```
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[
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}')
```

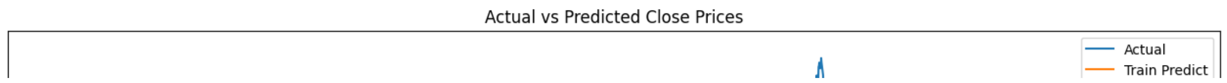
```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:
  super().__init__(**kwargs)
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 5s 1ms/step - loss: 0.0028
Epoch 2/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 5s 1ms/step - loss: 6.9141e-04
Epoch 3/10
1734/1734 ━━━━━━━━━━━━━━━━━━━━ 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
```

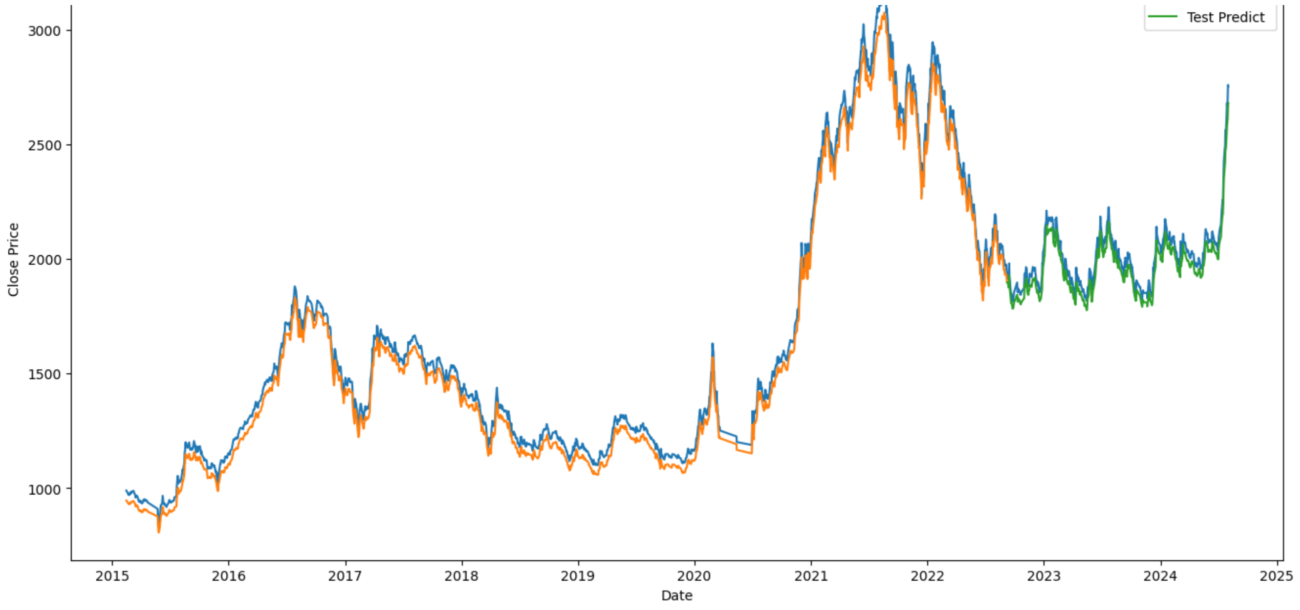
```
    14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
    Train RMSE: 49.69045808699103
    Test RMSE: 44.93775511511812
```

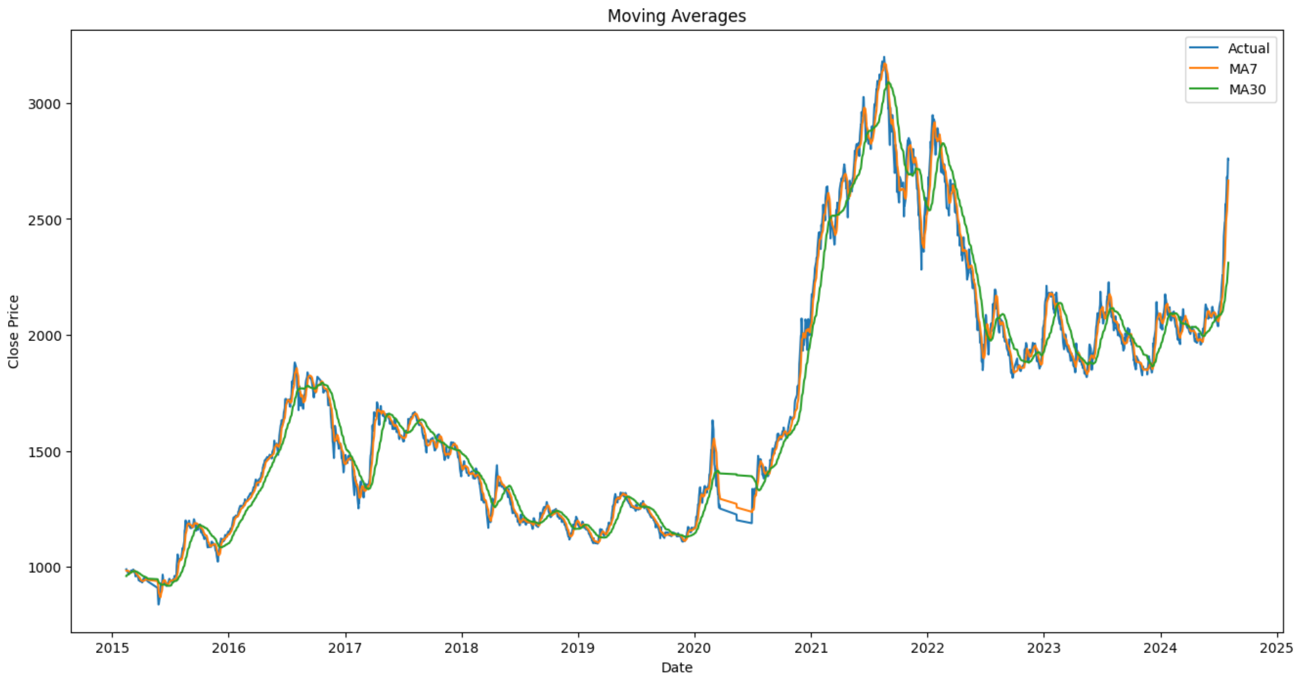
```
# Calculate MSE
train_mse = mean_squared_error(train_y, train_predict)
test_mse = mean_squared_error(test_y, test_predict)
print(f'Train MSE: {train_mse}')
print(f'Test MSE: {test_mse}')
