EXPLORATORY DATA ANALYSIS

APPLE STOCK DATASET

AppleStocks

June 18, 2025

[142]:
```
# Hello Everyone,
# Here We're going to perform an EDA on "Apple Stock Dataset From 2020␣
↪till 2025"
# You can find it here: https://www.kaggle.com/datasets/
↪hardikchhipa28/apple-stock-dataset-from-2020-till-2025/data

# You'll be finding:

# Overview of Apple’s stock data from 2020 to 2025
# Cleaning and Preprocessing
# Time series visualizations for Close, Open, High, and Low prices
# Distribution analysis using histograms and KDE plots
# Feature engineering to create metrics like daily returns,moving␣
↪averages, volatility.
# Extraction of date-based features like year, month, and weekday
# A correlation heatmap to understand relationships between numeric␣
↪variables
```

[143]:
```
# Importing Necessary Libarary

import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

[144]:
```
# Load Dataset
df = pd.read_csv('C:
↪\\Users\\nikrc\\OneDrive\\Desktop\\Datasets\\apple_stocks.csv')

df.head(5)
```

[144]:
```
         Date              Close               High                Low  \
0         NaN               AAPL               AAPL               AAPL
1  2020-06-04  78.32931518554688   79.1312690763083  77.95506657558614
2  2020-06-05  80.56021881103516  80.62097312386399  78.55046881252456
```

```
3  2020-06-08  81.03653717041016  81.07056314819836  79.54441498185327
4  2020-06-09  83.59550476074219  83.98919153470604  80.68416273702039

                Open     Volume
0               AAPL       AAPL
1  78.83236263047952   87560400
2  78.57962969607472  137250400
3  80.25645380649277   95654400
4  80.71575616737768  147712400
```

[145]:
```python
# Checking the data types and shape
df.shape
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1256 entries, 0 to 1255
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    1255 non-null   object
 1   Close   1256 non-null   object
 2   High    1256 non-null   object
 3   Low     1256 non-null   object
 4   Open    1256 non-null   object
 5   Volume  1256 non-null   object
dtypes: object(6)
memory usage: 59.0+ KB
```

[ ]:
```python

```

[146]:
```python
# As we see above that there are fields that are not in right data␣
↪type, We need convert them to their appropriate data type

df['Date'] = pd.to_datetime(df['Date'],format = "%Y-%m-%d",errors =␣
↪"coerce")
cols = ["Close","Open","High","Low","Volume"]
for col in cols:
    df[col] = pd.to_numeric(df[col],errors = "coerce")

# Next we remove any non-numeric data
df = df.dropna()
df["Volume"] = df["Volume"].astype(int).reset_index(drop = True)
df.head()
```

[146]:

	Date	Close	High	Low	Open	Volume
1	2020-06-04	78.329315	79.131269	77.955067	78.832363	137250400.0
2	2020-06-05	80.560219	80.620973	78.550469	78.579630	95654400.0

```
3 2020-06-08  81.036537  81.070563  79.544415  80.256454  147712400.0
4 2020-06-09  83.595505  83.989192  80.684163  80.715756  166651600.0
5 2020-06-10  85.746208  86.215230  84.105842  84.545702  201662400.0
```

[147]:
```python
# Statistical Data
df.describe().T
```

[147]:
```
         count                           mean                  min  \
Date      1255  2022-11-30 12:32:42.071713280  2020-06-04 00:00:00
Close   1255.0                     164.321062            78.329315
High    1255.0                     166.006163            79.131269
Low     1255.0                     162.443943            77.955067
Open    1255.0                     164.160646             78.57963
Volume  1254.0                80774969.457735           23234700.0

                        25%                  50%                  75%  \
Date    2021-08-31 12:00:00  2022-11-29 00:00:00  2024-02-29 12:00:00
Close            136.922234           162.264175           188.222137
High             139.392588           163.728834           189.675969
Low              134.935222           160.141728           186.846649
Open             136.720468           161.654384             188.1025
Volume           52391125.0           70451650.0           95646600.0

