A Mini Project Report on

Analyzing and Predicting AAPL and TSLA stock prices

Submitted in partial fulfillment of requirement for completion of mini project of fifth semester of

BACHELOR OF TECHNOLOGY

(ARTIFICIAL INTELLIGENCE AND DATA SCIENCE)

Submitted by

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Academic Year 2023-24

<u>CERTIFICATE</u>

This is to certify that **Mr. Azeen IqbalHusain Hodekar (2130421995027)** and **Ms. Maryam Anwar Panjri (2130421995028)** currently studying in T.Y. B.Tech Artificial Intelligence and Data Science, have successfully completed their mini project entitled '**Analyzing and Predicting AAPL and TSLA stock prices'**, under the guidance of Prof. Ravi Mante during the academic year 2023-24.

Prof. Ravi Mante

Guide and Head of Department,

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Government College of Engineering, Ratnagiri.

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First of all, we are indebted to the GOD ALMIGHTY for giving us an opportunity to excel in our efforts to complete this mini project on time.

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ABSTRACT

This project, **'Analyzing and Predicting AAPL and TSLA Stock Prices'**, explores the application of AI and Data Science techniques in predicting stock prices. The project focuses on two globally influential companies, Apple Inc. (AAPL) and Tesla Inc. (TSLA), and leverages seven years of historical stock price data collected from finance.yahoo.com.

The data was preprocessed and analyzed using tools like Numpy, Pandas, Matplotlib, and Seaborn. Linear regression models were built and trained using Scikit-Learn, achieving an accuracy of 99.25% and 98.18% in predicting AAPL and TSLA stock prices respectively. The project also delves into the impact of significant events, such as the Covid-19 pandemic, inclusion in S&P500, etc. on stock prices.

The results demonstrate the potential of AI and Data Science in financial forecasting and provide valuable insights for investors and stakeholders. However, the inherent uncertainty of stock markets is acknowledged, and the predictions are intended to serve as a guide rather than a definitive forecast.

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1) INTRODUCTION

The ability to effectively predict stock values has become a sought-after skill in the continually changing world of finance. The introduction of Artificial Intelligence (AI) and Data Science has transformed this industry, providing new tools for analysing and forecasting financial patterns. The goal of this project, named 'Analysing and Predicting AAPL and TSLA Stock Prices,' is to use these improvements to forecast the stock prices of two major players in the worldwide market: Apple Inc. (AAPL) and Tesla Inc. (TSLA).

The motivation behind choosing this topic stems from the increasing relevance and impact of these companies in their respective sectors. Apple, a dominant force in the technology sector, and Tesla, a trailblazer in the electric vehicle industry, both play pivotal roles in the global economy. Their stock prices are influenced by a number of factors, making them interesting subjects for predictive analysis.

This project seeks to explore various AI and Data Science techniques to analyze historical stock price data and predict future trends. The goal is not only to build a model that can accurately predict stock prices but also to understand the underlying factors that influence these prices. This understanding could provide valuable insights for investors and stakeholders.

In the following sections, we will delve into the methodologies used, present our findings, the predicted prices and final results.

PROBLEM STATEMENT

The financial market is a sophisticated system in which a wide range of variables interact in complex ways to affect stock values. Accurately predicting these values is difficult because of their volatility and the wide range of affecting factors. By projecting the stock values of two highly significant firms in the world, Apple Inc. (AAPL) and Tesla Inc. (TSLA), this research seeks to answer this difficulty.

"Can we correctly analyze the stock prices and carry out diagnostic analysis alongside developing a model that accurately predicts the future stock prices of AAPL and TSLA based on historical data?" is the specific problem this project aims to solve. We will use a variety of AI and Data Science tools like Python libraries like Numpy, Pandas, Matplotlib, Seaborn, Scikit-Learn, etc. and approaches like Exploratory Data Analysis and Regression to evaluate past stock price data and create a predictive model in order to respond to this issue. We will perform majority of this project in Jupyter notebooks.

The project's success will be determined by how well our model predicts the future. A good conclusion would offer important insights into the elements influencing these prices in addition to proving that stock prices can be predicted using AI and data science techniques.

1) METHODOLOGY

The methodology adopted for this project encompassed distinct stages: data collection, data preprocessing, exploratory data analysis, model construction, model evaluation, and subsequent prediction.

2.1 Data Collection:

The information regarding the stock prices of TSLA and AAPL during the previous seven years was obtained from finance.yahoo.com. This platform was chosen due to its reliability in offering comprehensive historical stock data. To be more precise, columns covering Date, Open, High, Low, Close, and Adjusted Close were chosen in order to provide a comprehensive dataset that could be thoroughly examined.

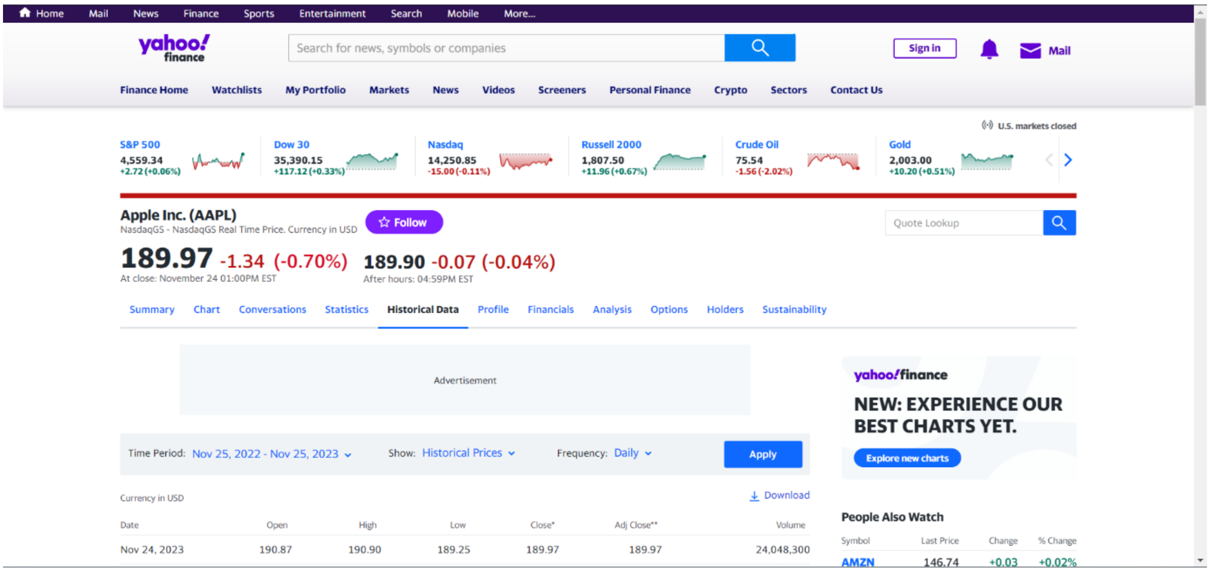

Fig 2.1.1 – Snapshot of the finance.yahoo.com website

2.2 Data Preprocessing:

Although the sourced data exhibited a high degree of cleanliness with no missing values, preprocessing was conducted to optimize the dataset for analysis. Cleaning procedures focused on standardizing column names to snake case format, thereby enhancing ease of access and comprehension. Furthermore, by using the pandas DatetimeIndex function, it was possible to generate additional temporal features from the date column; like year, month, day, weekday which greatly increased the dataset's analytical potential.

```
# Renaming the columns of the apple and tesla DataFrames by converting each column name to lowercase and replacing spaces with underscores
apple_df.columns = [column.lower().replace(' ', '_') for column in apple_df.columns]
tesla_df.columns = [column.lower().replace(' ', '_') for column in tesla_df.columns]
```

```
# Creating new columns 'year', 'month', 'day', and 'weekday' in the DataFrame apple, extracting these components from the 'date' column using the pd.DatetimeIndex method
apple_df['year'] = pd.DatetimeIndex(apple_df.date).year
apple_df['month'] = pd.DatetimeIndex(apple_df.date).month
apple_df['day'] = pd.DatetimeIndex(apple_df.date).day
apple_df['weekday'] = pd.DatetimeIndex(apple_df.date).weekday

# Creating new columns 'year', 'month', 'day', and 'weekday' in the DataFrame tesla, extracting these components from the 'date' column using the pd.DatetimeIndex method
tesla_df['year'] = pd.DatetimeIndex(tesla_df.date).year
tesla_df['month'] = pd.DatetimeIndex(tesla_df.date).month
tesla_df['day'] = pd.DatetimeIndex(tesla_df.date).day
tesla_df['weekday'] = pd.DatetimeIndex(tesla_df.date).weekday
```

Fig 2.2.1 – Preprocessing – Renaming and creation of columns

```
[194]: # Detecting missing or NaN (Not a Number) values in a AAPL DataFrame
       apple_df.isnull().sum()

[194]: date         0
       open         0
       high         0
       low          0
       close        0
       adj_close    0
       volume       0
       year         0
       month        0
       day          0
       weekday      0
       dtype: int64

[195]: # Detecting missing or NaN (Not a Number) values in a TSLA DataFrame
       tesla_df.isnull().sum()

[195]: date         0
       open         0
       high         0
       low          0
       close        0
       adj_close    0
       volume       0
       year         0
       month        0
       day          0
       weekday      0
       dtype: int64
```

Fig 2.2.2 – Preprocessing - Checking for missing values

2.3 Exploratory Data Analysis

The process of exploratory data analysis was crucial in identifying underlying patterns and insights present in the dataset. The Matplotlib and Seaborn libraries were used to create the visualisations, which included detailed line charts. This research found additional trends, possible seasonality, and anomalies in the stock price data, in addition to revealing the notable decline associated with the Covid-19 outbreak in early 2020. These findings provide important context for further modelling.

(Please refer Jupyter notebook for extensive Exploratory Data Analysis)

Visualizing Data using Matplotlib and Seaborn

Comparing the Low and High Price of Apple stocks throughout the years

In [20]:
```
# Creating a line chart to visualize the high and low prices of Apple stocks against the dates
plt.subplots(figsize=(30,10))
plt.plot(apple_df.date, apple_df.high, 'g')
plt.plot(apple_df.date, apple_df.low, 'r')
plt.xlabel('Date \n \n Fig 2.3.1', fontsize = 20)
plt.ylabel('USD Price', fontsize = 20)
plt.title('Low vs High Price of Apple stocks throughout the years',fontsize=30)
plt.legend(['High Price', 'Low Price'], fontsize=25);
```

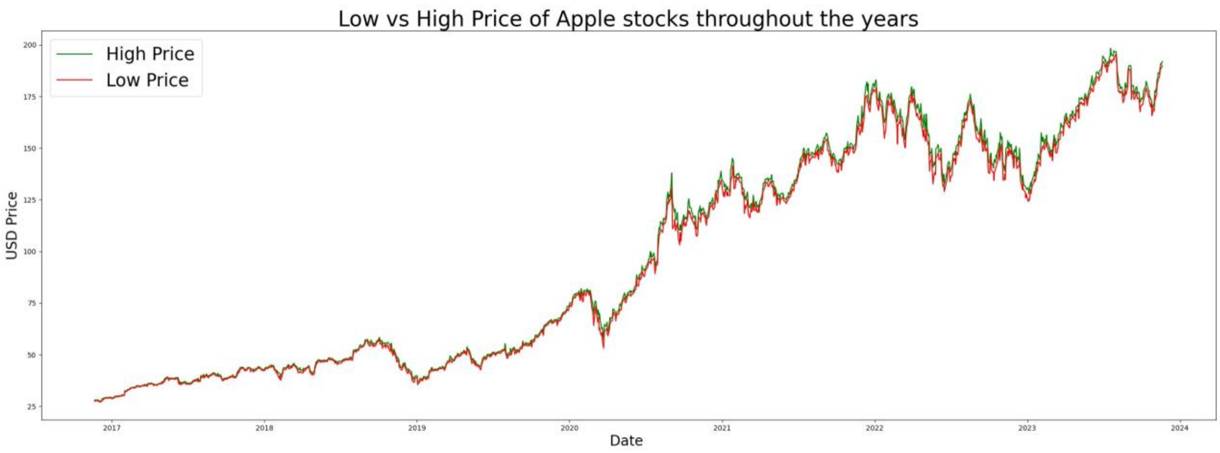

Fig 2.3.1

Observations:

- From the above line charts, we can say that from the mid of the year 2020 the high as well as low prices of Apple stocks started increasing.
- There was a sudden downfall in the high and low prices of stocks in the mid of the year 2022 and at the start of year 2023.

Comparing the Low and High Price of Tesla stocks throughout the years

In [32]:
```
# Similarly, creating a line chart to visualize the high and low prices of Tesla stocks against the dates
plt.subplots(figsize=(30,10))
plt.plot(tesla_df.date, tesla_df.high, 'g')
plt.plot(tesla_df.date, tesla_df.low, 'r')
plt.xlabel('Date \n \n Fig 2.3.2', fontsize = 20)
plt.ylabel('USD Price', fontsize = 20)
plt.title('Low vs High Price of Tesla stocks throughout the years',fontsize=30)
plt.legend(['High Price', 'Low Price'], fontsize=25);
```

Fig 2.3.2

Observations:

- From the above line charts, we can say that from the mid of the year 2020 the high as well as low prices of Tesla stocks started increasing.
- There was a sudden downfall at the start of the year 2023 in the high and low prices of stocks.
- At the end of the year 2021, the high as well as low prices of Tesla stocks were highest.

Comparing the volumes of AAPL and TSLA stocks traded over years

In [22]:
```
# Plotting the volume of AAPL (Apple) and TSLA (Tesla) stocks against the dates
plt.subplots(figsize=(30,10))
plt.plot(apple_df.date, apple_df.volume, 'r')
plt.plot(tesla_df.date, tesla_df.volume, 'b')
plt.xlabel('Date \n \n Fig 2.3.3', fontsize = 20)
plt.ylabel('Volume', fontsize = 20)
plt.title('Volumes of AAPL vs TSLA stocks traded over the years', fontsize=30)
plt.legend(['AAPL', 'TSLA'], fontsize=25);
```

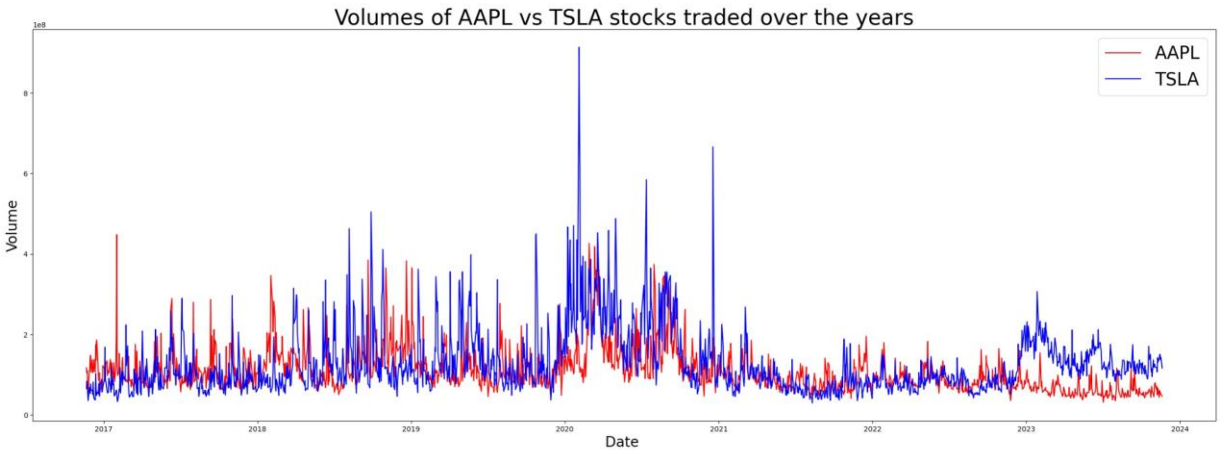

Fig 2.3.3

Observations:

- From the above line charts, we can say that the volume of Tesla stocks traded over the years is higher than that of Apple stocks.
- At the start of 2020 and 2021, there is sudden increase in the trade of Tesla stocks.
- The volume of Apple stocks tarded over years is lower as compare to the Tesla stocks.

