```
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
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# Load the data
data = pd.read_csv (r'/content/npa1.csv')
data.head()
```

	S.N.	Open	High	Low	Close	Change	Per Change (%)	Turnover	Dat
0	1	2,772.23	2,805.57	2,742.53	2,755.62	-5.29	-0.19	21,713,431,007.73	8/1/202
1	2	2,708.24	2,791.02	2,707.57	2,760.90	64.25	2.38	21,911,503,161.05	7/31/202
2	3	2,669.41	2,709.89	2,609.02	2,696.65	35.55	1.33	17,266,391,542.96	7/30/202
3	1	2,706.73	2,737.68	2,655.15	2,661.09	-20.46	-0.76	19,609,177,106.29	7/29/202
4	2	2,606.42	2,708.58	2,606.40	2,681.56	113.42	4.41	15,810,596,235.45	7/28/202

Next steps: Generate code with data | View recommended plots | New interactive sheet

```
# Convert the Date column to datetime format
data['Date'] = pd.to_datetime(data['Date'], format='%m/%d/%Y')

data = data.sort_values(by='Date')
data.head()
```

	S.N.	Open	High	Low	Close	Change	Per Change (%)	Turnover	Date
2196	314	904	904	904	904	1.35	0.15	0	2015-01-01
2195	313	918	918	918	918	13.82	1.53	0	2015-01-04
2194	312	920	920	920	920	2.27	0.25	0	2015-01-05
2193	311	917	917	917	917	-2.36	-0.26	0	2015-01-06
2192	310	925	925	925	925	7.13	0.78	0	2015-01-07

Next steps: Generate code with data | View recommended plots | New interactive sheet

```
# Remove commas from the numerical columns and convert them to float
data['Open'] = data['Open'].str.replace(',', '').astype(float)
data['High'] = data['High'].str.replace(',', '').astype(float)
data['Low'] = data['Low'].str.replace(',', '').astype(float)
data['Close'] = data['Close'].str.replace(',', '').astype(float)
data['Turnover'] = data['Turnover'].str.replace(',', '').astype(float)

# Create moving averages
data['MA7'] = data['Close'].rolling(window=7).mean()
data['MA30'] = data['Close'].rolling(window=30).mean()

# Create lag features
data['Lag1'] = data['Close'].shift(1)
data['Lag2'] = data['Close'].shift(2)
data['Lag3'] = data['Close'].shift(3)

# Extract date features
data['Day'] = data['Date'].dt.day
data['Month'] = data['Date'].dt.month
data['Year'] = data['Date'].dt.year
data['DayOfWeek'] = data['Date'].dt.dayofweek

# Drop rows with NaN values that were created by rolling window and lagging
data = data.dropna()

# Split the data into training and testing sets
train_size = int(len(data) * 0.8)
test_size = len(data) - train_size
train, test = data.iloc[:train_size], data.iloc[train_size:]

# Select the features for modeling
features = ['Close', 'MA7', 'MA30', 'Lag1', 'Lag2', 'Lag3']
train_X = train[features].values
train_y = train['Close'].values
test_X = test[features].values
test_y = test['Close'].values

# Scale the features
scaler_X = MinMaxScaler(feature_range=(0, 1))
train_X_scaled = scaler_X.fit_transform(train_X)
test_X_scaled = scaler_X.transform(test_X)

# Scale the target (Close price)
scaler_y = MinMaxScaler(feature_range=(0, 1))
train_y_scaled = scaler_y.fit_transform(train_y.reshape(-1, 1))
test_y_scaled = scaler_y.transform(test_y.reshape(-1, 1))

# Reshape the data to be compatible with LSTM [samples, time steps, features]
train_X_scaled = train_X_scaled.reshape((train_X_scaled.shape[0], 1, train_X_scaled.shape[1
test_X_scaled = test_X_scaled.reshape((test_X_scaled.shape[0], 1, test_X_scaled.shape[1]))
```

```
# Build the Vanilla RNN model
model = Sequential()
model.add(SimpleRNN(50, return_sequences=True, input_shape=(1, len(features))))
model.add(SimpleRNN(50, return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
history=model.fit(train_X_scaled, train_y_scaled, batch_size=1, epochs=10)

# Make predictions
train_predict_scaled = model.predict(train_X_scaled)
test_predict_scaled = model.predict(test_X_scaled)

# Inverse transform the predictions
train_predict = scaler_y.inverse_transform(train_predict_scaled)
test_predict = scaler_y.inverse_transform(test_predict_scaled)

# Calculate RMSE
train_rmse = np.sqrt(mean_squared_error(train_y, train_predict))
test_rmse = np.sqrt(mean_squared_error(test_y, test_predict))

print(f'Train RMSE: {train_rmse}')
print(f'Test RMSE: {test_rmse}')
```