                        max              std
Date    2025-06-02 00:00:00              NaN
Close            258.396667        38.179689
High             259.474086        38.364282
Low              257.010028        37.891117
Open             257.568678        38.094942
Volume          374336800.0  41929450.207341
```

[148]:
```python
# Overall, prices have more than tripled from the minimum to maximum
value
```

[149]:
```python
# Finding if any data is missing
df.isna().mean()*100
```

[149]:
```
Date      0.000000
Close     0.000000
High      0.000000
Low       0.000000
Open      0.000000
Volume    0.079681
dtype: float64
```

[150]:
```python
df["Volume"] = df["Volume"].fillna(method = "ffill")
df.isna().mean()*100
```

[150]:
```
Date      0.0
Close     0.0
High      0.0
Low       0.0
Open      0.0
Volume    0.0
dtype: float64
```

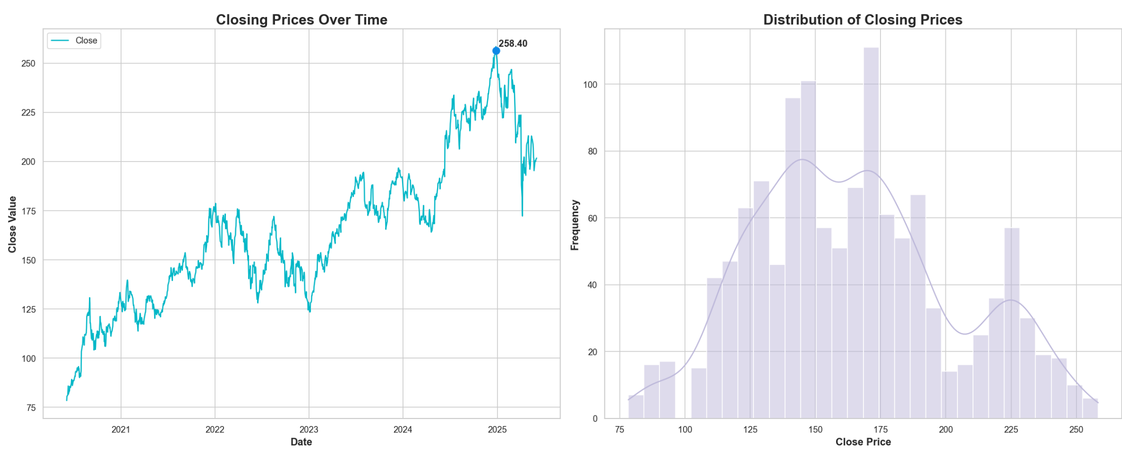
