Identification of Potential Landslide Disaster in East Java Using Neural Network Model (Case Study: District of Ponogoro)

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Abstract. Indonesia is the largest archipelagic country in the world, which is geographically located in areas prone to natural disasters. One of the frequent occurrences of natural disasters is a landslide. East Java Province is one of the areas that has the potential for landslides. This is due to the topography of the most mountainous and rugged territory. Besides that, it also caused high levels of population density in the region of hills so that raises pressure on ecosystems. The tendency of the occurrence of landslides in an area can be connected with the equality of land characteristics and climate in other regions on a landslide in the past. To reduce the risk of disaster will be designed the software-based neural network for identification of potential avalanche areas. With potential landslide identification software, it can help to identify other locations that have similar physical and soil characteristics, so that the area can be suspected of being a potentially landslide area. The overall test results of this study are using Backpropagation artificial neural networks with 7 inputs, 15 hidden and 1 output. The training function used is Resilient backpropagation (RP) with an accuracy of testing data is 90.56% and MSE of 0.0944.

1. Introduction
Natural disasters as one of the natural phenomena that can occur at anytime and anywhere, which can cause material and immaterial losses to the community. One of them is a landslide, which is a natural phenomenon that is common, especially in hilly or mountainous terrain. Landslides are defined as "the movement of masses of rock, debris, or earth (soil) down the slope (under the influence of gravity)" [1]. Landslides are one of the geological natural disasters that can cause huge casualties and material losses, such as siltation, disruption of traffic lanes, damage to agricultural land, settlements, bridges, irrigation channels and other physical infrastructure.

Indonesia is the largest archipelagic country in the world, which is geographically located in areas prone to natural disasters. One of the natural disasters that often occur is landslides. The regions in Indonesia with the highest frequency of landslides are Central Java, West Java Province and East Java Province [2]. Meanwhile, the three Provinces are also the region with the highest population in
Correlation of the most vulnerable areas to landslides as well as the most populated areas, makes the magnitude of disaster risk proportionally proportional to the number of fatalities and damage to infrastructure [2]. Landslides cannot be prevented with certainty so as to avoid a larger and many fall victim due to the danger of landslides, efforts are needed to minimize the risks posed by landslides. One effort to reduce the risk of landslide disasters is to create a system that can detect a potential landslide area in advance so that it can be an early warning of possible landslides to the community. The tendency of landslides in a region can be attributed to the similarity of land and climate characteristics in other regions to past landslides. With the identification of landslide prone areas, it can help to identify other locations that have similar soil physical and climate characteristics, so that the area can be suspected of being a potential landslide area.

For making a system that is able to detect in advance an area with landslide potential, a lot of data is needed in the form of factors that can affect the occurrence of landslides such as lithology, topography, geomorphology, rock mass structure, in situ pressure, surface water, groundwater, rainfall and human activity. Due to the influence of various factors, it is difficult to get a landslide prediction accuracy. In previous studies, experiments and software played an important role in predicting landslides. Artificial neural networks (ANN) have the characteristics of self adaptation, non-linear and tolerant of errors, and are very suitable for complex, uncertain and nonlinear problems. This study adopted the ANN model to obtain a vulnerability map. The landslide susceptibility maps produced resemble the location of existing landslides, so in many studies they report satisfactory results and are recommended for predictions of landslides [4]-[6].

For the algorithm used is one of the algorithms contained in artificial neural networks, namely the backpropagation algorithm, where the algorithm has a tendency to store experience knowledge and make it ready for use [7]. The backpropagation algorithm (BP) presents better performance and is used in this study. The BP algorithm is the learning of a set of input-output pairs that are specified, which, when interacting, produce the initial weight on all variables supplied to the system. This weight is assigned by the internal statistical parameters of the algorithm to produce errors transmitted backward to make adjustments to the initial weights [8]-[9].

Figure 1. Landslide Map Ponorogo Regency
Figure 2. a) Elevation, b) Slope, c) 2013 rainfall, d) 2017 rainfall, e) Distance from the roads, and f) Distance from the river.

2. Materials and Methods

2.1. Study Area

In this study, Ponorogo Regency was chosen for the implementation of the identification of potential landslide disaster in east java using neural network model. The study area, Figure 1 is in the Ponorogo
Regency, one of the districts in East Java that is often affected by landslides. Ponorogo Regency is located at 111° 7’ to 111° 52’ east longitude and 7° 49’ to 8° 20’ South latitude. The area of Ponorogo Regency reaches 1,371.78 km² consisting of 21 Subdistricts and 307 villages. Ponorogo Regency topography varies from lowlands to mountains. Based on existing data, a large district that is 79% of Ponorogo at an altitude of less than 500 m above sea level, 14.4% are between 500 and 700 m above sea level and the remaining 5.9% is at the height of the above 700 m, Figure 2. Topographically and climatologically, Ponorogo Regency a lowland tropical climates have two dry season and rainy season with temperatures ranging between 18 °- 31 ° Celsius.

2.2. Landslide
According to the Department of Energy and Mineral Resources, landslides are the displacement of slope-forming material in the form of rocks, scraps, soil, or mixed materials, moving downward or out of the slope. The process of landslides can be explained as follows: water that seeps into the soil will increase the weight of the soil. If the water penetrates to the water-resistant soil which acts as a slip plane, then the soil becomes slippery and the weathering soil on it will move along the slope and out of the slope. Whereas according to Varnes (1978) propose the slope movement terminology which is considered more appropriate to define avalanches, namely as a movement of material making up slopes downward or outward slopes under the influence of gravity.

In principle, landslides occur when the driving force on the slope is greater than the retaining force. Retaining forces are generally influenced by rock strength and soil density. While the driving force is influenced by the magnitude of the slope angle, water, load and rock soil specific gravity. Many factors such as geological and hydrological conditions, topography, climate, and weather changes can affect slope stability which results in avalanches. According to the Ministry of Energy and Mineral Resources, there are several factors that cause landslides, namely rain, steep slopes, less dense or thick soil, less strong rocks, land types, vibrations, shrinkage of lake water levels or dams, additional loads, erosion, the presence of embankment material on cliffs, old old landslides, discontinuities (non-continuous fields), and garbage disposal areas [10].

2.3. Artificial Neural Network
According to Fausett (1994) ANN is an information processing system that has characteristics resembling biological neural networks [11]. Human nerve tissue consists of cells called neurons. There are three main components of neurons whose functions can be analogous to those that occur in the Neural network, namely dendrites, soma, and axons. Dendrites will receive signals from other neuro. These signals are electrical impulses transmitted through synaptic gaps through chemical processes. Whereas soma or cell body will add input signals. If there is input, the cell will be active and transmit signals to other cells through axons and synaptic gaps.

Each neuron has an internal part, called activation or level of activation, where its function is to receive input. In particular, neurons send signal activation to several other neurons. It is important to remember that neurons can send one signal at a time, even though this signal is sent to several neurons.

The model of adoption of biological neural networks into artificial neural networks can be modeled as follows. Each neuron is connected to other neurons through a network of direct connections, each of which is linked to \( w_i \) weights. Weight represents the relationship between input \( x_i \) and the next neuron. The result of strengthening the input \( x_i \) by \( w_i \) weights is then summed in a processing element/ node and is subject to an activation \( f(.) \) to produce the output \( y \), Figure 3.

2.4. Backpropagation
In general, the nature of the backpropagation learning method is that backpropagation networks (a feedforward network, multi-layer trained by backpropagation) can be used to solve problems in various fields. Applications that use this method can be found in any field that uses neural net for problems that encapsulate a set of inputs given to a specified set of output targets. As with most artificial neural networks, the aim of this network training is to achieve a balance between the ability to respond correctly to the input patterns used for learning and the ability to provide reasonable responses to the
same, but not identical inputs, for use in learning.

![Diagram of Artificial Neural Networks](image.png)

**Figure 3.** Basic Elements of Artificial Neural Networks [12]

The training of the backpropagation algorithm includes three stages. The first stage is feedforward from the training input. The second stage is the calculation and back propagation of related errors. Then the third stage is the adjustment of the relevant weight until it reaches a minimum error. If the output does not match the target, the weight is updated until the minimum deviation is reached. The architecture of artificial neural network backpropagation is shown in **Figure 4**.

![Diagram of Backpropagation Neural Networks](image.png)

**Figure 4.** Architecture of Backpropagation Neural Networks [13]

3. **Simulation**

Artificial neural network models that have been formulated to identify potential landslide disasters will be simulated using Matlab. Later the source code of the simulation that has been made will be displayed in the Appendix. The simulation carried out in this study uses a series of examples of related input and output values. The purpose of artificial neural networks is to build a model of the data generation process so that the network can generalize and predict output from inputs that were not previously "visible". This learning algorithm is a multi-layer neural network consisting of input layers, hidden layers, and output layers. Artificial neural networks "learn" by adjusting the weights between nodes in response to errors between actual and target output values. At the end of this training phase, the neural network provides a model that must be able to predict the target value of the given input value. The steps taken are the training phase where the internal weights are adjusted and the classification stage. The backpropagation algorithm trains the network until the minimum number of errors targeted is reached.
between the desired and actual output values of the network. After the training is complete, the network is used as a feedforward structure to produce classifications for all data [12]. Artificial neural networks consist of a number of interconnected nodes. Each node is a simple processing element that responds to the weighted inputs it receives from other nodes. The arrangement of nodes is referred to as network architecture shown in Figure 5 and the diagram for the whole simulation can be seen in Figure 6.

