stock-price-prediction-corizo

August 3, 2023

[36]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import matplotlib.pyplot as plt
```

1 Data Preprocessing

[37]:
```
# Loading the dataset from CSV
df = pd.read_csv('Stock_Price_data_set.csv')
```

[38]:
```
df.head()
```

[38]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	250.100006	9306700
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	249.470001	16906900

[39]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1009 non-null   object
 1   Open       1009 non-null   float64
```

```
 2   High       1009 non-null   float64
 3   Low        1009 non-null   float64
 4   Close      1009 non-null   float64
 5   Adj Close  1009 non-null   float64
 6   Volume     1009 non-null   int64
dtypes: float64(5), int64(1), object(1)
memory usage: 55.3+ KB
```

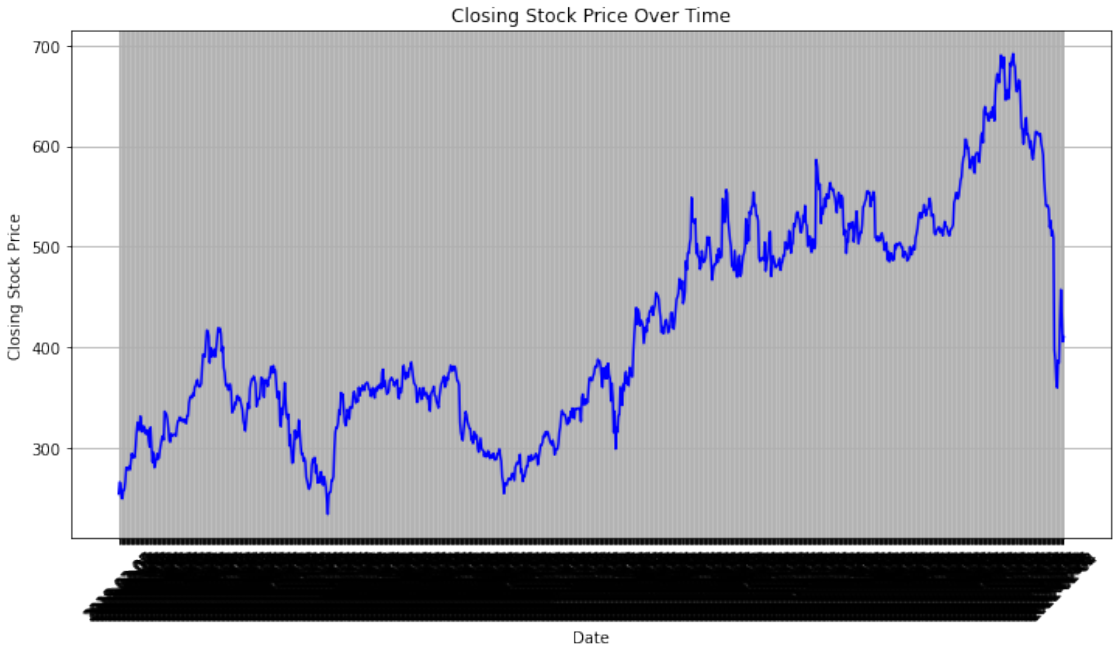
[40]:
```
df.describe()
```

[40]:

