International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 02, 2021

Earthquake Magnitude Prediction using Artificial Neural Network Model

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Abstract- The research based on Seismology gives the importance around the globe new tools methods, new tools and algorithms are needed in order to predict the magnitude, time and geographic location, and also to analyse the effects of earthquakes and in future to safeguard the human lives. Due to the highly random nature of the earthquakes gives the highly random nature of the earthquakes and the complexity in obtaining an efficient mathematical model, until now the efforts are insufficient and new methods are capable of contributing to this challenge is needed. In this present work a novel method based on earthquakes magnitude prediction method is proposed based on the measurements of more than two decades of seismology events which is modeled using machine learning. Richter magnitude (ML) of 5.3 and a depth of 299 km in the study region, located at 14º-37 º N and 68 º -95 º E, was used as a training data to construct an initial earthquake Richter magnitude (ML) prediction back propagation neural network model with two hidden layers. By using final weights and biases, the back propagation neural network model is implemented. It will be analysed for an embedded earthquake Richter magnitude (ML) prediction back propagation neural network (EEMPBPNN).

Keywords: Back propagation neural network, Artificial Neural Network, Feedforward Neural Network

1. INTRODUCTION

In the seismic prediction the earthquakes do not occur everywhere in the world, but they will be concentrated in few regions. The global standard seismic observation network **[1][2]** was established as part of Taiwan's Central Weather Bureau (CWB) in the 1960s, which allowed easier estimation of the locations and extents of earthquakes worldwide. There are three major seismic zones in the world, namely, the circum-Pacific seismic belt, the Eurasian seismic belt and the mid-ocean ridge seismic belt **[3][4].**Taiwan is an island in one of these great earthquake belts. Taiwan is located in one of these great earthquake belts, and, according to past earthquake catalogues [**5] [6]** the island has suffered many major earthquakes that have caused serious loss of life and property. One such earthquake occurred in 1999, known as the 921 earthquake **[7]**. It is inevitable that another major earthquake will occur in Taiwan, therefore, it is necessary to research the prediction of upcoming earthquakes. The previous chances of predicting earthquakes indicates as though it is having almost difficult situations. Statistical methods are a feasible option if major earthquakes are a regular occurrence **[8].** Taiwan is located at the collision between Eurasian and Philippine Sea which exhibits the structure of a continental margin island arising from such a collision. Six to seven million years ago, the Sea plate of Philippine Sea was collided with Eurasian plate which lead to the land reclamation and orogeny process which is active even today [**9] [10][11]**. Taiwan is located at the collision between Eurasian and Philippine Sea which exhibits the structure of a continental margin island arising from such a collision. Six to seven million years ago, the Sea plate of Philippine Sea was collided with Eurasian plate which lead to the land reclamation and orogeny process which is active even today. Thus this island is subject to intense seismic activity. The seismic activity sees the changes when a foreshock occurs and be used to predict the main shock. **[12].** The significant foreshock, prediction depends on the seismic characteristics prior to the main shock. The earthquake which occurs in the eastern region are relatively significant, but they are not typically accompanied by large earthquakes. From the basis of 921 earthquakes , the National Science Council and relevant research institutions invested a large amount of money and manpower into seismic research, and this effort has generated some useful information in recent years.

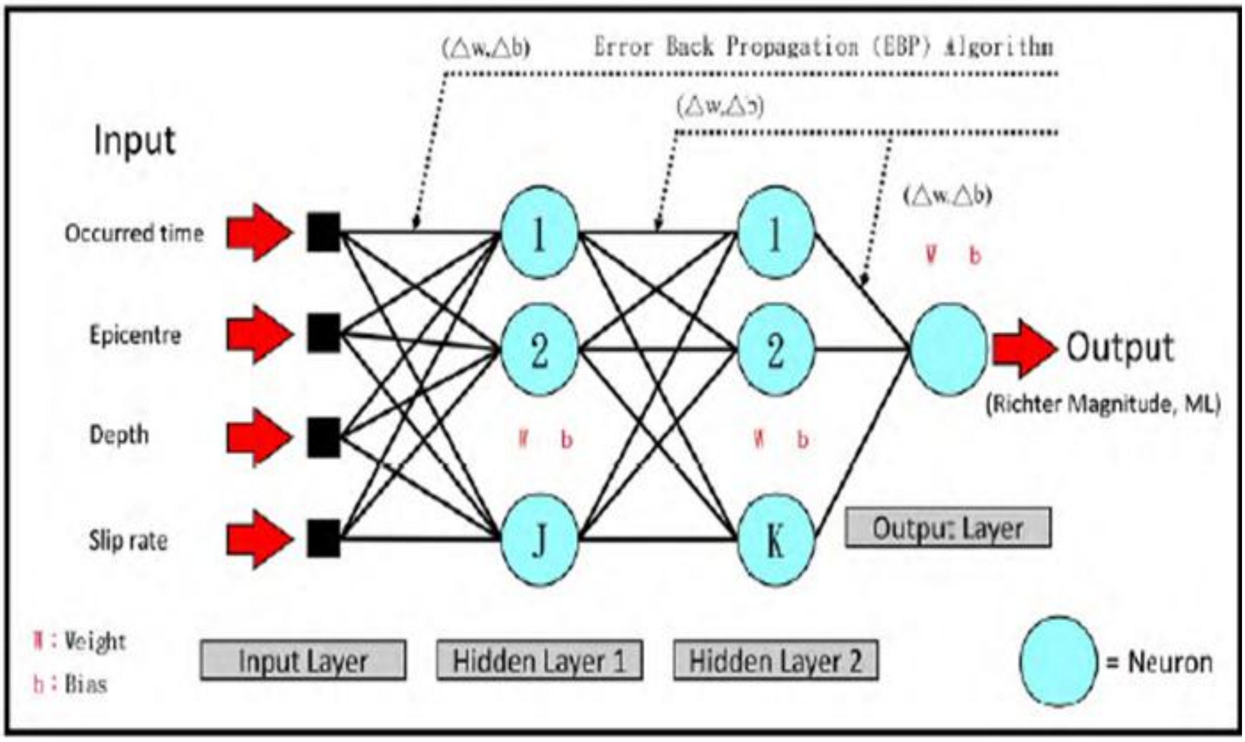

Figure 1. Back Propagation Neural Network block diagram with two hidden layers. [5]

The errors (ΔW, Δb) estimated from the error back propagation algorithm in terms of weights and biases between each hidden layer minimizes the errors which is shown in Figure 1. Training of Artificial Neural Network (ANN) to establish a network model with 2 hidden layers determines the optimal neuronal number in each hidden layer for predicting the magnitude of any future earthquake. This involved the re-training of a network model using a new earthquake catalogue without requiring a long significant computing time and relying on more initial inputs from earthquake catalogues. It was expected that the prediction error would be reduced when a long computing time was no longer required owing to the use of an earthquake catalogue covering a long time period. This was implemented without the use of localized geological features and could be accomplished by determining the optimal number of neurons through an intelligent optimization training algorithm using an inversion method to construct the ANN.

2. MODELING

The feed-forward neural network , which consists of a number of neurons linked with different input and output set of learning patterns, also consists of an input vector layers , more hidden layers and output vector layers . The single training pattern shown in Equations (1)-(3) I/O vector of pairs of input-output values in the entire matrix of I/O training set. The neuronal model is shown in Figure 2

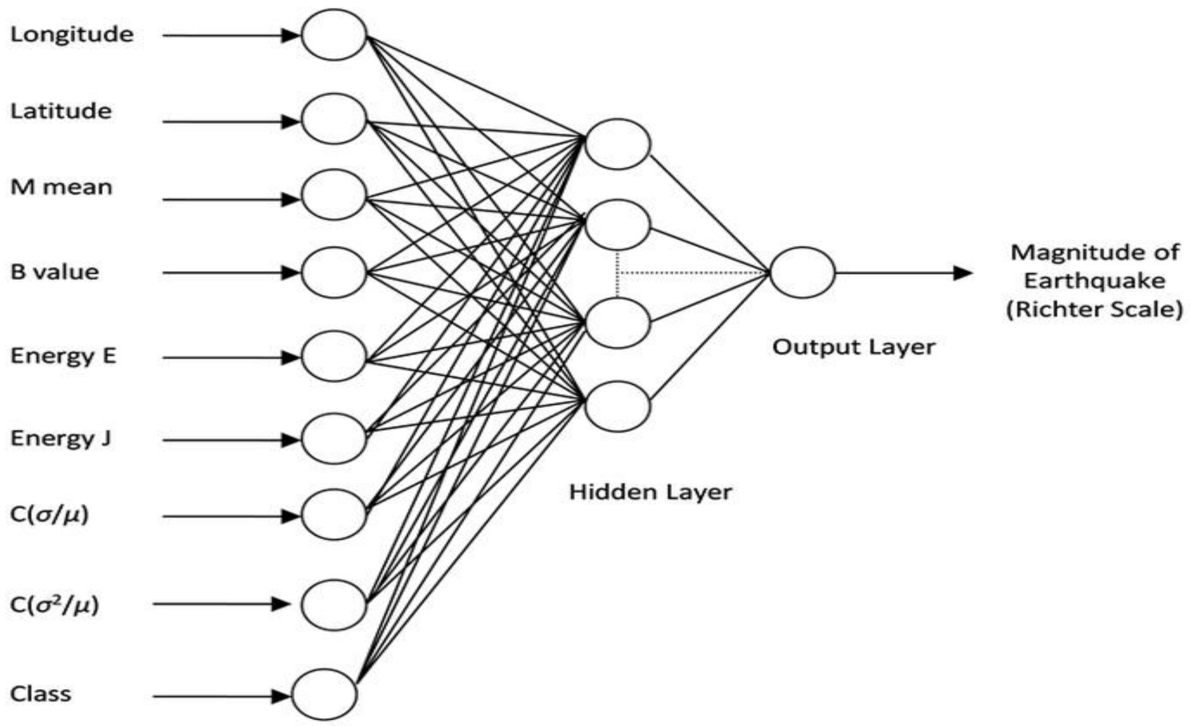

Figure 2. Neural Network Architecture representing the magnitude of earthquake [18]

Input layer applied to the electrical signal consisting of the inputs x_i, where i=1,2,…..n, received by neurons in human brain. These input signals are multiplied by connection weights $w_{p,ij}$ and the effective input $net_{p,j}$ to neurons is the weighted sum of the inputs

$$\mathbf{net_{p,j}} = \sum_{i=1}^{n} w_{pij} net_{q,i} \quad \textbf{(1)}$$

where w_{pij} is the connecting weight of the layer p from the I neuron in the q (source) layer to the j neuron in the p (target) layer, $net_{q,j}$ is the output produced at the i neuron of the layer q and $net_{q,j}$ is the output produced at the j neuron in the layer p. Inputs x_i correspond to $net_{q,j}$ for the input layer. At the output layer the computed output(s), otherwise known as the observed output(s), are subtracted from the desired or target output(s) to give the error signal

$$\boldsymbol{\varepsilon}(\boldsymbol{w}) = \frac{\mathbf{1}}{\mathbf{2}\boldsymbol{m}} \|\boldsymbol{E}(\boldsymbol{w})\|^2 \quad \textbf{(2)}$$

$$\mathbf{E_i\,(w)} = \sum_{j=1}^{t}\left[\boldsymbol{out_{k,j}} - \boldsymbol{tar_{k,j}}\right] \quad \textbf{(3)}$$

where m is the number of training pairs, tark, I and out k, I are the target and the observed output(s) for the node I in the output layer k, respectively. The numerical minimization algorithms used for the training generate a sequence of weights matrices through an iterative procedure. To apply an algorithmic operation A, the starting value of the weight matrix w(0) Equation (4) is needed, while the iteration formula can be written as follows.

$$\boldsymbol{w}^{(t+1)} = \boldsymbol{A}(\boldsymbol{w}^{(t)}) = \boldsymbol{w}^{(t)} + \Delta\boldsymbol{w}^{(t)} \quad \textbf{(4)}$$

The various methods applied in Artificial Neural Network is decomposed into two parts as shown in Equation (5)

$$\Delta\boldsymbol{w}^{(t)} = \boldsymbol{a_t}\mathbf{d}^{(\mathbf{t})} \quad \textbf{(5)}$$

where $d^{(t)}$ is a desired direction of the move and at the step size in that **[18]**. The approach related to ANN concept is more closely related to the ANN concept of distributed processing in which computations can be made independent to each other. Furthermore, it appears for many applications as it achieves faster and reliable prediction more than the global techniques. **[19]**

3. PREDICTION VERIFICATION AND RESULT

From the computed data, the trained values of ANN are compared with seismometer recorded values in different regions of India is shown in Figure 3

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ISSN: 2008-8019
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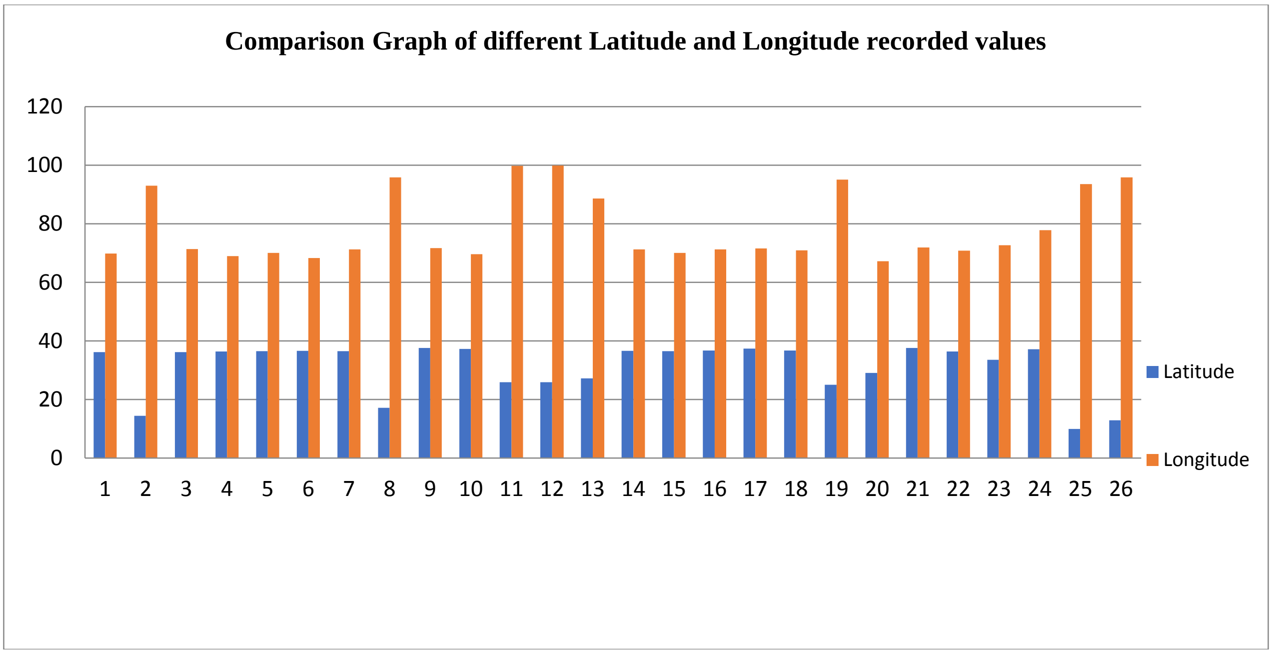

Figure 3. Comparison Graph of Different Latitude and Longitude recorded values

The earthquakes ranging in the magnitude range of 4-5, and the Seismometer records the magnitude 4.0 ~ 5.0 in our research, but Back propagation algorithm using ANN forecasted magnitude range from 3.5 – 5.4 it is more than the originally recorded values. The magnitude range of 5.8 and above is predicted for larger earthquakes. The following table shows the comparison between computed values of BPANN predicted values and originally recorded values for 2018.

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Table 1: Comparison between computed values of BPANN predicted values and originally recorded values for 2018

Input Class	Output Magnitude Range	ANN Predicted Values for 2018
Class 1	**4**	**4.1**
Class 2	**4**	**4.0**
Class 3	**4.2**	**4**
Class 4	**4.1**	**4**
Class 5	**4**	**3.5**
Class 6	**5**	**4.0**
Class 7	**4.6**	**4.4**
Class 8	**4.5**	**4.3**
Class 9	**4.5**	**4.2**
Class 10	**4**	**4**
Class 11	**4.4**	**4.3**
Class 12	**4.3**	**4.2**
Class 13	**4.3**	**4.1**
Class 14	**4.5**	**4.4**
Class 15	**4.9**	**5.4**

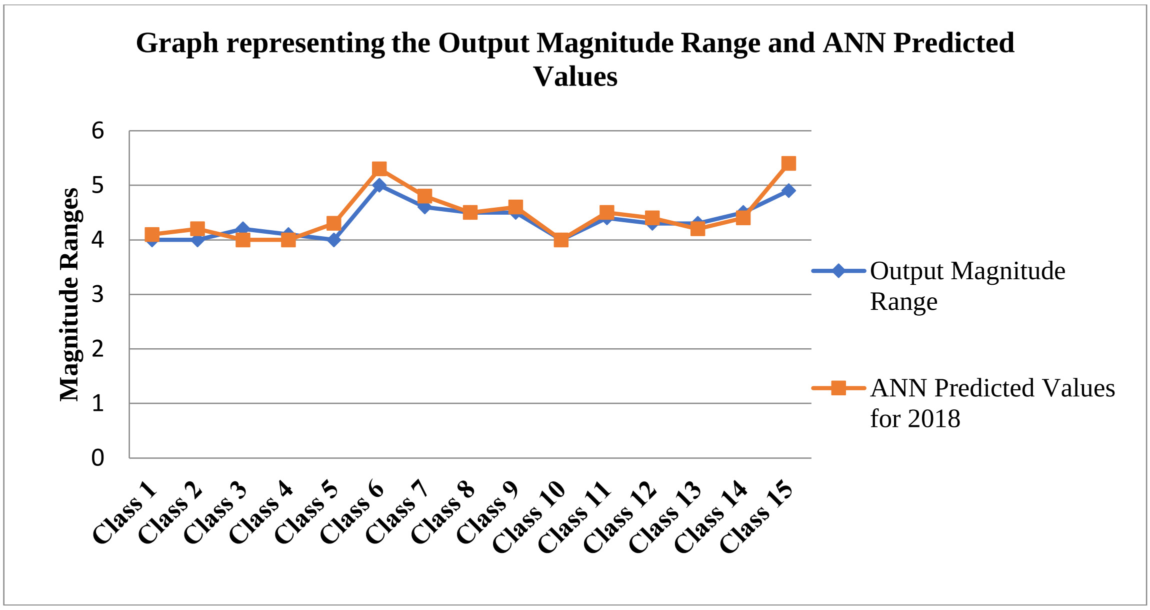

Figure 4. Earthquake prediction values using Back Propagation Algorithm

4. CONCLUSION

In this work, the prediction of the magnitude of the events occurring in the next was performed by using a Back Propagation Artificial Neural Network and the earthquake Richter magnitude (ML) prediction ranges was found using back propagation neural network model with two hidden layers, by taking as the only available information of the series of magnitudes. However, since earthquakes are characterized by several variables, we have included latitude and longitude which could add to the network and possibly find more robust patterns that could further minimize the prediction error. The results show that the BP Artificial Neural Network model provides higher prediction accuracy for the magnitude ranges from 3.5 – 5.4 and it is more than the originally recorded values. BP ANN model is better than the other proposed models for forecasting Earthquakes below Magnitude ranges 5. This is due to the fact that the BP ANN is capable to capture non-linear relationship compared with statistical methods and other proposed methods.

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