stock-price-prediction-using-lstm

August 30, 2023

[43]:
```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
```

[44]:
```python
# Load the data from the CSV file
df = pd.read_excel('/content/stock.xlsx')
```

[45]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2035 entries, 0 to 2034
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Date                  2035 non-null   datetime64[ns]
 1   Open                  2035 non-null   float64
 2   High                  2035 non-null   float64
 3   Low                   2035 non-null   float64
 4   Last                  2035 non-null   float64
 5   Close                 2035 non-null   float64
 6   Total Trade Quantity  2035 non-null   int64
 7   Turnover (Lacs)       2035 non-null   float64
dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 127.3 KB
```

[46]:
```python
df.describe()
```

[46]:
```
              Open         High          Low         Last        Close  \
count  2035.000000  2035.000000  2035.000000  2035.000000  2035.00000
mean    149.713735   151.992826   147.293931   149.474251   149.45027
std      48.664509    49.413109    47.931958    48.732570    48.71204
min      81.100000    82.800000    80.000000    81.000000    80.95000
25%     120.025000   122.100000   118.300000   120.075000   120.05000
```

```
50%      141.500000   143.400000   139.600000   141.100000   141.25000
75%      157.175000   159.400000   155.150000   156.925000   156.90000
max      327.700000   328.750000   321.650000   325.950000   325.75000

       Total Trade Quantity  Turnover (Lacs)
count          2.035000e+03      2035.000000
mean           2.335681e+06      3899.980565
std            2.091778e+06      4570.767877
min            3.961000e+04        37.040000
25%            1.146444e+06      1427.460000
50%            1.783456e+06      2512.030000
75%            2.813594e+06      4539.015000
max            2.919102e+07     55755.080000
```

[47]:
```python
# Convert the 'Date' column to datetime type
df['Date'] = pd.to_datetime(df['Date'])
```

[48]:
```python
# Sort the DataFrame by date in ascending order
df = df.sort_values('Date')
```

[49]:
```python
# Extract the 'Close' column (our target variable)
dataset = df[['Close']].values.astype(float)
```

[50]:
```python
# Normalize the dataset using Min-Max scaling to bring values between 0 and 1
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
```

[51]:
```python
# Function to create input sequences and corresponding target values
def create_sequences(dataset, look_back=1):
    data_X, data_y = [], []
    for i in range(len(dataset) - look_back):
        data_X.append(dataset[i:(i + look_back), 0])
        data_y.append(dataset[i + look_back, 0])
    return np.array(data_X), np.array(data_y)
```

[52]:
```python
# Set the look-back period (number of previous time steps to use for prediction)
look_back = 30
```

[53]:
```python
# Create input sequences and target values
X, y = create_sequences(dataset, look_back)
```

[54]:
```python
# Split the data into training and testing sets
train_size = int(len(X) * 0.7)
test_size = len(X) - train_size
X_train, X_test = X[0:train_size], X[train_size:len(X)]
y_train, y_test = y[0:train_size], y[train_size:len(y)]
```

[55]:
```
# Reshape the input data to fit the LSTM input shape (samples, time steps,␣
↪features)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

[56]:
```
# Create the LSTM model
model = Sequential()
model.add(LSTM(50, input_shape=(look_back, 1)))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
```