[151]:
```
# Cheching for Duplicates
df.duplicated().mean()*100
```

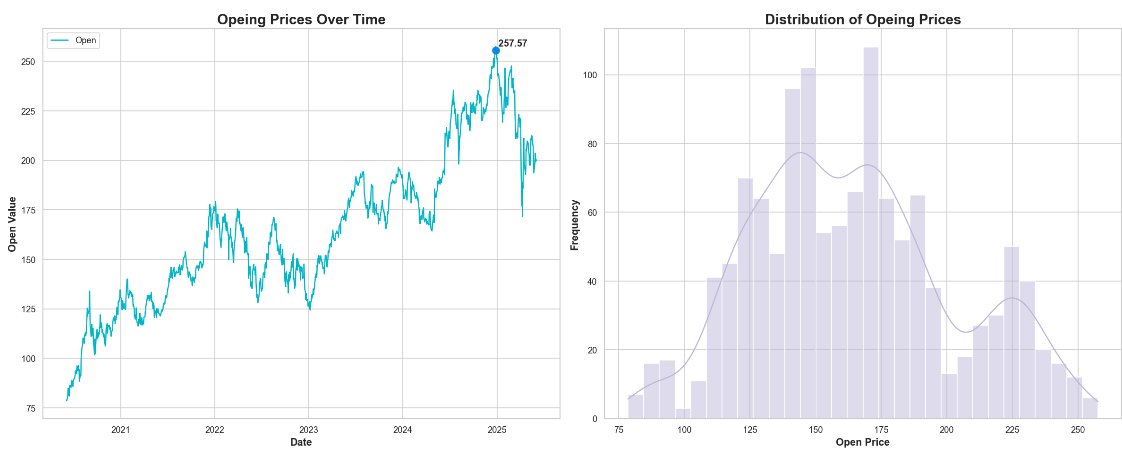
[151]:
```
np.float64(0.0)
```

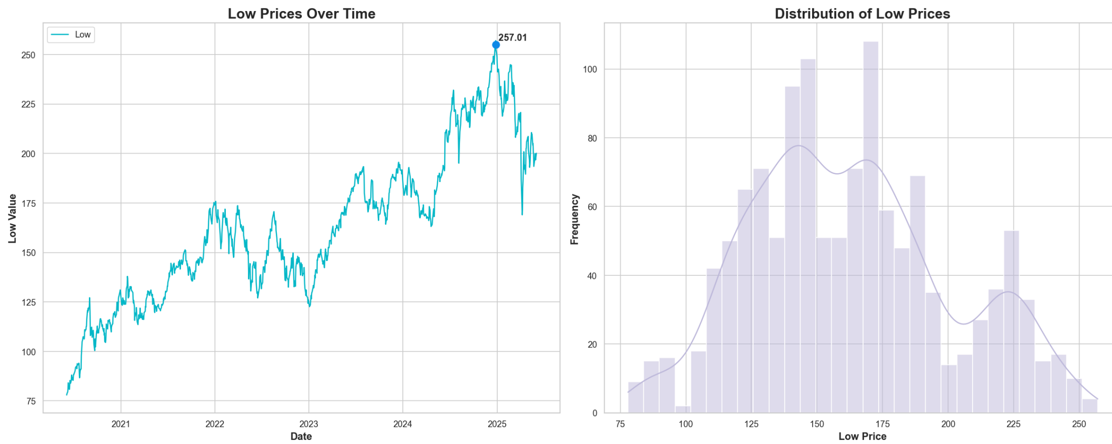
[152]:
```
# We're done with Cleaning the Dataset, Let's start with EDA
```

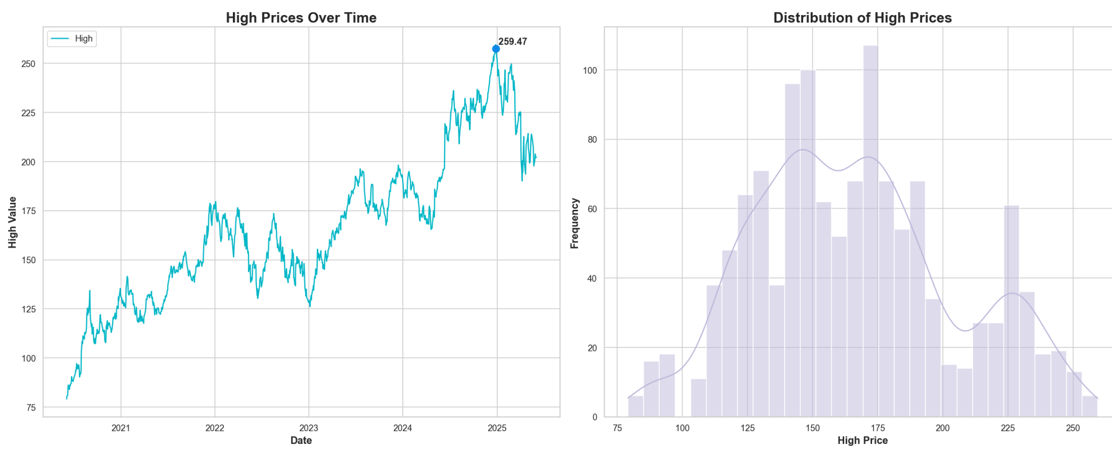
[153]:
```
# Time Series of Close
cols = ["Close","Open","Low","High"]
for col in cols:
    fig,axes = plt.subplots(1,2,figsize = (20,8),dpi = 120)
    sns.lineplot(x = df["Date"],y = df[col],ax = axes[0],color =␣
↪'#00b7c7',label = col)
    axes[0].set_xlabel("Date",fontsize = 13,fontweight = "semibold")
    axes[0].set_ylabel(f"{col} Value",fontsize = 13,fontweight =␣
↪"semibold")
    axes[0].set_title(f"{col[:-1] + 'ing' if col in ['Open', 'Close']␣
↪else col} Prices Over Time",fontsize = 18,fontweight = "bold")
    axes[0].legend()
    axes[0].grid(True)

    max_value = df[col].max()
    max_date = df.loc[df[col] == max_value,"Date"].values[0]
    axes[0].scatter(max_date, max_value - 2, color='#0d88e6', s=80,␣
↪zorder=5, label='Max Close')
    axes[0].annotate(
        f"{max_value: .2f}",
        xy = (max_date,max_value),
        fontsize = 12,
        fontweight ="semibold",
    )



    # Histogram of Closing Price
    sns.histplot(data = df[col],ax = axes[1],kde = True,bins =␣
↪30,color='#beb9db')
```

```
    axes[1].set_ylabel("Frequency",fontsize = 13,fontweight = "semibold")
    axes[1].set_xlabel(f'{col} Price',fontsize = 13,fontweight = "semibold")
    axes[1].set_title(f"Distribution of {col[:-1] + 'ing' if col in ['Open', 'Close'] else col} Prices",fontsize = 18,fontweight = "bold")
    axes[1].grid(True)

    plt.tight_layout()
    plt.show()
```





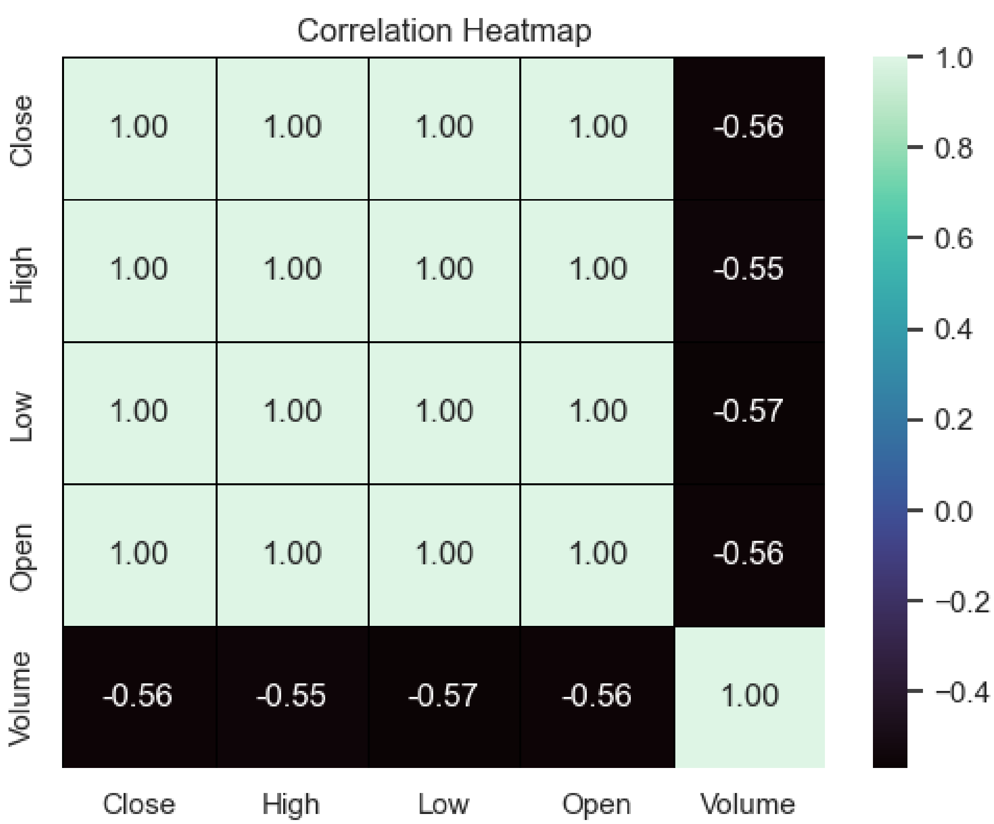


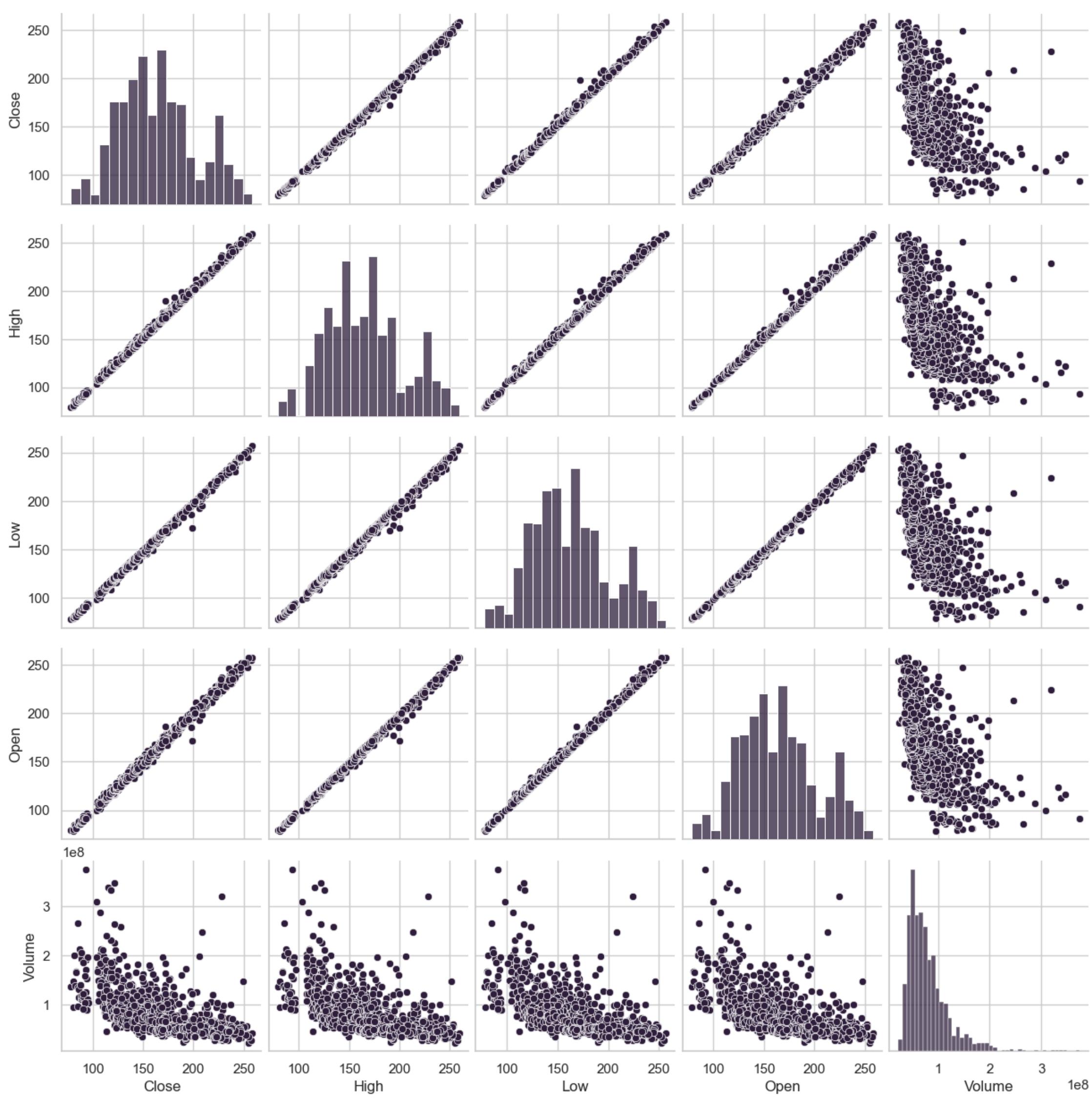


[154]:
```
# Time Series Trends

