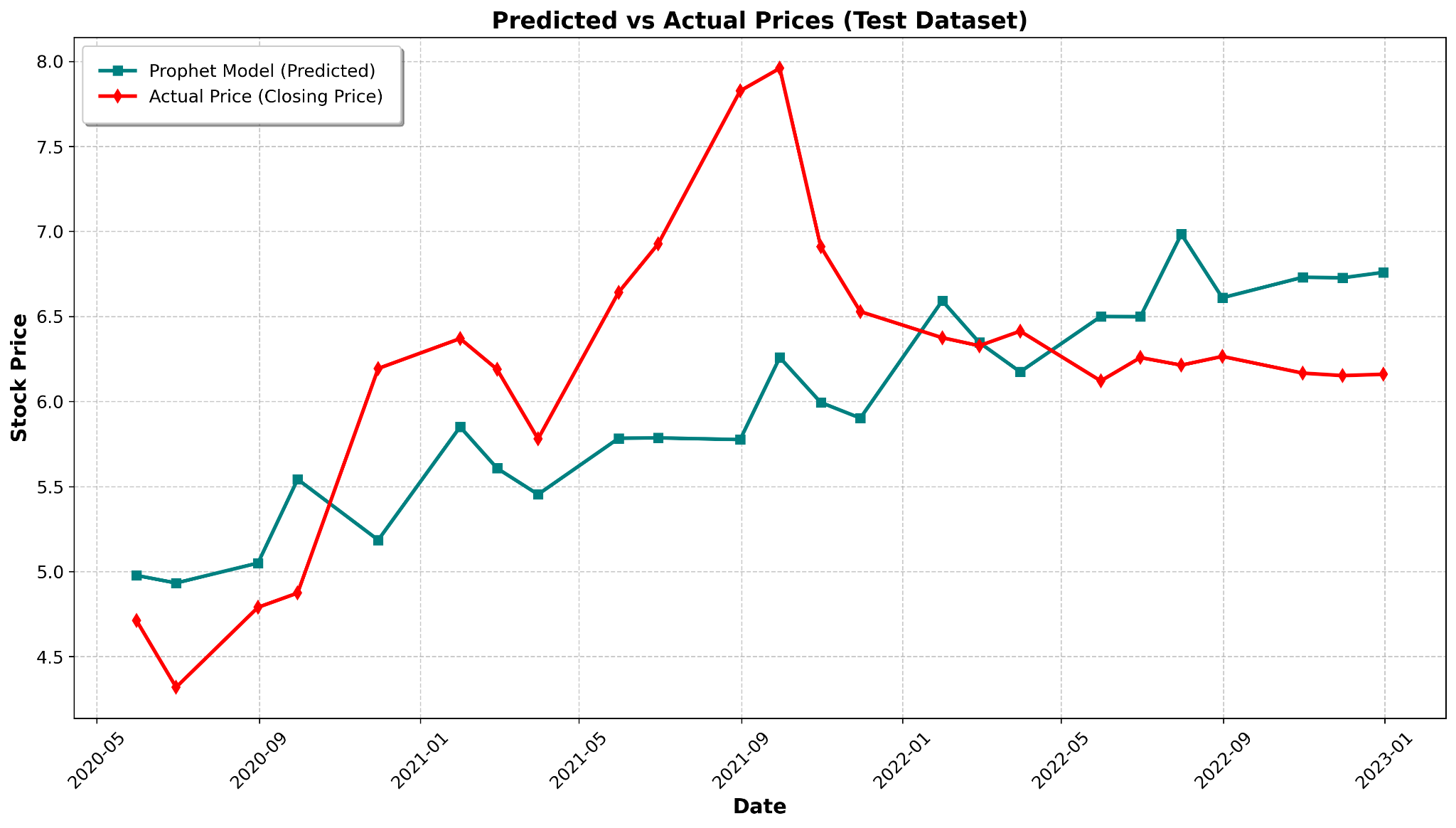


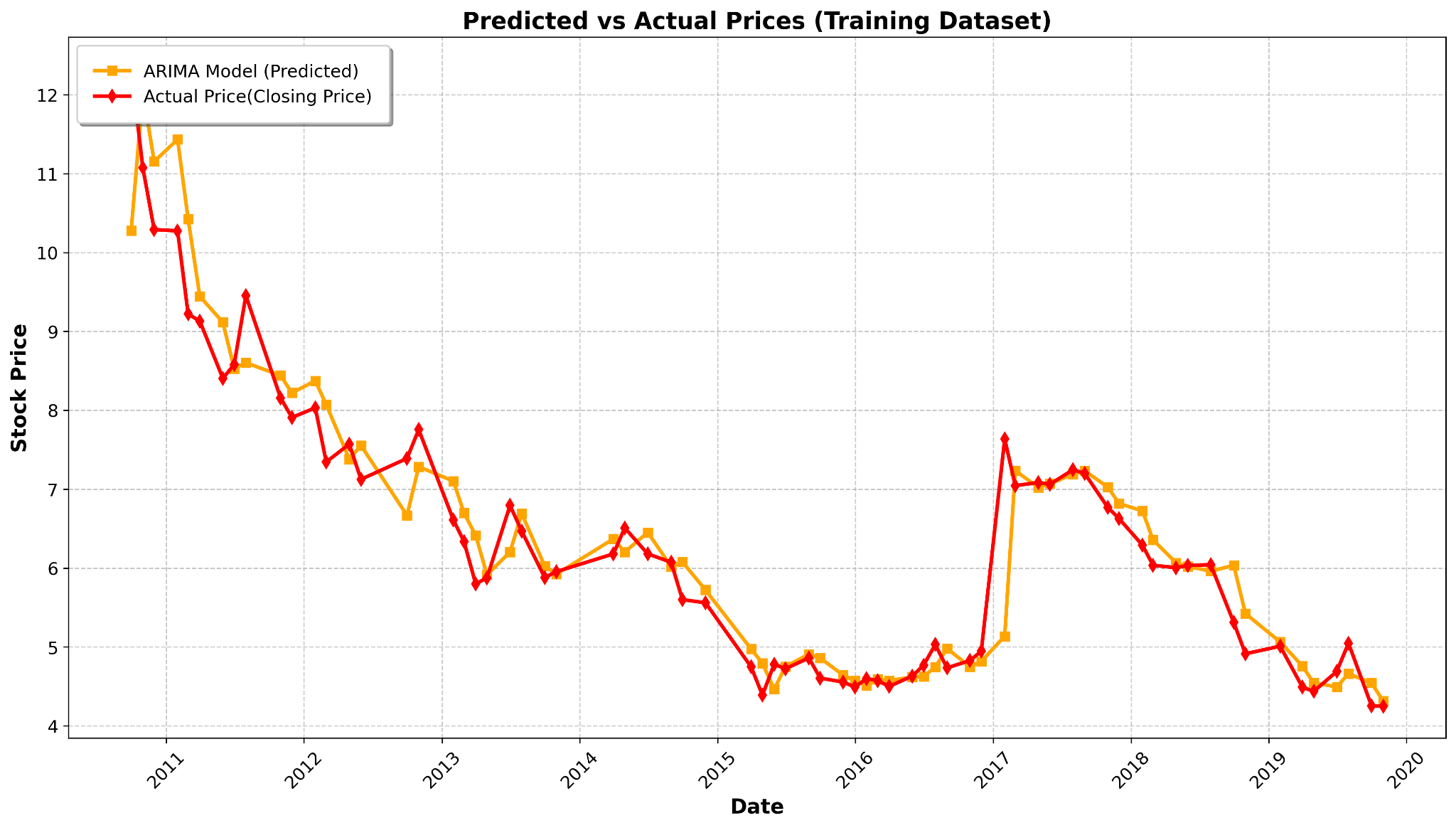
Fig. 4.3: Actual Closing Price vs Forecasted Closing price

