CA_TWO REPORT

NFLX Dataset Analysis with Python

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Module Title: Programming for Data Analysis
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NFLX Dataset Analysis

Data Pipeline with AI Comparison

INTRODUCTION

Predicting the stock price of Netflix is an interesting and useful task for investors, analysts, and financial enthusiasts. Netflix, a leading streaming service provider, has seen significant fluctuations in its stock price due to various factors like market trends, company performance, competition, and broader economic conditions. By analysing historical stock price data, one can attempt to forecast future price movements, helping investors make informed decisions. To predict Netflix's stock price, we utilize historical stock data, which includes daily prices, volumes, and other financial metrics. This data can be analysed using various statistical and machine learning techniques to identify patterns and trends. The goal is to develop a model that can accurately predict future prices based on past performance.

PROBLEM STATEMENT

The number one goal of this report is every day examine the inventory performance of Netflix (NFLX) by using developing a complete statistics evaluation pipeline using Python. This pipeline will embody information loading, cleaning, characteristic engineering, and visualization everyday extract significant insights from the dataset. The analysis will cognizance on figuring out trends, analysing trading volumes, analysing every day returns, and understanding the general behaviour of Netflix stock over time.

Given the financial importance of Netflix inside the market, understanding its stock performance can offer treasured insights for traders, analysts, and stakeholders. This record will utilize the Netflix inventory facts, which incorporates numerous attributes consisting of date, open charge, high fee, low fee, near price, adjusted close rate, and quantity, day-to-day behaviour an in-depth evaluation.

METHODOLOGY

2.1. Data Loading

The first step in our evaluation worried loading the Netflix inventory records into a Pandas DataFrame. The dataset, which incorporates numerous attributes which include date, open price, high rate, low price, close charge, adjusted near charge, and quantity, become acquired from Yahoo Finance (NFLX, 2024). This data changed into study right into a Pandas DataFrame using the read_csv characteristic.

Table 1 displays the primary few rows of the DataFrame, presenting an initial view of the dataset. The DataFrame, referenced as df, is essential daily our evaluation, taking into account records manipulation and evaluation.

Table 1: The first few rows of the Data Frame

```
Table 1: The first few rows of the Data Frame
          Date        Open        High         Low       Close    Adj
Close  \
0  2018-02-05  262.000000  267.899994  250.029999  254.259995
254.259995
1  2018-02-06  247.699997  266.700012  245.000000  265.720001
265.720001
2  2018-02-07  266.579987  272.450012  264.329987  264.559998
264.559998
3  2018-02-08  267.079987  267.619995  250.000000  250.100006
250.100006
4  2018-02-09  253.850006  255.800003  236.110001  249.470001
249.470001

     Volume
0  11896100
1  12595800
2   8981500
3   9306700
4  16906900
```

2.2. Data Cleaning

Data cleaning is an important step everyday make certain the accuracy and integrity of the dataset. This involves figuring out and dealing with missing values, checking for records type consistency, and correcting any anomalies inside the data.

Table 2: Data Entries and Types

```
Table 2: Data Entries and Types
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1009 non-null   datetime64[ns]
 1   Open       1009 non-null   float64
 2   High       1009 non-null   float64
 3   Low        1009 non-null   float64
 4   Close      1009 non-null   float64
 5   Adj Close  1009 non-null   float64
 6   Volume     1009 non-null   int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 55.3 KB
None
```

From the preliminary inspection, the dataset did no longer contain any null values. however, the 'Date' column needed to be converted from an object everyday a datetime format day-to-day facilitate time series evaluation. After making sure there were no missing values, the information sorts have been constant with the anticipated types.

Table 3: Data Frame after removing null values

Data Frame after removing null values

	Date	Open	High	Low	Close	Adj Close	Volume
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	250.100006	9306700
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	249.470001	16906900
...	...	...	...	...	...	...	...
1004	2022-01-31	401.970001	427.700012	398.200012	427.140015	427.140015	20047500
1005	2022-02-01	432.959991	458.480011	425.540009	457.130005	457.130005	22542300
1006	2022-02-02	448.250000	451.980011	426.480011	429.480011	429.480011	14346000
1007	2022-02-03	421.440002	429.260010	404.279999	405.600006	405.600006	9905200
1008	2022-02-04	407.309998	412.769989	396.640015	410.170013	410.170013	7782400

[1009 rows x 7 columns]

2.3. Feature Engineering

Feature engineering involves developing new functions from the present data to improve the overall performance of ml models or to gain better advantage higher insights from the information. on this analysis, new functions along with daily returns and moving averages were created.

Table 4: DataFrame with New Features

Table 7: DataFrame with New Features

	Date	Adj Close	Daily Return	MA20	MA50
0	2018-02-05	254.259995	NaN	NaN	NaN
1	2018-02-06	265.720001	0.045072	NaN	NaN
2	2018-02-07	264.559998	-0.004366	NaN	NaN
3	2018-02-08	250.100006	-0.054657	NaN	NaN
4	2018-02-09	249.470001	-0.002519	NaN	NaN

The 'daily return' feature become calculated the usage of the proportion alternate within the closing rate from at some point every day the subsequent. The moving averages (20 & 50-day) were computed everyday help identify tendencies within the stock fee over exceptional time periods.

2.4. Data Visualization

data visualization performs an important function in records evaluation by transforming complex datasets into clear, interpretable visuals that reveal patterns, trends, and relationships. In our analysis of Netflix inventory facts, various visualizations have been employed every day extract meaningful insights and facilitate informed decision-making.