# For each of Close, Open, High, Low:
# Line charts show a general uptrend with some fluctuations.
# And I've marked Max values using a scatter marker and label.
# Close peaked at ~$258, High and Low followed similar trends.

# Distributions

# All prices (Open, Close,Low and High) show a somewhat normal distribution but slightly right-skewed, meaning more values cluster on the lower end.
# Volume is heavily right-skewed, suggesting a few days with massive trading spikes.
```

[155]:

```
# Correlation Matrix
numeric_df = df.select_dtypes(include = [np.number])
if(numeric_df.shape[1] >= 4):
    corr_matrix = numeric_df.corr()
    sns.heatmap(data = corr_matrix,annot = True,cmap = 'mako',fmt = '.
↪2f',linewidths=0.5,linecolor='black')
    plt.title("Correlation Heatmap")
    plt.grid(True)
    plt.show()
else:
    print('Not enough numeric features for a correlation heatmap.')

# Pairplot for numeric values

sns.set(style="whitegrid", palette="mako")
sns.pairplot(numeric_df)

plt.show()
```

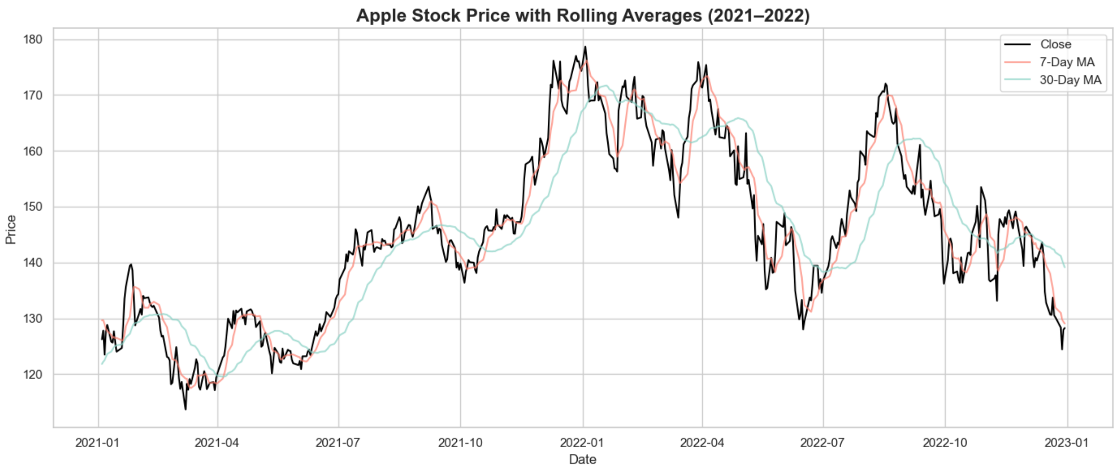




[156]:
```
# Correlation Insights