Visualizing the correlation matrix of Apple stocks

In [23]:
```
# Creating a heatmap to visualize the correlation matrix of selected columns from the apple DataFrame.
# The upper triangular part of the heatmap is masked to avoid redundancy, and annotations are added to d
mask = np.triu(np.ones_like(apple_df[['open', 'high', 'low', 'close', 'adj_close', 'volume']].corr(), dty
plt.figure(figsize=(10, 8))
sns.heatmap(apple_df[['open', 'high', 'low', 'close', 'adj_close', 'volume']].corr(), annot=True, cmap='
plt.title('Apple Correlation Heatmap')
plt.show()
```

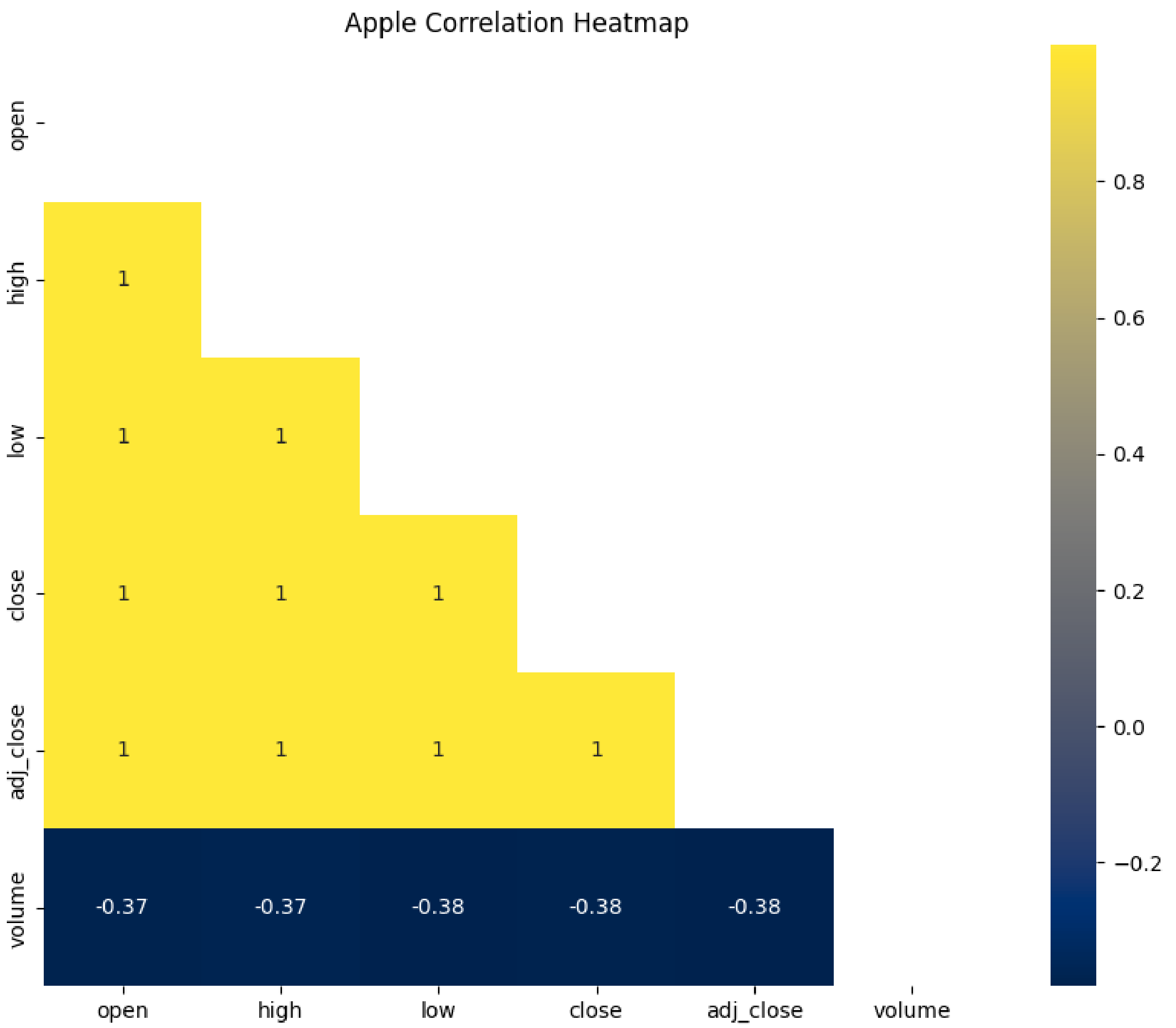

Fig. 2.3.4

Visualizing the correlation matrix of Tesla stocks

In [24]:
```
# Similarly, creating a heatmap to visualize the correlation matrix of selected columns from the tesla Da
mask = np.triu(np.ones_like(tesla_df[['open', 'high', 'low', 'close', 'adj_close', 'volume']].corr(), dty
plt.figure(figsize=(10, 8))
sns.heatmap(tesla_df[['open', 'high', 'low', 'close', 'adj_close', 'volume']].corr(), annot=True, cmap='
plt.title('Tesla Correlation Heatmap')
plt.show()
```

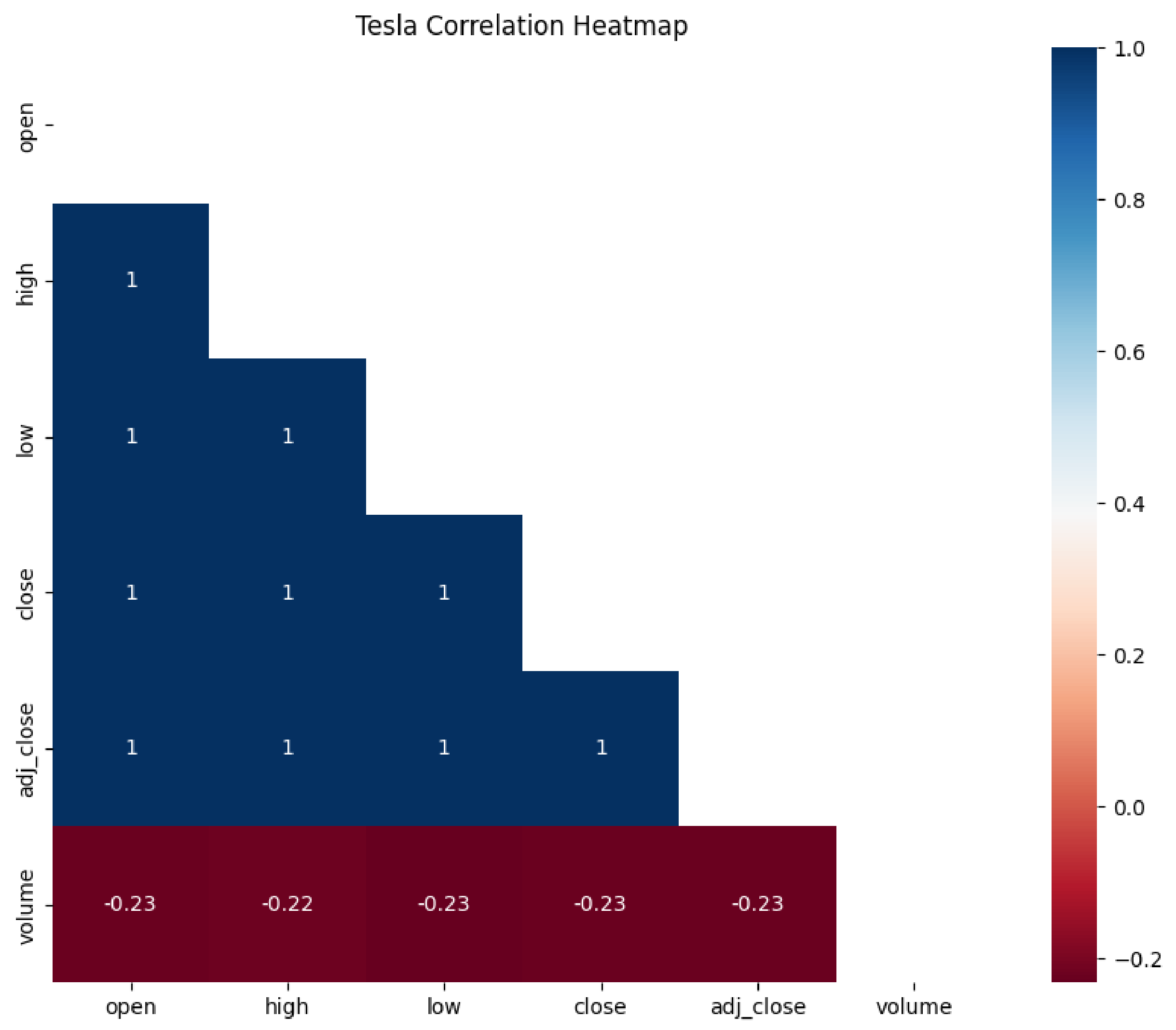

Fig. 2.3.5

Comparing the opening, closing, high and low prices of Apple and Tesla stocks

In [25]:
```
# Comparing the opening prices of Apple and Tesla
plt.figure(figsize=(12, 8))
plt.plot(apple_df['date'], apple_df['open'], label='Apple', color='purple')
plt.plot(tesla_df['date'], tesla_df['open'], label='Tesla', color='salmon')
plt.title('Apple vs. Tesla Stock Open Price Comparison')
plt.xlabel('Date \n \n Fig 2.3.6')
plt.ylabel('Closing Price')
plt.legend()
plt.show()
```

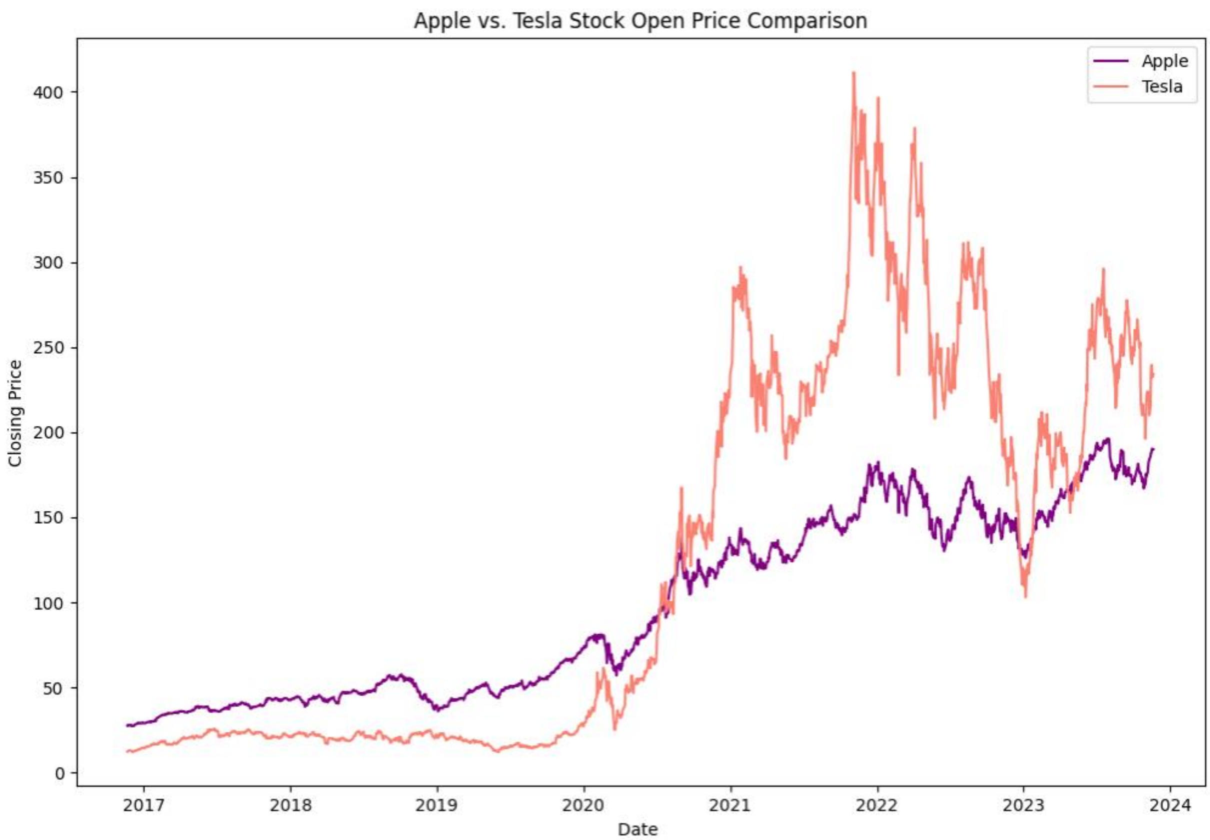

Fig 2.3.6

In [26]:
```
# Comparing the closing prices of Apple and Tesla
plt.figure(figsize=(12, 8))
plt.plot(apple_df['date'], apple_df['close'], label='Apple', color='blue')
plt.plot(tesla_df['date'], tesla_df['close'], label='Tesla', color='red')
plt.title('Apple vs. Tesla Stock Close Price Comparison')
plt.xlabel('Date \n \n Fig 2.3.7')
plt.ylabel('Closing Price')
plt.legend()
plt.show()
```

