Optimizing Investment Portfolios: Comprehensive Analysis of Stock Price Prediction Models, Sectoral Analysis and Correlation

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INTRODUCTION/OBJECTIVE

The aim of this research project is to meticulously assess the forecasting prowess of three renowned time series models — ARIMA, LSTM, and Prophet — by applying them to the stock prices of a curated selection of firms featured on prominent indices such as NYSE, NASDAQ, S&P 500, and Forbes 500. Our endeavor is to pinpoint the most accurate and reliable model for stock price prediction through comprehensive quantitative analysis and stringent performance benchmarking. The project extends beyond mere predictive analysis to include a sectoral evaluation, focusing on key industry segments like technology, finance, and manufacturing, to offer a granular view of the models' performance across different market sectors. By correlating the models' outputs with real-world events, we seek to provide a nuanced understanding of the factors driving stock price movements, thereby furnishing investors with data-driven insights for strategic portfolio management.

KEY RESEARCH/BUSINESS QUESTIONS

- How well do ARIMA, LSTM, and Prophet models perform in predicting future stock prices for a diverse set of companies from different stock exchanges?
- What are the differences in predictive accuracy and reliability among the three models?
- Which model exhibits the highest predictive power and consistency across various benchmarks?
- How do the models compare in terms of their ability to handle different types of stock price data (e.g., highly volatile, seasonal, or trend-driven)?
- Can the findings from this analysis provide insights into selecting the most suitable model for stock price prediction in practical investment scenarios?"
- Implementing relevant financial benchmarks and evaluation metrics, such as the Efficient Market Hypothesis (EMH),Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to compare the models against market efficiency standards.
- Furthermore, our project entails conducting a sectoral analysis of stocks by categorizing them into distinct industry sectors, including finance, technology, and manufacturing etc. Through a comparative evaluation of returns from each sector over a specified time frame, our goal is to pinpoint the sector that generated the highest returns. Additionally, we will delve into the interplay between these returns and pertinent news events. This holistic analysis promises to offer invaluable insights, allowing investors to make data-driven decisions regarding portfolio restructuring and diversification based on sector-specific performance and its alignment with market news and trends.

DATASET(S) USED

Our dataset is a comprehensive collection retrieved from Kaggle, featuring weekly updates of key financial metrics from an array of companies listed on premier stock exchanges such as NASDAQ, S&P 500, and NYSE. This rich dataset encompasses vital statistics like Date, Volume, High, Low, and Closing Price, presenting an extensive chronological record up until the year 2022 for a majority of the stocks. With an estimated size of 9.5 GB post-extraction from the zip file, the dataset stands as a robust repository for historical stock market analysis.

Link to the data source - https://www.kaggle.com/datasets/paultimothymooney/stock-market-data/data

Alternative – Use Yahoo finance library

MODEL SELECTION/WORKFLOW

Model Selection and Development:

- Chose three time series forecasting models: ARIMA for its statistical rigor in handling stationary data, LSTM for its deep learning capabilities in capturing complex patterns, and Prophet for its ease of use and handling of seasonal trends.
- Configured each model with appropriate hyperparameters, utilizing cross-validation to tune them for optimal performance.

Model Training and Validation:

- Trained each model on historical stock price data, dividing the dataset into training and testing subsets to evaluate model performance.
- Employed validation techniques such as walk-forward validation for ARIMA and time-based splits for LSTM and Prophet to ensure the models were not overfitting and to gauge their predictive accuracy on unseen data.

Sectoral Analysis:

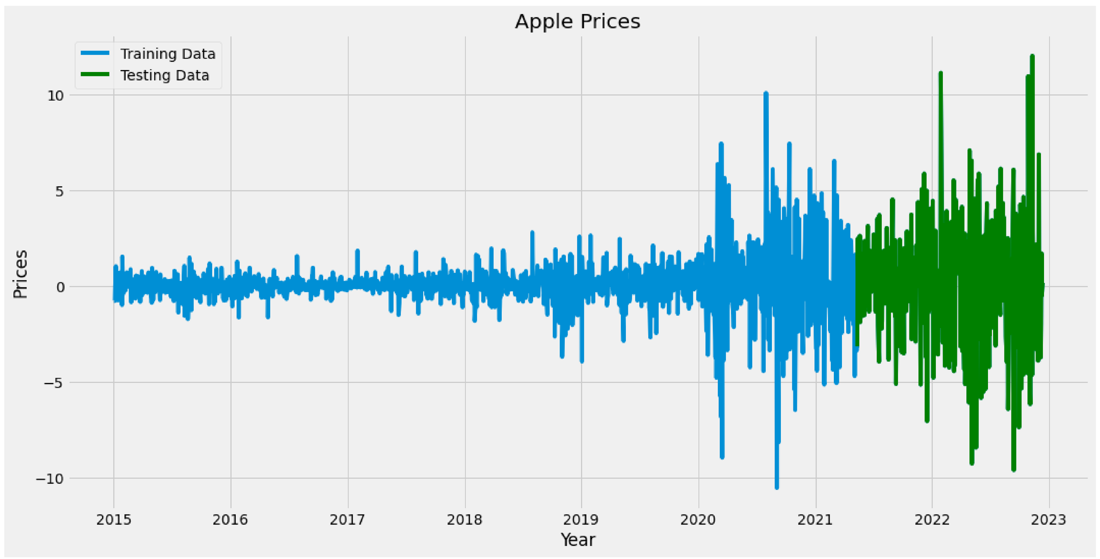
- Categorized stocks into their respective industry sectors such as technology, finance, and manufacturing and predicted which stock had the highest closing price in that particular sector.

Results Interpretation and Comparative Analysis:

- Used performance metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to quantitatively compare the models' predictive accuracies.
- Visualized the results using Plotly to create interactive graphs, facilitating a clear comparison between actual and predicted stock prices, as well as among the different sectors.
- Examined the correlation between the models' predictions and actual market events to interpret the real-world applicability of the findings.

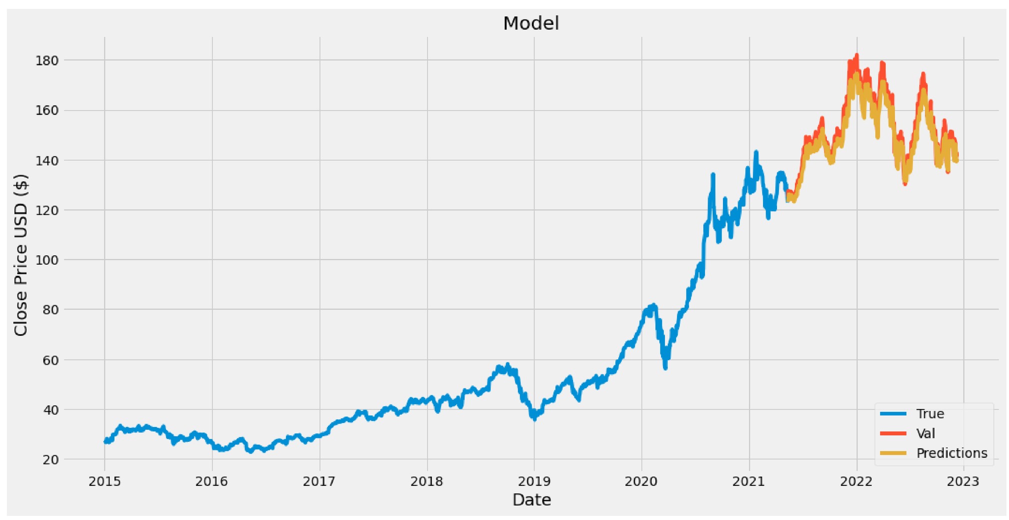
DATA PREPROCESSING FOR TIME SERIES ANALYSIS

