Hybrid Neural Network Methodology to Detect and Predict Seismic Activities

R. Lokesh Kumar

Associate Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India

E-mail: lokeshkumar.r@vit.ac.in

Abstract

The prediction of earthquakes, which can be devastating calamities, has proven to be a challenging research area. Because it involves filtering data to disturbed day changes, the contribution from multi-route effects and typical day-to-day fluctuations even on quiet days, the extraction of earthquake-induced features from this parameter requires intricate processing. Nevertheless, many researchers have successfully used several seismological concepts for computing the seismic features, employing the maximum Relevance and Minimum Redundancy (mRMR) criteria to extract the relevant features. The Artificial Neural Network (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) are the primary soft computing tools that can be collaborated to detect and estimate earthquakes positively. The model in ANFIS is developed using subtractive clustering and grid partitioning procedures. The outcome shows that compared to ANFIS, ANN is more effective at predicting earthquake magnitude. Furthermore, it has been discovered that using this method to estimate earthquake magnitude is highly quick and cost-effective. Compared to earlier prediction studies, the acquired numerical findings show enhanced prediction performance for all the regions considered.

Keywords: Earthquake, prediction, neural network, machine learning, neuro-fuzzy interference, performance enhancement

1. Introduction

One of the major disasters that causes panic and restlessness is an earthquake, and because they are unpredictable, they also inflict significant financial losses and human casualties. The ability to anticipate earthquakes has been the subject of a heated discussion between two opposing points of view. Some consider this prediction impossible, while others
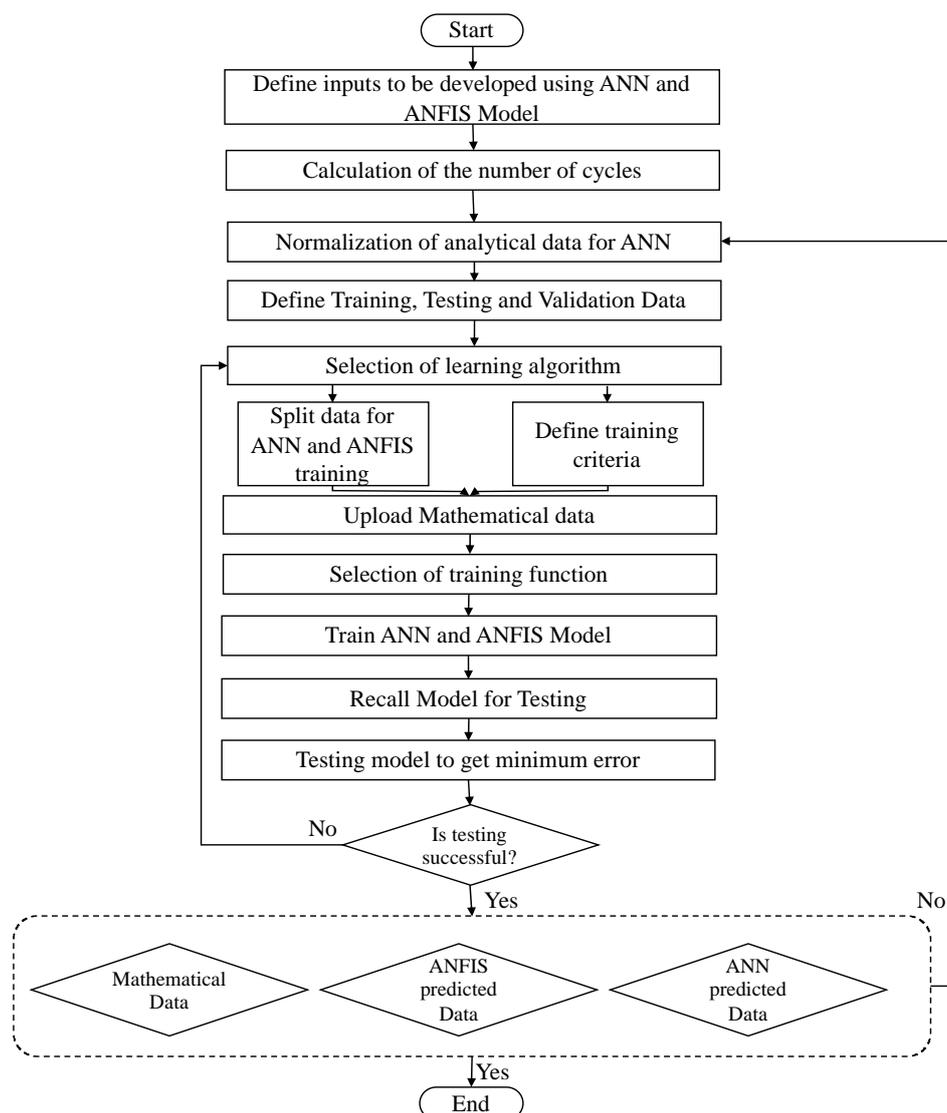
have expended their efforts and resources to attain this task. In [1], the authors compare the historical data for the seismic activity by employing ANFIS and ANN to predict the earthquake. The input parameters predict the earthquake's longitude [2], latitude [3], time [4], and focal depth [5]. Their main motive is to minimize earthquake-related damage by taking early preventative measures. Human labour can be reduced to a large extent by using this technique for the prediction of the magnitude of the earthquake [6].

The second challenging task is the disconnect between seismologists and computer scientists when it comes to utilizing the various technological platforms to find solutions. Significant advancements across multiple study domains have been made possible by the development of contemporary computer science-based intelligent algorithms. For example, there are weather forecasting [7], disease diagnosis [8], debris collapse [9], tsunamis [10], and researchers have been conducting in-depth studies for many years to raise people's understanding of the phenomenon of earthquakes along with their primary and secondary effects, because of the high mortality and damage rates [12], [13]. They have put forth a number of earthquake prediction strategies [8] and used Artificial Neural Networks (ANN) in conjunction with seismic characteristics [14], opening up new avenues for investigation and suggestions for future studies on earthquake prediction.

The Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Artificial Neural Networks (ANN) have been successfully used in multiple studies to forecast the highly chaotic behaviour of rainfall, forecast financial analysis, and recognise patterns of speech, images, etc. In challenging situations, an optimal solution is provided by the fuzzy inference systems (FIS) and ANN. A robust computational model, ANN has effective learning and adaptive capabilities. However, the foundation of FIS is the ability of human-like reasoning abilities. ANFIS is sometimes referred to as a hybrid of fuzzy logic and ANN as it combines the principles of fuzzy logic and neural networks. It is considered to be a hybrid and smart soft computing tool.

In [15], the authors used ANFIS to forecast the earthquake's location and magnitude. To identify the most important input factors, the authors in [16] performed a principal component analysis (PCA) study on earthquake prediction in Iran using ANN and ANFIS. ANFIS was used by the authors in [17]-[18] to try and forecast the size of earthquakes in Iran; however, the data set had already been normalized before training. Without utilizing any normalization techniques prior to training the data, researchers in [19] used ANFIS to forecast the earthquake's magnitude.

2. Proposed Work

```
                        ( Start )
                           |
        Define inputs to be developed using ANN and
                     ANFIS Model
                           |
            Calculation of the number of cycles
                           |
            Normalization of analytical data for ANN  <------+
                           |                                  |
         Define Training, Testing and Validation Data         |
                           |                                  |
              Selection of learning algorithm  <---+          |
                     |            |                |          |
         Split data for      Define training       |          |
         ANN and ANFIS         criteria            |          |
            training                               |          |
                     |            |                |          |
                Upload Mathematical data           |          |
                           |                       |          |
               Selection of training function      |          |
                           |                       |          |
                Train ANN and ANFIS Model          |          |
                           |                       |          |
                 Recall Model for Testing          |          |
                           |                       |          |
             Testing model to get minimum error    |          |
                           |                       |          |
          No       < Is testing successful? > ----+          |
                           |                                  |
                          Yes                              No |
     +-----------------------------------------------------+ |
     | < Mathematical     < ANFIS          < ANN             |
     |    Data >            predicted         predicted ----+
     |                      Data >            Data >
     +-----------------------------------------------------+
                           | Yes
                        ( End )
```

Figure 1. Flowchart of the proposed model

This section details the working process for our suggested method architecture of earthquake predication and its main components as follows:

- Definition of Inputs
- ANN and ANFIS technique for prediction
- Testing

Fig.1. represents the architecture of the proposed Neural Network model.

2.1 Artificial and Adaptive Neural Network model

An artificial Neurological Network is an affective computing system called an ANN that uses biological neural networks as an analogue for its main idea. Additionally known as "artificial neural systems," "parallel distributed processing systems," or "connectionist

systems," ANNs have several other names [20]. To enable communication between the units, ANN gathers a sizable group of units that are related in some way. These components, often called nodes or neurons, are basic parallel processors. Through a connecting link, every neuron is joined to every other neuron. Each connecting link is associated with a weight containing the information regarding the input signal. The conveyed information is either suppressed or excited by this weight. Hence, to resolve a specific issue, the neurons can make use of this data. The intrinsic state of each neuron is referred to as an activation signal. By combining the activation rule and the output signal, the signal may be received by other units in the network.
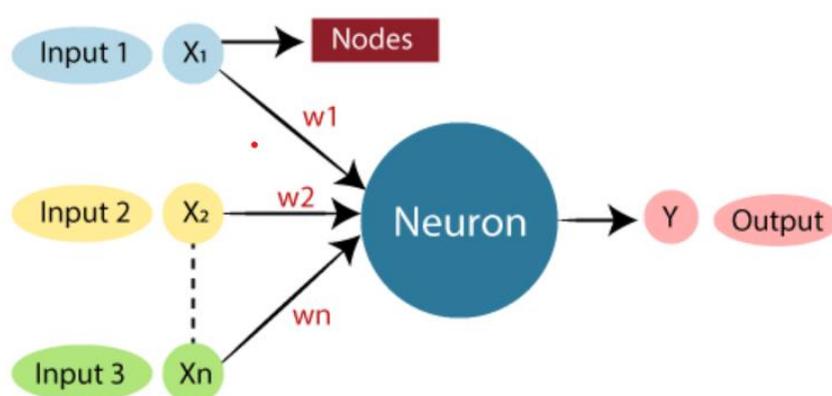
Figure 2. ANN model

The three layers of an ANN are hidden, input, and output layers, as shown in Fig.2. With some weights, every neuron in a specific layer, d, is linked to every neurone in the following layers.

$$W = \sum^{\eta k} - w\ x^k + \beta$$

In the above layer, the number of neurons is represented by η, and the bias of the individual neurons and weights of different connections are given by **w x^k**. The training input data is a significant factor in achieving the desired output. Meaningful data is available in the weights, and a random weight is picked. The training is terminated once the desired output is achieved. Further, the smart ANN system will predict the output for the given input data. To handle uncertainties, a mathematical technique termed fuzzy logic is used. Issues that need human instinct to be solved make use of fuzzy logic. The defuzzification interface, fuzzification interface, decision-making unit, database and rulebase are the five functional elements of the fuzzy inference system. Table 1 provides the details of the earthquakes considered in this research for analysis.

Table 1. Parameters of the earthquake considered for investigation

S.No	Time	Latitude	Longitude	Depth	Mag	Gap	Location Source	Mag Source
1.	2022-07-18T11:34:31.048Z	36.7085	71.0678	209.21	4.3	57	US	CE
2.	2022-07-18T11:34:25.281Z	19.16617	-155.463	41.9	2.9	158	AK	US
3.4.	2022-07-18T09:55:52.640Z	63.3071	-151.109	3.2	2.6	179	HV	AK
5.6.	2022-07-18T09:35:53.310Z	19.13483	-155.406	31.93	2.83	136	HV	HV
7.	2022-07-18T09:20:21.344Z	12.8477	-88.0844	73.11	4.3	133	US	HV
8.	2022-07-18T08:09:25.035Z	15.4311	-61.171	142.9	4.2	52	US	US
9.	2022-07-18T08:04:49.045Z	34.4697	45.5653	10	4.4	267	US	US
10.	2022-07-18T08:01:28.200Z	18.84467	-155.212	9.56	2.52	185	HV	US
11.	2022-07-18T07:58:45.510Z	18.0465	-67.9495	7	3.75	172	PR	HV
12.	2022-07-18T07:03:39.127Z	-5.3089	102.6686	29.76	4.4	167	US	PR
13.	2022-07-18T05:49:34.400Z	17.98133	-66.8518	12.9	2.54	168	PR	US
14.	2022-07-18T05:00:24.120Z	18.76133	-155.23	6.58	3	275	HV	PR
15.	2022-07-18T04:16:15.310Z	19.1665	-155.46	32.45	2.58	121	HV	HV

The capabilities of ANN and fuzzy logic are combined to create the ANFIS, a hybrid intelligent system that overcomes the limits of each. An adaptive network is a multilayer feed-forward network with directed links that connects its nodes to form. Each node applies a

specific function to its receiving signals for producing a single node output. Each connection defines the direction in which signals move from one node to another; the link has no associated weights in an adaptive network. In more detail, the adaptive node configuration applies a static node function to its incoming signals, thereby producing a single node output. Changeable parameters in the parameterized function are used for each node function. The overall behaviour of the network and the node functions can be altered by varying these parameters.

The least-square estimate and gradient descent methods are combined to create a hybrid approach for optimization. The premise parameters in ANFIS are the parameters that need to be optimized. This paper considers that ANFIS has two inputs, C1 and C2, and one output, E, as shown in Fig.3. Let's examine the order:

Rule 1: If (c is C1) and (d is D1) then E1=p1c1 + f1d1 + r1

Rule 2: If (c is C2) and (d is D2) then E2=p2c2 + f2d2 + r2

Here, p1,f1,p2, f2, r1 and r2 are linear parameters. C1, C2, E1 and E2 are non-linear parameters, in which C1 and E1 are the ANFIS membership functions. f1, p1, and r1 are the consequent parameters.
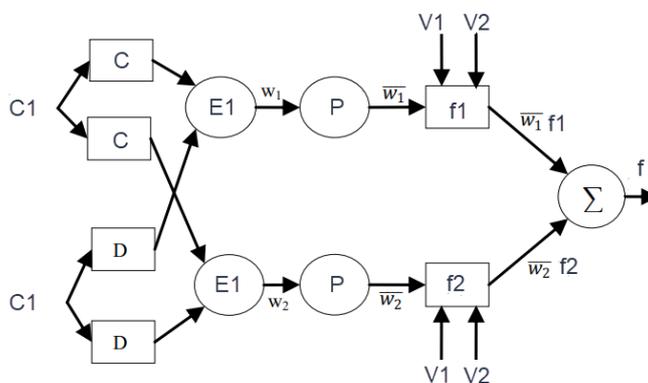
Figure 3. ANFIS Model

2.2 Layers of ANFIS

Layer 1: In this layer, each node is adaptive. Node functions include extended bell membership functions and Gaussian membership functions.

**Layer 2:** In this layer, the output of each node displays the firing strength of a rule.

Layer 3: Each node indicates the average firing strength of each rule.

Layer 4: Each node in this layer is adaptable and has a node function that shows how the rules contributed to the final output. In this layer, the parameters are referred to as subsequent parameters.

Layer 5: The sum of all the outputs from the rules is computed by a single node in layer 5 of the architecture.

3. Results

The greatest challenge for researchers is predicting earthquake magnitude. Since the impacts of the factors are not known in advance, it may be possible to predict earthquake magnitude with greater accuracy in a short amount of time. Full comprehension: In this study, soft computing tools such as ANN and ANFIS are used to calculate the earthquake magnitude. The comparison analysis demonstrates that ANN predicts earthquake magnitude more effectively than ANFIS. The accuracy rates reported in the study are based on the out-of-sample performance for each model.
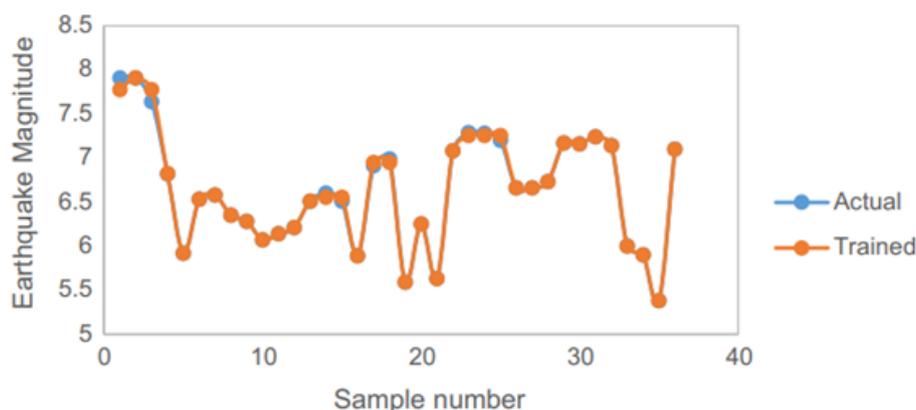
Figure 4. Comparison between the magnitude of the earthquake and the number of samples considered
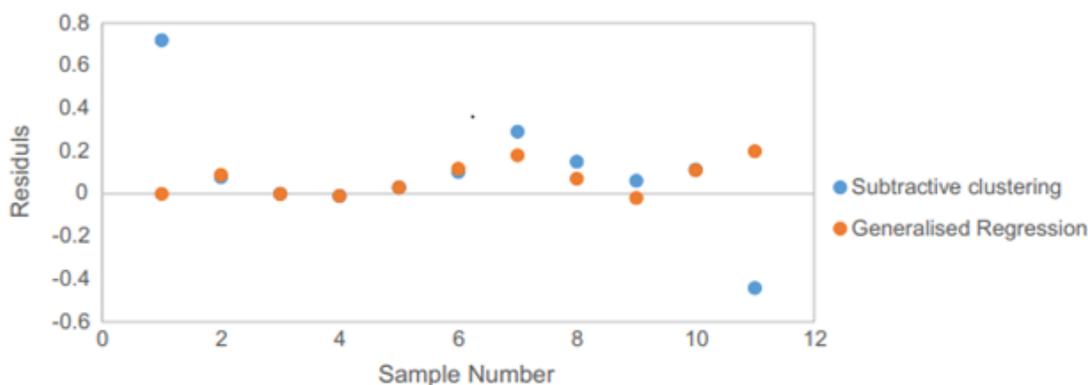
Figure 5. Comparison between the residue and the number of samples considered

It indicates that various sets of data are used for training and testing. This model can also forecast the size of impending earthquakes. It's possible that the current prediction is not very accurate, but it is hoped that this inquiry will give practitioners some important information. The scope of this inquiry can be expanded by adding more input variables for estimating earthquake magnitude. Fig.4 and Fig.5 compare the residue and magnitude of neural network data and actual data.

4. Conclusion

The interaction between the computer science-based soft computing smart methodologies and seismology-based earthquakes is used to predict an earthquake in the interdisciplinary research carried out in this paper. This research offers an innovative and effective general framework for earthquake prediction in terms of frequency and maximum magnitude, along with an ANN and ANFIS model method. For each month, the maximum magnitude and number of earthquakes that happened for a short duration are fed as an input to the model. This allows the model to extract important information from the historical data fully. Furthermore, ANFIS is used to extract spatial attributes after data pre-processing. Finally, the completely connected layers receive the ANFIS output to produce the finished product. The simulation results in two case studies show that the suggested method performs best when compared to existing shallow machine learning and deep learning approaches.

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Author's biography

R. Lokesh Kumar is currently working as an Associate Professor in the School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India. His area of research includes WSN, cloud computing, artificial intelligence, IoT and image Processing.