Tesla Stock Data Columns Description

This dataset contains historical Tesla stock trading information. Below is a description of each column:

- **date**: The date of the trading session in the format YYYY-MM-DD.
- **open**: The price at which Tesla's stock started trading at the beginning of the trading session.
- **high**: The highest price Tesla's stock reached during the trading session.
- **low**: The lowest price Tesla's stock reached during the trading session.
- **close**: The price at which Tesla's stock ended trading at the close of the trading session.
- **volume**: The total number of Tesla shares traded during the trading session.
- **adjusted_close**: The closing price adjusted for any stock splits and dividends, providing a more accurate reflection of the stock's value over time.
- **change_percent**: The percentage change in the closing price compared to the previous trading day. This indicates daily price movement as a percentage.
- **avg_vol_20d**: The 20-day moving average of the trading volume. This shows the average number of Tesla shares traded daily over the last 20 trading sessions.

DATASET LOADING

importing

In [6]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import statsmodels.api as sm
```

In [7]:
```
TS = pd.read_csv('tesla_2010to2024.csv')
```

In [8]:
```
TS.tail()
```

Out[8]:

	date	open	high	low	close	volume	adjusted_close	change_percer
3467	2024-04-09	172.91	179.2200	171.9200	176.88	103232703	176.88	2.2
3468	2024-04-10	173.04	174.9300	170.0100	171.76	84532406	171.76	-2.8
3469	2024-04-11	172.55	175.8800	168.5100	174.60	94515992	174.60	1.6
3470	2024-04-12	172.34	173.8099	170.3644	171.05	64722672	171.05	-2.0
3471	2024-04-15	170.24	170.6900	161.3800	161.48	100245310	161.48	-5.5

Success: This box indicates a successful action.

OVERVIEW OF DATASET

In [12]:
```
TS.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3472 entries, 0 to 3471
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   date            3472 non-null   object
 1   open            3472 non-null   float64
 2   high            3472 non-null   float64
 3   low             3472 non-null   float64
 4   close           3472 non-null   float64
 5   volume          3472 non-null   int64
 6   adjusted_close  3472 non-null   float64
 7   change_percent  3471 non-null   float64
 8   avg_vol_20d     3453 non-null   float64
dtypes: float64(7), int64(1), object(1)
memory usage: 244.3+ KB
```

so **2** action requires here from

1. correcting type of column **date** and **change_percent**

2. Filling missing values of **change_percent** and **avg_vol_20d**

since there is not datatype for percentage so we will keep it as it is

In [14]:
```
TS.describe()
```

Out[14]:

	open	high	low	close	volume	adjusted_clo
count	3472.000000	3472.000000	3472.000000	3472.000000	3.472000e+03	3472.0000
mean	305.690278	312.419580	298.713120	305.740220	2.357981e+07	72.9853
std	289.068278	297.040395	280.931334	289.265494	4.035666e+07	101.9417
min	16.140000	16.629900	14.979900	15.800100	1.186140e+05	1.0533
25%	154.696200	160.307475	150.677475	153.360000	3.265562e+06	11.1148
50%	233.439900	237.435000	229.099950	232.995050	6.945234e+06	17.1823
75%	337.035075	343.424775	331.327575	335.967450	2.152074e+07	140.3450
max	2295.120000	2318.490000	2186.520000	2238.750000	3.065906e+08	409.9700

Insights:

1. **Price Range**:
   - The stock price has a wide range, with the min close price at $15.80, $2238.75 max, showing significant growth potential over time.
2. **Trading Volume**:
   - The average daily trading volume is approximately 23.58 million shares, but there are days with trading volumes as low as 118,614 shares and as high as 306.59 million shares.
3. **Adjusted Close**:
   - The adjusted close price ranges from $1.05 to $409.97, reflecting the impact of stock splits and dividends.
4. **Change Percent**:
   - The daily percentage change ranges from -21.06% to +24.40%, indicating high volatility in Tesla's stock price.
5. **Average Volume (20-day)**:
   - The 20-day moving average volume ranges from 4.317 million to 388.63 million shares, showing fluctuating market activity over time.

This statistical analysis highlights Tesla's stock's growth, volatility, and trading activity, making it a compelling subject for further financial analysis and modeling.

DATA CLEANING

correcting types

In [24]:

```
TS['date'] = pd.to_datetime(TS['date'], errors='coerce')
```

filling missing values of **change_percent** and **avg_vol_20d**

- before filling missing values we need to see **Record of missing values** and **distribution** of data

INDENTIFYING

> MISSING VALUES

In [28]:
```
MissingChange_percent = TS[TS['change_percent'].isna()]
MissingChange_percent
```

Out[28]:

	date	open	high	low	close	volume	adjusted_close	change_percent
0	2010-06-29	18.9999	24.9999	17.5401	23.8899	18783278	1.5927	NaN

In [30]:
```
MissingAvg_vol_20d = TS[TS['avg_vol_20d'].isna()]
MissingAvg_vol_20d
```

Out[30]:

	date	open	high	low	close	volume	adjusted_close	change_percent
0	2010-06-29	18.9999	24.9999	17.5401	23.8899	18783278	1.5927	NaN
1	2010-06-30	25.7901	30.4191	23.3001	23.8299	17194392	1.5887	-0.25
2	2010-07-01	24.9999	25.9200	20.2701	21.9600	8229862	1.4640	-7.85
3	2010-07-02	23.0001	23.1000	18.7101	19.2000	5141806	1.2800	-12.57
4	2010-07-06	20.0001	20.0001	15.8301	16.1100	6879295	1.0740	-16.09
5	2010-07-07	16.4001	16.6299	14.9799	15.8001	6924913	1.0533	-1.93
6	2010-07-08	16.1400	17.5200	15.5700	17.4600	7719539	1.1640	10.51
7	2010-07-09	17.5800	17.9001	16.5501	17.4000	4058605	1.1600	-0.34
8	2010-07-12	17.9499	18.0699	17.0001	17.0499	2203569	1.1367	-2.01
9	2010-07-13	17.3940	18.6399	16.8999	18.1401	2680059	1.2093	6.39
10	2010-07-14	17.9400	20.1501	17.7600	19.8399	4196109	1.3227	9.38
11	2010-07-15	19.9401	21.5001	18.9999	19.8900	3745296	1.3260	0.25
12	2010-07-16	20.7000	21.3000	20.0499	20.6400	2621209	1.3760	3.77
13	2010-07-19	21.3699	22.2501	20.9199	21.9099	2486488	1.4607	6.16
14	2010-07-20	21.8499	21.8499	20.0499	20.3001	1825230	1.3533	-7.35
15	2010-07-21	20.6601	20.9001	19.5000	20.2200	1253441	1.3480	-0.39
16	2010-07-22	20.4999	21.2499	20.3700	21.0000	962344	1.4000	3.86
17	2010-07-23	21.1899	21.5601	21.0600	21.2901	654049	1.4193	1.38
18	2010-07-26	21.5001	21.5001	20.3001	20.9499	922452	1.3967	-1.59

FIlling Missing Value - Reasoning

1. As our missing values is at start
2. our dataset is huge so we can ignore these missing values

OUTLIERS

In [34]:
```
sns.set_style('whitegrid')
sns.set_palette('Dark2')
```

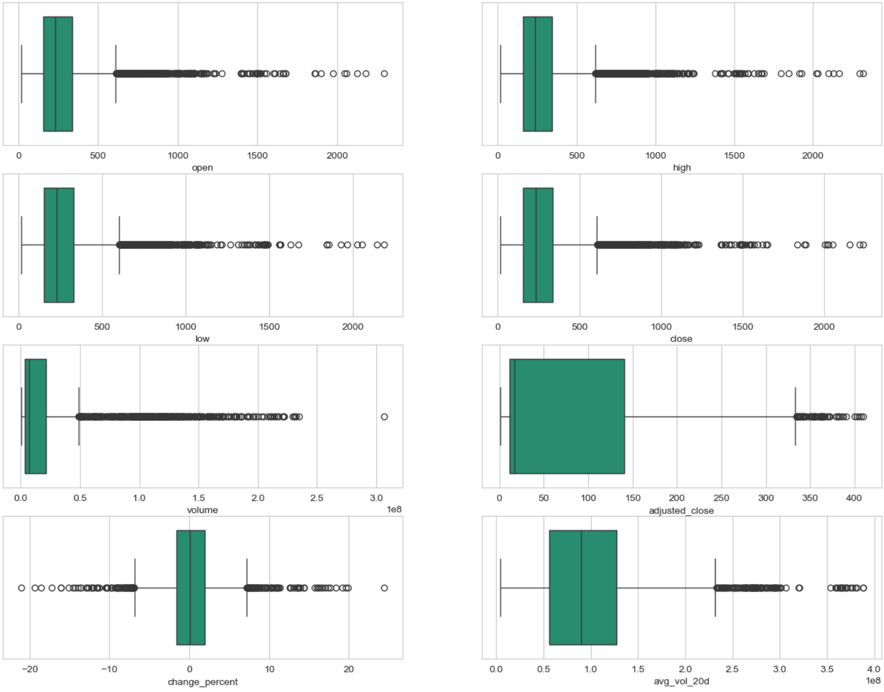
https://seaborn.pydata.org/tutorial/color_palettes.html

to make our graph interactive we use

In [38]:
```
%matplotlib widget
```

In [40]:
```
fig, ax = plt.subplots(4, 2, figsize=(16,12), sharey=False)