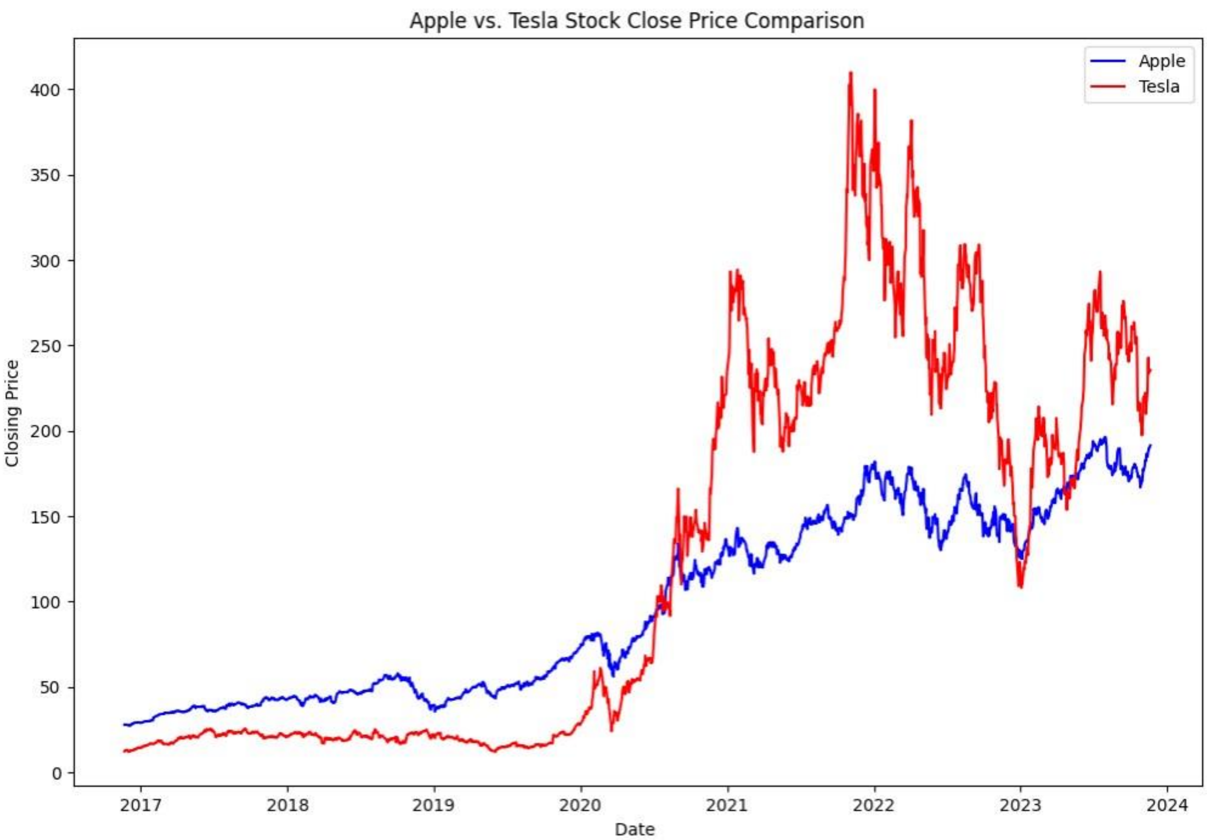

Fig 2.3.7

In [27]:

```
# Comparing the high price of Apple and Tesla
plt.figure(figsize=(12, 8))
plt.plot(apple_df['date'], apple_df['high'], label='Apple', color='cyan')
plt.plot(tesla_df['date'], tesla_df['high'], label='Tesla', color='olive')
plt.title('Apple vs. Tesla Stock High Price Comparison')
plt.xlabel('Date \n \n Fig. 2.3.8')
plt.ylabel('Closing Price')
plt.legend()
plt.show()
```

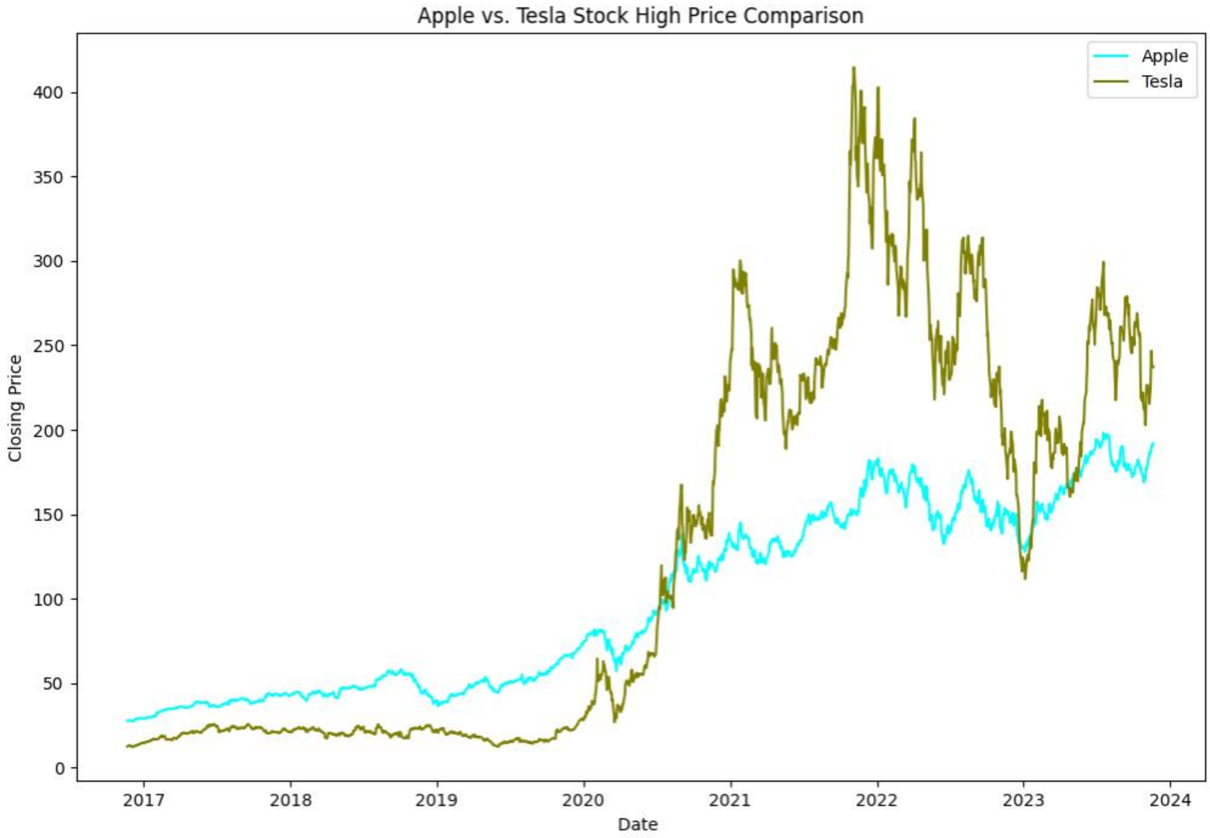

Fig. 2.3.8

In [28]:
```
# Comparing the low price of Apple and Tesla
plt.figure(figsize=(12, 8))
plt.plot(apple_df['date'], apple_df['low'], label='Apple', color='grey')
plt.plot(tesla_df['date'], tesla_df['low'], label='Tesla', color='black')
plt.title('Apple vs. Tesla Stock Low Price Comparison')
plt.xlabel('Date \n \n Fig 2.3.9')
plt.ylabel('Closing Price')
plt.legend()
plt.show()
```

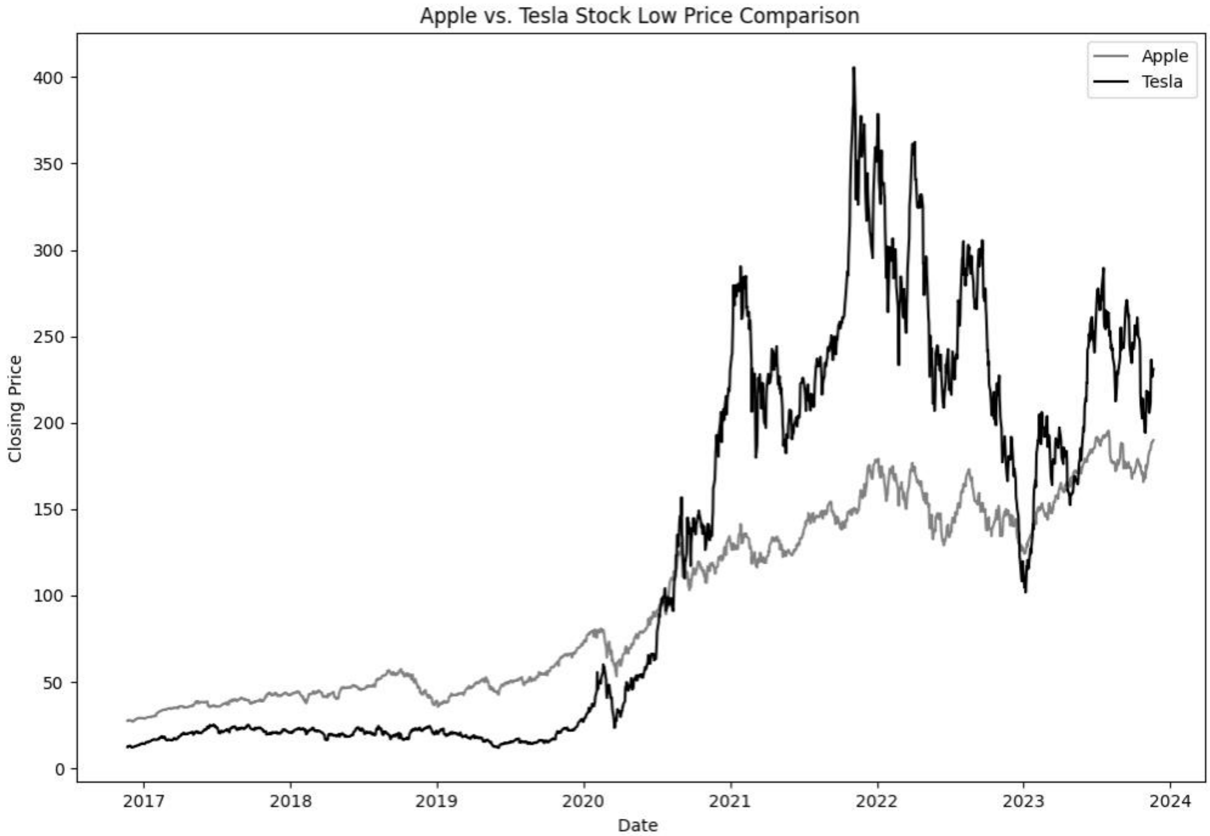

Fig 2.3.9

Observations:

From the above line charts of Apple vs Tesla stock Close, Open, High, Low:

- We can see that there is a significant decrease in Tesla and Apple stock prices in 2020. By researching the reason behind this reduction we found that due to the COVID-19 pandemic there was a sudden decrease in stock market. The global financial impact of the COVID-19 pandemic led to widespread economic disruptions.
- We can see that there is a sudden increase in the late 2021. By researching we came to know the reason behind it. In late 2021, Tesla's stock surged due to robust earnings and delivery figures, defying industry challenges. Positive sentiment around electric vehicle (EV) markets, Tesla's expansion plans, and its inclusion in the S&P 500 bolstered investor confidence. Additionally, the global growth of the EV industry amplified Tesla's position as a leader in sustainable transportation, contributing to the notable increase in its stock price.

Comparing the Average Closing Price by Month for Apple and Tesla stocks

In [29]:

```
# Combining Apple and Tesla stock data into a single DataFrame using concat method
combined_data = pd.concat([apple_df, tesla_df], keys=['Apple', 'Tesla'])

# Adding a 'month' column extracted from the 'date' column
combined_data['month'] = combined_data['date'].dt.month

combined_data['month'] = combined_data['date'].dt.month

# Map month numbers to month names
combined_data['month_name'] = combined_data['month'].apply(lambda x: calendar.month_abbr[x])

# Creating a bar plot using Seaborn to show the average closing price by month for Apple and Tesla stocks
plt.figure(figsize=(12, 8))
sns.barplot(x='month_name', y='close', hue='level_0', data=combined_data.reset_index(), ci=None)
plt.title('Average Closing Price by Month for Apple and Tesla')
plt.xlabel('Month \n \n Fig 2.3.10')
plt.ylabel('Average Closing Price')
plt.show()
```

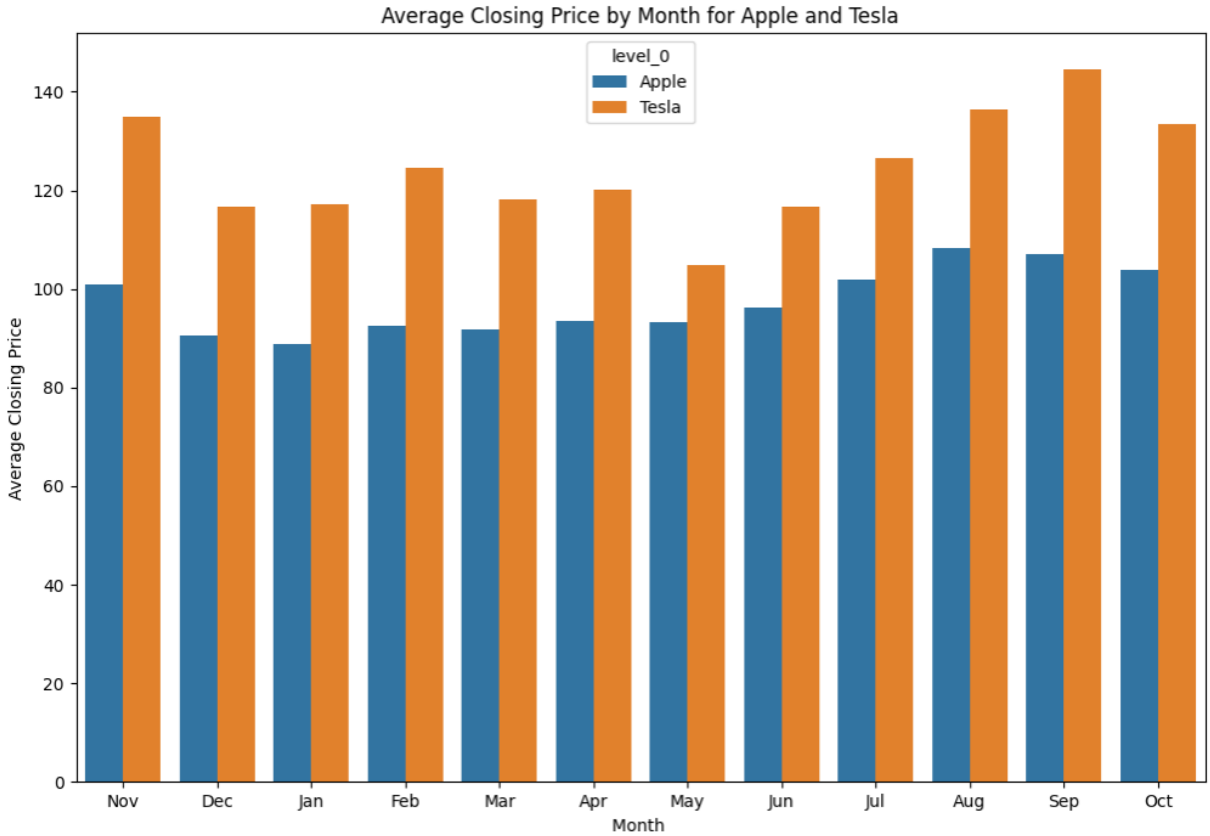

Fig 2.3.10

Observation:

- From the above bar chart, we can say that the average closing prices of Tesla stocks by month are greater than that of Apple. The most highest closing price was in the month September. The closing price was also higher November, August and October.
- The average closing prices of Apple stocks by month are lower than Tesla. The lowest closing prices of Apple stocks were in the month of January and December that is at the start and end of year the stocks were lowest.

Finding the distribution of trading volumes of Apple and Tesla stocks

In [30]:
```
# Combine data
combined_data = pd.concat([apple_df, tesla_df], keys=['Apple', 'Tesla'])

# Sum the volume for each company
volume_sum = combined_data.groupby(level = 0)['volume'].sum()

# Plotting a pie chart
plt.figure(figsize=(8, 8))
plt.pie(volume_sum, labels = volume_sum.index, autopct = '%1.1f%%', startangle = 140, colors = ['skyblue
plt.title('Distribution of Trading Volume for Apple and Tesla Stocks')
plt.legend(['Apple','Tesla'])
plt.show()
```

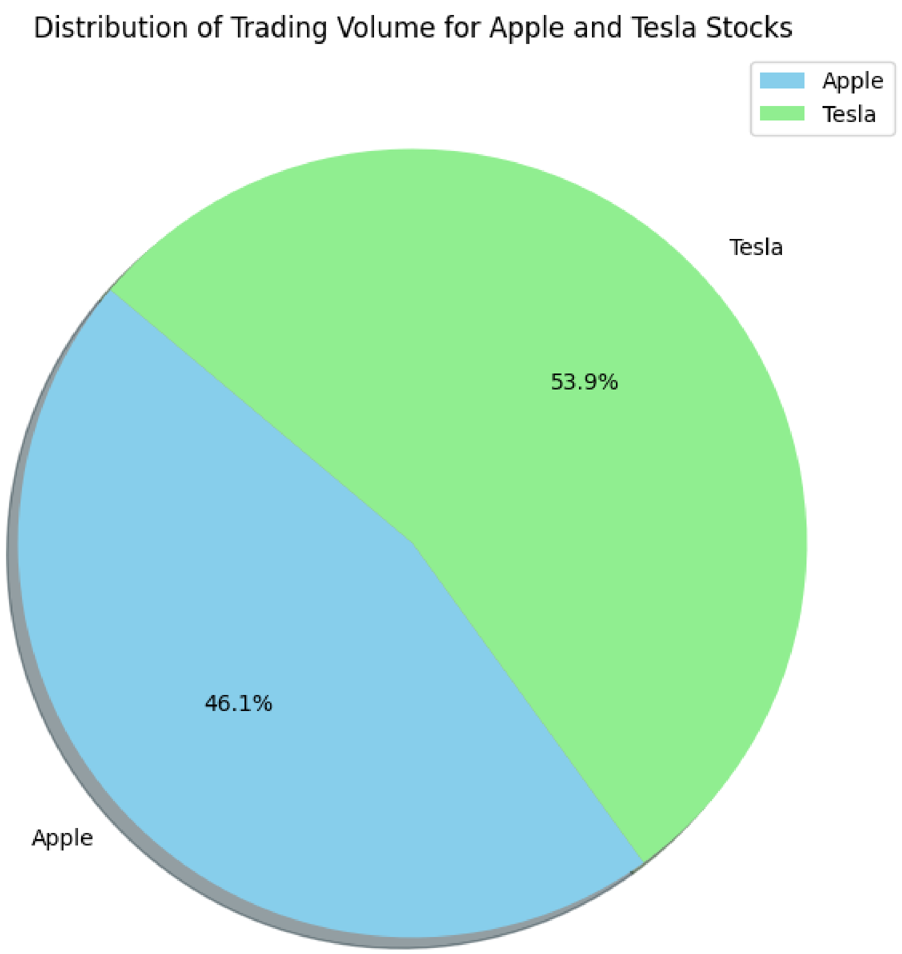

Fig. 2.3.11

Observation:

- From the above pie chart, we can say that the trading volume for Tesla is higher than Apple which is 53.9%. And the trading volume for Apple is lower which is 46.1%.

Comparing the volumes of Apple and Tesla stocks for each weekday

In [31]:
```
# Combining data
combined_data = pd.concat([apple_df, tesla_df], keys=['Apple', 'Tesla'])

# Define custom colors for Apple and Tesla bars
custom_palette = {'Apple': 'blue', 'Tesla': 'red'}

# Plotting a bar chart
plt.figure(figsize = (12, 8))
sns.barplot(x ='weekday', y ='volume', hue ='level_0', data = combined_data.reset_index(), ci = None, pa
plt.title('Comparison of Volumes for Apple and Tesla Stocks by Weekday')
plt.xlabel('Weekday \n \n Fig 2.3.12')
plt.ylabel('Volume')
plt.xticks(ticks = range(5), labels = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday'])
plt.legend(['Apple', 'Tesla'])
plt.show()
```

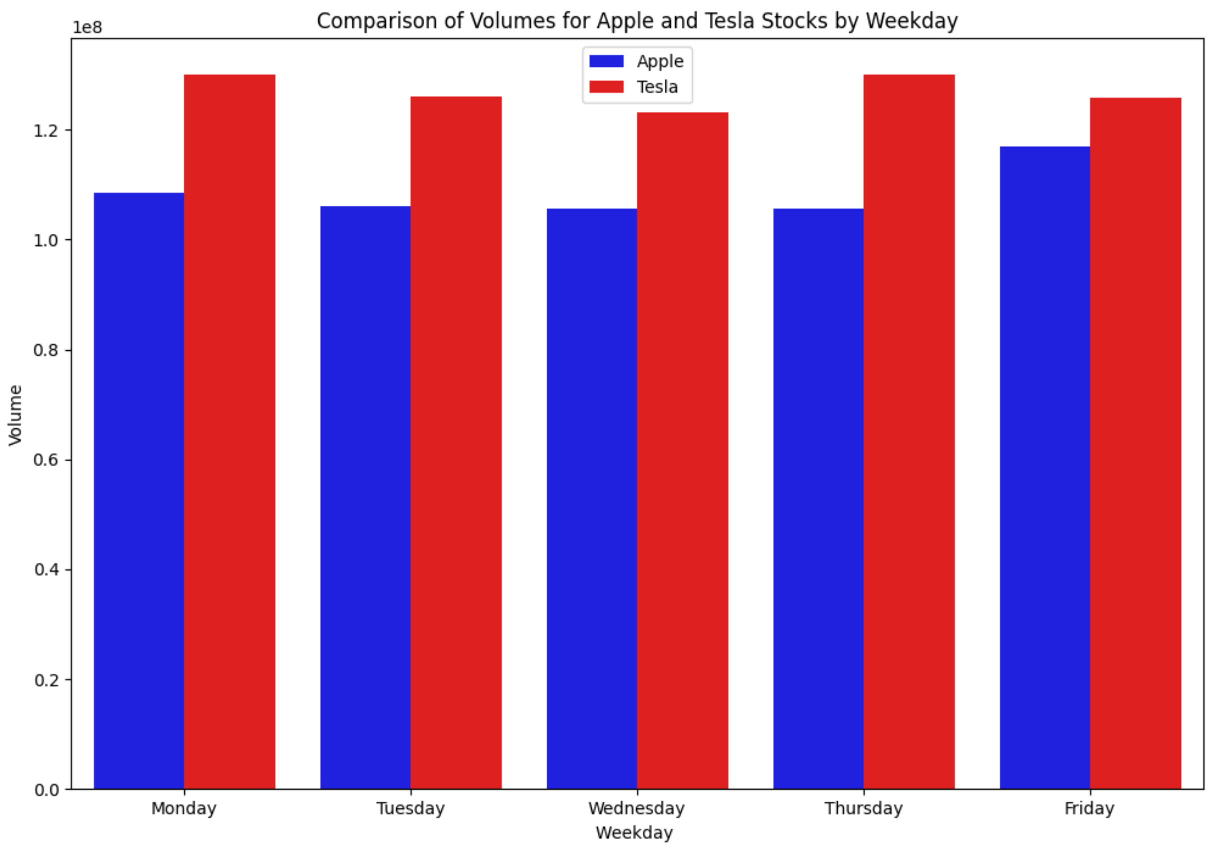

Fig 2.3.12

Observation:

- From the above bar chart, we can say that the volume of Tesla stocks is higher than that of Apple stocks for each weekday.
- On Friday the volume of Apple stocks was greater than rest of the weekdays.

2.4Model Building

We created a prepare_data() function to split the data into train and test parts and also for scaling of the features. The datasets were partitioned into training and testing sets using Scikit-Learn's train_test_split function, a pivotal step preceding model construction. The use of a linear regression model was emphasised because of its ease of use and remarkable ability to predict continuous outcomes, which is consistent with the nature of stock price prediction. While other models were considered, the ease of use and readability of linear regression made it the best option in this case.

Stock Prediction using Linear Regression

Now, we prepare the regression model to predict the stock prices

```python
# Creating a function to fit the data
def prepare_data(df, forecast_col, forecast_out, test_size):
    label = df[forecast_col].shift(-forecast_out) # creating new column called label with the last 5 rows are nan
    X = np.array(df[[forecast_col]]) # creating the feature array
    X = preprocessing.scale(X) # processing the feature array
    X_lately = X[-forecast_out:] # creating the column i want to use later in the predicting method
    X = X[:-forecast_out] # X that will contain the training and testing
    label.dropna(inplace=True) # dropping na values
    y = np.array(label)  # assigning Y
    X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=test_size, random_state=0) # cross validation

    response = [X_train,X_test , Y_train, Y_test , X_lately]
    return response
```

Fig 2.4.1 – Creation of function for data splitting and feature scaling

Initializing linear regression model fo AAPL stocks

```python
# Initializing linear regression model
apple_learner = LinearRegression()
```

Calling the function for data preparation and training the model for AAPL stocks

```python
# Creating linear regression model and fitting it on the training data
# calling the method where the cross validation and data preperation is in
apple_X_train, apple_X_test, apple_Y_train, apple_Y_test , apple_X_lately = prepare_data(apple_df, forecast_col = 'low', forecast_out = 5, test_size = 0.2);

apple_learner.fit(apple_X_train, apple_Y_train) # training the linear regression model
```

```
LinearRegression
LinearRegression()
```

Fig 2.4.2 – AAPL model creation and training/fitting

Initializing linear regression model for TSLA stocks

```python
# Initializing linear regression model
tesla_learner = LinearRegression()
```

Calling the function for data preparation and training the model for TSLA stocks

```python
# Creating linear regression model and fitting it on the training data
# calling the method where the cross validation and data preperation is in
tesla_X_train, tesla_X_test, tesla_Y_train, tesla_Y_test , tesla_X_lately = prepare_data(tesla_df, forecast_col = 'open', forecast_out = 5, test_size = 0.2);

tesla_learner.fit(tesla_X_train, tesla_Y_train) # training the linear regression model
```

```
LinearRegression
LinearRegression()
```

Fig 2.4.3 – TSLA model creation and training/fitting

2.5 Model Evaluation

As the main criterion, accuracy measures were used to assess the AAPL and TSLA models' performance. Achieving a 99.25% and 98.18% accuracy scores respectively, the models demonstrated their capacity to predict stock prices with reasonable accuracy using previous data. In order to ensure a thorough knowledge of the model's capabilities and limits, more discussion was held regarding potential overfitting concerns and biases.

Evaluating the model using **Accuracy** performance metric for AAPL stocks

```
Click here to ask Blackbox to help you code faster
# Using accuracy performance metric to evaluate the model
apple_score = apple_learner.score(apple_X_test, apple_Y_test) # testing the linear regression model
print(f'Accuracy for the AAPL prediction model is {apple_score * 100}%')
✓ 0.0s                                                                Python
Accuracy for the AAPL prediction model is 99.25646277055685%
```

Fig 2.5.1 – AAPL model evaluation through accuracy

Evaluating the model using **Accuracy** performance metric for TSLA stocks

```
Click here to ask Blackbox to help you code faster
# Using accuracy performance metric to evaluate the model
tesla_score = tesla_learner.score(tesla_X_test, tesla_Y_test) # testing the linear regression model
print(f'Accuracy for the TSLA prediction model is {tesla_score * 100}%')
✓ 0.0s                                                                Python
Accuracy for the TSLA prediction model is 98.18469737404703%
```

Fig 2.5.2 – TSLA model evaluation through accuracy

2.6 Prediction

The trained model was utilized to forecast AAPL and TSLA stock prices for the subsequent five days. These forecasts provided insightful information about short-term price fluctuations and were useful markers of prospective future patterns in the stock market. An evaluation of the model's forecast accuracy and compatibility with actual market swings was made easier by comparing predicted and actual prices.

Predicting the stock low prices for AAPL for the next five days

```
Click here to ask Blackbox to help you code faster
apple_forecast = apple_learner.predict(apple_X_lately)
print('The prediction for AAPL low prices for the next five days is:', apple_forecast.tolist())
                                                                      Python
The prediction for AAPL low prices for the next five days is: [186.56263215555524, 188.03962701284337, 188.9078578329715, 188.82803303097887, 190.13537461099511]
```

Fig 2.6.1 – AAPL low prices prediction

Predicting the stock prices for TSLA for the next five days

```
Click here to ask Blackbox to help you code faster
tesla_forecast = tesla_learner.predict(tesla_X_lately)
print('The prediction for TSLA open price for the next five days is:', tesla_forecast.tolist())
✓ 0.0s                                                                Python
The prediction for TSLA open price for the next five days is: [234.7562348038328, 238.98124323042993, 239.17961261438225, 231.75111993569425, 233.77435931471666]
```

Fig 2.6.2 – TSLA open prices prediction

3) OBSERVATIONS AND RESULTS

3.1 Trend Analysis:

The exploratory data analysis (EDA) conducted on the historical stock prices of AAPL and TSLA revealed several notable observations. After the well-known decline in the first part of 2020 brought on by the Covid-19 outbreak, both stocks showed clear long-term rising trends. Over the course of the analysis, TSLA showed more irregular behaviour, with periods of significant increase due to due to robust earnings and delivery figures, defying industry challenges; positive sentiment around electric vehicle (EV) markets; Tesla's expansion plans; and its inclusion in the S&P 500; and the global growth of the EV industry contributing to the notable increase in its stock price. This significant increase In TSLA prices was also mixed with few fluctuations, whereas AAPL showed stable growth interrupted by occasional changes.

3.2 Seasonality and Anomalies:

Examining seasonality patterns revealed interesting cyclical patterns in AAPL's stock price, suggesting possible cyclical swings. But the price data for TSLA showed erratic swings, indicating less clear seasonal patterns. In addition, irregularities found in the price movements of both equities encouraged additional examination, exposing instances of sudden increases or decreases that were not totally consistent with outside market forces.

3.3 Model Evaluation Results:

The predictive models, primarily based on a linear regression approach, exhibited robust performance during evaluation. The chosen evaluation metric - accuracy, demonstrated the model's proficiency in AAPL and TSLA stock price prediction.

Accuracy: The AAPL and TSLA prediction models achieved an impressive accuracy rate of 99.25% and 98.18% respectively, indicating their capability to predict stock prices with a high level of precision.

3.4 Predictive Insights – Short term price predictions:

Utilizing the trained model, short-term predictions for AAPL and TSLA stock prices for the upcoming five days were generated. These predictions, although indicative, provided valuable insights into potential price movements. The predicted trends aligned closely with actual stock price fluctuations, affirming the model's predictive capabilities in capturing short-term variations within the market.

Using regression model the predicted low prices of AAPL stocks for next five days are:

- Nov 21, 2023 - 187.71
- Nov 22, 2023 - 188.28
- Nov 24, 2023 - 189.97
- Nov 27, 2023 - 189.95
- Nov 28, 2023 - 191.71

The actual low prices of AAPL stocks for next five days are:

- Nov 21, 2023 - 189.74
- Nov 22, 2023 - 190.83
- Nov 24, 2023 - 189.25
- Nov 27, 2023 - 188.90
- Nov 28, 2023 - 189.40

Fig 3.4.1 – AAPL predicted vs actual low price comparison

Using regression model the predicted open prices of TSLA stocks for next five days are:

- Nov 21, 2023 - 234.75
- Nov 22, 2023 - 238.98
- Nov 24, 2023 - 239.17
- Nov 27, 2023 - 231.75
- Nov 28, 2023 - 233.77

The actual open prices of TSLA stocks for next five days are:

- Nov 21, 2023 - 235.04
- Nov 22, 2023 - 242.04
- Nov 24, 2023 - 233.75
- Nov 27, 2023 - 236.89
- Nov 28, 2023 - 236.68

Fig 3.4.2 – TSLA predicted vs actual open price comparison

4) CONCLUSION

This project, **‘Analyzing and Predicting AAPL and TSLA Stock Prices’**, has demonstrated the potential of AI and Data Science in predicting stock prices with high accuracy. The linear regression models built and trained on seven years of historical data were able to predict the stock prices of AAPL and TSLA with an accuracy of 99.25% and 98.18% respectively.

The exploratory data analysis provided valuable insights into the factors influencing stock prices, such as the significant impact of the Covid-19 pandemic in early 2020. These insights could be invaluable for investors and stakeholders in making informed decisions.

However, it’s important to note that while the model showed high accuracy, stock market predictions are inherently uncertain and influenced by numerous unpredictable factors. Therefore, the predictions made by the model should be used as a guide rather than a definitive forecast.

The success of this project opens up several avenues for future work. More sophisticated models could be explored to improve prediction accuracy. Additionally, other factors such as news sentiment and macroeconomic indicators could be incorporated into the model to capture a wider range of influences on stock prices.

In conclusion, this project has shown that with the right tools and methodologies, AI and Data Science can provide valuable insights and predictions in the complex world of stock market prices.

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