Original Research Paper

A New Algorithm for Earthquake Prediction Using Machine Learning Methods

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Abstract: Seismic tremors are among the foremost perilous normal fiascos individuals confront due to their event without earlier caution and their effect on their lives and properties. In expansion, to consider future disaster prevention measures for major earthquakes, it is necessary to predict earthquakes using Neural Networks (NN). A machine learning technique has developed a technology to predict earthquakes from ground controller data by measuring ground vibration and transmitting data by a sensor network. Devices to process this data and record it in a catalog of seismic data from 1900-2019 for Iraq and neighboring regions, then divide this data into 80% training data and 20% test data. It gave better results than other prediction algorithms, where the NN model performs better Seismic prediction than other machine learning methods.

Keywords: Earthquakes, Neural Networks, Machine Learning, Prediction, Earthquakes Data

Introduction

Seismic tremor is a fundamental normal wonder influencing organisms' life and their property. It is the sudden release of energy transmitted by waves from the ground. It destroys vast areas in a few minutes. It leads to considerable losses of lives and property and predicting earthquakes gives at least a little time to protect people and reduce earthquake damage (Bilal *et al*., 2022).

This research is considered the first informational study to predict earthquakes in Iraq, as the recording of earthquake data readings after installing seismic monitoring stations since 1914 in Iraqi territory. In addition to data recorded by international devices since 1900, many earthquakes in Iraq and areas far from the seismic fault line raised Geologists' fear of foreseeing an increment in seismic tremors for the coming long time (Jarah *et al*., 2023; Rouet-Leduc *et al*., 2017).

This research applied a technique to predict earthquakes using the data from several seismic monitoring stations. Machine learning calculations were utilized to prepare and analyze a design of information to anticipate the event of a seismic tremor and powerful computational techniques emerged from analyzing big data.

This study is the first in Iraq to use local data collected in Iraqi catalogs. The following are studies conducted by researchers in the field of earthquake prediction in different parts of the world.

Sathwik *et al*. (2022) employed a set of machine learning algorithms to predict future earthquakes such as logistic regression, Support Vector Machine (SVM), random forest classifier, and k-nearest neighbors. The examined dataset consists of 14 features to protect the assets of the residencies and the best efficiency reached over this study was around 0.9. This result was very high because of the number of training features in comparison with the predicted details.

Bangar *et al*. (2020) mixed the random forest and support vector machine algorithms to detect early signs of the earthquake, the tested dataset was related to India with the rest of the neighboring countries and all data were from government sources such as the united states geological survey and the India meteorological department. The accuracy of this study was enclosed to 0.74, 0.76, and 0.83 to provide the government with important details about future earthquakes.

Mallouhy *et al*. (2020) utilize different eight machine learning algorithms which are Random Forest (RF), Naive Bayes (NB), Logistic Regression (LR), Multi-Layer Perceptron (MLP), AdaBoost (AB), Support Vector Machine (SVM) and Regression Trees (RT). The examined dataset was public data related to world

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earthquakes and consisted of 139 features. Unfortunately, LR recorded the worst results over these algorithms which identified 52 wrong results over 139. The best accurate prediction values were archived by the SVM algorithm around 0.7 to provide the authority parties with the required information about future earthquakes.

Asencio-Cortés *et al*. (2018) combined several regression algorithms with ensemble learning algorithms to analyze the big data to identify the earthquake magnitude in the coming seven days in California only. This machine learning was used to analyze 1 Gigabyte dataset gathered over the duration between 1970-2017 by using R language and Amazon cloud infrastructure and the highest accuracy recorded over the examination rounds is 0.8.

Asim *et al*. (2018) used four machine learning techniques to predict the magnitude of upcoming earthquakes in Hindukush which are pattern recognition neural network, recurrent neural network, random forest, and linear programming boost ensemble classifier. The dataset consists of 441 vectors, each vector related to one month of the duration from 1977-2013. The prediction results were around 0.58, 0.64, 0.62and 0,65, the best accuracy meted by LPBoost ensemble technology.

We compared the proposed model with the results of others above, where the proposed model obtained 0.83 as a verification result while the others were separated at this upper and lower value. Mallouhy *et al*. (2020) recorded 0.76 as a distinct result, while Asim *et al*. (2018) reported 0.64. One of the featured studies was published higher than the proposed model, with the same other researchers (2022) scoring 0.9, while Bangar *et al*. (2020) achieved 0.83, which is what was recorded in the study. Recently (2022) Southwick's results were found to be better than the proposed model for several reasons such as the number of features for the training model is 14 incoming vectors with the proposed model only having 3 directions for the training model and this has more significant implications for a distinct model. Bangar *et al*. (2020) carried out the study and checked the model on an Indian database and the number of training options was 6 vectors, arriving at a result of 0.83. However, the model was tested in 5 directions and the size of the current dataset consists of 34.663 records which is less than the size of the dataset used by Bangar *et al*. (2020). Another independent research on top of the proposed model produced by Asencio-Cortés *et al*. (2018) recorded strength even in the next seven days in California, the main reason being related to the large data set used in this research which produced 600 million data records between 1970 and 1970. and 2019, showing comparable trend trends with the 34.663 records in our sample.

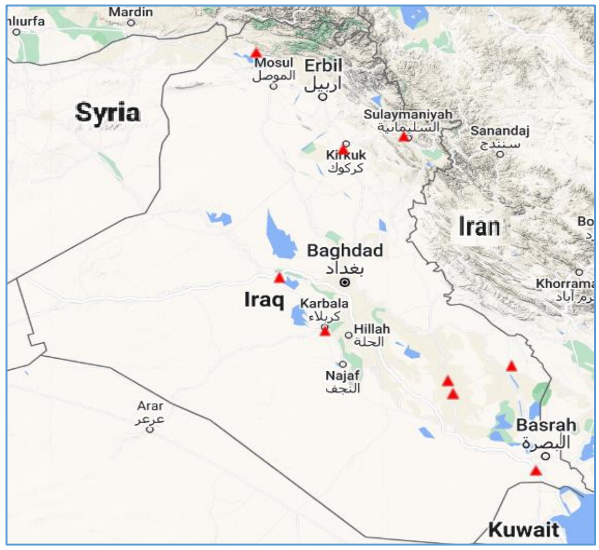

Fig. 1: Locations of earthquake monitoring stations

Earthquakes Data

Earthquakes are recorded with a device installed in an underground vault and at nine stations connected to a wireless sensor network whose center is the receiver at the Seismological Laboratory of the University of Basrah (SLUB). Figure 1 shows the locations of seismic stations. And the network address of these stations according to their location on the Internet page at the source (Fernandes *et al*., 2022).

The seismic recording device is called a broadband. As it records all waves or any human activity that leads to earthquakes that reach it, regardless of distance and magnitude, since 2014, it has converted earthquakes into electrical signals recorded and analyzed by the computer (Liu *et al*., 2018).

Broadband operates on the principle of inertia, which involves sensing motion relative to the movement of the ground and is recorded by a digitizer.

One of the most significant challenges is that most of the databases created by the geological centers need to adjust the timings and other details so that we can use them for the field of machine learning.

Machine Learning

There are multiple algorithms in machine learning, each with its strengths and weaknesses, so when solving a problem, first consider the necessary algorithm.

If it is still challenging to decide, the decision closest to the problem-solving process can be selected from the actual use example (Probst and Boulesteix, 2017).

The following are the three machine learning algorithms that were closest to predicting earthquakes that passed the earthquake data in this study.

Table 1: Application of LR, RFR, and NN algorithms

No.	Input features	Predicted features	LR	RFR	NN
1	Timestamp, latitude, magnitude	Depth, longitude	0.182	0.401	0.675
2	Timestamp, depth, longitude	Magnitude, latitude	0.249	0.658	0.839
3	Timestamp, latitude, depth	Magnitude, longitude	0.199	0.585	0.685
4	Timestamp, latitude, longitude	Magnitude, depth	0.250	0.398	0.489
5	Depth, longitude, magnitude	Timestamp, latitude	0.218	0.666	0.654
6	Latitude, depth, longitude	Magnitude, timestamp	0.122	0.441	0.702
7	Latitude, depth, magnitude	Timestamp, longitude	0.252	0.577	0.758
8	Timestamp, longitude, magnitude	Depth, latitude	0.116	0.477	0.634
9	Longitude, latitude, magnitude	Depth, timestamp	0.180	0.301	0.768
10	Timestamp, depth, magnitude	Longitude, latitude	0.114	0.495	0.775

Table 2: The catalog of Earthquake in Iraq and surrounding regions (1900-2019) (Onur *et al*., 2017)

<table>
<tr><th>Eventide</th><th>Year</th><th>Month</th><th>Day</th><th>Time</th><th>Lat</th><th>Lon</th><th>Depth (km)</th><th>MAG</th><th>Timestamp</th></tr>
<tr><td>10001</td><td>1900</td><td>2</td><td>24</td><td>06:00.0</td><td>38.45</td><td>44.8700</td><td>0.0</td><td>5.4</td><td>-2204312256</td></tr>
<tr><td>10002</td><td>1900</td><td>4</td><td>17</td><td>17:00.0</td><td>38.00</td><td>46.0000</td><td>0.0</td><td>6.2</td><td>-2200442256</td></tr>
<tr><td>10004</td><td>1901</td><td>2</td><td>6</td><td>48:00.0</td><td>33.00</td><td>49.0000</td><td>0.0</td><td>7.4</td><td>-2174266656</td></tr>
<tr><td>10005</td><td>1901</td><td>5</td><td>20</td><td>38:36.0</td><td>38.38</td><td>42.2300</td><td>10.0</td><td>5.5</td><td>-2165401296</td></tr>
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<tr><td>44659</td><td>2019</td><td>12</td><td>29</td><td>28:27.4</td><td>38.8709</td><td>43.5207</td><td>14.3</td><td>2.1</td><td>-1577582824</td></tr>
<tr><td>44660</td><td>2019</td><td>12</td><td>30</td><td>56:21.8</td><td>30.8205</td><td>50.0474</td><td>10.0</td><td>3.7</td><td>-1577682728</td></tr>
<tr><td>44662</td><td>2019</td><td>12</td><td>31</td><td>50:57.3</td><td>32.4992</td><td>46.9521</td><td>10.0</td><td>2.8</td><td>-1577750223</td></tr>
<tr><td>44663</td><td>2019</td><td>12</td><td>31</td><td>49:12.8</td><td>34.7548</td><td>45.5659</td><td>12.2</td><td>2.8</td><td>-1577743923</td></tr>
</table>

Linear Regression

A linear regression model was applied to the Iraqi data set. The result shown in Table 1. shows that the linear regression was not significant and could not meet any useful prediction. A test showed the worst prediction, with verification values ranging from 0.114-0.252. Thus, linear regression cannot predict the earthquake based on the current data and the parameters used. Although this model was not achieved, the required prediction must use other techniques to find the best prediction (Ranjan *et al.*, 2019).

Random Forest Regressor

It is a mechanism that generates multiple decision tree models and decides on the final prediction by the majority vote of those models. Because each model trains using sub-datasets generated by splitting the original training dataset, each model exhibits slightly different prediction performance. Therefore, the more it is generated, the more Decision tree models, the generalization ability of the random group as a whole increases, and the prediction performance better (González *et al*., 2019).

Neural Network

NN may be a machine learning strategy or calculation that attempts to reenact the working of neurons within the human brain for learning. At first, the results appear inaccurate and after a specific iteration of the data, they adjust themselves so that the results increase in accuracy. Moreover, each NN is organized within the frame of layers of counterfeit cells: An inward layer, an external layer, and layers between them, or covered-up layers between the two layers of the input and the outside layer (Alves, 2006). A NN that contains more than one hidden layer is known as a profound neural arrangement and learning is called profound learning. Each layer has a boundless number of hubs. The number of hubs within the input layer breaks even with the number of input information highlights. Covered-up layers comprise a boundless number of hubs. The yield layer comprises as it were one hub for understanding relapse issues and more than one hub for evaluating pictures, translation, audio, or solving classification issues (Tapia-Hernández *et al*., 2019). In Table 1. Application of the above three algorithms with different probabilities in input and output features.

Earthquake Prediction

Seismic tremors are a portion of earth's life and an appalling portion of human history and they are sudden unsettling influences within the earth's outside, as not a year goes by without hearing handfuls of seismic tremors, a few of them solid and destroying, wiping out whole cities. Consequently, the issue of anticipating their event appears exceptionally imperative.

Earthquake forecasting is the science of determining the details of impending earthquakes in terms of the location, magnitude, and time of the earthquake within a given area (Mavrodiev *et al.,* 2018).

Researchers face challenges in predicting earthquakes and dealing with natural phenomena. According to the study of (Li *et al*., 2022), there's no valid forecast within the brief term since the reason for the short-term expectation is to empower emergency measures to diminish activity and pulverization, which leads to untrue desires and dissatisfaction within the occasion of a critical seismic tremor, resulting in additional losses and legal penalties (Kiani *et al*., 2019).

Measurable speculation testing strategies and performing machine learning approaches, to be specific polynomial calculated relapse and bolster Vector Machine (SVM) for seismic tremor information, may be utilized in classification and relapse investigation to decide the likelihood of a seismic tremor (Onur *et al*., 2017).

Proposed Algorithm

The first step of the proposed algorithm reads the earthquake data file in Iraq and the surrounding area from 1900-2019, As in Table 2.

Furthermore, the second step is data preprocessing, which represents the six main features in earthquake data: Earthquake date (year, month, and day), time, longitude, latitude, depth, and earthquake strength.

The date and time data in this mechanism are not considered digital data. They cannot be addressed in a completed program owing to the complexity of the format, the reading process, and the training process with the existence of (:) In time. So, it is changed to digital data only, i.e., to Unix time, which is in seconds, where it can be easily used as an input to the network we have created. By merging the date and time data, converting its FORMAT, storing it in a variable called time stamp, and adding it to the database, they all were negative because they represent the past time.

Thus, the data will be dealt with after processing to be: Time stamp, longitude, latitude, depth, and earthquake strength. Part of it can be illustrated in Table 3.

The locations of earthquakes in the study area are indicated on the map, as shown in Fig. 2 (Wathiq *et al*., 2020).

A fundamental problem appeared, which is the missing data. Each implementation gives a significant error rate and the model cannot be trained. Therefore, a mechanism was adopted to delete all the missing data whose value is null to filter the earthquakes in Iraq. We used them in the training process and 123 rows were deleted.

The third step signifies the application of the algorithm; when the database is ready to form step two, data has been read and arranged to determine the fields that will be worked upon in the data Table 3. It has become limited to only five variables.

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The data is divided into determining the input X and featured three as input (latitude, longitude, and time stamp). Output Y has the features that predict them as output (Magnitude and Depth), where the best-fit parameters of the show are utilized to calculate the result utilizing preparing and test information.

Finally, the experimental practical step applies the machine learning methods. The data of 44540 earthquakes is divided into a training set of 80% and a testing set of 20%. Thus, it is 33405 for training and 11135 for testing. Three types of algorithms are learned as follows.

In the beginning, two types of linear regression are used: The first method of ML, which starts with Linear Regression to start predicting the data in the first experiment of the model and according to the instruction reg, fit and it contains the Train and y-train and the expectation is test. It means that the random forest regress or model or machine learning method is not successful.

Secondly, using the second ML method, which is random forest regress, and applying the training process, testing on test and Y_testand when implementing. The credibility of 0.6 is fitted, meaning that the model fails. Furthermore, the expected values are not correct.

Finally, the third method, NN, includes model building and model execution, i.e., building the model first, and after preparing it, implementing it. The model is in two types: The main one always used is called sequential and the dense is the starting point of the model, so the model type is sequential and adding the first layer, which is dense and needs activation and loss function and Input shape = 3, so it has three entries for this model.

Thus, building an NN model, according to the above method, has several features, namely: Loss function, optimizer, activation, and metrics that represent four variables that must be implemented to build this model here we have a process based on this data, the model should give the best options because there are several options, that is, Building the model requires several factors, namely:

a) The batch size can be either 10, 20, 50, or 100
b) Activation may be one of the following options: 'Relu', 'tanh', 'sigmoid', 'hard sigmoid', 'linear ', and 'exponential'
c) Optimizer, in which the result is checked for each cell. If it is weak, it returns to the input, adjusts the weights, and repeats the process of checking the output. It has several types: ('Stochastic Gradient Descent (SGD)', 'RMSprop', 'Adagrad', 'Adadelta', ' Adam', 'Adamax', 'And Nadam') and each has several options

Thus, an experiment will be made to choose the best in the model by trying all the options and then it will print the best options that this model can achieve based on this database, which is as follows.

Activation is relu, the optimizer is SGD, and the loss function is squared_hinge it takes accuracy in metrics.

A suitable NN has been built for the training data set using Unsupervised learning, using 16 nodes after testing with four. Then eight, the results were not satisfactory and in the case of 16, the results were acceptable. Figure 3 shows the components of the NN used to predict earthquakes.

The NN consists of the following layers: 3-layer Input, 16-layer hidden, 16-layer hidden, and 2-layer output.

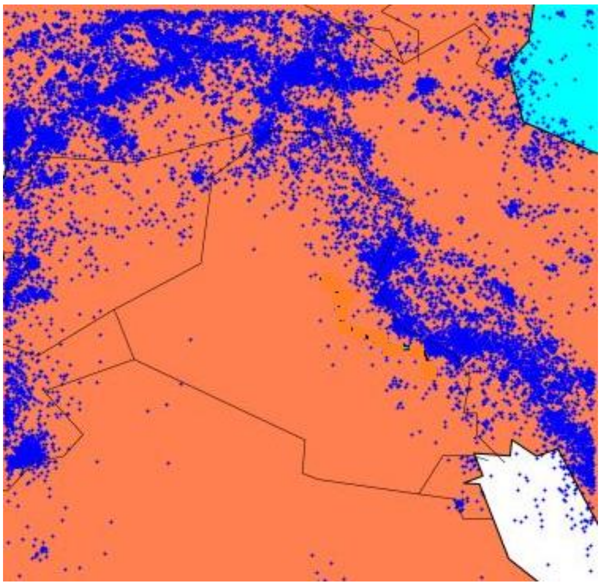

Fig. 2: Locations of earthquakes in the study area on the map

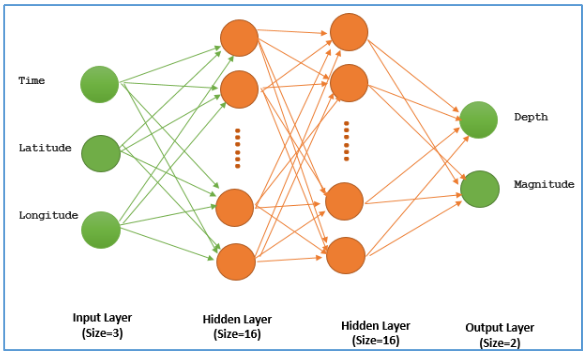

Fig. 3: NN in earthquake prediction

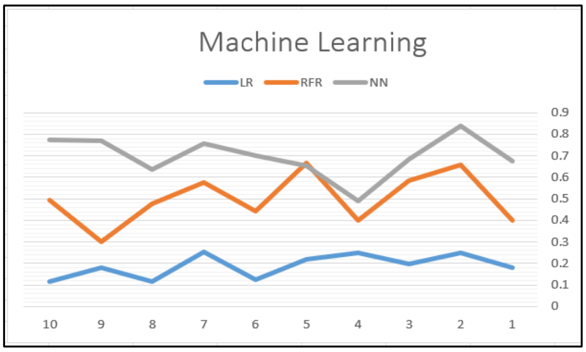

Fig. 4: Machine learning algorithms

It is executed 20 times for training on the data and we can increase it so that it does not go beyond overfitting. The accuracy value was equal to 0.5 and when the epochs were increased and became, for example, 40 times. We started the training process again. The accuracy started to equal 0.5. We continued Increasingly, it reached an accuracy: Of 0.839 and the execution of the program stopped and we got a loss function value equal to 0. 003 in Fig. 4. Performance of the proposed models.

Table 3: Part of the essential data for earthquakes in Iraq from 1900-2019

Latitude	Longitude	DEPTH (km)	Magnitude	Timestamp
38.4500	44.8700	0.0	5.4	-2204312256
38.0000	46.0000	0.0	6.2	-2200442256
33.0000	49.0000	0.0	7.4	-2174266656
38.3800	42.2300	10.0	5.5	-2165401296
|	|		|	|
|	|		|	|
38.8709	43.5207	14.3	2.1	-1577582824
30.8205	50.0474	10.0	3.7	-1577682728
32.4992	46.9521	10.0	2.8	-1577750223
34.7548	45.5659	12.2	2.8	-1577743923

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Materials and Methods

To evaluate the performance of the proposed model with regard to forecasting efficiency, the materials consisted of running the proposed scheme on a data set of 119 years with a size of (34663×14). Our experiments were conducted on an Intel i7-1065G7 processor at 2.5 GHz; with windows 11 64-bit, 16GB RAM (HP laptop). Furthermore, we used Python Colabe to conduct our experiments.

As for the research methods, it can be represented in Fig. 5 to illustrate the building of the model:

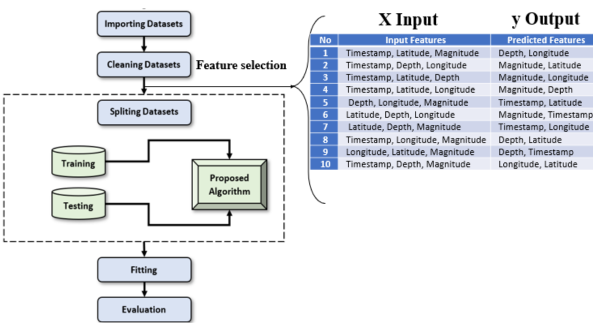

Fig. 5: Earthquake prediction model building

Results and Discussion

The results of applying the three machine learning algorithms, namely LR, RFR, and NN, to earthquake data in Iraq and the surrounding areas are as shown in Table 1. The five features of earthquakes used in this study were switched, and Fig. 4 shows the accuracy in using the three algorithms to predict earthquakes.

Conclusion

In recent years, Iraq has witnessed continuous activity of earthquakes in the governorates of Iraq. This study is considered a major challenge and its data are limited, as we need a larger number of inputs to obtain an accurate prediction of the outputs. In this study, we find that the number of inputs is 3 and the number of outputs is 2. The highest number of inputs was achieved. The accuracy result of the machine learning models, which is the neural network, reached about 0.839 using the seismic data catalog in Iraq and the surrounding areas for 119 years (1900-2019). The inputs are Timestamp, Depth, and Longitude to predict Magnitude and Latitude. The proposed model was compared with models proposed by others, we found that the proposed model achieves appropriate accuracy depending on the number of training features available as well as the size of the data set.

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Author's Contributions

Nada Badr Jarah: Collect data and written the research.

Abbas Hanon Hassin Alasadi: The idea of research, designed and analysis of data.

Kadhim Mahdi Hashim: Written the program and analyzing the results.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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