In [1]:
```
import numpy as np
import pandas as pd
```

EDA

In [2]:
```
import opendatasets as od
```

In [3]:
```
od.download('https://www.kaggle.com/datasets/luisandresgarcia/stock-market-prediction')
```

```
Skipping, found downloaded files in ".\stock-market-prediction" (use force=True to force download)
```

In [4]:
```
# Assuming the dataset is a CSV file, load it into a Pandas DataFrame
dataset_path = 'stock-market-prediction'
csv_file_path = f'{dataset_path}/infolimpioavanzadoTarget.csv'

# Load the CSV file into a Pandas DataFrame
df = pd.read_csv(csv_file_path)
```

In [5]:
```
df.head()
```

Out[5]:

	date	open	high	low	close	adjclose	volume	ticker	RSIadjclose15	RSIvolume15	...	high-15	K-15	D-15	stoch
0	2022-01-03	17.799999	18.219000	17.500000	17.760000	17.760000	106600	ASLE	NaN	NaN	...	NaN	NaN	NaN	
1	2022-01-04	17.700001	18.309999	17.620001	17.660000	17.660000	128700	ASLE	NaN	NaN	...	NaN	NaN	NaN	
2	2022-01-05	17.580000	17.799999	16.910000	16.950001	16.950001	103100	ASLE	NaN	NaN	...	NaN	NaN	NaN	
3	2022-01-06	16.650000	16.879999	16.139999	16.170000	16.170000	173600	ASLE	NaN	NaN	...	NaN	NaN	NaN	
4	2022-01-07	16.219999	16.290001	15.630000	15.710000	15.710000	137800	ASLE	NaN	NaN	...	NaN	NaN	NaN	

5 rows × 1285 columns

In [6]:
```
df.shape
```

Out[6]:
```
(7781, 1285)
```

In [7]:
```
df.info
```

```
Out[7]: <bound method DataFrame.info of             date       open       high        low      close   adjclose  \
0     2022-01-03  17.799999  18.219000  17.500000  17.760000  17.760000
1     2022-01-04  17.700001  18.309999  17.620001  17.660000  17.660000
2     2022-01-05  17.580000  17.799999  16.910000  16.950001  16.950001
3     2022-01-06  16.650000  16.879999  16.139999  16.170000  16.170000
4     2022-01-07  16.219999  16.290001  15.630000  15.710000  15.710000
...          ...        ...        ...        ...        ...        ...
7776  2022-12-23  23.250000  23.540001  23.250000  23.290001  22.699928
7777  2022-12-27  23.350000  23.610001  23.250000  23.350000  22.758406
7778  2022-12-28  23.450001  23.570000  23.219999  23.350000  22.758406
7779  2022-12-29  23.330000  23.740000  23.330000  23.610001  23.011820
7780  2022-12-30  23.680000  23.760000  23.610001  23.610001  23.011820

      volume ticker  RSIadjclose15  RSIvolume15  ...    high-15       K-15  \
0     106600   ASLE            NaN          NaN  ...        NaN        NaN
1     128700   ASLE            NaN          NaN  ...        NaN        NaN
2     103100   ASLE            NaN          NaN  ...        NaN        NaN
3     173600   ASLE            NaN          NaN  ...        NaN        NaN
4     137800   ASLE            NaN          NaN  ...        NaN        NaN
...      ...    ...            ...          ...  ...        ...        ...
7776    4900   ATLO      60.782255    47.081752  ...  23.600000  26.223672
7777    9200   ATLO      62.022801    47.747952  ...  23.610001  30.764722
7778   15200   ATLO      62.022801    48.713225  ...  23.610001  30.764722
7779    7100   ATLO      67.186408    47.445460  ...  23.740000  46.457382
7780    7100   ATLO      67.186408    47.445460  ...  23.760000  45.784072

           D-15  stochastic-k-15  stochastic-d-15  stochastic-kd-15  \
0           NaN              NaN              NaN               NaN
1           NaN              NaN              NaN               NaN
2           NaN              NaN              NaN               NaN
3           NaN              NaN              NaN               NaN
4           NaN              NaN              NaN               NaN
...         ...              ...              ...               ...
7776  27.022465        26.223672        27.022465         -0.798793
7777  28.003602        30.764722        28.003602          2.761119
7778  29.251039        30.764722        29.251039          1.513683
7779  35.995609        46.457382        35.995609         10.461773
7780  41.002059        45.784072        41.002059          4.782013

      volumenrelativo      diff  INCREMENTO  TARGET
0            0.919758 -1.900001   -9.664295       0
1            1.110440 -1.379999   -7.247895       0
2            0.889560 -0.930000   -5.201344       0
```

```
3           1.497843 -0.360000   -2.177856       0
4           1.188956 -0.120000   -0.758054       0
...              ...       ...         ...     ...
7776        0.333333       NaN         NaN       0
7777        0.625850       NaN         NaN       0
7778        1.034014       NaN         NaN       0
7779        0.482993       NaN         NaN       0
7780        0.482993       NaN         NaN       0

[7781 rows x 1285 columns]>
```

