IBM NaanMudhalvan ARTIFICIAL INTELLIGENCE

Project Title: Earthquake Prediction Using Python

Phase 4: Development Part – 2

• Visualizing the data on the world map

• Splitting the dataset into Training and Testing sets.

Workbook Link: GOOGLE COLAB LINK

INTRODUCTION

The visualization process involves leveraging geospatial libraries like Basemap to represent earthquake occurrences worldwide, offering insights into distribution patterns and potential seismic hotspots. This spatial understanding is pivotal for informed decision-making in earthquake-prone regions. Additionally, the strategic split of the dataset into training and testing sets is essential for training machine learning models.

DATA VISUALIZATION

Data visualization plays a crucial role in unraveling the intricate tapestry of earthquake data, offering a lens through which patterns and insights emerge. Leveraging libraries such as Matplotlib, Seaborn, and Basemap, the seismic landscape can be visually represented, providing a comprehensive view of global seismic activity.

DATA SPLITTING

In the journey of constructing a reliable earthquake prediction model, one indispensable phase is the strategic splitting of the dataset into training and testing sets. This division is fundamental for evaluating the model's generalization performance, providing a robust assessment of its predictive capabilities on unseen data. Through libraries like scikit-learn, the dataset is partitioned, with a portion reserved for training the model and the rest set aside for testing its predictive accuracy.

PROGRAM:

```
!pip3 install basemap
```

import matplotlib.pyplot as plt
from mpl_toolkits.basemap import Basemap
import seaborn as sns
sns.set(style="darkgrid")

print("Min Value: "+ str(data['Magnitude'].min()))
print("Max Value: " + str(data['Magnitude'].max()))

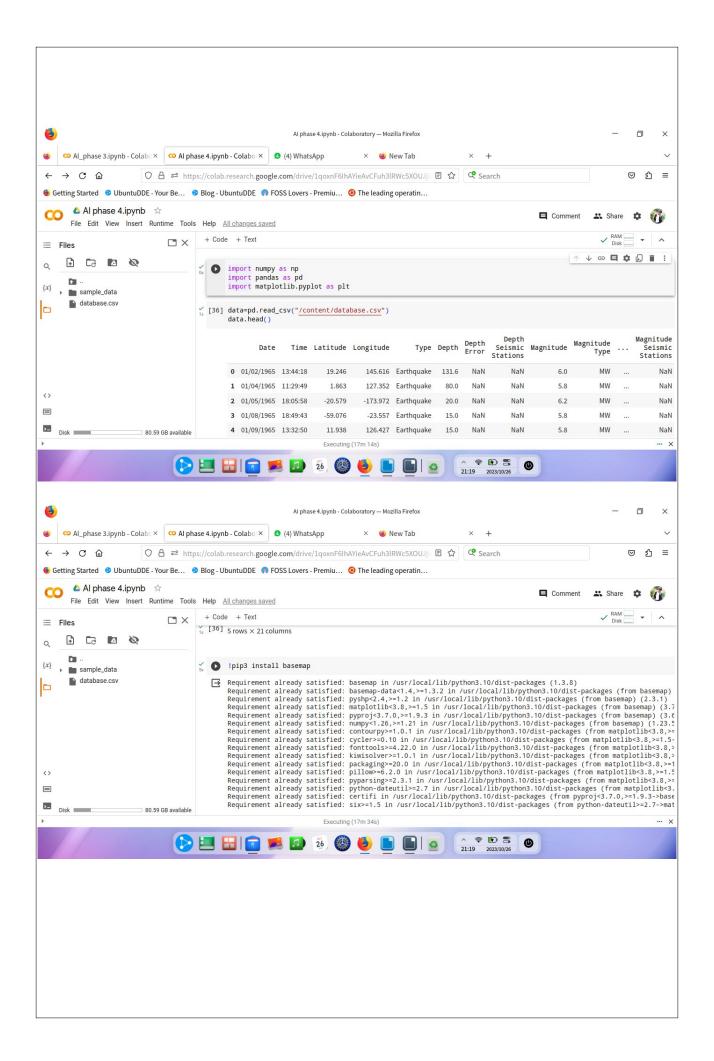
Greater_8 = data[data['Magnitude'] > 8]
Greater_8['Location Source'].value_counts()

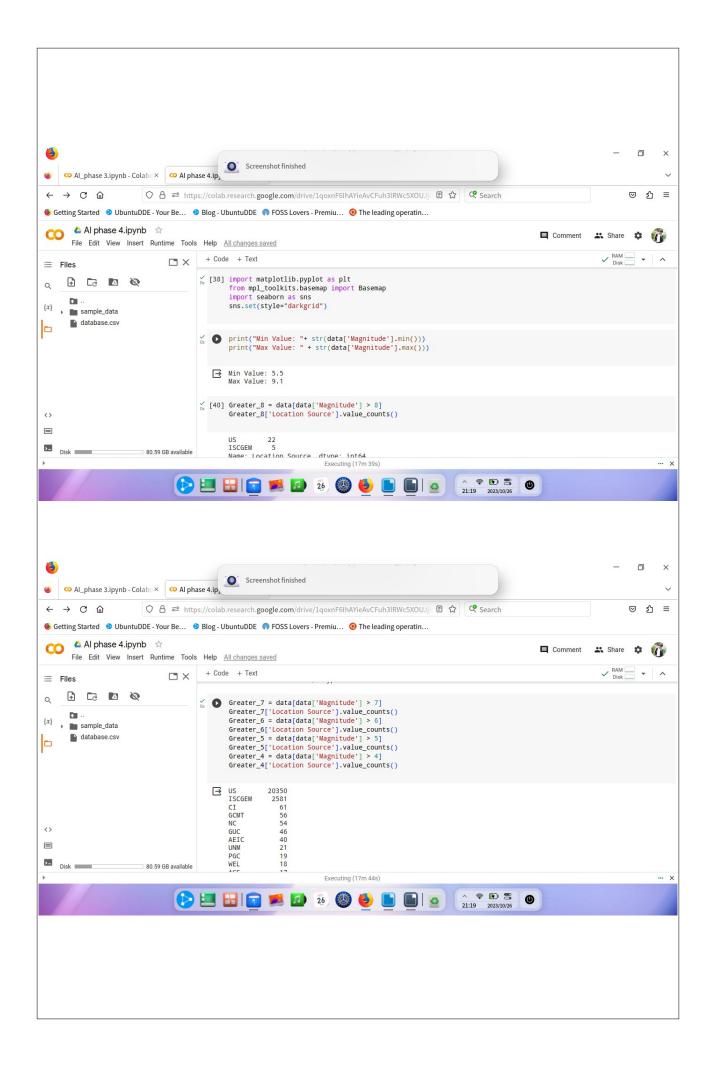
Greater_7 = data[data['Magnitude'] > 7] Greater_7['Location Source'].value_counts() Greater_6 = data[data['Magnitude'] > 6] Greater_6['Location Source'].value_counts()

