ARTIFICIAL INTELLIGENCE BASED TECHNIQUES FOR EARTHQUAKE PREDICTION: A REVIEW

Faisal Azam, Muhammad Sharif, Musarat Yasmin, Sajjad Mohsin
Department of Computer Science, COMSATS Institute of Information Technology, Islamabad, Pakistan
faisal@ciitwah.edu.pk, muhammadsharifmalik@yahoo.com,mussaratabdullah@yahoo.com,
smohsin@comsats.edu.pk
Phone: +92519272614

Abstract: *Reinforcement and evolutionary algorithms have been applied with a variety of features and parameters to predict the earthquake in the past. Normal artificial intelligence practices have contributed a significantly in determining the possibility of potential natural disasters. Many approaches have yielded comparatively better results when applied to a certain geographical area. This work covers the study and scientific analysis of the recent intelligence techniques that have been applied to the earthquake data sets. The survey indicates that the dynamics and the nature of potential seismic disasters cannot be predicted completely by applying the results of a single approach. Therefore, a multidimensional approach with diverse features along with good quality data is needed to predict future patterns. Moreover, for regional short term prediction of earthquakes the methods and techniques conventionally adopted may not work consistently and reliably with same strategy for future predictions because the nature and dynamics of underlying earth crust is continuously changing*.

Key words: Earthquake prediction, time series data, Artificial Neural Networks, Swarm Intelligence, Genetic Algorithm

INTRODUCTION

Natural hazards like earthquakes are generally the result of propagating seismic waves underneath the surface of the earth. The vertical motion of the surface waves are recorded by the seismometers installed in different geographical positions to measure the earthquake across the globe [1]. The earth surface formally called the crust is divided into seven large tectonic plates. These larger plates are further divided into several small sub-plates which are continuously in the process of deformation and moving apart. There are several types of ground motion types [2]. These are divergence, convergence which result into transforming plate boundaries. When the plates move apart from each other, it forms divergence of plate boundaries [3]. In the phenomenon of convergence, plates of different densities move towards each other; thereby giving rise to the large mountain ranges [4]. When these plates slide apart from each other, this type of motion is called transformation [5]. Major earthquakes are caused by the divergence, convergence and transformation of plate boundaries commonly known as faults [3]. A fault in any geological region causes stress. On the release of this stress, bigger energy patterns are produced which are referred to as seismic waves or formally seismic activity. Beside the faults, there are other causes of the earthquake like volcanic activity, nuclear tests, mine blasts etc. The origin where earthquake takes place is called the focus point [6]. Table 1 shows layers of earth and their respective depths.

On surface, earthquakes are recorded by a modern form of geophones called seismometers. They are very sensitive to record a small energy pattern from very far off distances. On land, geophones or seismometers are mostly deployed in the form of groups. This cluster of geophones is deployed to increase the accuracy in measurement of seismic values. Geophones serve two purposes. Firstly, they increase the accuracy by reducing noise results; and secondly, they discard the effects of horizontal seismic patterns [7]. These horizontally moving seismic waves are also called ground rolls. They are considered as noise which is caused as a side effect of seismic energy patterns. Vertically propagating waves almost simultaneously strike the seismometers installed in a group and are recorded. Other waves which do not hit the seismometers at the same time like vertical waves are discarded. Thus the total sum of vertically propagating waves is calculated. At the end of this process, the time series data is recorded.

Table 1: Earth Layers and their depth

Layer	Thickness	Nature
Inner Core	1216 Km	Solid iron-nickel alloy
Outer Core	2270 Km	Liquid iron-nickel alloy
Mantle	2885 Km	Solid (Rich Silicates)
Curst	<=65 Km	Solid (intermediate density silicates) Ocean crust Continental Curst

The recording of each receiver or seismometer group is identified by a term known as 'trace' [8; 9]. An earthquake recording of the same source by the installed receiver group is called common source gather. For different sources of earthquakes, this receiver group shows recording as common receiver gather. If the trace of time series data has source receiver at a fixed distance, then this value is called common offset gather. Hence, earthquake time series data can be analyzed by keeping in view all these perspectives.