In [8]:
```python
import warnings
warnings.filterwarnings('ignore')
```

In [9]:
```python
df.describe()
```

Out[9]:

	open	high	low	close	adjclose	volume	RSIadjclose15	RSIvolume15	RSIadjclose25	RSIvolu
count	7781.000000	7781.000000	7781.000000	7781.000000	7781.000000	7.781000e+03	7316.000000	7316.000000	7006.000000	7006.0
mean	34.990220	35.655999	34.301243	34.964414	34.483147	7.586022e+05	46.817434	49.814790	46.966016	49.8
std	99.841502	101.451058	98.073945	99.790823	98.603879	3.934491e+06	11.672838	5.002664	8.760961	3.4
min	0.410000	0.435000	0.405000	0.408000	0.408000	0.000000e+00	6.837461	35.303213	17.693637	39.5
25%	4.050000	4.130000	3.980000	4.030000	3.960000	1.080000e+04	38.946316	47.182234	40.954487	48.2
50%	10.080000	10.110000	10.005000	10.080000	10.061000	8.406000e+04	46.259711	48.356834	46.459477	48.9
75%	24.350000	24.500000	24.080000	24.250000	22.466007	6.724000e+05	54.061089	50.902284	52.289893	50.5
max	795.739990	799.359985	784.960022	797.489990	783.376221	1.615550e+08	96.365095	99.622735	91.023108	97.7

8 rows × 1283 columns

In [10]:
```python
df_new = df[['date','open', 'high', 'low', 'close']]
df_new
```

Out[10]:

	date	open	high	low	close
0	2022-01-03	17.799999	18.219000	17.500000	17.760000
1	2022-01-04	17.700001	18.309999	17.620001	17.660000
2	2022-01-05	17.580000	17.799999	16.910000	16.950001
3	2022-01-06	16.650000	16.879999	16.139999	16.170000
4	2022-01-07	16.219999	16.290001	15.630000	15.710000
...	...	...	...	...	...
7776	2022-12-23	23.250000	23.540001	23.250000	23.290001
7777	2022-12-27	23.350000	23.610001	23.250000	23.350000
7778	2022-12-28	23.450001	23.570000	23.219999	23.350000
7779	2022-12-29	23.330000	23.740000	23.330000	23.610001
7780	2022-12-30	23.680000	23.760000	23.610001	23.610001

7781 rows × 5 columns

In [11]:
```
df_new.isnull().sum()
```

Out[11]:
```
date     0
open     0
high     0
low      0
close    0
dtype: int64
```