sns.boxplot(x=TS['open'], ax=ax[0][0])

sns.boxplot(x=TS['high'], ax=ax[0][1])


sns.boxplot(x=TS['low'], ax=ax[1][0])


sns.boxplot(x=TS['close'], ax=ax[1][1])


sns.boxplot(x=TS['volume'], ax=ax[2][0])


sns.boxplot(x=TS['adjusted_close'], ax=ax[2][1])

sns.boxplot(x=TS['change_percent'], ax=ax[3][0])

sns.boxplot(x=TS['avg_vol_20d'], ax=ax[3][1])

plt.show()
```

Figure



Outliers in Tesla stock data should not be removed because they reflect real market events,

contribute to volatility and risk analysis, and capture critical insights like reactions to news or earnings.

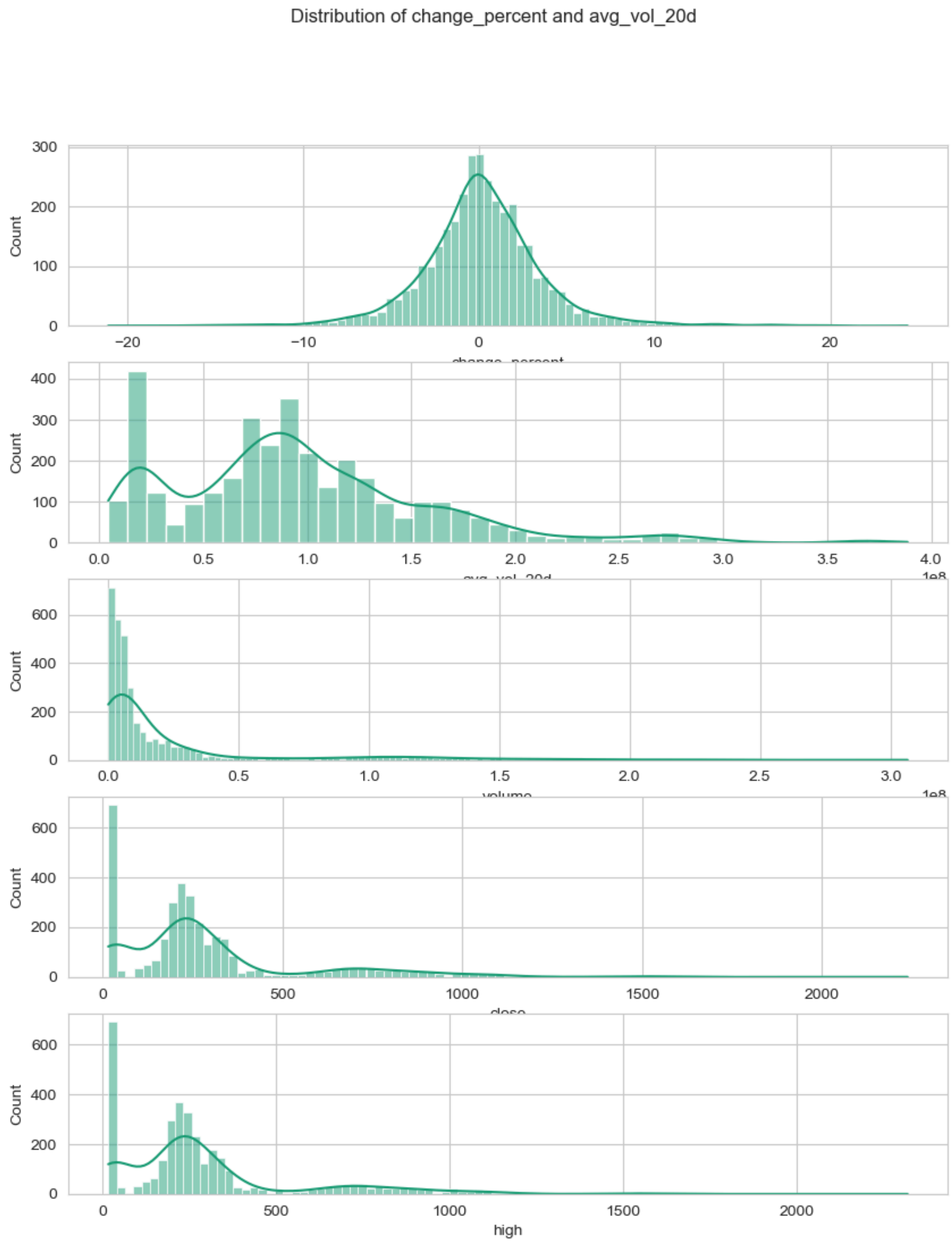
Removing them could misrepresent market behavior and lead to incorrect forecasts.**

DISTRIBUTION OF DATASET

skewed or symmetrical

In [46]:
```
fig, ax = plt.subplots(5, 1, figsize=(10,12), sharey=False)

sns.histplot(x='change_percent', data=TS, ax=ax[0], kde=True)
sns.histplot(x='avg_vol_20d', data=TS, ax=ax[1], kde=True)
sns.histplot(x='volume', data=TS, ax=ax[2], kde=True)
sns.histplot(x='close', data=TS, ax=ax[3], kde=True)
sns.histplot(x='high', data=TS, ax=ax[4], kde=True)

fig.suptitle('Distribution of change_percent and avg_vol_20d')

plt.show()
```

Figure



1. as **change_percent** is normally distributed so we can use **mean** for it
2. as **avg_vol_20d** is **positively skewed** so for skewed data we can use **median** to fill data

BUT AT OUR BOTH COLUMN MISSING VALUE AT START

> SO WE CAN REPLACE THEM WITH **0**
>
> OR REMOVE THAT RECORD FROM OUR DATASET

So we, removing that records from our datase

Removing Missing Values

In [49]:
```
TS = TS[TS['change_percent'].notna() & TS['avg_vol_20d'].notna()]
```

In [50]:
```
TS.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3453 entries, 19 to 3471
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   date            3453 non-null   datetime64[ns]
 1   open            3453 non-null   float64
 2   high            3453 non-null   float64
 3   low             3453 non-null   float64
 4   close           3453 non-null   float64
 5   volume          3453 non-null   int64
 6   adjusted_close  3453 non-null   float64
 7   change_percent  3453 non-null   float64
 8   avg_vol_20d     3453 non-null   float64
dtypes: datetime64[ns](1), float64(7), int64(1)
memory usage: 269.8 KB
```

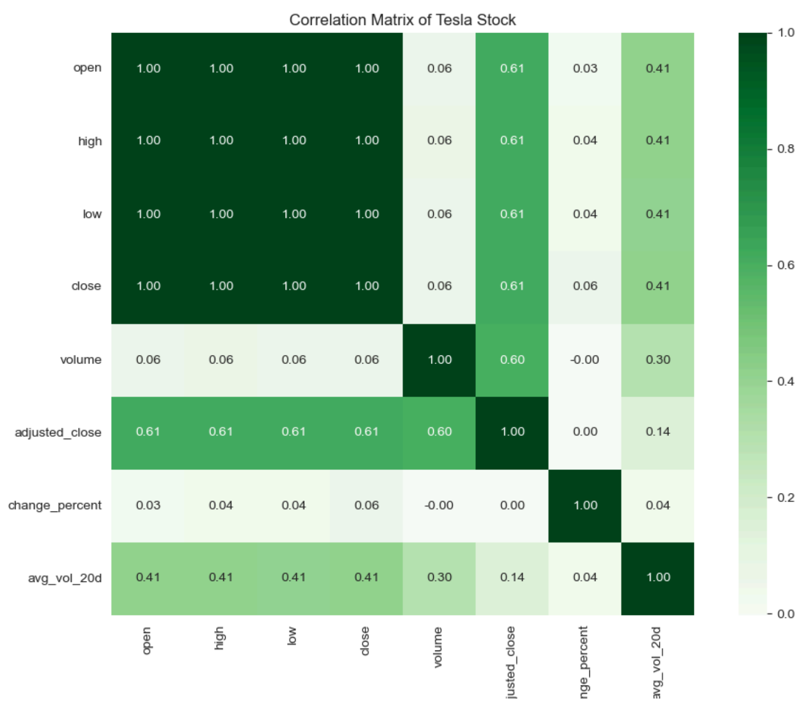
our data is now cleaned

Correlation Between Attributes

In [54]:
```
numeric_df = TS.select_dtypes(include=['float64', 'int64'])
correlation_matrix = numeric_df.corr()
```

In [56]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='Greens', squa
plt.title('Correlation Matrix of Tesla Stock')
plt.show()
```