[57]:
```
# Train the model
model.fit(X_train, y_train, epochs=100, batch_size=1, verbose=2)
```

```
Epoch 1/100
1403/1403 - 7s - loss: 0.0011 - 7s/epoch - 5ms/step
Epoch 2/100
1403/1403 - 6s - loss: 3.1839e-04 - 6s/epoch - 4ms/step
Epoch 3/100
1403/1403 - 5s - loss: 2.2856e-04 - 5s/epoch - 4ms/step
Epoch 4/100
1403/1403 - 5s - loss: 1.9015e-04 - 5s/epoch - 4ms/step
Epoch 5/100
1403/1403 - 6s - loss: 1.7095e-04 - 6s/epoch - 4ms/step
Epoch 6/100
1403/1403 - 5s - loss: 1.5696e-04 - 5s/epoch - 4ms/step
Epoch 7/100
1403/1403 - 6s - loss: 1.6155e-04 - 6s/epoch - 4ms/step
Epoch 8/100
1403/1403 - 5s - loss: 1.6143e-04 - 5s/epoch - 4ms/step
Epoch 9/100
1403/1403 - 6s - loss: 1.5766e-04 - 6s/epoch - 4ms/step
Epoch 10/100
1403/1403 - 5s - loss: 1.5135e-04 - 5s/epoch - 4ms/step
Epoch 11/100
1403/1403 - 5s - loss: 1.4389e-04 - 5s/epoch - 4ms/step
Epoch 12/100
1403/1403 - 5s - loss: 1.4982e-04 - 5s/epoch - 4ms/step
Epoch 13/100
1403/1403 - 5s - loss: 1.4415e-04 - 5s/epoch - 4ms/step
Epoch 14/100
1403/1403 - 6s - loss: 1.4274e-04 - 6s/epoch - 4ms/step
Epoch 15/100
1403/1403 - 5s - loss: 1.4330e-04 - 5s/epoch - 4ms/step
Epoch 16/100
1403/1403 - 7s - loss: 1.3856e-04 - 7s/epoch - 5ms/step
Epoch 17/100
```

```
1403/1403 - 5s - loss: 1.3914e-04 - 5s/epoch - 4ms/step
Epoch 18/100
1403/1403 - 5s - loss: 1.4332e-04 - 5s/epoch - 4ms/step
Epoch 19/100
1403/1403 - 6s - loss: 1.4010e-04 - 6s/epoch - 4ms/step
Epoch 20/100
1403/1403 - 5s - loss: 1.4342e-04 - 5s/epoch - 4ms/step
Epoch 21/100
1403/1403 - 6s - loss: 1.4349e-04 - 6s/epoch - 4ms/step
Epoch 22/100
1403/1403 - 5s - loss: 1.4603e-04 - 5s/epoch - 4ms/step
Epoch 23/100
1403/1403 - 6s - loss: 1.3980e-04 - 6s/epoch - 4ms/step
Epoch 24/100
1403/1403 - 5s - loss: 1.3868e-04 - 5s/epoch - 4ms/step
Epoch 25/100
1403/1403 - 5s - loss: 1.3650e-04 - 5s/epoch - 4ms/step
Epoch 26/100
1403/1403 - 5s - loss: 1.4056e-04 - 5s/epoch - 4ms/step
Epoch 27/100
1403/1403 - 5s - loss: 1.3894e-04 - 5s/epoch - 4ms/step
Epoch 28/100
1403/1403 - 6s - loss: 1.3811e-04 - 6s/epoch - 4ms/step
Epoch 29/100
1403/1403 - 5s - loss: 1.4271e-04 - 5s/epoch - 4ms/step
Epoch 30/100
1403/1403 - 5s - loss: 1.3877e-04 - 5s/epoch - 4ms/step
Epoch 31/100
1403/1403 - 5s - loss: 1.4090e-04 - 5s/epoch - 4ms/step
Epoch 32/100
1403/1403 - 5s - loss: 1.3406e-04 - 5s/epoch - 4ms/step
Epoch 33/100
1403/1403 - 6s - loss: 1.3943e-04 - 6s/epoch - 4ms/step
Epoch 34/100
1403/1403 - 5s - loss: 1.3886e-04 - 5s/epoch - 3ms/step
Epoch 35/100
1403/1403 - 6s - loss: 1.3562e-04 - 6s/epoch - 4ms/step
Epoch 36/100
1403/1403 - 5s - loss: 1.3359e-04 - 5s/epoch - 4ms/step
Epoch 37/100
1403/1403 - 6s - loss: 1.3913e-04 - 6s/epoch - 4ms/step
Epoch 38/100
1403/1403 - 5s - loss: 1.3191e-04 - 5s/epoch - 4ms/step
Epoch 39/100
1403/1403 - 5s - loss: 1.4324e-04 - 5s/epoch - 4ms/step
Epoch 40/100
1403/1403 - 6s - loss: 1.3309e-04 - 6s/epoch - 4ms/step
Epoch 41/100
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1403/1403 - 5s - loss: 1.3858e-04 - 5s/epoch - 4ms/step
Epoch 42/100
1403/1403 - 6s - loss: 1.3314e-04 - 6s/epoch - 4ms/step
Epoch 43/100
1403/1403 - 5s - loss: 1.3464e-04 - 5s/epoch - 4ms/step
Epoch 44/100
1403/1403 - 5s - loss: 1.3288e-04 - 5s/epoch - 4ms/step
Epoch 45/100
1403/1403 - 5s - loss: 1.3496e-04 - 5s/epoch - 4ms/step
Epoch 46/100
1403/1403 - 5s - loss: 1.3524e-04 - 5s/epoch - 4ms/step
Epoch 47/100
1403/1403 - 6s - loss: 1.3502e-04 - 6s/epoch - 4ms/step
Epoch 48/100
1403/1403 - 5s - loss: 1.3522e-04 - 5s/epoch - 4ms/step
Epoch 49/100
1403/1403 - 6s - loss: 1.3292e-04 - 6s/epoch - 4ms/step
Epoch 50/100
1403/1403 - 5s - loss: 1.3475e-04 - 5s/epoch - 4ms/step
Epoch 51/100
1403/1403 - 5s - loss: 1.3313e-04 - 5s/epoch - 4ms/step
Epoch 52/100
1403/1403 - 5s - loss: 1.3571e-04 - 5s/epoch - 4ms/step
Epoch 53/100
1403/1403 - 5s - loss: 1.3198e-04 - 5s/epoch - 4ms/step
Epoch 54/100
1403/1403 - 6s - loss: 1.3024e-04 - 6s/epoch - 4ms/step
Epoch 55/100
1403/1403 - 5s - loss: 1.3032e-04 - 5s/epoch - 4ms/step
Epoch 56/100
1403/1403 - 6s - loss: 1.3327e-04 - 6s/epoch - 4ms/step
Epoch 57/100
1403/1403 - 5s - loss: 1.3344e-04 - 5s/epoch - 4ms/step
Epoch 58/100
1403/1403 - 5s - loss: 1.3310e-04 - 5s/epoch - 4ms/step
Epoch 59/100
1403/1403 - 5s - loss: 1.3102e-04 - 5s/epoch - 4ms/step
Epoch 60/100
1403/1403 - 5s - loss: 1.3657e-04 - 5s/epoch - 3ms/step
Epoch 61/100
1403/1403 - 6s - loss: 1.3537e-04 - 6s/epoch - 4ms/step
Epoch 62/100
1403/1403 - 5s - loss: 1.3437e-04 - 5s/epoch - 4ms/step
Epoch 63/100
1403/1403 - 6s - loss: 1.3319e-04 - 6s/epoch - 4ms/step
Epoch 64/100
1403/1403 - 5s - loss: 1.3166e-04 - 5s/epoch - 4ms/step
Epoch 65/100
```