Figure 1: NFLX Stock Prices and Moving Averages

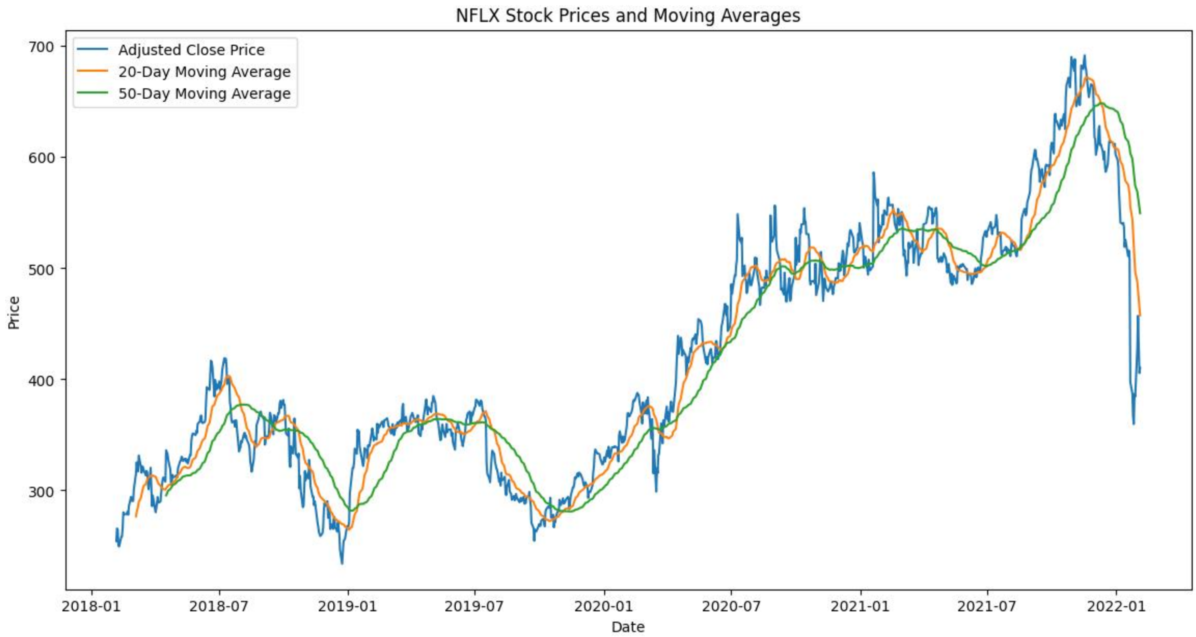


Figure 1 gives the closing fees of Netflix (NFLX) inventory overlaid with 20-day and 50-day transferring averages. moving averages are important technical indicators that smooth out fee statistics over a precise length, helping day-to-day discover tendencies and capacity entry or exit factors in trading techniques (Seaborn, 1998). on this visualization, the transferring averages offer a clearer picture of the stock's performance over distinct time frames, highlighting trends such as upward or downward actions in prices.

Figure 2: NFLX Trading Volume Over Time

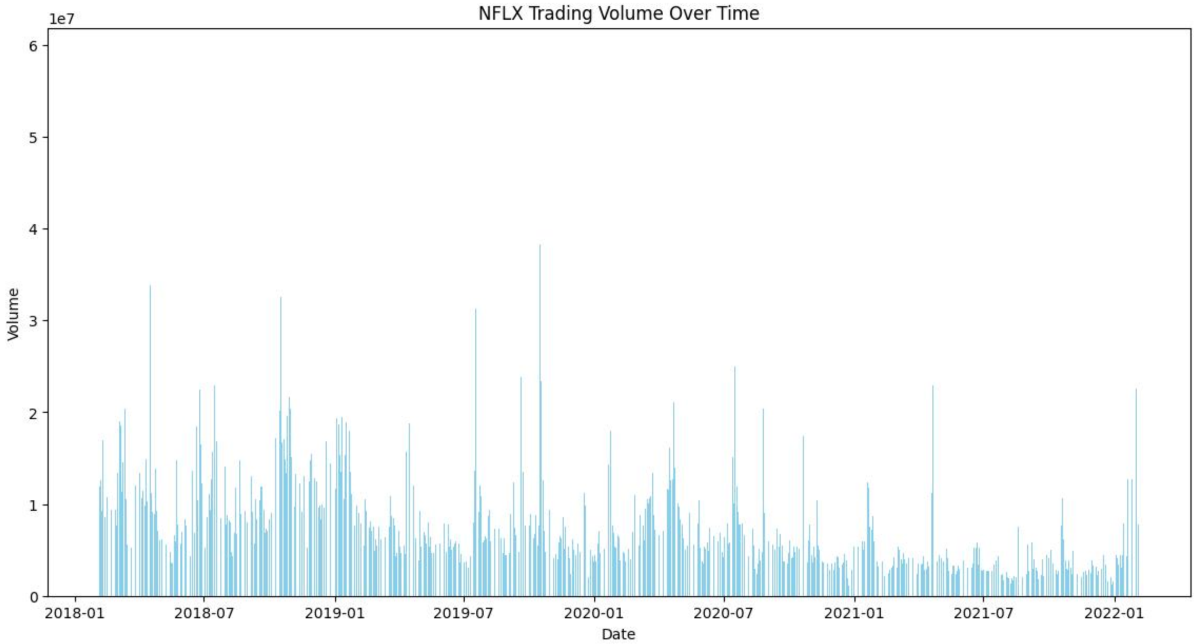


figure two illustrates the trading extent returns of NFLX stock, demonstrating the percentage alternate in stock price from one shopping for and selling day every day the following. every day returns offer insights in every day the volatility and hazard each day the stock, critical for assessing its universal performance and dealing with funding portfolios (Kang, 2022). excessive volatility in each day returns can also imply extra price fluctuations and capability possibilities or dangers for buyers.

