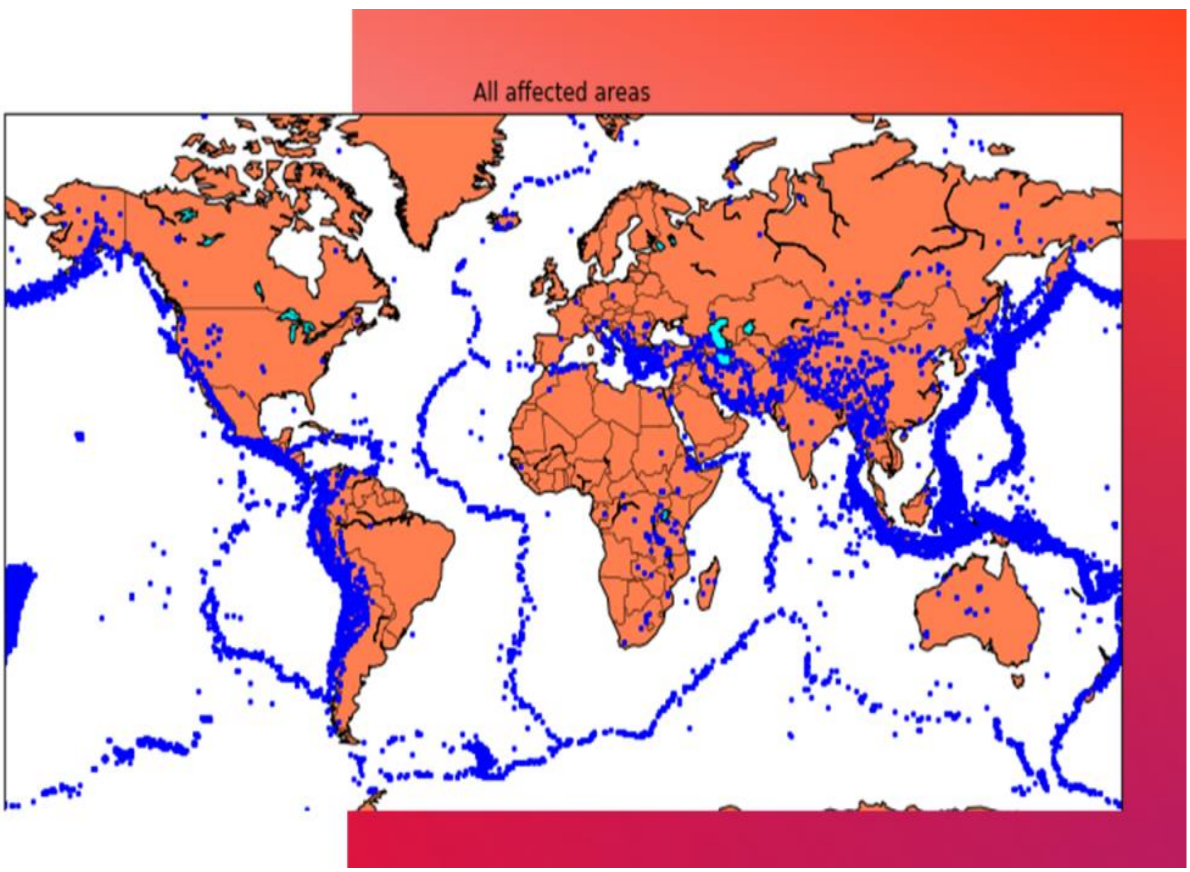
EARTHQUAKE PREDICTION MODEL USING PYTHON

Phase 3 submission document

Project Title: Earthquake Predictions Model Using Python

Phase 3: Development Part 1

Topic: Start building the earthquake prediction model by loading and pre-processing the dataset.