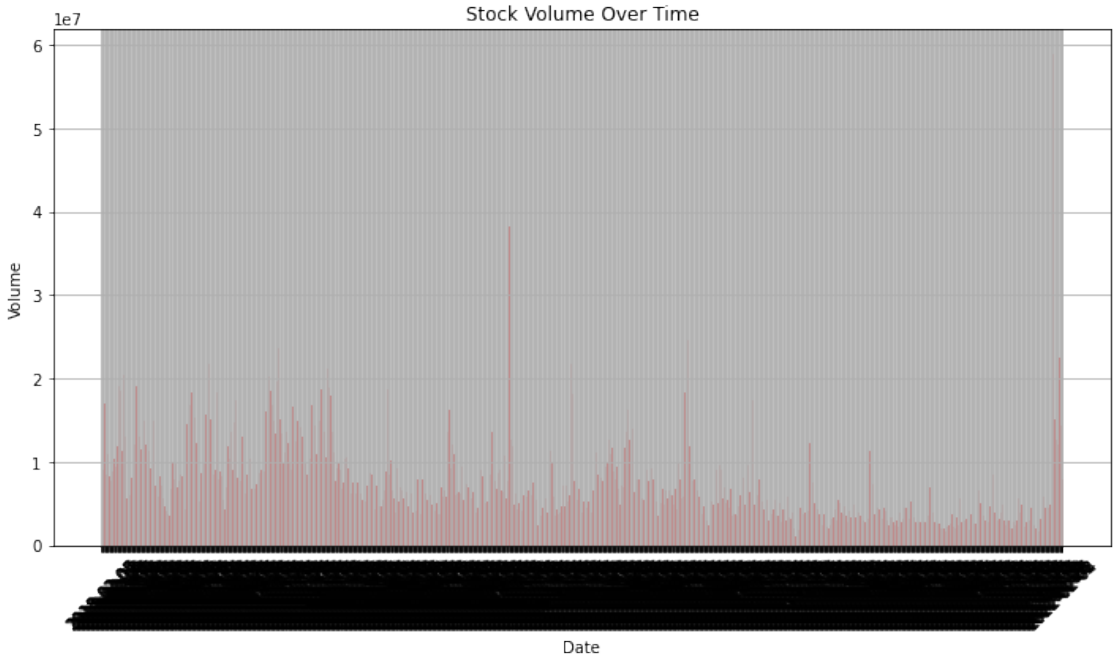
	Open	High	Low	Close	Adj Close	Volume
count	1009.000000	1009.000000	1009.000000	1009.000000	1009.000000	1.009000e+03
mean	419.059673	425.320703	412.374044	419.000733	419.000733	7.570685e+06
std	108.537532	109.262960	107.555867	108.289999	108.289999	5.465535e+06
min	233.919998	250.649994	231.229996	233.880005	233.880005	1.144000e+06
25%	331.489990	336.299988	326.000000	331.619995	331.619995	4.091900e+06
50%	377.769989	383.010010	370.880005	378.670013	378.670013	5.934500e+06
75%	509.130005	515.630005	502.529999	509.079987	509.079987	9.322400e+06
max	692.349976	700.989990	686.090027	691.690002	691.690002	5.890430e+07

2 Visualization

[41]:
```
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], color='blue')
plt.xlabel('Date')
plt.ylabel('Closing Stock Price')
plt.title('Closing Stock Price Over Time')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

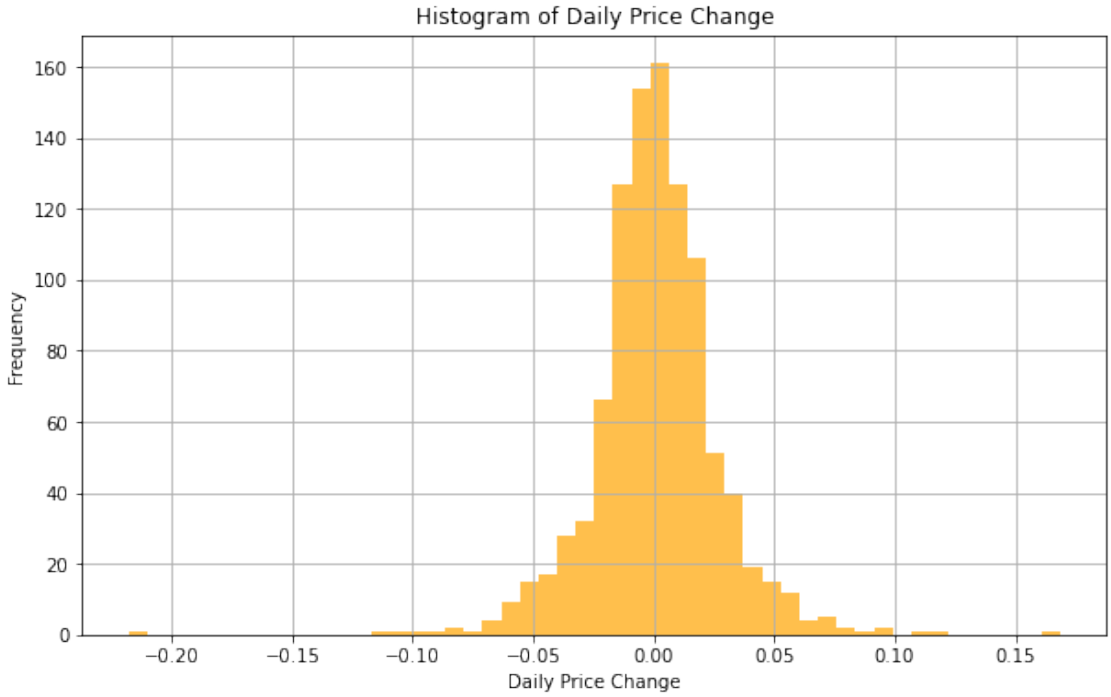


[42]:
```
plt.figure(figsize=(12, 6))
plt.bar(df['Date'], df['Volume'], color='red')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.title('Stock Volume Over Time')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