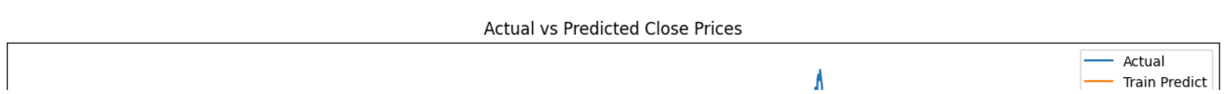
```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:
  super().__init__(**kwargs)
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 5s 1ms/step - loss: 0.0028
Epoch 2/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 5s 1ms/step - loss: 6.9141e-04
Epoch 3/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - loss: 3.1506e-04
Epoch 4/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3.3469e-04
Epoch 5/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 5.1667e-04
Epoch 6/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - loss: 5.0864e-04
Epoch 7/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - loss: 1.5808e-04
Epoch 8/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 1.3216e-04
Epoch 9/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 4s 1ms/step - loss: 1.4885e-04
Epoch 10/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - loss: 1.8923e-04
55/55 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
```

```
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
Train RMSE: 49.69045808699103
Test RMSE: 44.93775511511812
```

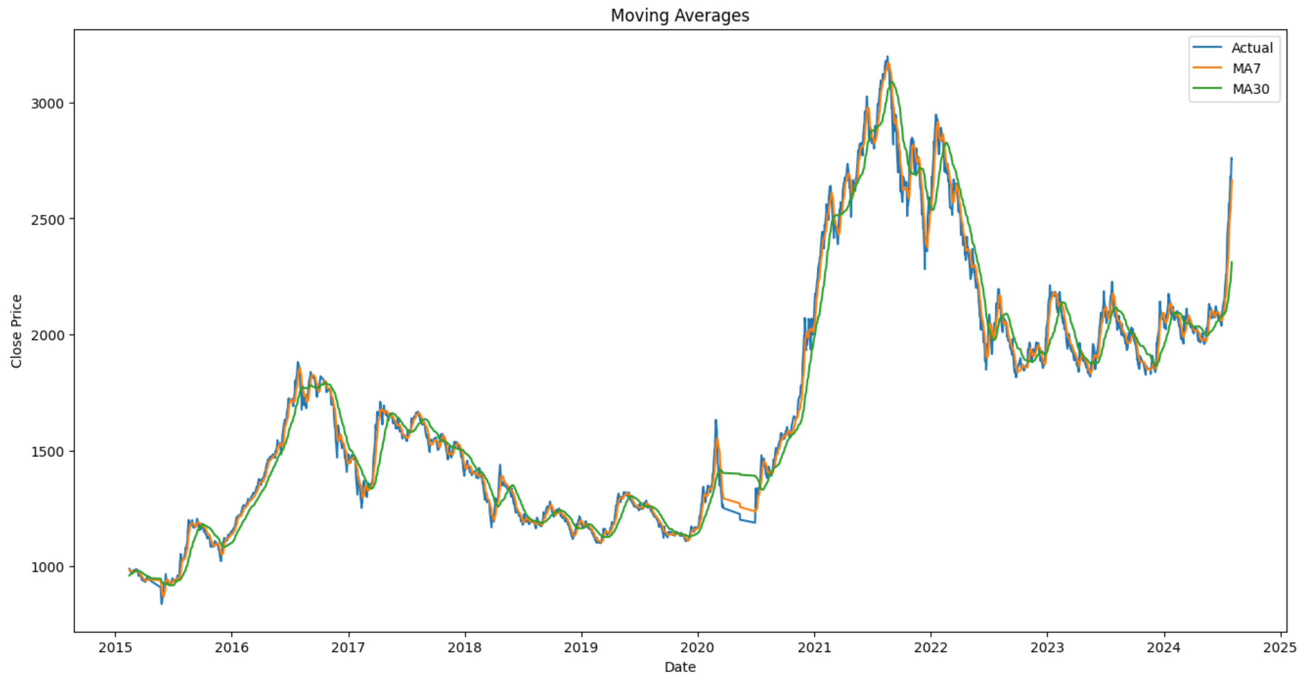
```
# Calculate MSE
train_mse = mean_squared_error(train_y, train_predict)
test_mse = mean_squared_error(test_y, test_predict)
print(f'Train MSE: {train_mse}')
print(f'Test MSE: {test_mse}')
```

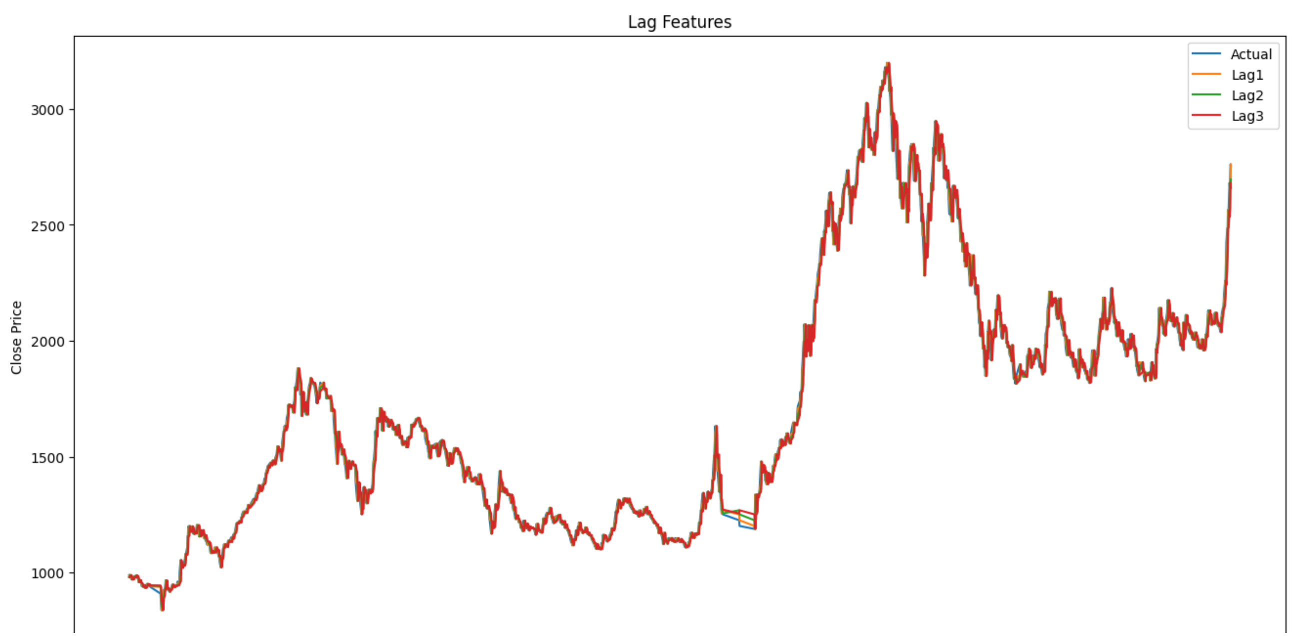
```
Train MSE: 2469.1416248950122
Test MSE: 2019.4018347863253
```

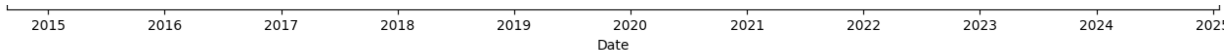
```
# Plot the results: Actual vs Predicted Close Prices
plt.figure(figsize=(16,8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(data['Date'][:train_size], train_predict, label='Train Predict')
plt.plot(data['Date'][train_size:], test_predict, label='Test Predict')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.title('Actual vs Predicted Close Prices')
plt.show()

# Plot the Moving Averages
plt.figure(figsize=(16,8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(data['Date'], data['MA7'], label='MA7')
plt.plot(data['Date'], data['MA30'], label='MA30')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.title('Moving Averages')
plt.show()

# Plot the Lag Features
plt.figure(figsize=(16,8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(data['Date'], data['Lag1'], label='Lag1')
plt.plot(data['Date'], data['Lag2'], label='Lag2')
plt.plot(data['Date'], data['Lag3'], label='Lag3')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.title('Lag Features')
plt.show()
```




Test Predict
Close Price
3000
2500
2000
1500
1000
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Date


Moving Averages
Actual
MA7
MA30
Close Price
3000
2500
2000
1500
1000
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Date


Lag Features
Actual
Lag1
Lag2
Lag3
Close Price
3000
2500
2000
1500
1000



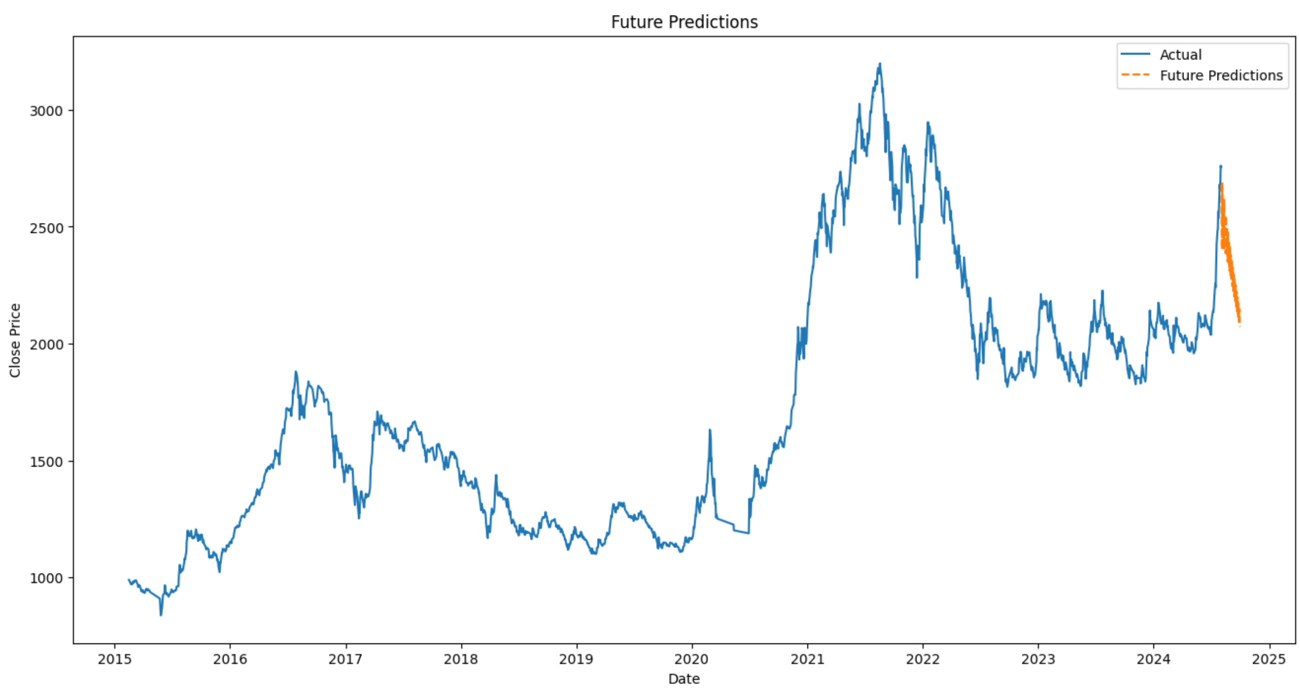

```
# Prepare the last available data point for future prediction
last_data_point = data[features].iloc[-1].values.reshape(1, -1)
scaled_last_data_point = scaler_X.transform(last_data_point)

# Initialize lists to store future predictions
future_predictions = []
num_future_days = 60  # Number of future days to predict

# Predict future values
for _ in range(num_future_days):
    scaled_last_data_point = scaled_last_data_point.reshape((1, 1, len(features)))
    future_pred_scaled = model.predict(scaled_last_data_point)
    future_pred = scaler_y.inverse_transform(future_pred_scaled)

    # Append the prediction to the future_predictions list
    future_predictions.append(future_pred[0][0])

    # Update the scaled_last_data_point with the new predicted value
    new_data_point = np.append(scaled_last_data_point.flatten()[1:], future_pred_scaled)
    scaled_last_data_point = new_data_point.reshape(1, -1)

# Create a DataFrame for future predictions
future_dates = pd.date_range(data['Date'].iloc[-1] + pd.Timedelta(days=1), periods=num_fu
future_df = pd.DataFrame({'Date': future_dates, 'Predicted Close': future_predictions})
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 210ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 210ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
```

```
# Plot the future predictions
plt.figure(figsize=(16,8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(future_df['Date'], future_df['Predicted Close'], label='Future Predictions', lines
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.title('Future Predictions')
plt.show()

# Create a DataFrame for future predictions
future_dates = pd.date_range(data['Date'].iloc[-1] + pd.Timedelta(days=1), periods=num_futu
print(pd.DataFrame({'Date': future_dates, 'Predicted Close': future_predictions}))

# Plot the actual data and future predictions
plt.figure(figsize=(16, 8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(future_df['Date'], future_df['Predicted Close'], label='Future Predictions', lines
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.title('Future Predictions')
plt.savefig('future_predictions.png')  # Save the plot
plt.show(block=True)  # Prevent the plot from disappearing immediately
```




```
         Date  Predicted Close
0  2024-08-02      2681.122803
1  2024-08-03      2583.027588
```

2	2024-08-04	2403.443115
3	2024-08-05	2685.738770
4	2024-08-06	2621.886719
5	2024-08-07	2540.573486
6	2024-08-08	2611.764160
7	2024-08-09	2516.338867
8	2024-08-10	2406.755859
9	2024-08-11	2614.525879
10	2024-08-12	2542.761719
11	2024-08-13	2457.254150
12	2024-08-14	2548.495850
13	2024-08-15	2459.779297
14	2024-08-16	2385.295898
15	2024-08-17	2546.201172
16	2024-08-18	2468.400146
17	2024-08-19	2393.378662
18	2024-08-20	2489.539062
19	2024-08-21	2406.176514
20	2024-08-22	2351.372314
21	2024-08-23	2481.073730
22	2024-08-24	2400.535889
23	2024-08-25	2339.706299
24	2024-08-26	2433.290039
25	2024-08-27	2353.454102
26	2024-08-28	2311.431641
27	2024-08-29	2419.245117
28	2024-08-30	2338.460449
29	2024-08-31	2291.344727
30	2024-09-01	2378.776611
31	2024-09-02	2301.280029
32	2024-09-03	2268.810791
33	2024-09-04	2360.469971
34	2024-09-05	2280.910645
35	2024-09-06	2245.707764
36	2024-09-07	2325.501465
37	2024-09-08	2249.787354
38	2024-09-09	2225.179688
39	2024-09-10	2304.311523
40	2024-09-11	2226.713623
41	2024-09-12	2201.446289
42	2024-09-13	2273.227539
43	2024-09-14	2199.134033
44	2024-09-15	2181.321777
45	2024-09-16	2250.289062
46	2024-09-17	2174.952637
47	2024-09-18	2157.868652
48	2024-09-19	2221.830322
49	2024-09-20	2149.389648
50	2024-09-21	2137.560303
51	2024-09-22	2197.957031
52	2024-09-23	2124.960205
53	2024-09-24	2114.625000
54	2024-09-25	2171.221191
55	2024-09-26	2100.533936
56	2024-09-27	2093.989502

```
56 2024-09-27      2095.989502
57 2024-09-28      2146.939453
58 2024-09-29      2076.262695
59 2024-09-30      2071.536133
```