```

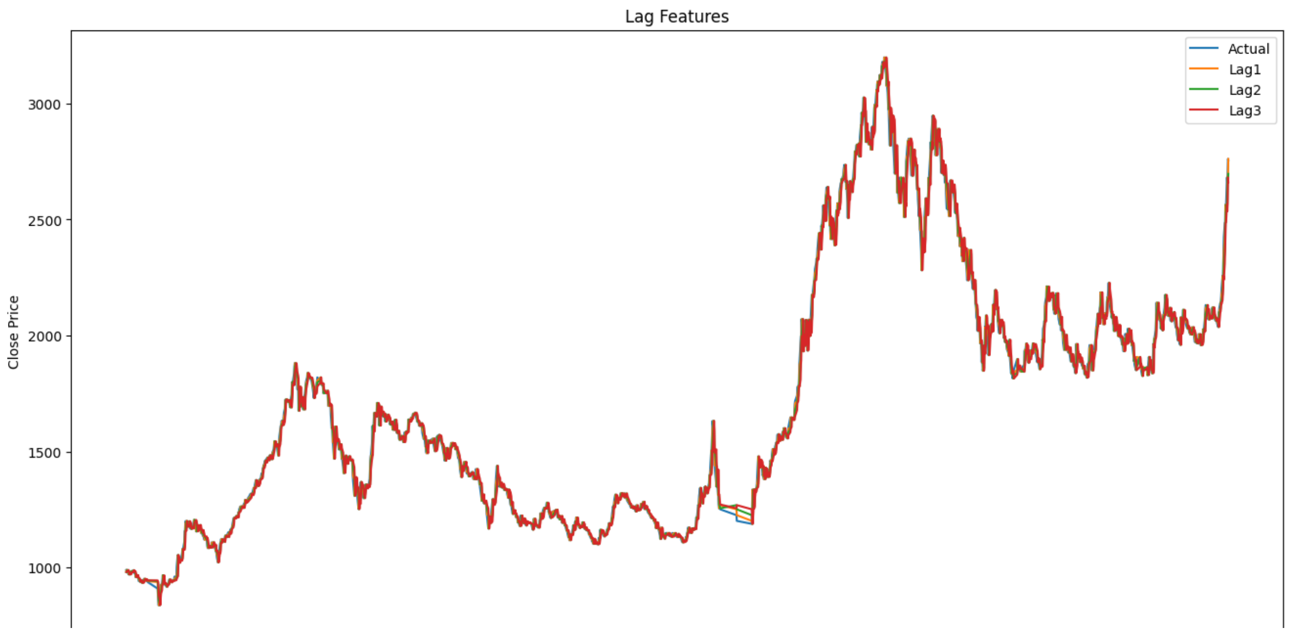
```
    Train MSE: 2469.1416248950122
    Test MSE: 2019.4018347863253
```

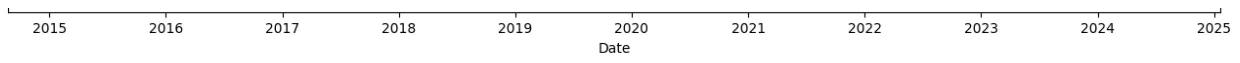
```
# Plot the results: Actual vs Predicted Close Prices
plt.figure(figsize=(16,8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(data['Date'][:train_size], train_predict, label='Train Predict')
plt.plot(data['Date'][train_size:], test_predict, label='Test Predict')
plt.xlabel('Date')
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
Date
1000
1500
2000
2500
3000
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025


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


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



```
# 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
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
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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
```
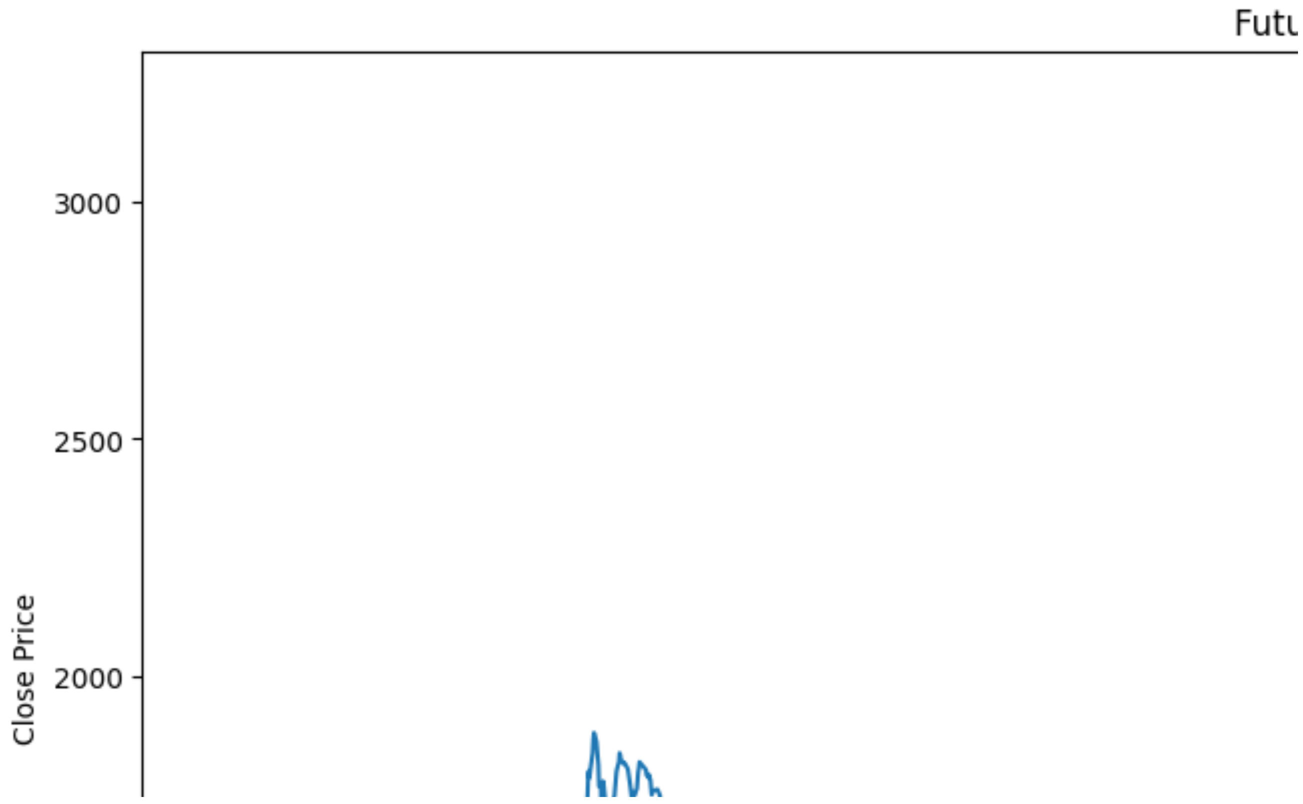
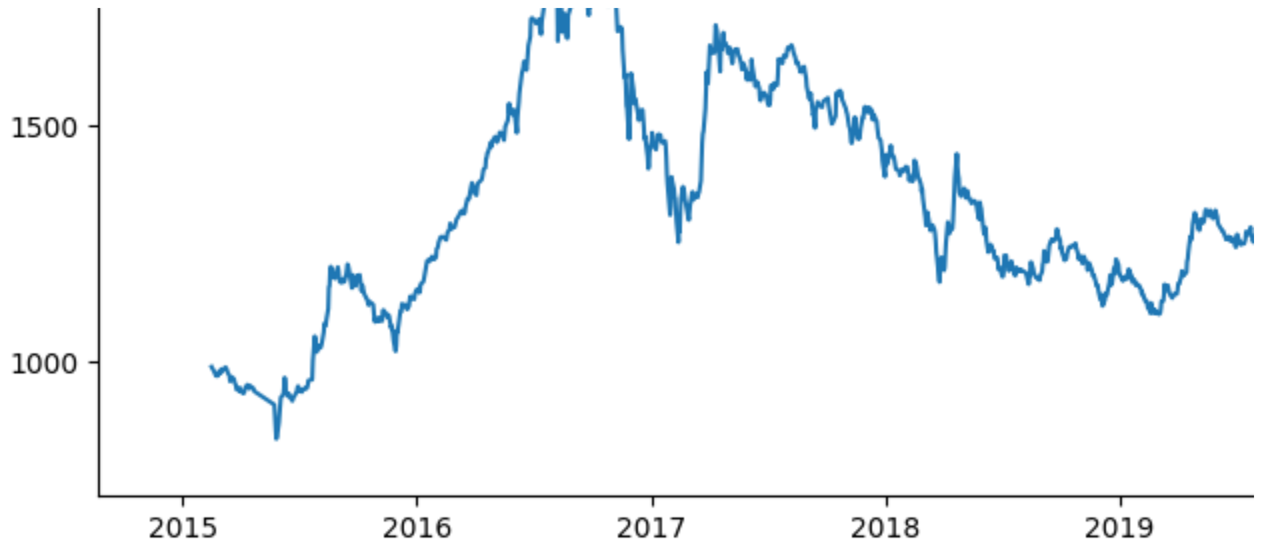

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
```

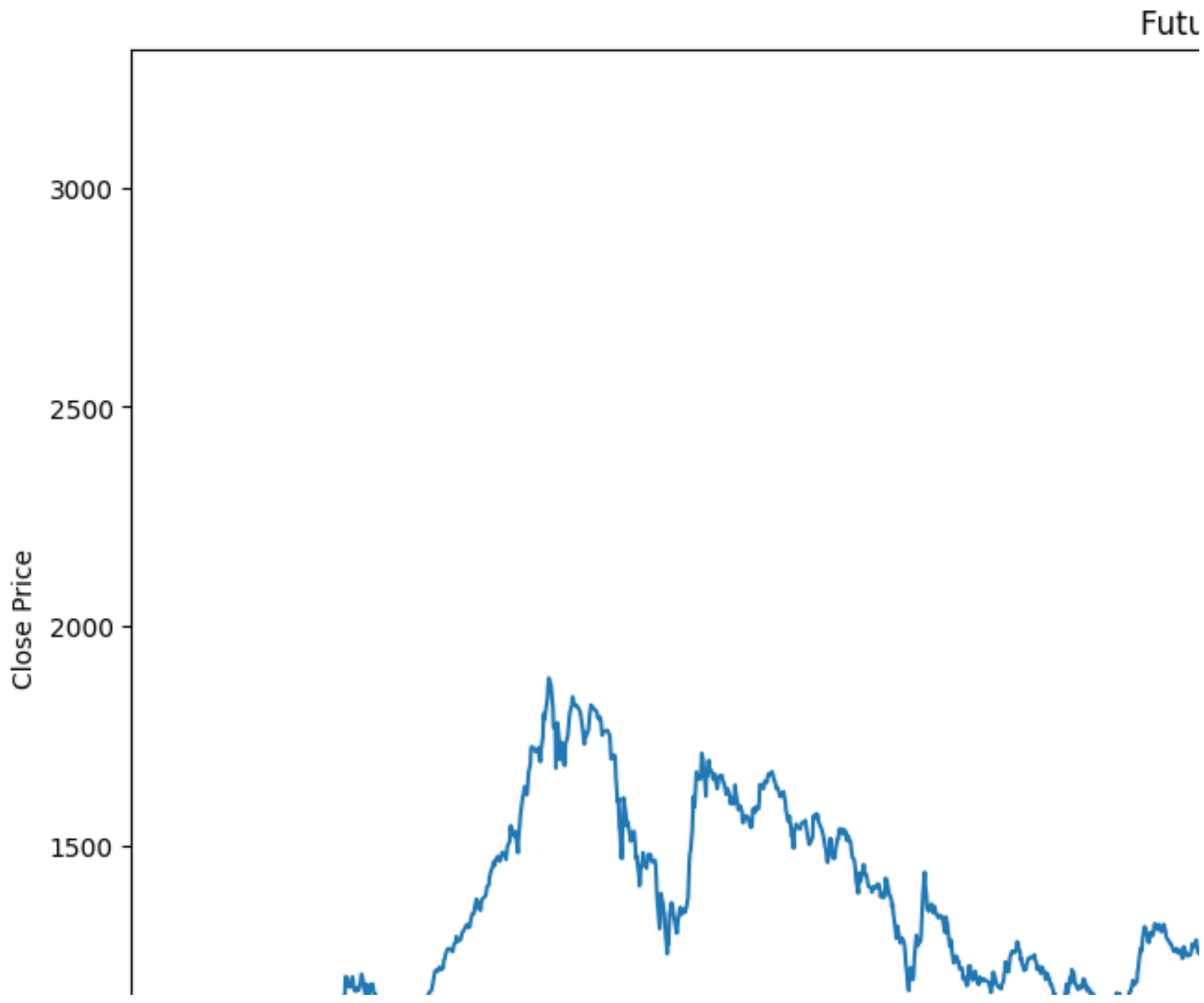
```
# Plot the future predictions
plt.figure(figsize=(16,8))
plt.plot(data['Date'], data['Close'], label='Actual')
plt.plot(future_df['Date'], future_df['Predicted Close'], label='Future Predictions', lin
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.title('Future Predictions')
plt.show()

# Create a DataFrame for future predictions
future_dates = pd.date_range(data['Date'].iloc[-1] + pd.Timedelta(days=1), periods=num_fu
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', lin
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
```

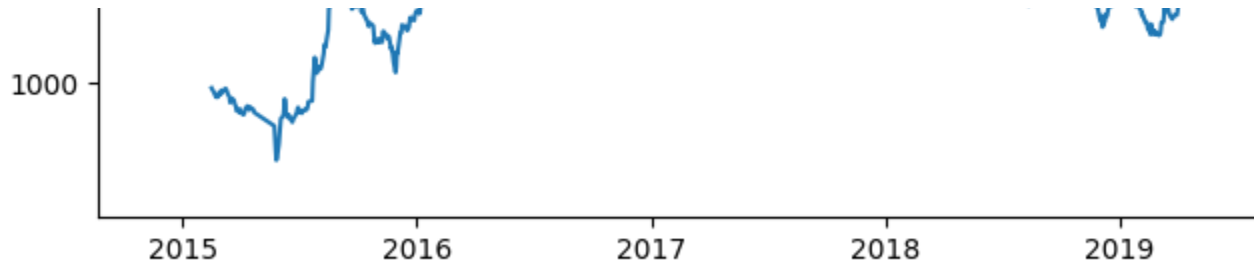




```
          Date  Predicted Close
0   2024-08-02      2681.122803
1   2024-08-03      2583.027588
2   2024-08-04      2403.443115
3   2024-08-05      2685.738770
4   2024-08-06      2621.886719
5   2024-08-07      2540.573486
6   2024-08-08      2611.764160
7   2024-08-09      2516.338867
8   2024-08-10      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
57 2024-09-28       2146.939453
58 2024-09-29       2076.262695
59 2024-09-30       2071.536133
```

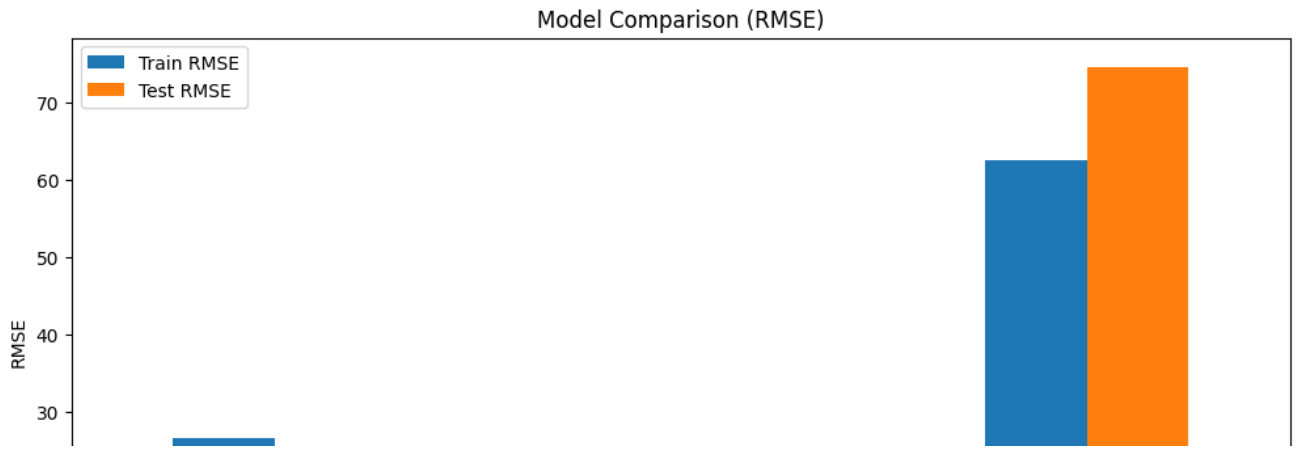


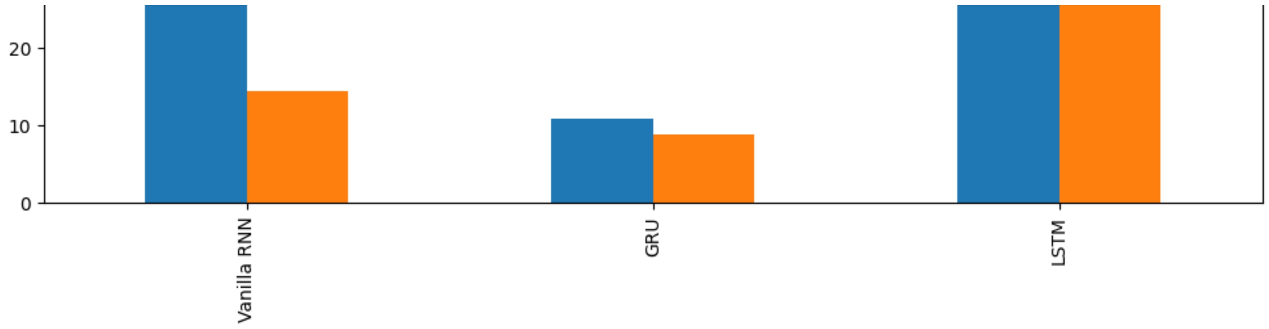


```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, GRU, LSTM, Dense
import matplotlib.pyplot as plt

# Load the data
data = pd.read_csv('/content/npa1.csv')  # Update this path to your dataset
data['Date'] = pd.to_datetime(data['Date'], format='%m/%d/%Y')
data = data.sort_values(by='Date')

# Remove commas from numerical columns and convert them to float
for col in ['Open', 'High', 'Low', 'Close', 'Turnover']:
    data[col] = data[col].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