# A correlation heatmap shows:
# Open, Close, High, Low are strongly correlated (r > 0.95).
# Volume shows a weaker correlation with the price-related features —
  ↪expected, as price doesn't always track with trading volume.

#  Pairplot Insights

# Confirmed linear relationships between price features.
# Showed clear scatter clusters for price comparisons.
# Volume shows spread, not tightly correlated with price metrics.
```

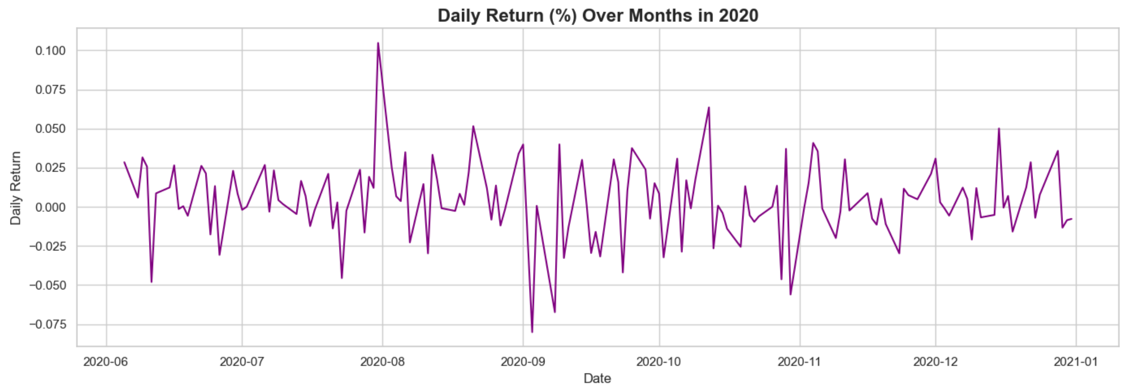
[157]:
```python
# Feature Engineering

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

# Rolling Means(7 Days and 30 Days)
df['MA_7'] = df['Close'].rolling(window = 7).mean()
df['MA_30'] = df['Close'].rolling(window = 30).mean()

# Rolling Volatility
df['Volatility_7'] = df['Close'].rolling(window = 7).std()
df['Volatility_30'] = df['Close'].rolling(window = 30).std()

# Cumulative Return
df['Cumulative Return'] = (1 + df['Daily Return(%)']).cumprod()

# Date Feature
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['Day'] = df['Date'].dt.day
df["Day Of Week"] = df['Date'].dt.dayofweek
```

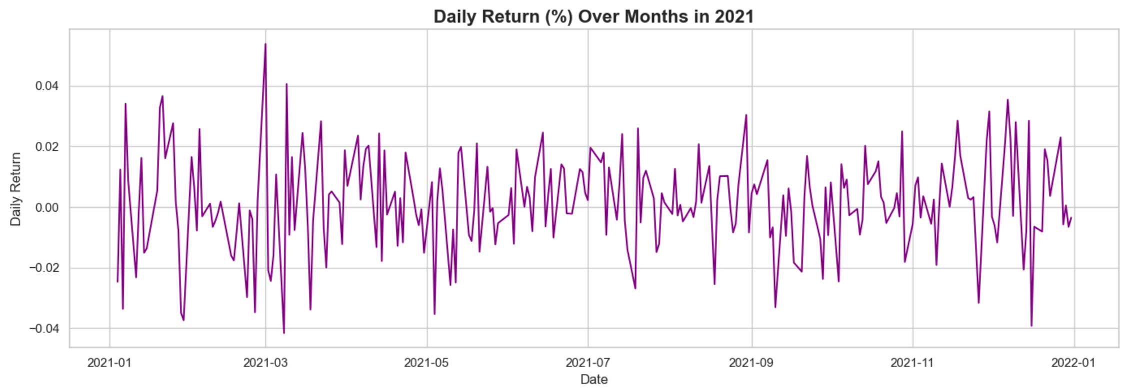
[158]:
```python
df_filtered = df[df['Year'].isin([2021, 2022])]