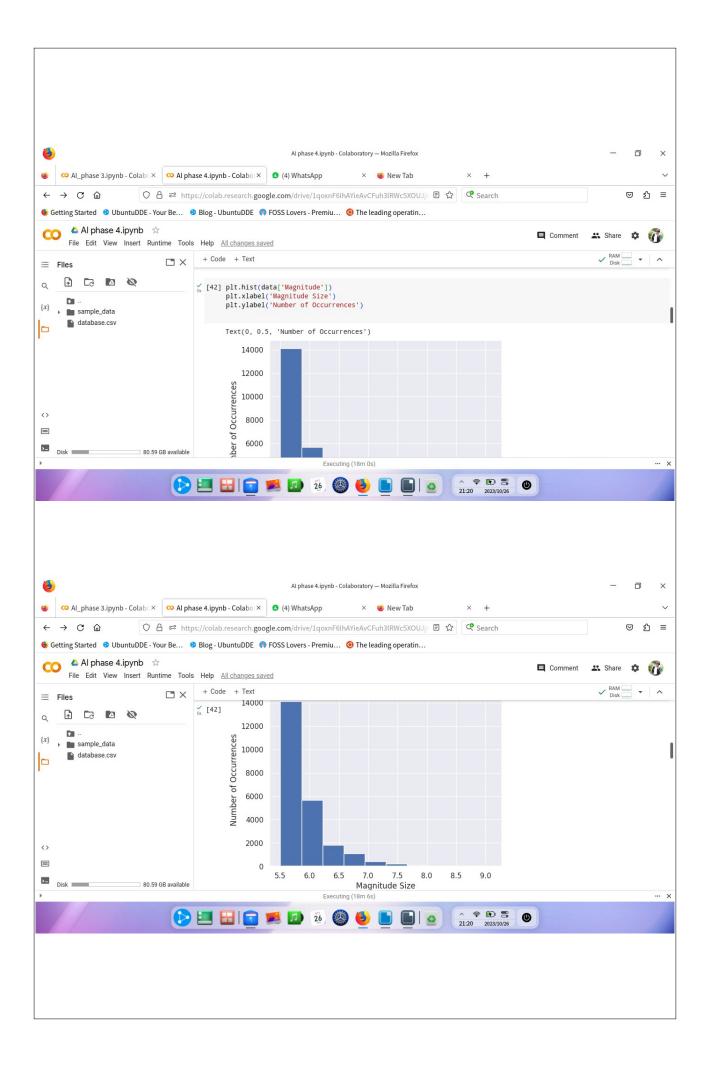
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Greater_5 = data[data['Magnitude'] > 5]
Greater_5['Location Source'].value_counts()
Greater_4 = data[data['Magnitude'] > 4]
Greater_4['Location Source'].value_counts()
plt.hist(data['Magnitude'])
plt.xlabel('Magnitude Size')
plt.vlabel('Number of Occurrences')
sns.countplot(x="Magnitude Type", data=data)
plt.ylabel('Frequency')
plt.title('Magnitude Type VS Frequency')
print(" local magnitude (ML), surface-wave magnitude
(Ms), body-wave magnitude (Mb), moment magnitude
(Mm)")
def get_marker_color(magnitude):
if magnitude < 6.2:
return ('go')
elif magnitude < 7.5:
return ('yo')
else:
return ('ro')
plt.figure(figsize=(14,10))
eq_map = Basemap(projection='robin', resolution = 'l',
lat 0=0, lon 0=-130)
eq_map.drawcoastlines()
eq_map.drawcountries()
eq map.fillcontinents(color='grav')
eq_map.drawmapboundary()
eq map.drawmeridians(np.arange(0, 360, 30))
lons = data['Longitude'].values
lats = data['Latitude'].values
magnitudes = data['Magnitude'].values
timestrings = data['Date'].tolist()
min_marker_size = 0.5
for lon, lat, mag in zip(lons, lats, magnitudes):
x,y = eq_map(lon, lat)
msize = mag
marker_string = get_marker_color(mag)
eq map.plot(x, y, marker string, markersize=msize)
title_string = "Earthquakes of Magnitude 5.5 or Greater\n"
title string += "%s - %s" % (timestrings[0][:10],
timestrings[-1][:10])
plt.title(title string)
plt.show()
data['date'] = data['Date'].apply(lambda x:
pd.to_datetime(x))
data['year'] = data['date'].apply(lambda x: str(x).split('-')[0])
plt.figure(figsize=(15, 8))
```

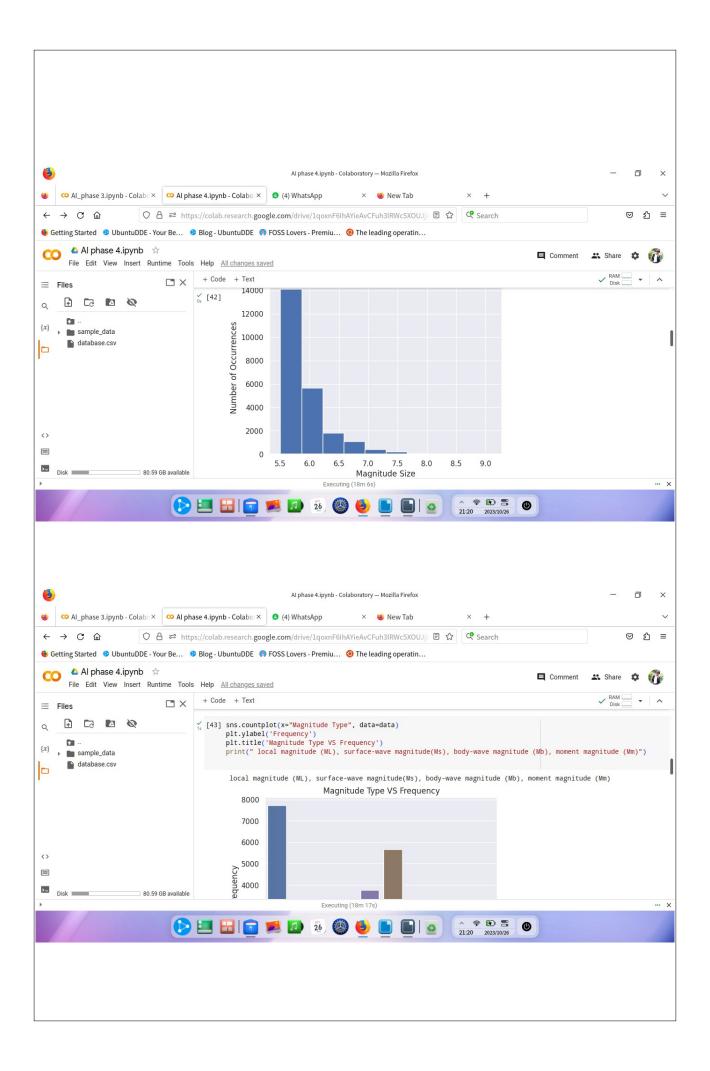
