Predicting Tech Stock Dynamics: A Comparative Analysis of ETS and ARIMA Models on NVIDIA's Stock

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***Abstract*— This study explores the forecasting of Nvidia's stock prices using two prominent time-series models: Exponential Smoothing (ETS) and AutoRegressive Integrated Moving Average (ARIMA). Nvidia, a leader in the technology sector, experiences significant market volatility influenced by advancements in AI and semiconductors, making it an ideal case for financial forecasting. The research utilized daily stock data from the past five years to compare the performance of ETS and ARIMA in predicting future stock prices.**

The ETS model demonstrated strength in capturing long-term trends and seasonal patterns, while ARIMA excelled in addressing short-term volatility and dynamic price movements. The models were rigorously evaluated using statistical metrics such as AIC, BIC, and residual diagnostics. Insights were further visualized through an interactive Power BI dashboard, enabling investors and analysts to explore trends, patterns, and actionable forecasts interactively. The findings highlight the complementary nature of ETS and ARIMA, making them valuable tools for strategic and tactical investment decisions. Recommendations for future research include incorporating macroeconomic indicators, automating parameter tuning, and exploring advanced machine learning models like LSTM to enhance predictive accuracy.

Keywords* ---- *Nvidia Stock, Time-Series Forecasting, ETS vs. ARIMA.

I. Introduction

In the volatile landscape of financial markets, the ability to predict stock behaviors is crucial for investors and analysts alike. NVIDIA Corporation, a key player in technology sectors like artificial intelligence and gaming, represents a unique case study due to its significant market influence and rapid sectoral shifts. This research aims to refine financial forecasting methods by applying sophisticated time series models—**Exponential Smoothing (ETS)** [1]and **AutoRegressive Integrated Moving Average (ARIMA)** [2] —to NVIDIA's stock data, offering insights into both the academic field of economic predictions and practical investment strategies.

Given the challenges in capturing the complex dynamics of stock prices influenced by a variety of unpredictable factors, this study tests the efficacy of these models in a real-world context. The comparison aims not only to enhance theoretical understanding but also to provide empirical evidence that can guide practical investment decisions in fast-evolving industries. Focusing on NVIDIA, this research addresses critical gaps in current forecasting practices, marking its significance in the contemporary economic landscape

II. Literature Review

The exploration of stock price forecasting in the literature reveals a continuous evolution of methodologies, from traditional statistical models to more sophisticated time series analyses. Among these, the ARIMA and Exponential Smoothing State Space Model (ETS) stand out due to their ability to adapt to various market conditions and their robustness in handling data with underlying trends and seasonality. Historically, the ARIMA model, introduced by Box and Jenkins, has been pivotal in shaping the approach to economic data analysis, offering a systematic method to forecast future points in a series [3]. In contrast, ETS models, as refined by Hyndman and colleagues, provide a flexible framework that accounts for trends and seasonal variations more dynamically, which is crucial in volatile sectors like technology [1]

Despite the advancements in forecasting techniques, significant gaps remain, particularly in comparative studies that analyze the efficacy of different models under identical market conditions. While ARIMA has been widely validated in various sectors, including energy and finance, for its precision in linear relationship analysis [2], ETS models have been noted for their superior performance in scenarios where data exhibit non-linear patterns [4]. However, few studies have undertaken a direct comparison between these models within the context of highly volatile technology stocks, such as those of NVIDIA, which are influenced by rapid technological advancements and market sentiment shifts.

This research seeks to fill this gap by employing both ARIMA and ETS models to forecast NVIDIA's stock prices, providing a unique contribution to the literature on financial forecasting in the technology sector. The comparative analysis will not only enhance the understanding of each model's strengths and limitations but also offer valuable insights into their applicability to real-world stock market data. Such studies are essential for investors and analysts who rely on accurate forecasts to make informed decisions in a market where the correct prediction can lead to significant financial advantage.

III. Methodology

A. Discover

Nvidia, a global leader in semiconductor technology, has shown significant market volatility over the years. Accurate stock price forecasting is crucial for investors, analysts, and stakeholders to make timely and effective decisions. Time-series forecasting models such as ETS and ARIMA are valuable tools for analyzing historical data and predicting future trends.