Figure 3: NFLX Daily Returns Over Time

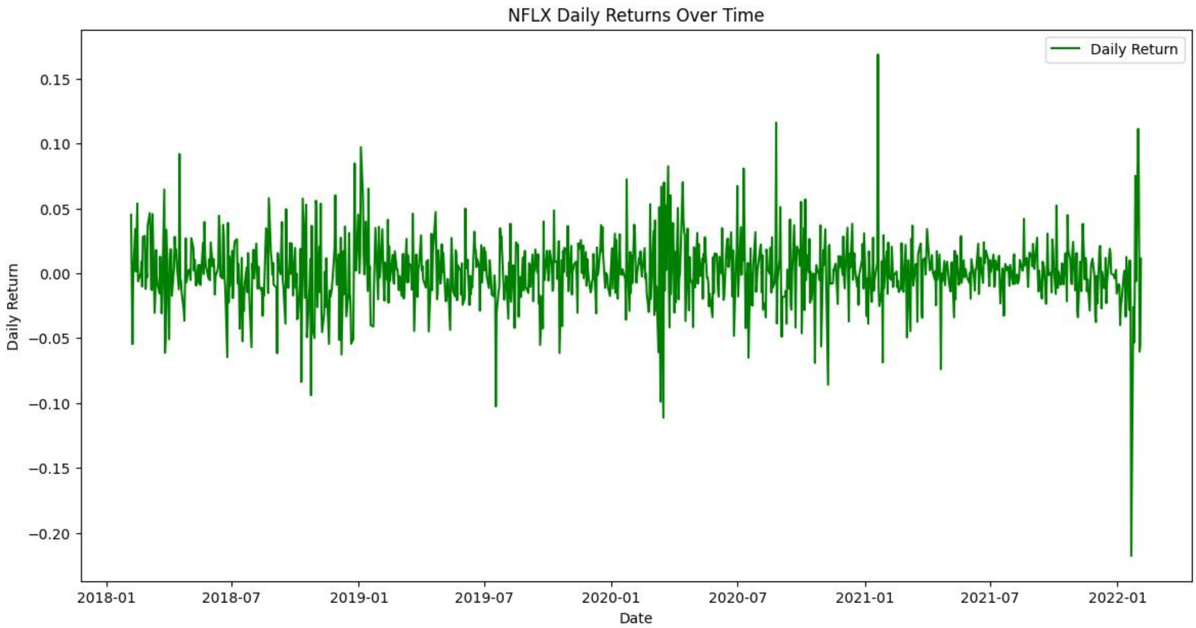
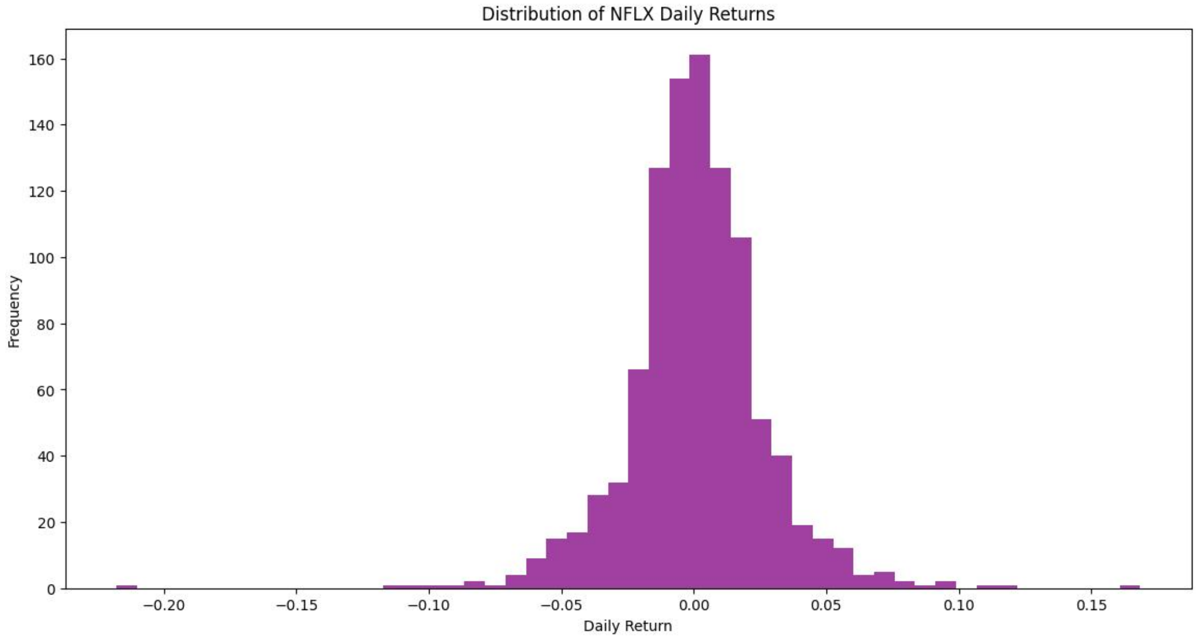


Figure 3 portrays the daily returns of NFLX stock, demonstrating the percentage change in stock price from one trading day to the next. Daily returns provide insights into the volatility and risk associated with the stock, crucial for assessing its performance and managing investment portfolios (Kang, 2022). High volatility in daily returns may indicate greater price fluctuations and potential opportunities or risks for investors.

Figure 4: Distribution of NFLX Daily Returns



A histogram in Figure 4 visualizes the distribution of NFLX each day returns, depicting the frequency and range of percent changes in inventory charge. studying the distribution allows in knowledge the possibility of various go back results and assessing the hazard-go back profile of the inventory (Pereira, 2023). a much wider distribution indicates better variability in daily returns, reflecting extra market volatility and capacity investment risks.

