Stock price Prediction of TCS using LSTM Neural Networks:

```
## import essential libraries

import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib
from sklearn.preprocessing import MinMaxScaler
from keras.layers import LSTM,Dense,Dropout
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.dates as mdates
from sklearn import linear_model
from math import sqrt
from statsmodels.tsa.arima.model import ARIMA
```

Reading data using parse date

As it is timeseries data so we have to read the data by parsing date means making data column as index.

```
## read csv file
df_final = pd.read_csv("TCS.csv",na_values=['null'],index_col='Date',parse_dates=True,in
```

```
df_final.head()
```

Date	Open	High	Low	Close	Adj Close	Volume
2006-04-03	241.125	244.125000	240.25000	243.431244	132.405640	459912.0
2006-04-04	244.375	245.975006	241.90625	243.481247	132.432800	553648.0
2006-04-05	244.000	245.375000	239.87500	241.243744	131.215805	732216.0
2006-04-07	243.500	250.000000	235.00000	236.100006	128.418030	2982344.0
2006-04-10	235.625	239.750000	235.00000	236.975006	128.893967	1666248.0

Next steps: View recommended plots

```
df_final.shape
```

```
(4444, 6)
```

```
df_final.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	4413.000000	4413.000000	4413.000000	4413.000000	4413.000000	4.413000e+03
mean	1411.437896	1425.654315	1396.070607	1410.645709	1296.661451	4.463599e+05
std	1124.707336	1133.897610	1114.383965	1124.101775	1141.365985	1.030609e+06
min	112.500000	116.224998	104.500000	111.287498	71.213020	9.598000e+03
25%	464.399994	472.225006	458.024994	464.899994	335.009216	9.506800e+04
50%	1190.000000	1200.750000	1178.224976	1190.375000	1050.273926	1.841940e+[illegible]
75%	2088.000000	2111.000000	2062.600098	2082.750000	2010.980469	4.944340e[illegible]
max	4217.500000	4254.450195	4177.000000	4217.500000	4217.500000	3.557355e[illegible]

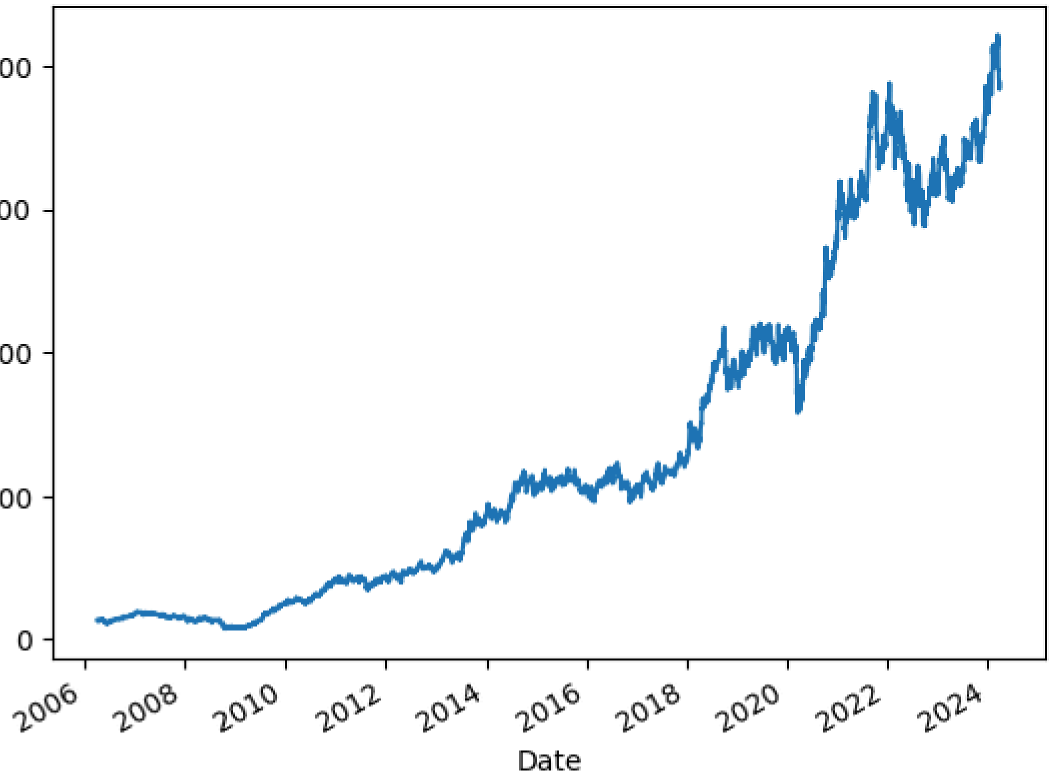
```
df_final.isnull().values.any()
```

```
True
```

```
df_final.dropna(inplace=True)
```

```
df_final['Adj Close'].plot()
```

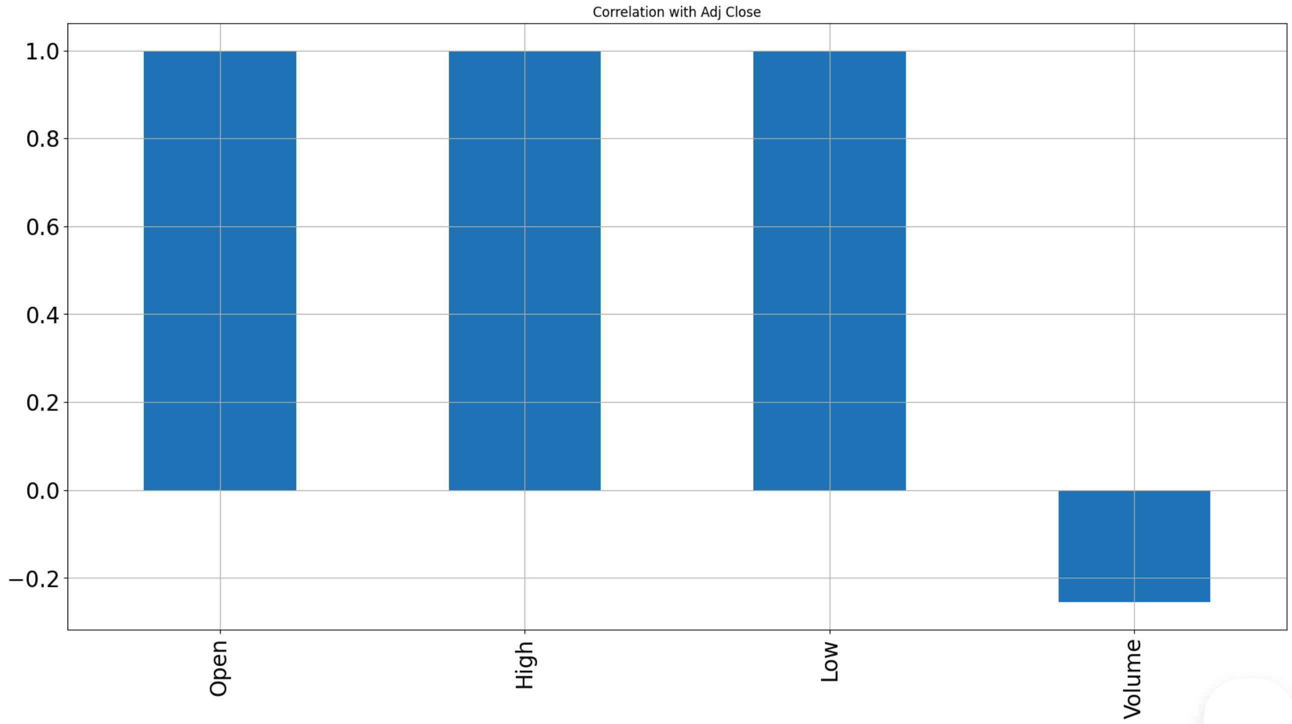
<Axes: xlabel='Date'>



Correlation Analysis

```
X=df_final.drop(['Adj Close'],axis=1)
X=X.drop(['Close'],axis=1)


## correlation matrix

X.corrwith(df_final['Adj Close']).plot.bar(
        figsize = (20, 10), title = "Correlation with Adj Close", fontsize = 20,
        rot = 90, grid = True)
```

```
<Axes: title={'center': 'Correlation with Adj Close'}>
```




```
test = df_final
# Target column
target_adj_close = pd.DataFrame(test['Adj Close'])
display(test.head())
```

Date	Open	High	Low	Close	Adj Close	Volume
2006-04-03	241.125	244.125000	240.25000	243.431244	132.405640	459912.0
2006-04-04	244.375	245.975006	241.90625	243.481247	132.432800	553648.0
2006-04-05	244.000	245.375000	239.87500	241.243744	131.215805	732216.0
2006-04-07	243.500	250.000000	235.00000	236.100006	128.418030	2982344.0
2006-04-10	235.625	239.750000	235.00000	236.975006	128.893967	1666248.0

```
# selecting Feature Columns
feature_columns = ['Open', 'High', 'Low', 'Volume']
```

Normalizing the data

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
feature_minmax_transform_data = scaler.fit_transform(test[feature_columns])
feature_minmax_transform = pd.DataFrame(columns=feature_columns, data=feature_minma
feature_minmax_transform.head()
```

Date	Open	High	Low	Volume
2006-04-03	0.031334	0.030907	0.033333	0.012662
2006-04-04	0.032125	0.031354	0.033740	0.015298
2006-04-05	0.032034	0.031209	0.033241	0.020319
2006-04-07	0.031912	0.032327	0.032044	0.083589
2006-04-10	0.029994	0.029850	0.032044	0.046582

Next steps: View recommended plots

```
display(feature_minmax_transform.head())
print('Shape of features : ', feature_minmax_transform.shape)
print('Shape of target : ', target_adj_close.shape)

# Shift target array because we want to predict the n + 1 day value


target_adj_close = target_adj_close.shift(-1)
validation_y = target_adj_close[-90:-1]
target_adj_close = target_adj_close[:-90]

# Taking last 90 rows of data to be validation set
validation_X = feature_minmax_transform[-90:-1]
feature_minmax_transform = feature_minmax_transform[:-90]
display(validation_X.tail())
display(validation_y.tail())

print("\n -----After process------ \n")
print('Shape of features : ', feature_minmax_transform.shape)
print('Shape of target : ', target_adj_close.shape)
display(target_adj_close.tail())
```

Date	Open	High	Low	Volume
2006-04-03	0.031334	0.030907	0.033333	0.012662
2006-04-04	0.032125	0.031354	0.033740	0.015298
2006-04-05	0.032034	0.031209	0.033241	0.020319
2006-04-07	0.031912	0.032327	0.032044	0.083589
2006-04-10	0.029994	0.029850	0.032044	0.046582

```
Shape of features :  (4413, 4)
Shape of target :  (4413, 1)
```

Date	Open	High	Low	Volume
2024-03-20	0.943605	0.942862	0.946839	0.003581
2024-03-21	0.943459	0.940554	0.943978	0.001556
2024-03-22	0.922412	0.923627	0.921179	0.007489
2024-03-26	0.922058	0.925463	0.925107	0.005462
2024-03-27	0.921912	0.913610	0.914438	0.001739

Date	Adj Close
2024-03-20	3974.050049
2024-03-21	3913.100098
2024-03-22	3877.100098
2024-03-26	3837.500000
2024-03-27	3883.550049

```
 -----After process------

Shape of features :  (4323, 4)
Shape of target :  (4323, 1)
```

Date	Adj Close
2023-11-07	3380.750000
2023-11-08	3348.250000
2023-11-09	3332.800049
2023-11-10	3331.699951
2023-11-13	3399.300049

Train test Split using Timeseriessplit

```
ts_split= TimeSeriesSplit(n_splits=10)
for train_index, test_index in ts_split.split(feature_minmax_transform):
        X_train, X_test = feature_minmax_transform[:len(train_index)], feature_minmax_tra
        y_train, y_test = target_adj_close[:len(train_index)].values.ravel(), target_adj_
```

```
X_train.shape
```

```
(3930, 4)
```

```
X_test.shape
```

```
(393, 4)
```

```
y_train.shape
```

```
(3930,)
```

```
y_test.shape
```

```
(393,)
```

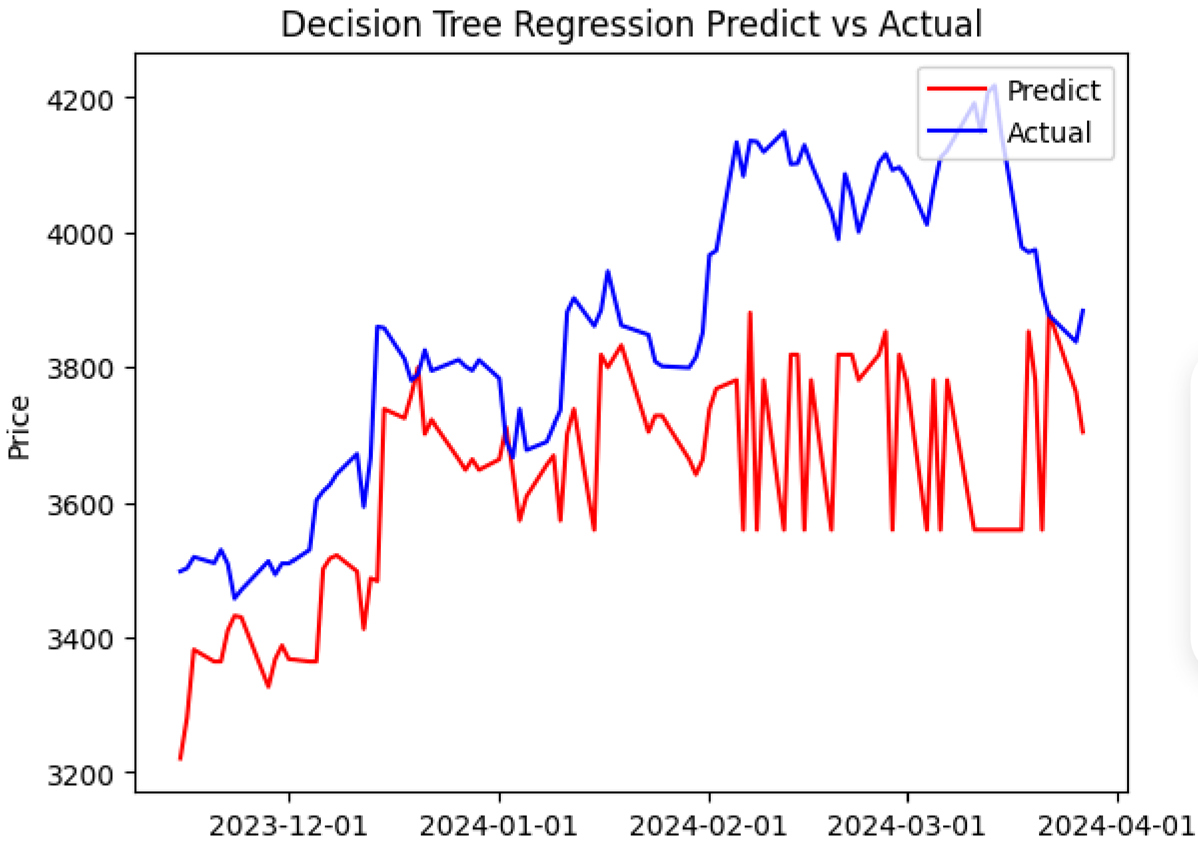
```
def validate_result(model, model_name):
    predicted = model.predict(validation_X)
    RSME_score = np.sqrt(mean_squared_error(validation_y, predicted))
    print('RMSE: ', RSME_score)

    R2_score = r2_score(validation_y, predicted)
    print('R2 score: ', R2_score)

    plt.plot(validation_y.index, predicted,'r', label='Predict')
    plt.plot(validation_y.index, validation_y,'b', label='Actual')
    plt.ylabel('Price')
    plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
    plt.gca().xaxis.set_major_locator(mdates.MonthLocator())
    plt.title(model_name + ' Predict vs Actual')
    plt.legend(loc='upper right')
    plt.show()
```

Benchmark Model

Decision_Tree_Regressor

```
from sklearn.tree import DecisionTreeRegressor

dt = DecisionTreeRegressor(random_state=0)

benchmark_dt=dt.fit(X_train, y_train)

validate_result(benchmark_dt, 'Decision Tree Regression')
```

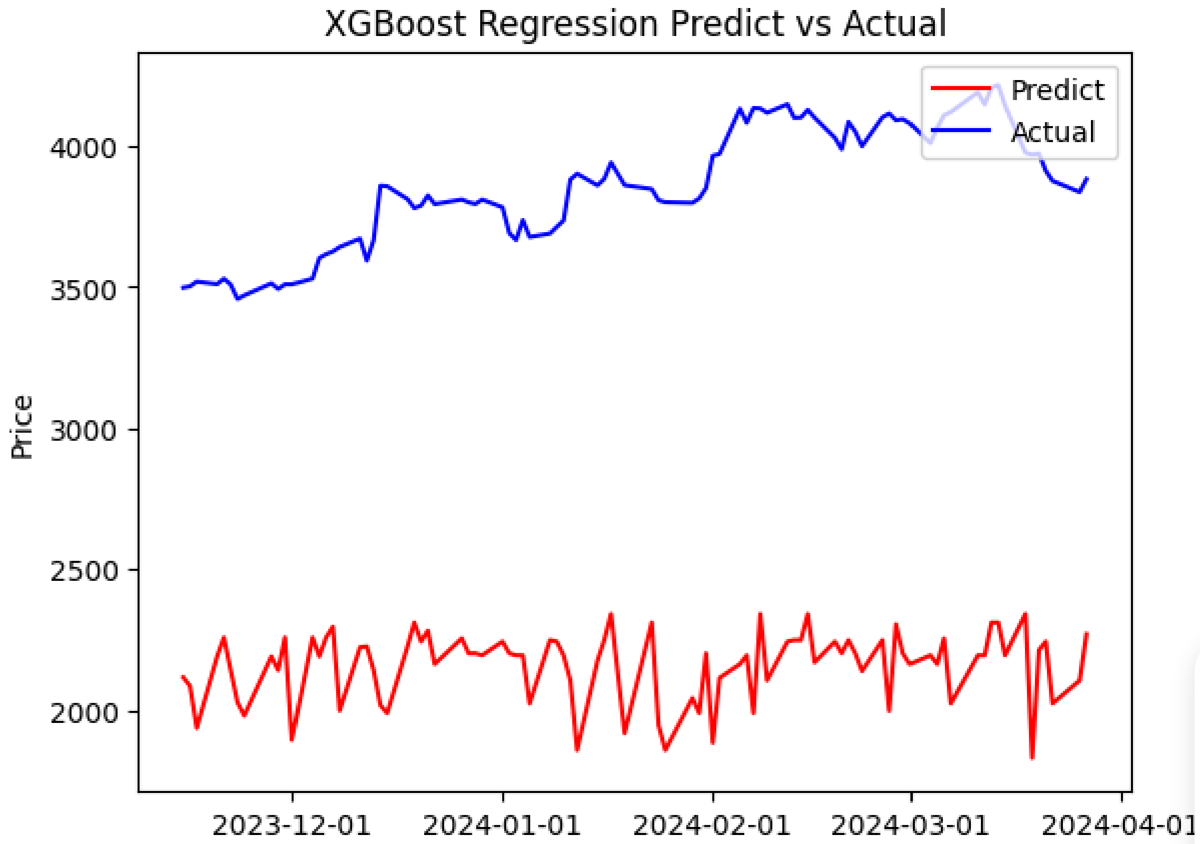
```
RMSE:  283.43805863878754
R2 score:  -0.7198385243711785
```