data = data.dropna()

# Train-test split
train_size = int(len(data) * 0.8)
train, test = data.iloc[:train_size], data.iloc[train_size:]
```

```
# Feature selection
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 [samples, time steps, features]
train_X_scaled = train_X_scaled.reshape((train_X_scaled.shape[0], 1, train_X_scaled.shape[
test_X_scaled = test_X_scaled.reshape((test_X_scaled.shape[0], 1, test_X_scaled.shape[1]))

# Function to build and train models
def build_and_train(model_type):
    model = Sequential()
    if model_type == "Vanilla RNN":
        model.add(SimpleRNN(50, return_sequences=True, input_shape=(1, len(features))))
        model.add(SimpleRNN(50, return_sequences=False))
    elif model_type == "GRU":
        model.add(GRU(50, return_sequences=True, input_shape=(1, len(features))))
        model.add(GRU(50, return_sequences=False))
    elif model_type == "LSTM":
        model.add(LSTM(50, return_sequences=True, input_shape=(1, len(features))))
        model.add(LSTM(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
    model.fit(train_X_scaled, train_y_scaled, batch_size=1, epochs=10, verbose=0)

    return model

# Train each model and evaluate performance
results = {}
for model_type in ["Vanilla RNN", "GRU", "LSTM"]:
    print(f"Training {model_type}...")
    model = build_and_train(model_type)

    # Predictions
    train_predict_scaled = model.predict(train_X_scaled)
    test_predict_scaled = model.predict(test_X_scaled)

    # Inverse scaling
    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))
    results[model_type] = {'Train RMSE': train_rmse, 'Test RMSE': test_rmse}
    print(f"{model_type} - Train RMSE: {train_rmse}, Test RMSE: {test_rmse}")

# Compare results
results_df = pd.DataFrame(results).T
results_df.plot(kind='bar', figsize=(12, 6), title="Model Comparison (RMSE)")
plt.ylabel('RMSE')
plt.show()

print(results_df)
```

```
Training Vanilla RNN...
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:
  super().__init__(**kwargs)
55/55 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
Vanilla RNN - Train RMSE: 26.620208980216077, Test RMSE: 14.385940069854856
Training GRU...
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:
  super().__init__(**kwargs)
55/55 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
GRU - Train RMSE: 10.727393194263925, Test RMSE: 8.80063260657778
Training LSTM...
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:
  super().__init__(**kwargs)
55/55 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
LSTM - Train RMSE: 62.53806252196723, Test RMSE: 74.62829063601401
```





```
             Train RMSE  Test RMSE
Vanilla RNN   26.620209  14.385940
GRU           10.727393   8.800633
LSTM          62.538063  74.628291
```