[43]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df['Close'], df['Volume'], color='purple', alpha=0.5)
plt.xlabel('Closing Stock Price')
plt.ylabel('Volume')
plt.title('Closing Price vs. Volume')
plt.grid(True)
plt.show()
```

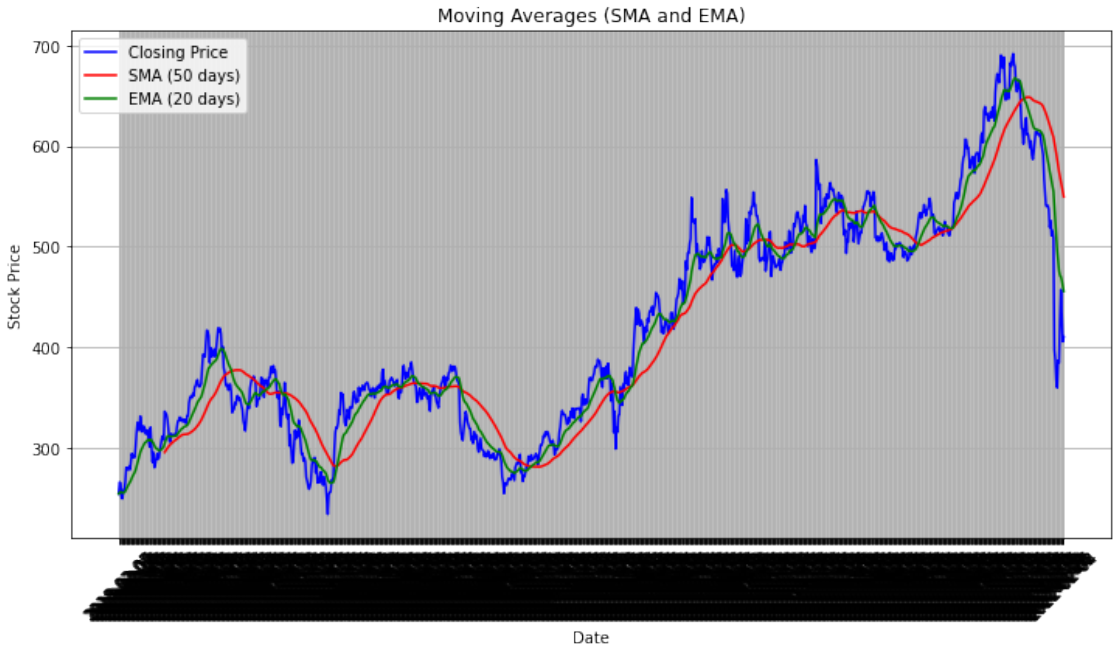
[44]:
```
daily_returns = df['Close'].pct_change()
plt.figure(figsize=(10, 6))
plt.hist(daily_returns.dropna(), bins=50, color='orange', alpha=0.7)
plt.xlabel('Daily Price Change')
plt.ylabel('Frequency')
plt.title('Histogram of Daily Price Change')
plt.grid(True)
plt.show()
```



[45]:
```
plt.figure(figsize=(12, 6))
df['SMA_50'] = df['Close'].rolling(window=50).mean()
df['EMA_20'] = df['Close'].ewm(span=20, adjust=False).mean()

plt.plot(df['Date'], df['Close'], label='Closing Price', color='blue')
plt.plot(df['Date'], df['SMA_50'], label='SMA (50 days)', color='red')
plt.plot(df['Date'], df['EMA_20'], label='EMA (20 days)', color='green')

plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.title('Moving Averages (SMA and EMA)')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.show()
```

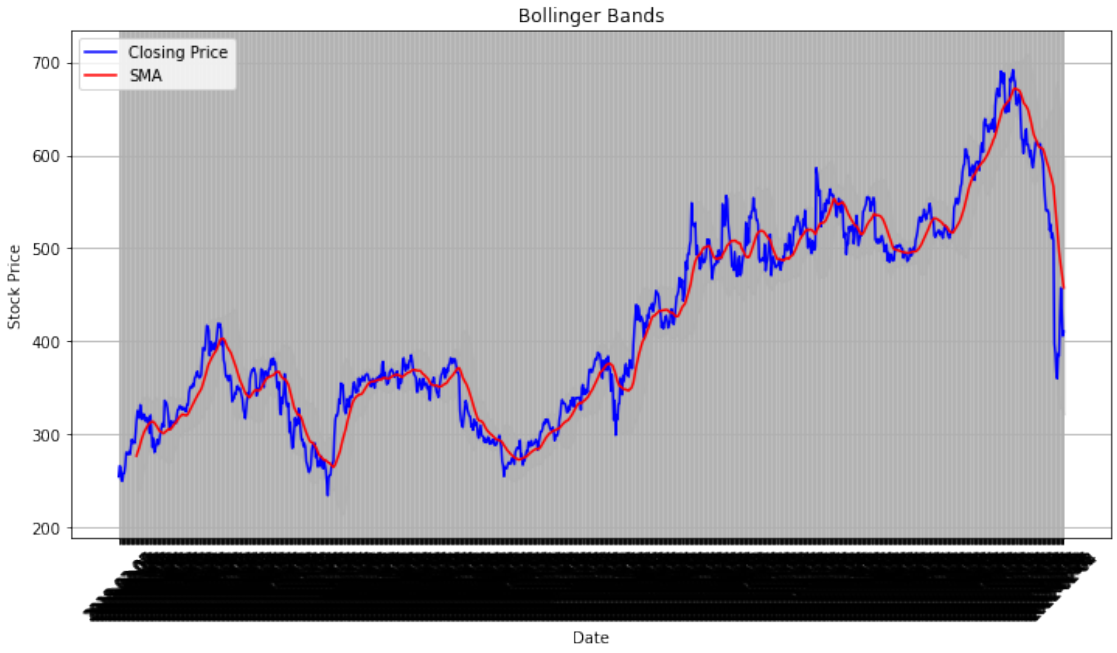


[46]:
```
plt.figure(figsize=(12, 6))
window = 20  # Adjust the window size if needed
df['SMA'] = df['Close'].rolling(window=window).mean()
df['STD'] = df['Close'].rolling(window=window).std()

df['Upper'] = df['SMA'] + 2 * df['STD']
df['Lower'] = df['SMA'] - 2 * df['STD']

plt.plot(df['Date'], df['Close'], label='Closing Price', color='blue')
plt.plot(df['Date'], df['SMA'], label='SMA', color='red')
plt.fill_between(df['Date'], df['Upper'], df['Lower'], color='gray', alpha=0.3)

plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.title('Bollinger Bands')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.show()
```



[47]:
```
# Handle missing data and data cleaning (imputation for missing values)
df.fillna(method='ffill', inplace=True)  # Forward fill missing values
df.dropna(inplace=True)  # Drop any remaining rows with missing values
```

3 Feature Engineering

[48]:
```
# Extracting relevant features and target variable
X = df[['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']]  # Select␣
↪features
y = df['Close']  # Target variable, predicting the 'Close' stock price
```

4 Data Split

[49]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

5 Model Selection and Training

[50]:
```
model = RandomForestRegressor(n_estimators=100, random_state=42)  # Using 100␣
↪decision trees
model.fit(X_train, y_train)
```

[50]:
```
RandomForestRegressor(random_state=42)
```

6 Model Evaluation

[51]:
```
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("Mean Absolute Error:", mae)
print("R^2 Score:", r2)
```

```
Mean Squared Error: 3.8782310623426395
Root Mean Squared Error: 1.9693224881523694
Mean Absolute Error: 0.6671437576562383
R^2 Score: 0.999666196046549
```

[ ]: