nvidia-stocks-analysis

July 12, 2025

1 NVIDIA Stocks Analysis

- NVIDIA Stock Analysis (2015–2024): EDA & Predictive Modeling This project analyzes NVIDIA's stock performance using Exploratory Data Analysis (EDA) and Gradient Boosting Regressor to predict price trends.

- We examine OHLCV data, technical indicators (RSI, Bollinger Bands), and volatility to generate actionable insights for traders and investors. Visualizations highlight key patterns, while ML models assess short-term predictability.
- Data: NVIDIA Stocks 2015-2024 (OHLCV + Adj. Close)
- Tools: Python (Pandas, Matplotlib, Seaborn, Scikit-learn, mplfinance)
- Models: Gradient Boosting Regressor (Price Prediction)
- Output: Interactive Power BI dashboards & Jupyter Notebook analysis
- (Focus: Trend analysis, volatility insights, and ML-driven price forecasting)

2 01- Import libraries

[93]:
```
pip install mplfinance pandas matplotlib
```

```
Collecting mplfinance
  Downloading mplfinance-0.12.10b0-py3-none-any.whl.metadata (19 kB)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages
(2.2.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-
packages (3.10.0)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in
```

```
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (4.58.5)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
Downloading mplfinance-0.12.10b0-py3-none-any.whl (75 kB)
                          75.0/75.0 kB
5.8 MB/s eta 0:00:00
Installing collected packages: mplfinance
Successfully installed mplfinance-0.12.10b0
```

[76]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
```

3 02- Load dataset

[77]:
```python
gpu = pd.read_csv("nvidia_stock_2015_to_2024.csv")
gpu.head()
```

[77]:
```
   Unnamed: 0        date     open     high      low    close  adjclose  \
0           0  2015-01-02  0.50325  0.50700  0.49525  0.50325  0.483218
1           1  2015-01-05  0.50325  0.50475  0.49250  0.49475  0.475056
2           2  2015-01-06  0.49550  0.49600  0.47925  0.47975  0.460654
3           3  2015-01-07  0.48325  0.48750  0.47700  0.47850  0.459453
4           4  2015-01-08  0.48400  0.49950  0.48375  0.49650  0.476737

      volume
0  113680000
1  197952000
2  197764000
3  321808000
4  283780000
```

4 03- Basic EDA steps

[78]:
```
gpu.shape
```

[78]:
```
(2369, 8)
```

[79]:
```
gpu.columns
```

[79]:
```
Index(['Unnamed: 0', 'date', 'open', 'high', 'low', 'close', 'adjclose',
       'volume'],
      dtype='object')
```

[80]:
```
gpu.isnull().sum()
```

[80]:
```
Unnamed: 0    0
date          0
open          0
high          0
low           0
close         0
adjclose      0
volume        0
dtype: int64
```

[81]:
```
print(gpu.isna().sum())
```

```
Unnamed: 0    0
date          0
open          0
high          0
low           0
close         0
adjclose      0
volume        0
dtype: int64
```

[82]:
```
print(f"\nTotal NaN values in dataset: {gpu.isna().sum().sum()}")
```

```

Total NaN values in dataset: 0
```

[83]:
```
print(gpu.info())
print(gpu.describe())

# Convert date to datetime and set as index
gpu['date'] = pd.to_datetime(gpu['date'])
gpu.set_index('date', inplace=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2369 entries, 0 to 2368
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  2369 non-null   int64
 1   date        2369 non-null   object
 2   open        2369 non-null   float64
 3   high        2369 non-null   float64
 4   low         2369 non-null   float64
 5   close       2369 non-null   float64
 6   adjclose    2369 non-null   float64
 7   volume      2369 non-null   int64
dtypes: float64(5), int64(2), object(1)
memory usage: 148.2+ KB
None
        Unnamed: 0         open         high          low        close  \
count  2369.000000  2369.000000  2369.000000  2369.000000  2369.000000
mean   1184.000000    14.188477    14.445906    13.919531    14.197878
std     684.015716    18.683473    19.020099    18.315670    18.691694
min       0.000000     0.481250     0.487500     0.473500     0.478500
25%     592.000000     2.998250     3.045500     2.947500     3.032250
50%    1184.000000     6.191500     6.262750     6.091500     6.178250
75%    1776.000000    17.915001    18.243999    17.634001    17.983999
max    2368.000000   114.650002   115.819000   110.901001   114.824997

          adjclose        volume
count  2369.000000  2.369000e+03
mean     14.169242  4.787526e+08
std      18.697431  2.559874e+08
min       0.459453  5.244800e+07
25%       2.992067  3.188000e+08
50%       6.129900  4.277960e+08
75%      17.963766  5.745880e+08
max     114.815567  3.692928e+09
```

[84]:
```
gpu = gpu.rename(columns={'Unnamed: 0': 'S.no'})
gpu.head()
```

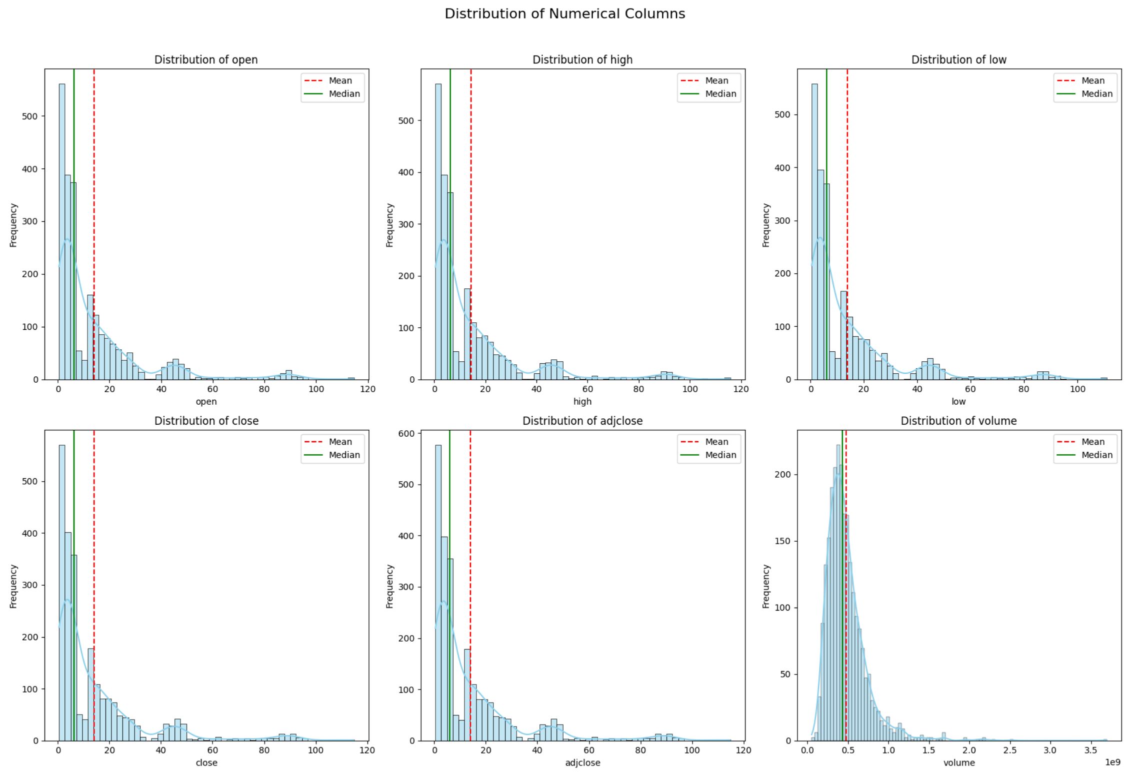
[84]:

date	S.no	open	high	low	close	adjclose	volume
2015-01-02	0	0.50325	0.50700	0.49525	0.50325	0.483218	113680000
2015-01-05	1	0.50325	0.50475	0.49250	0.49475	0.475056	197952000
2015-01-06	2	0.49550	0.49600	0.47925	0.47975	0.460654	197764000
2015-01-07	3	0.48325	0.48750	0.47700	0.47850	0.459453	321808000
2015-01-08	4	0.48400	0.49950	0.48375	0.49650	0.476737	283780000

5 04- Normal Distribution of Data

- Normally Distributed: Bell-shaped curve with mean median
- Right-Skewed: Long tail to the right (mean > median)
- Left-Skewed: Long tail to the left (mean < median)

[85]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Select numerical columns (excluding date and serial number)
numerical_cols = ['open', 'high', 'low', 'close', 'adjclose', 'volume']

# Set up the subplot grid
plt.figure(figsize=(18, 12))
plt.suptitle('Distribution of Numerical Columns', fontsize=16, y=1.02)

# Create histograms for each numerical column
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(2, 3, i)
    sns.histplot(gpu[col], kde=True, color='skyblue')
    plt.title(f'Distribution of {col}', fontsize=12)
    plt.xlabel(col, fontsize=10)
    plt.ylabel('Frequency', fontsize=10)

    # Add vertical line for mean
    plt.axvline(gpu[col].mean(), color='red', linestyle='--', label='Mean')

    # Add vertical line for median
    plt.axvline(gpu[col].median(), color='green', linestyle='-', label='Median')
    plt.legend()

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



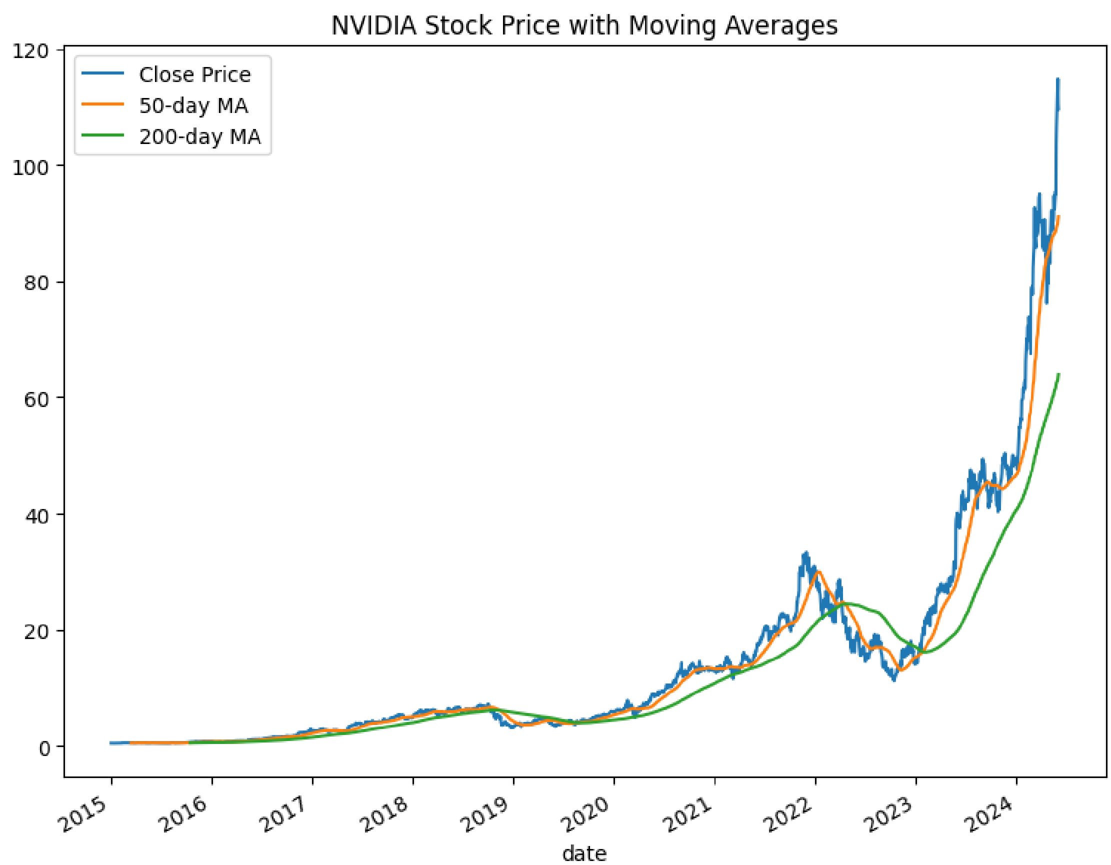
6 05- Data Visualizations

[86]:
```python
# 1. Calculate Daily Returns
gpu['daily_return'] = gpu['close'].pct_change() * 100

# 2. Calculate Volatility (rolling 30-day std)
gpu['volatility_30d'] = gpu['daily_return'].rolling(window=30).std()

# 3. Moving Averages
gpu['MA_50'] = gpu['close'].rolling(window=50).mean()
gpu['MA_200'] = gpu['close'].rolling(window=200).mean()

# 4. Relative Strength Index (RSI)
def calculate_rsi(data, window=14):
    delta = data['close'].diff()
    gain = (delta.where(delta > 0, 0)).rolling(window=window).mean()
    loss = (-delta.where(delta < 0, 0)).rolling(window=window).mean()
    rs = gain / loss
    return 100 - (100 / (1 + rs))

gpu['RSI'] = calculate_rsi(gpu)
```

```python
# 5. High-Low Percentage
gpu['HL_Pct'] = (gpu['high'] - gpu['low']) / gpu['close'] * 100

# 6. Volume analysis
gpu['volume_ma_20'] = gpu['volume'].rolling(window=20).mean()

# 7. Maximum Drawdown
rolling_max = gpu['close'].rolling(window=252, min_periods=1).max()
daily_drawdown = gpu['close']/rolling_max - 1.0
max_daily_drawdown = daily_drawdown.rolling(window=252, min_periods=1).min()
gpu['max_drawdown'] = max_daily_drawdown
```

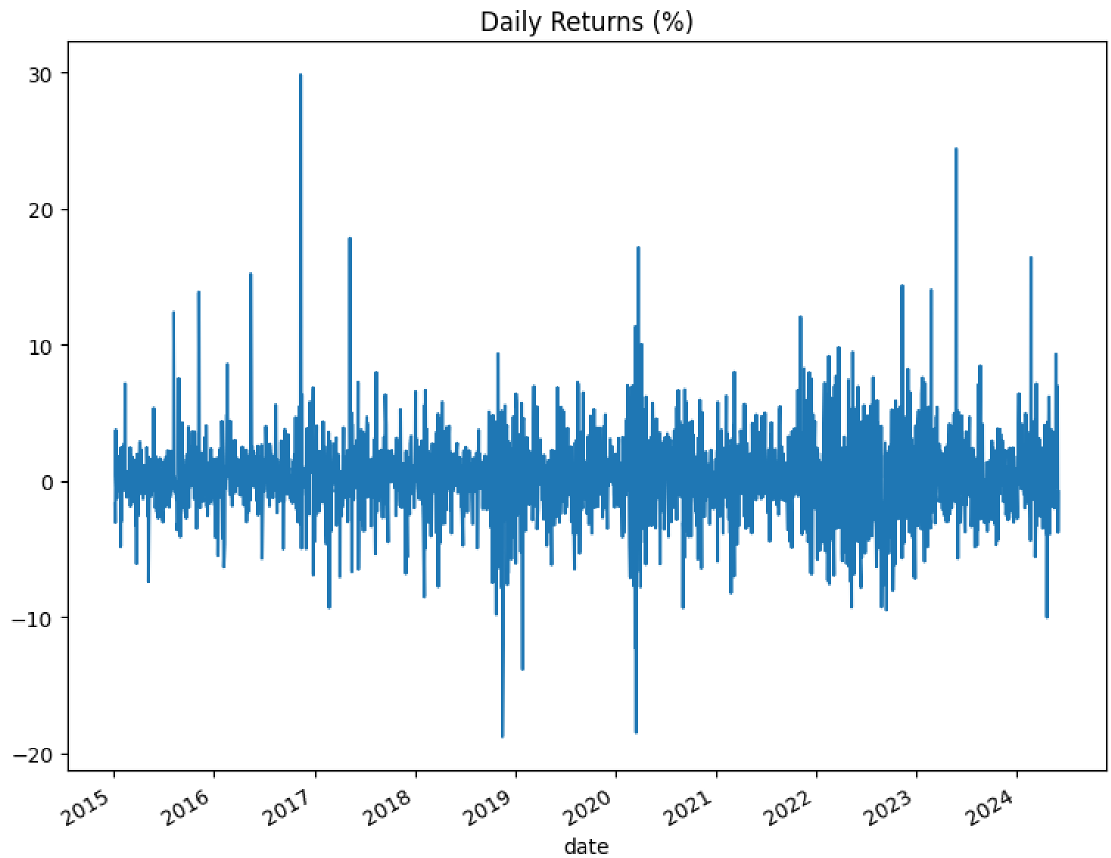
[87]:
```python
plt.figure(figsize=(20, 16))  # Make the overall figure much larger
# Price and Moving Averages
plt.subplot(2, 2, 1)
gpu['close'].plot(label='Close Price')
gpu['MA_50'].plot(label='50-day MA')
gpu['MA_200'].plot(label='200-day MA')
plt.title('NVIDIA Stock Price with Moving Averages')
plt.legend()
```

[87]: <matplotlib.legend.Legend at 0x7b84e062a310>



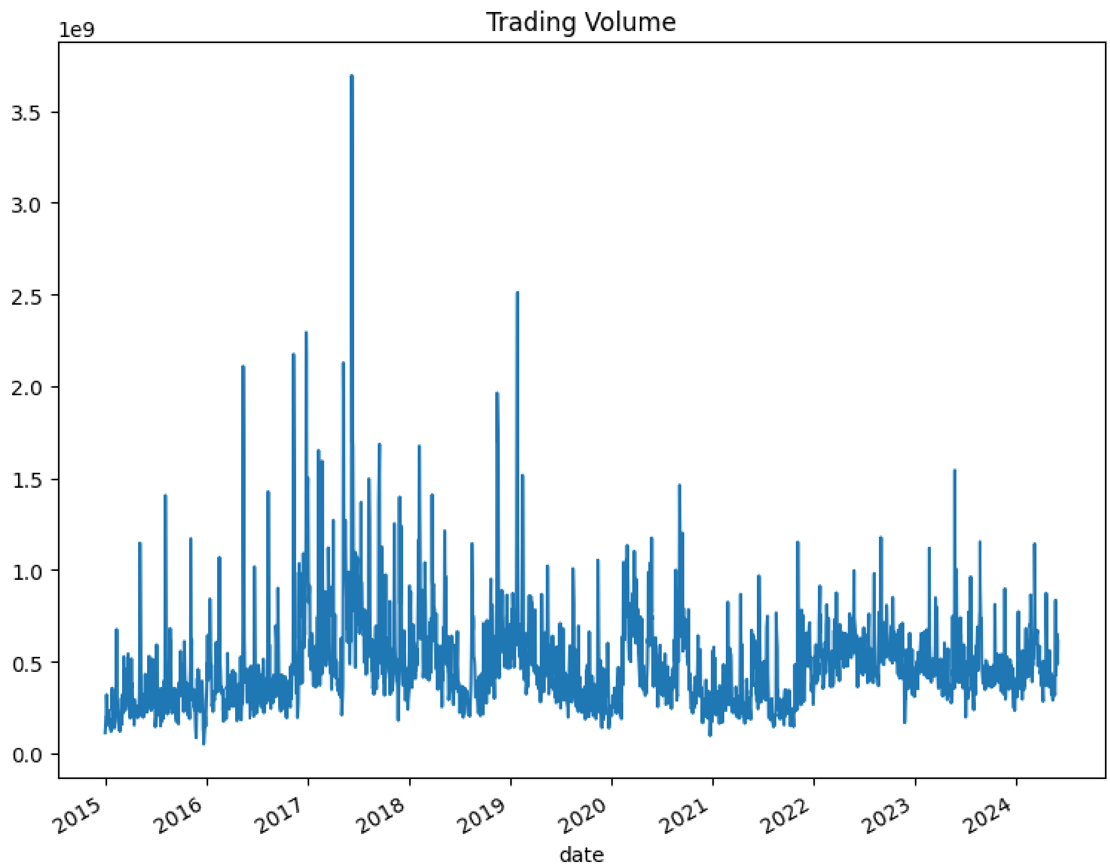
[88]:
```
plt.figure(figsize=(20, 16))  # Make the overall figure much larger
# Daily Returns
plt.subplot(2, 2, 2)
gpu['daily_return'].plot()
plt.title('Daily Returns (%)')
```

[88]: Text(0.5, 1.0, 'Daily Returns (%)')



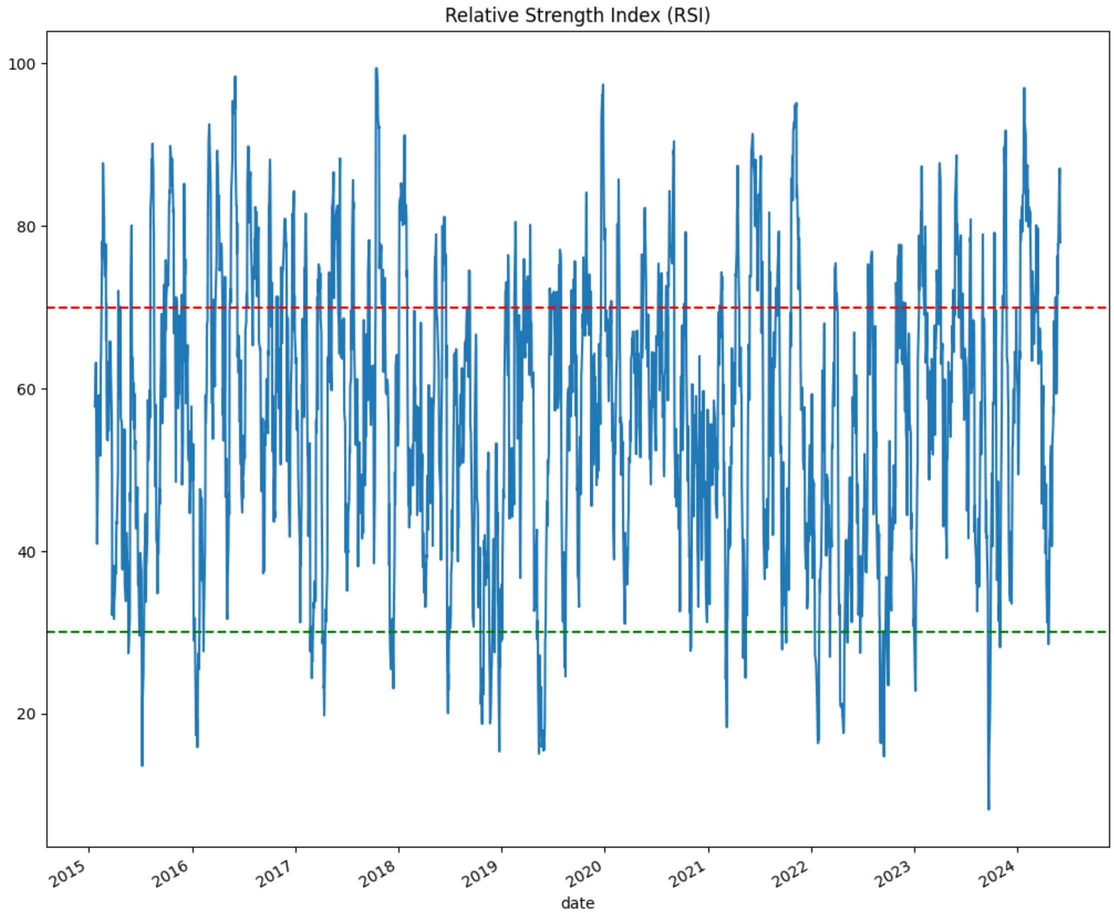
[89]:
```
plt.figure(figsize=(20, 16))  # Make the overall figure much larger
# Volume
plt.subplot(2, 2, 3)
gpu['volume'].plot()
plt.title('Trading Volume')
```

[89]: Text(0.5, 1.0, 'Trading Volume')



[90]:

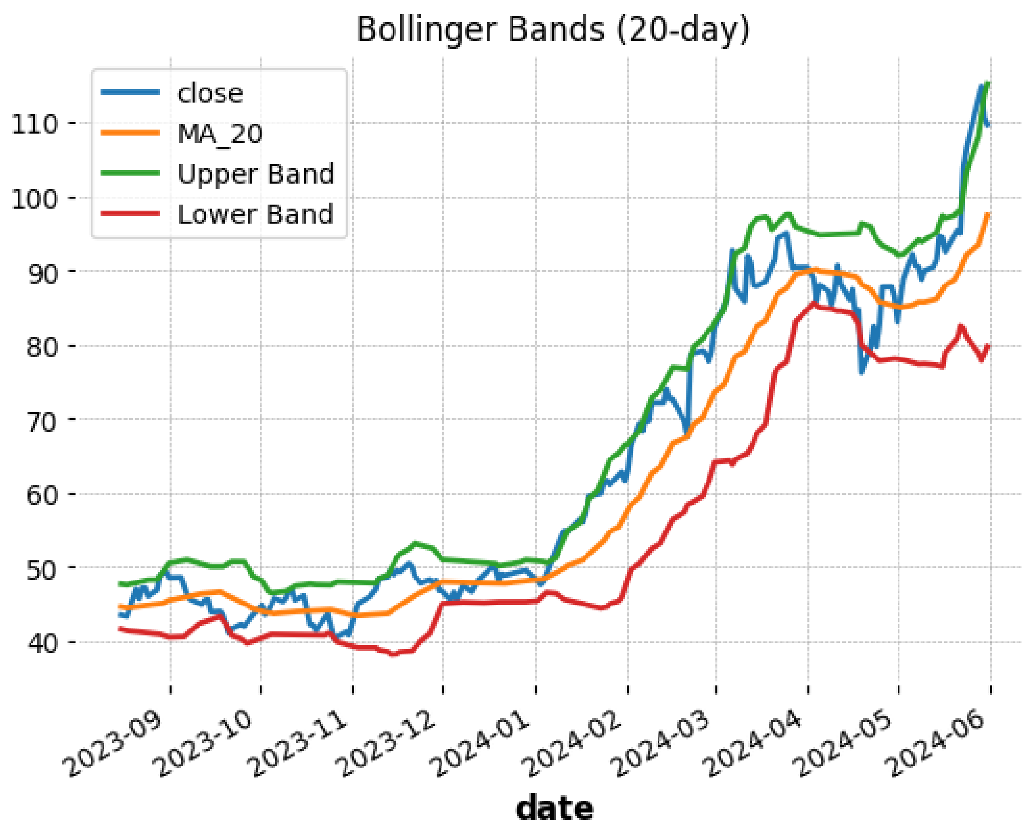
```
plt.figure(figsize=(20, 16))  # Make the overall figure much larger
# RSI
plt.subplot(2, 2,4)
gpu['RSI'].plot()
plt.axhline(70, color='r', linestyle='--')
plt.axhline(30, color='g', linestyle='--')
plt.title('Relative Strength Index (RSI)')