In [12]:
```
import matplotlib.pyplot as plt
```

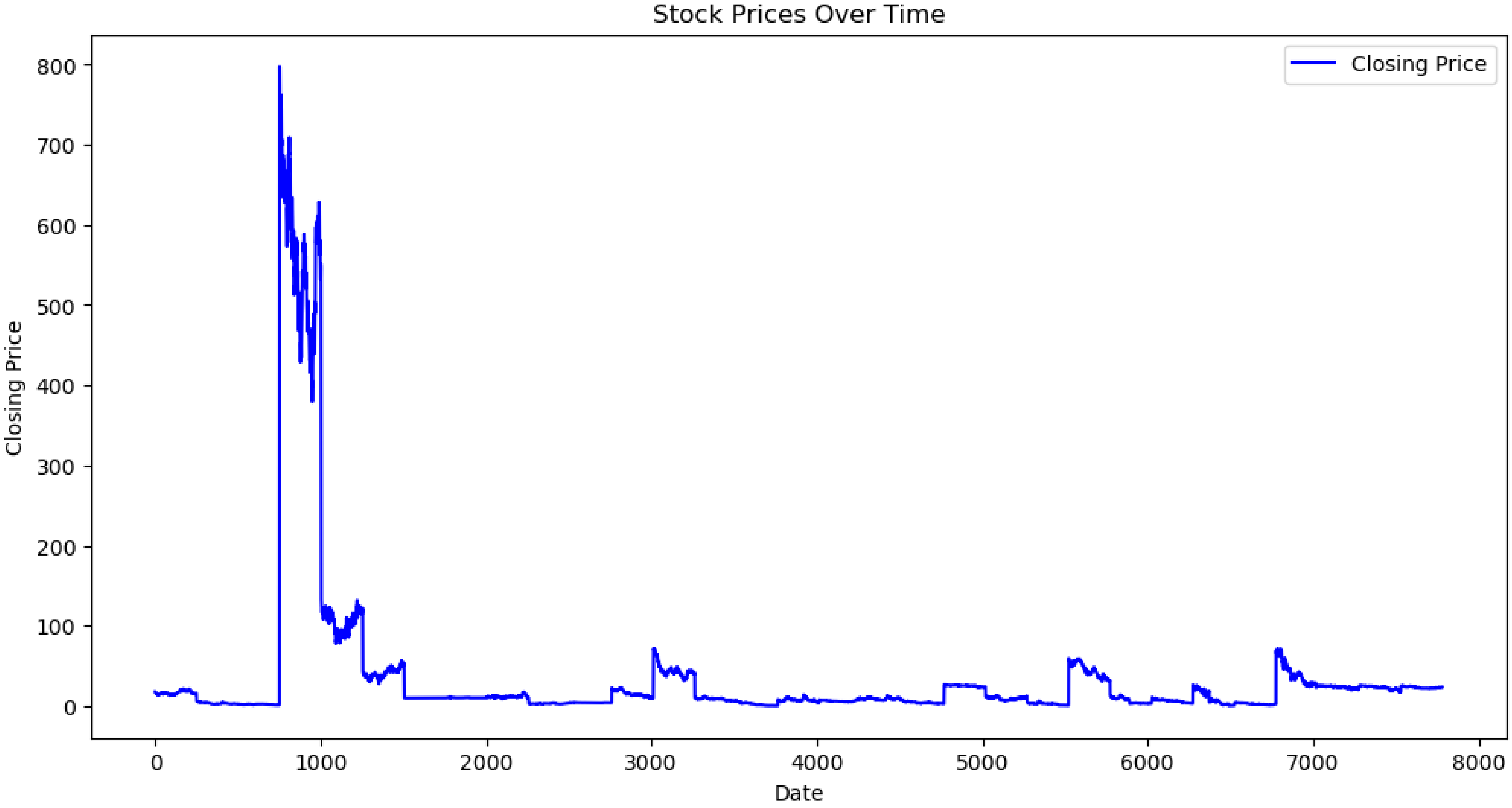
In [13]:
```
import seaborn as sns
```

In [14]:
```
import sklearn
```

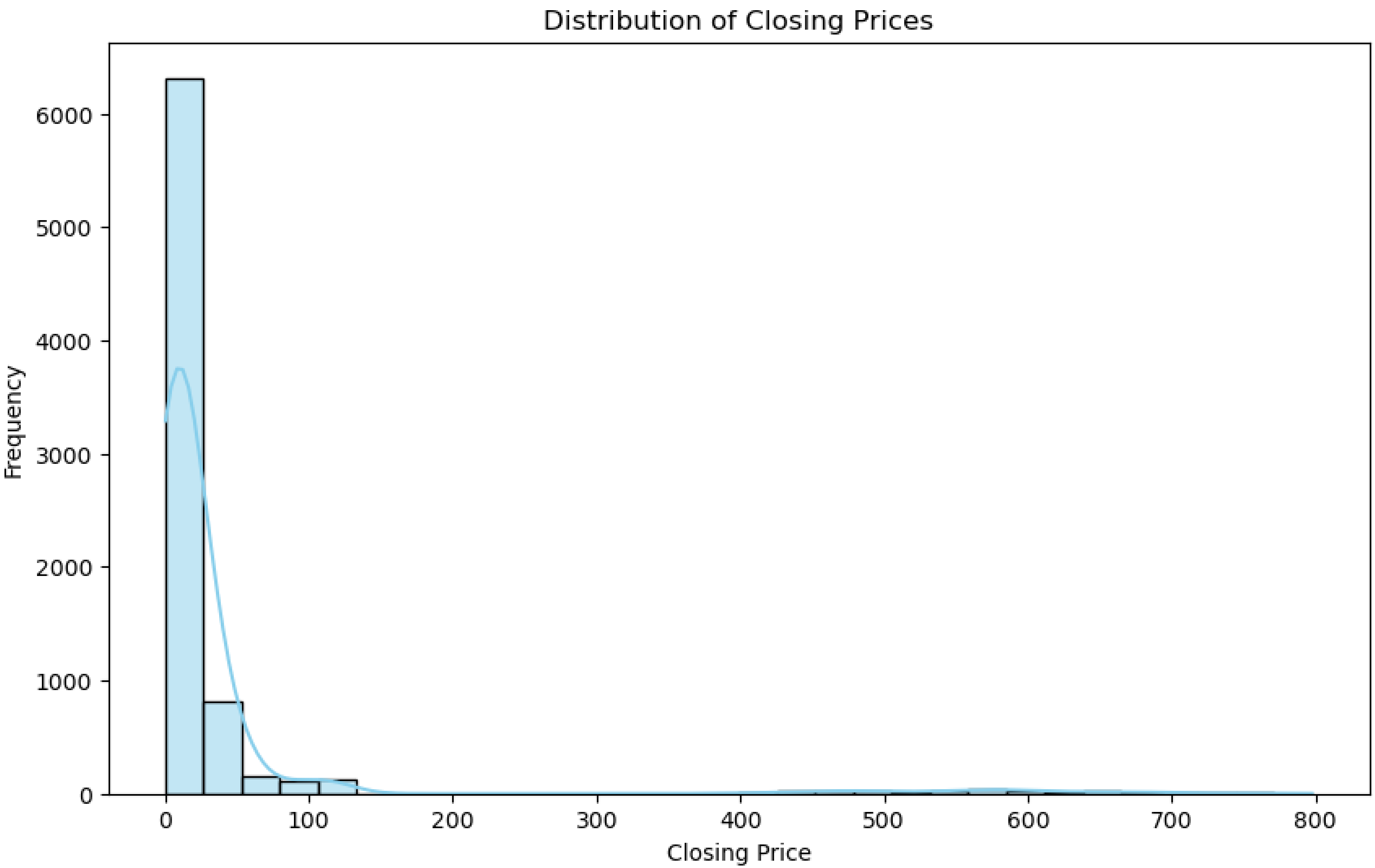
#Adding another column tommorrow to have the closing stock value for the next day df_new["tomorrow"]= df_new["close"].shift(-1) df_new

In [15]:
```
# Convert 'date' column to datetime format
df_new['date'] = pd.to_datetime(df_new['date'])
df.set_index('date', inplace=True)
```

In [16]:
```
# Plotting stock prices over time
plt.figure(figsize=(12, 6))
plt.plot(df_new['close'], label='Closing Price', color='blue')
plt.title('Stock Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.legend()
plt.show()
```