Four different aspects of this time series data with respect to geophysical analysis can be considered for experimentation. These are a) analyze the earthquake data recording in different time points independent of common source gather or common receiver gather recordings, b) analyze the earthquake data set in fixed or variable length time intervals to predict different hidden patterns, c) gathering layers data, like layer between Euroasian and Indian plate etc, in time points to better analyze and study the seismic patterns of layer with respect to time, d) gather and analyze the earth lithosphere layer data with respect to time intervals [10; 11]. This is typically the most complex scenario as it involves the study of geophysical layer, its actual deformations and alteration in structural parameters with respect to different time points. Different recording units are also used for generating time series. They are Local Magnitude (ML), Body wave magnitude (Mb), Surface wave magnitude (MS), Moment Magnitude (Mw), Energy Magnitude (Me), Duration Magnitude (MD), Felt Area Magnitude (Fa) and Unknown Magnitude (UK) [12]. Different monitoring stations can have variety of recording formats based upon these measurement units. For example, when the receiver is close to the focus point, recording will be in Ml, measuring the pressure waves or primary waves, which are high velocity waves on seismogram, results in Mb recording, earthquake with receiver and focal point distant 20 degree (approximately 2000 Km apart) yields Ms recording, Mw recording has turned up to be a standard measurement and is directly concerned with the physics of the seismic source [13] have explained the method for calculating radiation energy and is recorded in Me format. Specified formulas for particular geography and recording instruments are used by applying coda length of seismic patterns and they are recorded in MD format. Fe magnitude is like Mb magnitude, it is computed for any focus point for time before the general usage of seismic tools. Beside these known measurement units, there also exist some unknown computational techniques and the recordings of those techniques cannot be published for further analysis. Such techniques are termed as UK [14; 15; 16; 17].

LITERATURE REVIEW

Different algorithms based upon artificial intelligence techniques have been adopted by researchers over the past decade to foresee and predict the future earthquake challenges. Such algorithms and techniques included traditional space time based approaches and nature inspired algorithms. What follows below is an overview of the recent developments in the use of intelligent algorithms for earthquake prediction tasks.

The Artificial Neural Networks

Earthquake patterns have been classified with respect to identified features using ANN based networks. Both supervised and unsupervised techniques are utilized for prediction purpose. Dangerous earthquakes can be identified by developing a reliable activation or threshold function in the network. For example earthquakes with larger magnitude and less depth can be most dangerous. However, the earthquakes with larger magnitude and larger depth are often less dangerous. Although, such earthquakes may cause inner energy release patterns or may affect other layers but their affect is not spontaneous. Earthquakes with smaller magnitude and small depth may be sensitive if they prolong over a certain period of time. Such identified characteristics of earthquake can be easily scaled down using some activation function. A typical function is identified by the figure 1.

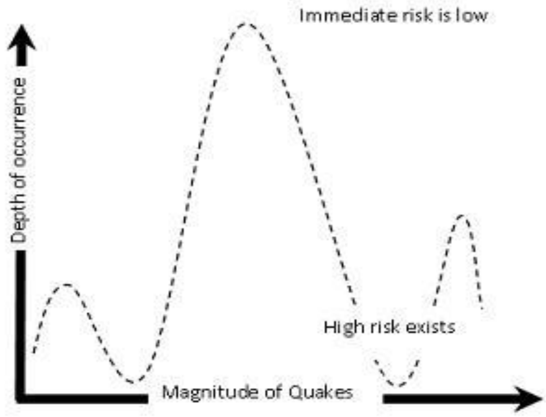

Figure 1: Illustration of criteria for fitness function

Using eight different identified seismic indicators, a probability model is built for future earthquakes by using a probabilistic neural network approach [18]. Output results are tested by using three approaches to increase reliability. These approaches are i) positive chances of occurrences of earthquakes, the prediction probability, ii) probability at which earthquakes were not predicted correctly, the false alarms and iii) true skill statistics. . Data related to South California has been used for this model. Results indicate that this model is suitable for predicting medium range earthquakes i.e. between 4.0 and 6.0 magnitudes. This work is significant because it classifies the input data into seven different classes; based upon its correlation with pre-defined output groups. The output groups in this technique are formed with respect to the magnitude at the difference of 0.5. Each output node in the network is trained based upon its associated input class.

During the testing period 2 of 4 earthquakes were predicted by this technique. Higher magnitude earthquakes are not successfully predicted by PNN model. Recurrent Neural Network model has been suggested for predicting 6.0 and above magnitudes [19]. For predicting medium to large earthquakes, larger geography is divided into smaller regions and time based seismic data sets are also divided into a fixed set of intervals. A recurrent neural network model is used to analyze the changing seismic indicators in sub regions and their relationship with larger earthquakes in the overall region under study. Both the location and time of a potential earthquake are identified by using this approach. This has been identified that dividing the region into sub-regions and data into fixed time intervals improves the prediction performance of Recurrent Neural Network. During iterations of seismic data input, output is given to the recurrent layer. Furthermore, output of the recurrent layer is summed up with the output of hidden layer. This sum is used in activation function for final output of the network. A threshold activation function is used with 1 or 0 as an output, where 1 shows the possibility of an earthquake.

The higher magnitude is predicted by slowly increasing the threshold value by 0.5. Levenberg-Marquardt model is used to minimize the mean square error of the actual output and the desired output of the network. Maximum 1000 iterations are performed. This has been concluded that by increasing the number of days for prediction i.e. 15 days, the prediction accuracy improves significantly. This is mainly because of the availability of sufficient number of training data set. The largest number of earthquakes in the past has been recorded in Chile. A novel neural network technique has been proposed to predict earthquakes in that disaster prone country [20]. In this new technique, three input values to the network are selected which are i) b-value, calculated according to the Gutenberg-Richter law the association between the magnitude and number of earthquakes and time in the region, ii) Bath's Law, which says that the measurement difference between a major earthquake and its largest aftershock is almost constant. This difference is independent of the main earthquake magnitude, and therefore, it is kept constant at approximately 1.1-1.2 Mw and iii) the Omori-Utsu's Law, which is the time based decay of the rate at which aftershocks happen. Probability is calculated for next 5 days for the earthquakes that happen below the threshold value of the magnitude and larger earthquakes that happen more than 5 days time in fixed interval. Threshold value is adjusted according to the result of false and positive alarms in the region. Earthquake prediction has been defined by this work in four aspects i) A defined location i.e. Chile ii) defined interval of time i.e 5 days or more, iii) magnitude minimum and maximum limit and iIV) common probability of occurrence. For each defined area in Chile, one neural network is used with all mentioned parameters. Each time, on encountering earthquake, values and matrixes related to ANN is updated in for each defined area. Sigmoid activation function is selected for experimentation under feed forward network topology. Back propagation based learning algorithm is used for training the data. A comparative analysis of selected approach with k-nearest neighbors, SVM and k-means clustering has been performed. On average more than 71% accurate results are achieved using this approach. Seismogenic areas of Peninsula are studied using multi-layer neural network model. Experiments focus on the twofold area of prediction. These are i) larger earthquakes than the defined probability set by the threshold value of neural network architecture and ii) earthquake magnitudes that happen under certain limit as set by the threshold value. At the start of this work, basic scenarios related to the happening of earthquakes in the region are determined. Later, neural network model is built by identifying parameters. For this purpose seven days are selected for measuring prediction. Four parameters are selected to check the performance of the network. These four parameters are i) True positives, the total number of times neural network correctly determined earthquakes in 7 days, ii) True negatives, the total number of times neural network did not generated probability of earthquake and earthquake did not occur at that time, iii) False positive, neural network predicted an earthquake and earthquake did not happen during the defined time, iv) False negatives, no forecast was measured and earthquake did occur in the defined time. Spanish geographical data has been utilized for these experiments. The results are summarized in the figure 2.

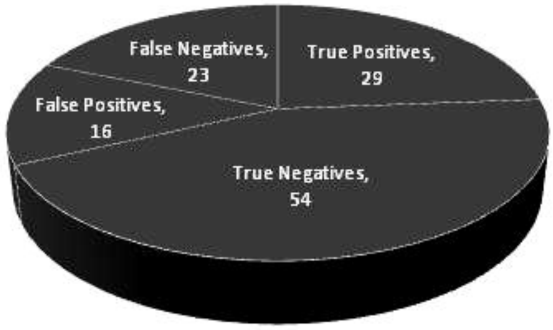

Figure 2: Multilayer Perceptron results

For true positives, actual reading of earthquake magnitude was detected to be 3.70, whereas the prediction was 3.65. Thus the prediction accuracy remained 99%. Later these experiments are extended for other areas in the region. This shows that ANN can yield better results if trained using proper parameters and threshold for earthquake prediction [21]. An adaptive fuzzy neural inference model is built for determining earthquake occurrences in Iran. A long 6.1 magnitude Qeshm's earthquake happened on September 10, 2008. A main characteristic of this work is the analysis of alterations in spatial geographical parameters that were caused by this earthquake. Supervised model of radial basis function with ANFIS has been implemented. Data is normalized and principle component analysis is performed before the final analysis on data. Gridding technique has been utilized to determine the parameters for neural network model. The RBF and ANFIS model is iteratively improved by seeing the quality of final results. Genetic algorithms were used to determine the topology of radial based function network. Data related to the experimented area was divided into three zones. Zone near to the epicenter predicted high chances of earthquakes. Other zones have almost similar type of prediction with no major difference in upcoming magnitude. Results show the true chances of future main shocks by evaluating spatial and time based conditions. Research also determines the need of using more proper parameters for the experiments [22]. This has been observed that back propagation based ANN carries many local minima while training the earthquake data sets. In order to overcome this problem research related to Southern California data set used Bee Colony algorithm. Four main parameters used are i) geographical distance to be predicted, ii) Depth of earthquakes, iii) Temporal parameters and iv) magnitude [23]. Wavelet analysis main principles are used with artificial neural network to determine the time delay between two earthquakes. This combination is used to train and test non linear magnitudes [24]. Prior warnings system in the Bay of Bengal is built using back propagation neural network. Parameters used for training are atmospheric pressure, weather, salinity and conductivity [25]. Earthquakes may cause damage to the dams in their domain. Possibility of damage measurements to the Fei-Tsu dam due to main shocks have been studied using ANN based approaches. An early warning system has been built for on hand preparing activities. Water pressure and temperature distribution like parameters are analyzed. A dynamic neural network using non-linear autoregressive with exogenous (NARX) model base class is used for studying the dam damages. A regression standard deviation is calculated and a threshold level is measured for the deformation. ANN is used to watch the health of the dam [26].

Swarm Intelligence

Different versions of SI algorithms are employed using earthquake data sets to predict shape, size, sequence, variations and structure of layers. Artificial Bee Colony algorithm has proved useful for solving different complex problems. Neural networks can also be trained using ABC. In common swarm intelligence is the investigation in the social life of different natural inhabitants and Stimergy. These can be bacteria, for which E-Coli has been studied to form Bacterial Foraging algorithm, ants pheromone are used to develop Ant colony algorithm, and immune system of human being are modeled into population based immune system. This has been observed that Back propagation neural network often trap into local minima while training the earthquake data set. Also it has slow convergence rate and often it might fail. In order to minimize these bottlenecks, SI is being used in most of the research works [23]. Results of BNN and ABC algorithm are compared for seismic data set. 1000 records are tested by both algorithms with different weights. Training of BNN is stopped on getting 0.0001 error set. ABC and Hybrid ABC is stopped on MCN. Sigmoid function is used as an activation function. Average mean square error of HABC, ABC and BP remained 0.00151229, 0.00164425 and 0.0016 respectively. Results claim that HABC remained more effective and efficient. Later CPU usage time, Signal to noise ratio and normalized mean square error comparison of all the techniques has been performed for earthquake data set. Previously, similar work used Artificial Bee Colony algorithm is used for Multilayer Perceptron training on earthquake data set. Parameters used by the research are number of food sources, which are similar to the total number of employed bees, limit of value, maximum cycles performed by MLP-ABC algorithm. Weights are initialized based upon comparison with the actual output. Scout bees are then assigned weights. Bees search till the last cycle to determine the most suitable weights for the network. Source of food which was neglected earlier by the bees called scout is replaced with the new source of food. Each bee determines the new dimension and velocity based area and best area is determined by Greedy Selection based approach. Food area is kept in range in order to avoid infinite results. It is applied at random. Best source of food and the bee position is kept in memory by replacing the older values. Basically, bees here are searching for the best values in the network. South California earthquake data set has been applied to this algorithm. Data consist of limited latitude and longitude positions. Four common parameters are selected which are, depth of occurrence, time, area and magnitude. Earthquake magnitude is predicted using this approach. This work claimed the better results of ABC over BP [27]. Overall scenario is depicted in the figure 3.

Figure 3: SI-MLP training concept

Advanced inversion techniques using Particle Swarm optimization algorithm are used to find the local earthquake locations. Time based arrivals of seismic waves at different seismic stations are formulated as an inverse problem, using which location of earthquake epicenter is predicted. Longitude, latitude and depth based position vectors are used. Travel times of waves are calculated of seismic waves for different stations. Quadratic and standard PSO based models are used to calculate travel time. Both PSO's have different mathematical properties. This has been concluded that PSO following different mathematical models can compute the epicenter position based upon inverse problem. The observed hypocenter or epicenter points are calculated very near to the actual source. Moreover, efficiency of QPSO was found better over SPSO ([28]. In a similar work, slope stability of earth surface has been analyzed by using Ant Colony algorithm. This is an NP hard problem to determine and estimate the slop slip position and its rate mainly because of structural deformation of the earth crust. First of all population is initialized using slope geometry, nature of soil, water, number of ants and limited iterations based parameters. Problem is formulated in the form of a graph with the assignment of initial pheromone component value to each ant. Ants are placed on the graph and network is started to obtain acceptable solution, pheromone value is revised and updated iteration by iteration. At last the graph is evaluated to determine with the best and worst pheromone value of surface. This has been observed that soil to soil condition, number of iterations and ants, affect the overall results. Thus this needed to be carefully selected [29]. Ant colony and K-means clustering was analyzed for earthquake prediction. Non-linear characteristics of upcoming magnitude and its prior and post effects can be monitored using ant colony algorithm [30]. Results indicate that ant colony algorithm moves shorter distance on average i.e. yields better results than the k-means clustering. ACO takes more time to execute comparatively with the k-means clustering. Thus, ACO algorithm has concluded better option for earthquake future researches. In order to avoid structure failures of buildings, tuned mass damper device is installed. Particle swarm optimization is utilized to observe excitation of TMD devices during earthquakes. Parameters utilized are suitable mass ratio, damper damaging by time, and tuning frequency. This has been concluded that PSO can be used to measure and observe all the stated parameters affectively [31]. A geophysical inverse model is prepared artificially as a M-dimensional model. Goal has been to develop the model that suitably explains the behavior of data. Experiments show that global best optima can be reached before 100 iterations of the PSO algorithm [32].

Genetic Algorithm

GA has been applied in past to solve NP hard problems for optimal results. The advantage of using GA on seismic data is that GA can manage uncertain and incomplete information. For example we may have missing many values of magnitude in certain period of time. Previously GA has yielded better results when applied as an optimization procedure over structural formation study. Today, GA is being applied with variations in different experiments. All these variations are the extensions of simple GA, SGA [33]. Simple GA constitutes selection of population called chromosomes, cross over and mutation operation. A fitness value is estimated which allow population to survive into next iteration. Often elitism is performed which allows parent value to be selected in next iteration based upon biasness. These iterations are kept on until some limit criteria is achieved. Ground motion in a defined region is observed by developing a GA based model. Mainly GA is used to lower down uncertainty which exists in the data set. The synthesized data is found similar to that of recorded data because of the applied procedures of validation based upon elastic response spectra. These uncertainties are reduced or eliminated by comparing the input population with the synthesized earthquake data. Later fitness value is calculated. Initial population is also passed to the EMPSYN software program which works on the principle of EGF technique. This procedure can be adopted for the regions where some data values are missing. The artificial data may not be free from uncertainties, however it is found suitable in its relation with the recorded seismic data [34]. Unusual variations caused in the Total Electron Content Seismo-Ionospheric anomalies due to a recent strong earthquake in Solomon Island, Febuary, 2013 have been studied. Genetic Algorithm was used for the said purpose. GA successfully detected anomalies and also predicted earthquakes in next 7 to 8 days. Normally ionospheric conditions are affected by weather and solar extreme conditions. Later the findings of GA are matched with other algorithms like Median, ANN, Support Vector Machines, ARIMA and Wavelet. Almost all the algorithms yielded similar results which is the successful forecast of main earthquake after seven days and main shock after three days [35]. A least mean square LMS method and GA is used to increase the efficiency and reduce the time taken by prediction system. The database consisting 5323 records related to 208 earthquakes are tested for magnitudes between 4.5 and 7.3. Method of string representations of GA is used wherein a main string is represented by k-bit binary integers. GA with three different fitness functions, are applied by the name of GA1, GA2 and GA3. It has been observed that when the GA is optimized; it increases the optimization capability of fitness function. While changing the fitness function decreases the GA performance. For this reason, the fitness functions were kept constant while performing a total of 5000 iteration steps. Crossover and mutation probability is also set constant to 0.8 and 0.05 respectively [36]. Figure 4 illustrates the experimentation process of this work,

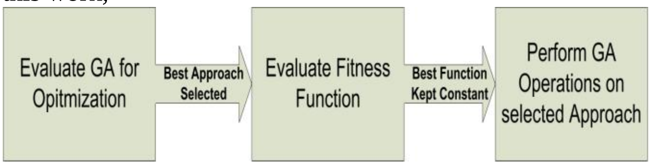

Figure 4: Optimization steps of GA for earthquake data set

This has been found after experiments that GA is much better in optimization and performance then other methods like Least Mean Square method. This is mainly because LSM cannot converge easily to optimal solution if the initial guess or probability provided is far from the optimal points. In table 2 Different AI based approaches are summarized for their recent uses.

CONCLUSION

Until recently, Artificial Intelligence based techniques were widely used for earthquake time series prediction. As the prediction failure problem resulting from the changes in lithosphere is non-linear in nature, the results of traditional approaches of probability estimation should be enhanced by using the particle swarm optimization and genetic algorithms based approaches. PSO, GA and ANN are capable to find actual fault intensity in any particular region. They are also used to estimate the possibility of potential damage likely to be caused by a certain earthquake. For complex nature of earthquake structures, prediction of this natural disaster is not a simple job. A formal and conventional regional earthquake prediction approach may not work for predicting the future earthquakes. In view of this difficulty, a dynamic and self adaptive strategy is required which should have the features of adjusting itself with the changes in structure and size of regional faults. For this purpose, self organization maps have proved very successful as they contain the capability of self adaptation and learning quality. This work is an attempt to cover different strategies related to AI for earthquake prediction and crosscheck their reliability. Although these strategies have been designed and tested for regional earthquakes, yet their results need to be evaluated on the data obtained from other regions so that the standardized and fully reliable mechanisms for prediction this frequently-occurring natural calamity can be developed.

Table 1: AI Inspired methods for earthquake prediction

Algorithm	Illustrated recent usages	Comments
Feed Forward Neural Network	Used with sigmoid function [37] Used on Seismic Electric signals, predicted magnitude and pre-determined future seismic events. 80.55% accuracy [38] Prediction of structural responses for a structure [39; 40].	Able to predict both long term and short term shocks. Outputs of different layers are not feedback.
Back Propagation Neural Network	Prediction efficiency is 71% [20]. Output Error of prediction is propagated backward to inner layers with constant ratio. Used for building prior warning system [25]	Often stuck in many local minima while training earthquake data sets. Yields more desirable results when tested with tested with optimal designed inputs.
Particle Swarm Optimization	Used for selection of input values for the BPN based network [27]. Can determine earthquake local earthquake location [28].	Works on the principles of Swarms of particles searching for optimal solution in the defined search space. Converge to the solution more efficiently then general BPN.
Artificial Bee Colony Algorithm	Hybrisd strategy of development is used [23; 27]. Used to predict Tsunami intensity [41]. Rock mass stability is estimated for planning purpose [42].	Lower mean square error rate then other algorithms. A part of Swarm Intelligence algorithms, inspired by the working of honey bees in colony.
Genetic Algorithm	Structural formation has been studied using GA [33]. Lower the data uncertainty [34]. Used for building settlement forecast after main shocks. Used in combination with support vector machines for earthquake data set [43].	Can work with improper or incomplete seismic data. Found highly efficient in prediction for future earthquakes. Commonly used in research with different alterations.
Clustering	Spatial clustering is used versus temporal clustering for earthquake data sets [44]. Spatial clustering has been identified in data set while building earthquake forecast model using differential probability [45].	Set of clusters is developed from huge set of unsupervised data. This makes the overall scenario to be divided into many sub-scenarios. Used in MSc algorithm with different aspect.
Fuzzy Logic	Applied to synthetic seismic data to determine the parameters of earthquakes [46]. Used for degradation detection along with Self Organization Maps. Produces results better then Multiple Regression Model [47]. Hazard's assessments [48].	Capable of dealing with uncertain seismic data. Works on the principle of quantified and identified rules related to seismic features and their relationships.
Hidden Markov model	Applied to earthquake classification. Regions are divided into different sets of clusters to identify future changes [49; 50]. Used for identifying key features related to seismic stress patterns which are not directly observable under normal conditions [51]. Used with Poisson process [52].	When change occurs in specific class, variations can be easily modeled. Can be termed as statistical inspired model. Also used for time series analysis besides normal applications of speech recognition and synthesis.
Kohonen Maps	Tectonic regions with sparse and non-redundant data are analyzed [20]. High dimensions of seismic data and its strong correlation with actual tectonic activities are forecasted [20; 53].	Unsupervised learning of training data set. Automatically adjust itself to the optimal solution.
Association rules mining	Rules of different instances of earthquakes are formed with the identified relationship between them. Have been applied to Spanish earthquake data set [21].	Significantly useful results are obtained by this technique. A novel approach for future earthquake evaluation.

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