pandemic-forecaster-morocco-agadir

September 11, 2023

1 Forecasting of COVID-19 Cases and Deaths In the region of Souss-Massa Morocco Using LSTM

[ ]:
```
# %pip install tabula-py
# %pip install pandas
# %pip install bs4
# %pip install requests
```

2 Import package

[2]:
```
# from bs4 import BeautifulSoup
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential,load_model
from tensorflow.keras.layers import LSTM, Dense,Dropout,Input
import os
from tensorflow.keras.callbacks import TensorBoard
# from tabula import read_pdf
```

3 Data collecting

[ ]:
```
page = requests.get("http://www.covidmaroc.ma/Documents/BULLETIN/COVID-19.
 ↪Morocco.13.19.05.2023.pdf", headers=headers, stream=True)
soup = BeautifulSoup(page.content,"html.parser")
date_page = soup.select('td[class = "ms-rteTableOddCol-5"]')
dates_span=[]
for date_span in date_page:
  unique_date  = date_span.select('span', {'class' : "ms-rteTableOddCol-5"})
  dates_span.append(unique_date)
dates_span
```

```python
dates=[]
for global_date in dates_span:
  for date in global_date:
    cov_date = date.get_text()
    cov_date = cov_date.strip().split('\n')[0]
    dates.append(cov_date)

# dates

# pdf = pdfquery.PDFQuery("http://www.covidmaroc.ma/Documents/BULLETIN/COVID-19.
↪Morocco.13.19.05.2023.pdf")
```

[ ]:
```python
dates=[]
for month in range(1,7):
  for day in range(1,32):
    if 1 <= month < 10 :
      if 1 <= day < 10 :
        date = "0"+str(day)+"."+str(month)+".21"
      else :
        date = str(day)+"."+str(month)+".21"
    else :
      if 1 <= day < 10 :
        date = "0"+str(day)+"."+str(month)+".21"
      else :
        date = str(day)+"."+str(month)+".21"
    dates.append(date)

dates.remove('30.2.21')
dates.remove('02.2.21')
dates.remove('31.2.21')
dates.remove('29.2.21')
dates.remove('31.4.21')
dates.remove('31.6.21')

print(dates)
```

```
['01.1.21', '02.1.21', '03.1.21', '04.1.21', '05.1.21', '06.1.21', '07.1.21',
'08.1.21', '09.1.21', '10.1.21', '11.1.21', '12.1.21', '13.1.21', '14.1.21',
'15.1.21', '16.1.21', '17.1.21', '18.1.21', '19.1.21', '20.1.21', '21.1.21',
'22.1.21', '23.1.21', '24.1.21', '25.1.21', '26.1.21', '27.1.21', '28.1.21',
'29.1.21', '30.1.21', '31.1.21', '01.2.21', '03.2.21', '04.2.21', '05.2.21',
'06.2.21', '07.2.21', '08.2.21', '09.2.21', '10.2.21', '11.2.21', '12.2.21',
'13.2.21', '14.2.21', '15.2.21', '16.2.21', '17.2.21', '18.2.21', '19.2.21',
'20.2.21', '21.2.21', '22.2.21', '23.2.21', '24.2.21', '25.2.21', '26.2.21',
'27.2.21', '28.2.21', '01.3.21', '02.3.21', '03.3.21', '04.3.21', '05.3.21',
'06.3.21', '07.3.21', '08.3.21', '09.3.21', '10.3.21', '11.3.21', '12.3.21',
'13.3.21', '14.3.21', '15.3.21', '16.3.21', '17.3.21', '18.3.21', '19.3.21',
```

```
'20.3.21', '21.3.21', '22.3.21', '23.3.21', '24.3.21', '25.3.21', '26.3.21',
'27.3.21', '28.3.21', '29.3.21', '30.3.21', '31.3.21', '01.4.21', '02.4.21',
'03.4.21', '04.4.21', '05.4.21', '06.4.21', '07.4.21', '08.4.21', '09.4.21',
'10.4.21', '11.4.21', '12.4.21', '13.4.21', '14.4.21', '15.4.21', '16.4.21',
'17.4.21', '18.4.21', '19.4.21', '20.4.21', '21.4.21', '22.4.21', '23.4.21',
'24.4.21', '25.4.21', '26.4.21', '27.4.21', '28.4.21', '29.4.21', '30.4.21',
'01.5.21', '02.5.21', '03.5.21', '04.5.21', '05.5.21', '06.5.21', '07.5.21',
'08.5.21', '09.5.21', '10.5.21', '11.5.21', '12.5.21', '13.5.21', '14.5.21',
'15.5.21', '16.5.21', '17.5.21', '18.5.21', '19.5.21', '20.5.21', '21.5.21',
'22.5.21', '23.5.21', '24.5.21', '25.5.21', '26.5.21', '27.5.21', '28.5.21',
'29.5.21', '30.5.21', '31.5.21', '01.6.21', '02.6.21', '03.6.21', '04.6.21',
'05.6.21', '06.6.21', '07.6.21', '08.6.21', '09.6.21', '10.6.21', '11.6.21',
'12.6.21', '13.6.21', '14.6.21', '15.6.21', '16.6.21', '17.6.21', '18.6.21',
'19.6.21', '20.6.21', '21.6.21', '22.6.21', '23.6.21', '24.6.21', '25.6.21',
'26.6.21', '27.6.21', '28.6.21', '29.6.21', '30.6.21']
```

[ ]:

```
Cases = []
cities = ["Agadir-Ida -Ou-Tanane","Inezgane- Ait␣
↪Melloul","Taroudannt","Tiznit","Chtouka- Ait Baha","Tata"]
Deaths = []
city = []
days = []


for date in dates:
  pdf_file = read_pdf("C:/oussamaboussaid/DataSet/"+date+".COVID-19.
↪pdf",pages="all",stream="True",encoding='latin1')
  for pdf in pdf_file[-2].values:
    if pdf[0] in cities:
      city.append(pdf[0])
      print(city)
      days.append(date)
      Cases.append(pdf[1])
      Deaths.append(pdf[2])

print(Cases)
print(Deaths)
```

[ ]:

```
print(len(Deaths))
print(len(days))
print(len(city))
```

```
400
400
400
```

Creat DataSet

[ ]:
```
Covid_dataSet_dict = {
    "Deaths":Deaths,
    "Cases":Cases,
    "dates":days,
    "cities":city
}
Covid_dataSet = pd.DataFrame(Covid_dataSet_dict)
```

[ ]:
```
    Deaths Cases    dates                cities
0        2    48  01.1.21  Agadir-Ida -Ou-Tanane
1      NaN    37  01.1.21  Inezgane- Ait Melloul
2      NaN    35  01.1.21                 Tiznit
3      NaN    16  01.1.21      Chtouka- Ait Baha
4        2    13  01.1.21             Taroudannt
..     …    …        …                    …
395    NaN     1  29.6.21             Taroudannt
396    NaN    31  30.6.21  Agadir-Ida -Ou-Tanane
397    NaN    26  30.6.21  Inezgane- Ait Melloul
398    NaN     4  30.6.21                 Tiznit
399    NaN     2  30.6.21      Chtouka- Ait Baha

[400 rows x 4 columns]
```

[ ]:
```
Covid_dataSet
```

[ ]:
```
    Deaths Cases    dates                cities
0        2    48  01.1.21  Agadir-Ida -Ou-Tanane
1      NaN    37  01.1.21  Inezgane- Ait Melloul
2      NaN    35  01.1.21                 Tiznit
3      NaN    16  01.1.21      Chtouka- Ait Baha
4        2    13  01.1.21             Taroudannt
..     …    …        …                    …
395    NaN     1  29.6.21             Taroudannt
396    NaN    31  30.6.21  Agadir-Ida -Ou-Tanane
397    NaN    26  30.6.21  Inezgane- Ait Melloul
398    NaN     4  30.6.21                 Tiznit
399    NaN     2  30.6.21      Chtouka- Ait Baha

[400 rows x 4 columns]
```

Save DataSet As CSV File

[ ]:
```
Covid_dataSet.to_csv("Covid_dataSet.csv", index=False)
```

4 Data Preprocessing (Data Cleaning, Data Visualisation, Scaling and Normalizing cte..)

DataSet Summary

Load The Data

[5]:
```
Covid_data = pd.read_csv("Covid_dataSet.csv")
```

[ ]:
```
#show the first 10 rows of the DataSet
Covid_data.head(20)
```

[ ]:

	Deaths	Cases	dates	cities
0	2	48.0	01.1.21	Agadir-Ida -Ou-Tanane
1	NaN	37.0	01.1.21	Inezgane- Ait Melloul
2	NaN	35.0	01.1.21	Tiznit
3	NaN	16.0	01.1.21	Chtouka- Ait Baha
4	2	13.0	01.1.21	Taroudannt
5	2	64.0	02.1.21	Agadir-Ida -Ou-Tanane
6	NaN	22.0	02.1.21	Inezgane- Ait Melloul
7	NaN	11.0	02.1.21	Taroudannt
8	NaN	10.0	02.1.21	Chtouka- Ait Baha
9	1	9.0	02.1.21	Tiznit
10	NaN	4.0	02.1.21	Tata
11	1	66.0	03.1.21	Agadir-Ida -Ou-Tanane
12	NaN	32.0	03.1.21	Tata
13	NaN	12.0	03.1.21	Tiznit
14	NaN	11.0	03.1.21	Inezgane- Ait Melloul
15	NaN	7.0	03.1.21	Taroudannt
16	NaN	1.0	03.1.21	Chtouka- Ait Baha
17	1	56.0	04.1.21	Agadir-Ida -Ou-Tanane
18	NaN	18.0	04.1.21	Inezgane- Ait Melloul
19	1	13.0	04.1.21	Tiznit

[ ]:
```
# describe the DataSet
print(Covid_data.describe())

print("\n**********************\n")

# get some infos about the DataSet
print(Covid_data.info())
```

	Deaths	Cases	dates	cities
count	108	399	400	400
unique	10	60	110	6
top	1	1	23.1.21	Agadir-Ida -Ou-Tanane
freq	36	64	6	108

```
**********************

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Deaths  108 non-null    object
 1   Cases   399 non-null    object
 2   dates   400 non-null    object
 3   cities  400 non-null    object
dtypes: object(4)
memory usage: 12.6+ KB
None
```

Data Cleaning

Detect Missing Values

[ ]:
```
Covid_data.isnull().sum()
```

[ ]:
```
Deaths    292
Cases       1
dates       0
cities      0
dtype: int64
```

[ ]:
```
Covid_data[Covid_data['Deaths'].isnull()]
```

[ ]:
```
    Deaths  Cases   dates                cities
1      NaN   37.0  01.1.21  Inezgane- Ait Melloul
2      NaN   35.0  01.1.21                 Tiznit
3      NaN   16.0  01.1.21      Chtouka- Ait Baha
6      NaN   22.0  02.1.21  Inezgane- Ait Melloul
7      NaN   11.0  02.1.21             Taroudannt
..     …     …      …                    …
395    NaN    1.0  29.6.21             Taroudannt
396    NaN   31.0  30.6.21  Agadir-Ida -Ou-Tanane
397    NaN   26.0  30.6.21  Inezgane- Ait Melloul
398    NaN    4.0  30.6.21                 Tiznit
399    NaN    2.0  30.6.21      Chtouka- Ait Baha

[292 rows x 4 columns]
```

[ ]:
```
Covid_data[Covid_data['Cases'].isnull()]
```

[ ]:
```
   Deaths  Cases    dates cities
38    NaN    NaN  08.1.21   Tata
```

Convert Our Date column to datetime

[ ]:
```
# dates's type is String
Covid_data["dates"].iloc[0]
```

[ ]:
```
'01.1.21'
```

[ ]:
```
# thpr of Dates colomn is Object
Covid_data["dates"].dtype
```

[ ]:
```
dtype('O')
```

[6]:
```
# Convert Date column to datetime
Covid_data["dates"] = pd.to_datetime(Covid_data["dates"],dayfirst=True).dt.
 ↪strftime('%d-%m-%Y')
Covid_data["dates"]
```

[6]:
```
0      01-01-2021
1      01-01-2021
2      01-01-2021
3      01-01-2021
4      01-01-2021
          …
395    29-06-2021
396    30-06-2021
397    30-06-2021
398    30-06-2021
399    30-06-2021
Name: dates, Length: 400, dtype: object
```

[ ]:
```
Covid_data["dates"].iloc[0]
```

[ ]:
```
'01-01-2021'
```

Remove all withspaces & "?" char

[ ]:
```
Covid_data["Deaths"][232:260]
```

[ ]:
```
232                   NaN
233                     1
234                   NaN
235                   NaN
236                   NaN
237                   NaN
238                   NaN
239                   NaN
240    ?????? ??? ?????
241            ????????
```

```
242     ?????? ??? ????
243     ?????? ??? ????
244    ?????? ??? ?????
245     ?????? ??? ????
246     ?????? ??? ????
247               ?????
248            ????????
249                 NaN
250                 NaN
251                 NaN
252                 NaN
253                 NaN
254                 NaN
255                 NaN
256                   2
257                 NaN
258                 NaN
259                 NaN
Name: Deaths, dtype: object
```

[7]:
```
Covid_data["Deaths"] = Covid_data["Deaths"].replace('[\?\s]+', '0', regex=True)
Covid_data["Deaths"][232:260]
```

[7]:
```
232    NaN
233      1
234    NaN
235    NaN
236    NaN
237    NaN
238    NaN
239    NaN
240      0
241      0
242      0
243      0
244      0
245      0
246      0
247      0
248      0
249    NaN
250    NaN
251    NaN
252    NaN
253    NaN
254    NaN
255    NaN
```

```
256      2
257    NaN
258    NaN
259    NaN
Name: Deaths, dtype: object
```

Replace All NaN Values (Numeric values) with Median

[8]:
```python
Covid_data.Deaths = Covid_data.Deaths.fillna(Covid_data.Deaths.median())
Covid_data.Cases = Covid_data.Cases.fillna(Covid_data.Cases.median())
# Covid_data.Deaths = Covid_data.Deaths.fillna(0)
# Covid_data.Cases = Covid_data.Cases.fillna(0)

Covid_data
```

[8]:
```
    Deaths  Cases       dates                 cities
0        2   48.0  01-01-2021  Agadir-Ida -Ou-Tanane
1      0.0   37.0  01-01-2021  Inezgane- Ait Melloul
2      0.0   35.0  01-01-2021                 Tiznit
3      0.0   16.0  01-01-2021      Chtouka- Ait Baha
4        2   13.0  01-01-2021             Taroudannt
..     …     …            …                    …
395    0.0    1.0  29-06-2021             Taroudannt
396    0.0   31.0  30-06-2021  Agadir-Ida -Ou-Tanane
397    0.0   26.0  30-06-2021  Inezgane- Ait Melloul
398    0.0    4.0  30-06-2021                 Tiznit
399    0.0    2.0  30-06-2021      Chtouka- Ait Baha

[400 rows x 4 columns]
```

[ ]:
```python
Covid_data.isnull().sum()
```

[ ]:
```
Deaths    0
Cases     0
dates     0
cities    0
dtype: int64
```

Convert Deaths Column to int

[9]:
```python
#convert the Deaths column to int
Covid_data["Deaths"] = Covid_data["Deaths"].astype(float).astype(int)
Covid_data["Deaths"]
```

[9]:
```
0      2
1      0
2      0
3      0
```

```
4      2
      ..
395    0
396    0
397    0
398    0
399    0
Name: Deaths, Length: 400, dtype: int64
```

Convert Cases Column to int

[ ]:
```
Covid_data["Cases"].dtype
```

[ ]:
```
dtype('float64')
```

[10]:
```
Covid_data["Cases"] = Covid_data["Cases"].astype(int)
Covid_data["Cases"]
```

[10]:
```
0      48
1      37
2      35
3      16
4      13
       ..
395     1
396    31
397    26
398     4
399     2
Name: Cases, Length: 400, dtype: int64
```

[ ]:
```
Covid_data
```

[ ]:
```
     Deaths  Cases       dates                cities
0         2     48  01-01-2021  Agadir-Ida -Ou-Tanane
1         0     37  01-01-2021  Inezgane- Ait Melloul
2         0     35  01-01-2021                 Tiznit
3         0     16  01-01-2021      Chtouka- Ait Baha
4         2     13  01-01-2021             Taroudannt
..      …      …          …                    …
395       0      1  29-06-2021             Taroudannt
396       0     31  30-06-2021  Agadir-Ida -Ou-Tanane
397       0     26  30-06-2021  Inezgane- Ait Melloul
398       0      4  30-06-2021                 Tiznit
399       0      2  30-06-2021      Chtouka- Ait Baha

[400 rows x 4 columns]
```

Data Visualization

[11]:
```
#Groupe all Case and Death data by City
Covid_data_GpByCyties = Covid_data.groupby("cities")
Covid_data_GpByCyties
```

[11]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7f79b4c5b850>
```

Distribuation of Cases in different City

[ ]:
```
#Count Number of All Cases in each City
Covid_data_GpByCyties_Cases = Covid_data_GpByCyties.Cases.sum()

#print data
for city, cases in Covid_data_GpByCyties_Cases.items():
    print("Number of Cases in "+city+" : ",cases,end="\n")

print("\nSum of all Case in all Cities is ",sum(Covid_data_GpByCyties_Cases))
```

```
Number of Cases in Agadir-Ida -Ou-Tanane :  2072
Number of Cases in Chtouka- Ait Baha :  212
Number of Cases in Inezgane- Ait Melloul :  832
Number of Cases in Taroudannt :  246
Number of Cases in Tata :  91
Number of Cases in Tiznit :  411

Sum of all Case in all Cities is  3864
```

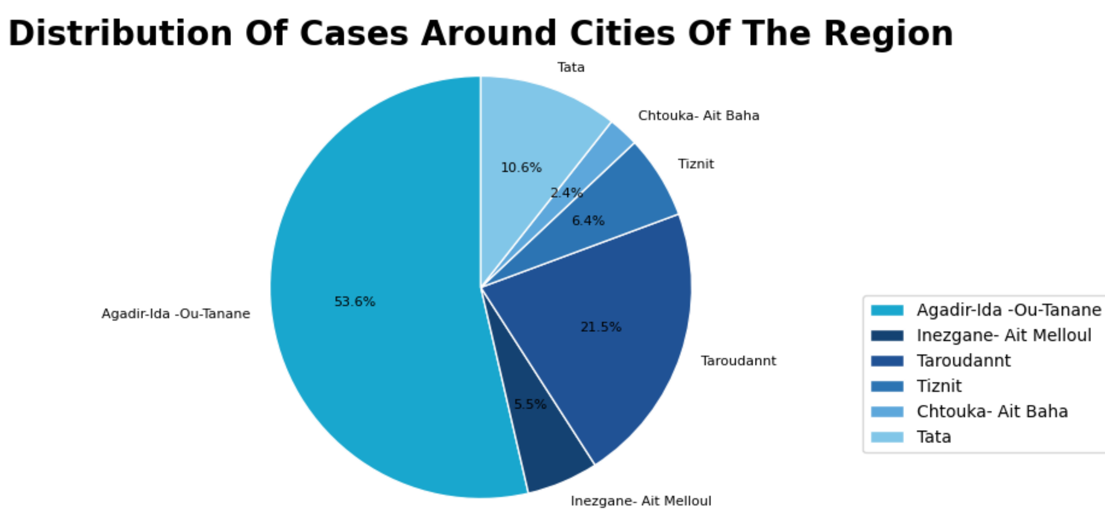
[ ]:
```
len(Covid_data_GpByCyties.cities)
```

[ ]:
```
6
```

[ ]:
```
# Convert Valus to percent (case * 100)/3858
Cases_In_City_per = []

for nb_case in Covid_data_GpByCyties_Cases:
  case_per = (nb_case * 100)/3858
  Cases_In_City_per.append(case_per)

#print data
cities = ["Agadir-Ida -Ou-Tanane","Inezgane- Ait␣
↪Melloul","Taroudannt","Tiznit","Chtouka- Ait Baha","Tata"]
for ele in range(len(cities)) :
  print("Number of Cases in "+cities[ele]+" : {:.2f}%".
↪format(Cases_In_City_per[ele]),end="\n")

print("\nSum of all Case in all Cities is {:.2f}%".
↪format(sum(Cases_In_City_per)))
```

```
Number of Cases in Agadir-Ida -Ou-Tanane : 53.71%
Number of Cases in Inezgane- Ait Melloul : 5.50%
Number of Cases in Taroudannt : 21.57%
Number of Cases in Tiznit : 6.38%
Number of Cases in Chtouka- Ait Baha : 2.36%
Number of Cases in Tata : 10.65%

Sum of all Case in all Cities is 100.16%
```

[ ]:
```python
# Pie chart
colors=["#19A7CE","#144272","#205295","#2C74B3","#5DA7DB","#81C6E8"]
wedgeprops = {'linewidth': 1, 'edgecolor': 'white'}

fig1, ax1 = plt.subplots(figsize=(8, 5))
ax1.pie(Cases_In_City_per,labels=cities,autopct='%1.
↪1f%%',colors=colors,wedgeprops=wedgeprops,  startangle=90,␣
↪textprops={'fontsize': 8})
ax1.axis('equal')
plt.legend(labels=cities, loc='best', bbox_to_anchor=(1, 0.5))

ax1.set_title('Distribution Of Cases Around Cities Of The Region', fontsize=20,␣
↪fontweight='bold')

plt.show()
```



Distribuation of Deaths in different City

[ ]:
```python
#Count Number of All Deaths in each City
Covid_data_GpByCyties_Deaths = Covid_data_GpByCyties.Deaths.sum()
```

```
#print data
for city, cases in Covid_data_GpByCyties_Deaths.items():
    print("Number of Deaths in "+city+" : ",cases,end="\n")

print("\nSum of all Deaths in all Cities is ",sum(Covid_data_GpByCyties_Deaths))
```

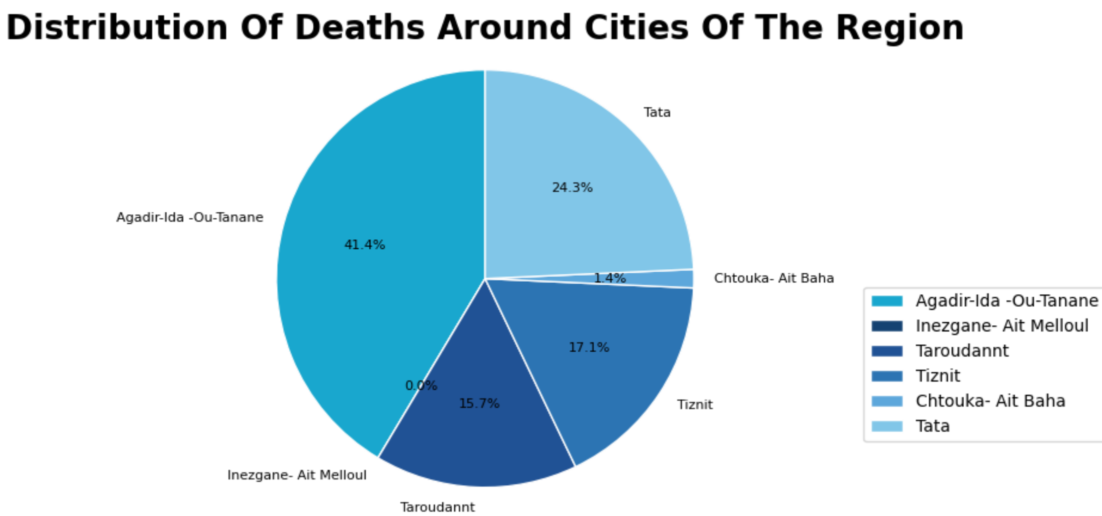
```
Number of Deaths in Agadir-Ida -Ou-Tanane :  29
Number of Deaths in Chtouka- Ait Baha :  0
Number of Deaths in Inezgane- Ait Melloul :  11
Number of Deaths in Taroudannt :  12
Number of Deaths in Tata :  1
Number of Deaths in Tiznit :  17

Sum of all Deaths in all Cities is  70
```

[ ]:
```
# Convert Valus to percent (Deaths * 100)/70
Cases_In_City_Deaths_per = []

for nb_death in Covid_data_GpByCyties_Deaths:
  death_per = (nb_death * 100)/70
  Cases_In_City_Deaths_per.append(death_per)

#print data
cities = ["Agadir-Ida -Ou-Tanane","Inezgane- Ait␣
 ↪Melloul","Taroudannt","Tiznit","Chtouka- Ait Baha","Tata"]
for ele in range(len(cities)) :
  print("Number of Deaths in "+cities[ele]+" : {:.2f}%".
 ↪format(Cases_In_City_Deaths_per[ele]),end="\n")

print("\nSum of all Case in all Cities is {:.2f}%".
 ↪format(sum(Cases_In_City_Deaths_per)))
```

```
Number of Deaths in Agadir-Ida -Ou-Tanane : 41.43%
Number of Deaths in Inezgane- Ait Melloul : 0.00%
Number of Deaths in Taroudannt : 15.71%
Number of Deaths in Tiznit : 17.14%
Number of Deaths in Chtouka- Ait Baha : 1.43%
Number of Deaths in Tata : 24.29%

Sum of all Case in all Cities is 100.00%
```

[ ]:
```
# Pie chart
colors=["#19A7CE","#144272","#205295","#2C74B3","#5DA7DB","#81C6E8"]

# fig1 = plt.figure(figsize=(12, 5))
# ax1 = fig1.add_subplot(121)  # Pie chart
# ax2 = fig1.add_subplot(122)
```

```
wedgeprops = {'linewidth': 1, 'edgecolor': 'white'}
fig1, ax1 = plt.subplots(figsize=(8, 5))
ax1.pie(Cases_In_City_Deaths_per,labels=cities,autopct='%1.
 ↪1f%%',colors=colors,wedgeprops=wedgeprops, startangle=90,␣
 ↪textprops={'fontsize': 8})
ax1.axis('equal')
plt.legend(labels=cities, loc='best', bbox_to_anchor=(1, 0.5))

ax1.set_title('Distribution Of Deaths Around Cities Of The Region',␣
 ↪fontsize=20, fontweight='bold')