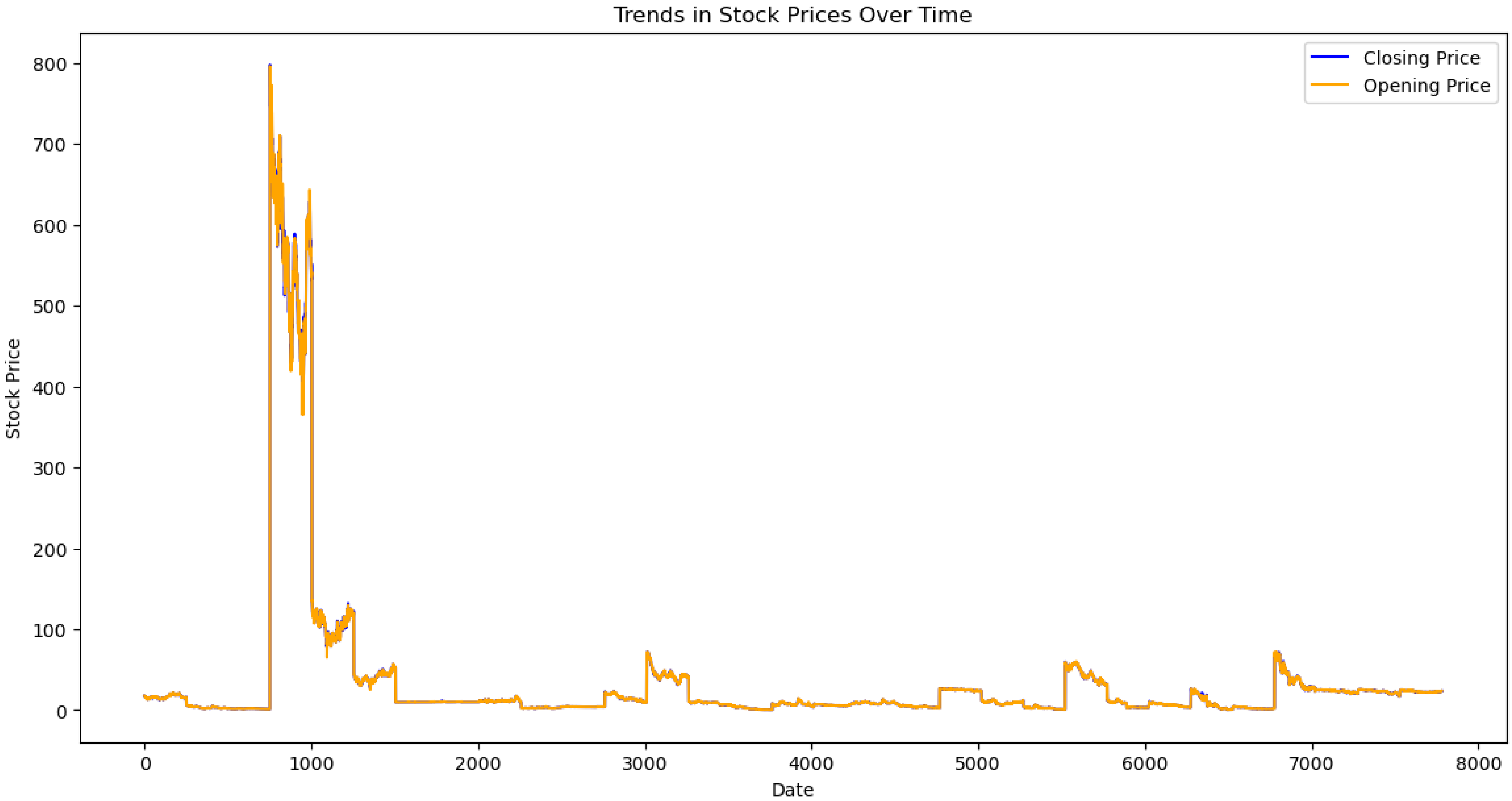


In [17]:
```
# Plotting distribution of closing prices
plt.figure(figsize=(10, 6))
sns.histplot(df_new['close'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Closing Prices')
plt.xlabel('Closing Price')
plt.ylabel('Frequency')
plt.show()
```



