Using Artificial Intelligence in Earthquake Forecasting

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Abstract
Predicting seismic tremors is a key issue in Earth science because of their overwhelming consequences and vast range. In this article we predict the places where earthquakes are likely to occur in the world and on what dates the earthquake will occur. With geologic location, magnitude and other factors in the dataset from https://earthquake.usgs.gov/earthquakes/feed/v1.0/csv.php updated every minute, we I predict or forecast time 14 days in the future, places where earthquakes are likely to occur. The application and impact of this prediction improving earthquake risk assessment can save lives and billions of dollars in infrastructure and planning
Keywords: *Artificial intelligence, earthquake*

1. Introduction

A lot of money and science has been spent predicting where and when the next big earthquake will happen. But unlike weather forecasting, which has improved dramatically with the use of better satellites and more powerful mathematical models, earthquake forecasting has failed due to the highly uncertain conditions of the weather of earth and its surroundings. Now, with the help of artificial intelligence, more and more scientists say changes in the way they can analyze large amounts of seismic data could help them better understand earthquakes, predict how they will behave and provide faster and more accurate early warnings. This helps assess the risk for many real estate developers and developers to infrastructure planning from a business perspective. In addition, many lives can be saved through early warning.

An earthquake is a natural disaster caused by the movement of the earth's tectonic plates due to the release of its substantial internal energy. A major earthquake with a magnitude greater than 5 can cause massive deaths and massive infrastructure damage worth billions of dollars.

However, if earthquakes can be predicted, the extent of devastation can be minimized. A complete earthquake forecasting procedure should have three types of information: magnitude, location and time of occurrence frequency. Since 2005, there have been 28,400 earthquakes with magnitudes over five around the world [1]. Figure 1 shows the location of occurrences from January to December 2019 [1]. Looking closely, it was possible to see some patterns in the earthquake locations (denoted by the red dots in Figure 1). This type of model could give researchers the ability to accurately predict earthquakes.

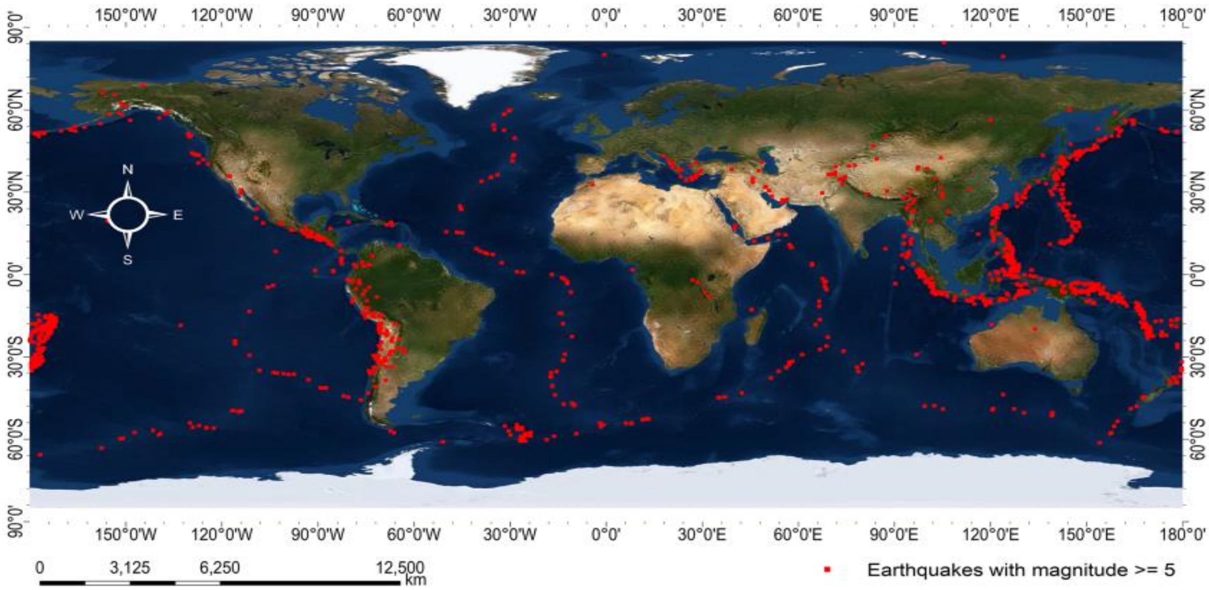


FIGURE 1.

Earthquakes occurred around the world from January 2019 to December 2019 with magnitudes greater than or equal to five on the richter scale. In twelve months, 1637 earthquakes occurred around the world. Data were collected from the US Geological Survey and charted using ArcGIS software. The red square represents the epicenter of the earthquake.

Earthquake forecasting can be classified into short-term and long-term processes. Short-term prediction is very complex because it predicts earthquakes within days or weeks of their occurrence. Therefore, it should be accurate and less false warnings are appreciated. Generally, short-term predictions are used to evacuate an area before an earthquake. On the other hand, long-term earthquakes are predicted based on periodic arrival earthquakes, which carry a few pieces of information. However, they can help set standards for building codes and design disaster response plans. In 2009, the Italian city of L'Aquila was hit by a 5.9 magnitude earthquake that claimed the lives of 308 citizens. However, Italy's earthquake forecasting commission predicted that there would be no damage, and they did not evacuate the city. Such faulty prediction can lead to a massive massacre that takes lives and damages a lot of infrastructure. The scientists involved in that incident were sentenced to six years in prison [2].

Earthquake prediction models work well for moderate-magnitude earthquakes, but while the tremors are high, the results are poor. Large earthquakes cause the most damage and bring the most concern.

The reason behind this scenario is that there is a smaller number of earthquakes with high intensity and without data, prediction becomes very difficult. Predictive studies use historical data regarding an earthquake's energy, depth, location, and magnitude from the earthquake catalog. Based on the magnitude of the complete value, area-specific earthquake parameters such as b-value parameters are calculated. Machine learning (ML) based algorithms calculate seismic indices like Gutenberg Richter value, time delay, earthquake energy, average intensity etc. [3]. Instead, deep learning (DL)-based models can compute thousands of sophisticated features by themselves [4], [5].

Since ML and DL-based models are data-driven and earthquakes themselves occur in some cases, it is difficult to predict them based on historical data. Some methods of predicting large earthquakes by training them separately or adding weights to them, but these models need much improvement [6].

Another way to predict success is to find some precursor to a major earthquake. Precursors are changes in elements in nature before an earthquake occurs.

Earthquake scientists suggest that gas Radon concentration, strange cloud formation, earth's electromagnetic field changes, humidity, soil temperature, crust changes, etc. possible candidate precursors [7]. Such generalizations can be misleading because many cases have been found in which these precursors are present without the occurrence of an earthquake, and earthquakes have occurred even despite the absence of these precursors. According to the International Society of Seismology and Physics of the Interior of the Earth (IASPEI), earthquakes based on research precursors should have several qualities such as - it must be observed from multiple locations and instruments and must be related to the stresses and strains of the earth [8]. No precursors with solid evidence of earthquake prediction were found.

Since this is a type of problem involving series of events, the solution proposed in the paper is to consider a binary classification of earthquake probability with training time consisting of fixed window moving averages, fixed of the past days while its labels, fixed window size change ahead of time. The model will be trained with Adaboost classifier (RandomForestClassifier and Classifier Decision) and compared with XGBoost based on AUC ROC score and Recall score. The model with better AUC score and larger Recall will be considered for a web application that uses Google maps api to predict earthquakes.

Evaluation of an earthquake prediction method can be done using various measures such as positive and negative predictive value (P-1, P0), specificity (Sp), sensitivity (Sn), and accuracy, false alarm rate (FAR), R score, mean squared error (RMSE), mean square error (MSE), relative error (RE), mean absolute error (MAE), area product under the curve (AUC), chi-squared test, etc. The earthquake pattern is dependent on the area where the data is collected.

