ACFI827 - Introduction to Programming (Python)

Assignment 2

Thana Nassr

Student No.201686722

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Contents

1. Introduction

Due to their high volatility, decentralized trading, and quickly changing market dynamics, cryptocurrencies have grown to be a significant asset class in today's financial markets.This report focuses on Bitcoin (BTC) and Solana (SOL), two popular cryptocurrencies with distinct market structures, adoption trends, and risk characteristics. The report analyzes the historical performance, volatility, and trading patterns of Bitcoin and Solana using daily price and transaction data from Yahoo Finance from January 2022 to December 2025.The data was sourced and analyzed using Python and a Google Colab notebook.

The analysis has four stages. Initially, the datasets are imported and examined to comprehend their structure and primary variables. Secondly, descriptive statistics, correlation analysis, and outlier detection are employed to analyze price behavior.Third, time-series visualisations and weekly aggregations identify trends and volume patterns. Finally, performance metrics—including daily returns, cumulative returns, and rolling volatility—are computed to compare the risk–return profiles of the two cryptocurrencies.

2. Data Description and Preparation(Task 1)

2.1 Data Source and Loading

Yahoo Finance provided daily historical price data for Bitcoin (BTC) and Solana (SOL) using the yfinance Python library.The datasets were imported into Pandas DataFrames for further analysis, and they range from January 1, 2022, to December 20, 2025.The Open, High, Low, Close, and Volume columns, which represent daily price fluctuations and trading activity, are incorporated into each dataset.

2.2 Initial Inspection

Both Bitcoin and Solana have 1,449 daily observations across five variables, according to our first examination of the datasets (Appendix Figure 2). This ensures complete temporal alignment and permits direct comparison without a requirement for any data preparation.The daily frequency captures both short-term price fluctuations and longer-term market dynamics.

While trading volume offers information on market participation and liquidity conditions, the inclusion of Open, High, Low, and Close prices enables the analysis of volatility and price direction from multiple viewpoints. increasing investor interest or increasing uncertainty may be indicated by periods of high volume. Overall, the structure and completeness of the datasets support robust descriptive analysis, visualisation, and the computation of advanced performance metrics in subsequent sections.

3. Descriptive Statistics and Correlation Analysis(Task 2)

3.1 Descriptive Statistics

The price levels and volatility profiles of Bitcoin and Solana vary significantly, as seen by descriptive data for the Open, High, Low, and Close values (Appendix Figure 4). The average closing price of Bitcoin, at approximately \$55,910, is far greater than Solana's closing price of roughly \$103, proving its more dominant market position across all metrics. Similar differences in median prices show that this volatility lasts even when the market is regular, rather than being caused by unusual events.

Price ranges further emphasize these contrasts: Bitcoin's maximum closing price exceeds \$124,700, while Solana's remains below \$262, indicating far larger absolute price movements for Bitcoin. Although Bitcoin displays higher absolute volatility in dollar terms, Solana exhibits greater relative variability when scaled by price level, consistent with its more speculative risk profile.

3.2 Correlation Analysis

A correlation analysis of daily prices and trading volume for Bitcoin and Solana (refer to Appendix Figures 3 and 4) uncovers distinctive market trends. The price variables (Open, High, Low, and Close) exhibit an almost perfect correlation for both cryptocurrencies, with correlation coefficients exceeding 0.99, reflecting highly consistent intraday price patterns and minimal short-term reversals.

In contrast, the relationship between trading volume and closing price differs across assets. Solana exhibits a stronger positive correlation (≈0.71) than Bitcoin (≈0.61), suggesting greater sensitivity of prices to changes in trading activity. This pattern is consistent with Solana's smaller size and more speculative trading environment, where fluctuations in investor participation have a larger price impact. Bitcoin's weaker volume–price relationship reflects deeper liquidity and more stable trading conditions typical of a mature cryptocurrency market (Corbet et al., 2019).

3.3 Outlier Detection

No outliers were found in either the High or Low price series for Solana or Bitcoin using the interquartile range (IQR) approach of outlier identification.This implies that, in spite of notable volatility, price fluctuations over the period remained within statistically expected ranges. The inherent volatility of cryptocurrency markets, where notable price swings occur often enough to be seen as usual rather than unusual, is reflected in the absence of extreme outliers. A larger interquartile range is also produced by using many years' worth of daily aggregated data, which lessens the possibility that significant but frequent price changes may be categorized as statistical outliers.

4. Data Visualization and Time-Based Analysis(Task 3)

4.1 Price Trends Over Time

According to Appendix Figures 6 and 7 ,the Open, High, Low, and Close prices of Solana (SOL) and Bitcoin (BTC) tend to move somewhat close together, suggesting minimal intraday divergence and price behaviour largely shaped by broader market forces.The figure shows Solana with clear shifts in market regimes,a steep downturn in early 2022, a prolonged period of consolidation throughout 2023, and an unstable rebound beginning in 2024.Increasing speculative trading activity and heightened responsiveness to investor sentiment can be concluded from this. A more gradual and stable evolution is seen for Bitcoin, showing that it experiences a downturn in 2022 before transitioning into a persistent upward trend between 2023 and 2025 with relatively limited corrective movements. Although both cryptocurrencies are influenced by macroeconomic developments and changes in market participation, the greater amplitude of Solana’s price fluctuations points to stronger asset-specific and network-driven influences.

4.2 Weekly Aggregation

By normalizing the high-frequency volatility typical of cryptocurrency markets, daily price and volume data for Solana and Bitcoin were resampled into weekly averages to eliminate short-term noise and facilitate a clearer identification of underlying market trends.Solana's weekly averaged prices in early 2022 exhibit a distinct and persistent decreasing trend, supporting the bearish phase seen in daily data, as shown in Appendix Figure 8. Trading volumes are fairly large show that market activity is continuing even while prices are falling. Because of its larger market size and liquidity, Bitcoin has had a comparable but more consistent weekly price reduction over the same time, with fewer weekly changes and more constant volumes. In general, weekly aggregation provides a better picture of longer-term market direction and trade activity while also confirming current price patterns.

4.3 Volume Analysis

The daily trading volume for Bitcoin (BTC) and Solana (SOL) is shown in Figures 10 and 11, with the mean volume serving as a benchmark. Periods of increased market activity are indicated by the regular volume spikes that both assets endure. More noticeable and unpredictable spikes are shown in Solana, with many sharp increases starting in 2024. This suggests a rise in speculative trading and quick changes in investor sentiment. This behavior is comparable with less mature digital asset markets, where sentiment-driven volatility is amplified and price discovery is weakened due to inadequate liquidity and a greater percentage of inexperienced retail trading (Baur and Dimpfl 2021; Kitvanitphasu et al. 2025).