INTRODUCTION:

The SOCR Earthquake Dataset can be used to build machine learning models to predict earthquakes or to better understand earthquake patterns and characteristics. Here are a few possible ways machine learning models can be used with this dataset:

1. Earthquake prediction: You can use this dataset to build a model that predicts when and where an earthquake might occur based on past earthquake data. You could use techniques such as time series analysis, clustering, or classification to identify patterns in the data and make predictions.
2. Magnitude prediction: You can use this dataset to build a model that predicts the magnitude of an earthquake based on other factors such as location, depth, or the number of seismic stations that recorded the earthquake. You could use regression techniques to build this model.
3. Risk assessment: You can use this dataset to identify areas that are at higher risk of earthquakes based on historical earthquake data. You could use clustering or classification techniques to identify patterns in the data and identify areas with similar characteristics.
4. Anomaly detection: You can use this dataset to detect anomalies or outliers in the data, which could represent earthquakes that are unusual or unexpected. You could use techniques such as clustering or classification to identify patterns in the data and detect anomalies.
5. Data visualization: You can use this dataset to create visualizations of earthquake data, which could help you identify patterns and relationships in the data. You could use techniques such as scatter plots, heat maps, or geographic information systems (GIS) to visualize the data.

These are just a few examples of the many ways that machine learning models can be used with the SOCR Earthquake Dataset. The specific approach you take will depend on your research question and the goals of your analysis. In this project we focus mainly on earthquake prediction and Magnitude prediction.

GIVEN DATA SET:

1	Date	Time	Latitude	Longitude	Type	Depth	Depth Err	Depth Sei	Magnitud	Magnitud	Magnitud	Magnitud	Azimuthal	Horizonta	Horizonta	Root Mea	ID	Source	Location S
2	01-02-1965	13:44:18	19.246	145.616	Earthquak	131.6			6	MW							ISCGEM86	ISCGEM	ISCGEM
3	01-04-1965	11:29:49	1.863	127.352	Earthquak	80			5.8	MW							ISCGEM86	ISCGEM	ISCGEM
4	01-05-1965	18:05:58	-20.579	-173.972	Earthquak	20			6.2	MW							ISCGEM86	ISCGEM	ISCGEM
5	01-08-1965	18:49:43	-59.076	-23.557	Earthquak	15			5.8	MW							ISCGEM86	ISCGEM	ISCGEM
6	01-09-1965	13:32:50	11.938	126.427	Earthquak	15			5.8	MW							ISCGEM86	ISCGEM	ISCGEM
7	01-10-1965	13:36:32	-13.405	166.629	Earthquak	35			6.7	MW							ISCGEM86	ISCGEM	ISCGEM
8	01-12-1965	13:32:25	27.357	87.867	Earthquak	20			5.9	MW							ISCGEM86	ISCGEM	ISCGEM
9	01/15/1965	23:17:42	-13.309	166.212	Earthquak	35			6	MW							ISCGEM86	ISCGEM	ISCGEM
10	01/16/1965	11:32:37	-56.452	-27.043	Earthquak	95			6	MW							ISCGEMSU	ISCGEMSU	ISCGEM
11	01/17/1965	10:43:17	-24.563	178.487	Earthquak	565			5.8	MW							ISCGEM86	ISCGEM	ISCGEM
12	01/17/1965	20:57:41	-6.807	108.988	Earthquak	227.9			5.9	MW							ISCGEM86	ISCGEM	ISCGEM
13	01/24/1965	00:11:17	-2.608	125.952	Earthquak	20			8.2	MW							ISCGEM86	ISCGEM	ISCGEM
14	01/29/1965	09:35:30	54.636	161.703	Earthquak	55			5.5	MW							ISCGEM86	ISCGEM	ISCGEM
15	02-01-1965	05:27:06	-18.697	-177.864	Earthquak	482.9			5.6	MW							ISCGEM85	ISCGEM	ISCGEM
16	02-02-1965	15:56:51	37.523	73.251	Earthquak	15			6	MW							ISCGEM85	ISCGEM	ISCGEM
17	02-04-1965	03:25:00	-51.84	139.741	Earthquak	10			6.1	MW							ISCGEM85	ISCGEM	ISCGEM
18	02-04-1965	05:01:22	51.251	178.715	Earthquak	30.3			8.7	MW							OFFICIAL1	OFFICIAL	ISCGEM
19	02-04-1965	06:04:59	51.639	175.055	Earthquak	30			6	MW							ISCGEMSU	ISCGEMSU	ISCGEM
20	02-04-1965	06:37:06	52.528	172.007	Earthquak	25			5.7	MW							ISCGEM85	ISCGEM	ISCGEM
21	02-04-1965	06:39:32	51.626	175.746	Earthquak	25			5.8	MW							ISCGEM85	ISCGEM	ISCGEM
22	02-04-1965	07:11:23	51.037	177.848	Earthquak	25			5.9	MW							ISCGEMSU	ISCGEMSU	ISCGEM

23413 Rows * 21 Columns

NECESSARY STEP TO FOLLOW:

1. Import the Necessary Libraries:

First, you need to import the libraries you'll be using. You can use libraries such as Pandas, NumPy, and scikit-learn for this task.

Program:

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler
```

2. Load the Dataset:

For this example, let's assume you have a CSV file with earthquake-related data. You can use Pandas to load the dataset.

Program:

```
# Load the dataset (replace 'your_dataset.csv' with the actual file path)

data = pd.read_csv('your_dataset.csv')
```

3. Explore the Dataset:

It's important to understand your data. Check the first few rows, data types, and summary statistics.

Program:

```
print(data.head())

print(data.info())

print(data.describe())
```

4. Data Preprocessing:

Data preprocessing is a crucial step in machine learning. It involves handling missing values, encoding categorical variables, and scaling numerical features. Here's a basic example.

Program:

```
# Handle missing values (replace NaN with mean or other suitable strategies)

data = data.fillna(data.mean())
```

Split the dataset into features (X) and target (y)

X = data.drop('earthquake_occurred', axis=1) # Replace 'earthquake_occurred' with your target column

y = data['earthquake_occurred']

Encode categorical variables if necessary (e.g., using one-hot encoding or label encoding)

Scale the numerical features to have mean=0 and variance=1

scaler = StandardScaler()

X = scaler.fit_transform(X)

5. Split the Data into Training and Testing Sets:

It's essential to split your data into training and testing sets to evaluate your model's performance.

Program:

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Data Visualization:

Now, before we create the earthquake prediction model, let's visualize the data on a world map that shows a clear representation of where the earthquake frequency will be more:

```
from mpl_toolkits.basemap import Basemap
```

```
m = Basemap(projection='mill',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(longitudes,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()
```

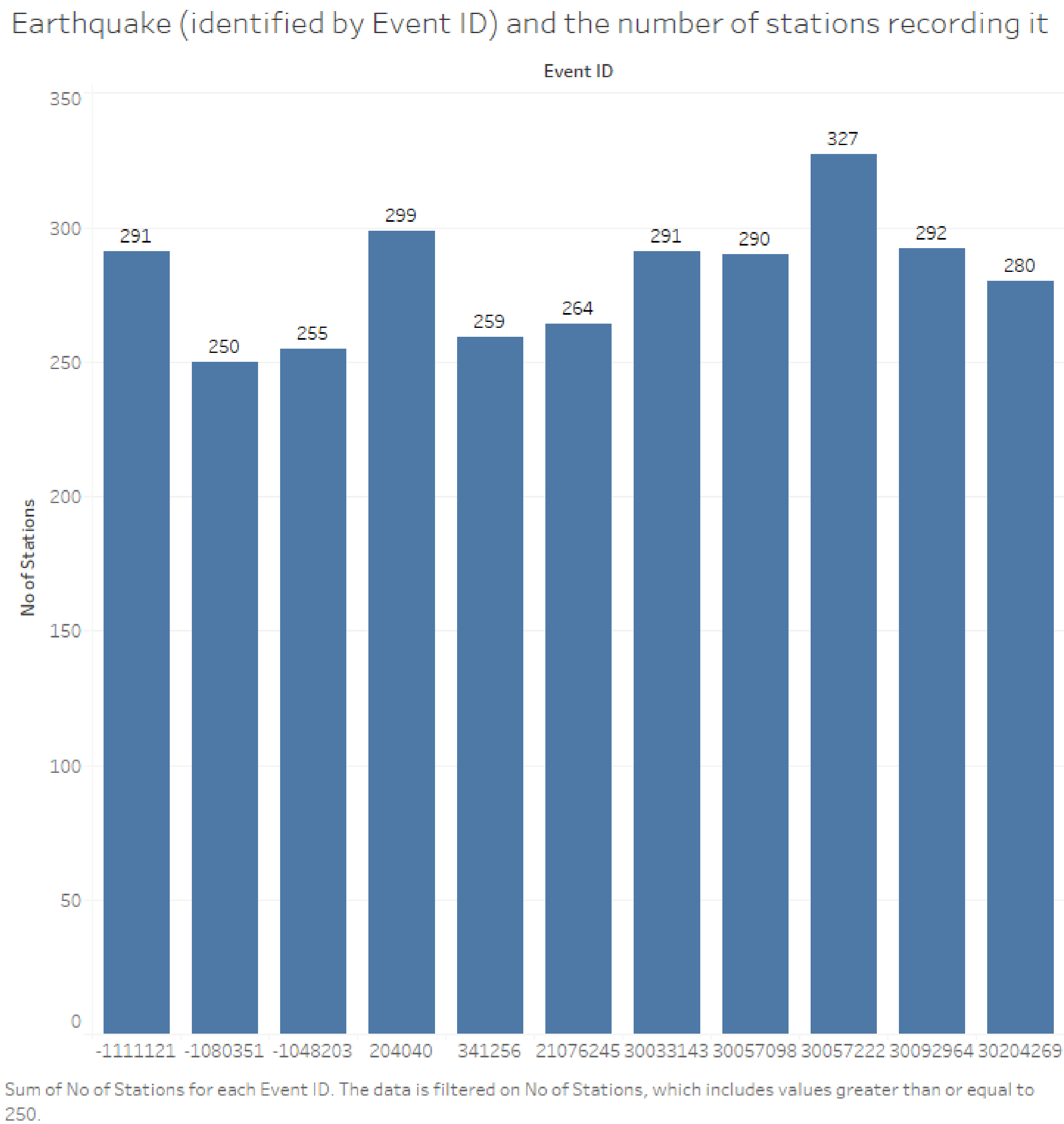


Figure 1

Earthquake (identified by Event ID) and the number of stations recording it

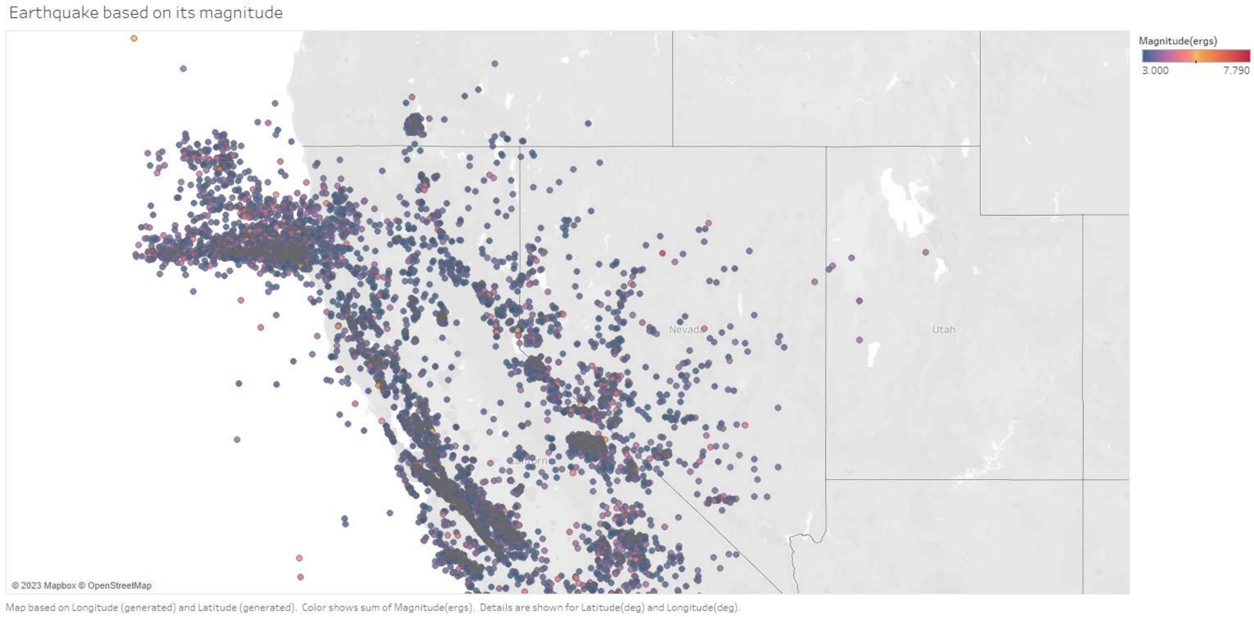


Figure 2

Earthquake based on its magnitude

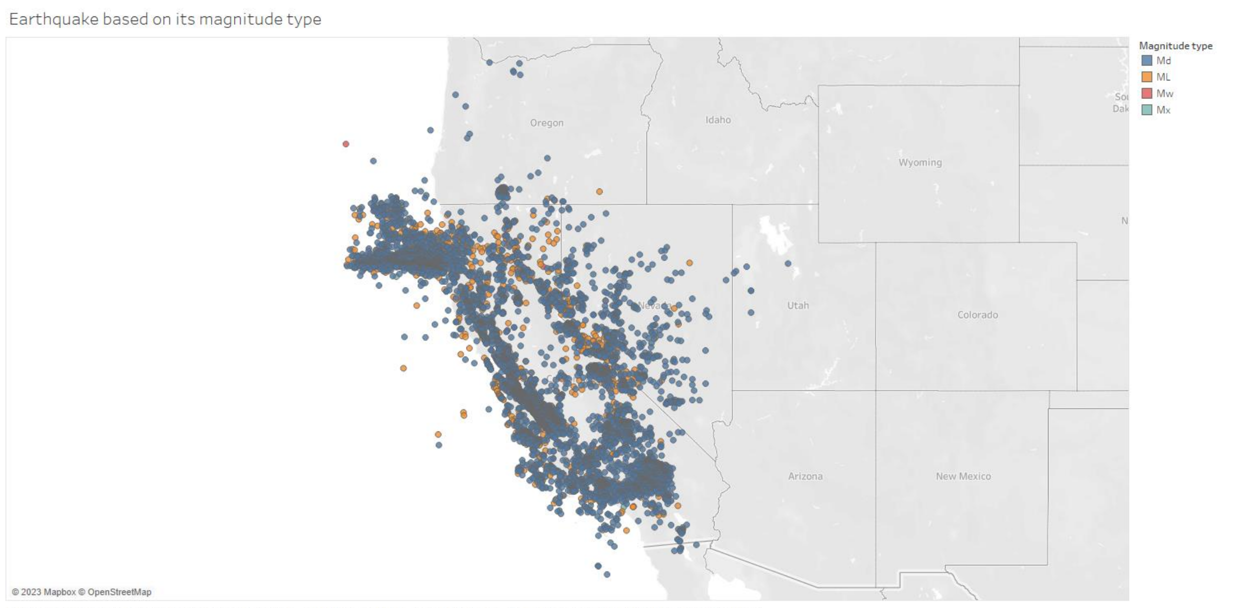


Figure 3

Earthquake based on its magnitude type

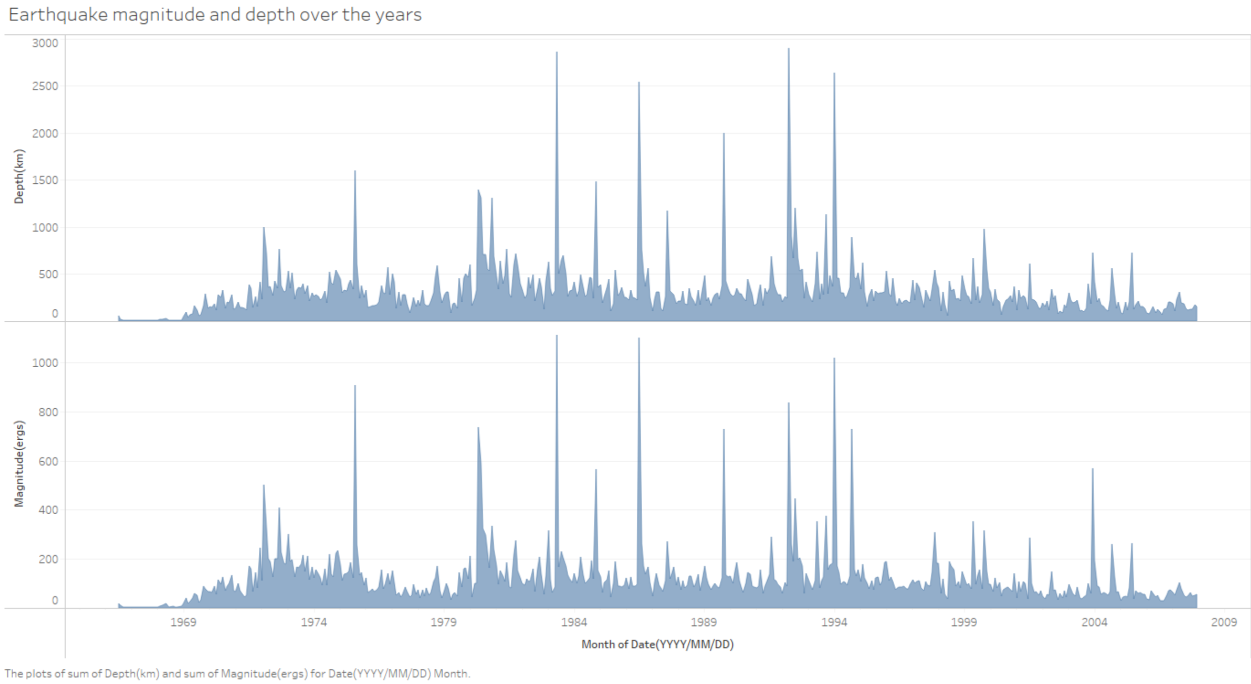


Figure 4
Earthquake magnitude and depth over the years

Splitting the Dataset:

Now, to create the earthquake prediction model, we need to divide the data into Xs and ys which respectively will be entered into the model as inputs to receive the output from the model.

Here the inputs are TImestamp, Latitude and Longitude and the outputs are Magnitude and Depth. I'm going to split the xs and ys into train and test with validation. The training set contains 80% and the test set contains 20%:

```
X = final_data[['Timestamp', 'Latitude', 'Longitude']]
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, rando
print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
```

CONCLUSION:

When comparing two models, both the mean squared error (MSE) and R-squared (R2) score can be used to evaluate the performance of the models.

In general, a model with a lower MSE and a higher R2 score is considered a better model. This is because the MSE measures the average difference between the predicted and actual values, and a lower MSE indicates that the model is making more accurate predictions. The R2 score measures the proportion of the variance in the target variable that is explained by the model, and a higher R2 score indicates that the model is able to explain more of the variability in the target variable.

From the results of this project we can conclude that random forest is the most accurate model for predicting the magnitude of Earthquake compared to all other models used in this project.

However, it's important to keep in mind that the relative importance of MSE and R2 score may vary depending on the specific problem and the context in which the models are being used. For example, in some cases, minimizing the MSE may be more important than maximizing the R2 score, or vice versa. It's also possible that one model may perform better on one metric and worse on another, so it's important to consider both metrics together when evaluating the performance of the models.