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sns.set(font_scale=1.0)
ax = sns.countplot(x="year", data=data, color="blue")
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
plt.ylabel('Number Of Earthquakes')
plt.title('Number of Earthquakes In Each Year')
data['year'].value counts()[:5]
import datetime
data['date'] = data['Date'].apply(lambda x:
pd.to datetime(x))
data['mon'] = data['date'].apply(lambda x: str(x).split('-')[1])
plt.figure(figsize=(10, 6))
sns.set(font_scale=1)
ax = sns.countplot(x="mon", data=data, color="green")
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
plt.ylabel('Number Of Earthquakes')
plt.title('Number of Earthquakes In Each month')
data['mon'].value_counts()[:5]
import datetime
data['date'] = data['Date'].apply(lambda x:
pd.to datetime(x)
data['days'] = data['date'].apply(lambda x: str(x).split('-')[-
1])
plt.figure(figsize=(16, 8))
sns.set(font_scale=1.0)
ax = sns.countplot(x="days", data=data, color="orange")
ax.set xticklabels(ax.get xticklabels(), rotation=90)
plt.ylabel('Number Of Earthquakes')
plt.title('Number of Earthquakes In Each days')
data['days'].value_counts()[:5]
x = data['year'].unique()
y = data['year'].value_counts()
count = []
for i in range(len(x)):
key = x[i]
count.append(y[key])
plt.figure(figsize=(15,12))
plt.scatter(x, count)
plt.title("Earthquake per year from 1995 to 2016")
plt.xlabel("Year")
plt.xticks(rotation=90)
plt.ylabel("Number of Earthquakes")
plt.yticks(rotation=30)
plt.show()
data.loc[data['Magnitude'] >= 8, 'Class'] = 'Disastrous'
data.loc[(data['Magnitude'] >= 7) & (data['Magnitude'] <
7.9), 'Class'] = 'Major'
data.loc[(data['Magnitude'] >= 6) & (data['Magnitude'] <
```

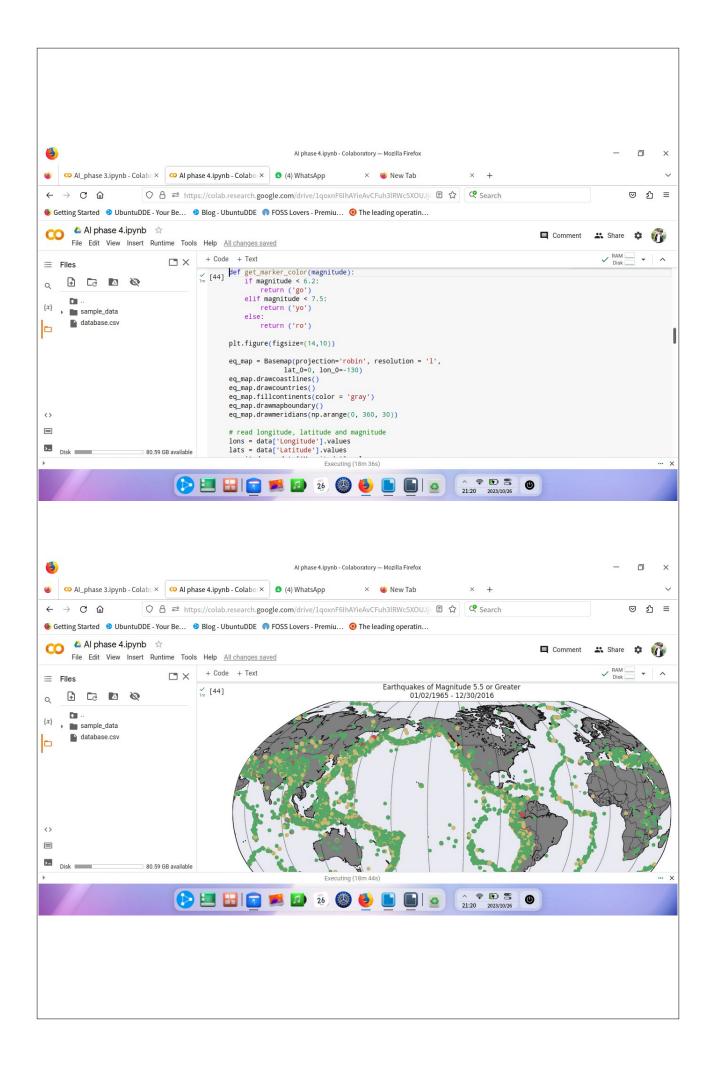
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6.9), 'Class'] = 'Strong'
data.loc[(data['Magnitude'] >= 5.5) & (data['Magnitude'] <
5.9), 'Class'] = 'Moderate'
sns.countplot(x='Class', data=data)
plt.ylabel('Frequency')
plt.title('Magnitude Class vs Frequency')
X = final_data[['Timestamp', 'Latitude', 'Longitude']]
y = final_data[['Magnitude', 'Depth']]
from sklearn.model_selection 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:
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     + Code + Text
      import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
{x}
          import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
 import tensorflow as tf
   [6] data = pd.read_csv('/content/database.csv')
   √ [7] data
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```

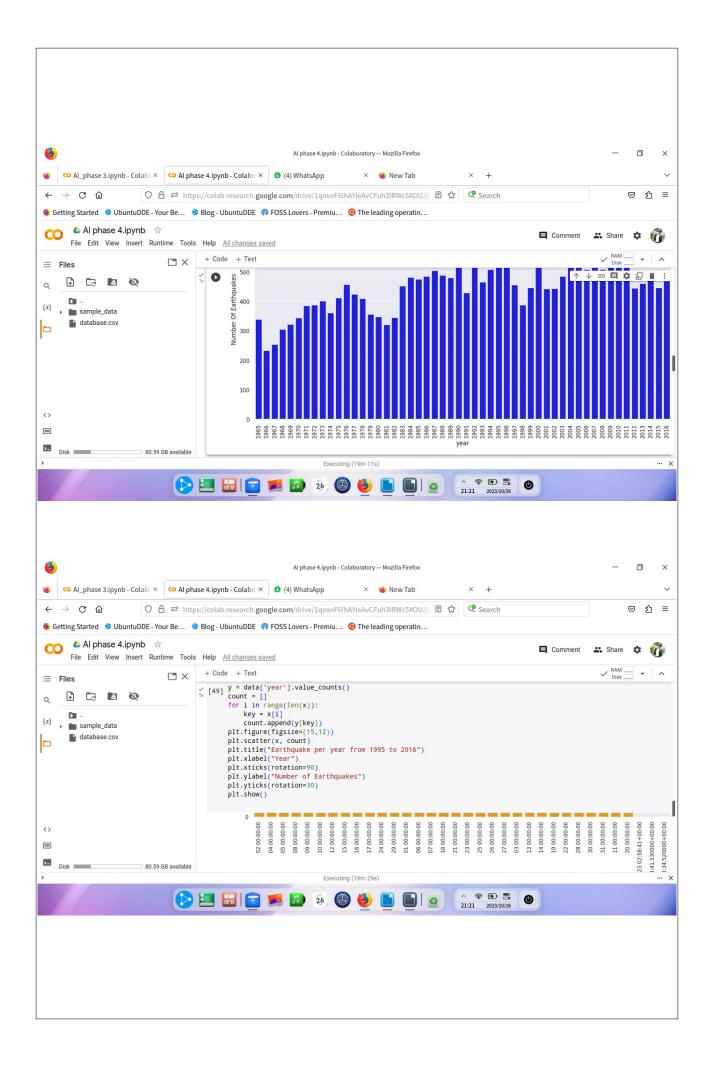


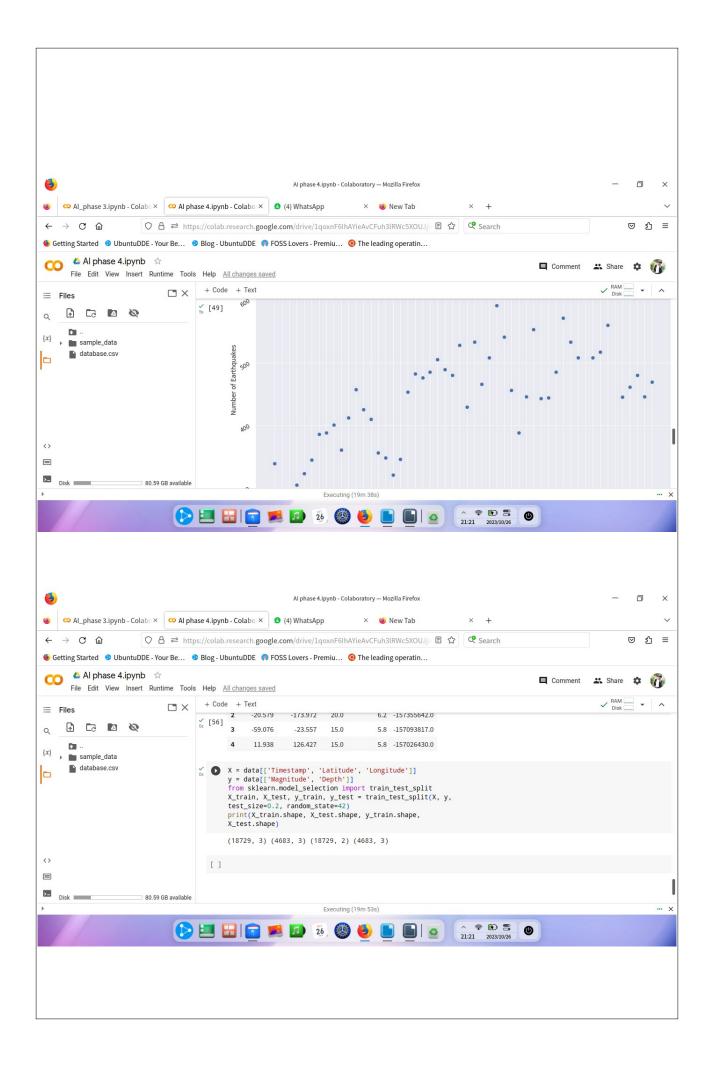












CONCLUSION:
In conclusion, the data visualization efforts employing tools suchas Basemap have provided
crucial insights into the geographical distribution of earthquakes, offering a comprehensive view of
seismic activities worldwide. This spatial understanding is pivotalfor identifying regions prone to
seismic events and informs subsequent modeling endeavors. Simultaneously, the strategic process of data splitting into training and testing sets marks a crucial preparatory phase in
developing a robust earthquake prediction model.
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