The primary question this study aims to address is: *"Which to compare the forecasting results of ETS and ARIMA Time Series models for Nvidia's stock prices to identify future trends and patterns?"*
This involves identifying patterns, trends, and seasonality in Nvidia's historical stock data and evaluating the performance of these two widely used time-series forecasting models. The focus is to determine which model better predicts future prices, supporting informed investment and market analysis decisions.

B. *Data Preparation*

The dataset used for this study comprises daily stock price records of NVIDIA Corporation for last 5 years, sourced from yahoo finance [5] This dataset includes critical metrics such as open, high, low, close prices, and volume of shares traded, which are essential for conducting robust time-series analysis.

To generate a reliable time series model, the dataset continuity plays a vital role. The NVIDIA stock dataset required several specific steps to transform it into a continuous and reliable time series which includes:

- Date column was in a datetime format, to maintain uniformity and to reduce complexity, it is standardized by removing the time component.

	Date
0	2019-10-10
1	2019-10-11
2	2019-10-12
3	2019-10-13
4	2019-10-14
...	...

Figure 1:Formatted Date Column

- Since the data is of daily stock prices for 5 years there is a total of 1258 rows which is of 256 trading days per year for 5 years. In that there is no duplicate value of data is present.
- Not all dates were represented in the dataset, possibly due to non-trading days like weekends and holidays. To create a continuous time series, a complete date ranges from the earliest to the latest date in the dataset was generated. Missing dates were then filled with the last available stock price using forward fill, ensuring no gaps in the data.

	Date	Open	High	Low	Close	Volume
0	2019-10-10	4.493643	4.604603	4.488418	4.553601	309124000.0
1	2019-10-11	4.637693	4.710588	4.618785	4.627244	446404000.0
2	2019-10-12	NaN	NaN	NaN	4.627244	NaN
3	2019-10-13	NaN	NaN	NaN	4.627244	NaN
4	2019-10-14	4.618536	4.661577	4.587437	4.640678	200040000.0
...	...	...	...	...	...	...

Figure 2 Missing Value on Non trading Days replaced with last traded close price

- Now the dataset is fully continuous and uniform for model prediction, with 1825 rows with holidays and weekend filled with last traded close price.

C. *Plan Model*

This study employs two widely used time-series models, **Exponential Smoothing (ETS)** [3] and **Autoregressive Integrated Moving Average (ARIMA)**, [2] to forecast Nvidia's stock prices. Both models are selected due to their unique strengths in handling time-series data. ETS focuses on capturing components such as trends and seasonality, while ARIMA is adept at managing short-term dynamics and volatility in data.

The **ETS model** is particularly suitable for datasets that exhibit clear patterns of trend and seasonality. Nvidia's stock prices show persistent trends and potential seasonal influences, making ETS an effective choice for understanding long-term movements. Additionally, ETS requires minimal preprocessing and provides an intuitive breakdown of the time series into error, trend, and seasonal components, enabling straightforward interpretation of results.

The **ARIMA model**, on the other hand, is well-suited for data that exhibits non-stationary behavior and short-term fluctuations. Nvidia's stock prices are characterized by volatility, and ARIMA's ability to handle noise and model relationships between past and current values makes it ideal for capturing these dynamics. By combining the strengths of ETS and ARIMA, this study ensures comprehensive analysis, comparing long-term forecasting with ETS to ARIMA's focus on short-term accuracy.

D. *Build Model*

For the analysis of Nvidia's stock price data, time-series forecasting techniques were explored, with a focus on supervised machine learning models. Among these, **Exponential Smoothing (ETS)** and **AutoRegressive Integrated Moving Average (ARIMA)** were identified as the most suitable for the dataset due to their proven performance in handling time-series data with trends and potential seasonal components.

Both ETS and ARIMA fall under the umbrella of supervised learning because they rely on historical data with known outputs (e.g., past stock prices) to train the model and predict future values. ETS was chosen for its strength in explicitly modeling components such as trend and seasonality, making it particularly effective for datasets with consistent patterns over time. ARIMA, on the other hand, excels in capturing relationships between current and past values, especially for datasets exhibiting volatility and noise, which are common in stock market data.

E. Communicate

The Power BI dashboard is designed to effectively visualize the analysis and results of the time-series models, ETS and ARIMA. It provides intuitive and actionable insights into Nvidia's stock prices, allowing users to explore trends, patterns, and forecast comparisons interactively.

The Dashboard will consist of two pages in which the first page will of **Historical Price** data and their related trends and the second page with **Future Projections** using modelling and **Moving Averages**.

The key charts which are planned to implement in the dashboard for clear understanding and depth representation include:

- **Line Charts** for representing Trends and Forecasted results
- **Donut Chart** for average volume traded
- **Cards** for key metrices
- **Slicers** and other Variable **Moving Average** components for custom time range analysis.

F. Measure effectiveness/Apply Live

Ethical considerations were central to this analysis, focusing on the responsible use of publicly available stock price data to prevent misuse and ensure transparency. The study emphasizes that the forecasts provided are for educational and analytical purposes, not financial advice. Key ethical practices included maintaining data integrity through rigorous preprocessing, transparently communicating the limitations of the models, and ensuring that the probabilistic nature of the forecasts was clearly understood.

The methodology adhered to the Data Analytics Lifecycle, encompassing problem definition, data preparation, model selection (ETS and ARIMA), implementation, and result visualization in a Power BI dashboard. ETS and ARIMA were chosen for their ability to capture long-term trends and handle short-term volatility, respectively, allowing for a comprehensive comparison. By integrating ethical considerations and following a structured approach, the study reinforces the appropriateness and credibility of the models used in addressing the research problem.

IV. Results and Discussion

This study employs two sophisticated time-series forecasting models, **Exponential Smoothing** (ETS) and **AutoRegressive Integrated Moving Average** (ARIMA), which are supervised in their learning phase. These models utilize historical data to predict future outcomes, with ETS focusing on error, trend, and seasonality, and ARIMA emphasizing the relationships between past and future values through differencing, autoregression, and moving averages.

ETS model is particularly sensitive to pattern changes over time, making it ideal for data with underlying seasonal behaviors. ETS decomposes the time series into three main components—error, trend, and seasonal—each modeled explicitly. **ARIMA** operates through a combination of differencing(d) [6] (to achieve stationarity), autoregression(p) (a variable's relationship with its previous values), and moving averages(q) (smoothing out noise). Key variables in ARIMA include the order of differencing (d), the number of past values (p), and the size of the moving average window (q).

Modeling involved selecting optimal parameters for each model—smoothing parameters for ETS and (p, d, q) values for ARIMA [6]. Predictions were then generated to align with the study's objectives of comparing model performance and identifying reliable investment insights.

