AI_PHASE5

EARTHQUAKE PREDITION MODEL USING PYTHON PROJECT DOCUMENTATION

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Phase 1: Problem Definition and Design Thinking

Problem Definition: The problem is to develop an earthquake prediction model using a Kaggle dataset. The objective is to explore and understand the key features of earthquake data, visualize the data on a world map for a global overview, split the data for training and testing, and build a neural network model to predict earthquake magnitudes based on the given features.

Design Thinking:

11. Data Source:

The appropriate dataset containing earthquake data with features like date, time, latitude, longitude, depth, and magnitude is Kaggle dataset.

Dataset Link: https://www.kaggle.com/datasets/usgs/earthquake-database

2. Feature Exploration:

To Analyze and understand the distribution, correlations, and characteristics of the key features.

Distribution:

The distribution is done by the key features as histogram, the depth latitude, longitude, magnitude are as distributed as histograms. As head, describe methods are used

Correlations:

Exploring the correlation between features to identify any potential relationships. The correlation of the variables is done by corr() function**.**

Characteristics of key features:

Refers to the attributes, properties, and behaviors of the variables or attributes that are considered important or influential in a dataset. Key features are those that have a significant impact on the target variable or the outcome of the analysis, and understanding their characteristics is crucial for making informed decisions in data analysis and modelling.

3.VISUALIZATION:

A world map visualization to display earthquake frequency distribution. Creating a world map visualization to display earthquake frequency distribution requires geographic data and a suitable library for plotting

4. Data Splitting:

Splitting the dataset into a training set and a test set for model validation. Firstly, split the data into Xs and ys which are input to the model and output of the model respectively. Here, inputs are Timestamp, Latitude and Longitude and outputs are Magnitude and Depth. Split the Xs and Ys into train and test with validation. Training dataset contains 80% and Test dataset contains 20%.

The RandomForestRegressor model to predict the outputs, we see the strange prediction from this with score above 80% which can be assumed to be best fit but not due to its predicted values

5. Model Development:

Building the neural network for earthquake magnitude prediction. Defining by the neural network architecture, including the number of layers, neurons per layer, and activation functions.

6. Training and Evaluation:

Training the model on the training set and evaluating its performance on the test set. Fit the chosen model to the training data. This involves setting hyperparameters and using the training data to adjust the model's internal parameters.

Evaluation:

Once the model is trained, evaluate its performance on the test set using appropriate evaluation metrics. Common metrics for earthquake prediction include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). the model.evaluate() method is that evaluates the x_test and y_test and the evaluation result on test data is displayed.

Phase 2: Innovation

In this section need to put design into innovation to solve the problem

HYPERPARAMETER TUNING:

1. **Define Hyperparameters to Search:**

```
param_grid = {
    'model__n_estimators': [100, 200, 300],
    'model__max_depth': [None, 10, 20, 30],
    'model__min_samples_split': [2, 5, 10],
    'model__min_samples_leaf': [1, 2, 4]
}
```

This dictionary defines the hyperparameters and their corresponding values to search for using grid search.

2. Grid Search with Cross-Validation:

```
grid_search = GridSearchCV(estimator=pipeline, param_grid=param_grid, cv=5, n_jobs=-1, verbose=2, error_score='raise')
```

`GridSearchCV` is used to perform a grid search with 5-fold cross-validation to find the best hyperparameters. It utilizes the full pipeline (`pipeline`) and the hyperparameter grid (`param_grid`).

3. Fit the Model with the Best Hyperparameters:

```
grid_search.fit(X_train, y_train)
```

This code fits the model with the training data using the best hyperparameters found during grid search.

4. Get the Best Hyperparameters:

```
best_params = grid_search.best_params_     print("Best Hyperparameters:", best_params)
```

After grid search, this prints out the best hyperparameters that were found during the search.

5. Use the Best Model for Prediction:

```
best_model = grid_search.best_estimator_    y_pred
= best_model.predict(X_test)
```

We use the best model (which includes the best hyperparameters) to make predictions on the testing data.

6. Evaluate the Model's Performance:

```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Finally, the code calculates and prints the accuracy score, which is a measure of the model's performance on the test set.

FEATURE ENGINEERING:

1. Creating a New Feature - Earthquake Magnitude Squared:

```
X['magnitude_squared'] = X['magnitude'] ** 2
```

- In this step, a new feature named 'magnitude_squared' is created in the DataFrame `X`.
- It is calculated by squaring the values in the existing 'magnitude' feature. This can be a meaningful transformation if the relationship between the squared magnitude and the

target variable is non-linear and can improve the model's performance.

2. Splitting the Updated Data into Training and Testing Sets:

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

- This code splits the updated DataFrame `X` and the target labels `y` into training and testing sets using the `train_test_split` function.
- The `test_size` parameter specifies that 20% of the data should be reserved for testing, and `random_state` ensures reproducibility by fixing the random seed.

3. Retraining the Model with Updated Features:

```
best_model.fit(X_train, y_train)
```

- The `fit` method is called on the best model (`best_model`) to train it using the updated training data (`X_train` and `y_train`).
- This step reuses the best model found during hyperparameter tuning, which is assumed to be stored in the `best_model` variable.

4. Making Predictions and Evaluating:

```
y_pred = best_model.predict(X_test)    accuracy
= accuracy_score(y_test, y_pred)
```

- Here, predictions are made on the test data (`X_test`) using the trained `best_model`.
- The accuracy of the model is calculated by comparing the predicted labels (`y_pred`) with the true labels (`y_test`) using the `accuracy_score` function from scikit-learn.
- The accuracy score measures the proportion of correctly predicted labels in the test set.

5. Printing the Accuracy with Feature Engineering:

```
print("Accuracy with Feature Engineering:", accuracy)
```

- Finally, the code prints the accuracy of the model on the test set after feature engineering.
- This allows you to assess whether the addition of the squared magnitude feature improved the model's predictive performance.

By following these steps, advanced techniques such as hyperparameter tuning and feature engineering to improve the prediction model's can be performed.

Phase 3: Development Part 1

In this section building project by loading and preprocessing the dataset.

DATA COLLECTION

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import os
print(os.listdir("../input"))
```

```
['earthquake-database']
```

DATA LOADING

```
data = pd.read_csv("../input/earthquake-database/database.csv")
data.head()
```

OUTPUT:

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

   Depth Seismic Stations  Magnitude Magnitude Type  ...   \
0                     NaN        6.0             MW  ...
1                     NaN        5.8             MW  ...
2                     NaN        6.2             MW  ...
3                     NaN        5.8             MW  ...
4                     NaN        5.8             MW  ...

   Magnitude Seismic Stations  Azimuthal Gap  Horizontal Distance  \
0                         NaN            NaN                  NaN
1                         NaN            NaN                  NaN
2                         NaN            NaN                  NaN
3                         NaN            NaN                  NaN
4                         NaN            NaN                  NaN

   Horizontal Error  Root Mean Square            ID  Source Location Source
\
0               NaN               NaN  ISCGEM860706  ISCGEM          ISCGEM
1               NaN               NaN  ISCGEM860737  ISCGEM          ISCGEM
```

```
2              NaN              NaN  ISCGEM860762  ISCGEM          ISCGEM
3              NaN              NaN  ISCGEM860856  ISCGEM          ISCGEM
4              NaN              NaN  ISCGEM860890  ISCGEM          ISCGEM

  Magnitude Source     Status
0           ISCGEM  Automatic
1           ISCGEM  Automatic
2           ISCGEM  Automatic
3           ISCGEM  Automatic
4           ISCGEM  Automatic

[5 rows x 21 columns]
```

QUICK OVERVIEW OF DATAS

```
data.head()
```

OUTPUT:

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

   Depth Seismic Stations  Magnitude Magnitude Type  ...   \
0                     NaN        6.0             MW  ...
1                     NaN        5.8             MW  ...
2                     NaN        6.2             MW  ...
3                     NaN        5.8             MW  ...
4                     NaN        5.8             MW  ...

   Magnitude Seismic Stations  Azimuthal Gap  Horizontal Distance  \
0                         NaN            NaN                  NaN
1                         NaN            NaN                  NaN
2                         NaN            NaN                  NaN
3                         NaN            NaN                  NaN
4                         NaN            NaN                  NaN

   Horizontal Error  Root Mean Square            ID  Source Location Source
\
0              NaN              NaN  ISCGEM860706  ISCGEM          ISCGEM
1              NaN              NaN  ISCGEM860737  ISCGEM          ISCGEM
```

```
2                NaN               NaN  ISCGEM860762  ISCGEM          ISCGEM
3                NaN               NaN  ISCGEM860856  ISCGEM          ISCGEM
4                NaN               NaN  ISCGEM860890  ISCGEM          ISCGEM

  Magnitude Source     Status
0           ISCGEM  Automatic
1           ISCGEM  Automatic
2           ISCGEM  Automatic
3           ISCGEM  Automatic
4           ISCGEM  Automatic

[5 rows x 21 columns]
```

COLUMNS NAMES

```
data.columns
```

OUTPUT:

```
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')
```

MAIN FEATURES OF EARTHQUAKE DATA

```
# The main features from earthquake data creating a object namely, Date,
Time, Latitude, Longitude, Depth, Magnitude
data = data[['Date', 'Time', 'Latitude', 'Longitude', 'Depth', 'Magnitude']]
data.head()

         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

data.describe()
```

OUTPUT:

```
           Latitude     Longitude         Depth     Magnitude
count  23412.000000  23412.000000  23412.000000  23412.000000
mean       1.679033     39.639961     70.767911      5.882531
std       30.113183    125.511959    122.651898      0.423066
min      -77.080000   -179.997000     -1.100000      5.500000
25%      -18.653000    -76.349750     14.522500      5.600000
50%       -3.568500    103.982000     33.000000      5.700000
75%       26.190750    145.026250     54.000000      6.000000
max       86.005000    179.998000    700.000000      9.100000
```

SCALING THE RANDOM DATA

```
#Here, the data is random we need to scale according to inputs to the model.
So, we convert given Date and Time to Unix time which is in seconds and a
numeral. This can be easily used as input for the network we built
import datetime
import time
# Create a list to store Unix timestamps
timestamp = []
# Iterate through the "Date" and "Time" columns
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(ts.timetuple()))
 except ValueError:
   timestamp.append('ValueError')

# Create a Pandas Series from the timestamp list
timeStamp = pd.Series(timestamp)
# Add the "Timestamp" column to the DataFrame
data['Timestamp'] = timeStamp.values
# Drop the "Date" and "Time" columns
final_data = data.drop(['Date', 'Time'], axis=1)
# Remove rows with 'ValueError' in the "Timestamp" column
final_data = final_data[final_data['Timestamp'] != 'ValueError']
# Display the first few rows of the final dataset
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
```

Phase 4: Development Part 2

In this section buildinging the project by performing different activities like feature engineering, model training, evaluation

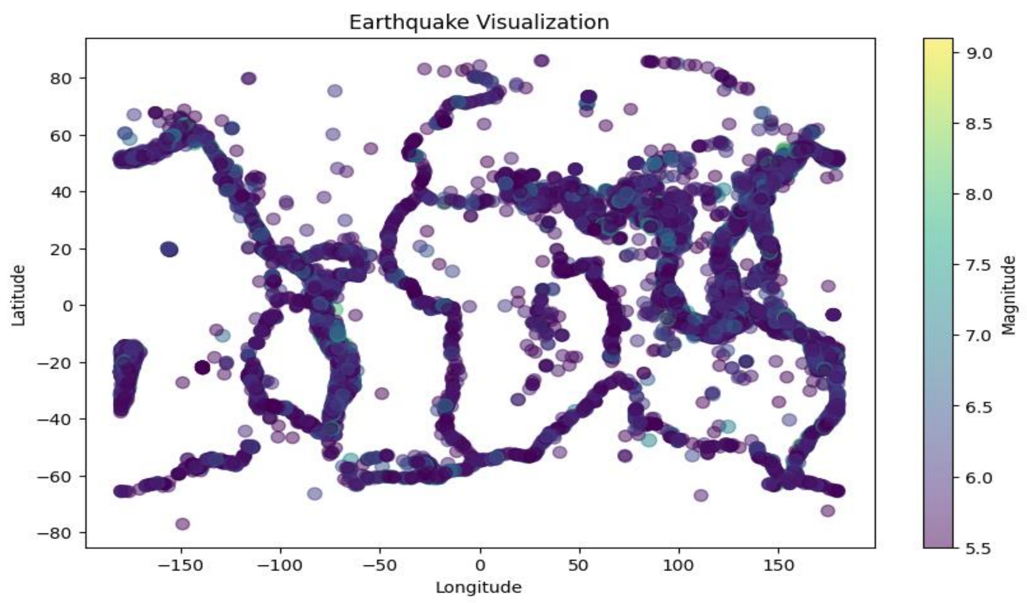
VISUALIZATION

```
# Extract latitude, longitude, and magnitude columns
latitude = data['Latitude']
longitude = data['Longitude']
magnitude = data['Magnitude']

# Create a scatter plot to visualize earthquakes on a map
plt.figure(figsize=(10, 6))
plt.scatter(longitude, latitude, c=magnitude, cmap='viridis', s=magnitude *
10, alpha=0.5)
plt.colorbar(label='Magnitude')
plt.title('Earthquake Visualization')
plt.xlabel('Longitude')
plt.ylabel('Latitude')

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

OUTPUT:



FEATURE ENGINEERING

```
import numpy as np
import pandas as pd

# Synthetic seismic data (replace this with your real data)
data = pd.DataFrame({
    'time': np.arange(0, 100, 0.1),
    'acceleration': np.random.rand(1000),
    # Add more columns for other sensor data if available
})

# Define functions for feature engineering
def basic_statistics(data):
    # Calculate basic statistical features
    features = {
        'mean': data['acceleration'].mean(),
        'std_dev': data['acceleration'].std(),
        'min': data['acceleration'].min(),
        'max': data['acceleration'].max(),
    }
    return features

def time_domain_features(data):
    # Calculate time domain features
    # For example, root mean square (RMS) amplitude
    rms = np.sqrt(np.mean(data['acceleration']**2))
    return {'RMS_amplitude': rms}
```

```python
def frequency_domain_features(data):
    # Calculate frequency domain features using Fourier transform
    fft_result = np.fft.fft(data['acceleration'])
    # Extract amplitude and frequency information
    amplitude = np.abs(fft_result)
    frequency = np.fft.fftfreq(len(fft_result))
    # Find the dominant frequency component
    dominant_frequency = frequency[np.argmax(amplitude)]
    return {'dominant_frequency': dominant_frequency}

# Apply feature engineering functions to your data
statistical_features = basic_statistics(data)
time_domain_features = time_domain_features(data)
frequency_domain_features = frequency_domain_features(data)

# Combining all features into a single feature vector
feature_vector = {**statistical_features, **time_domain_features,
**frequency_domain_features}

# Your feature vector is now ready for use in training your earthquake
prediction model
print(feature_vector)
```

OUTPUT:

```
{'mean': 0.49201126044541615, 'std_dev': 0.29111111319763416, 'min':
0.0012840627090102696, 'max': 0.9997457913830645, 'RMS_amplitude':
0.5716082705420084, 'dominant_frequency': 0.0}
```

MODEL TRAINING

```python
X = final_data[['Timestamp', 'Latitude', 'Longitude']]
y = final_data[['Magnitude', 'Depth']]

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Creating a Random Forest regressor
model = RandomForestRegressor(n_estimators=100, random_state=42)

# Training the model on the training data
```

```
model.fit(X_train, y_train)

# Making predictions on the test data
y_pred = model.predict(X_test)

# Evaluating the model's performance (for regression tasks)
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)
```

OUTPUT:

```
Mean Squared Error: 968.4488974862994
```

```
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:

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

```
from sklearn.ensemble import RandomForestRegressor

reg = RandomForestRegressor(random_state=42)
reg.fit(X_train, y_train)
reg.predict(X_test)
```

OUTPUT:

```
array([[  5.865,  42.024],
       [  5.826,  33.09 ],
       [  6.082,  39.741],
       ...,
       [  6.306,  23.059],
       [  5.96 , 592.283],
       [  5.808,  38.222]])
```

```
reg.score(X_test, y_test)
```

OUTPUT:

```
0.3926671400442392
```

```python
from sklearn.model_selection import GridSearchCV

parameters = {'n_estimators':[10, 20, 50, 100, 200, 500]}

grid_obj = GridSearchCV(reg, parameters)
grid_fit = grid_obj.fit(X_train, y_train)
best_fit = grid_fit.best_estimator_
best_fit.predict(X_test)
```

OUTPUT:

```
array([[  5.886 ,  43.031 ],
       [  5.82  ,  31.3982],
       [  6.0124,  39.5216],
       ...,
       [  6.294 ,  22.9908],
       [  5.9218, 592.385 ],
       [  5.7894,  39.2764]])
```

NEURAL NETWORK MODEL

```python
import numpy as np
import tensorflow as tf
from tensorflow import keras
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Generate synthetic seismic and geological data (replace with real data)
n_samples = 1000
n_features = 10

X = np.random.rand(n_samples, n_features)
y = np.random.randint(2, size=n_samples)  # Binary labels (0: no earthquake,
1: earthquake)

# Feature engineering and preprocessing (replace with actual preprocessing
steps)
scaler = StandardScaler()
X = scaler.fit_transform(X)
# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Building a basic feedforward neural network model
model = keras.Sequential([
    keras.layers.Dense(128, activation='relu',
input_shape=(X_train.shape[1],)),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])

# Compiling the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

# Training the model
model.fit(X_train, y_train, epochs=50, batch_size=32,
validation_data=(X_test, y_test))
```

MODEL EVALUATION

```
# Evaluating the model on the test data
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss}, Test Accuracy: {accuracy}")
```

OUTPUT:

```
Epoch 1/50
25/25 [==============================] - 1s 13ms/step - loss: 0.7015 -
accuracy: 0.5000 - val_loss: 0.7059 - val_accuracy: 0.4400
Epoch 2/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6850 -
accuracy: 0.5425 - val_loss: 0.7107 - val_accuracy: 0.4600
Epoch 3/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6771 -
accuracy: 0.5813 - val_loss: 0.7109 - val_accuracy: 0.4550
Epoch 4/50
25/25 [==============================] - 0s 8ms/step - loss: 0.6713 -
accuracy: 0.5738 - val_loss: 0.7097 - val_accuracy: 0.4600
Epoch 5/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6646 -
accuracy: 0.6075 - val_loss: 0.7112 - val_accuracy: 0.4400
Epoch 6/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6595 -
accuracy: 0.5938 - val_loss: 0.7147 - val_accuracy: 0.4550
Epoch 7/50
```

```
25/25 [==============================] - 0s 4ms/step - loss: 0.6534 -
accuracy: 0.6162 - val_loss: 0.7126 - val_accuracy: 0.4500
Epoch 8/50
25/25 [==============================] - 0s 4ms/step - loss: 0.6470 -
accuracy: 0.6250 - val_loss: 0.7141 - val_accuracy: 0.4400
Epoch 9/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6420 -
accuracy: 0.6313 - val_loss: 0.7181 - val_accuracy: 0.4650
Epoch 10/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6358 -
accuracy: 0.6313 - val_loss: 0.7191 - val_accuracy: 0.4650
Epoch 11/50
25/25 [==============================] - 0s 4ms/step - loss: 0.6259 -
accuracy: 0.6662 - val_loss: 0.7170 - val_accuracy: 0.4850
Epoch 12/50
25/25 [==============================] - 0s 5ms/step - loss: 0.6199 -
accuracy: 0.6712 - val_loss: 0.7249 - val_accuracy: 0.4850
Epoch 13/50
25/25 [==============================] - 0s 4ms/step - loss: 0.6113 -
accuracy: 0.6900 - val_loss: 0.7219 - val_accuracy: 0.4950
Epoch 14/50
25/25 [==============================] - 0s 4ms/step - loss: 0.6047 -
accuracy: 0.7025 - val_loss: 0.7189 - val_accuracy: 0.5000
Epoch 15/50
25/25 [==============================] - 0s 5ms/step - loss: 0.5968 -
accuracy: 0.7075 - val_loss: 0.7280 - val_accuracy: 0.4850
Epoch 16/50
25/25 [==============================] - 0s 4ms/step - loss: 0.5878 -
accuracy: 0.7262 - val_loss: 0.7263 - val_accuracy: 0.4700
Epoch 17/50
25/25 [==============================] - 0s 5ms/step - loss: 0.5785 -
accuracy: 0.7250 - val_loss: 0.7319 - val_accuracy: 0.4800
Epoch 18/50
25/25 [==============================] - 0s 5ms/step - loss: 0.5697 -
accuracy: 0.7362 - val_loss: 0.7417 - val_accuracy: 0.4650
Epoch 19/50
25/25 [==============================] - 0s 5ms/step - loss: 0.5598 -
accuracy: 0.7538 - val_loss: 0.7333 - val_accuracy: 0.4900
Epoch 20/50
25/25 [==============================] - 0s 5ms/step - loss: 0.5501 -
accuracy: 0.7650 - val_loss: 0.7402 - val_accuracy: 0.4650
Epoch 21/50
25/25 [==============================] - 0s 5ms/step - loss: 0.5408 -
accuracy: 0.7638 - val_loss: 0.7440 - val_accuracy: 0.4650
Epoch 22/50
25/25 [==============================] - 0s 4ms/step - loss: 0.5300 -
accuracy: 0.7763 - val_loss: 0.7530 - val_accuracy: 0.4700
Epoch 23/50
25/25 [==============================] - 0s 4ms/step - loss: 0.5202 -
accuracy: 0.7800 - val_loss: 0.7539 - val_accuracy: 0.4950
```

```
Epoch 24/50
25/25 [==============================] - 0s 4ms/step - loss: 0.5113 -
accuracy: 0.8000 - val_loss: 0.7617 - val_accuracy: 0.4850
Epoch 25/50
25/25 [==============================] - 0s 4ms/step - loss: 0.5043 -
accuracy: 0.7900 - val_loss: 0.7582 - val_accuracy: 0.4850
Epoch 26/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4944 -