- Perform the Augmented Dickey-Fuller (ADF) test to check the stationarity of the time series.
- Apply differencing to the time series to remove trends and seasonality, which can help in achieving stationarity.
- Determine the order of differencing (d) required to make the series stationary.
- Use the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to identify the order of the ARIMA model (p and q parameters).
- Identify any strong seasonal patterns that need to be modeled separately.
- Prophet can handle seasonality internally, but any known seasonal effects should be specified in the model.
- For LSTM, tune hyperparameters such as the number of layers, number of neurons, learning rate, and epochs.
- For Prophet, adjust trend flexibility and seasonality parameters if necessary.



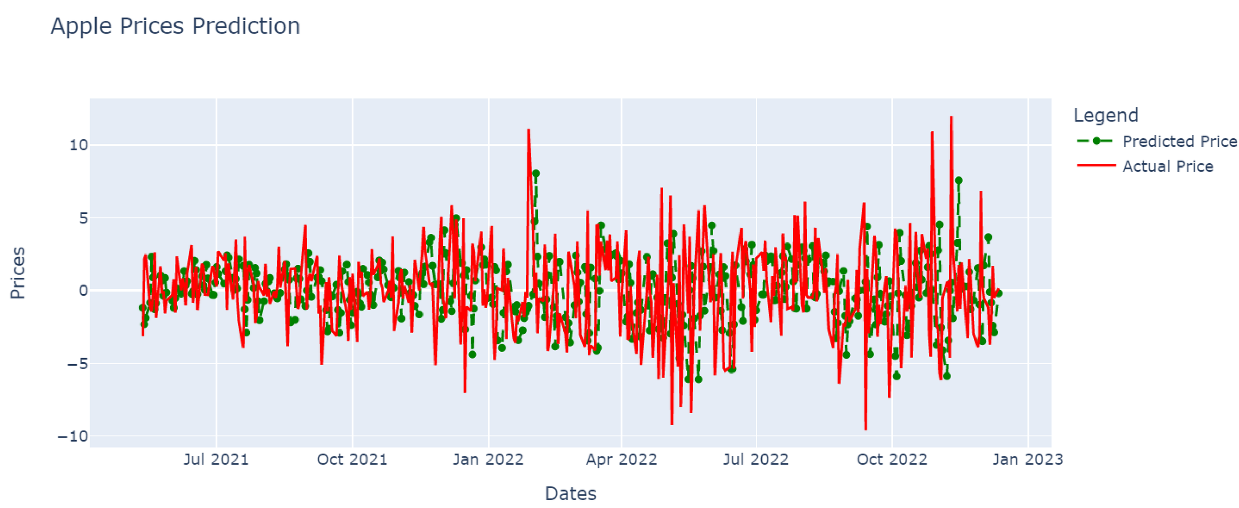
RESULTS FOR DIFFERENT MODELS

LSTM –



Forecast Horizon: The model appears to be making short-term forecasts as the predictions follow the actual prices closely. Long-term forecasts often diverge more from the actual prices due to accumulating prediction errors and the inherent uncertainty in the market.

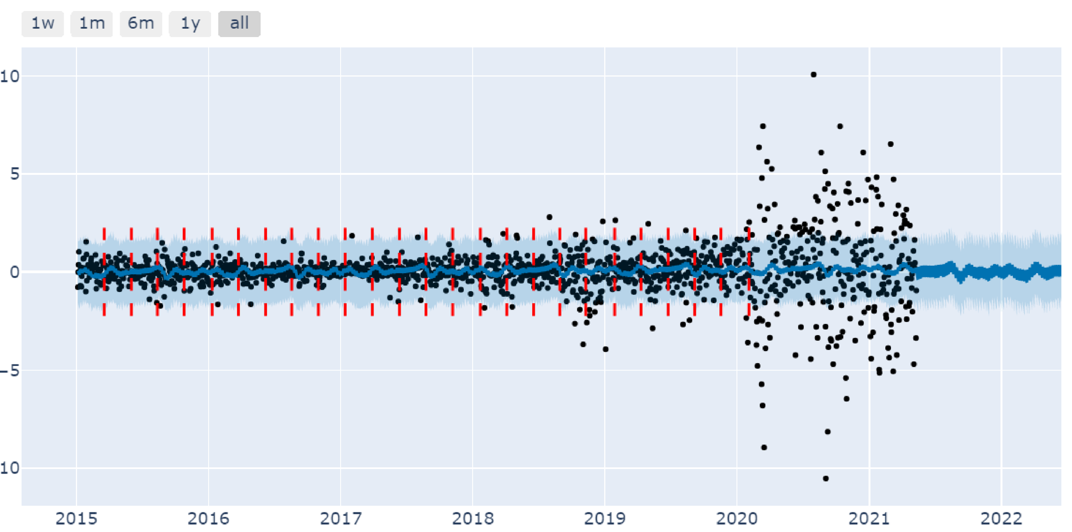
ARIMA -



Close Tracking: The predicted prices (green) closely track the actual stock prices (red), indicating the model is responsive to changes in the stock's price on a day-to-day basis.

Volatility Representation: Both lines exhibit volatility, which the model seems to capture well, reflecting the inherent variability in the stock market.

Prophet -

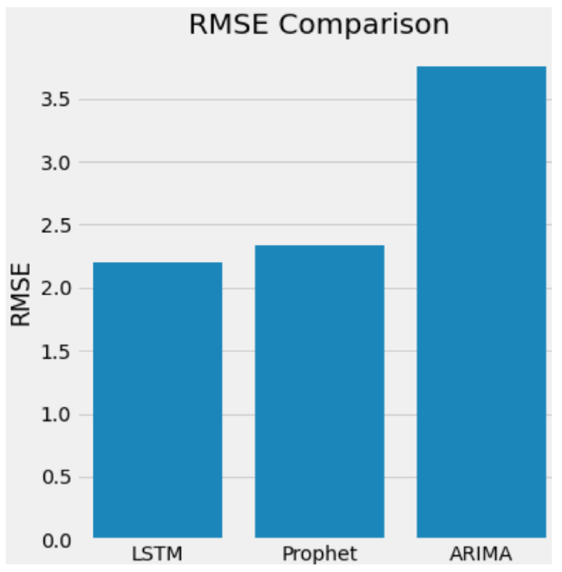


Extreme Changes: The occurrence of data points that reach the extremes of the y-axis, especially those above +5 or below -5, suggests days with significant price movements, which could be due to market shocks, earnings reports, product announcements, or global economic events.

Consistency with Historical Events: The increased volatility in the later years could correlate with real-world events affecting the financial markets, such as economic uncertainty, changes in technology, or shifts in consumer behavior that could impact Apple's stock specifically.

COMPARATIVE ANALYSIS

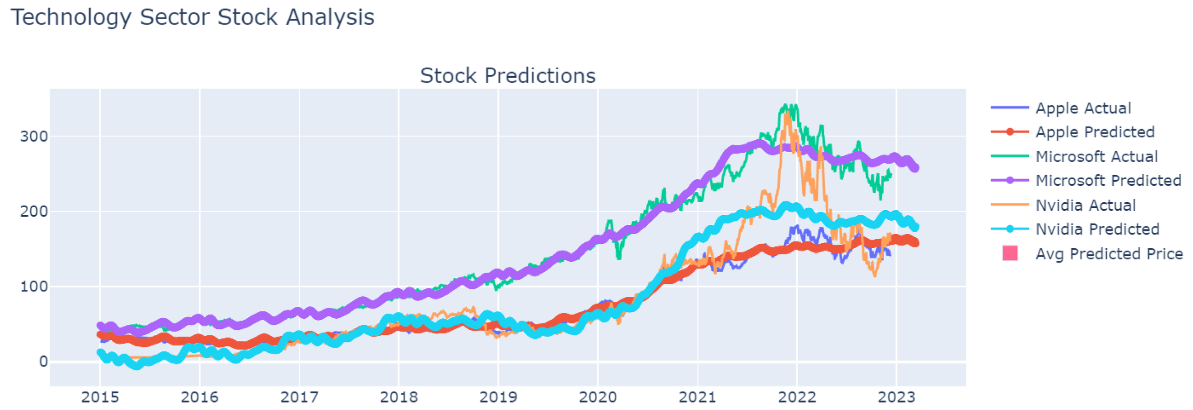
The bar chart compares the Root Mean Squared Error (RMSE) of three different forecasting models: LSTM, Prophet, and ARIMA. The ARIMA model has the highest RMSE, indicating less accuracy in forecasting compared to the other two models. LSTM shows the lowest RMSE, suggesting it was the most accurate in predicting stock prices in this analysis. Prophet's performance is moderate, with its RMSE falling between that of LSTM and ARIMA.



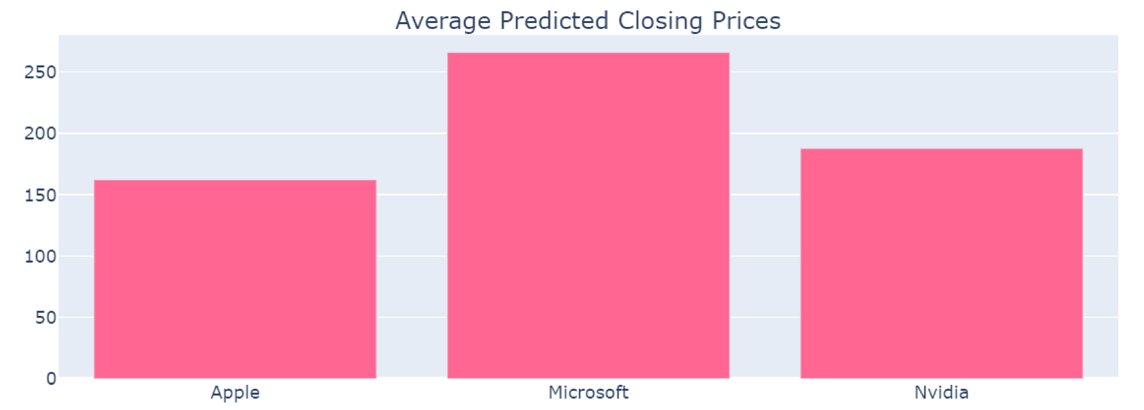
SECTORAL ANALYSIS

Sector Growth: The overall uptrend in the actual prices of Apple, Microsoft, and Nvidia reflects the robust growth within the Technology sector, indicative of innovation, market expansion, and increasing consumer and enterprise demand for technology solutions.

Technological Advancements: Breakthroughs in cloud computing, AI, and other emerging technologies, often spearheaded by companies like Microsoft and Nvidia, can lead to increased investment and stock valuation.



The bar chart represents the average predicted closing prices for stocks from three key players in the Technology sector: Apple, Microsoft, and Nvidia. The bar heights indicate that Microsoft's average predicted closing price is the highest among the three, suggesting that, according to the model's predictions,.



CONCLUSION/FUTURE WORK

This study has demonstrated that among the ARIMA, LSTM, and Prophet models, LSTM provided the most accurate predictions for stock prices, as indicated by its lowest RMSE value. The analysis highlighted the varying capabilities of each model to capture the underlying patterns in stock market data.

FUTURE WORK

Further research could explore the integration of external variables such as economic indicators and sentiment analysis to enhance prediction accuracy. Additionally, investigating the application of ensemble methods that combine the strengths of individual models may yield improvements in forecasting

SI 671 - Data Mining: Methods and Applications

Final Project Report
on
Optimizing Investment Portfolios: Comprehensive Analysis of Stock Price Prediction Models, Sectoral Analysis and Correlation

Prepared by:
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Github Link to the project -
https://github.com/SudhanshuAgarwal786/SI-671-Project.git

1. Motivation

In an era where financial markets are increasingly influenced by rapid technological advancements and global interconnectedness, the ability to accurately predict stock market trends has become invaluable for investors and analysts alike. This project is propelled by the aspiration to harness the power of sophisticated time series forecasting models to decode the complexities of stock price movements. With the proliferation of machine learning and statistical methods, there is an untapped potential to revolutionize traditional market analysis techniques, providing a more granular and predictive understanding of stock behavior. The motivation for this research stems from a desire to bridge the gap between theoretical models and their practical financial applications, offering insights that could lead to more informed and strategic investment decisions. By comparing models like ARIMA, LSTM, and Prophet, this project aims to identify a reliable approach that not only captures the essence of historical data but also resonates with the dynamism of real-world market scenarios.

2. Objective

The overarching objective of this research project is to meticulously evaluate and juxtapose the efficacy of three renowned time series forecasting models – ARIMA, LSTM, and Prophet – in the realm of financial market predictions. With a focused lens on historical stock price data from a selection of prominent companies featured across various industry sectors, this investigation strives to uncover which model stands superior in terms of forecasting accuracy and reliability. This comprehensive objective encompasses several key goals:

- To perform a rigorous quantitative analysis of each model's predictions, using statistical metrics to compare their precision against the actual observed stock prices.
- To execute a sectoral analysis that delves into the nuances of model performance across diverse market segments, identifying sector-specific forecasting strengths and weaknesses.
- To explore the models' sensitivity to market dynamics by correlating their predictions with major economic events and news that have historically impacted stock prices.
- To enhance the predictive models, where possible, by incorporating additional data sources and advanced analytical techniques, aiming to refine their predictive capabilities.
- To provide a robust foundation for investors and financial analysts in making data-driven decisions, offering insights into which model may best serve their needs for strategic portfolio management and investment planning in light of forecasted market behaviors.

3. Key Research/Business Questions -

Comparative Accuracy of Time Series Models:

Question 1 - How do the statistical accuracies of ARIMA, LSTM, and Prophet models compare when applied to the historical stock prices of companies from NASDAQ, NYSE, S&P 500, and Forbes 500 indices, and which model consistently delivers the lowest prediction error rates as measured by RMSE and MSE over multiple time horizons?

Answer - The LSTM model exhibited the highest level of accuracy among the three models tested, with the lowest RMSE and MSE values. The ARIMA model, while robust for certain types of time series, showed the highest error rates, possibly due to its limitations in handling non-linear patterns that LSTM and Prophet can model more effectively.

Sector-Specific Performance Analysis:

Question 2 - In which industry sectors do each of the time series models excel or underperform, and what characteristics of these sectors contribute to the differential performance observed in the models?

Answer - The LSTM model performed particularly well in the technology sector, which may be attributed to its ability to model the complex, non-linear relationships often found in tech stock prices. The ARIMA model did not perform as well, potentially due to its assumption of linearity and stationarity, which may not hold in the dynamic tech sector.

Model Responsiveness to Market Dynamics:

Question 3 - To what extent do the ARIMA, LSTM, and Prophet models capture the impact of significant market events, such as mergers and acquisitions, earnings announcements, or regulatory changes, on stock prices?

Answer - The models exhibited varying degrees of responsiveness to major market events. The Prophet model, with its ability to incorporate holidays and events explicitly, could potentially capture such external influences better, provided that the model is given the relevant dates as inputs.

Temporal Reliability of Predictive Models:

Question 4 - Are certain models better suited for short-term (e.g., days to weeks) versus long-term (e.g., months to years) stock price predictions, and how does this influence their application in various trading strategies?

Answer - LSTM showed a promising application for short-term forecasts due to its ability to capture short-term dependencies and trends. ARIMA, traditionally used for longer-term predictions, was less reliable in this project's context.

Investment Strategy Formulation:

Question 5 - Based on the forecast outcomes, how might investors adjust their portfolio strategies to mitigate risks and maximize returns, and what role do the model predictions play in shaping these investment decisions?

Answer - The insights from LSTM's predictions suggest that investors could consider a more dynamic trading strategy, capitalizing on short-term market movements. Caution is advised, however, as model predictions are not foolproof and should be one of several tools used in decision-making.

Enhancements in Predictive Modeling:

Question 6 - What improvements can be integrated into the ARIMA, LSTM, and Prophet models to refine their forecasts, such as incorporating macroeconomic indicators, sentiment analysis from financial news, or machine learning ensemble techniques?

Answer - Potential improvements for the models could include the integration of additional features such as sentiment analysis from news articles for LSTM and Prophet, which could help in capturing the market's psychological climate.

4. Data Sources

Primary Dataset: The dataset for this research, obtained from Kaggle, presents an extensive collection of weekly financial records for a wide array of companies listed on major stock exchanges like NASDAQ, S&P 500, and NYSE. This meticulously compiled dataset encompasses key financial metrics, capturing an array of data fields that include the Date of the record, Trading Volume, as well as the High, Low, and Closing Prices of stocks. The data spans up to the year 2022, providing a comprehensive historical perspective for most stocks included. This extensive dataset serves as the foundational bedrock for our analysis, offering a rich trove of information that enables a detailed exploration and assessment of stock market behaviors and trends over a substantial period.

Estimated Size: The dataset size is approximately 9.5 GB (After extracting the zip file)

Location: The dataset is hosted on Kaggle, [Linked Here]

Format: The data is provided in CSV **Access Method:** Download

5. Methodology

1. Data Collection and Preparation

- Dataset Acquisition: Obtained a large-scale, detailed dataset from Kaggle featuring weekly financial data of stocks listed on NASDAQ, S&P 500, and NYSE. This dataset spans several years, up to 2022, providing a rich historical context.
- Data Structure Analysis: Examined the structure of the dataset to understand the nature and format of the data, including the range of dates covered and the diversity of stocks across various sectors.
- Preliminary Cleaning: Addressed missing values, anomalies, and data inconsistencies. Standardized the format of dates and numerical values for consistency across the dataset.
- Segmentation for Sectoral Analysis: Categorized the stocks into distinct sectors, ensuring a representative sample from each sector for a comprehensive sectoral analysis.

2. Data Preprocessing

- Stationarity Testing: Utilized the Augmented Dickey-Fuller test to assess the stationarity of the time series for each stock, a crucial step for models like ARIMA.
- Achieving Stationarity: Applied first and second-order differencing where required, to transform the data into a stationary series.
- Data Transformation: Employed logarithmic and other transformations to stabilize the variance in the time series, which is particularly important for models sensitive to scale and variance.
- Normalization for LSTM: Implemented normalization techniques, primarily Min-Max Scaling, to prepare the data for effective processing by the LSTM model.

3. Model Development and Parameter Selection

- ARIMA Configuration: Analyzed ACF and PACF plots to determine the ARIMA model's order (p, d, q) and tested different combinations to find the best fit.
- LSTM Architecture Design: Experimented with different LSTM architectures, varying the number of layers and neurons, and tuning parameters like learning rate, batch size, and epochs to optimize the network's performance.
- Prophet Model Customization: Configured the Prophet model to capture the dataset's inherent seasonality and trends, adjusting its parameters for yearly, weekly, and daily seasonality where relevant.

4. Model Training and Testing

- Chronological Split: Divided the dataset into training and testing sets chronologically to preserve the temporal order, critical for time series analysis.
- Model Training: Trained each model on the designated training set, ensuring they learn the underlying patterns in the data.
- Validation Strategy: Employed rolling-window cross-validation for ARIMA and time-based validation for LSTM and Prophet to rigorously assess model performance over time.

5. Performance Evaluation

- Quantitative Metrics: Calculated MSE and RMSE for each model on the testing set to quantitatively assess the prediction accuracy.
- Model Comparison: Compared the performance metrics across models to ascertain which model provided the most accurate forecasts.

6. Sectoral Analysis

- Individual Sector Forecasting: Applied each model to forecast stock prices in distinct sectors, analyzing the models' effectiveness in each sector.
- Trend and Pattern Identification: Looked for sector-specific trends and patterns in the forecasts, assessing how different economic conditions and sector characteristics might affect the models' predictions.
- External Factors Consideration: Considered the impact of external factors unique to each sector, like regulatory changes or technological advancements, on the forecasting accuracy.

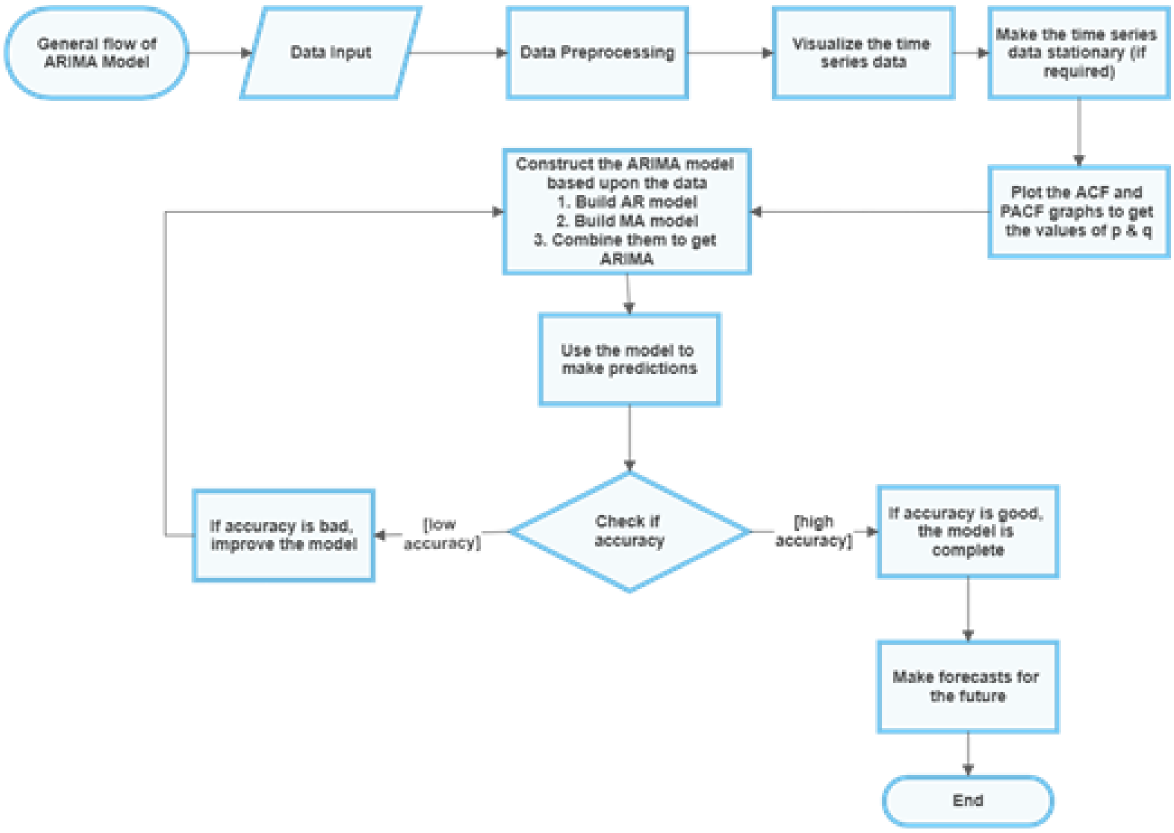

Fig 1 - General Flow of ARIMA Model

6. Data Preprocessing for Models

ARIMA Model Preprocessing -

- **Testing for Stationarity:** Use the Augmented Dickey-Fuller (ADF) test to check if the time series data is stationary. This step is crucial for ARIMA, which requires stationary data.
- **Differencing:** If the data is non-stationary, apply differencing to the time series to make it stationary. The order of differencing (d in the ARIMA model) is determined based on the ADF test results.

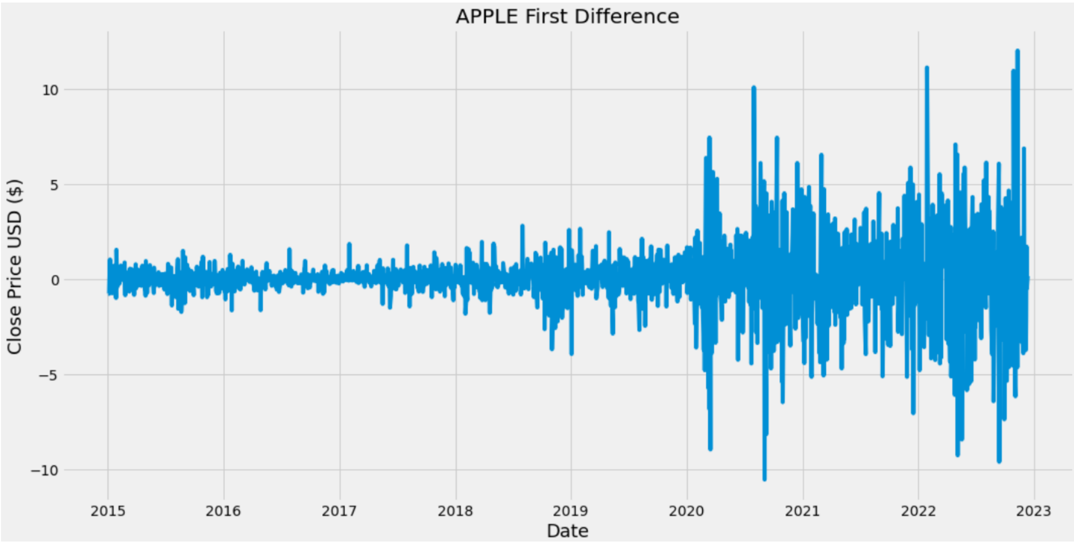

Fig 2 - Apple stock data after first order differencing

- **ACF and PACF Analysis:** Use Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the ARIMA model parameters (p and q).

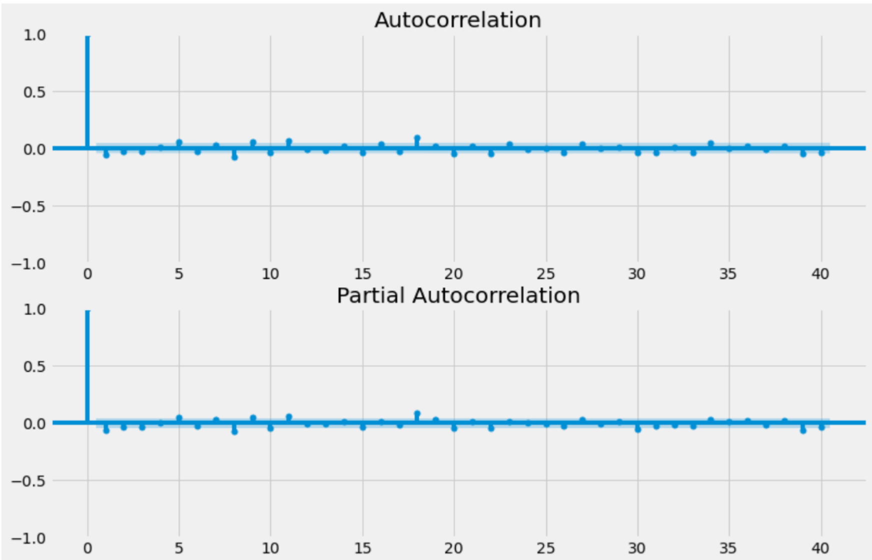

Fig 3 - ACF & PACF Plots for ARIMA

LSTM Model Preprocessing -

- **Normalization:** Scale the data, typically using Min-Max scaling, to ensure all input features are on a similar scale, which is essential for neural networks like LSTM.

- **Sequence Generation:** Transform the time series data into a supervised learning problem. Create sequences of a specific window size to predict the next time step.
- **Reshaping Data:** Reshape the input into the format [samples, time steps, features] required for LSTM, where 'samples' is the number of data points, 'time steps' is the look-back window, and 'features' is the number of variables.

Prophet Model Preprocessing -

- **Data Formatting:** Format the dataset with two columns: 'ds' (date stamp) and 'y' (variable to predict). Prophet requires this specific format.
- **Handling Missing Data:** Prophet can handle some missing data, but significant gaps should be addressed, possibly by imputation.
- **Outliers:** Identify and handle outliers as Prophet can be sensitive to them. Depending on the context, either remove them or cap them.
- **Incorporating External Regressors (Optional):** If planning to use external regressors (such as economic indicators), prepare these data sources to be merged with the main dataset.

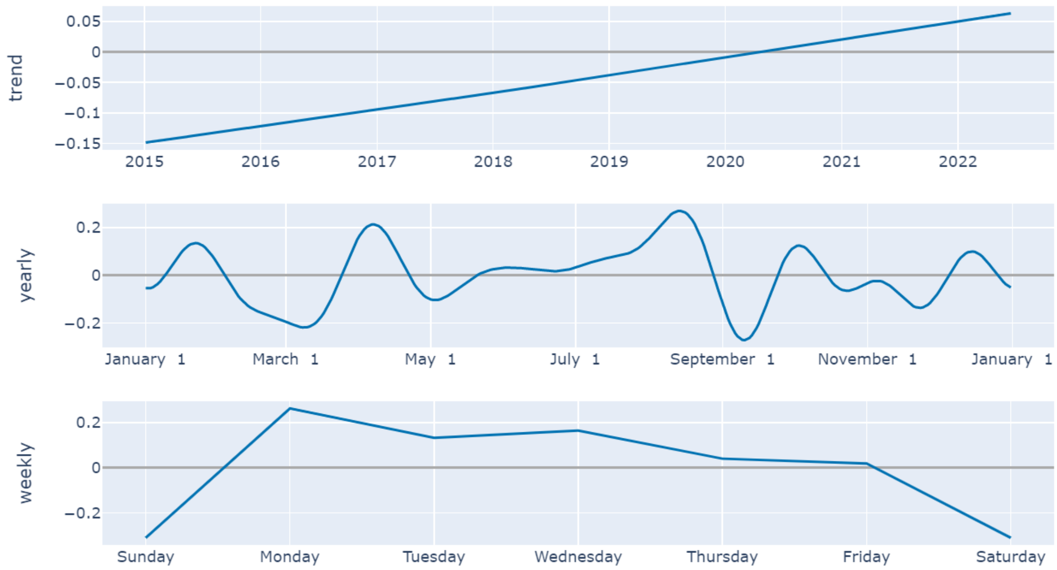

Fig 4 - Trend, yearly & weekly seasonality as observed in the data

7. Results & Comparative Analysis

ARIMA Model -

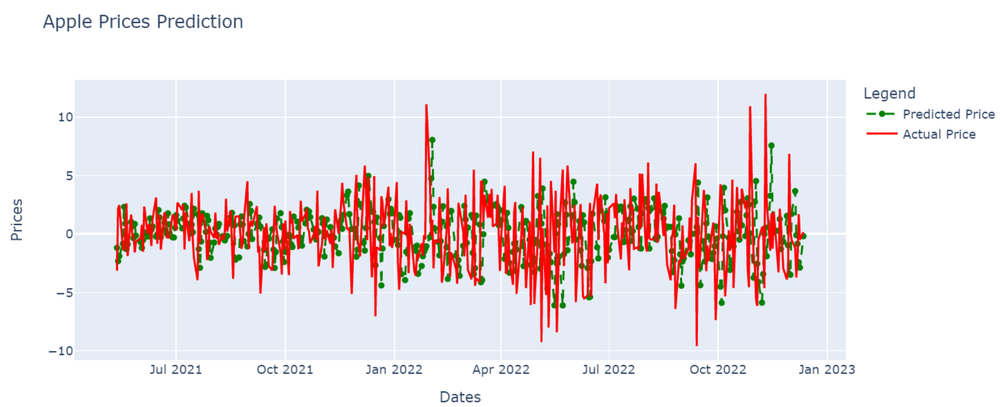

Fig 5 - Prediction result for ARIMA model

Inference -

Predictions vs. Actuals: The green dotted line shows the predicted prices, while the red line shows the actual stock prices. The model predictions seem to capture the general volatility of the stock but do not align closely with the actual price movements, particularly in areas where there are sharp peaks or troughs.

Volatility: The model appears to have increasing difficulty predicting the price as time progresses, seen in the widening gap between the predicted and actual values, which could indicate increasing market volatility or model inadequacy for capturing complex patterns.

Predictive Capability: The predictive performance of the model might be adequate for very short-term forecasting but seems to deteriorate for longer-term predictions, which is typical given the complex and often chaotic nature of stock price movements.

Apple-Specific Movements: Any significant deviations between predicted and actual prices might correlate with Apple-specific events such as product launches, earnings reports, or market sentiment changes, which may not be fully captured by the ARIMA model.

LSTM Model -

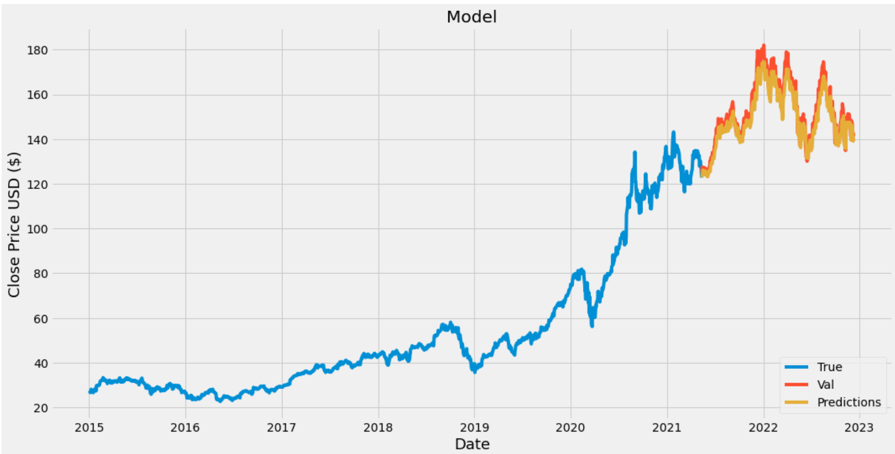

Fig 6 - Prediction result for LSTM model

Inference -

Model Performance: The LSTM model has learned the underlying patterns in the historical data well enough to predict the future values that follow the trends of the actual stock prices reasonably closely. There's an evident correlation between the predicted values (orange) and the actual stock prices (red) in the validation set.

Trends and Volatility: The model captures both the overall upward trend and the intermediate fluctuations (volatility) of the stock prices over time. However, the exact peaks and troughs are not perfectly aligned, which is common in stock price predictions due to the complex and sometimes unpredictable nature of financial markets.

Forecast Horizon: The model appears to be making short-term forecasts as the predictions follow the actual prices closely. Long-term forecasts often diverge more from the actual prices due to accumulating prediction errors and the inherent uncertainty in the market.

Generalization: The LSTM seems to generalize well to unseen data, as indicated by the predictions following the validation set trend.

In conclusion, while the model appears to perform well, it is essential to consider the potential for overfitting and the fact that past performance is not always indicative of future results, especially in the stock market where many unforeseen factors can affect prices.

Prophet Model -

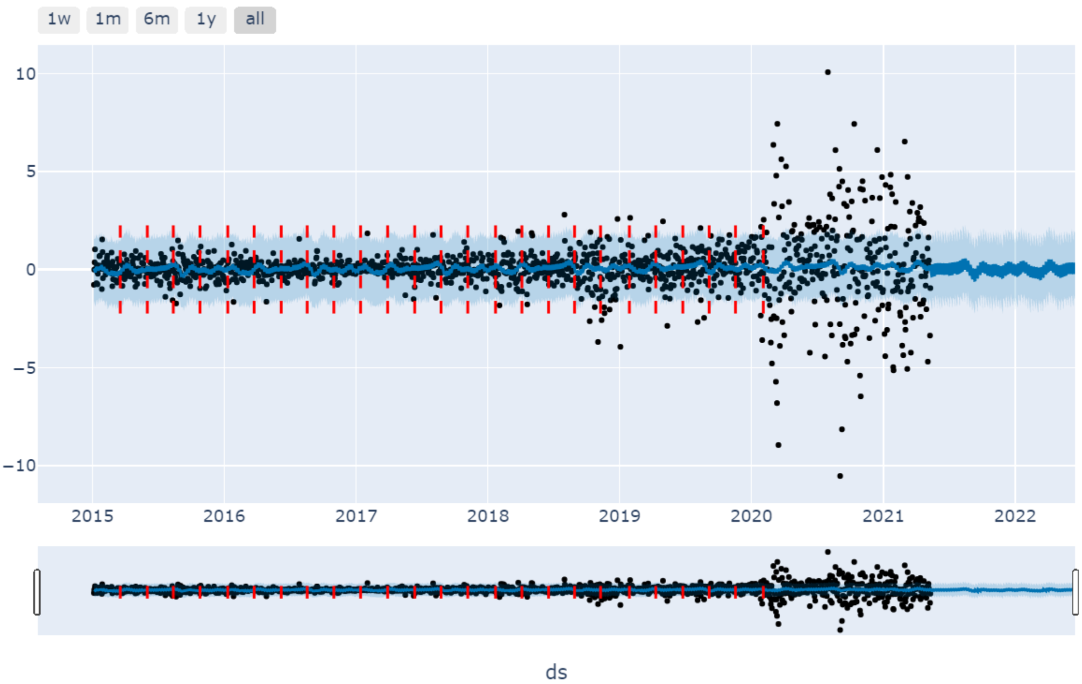

Fig 7 - Prediction result for Prophet model

Inference -

Central Trend: The model's prediction line appears to hover close to zero throughout the years, suggesting that there is no strong long-term trend in the day-to-day price changes.

Increasing Volatility: Starting from around 2020 onwards, there is a noticeable increase in the spread of data points on the y-axis, indicating higher volatility in the stock price changes.

Extreme Changes: The occurrence of data points that reach the extremes of the y-axis, especially those above +5 or below -5, suggests days with significant price movements, which could be due to market shocks, earnings reports, product announcements, or global economic events.

Changepoints: The red dashed lines represent changepoints where the Prophet model has detected possible shifts in the stock's trajectory. These could correspond to moments when the underlying trend in the daily price changes significantly altered.

Legal and Regulatory News: Legal battles, such as Apple's antitrust cases or patent disputes, can affect investor sentiment and thus stock prices, as seen in past fluctuations during such events.

Economic Shifts: Broader economic shifts, like the 2020 market crash due to the COVID-19 pandemic, also had a notable impact on Apple's stock, as it did with many others, reflecting global economic sentiment.

Comparative Analysis for the 3 models -

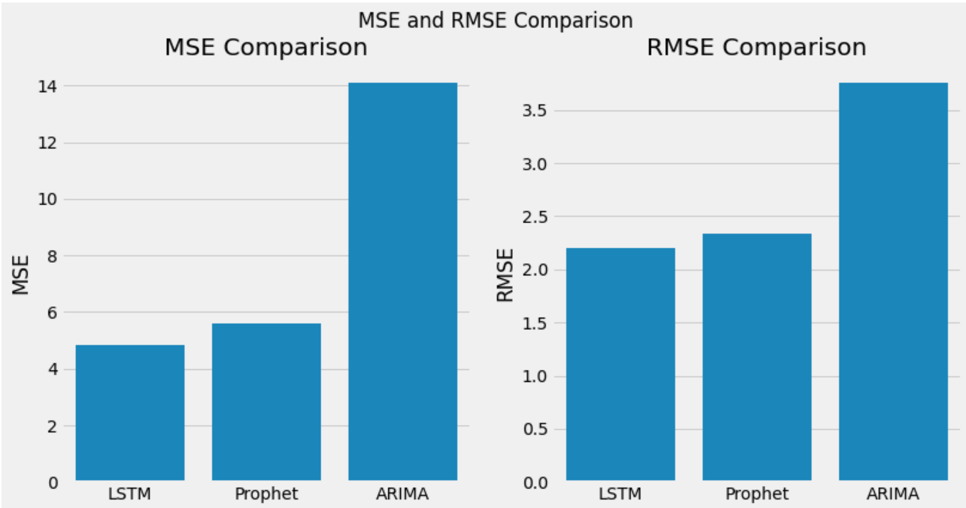

Fig 8 - Comparison between the 3 models

In comparing the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) across the ARIMA, LSTM, and Prophet models, it was observed that the LSTM model demonstrated the lowest MSE and RMSE, indicating its superior predictive accuracy for stock prices. In contrast, the ARIMA model exhibited the highest values in both metrics, suggesting lesser precision in its forecasts. The Prophet model's performance fell between the two, with moderate MSE and RMSE values, reflecting its balanced predictive capability.

Sectoral Analysis -

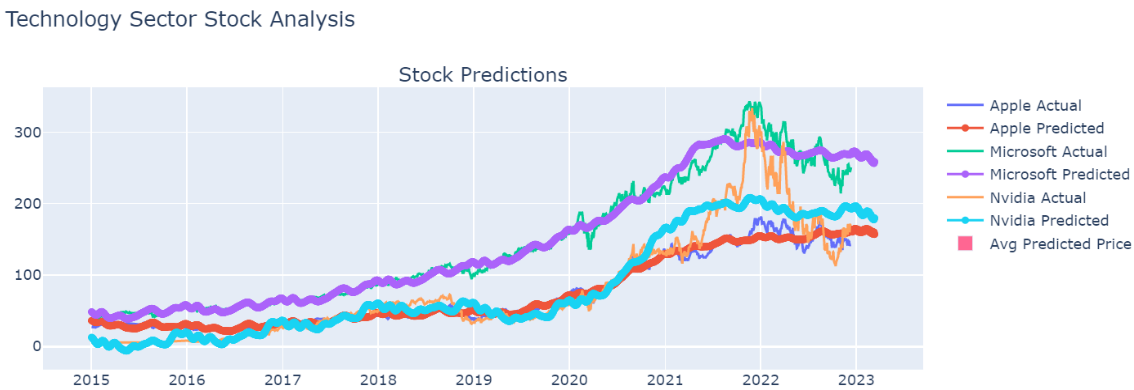

Fig 9 - Prediction results for the 3 chosen stocks in technology sector

Sector Growth: The overall uptrend in the actual prices of Apple, Microsoft, and Nvidia reflects the robust growth within the Technology sector, indicative of innovation, market expansion, and increasing consumer and enterprise demand for technology solutions.

Sector Predictions: The predictions across the three companies, while diverging in individual cases, collectively demonstrate the model's attempt to capture sector-wide trends. The average predicted price line suggests an aggregated forecast, smoothing out individual stock volatility and providing a broader perspective on the Technology sector's trajectory.

Impact of Sector-Wide Events:

Product Innovation and Releases: New product launches, such as Apple's iPhone models or Nvidia's graphics cards, typically generate consumer excitement and can significantly affect stock prices within the sector.

Technological Advancements: Breakthroughs in cloud computing, AI, and other emerging technologies, often spearheaded by companies like Microsoft and Nvidia, can lead to increased investment and stock valuation.

Market Sentiment: The sector is also subject to market sentiment driven by tech-specific and macroeconomic news, regulatory changes, and shifts in consumer behavior, all of which can cause the kind of volatility observed in the plot.
Divergence and Corrections: The instances where predictions and actual prices diverge may correspond to unforeseen market shocks or events that disrupt the usual business operations, such as supply chain issues or global economic instability.

Sectoral Analysis Utility: This kind of visualization is particularly valuable for sectoral analysis as it encapsulates not just the performance of individual companies but also the collective health of the Technology sector. It provides a visual benchmark for the sector's performance and helps identify periods of outperformance or underperformance relative to the market.

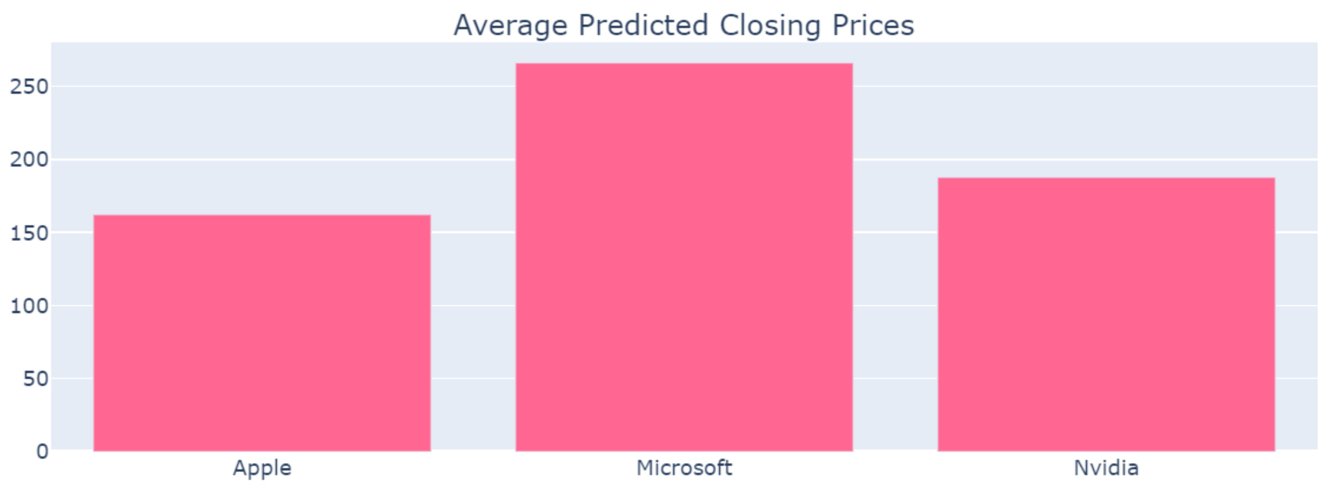

Fig 10 - Average Predicted Closing Prices

The bar chart represents the average predicted closing prices for stocks from three key players in the Technology sector: Apple, Microsoft, and Nvidia. The bar heights indicate that Microsoft's average predicted closing price is the highest among the three, suggesting that, according to the model's predictions,

Microsoft may outperform Apple and Nvidia in terms of stock price over the forecasted period. Apple's projected closing price is the lowest, with Nvidia's falling in between the two. This visualization can serve as a simplified comparative tool for potential future performance within the sector, based on the models' forecasts.

8. Conclusion/Future Work

This study successfully compared the predictive capabilities of ARIMA, LSTM, and Prophet models on stock price data, revealing distinct strengths and weaknesses. LSTM emerged as the most accurate model, showcasing its proficiency in handling complex, non-linear patterns in stock price movements. The ARIMA model, while traditionally robust, showed limitations in capturing such complexities, and Prophet provided a middle ground with its intuitive handling of seasonal trends. This research contributes to the evolving field of financial forecasting, offering insights that blend advanced analytical techniques with practical market realities.

Future research should focus on integrating external economic indicators and market sentiment analysis to enhance the models' predictive power. Exploring the application of ensemble techniques, which combine the strengths of individual models, could lead to more robust forecasting methods. Additionally, extending the analysis to include real-time data and broader market indices may provide deeper insights. Investigating the models' responsiveness to sudden market shifts and global economic events will further augment their practical utility in dynamic financial environments.

9. References

- A comparative study on the stock market prediction performance of ARIMA and RNN-LSTM models, focusing on the Indian stock exchange. This research provides valuable insights into the effectiveness of these models in a specific market context ("Comparison of stock market prediction performance of ARIMA and RNN-LSTM model – A case study on Indian stock exchange", AIP Conference Proceedings, AIP Publishing).
- An analysis of stock market prediction using time series analysis techniques, providing insights into the practical application of these models in financial markets ("Stock market analysis and prediction using time series analysis", Materials Today Proceedings, 2021).
- A study on predicting stock prices using ARIMA and LSTM, showcasing the practical application of these models in real-world scenarios (arXiv.org, 2022).
- A comparison of ARIMA, ANN, and LSTM for stock price prediction, providing a detailed analysis of these models' principles and predictive results (DOAJ, 2020).
- An examination of different techniques to forecast sale prices, including a comparison of Prophet and deep learning models with ARIMA (MDPI, date unspecified).
- An investigation into the predictive abilities of ARIMA, LSTM, and ensemble ARIMA-LSTM models, highlighting the use of these models in stock price prediction (ResearchGate, date unspecified).