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1403/1403 - 5s - loss: 1.3516e-04 - 5s/epoch - 4ms/step
Epoch 66/100
1403/1403 - 6s - loss: 1.3612e-04 - 6s/epoch - 4ms/step
Epoch 67/100
1403/1403 - 5s - loss: 1.2902e-04 - 5s/epoch - 4ms/step
Epoch 68/100
1403/1403 - 6s - loss: 1.3310e-04 - 6s/epoch - 4ms/step
Epoch 69/100
1403/1403 - 5s - loss: 1.2993e-04 - 5s/epoch - 4ms/step
Epoch 70/100
1403/1403 - 5s - loss: 1.3015e-04 - 5s/epoch - 4ms/step
Epoch 71/100
1403/1403 - 5s - loss: 1.3303e-04 - 5s/epoch - 4ms/step
Epoch 72/100
1403/1403 - 5s - loss: 1.3060e-04 - 5s/epoch - 4ms/step
Epoch 73/100
1403/1403 - 6s - loss: 1.3248e-04 - 6s/epoch - 4ms/step
Epoch 74/100
1403/1403 - 5s - loss: 1.3318e-04 - 5s/epoch - 4ms/step
Epoch 75/100
1403/1403 - 6s - loss: 1.3325e-04 - 6s/epoch - 4ms/step
Epoch 76/100
1403/1403 - 5s - loss: 1.3204e-04 - 5s/epoch - 4ms/step
Epoch 77/100
1403/1403 - 5s - loss: 1.3397e-04 - 5s/epoch - 4ms/step
Epoch 78/100
1403/1403 - 5s - loss: 1.2952e-04 - 5s/epoch - 4ms/step
Epoch 79/100
1403/1403 - 5s - loss: 1.3401e-04 - 5s/epoch - 4ms/step
Epoch 80/100
1403/1403 - 6s - loss: 1.3165e-04 - 6s/epoch - 4ms/step
Epoch 81/100
1403/1403 - 5s - loss: 1.2845e-04 - 5s/epoch - 4ms/step
Epoch 82/100
1403/1403 - 6s - loss: 1.2964e-04 - 6s/epoch - 4ms/step
Epoch 83/100
1403/1403 - 5s - loss: 1.3009e-04 - 5s/epoch - 4ms/step
Epoch 84/100
1403/1403 - 5s - loss: 1.3029e-04 - 5s/epoch - 4ms/step
Epoch 85/100
1403/1403 - 5s - loss: 1.3657e-04 - 5s/epoch - 4ms/step
Epoch 86/100
1403/1403 - 5s - loss: 1.3615e-04 - 5s/epoch - 4ms/step
Epoch 87/100
1403/1403 - 6s - loss: 1.3077e-04 - 6s/epoch - 4ms/step
Epoch 88/100
1403/1403 - 5s - loss: 1.2844e-04 - 5s/epoch - 4ms/step
Epoch 89/100
```

```
1403/1403 - 5s - loss: 1.3305e-04 - 5s/epoch - 4ms/step
Epoch 90/100
1403/1403 - 5s - loss: 1.3090e-04 - 5s/epoch - 4ms/step
Epoch 91/100
1403/1403 - 5s - loss: 1.2979e-04 - 5s/epoch - 4ms/step
Epoch 92/100
1403/1403 - 6s - loss: 1.3626e-04 - 6s/epoch - 4ms/step
Epoch 93/100
1403/1403 - 5s - loss: 1.2752e-04 - 5s/epoch - 4ms/step
Epoch 94/100
1403/1403 - 6s - loss: 1.2928e-04 - 6s/epoch - 4ms/step
Epoch 95/100
1403/1403 - 5s - loss: 1.2946e-04 - 5s/epoch - 4ms/step
Epoch 96/100
1403/1403 - 5s - loss: 1.2856e-04 - 5s/epoch - 4ms/step
Epoch 97/100
1403/1403 - 5s - loss: 1.3074e-04 - 5s/epoch - 4ms/step
Epoch 98/100
1403/1403 - 5s - loss: 1.2980e-04 - 5s/epoch - 4ms/step
Epoch 99/100
1403/1403 - 6s - loss: 1.3099e-04 - 6s/epoch - 4ms/step
Epoch 100/100
1403/1403 - 5s - loss: 1.2635e-04 - 5s/epoch - 4ms/step
```

[57]:
```
<keras.callbacks.History at 0x7ab75cba1210>
```

[58]:
```
# Generate predictions on the training and test data
train_predict = model.predict(X_train)
test_predict = model.predict(X_test)
```

```
44/44 [==============================] - 0s 2ms/step
19/19 [==============================] - 0s 2ms/step
```

[59]:
```
# Inverse transform the predictions to the original scale
train_predict = scaler.inverse_transform(train_predict)
y_train = scaler.inverse_transform([y_train])
test_predict = scaler.inverse_transform(test_predict)
y_test = scaler.inverse_transform([y_test])
```

[60]:
```
# Calculate the root mean squared error (RMSE) to evaluate the model's␣
↪performance
train_score = np.sqrt(np.mean((y_train[0] - train_predict[:, 0])**2))
print(f"Train RMSE: {train_score:.2f}")
```

```
Train RMSE: 3.08
```

[61]:
```
test_score = np.sqrt(np.mean((y_test[0] - test_predict[:, 0])**2))
print(f"Test RMSE: {test_score:.2f}")
```