accuracy: 0.7937 - val_loss: 0.7634 - val_accuracy: 0.4950
Epoch 27/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4820 -
accuracy: 0.8175 - val_loss: 0.7699 - val_accuracy: 0.4800
Epoch 28/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4719 -
accuracy: 0.8150 - val_loss: 0.7832 - val_accuracy: 0.4750
Epoch 29/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4603 -
accuracy: 0.8263 - val_loss: 0.7937 - val_accuracy: 0.4800
Epoch 30/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4600 -
accuracy: 0.8250 - val_loss: 0.7819 - val_accuracy: 0.5100
Epoch 31/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4462 -
accuracy: 0.8225 - val_loss: 0.8214 - val_accuracy: 0.4800
Epoch 32/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4316 -
accuracy: 0.8450 - val_loss: 0.8068 - val_accuracy: 0.4800
Epoch 33/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4133 -
accuracy: 0.8587 - val_loss: 0.8268 - val_accuracy: 0.4600
Epoch 34/50
25/25 [==============================] - 0s 4ms/step - loss: 0.4042 -
accuracy: 0.8675 - val_loss: 0.8109 - val_accuracy: 0.4750
Epoch 35/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3955 -
accuracy: 0.8775 - val_loss: 0.8383 - val_accuracy: 0.4850
Epoch 36/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3863 -
accuracy: 0.8900 - val_loss: 0.8515 - val_accuracy: 0.5000
Epoch 37/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3807 -
accuracy: 0.8725 - val_loss: 0.8455 - val_accuracy: 0.5000
Epoch 38/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3745 -
accuracy: 0.8863 - val_loss: 0.8584 - val_accuracy: 0.5000
Epoch 39/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3564 -
accuracy: 0.9000 - val_loss: 0.8744 - val_accuracy: 0.4750
Epoch 40/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3484 -
```

```
accuracy: 0.9137 - val_loss: 0.8772 - val_accuracy: 0.4850
Epoch 41/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3338 -
accuracy: 0.9000 - val_loss: 0.8788 - val_accuracy: 0.5050
Epoch 42/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3304 -
accuracy: 0.9000 - val_loss: 0.9459 - val_accuracy: 0.4600
Epoch 43/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3270 -
accuracy: 0.8988 - val_loss: 0.9118 - val_accuracy: 0.4950
Epoch 44/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3149 -
accuracy: 0.9275 - val_loss: 0.9395 - val_accuracy: 0.4400
Epoch 45/50
25/25 [==============================] - 0s 4ms/step - loss: 0.3010 -
accuracy: 0.9237 - val_loss: 0.9541 - val_accuracy: 0.4600
Epoch 46/50
25/25 [==============================] - 0s 4ms/step - loss: 0.2908 -
accuracy: 0.9262 - val_loss: 0.9331 - val_accuracy: 0.4650
Epoch 47/50
25/25 [==============================] - 0s 4ms/step - loss: 0.2813 -
accuracy: 0.9350 - val_loss: 0.9438 - val_accuracy: 0.4900
Epoch 48/50
25/25 [==============================] - 0s 4ms/step - loss: 0.2721 -
accuracy: 0.9425 - val_loss: 0.9695 - val_accuracy: 0.4850
Epoch 49/50
25/25 [==============================] - 0s 4ms/step - loss: 0.2704 -
accuracy: 0.9337 - val_loss: 1.0072 - val_accuracy: 0.4450
Epoch 50/50
25/25 [==============================] - 0s 4ms/step - loss: 0.2602 -
accuracy: 0.9425 - val_loss: 0.9908 - val_accuracy: 0.4700
7/7 [==============================] - 0s 3ms/step - loss: 0.9908 - accuracy:
0.4700
Test Loss: 0.9907826781272888, Test Accuracy: 0.4699999988079071
```

CONCLUSION OF DOCUMENT:

Thus the entire Earthquake prediction Model using python has been builded with the essential techniques such as Loading the dataset, preprocessing the datatset, and other included technical steps such as feature engineering, Model training, Model evaluation and various features are explained and builded Successfully.