plt.show()
```



Sum of Cases in Around cities in the period of 6 months

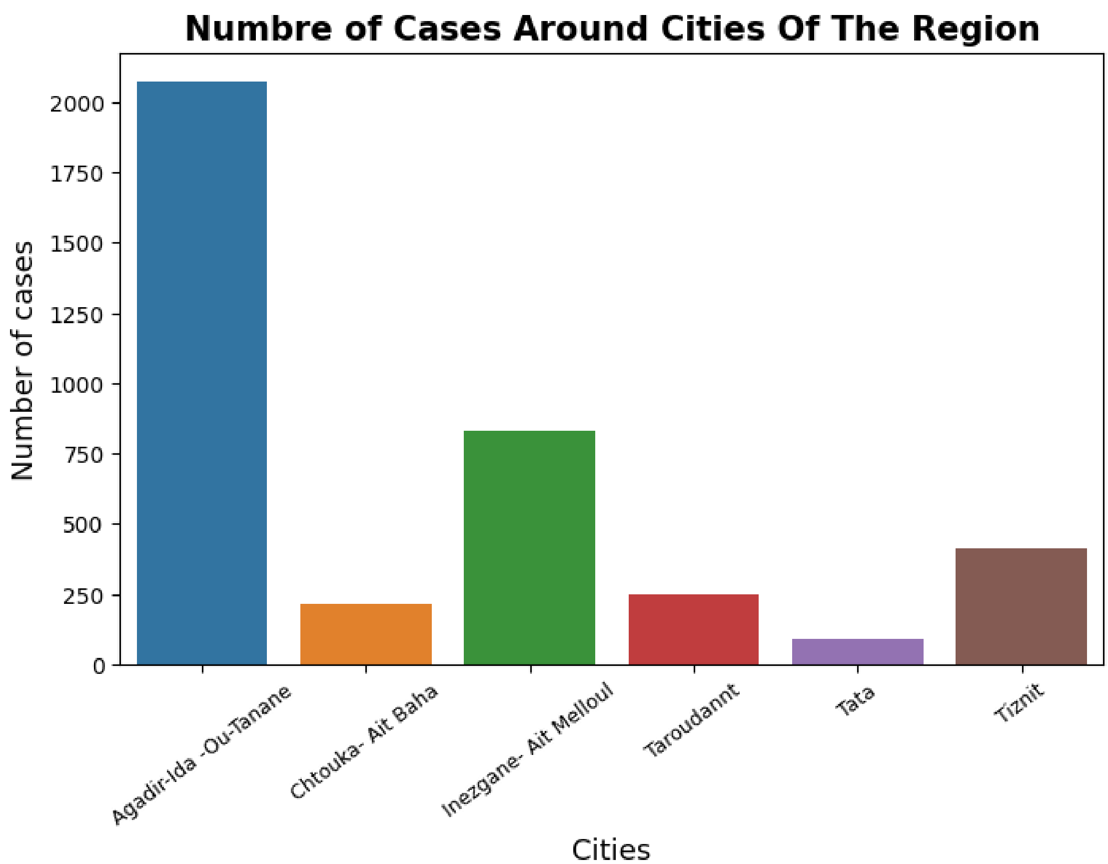
[ ]:
```
Covid_data_GpByCyties_Cases_df = pd.DataFrame(Covid_data_GpByCyties_Cases)
```

[ ]:
```
Covid_data_GpByCyties_Cases_df.columns
```

[ ]:
```
Index(['Cases'], dtype='object')
```

[ ]:
```
## Bar Plot
fig, ax = plt.subplots(figsize=(8, 5))
plt.title('Numbre of Cases Around Cities Of The Region', fontsize=15,␣
 ↪fontweight='bold')
sns.barplot(x=Covid_data_GpByCyties_Cases_df.
 ↪index,y=Covid_data_GpByCyties_Cases_df.Cases)
ax.set_xlabel('Cities', size=13)
```

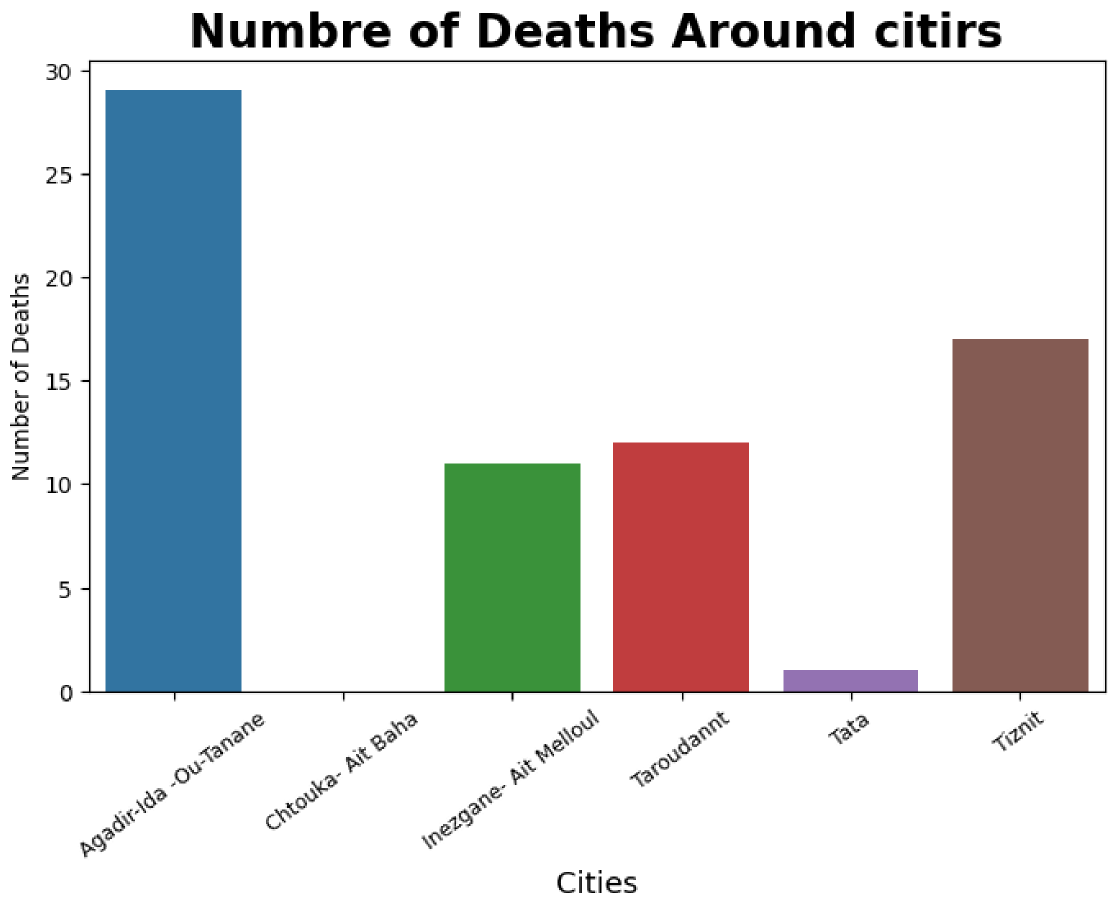
```
ax.set_ylabel('Number of cases', size=13)
plt.xticks(rotation=37, size=9)
plt.show()
```



Sum of Cases in Around Deaths in the period of 6 months

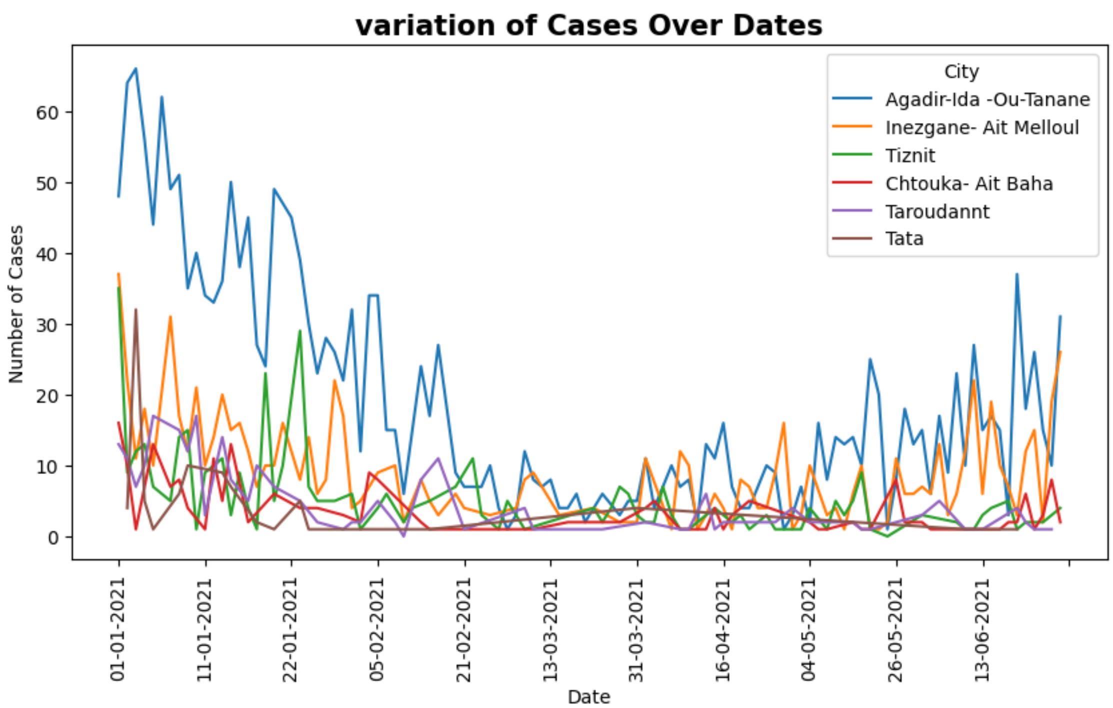
[ ]:
```
Covid_data_GpByCyties_Deaths_df = pd.DataFrame(Covid_data_GpByCyties_Deaths)
```

[ ]:
```
##  Bar Plot
fig, ax = plt.subplots(figsize=(8, 5))
plt.title('Numbre of Deaths Around citirs', fontsize=20, fontweight='bold')
sns.barplot(x=Covid_data_GpByCyties_Deaths_df.
 ↪index,y=Covid_data_GpByCyties_Deaths_df.Deaths)
ax.set_xlabel('Cities', size=13)
ax.set_ylabel('Number of Deaths', size=10)
plt.xticks(rotation=37, size=9)
plt.show()
```



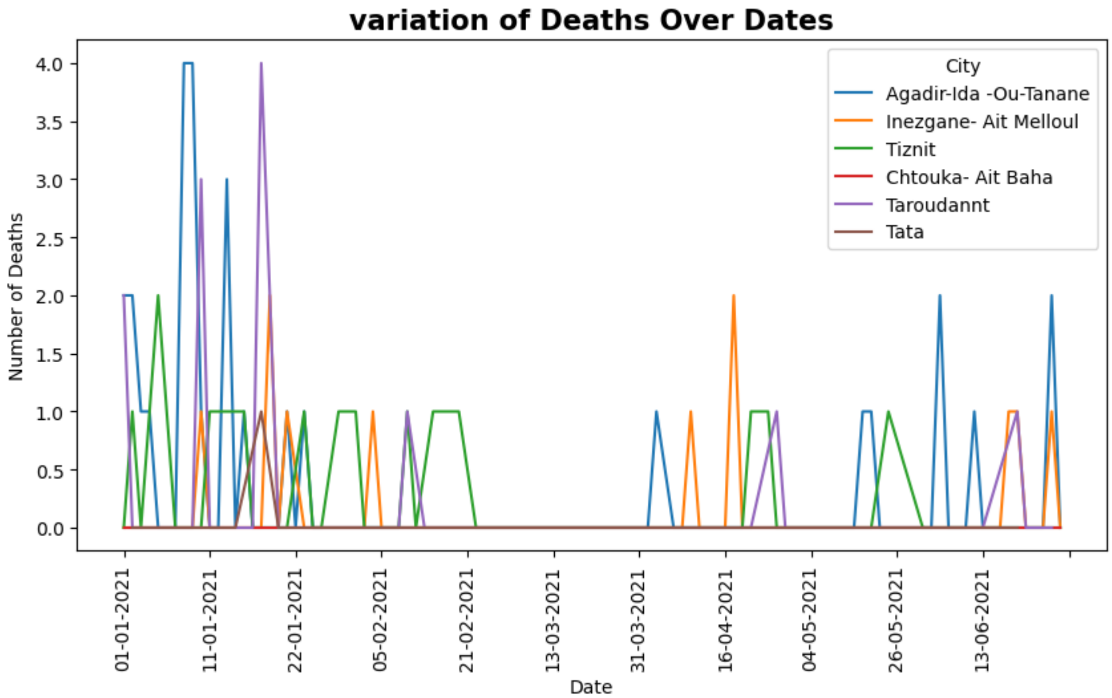
variation of Cases Over Dates In each city

[ ]:
```
# Line plot
plt.figure(figsize=(10, 5))
sns.lineplot(data=Covid_data, x=Covid_data.dates, y=Covid_data.Cases,␣
↪hue=Covid_data.cities)
plt.title('variation of Cases Over Dates', fontsize=15, fontweight='bold')
plt.xlabel('Date')
plt.ylabel('Number of Cases')
plt.xticks(rotation=90)
plt.legend(title='City', loc='upper right',)

#display only the month
ax = plt.gca()
ax.xaxis.set_major_locator(plt.MaxNLocator(12))

plt.show()
```



variation of Deaths Over Dates In each city

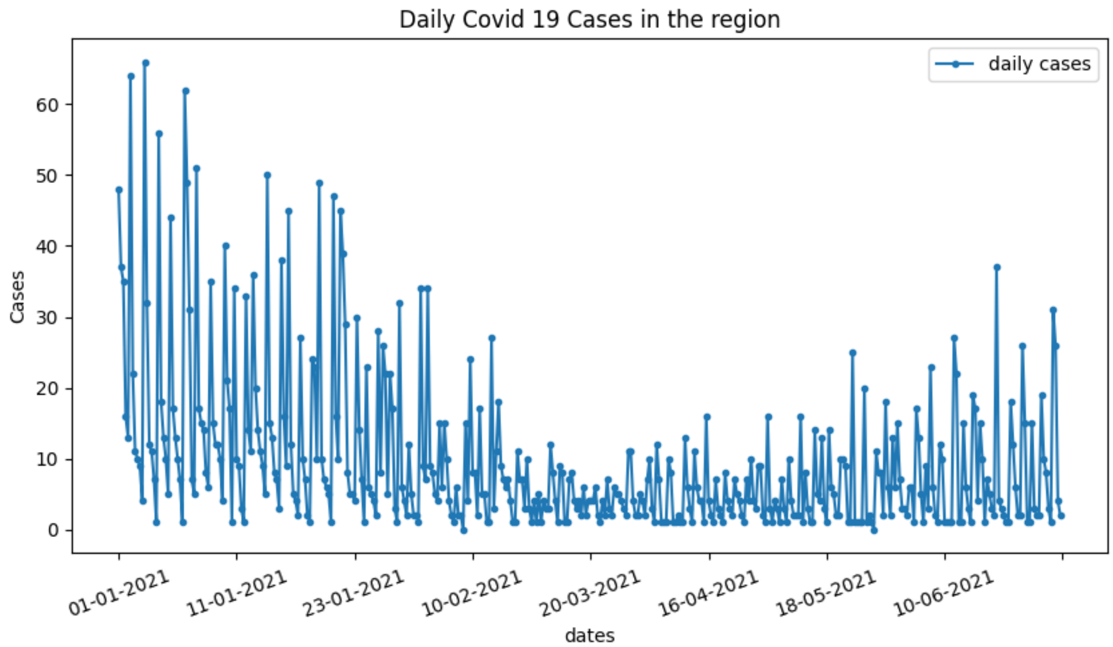
[ ]:
```
# line plot
plt.figure(figsize=(10, 5))
sns.lineplot(data=Covid_data, x="dates", y="Deaths", hue="cities")
plt.title('variation of Deaths Over Dates', fontsize=15, fontweight='bold')
plt.xlabel('Date')
plt.ylabel('Number of Deaths')
plt.xticks(rotation=90)
plt.legend(title='City', loc='upper right',)

#display only the month
ax = plt.gca()
ax.xaxis.set_major_locator(plt.MaxNLocator(12))

plt.show()
```



Daily Covid 19 Cases in the region

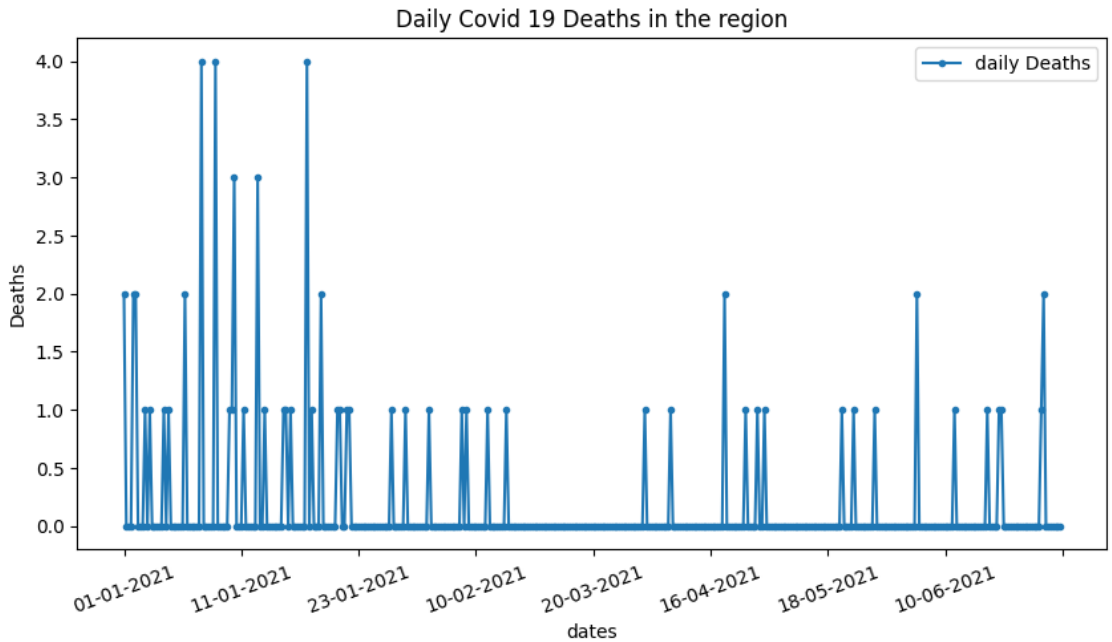
```
[ ]: #set dates as index
     Covid_data_toplot = Covid_data.set_index('dates')
```

```
[ ]: Covid_data_toplot.Cases.plot(title="Daily Covid 19 Cases in the␣
      ↪region",marker=".",figsize=(10,5),label="daily cases")
     plt.ylabel("Cases")
     plt.xlabel("dates")
     plt.xticks(rotation=20)
     plt.legend()
     plt.show()
```



Daily Covid 19 Deaths in the region

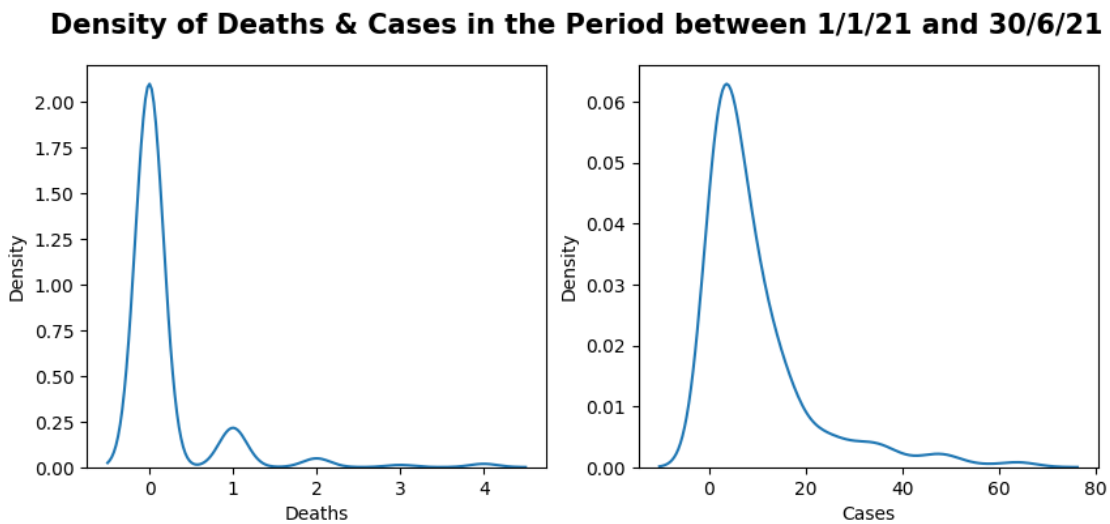
[ ]:
```
Covid_data_toplot.Deaths.plot(title="Daily Covid 19 Deaths in the␣
 ↪region",marker=".",figsize=(10,5),label="daily Deaths")
plt.ylabel("Deaths")
plt.xlabel("dates")
plt.xticks(rotation=20)
plt.legend()
plt.show()
```



Density of Deaths & Cases

[ ]:
```
# Kde plot
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(10, 4))
# plt.figure(figsize=(15,8))
sns.kdeplot(data=Covid_data,x='Deaths',ax=ax1)
sns.kdeplot(data=Covid_data,x='Cases',ax=ax2)

fig.suptitle("Density of Deaths & Cases in the Period between 1/1/21 and 30/6/
↪21", fontsize=15, fontweight='bold')
```

[ ]:
```
Text(0.5, 0.98, 'Density of Deaths & Cases in the Period between 1/1/21 and
30/6/21')
```



Visualisation of where death cases are reported

[ ]:
```
Covid_data.cities.unique()
```

[ ]:
```
array(['Agadir-Ida -Ou-Tanane', 'Inezgane- Ait Melloul', 'Tiznit',
       'Chtouka- Ait Baha', 'Taroudannt', 'Tata'], dtype=object)
```

[ ]:
```
Covid_data_coord.lon[Covid_data_coord.city == 'Agadir-Ida -Ou-Tanane']
```

[ ]:
```
0    30.4278
Name: lon, dtype: float64
```

[39]:
```
map_Covid_data = {
    'cities': Covid_data.cities.unique(),
    'Cases' : Covid_data_GpByCyties.Cases.sum().values,
    'Deaths' : Covid_data_GpByCyties.Deaths.sum().values,
}
map_Covid_data_df = pd.DataFrame(map_Covid_data)
map_Covid_data_df
```

[39]:

	cities	Cases	Deaths
0	Agadir-Ida -Ou-Tanane	2072	29
1	Inezgane- Ait Melloul	212	0
2	Tiznit	832	11
3	Chtouka- Ait Baha	246	12
4	Taroudannt	91	1
5	Tata	411	17

[48]:

```
import folium

Covid_data_coord = pd.DataFrame({
    'city' : Covid_data.cities.unique(),
    'lon':[30.4278,-9.439073698,-9.733198,-9.30909, -8.8666632,-7.83333],
    'lat':[-9.5981,30.357038687,29.696901,30.02948,30.4666648,29.66667]
})

Morocco_map = folium.Map(location=[31.7917, -7.0926], zoom_start=7,␣
↪tiles='Stamen Terrain')

for index, row in map_Covid_data_df.iterrows():
    if row['cities'] in list(Covid_data_coord.city):
        latitude = Covid_data_coord.lat[Covid_data_coord.city == row['cities']].
↪values[0]
        longitude = Covid_data_coord.lon[Covid_data_coord.city ==␣
↪row['cities']].values[0]
        folium.CircleMarker(
            location=[latitude, longitude],
            radius=row['Cases'] * 0,
            popup=f'City: {row["cities"]}<br>Cases: {row["Cases"]}<br>Deaths:␣
↪{row["Cases"]}',
            color='red',
            fill=True,
            fill_color='red',
            fill_opacity=0.4
        ).add_to(Morocco_map)

# Save the map
Morocco_map.save('styled_morocco_map.html')
Morocco_map
```

[48]: <folium.folium.Map at 0x7f79b314a140>

Relationships between deaths & Cases

[ ]:

```
corr_Death_cases = Covid_data.corr()
corr_Death_cases
```

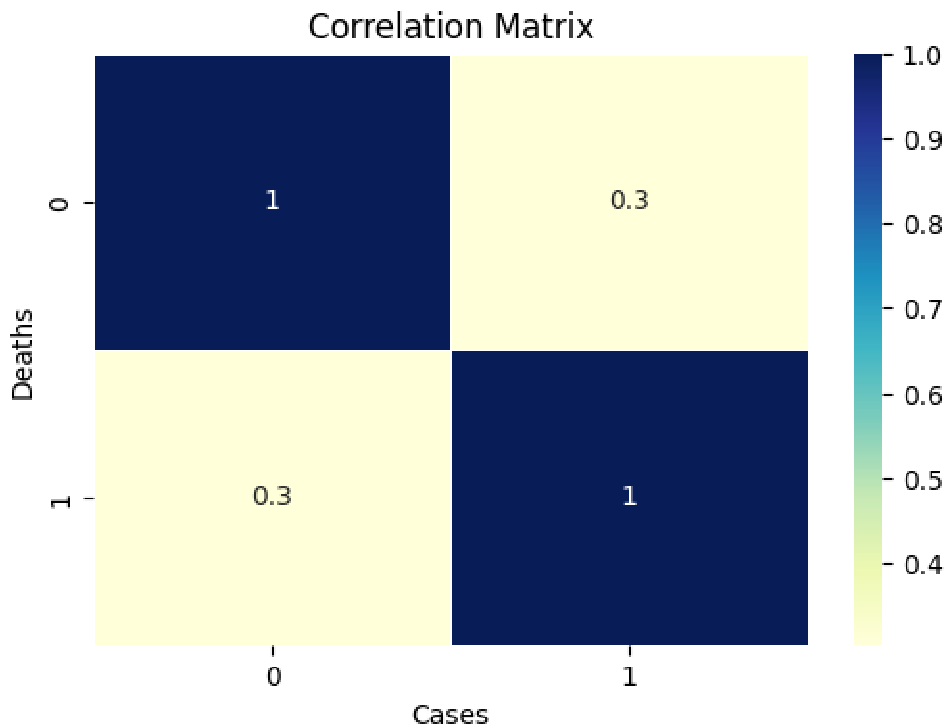
```
<ipython-input-38-e60862a0fa6f>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr_Death_cases = Covid_data.corr()
```

[ ]:

	Deaths	Cases
Deaths	1.000000	0.303203

```
Cases    0.303203  1.000000
```

[ ]:
```
# Define the correlation matrix
correlation_matrix = np.array(corr_Death_cases)

# Create a heatmap plot
plt.figure(figsize=(6, 4))
sns.heatmap(correlation_matrix, annot=True,linewidths=.5,cmap='YlGnBu')
plt.title('Correlation Matrix')
plt.xlabel('Cases')
plt.ylabel('Deaths')
plt.show()
```



5 Forecasting Deaths and Cases Using LSTM Model

Preper Data for The model

[ ]:
```
# make Dates column as index column
Covid_data = Covid_data.set_index('dates')
Covid_data
```

We split the X and y in such a way that X will contain cases for a certain amount of previous days(time_step) and y contains the reading for the next day.

This way the model will be trained to predict the number of cases on a certain day based on the trend in the number of cases within the previous time_steps number of days

[ ]:
```
import random

# features to train
X_features = Covid_data[ ['Cases','Deaths']]

#normlise X_features
scaler = MinMaxScaler(feature_range=(0,1))
scaled_X_features = scaler.fit_transform(X_features)
print("features shape : ",scaled_X_features.shape)


# Split the data into training and testing sets
train_size = int(0.8 * len(scaled_X_features))
train_data = scaled_X_features[:train_size]
test_data = scaled_X_features[train_size:]
# random.shuffle(train_data)
# random.shuffle(test_data)

# Create input features and labels for training
def create_sequences(data, seq_length):
    X = []
    y = []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

# Define the input sequence length (timesteps) for the LSTM model One month !!!
sequence_length = 30
X_train, y_train = create_sequences(train_data, sequence_length)
X_test, y_test = create_sequences(test_data, sequence_length)


print("*****************************")
print("X_train shape : ",X_train.shape)
print("y_train shape : ",y_train.shape)
print("X_test shape : ",X_test.shape)
print("y_test shape : ",y_test.shape)
```

```
features shape :  (400, 2)
*****************************
X_train shape :  (290, 30, 2)
y_train shape :  (290, 2)
X_test shape :  (50, 30, 2)
y_test shape :  (50, 2)
```

6 Model Architecture

[ ]:
```
!pip install Tensorboard
```

[ ]:
```
# creat log folder
log_dir = os.path.join('Logs')
TB_callback = TensorBoard(log_dir=log_dir)
```

[ ]:
```
# Build the LSTM model
model = Sequential()
# Add a LSTM layer with 64 internal units
model.add(LSTM(64, input_shape=(sequence_length,2),activation='relu'))
# model.add(LSTM(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(2)) # Two units (class Cases and Deaths)
# compile the model
model.compile(loss='mean_squared_error', optimizer='adam', metrics=['accuracy'])
model.summary()
```

```
Model: "sequential_31"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_39 (LSTM)              (None, 64)                17152

 dropout_7 (Dropout)         (None, 64)                0

 dense_26 (Dense)            (None, 2)                 130

=================================================================
Total params: 17282 (67.51 KB)
Trainable params: 17282 (67.51 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

7 Train The Model

[ ]:
```
# Train the model
model.fit(X_train, y_train, epochs=100,validation_split=0.
 ↪2,validation_data=[X_test, y_test], batch_size=56,verbose=2)
```

```
Epoch 1/100
6/6 - 1s - loss: 0.0134 - accuracy: 0.9069 - val_loss: 0.0154 - val_accuracy:
0.9200 - 827ms/epoch - 138ms/step
Epoch 2/100
6/6 - 0s - loss: 0.0119 - accuracy: 0.9172 - val_loss: 0.0156 - val_accuracy:
0.9200 - 467ms/epoch - 78ms/step
```

```
Epoch 3/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9000 - val_loss: 0.0157 - val_accuracy:
0.9200 - 452ms/epoch - 75ms/step
Epoch 4/100
6/6 - 1s - loss: 0.0122 - accuracy: 0.9103 - val_loss: 0.0161 - val_accuracy:
0.9200 - 542ms/epoch - 90ms/step
Epoch 5/100
6/6 - 0s - loss: 0.0126 - accuracy: 0.9103 - val_loss: 0.0162 - val_accuracy:
0.9200 - 447ms/epoch - 74ms/step
Epoch 6/100
6/6 - 0s - loss: 0.0123 - accuracy: 0.8862 - val_loss: 0.0161 - val_accuracy:
0.9200 - 490ms/epoch - 82ms/step
Epoch 7/100
6/6 - 0s - loss: 0.0144 - accuracy: 0.9103 - val_loss: 0.0159 - val_accuracy:
0.9200 - 315ms/epoch - 53ms/step
Epoch 8/100
6/6 - 0s - loss: 0.0146 - accuracy: 0.9103 - val_loss: 0.0161 - val_accuracy:
0.9200 - 422ms/epoch - 70ms/step
Epoch 9/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.9103 - val_loss: 0.0155 - val_accuracy:
0.9200 - 386ms/epoch - 64ms/step
Epoch 10/100
6/6 - 0s - loss: 0.0139 - accuracy: 0.8931 - val_loss: 0.0156 - val_accuracy:
0.9200 - 335ms/epoch - 56ms/step
Epoch 11/100
6/6 - 0s - loss: 0.0133 - accuracy: 0.9034 - val_loss: 0.0152 - val_accuracy:
0.9200 - 254ms/epoch - 42ms/step
Epoch 12/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.9069 - val_loss: 0.0152 - val_accuracy:
0.9200 - 220ms/epoch - 37ms/step
Epoch 13/100
6/6 - 0s - loss: 0.0125 - accuracy: 0.9069 - val_loss: 0.0158 - val_accuracy:
0.9200 - 230ms/epoch - 38ms/step
Epoch 14/100
6/6 - 0s - loss: 0.0125 - accuracy: 0.9069 - val_loss: 0.0159 - val_accuracy:
0.9200 - 243ms/epoch - 41ms/step
Epoch 15/100
6/6 - 0s - loss: 0.0122 - accuracy: 0.8966 - val_loss: 0.0161 - val_accuracy:
0.9200 - 218ms/epoch - 36ms/step
Epoch 16/100
6/6 - 0s - loss: 0.0137 - accuracy: 0.9207 - val_loss: 0.0161 - val_accuracy:
0.9200 - 291ms/epoch - 48ms/step
Epoch 17/100
6/6 - 0s - loss: 0.0131 - accuracy: 0.9138 - val_loss: 0.0155 - val_accuracy:
0.9200 - 220ms/epoch - 37ms/step
Epoch 18/100
6/6 - 0s - loss: 0.0130 - accuracy: 0.9034 - val_loss: 0.0156 - val_accuracy:
0.9200 - 168ms/epoch - 28ms/step
```

```
Epoch 19/100
6/6 - 0s - loss: 0.0110 - accuracy: 0.9138 - val_loss: 0.0159 - val_accuracy:
0.9200 - 152ms/epoch - 25ms/step
Epoch 20/100
6/6 - 0s - loss: 0.0113 - accuracy: 0.9138 - val_loss: 0.0160 - val_accuracy:
0.9200 - 149ms/epoch - 25ms/step
Epoch 21/100
6/6 - 0s - loss: 0.0123 - accuracy: 0.9034 - val_loss: 0.0160 - val_accuracy:
0.9200 - 172ms/epoch - 29ms/step
Epoch 22/100
6/6 - 0s - loss: 0.0129 - accuracy: 0.8793 - val_loss: 0.0161 - val_accuracy:
0.9200 - 155ms/epoch - 26ms/step
Epoch 23/100
6/6 - 0s - loss: 0.0132 - accuracy: 0.9138 - val_loss: 0.0155 - val_accuracy:
0.9200 - 154ms/epoch - 26ms/step
Epoch 24/100
6/6 - 0s - loss: 0.0117 - accuracy: 0.9103 - val_loss: 0.0153 - val_accuracy:
0.9200 - 162ms/epoch - 27ms/step
Epoch 25/100
6/6 - 0s - loss: 0.0126 - accuracy: 0.9069 - val_loss: 0.0160 - val_accuracy:
0.9200 - 149ms/epoch - 25ms/step
Epoch 26/100
6/6 - 0s - loss: 0.0117 - accuracy: 0.9103 - val_loss: 0.0165 - val_accuracy:
0.9200 - 146ms/epoch - 24ms/step
Epoch 27/100
6/6 - 0s - loss: 0.0128 - accuracy: 0.9103 - val_loss: 0.0165 - val_accuracy:
0.9200 - 157ms/epoch - 26ms/step
Epoch 28/100
6/6 - 0s - loss: 0.0125 - accuracy: 0.9000 - val_loss: 0.0158 - val_accuracy:
0.9200 - 149ms/epoch - 25ms/step
Epoch 29/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.9069 - val_loss: 0.0159 - val_accuracy:
0.9200 - 148ms/epoch - 25ms/step
Epoch 30/100
6/6 - 0s - loss: 0.0114 - accuracy: 0.9103 - val_loss: 0.0159 - val_accuracy:
0.9200 - 132ms/epoch - 22ms/step
Epoch 31/100
6/6 - 0s - loss: 0.0124 - accuracy: 0.9000 - val_loss: 0.0159 - val_accuracy:
0.9200 - 154ms/epoch - 26ms/step
Epoch 32/100
6/6 - 0s - loss: 0.0123 - accuracy: 0.9034 - val_loss: 0.0161 - val_accuracy:
0.9200 - 145ms/epoch - 24ms/step
Epoch 33/100
6/6 - 0s - loss: 0.0120 - accuracy: 0.9034 - val_loss: 0.0158 - val_accuracy:
0.9200 - 142ms/epoch - 24ms/step
Epoch 34/100
6/6 - 0s - loss: 0.0119 - accuracy: 0.8931 - val_loss: 0.0157 - val_accuracy:
0.9200 - 135ms/epoch - 23ms/step
```

```
Epoch 35/100
6/6 - 0s - loss: 0.0130 - accuracy: 0.9138 - val_loss: 0.0160 - val_accuracy:
0.9200 - 146ms/epoch - 24ms/step
Epoch 36/100
6/6 - 0s - loss: 0.0158 - accuracy: 0.8931 - val_loss: 0.0174 - val_accuracy:
0.9200 - 141ms/epoch - 24ms/step
Epoch 37/100
6/6 - 0s - loss: 0.0180 - accuracy: 0.9103 - val_loss: 0.0169 - val_accuracy:
0.9200 - 142ms/epoch - 24ms/step
Epoch 38/100
6/6 - 0s - loss: 0.0178 - accuracy: 0.9103 - val_loss: 0.0159 - val_accuracy:
0.9200 - 134ms/epoch - 22ms/step
Epoch 39/100
6/6 - 0s - loss: 0.0144 - accuracy: 0.9103 - val_loss: 0.0150 - val_accuracy:
0.9200 - 154ms/epoch - 26ms/step
Epoch 40/100
6/6 - 0s - loss: 0.0156 - accuracy: 0.9069 - val_loss: 0.0152 - val_accuracy:
0.9200 - 151ms/epoch - 25ms/step
Epoch 41/100
6/6 - 0s - loss: 0.0141 - accuracy: 0.9172 - val_loss: 0.0156 - val_accuracy:
0.9200 - 146ms/epoch - 24ms/step
Epoch 42/100
6/6 - 0s - loss: 0.0143 - accuracy: 0.8931 - val_loss: 0.0158 - val_accuracy:
0.9200 - 141ms/epoch - 24ms/step
Epoch 43/100
6/6 - 0s - loss: 0.0135 - accuracy: 0.8931 - val_loss: 0.0157 - val_accuracy:
0.9200 - 148ms/epoch - 25ms/step
Epoch 44/100
6/6 - 0s - loss: 0.0129 - accuracy: 0.9034 - val_loss: 0.0155 - val_accuracy:
0.9200 - 150ms/epoch - 25ms/step
Epoch 45/100
6/6 - 0s - loss: 0.0124 - accuracy: 0.9103 - val_loss: 0.0156 - val_accuracy:
0.9200 - 167ms/epoch - 28ms/step
Epoch 46/100
6/6 - 0s - loss: 0.0123 - accuracy: 0.9172 - val_loss: 0.0157 - val_accuracy:
0.9200 - 157ms/epoch - 26ms/step
Epoch 47/100
6/6 - 0s - loss: 0.0120 - accuracy: 0.9034 - val_loss: 0.0158 - val_accuracy:
0.9200 - 157ms/epoch - 26ms/step
Epoch 48/100
6/6 - 0s - loss: 0.0126 - accuracy: 0.8966 - val_loss: 0.0159 - val_accuracy:
0.9200 - 148ms/epoch - 25ms/step
Epoch 49/100
6/6 - 0s - loss: 0.0126 - accuracy: 0.9034 - val_loss: 0.0159 - val_accuracy:
0.9200 - 142ms/epoch - 24ms/step
Epoch 50/100
6/6 - 0s - loss: 0.0124 - accuracy: 0.9034 - val_loss: 0.0160 - val_accuracy:
0.9200 - 132ms/epoch - 22ms/step
```

```
Epoch 51/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9103 - val_loss: 0.0161 - val_accuracy:
0.9200 - 136ms/epoch - 23ms/step
Epoch 52/100
6/6 - 0s - loss: 0.0119 - accuracy: 0.9103 - val_loss: 0.0161 - val_accuracy:
0.9200 - 145ms/epoch - 24ms/step
Epoch 53/100
6/6 - 0s - loss: 0.0115 - accuracy: 0.9034 - val_loss: 0.0161 - val_accuracy:
0.9200 - 156ms/epoch - 26ms/step
Epoch 54/100
6/6 - 0s - loss: 0.0124 - accuracy: 0.9172 - val_loss: 0.0160 - val_accuracy:
0.9200 - 134ms/epoch - 22ms/step
Epoch 55/100
6/6 - 0s - loss: 0.0110 - accuracy: 0.9034 - val_loss: 0.0162 - val_accuracy:
0.9200 - 143ms/epoch - 24ms/step
Epoch 56/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.8931 - val_loss: 0.0159 - val_accuracy:
0.9200 - 147ms/epoch - 25ms/step
Epoch 57/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9103 - val_loss: 0.0157 - val_accuracy:
0.9200 - 155ms/epoch - 26ms/step
Epoch 58/100
6/6 - 0s - loss: 0.0125 - accuracy: 0.9069 - val_loss: 0.0157 - val_accuracy:
0.9200 - 152ms/epoch - 25ms/step
Epoch 59/100
6/6 - 0s - loss: 0.0123 - accuracy: 0.9034 - val_loss: 0.0162 - val_accuracy:
0.9200 - 161ms/epoch - 27ms/step
Epoch 60/100
6/6 - 0s - loss: 0.0138 - accuracy: 0.8966 - val_loss: 0.0160 - val_accuracy:
0.9200 - 154ms/epoch - 26ms/step
Epoch 61/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9103 - val_loss: 0.0157 - val_accuracy:
0.9200 - 164ms/epoch - 27ms/step
Epoch 62/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.9000 - val_loss: 0.0158 - val_accuracy:
0.9200 - 160ms/epoch - 27ms/step
Epoch 63/100
6/6 - 0s - loss: 0.0122 - accuracy: 0.9138 - val_loss: 0.0160 - val_accuracy:
0.9200 - 176ms/epoch - 29ms/step
Epoch 64/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9103 - val_loss: 0.0156 - val_accuracy:
0.9200 - 154ms/epoch - 26ms/step
Epoch 65/100
6/6 - 0s - loss: 0.0126 - accuracy: 0.9103 - val_loss: 0.0158 - val_accuracy:
0.9200 - 145ms/epoch - 24ms/step
Epoch 66/100
6/6 - 0s - loss: 0.0119 - accuracy: 0.9069 - val_loss: 0.0161 - val_accuracy:
0.9200 - 152ms/epoch - 25ms/step
```

```
Epoch 67/100
6/6 - 0s - loss: 0.0112 - accuracy: 0.9103 - val_loss: 0.0158 - val_accuracy:
0.9200 - 142ms/epoch - 24ms/step
Epoch 68/100
6/6 - 0s - loss: 0.0122 - accuracy: 0.9103 - val_loss: 0.0162 - val_accuracy:
0.9200 - 150ms/epoch - 25ms/step
Epoch 69/100
6/6 - 0s - loss: 0.0122 - accuracy: 0.9000 - val_loss: 0.0164 - val_accuracy:
0.9200 - 153ms/epoch - 25ms/step
Epoch 70/100
6/6 - 0s - loss: 0.0105 - accuracy: 0.9069 - val_loss: 0.0163 - val_accuracy:
0.9200 - 214ms/epoch - 36ms/step
Epoch 71/100
6/6 - 0s - loss: 0.0110 - accuracy: 0.8966 - val_loss: 0.0161 - val_accuracy:
0.9200 - 222ms/epoch - 37ms/step
Epoch 72/100
6/6 - 0s - loss: 0.0124 - accuracy: 0.9103 - val_loss: 0.0162 - val_accuracy:
0.9200 - 216ms/epoch - 36ms/step
Epoch 73/100
6/6 - 0s - loss: 0.0120 - accuracy: 0.9000 - val_loss: 0.0163 - val_accuracy:
0.9200 - 219ms/epoch - 37ms/step
Epoch 74/100
6/6 - 0s - loss: 0.0109 - accuracy: 0.9000 - val_loss: 0.0160 - val_accuracy:
0.9200 - 209ms/epoch - 35ms/step
Epoch 75/100
6/6 - 0s - loss: 0.0125 - accuracy: 0.9103 - val_loss: 0.0160 - val_accuracy:
0.9200 - 203ms/epoch - 34ms/step
Epoch 76/100
6/6 - 0s - loss: 0.0117 - accuracy: 0.9103 - val_loss: 0.0164 - val_accuracy:
0.9200 - 222ms/epoch - 37ms/step
Epoch 77/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.9034 - val_loss: 0.0157 - val_accuracy:
0.9200 - 227ms/epoch - 38ms/step
Epoch 78/100
6/6 - 0s - loss: 0.0114 - accuracy: 0.9069 - val_loss: 0.0155 - val_accuracy:
0.9200 - 231ms/epoch - 38ms/step
Epoch 79/100
6/6 - 0s - loss: 0.0117 - accuracy: 0.9069 - val_loss: 0.0155 - val_accuracy:
0.9200 - 208ms/epoch - 35ms/step
Epoch 80/100
6/6 - 0s - loss: 0.0108 - accuracy: 0.9034 - val_loss: 0.0157 - val_accuracy:
0.9200 - 218ms/epoch - 36ms/step
Epoch 81/100
6/6 - 0s - loss: 0.0122 - accuracy: 0.9034 - val_loss: 0.0161 - val_accuracy:
0.9200 - 238ms/epoch - 40ms/step
Epoch 82/100
6/6 - 0s - loss: 0.0119 - accuracy: 0.9034 - val_loss: 0.0161 - val_accuracy:
0.9200 - 222ms/epoch - 37ms/step
```

```
Epoch 83/100
6/6 - 0s - loss: 0.0114 - accuracy: 0.9138 - val_loss: 0.0161 - val_accuracy:
0.9200 - 213ms/epoch - 36ms/step
Epoch 84/100
6/6 - 0s - loss: 0.0127 - accuracy: 0.9069 - val_loss: 0.0162 - val_accuracy:
0.9200 - 180ms/epoch - 30ms/step
Epoch 85/100
6/6 - 0s - loss: 0.0144 - accuracy: 0.9000 - val_loss: 0.0166 - val_accuracy:
0.9200 - 150ms/epoch - 25ms/step
Epoch 86/100
6/6 - 0s - loss: 0.0126 - accuracy: 0.9103 - val_loss: 0.0165 - val_accuracy:
0.9200 - 168ms/epoch - 28ms/step
Epoch 87/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9172 - val_loss: 0.0160 - val_accuracy:
0.9200 - 140ms/epoch - 23ms/step
Epoch 88/100
6/6 - 0s - loss: 0.0111 - accuracy: 0.9138 - val_loss: 0.0160 - val_accuracy:
0.9200 - 146ms/epoch - 24ms/step
Epoch 89/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9103 - val_loss: 0.0163 - val_accuracy:
0.9200 - 138ms/epoch - 23ms/step
Epoch 90/100
6/6 - 0s - loss: 0.0109 - accuracy: 0.9069 - val_loss: 0.0163 - val_accuracy:
0.9200 - 162ms/epoch - 27ms/step
Epoch 91/100
6/6 - 0s - loss: 0.0118 - accuracy: 0.9069 - val_loss: 0.0162 - val_accuracy:
0.9200 - 136ms/epoch - 23ms/step
Epoch 92/100
6/6 - 0s - loss: 0.0120 - accuracy: 0.9034 - val_loss: 0.0161 - val_accuracy:
0.9200 - 162ms/epoch - 27ms/step
Epoch 93/100
6/6 - 0s - loss: 0.0104 - accuracy: 0.9172 - val_loss: 0.0159 - val_accuracy:
0.9200 - 134ms/epoch - 22ms/step
Epoch 94/100
6/6 - 0s - loss: 0.0116 - accuracy: 0.9000 - val_loss: 0.0161 - val_accuracy:
0.9200 - 160ms/epoch - 27ms/step
Epoch 95/100
6/6 - 0s - loss: 0.0102 - accuracy: 0.9138 - val_loss: 0.0158 - val_accuracy:
0.9200 - 148ms/epoch - 25ms/step
Epoch 96/100
6/6 - 0s - loss: 0.0110 - accuracy: 0.9034 - val_loss: 0.0155 - val_accuracy:
0.9200 - 157ms/epoch - 26ms/step
Epoch 97/100
6/6 - 0s - loss: 0.0110 - accuracy: 0.9138 - val_loss: 0.0164 - val_accuracy:
0.9200 - 139ms/epoch - 23ms/step
Epoch 98/100
6/6 - 0s - loss: 0.0115 - accuracy: 0.9103 - val_loss: 0.0169 - val_accuracy:
0.9200 - 145ms/epoch - 24ms/step
```

```
Epoch 99/100
6/6 - 0s - loss: 0.0114 - accuracy: 0.9034 - val_loss: 0.0167 - val_accuracy:
0.9200 - 166ms/epoch - 28ms/step
Epoch 100/100
6/6 - 0s - loss: 0.0114 - accuracy: 0.9172 - val_loss: 0.0163 - val_accuracy:
0.9200 - 151ms/epoch - 25ms/step
```

[ ]:
```
<keras.src.callbacks.History at 0x7d62002bdba0>
```

8 Evaluate The Model

[ ]:
```python
# Evaluate the model
train_loss = model.evaluate(X_train, y_train)
test_loss = model.evaluate(X_test, y_test)
```

```
10/10 [==============================] - 0s 9ms/step - loss: 0.0095 - accuracy:
0.9172
2/2 [==============================] - 0s 16ms/step - loss: 0.0163 - accuracy:
0.9200
```

visualize loss and accurancy

[ ]:
```
%load_ext tensorboard
```

[ ]:
```
%tensorboard --logdir={log_dir}
```

9 Save The Model

[ ]:
```python
model.save("Covid19_agadir-souss.h5")
```

[ ]:
```python
import shutil
shutil.make_archive('Logs', 'zip', 'Logs')
```

[ ]:
```
'/content/Logs.zip'
```

[ ]:
```
! unzip -q Logs.zip
```

10 STAY SAFE !