Bitcoin also displays repeated volume spikes, but these are more evenly distributed and less extreme in relative magnitude. This reflects Bitcoin’s deeper liquidity and more mature market structure, where higher trading activity is absorbed with reduced price impact, supporting more orderly price discovery (Baur and Dimpfl 2021; Kitvanitphasu et al. 2025; Rudd and Porter 2025).

The closing prices and trading volume of the two assets are shown in Figures 12 and 13. For Solana, the relationship between trading intensity and price volatility is reinforced by the fact that sudden rises in prices or abrupt corrections often follow strong spikes in volume, especially during the post-2023 recovery period. Rather than brief spikes, Bitcoin's larger volumes often correspond with long-term price trends, indicating that volume acts as a stabilizing element during significant price movements.The Sequential Information Arrival Hypothesis and the Mixture of Distributions Hypothesis, which relate trading volume to information arrival and gradual price adjustment, are in line with this trend (Andersen 1996; Karpoff 1987; Suominen 2001; Wang et al. 2019).As Bitcoin's market matures, increasing liquidity and order book depth further support this liquidity–stability dynamic (Kitvanitphasu et al. 2025).

5. Comparative Performance and Risk Analysis(Task 4)

5.1 Daily and Cumulative Returns

The daily return data for Solana (SOL) and Bitcoin (BTC) are presented in Appendix Figure 15, which reveals that while both assets have very distinct volatility characteristics, they provide comparable average daily returns (about 0.11% for SOL and 0.08% for BTC). In comparison to Bitcoin, Solana is a riskier and more speculative asset because of its significantly larger standard deviation of daily returns, which suggests more dramatic price swings and greater downside risk. This interpretation is in line with the research on asset pricing, which finds that return volatility is a primary indicator of investment risk, particularly for newer crypto-assets that exhibit heightened sensitivity to market shocks(Prashayuniar and Syafrida, 2025; Agyei *et al.*, 2025).

Appendix Figure 16, which presents Solana's cumulative return over time, reveals a deep drawdown during 2022 followed by a prolonged consolidation phase and a sharp yet unstable recovery from 2024 onwards. According to earlier research on high-beta cryptocurrency assets (Bouri et al., 2024; Corbet et al., 2025), the notable volatility seen during the recovery phase show a high degree of sensitivity to changes in market sentiment and liquidity conditions, with gains frequently followed by abrupt corrections. In comparison, Appendix Figure 17 demonstrates that Bitcoin's cumulative returns rise more gradually, starting in 2023 and continuing to rise despite intermittent setbacks. The greater liquidity and sophisticated market infrastructure of Bitcoin, which support longer trend continuation, more effective return compounding, and comparatively higher stability in long-term performance, are shown by this refined trajectory (Brauneis & Mitusch, 2025; Chod & Lyandres, 2024).

5.2 Rolling Volatility

The 30-day rolling volatility of daily returns for Solana (SOL) and Bitcoin (BTC) is shown in Appendix Figure 18, which highlights persisting variations in their risk dynamics over time. Throughout the observation window, Solana displays markedly elevated and irregular volatility behavior, with pronounced swings emerging during periods of heightened market turbulence and subsequent rebounds, most notably toward the end of 2022 and in the expansionary phases thereafter. Such volatility surges align with Solana's highly speculative market profile, reflecting heightened exposure to uncertainty and sensitivity to changes in investor sentiment and liquidity conditions (Bouri et al., 2024; Sensoy et al., 2025).

By comparison, Bitcoin demonstrates relatively subdued and steady volatility dynamics, with price movements unfolding in a more controlled and continuous manner rather than through sudden surges. This behavior implies that return disturbances are integrated into prices over a longer horizon, highlighting the depth of liquidity and the advanced state of Bitcoin's market infrastructure (Alexander et al., 2025).From an economic perspective, the divergence in rolling vzolatility reinforces the interpretation that Solana is more exposed to regime-dependent risk, where volatility escalates during transitions between risk-off and risk-on market conditions (Goutte et al., 2025; Nguyen and Walther, 2026). Lower volatility in Bitcoin indicates structural strength, promoting dependable price discovery and affirming its status as a foundational benchmark asset.

Conclusion

This report compares the risk and performance characteristics of Solana (SOL) and Bitcoin (BTC) using daily data from January 2022 to December 2025.Both cryptocurrencies exhibit similar average returns; however, their risk profiles differ.Bitcoin exhibits more stable price fluctuations, reduced volatility, and greater overall consistency, attributable to its higher liquidity and well-established market position.In contrast, Solana demonstrates higher relative volatility, more substantial drawdowns, and increased susceptibility to market sentiment.Generally, Solana exhibits greater volatility and speculative characteristics, while Bitcoin serves as a more reliable benchmark asset.

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Appendix

```
#TASK 1
#Use the date range from January 1, 2022, to current date
# Download Solana data
import pandas as pd
sol = yf.download("SOL-USD", start="2022-01-01", end="2025-12-20")
# Download Bitcoin data
btc = yf.download("BTC-USD", start="2022-01-01", end="2025-12-20")

# Flatten yfinance MultiIndex columns - for later
if isinstance(sol.columns, pd.MultiIndex):
    sol.columns = sol.columns.get_level_values(0)

if isinstance(btc.columns, pd.MultiIndex):
    btc.columns = btc.columns.get_level_values(0)

#Display the first 8 rows of each DataFrame (one for SOL and one for BTC
print("Solana (SOL) – first 8 rows:")
print(sol.head(8))

print("\nBitcoin (BTC) – first 8 rows:")
print(btc.head(8))
#Print the shape (total rows and columns) of both datasets
print("Solana (SOL) dataset shape:")
print(sol.shape)

print("\nBitcoin (BTC) dataset shape:")
print(btc.shape)

# Print the names of all columns in each DataFrame and describe what each column likely represents
print("Solana (SOL) columns:")
print(sol.columns)

print("\nBitcoin (BTC) columns:")
print(btc.columns)
```

