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Neural Network on Tsunami Waves Prediction Detector Tools Using Tectonic Earthquakes Data

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Abstract: On 26 December 2004, tsunami waves were generated by undersea megathrust earthquakes, particularly hit the Banda Aceh-Indonesia, also Thailand, Sri Lanka, India. The effect of tsunami waves can be very damaging to the coastal areas even more for the land around the coast. It is very interesting to study about the relation between the magnitude of the undersea earthquakes and the tsunami. Therefore, we construct an early warning system using Neural Network to predict the tsunami, it uses data from Indonesian Meteorology, Climatology, and Geophysical Agency that integrated with a hardware tool. The hardware tools will show the prediction result and send a short message.

2010 Mathematical Subject Classification: 68T07, 68P01, 62P30.
Keywords: Data earthquakes, neural network, prediction tools, tsunami.

1. Introduction

Indonesia is an archipelago which has a geographical location on the triple junction plate; the Indo-Australian plates in the south, Eurasian plates in the north and the Pacific plates in the east [5,7]. Consequently, the Indonesian islands are very vulnerable to earthquakes and tsunamis [4,8,11]. Tsunami means a series of wave that is usually generated by seabed earthquakes. On 26 December 2004, the tsunami was generated by seabed earthquakes (magnitude 9.0 - 9,3) that located in Indian Ocean-the northern Sumatra, Indonesia [9, 12,17]. It was one of the largest tsunamis on this half-century, which killed more than 250.000 people. This wave is not like common waves that we usually encounter, it can hit the beach with enormous energy. Tsunami's effect can be very devastating, causing huge destruction to the coast and swept the human populated in the coastal area. On 26 December 2004, tsunami waves had length 1300 km width 200km and height 15 m [12].

Tsunamis was occurred in Indonesia mostly caused by tectonic earthquakes along subduction areas and other active seismic areas [13]. The speed of tsunami waves depends on the depth of the sea and the propagation can reach thousand kilometers [12]. Moreover, the tsunami can propagate about 1-8 hours to the area that the people does not feel the earthquake itself.

Tsunami is generally happened around 10-20 minutes after the earthquake. In Indonesia, the historical data shows that approximately 172 tsunamis was occurred in the period between 1600-2012, 90% caused by tectonic earthquake activity, 9% due to volcanic activity and 1% by landslides from land that enter to sea [13]. The motion of crustal blocks will create a potential energy to the seawater. It will make a drastic change in the surface of sea. The energy released into the sea can create a tsunami – the energy will propagate in the form of long waves with relatively small amplitudes. If these waves propagate closer to the coast, the waves have a shoaling effect, amplitude increases, wavelength and speed decrease. Consequently, when it reaches the shore, the waves that have been propagating will produce a powerful tsunami wave energy [12,13].

Modelling for tsunami prediction has been developed by some researcher using various algorithm [1, 2,3, 6, 10, 14]. Tanioka et al using the NearTIF method to calculate the tsunami height and tsunami inundation based on the 1992 Nicaragua tsunami [16]. Strauch et al develop an early warning system for tsunami for Nicaragua and Central America [15]. In order to reduce the fatalities effect, the tsunami warning system which integrated with short message systems is very important tool. Therefore, in this paper, we construct a real-time early warning system using Neural Network to predict the tsunami using BMKG (Meteorology, Climatology, and Geophysical Agency) data and built hardware tools to send the prediction result via Short Message Service (SMS). Hopefully, by this early warning tool, we can reduce the risk of the impact of the tsunami by sending the warning using short message/text message and alarm using a buzzer.

2. Methods

2.1. Design of Prediction System

The principle work of this system is to analyze the input of training data, how big the magnitude of the tectonic earthquake can cause a tsunami or not (no-tsunami). A learning process needed to be done using the Neural Network to construct the prediction model. Furthermore, the system provides a data training process in order to get the characterization of magnitude earthquakes for each data that leads to decision whether tsunami will happen or not. Training data that has been processed in learning process will produce maximum weight and bias. The results of the learning process will be tested using predetermined test data. It will give a result tsunami or no-tsunami. If it is a tsunami, an early warning system will send Short Message Service (SMS).

In brief, the work process in this research given by:

1. Input the training data
2. Data normalization
3. Training the data using Backpropagation Neural Network
4. Validation model
5. Testing the data using Neural Network
6. Analyze the predictive result performance (the accuracy, precision, recall, misclassification rate, FN rate, prevalence and FScore)
7. Sending a notification about prediction result using Short Message Service (SMS) or text messages.

2.2. Neural Network

Neural Network has been widely known for prediction model for example tsunami travel time prediction that was done by Barman [1]. The architecture of neural network that used in this work is single hidden layer neuron that can be seen in Fig 1.

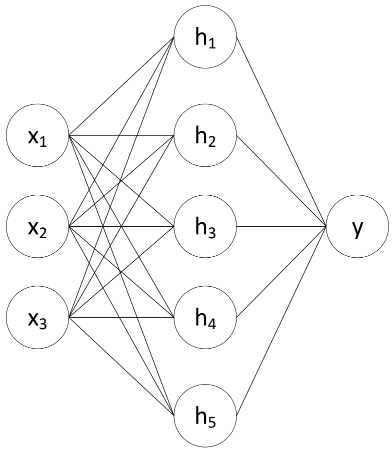

Fig 1. Single hidden layer neural network.

In this work, 5 nodes hidden layers, 3 input, and 1 output was considered to analyze more further. Meanwhile, for testing process, we use supervised learning with input and target:
$\{\mathbf{x_1}, t_1\}, \{\mathbf{x_2}, t_2\}, \dots, \{\mathbf{x_n}, t_n\}$.
Difference between target (t) and predicted output (y):

$$e = t - y$$

Objective function:

$$E = -\frac{1}{2}e^2 = -\frac{1}{2}(t-y)^2$$

Feedforward propagation:

$$\mathbf{h} = f(\mathbf{w_1}.\mathbf{x} + \mathbf{b_1}) = f(\mathbf{n_1})$$
$$y = g(\mathbf{w_2}.\mathbf{h} + \mathbf{b_2}) = f(\mathbf{n_2})$$

Where $\mathbf{w}$ is weight, $\mathbf{b}$ is bias, f and g are activation function using log-sigmoid (logsig) and hyperbolic tangent (tanh), respectively:

$$f(\mathbf{n_1}) = \frac{1}{1+e^{-\mathbf{n_1}}}$$
$$g(\mathbf{n_2}) = \frac{e^{\mathbf{n_2}} - e^{-\mathbf{n_2}}}{e^{\mathbf{n_2}} + e^{-\mathbf{n_2}}}$$

The derivative of activation function:

$$\frac{df(\mathbf{n_1})}{d\mathbf{n_1}} = \left(1 - f(\mathbf{n_1})\right)f(\mathbf{n_1})$$
$$\frac{dg(\mathbf{n_2})}{d\mathbf{n_2}} = (1 - g^2(\mathbf{n_2}))$$

Backpropagation for updating the weight and bias:

- Output layer

$$\frac{\partial E}{\partial w_2} = \frac{\partial E}{\partial y}\frac{\partial y}{\partial n_2}\frac{\partial n_2}{\partial w_2} = (t-y)y(1-y)h$$
$$\frac{\partial E}{\partial b_2} = \frac{\partial E}{\partial y}\frac{\partial y}{\partial n_2}\frac{\partial n_2}{\partial b_2} = (t-y)y(1-y)$$

- Hidden layer

$$\frac{\partial E}{\partial w_2} = \frac{\partial E}{\partial y}\frac{\partial y}{\partial n_2}\frac{\partial n_2}{\partial h}\frac{\partial h}{\partial n_1}\frac{\partial n_1}{\partial w_1} = (t-y)y(1-y)w_2(1-h^2)x$$
$$\frac{\partial E}{\partial b_2} = \frac{\partial E}{\partial y}\frac{\partial y}{\partial n_2}\frac{\partial n_2}{\partial h}\frac{\partial h}{\partial y}\frac{\partial h}{\partial n_1}\frac{\partial n_1}{\partial b_1} = (t-y)y(1-y)w_2(1-h^2)$$

Updating the weight and bias at output layer:

- Output layer

$$w_2 := w_2 - \eta \frac{\partial E}{\partial w_2}$$
$$b_2 := b_2 - \eta \frac{\partial E}{\partial b_2}$$

- Hidden layer

$$w_1 := w_1 - \eta \frac{\partial E}{\partial w_1}$$
$$b_1 := b_1 - \eta \frac{\partial E}{\partial b_1}$$

where η is a learning rate.

2.3. Hardware Design

The hardware design for this work can be seen in Fig 2. The hardware components that used are Arduino Uno board based on microcontroller on ATMega 328, LCD (Liquid Crystal Display) 16x2, keypad 4×4, Buzzer Piezoelectric and GSM Module.

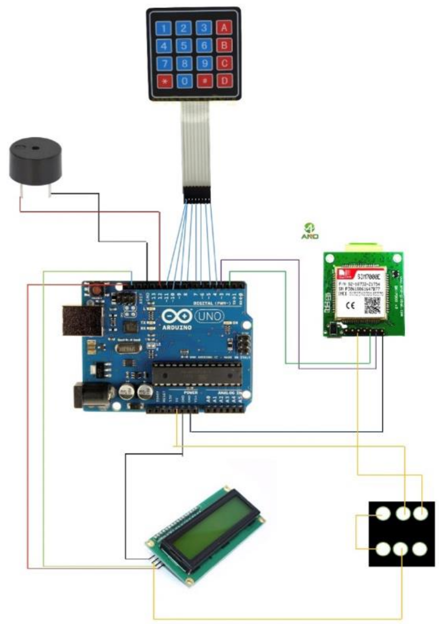

Fig 2. Hardware Design

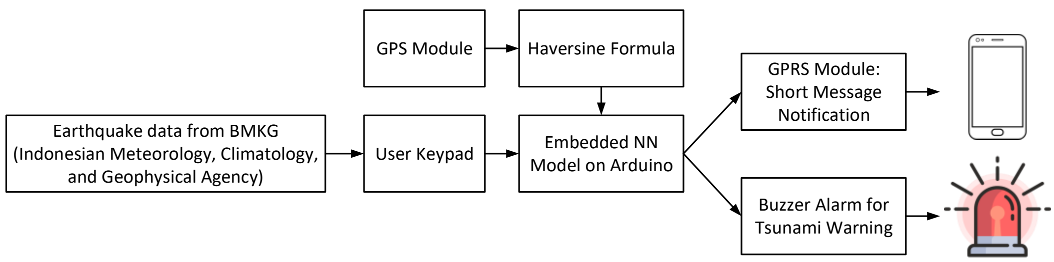

Fig 3. Block Diagram of Hardware

Fig 3 shows the early warning in the whole process to predict tsunami. The requirements data for input in this system are magnitude of earthquakes, the distance and depth. Some data can be directly obtained from

BMKG real time data, furthermore the user input the three data entries using a keypad. At the same time, GPS will take the location of this device and converts it to the haversine formula in accordance with the BMKG data format. The distance between the earthquake point and this tool's coordinates where the device is installed can be calculated in Arduino. Furthermore, the three inputs will be processed using the Neural Network model to obtain the prediction of a potential tsunami or no-tsunami. If the prediction result is a potential tsunami, the system will send a notification via SMS using the GPRS module and also a warning alarm using a buzzer will loudly sound.

3. Results and Discussion

3.1. Modelling

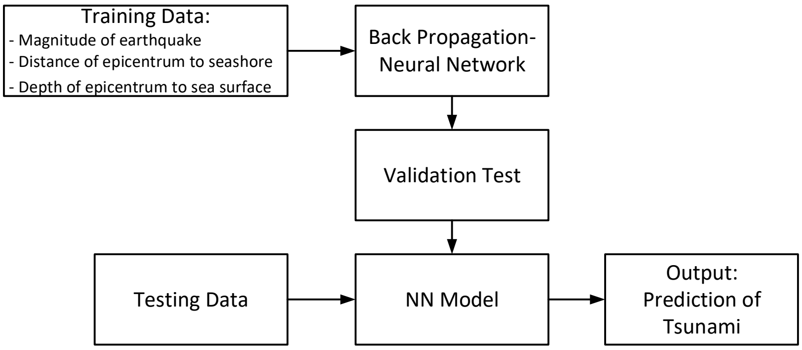

Fig 4. Block diagram for prediction training and testing

The block diagram for modelling process can be seen in Fig 4. BMKG releases the earthquake data in their website or social media, thus we compute the training data with backpropagation neural network in order to find the optimal weight and bias. In this section, the results of testing process using 881 data will analyzed. The test was conducted 36 times which aimed to determine the accuracy of the data which will be used in further prediction using Neural Network. The initialization for Neural Network setting can be seen in Table 1.

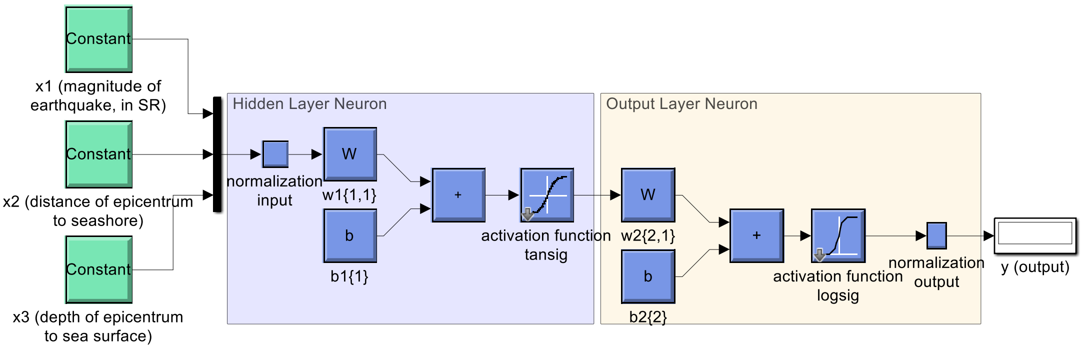

Fig 5. The archithecture of prediction model

Input X: [magnitude of earthquake, the distance of epicenter to shoreline, the depth of epicenter that measured from sea level]
Output Y: actual target (whether tsunami or no-tsunami)
Total of testing data: 881 data that will split into 88% testing (742 data), 12% validation (139 data)

Table 1. Neural Network Initialization Setting

Parameter	Learning Rate	Maximum Epoch	Input Neuron	Hidden Layer	Output Neuron	Training Function	Activation Function
Value	0.7	36	3	5	1	Tanh	Log-sigmoid

3.2. Results and Analysis

The tectonic data in seashore consist by 742 for training process and 139 data for validation process. The results for training process are True Negative (TN) 97.7% dan True Positive (TP) 2.3%, meanwhile the results for validation process are TN 97.1% and TP 2.9%. The confusion matrix for training and validation process can be seen in Fig 6.

We apply confusion matrix to evaluate the performance. The performance can be calculated by counting how many the result that confirm with the actual data.

- TP (true positive): actual target condition “tsunami” and prediction result “potentially tsunami”
- TN (true negative): actual target condition “no-tsunamis” and prediction result “no potentially tsunami”
- FP (false positive): actual target condition “no potentially tsunami” and prediction result “potentially tsunami”
- FN (false negative): actual target condition “potentially tsunami” and prediction result “no potentially tsunami”

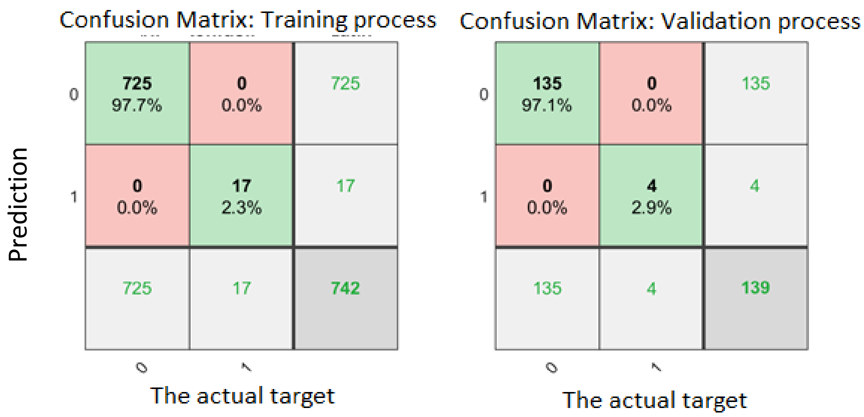

Fig 6. (Left) confusion matrix for training process and (right) validation process

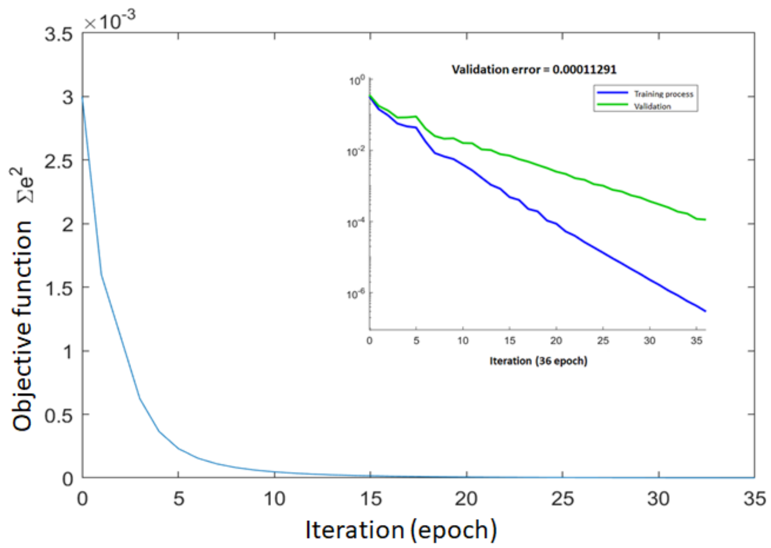

Fig 7. Quadratic Error from the weight and bias for every iteration (total of epoch)

The performance of the model for tsunami prediction using Backpropagation Neural Network in the training and validation process can be seen in Fig 7, where the objective function states the quadratic error between the target and the predicted results. From iterations by 35 epochs, it can be shown in Fig 7 that the RMSE value converges toward zero. Meanwhile, in the validation process, we can see that the error is quite small. Thus, the model is good enough to predict tsunamis. We do the augmentation data process because the initial training data was imbalanced (training data when tsunami potential data is smaller than no-tsunami potential data). After the augmentation process, the data is proportionally reduced and then it will be trained by Neural Network method to increasing the accuracy of the data testing.

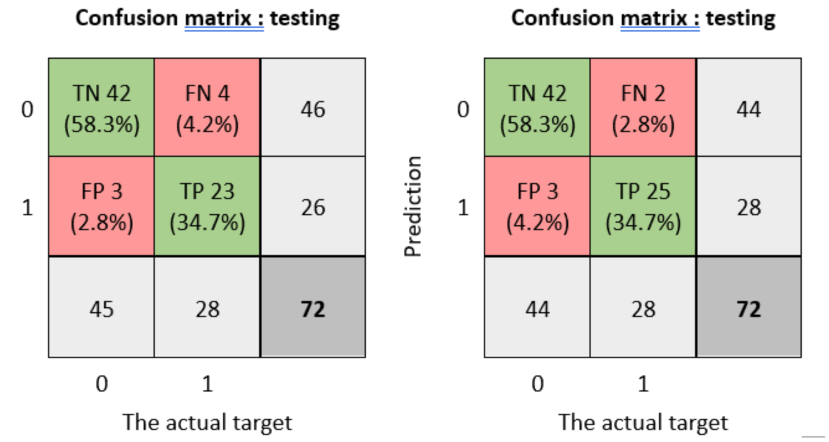

Fig 8. Left side (Imbalance Data), Right side (Augmented Data). Confusion matrix for testing process

The reduction of test data for FN (false negative) becomes very important to increase the accuracy because FN shows the prediction of no-tsunami potential while the actual target data indicates a tsunami event. For the tsunami prediction cases, it is important to avoid the wrong predictions. Especially, the prediction that shows no-tsunami but in the real condition tsunami was happened. It would be fatal consequences even though in mathematics calculation the accuracy of prediction using Neural Network is quite high. In this work, the Neural Network can reduce false negative (FN) conditions as small as possible. Table 2 shows that through augmented data process the accuracy, precision, recall, and FScore are increase; misclassification rate, FN rate and prevalence are decrease. It means that the results by using augmented data process is better that imbalance data. FN (false negative) decrease from 4 to 2 from 72 test data, and accuracy increase from 90.3% to 93.1%. The augmentation data succeeded in reducing the FN (false negative) prediction due to overfitting while training with unbalanced data.

Table 2. Prediction result imbalance data testing process vs augmented data testing process

(%)	Accuracy	Precision	Recall	Misclassi-fication rate	FN rate	Prevalance	FScore
Imbalance Data	90.3	88.5	85.2	9.7	14.8	37.5	86.8
Augmented Data	93.1	89.3	92.6	6.9	7.4	37.5	90.1

In this work, we also compute the distance of epicentrum to user's position. GPS can detect the user's position (latitude and longitude) which shown in the hardware tools. Furthermore, by following this algorithm, the distance between user and epicentrum can be calculate.

1. Get coordinate latitude and longitude of epicentrum from BMKG (lat_1, lon_1)
2. Get data latitude and longitude from GPS, placed in seashore coast guard tower (lat_2, lon_2)
3. Calculate

$$\Delta lat = lat_2 - lat_1$$
$$\Delta lon = lon_2 - lon_1$$
$$a = \left(\sin\left(\frac{\Delta lat}{2}\right)\right)^2 + \cos(lat_1)\cos(lat_2)\left(\sin\left(\frac{\Delta lon}{2}\right)\right)^2$$
$$c = 2\tan^{-1}\left(\sqrt{\frac{a}{1-a}}\right)$$

4. Use earth radius $R \approx 6371km$, find eucledian distance of epicentrum to seashore

$$d = Rc$$

3.3. Hardware and Results

In this study, we also made a hardware tool to predict whether a tsunami will occur or not through the data that sent by BMKG. In Fig 10, we can see all step that required to predict whether is potentially tsunami (***alert***) or no-tsunami (***safe***) using the real data from BMKG. For example for a magnitude of the earthquakes is 9 SR, the distance of epicentrum to seashore is 8 km that calculate using algorithm in above, and the depth of epicentrum is 30 m. The result that shows in the hardware tool is alert, it means potentially tsunami or in Bahasa Indonesia is *waspada*.

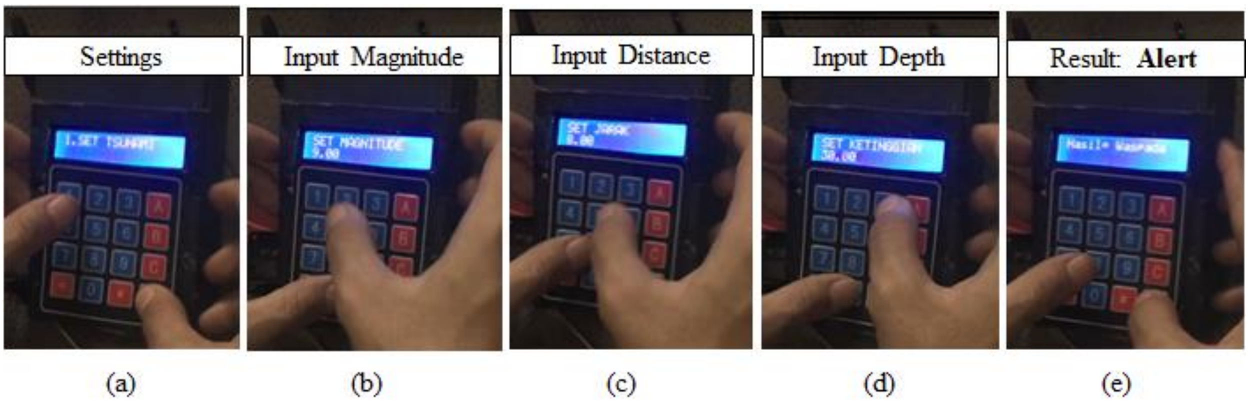

Fig 10. (a). Parameter setting for prediction with *Single Hidden Layer Neuron*; (b). Setting the input x_1, the magnitude of earthquakes (in SR); (c). Setting the input x_2, the distance of epicentrum to seashore (km); (d). Setting the input x_3, the depth of epicentrum (meter); (e). Prediction results according the data input in figure (b), (c), and (d).

As we can be seen in Fig 11, the hardware tool shows the prediction result is potentially tsunami, the hardware tool sends the prediction result via Short Message Service (SMS) or text message.

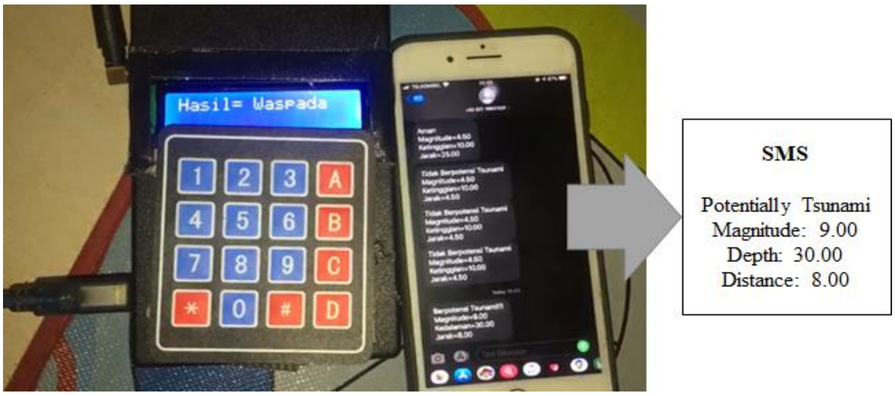

Fig 11. Early warning systems integrated with short message service or text message

4. Conclusions

Neural Networks for predicting by using earthquake data on the undersea are very good to predict the tsunami. Early warning systems that built are very important to increase the level of awareness of tsunamis when the earthquakes in undersea happened, especially in Indonesia. The accuracy of predictions is needed for tsunami prediction cases because it impacts on public safety. In this study, prediction using Backpropagation Neural Network shows the best accuracy result 93.1%. The compositions data are 88% testing (742 data) and 12% validation (139 data). Also, besides of being able to predict the potential for tsunamis, the early warning system can also operate properly, when prediction result is potentially tsunami then SMS / text messages can be received directly as soon as after it delivered.

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