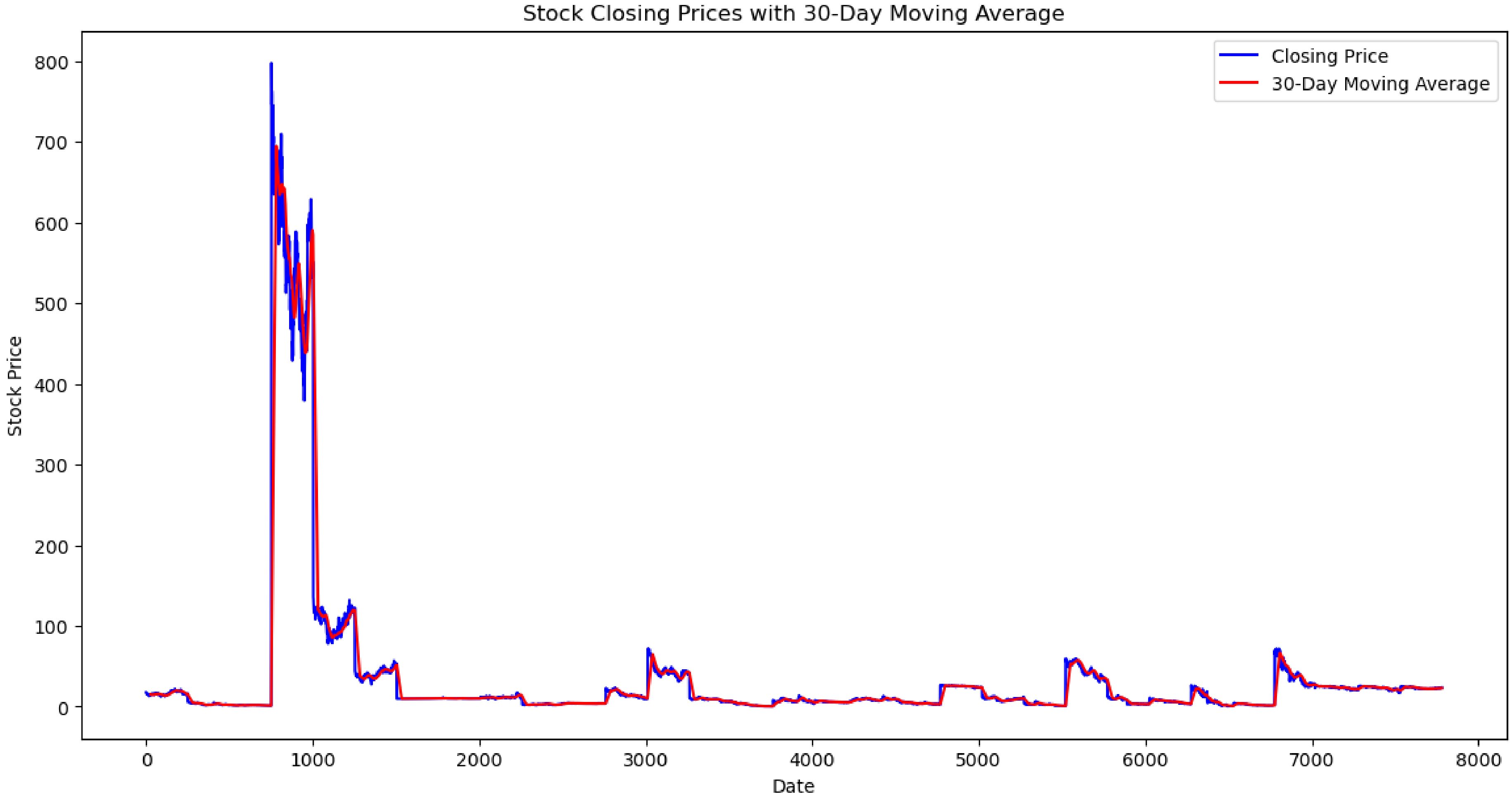
In [18]:
```
# Plotting trends in stock prices
plt.figure(figsize=(14, 7))
```

```
sns.lineplot(x=df_new.index, y=df_new['close'], label='Closing Price', color='blue')
sns.lineplot(x=df_new.index, y=df_new['open'], label='Opening Price', color='orange')
plt.title('Trends in Stock Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```



In [19]:
```
# Plotting rolling mean (moving average) to smooth out fluctuations
plt.figure(figsize=(14, 7))
df_new['close'].plot(label='Closing Price', color='blue')
df_new['close'].rolling(window=30).mean().plot(label='30-Day Moving Average', color='red')
plt.title('Stock Closing Prices with 30-Day Moving Average')
```

```
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```



In [20]:
```
df_new
```

Out[20]:

	date	open	high	low	close
0	2022-01-03	17.799999	18.219000	17.500000	17.760000
1	2022-01-04	17.700001	18.309999	17.620001	17.660000
2	2022-01-05	17.580000	17.799999	16.910000	16.950001
3	2022-01-06	16.650000	16.879999	16.139999	16.170000
4	2022-01-07	16.219999	16.290001	15.630000	15.710000
...	...	...	...	...	...
7776	2022-12-23	23.250000	23.540001	23.250000	23.290001
7777	2022-12-27	23.350000	23.610001	23.250000	23.350000
7778	2022-12-28	23.450001	23.570000	23.219999	23.350000
7779	2022-12-29	23.330000	23.740000	23.330000	23.610001
7780	2022-12-30	23.680000	23.760000	23.610001	23.610001

7781 rows × 5 columns

Predictive Modelling - Regression

In [21]:

```
# Feature Engineering
# Assuming 'date' is in datetime format
df_new['Day_of_Week'] = df_new['date'].dt.dayofweek
df_new['Month'] = df_new['date'].dt.month
```

In [22]:

```
df_new
```

Out[22]:

	date	open	high	low	close	Day_of_Week	Month
0	2022-01-03	17.799999	18.219000	17.500000	17.760000	0	1
1	2022-01-04	17.700001	18.309999	17.620001	17.660000	1	1
2	2022-01-05	17.580000	17.799999	16.910000	16.950001	2	1
3	2022-01-06	16.650000	16.879999	16.139999	16.170000	3	1
4	2022-01-07	16.219999	16.290001	15.630000	15.710000	4	1
...	...	...	...	...	...	...	...
7776	2022-12-23	23.250000	23.540001	23.250000	23.290001	4	12
7777	2022-12-27	23.350000	23.610001	23.250000	23.350000	1	12
7778	2022-12-28	23.450001	23.570000	23.219999	23.350000	2	12
7779	2022-12-29	23.330000	23.740000	23.330000	23.610001	3	12
7780	2022-12-30	23.680000	23.760000	23.610001	23.610001	4	12