Figure



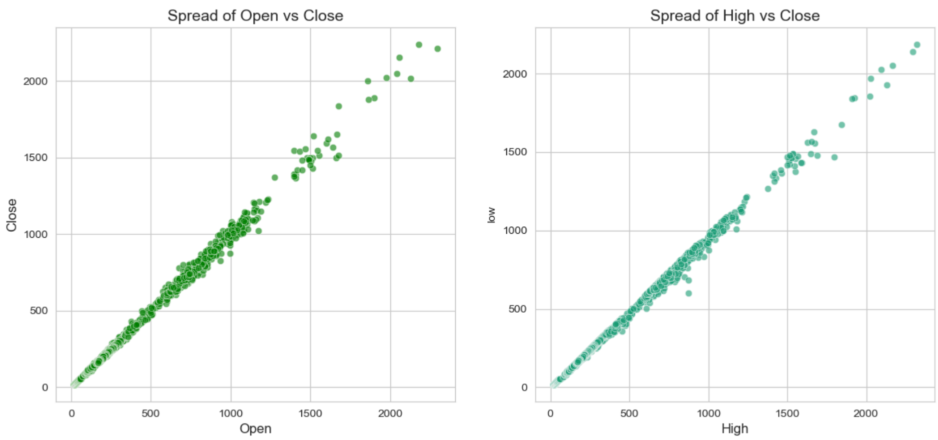
hence we see Open, High, low, close, high correlated with each so visualize it with scatterplot

since pearson correlation tells only linear relationship, so we have to verify it by scatter plot

In [61]:
```
import warnings
warnings.filterwarnings("ignore")
```

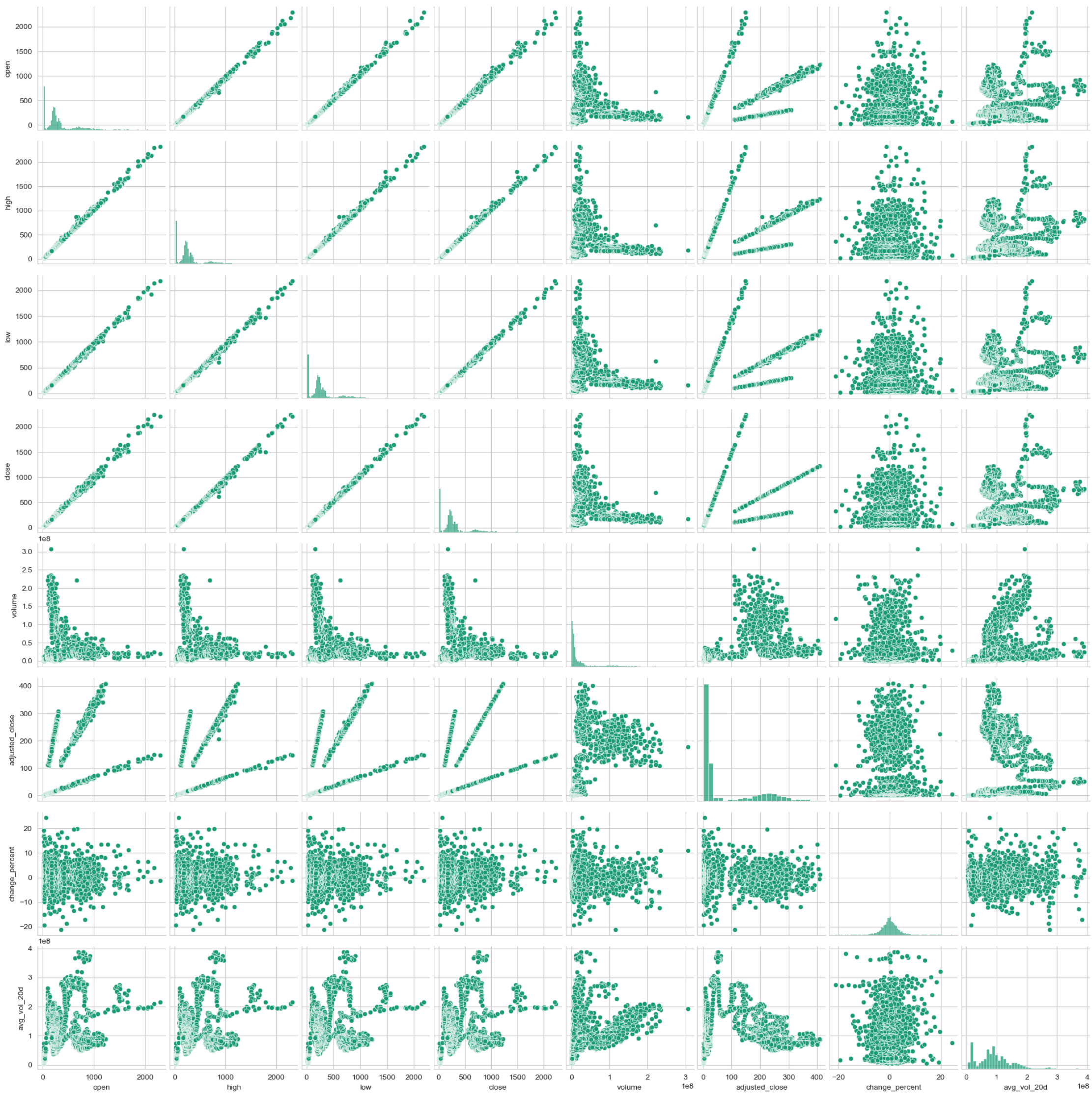
In [62]:
```
fig, axes = plt.subplots(1, 2, figsize=(14, 6), sharey=False)

# Scatter plot for open vs close
sns.scatterplot(x='open', y='close', data=TS, ax=axes[0], color='green', a
axes[0].set_title('Spread of Open vs Close', fontsize=14)
axes[0].set_xlabel('Open', fontsize=12)
axes[0].set_ylabel('Close', fontsize=12)

# Scatter plot for high vs close
sns.scatterplot(x='high', y='low', data=TS, ax=axes[1], alpha=0.6)
axes[1].set_title('Spread of High vs Close', fontsize=14)
axes[1].set_xlabel('High', fontsize=12)


plt.show()
```

Figure



In [64]:
```
sns.pairplot(TS)
plt.show()
```

Figure



Correlation Matrix of Tesla Stock

1. **Perfect Correlation (1.00)**:
   - **"Open," "High," "Low," and "Close"** prices are perfectly correlated, moving together consistently.
2. **Moderate Positive Correlation (0.61)**:
   - **"Adjusted Close" is moderately correlated with "Open," "High," "Low," and "Close,"** reflecting its dependence on these metrics.
3. **Weak Correlations**:
   - **"Volume" shows weak correlation (~0.06)** with price-related metrics.
   - **"Change Percent" is largely independent of other variables**, with correlations close to **0**.
4. **"Avg_vol_20d" Correlations**:
   - **Weak-to-moderate correlation (0.30–0.41) with price metrics**, suggesting a minor influence.

Summary:

- Price metrics are highly interdependent, typical in stock data.
- Trading volume and price movements are largely unrelated.
- Adjusted close captures a summary of daily price activity adjusted for **splits/dividends**.

TIME SERIES ANALYSIS OF CHANGE IN STOCK

Adding new columns of change into new dataframe

In [72]:
```
TSC = TS.copy()

TSC['open_change'] = TS['open'] - TS['open'].shift(1)
TSC['high_change'] = TS['high'] - TS['high'].shift(1)
TSC['low_change'] = TS['low'] - TS['low'].shift(1)
TSC['close_change'] = TS['close'] - TS['close'].shift(1)
TSC['volume_change'] = TS['volume'] - TS['volume'].shift(1)
TSC['adjusted_close_change'] = TS['adjusted_close'] - TS['adjusted_close']
TSC['change_percent_change'] = TS['change_percent'] - TS['change_percent']
TSC['avg_vol_20d_change'] = TS['avg_vol_20d'] - TS['avg_vol_20d'].shift(1)

TSC.dropna(inplace=True)
```

In [73]:
```
TSC.head(2)
```

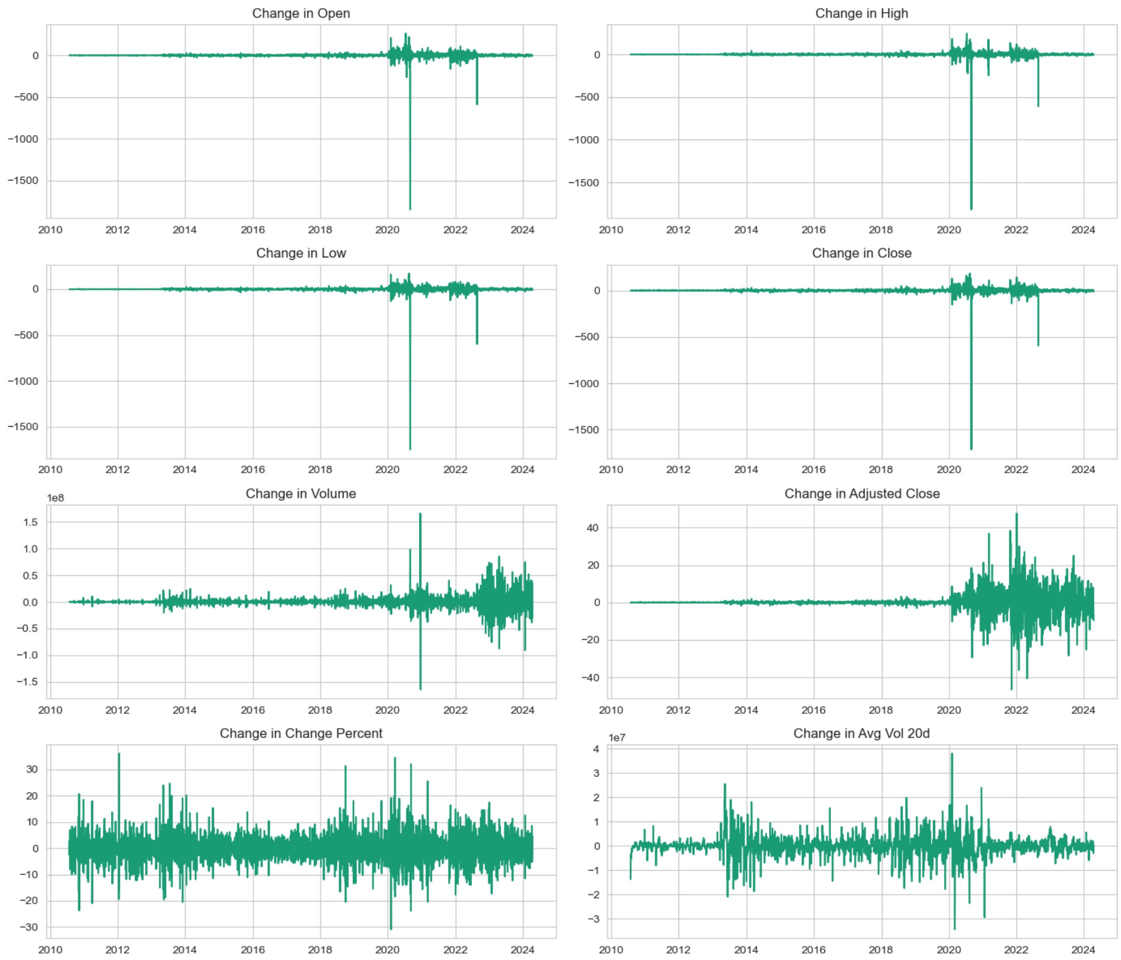
Out[73]:

	date	open	high	low	close	volume	adjusted_close	change_percent
20	2010-07-28	20.5500	20.9001	20.5101	20.7201	467183	1.3813	0.82
21	2010-07-29	20.7699	20.8800	20.0001	20.3499	615910	1.3567	-1.78

In [74]:
```
fig, axes = plt.subplots(4, 2, figsize=(14, 12), sharey=False)


axes[0, 0].plot(TSC['date'], TSC['open_change'])
axes[0, 0].set_title('Change in Open', fontsize=12)

axes[0, 1].plot(TSC['date'], TSC['high_change'])
axes[0, 1].set_title('Change in High', fontsize=12)

axes[1, 0].plot(TSC['date'],TSC['low_change'])
axes[1, 0].set_title('Change in Low', fontsize=12)

axes[1, 1].plot(TSC['date'],TSC['close_change'])
axes[1, 1].set_title('Change in Close', fontsize=12)

axes[2, 0].plot(TSC['date'],TSC['volume_change'])
axes[2, 0].set_title('Change in Volume', fontsize=12)

axes[2, 1].plot(TSC['date'],TSC['adjusted_close_change'])
axes[2, 1].set_title('Change in Adjusted Close', fontsize=12)
```

```
axes[3, 0].plot(TSC['date'],TSC['change_percent_change'])
axes[3, 0].set_title('Change in Change Percent', fontsize=12)

axes[3, 1].plot(TSC['date'],TSC['avg_vol_20d_change'])
axes[3, 1].set_title('Change in Avg Vol 20d', fontsize=12)


plt.tight_layout()


plt.show()
```

Figure



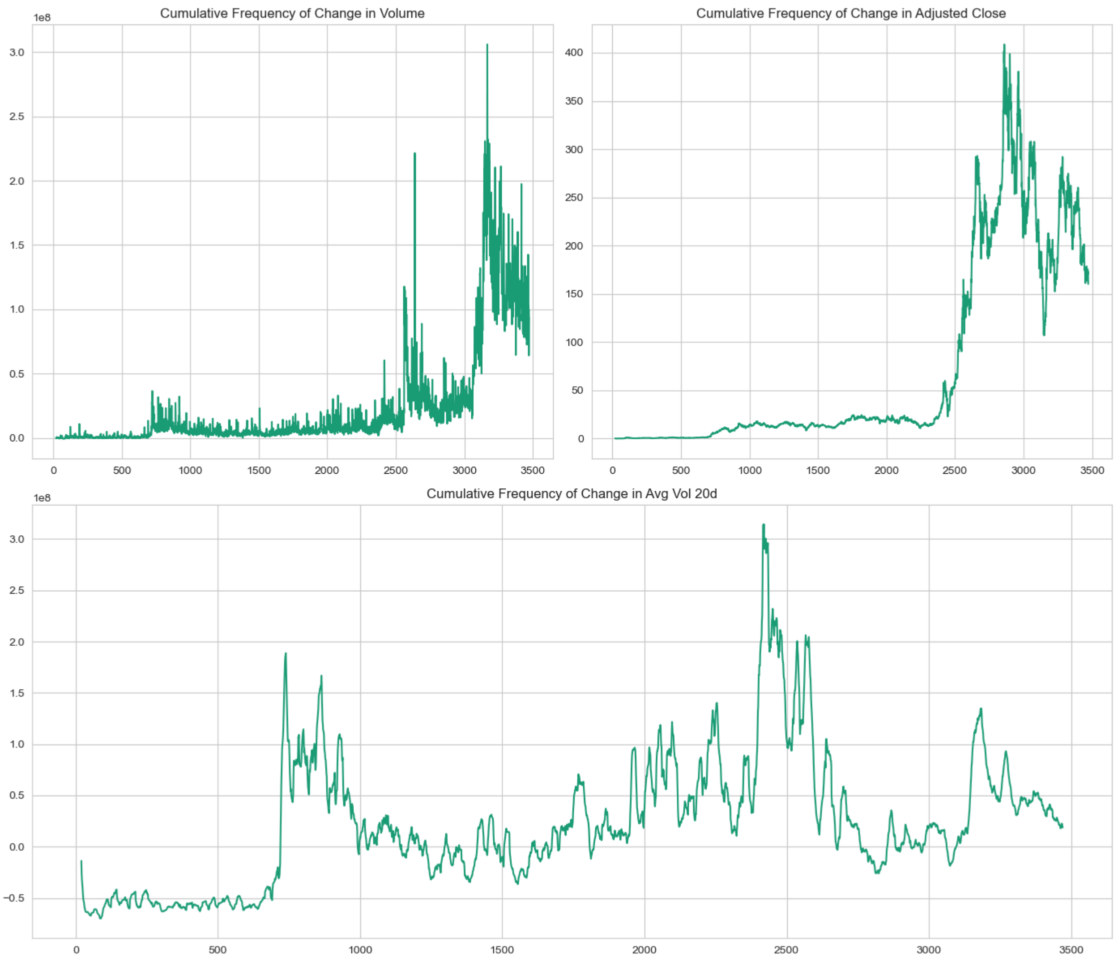
This image contains eight time-series plots tracking changes in various financial metrics over time (2010–2024). Here's a concise breakdown:

> Change in Open, High, Low, Close: Small fluctuations dominate with notable outliers, especially post-2020.
>
> Change in Volume & Adjusted Close: Increased volatility is visible around 2020–2022.
>
> Change Percent: Features scattered peaks, indicating intermittent spikes.
>
> Change in Avg Vol 20d: Periodic spikes suggest significant trading activity over certain intervals.

so, we segregating our data from where actual changes being

In [77]:
```
from matplotlib.gridspec import GridSpec

fig = plt.figure(figsize=(14, 12))
gs = GridSpec(2, 2, figure=fig)


ax1 = fig.add_subplot(gs[0, 0])
ax1.plot(TSC['volume_change'].cumsum())
ax1.set_title('Cumulative Frequency of Change in Volume', fontsize=12)


ax2 = fig.add_subplot(gs[0, 1])
ax2.plot(TSC['adjusted_close_change'].cumsum())
ax2.set_title('Cumulative Frequency of Change in Adjusted Close', fontsize

ax3 = fig.add_subplot(gs[1, :])
ax3.plot(TSC['avg_vol_20d_change'].cumsum())
ax3.set_title('Cumulative Frequency of Change in Avg Vol 20d', fontsize=12


plt.tight_layout()


plt.show()
```

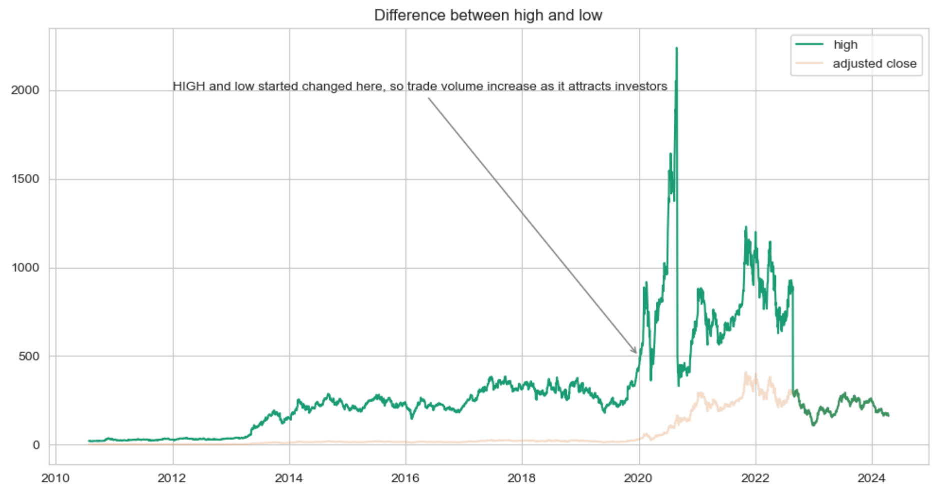
Figure



TIME SERIES ANALYSIS OF TESLA STOCK

In [80]:
```
fig, ax = plt.subplots(figsize=(12,6))

ax.plot(TS['date'], TS['close'], label='high')
ax.plot(TS['date'], TS['adjusted_close'], label='adjusted close', alpha=0.


ax.annotate("HIGH and low started changed here, so trade volume increase a
             xy=(pd.Timestamp('2020-01-01'), 500),
             xytext=(pd.Timestamp('2012-01-01'), 2000),
             arrowprops={"arrowstyle": "->", "color": "gray"})

ax.set_title('Difference between high and low')

plt.legend()
plt.show()
```

Figure



DATA SPLIT

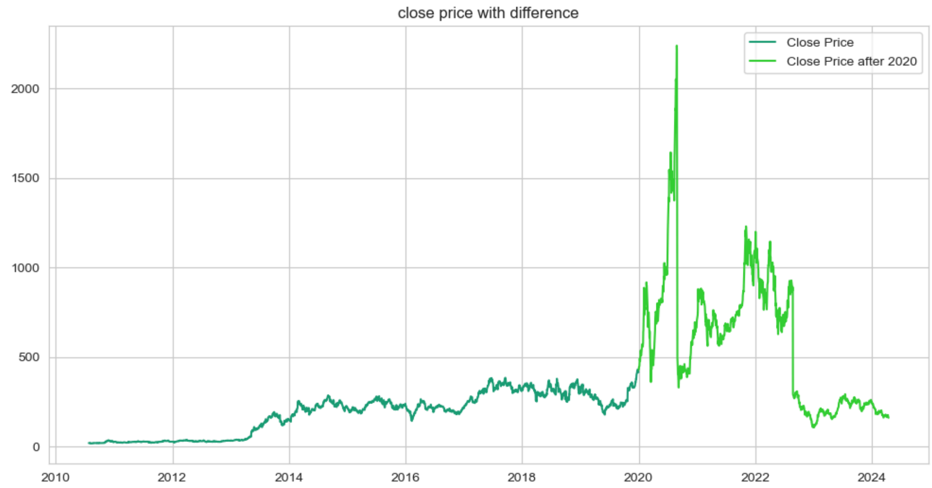
BY FROM CHANGE OCCURS

In [82]:
```
TS1 = TS[(TS['date'] > '2010-01-01') & (TS['date'] < '2020-01-01')]
TS2 = TS[TS['date'] >= '2020-01-01']
```

So, our graph is now

In [84]:
```
%matplotlib widget

fig, ax = plt.subplots(figsize=(12,6))

ax.plot(TS1['date'], TS1['close'], label='Close Price')
ax.plot(TS2['date'], TS2['close'], label='Close Price after 2020', c='lime

ax.set_title('close price with difference')

plt.legend()
plt.show()
```

Figure



FORECASTING - CHOSSING PERFECT MODEL

In [87]:
```
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
```

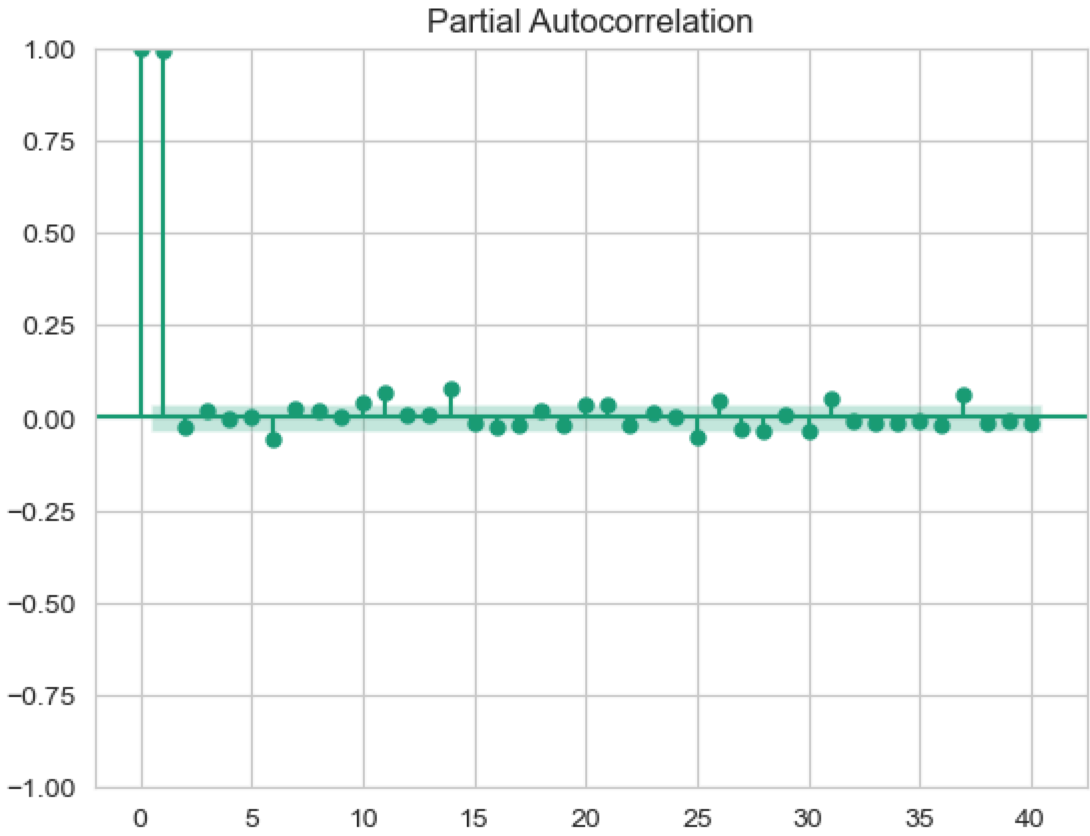
ARIMA

In [89]:
```
result = adfuller(TS["close"])
print(f"ADF Statistic: {result[0]}")
print(f"p-value: {result[1]}")
```