```
Test RMSE: 13.28
```

[62]:

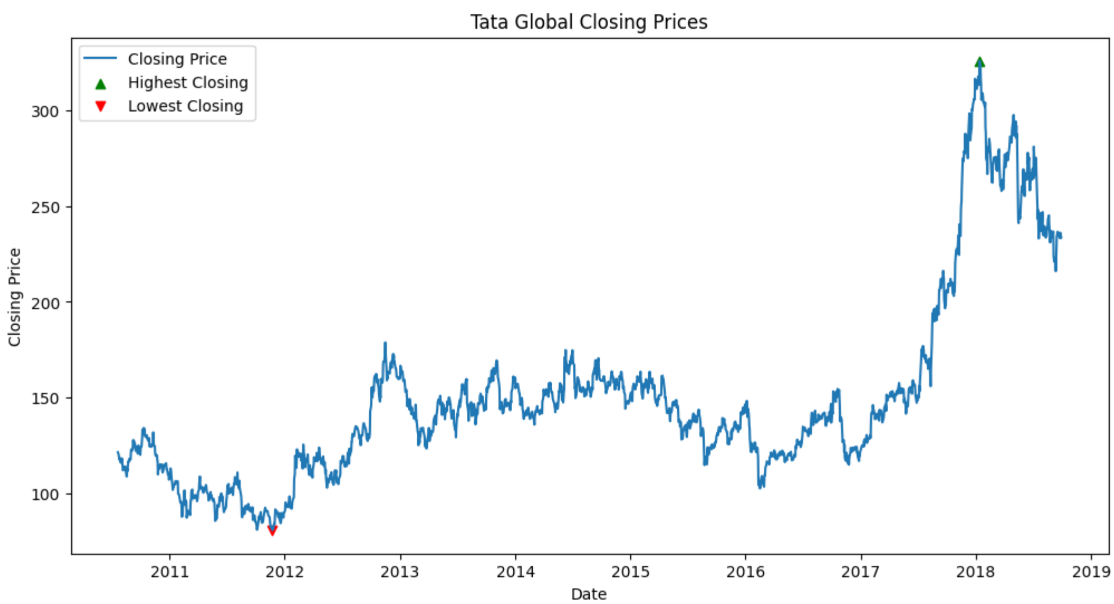
```python
# Find the day with the highest and lowest closing value
max_close_day = df.loc[df['Close'].idxmax()]['Date']
min_close_day = df.loc[df['Close'].idxmin()]['Date']

print(f"Day with highest closing value: {max_close_day}")
print(f"Day with lowest closing value: {min_close_day}")
```

```
Day with highest closing value: 2018-01-12 00:00:00
Day with lowest closing value: 2011-11-23 00:00:00
```

[63]:

```python
# Plot the historical closing prices over time
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Closing Price')
plt.scatter(max_close_day, df.loc[df['Close'].idxmax()]['Close'],␣
 ↪color='green', label='Highest Closing', marker='^')
plt.scatter(min_close_day, df.loc[df['Close'].idxmin()]['Close'], color='red',␣
 ↪label='Lowest Closing', marker='v')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.title('Tata Global Closing Prices')
plt.legend()
plt.show()
```

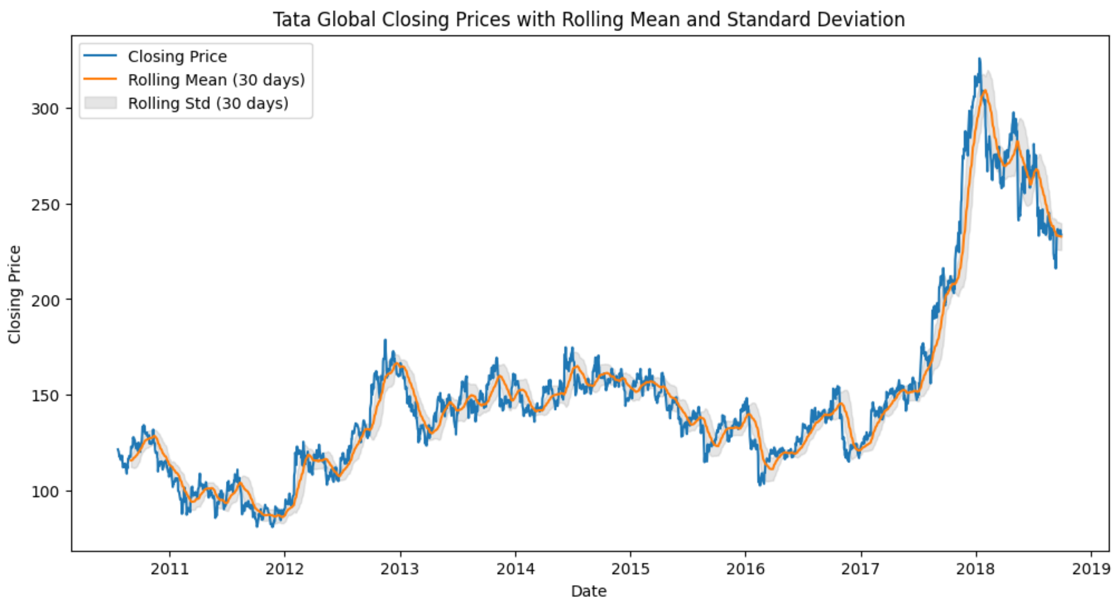


[64]:

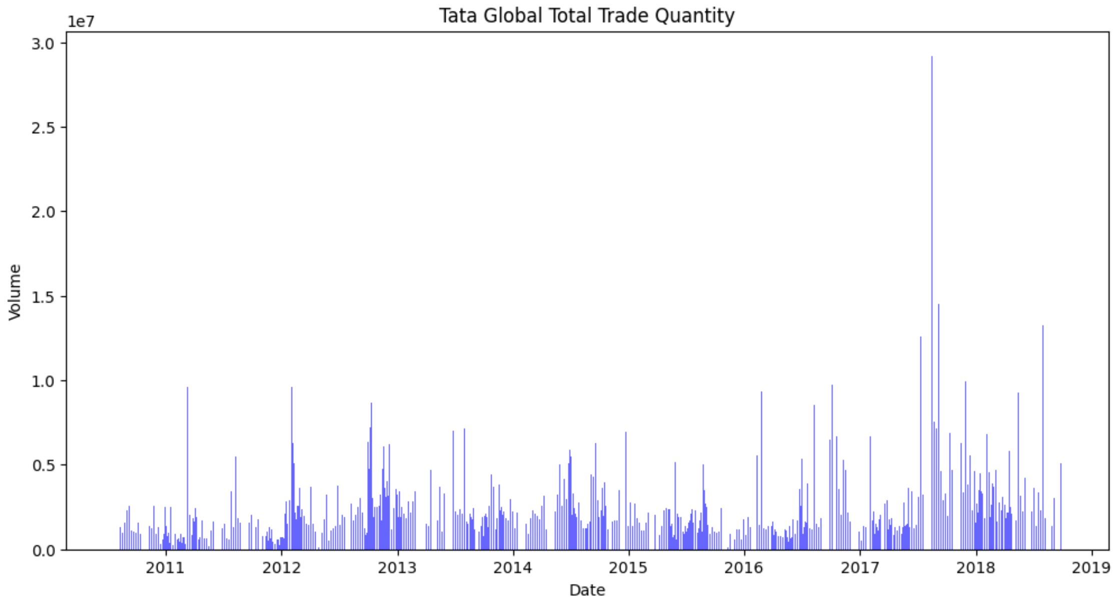
```python
# Calculate the rolling mean and standard deviation of the closing prices
rolling_mean = df['Close'].rolling(window=30).mean()
```

```
rolling_std = df['Close'].rolling(window=30).std()
```

[65]:
```
# Plot the rolling mean and standard deviation
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Closing Price')
plt.plot(df['Date'], rolling_mean, label='Rolling Mean (30 days)')
plt.fill_between(df['Date'], rolling_mean - rolling_std, rolling_mean +␣
 ↪rolling_std, alpha=0.2, color='gray', label='Rolling Std (30 days)')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.title('Tata Global Closing Prices with Rolling Mean and Standard Deviation')
plt.legend()
plt.show()
```



[66]:
```
# Plot the Total Trade Quantity
plt.figure(figsize=(12, 6))
plt.bar(df['Date'], df['Total Trade Quantity'], color='blue', alpha=0.6)
plt.xlabel('Date')
plt.ylabel('Volume')
plt.title('Tata Global Total Trade Quantity')
plt.show()
```



[67]:
```python
# Extend the dataset to simulate future predictions (e.g., 30 days beyond the␣
↪available data)
extended_dates = pd.date_range(start=df['Date'].max(), periods=30, freq='D')
extended_dates = pd.DataFrame({'Date': extended_dates})
extended_df = pd.concat([df, extended_dates], ignore_index=True)
```

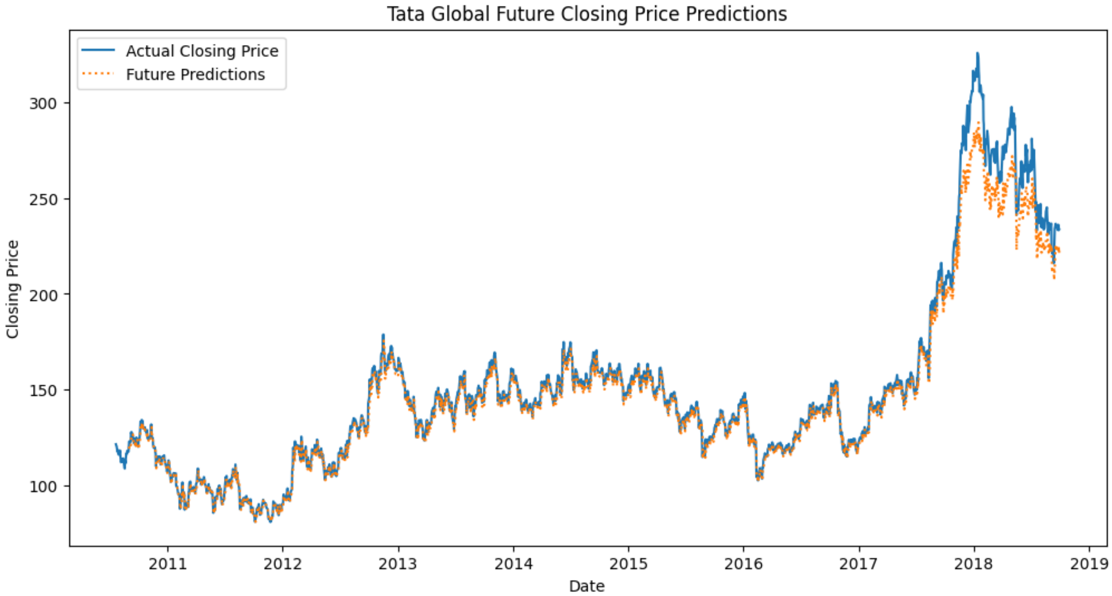
[68]:
```python
# Preprocess the extended dataset for prediction
extended_dataset = scaler.transform(extended_df[['Close']].values.astype(float))
X_extended, y_extended = create_sequences(extended_dataset, look_back)
X_extended = np.reshape(X_extended, (X_extended.shape[0], X_extended.shape[1],␣
↪1))
```

[69]:
```python
# Generate predictions for the extended dataset
extended_predict = model.predict(X_extended)
extended_predict = scaler.inverse_transform(extended_predict)
```

```
64/64 [==============================] - 0s 3ms/step
```

[70]:
```python
# Plot the actual data and future predictions
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Actual Closing Price')
plt.plot(extended_df.iloc[look_back:]['Date'], extended_predict, label='Future␣
↪Predictions', linestyle='dotted')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.title('Tata Global Future Closing Price Predictions')
plt.legend()
```

```
plt.show()
```



[71]:
```
# Filter the data for the year 2018
df_2018 = df[df['Date'].dt.year == 2018]

# Create a DataFrame for actual and predicted closing prices in 2018
dates_2018 = df_2018['Date'][look_back + 1:].reset_index(drop=True)  # Adjusted␣
 ↪indexing
actual_prices_2018 = df_2018['Close'][look_back:-1].reset_index(drop=True)  #␣
 ↪Adjusted indexing
predicted_prices_2018 = extended_predict[-len(dates_2018):].flatten()  #␣
 ↪Flattening the predicted prices array

closing_prices_2018_df = pd.DataFrame({'Date': dates_2018, 'Actual':␣
 ↪actual_prices_2018, 'Predicted': predicted_prices_2018})

# Display the actual and predicted closing prices for the year 2020 in a␣
 ↪tabular form
print(closing_prices_2018_df)
```

```
          Date  Actual   Predicted
0   2018-02-15  281.95  257.671783
1   2018-02-16  279.05  257.484558
2   2018-02-19  275.60  244.833466
3   2018-02-20  267.95  256.662445
4   2018-02-21  262.85  252.915573
..         …       …          …
```

```
149 2018-09-24  234.60         NaN
150 2018-09-25  233.30         NaN
151 2018-09-26  236.10         NaN
152 2018-09-27  234.25         NaN
153 2018-09-28  233.25         NaN

[154 rows x 3 columns]
```

[72]:
```python
# Calculate the 50-day and 200-day moving averages
df['MA_50'] = df['Close'].rolling(window=50).mean()
df['MA_200'] = df['Close'].rolling(window=200).mean()
```

[73]:
```python
# Plot the moving averages
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Closing Price')
plt.plot(df['Date'], df['MA_50'], label='50-day Moving Average',␣
 ↪linestyle='dashed')
plt.plot(df['Date'], df['MA_200'], label='200-day Moving Average',␣
 ↪linestyle='dotted')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.title('Tata Global with Moving Averages')
plt.legend()
plt.show()
```