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Tech Stock Analysis and Stock Price Prediction with LSTM

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Abstract: *The stock market's quickly changing environment presents investors with both opportunities and difficulties. This article explores the complex field of stock market analysis, focusing on industry leaders in technology such as Apple, Amazon, Google, and Microsoft. The study provides critical insights into stock price variations, moving averages, daily returns, and inter-stock linkages through a thorough analysis of stock prices. Visualizations are like a lighthouse, revealing trends and actions over the course of a year. The use of Long Short-Term Memory (LSTM) networks, a subset of recurrent neural networks renowned for their skill in processing time series data, is essential to our research endeavors. With layers specifically designed for temporal data, our long short-term memory (LSTM) model is trained on past stock prices with the goal of forecasting future values. The preliminary findings demonstrate how well LSTMs can capture past stock patterns. But the study also highlights how unpredictable financial markets are by nature, which serves as a reminder to exercise caution when using machine learning to predict stocks. This study opens the door for more research in this area and serves as evidence of how technology and finance may coexist.*

Keywords: **Stock Market Analysis, LSTM, Data Visualization, Stock Price Prediction**

1. Introduction

Microsoft, Apple, Amazon, and Google. These tech giants provide substantial investment potential and hazards in the financial sector, having completely changed how the world functions in the digital age. This study explores the complex dance that their stock values have been doing for the past year. We show the rise and fall of these stock prices using a variety of graphical methods, marking the pinnacles of economic growth and the valleys of recessions. Remarkably, these kinds of visualizations aid not only in comprehending previous actions but also in forecasting future patterns. In order to achieve this, this research makes use of Long Short-Term Memory (LSTM) networks, a highly developed computer algorithm that is skilled at identifying patterns in time-based data, such as stock prices. We hope to give a window into the future through our analysis of the past data, providing financial analysts, investors, and other stakeholders in the tech sector with potentially priceless information. We will learn about the intricacies of the stock market, the possibilities of contemporary computational methods, and the dynamic story of technology's relationship to finance as we proceed through this investigation.

2. Literature Review

The adoption of machine learning, deep learning, and data analysis tools for stock analysis has been fueled by the dynamic nature of the stock market and the abundance of available data. We examine a broad range of research publications that use these techniques in this review of the literature, highlighting their development, advantages, disadvantages, and areas of success. Eunsuk Chong et al.'s study [1] examined the application of deep learning networks to stock market forecasting. They investigated the advantages and disadvantages of these networks, taking activation functions and network structure into account. The study discovered that by extracting information from autoregressive model residuals, deep neural networks can improve prediction using high-frequency stock data. Nevertheless, the same advantages were not obtained when the autoregressive model was applied to network residuals. Additionally, the study enhanced covariance estimates when applying predictive networks to market structure analysis, providing useful information for forecasting and analyzing the stock market. Gozde Sismanoglu et al. [2] investigated the use of Deep Learning methods for stock market forecasting in their study. They used historical time series data from the New York Stock Exchange, which covered a sizable period from 1968 to 2018, to create a method specifically for predicting particular stock prices. Their results were striking, demonstrating the potential of their Deep Learning-based methodology to produce remarkably precise forecasts for specific equities. This study highlights the usefulness and efficiency of deep learning for stock market analysis and forecasting, emphasizing how it can improve financial sector forecasting and decision-making. For traders and analysts looking to maximize profits, predicting stock price changes is a critical task that is the focus of research by Nagaraj Naik et al. [3]. In this study, a new method is presented for extracting 33 technical indicators (open, high, low, and closing prices) from daily stock price data. There are two main issues this study aims to address. To solve the feature selection issue, it first uses the Boruta feature selection technique to find and choose pertinent technical indicators. Second, it combines deep learning and machine learning methods to create a prediction model for stock price fluctuations. The research's main conclusion is that the deep learning model works better than conventional machine learning techniques, leading to a noticeable 5%–6% increase in classification accuracy rates. Using stocks from the National Stock Exchange of India (NSE), the experiment shows how deep learning and a large collection of technical indicators can improve the accuracy of stock price predictions. The focus of Xia Liu's research [4] is on social media user-generated content (UGC) in marketing. There is a deficiency in business-to-business (B2B) research because the majority of UGC research focuses on business-to-consumer (B2C) situations. Liu uses vast data from 84 million tweets and eight years of stock data for 407 S&P500 businesses to explore the impact of user-generated content (UGC) on stock performance for B2B and B2C organizations. We use machine learning techniques to examine the information. The findings demonstrate that UGC has a major impact on stock performance, with a greater effect on B2C companies. Notably, word-of-mouth and negative sentiment have a major impact on stock prices, whereas positive sentiment has no such effect. This study demonstrates the significance of user-generated content (UGC) in evaluating stock performance and uncovers complex connections between stock prices and customer sentiment in B2B and B2C contexts. Machine learning and deep learning techniques are used in Mojtaba Nabipour et al.'s study [5] to lower the risk in stock market trend prediction for several sectors from the Tehran stock exchange. The study uses ten technical indicators from ten years of historical data in both continuous and binary formats, together with nine machine learning models and two deep learning techniques. The outcomes demonstrate how remarkably effectively RNN and LSTM function with continuous data. Deep learning techniques are superior when it comes to binary data, but the performance gap narrows as a result of better models. This study emphasizes the value of selecting the right data format as well as the algorithms' potential for predicting stock market trends. The goal of Hui Liu et al.'s research [6] is to enhance stock market prediction. This work presents a novel framework that takes advantage of deep learning capabilities, especially those of LSTM networks, whereas previous approaches mostly relied on statistical and conventional neural network models. The approach integrates empirical wavelet transform (EWT) for preprocessing data, LSTM-based deep learning prediction, and an outlier-robust extreme learning machine (ORELM) model for post-processing. The hybrid framework is a useful tool for financial data analysis and stock market monitoring since it outperforms traditional models in terms of prediction accuracy.

Rob Alessie et al.'s study [7] uses Dutch household panel data from 1993 to 1998 to examine the patterns of stock and mutual fund ownership. They present a dynamic binary-choice model to look into how these assets interact with one another. The analysis emphasizes how important state dependency and unseen factors are in shaping ownership patterns of mutual funds and equities. Correlated unobserved factors are thought to be responsible for the positive correlations between owning one sort of asset in one period and the other in the next. Interestingly, owning stocks in the past has a negative influence on owning mutual funds, probably because switching costs are high. This study provides insight into how households invest in mutual funds and stocks. Chonghui Guo et al. [8] address time series clustering, a difficult topic in time series data mining, in their research. The researchers suggest using a feature-based strategy to get over the particular difficulties associated with time series data. Using the Independent Component Analysis (ICA) approach, raw time series data are converted into lower-dimensional feature vectors in this method. A modified k-means algorithm is then applied. Using real-world stock time series data, the study validates the approach and obtains reasonable results. This study emphasizes how useful feature-based methods, ICA, and modified k-means algorithms are for solving time series clustering problems. Predictive technologies, data mining, and automated computer programs are the main topics of inquiry in a study by K. Senthamarai Kannan and associates [9]. To determine whether the day's closing stock price will rise or fall, the study integrates five different stock analysis techniques: Bollinger Bands, Typical Price (TP), Relative Strength Index (RSI), CMI, and Moving Average (MA). With the help of numbers and graphics, the study highlights how well these methods work to forecast stock market movements and looks at how world events affect stock markets. The work of Zhihao Peng [10] focuses on using big data analytics to precisely forecast and analyze large amounts of data. A solid Cloudera-Hadoop data pipeline for evaluating data of various sizes and kinds is shown in the paper. It uses real-time data from Yahoo Finance to precisely target US stock research and forecast daily gains. Large data sets can be handled more easily with the help of the Apache Hadoop framework's distributed processing and storage. High daily gain stock predictions are made using Spark's machine learning modules. The potential of big data analytics for stock market prediction is demonstrated by this study. In order to look at how stock market correlations are impacted by global crises, Sonali Das et al.'s work [11] introduces a novel mixed-frequency regression approach built from functional data analysis. Their vast dataset covers a wide range of worldwide problems and dates back to the 1800s. The study, which focuses on the G7 countries, finds that while stock market correlations with European and Japanese markets tend to decline, they often grow in the US, UK, and Canada at times of global crisis. This implies that although stock market convergence is influenced by global crises, the nature of the crisis influences the final result. From the standpoint of investments, the advantages of diversity between the US and UK markets decrease following crises, highlighting the significance of emerging markets and alternative assets for contemporary diversification benefits. Driven by new machine learning models and technological breakthroughs, Sahil Vazirani et al. [12] concentrate on stock market data analysis. They compare and contrast current stock market trade models in detail and suggest new linear regression models that drastically cut down on errors. The study demonstrates how effective it is to use two successive linear regression models for better daily stock market predictions, with the first model's output serving as the second model's input. Machine learning algorithms for daily stock market analysis are advanced by this work. Using an event research methodology, Bhanwar Singh et al. [13] look at how the COVID-19 epidemic affected the stock markets of G-20 nations. Within 58 days of the epidemic, they discovered statistically significant negative abnormal returns (ARs) that affected both industrialized and developing nations throughout four sub-event windows. The market panic brought on by a rise in COVID-19 instances is responsible for the cumulative average abnormal return (CAAR), which ranges from -0.70% to -42.69% from day 0 to day 43. After a large price correction, the market recovers from day 43 to day 57, as indicated by the CAAR, which spans from –42.69% to –29.77%. Panel data study highlights the significant impact of the pandemic on international stock markets by confirming the post-correction rebound.