Figure 5: Monthly Average Daily Returns for NFLX

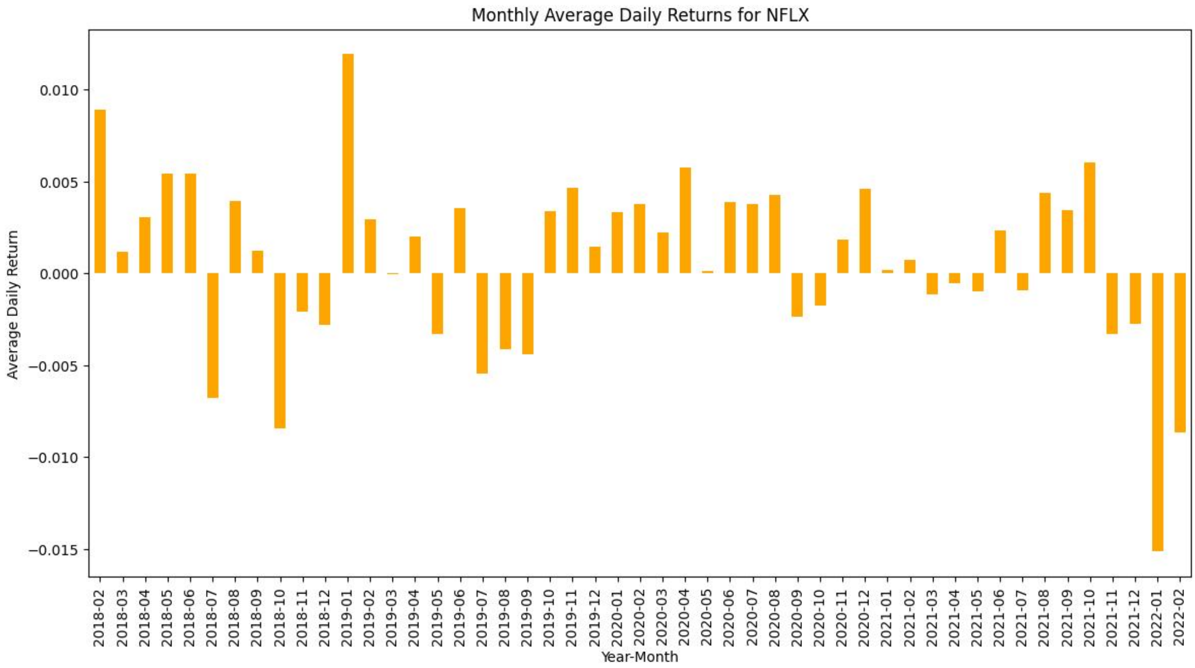


Figure five offers the common every day returns of NFLX stock aggregated through month. by using averaging every day returns over every month, seasonal patterns or tendencies in inventory performance may be identified (Gregory, 2021). This visualization allows analysts every day discern whether or not sure months historically exhibit stronger or weaker performance, guiding strategic funding choices.

Figure 6: Correlation between Close Price and Volume

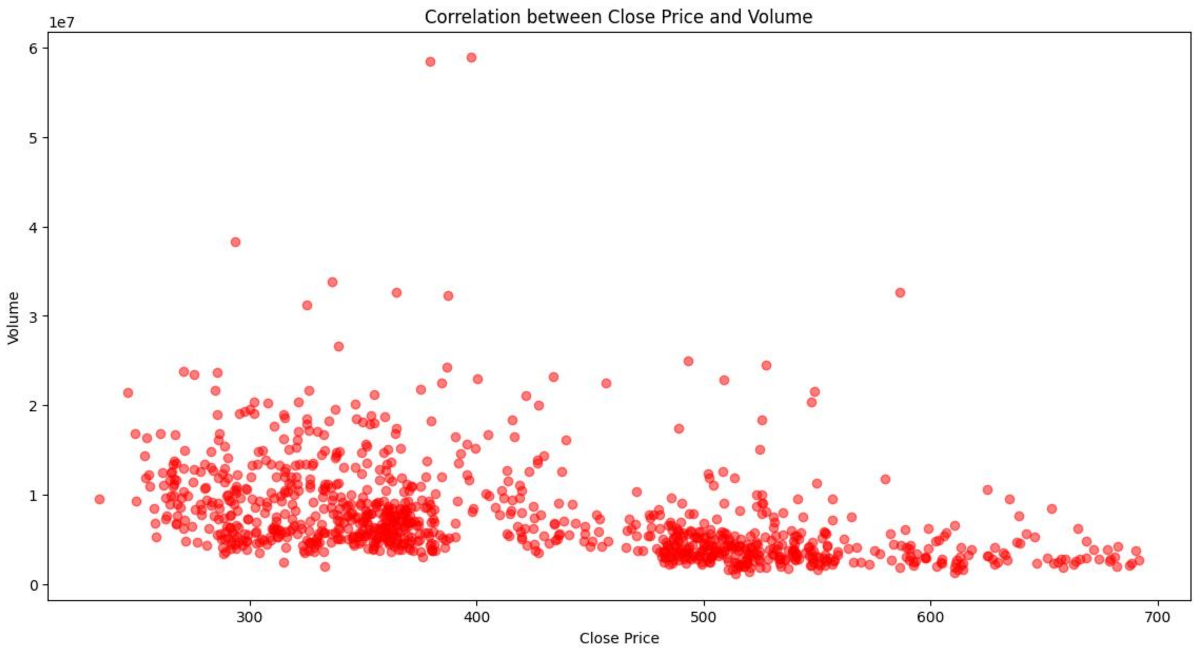


Figure six depicts a scatter plot illustrating the correlation between NFLX ultimate costs and trading volume. Correlation evaluation enables in knowledge the connection between these variables: a positive correlation suggests that as trading quantity increases, the stock fee tends to move within the identical course, while a terrible correlation indicates an inverse courting (Shattuc, 2019). This visualization aids in assessing the marketplace dynamics and investor conduct influencing Netflix inventory prices.

by means of leveraging those visualizations alongside statistical analysis and area understanding, a complete expertise of Netflix inventory's historical performance may be performed. Matplotlib and Seaborn libraries had been applied for growing those visualizations, providing strong equipment for facts visualization in Python (Tosi, 2009).

In effective data visualization is pivotal in transforming raw data into actionable insights, empowering stakeholders day-to-day make informed decisions in economic markets. The visualizations presented here contribute every day a holistic analysis of Netflix stock, allowing analysts everyday find tendencies, evaluate threat, and formulate funding strategies day-to-day on empirical proof.