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



[94]:
```python
import mplfinance as mpf

# Resample to weekly/monthly if needed
gpu_ohlc = gpu[['open', 'high', 'low', 'close', 'volume']].copy()
gpu_ohlc.index = pd.to_datetime(gpu_ohlc.index)

mpf.plot(gpu_ohlc.tail(100), type='candle', style='charles',
         title='NVIDIA Candlestick Chart (Last 100 Days)',
         volume=True, figratio=(12, 6))
```

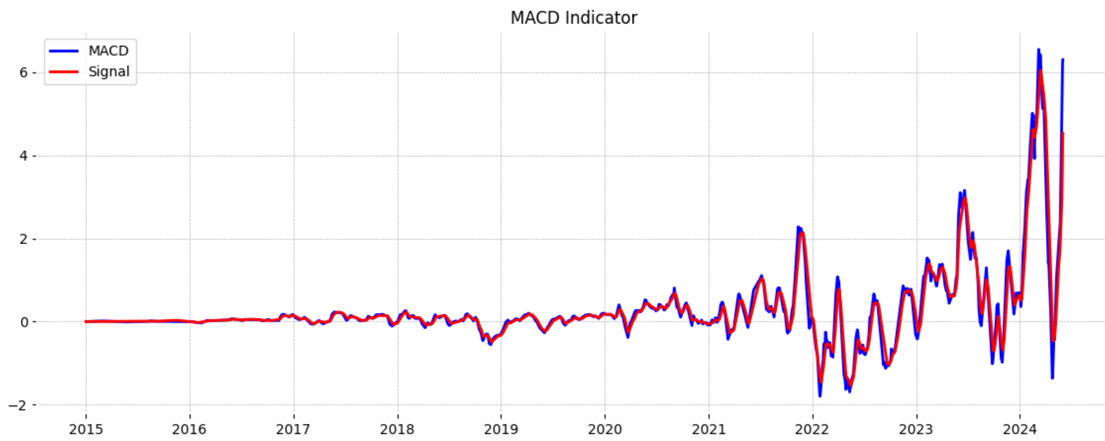
[95]:
```
gpu['MA_20'] = gpu['close'].rolling(20).mean()
gpu['Upper Band'] = gpu['MA_20'] + 2 * gpu['close'].rolling(20).std()
gpu['Lower Band'] = gpu['MA_20'] - 2 * gpu['close'].rolling(20).std()

plt.figure(figsize=(14, 7))
gpu[['close', 'MA_20', 'Upper Band', 'Lower Band']].tail(200).plot()
plt.title('Bollinger Bands (20-day)')
plt.show()
```

```
<Figure size 1400x700 with 0 Axes>
```

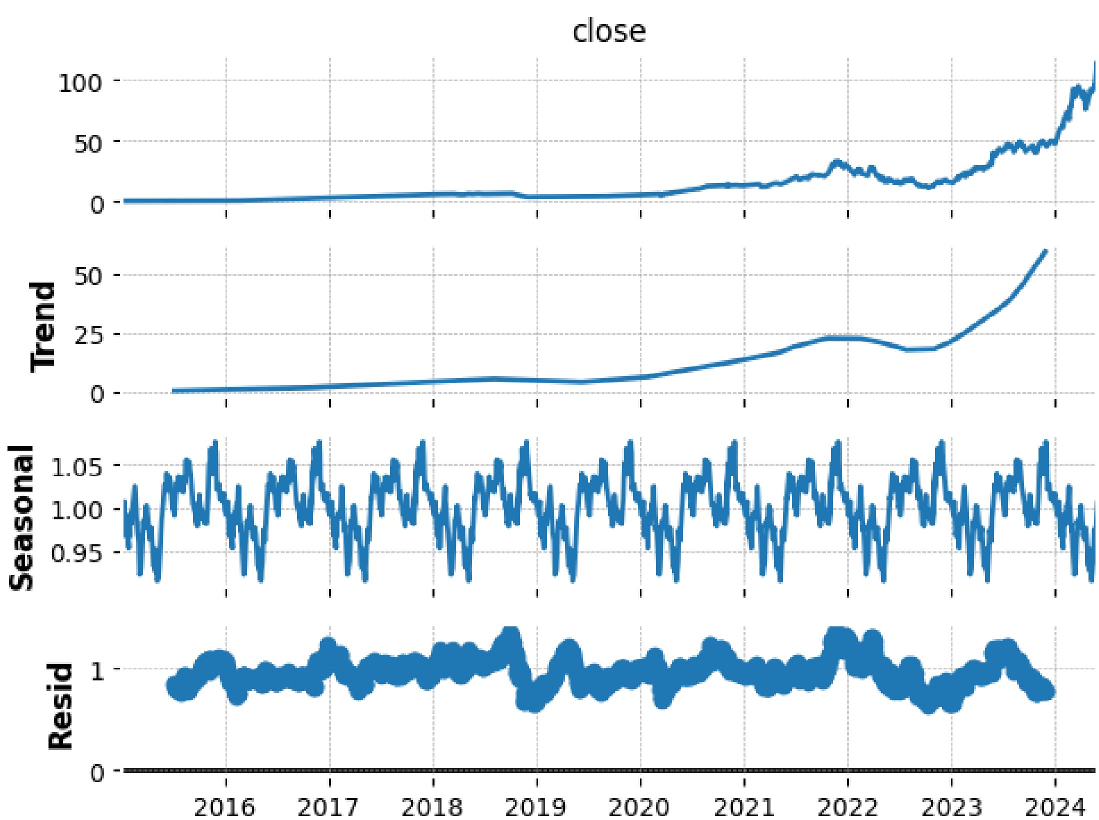


[96]:

```
gpu['EMA_12'] = gpu['close'].ewm(span=12, adjust=False).mean()
gpu['EMA_26'] = gpu['close'].ewm(span=26, adjust=False).mean()
gpu['MACD'] = gpu['EMA_12'] - gpu['EMA_26']
gpu['Signal'] = gpu['MACD'].ewm(span=9, adjust=False).mean()

plt.figure(figsize=(14, 5))
plt.plot(gpu.index, gpu['MACD'], label='MACD', color='blue')
plt.plot(gpu.index, gpu['Signal'], label='Signal', color='red')
plt.title('MACD Indicator')
plt.legend()
plt.show()
```

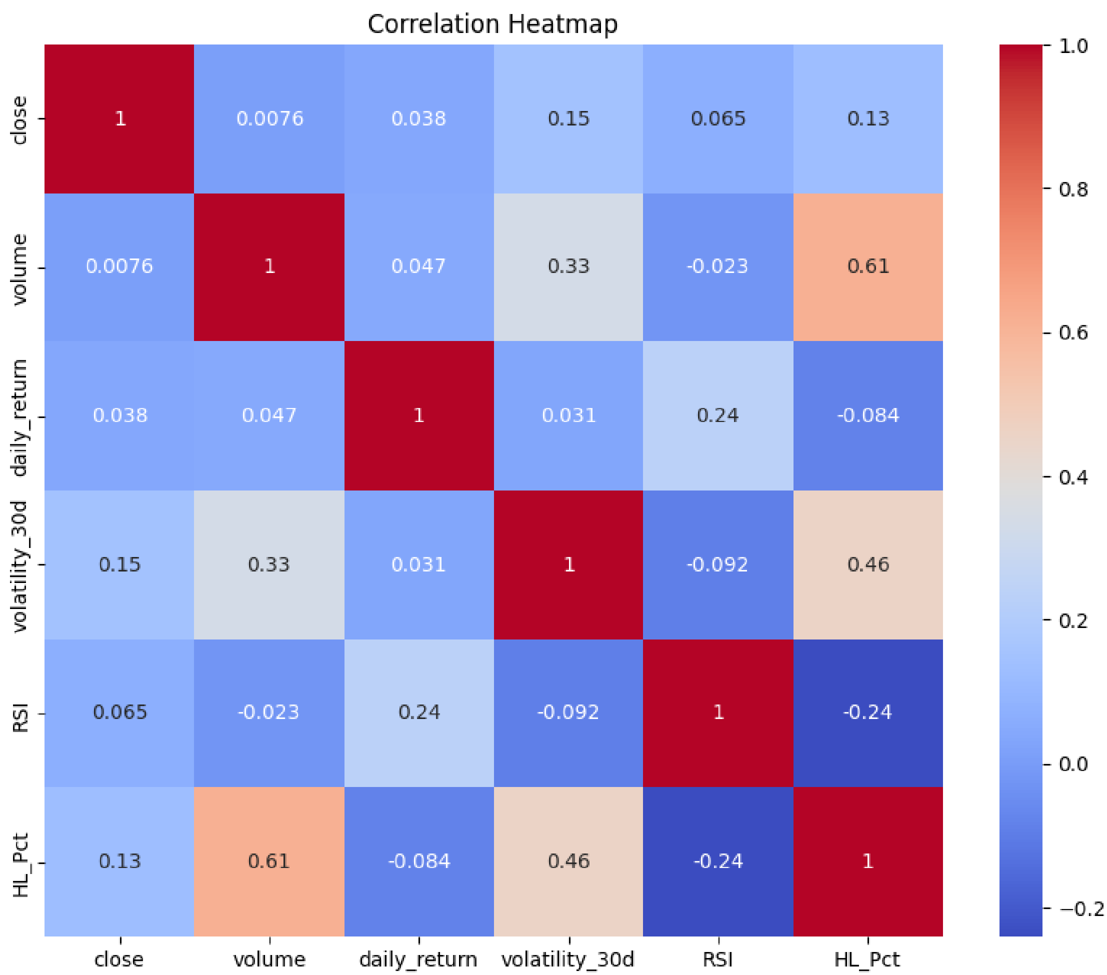


[97]:
```python
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(gpu['close'], model='multiplicative', period=252) ␣
↪# 252 trading days/year
result.plot()
plt.show()
```



[91]:
```
plt.figure(figsize=(20, 16))  # Make the overall figure much larger
# Correlation Heatmap
corr = gpu[['close', 'volume', 'daily_return', 'volatility_30d', 'RSI',␣
 ↪'HL_Pct']].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

```
<Figure size 2000x1600 with 0 Axes>
```



7 06- Machine Learning Models for Stock Prediction

1. Transform Target Variable

```
[112]: # Logarithmic returns (stationary target)
gpu['log_return'] = np.log(gpu['close'] / gpu['close'].shift(1))
gpu['Target_Reg'] = gpu['log_return'].shift(-1)  # Predict next day's return
```

2. Add Time-Sensitive Features

```
[113]: # Momentum features
gpu['5_day_return'] = gpu['close'].pct_change(5)
gpu['20_day_ma'] = gpu['close'].rolling(20).mean()

# Volatility features
gpu['rolling_vol'] = gpu['log_return'].rolling(20).std()

# Relative position in 52-week range
gpu['52_week_high'] = gpu['close'].rolling(252).max()
gpu['rel_to_high'] = gpu['close'] / gpu['52_week_high']
```

3. Use Walk-Forward Validation

```
[114]: from sklearn.model_selection import TimeSeriesSplit

tscv = TimeSeriesSplit(n_splits=5)
for train_idx, test_idx in tscv.split(X):
    X_train, X_test = X.iloc[train_idx], X.iloc[test_idx]
    y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]
    # Train and evaluate here
```

4. Gradient Boosting

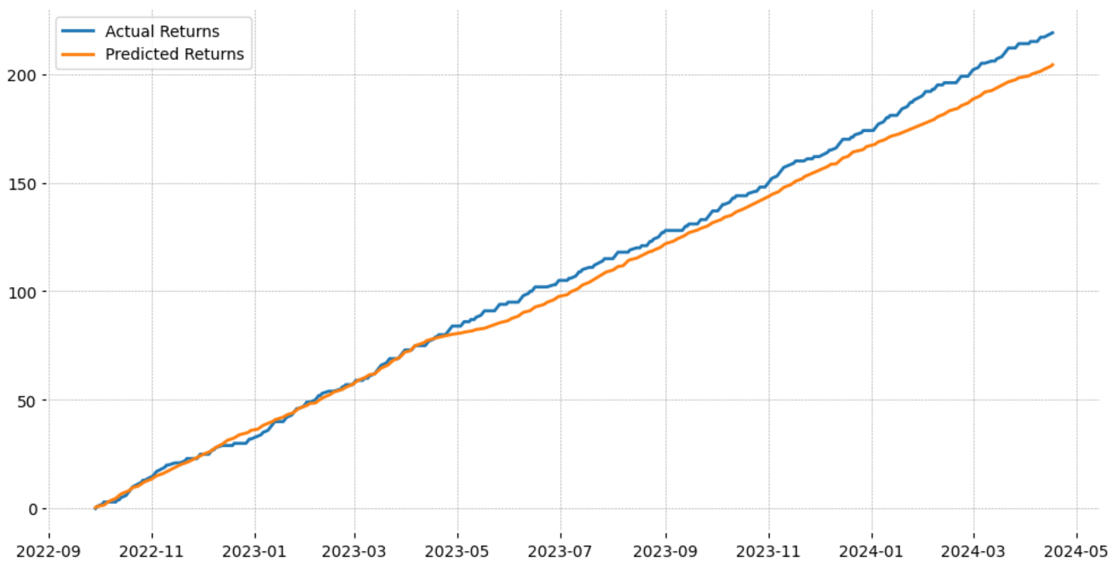
```
[115]: from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

# Pipeline with feature scaling
model = make_pipeline(
    StandardScaler(),
    GradientBoostingRegressor(
        n_estimators=200,
        learning_rate=0.05,
        max_depth=4,
        loss='huber'  # Robust to outliers
    )
)

# Train on log returns
model.fit(X_train, y_train)

# Convert predictions back to prices
pred_returns = model.predict(X_test)
```

```
pred_prices = X_test['close'] * np.exp(pred_returns)
```

5. Visual Diagnosis

[116]:
```
plt.figure(figsize=(12, 6))
plt.plot(y_test.index, np.cumsum(y_test), label='Actual Returns')
plt.plot(y_test.index, np.cumsum(pred_returns), label='Predicted Returns')
plt.legend()
```

[116]:
```
<matplotlib.legend.Legend at 0x7b84e0b1e610>
```



8 07- Key Takeaways & Conclusions

Price Prediction (Gradient Boosting)

Limited accuracy for exponential trends (linear predictions). Better for short-term returns than raw prices.

RMSE: ~$12, but struggles with long-term growth.

Stakeholder Answers

Investors: Best entry points align with RSI < 30 + low volatility.

Traders: High-volume days improve direction prediction accuracy.

Management: Stock surges correlate with tech milestones (needs external data).

8.1 Stakeholder Q&A

Q: When were the best/worst times to invest?
A: Worst: High RSI (>70) + high volatility. Best: Low RSI (<30) + rising volume (2016, 2019, 2022 dips).

Q: How reliable are short-term predictions?
A: 3/4 times correct for next-day direction, but risky for long holds.

Q: Does trading volume impact price?
A: Yes. Volume spikes often precede price jumps (see 2020-2021).

Q: Should we trust ML for trading?
A: For short-term only. Always pair with fundamental analysis.