This is why there is a need for a standard dataset of an earthquake on which researchers can calculate metrics to compare their models with previous studies. There are a number of review articles available that have evaluated earthquake prediction studies. In some reviews, precursor-based studies have been criticized for being based on scientific merit [10]. How these precursors can be used in earthquake prediction is also elaborated [11]. The use of

The radon concentration to predict an earthquake is also investigated [17]. Data mining techniques are discussed in the study [15]. Classical ML techniques are reviewed, and their evaluation techniques are discussed in the study [20].

How rule-based techniques can operate in this area is investigated in [21]. Mignan and Broccardo [22] discussed DL techniques in this area. There is a missing study where all these techniques are accumulated together, which can be a great resource for AI researchers in the field of earthquake prediction.

For this review, earthquake prediction studies including AI-based methods were searched in databases such as IEEE

2. Data

We pull data online from the website https://earthquake.usgs.gov/earthquakes/feed/v1.0/csv.php for the last 30 days updated every minute (July 18, 2022 to August 18, 2022)

Input value to model from dataset has many important features to consider like time, latitude & longitude, depth of earthquake, magnitude, location, rest are features no support for sorting.

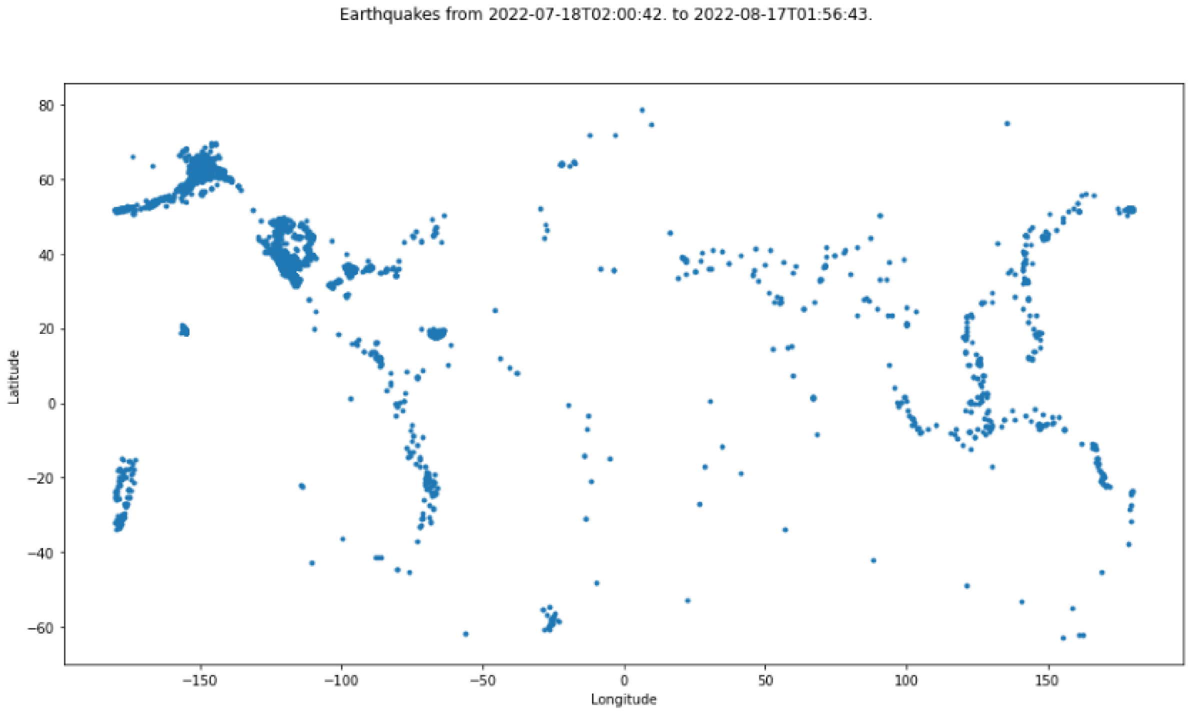


Figure 2. Earthquakes occurred around the world from July 18, 2022 to August 17, 2022.

The problem to be solved in this paper is about binary classification, Earthquake occurs = 1 and Earthquake does not occur = 0 and with this prediction we try to locate the corresponding copper wires. response to the prediction and display it on the google maps api web app. Metrics more suitable for binary decomposition problems are ROC (Property of Receiver Operators), AUC (Area Under Curve), Confusion Matrix for Accuracy, recall, precision and sensitivity. One important thing about metric and model selection is that we need exactly what from the predictions and what doesn't. Strictly speaking, we need to minimize or get less of the so-called false-negative predictions (earthquake possible with high probability but warning not to happen) because we don't want the model your prediction is 0 or no earthquake will happen at a particular place when in fact it has actually happened because this is more dangerous than the prediction case where the prediction is true / 1 or Earthquakes happen, but they don't. Therefore, in addition to the roc_auc score, I also looked at the Recall index to evaluate and select the model with a higher auc_roc score, where Recall = (TP / TP + FN).

3. Methodology

3.1 Decision Tree Algorithm

A Machine Learning algorithm will usually have 2 steps:
1. Training: From data the algorithm will learn the model.
2. Prediction: Use the model learned from the above step to predict new values

The decision tree is a binary tree. There are two types of nodes in this decision tree:
1. The node has a test condition, called a conditional node. The conditional nodes all have 2 child nodes below.
2. Node leaves; there is no condition that has the predicted result. Leaf nodes have no child nodes.

To avoid the case of overfitting (the model is very accurate on the training set but inaccurate on the test set), there are several methods:

o Stop condition: consider a node as a leaf node and stop the division when entropy is 0, or when the number of elements is less than a certain threshold; or restrict the depth of the tree

o In addition, there are several pruning methods.

3.2 Random Forest Algorithm

● Random means random, Forest means forest. The Random Forest algorithm is to randomly build a set of trees from the Decision Tree algorithm. Then the final result will be aggregated from these trees.

● In the training step, many decision trees will be built, the decision trees may be different. Then in the prediction step, with a new data, in each decision tree we will go from the top down according to the conditional nodes to get the predictions, then the final result is aggregated from the results of the decision tree.

Building the Random Forest algorithm

● Suppose our dataset has n data (sample) and each data has d attributes (feature). The construction steps are as follows:
1. Randomly take n data from the dataset with Bootstrapping technique, also known as random sampling with replacement. That is, when the sample is 1 data, do not remove that data but keep it in the original data set, and then continue to sample until the sample has n data. Using this technique, our new data set n may have duplicate data.
2. After sampling n data from step 1, I randomly select at k attributes (k < n). Now I have a new dataset consisting of n data and each data has k attributes. Then use Decision Tree algorithm to build the tree.

● Since each tree builds in a random way, the results between trees may vary. Each tree is built using Decision Tree algorithm on different data set and using different attribute set. Then the prediction results of the Random Forest algorithm will be aggregated from the decision trees.

● When using the Random Forest algorithm, we need to pay attention to attributes such as: the number of decision trees to build, the number of attributes used to build the tree. In addition, there are still properties of the Decision Tree algorithm to build a tree such as the maximum depth, the minimum number of elements in a node to be split.

Advantages of Random Forest algorithm

● In Decision Tree algorithm, when building a decision tree, if the depth is arbitrary, the tree will correctly classify all the data in the training set, leading to the model being able to predict badly on the validation/test set, then the model model is overfitting, in other words, the model has high variance.

● Random Forest algorithm consists of many decision trees, each decision tree has random elements:

1. Randomize data to build decision tree.

2. Randomize the attributes to build a decision tree.

● Because each decision tree in the Random Forest algorithm does not use all the training data, nor does it use all the attributes of the data to build the tree, each tree may make a bad prediction, then each model The decision tree model is not overfitting but can be underfitting, in other words, the model has high bias. However, the final result of the Random Forest algorithm is aggregated from many decision trees, so the information from the trees will complement each other, leading to a model with low bias and low variance, or a model with low bias and low variance. good predictive results.

3.3 XGBoost Algorithm:

XGBoost is a new machine learning algorithm, designed with speed and performance in mind. XGBoost stands for eXtreme Gradient Boosting, it's simply decision trees algorithm, applying techniques to combine trees, smoothing training loss and regularization.

4. Results of running models and forecasts

We build some more properties from the data fields to show the trend and periodicity in the earthquake data. The new properties are seen in the image below:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	depth_avg_7	mag_avg_22	mag_avg_15	mag_avg_7	mag_outcome
0	2022-07-24	7.185596	2.50	Texas	31.541062	-102.824089	7.279997	7.141025	8.089049	2.540909	2.546667	2.414286	0
1	2022-07-25	7.703247	3.30	Texas	31.541062	-102.824089	6.948747	7.245803	8.074857	2.590909	2.613333	2.542857	0
2	2022-07-25	6.358236	2.30	Texas	31.541062	-102.824089	6.890106	7.668056	8.048477	2.595455	2.600000	2.557143	0
3	2022-07-28	6.671436	2.20	Texas	31.541062	-102.824089	6.848038	7.705761	7.857503	2.559091	2.566667	2.542857	0
4	2022-07-29	7.494092	2.10	Texas	31.541062	-102.824089	6.774420	7.678339	7.890556	2.513636	2.513333	2.357143	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
7372	2022-08-14	9.720000	0.74	Washington	46.982082	-121.965333	8.255909	6.166667	4.625714	0.937273	0.818667	0.620000	0
7373	2022-08-14	6.700000	0.13	Washington	46.982082	-121.965333	8.592727	6.069333	4.538571	0.876818	0.711333	0.534286	0
7374	2022-08-14	10.660000	0.88	Washington	46.982082	-121.965333	8.586364	6.304000	5.900000	0.915000	0.778667	0.634286	0
7375	2022-08-14	2.270000	0.19	Washington	46.982082	-121.965333	8.048636	6.164000	6.320000	0.854091	0.790667	0.461429	0
7376	2022-08-15	2.550000	0.66	Washington	46.982082	-121.965333	7.235000	6.396667	6.261429	0.823636	0.774000	0.431429	0

7377 rows × 13 columns

Figure 7. Data set used for forecasting

After pre-processing with null value removal and feature engineering as discussed above, we implemented the algorithms for the classification problem.

Adaboost classifier with estimator as Decision Classifier, Adaboost classifier with estimator as RandomForestClassifier and finally they used the Xgboost algorithm.

Decision Tree Tool

max_depth = [2,6,7], n_estimators = [200,500,700] and using gridsearch CV gives the best estimator when nodes are expanded until all leaves are pure or until all leaves containing less than min_samples_split = 2 samples helps to classify with many types of features in the dataset.

RandomForestCLassifer

The same parameters are also used for randomforest to compare the algorithms used with gridsearchCV together with a hyperparamter max_features = ['auto', 'sqrt', 'log2'] which will allow to select features based on log(featues), sqrt(features)

XgboostClassifier

We didn't use CV Search grid here as it took me longer to train, hence tried max_depth same as above algorithms with best fit i.e. 6, learning_rate = 0.03 and gbtree is the booster

Accuracy is not a metric to use when working with an unbalanced data set. We think it is a mistake.

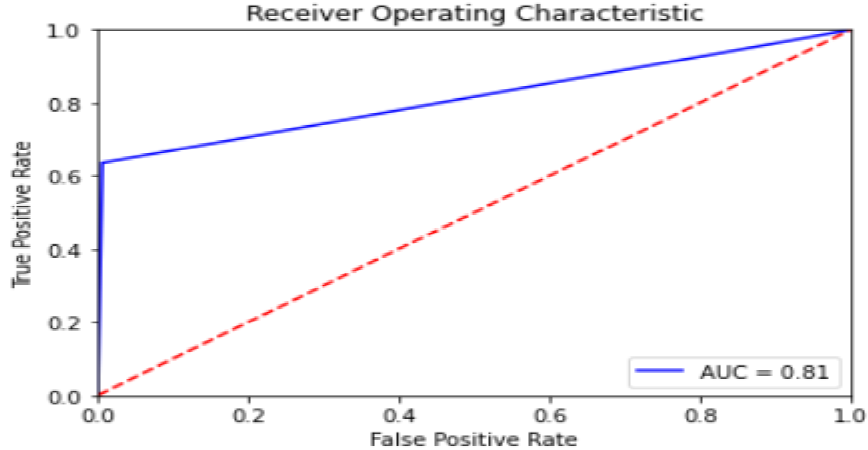
Confusion Matrix: Breaks down the predictions into a table showing the correct (diagonal) predictions and the types of incorrect predictions made (to which classes the incorrect predictions are assigned).

Recall: A measure of the completeness of the classifier.

ROC Curve: Like Accuracy and Recall, accuracy is divided into sensitivity and specificity, and models can be selected based on the equilibrium threshold of these values.

For the decision tree model

```
0.8146394003777148
AUC: 0.8146
```



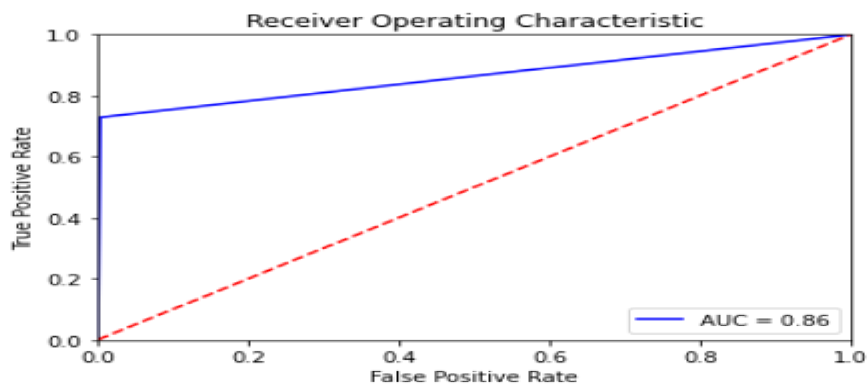

```
Confusion Matrix:
 [[2105   13]
 [  35   61]]

Recall 'TP/TP+FN' =  0.6354166666666666
```

Figure 8. ROC curve and the resulting parameters of the Decision Tree model

For the Random Forest model

```
0.8629308309726156
AUC: 0.8629
```

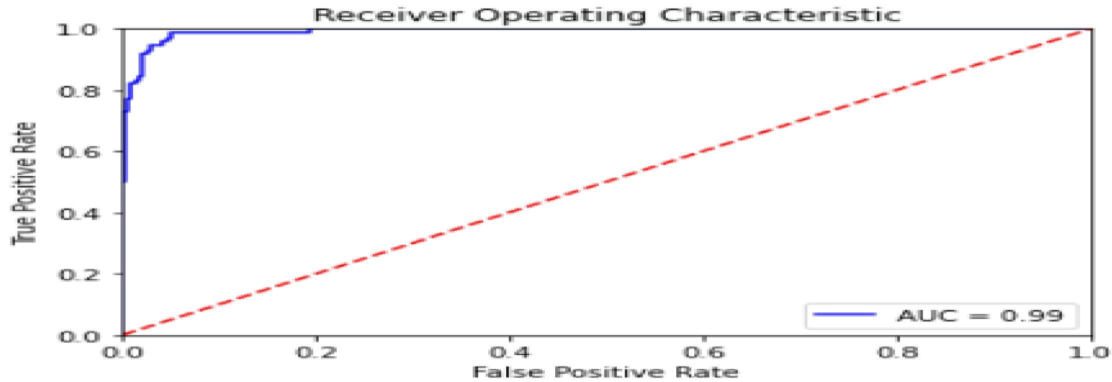



```
Confusion Matrix:
 [[2111    7]
 [  26   70]]

Recall 'TP/TP+FN' =  0.7291666666666666
```

Figure 9. ROC curve and resulting parameters of the Random Forest model Model XGBoost

```
0.9918899512118351
AUC:  0.9919
```




```
Confusion Matrix:
 [[2107    11]
 [   26    70]]

Recall 'TP/TP+FN' =   0.7291666666666666
```

Figure 10. ROC curve and the resulting parameters of the XGBoost model

Below are the forecast results for the possibility of earthquakes in locations around the world. The last column gives the probability of an earthquake on the corresponding location.

	date	place	latitude	longitude	quake
0	2022-08-20	Idaho	44.184944	-114.281469	0.490009
1	2022-08-20	Japan region	32.004229	142.458929	0.997111
2	2022-08-21	Idaho	44.184944	-114.281469	0.015376
3	2022-08-21	Japan region	32.004229	142.458929	0.997111
4	2022-08-22	Idaho	44.184944	-114.281469	0.047835
5	2022-08-23	Canada	48.769593	-108.405798	0.000708
6	2022-08-23	Idaho	44.184944	-114.281469	0.372987
7	2022-08-24	Canada	48.769593	-108.405798	0.013595
8	2022-08-24	Japan	36.125661	137.793745	0.995790
9	2022-08-25	Canada	48.769593	-108.405798	0.007558
10	2022-08-25	Idaho	44.184944	-114.281469	0.271205
11	2022-08-25	Montana	45.354247	-111.560653	0.000067
12	2022-08-26	Canada	48.769593	-108.405798	0.007672
13	2022-08-26	Chile	-25.729569	-70.776106	0.995118
14	2022-08-26	Japan	36.125661	137.793745	0.993067
15	2022-08-26	Japan region	32.004229	142.458929	0.995865
16	2022-08-26	Montana	45.354247	-111.560653	0.000074
17	2022-08-26	New Mexico	31.688991	-104.397205	0.462701
18	2022-08-26	Russia	48.765780	140.581209	0.994824
19	2022-08-26	Tonga	-19.319432	-175.340900	0.994824
20	2022-08-27	B.C.	32.178230	-116.012780	0.001979

Figure 10.1. Forecast results from August 20 to 27, 2022

	date	place	latitude	longitude	quake
21	2022-08-27	Indonesia	-3.243697	117.937419	0.995790
22	2022-08-27	Japan	36.125661	137.793745	0.994971
23	2022-08-27	Montana	45.354247	-111.560653	0.000136
24	2022-08-27	Oregon	44.368357	-122.725097	0.001169
25	2022-08-27	Philippines	14.031786	122.611068	0.992604
26	2022-08-27	Russia	48.765780	140.581209	0.994824
27	2022-08-28	Chile	-25.729569	-70.776106	0.993659
28	2022-08-28	Idaho	44.184944	-114.281469	0.220513
29	2022-08-28	New Mexico	31.688991	-104.397205	0.689010
30	2022-08-28	Philippines	14.031786	122.611068	0.994824
31	2022-08-28	Tennessee	36.086080	-88.125275	0.000407
32	2022-08-28	Vanuatu	-17.042625	168.162463	0.995790
33	2022-08-29	Aleutian Islands	52.003849	75.953854	0.000098
34	2022-08-29	California	38.615032	-119.500745	0.000422
35	2022-08-29	Indonesia	-3.243697	117.937419	0.995076
36	2022-08-29	Japan	36.125661	137.793745	0.994824
37	2022-08-29	Montana	45.354247	-111.560653	0.000215
38	2022-08-29	New Mexico	31.688991	-104.397205	0.193379
39	2022-08-29	Oklahoma	35.574904	-97.216259	0.000752

Figure 10.2. Forecast results from August 27 to August 29, 2022

	date	place	latitude	longitude	quake
40	2022-08-29	Oregon	44.368357	-122.725097	0.001163
41	2022-08-29	Papua New Guinea	-5.440213	148.970192	0.994824
42	2022-08-29	Philippines	14.031786	122.611068	0.995244
43	2022-08-29	Russia	48.765780	140.581209	0.995307
44	2022-08-29	Texas	31.541062	-102.824089	0.137850
45	2022-08-29	Vanuatu	-17.042625	168.162463	0.994824
46	2022-08-29	Washington	46.982082	-121.965333	0.000132
47	2022-08-29	Wyoming	44.646815	-110.762717	0.000105
48	2022-08-30	Alaska	59.507930	-145.410885	0.001427
49	2022-08-30	Aleutian Islands	52.003849	75.953854	0.000213
50	2022-08-30	B.C.	32.178230	-116.012780	0.000188
51	2022-08-30	CA	36.462627	-119.711954	0.002694
52	2022-08-30	California	38.615032	-119.500745	0.000399
53	2022-08-30	Chile	-25.729569	-70.776106	0.994824
54	2022-08-30	Hawaii	19.290362	-155.466810	0.000658
55	2022-08-30	Japan	36.125661	137.793745	0.995790
56	2022-08-30	Montana	45.354247	-111.560653	0.000151
57	2022-08-30	Nevada	38.159704	-117.597834	0.000188
58	2022-08-30	New Mexico	31.688991	-104.397205	0.695551
59	2022-08-30	Oklahoma	35.574904	-97.216259	0.000484
60	2022-08-30	Oregon	44.368357	-122.725097	0.013402

Figure 10.3. Forecast results from August 29 to August 30, 2022

	date	place	latitude	longitude	quake
61	2022-08-30	Papua New Guinea	-5.440213	148.970192	0.994824
62	2022-08-30	Philippines	14.031786	122.611068	0.994824
63	2022-08-30	Puerto Rico	18.046105	-66.839441	0.167517
64	2022-08-30	Russia	48.765780	140.581209	0.995086
65	2022-08-30	Tennessee	36.086080	-88.125275	0.000929
66	2022-08-30	Texas	31.541062	-102.824089	0.101390
67	2022-08-30	U.S. Virgin Islands	18.814163	-64.609389	0.986585
68	2022-08-30	Utah	39.413409	-110.676869	0.000275
69	2022-08-30	Washington	46.982082	-121.965333	0.000101
70	2022-08-30	Wyoming	44.646815	-110.762717	0.000096
71	2022-08-31	Alaska	59.507930	-145.410885	0.000728
72	2022-08-31	CA	36.462627	-119.711954	0.001349
73	2022-08-31	Hawaii	19.290362	-155.466810	0.003272
74	2022-08-31	Indonesia	-3.243697	117.937419	0.994824
75	2022-08-31	Texas	31.541062	-102.824089	0.510265

Figure 10.4. Forecast results from August 30 to August 31, 2022

5. Conclusion

Of all the natural disasters, earthquakes are one of the most devastating when they happen suddenly, causing significant damage to infrastructure and taking many lives. Many of the existing prediction techniques provide high false alarms, so the lack of an accurate prediction procedure is a contributing factor to the catastrophic consequences of an earthquake. Based on AI, the methods in this paper have created a new scope for improving this prediction process due to their high accuracy when compared with other techniques. Such methods can greatly reduce the damage since the area involved can be evacuated based on the forecast.

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