

Comparison of B-Value Predictions as Earthquake Precursors using Extreme Learning Machine and Deep Learning

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Abstract—Knowledge of earthquake predictions is very important, especially to identify patterns of occurrence of earthquakes based on data obtained from the Meteorology and Geophysics Agency (MGA). This paper proposes an earthquake prediction system, in the form of predicting the b-value as a parameter that indicates the precursor to earthquakes. A precursor is something that precedes or is thought to indicate the appearance of something, in this case, an earthquake. The paper considers two methods which are Extreme Learning Machine and Deep Learning. The simulation results show, in the training process, Deep Learning produces better b-value prediction performance as an earthquake precursor compared to Extreme Learning Machine. Meanwhile, in the testing process, the Extreme Learning Machine produces a slightly better b-value prediction performance as an earthquake precursor compared to Deep Learning. Both in the training process and in the testing process, in solving the case of predicting b-values as earthquake precursors, deep learning is more superior.

Index Terms— b-value, Extreme, Deep, Learning, predictions.

I. INTRODUCTION

AN earthquake could be a vibration that happens on the surface of the planet because of the sudden unleash of energy that makes unstable waves. Earthquakes are usually caused by the movement of the Earth's crust (Earth's plate). The frequency of a section refers to the sort and size of the earthquake experienced over a period of time. Earthquakes are measured by employing a Seismometer tool. Moment magnitudes are the foremost common scale wherever earthquakes occur for the total world [1].

For earthquake monitoring purposes, among others, based

on groundwater level fluctuations. Where if there is a lot of groundwater level fluctuation in a certain period, it is likely that an earthquake will occur in the next 4 to 50 days [2]. In terms of earthquake monitoring needs, it can take advantage of the application of the Wireless Sensor Network. With the application of Wireless Sensor Networks, it is hoped that the results of monitoring groundwater level fluctuations can be known earlier. Thus it can provide early warning and predictions of earthquakes [3].

An earthquake will produce seismic information in the form of a recorded signal in the form of a wave which, after going through manual or non-manual processing, will become phase reading data. Seismic information then undergoes a process of collection, processing, and analysis so that it becomes earthquake parameters as follow [4]:

- Time of an earthquake (Origin Time) is the time when stress is released in the form of earthquake wave propagation and is expressed in days, dates, months, years, hours, minutes, seconds in UTC (Universal Time Coordinated) units.
- An epicenter is a point on the earth's surface which is a perpendicular reflection of the hypocenter or focus of an earthquake. Epicenter locations are made in the Cartesian coordinate system of the globe or geographic coordinate system and are expressed in degrees of latitude and longitude.
- The depth of the earthquake source is the hypocenter distance calculated perpendicular to the earth's surface. Depth is expressed by the distance in km.
- Earthquake strength or Magnitude is a measure of the strength of an earthquake, describes the amount of energy released when an earthquake occurs and is the result of Seismograph observations. Magnitude uses the Richter scale (SR).
- Earthquake intensity is a measure of the damage caused by an earthquake based on the results of observations of the effects of the earthquake on humans, building structures and the environment in a certain place, expressed in the MMI (Modified Mercalli Intensity) scale.

The relationship of frequency-magnitude (Frequency-Magnitude Distribution, FMD) is a way to see seismic activity. FMD from earthquakes was first indicated by

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Gutenberg-Richter [5], which may be a Stevens' power law. Globally the b-value approaches one, which suggests that ten times the decrease in activity is expounded to the rise in every unit of magnitude. This relationship is understood because of the Gutenberg-Richter relation, written as in (1):

$$\log n(M) = a - b M \quad (1)$$

where $n(M)$ is the number of earthquakes with magnitude M . Whereas the a-value could be a seismic parameter whose magnitude depends on the number of earthquakes and certainly regions betting on the determination of volume and time window. For further information, regarding the effect of the b-value parameter as a tectonic parameter, please read paper [1].

II. RELATED WORKS

Research on earthquakes or earthquake predictions from previous studies, among others, can be stated as follows: Time-series estimation of earthquakes using ANFIS with mapping functions [6], Analysis of Ionospheric Precursors from Earthquakes using GIM-TEC, Kriging and Neural Network [7], and Earthquake Prediction Systems using Neuro-Fuzzy and Extreme Learning Machine [1]. Each comparison of the results of previous studies is as presented in Table I.

TABLE I
COMPARISON WITH PREVIOUS RESEARCH

No.	Authors	Research Title	Research methods	Result
1	Endra Joelianto, Sri Widiyanto, and Muhammad Ichsana	Time series estimation on earthquake events using ANFIS with mapping function	Using Adaptive Neuro-Fuzzy Inference System (ANFIS) which has been modified using the Mapping Function	The effectiveness of the modified ANFIS has been compared with the ANFIS standard which is shown by the simulation results both the frequency and magnitude of the earthquake. The modified ANFIS has demonstrated satisfactory validation and prediction of earthquake events compared to the standard ANFIS.
2	Armstrong F. Sompotan, Nanang T. Puspito, Endra Joelianto, and Katsumi Hattori	Analysis of Ionospheric Precursor of Earthquake using GIM-TEC, Kriging and Neural Network	Using Global Ionosphere Maps (GIM) - TEC, Kriging and Neural Network methods	The Kriging method is good for interpolating GIM-TEC star data as neural network input data to estimate the epicenter area. The success of neural networks to estimate the epicenter area is a new stage for the development of earthquake prediction methods.
3	Basuki Rahmat, Fitri Afiadi, and Endra Joelianto	Earthquake Prediction System using Neuro-Fuzzy and Extreme Learning Machine	Using Neuro-fuzzy with ANFIS and Extreme Learning Machine (ELM)	From the experimental results in this earthquake prediction, it can be seen that the Extreme Learning Machine (ELM) method has better performance than Neuro-fuzzy with ANFIS structure.

From previous studies according to Table I, this paper considers another approach to predict the occurrence of potential earthquakes by predicting the b-value. The b-value is a value that describes the seismotectonic state of an area which can be seen from the relative frequency of major earthquakes and minor earthquakes that occur. The earthquake parameter estimated from this b-value is a precursor to strong earthquakes based on time series data, without considering the characteristics of other earthquake physical parameters. While the paper is aimed to compare the Extreme Learning Machine and Deep Learning methods.

The internetworking between nodes in the Extreme Learning Machine and Deep Learning architecture is as if internetworking between PCs in a computer network architecture. However, the number of nodes is usually large, making the problem complex and challenging to be continuously researched. Extreme Learning Machine and Deep Learning have been proven to solve the problem of time-series prediction. Some examples of Extreme Learning Machine in time-series prediction, among others, can be found in the following papers [8]–[12]. Meanwhile, some examples of Deep Learning in solving time-series prediction problems can be found in the following papers [13]–[17].

III. PROPOSED METHODOLOGY

A. Research Data

The significance of information and communications technologies (ICTs) for disaster management and how they can assist in distributing earthquake warnings has been considered in [18-19]. In general, the block diagram of the ICT base station system for earthquake warning and prediction is shown in Fig. 1.

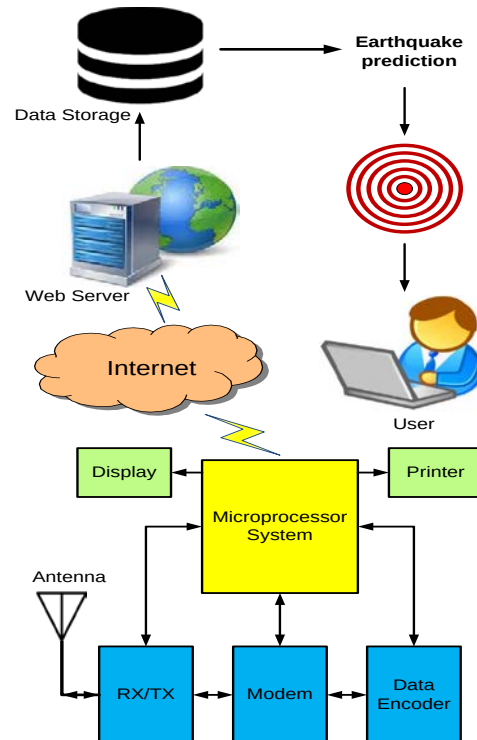


Fig. 1. Block diagram of the ICT base station system

The data used in this study are earthquake data from the catalog of the International Seismological Center (ISC) Sumatra-Andaman region, which includes the boundaries of 92° - 106° East Longitude (EL) and 6.5° South Latitude (SL) - 8° North Latitude (NL), period January 1973 - November 2014. Magnitude greater than 3.0 SR, with a depth of less than 300 km [1].

The curves of change in b-mean values for time for the entire study area are shown in Fig. 2. The red bar shows when a large earthquake occurred with $M > 6.5$. The curve shows that almost all earthquake occurrences $M > 6.5$ are close to ideal conditions, that is, the b-value decreases in the period nearing the time of the earthquake and increases in <1 year intervals [1].

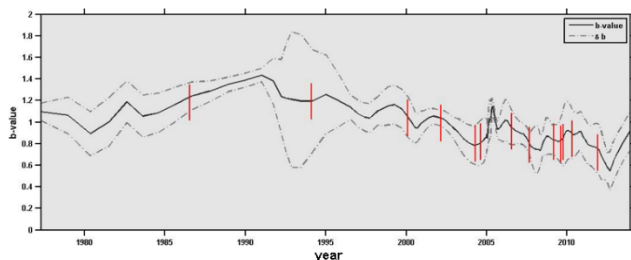


Fig. 2. The b-value plot is averaged over time

B. Model Structure

The data used are the b-value data from January 1973 - November 2014, or as much as 455 months. For ease of data formatting, only 444 months (37 years) were used. So, the data used is the b-value data from December 1973 to November 2014. The structure of the training data model and data validation of this study are designed as shown in Fig. 3.

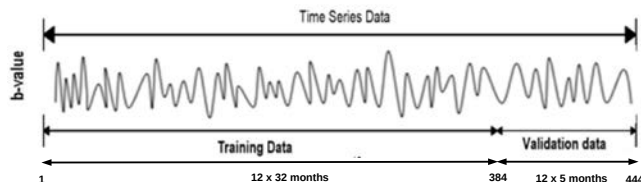


Fig. 3. The b-value training data model structure and data validation

In the design of the model structure as in Fig. 3, it can be seen, from the earthquake dataset 444 months, 12×32 months, or 384 months were used for the training process. The remaining 60 months are used for the validation process. Furthermore, from the structure of the b-value training data model and the validation data, it is used to design the Extreme Learning Machine and Deep Learning network architecture.

C. Extreme Learning Machine and Deep Learning Architecture

According to the structure of the b-value training data model in Fig. 3, each data is divided into 12 months or 1-year data. If x is the training data for 12 months, then the training data is arranged into $(x(1) \dots x(31))$ as training data input, $x(32)$ as the training data output. Then $(x(33) \dots x(37))$ or 5 years (5×12 months) data are used as test data. Used in five tests. Each of these is used to predict the next year. Then the Extreme Learning Machine and Deep Learning network

architectures that are suitable for this structure is a system with 31 inputs and one output. Or a system with 31 years of data (31×12 months) is used to predict earthquakes in the next year.

The Extreme Learning Machine network architecture suitable for this training data model is designed as shown in Fig. 4. Where the system is designed with 31 input nodes, 1024 hidden nodes, and 1 output node. Whereas the Deep Learning network architecture suitable for this training data model, if three hidden layers are used, each with the same number of nodes as the number of input nodes, namely 31, is designed as in Fig. 5.

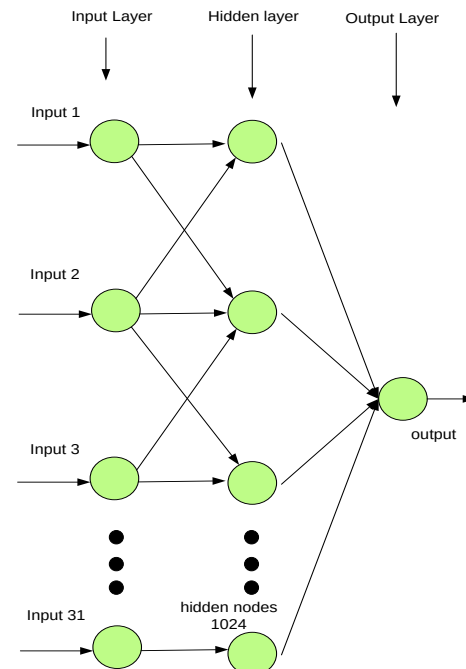


Fig. 4. Extreme Learning Machine Architecture

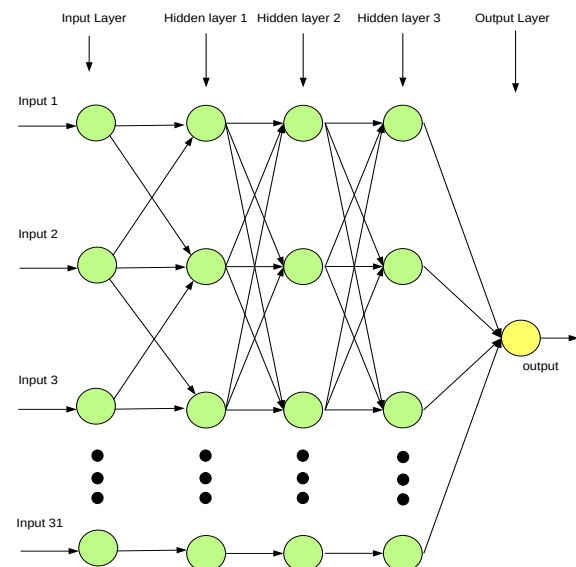


Fig. 5. Deep Learning Architecture

From Fig. 5, there are green and yellow nodes. The green nodes in the input layer and the hidden layer are designed to

use the ReLU activation function, while the yellow nodes in the output layer are designed using the Sigmoid activation function.

D. Training and Testing Flowchart

By the Extreme Learning Machine network architecture in Fig. 4, and the Deep Learning network in Fig. 5, the training and testing process for Extreme Learning Machine and Deep Learning are designed as shown in Fig. 6.

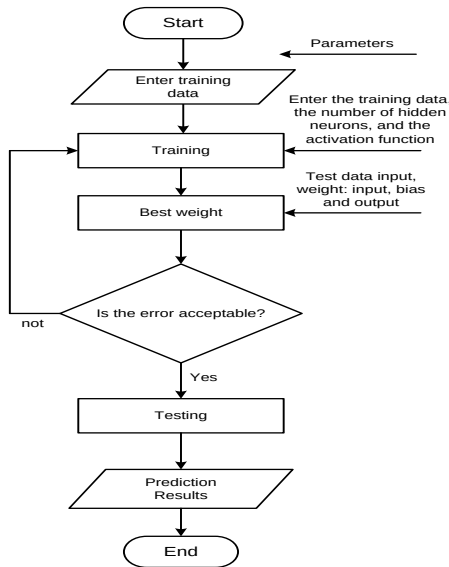


Fig. 6. Flowchart of the training and testing process for Extreme Learning Machine and Deep Learning

Following Fig. 6, Extreme Learning Machine and Deep Learning networks are trained using training data in the form of pairs of input and output data according to the training data model. In the training process, it is processed with weights and biases using the appropriate activation function. Then the Extreme Learning Machine and Deep Learning network output is compared with the target or desired output, until the error can be accepted. Furthermore, using the best weight is used for the testing process. In the testing process, new data is given, then it is processed at each layer until a network output called prediction is obtained. The results of this prediction will be used later in this study to predict the b-value as a parameter that is believed to be a precursor to an earthquake. The results of performance appraisal in the prediction process for each method are expressed in the form of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Success Percentage (%).

IV. RESULTS AND DISCUSSION

The training process for the Extreme Learning Machine and Deep Learning system network is with 31 inputs and 1 output, using b-value input data from December 1973 to November 2008. The target data or desired output is data from December 2008 to November 2009. The results of the one iteration training process for Extreme Learning Machine and 10,000 iterations for Deep Learning are shown in Fig. 7, Fig. 8 and Fig. 9.

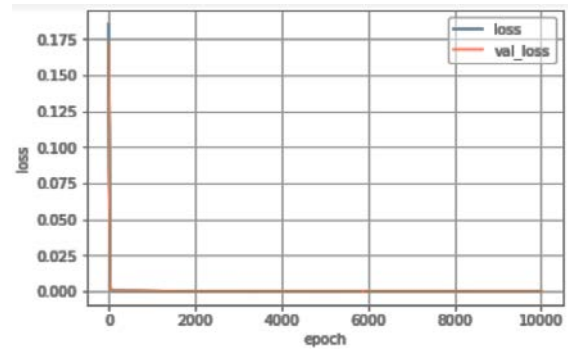


Fig. 7. The process of reducing the loss in the mean squared error in the Deep Learning training process

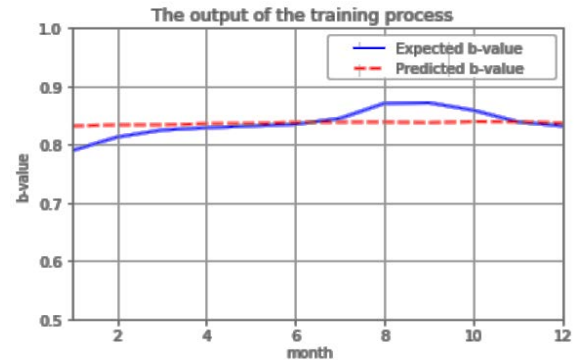


Fig. 8. The output of the Extreme Learning Machine training process

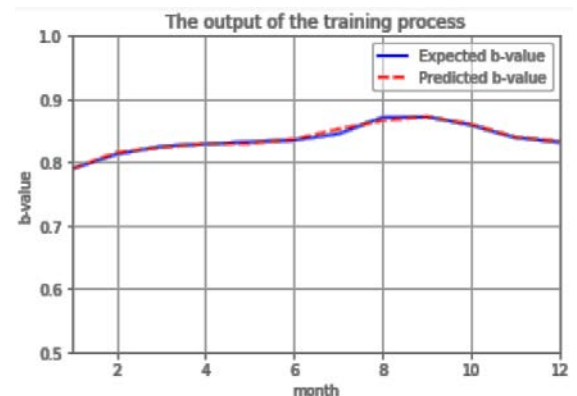


Fig. 9. The output of the Deep Learning training process

The results of the Extreme Learning Machine and Deep Learning training process for the b-value prediction system as earthquake precursors are briefly presented in tabular form, as shown in Table II.

TABLE II
RESULTS OF THE TRAINING PROCESS

Method	Iteration	MSE	RMSE	MAPE	Success Percentage (%)
Extreme Learning Machine	1	0.00042	0.02042	1.83176	98.17
Deep Learning	10.000	$7,72 \times 10^{-6}$	0,00278	0,22386	99.78

From the results of the training process in Table II, it can be seen that for predicting the b-value as an earthquake precursor, Deep Learning produces better performance compared to Extreme Learning Machine, indicated by a better success percentage value. To produce this performance, Deep Learning must be iterated 10,000 times, compared to Extreme Learning Machine which is only one step. Thus, the training process using Deep Learning takes longer.

Furthermore, for testing, it was tested 5 times. In the first test, the Extreme Learning Machine and Deep Learning network systems were given b-value input data from December 1974 to November 2009 used to predict the b-value as a precursor to earthquakes for the next year, starting from December 2009 to the month November 2010. The second test, the Extreme Learning Machine and Deep Learning network systems were given b-value input data from December 1975 to November 2010. It was used to predict the b-value as a precursor to earthquakes for the next year, from December 2010 to with the month of November 2011. The third test, the Extreme Learning Machine and Deep Learning network systems were given b-value input data from December 1976 to November 2011. It was used to predict the b-value as a precursor to earthquakes for the next year, starting in December 2011 to November 2012. In the fourth test, the Extreme Learning Machine and Deep Learning network systems were given b-value input data from December 1977 to November 2012. It was used to predict the b-value as a precursor for earthquakes for the next year, from December 2012 to the month November 2013.

Finally, in the fifth test, the Extreme Learning Machine and Deep Learning network systems were given b-value input data from December 1978 to November 2013. It is used to predict the b-value as a precursor for earthquakes for the next year, starting in December 2013 to November 2014. An example of the results of the first testing process is shown in Fig. 10 and Fig. 11.

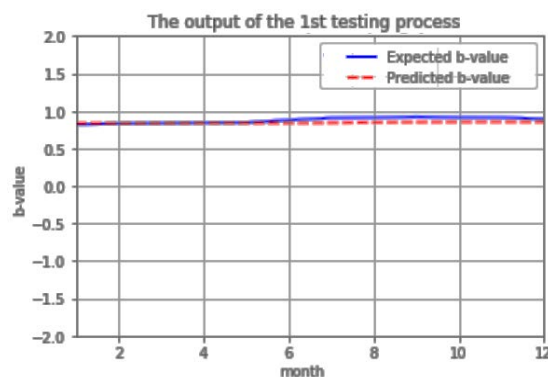


Fig. 10. The output of the 1st Extreme Learning Machine testing process

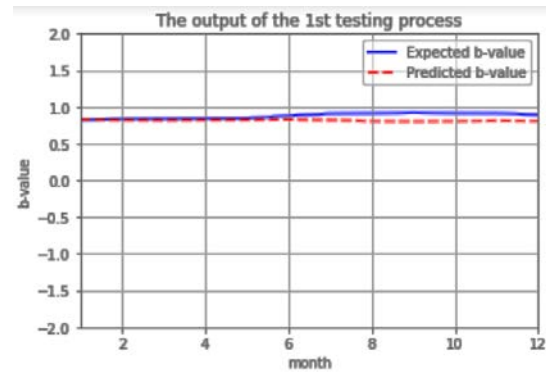


Fig. 11. The output of the 1st Deep Learning testing process

The results of the Extreme Learning Machine and Deep Learning testing process for the b-value prediction system as an earthquake precursor are briefly presented in tabular form, as shown in Table III and Table IV.

TABLE III
THE RESULTS OF TESTING THE PREDICTION OF B-VALUES AS EARTHQUAKE PRECURSORS BASED ON EXTREME LEARNING MACHINE

Testing	MSE	RMSE	MAPE	Success Percentage (%)
1	0.00191	0.04367	3.84401	96.16
2	0.00181	0.04260	4.40522	95.59
3	0.01633	0.12779	17.33621	82.66
4	0.03681	0.19185	30.63310	69.37
5	0.01105	0.10511	14.19340	85.81
Average	0.01358	0.10220	14.08239	85.92

TABLE IV
THE RESULTS OF TESTING THE PREDICTION OF B-VALUES AS EARTHQUAKE PRECURSORS BASED ON DEEP LEARNING

Testing	MSE	RMSE	MAPE	Success Percentage (%)
1	0.00552	0.07431	6.83788	93.16
2	0.00501	0.07079	6.91496	93.09
3	0.01241	0.11140	15.08845	84.91
4	0.02917	0.17079	27.70479	72.30
5	0.01537	0.12398	14.37311	85.63
Average	0.01350	0.11025	14.18384	85.82

In solving the case of predicting the b-value as an earthquake precursor, the simulation results showed that, in the training process, Deep Learning produces better prediction performance of the b-value as an earthquake precursor compared to Extreme Learning Machine. Deep Learning resulted in success rate of 99.78 percent, while Extreme Learning Machine had 98.17 percent as shown in Table II. Hence, Deep Learning produced 1.61 percent improvement.

Based on the results of the testing process five times in Table III and Table IV, the Extreme Learning Machine produced a slightly better b-value prediction performance as an earthquake precursor compared to Deep Learning. Extreme

Learning Machine obtained average success rate of 85.92 percent, while Deep Learning 85.82 percent. Thus, the Extreme Learning Machine has a slight improvement by 0.10 percent. Overall, both the training process and the testing process, in solving the prediction case of the b-value as a precursor to this earthquake, Deep Learning was superior by 1.51 percent.

V. CONCLUSION

In the paper, it was shown that to predict the b-value as an earthquake precursor, the Extreme Learning Machine produced an average performance almost the same or slightly better than Deep Learning indicated by the average of success percentage better. From the whole, both the training process and the testing process can be carried out a total assessment. Where in the training process, Deep Learning showed better performance than the Extreme Learning Machine with a difference of 1.61 percent. However, in testing, it was only slightly less, namely 0.10 percent of Extreme Learning for solving the prediction case of the b-value as a precursor to the earthquake. In general, namely for the training and testing process, Deep Learning was superior by 1.51 percent.

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