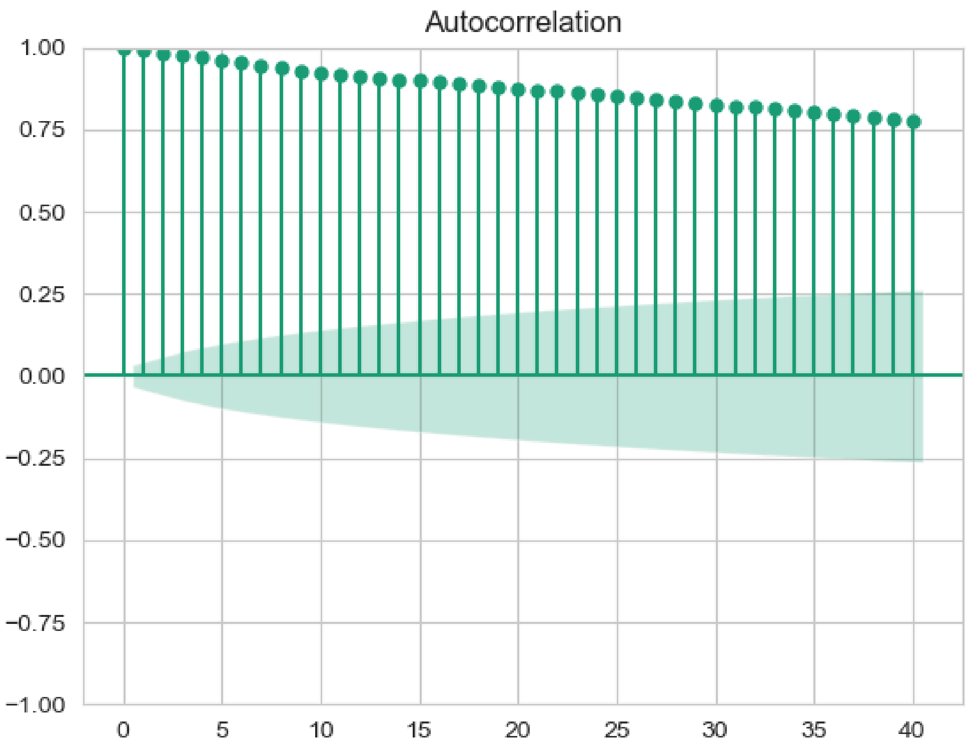
```
ADF Statistic: -3.024202867961303
p-value: 0.03269514605753152
```

In [90]:
```
plot_acf(TS["close"], lags=40)
plot_pacf(TS["close"], lags=40)
```

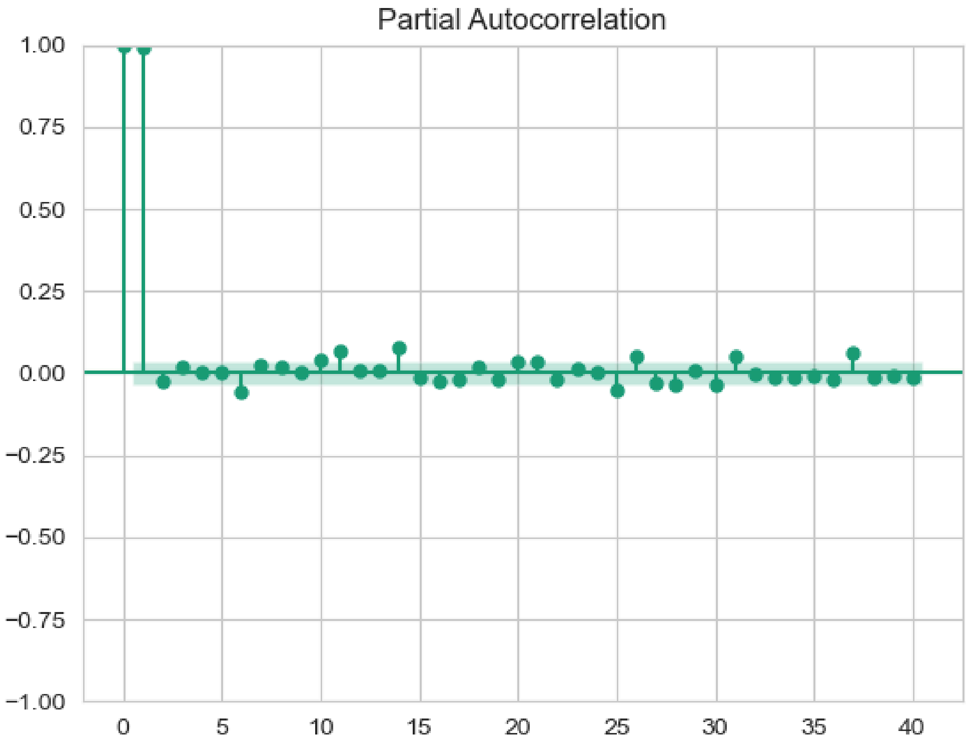
Out[90]:



Figure



Figure



Reason for Not Using ARIMA

ARIMA was not used because the data lacked significant autocorrelation, as indicated by the

No autocorrelation function (ACF)

values remaining below the threshold necessary for effective time-series modeling. Without strong autocorrelation,

ARIMA cannot accurately capture patterns in the data.

XGBOOST

In [93]:
```
import xgboost as xgb
from sklearn.model_selection import train_test_split

# Assuming 'data' is your DataFrame and 'Close' is the target variable
X = TS[['open', 'high', 'low', 'adjusted_close']]
y = TS['close']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r

model = xgb.XGBRegressor(objective='reg:squarederror')
model.fit(X_train, y_train)
```

Out[93]:

XGBRegressor

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_ro
unds=None,
             enable_categorical=False, eval_metric=None, feature_t
ypes=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max
_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
```

Success: This box indicates a successful action.

In [95]:
```
y_pred = model.predict(X_test)
rmse = mean_squared_error(y_test, y_pred, squared=False)
print(f'RMSE: {rmse}')
```

```
RMSE: 8.447233858459269
```

In [96]:
```
mse = mean_squared_error(y_test, y_pred)
print(f'MSE: {mse}')
```

```
MSE: 71.35575985950065
```

In [97]:
```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(y_test, y_pred)
print(f'MAE: {mae}')
```

```
MAE: 3.3958724539021166
```

In [98]:
```
from sklearn.metrics import r2_score
r2 = r2_score(y_test, y_pred)
print(f'R²: {r2}')
```