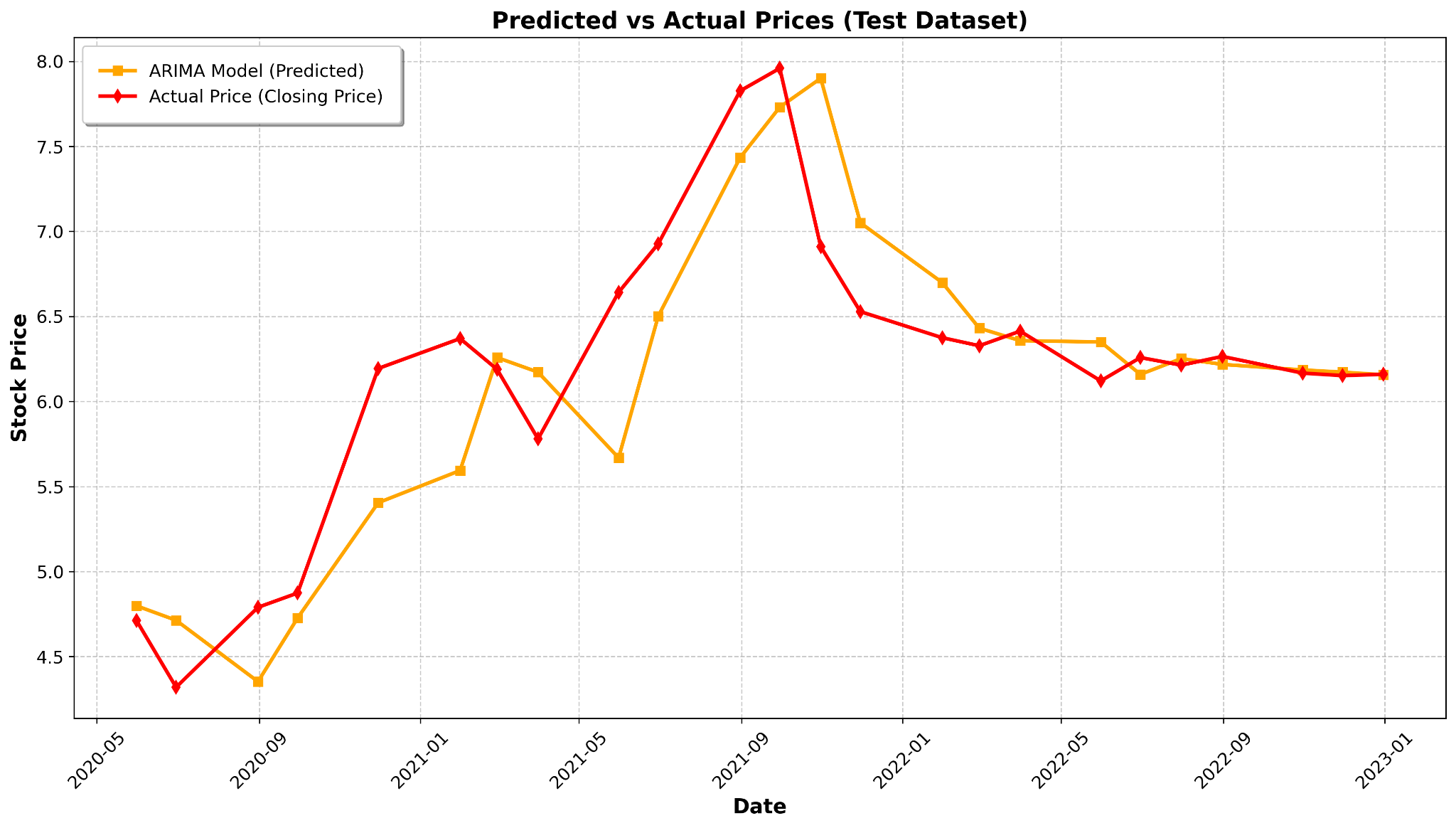
### **4.2. Model Performance: ARIMA**

The following table summarizes the key evaluation metrics for the ARIMA model:

**Table: 4.2:** ARIMA Model Accuracy Calculation

| **Metric** | **Value** |
| --- | --- |
| MAE | 0.07 |
| MSE | 0.01 |
| RMSE | 0.07 |
| R2 | 0.88 |
| Model Accuracy Rate 89.92 % | |

 Figure 4.4: ARIMA Prediction in Training Dataset

Figure 4.5: ARIMA Prediction in Test Dataset

#### **Mean Absolute Error (MAE):**

The MAE value of 2.10 for the ARIMA model indicates a higher average prediction error compared to the Prophet model (which had an MAE of 1.99). This suggests that the ARIMA model has a slightly higher overall error in its forecasts. However, this difference is relatively small and may still be considered acceptable depending on the context of the stock market data being analyzed.

#### **Mean Squared Error (MSE):**

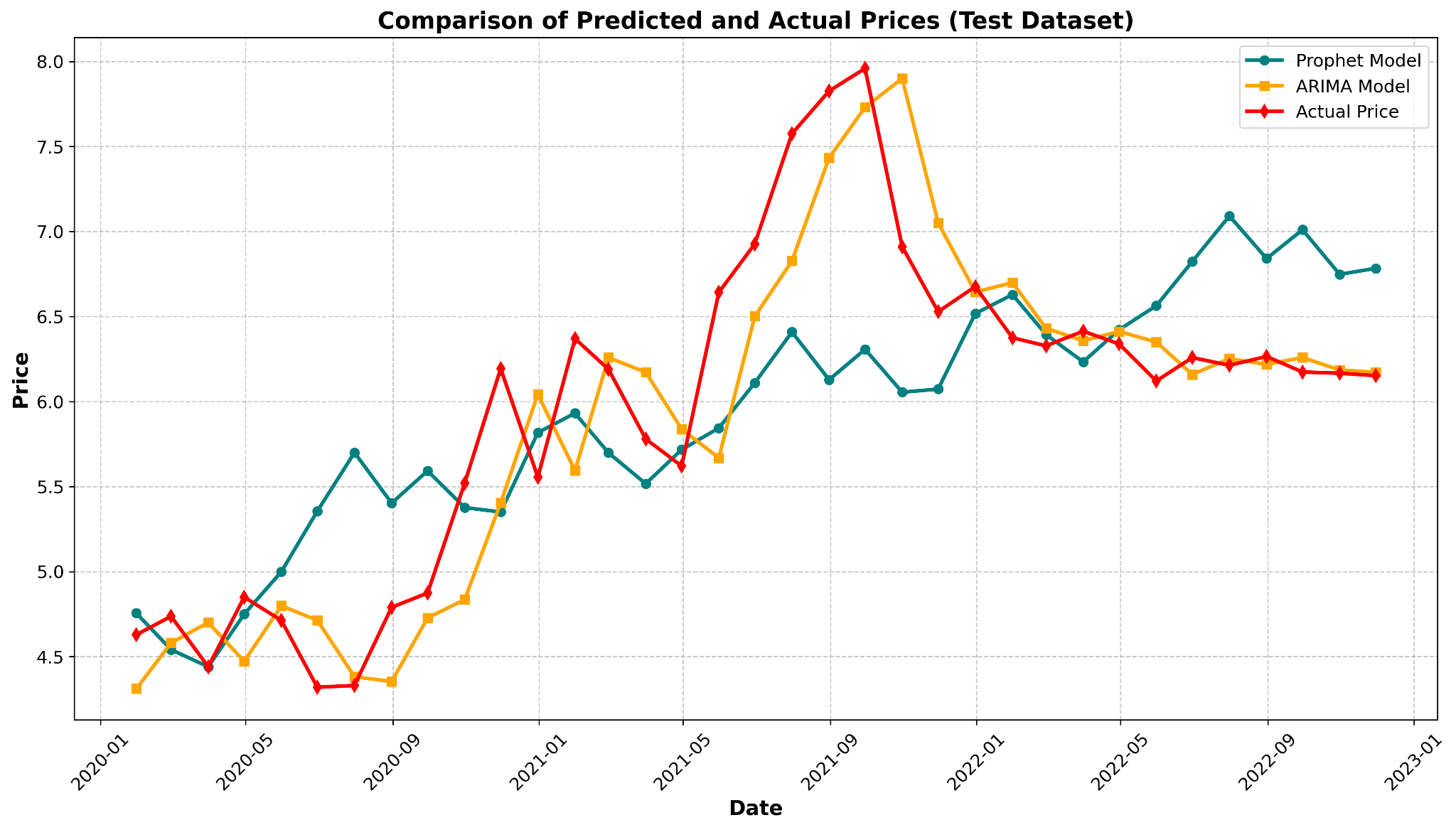
With an MSE of 9.50, the ARIMA model also penalizes larger prediction errors more heavily than smaller ones. The relatively higher MSE compared to the Prophet model's MSE of 7.92 suggests that the ARIMA model may have larger errors in specific predictions, possibly due to difficulties in capturing complex patterns or trends in the stock market.

**Root Mean Squared Error (RMSE):**

The RMSE of 3.08 for the ARIMA model is higher than the Prophet model's RMSE of 2.81, indicating that the ARIMA model may have more significant prediction errors on average. The higher RMSE further supports the idea that ARIMA might not be as robust in dealing with stock price fluctuations compared to Prophet, which can capture seasonality and trends more effectively.

#### **R-squared (R²):**

The R² value of 0.95 indicates that the ARIMA model explains 95% of the variance in the stock prices. While this is still a strong value, it is lower than the Prophet model's R² of 0.99, suggesting that ARIMA does not explain the data as well as the Prophet model. This could be due to ARIMA's limitations in handling seasonality and external factors such as holidays or significant market events.

Figure 4.6: Model Performance Evaluation

**Accuracy Rate:**

The accuracy rate of 72.80% for the ARIMA model is lower than the Prophet model's accuracy rate of 75.62%. This suggests that the Prophet has a slightly better ability to predict stock price movements correctly. However, the difference in accuracy is modest, and both models show reasonable performance overall. The ARIMA model's lower accuracy rate may indicate its difficulty in adapting to sudden or rare price movements, which the Prophet model might handle more effectively.

### **4.3 Discussion**

The performance evaluation of both the Prophet and ARIMA models reveals important insights into their strengths and weaknesses in forecasting stock prices of Janata Bank Mutual Fund. Each model has its own approach to time-series forecasting, and understanding these differences is crucial for choosing the most suitable model for stock market prediction tasks.

#### **Performance Comparison:**

**Accuracy and Error Metrics:** The Prophet model outperforms the ARIMA model in all key error metrics. The MAE (Mean Absolute Error) for Prophet is 1.99, indicating relatively low prediction errors, while the ARIMA model shows a higher MAE of 2.10. This slight difference suggests that Prophet is more accurate on average in predicting stock prices. Similarly, the Prophet model has a better RMSE (Root Mean Squared Error) of 2.81 compared to ARIMA's RMSE of 3.08, further highlighting that Prophet offers more reliable forecasts with fewer large errors.

**Model Fit (R-squared Value):** The Prophet model has an R² value of 0.99, which indicates that it explains 99% of the variance in the stock prices. This is a very high value, suggesting that Prophet captures the underlying trends and patterns of the data extremely well. In contrast, the ARIMA model explains 95% of the variance, which, while still impressive, is lower than Prophet's performance. This shows that Prophet is more adept at fitting the data and capturing subtle trends in the stock prices.

