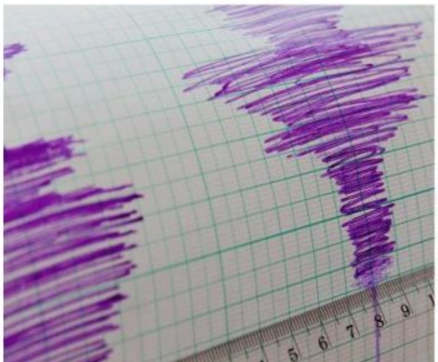
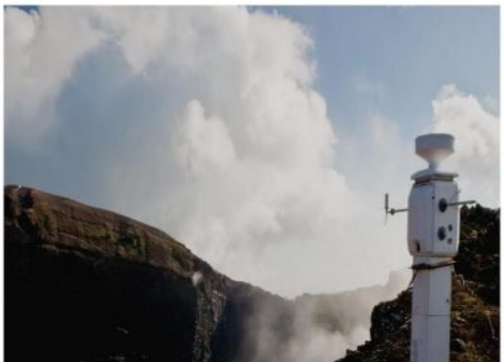
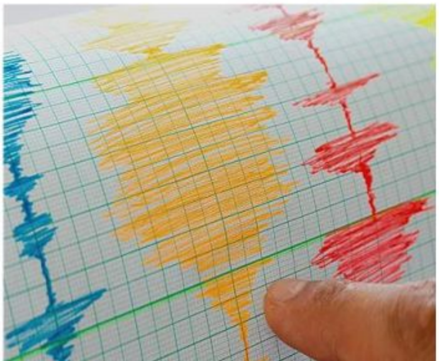
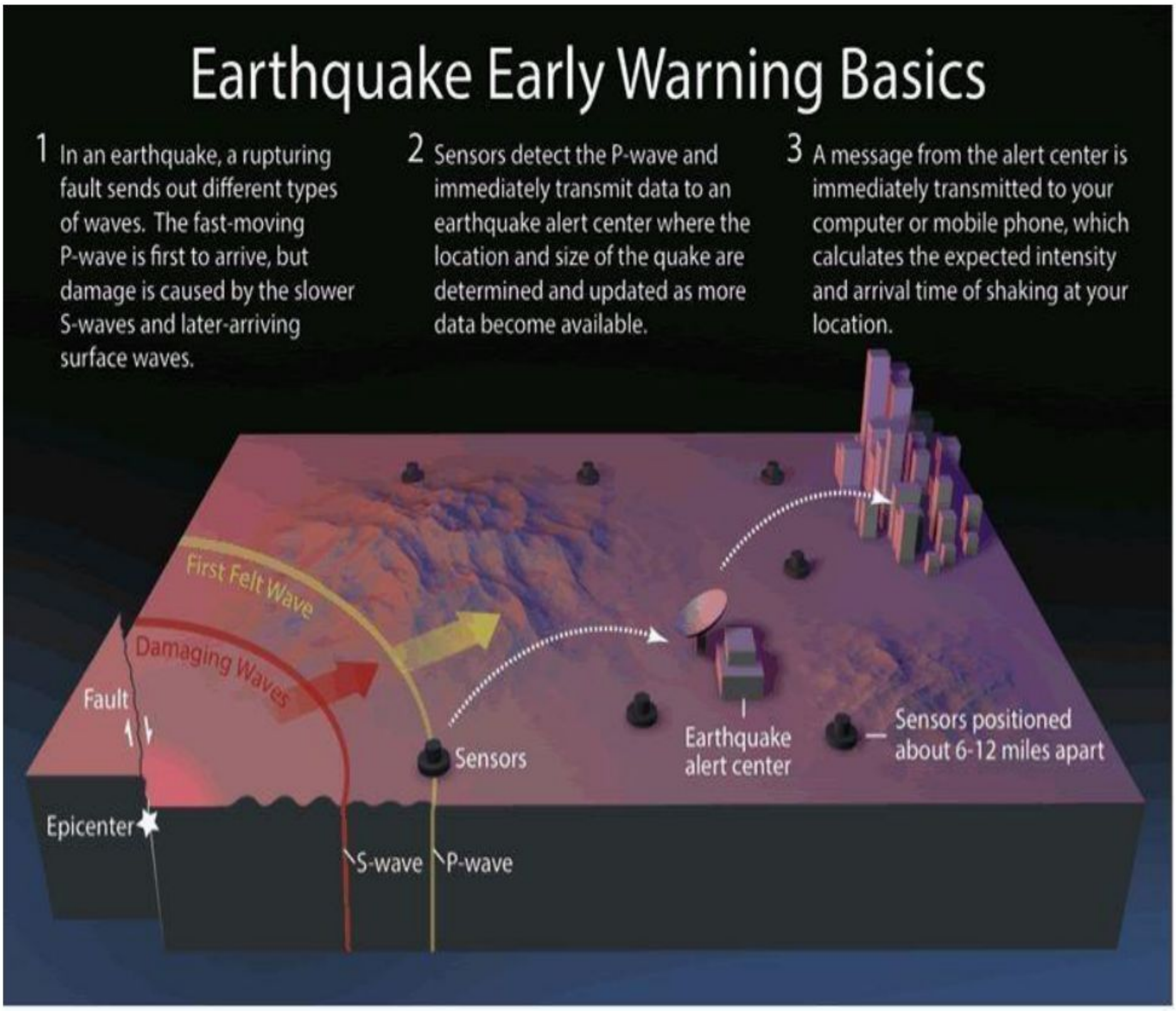
EARTHQUAKE PREDICTION WITH ARTIFICIAL INTELLIGENCE

Earthquake detection in python

Introduction:

Developed by researchers at The University of Texas at Austin, the AI algorithm correctly predicted 70% of earthquakes a week before they happened during a seven-month trial in China. The AI was trained to detect statistical bumps in real-time seismic data that researchers had paired with previous earthquakes.



Predicting earthquakes with high precision remains a significant scientific challenge. While researchers study various methods and indicators, there's no universally reliable earthquake prediction model. Earthquake forecasting typically relies on historical data, fault mapping, and seismic monitoring to estimate the likelihood of future seismic activity in a given region. Early warning systems can provide seconds to minutes of advance notice, but long-term prediction remains exclusive.

Artificial intelligence (AI) is being explored as a tool to improve earthquake prediction, but it's important to understand that AI is not a crystal ball for earthquake forecasting. AI-based models are typically used for short-term earthquake early warning systems and seismic event detection, rather than long-term prediction. Here are a few ways AI is applied:

Seismic Pattern Recognition: AI can analyze historical seismic data to identify patterns and anomalies. When unusual patterns are detected, it can trigger alerts, potentially providing seconds to minutes of warning.

Machine Learning for Event Detection: Machine learning algorithms can be used to detect seismic events in real-time, helping to locate and assess the magnitude of earthquakes as they occur.

GPS and Satellite Data Analysis: AI can process data from GPS and satellites to monitor ground displacement, which can be an early indicator of stress accumulation along fault lines.

Deep Learning for Tsunami Prediction: AI, particularly deep learning models, can be used to predict tsunamis by analyzing data from seafloor sensors and buoys.

While AI can enhance our ability to respond to earthquakes and mitigate their impact, predicting the exact time, location, and magnitude of future earthquakes is still highly uncertain due to the complexity of Earth's geological processes. Earthquake prediction remains an ongoing area of research, and AI plays a supportive role in this field rather than being the sole solution for long-term forecasting.

Earthquake Prediction Model using Python

Problem Definition:

The project objective is to develop a sophisticated earthquake prediction model using aKaggle dataset. This involves comprehensive exploration of key earthquake data features, global visualization on a world map, and data segmentation for training and testing. Utilizing advanced machine learning techniques, the aim is to build a robust neural network model, enhancing its accuracy through meticulous feature engineering, hyperparameter tuning, and comparative analysis of multiple algorithms, ensuring a reliable prediction system for real-world applications.

Data Source

Data Source: Kaggle dataset containing earthquake
dataFeatures:

- Date
- Time
- Latitude
- Longitude
- Depth
- Magnitude

Feature Exploration

Feature Distribution

- Date: Analyzed the distribution of earthquake occurrences over time.
- Time: Examined the time of day when earthquakes are more likely to happen.
- Latitude and Longitude: Explored the geographic distribution of earthquakes.
- Depth: Investigated the distribution of earthquake depths.
- Magnitude: Studied the distribution of earthquake magnitudes.

Feature Correlations

- Analyzed correlations between features to identify potential relationships.

Earthquake Prediction System

Earthquakes were once thought to result from supernatural forces in the prehistoric era. Aristotle was the first to identify earthquakes as a natural occurrence and to provide some potential explanations for them in a truly scientific manner. One of nature's most destructive dangers is earthquakes. Strong earthquakes frequently have negative effects.

A lot of devastating earthquakes occasionally occur in nations like Japan, the USA, China, and nations in the middle and far east. Several major and medium-sized earthquakes have also occurred in India, which have resulted in significant property damage and fatalities. One of the most catastrophic earthquakes ever recorded occurred in Maharastra early on September 30, 1993. One of the main goals of researchers studying earthquake seismology is to develop effective predicting methods for the occurrence of the next severe earthquake event that may allow us to reduce the death toll and property damage.

Most earthquakes, or 90%, are natural and result from tectonic activity. 10% of the remaining characteristics are associated with volcanism, man-made consequences, or other variables. Natural earthquakes are those that occur naturally and are typically far more powerful than other kinds of earthquakes. The continental drift theory and the plate-tectonic theory are the two hypotheses that deal with earthquakes.

Random Forest

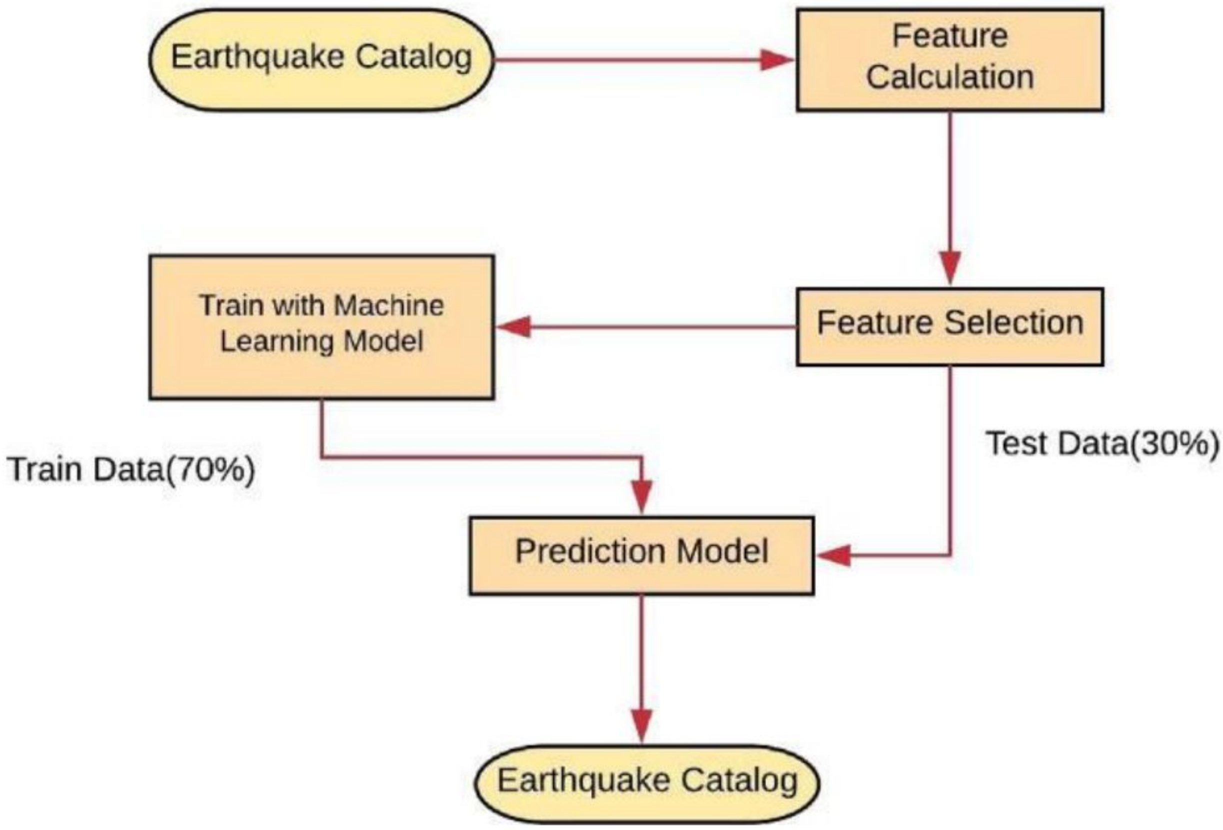
It is a type of machine learning algorithm that is very famous nowadays. It generates a random decision tree and combines it into a single forest. It features a decision model to increase accuracy. These trees divide the predictor space using a series of binary splits ("splits") on distinct variables. The tree's "root" node represents the entire predictor space. The final division of the predictor space is made up of the "terminal nodes," which are nodes that are not split. Depending on the value of one of the predictor variables, each nonterminal node divides into two descendant nodes, one on the left and one on the right. If a continuous predictor variable is smaller than a split point, the points to the left will be the smaller predictor points, and the points to the right will be the larger predictor points. The values of a categorical predictor variable Xi come from a small number of categories. To divide a node into its two descendants, a tree must analyze every possible split on each predictor variable and select the "best" split based on some criteria. A common splitting criterion in the context of regression is the mean squared residual at the node.

It is also a classification technique that uses ensemble learning. The random forest generates a root node feature by randomly dividing, which is the primary distinction between it and the decision tree. To enhance its accuracy, the Random forest chooses a random feature. The random forest approach is faster than the bagging and boosting method. In some circumstances, the neural network Support Vector Machine performs better when using the random forest.

Support Vector Classifier

There is a computer algorithm known as a support vector machine (SVM) that learns to name objects. For instance, by looking at hundreds or thousands of reports of both fraudulent and legitimate credit card activity, an SVM can learn to identify fraudulent credit card activity. A vast collection of scanned photos of handwritten zeros, ones, and other numbers can also be used to train an SVM to recognize handwritten numerals.

Additionally, SVMs have been successfully used in a growing number of biological applications. The automatic classification of microarray gene expression profiles is a typical use of support vector machines in the biomedical field. Theoretically, an SVM can examine the gene expression profile derived from a tumor sample or from peripheral fluid and arrive at a diagnosis or prognosis. An SVM could theoretically analyze the gene expression profile obtained from a tumor sample or from peripheral fluid and determine a diagnosis or prognosis.



Building an earthquake prediction model involves several steps. Here’s an overview of how to load and preprocess the dataset:

Data Collection: Obtain earthquake data from reliable sources like the US Geological Survey (USGS) or other seismic monitoring agencies. You can download earthquake datasets in various formats, such as CSV or JSON.

Data Loading: Import the earthquake dataset into your preferred programming environment. You can use libraries like Pandas in Python to read and manipulate the data.

Data Exploration: Explore the dataset to understand its structure, features, and any missing or erroneous data. Visualize the data to get a better sense of its distribution and characteristics.

Feature Engineering: Identify relevant features for earthquake prediction. These features may include seismic activity indicators, geographic data, historical earthquake records, or environmental factors. Create new features if necessary.

Data Preprocessing:

Data Cleaning: Handle missing values and outliers.

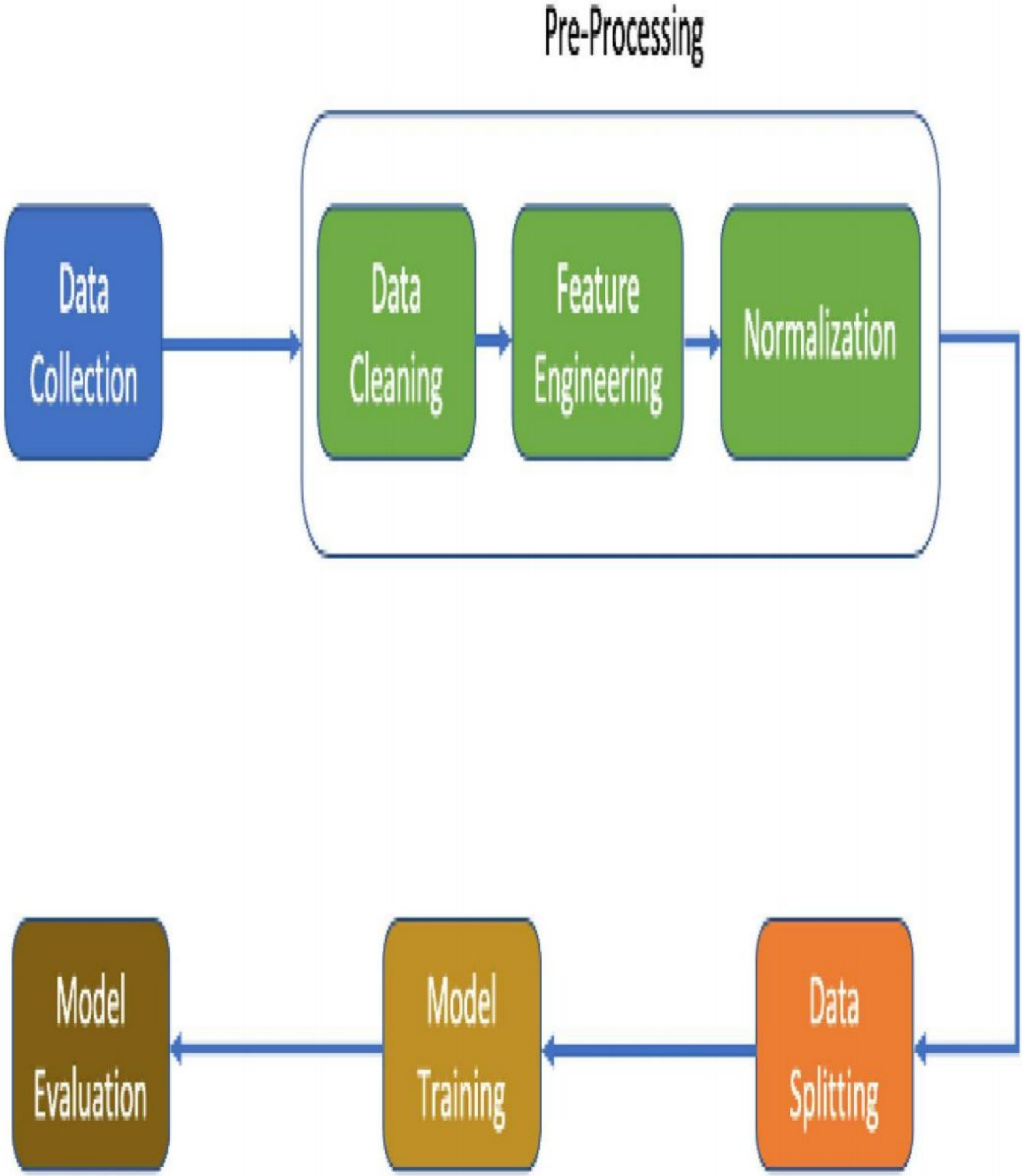
Normalization/Scaling: Scale numerical features if needed.

Encoding: Convert categorical variables into numerical representations, e.g., one-hot encoding.

Split Data: Divide the dataset into training, validation, and test sets for model evaluation.

Time Series Data: If you’re working with time series data, consider time-based features, and time windowing for prediction.

Target Variable: Define the target variable, which could be binary (e.g., earthquake or no earthquake) or a regression task predicting earthquake magnitude or time until the next earthquake.


Pre-Processing
Data Collection
Data Cleaning
Feature Engineering
Normalization
Data Splitting
Model Training
Model Evaluation

Model Selection: Choose an appropriate machine learning model for earthquake prediction, such as decision trees, random forests, support vector machines, or neural networks. Select the model based on the nature of your problem (classification or regression).

Training: Train the chosen model on the training data, using suitable training techniques, hyperparameter tuning, and cross-validation.

Evaluation: Evaluate the model's performance on the validation dataset using appropriate metrics like accuracy, F1-score, Mean Absolute Error (MAE), or Root Mean Squared Error (RMSE).

Model Optimization: Fine-tune the model to improve its performance, which may involve adjusting hyperparameters, feature selection, or using more advanced techniques like deep learning.

Testing: Assess the model's performance on the test dataset to ensure it generalizes well.

Deployment: Once you're satisfied with the model's performance, deploy it for earthquake prediction. You can create an application or system that provides real-time or periodic predictions.

Monitoring and Maintenance: Continuously monitor the model's performance and update it as new earthquake data becomes available.

Remember that earthquake prediction is a complex task, and accurate predictions are challenging due to the inherent unpredictability of earthquakes. Consider collaborating with experts in the field and using the latest research to enhance your model's accuracy.

Earthquake prediction model

Data Collection:

Obtain earthquake data from reliable sources such as the USGS Earthquake Catalog or seismic observatories.

Data Preprocessing:

Clean and preprocess the data:

Remove duplicates and irrelevant columns.

Handle missing values (e.g., by imputing or removing them).

Convert date/time information into a suitable format.

Feature engineering: Extract relevant features like earthquake depth, magnitude, location, etc.

Feature Scaling:

Normalize or standardize your feature data, especially if you're using algorithms sensitive to the scale of the features.

Data Splitting:

Split your data into training and testing sets. A typical split might be 80% for training and 20% for testing.

Model Selection:

Choose a machine learning algorithm suitable for your problem. For earthquake prediction, you might consider using techniques like decision trees, random forests, or neural networks.

Model Training:

Train your selected model on the training data.

Model Evaluation:

Evaluate your model's performance using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or others, depending on your specific goals.

Hyperparameter Tuning:

Optimize your model's hyperparameters for better performance.

Prediction:

Use your trained model to make predictions on the testing data.

Performance Assessment:

Assess how well your model performs and make adjustments as needed.

Deployment:

If the model is satisfactory, deploy it in a real-time environment for continuous earthquake prediction.

You'll need to implement these steps in your chosen programming language and environment. If you have specific questions or need code examples for any of these steps, feel free to ask for more guidance.

Map and Split Data

Visualizing the data on a world map

Splitting it into training and testing sets of earthquake prediction model

To visualize earthquake data on a world map and split it into training and testing sets for an earthquake prediction model, you'll need to use various libraries and tools like Python, pandas, scikit-learn, and possibly a mapping library such as Folium. Here's a high-level overview with some example code to get you started:

Import Libraries:

Start by importing the necessary libraries.

Python

Copy code

Import pandas as pd

Import numpy as np

From sklearn.model_selection import train_test_split

Import folium

From folium.plugins import HeatMap

Load Data:

Load your earthquake data into a DataFrame. Ensure your data contains columns like latitude, longitude, and any relevant earthquake prediction features.

Python

Copy code

Earthquake_data = pd.read_csv("earthquake_data.csv")

Data Visualization:

Use Folium to create a world map and visualize earthquake data as points or a heatmap.

Python

Copy code

Create a base map

M = folium.Map(location=[0, 0], zoom_start=2)

Add earthquake data as points on the map

For index, row in earthquake_data.iterrows():

Folium.CircleMarker(location=[row['latitude'], row['longitude']], radius=5, color='red', fill=True).add_to(m)

Or, use a heatmap for better visualization

Heat_data = [[row['latitude'], row['longitude']] for index, row in earthquake_data.iterrows()]

HeatMap(heat_data).add_to(m)

Save the map to an HTML file

m.save("earthquake_map.html")

Split Data:

Split your data into training and testing sets using scikit-learn.

Python

Copy code

X = earthquake_data[['feature1', 'feature2', …]] # Features for prediction

Y = earthquake_data['target'] # Target variable

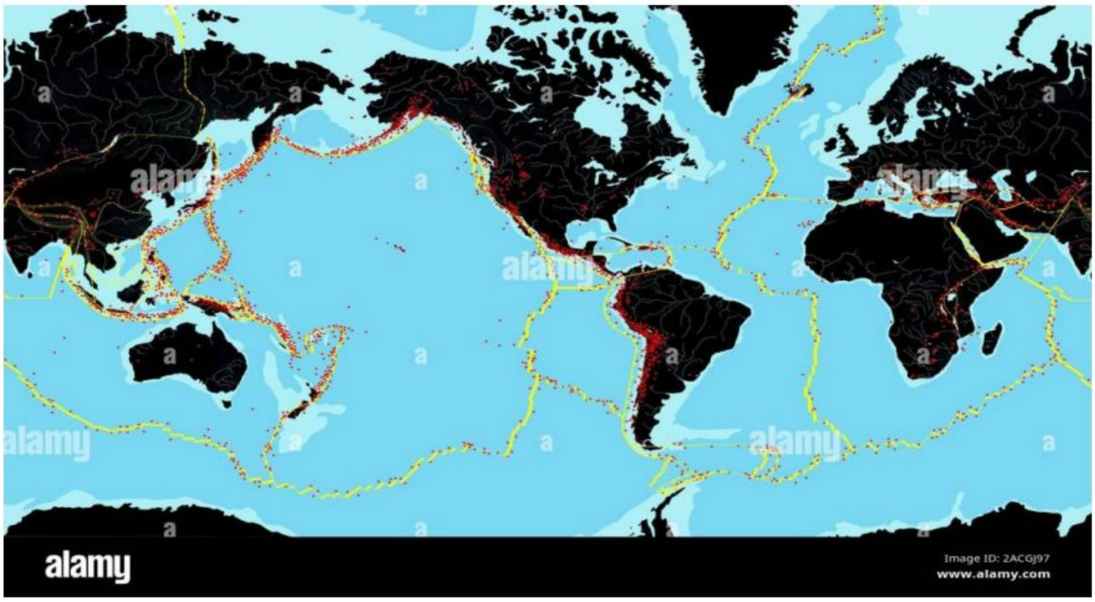
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

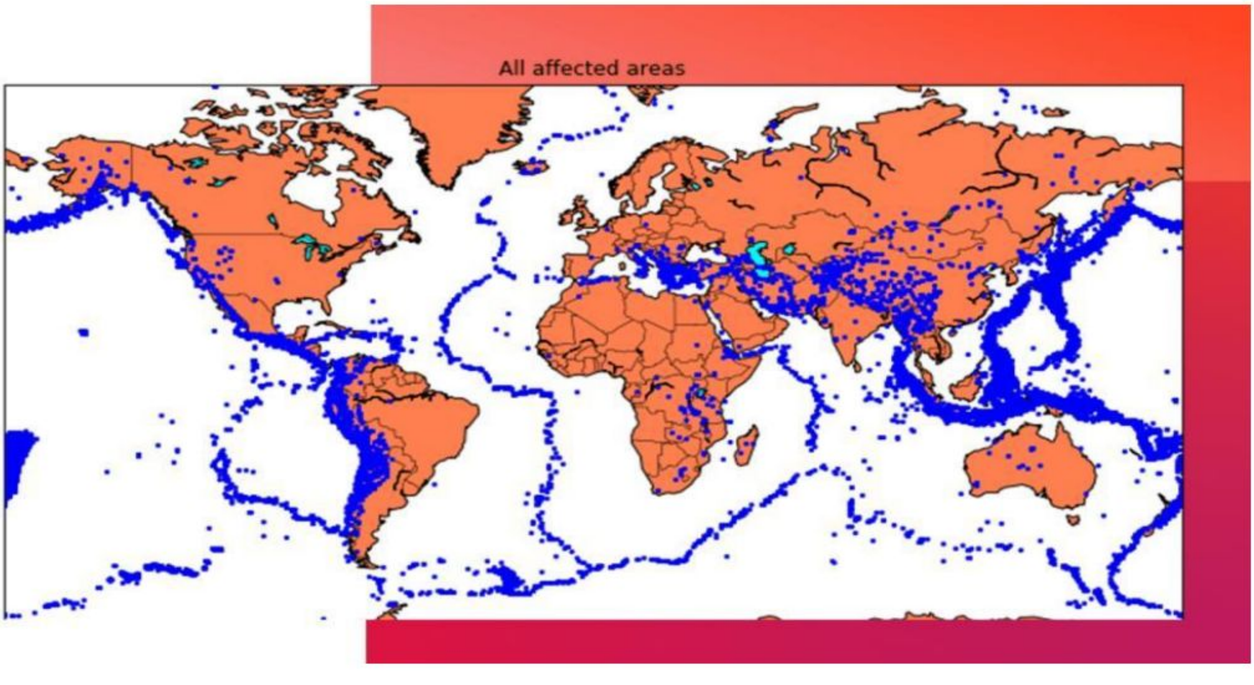
Now you have your data visualized on a map and split into training and testing sets. You can use X_train and y_train for training your earthquake prediction model and X_test for testing its performance.

Make sure to replace 'earthquake_data.csv' with the path to your earthquake data file, and 'feature1', 'feature2', etc., with the actual feature names you want to use for prediction.

Remember that building an earthquake prediction model is a complex task, and you may need to use machine learning algorithms suitable for this purpose, such as decision trees, random forests, or neural networks, depending on the nature of your data.

Earthquake predictions in world map :





earthquakemagnitudepredicton

0.1 Importing Required Packaged

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import geopandas as gpd
import cufflinks as cf

%matplotlib inline
```

1 1) Data Source

[2]:
```
data = pd.read_csv("database.csv",
                   header=0,
                   index_col=None,
                   sep=","
                  )
```

[3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23412 entries, 0 to 23411
Data columns (total 21 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Date                        23412 non-null  object
 1   Time                        23412 non-null  object
 2   Latitude                    23412 non-null  float64
 3   Longitude                   23412 non-null  float64
 4   Type                        23412 non-null  object
 5   Depth                       23412 non-null  float64
 6   Depth Error                 4461 non-null   float64
 7   Depth Seismic Stations      7097 non-null   float64
 8   Magnitude                   23412 non-null  float64
 9   Magnitude Type              23409 non-null  object
```

```
 10  Magnitude Error             327 non-null    float64
 11  Magnitude Seismic Stations  2564 non-null   float64
 12  Azimuthal Gap               7299 non-null   float64
 13  Horizontal Distance         1604 non-null   float64
 14  Horizontal Error            1156 non-null   float64
 15  Root Mean Square            17352 non-null  float64
 16  ID                          23412 non-null  object
 17  Source                      23412 non-null  object
 18  Location Source             23412 non-null  object
 19  Magnitude Source            23412 non-null  object
 20  Status                      23412 non-null  object
dtypes: float64(12), object(9)
memory usage: 3.8+ MB
```

1.0.1 Required Feautures

- **Latitude**
- **Longitude**
- **Depth**
- **Depth Error**
- **Root Mean Square**

[4]:
```
data = data[["Latitude","Longitude","Root Mean Square","Depth","Depth␣
↪Error","Magnitude"]]
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23412 entries, 0 to 23411
Data columns (total 6 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Latitude          23412 non-null  float64
 1   Longitude         23412 non-null  float64
 2   Root Mean Square  17352 non-null  float64
 3   Depth             23412 non-null  float64
 4   Depth Error       4461 non-null   float64
 5   Magnitude         23412 non-null  float64
dtypes: float64(6)
memory usage: 1.1 MB
```

[6]:
```
data.describe()
```

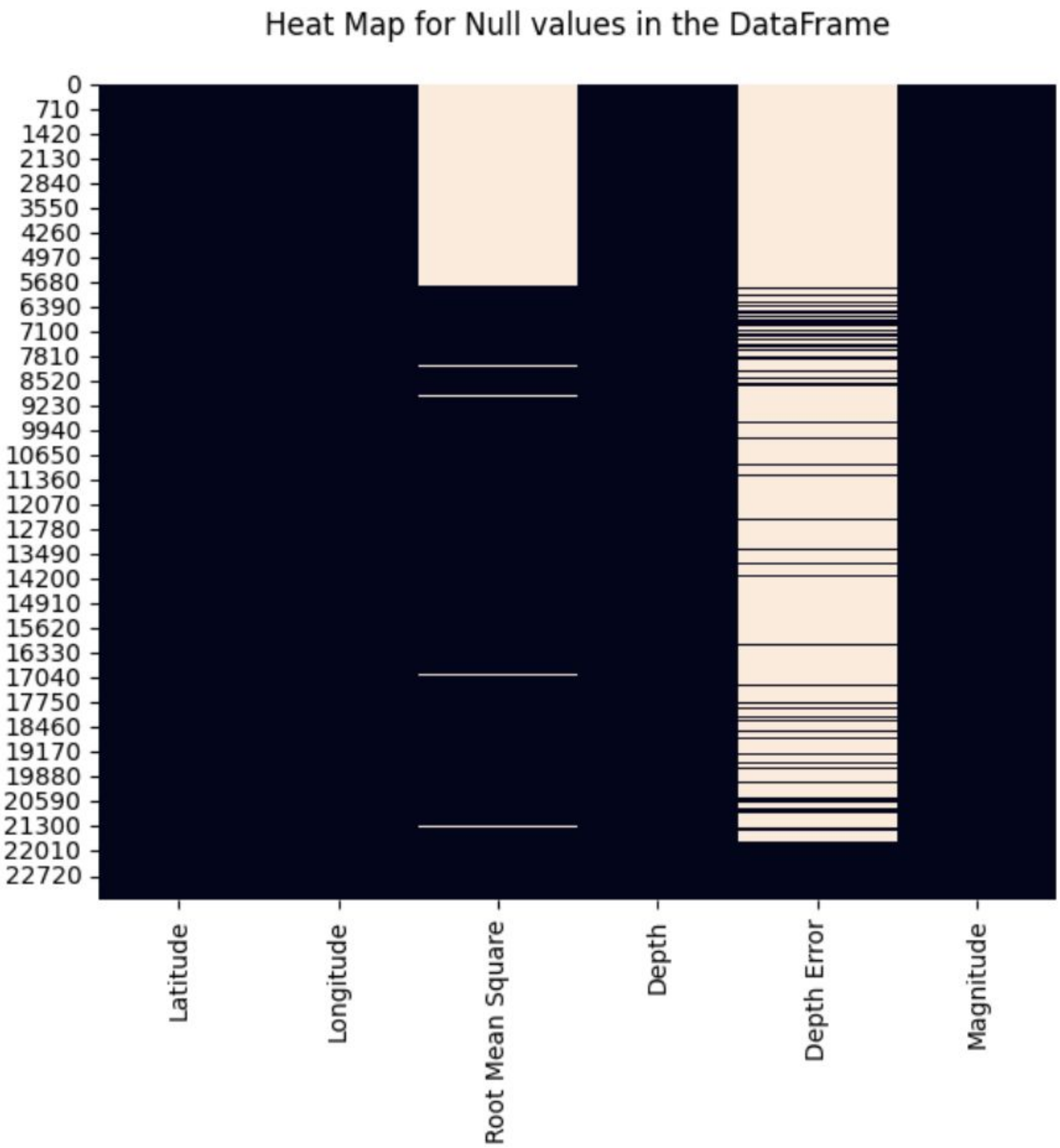
[6]:
```
           Latitude     Longitude  Root Mean Square         Depth  \
count  23412.000000  23412.000000      17352.000000  23412.000000
mean       1.679033     39.639961          1.022784     70.767911
std       30.113183    125.511959          0.188545    122.651898
min      -77.080000   -179.997000          0.000000     -1.100000
```

```
25%      -18.653000    -76.349750              0.900000     14.522500
50%       -3.568500    103.982000              1.000000     33.000000
75%       26.190750    145.026250              1.130000     54.000000
max       86.005000    179.998000              3.440000    700.000000

       Depth Error     Magnitude
count  4461.000000  23412.000000
mean      4.993115      5.882531
std       4.875184      0.423066
min       0.000000      5.500000
25%       1.800000      5.600000
50%       3.500000      5.700000
75%       6.300000      6.000000
max      91.295000      9.100000
```

2 2) Feauture Exploration

2.1 Exploratory Data Analysis (EDA)

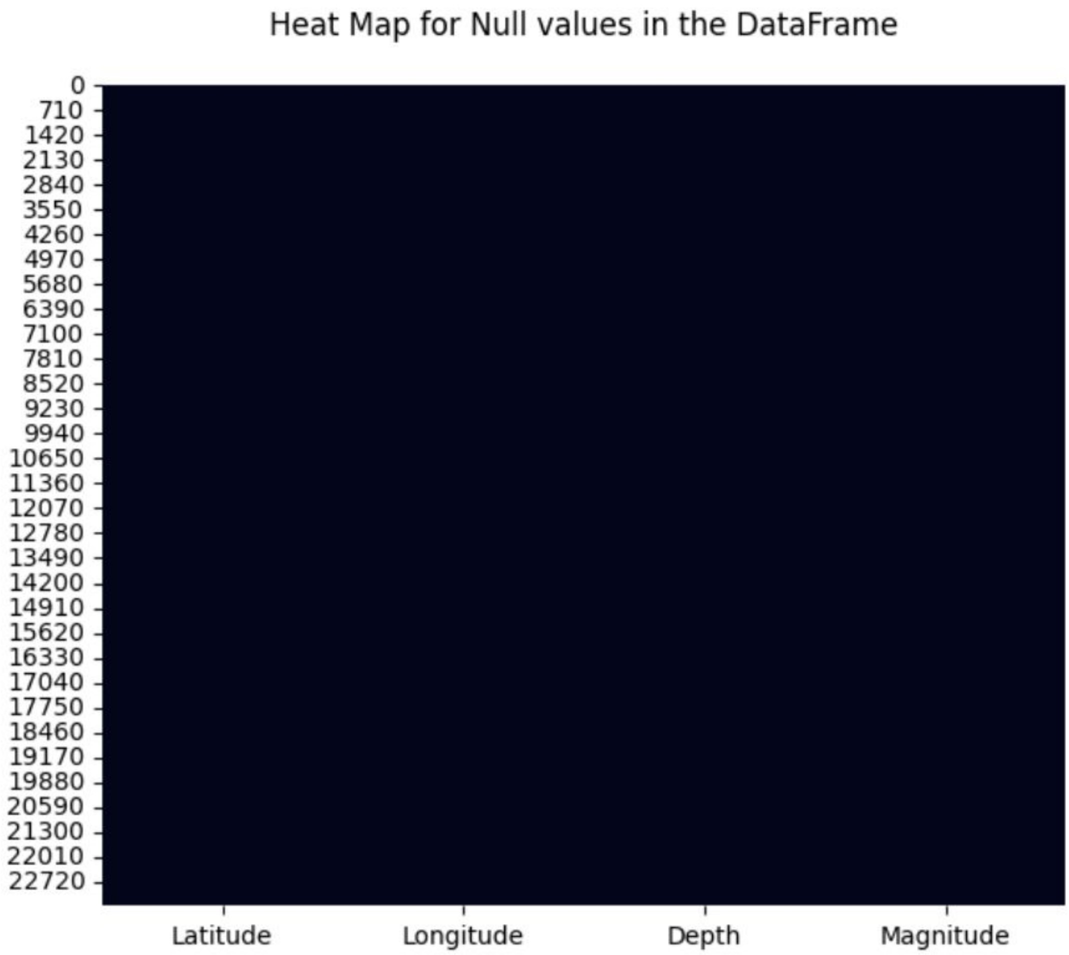
[7]:
```
plt.figure(figsize=(7,6))
sns.heatmap(data=data.isnull(),
           cbar=False)
txt = plt.title("\nHeat Map for Null values in the DataFrame\n")
```



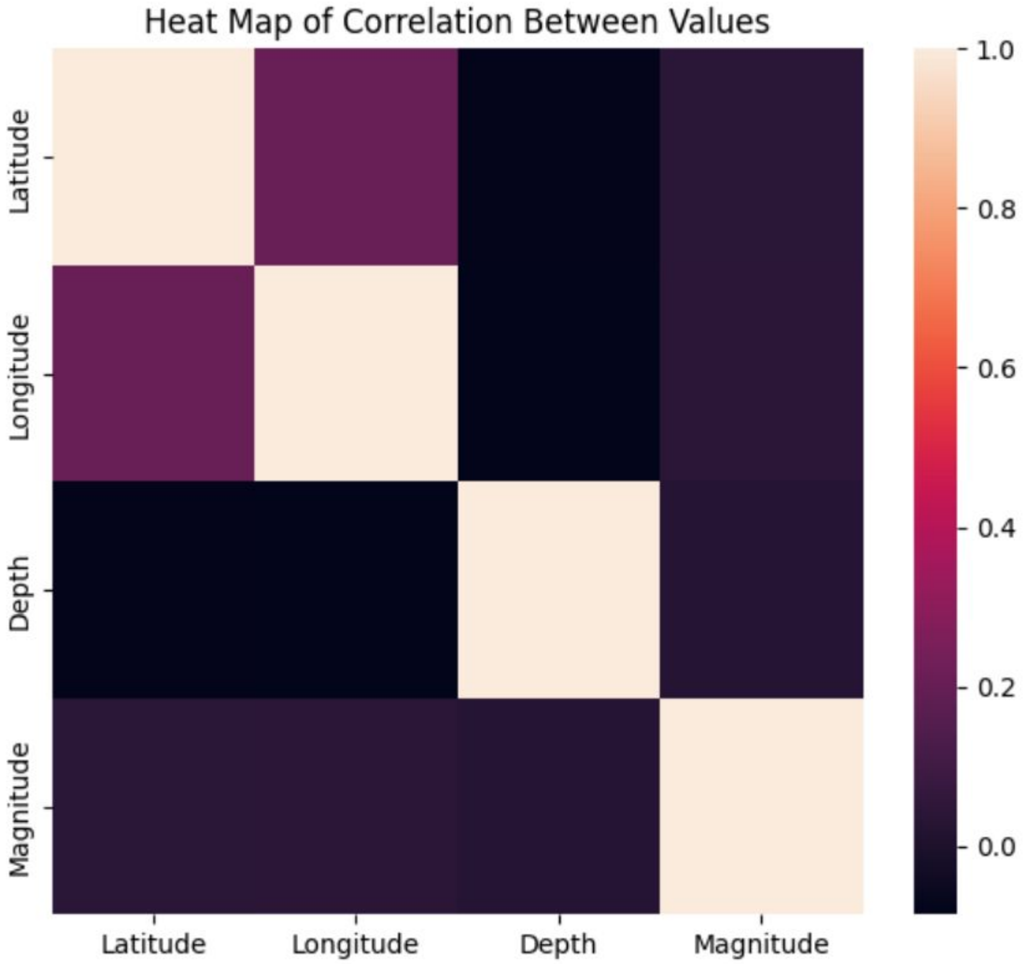
Dropping Depth Error And Root Mean Square, It is having null values and it is not gonna make much more change in model

[8]:
```
data = data.drop(["Depth Error","Root Mean Square"],axis=1)
```

[9]:
```
plt.figure(figsize=(7,6))
sns.heatmap(data=data.isnull(),
            cbar=False)
txt = plt.title("\nHeat Map for Null values in the DataFrame\n")
```



[10]:
```
plt.figure(figsize=(7,6))
sns.heatmap(data=data.corr())
txt = plt.title("Heat Map of Correlation Between Values")
```



[11]:
```
correlation = data['Depth'].corr(data['Magnitude'])
print(f"Correlation Between Depth and Magnitude is {correlation}")
correlation = data['Latitude'].corr(data['Magnitude'])
print(f"Correlation Between Lattitude and Magnitude is {correlation}")
correlation = data['Longitude'].corr(data['Magnitude'])
print(f"Correlation Between Longitude and Magnitude is {correlation}")
```

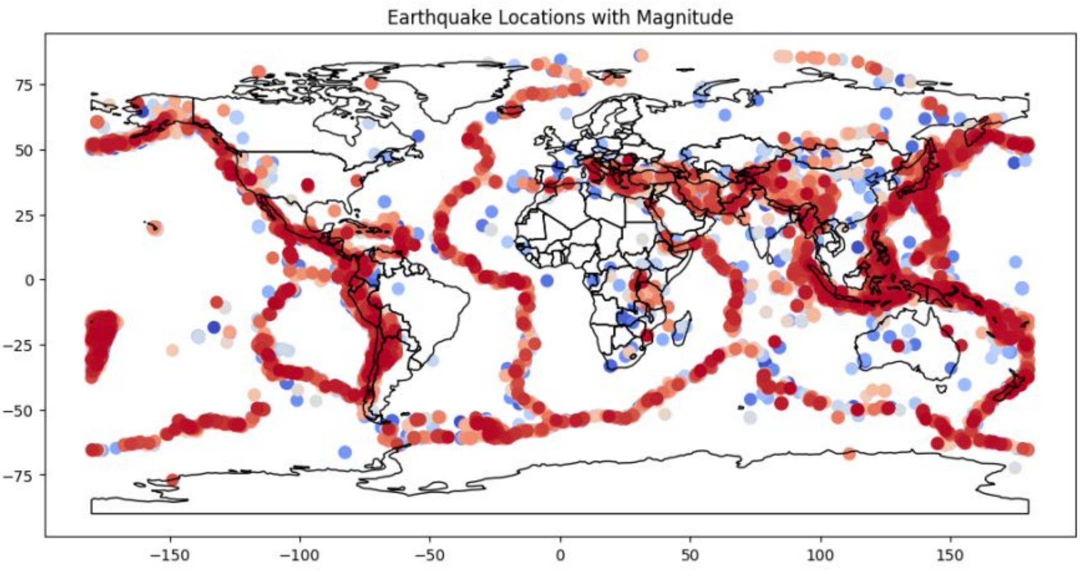
```
Correlation Between Depth and Magnitude is 0.023457312492053895
Correlation Between Lattitude and Magnitude is 0.03498650628261446
Correlation Between Longitude and Magnitude is 0.03857859753074192
```

[ ]:

3 3) Visualization

[12]:
```
df = data
gdf = gpd.GeoDataFrame(df, geometry=gpd.points_from_xy(df.Longitude, df.
 ↪Latitude))

world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

fig, ax = plt.subplots(figsize=(12, 8))
world.boundary.plot(ax=ax, linewidth=1, color='k')

gdf.plot(ax=ax, markersize=df['Magnitude'] * 10, cmap='coolwarm', legend=True)

ax.set_title('Earthquake Locations with Magnitude')
# plt.legend(title='Magnitude')

plt.show()
```

```
/tmp/ipykernel_33037/249791788.py:4: FutureWarning:

The geopandas.dataset module is deprecated and will be removed in GeoPandas 1.0.
You can get the original 'naturalearth_lowres' data from
https://www.naturalearthdata.com/downloads/110m-cultural-vectors/.
```



[13]:
```
df = pd.DataFrame(data)

fig = df.iplot(
```

```
    kind='scattergeo',
    lon='Longitude',
    lat='Latitude',
    size='Magnitude',
    text='Magnitude',
    colorscale='YlOrRd',
    dimensions=(800, 600),
    title='Earthquake Locations with Magnitude',
    asFigure=True
)

fig.update_geos(
    projection_type="natural earth",
    coastlinecolor="black",
    landcolor="white",
    showland=True,
    showcoastlines=True,
    showocean=True,
    oceancolor="lightblue"
)

# Show the plot
fig.show()
```

[14]:
```
df = pd.DataFrame(data)
plt.figure(figsize=(20,20))
fig = px.scatter_geo(
    df,
    lat='Latitude',
    lon='Longitude',
    color='Magnitude',
    size='Magnitude',
    hover_name='Magnitude',
    projection='natural earth'
)

fig.update_geos(showcoastlines=True, coastlinecolor="Black", showland=True,
 ↪landcolor="lightgray")

fig.show()
```

```
<Figure size 2000x2000 with 0 Axes>
```

[ ]:

4 4) Data Splitting

[15]:
```
from sklearn.model_selection import train_test_split
```

[16]:
```
X = data.drop("Magnitude",axis=1)
y = data["Magnitude"]
```

[17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
↪random_state=42)
```

[ ]:
```

```

5 5) Model Development

[18]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

```
2023-10-04 18:35:28.257319: I tensorflow/core/util/port.cc:110] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-10-04 18:35:28.284433: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not
find cuda drivers on your machine, GPU will not be used.
2023-10-04 18:35:28.318832: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not
find cuda drivers on your machine, GPU will not be used.
2023-10-04 18:35:28.319665: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other
operations, rebuild TensorFlow with the appropriate compiler flags.
2023-10-04 18:35:29.468449: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not
find TensorRT
```

5.0.1 Scaling the feautures

[19]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[20]:
```
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(3,)),
    layers.Dense(32, activation='relu'),
```

```
    layers.Dense(1)
])
```

[21]:
```
model.compile(optimizer='adam',
              loss='mean_squared_error',
             )
```

[22]:
```
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                256

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 1)                 33

=================================================================
Total params: 2369 (9.25 KB)
Trainable params: 2369 (9.25 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

6 6) Training and Evaluation

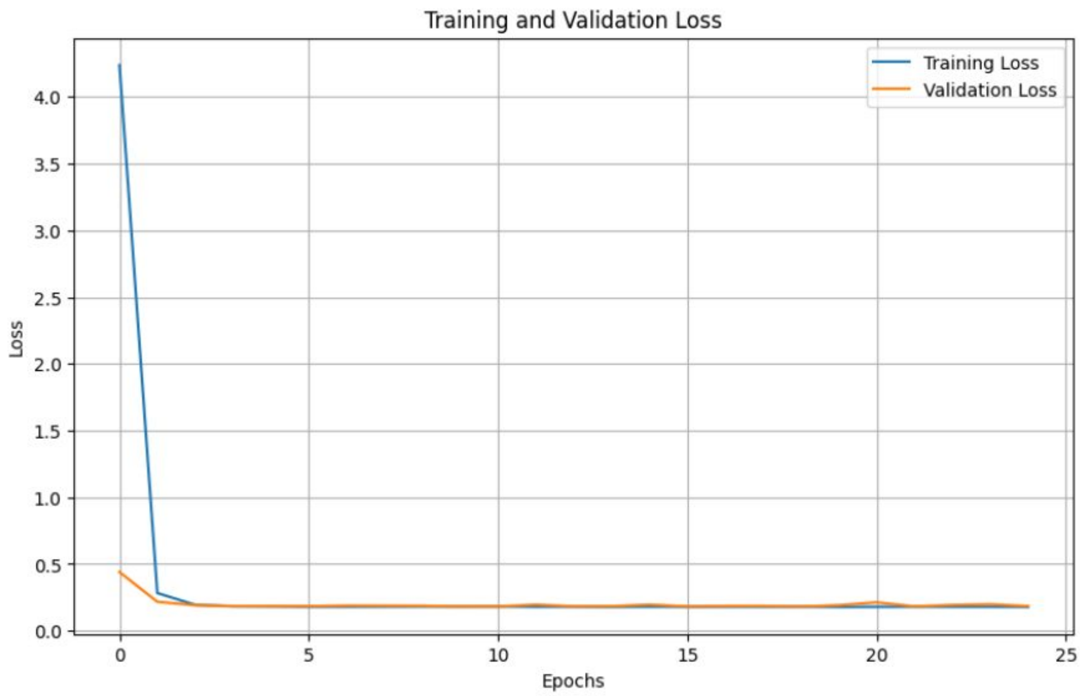
[23]:
```
history = model.fit(X_train,
                    y_train,
                    epochs=25,
                    batch_size=32,
                    validation_split=0.2,
                    validation_data=(X_test,y_test))
```

```
Epoch 1/25
491/491 [==============================] - 2s 2ms/step - loss: 4.2382 -
val_loss: 0.4398
Epoch 2/25
491/491 [==============================] - 1s 2ms/step - loss: 0.2826 -
val_loss: 0.2169
Epoch 3/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1940 -
val_loss: 0.1913
Epoch 4/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1831 -
val_loss: 0.1851
Epoch 5/25
```

```
491/491 [==============================] - 1s 2ms/step - loss: 0.1821 -
val_loss: 0.1843
Epoch 6/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1800 -
val_loss: 0.1837
Epoch 7/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1796 -
val_loss: 0.1881
Epoch 8/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1805 -
val_loss: 0.1874
Epoch 9/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1812 -
val_loss: 0.1867
Epoch 10/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1814 -
val_loss: 0.1822
Epoch 11/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1819 -
val_loss: 0.1818
Epoch 12/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1798 -
val_loss: 0.1955
Epoch 13/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1803 -
val_loss: 0.1826
Epoch 14/25
491/491 [==============================] - 1s 1ms/step - loss: 0.1788 -
val_loss: 0.1834
Epoch 15/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1802 -
val_loss: 0.1955
Epoch 16/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1799 -
val_loss: 0.1816
Epoch 17/25
491/491 [==============================] - 1s 1ms/step - loss: 0.1798 -
val_loss: 0.1854
Epoch 18/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1796 -
val_loss: 0.1856
Epoch 19/25
491/491 [==============================] - 1s 1ms/step - loss: 0.1806 -
val_loss: 0.1812
Epoch 20/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1783 -
val_loss: 0.1910
Epoch 21/25
```

```
491/491 [==============================] - 1s 2ms/step - loss: 0.1795 -
val_loss: 0.2128
Epoch 22/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1805 -
val_loss: 0.1824
Epoch 23/25
491/491 [==============================] - 1s 2ms/step - loss: 0.1796 -
val_loss: 0.1927
Epoch 24/25
491/491 [==============================] - 1s 3ms/step - loss: 0.1800 -
val_loss: 0.1982
Epoch 25/25
491/491 [==============================] - 1s 3ms/step - loss: 0.1785 -
val_loss: 0.1841
```

[24]:
```python
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.grid(True)
plt.show()
```



[25]:
```
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error on Test Set: {mse:.2f}")
```

```
242/242 [==============================] - 0s 1ms/step
Mean Squared Error on Test Set: 0.18
```

[26]:
```
model.evaluate(X_test,y_test)
```

```
242/242 [==============================] - 0s 1ms/step - loss: 0.1841
```

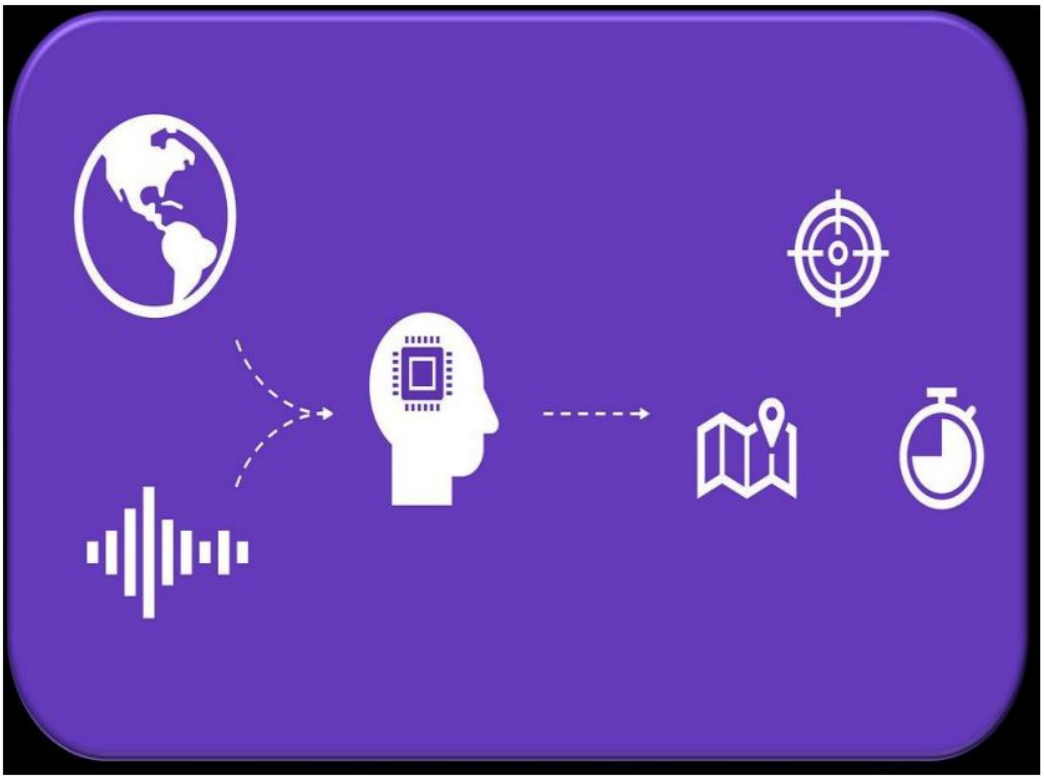
[26]: 0.18406274914741516

6.1 Conclusion:

Mean Squared Error on Test Data : 0.19

[ ]:
```

```

Conclusion :



The conclusion of an earthquake prediction model would typically depend on the specific model and its performance. However, in general, a conclusion might include:

Evaluation of Model Performance: Assess how well the model performed in predicting earthquakes. This could involve statistical metrics like accuracy, precision, recall, or F1 score.

Data and Features: Discuss the importance of the data used and the features selected for prediction. Highlight any limitations or improvements in data collection and feature engineering.

Model Validation: Explain the methodology used for validating the model, such as cross-validation or split-sample testing.

Predictive Power: Discuss the practical significance of the model's predictions and its potential for early warning or risk mitigation.

Limitations: Address the limitations of the model, including factors that may affect its accuracy, such as limited historical data, geological variations, or uncertainties in the earthquake prediction process.

Future Work: Suggest areas for future research and improvements, like incorporating more data sources, enhancing the model's robustness, or exploring different machine learning algorithms.

Remember that earthquake prediction is a complex and challenging field, and while significant progress has been made, it remains an ongoing area of research.


Thank you!