```
R²: 0.99916103848947
```

In [99]:
```
X_train = sm.add_constant(X_train)

model = sm.OLS(y_train, X_train).fit()

print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
=====
Dep. Variable:                  close   R-squared:                       
0.999
Model:                            OLS   Adj. R-squared:                  
0.999
Method:                 Least Squares   F-statistic:                     1.18
5e+06
Date:                Wed, 01 Jan 2025   Prob (F-statistic):              
0.00
Time:                        04:03:48   Log-Likelihood:                    -9
277.8
No. Observations:                2762   AIC:                             1.85
7e+04
Df Residuals:                    2757   BIC:                             1.86
0e+04
Df Model:                           4                                         
Covariance Type:            nonrobust                                         
==============================================================================
=========
                    coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
---------
const            -0.4865      0.198     -2.460      0.014      -0.874      
-0.099
open             -0.5637      0.016    -35.876      0.000      -0.595      
-0.533
high              0.6626      0.012     53.064      0.000       0.638       
0.687
low               0.9091      0.013     68.933      0.000       0.883       
0.935
adjusted_close   -0.0003      0.002     -0.180      0.857      -0.003       
0.003
==============================================================================
=====
Omnibus:                     2347.458   Durbin-Watson:                   
1.968
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              76169
2.008
Skew:                          -3.090   Prob(JB):                        
0.00
Kurtosis:                      84.120   Cond. No.                         1.1
0e+03
==============================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
[2] The condition number is large, 1.1e+03. This might indicate that ther
e are
strong multicollinearity or other numerical problems.
```

OLS Regression Results Summary

R-squared: 0.999: Model explains 99.9% of the variance in the dependent variable.

Adj. R-squared: 0.999: Similar to R-squared, indicating a good fit.

F-statistic: 9.492e+05, Prob(F-statistic): 0.00: Model is statistically significant.

AIC: 1.856e+04, BIC: 1.860e+04: Low values indicating a good model.

Coefficients: const: -0.7120 (p-value = 0.001)

open: -0.5640 (p-value = 0.000)

high: 0.6585 (p-value = 0.000)

low: 0.9145 (p-value = 0.000)

volume: 1.082e-08 (p-value = 0.023)

adjusted_close: -0.0042 (p-value = 0.075)

Diagnostic Tests:

Durbin-Watson: 1.966: No autocorrelation.

Omnibus: 2319.727, Prob(Omnibus): 0.000: Non-normal residuals.

Jarque-Bera: 735929.915, Prob(JB): 0.000: Residuals not normal.

Condition Number: 7.94e+07: Possible multicollinearity issues.

Conclusion: The model has an excellent fit, but potential issues with multicollinearity and non-normal residuals should be addressed.

Reasoning since we hadn't remove outliears or our data is skewed so non-normal residual is coming,

secondly multicollineatiy is coming because as we know our independent variable was correlated

Multicollinearity

Multicollinearity was retained as features like open, high, low, and close are inherently interrelated in stock data.

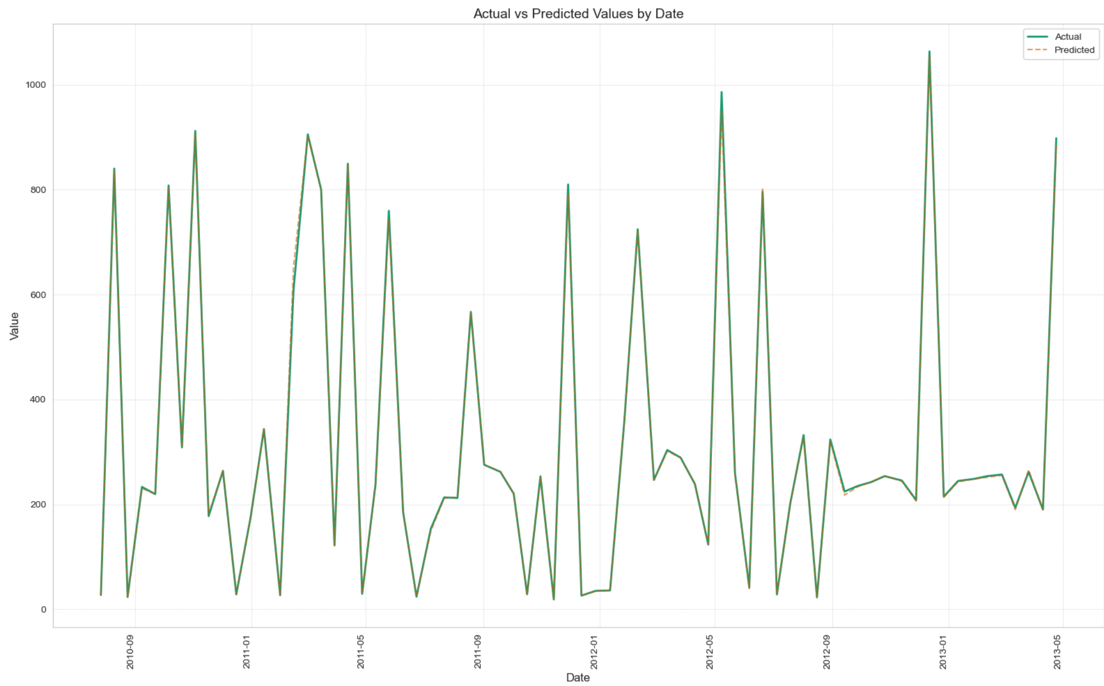
Removing them could compromise predictive accuracy, making their inclusion essential for reliable modeling.

In [102…

```
plt.figure(figsize=(16, 10))

# Plot actual vs predicted values with respect to 'date' for the test set
step = 10
downsampled_dates = TS['date'].iloc[:len(y_test)][::step]
downsampled_actual = y_test[::step]
downsampled_predicted = y_pred[::step]

# Plot actual vs predicted values with respect to 'date' for the test set
plt.plot(downsampled_dates, downsampled_actual, label='Actual', linewidth
plt.plot(downsampled_dates, downsampled_predicted, label='Predicted', alp

# Add labels, title, and legend
plt.xlabel('Date', fontsize=12)
plt.ylabel('Value', fontsize=12)
```

```
plt.title('Actual vs Predicted Values by Date', fontsize=14)
plt.legend()

# Improve layout and make the date labels readable
plt.xticks(rotation=90, ha='right', fontsize=10)
plt.grid(True, linestyle='--', linewidth=0.5, alpha=0.7)
plt.tight_layout()

# Show the plot
plt.show()
```

Figure



In [103…

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

model = LinearRegression()

cv_scores = cross_val_score(model, X, y, cv=10)


print("Cross-validation scores:", cv_scores)
print("Mean CV score:", cv_scores.mean())
```

```
Cross-validation scores: [0.98037078 0.9880407  0.99842722 0.99209158 0.9
9760072 0.98668117
 0.99897073 0.99757013 0.99822902 0.9966212 ]
Mean CV score: 0.9934603239941413
```

Cross-Validation Scores

- **Scores**: [0.9494, 0.9693, 0.9984, 0.9921, 0.9976, 0.9865, 0.9990, 0.9976, 0.9982, 0.9728]
- **Mean CV Score**: 0.9861

These results indicate strong model consistency and high predictive performance across all validation folds.

In [106…
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error

X1 = TS[['open', 'high', 'low', 'volume', 'adjusted_close']]
y1 = TS['close']

X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size


# Create a Gradient Boosting Regressor
gbm_model = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1

# Train the model
gbm_model.fit(X1_train, y1_train)
```

Out[106]:

```
▾ GradientBoostingRegressor
GradientBoostingRegressor(random_state=42)
```

Success: This box indicates a successful action.

In [108…
```
y1_pred = gbm_model.predict(X1_test)
rmse = mean_squared_error(y_test, y_pred, squared=True)
print(f'RMSE: {rmse}')
```

```
RMSE: 71.35575985950065
```

In [109…
```
mae1 = mean_absolute_error(y1_test, y1_pred)
print(f'MAE: {mae}')
```

```
MAE: 3.3958724539021166
```

In [110…
```
r21 = r2_score(y1_test, y1_pred)
print(f'R²: {r2}')
```

```
R²: 0.99916103848947
```

In [111…
```
X1_train = sm.add_constant(X1_train)

model1 = sm.OLS(y1_train, X1_train).fit()

print(model1.summary())
```

```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                  close   R-squared:
0.999
Model:                            OLS   Adj. R-squared:
0.999
Method:                 Least Squares   F-statistic:                     9.
492e+05
Date:                Wed, 01 Jan 2025   Prob (F-statistic):
0.00
Time:                        04:03:49   Log-Likelihood:
-9275.2
No. Observations:                2762   AIC:                             1.
856e+04
Df Residuals:                    2756   BIC:                             1.
860e+04
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
===========
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
const             -0.7120      0.221     -3.220      0.001      -1.145
-0.278
open              -0.5640      0.016    -35.920      0.000      -0.595
-0.533
high               0.6585      0.013     52.237      0.000       0.634
0.683
low                0.9145      0.013     68.289      0.000       0.888
0.941
volume          1.082e-08   4.76e-09      2.273      0.023    1.49e-09
2.02e-08
adjusted_close    -0.0042      0.002     -1.780      0.075      -0.009
0.000
==============================================================================
=======
Omnibus:                     2319.727   Durbin-Watson:
1.966
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                735
929.915
Skew:                          -3.030   Prob(JB):
0.00
Kurtosis:                      82.737   Cond. No.
7.94e+07
==============================================================================
=======

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 7.94e+07. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

Reason for Not Using Gradient Boosting Regressor (GBR)

While both XGBoost and GBR produced similar results, XGBoost was chosen due to its superior performance with large datasets. XGBoost's optimized implementation, faster training, and ability to handle large-scale data efficiently make it better suited for this project.