XG_Boost_Regressor

```
from xgboost import XGBRegressor


xg_reg = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.3, learning_ra
                max_depth = 5, alpha = 10, n_estimators = 10, random_state=0)

xg_reg.fit(X_train, y_train)


validate_result(xg_reg, 'XGBoost Regression')
```

```
RMSE:  1712.360752384338
R2 score:  -61.77140851929769
```

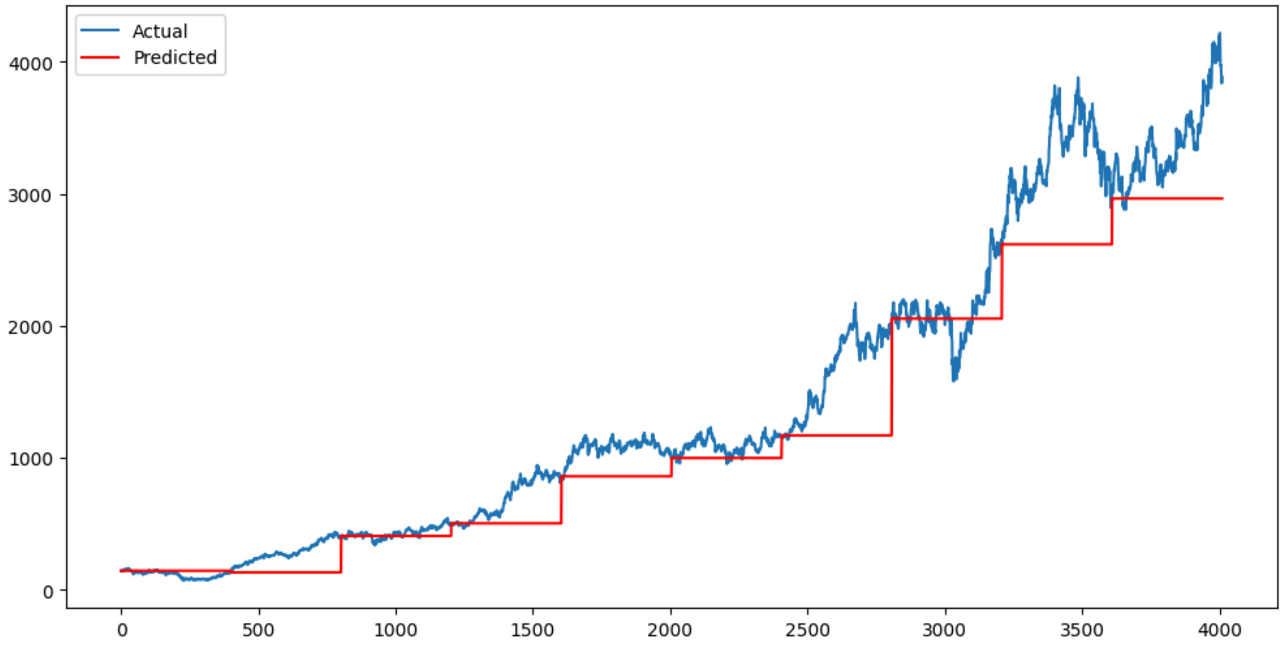


Time_Series_Arima_model

```
# Preprocess features (assuming 'Open', 'High', 'Low', 'Volume' are your features)
features = df_final[['Open', 'High', 'Low', 'Volume']]
target = df_final['Adj Close']

# Scale features
scaler = MinMaxScaler(feature_range=(0, 1))
feature_scaled = scaler.fit_transform(features)

# Initialize TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)

# Placeholder for model predictions and actual values
predictions = []
actuals = []

# Cross-validation for time series data
for train_index, test_index in tscv.split(feature_scaled):
    X_train, X_test = feature_scaled[train_index], feature_scaled[test_index]
    y_train, y_test = target[train_index], target[test_index]

    # Fit ARIMA model (you can replace this with any other model)
    model = ARIMA(y_train, order=(5,1,0))
    model_fit = model.fit()

    # Forecast
    forecast = model_fit.get_forecast(steps=len(test_index))
    predictions.append(forecast.predicted_mean)
    actuals.append(y_test)

# Flatten the list of predictions and actuals
predictions = [item for sublist in predictions for item in sublist]
actuals = [item for sublist in actuals for item in sublist]

# Calculate RMSE over all predictions
rmse = sqrt(mean_squared_error(actuals, predictions))
print('Overall Test RMSE: %.3f' % rmse)
```

```
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: Val
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: Fut
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: Val
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: Fut
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: Val
  self._init_dates(dates, freq)
Overall Test RMSE: 360.757
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: Val
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: Fut
  return get_prediction_index(
```

```
# Plot the predicted vs actual values
plt.figure(figsize=(12,6))
plt.plot(actuals, label='Actual')
plt.plot(predictions, label='Predicted', color='red')
plt.legend()
plt.show()
```



Process the data for LSTM

```
X_train =np.array(X_train)
X_test =np.array(X_test)

X_tr_t = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