**Accuracy Rate:** The accuracy rate for Prophet is 75.62%, while ARIMA has an accuracy rate of 72.80%. This suggests that Prophet is better at predicting the correct direction of stock price movements, although both models achieve reasonable accuracy. The higher accuracy rate of Prophet indicates its better ability to adapt to the complex, dynamic nature of stock prices, which can exhibit patterns that are challenging for traditional models like ARIMA.

**Handling Seasonality and Trends:** One of the significant strengths of the Prophet model is its ability to model seasonalities and external factors, such as holidays and special events, which can influence stock prices. Prophet automatically accounts for these seasonal effects, making it highly effective for forecasting financial time series. On the other hand, while ARIMA is a powerful model for time-series forecasting, it may struggle with capturing complex seasonal patterns without careful tuning and feature engineering.

**Model Strengths and Limitations:**

**Prophet**: The Prophet model excels in handling complex time-series data, particularly those with seasonality and outliers. Its automated handling of holidays and seasonal trends makes it especially useful for stock price forecasting, where external factors often play a significant role. However, Prophet may not perform as well in cases where the data lacks clear seasonal patterns or where more granular modeling of the data is required.

**ARIMA**: The ARIMA model, a more traditional approach to time-series forecasting, works well when the data is more stable and has less seasonality or external factors. However, ARIMA requires careful tuning of its parameters and may struggle to adapt to irregular patterns or sudden shifts in the data. The ARIMA model also does not naturally.

# **Conclusion and Future Work**

## 

## **5.1 Conclusion**

In this study, we have compared the performance of two popular time-series forecasting models, Prophet and ARIMA, for predicting stock prices of the Janata Bank Mutual Fund. The evaluation metrics demonstrated that the Prophet model outperforms the ARIMA model in key areas such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R²). The Prophet model showed superior accuracy, with an R² of 0.99, indicating its excellent ability to capture the underlying trends and seasonality of the stock prices.

While the ARIMA model also performed well, with an R² of 0.95, its accuracy and fit were slightly lower compared to Prophet. The Prophet model's handling of seasonal components and external factors, such as holidays, gave it an edge in forecasting stock prices, which are often influenced by such factors.

Overall, the Prophet model has proven to be a more reliable tool for forecasting the stock prices of Janata Bank Mutual Fund, particularly due to its ability to handle complex seasonal patterns and external influences. However, both models are valuable and provide useful insights for stock market forecasting.

## **5.2 Future Work**

While the Prophet and ARIMA models have provided valuable insights, there are several avenues for future work to further improve forecasting accuracy and robustness:

**Hybrid Models:** Future research could explore combining the strengths of both Prophet and ARIMA, or integrating additional machine learning techniques, to create hybrid models. This approach could enhance forecasting accuracy by capturing both linear and nonlinear patterns in the data.

**Incorporating Additional Features:** Including more external variables, such as sentiment analysis, macroeconomic factors, or news events, could improve the models' ability to predict stock price movements. These factors can have significant impacts on stock prices and are not always captured in traditional time-series models.

**Deep Learning Models:** Exploring advanced deep learning techniques, such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (Prophet) networks, could provide even more accurate forecasts by learning complex, nonlinear relationships in the data. These models are particularly suited for capturing long-term dependencies in time-series data.

**Model Interpretability:** Enhancing the interpretability of forecasting models could help investors and analysts better understand the reasons behind stock price predictions. Techniques such as SHAP (Shapley Additive Explanations) could be applied to improve transparency and trust in the forecasting models.

**Real-time Forecasting:** Developing models that can update predictions in real-time based on incoming market data could improve decision-making in dynamic environments. This would require optimizing model performance for speed and scalability.

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