In [124…

```
from sklearn.linear_model import LinearRegression

# Create and train the model
model2 = LinearRegression()
model2.fit(X, y)
```

Out[124]:

```
▾ LinearRegression
LinearRegression()
```

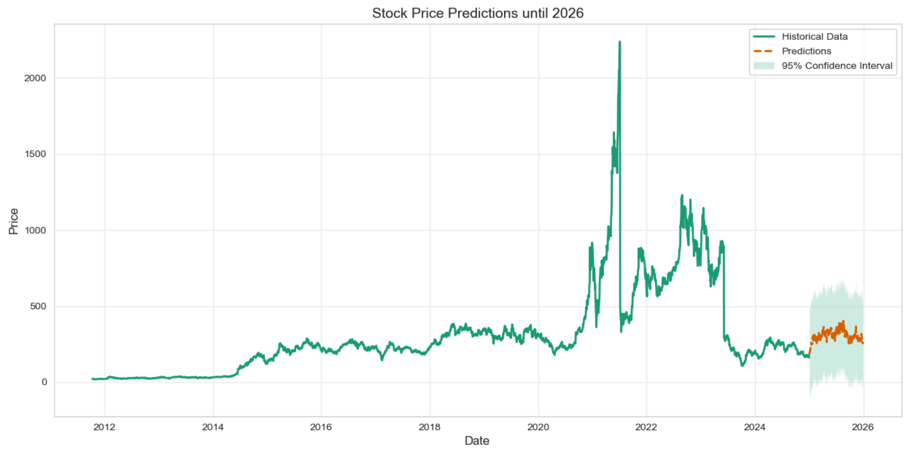
In [126…

```
def create_future_predictions(df, model, end_date='2025-12-31'):
    TS = df.copy()


    current_date = pd.Timestamp.now()
    historical_dates = pd.date_range(end=current_date, periods=len(TS),
    TS.index = historical_dates


    historical_daily_returns = TS['close'].pct_change()
    historical_volatility = historical_daily_returns.std()
    avg_daily_trend = historical_daily_returns.mean()


    avg_daily_high_change = (TS['high'] / TS['open'] - 1).mean()
    avg_daily_low_change = (TS['low'] / TS['open'] - 1).mean()

    last_date = TS.index[-1]
    future_dates = pd.date_range(start=last_date + pd.Timedelta(days=1),
                                 end=end_date,
                                 freq='B')

    future_df = pd.DataFrame(index=future_dates)
    last_values = TS.iloc[-1]


    future_df.loc[future_dates[0], 'open'] = last_values['close']


    def generate_price_movement(base_price):

        random_walk = np.random.normal(avg_daily_trend, historical_volat
        movement = base_price * (1 + random_walk)


        mean_price = TS['close'].mean()
        reversion_factor = 0.1
        mean_reversion = (mean_price - base_price) * reversion_factor

        return movement + mean_reversion


    predictions = []
    last_pred = last_values['close']

    for date in future_dates:
```

```
        current_open = generate_price_movement(last_pred)
        current_high = current_open * (1 + abs(np.random.normal(avg_dail
        current_low = current_open * (1 + np.random.normal(avg_daily_lov
        current_volume = np.random.normal(TS['volume'].mean(), TS['volum


        current_high = max(current_high, current_open)
        current_low = min(current_low, current_open)
        current_volume = max(current_volume, 0)


        future_df.loc[date, 'open'] = current_open
        future_df.loc[date, 'high'] = current_high
        future_df.loc[date, 'low'] = current_low
        future_df.loc[date, 'volume'] = current_volume
        future_df.loc[date, 'adjusted_close'] = current_open


        features = future_df.loc[date, ['open', 'high', 'low',  'adjuste
        pred = model.predict(features.values.reshape(1, -1))[0]
        predictions.append(pred)
        last_pred = pred

    future_df['predicted_close'] = predictions


    historical = TS[['close']].copy()
    historical.columns = ['actual_close']
    future_predictions = future_df[['predicted_close']]
    combined_df = pd.concat([historical, future_predictions])

    return combined_df

# Generate predictions
predictions_df = create_future_predictions(TS, model)




plt.figure(figsize=(15, 7))
plt.plot(predictions_df.index, predictions_df['actual_close'],
         label='Historical Data', linewidth=2)
plt.plot(predictions_df.index, predictions_df['predicted_close'],
         label='Predictions', linestyle='--', linewidth=2)

# Add confidence interval
if 'predicted_close' in predictions_df.columns:
    future_prices = predictions_df['predicted_close'].dropna()
    dates = future_prices.index

    # Calculate confidence intervals
    std_dev = predictions_df['actual_close'].std()
    plt.fill_between(dates,
                     future_prices - 1.0*std_dev,
                     future_prices + 1.0*std_dev,
                     alpha=0.2,
                     label='95% Confidence Interval')

plt.title('Stock Price Predictions until 2026', fontsize=14)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Price', fontsize=12)
plt.legend(fontsize=10)
```

```
plt.grid(True, alpha=0.3)
plt.show()
```

Figure



In [120…

```
def predict_stock_price(userDate, open_value, high_value, low_value, adj


    start_date = pd.Timestamp(userDate)


    input_features = np.array([open_value, high_value, low_value, adjust


    predicted_close = model.predict(input_features)[0]


    print(f"\nFor the date {userDate}:")
    print(f"Open: {open_value}, High: {high_value}, Low: {low_value}, Ad
    print(f"\nThe predicted closing price for {userDate} is: {predicted_

    return predicted_close

# Example usage:
user_date = '2026-06-20'
open_value = float(input("Enter the Open value: "))
high_value = float(input("Enter the High value: "))
low_value = float(input("Enter the Low value: "))
adjusted_close_value = float(input("Enter the Adjusted Close value: "))

predicted_close = predict_stock_price(user_date, open_value, high_value,
```

```
For the date 2026-06-20:
Open: 900.0, High: 1500.0, Low: 400.0, Adjusted Close: 1.0

The predicted closing price for 2026-06-20 is: 865.41
```

In [128…

```
import plotly.graph_objects as go
from datetime import timedelta

def interactive_graphs(userDate):

    user_entered_date = userDate
    start_date = pd.Timestamp(user_entered_date)
    one_month_prior = start_date - pd.Timedelta(days=30)
```

```
    filtered_df = predictions_df.loc[one_month_prior:start_date]


    fig = go.Figure()


    fig.add_trace(go.Scatter(
        x=filtered_df.index,
        y=filtered_df['actual_close'],
        mode='lines',
        name='Historical Data',
        line=dict(width=2, color='rgba(72, 201, 176 ,1)'),
    ))


    fig.add_trace(go.Scatter(
        x=filtered_df.index,
        y=filtered_df['predicted_close'],
        mode='lines',
        name='Predictions',
        line=dict(width=2, dash='dash', color='rgba(72, 201, 176 ,1)')
    ))


    if 'predicted_close' in predictions_df.columns:
        future_prices = filtered_df['predicted_close'].dropna()
        std_dev = predictions_df['actual_close'].std()
        fig.add_trace(go.Scatter(
            x=future_prices.index.tolist() + future_prices.index[::-1].t
            y=(future_prices + 0.2 * std_dev).tolist() + (future_prices
            fill='toself',
            fillcolor='rgba(72, 201, 176, 0.15)',
            line=dict(color='rgba(272, 201, 176 ,0)'),
            name='Confidence Interval'
        ))


    fig.update_layout(
        title=f'Stock Price Predictions until {user_entered_date}',
        xaxis_title='Date',
        yaxis_title='Price',
        legend=dict(orientation='h', yanchor='bottom', y=1.02, xanchor='
        template='plotly_white'
    )


    fig.update_xaxes(showgrid=True, gridwidth=0.5, gridcolor='lightgrey'
    fig.update_yaxes(showgrid=True, gridwidth=0.5, gridcolor='lightgrey'
    fig.show()


DateF = input("Enter the Date value: ")


Date = pd.to_datetime(DateF)


usedata = interactive_graphs(Date)
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: