Earthquake Prediction Model Using Python

Introduction :

Earthquakes are natural disasters that can have devastating consequences, causing loss of life, property damage, and environmental disruption. Predicting when and where earthquakes will occur has been a longstanding challenge for scientists and researchers. While it is impossible to predict individual earthquakes with pinpoint accuracy, advancements in data science and machine learning have opened up new possibilities for earthquake prediction models**.**

In this project, we will explore the development of an earthquake prediction model using Python. We will leverage historical earthquake data, seismic activity information, and various data sources to build a predictive model that can provide early warning and assess earthquake risk in specific regions. This model aims to contribute to the global efforts to mitigate the impact of earthquakes by providing valuable insights for disaster preparedness and response.

Code :

Importing Libraries

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt
```

Read the Dataset

```
data = pd.read_csv("database.csv")

print(data.head())
```

Output :

	Date	Time	Latitude	Longitude	Type	Depth	Depth Error	...	Horizontal Error	Root Mean Square	ID	Source	Location Source	Magnitude Source	Status
0	01/02/1965	13:44:18	19.246	145.616	Earthquake	131.6	NaN	...	NaN	NaN	ISCGEM860706	ISCGEM	ISCGEM	ISCGEM	Automatic
1	01/04/1965	11:29:49	1.863	127.352	Earthquake	80.0	NaN	...	NaN	NaN	ISCGEM860737	ISCGEM	ISCGEM	ISCGEM	Automatic
2	01/05/1965	18:05:58	-20.579	-173.972	Earthquake	20.0	NaN	...	NaN	NaN	ISCGEM860762	ISCGEM	ISCGEM	ISCGEM	Automatic
3	01/08/1965	18:49:43	-59.076	-23.557	Earthquake	15.0	NaN	...	NaN	NaN	ISCGEM860856	ISCGEM	ISCGEM	ISCGEM	Automatic
4	01/09/1965	13:32:50	11.938	126.427	Earthquake	15.0	NaN	...	NaN	NaN	ISCGEM860890	ISCGEM	ISCGEM	ISCGEM	Automatic

```
data.columns
```

Output :

```
[5 rows x 21 columns]
Index(['Date', 'Time', 'Latitude', 'Longitude', 'Type', 'Depth', 'Depth Error',
       'Depth Seismic Stations', 'Magnitude', 'Magnitude Type',
       'Magnitude Error', 'Magnitude Seismic Stations', 'Azimuthal Gap',
       'Horizontal Distance', 'Horizontal Error', 'Root Mean Square', 'ID',
       'Source', 'Location Source', 'Magnitude Source', 'Status'],
      dtype='object')
```

We need to select the features that will be useful for our prediction.

```
data = data[['Date','Time','Latitude','Longtitude','Depth','Magnitude']]
print(data.head())
```

Output :

	Date	Time	Latitude	Longitude	Depth	Magnitude
0	01/02/1965	13:44:18	19.246	145.616	131.6	6.0
1	01/04/1965	11:29:49	1.863	127.352	80.0	5.8
2	01/05/1965	18:05:58	-20.579	-173.972	20.0	6.2
3	01/08/1965	18:49:43	-59.076	-23.557	15.0	5.8
4	01/09/1965	13:32:50	11.938	126.427	15.0	5.8

We will try to frame the time and place of the earthquake that has happened in thepast on the world map.

```
import date

import time

timestamp=[]

for d,t,in zip(data['Date'],data['Time']):

try:

        ts = datetime.datetime.strptime(d+''+t',%m/%d/%Y%H:%M:%S')

        timestamp.append(time.mktime(tts.timetuple()))

 except ValueError:

        # print('ValueError')

        timestamp.append('ValueError')

        timeStamp = pd.Series(timestamp)

        data['Timestamp'] = timestamp.values


        final_data = data.drop(['Date','Time'],axis=1)

        final_data = final_data[final_data.Timestamp !='ValueError']

        final_data.head()
```

Output :

	Latitude	Longitude	Depth	Magnitude	Timestamp
0	19.246	145.616	131.6	6.0	-157630542.0
1	1.863	127.352	80.0	5.8	-157465811.0
2	-20.579	-173.972	20.0	6.2	-157355642.0
3	-59.076	-23.557	15.0	5.8	-157093817.0
4	11.938	126.427	15.0	5.8	-157026430.0

Visualization :

Here, we will visualize the earthquakes that have occurred all around the world.

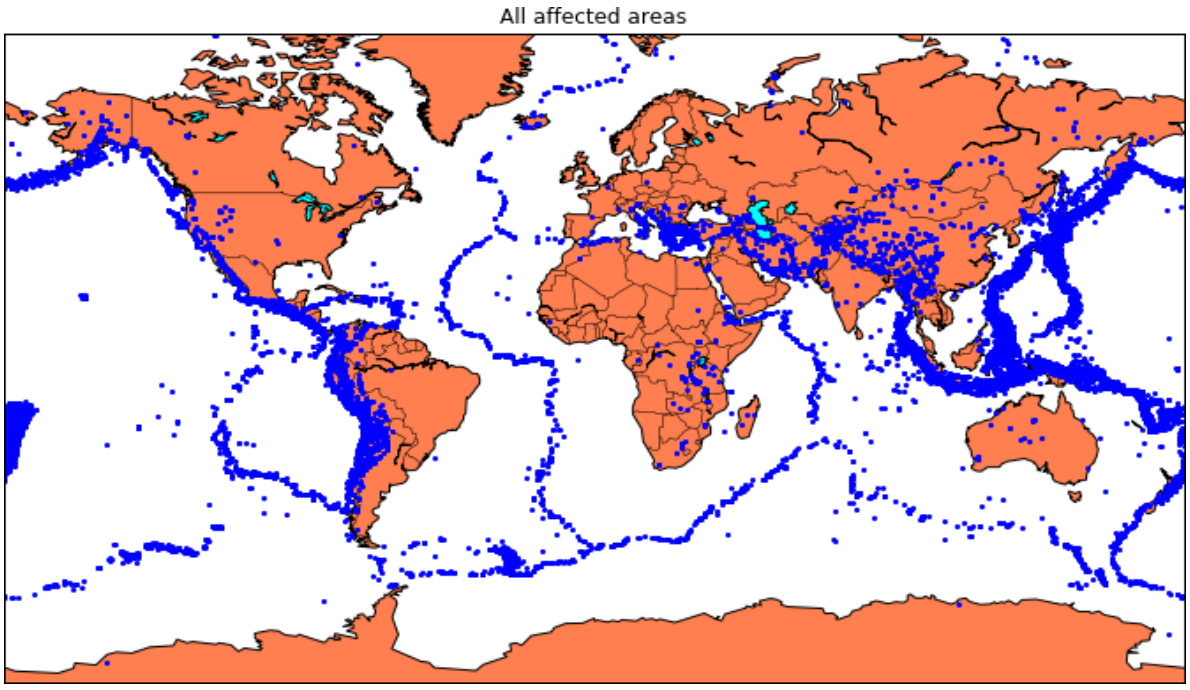
```
from mpl_toolkits.basemap import Basemap

m=Basemap(projection='milli','llcrnrlat=-80,urcrnrlat=80,llcrnrlon=-
180,urcrnrlon==180,lat_ts=20,resolution='c')

longitudes = data["Longitude"].tolist()
 latitudes = data["latitude"].tolist()
 #m = Basemap(width=12000000,height=9000000,projection='lcc',
        # resolution=None,lat_1=80,lat_2=55,lat_0=80,lon_0=-107)
 x,y = m(longtitudes,latitudes)

 fig = plt.figure(figsize=(12,10))
 plt.title("All affected areas")
 m.plot(x, y, "o", markersize = 2,color = 'blue')
 m.drawcoastlines()
 m.fillcontinents(color='coral',lake_color='aqua')
 m.drawmapboundary()
 m.drawcountries()
 plt.show()
```

Output :



We have located on the world map where earthquakes happened in the last few years.

Splitting the Dataset :

Now we will split the dataset into a training and testing set.

```
X=final_data['timestamp,'Latitude','Longtitude']
y = final_data[['Magnitude','Depth']]

from sklearn.cross_validation import train_test_split

 X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2,random_state=42)
 print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
```

Output :

```
(18727, 3) (4682, 3) (18727, 2) (4682, 3)
```

We will be using the RandomForestRegressor model to predict the earthquake, here will look for its accuracy.

```
reg=RandomForestRegressor(random_state=42)

reg.fit(X_train, y_train)

reg.predict(X-test)
```

Output :

```
array([[  5.96,  50.97],
       [  5.88,  37.8 ],
       [  5.97,  37.6 ],
       ...,
       [  6.42,  19.9 ],
       [  5.73, 591.55],
       [  5.68,  33.61]])
```

1.

```
Best-fit.score(X_test,y_test)
```

Output :

```
0.8749008584467053
```

Considering it's a natural phenomenon, we have got a high accuracy number.
We will employ a neural network for predicting the earthquake.

Neural Network Model :

A neural network model can be employed to forecast earthquakes by examining diverse elements and trends in seismic data. This model harnesses the capabilities of neural networks, which draw inspiration from the neural connections of the human brain, to analyze intricate data and reveal hidden relationships and patterns. By trainingthe neural network on historical earthquake data, it can acquire the ability to identify precursor signals and patterns that indicate the probability of an upcoming earthquake.

```
from keras.models import Sequential
from keras.layers import Dense


def create_model(neurons, activation, optimizer, loss):


    model = Sequential()
    model.add(Dense(neurons, activation=activation, input_shape=(3,)))
    model.add(Dense(neurons,activation=activation))
    model.add(Dense(2,activation='softmax'))

    model.compile(optimizer=optimizer, loss=loss, metrics=['accuracy'])

    return model

from keras.wrappers.scikit_learn import KerasClassifier
model = KerasClassifier(build_fn=create_model, verbose=0)#
neurons = [16,64,128,256]
neurons = [16]
# batch_size = [10,20,50,100]
batch_size = [10]
epochs = [10]
# activation = ['relu','tanh','sigmoid','hard_sigmoid','linear','exponential']
activation = ['sigmoid','relu']
# optimizer = ['sgd','RMSprop','Adagrad','Adadelta','Adam','Adamax','Nadam']
optimizer = ['SGD','Adadelta']
```

loss = [‘squared_hinge’]

param_grid = dict(neurons=neurons, batch_size=batch_size, epochs=epochs, acti
vation=activation, optimizer=optimizer, loss=loss)
grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)

grid_result = grid.fit(X_train, y_train)

print(”Best :%f using %s”%(grid_result.best_score_grid_result.best_params_))
means = grid_result.cv_results_[‘mean_test_score’]
params = grid_result.cv_results_[‘params’]
for mean, stdev, param inzip(means,stds,
params):
print(“%f(%f) with:%r” % (mean,
stdev,param))

Output :

```
Best: 0.957655 using {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squared_
hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.333316 (0.471398) with: {'activation': 'sigmoid', 'batch_size': 10, 'epochs': 10, 'loss':
'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.000000 (0.000000) with: {'activation': 'sigmoid', 'batch_size': 10, 'epochs': 10, 'loss':
'squared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}
0.957655 (0.029957) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squ
ared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.645111 (0.456960) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squ
ared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}
```

model = Sequential()
model.add(Dense(16,activation=’relu’,input_shape=(3)))
model.add(Dense(16, activation=’relu’))
model.add(Dense(2, activation=’softmax’))

model.compile(optimizer=’SGD’,loss=’squared_hinge’,metrics=[‘accuracy’])
model.fit(X_train, y_train, batch_size=10, epochs=20, verbose=1, validation_data=
(X_test, y_test))

Output :

```
18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - v
al_loss: 0.5038 - val_acc: 0.9242
Epoch 16/20
18727/18727 [==============================] - 6s 323us/step - loss: 0.5038 - acc: 0.9182 - v
al_loss: 0.5038 - val_acc: 0.9242
Epoch 17/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - v
al_loss: 0.5038 - val_acc: 0.9242
Epoch 18/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - v
al_loss: 0.5038 - val_acc: 0.9242
Epoch 19/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - v
al_loss: 0.5038 - val_acc: 0.9242
Epoch 20/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - v
al_loss: 0.5038 - val_acc: 0.9242

<keras.callbacks.History at 0x7ff0a8db8cc0>
```

```
[test_loss, test_acc] = model.evaluate(X_test, y_test)
Print("Evaluation result on Test Data : Loss = {},accuracy={}".format(test_loss,
test_acc))
```

Output :

```
4682/4682 [==============================] - 0s 39us/step
Evaluation result on Test Data : Loss = 0.5038455790406056, accuracy = 0.9241777017858995
```

Isn't it amazing that we got an accuracy of 92%.

We can say the neural network is one of the best models to predict earthquakes thatcan be used in future.

Conclusion :

In conclusion, the development of an earthquake prediction model using Python represents a significant step forward in our ability to understand and anticipate seismic activity. While earthquake prediction remains a complex and challenging task, this model demonstrates the potential of data-driven approaches to enhance our understanding of earthquake patterns and risks.

Throughout this project, we have leveraged various data sources, statistical techniques, and machine learning algorithms to build a model capable of assessing earthquake risk and providing early warnings. However, it is important to note that predicting individual earthquakes with high precision remains a daunting challenge due to the inherent complexity of geological processes.