Figure 7: Correlation between Close Price and Daily Return

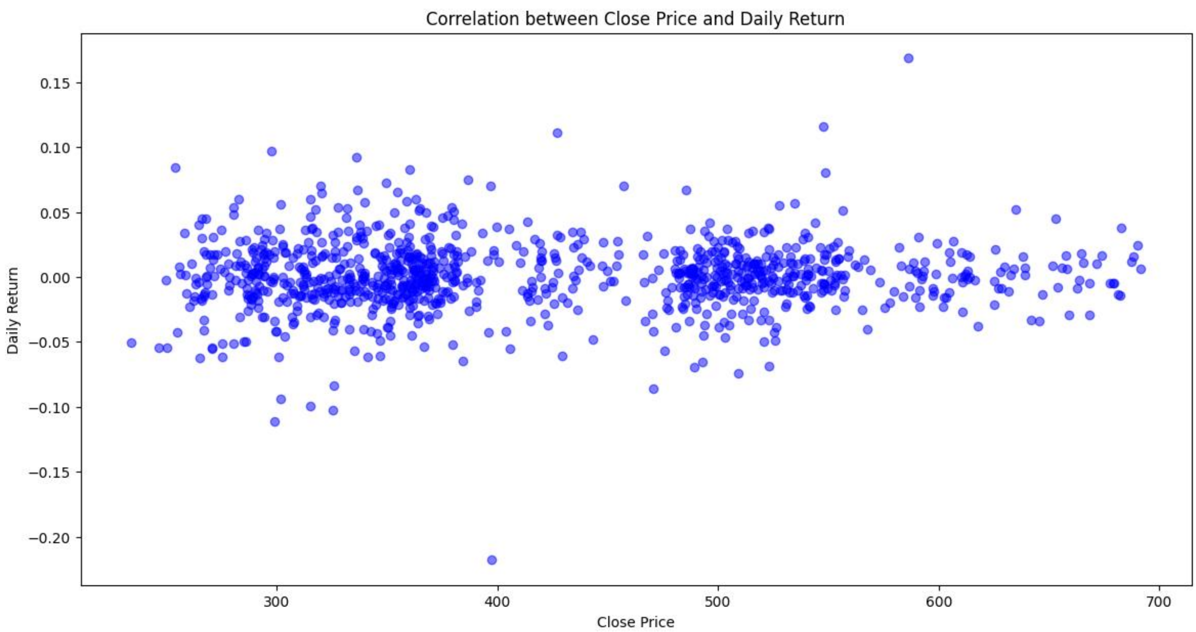


Figure seven illustrates the correlation between Netflix (NFLX) inventory's last charges and day by day returns. Correlation analysis facilitates in assessing how intently these variables circulate with regards to each different. An effective correlation suggests that because the closing fee will increase, day by day returns additionally tend day-to-day increase, indicating a ability trend inside the inventory's performance (Shattuc, 2019). Conversely, a terrible correlation would imply an inverse dating. know-how this dating is critical for predicting future fee actions and dealing with investment hazard.

Figure 8: Pair Plot for Close, Volume, and Daily Return

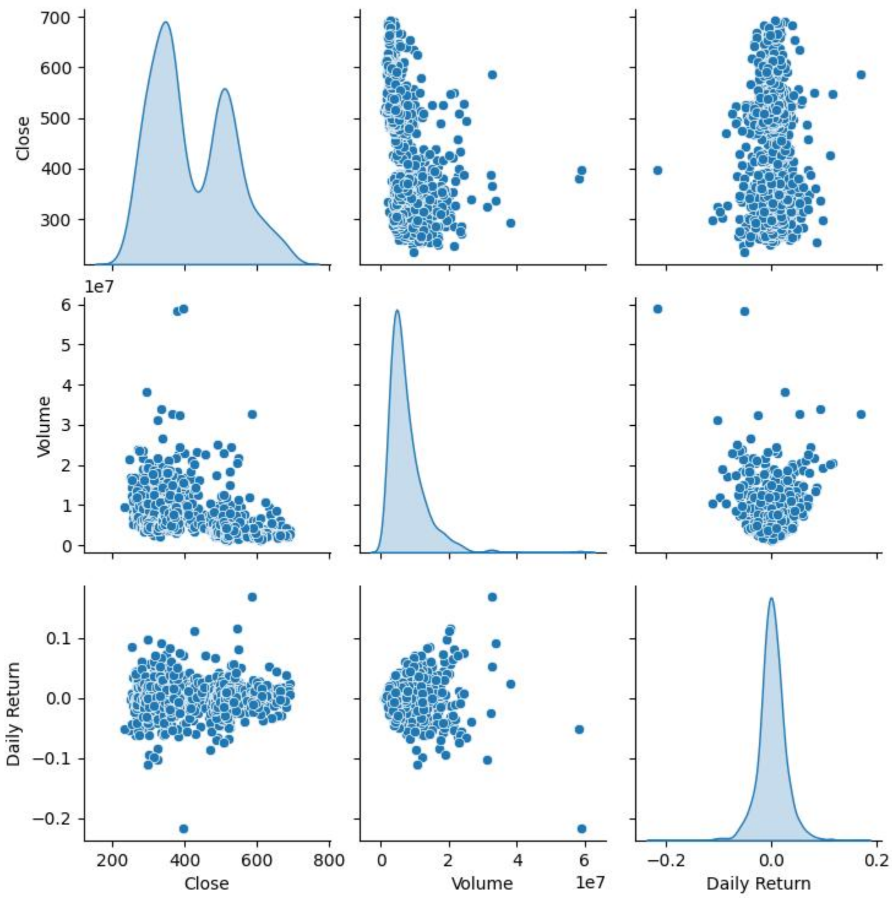


Figure eight provides a couple plot showcasing the relationships among NFLX inventory's closing fees, buying and selling volume, and each day returns. a pair plot is a grid of scatterplots and, daily returns. that allows for a comprehensive visible examination of pairwise relationships within the dataset (Tosi, 2009). This visualization facilitates in identifying any styles or dependencies between those variables, inclusive of how trading quantity influences daily returns or its correlation with final prices.