Appendix Figure 1 – Task 1 Data exploration & preparation code

```
/tmp/ipython-input-1003628034.py:5: FutureWarning: YF.download() has changed argument auto_adjust default to True
  sol = yf.download("SOL-USD", start="2022-01-01", end="2025-12-20")
[*********************100%***********************]  1 of 1 completed
/tmp/ipython-input-1003628034.py:7: FutureWarning: YF.download() has changed argument auto_adjust default to True
  btc = yf.download("BTC-USD", start="2022-01-01", end="2025-12-20")
[*********************100%***********************]  1 of 1 completedSolana (SOL) - first 8 rows:
Price            Close        High         Low        Open      Volume
Date
2022-01-01  178.517944  178.962250  170.195541  170.310837  1084780603
2022-01-02  176.382843  179.432358  175.012314  178.532410   995389409
2022-01-03  170.297745  176.386307  167.533981  176.386307  1345778058
2022-01-04  167.938904  173.735107  166.740128  170.286118  1499265336
2022-01-05  155.099731  171.110458  148.216110  167.940338  2123759721
2022-01-06  150.431351  155.105927  146.667664  155.105927  2097172620
2022-01-07  136.402817  150.520950  135.149994  150.413406  2926269672
2022-01-08  142.513458  147.837311  134.021011  136.400162  2730000333

Bitcoin (BTC) - first 8 rows:
Price              Close          High           Low          Open  \
Date
2022-01-01  47686.812500  47827.312500  46288.484375  46311.746094
2022-01-02  47345.218750  47881.406250  46856.937500  47680.925781
2022-01-03  46458.117188  47510.726562  45835.964844  47343.542969
2022-01-04  45897.574219  47406.546875  45752.464844  46458.851562
2022-01-05  43569.003906  46929.046875  42798.222656  45899.359375
2022-01-06  43160.929688  43748.718750  42645.539062  43565.511719
2022-01-07  41557.902344  43153.570312  41077.445312  43153.570312
2022-01-08  41733.941406  42228.941406  40672.277344  41561.464844

Price            Volume
Date
2022-01-01  24582667004
2022-01-02  27951569547
2022-01-03  33071628362
2022-01-04  42494677905
2022-01-05  36851084859
2022-01-06  30208048289
2022-01-07  84196607520
2022-01-08  28066355845
Solana (SOL) dataset shape:
(1449, 5)

Bitcoin (BTC) dataset shape:
(1449, 5)
Solana (SOL) columns:
Index(['Close', 'High', 'Low', 'Open', 'Volume'], dtype='object', name='Price')

Bitcoin (BTC) columns:
Index(['Close', 'High', 'Low', 'Open', 'Volume'], dtype='object', name='Price')
```

Appendix Figure 2 – Task 1 Data exploration & preparation output

```python
# TASK 2 - Descriptive Statistics
#Calculate basic statistics
# Select the relevant price columns
price_cols = ['Open', 'High', 'Low', 'Close']

# Calculate statistics for Solana
sol_stats = sol[price_cols].agg(['mean', 'median', 'min', 'max', 'std'])

# Calculate statistics for Bitcoin
btc_stats = btc[price_cols].agg(['mean', 'median', 'min', 'max', 'std'])

print("Solana (SOL) price statistics:")
print(sol_stats)

print("\nBitcoin (BTC) price statistics:")
print(btc_stats)

#Compute the correlation matrix for the numerical columns
# Select numerical columns
num_cols = ['Open', 'High', 'Low', 'Close', 'Volume']

# Correlation matrix for Solana
sol_corr = sol[num_cols].corr()

print("Solana (SOL) correlation matrix:")
print(sol_corr)

# Correlation matrix for Bitcoin
btc_corr = btc[num_cols].corr()

print("\nBitcoin (BTC) correlation matrix:")
print(btc_corr)


# Identify potential outliers in the 'High' and 'Low' prices using the IQR (Interquartile Range) rule.
#Print the number of outliers found in each dataset and suggest why they might occur

def count_outliers_iqr(series):
    Q1 = series.quantile(0.25)
    Q3 = series.quantile(0.75)
```

```
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = series[(series < lower_bound) | (series > upper_bound)]
    return len(outliers)

sol_high_outliers = count_outliers_iqr(sol['High'])
sol_low_outliers = count_outliers_iqr(sol['Low'])

print("\nSolana (SOL) outliers:")
print(f"High price outliers: {sol_high_outliers}")
print(f"Low price outliers: {sol_low_outliers}")

btc_high_outliers = count_outliers_iqr(btc['High'])
btc_low_outliers = count_outliers_iqr(btc['Low'])

print("\nBitcoin (BTC) outliers:")
print(f"High price outliers: {btc_high_outliers}")
print(f"Low price outliers: {btc_low_outliers}")
```

Appendix Figure 3 – Task 2 Descriptive Statistics & Correlation Analysis Code

```
Solana (SOL) price statistics:
Price         Open        High         Low       Close
mean    103.032498  106.546967   99.495025  102.998928
median  106.298500  110.580353  101.109390  106.311516
min       9.651915    9.827129    8.141268    9.651783
max     261.872437  294.334961  253.187439  261.869751
std      69.628000   71.808458   67.382326   69.603187

Bitcoin (BTC) price statistics:
Price             Open           High            Low          Close
mean     55881.290459   56868.662340   54855.347236   55910.499273
median   43728.367188   44265.769531   42775.957031   43725.984375
min      15782.300781   16253.047852   15599.046875   15787.284180
max     124752.140625  126198.070312  123196.046875  124752.531250
std      32336.442115   32823.581257   31807.225195   32346.548120
Solana (SOL) correlation matrix:
Price       Open      High       Low     Close    Volume
Price
Open    1.000000  0.998644  0.998195  0.996692  0.708226
High    0.998644  1.000000  0.997926  0.998549  0.723413
Low     0.998195  0.997926  1.000000  0.998452  0.693071
Close   0.996692  0.998549  0.998452  1.000000  0.710033
Volume  0.708226  0.723413  0.693071  0.710033  1.000000

Bitcoin (BTC) correlation matrix:
Price       Open      High       Low     Close    Volume
Price
Open    1.000000  0.999448  0.999264  0.998859  0.613384
High    0.999448  1.000000  0.999072  0.999508  0.621684
Low     0.999264  0.999072  1.000000  0.999417  0.599555
Close   0.998859  0.999508  0.999417  1.000000  0.611365
Volume  0.613384  0.621684  0.599555  0.611365  1.000000

Solana (SOL) outliers:
High price outliers: 0
Low price outliers: 0

Bitcoin (BTC) outliers:
High price outliers: 0
Low price outliers: 0
```

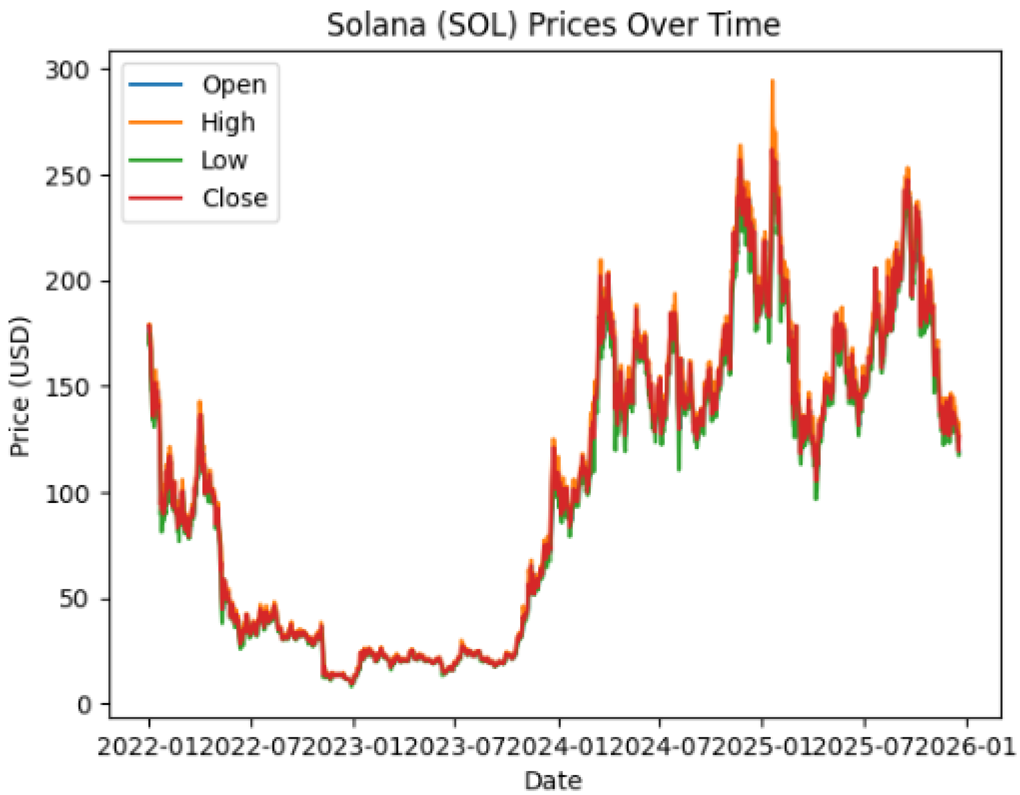
Appendix Figure 4 – Task 2 Descriptive Statistics & Correlation Analysis Output

```
#TASK 3 - Visualization and Time-Based Aggregation

#Using Matplotlib or Pandas plotting, create line plots for 'Open' , 'High' , 'Low' , and 'Close' prices over time
for both SOL and BTC.
import matplotlib.pyplot as plt

# Plot SOL prices
plt.figure()
plt.plot(sol.index, sol['Open'], label='Open')
plt.plot(sol.index, sol['High'], label='High')
plt.plot(sol.index, sol['Low'], label='Low')
plt.plot(sol.index, sol['Close'], label='Close')

plt.title('Solana (SOL) Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()

# Plot BTC prices
plt.figure()
plt.plot(btc.index, btc['Open'], label='Open')
plt.plot(btc.index, btc['High'], label='High')
plt.plot(btc.index, btc['Low'], label='Low')
plt.plot(btc.index, btc['Close'], label='Close')

plt.title('Bitcoin (BTC) Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()


# Resample the data by weekly intervals and calculate the average 'Open' , 'Close' , and 'Volume'
# Display the first 5 rows and discuss observed trends
cols = ['Open', 'Close', 'Volume']
sol_weekly = sol[cols].resample('W').mean()

print("Solana (SOL) weekly averages – first 5 rows:")
print(sol_weekly.head())
```

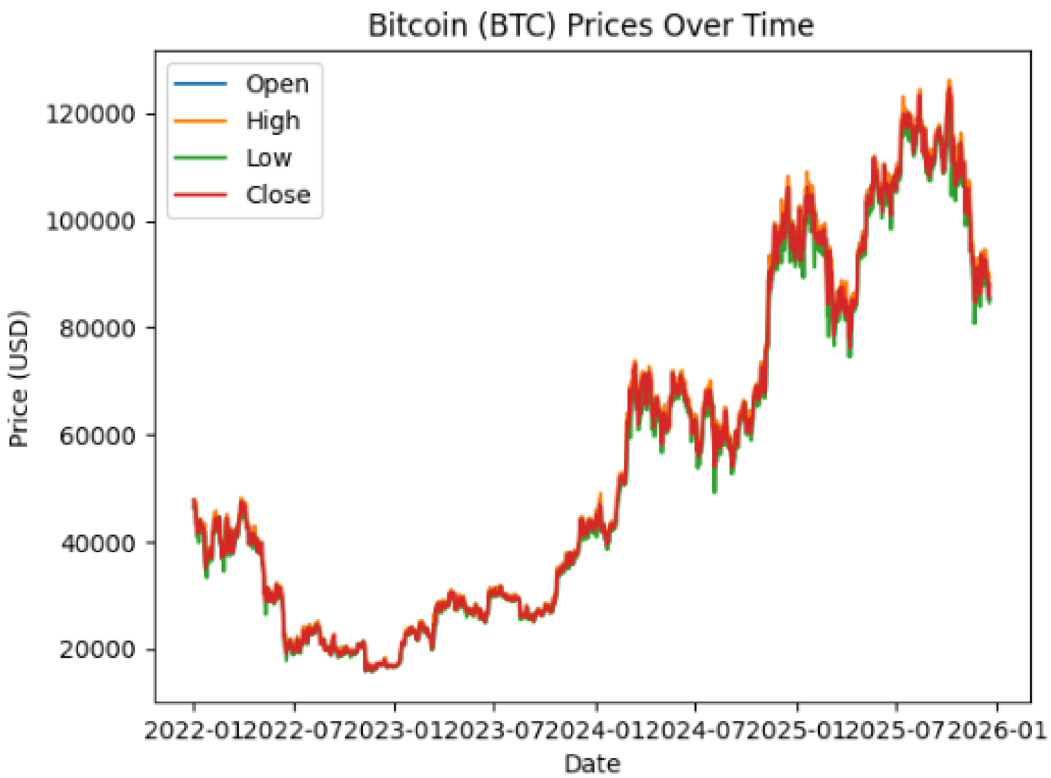
```
btc_weekly = btc[cols].resample('W').mean()

print("\nBitcoin (BTC) weekly averages – first 5 rows:")
print(btc_weekly.head())

# Volume Analysis: - (c.1) Plot 'Volume' over time for both SOL and BTC, identifying spikes above the mean.
import matplotlib.pyplot as plt

sol_mean_vol = sol['Volume'].mean()

plt.figure()
plt.plot(sol.index, sol['Volume'], label='Daily Volume')
plt.axhline(y=sol_mean_vol, linestyle='--', label='Mean Volume')

sol_spikes = sol[sol['Volume'] > sol_mean_vol]
plt.scatter(sol_spikes.index, sol_spikes['Volume'], label='Spikes Above Mean')

plt.title('Solana (SOL) Trading Volume Over Time')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.legend()
plt.show()

btc_mean_vol = btc['Volume'].mean()

plt.figure()
plt.plot(btc.index, btc['Volume'], label='Daily Volume')
plt.axhline(y=btc_mean_vol, linestyle='--', label='Mean Volume')

btc_spikes = btc[btc['Volume'] > btc_mean_vol]
plt.scatter(btc_spikes.index, btc_spikes['Volume'], label='Spikes Above Mean')

plt.title('Bitcoin (BTC) Trading Volume Over Time')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.legend()
plt.show()

#(c.2) Create an overlay plot comparing 'Volume' and 'Close' prices using dual y-axes.
import matplotlib.pyplot as plt

fig, ax1 = plt.subplots()

# Left y-axis: Close price
ax1.plot(sol.index, sol['Close'], label='Close Price')
```

```python
ax1.set_xlabel('Date')
ax1.set_ylabel('Close Price (USD)')

# Right y-axis: Volume
ax2 = ax1.twinx()
ax2.plot(sol.index, sol['Volume'], label='Volume')
ax2.set_ylabel('Volume')

# Title
fig.suptitle('Solana (SOL): Close Price vs Trading Volume')

# Combine legends
lines1, labels1 = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax1.legend(lines1 + lines2, labels1 + labels2)

plt.show()

fig, ax1 = plt.subplots()

# Left y-axis: Close price
ax1.plot(btc.index, btc['Close'], label='Close Price')
ax1.set_xlabel('Date')
ax1.set_ylabel('Close Price (USD)')

# Right y-axis: Volume
ax2 = ax1.twinx()
ax2.plot(btc.index, btc['Volume'], label='Volume')
ax2.set_ylabel('Volume')

# Title
fig.suptitle('Bitcoin (BTC): Close Price vs Trading Volume')

# Combine legends
lines1, labels1 = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax1.legend(lines1 + lines2, labels1 + labels2)

plt.show()
```

Appendix Fig 5 – Task 3 Visualization and Time-Based Aggregation Code



Appendix Fig 6 – Task 3 Solana Prices over time



Appendix Fig 7 – Task 3 Bitcoin Prices over time

```
Solana (SOL) weekly averages – first 5 rows:
Price             Open       Close        Volume
Date
2022-01-02  174.421623  177.450394  1.040085e+09
2022-01-09  157.010768  151.931859  2.045910e+09
2022-01-16  144.094489  145.095524  1.733270e+09
2022-01-23  128.395052  121.461932  2.246474e+09
2022-01-30   93.621050   92.725016  2.598870e+09

Bitcoin (BTC) weekly averages – first 5 rows:
Price               Open         Close        Volume
Date
2022-01-02  46996.335938  47516.015625  2.626712e+10
2022-01-09  44245.289621  43469.867188  3.945468e+10
2022-01-16  42755.924107  42926.966518  2.849626e+10
2022-01-23  40243.545201  39259.328683  2.804658e+10
2022-01-30  37112.001674  37348.400112  2.553249e+10
```

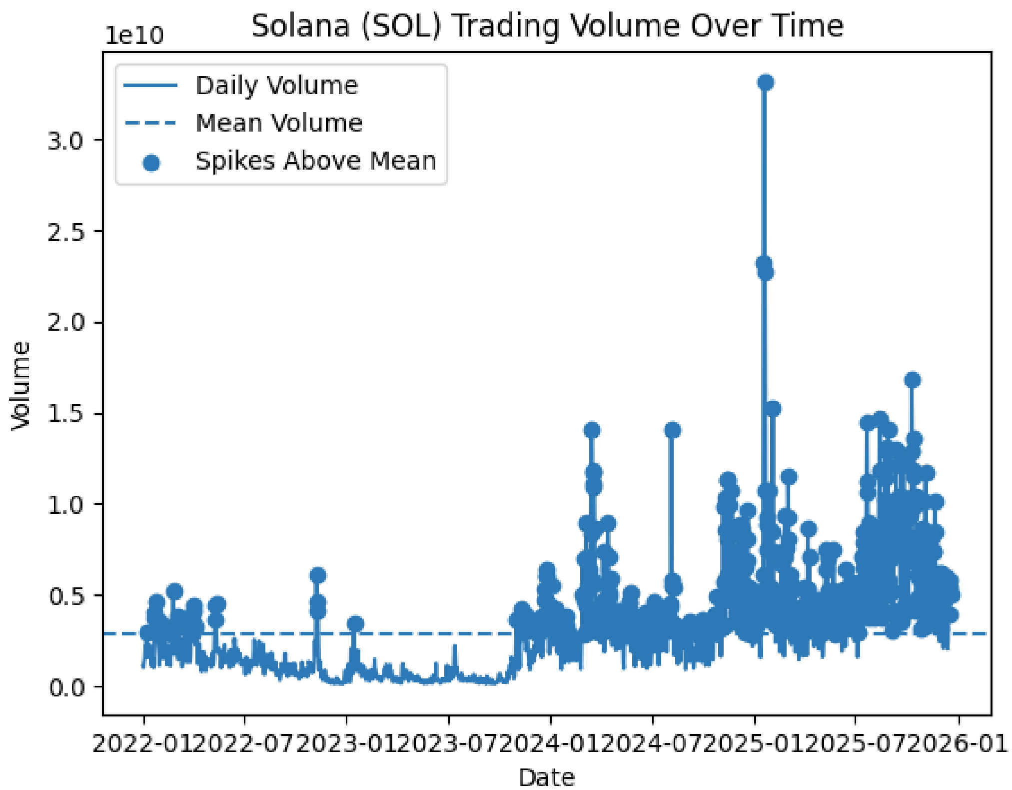
Appendix Fig 8 – Task 3 Weekly averages resampling

```
# Volume Analysis: - (c.1) Plot 'Volume' over time for both SOL and BTC, identifying spikes above the mean.
import matplotlib.pyplot as plt

sol_mean_vol = sol['Volume'].mean()
```

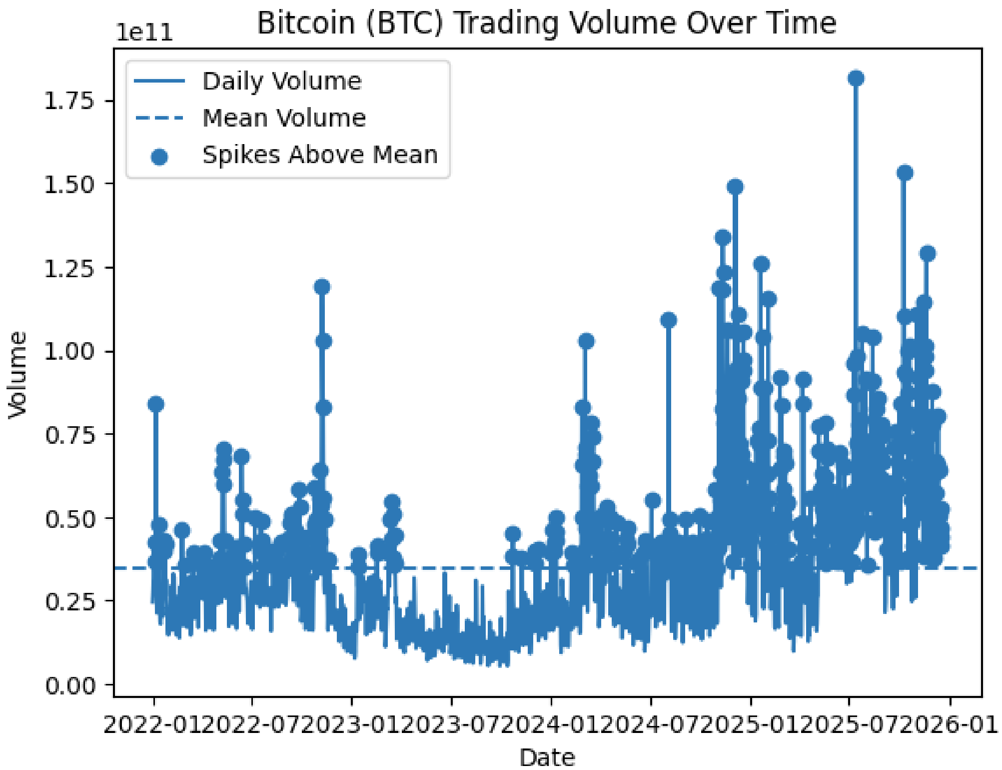
```
plt.figure()
plt.plot(sol.index, sol['Volume'], label='Daily Volume')
plt.axhline(y=sol_mean_vol, linestyle='--', label='Mean Volume')

sol_spikes = sol[sol['Volume'] > sol_mean_vol]
plt.scatter(sol_spikes.index, sol_spikes['Volume'], label='Spikes Above Mean')

plt.title('Solana (SOL) Trading Volume Over Time')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.legend()
plt.show()

btc_mean_vol = btc['Volume'].mean()

plt.figure()
plt.plot(btc.index, btc['Volume'], label='Daily Volume')
plt.axhline(y=btc_mean_vol, linestyle='--', label='Mean Volume')

btc_spikes = btc[btc['Volume'] > btc_mean_vol]
plt.scatter(btc_spikes.index, btc_spikes['Volume'], label='Spikes Above Mean')

plt.title('Bitcoin (BTC) Trading Volume Over Time')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.legend()
plt.show()

#(c.2) Create an overlay plot comparing 'Volume' and 'Close' prices using dual y-axes.
import matplotlib.pyplot as plt

fig, ax1 = plt.subplots()

# Left y-axis: Close price
ax1.plot(sol.index, sol['Close'], label='Close Price')
ax1.set_xlabel('Date')
ax1.set_ylabel('Close Price (USD)')

# Right y-axis: Volume
ax2 = ax1.twinx()
ax2.plot(sol.index, sol['Volume'], label='Volume')
ax2.set_ylabel('Volume')

# Title
```

```
fig.suptitle('Solana (SOL): Close Price vs Trading Volume')

# Combine legends
lines1, labels1 = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax1.legend(lines1 + lines2, labels1 + labels2)

plt.show()

fig, ax1 = plt.subplots()

# Left y-axis: Close price
ax1.plot(btc.index, btc['Close'], label='Close Price')
ax1.set_xlabel('Date')
ax1.set_ylabel('Close Price (USD)')

# Right y-axis: Volume
ax2 = ax1.twinx()
ax2.plot(btc.index, btc['Volume'], label='Volume')
ax2.set_ylabel('Volume')

# Title
fig.suptitle('Bitcoin (BTC): Close Price vs Trading Volume')

# Combine legends
lines1, labels1 = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax1.legend(lines1 + lines2, labels1 + labels2)

plt.show()
```

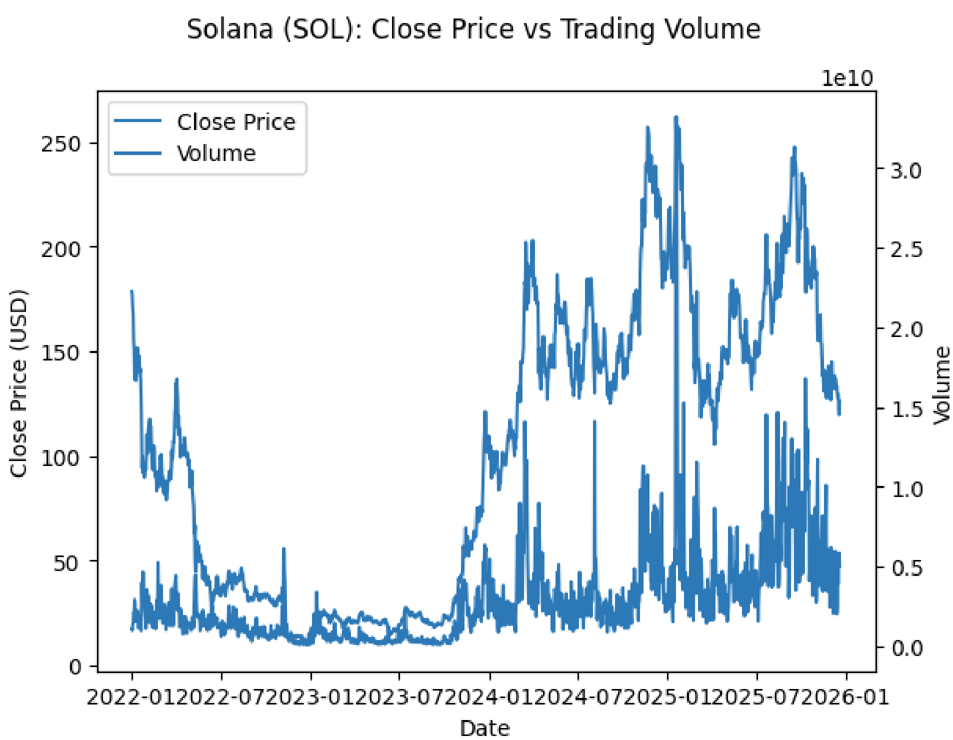
Appendix Fig 9 – Task 3 Volume Analysis Code



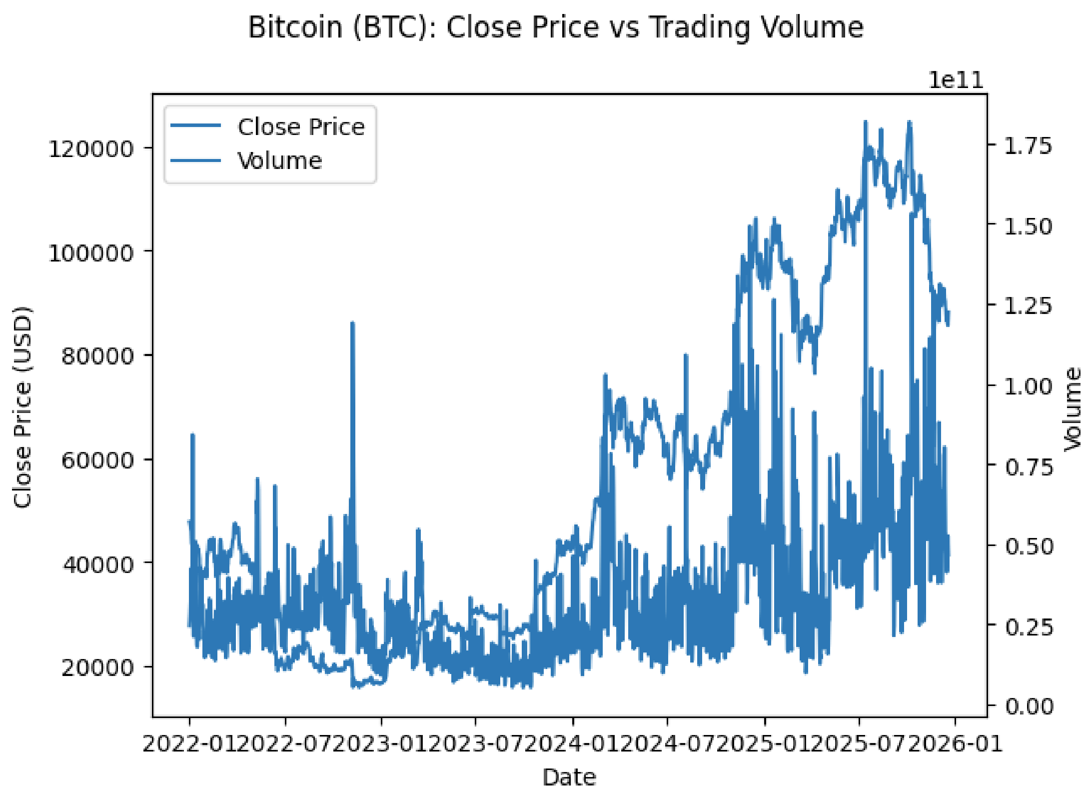
Appendix Figure 10 - Task 3 Volume Analysis Code - Solana (SOL) Trading Volume Over Time



Appendix Figure 11 - Task 3 Volume Analysis Code – Bitcoin (BTC) Trading Volume Over Time



Appendix Figure 12 - Task 3 Volume Analysis Code – Solana (SOL) Close Price vs Trading Volume



Appendix Figure 13 - Task 3 Volume Analysis Code – Bitcoin (BTC) Close Price vs Trading Volume

```
#TASK 4 - Comparative Analysis and Advanced Metrics


# Calculate daily returns for both SOL and BTC using  : daily return = (Close − Open)/Open
# Daily returns for Solana
sol['Daily_Return'] = (sol['Close'] - sol['Open']) / sol['Open']


print("Solana daily returns (first 5 rows):")
print(sol[['Open', 'Close', 'Daily_Return']].head())


# Daily returns for Bitcoin
btc['Daily_Return'] = (btc['Close'] - btc['Open']) / btc['Open']


print("\nBitcoin daily returns (first 5 rows):")
print(btc[['Open', 'Close', 'Daily_Return']].head())
#Returns as percentages
sol['Daily_Return_Pct'] = sol['Daily_Return'] * 100
btc['Daily_Return_Pct'] = btc['Daily_Return'] * 100
#Add them as new columns and compute the mean and standard deviation of daily returns


# Solana statistics
sol_mean_return = sol['Daily_Return'].mean()
sol_std_return = sol['Daily_Return'].std()


# Bitcoin statistics
btc_mean_return = btc['Daily_Return'].mean()
btc_std_return = btc['Daily_Return'].std()


print(f"\nSOL Mean Daily Return: {sol_mean_return * 100:.2f}%")
print(f"SOL Daily Return Std Dev: {sol_std_return * 100:.2f}%")
```

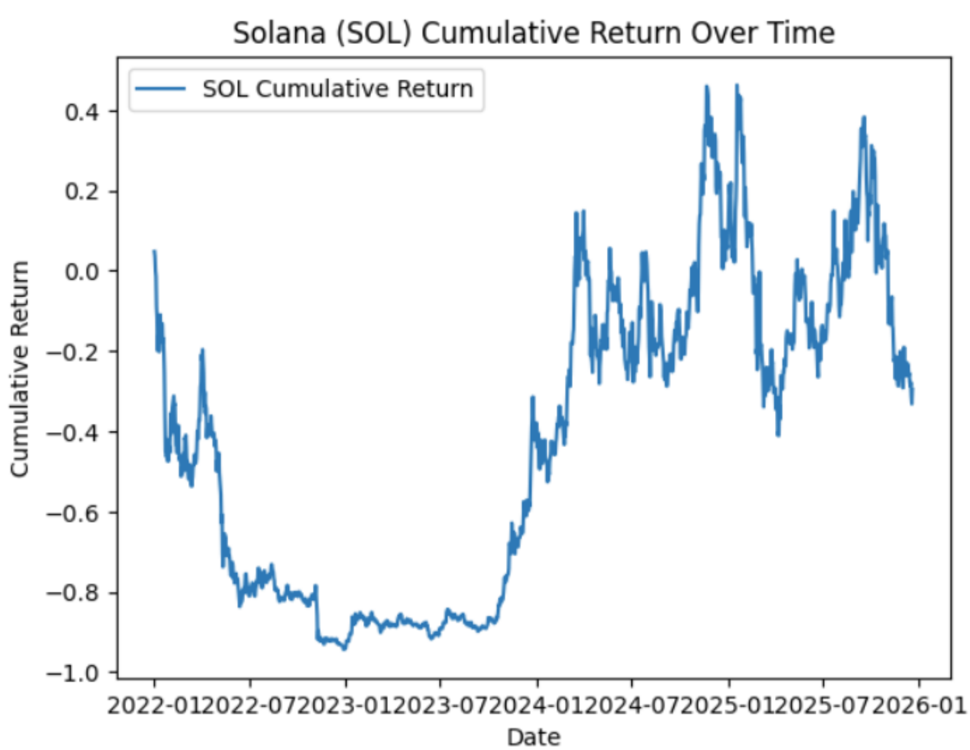
```
print(f"BTC Mean Daily Return: {btc_mean_return * 100:.2f}%")

print(f"BTC Daily Return Std Dev: {btc_std_return * 100:.2f}%")


#Plot cumulative returns to measure the overall performance of each cryptocurrency by calculating the cumulative return over time.

#cumulative_return = (1 + Daily_Return).cumprod() - 1

# Cumulative returns for Solana

sol['Cumulative_Return'] = (1 + sol['Daily_Return']).cumprod() - 1


# Cumulative returns for Bitcoin

btc['Cumulative_Return'] = (1 + btc['Daily_Return']).cumprod() - 1


plt.figure()

plt.plot(sol.index, sol['Cumulative_Return'], label='SOL Cumulative Return')

plt.title('Solana (SOL) Cumulative Return Over Time')

plt.xlabel('Date')

plt.ylabel('Cumulative Return')

plt.legend()

plt.show()


plt.figure()

plt.plot(btc.index, btc['Cumulative_Return'], label='BTC Cumulative Return')

plt.title('Bitcoin (BTC) Cumulative Return Over Time')

plt.xlabel('Date')

plt.ylabel('Cumulative Return')

plt.legend()

plt.show()

#Compute the rolling 30-day volatility &  Plot the rolling volatility of both cryptocurrencies on a single graph
```

```
# 30-day rolling volatility
sol['Rolling_30D_Volatility'] = sol['Daily_Return'].rolling(window=30).std()
btc['Rolling_30D_Volatility'] = btc['Daily_Return'].rolling(window=30).std()


plt.figure()
plt.plot(sol.index, sol['Rolling_30D_Volatility'], label='SOL 30-Day Volatility')
plt.plot(btc.index, btc['Rolling_30D_Volatility'], label='BTC 30-Day Volatility')


plt.title('30-Day Rolling Volatility of Daily Returns')
plt.xlabel('Date')
plt.ylabel('Rolling Volatility (Std Dev of Returns)')
plt.legend()
plt.show()
```