plt.figure(figsize=(14, 6))
sns.lineplot(x='Date', y='Close', data=df_filtered, label='Close',
    color='black')
sns.lineplot(x='Date', y='MA_7', data=df_filtered, label='7-Day MA',
    color='#fd7f6f', alpha=0.7)
sns.lineplot(x='Date', y='MA_30', data=df_filtered, label='30-Day
    MA', color='#8bd3c7', alpha=0.7)

plt.title("Apple Stock Price with Rolling Averages (2021-2022)",
    fontsize=16, fontweight="bold")
plt.xlabel("Date")
plt.ylabel("Price")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

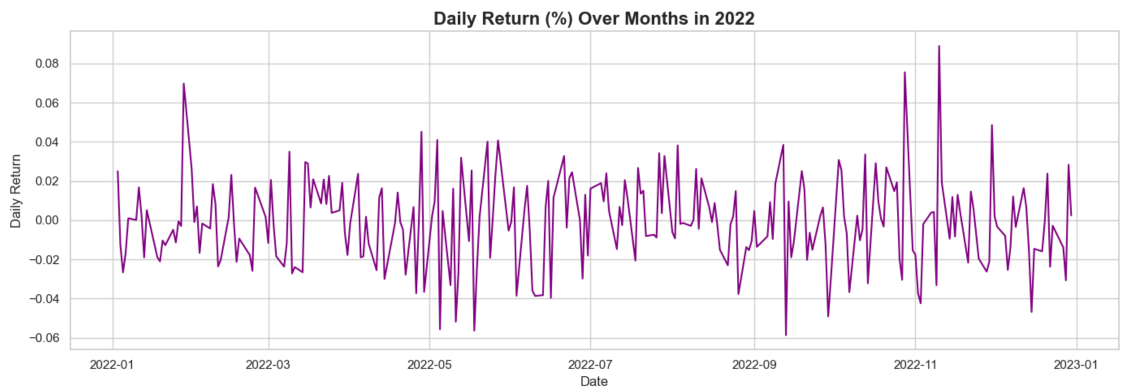


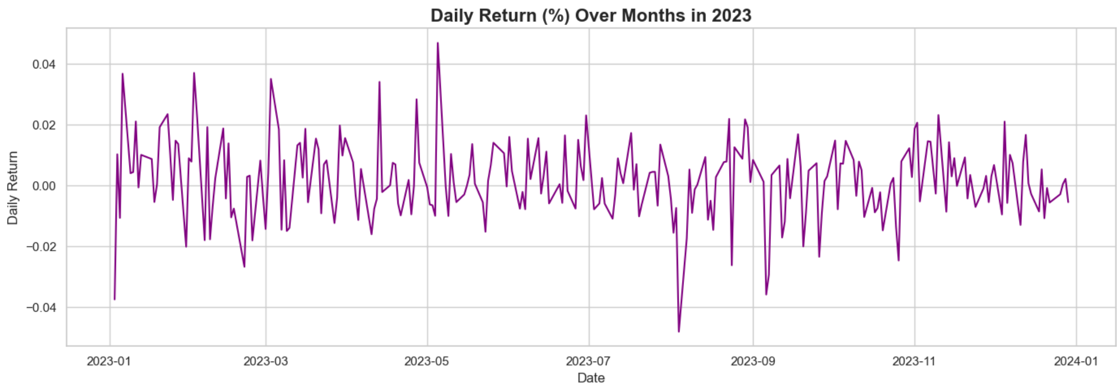
[159]:
```
# Between 2021 and 2022, Apple stock price moved in sync with short-term trends (7-day MA) and stayed slightly above the long-term trend␣
↪(30-day MA) — a sign of steady, healthy upward momentum.
# This likely indicates investor confidence, low short-term␣
↪volatility, and a gradual bullish build-up during that period.
```

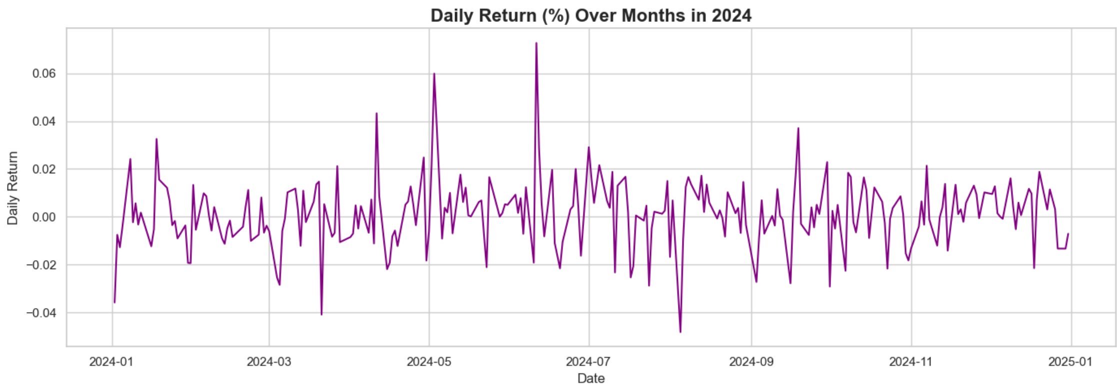
[160]:
```
# Daily Return Plot

for year in df['Year'].unique():
    df_filtered = df[df['Date'].dt.year == year]
    plt.figure(figsize=(14, 5))
    sns.lineplot(x='Date', y='Daily Return(%)', data=df_filtered,␣
↪color='purple')
    plt.title(f"Daily Return (%) Over Months in {year}", fontsize=16,␣
↪fontweight="bold")
    plt.xlabel("Date")
    plt.ylabel("Daily Return")
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

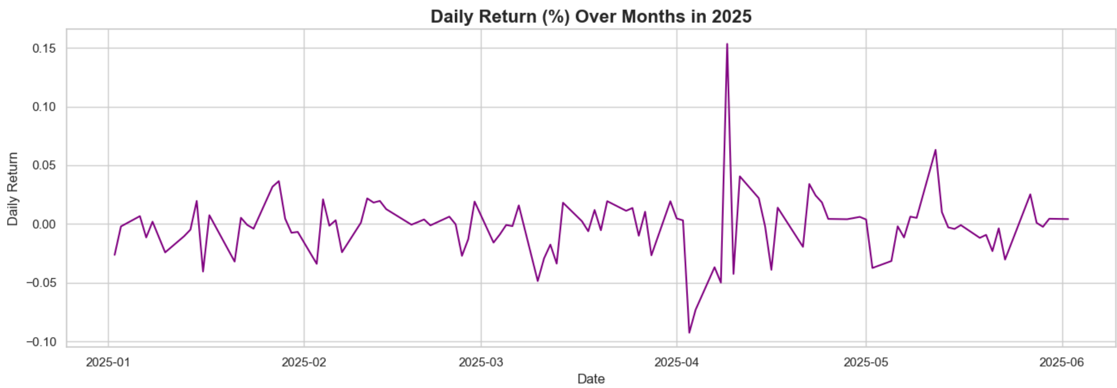

Daily Return (%) Over Months in 2020
Daily Return
Date


Daily Return (%) Over Months in 2021
Daily Return
Date


Daily Return (%) Over Months in 2022
Daily Return
Date







[161]:
```
# In 2020, Apple stock exhibited extreme daily returns, including a
  ↪100% spike, likely caused by high market volatility, major events
  ↪like COVID, and possibly a stock split in August.
# Daily returns smoothed out in later years (2022-2025), signaling
  ↪more market stability and less speculative movement.
```

[162]:
```python
plt.figure(figsize=(14, 5))
sns.lineplot(x='Date', y='Cumulative Return', data=df, color='seagreen')
plt.title("Cumulative Return Since 2020", fontsize=16, fontweight="bold")
plt.xlabel("Date")
plt.ylabel("Cumulative Return (Relative Growth)")
plt.grid(True)
plt.tight_layout()
plt.show()
```

[163]:
```python
# Tripled investment: From 1.0 to ~3.0 at the peak → 200% growth over 5 years.
# Market cycles are clear: growth → correction → rebound.
# The chart reflects Apple’s strength as a long-term investment, despite short-term volatility.
# Highlights why holding long-term pays off, but also shows why timing and diversification matter.
```

[164]:
```python
# This marks the end of the Exploratory Data Analysis (EDA) for the "Apple Stock Dataset from 2020 to 2025".
# I hope this deep dive helped you understand how Apple's stock has evolved over the years — from trends and volatility to cumulative returns and engineered insights.

# I genuinely hope the analysis was insightful, and that I was able to provide value throughout this exploration.
# Your feedback and suggestions are always welcome — I’d truly appreciate them as I continue learning and improving.

# Thank you!
```