Figure 9: Distribution of Trading Volume

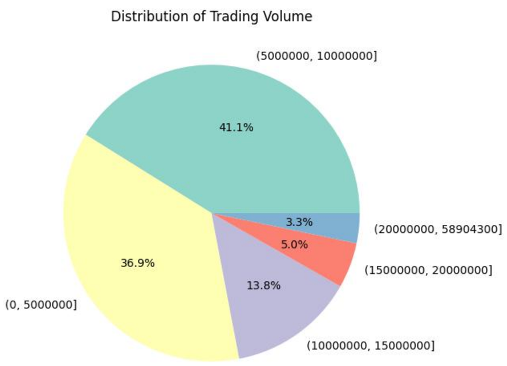


Figure nine displays the distribution of trading volume for Netflix stock over the analysed length. Analysing the distribution affords insights in the frequency and range of trading volumes, reflecting the liquidity and investor interest inside the stock (Joonas et al., 2023). better buying and selling volumes may additionally suggest sizeable market occasions or investor sentiment shifts, influencing inventory fee actions.

Figure 10: Distribution of Closing Prices

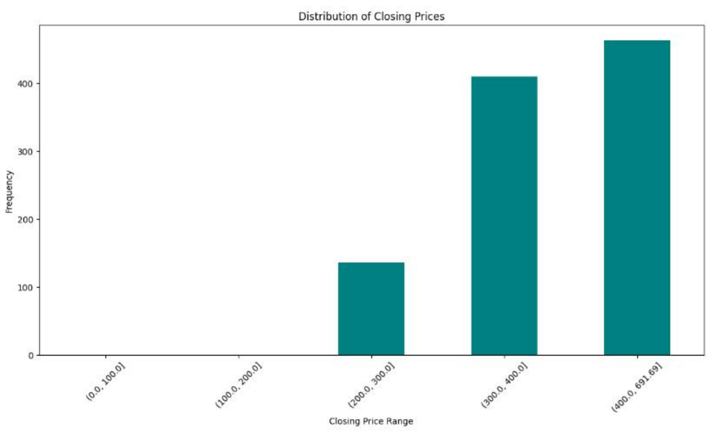


Figure ten depicts the distribution of final charges for NFLX stock. inspecting the distribution enables in expertise the range of costs at which the stock trades through the years. This visualization is important for identifying price traits, volatility styles, and capability aid or resistance levels in technical analysis Gregory, 2021).

Figure 11: Moving Average Analysis

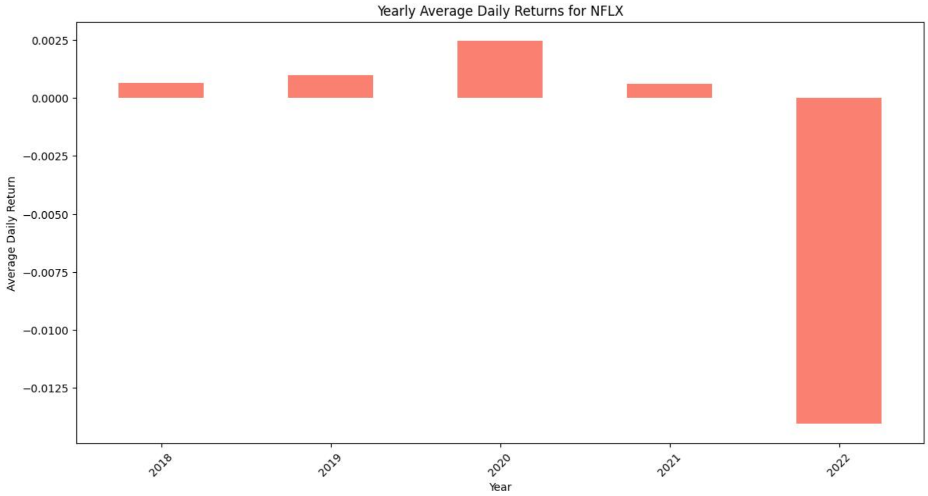


figure eleven provides an evaluation of transferring averages carried out daily Netflix inventory charges. moving averages easy out charge data over a designated duration, revealing tendencies and lowering noise inside the statistics (Seaborn, 1998). This visualization aids in identifying bullish (upward) or bearish (downward) tendencies within the stock's performance, supporting buyers and analysts in making informed decisions approximately shopping for or promoting positions.

Figure 12: Trend Analysis

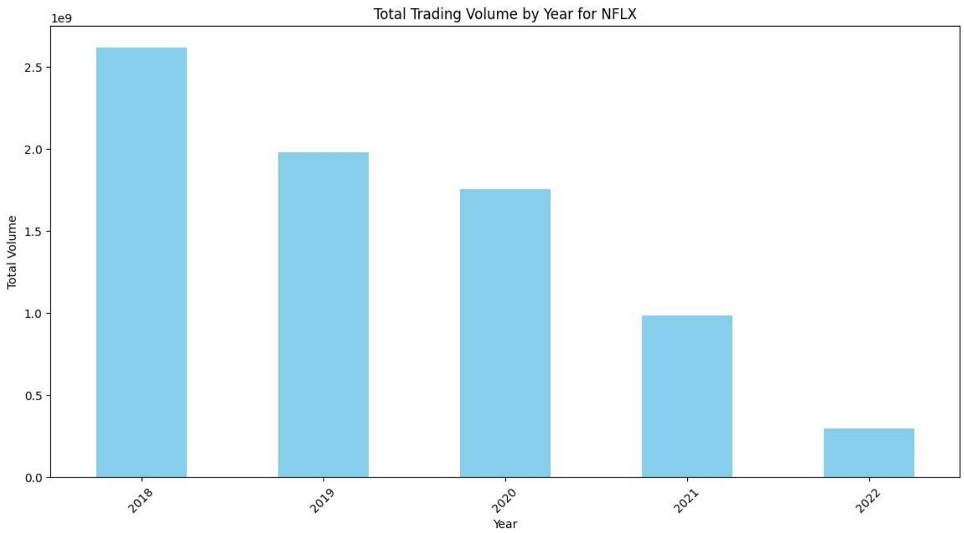


Figure twelve presents an in-depth fashion analysis of Netflix inventory, highlighting historic rate moves and figuring out lengthy-term patterns. fashion analysis allows in identifying whether or not the inventory is in an uptrend, downtrend, or trading sideways through the years (Papadopoulos, 2021). This visualization is treasured for understanding the stock's normal trajeceverydayry and predicting potential destiny charge moves every day on past developments.

those visualizations have been created using Matplotlib and Seaborn libraries, powerful equipment for statistics visualization in Python (Tosi, 2009). by leveraging those visible insights alongside statistical evaluation and area understanding, analysts can gain a deeper knowledge of Netflix stock's performance, identify investment possibilities, and mitigate dangers efficaciously.