In the analysis of Nvidia's stock prices, an ARIMA(1, 0, 1) model was rigorously tested to evaluate its predictive accuracy and reliability. The model was designed to incorporate one autoregressive term and one moving average term, with no differencing, indicating the assumption of inherent stationarity in the series. The primary tests conducted included evaluating the statistical significance of the model’s coefficients, the goodness of fit through AIC and BIC scores, and residual diagnostics using the Ljung-Box [7] and Jarque-Bera test [8]. These tests aimed to validate the model's ability to effectively capture the dynamics of Nvidia’s stock price movements and to ensure that the residuals behave in a manner consistent with the assumptions of the chosen model.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Close   No. Observations:                 1827
Model:                 ARIMA(1, 0, 1)   Log Likelihood               -3063.284
Date:                Mon, 25 Nov 2024   AIC                           6134.568
Time:                        12:19:58   BIC                           6156.609
Sample:                             0   HQIC                          6142.698
                               - 1827
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         33.2664    334.273      0.100      0.921    -621.896     688.428
ar.L1          0.9998      0.001   1220.708      0.000       0.998       1.001
ma.L1         -0.0780      0.009     -8.592      0.000      -0.096      -0.060
sigma2         1.6673      0.016    102.947      0.000       1.636       1.699
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):             45970.63
Prob(Q):                              0.88   Prob(JB):                         0.00
Heteroskedasticity (H):              65.98   Skew:                             0.55
Prob(H) (two-sided):                  0.00   Kurtosis:                        27.55
===================================================================================
```

Figure 3 SARIMAX TEST RESULTS W.R.T MODEL PARAMETERS

The results from the ARIMA model highlighted the strong influence of past stock prices on future values, with an autoregressive coefficient close to 1 (0.9998), suggesting a significant reliance on the immediate past value for predicting the current price. The moving average coefficient was slightly negative (-0.0780), indicating adjustments for previous forecast errors that enhance the model's accuracy by smoothing fluctuations. Both coefficients were statistically significant, with p-values near zero, strongly rejecting the null hypothesis of no effect, which underscores the relevance of these components in the model.

The model's overall fit, indicated by AIC(Akaike's information criterion) [9] (6134.568) and BIC(Bayesian information criterion) [9](6156.609), while not minimal, suggested a reasonable balance between model complexity and fit to the data. The Ljung-Box test with a p-value of 0.88 confirmed no significant autocorrelation in the residuals, supporting the model's specification. However, the Jarque-Bera test [8] [10] result indicated that the residuals do not follow a normal distribution, signaling potential areas for model refinement, such as incorporating non-linear transformations or exploring additional lags.

The visualizations used in the dashboard consist of:

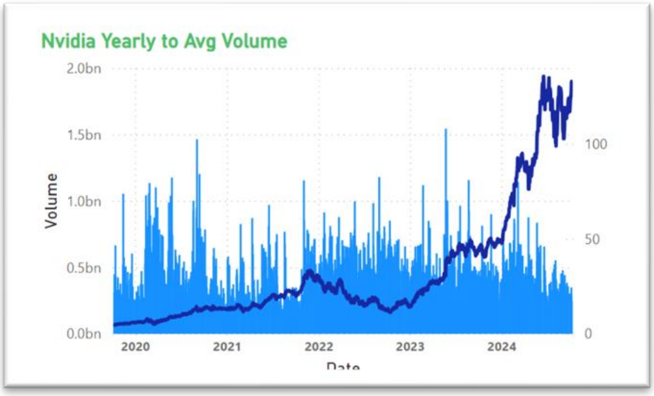

Figure 4 Yearly Price and Volume Trends

The yearly visualization combines Nvidia's stock prices and trading volumes, revealing a strong positive correlation—rising prices align with increasing volumes, particularly post-2022. This trend reflects heightened investor interest and market activity, driven by Nvidia's [10] advancements in AI and semiconductor technologies. Notable volume spikes during 2022-2024 coincide with significant price movements, emphasizing the role of volume as a leading market sentiment indicator. The sharp post-2022 growth highlights a high-demand phase, influenced by technological advancements, while the steady rise in trading volumes signals strong liquidity, reinforcing Nvidia's appeal to both institutional and retail investors. This interplay between demand and valuation makes the visualization vital for understanding Nvidia's market dynamics.

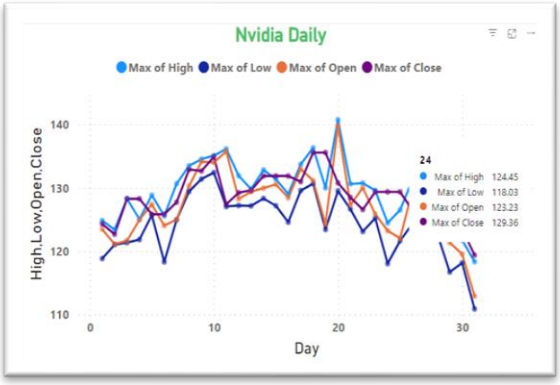

Figure 5 Daily Historical Trends

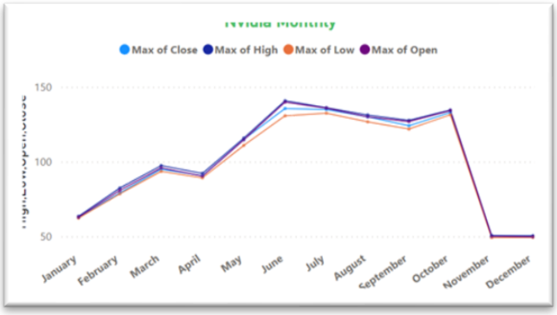

Figure 6 Monthly Historical Trends

The daily and monthly visualizations of Nvidia's stock prices offer complementary insights into market trends. The daily chart highlights short-term volatility, with noticeable peaks and troughs reflecting intraday and event-driven fluctuations. In contrast, the monthly chart reveals broader seasonal patterns, showing a steady rise in prices from January to July, followed by stabilization and a sharp decline in November and December. While the daily trends are useful for tactical decisions and identifying immediate market movements, the monthly trends provide a strategic overview of longer-term cycles, emphasizing the value of analyzing both time frames for a holistic understanding of stock behavior.

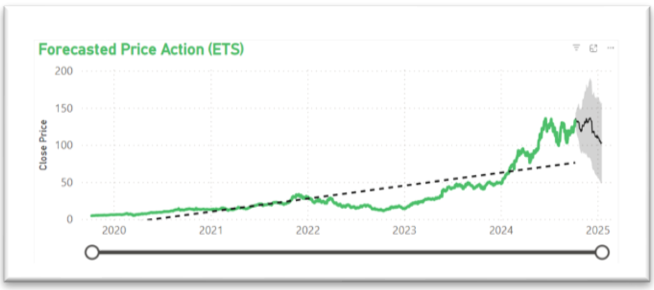

Figure 7 Forecasted Price Action (ETS)

The visualization of Nvidia's forecasted stock prices using the ETS model highlights a steady upward trend, emphasizing the model's focus on long-term stability and growth. The predicted values (black dashed line) closely follow historical data (green line), while the widening confidence intervals (gray area) reflect increasing uncertainty over time. The model incorporates seasonal adjustments, evident in slight periodic fluctuations, making it effective for capturing long-term patterns. While ideal for long-term investment strategies, the ETS model's smooth predictions may overlook short-term volatility, suggesting the need to complement it with other models for more dynamic market analysis.

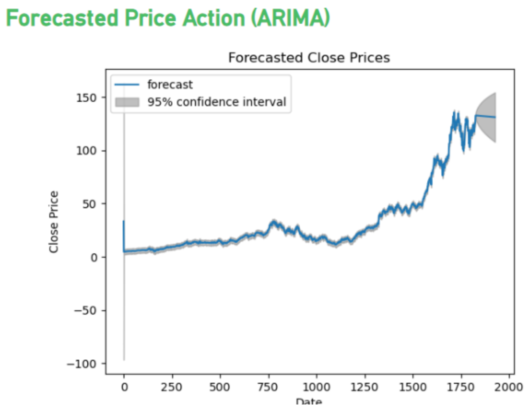

Figure 8 Forecasted Price Action (ARIMA)

The visualization of Nvidia's forecasted stock prices using the ARIMA model illustrates its ability to capture short-term fluctuations and adapt to dynamic market conditions. The forecast line (blue) closely follows historical price trends, demonstrating the model's effectiveness in aligning with past patterns. The confidence interval (gray area) widens for future predictions, reflecting greater uncertainty over time. Unlike ETS, ARIMA is better suited for handling short-term volatility, making it ideal for traders focusing on immediate market movements. The model's responsiveness to recent trends, coupled with its predictive accuracy, provides valuable insights for tactical decision-making, particularly during volatile periods.

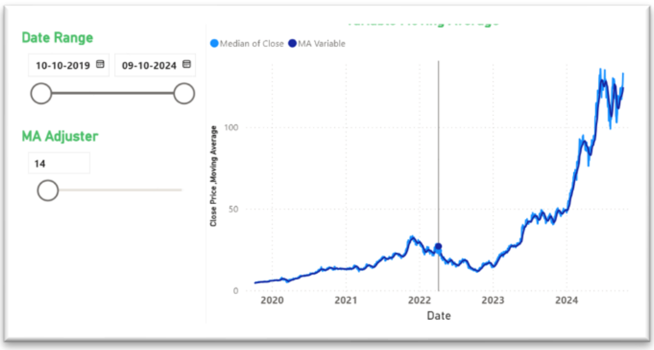

Figure 9 Variable Moving Average

The visualizations of the **Variable Moving Average** and **Moving Average Crossover** highlight trends in Nvidia's stock prices by smoothing out short-term fluctuations to focus on overall movement. The variable moving average graph dynamically adjusts based on the selected MA period, allowing for tailored analysis of price trends over custom timeframes. This helps identify long-term directional patterns, providing clarity in periods of volatility.

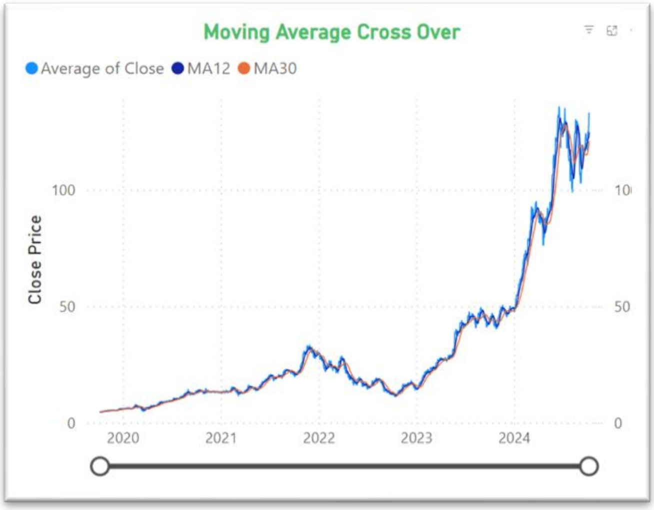

Figure 10 Moving Average Cross Over

