

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

```
In [2]: df = pd.read_csv('Kerala_FINAL_new.csv')
df.set_index('Date', inplace=True)
```

```
In [3]: df.head()
```

```
Out[3]:
```

	Tourists	Year	Month	No_of_flight_bookings	No_of_hotel_booked	Tourism	Tourism_Packages	Tourist_Places	Travel	Food_Drink	Flights_Kerala	Train
Date												
2010-01-01	818356.0	2010	1	2991	2123306.250	86	82	24	51	78	0	
2010-02-01	721201.0	2010	2	2812	1861236.000	89	32	0	44	72	0	
2010-03-01	719944.0	2010	3	3136	1797776.875	100	100	33	47	66	0	
2010-04-01	735432.0	2010	4	2668	1787449.625	92	85	32	49	65	0	
2010-05-01	803431.0	2010	5	2518	1795854.375	100	29	18	54	64	0	

```
In [ ]:
```

```
In [4]: # data = df.copy() # Create a copy of the DataFrame

# month_mapping = {
#     'Jan': 1,
#     'Feb': 2,
#     'Mar': 3,
#     'Apr': 4,
#     'May': 5,
#     'Jun': 6,
#     'Jul': 7,
#     'Aug': 8,
#     'Sep': 9,
#     'Oct': 10,
#     'Nov': 11,
#     'Dec': 12
# }

# data['Month'] = data['Month'].map(month_mapping)
# data['Date'] = pd.to_datetime(data[['Year', 'Month']].assign(day=1))
# data.set_index('Date', inplace=True)
```

```
In [5]: # Split your data into training and testing (e.g., use 2010-2018 for training and 2019 for testing)
data=df
train_data = data['2010-01-01':'2019-12-01']
test_data = data['2017-01-01':'2019-12-01']
```

```
In [6]: # data.info()
```

```
In [7]: data.head()
```

```
Out[7]:
```

	Tourists	Year	Month	No_of_flight_bookings	No_of_hotel_booked	Tourism	Tourism_Packages	Tourist_Places	Travel	Food_Drink	Flights_Kerala	Train
Date												
2010-01-01	818356.0	2010	1	2991	2123306.250	86	82	24	51	78	0	
2010-02-01	721201.0	2010	2	2812	1861236.000	89	32	0	44	72	0	
2010-03-01	719944.0	2010	3	3136	1797776.875	100	100	33	47	66	0	
2010-04-01	735432.0	2010	4	2668	1787449.625	92	85	32	49	65	0	
2010-05-01	803431.0	2010	5	2518	1795854.375	100	29	18	54	64	0	

```
In [8]: data=data[:108]
```

```
In [9]: import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from keras.layers import RNN
```

```
from keras.layers import SimpleRNN
```

```
In [10]: # Load the dataset
# data = pd.read_csv("your_data.csv")

# Select the relevant columns
data1 = data[['No_of_flight_bookings', 'No_of_hotel_booked', 'Tourism', 'Tourism_Packages', 'Tourist_Places', 'Travel', 'Food_Drinks']]
data2=data[['Tourists']]

# Normalize the data

scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(data1)
# Define the sequence length and split the data into input sequences and target values
sequence_length = 12 # You can adjust this value

X, y = [], []

for i in range(len(data_scaled) - sequence_length):
    X.append(data_scaled[i:i + sequence_length, 1:]) # Use iloc to select features from the second column onwards
    y.append(data2.iloc[i + sequence_length, 0]) # Select the "Total Tourists" column as the target

X = np.array(X)
y = np.array(y)

# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train=X[:96]
y_train=y[:96]

model = Sequential()
model.add(LSTM(100, activation='relu', return_sequences=True, input_shape=(sequence_length, X.shape[2]))) # Increase the number
model.add(LSTM(100, activation='relu', return_sequences=True)) # Add another LSTM layer with 100 units
model.add(LSTM(50, activation='relu')) # Add one more LSTM layer with 50 units
model.add(Dense(1)) # Output size is 1 for the "Total Tourists" prediction

# Compile the model
model.compile(optimizer='adam', loss='mse') # You can choose a different Loss function if needed

model.fit(X_train, y_train, epochs=600, batch_size=32) # You can adjust the number of epochs and batch size

3/3 [=====] - 0s 45ms/step - loss: 1244085616640.0000
Epoch 11/600
3/3 [=====] - 0s 48ms/step - loss: 1142340321280.0000
Epoch 12/600
3/3 [=====] - 0s 50ms/step - loss: 735597756416.0000
Epoch 13/600
3/3 [=====] - 0s 44ms/step - loss: 445647290368.0000
Epoch 14/600
3/3 [=====] - 0s 50ms/step - loss: 274159779840.0000
Epoch 15/600
3/3 [=====] - 0s 54ms/step - loss: 336153182208.0000
Epoch 16/600
3/3 [=====] - 0s 43ms/step - loss: 284517367808.0000
Epoch 17/600
3/3 [=====] - 0s 45ms/step - loss: 179789840384.0000
Epoch 18/600
3/3 [=====] - 0s 42ms/step - loss: 224927072256.0000
Epoch 19/600
3/3 [=====] - 0s 43ms/step - loss: 174259273728.0000
Epoch 20/600
```

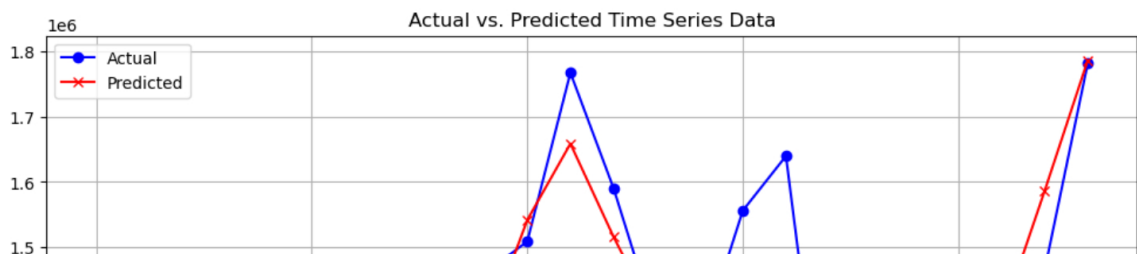
```
In [11]: # Use the last data points from the test set as input
predictions = model.predict(X[72:96]) # Predict the "Total Tourists" for the next time step

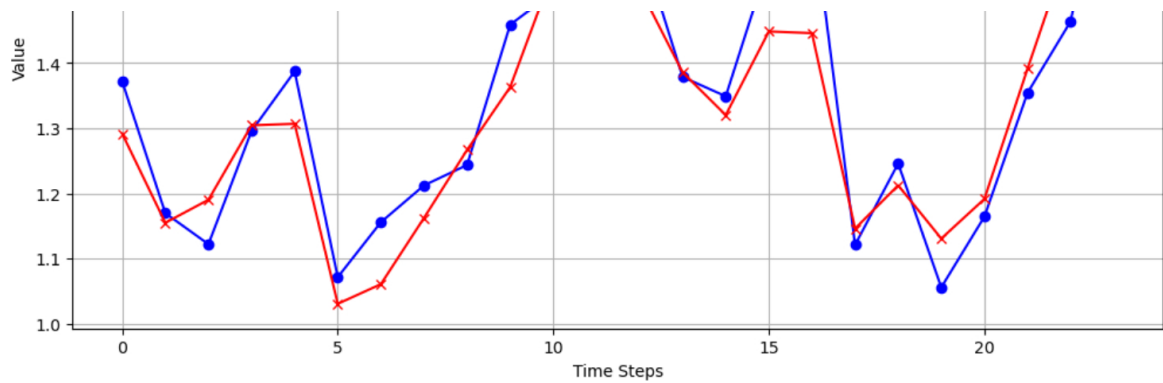
1/1 [=====] - 1s 1s/step
```

```
In [12]: import matplotlib.pyplot as plt

# Inverse transform the actual test data to get it in the original scale

# Plot actual and predicted values
plt.figure(figsize=(12, 6))
plt.plot(y[96:120], label='Actual', color='blue', marker='o')
plt.plot(predictions, label='Predicted', color='red', marker='x')
plt.title('Actual vs. Predicted Time Series Data')
plt.xlabel('Time Steps')
plt.ylabel('Value')
plt.legend()
plt.grid(True)
plt.show()
```





```
In [13]: y[72:96].shape
```

```
Out[13]: (24,)
```

```
In [14]: predictions.shape
```

```
Out[14]: (24, 1)
```

```
In [15]: y_act2=y[72:96].reshape(24,1)
y_pred2=predictions
import numpy as np

# Calculate MAE (Mean Absolute Error)
mae = np.mean(np.abs(y_act2 - y_pred2))

# Calculate RMSE (Root Mean Squared Error)
rmse = np.sqrt(np.mean((y_act2 - y_pred2) ** 2))

# Calculate MAPE (Mean Absolute Percentage Error)
mape = np.mean(np.abs((y_act2 - y_pred2) / y_act2)) * 100

print("MAE:", mae)
print("RMSE:", rmse)
print("MAPE:", mape)

MAE: 37155.966666666665
RMSE: 42058.99635271269
MAPE: 2.705003119383127
```

```
In [16]: y[96:108]
```

```
Out[16]: array([], dtype=float64)
```

```
In [17]: y
```

```
Out[17]: array([[ 872030.,  770512.,  753599.,  779712.,  853926.,  680654.,
  684737.,  776193.,  791985., 1013044.,  987385., 1150663.,
  937791.,  815119.,  803386.,  821615.,  923932.,  724177.,
  722192.,  837464.,  862020., 1122220., 1081390., 1219244.,
 1026830.,  887283.,  865039.,  879626., 1019007.,  774461.,
  769908.,  907513.,  943445., 1183420., 1155608., 1303814.,
 1116473.,  969718.,  939050.,  956550., 1130388.,  831745.,
  826525.,  969382., 1024381., 1246412., 1230830., 1377323.,
 1171592., 1063128., 1007669., 1032072., 1203223.,  893161.,
  899444., 1042686., 1103688., 1311865., 1283466., 1431056.,
 1213770., 1146254., 1067504., 1090943., 1244344.,  928982.,
  970552., 1124432., 1191859., 1419742., 1283775., 1527797.,
 1371882., 1169652., 1122018., 1295885., 1387403., 1071401.,
 1155714., 1212269., 1243659., 1459147., 1508638., 1767722.,
 1590463., 1378781., 1349162., 1556044., 1639759., 1120984.,
 1245862., 1055698., 1164214., 1354291., 1464076., 1781733.]])
```

```
In [18]: import numpy as np
```

```
# Assuming y_act1 and y_pred1 are NumPy arrays
y_act1 = np.array([1371882., 1169652., 1122018., 1295885., 1387403., 1071401.,
 1155714., 1212269., 1243659., 1459147., 1508638., 1767722.,
 1590463., 1378781., 1349162., 1556044., 1639759., 1120984.,
 1245862., 1055698., 1164214., 1354291., 1464076., 1781733.])

y_pred1 = np.array([1334964.8, 1126671.8, 1101899.2, 1273052.,
 1335171.2, 1044277.5, 1109315.6, 1214128.8,
 1229625.6, 1392470.6, 1517593.6, 1689779.8,
 1553321.5, 1349165.8, 1300200.4, 1506256.8,
 1582962.4, 1119057.1, 1195778.6, 1031455.,
 1113563.1, 1298442.9, 1443975.6, 1733214.9])

# Calculate MAE (Mean Absolute Error)
mae = np.mean(np.abs(y_act1 - y_pred1))

# Calculate RMSE (Root Mean Squared Error)
rmse = np.sqrt(np.mean((y_act1 - y_pred1)**2))

# Calculate MAPE (Mean Absolute Percentage Error)
mape = np.mean(np.abs((y_act1 - y_pred1) / y_act1)) * 100

print("MAE:", mae)
print("RMSE:", rmse)
```

```
print("MAPE:", mape)
```

```
MAE: 37155.96666666665  
RMSE: 42058.99635271269  
MAPE: 2.705003119383127
```

```
In [19]: model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
=====		
lstm (LSTM)	(None, 12, 100)	44800
lstm_1 (LSTM)	(None, 12, 100)	80400
lstm_2 (LSTM)	(None, 50)	30200
dense (Dense)	(None, 1)	51
=====		
Total params: 155,451		
Trainable params: 155,451		
Non-trainable params: 0		

```
In [ ]:
```