7781 rows × 7 columns

In [23]:

```
# Regression Models
X = df_new[['Day_of_Week', 'Month', 'open', 'high', 'low']]
y = df_new[['close']]
```

In [24]:

```
from sklearn.ensemble import RandomForestRegressor
```

In [25]:

```
#splitting data into training and testing set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 0)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[25]:

```
((5446, 5), (2335, 5), (5446, 1), (2335, 1))
```

In [26]:

```
model_rf = RandomForestRegressor()
model_rf.fit(X_train, y_train)
```

Out[26]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [27]:
```
y_pred = model_rf.predict(X_test)
```

In [28]:
```
model_rf.score(X_train, y_train)
```

Out[28]:
```
0.9999573912798683
```

In [29]:
```
model_rf.score(X_test, y_test)
```

Out[29]:
```
0.9997122086695884
```

In [30]:
```
from sklearn import metrics
```

In [31]:
```
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MAE: 0.43130190069072155
MSE: 2.6559188507639466
RMSE: 1.6296990061860952
```

In [32]:
```
y_test = y_test.values.ravel()
```

In [33]:
```
result = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
result
```

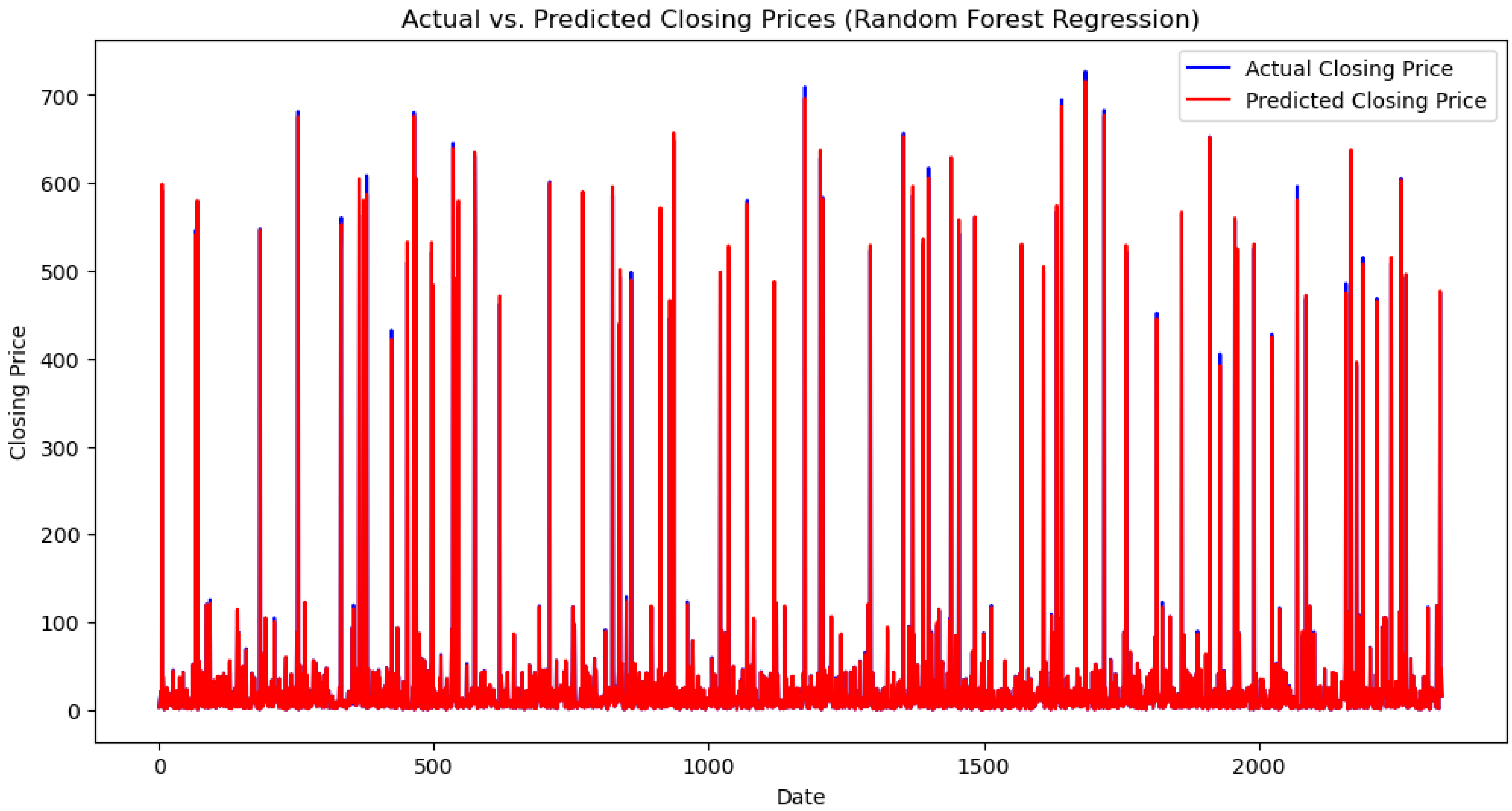
Out[33]:

	Actual	Predicted
0	2.960000	2.89730
1	8.930000	9.07860
2	13.250000	13.19930
3	20.820000	20.95520
4	3.390000	3.35975
...	...	...
2330	475.380005	476.81581
2331	45.560001	45.46680
2332	45.330002	46.69730
2333	25.230000	25.26202
2334	15.970000	15.87570

2335 rows × 2 columns

In [45]:

```
# Visualize actual vs. predicted prices
y_test_df=pd.DataFrame(y_test)
y_pred_df=pd.DataFrame(y_pred)
plt.figure(figsize=(12, 6))
plt.plot(y_test_df.index, y_test, label='Actual Closing Price', color='blue')
plt.plot(y_pred_df.index, y_pred, label='Predicted Closing Price', color='red')
plt.title('Actual vs. Predicted Closing Prices (Random Forest Regression)')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.legend()
plt.show()
```



Documentation for Stock Market Prediction Project

Approach and Methodologies:

Exploratory Data Analysis (EDA):

1. **Data Loading and Inspection:**

- Used the opendatasets library to load dataset directly from kaggle
- Loaded the stock market dataset using Pandas.
- Checked for the presence of missing values and data types.

2. **Data Cleaning:**
   - Handled missing values and converted data types if necessary
   - Ensured data integrity and consistency.
3. **Exploration and Visualization:**
   - Explored the distribution of key variables (open, high, low, close).
   - Visualized trends over time using line plots and candlestick charts.
   - Calculated and visualized summary statistics.
   - Investigated the correlation matrix to understand relationships between variables.

Predictive Modeling:

1. **Feature Engineering:**
   - Selected relevant features for predicting stock prices (open, high, low).
   - Considered additional features based on domain knowledge.
2. **Train-Test Split:**
   - Split the dataset into training and testing sets, ensuring a reasonable time range for training.
3. **Regression Model:**
   - Implemented Random Forest Regression model.
   - Chose these models due to their simplicity and effectiveness in capturing linear and non-linear relationships.
4. **Evaluation:**
   - Evaluated the model using Mean Squared Error (MSE) as a performance metric.
   - Considered the trade-offs between model complexity and performance.

Insights Gained:

1. **Trends in Stock Prices:**
   - Identified trends and patterns in stock prices over time.
   - Observed relationships between opening, closing, high, low prices, and trading volume.
2. **Statistical Summary:**

- Gained insights into the statistical distribution of stock prices.
- Detected outliers and anomalies that might impact predictions.

3. **Correlation Analysis:**

- Analyzed the correlation matrix to understand the relationships between features.
- Identified potential multicollinearity among variables.

Chosen Predictive Model:

1. **Random Forest Regression:**
    - Opted for Random Forest Regression for its ability to handle non-linear relationships and capture complex patterns.
    - Robust to outliers and less prone to overfitting.

Model Evaluation:

1. **Performance Metrics:**

- Used Mean Squared Error (MSE) to quantify the accuracy of predictions.
- Evaluated both Linear Regression and Random Forest Regression models.

2. **Visualizations:**

- Visualized actual vs. predicted stock prices to assess model performance visually.
- Plotted additional visualizations to aid in understanding model behavior.

Challenges and Limitations:

1. **Data Challenges:**

- Addressed missing values and data inconsistencies.
- Dealt with potential outliers that might affect model performance.

2. **Model Limitations:**

- Acknowledged the limitations of linear models in capturing complex relationships.
- Considered the need for more sophisticated time series models for improved forecasting.

Conclusion:

In conclusion, this project aimed to analyze and predict stock prices using a combination of exploratory data analysis and regression models. Insights gained from EDA provided a foundational understanding of the dataset, while the predictive models offered an initial attempt at forecasting stock prices. Moving forward, more advanced models and feature engineering techniques could be explored for enhanced predictive capabilities.