The moving average crossover chart compares short-term (12-day) and long-term (30-day) averages against the closing price. Crossovers—where the short-term average crosses above or below the long-term average—serve as critical indicators for potential buy or sell signals. For instance, upward crossovers suggest bullish trends, while downward crossovers signal bearish momentum. Together, these visuals provide complementary insights: the variable moving average emphasizes trend stability, while the crossover chart identifies actionable trading opportunities, enhancing both strategic and tactical decision-making.

The results and discussions highlight the effectiveness of the ETS and ARIMA models in forecasting Nvidia's stock prices and their practical applicability for various investment strategies. The ETS model excels in capturing long-term trends and seasonal patterns, making it suitable for strategic portfolio planning. In contrast, the ARIMA model demonstrates superior responsiveness to short-term market volatility, offering actionable insights for tactical trading. The complementary use of both models ensures a holistic approach to decision-making, balancing the stability of long-term projections with the adaptability of short-term predictions. Validation through statistical metrics, residual diagnostics, and cross-validation confirms the reliability of these models, while visualizations provide clarity and accessibility to the findings. These insights enable stakeholders to make informed, data-driven decisions in a highly dynamic market environment.

V. PEER REVIEW

The major feedbacks was to follow the journal template as which is being precisely adhered to now and is to simply the literature review which has been taken in to account by providing more reference to the citations included.

Figure 11 Peer Feedback

VI. CONCLUSION AND RECOMMENDATION

This study applied ETS and ARIMA models to forecast Nvidia's stock prices, revealing complementary strengths and generating actionable insights. The ETS model provided stability by capturing long-term trends and seasonal patterns, supporting strategic investment decisions, while ARIMA excelled in short-term responsiveness, enabling tactical trading strategies. The analysis effectively met its objectives, confirming the utility of these models for financial forecasting. Additionally, the integration of Power BI dashboards enhanced the accessibility of findings, making the insights practical for investors and analysts.

For Future work can improve predictions by incorporating additional data, such as macroeconomic indicators, to account for broader market influences. Automated hyperparameter tuning for ARIMA and ETS models could further enhance accuracy, while advanced models like LSTM could address highly volatile periods. Expanding forecast scenarios (e.g., bullish vs. bearish conditions) and refining visualization features, such as real-time updates or scenario testing, would enhance usability and engagement. These enhancements would provide more robust and versatile tools for navigating dynamic financial markets.

VII. REFERENCES

[1] R. J. Hyndman, A. B. Koehler, R. D. Snyder and S. Grose, "A state space framework for automatic forecasting using exponential smoothing methods," *elsevier,* vol. 18, no. 3, 2002.

[2] j. Contreras, R. Espinola, F. J. Nogales and A. J. Conejo, "ARIMA models to predict next-day electricity prices," *ResearchGate,* 2003.

[3] G. E. Box, "Box G E P & Jenkins G M,Time series analysis: forecasting and control," *Scientific Research An Academic Publisher* , 1976.

[4] R. J. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice, Melbourne: OText, 2021.

[5] Yahoo Finance, "Yahoo Finance," Yahoo Finance, 2024. [Online]. Available: https://finance.yahoo.com/quote/NVDA/. [Accessed 31 October 2024].

[6] datacamp, "ARIMA for Time Series Forecasting: A Complete Guide," datacamp, 9 september 2024. [Online]. Available: https://www.datacamp.com/tutorial/arima. [Accessed 24 November 2024].

[7] statisticshowto, "ljung-box-test," statisticshowto, 2024. [Online]. Available: https://www.statisticshowto.com/ljung-box-test/. [Accessed 24 november 2024].

[8] statisticshowto, "Jarque-Bera Test," statisticshowto, 2024. [Online]. Available: https://www.statisticshowto.com/jarque-bera-test/. [Accessed 24 november 2024].

[9] "Probabilistic Model Selection with AIC, BIC, and MDL," machinelearningmastery, 2024. [Online]. Available: https://machinelearningmastery.com/probabilistic-model-selection-measures/. [Accessed 24 November 2024].

[10] NVIDIA Corporation, "nvidia," NVIDIA Corporation, 2024. [Online]. Available: https://www.nvidia.com/en-gb/. [Accessed 24 November 2024].

VI. APPENDIX

PYTHON CODING USED FOR DATA CLEANING AND ARIMA MODELLING

Figure 12 Python Coding

POWER BI DASHBOARD

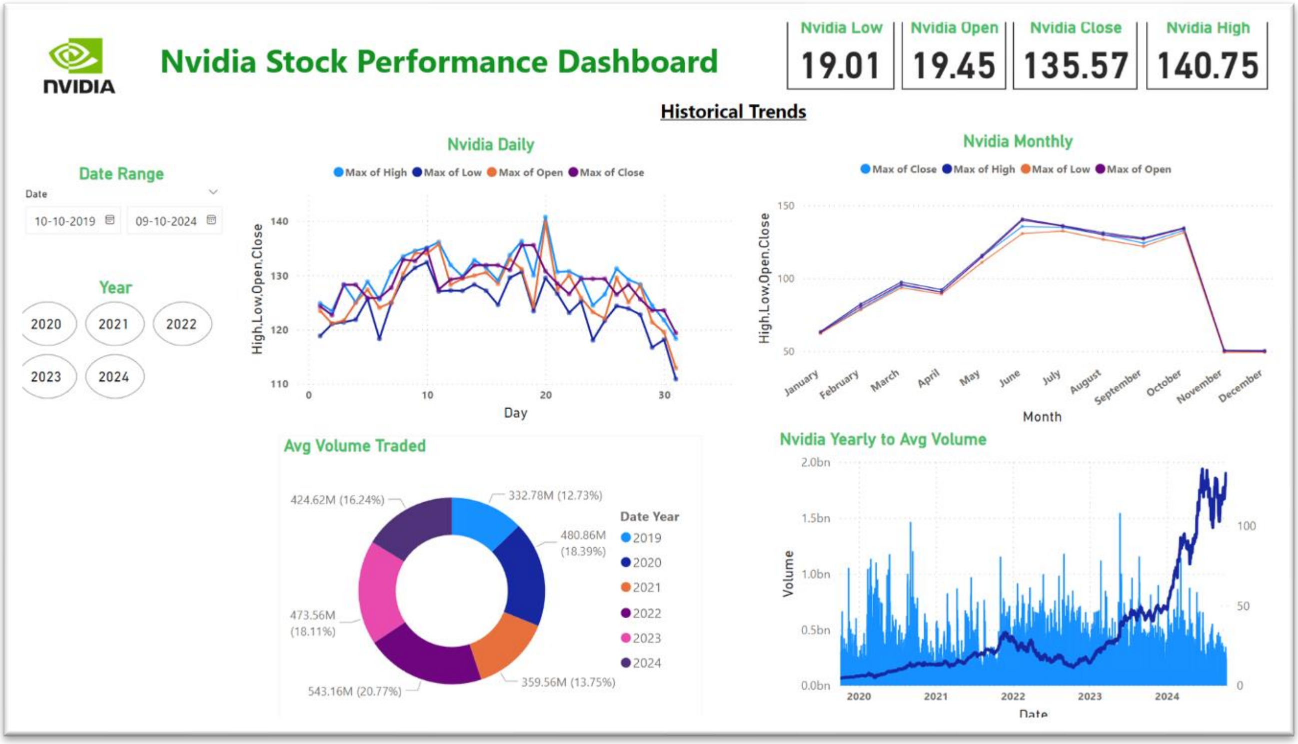

Figure 13 PAGE 1 with Historical Trends

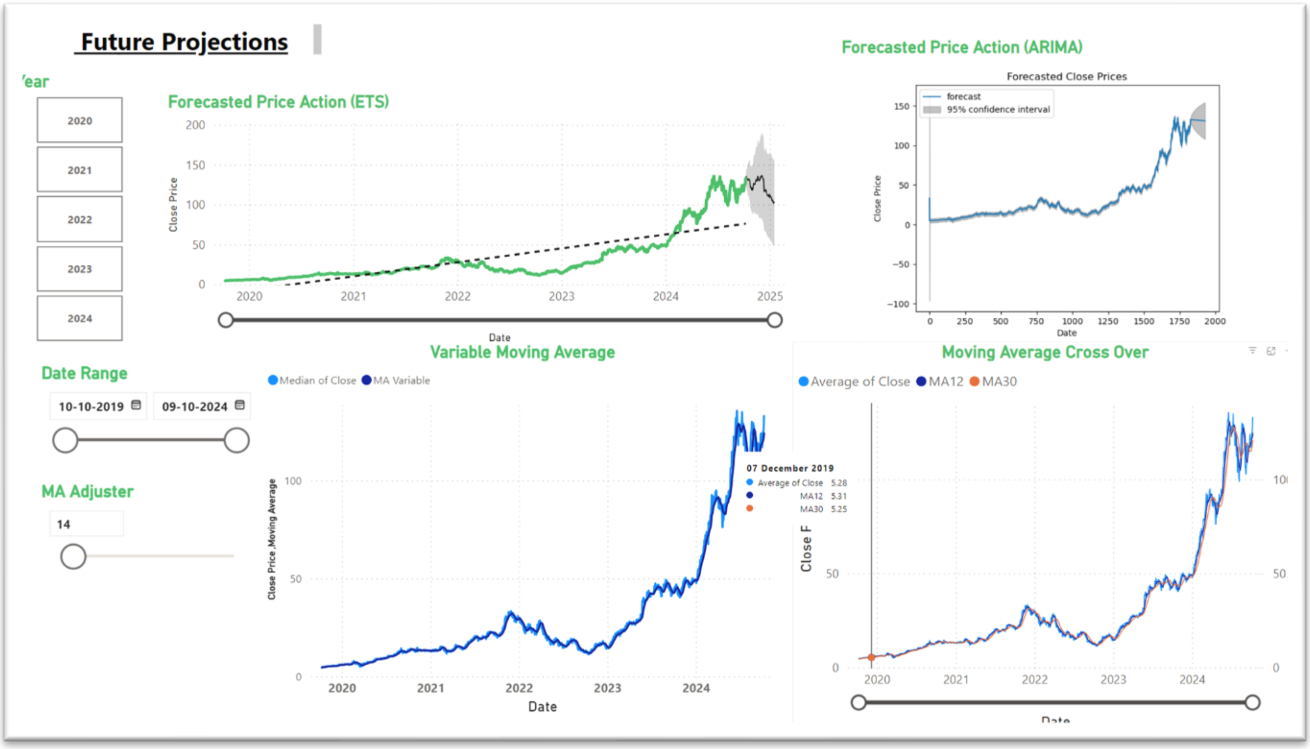

Figure 14 PAGE 2 with Future Projections

<u>Power Bi Link</u>

https://londonmet-my.sharepoint.com/:u:/g/personal/has1518_my_londonmet_ac_uk/EVTpYwPWXV9KimDMuHiqUjgBJOQa5dQxSHL3jgPr9OahCQ?e=MWpMkX