Data mining is used by Zhou Yixin et al. [14] to forecast price trends and market volatility in the Chinese stock market. They use a three-tier BP neural network technique to overcome the drawbacks of conventional statistical analysis. The research uses popular technical indicators of the stock market to improve prediction accuracy. This work uses neural network techniques and data mining to increase stock market trend research and prediction. The work by Aparna Nayak et al. [15] focuses on the difficulties caused by the large number of quickly fluctuating stock market price data. Using supervised machine learning techniques, they create two models for predicting stock market trends: one for daily forecasts and another for monthly projections. The daily model achieves up to 70% accuracy by combining sentiment analysis with previous prices. On the other hand, the monthly model looks at the relationship between the patterns of several months and finds just a little overlap. This study demonstrates how machine learning may be used to forecast monthly patterns as well as daily movements in the stock market. Uma Gurav et al. [16] face the difficulty of forecasting the volatile and dynamic stock market. Their work includes mathematical models, widely-used data science techniques, and technical indicators. The paper provides a thorough overview of solutions and assesses several machine learning techniques. It highlights how crucial it is to keep predicting errors to a minimum in order to lower stock market investment risk. The comprehension of stock market prediction in a complicated and turbulent environment is improved by this work. The importance of time series analysis and forecasting is emphasized by Sheikh Mohammad Idrees et al. [17], particularly in light of the dynamic stock market. Understanding patterns and variations across time is aided by time series data. Because of the complexity and volatility of stock markets, forecasting is essential for investors looking to reduce risk and maximize profits. The goal of the project is to develop an effective statistical model for stock prediction by examining time series data from the Indian stock market. Predictive models for the difficult realm of stock trading are advanced by this work. The intricacy of the stock market, which is essential for many industries, is discussed by Kunal Pahwa et al. [18]. To provide predictability to this complex environment, they suggest predicting future stock prices using machine learning techniques and open-source tools. The study evaluates the viability of this strategy while acknowledging that the results depend on quantitative data and a few presumptions that might change in actual situations. The potential of machine learning to enhance stock price forecasts is investigated in this paper. Irfan Ramzan Parray and colleagues [19] underscore the importance of the stock market as an economic indicator. They forecast stock market trends by utilizing machine learning techniques. They predict stock trends with noteworthy accuracy using data from about fifty stocks in the Indian National Stock Exchange's NIFTY 50 index. The accuracy of the support vector machine is 87.35%, the perceptron is 75.88%, and the logistic regression is 86.98%. Accuracy increases when the dataset is rearranged into a supervised learning format; logistic regression achieves 89.93%, support vector machine reaches 89.93%, and perceptron achieves 76.68%. The efficacy of machine learning in stock market prediction is demonstrated by this study. Marxia Oli Sigo et al. [20] draw attention to the data-driven world and the intricacy of how economic factors and regulatory policies affect stock market price movements. Market volatility and stochastic behavior are obstacles to accurate stock price forecasting. Using ensemble machine learning, their study examines the stochastic patterns of the fifty most volatile firm stocks in the NSE-Nifty. The goal of the study is to provide investors with knowledge that will enable them to make wise decisions and maximize stock returns. The inherent volatility and unpredictability of the stock market present issues that are addressed in this study. In order to address the problem of stock market price prediction, Jordan Ayala et al. [21] suggest a hybrid strategy that creates trading signals by fusing machine learning and technical analysis indicators. This method adapts trading rules to different technical indicators while streamlining and enhancing their efficacy.To determine which machine learning technique is best, they assess Support Vector Regression (SVR), Random Forests (RF), Artificial Neural Networks (ANN), and Linear Models (LM). When the method is tested using data from important indexes, such as Dow Jones Industrial (DJI), DAX, and Ibex35 (IBEX), trading signals and competitiveness are improved. This study advances the techniques for predicting the stock market. The Chinese market's ESG (environmental, social, and governance) equities are examined by Guangliang Yu et al. [22]. They compare the ESG 300 Index's performance and volatility with that of major stock indices throughout the period of April 2020 to September 2021. To investigate the connection between ESG scores and stock returns, their methodology makes use of machine learning techniques like KNN, SVM, and AdaBoost as well as the GARCH (1,1) model for volatility. Based on ESG scores, hedge fund portfolios are put together, divided into four groups, and then contrasted using the Sharpe ratio. The findings indicate that while ESG-related stocks do not outperform non-ESG stocks in terms of returns, they do perform better at risk during regular times. Understanding ESG investments in the Chinese market is aided by this study.

3. Methodology

3.1. Data Collection

The present study's dataset was carefully obtained from Yahoo Finance, a well-known platform that is widely recognized for its extensive financial data and insights. Using pandas_datareader in conjunction with the yfinance library, we methodically extracted stock market data for four significant technological firms: Apple (AAPL), Google (GOOG), Microsoft (MSFT), and Amazon (AMZN). The interest period was one year, starting from the present and working backward. The distinct datasets for each organization were merged into a single, cohesive dataframe following the data's retrieval. This facilitated analysis and ensured consistency throughout the subsequent study phases.

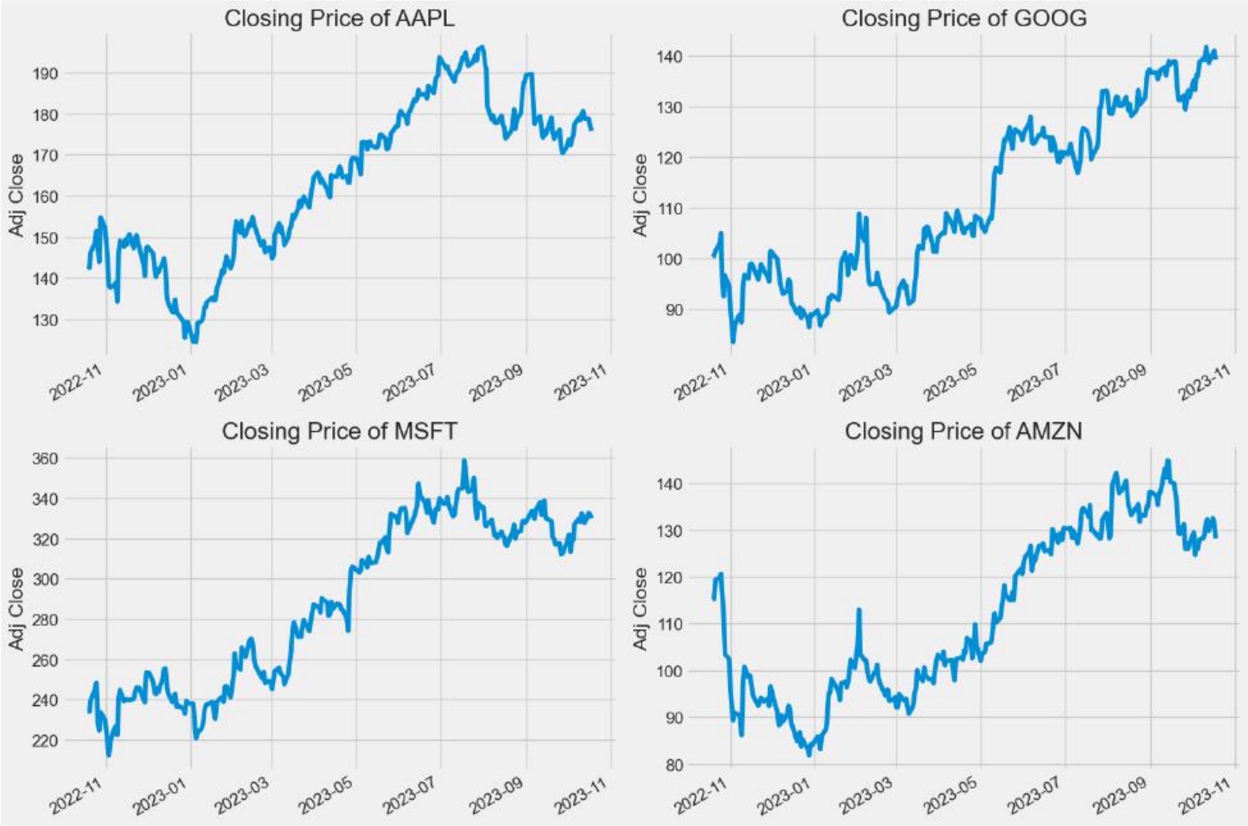
3.2. Data Preprocessing

To guarantee that the data was accurate, dependable, and consistent with the selected modeling methodologies, a rigorous set of data pretreatment steps was employed. In order to prepare the dataset for thorough time series analysis and subsequent predictive modeling, this was done.

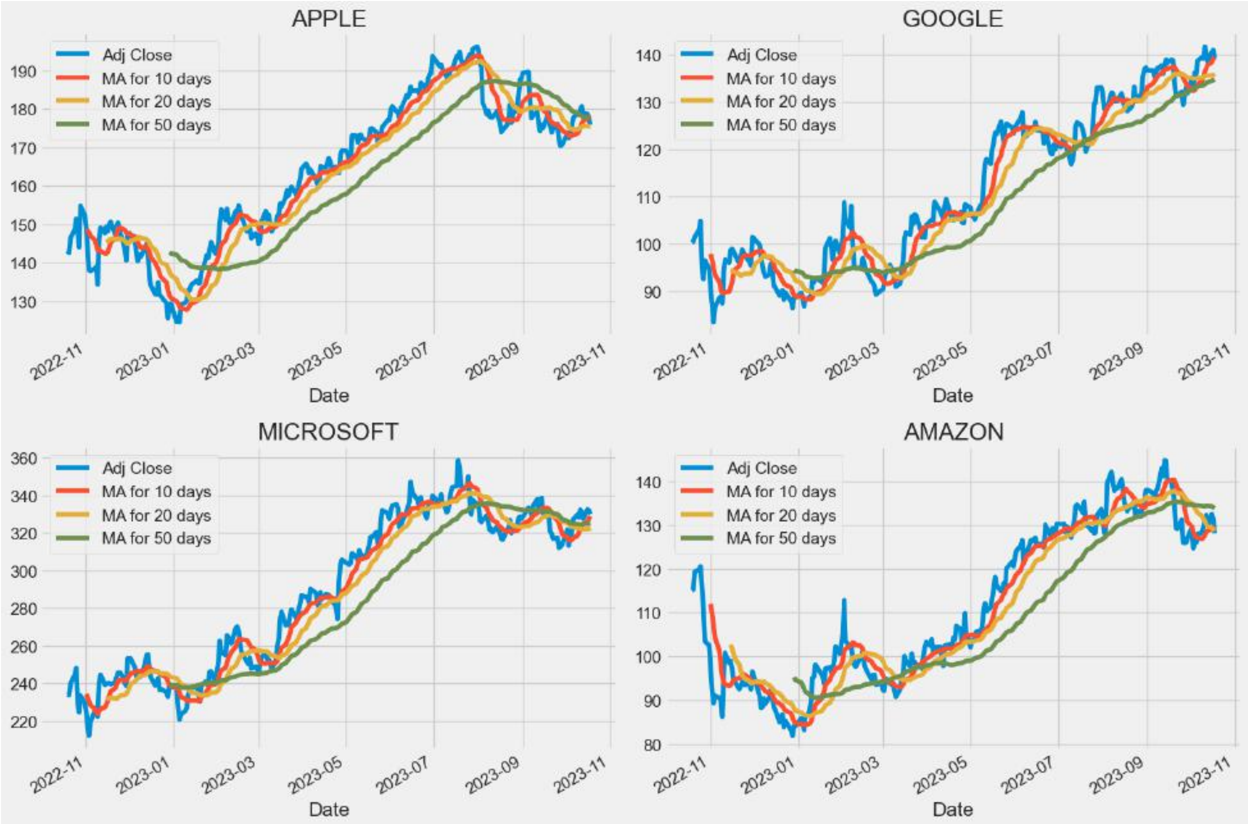
1. Handling Missing Data: The possibility of missing values is one of the main difficulties in time series research, especially when working with financial datasets. These gaps can be caused by a number of things, including disparities in the data collection process or non-trading days. Such missing numbers were seen in our study's `tech_rets} dataframe, which contains the returns of technology stocks. Rows with {NaN} values were routinely eliminated in order to preserve consistency in our time series data and avoid potential biases or mistakes in the study. By using this method, it is guaranteed that the dataset used for the analysis and modeling stages that follow will be full and devoid of errors.
2. Normalizing the data: In order to maintain model stability and hasten training convergence, normalizing the data is necessary because stock market data is dynamic and has fluctuating scales and magnitudes. The `MinMaxScaler} from the `sklearn` package, a commonly used normalization method in time series research, was utilized in this investigation. Not only does this make the original stock data more compatible with neural network architectures, but it also reduces the potential for issues arising from differing feature scales during the training phase, making the training phase more stable.
3. Get Sequence Data Ready for LSTM: Recurrent neural networks (RNNs), of which Long Short-Term Memory (LSTM) networks are a kind, are excellent at modeling sequences, which makes them perfect for time series data. Nevertheless, the data must be organized in particular sequence patterns in order to fully utilize their potential. Using the previous sixty data points, we created sequences in our method to forecast the next data point in real time. After practical testing, this 60-point frame was selected to balance the need to capture long-term dependencies with computing speed. In order to guarantee that the training and testing datasets were best suited for LSTM modeling, they were both modified to follow this sequence pattern.
4. LSTM Model – Future stock values are predicted by utilizing the power of Long Short-Term Memory (LSTM) networks, a kind of Recurrent Neural Network (RNN). The initiative uses time series data, which are collections of data points indexed in chronological order, and focuses on technology stocks like Apple, Amazon, Google, and Microsoft. LSTMs are particularly well-suited for time series data, such as stock prices, because of their innate capacity to recognize and retain long-term dependencies. The model's architecture consists of two LSTM layers followed by two dense layers, and it is built using the Keras framework. There are 128 units in the first LSTM layer and 64 units in the second. These strata are intended to identify the stock prices' temporal patterns. The prediction is generated with the help of subsequent thick layers, and the projected stock price is output by the final layer. The'mean_squared_error' loss function and the Adam optimizer are used to assemble the model with the goal of minimizing the average squared difference between the actual and predicted values. The model is trained using training data, which most likely consists of series of historical stock price data. It seems that forecasting Apple's stock prices is the main focus, based on the text that has been extracted. The training process runs for one epoch with a batch size of 1, however several epochs would normally be needed in a real-world application to guarantee the model's loss converges.

3.3. Observation and Data Visualisation

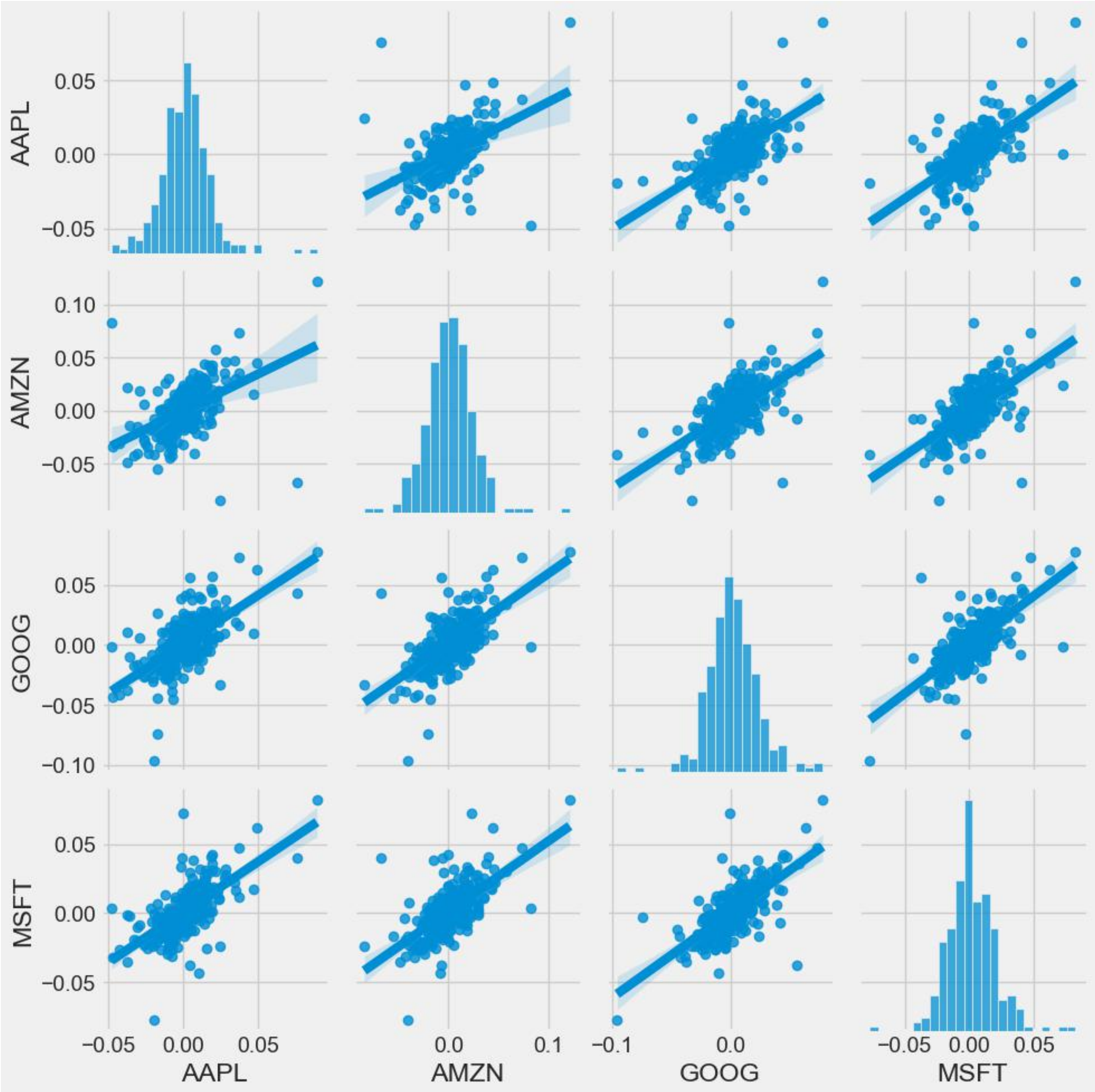
We looked closely at the stock data of well-known IT companies like Microsoft, Apple, Amazon, Google, and others in our study. Our main goal was to track the daily changes in stock prices and, by averaging these prices across different time periods, to find general trends. We also evaluated the average daily fluctuations in the stock values, both upward and downward. Determining the connections and linkages among these tech stocks was a fascinating part of our research. We also looked into the possible risks of investing in these companies given how volatile the stock market can be. A large amount of our study was devoted to forecasting, in which we attempted to project these stock values' future trajectories using data and patterns from the past.



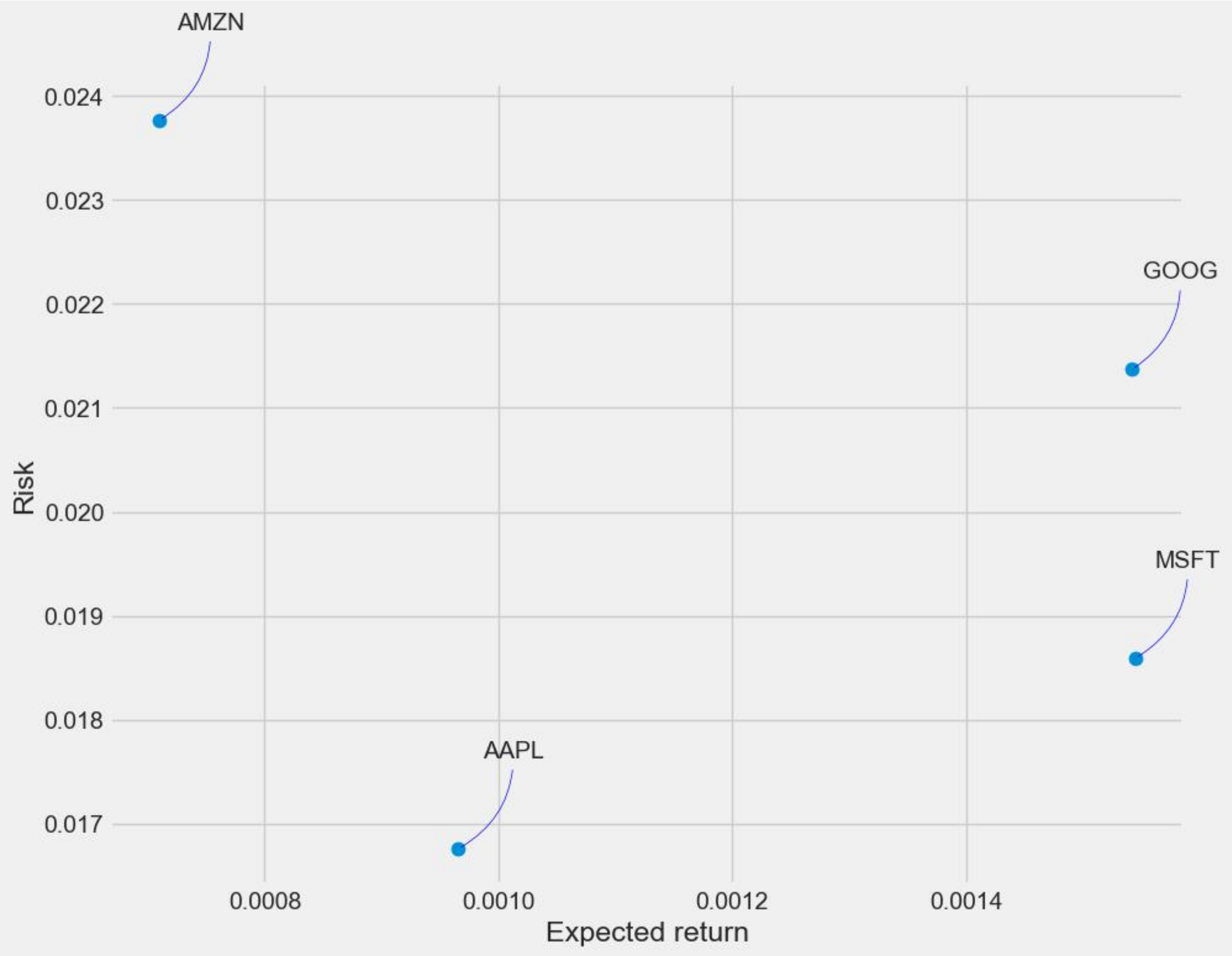
This chart shows how the tech stocks we're studying have performed over time. By looking at it, we can get a clear idea of how each company's stock has gone up or down



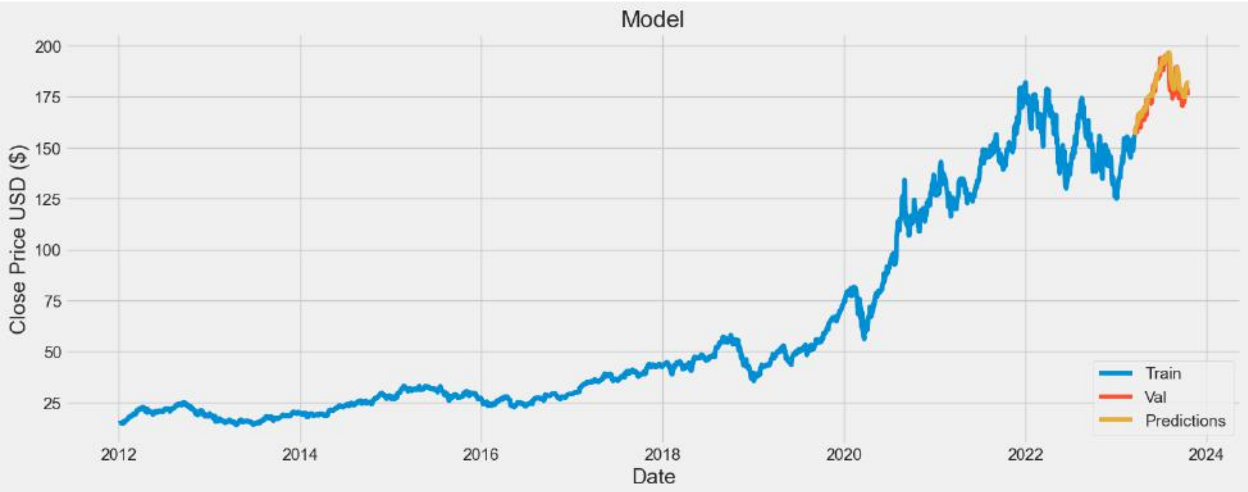
Apple, Microsoft, and Amazon all saw notable increase in the first half of the year before seeing a discernible decrease in the later months, as seen in the above graphic by their short-term moving averages crossing below the 50-day average, which implies probable bearish sentiment. As an illustration of potential future volatility or a trend shift, Google's moving averages did, however, eventually converge, continuing its upward track throughout. It's important to remember that a variety of factors affect the trajectory of the stock market, and past performance cannot predict future results.



The return correlations between the tech giants Apple (AAPL), Amazon (AMZN), Google (GOOG), and Microsoft (MSFT) are represented graphically in the matrix. The distribution of individual returns is shown by the diagonal histograms, which show a general tendency towards normalcy with some variances in skewness. There is a constant high positive association across company scatter plots. For example, there are significant positive correlations between AAPL's returns and AMZN, GOOG, and MSFT. In a similar vein, there are significant return correlations between AMZN, GOOG, and MSFT. This pattern raises the possibility that synchronized stock fluctuations among these titans could be caused by industry-wide issues or common market effects.



Microsoft (MSFT), Apple (AAPL), Amazon (AMZN), and Google (GOOG). The expected returns are plotted on the x-axis, and the associated risks are plotted on the y-axis. Notably, AMZN has the strongest risk-return combination, with GOOG trailing closely behind. By comparison, MSFT displays a somewhat reduced risk and nearly identical projected return to GOOG. Conversely, out of the four, AAPL has the lowest predicted return and the lowest risk profile. Potential trajectories of their alterations in risk-return are represented by the curves joining each point.



The time series model of Apple's stock close prices (in USD) from 2012 to 2024 forecasts is depicted in the chart. The blue-colored 'Train' dataset shows historical Apple stock values from 2012 until around 2020. The 'Val' (validation) dataset, which is represented by a darker blue color, spans the period from about 2020 to 2023 and reflects Apple's actual stock price values during that time. The 'Predictions' section, which is displayed in orange and goes through 2024, shows the model's estimated Apple stock prices. Based on the visual depiction, it seems that the model predicted the data rather well, as it closely matched the path of the 'Val' dataset.

4. Conclusion

Using visualizations to identify patterns and connections, we investigated the stock market activities of internet behemoths such as Apple, Amazon, Google, and Microsoft for this project. Utilizing Long Short-Term Memory (LSTM) networks to forecast future stock values was a key component of our work. The dynamic nature of the stock market serves as a reminder of the difficulties in accurately projecting the future, even if LSTMs have demonstrated promise in capturing historical patterns. The project demonstrates how machine learning's potential can be combined with the volatile vagaries of the financial markets.

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