A Neurocomputing Approach for Anomaly Detection of Mt. Merapi Monitoring Activity

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***Abstract*— Monitoring volcanic activity is extremely important to detect anomalies that may changes in the activity of Mt. Merapi. In this paper we proposed Multi Layer Perceptron (MLP) method to detect anomaly and to determine activities of each quake in seismic data. This method that has been developed in this research has been tasted against such several types of quakes as volcanic A (VA), volcanic B (VB), *multiphase* (MP), and *avalance* using data of the same time period. The experimetal results showed an average accuracy of 81,7 % in determining the activity of each quake type of Mt. Merapi seismic activity.**

Keywords*— *Mt Merapi; seismic monitoring data; anomaly detection; multilayer perceptron

I. Introduction

About 127 volcanoes throghout Indonesia and approximately 5 million people live nearby. This is certainly a special concern of the government because it is part of disaster prone areas. Mount Merapi is one of the worst active volcanoes and there are still settlement slopes to a height of 1700 Meters and only four kilometres from the summit. This is what makes Mount Merapi as a centre of disaster mitigation research impact of eruption of Mount Merapi.

Determining the status of the mountain requires a special assessment of several factors as material consideration in decision making. Some of these factors include the condition of mountain activities, victim of psychological preparation, readiness of evacuation routes, and economic situation as well as political. Of these factors, volcanic activity condition is important so we need Merapi activity monitoring to detect changes in the activity of volcanoes. The purpose of monitoring volcanic activity is to determine whether the absence of data on anomalies that indicate that the mountain would have erupted or otherwise [1]. So far, to find anomalies in seismic monitoring data is by calculating the change of data, acceleration of change, and continuity of change. This requires a long time and does not show an anomaly pattern that allows users make decisions related to the activities of Mt. Merapi.

Previous research tested several methods proposed to detect any anomalies in the seismic data that are non-linear which ARIMA *(Auto Regressive Integrated Moving Average),* GA (Genetic Algorithm), SVM *(Support Vector Machine),* and ANFIS [2]. Based on the development of some of these methods was concluded that the ARIMA method was less suitable for application of non-linear data such as seismic data, then SVM method provided a better result but the performance results decreased if data were in large numbers. While the method of GA had the same ability, accurately to detect anomalies but GA had drawbacks such as the number of t ahapan that must be taken. Based on consideration of the advantages and disadvantages some of these methods, the proposed method in this study Multilayer Perceptron (MLP) has the best accuracy to determine Mt. Merapi seismic activity.

II. Material and methods

A. Material

This research selected Mt. Merapi seismic monitoring data to be processed into MLP method. This type of seismic monitoring was used in this study because it proved to have an effect on data changes that indicate eruption in 2006 and 2010. The data period used was data period that has showing data changes indicating an increase in activity just before the eruption of Mt. Merapi 2010 [3]. The author chose the period of seismic monitoring data between 2002 and 2012. The seismic monitoring data included data on volcanic earthquakes (VA), the data on shallow volcanic earthquakes (VB), *multiphase* seismic data (MP), and the data avalanches (RF).

Seismic monitoring data were recording the number of earthquake events each day. Monitoring the number of earthquake events conducted in each type of earthquake data. In this study, the data were divided into two types data for training and testing data respectively 60% and 40%. Seismic monitoring data obtained through the official report released weekly official through the official *website* owned by PVMBG Yogyakarta.

B. Methods

In this research, the MLP method contributed to detect the presence of data indicating anomalies and resulted in the activity conditions of each type of earthquake mentioned in the sub-section of the material. Detection of anomalies of each type of earthquake was done through the introduction of patterns of sismic activity consisting of normal, increased, and decreased patterns. The seismic data consisting of volcanic earthquakes (VA), the data shallow volcanic earthquakes (VB), data *multiphase* (MP), and the data avalanches (RF) divided into two sets of data, training data set and testing data sets. To be able to produce the pattern of earthquake activity correctly then prepared a set of training data to be trained using the MLP method. The training process is done to produce the best weight that has the smallest error value. Then the weights are used on the set of testing data to determine the accuracy of the performance of the MLP method in determining the conditions of each type of earthquake activity in an seismic monitoring. Figure 1 shows the methods to the study.

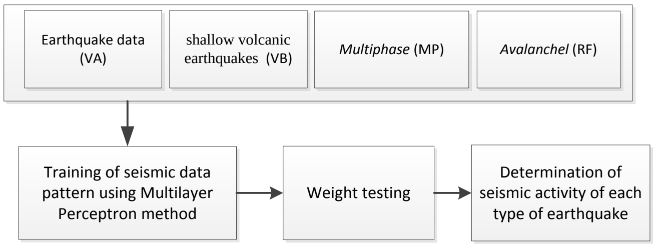


Figure 1. Research methodology

Data Pattern Training Method Using MLP

In the implementation of the MLP *method*, there were two steps that had to be followed was the process of training to gain weight *(w_{ij})* best as pattern recognition. In this study, first conducted supervised training *(supervised learning)* to produced a pattern of any monitoring data that has a high degree of accuracy. The training process begins with reading the *input* data, initial weights, *training* parameters *(learning rate,* the maximum *epoch,* the target *error),* and the target *output.* A total of 366 data sets prepared covers 59 increased activity data sets, 10 sets of data decreased activity, and 297 active data sets of normal *activity.* Function activation plays a role in the process of training iterations to obtain *the minimum* value of *predictive error.* Figure 2 is a picture of the architecture of the MLP method used in this research.

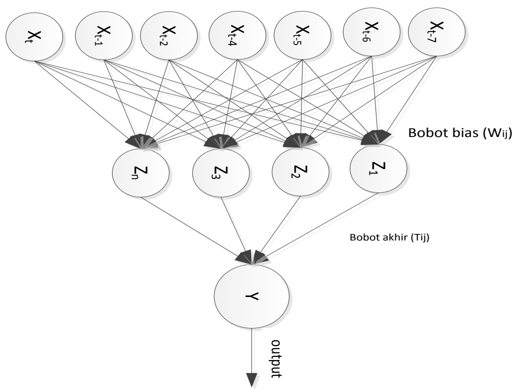


Figure 2. Network Architecture MLP Method Seismic Data of Mt. Merapi

Based on Figure 2 could be seen that there were similarities network architecture for the process of training and testing of each earthquake. Network was formed with 7 inputs *(x)* which contains the number of daily earthquakes, one output (y), then performed a number of trials by changing the number of *hidden layer (z)* to get the best weight that has *predictive* value *error* (P E) the smallest. In the training process every type of earthquake is determined a target value of *predictive error* (P E) of 1×10^{-5} and the maximum number is 5000 repetitions *epoch.*

In the training process required the activation function to run the algorithm in the best weight search. In the current study tan sigmoid activation function shown in Equation (1).

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \quad (1)$$

Training Weight Testing

After getting the best weight of the training process, then this is the weight used for the MLP method performance testing process. This process aims to test the accuracy of the training *process.* The final weighting value in the training process will be used to test the prepared data sets. In the process of performance testing will be generated accuracy level as a benchmark of the success of the software created. The accuracy of the testing process is obtained from the equation (2).

$$accuracy = \frac{amount\ of\ invalid\ data\ training}{amount\ of\ data\ training}\ x\ 100\% \quad (2)$$

Anomaly Detection

In this research, the determination of a data classified into anomaly data or not requires statistical calculations. This was to determine the upper and lower limits of normal activity conditions for each type of earthquake. In the process of testing data, if the data value was beyond the limit that has been determined by the formula (3).

$$\mu \pm 1.5 \times \sigma \quad (3)$$

where μ is average value and σ is standars deviation, so anomali data was detected.

III. RESULTS

Multilayer perceptron method in detecting anomalies devided the seismic data with data sets into 2 parts training data and testing data with the composition of the data set representativly 60% and 40% third consecutive. The data sharing set for the training and testing process applied to all types of earthquakes including in the seismic monitoring method. The results of the training process for all types of earthquakes in the (VA), shallow earthquake (VB), the earthquake *multiphase* (MP), and avalanches (RF) showed 100% accuracy with the prescribed *minimum* target *error* of 1×10^{-5}. Then the testing process was also done on all types of earthquake that is 157 sets of data. The testing process was also performed on all types of data on seismic monitoring. Table 1 shows the test results of *the MLP* method.

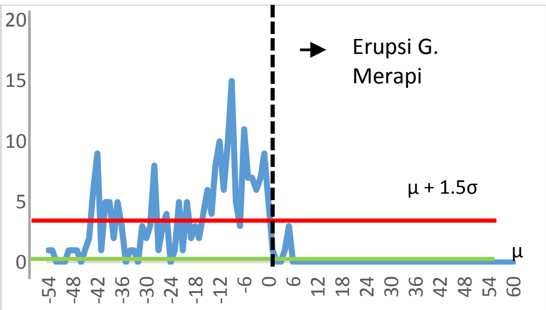
Table 1 Fifth MLP Method Test Result Type Earthquake

No	Type of eathquake	Accuracy result	Percentage
1	Earthquake inside (VA)	133	85 %
2	Shallow earthquake (VB)	136	87 %
3	*Multiphase* (MP)	122	78 %
4	Avalanche (RF)	121	77 %

Based on Table 1 it could be seen that the test results of the performance of *the MLP* method to all kinds of data on seismic monitoring methods at 81,7 %.

The output of the MLP method a value linguistic circumstances of each shallow volcanic earthquakes (VB), seismic data *multiphase* (MP), and the data avalanches (RF) ie active normal, increased, or decreased. Comparative analysis uses a period of data one month before Mt. Merapi erupted and 1 month after experiencing an eruption. The results show similarities between the results of the real conditions that released by PVMBG Yogyakarta.

a



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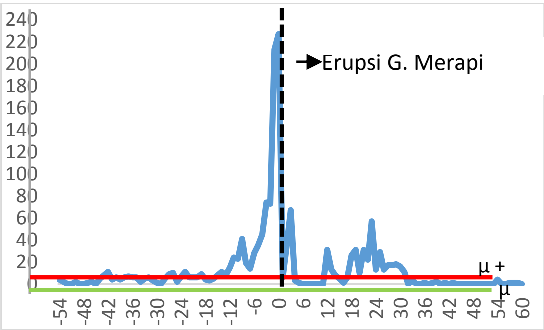

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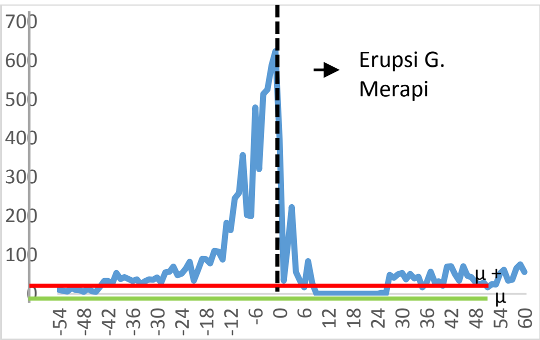

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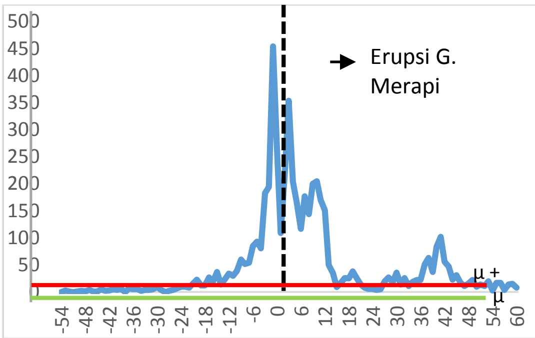

Figure 3 Graphs of Earthquake Anomalies Inside (a), shallow earthquakes (b), Multiphase Earthquakes (c), Avalanche (d) on Mt. Merapi Eruptions 2010

Based on the fourth graph shown in Figure 3 could be seen that the method of *the MLP* was able to detect changes in the activity of volcanic earthquake inside (VA) 44 days before the eruption 3(a), while the volcanic tremor shallow (VB) shown in Figure 3(b) visible indicate anomalies that indicate changes in activity since 54 days before eruption on October 26, 2010. Whereas in *multiphase* earthquakes *(MP)*, the data show anomalies that indicate the increase seen since the 28 days prior to the eruption of up to 60 days after the eruption indicated on figure 3(c). This indicates that lava dome growth continues after eruption. Then figure 3(d) showed anomaly detection results that indicate an increase in miscarriages occur 18 days before the eruption and continued until 12 days after the eruption. Then decreased in the week after.

In addition to analyzing the performance of the MLP detect anomalies that indicate changes in the activity of each type of earthquake, the analysis was also conducted to determine the changes in seismic activity globally. Results of research shows the change in conditions that indicate an increased seismic activity began to be seen in 3 to 6 days before the eruption occurred. This shows the difference with the results that have been released by the PVMBG stating increased seismic activity 3 to 5 days before the eruption. In addition, there were differences in the conclusions of current activity after the eruption, which the method of MLP concludes condition has decreased 23 days after the first eruption on October 26, 2010 while PVMBG still releasing activity decreased at 28 days after the eruption that on December 3, 2010, a different 7 days with Calculation of MLP method.

IV. CONCLUSIONS

Monitoring activity of Merapi is one form disaster mitigation of the negative impact of the eruption. The monitoring was aims at determining the changes in volcanic activity indicated through the discovery of data anomalies. In this study, the proposed method of MLP was to facilitate the process in evaluating the condition of each seismic activity and seismic monitoring activity of Merapi. Methods were selected based on references from several previous studies showing an advantage in detecting data anomalies before the earthquake. This was done because there was a similarity of the seismic data used as indicators of impending earthquakes that LST *(Land Surface Temperature)* and TEC *(Total Electron Content)* upon the occurrence of an earthquake in Verzeghan, Iran which was non-linear. The results of the implementation of both methods to detect anomalies before the earthquake showed a percentage of 51.23% for anomaly detection in LST data and 85.26% for anomalies in the TEC data on 2 days before the earthquake and 5 days after the earthquake struck.

Whereas in this study, the MLP method employed to determine the condition of any seismic activity in the seismic monitoring method that volcanic earthquakes (VA), shallow volcanic earthquakes (VB), the earthquake multiphase (MP), and avalanches (RF). The results showed the method had an accuracy of MLP average performance of all types of the earthquake of 81,7% and was able to detect any anomaly 36 days before the eruption. This had the considerable difference compared with the implementation of the MLP method in detecting anomalies before the earthquake that hit Iran.

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