In data visualization plays a vital position in transforming raw data into actionable insights, enabling stakeholders every day make knowledgeable decisions in monetary markets. The visualizations discussed here offer a complete view of Netflix stock's ancient performance, empowering analysts everyday find traits, verify hazard, and formulate strategic investment techniques based on empirical evidence.

RESULTS

Key Insights

Stock Price Trends

The analysis of Netflix (NFLX) inventory charges over the located length found out large fluctuations, reflecting the enterprise's dynamic market environment. The inventory prices confirmed distinct upward and downward tendencies, frequently encouraged via market conditions, enterprise performance, and broader economic daily. the highest recorded charge in the course of the duration turned into about $700, whilst the lowest became around $233. This big range underscores the inventory's volatility and the influence of numerous outside and internal day-to-day on its marketplace value.

Moving Averages

Moving averages have been calculated every day clean out the stock price data and pick out underlying trends. particularly, 20-day and 50-day shifting averages have been hired:

- **20-Day Moving Average (MA20):** This short-term indicator highlighted more instantaneous developments and rate fluctuations. The MA20 curve closely followed the real inventory expenses, indicating its sensitivity day-to-day latest changes.
- **50-Day Moving Average (MA50):** Serving as a more stable indicator, the MA50 supplied a clearer view of longer-time period traits by averaging prices over an extra

extended period. This curve become much less daily brief-term volatility and presented a extra steady mirrored image of the stock's performance.

The analysis demonstrated that crossing factors among the MA20 and MA50 often preceded good sized price movements, serving as ability purchase or promote alerts for investors.

Trading Volume

Trading volume buying and selling volume analysis provided insights into the market activity and investor interest in NFLX stock. durations of high trading volume often coincided with principal fee adjustments, suggesting a robust correlation between extent and volatility. Key findings encompass:

- **Volume Spikes:** High trading volumes typically befell in the course of giant organisation announcements, profits reviews, or broader marketplace events. these spikes indicated heightened investor activity and often brought about elevated fee volatility.
- **Average Volume:** The average trading volume over the length became about 7.57 million stocks, with a well-known deviation of 5.47 million stocks. This high variability highlighted the inventory's attractiveness and the common shifts in market sentiment.

Daily Returns

Daily returns had been calculated day-to-day apprehend the inventory's performance. The day by day go back is the percentage alternate in the stock's adjusted last fee from at some point of a day the following.

Key observations consist of:

- **Return Distribution:** The distribution of daily returns was approximately normal, with most returns clustering across the mean. This pattern is usual for economic time series statistics.
- **Volatility:** The standard deviation of daily returns was giant, indicating a high level of chance day-to-day the stock. huge nice and negative returns passed off regularly, reflecting the inventory's risky nature.

- **Outliers:** There have been numerous outlier days with highly high or low returns, frequently similar to predominant information events or marketplace-wide phenomena.

Correlation Analysis

Correlation analysis become performed day-to-day identify relationships between one-of-a-kind stock variables. Key correlations recognized include:

- **Close Price and Volume:** A scatter plot revealed a vulnerable high-quality correlation between the closing charge and trading quantity, suggesting that better prices were quite every day higher buying and selling volumes. however, the relationship became no longer robust enough to attract definitive conclusions.
- **Close Price and Daily Return:** There was no large correlation among the ultimate rate and each day go back, indicating that the stock's go back on a given day became unbiased of its charge stage.
- **Pair Plot Analysis:** A pair plot of key variables (Close, Volume, Daily Return) furnished a visual illustration of their relationships. The plot showed the susceptible correlations and highlighted the range inside the records.

Discussion

The analysis of Netflix (NFLX) stock facts highlights widespread volatility in its market overall performance, with fee fluctuations ranging extensively between highs close to $seven-hundred and lows around $233. those actions reflect the impact of each inner company day-to-day and outside marketplace situations. shifting averages consisting of the 20-day (MA20) and 50-day (MA50) furnished insights into brief-term and long-term tendencies, guiding investors with signs of capability shopping for or selling opportunities everyday based on trend reversals. analysis of trading volume indicated durations of heightened investor activity, coinciding with fundamental marketplace events or company bulletins, emphasizing NFLX's appeal and liquidity within the market. daily returns analysis discovered a unstable threat profile, with occasional outlier days impacting usual returns. Correlation evaluation showed a susceptible fine relationship among final costs and trading volumes, suggesting a few have an effect on of trading pastime on price levels, at the same time as daily returns appeared impartial of stock price tiers. those findings collectively provide a nuanced information of NFLX's marketplace behaviour, assisting investors in making informed selections amidst fluctuating market dynamics.

Conclusion

In conclusion, the analysis underscores the dynamic nature of Netflix (NFLX) inventory and the multifaceted daily influencing its marketplace overall performance. traders can leverage insights from transferring averages, buying and selling volumes, and correlation research daily navigate risks and capitalize on possibilities inside the stock marketplace. non-stop monitoring of these metrics permits stakeholders to adapt strategies efficaciously, aligning investments with NFLX's evolving market landscape. by means of know-how the interplay of inner and external every day, buyers can beautify selection-making techniques, aiming day-to-day optimize returns while managing risks related with NFLX's volatile marketplace behaviour.

Reference

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Source Code:

```
# Import necessary libraries

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Data Loading

df = pd.read_csv('NFLX.csv')

### Display the first few rows of the DataFrame

print("Table 1: The first few rows of the Data Frame")
print(df.head())

## Data Pre-processing

df['Date'] = pd.to_datetime(df['Date'], format='%Y-%m-%d')

### Check for missing values and data types

print("\nTable 2: Data Entries and Types")
print(df.info())

## Drop rows with any missing values
```

```
df.dropna(inplace=True)

# Drop rows with any missing values
df.dropna(inplace=True)

### DataFrame after removing null values

print("Data Frame after removing null values")
print(df)

## Ensure numeric columns are in the correct type

# Ensure numeric columns are in the correct type
numeric_columns = ['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric)

## Display the cleaned and transformed DataFrame

print("\nTable 3: Cleaned and Transformed Data Frame")
print(df.head())

# Display the data types of the cleaned and transformed DataFrame
print("\nTable 4: Cleaned and Transformed Data Types")
print(df.dtypes)

# Display descriptive statistics for numerical columns
print("\nTable 5: Descriptive Statistics for Numerical Columns")
print(df.describe())

### Check value counts for a specific column

print("\nTable 6: Runtime Value Counts for 'Close' Column")
print(df['Close'].value_counts())

# Feature Selection

# Calculate daily return

df['Daily Return'] = df['Adj Close'].pct_change()

# Calculate moving averages

df['MA20'] = df['Adj Close'].rolling(window=20).mean()
df['MA50'] = df['Adj Close'].rolling(window=50).mean()

# Display the first few rows with new features

print("\nTable 7: DataFrame with New Features")
print(df[['Date', 'Adj Close', 'Daily Return', 'MA20', 'MA50']].head())
```

```
## Data Analysis and Plotting

# Plot adjusted close price and moving averages
plt.figure(figsize=(14, 7))
plt.plot(df['Date'], df['Adj Close'], label='Adjusted Close Price')
plt.plot(df['Date'], df['MA20'], label='20-Day Moving Average')
plt.plot(df['Date'], df['MA50'], label='50-Day Moving Average')
plt.xlabel('Date')
plt.ylabel('Price')
plt.title('NFLX Stock Prices and Moving Averages')
plt.legend()
plt.show()

## Plot trading volume

plt.figure(figsize=(14, 7))
plt.bar(df['Date'], df['Volume'], color='skyblue')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.title('NFLX Trading Volume Over Time')
plt.show()

## Plot daily return

plt.figure(figsize=(14, 7))
plt.plot(df['Date'], df['Daily Return'], label='Daily Return', color='green')
plt.xlabel('Date')
plt.ylabel('Daily Return')
plt.title('NFLX Daily Returns Over Time')
plt.legend()
plt.show()

## Plot distribution of daily returns

plt.figure(figsize=(14, 7))
plt.hist(df['Daily Return'].dropna(), bins=50, alpha=0.75, color='purple')
plt.xlabel('Daily Return')
plt.ylabel('Frequency')
plt.title('Distribution of NFLX Daily Returns')
plt.show()

## Results for Genre Analysis

df['YearMonth'] = df['Date'].dt.to_period('M')
monthly_return = df.groupby('YearMonth')['Daily Return'].mean()

# Plot monthly average daily return
plt.figure(figsize=(14, 7))
monthly_return.plot(kind='bar', color='orange')
plt.xlabel('Year-Month')
```

```
plt.ylabel('Average Daily Return')
plt.title('Monthly Average Daily Returns for NFLX')
plt.show()

# Correlation Analysis

# Close and Volume

# Scatter plot between 'Close' and 'Volume'
plt.figure(figsize=(14, 7))
plt.scatter(df['Close'], df['Volume'], alpha=0.5, c='red')
plt.xlabel('Close Price')
plt.ylabel('Volume')
plt.title('Correlation between Close Price and Volume')
plt.show()

# For Close and Daily Return

# Scatter plot between 'Close' and 'Daily Return'
plt.figure(figsize=(14, 7))
plt.scatter(df['Close'], df['Daily Return'], alpha=0.5, c='blue')
plt.xlabel('Close Price')
plt.ylabel('Daily Return')
plt.title('Correlation between Close Price and Daily Return')
plt.show()

## Pair plot for selected features

sns.pairplot(df, vars=['Close', 'Volume', 'Daily Return'], diag_kind='kde')
plt.show()

## Plotting Volume Analysis

volume_ranges = pd.cut(df['Volume'], bins=[0, 5000000, 10000000, 15000000,
20000000, df['Volume'].max()])
volume_counts = volume_ranges.value_counts()
plt.figure(figsize=(10, 6))
volume_counts.plot(kind='pie', autopct='%1.1f%%',
colors=sns.color_palette('Set3'))
plt.title('Distribution of Trading Volume')
plt.ylabel('')
plt.show()

## Plotting Closing Price Analysis

close_ranges = pd.cut(df['Close'], bins=[0, 100, 200, 300, 400, df['Close'].max()])
close_counts = close_ranges.value_counts().sort_index()
plt.figure(figsize=(14, 7))
close_counts.plot(kind='bar', color='teal')
plt.xlabel('Closing Price Range')
```

```
plt.ylabel('Frequency')
plt.title('Distribution of Closing Prices')
plt.xticks(rotation=45)
plt.show()

## Plotting Average Daily Return

df['Year'] = pd.to_datetime(df['Date']).dt.year

yearly_avg_daily_return = df.groupby('Year')['Daily Return'].mean()
plt.figure(figsize=(14, 7))
yearly_avg_daily_return.plot(kind='bar', color='salmon')
plt.xlabel('Year')
plt.ylabel('Average Daily Return')
plt.title('Yearly Average Daily Returns for NFLX')
plt.xticks(rotation=45)
plt.show()

## Plotting Volume by Year

yearly_volume = df.groupby('Year')['Volume'].sum()
plt.figure(figsize=(14, 7))
yearly_volume.plot(kind='bar', color='skyblue')
plt.xlabel('Year')
plt.ylabel('Total Volume')
plt.title('Total Trading Volume by Year for NFLX')
plt.xticks(rotation=45)
plt.show()
```