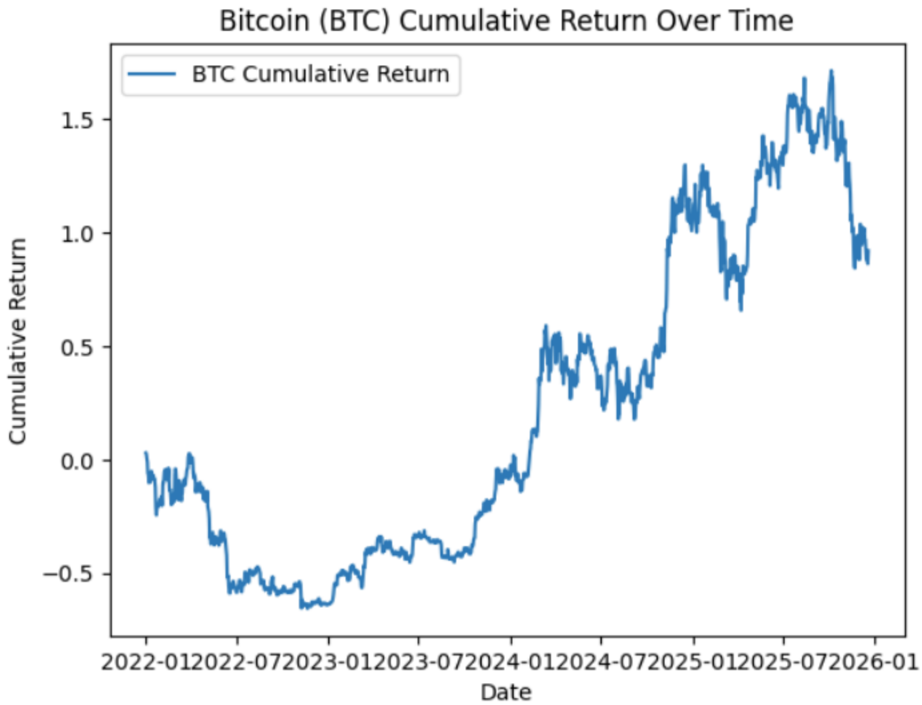
Appendix Figure 14 – Task 4 Comparative Analysis and Advanced Metrics Full Code

```
Solana daily returns (first 5 rows):
Price             Open       Close  Daily_Return
Date
2022-01-01  170.310837  178.517944      0.048189
2022-01-02  178.532410  176.382843     -0.012040
2022-01-03  176.386307  170.297745     -0.034518
2022-01-04  170.286118  167.938904     -0.013784
2022-01-05  167.940338  155.099731     -0.076459

Bitcoin daily returns (first 5 rows):
Price               Open         Close  Daily_Return
Date
2022-01-01  46311.746094  47686.812500      0.029692
2022-01-02  47680.925781  47345.218750     -0.007041
2022-01-03  47343.542969  46458.117188     -0.018702
2022-01-04  46458.851562  45897.574219     -0.012081
2022-01-05  45899.359375  43569.003906     -0.050771

SOL Mean Daily Return: 0.11%
SOL Daily Return Std Dev: 5.12%
BTC Mean Daily Return: 0.08%
BTC Daily Return Std Dev: 2.70%
```

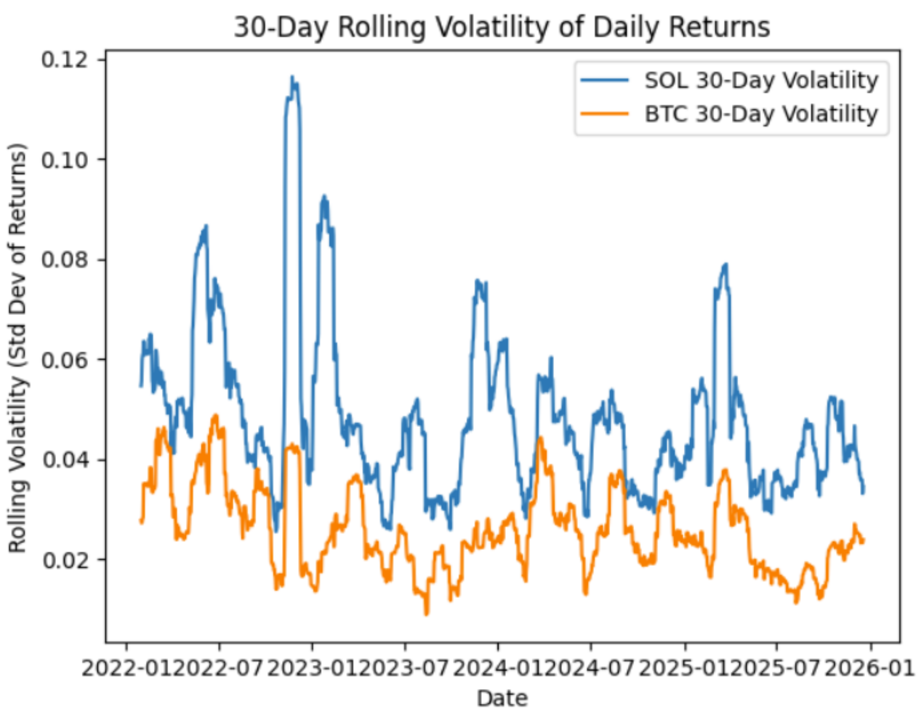
Appendix Figure 15 – Task 4 Daily Returns



Appendix Figure 16 – Task 4 Solana Cumulative Returns



Appendix Figure 17 – Task 4 Bitcoin Cumulative Returns



Appendix Figure 18 – Task 4 30-Day Rolling Volatility of Daily Returns