X_tst_t = X_test.reshape(X_test.shape[0], 1, X_test.shape[1])
```

Model building : LSTM

```
from keras.models import Sequential
from keras.layers import Dense
import keras.backend as K
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
from keras.models import load_model
from keras.layers import LSTM
K.clear_session()
model_lstm = Sequential()
model_lstm.add(LSTM(16, input_shape=(1, X_train.shape[1]), activation='relu', return_seq
model_lstm.add(Dense(1))
model_lstm.compile(loss='mean_squared_error', optimizer='adam')
early_stop = EarlyStopping(monitor='loss', patience=5, verbose=1)
history_model_lstm = model_lstm.fit(X_tr_t, y_train, epochs=200, batch_size=8, verbose=1
```

```
502/502 [==============================] - 1s 2ms/step - loss: 3592.7478
Epoch 48/200
502/502 [==============================] - 1s 3ms/step - loss: 3049.0271
Epoch 49/200
502/502 [==============================] - 1s 2ms/step - loss: 2638.2642
Epoch 50/200
502/502 [==============================] - 1s 2ms/step - loss: 2338.9436
Epoch 51/200
502/502 [==============================] - 1s 3ms/step - loss: 2120.9207
Epoch 52/200
502/502 [==============================] - 1s 3ms/step - loss: 1956.1094
Epoch 53/200
502/502 [==============================] - 1s 2ms/step - loss: 1824.1105
Epoch 54/200
502/502 [==============================] - 1s 2ms/step - loss: 1712.3961
Epoch 55/200
502/502 [==============================] - 2s 4ms/step - loss: 1614.2424
Epoch 56/200
502/502 [==============================] - 1s 3ms/step - loss: 1526.5024
Epoch 57/200
502/502 [==============================] - 1s 2ms/step - loss: 1447.9760
Epoch 58/200
502/502 [==============================] - 1s 2ms/step - loss: 1378.3101
Epoch 59/200
502/502 [==============================] - 1s 3ms/step - loss: 1317.3724
Epoch 60/200
502/502 [==============================] - 1s 2ms/step - loss: 1264.9468
Epoch 61/200
502/502 [==============================] - 1s 2ms/step - loss: 1220.6526
Epoch 62/200
502/502 [==============================] - 1s 2ms/step - loss: 1183.9562
Epoch 63/200
502/502 [==============================] - 1s 2ms/step - loss: 1154.1979
Epoch 64/200
502/502 [==============================] - 1s 2ms/step - loss: 1130.6658
Epoch 65/200
502/502 [==============================] - 2s 3ms/step - loss: 1112.6184
Epoch 66/200
502/502 [==============================] - 1s 3ms/step - loss: 1099.3127
Epoch 67/200
502/502 [==============================] - 1s 3ms/step - loss: 1090.0347
Epoch 68/200
502/502 [==============================] - 1s 2ms/step - loss: 1084.1229
```