4. Results and Discussions

4.1. Training ANN

The probabilities of occurrence of landslides were calculated based on various input parameters (Fig 2), such as elevation, slope, rainfall, soil type, distance to the road, distance to the river, and landslide (2013-2016 for training and 2017 for testing). These data were taken randomly. Thematic GIS layers are input mostly in vector data formats and formulated into grid format with polygon rasterization and segmented data in Arcgis. Before running an artificial neural network program, the training location is chosen. Therefore, landslides and landslides are not prone chosen as a training site. Cells from each of the two classes were randomly selected as training cells indicating areas where landslides did not occur or occurred. To calculate weights using the backpropagation algorithm to calculate the weights between the input layer and the hidden layer and also between the hidden layer and the output layer by modifying the number of hidden nodes. In this study, structure 7 (input layer) × 5 (hidden layer) × 1 (outputlayer), 7×15×1, and 7×30×1 are selected for the network, with input data normalized in the range 0.1-0.9. The learning rate is set to 0.01 and the number of times is set to 2,000. The back-propagation algorithm is used to minimize errors between predicted output values and calculated output values. Algorithms spread errors backwards and iteratively adjust weights. There are several architectures for BP algorithms for network training that update weight values and can refer to selection parameters in ANN learning; The architecture is Resilient backpropagation (RP), Bayesian regularization backpropagation (BR), Levenberg-Marquardt backpropagation (LM), One-step secant backpropagation (OSS), Gradient descent with momentum and adaptive learning rate backpropagation (GDX), and Scaled conjugate gradient backpropagation (SCG) and much more. in this study I tried to use them.

![Figure 5. Artificial Neural Network Architecture for landslide identification](image)
Figure 6. Backpropagation Application for Identifying Landslide Potential Potentials

4.2. Testing ANN
After training, testing will then be carried out using the weights generated from the training process with input in the form of landslide data in 2017. The testing process requires input parameters, such as altitude, slope, rainfall, soil type, distance to road, distance to river and landslides, and will provide output in the form of identification of potential landslides in the study area. Just like the training process, before testing the data, the input data must first be normalized.

4.3. Result
After training data and testing data, to get the landslide prediction results the results are put back into Arcgis to get a visualization of the landslide susceptibility. The results show five classification ranges of susceptibility to landslides: very high, high, moderate, low and very low, calculated through the information simulated in the ANN. The results of this study can be seen in the Table 1 and Table 2

| Structure Of ANN | Training Function | Iteration | Training Data Accuracy (%) | Testing Data Accuracy (%) | Average Accuracy (%) |
|-----------------|-------------------|-----------|----------------------------|--------------------------|----------------------|
| 7-5-1           | RP                | 33        | 92.01                      | 83.06                    | 87.54                |
| 7-5-1           | BR                | 1467      | 91.18                      | 86.39                    | 88.79                |
| 7-5-1           | LM                | 9         | 90.36                      | 88.33                    | 89.35                |
| 7-5-1           | OSS               | 35        | 91.46                      | 86.94                    | 89.20                |
| 7-5-1           | GDX               | 176       | 90.36                      | 87.5                     | 88.93                |
| 7-5-1           | SCG               | 13        | 90.91                      | 87.5                     | 89.21                |
| Structure Of ANN | Training Function | Iteration | Training Data Accuracy (%) | Testing Data Accuracy (%) | Average Accuracy (%) |
|------------------|-------------------|-----------|-----------------------------|---------------------------|-----------------------|
| 7-15-1           | RP                | 31        | 90.91                       | 90.56                     | 90.74                 |
| 7-15-1           | BR                | 1077      | 90.63                       | 87.78                     | 92.21                 |
| 7-15-1           | LM                | 13        | 93.94                       | 91.25                     | 92.59                 |
| 7-15-1           | OSS               | 31        | 91.46                       | 85.83                     | 90.12                 |
| 7-15-1           | GDX               | 159       | 91.18                       | 86.74                     | 92.35                 |
| 7-15-1           | SCG               | 18        | 91.46                       | 87.5                      | 90.41                 |
| 7-30-1           | RP                | 42        | 92.29                       | 87.22                     | 91.24                 |
| 7-30-1           | BR                | 1943      | 98.07                       | 79.72                     | 89.39                 |
| 7-30-1           | LM                | 8         | 92.29                       | 88.33                     | 91.36                 |
| 7-30-1           | OSS               | 27        | 90.91                       | 87.78                     | 90.74                 |
| 7-30-1           | GDX               | 146       | 91.46                       | 84.17                     | 88.78                 |
| 7-30-1           | SCG               | 43        | 91.46                       | 88.06                     | 90.28                 |

Table 2. Comparison of MSE

| Structure Of ANN | Training Function | Iteration | Training Data Accuracy (%) | Testing Data Accuracy (%) | Average Accuracy (%) |
|------------------|-------------------|-----------|-----------------------------|---------------------------|-----------------------|
| 7-5-1            | RP                | 33        | 0.0391                      | 0.1694                    | 0.1043                |
| 7-5-1            | BR                | 1467      | 0.0429                      | 0.1361                    | 0.0928                |
| 7-5-1            | LM                | 9         | 0.0433                      | 0.1167                    | 0.0800                |
| 7-5-1            | OSS               | 35        | 0.0447                      | 0.1306                    | 0.0930                |
| 7-5-1            | GDX               | 176       | 0.0441                      | 0.125                     | 0.0846                |
| 7-5-1            | SCG               | 13        | 0.0491                      | 0.125                     | 0.0871                |
| 7-15-1           | RP                | 31        | 0.0414                      | 0.0944                    | 0.0679                |
| 7-15-1           | BR                | 1077      | 0.0432                      | 0.1222                    | 0.0827                |
| 7-15-1           | LM                | 13        | 0.0317                      | 0.1278                    | 0.0792                |
| 7-15-1           | OSS               | 31        | 0.0409                      | 0.1417                    | 0.0913                |
| 7-15-1           | GDX               | 159       | 0.0419                      | 0.1389                    | 0.0904                |
| 7-15-1           | SCG               | 18        | 0.0426                      | 0.125                     | 0.0838                |
| 7-30-1           | RP                | 42        | 0.0423                      | 0.1278                    | 0.0851                |
| 7-30-1           | BR                | 1943      | 0.0162                      | 0.2444                    | 0.1303                |
| 7-30-1           | LM                | 8         | 0.0382                      | 0.1167                    | 0.0775                |
| 7-30-1           | OSS               | 27        | 0.0424                      | 0.1222                    | 0.0823                |
| 7-30-1           | GDX               | 146       | 0.042                       | 0.1583                    | 0.1002                |
| 7-30-1           | SCG               | 43        | 0.0376                      | 0.1194                    | 0.0785                |

From the results in table 1 and table 2, according to the highest accuracy and lowest MSE from testing data, the results for identification of landslide potential in Ponorogo Regency using Backpropagation...
Artificial Neural Network are Resilient backpropagation (RP) Training Function with a structure of $7 \times 15 \times 1$, MSE results 0.0944 and accuracy of 90.56%.

5. Conclusion

In this study, the neural network method was used to identify potential of landslide using the integration of various parameters, elevation, slope, rainfall, soil type, distance to the river, land cover and distance to the road in GIS. From this study, the following results and conclusions can be drawn. The overall test results from this study are the highest accuracy and the lowest MSE found in the Backpropagation artificial neural network using a structure of 7 inputs, 15 hidden and 1 output. The training function used is Resilient backpropagation with an accuracy of 90.56% and MSE of 0.0944. So that the results of the potential landslide disaster map can be seen in Figure 7.

The landslide vulnerability map is very helpful for planners and engineers to choose suitable locations to carry out development. These results can be used as baseline data to assist slope management, urban development, and land use planning. To apply the model in more general areas, more landslide data is needed, and the model must be verified in different geological and environmental settings. In this study I want to develop again for making vulnerability identification maps with different input parameters and also algorithms giving different weights to get smaller MSE errors.

![Figure 7. Potential landslide maps using the Resilient backpropagation (RP) $7 \times 15 \times$](image)

1 References

[1] Cruden, D.M. 1990 “A Simple Definition of a Landslide”. Bulletin IAEG, 43: 27-29
[2] Badan Nasional Penanggulangan Bencana 2018, Data Informasi Bencana Indonesia http://dibi.bnpb.go.id/
[3] Badan Pusat Statistik 2010, Data Sensus Penduduk Tahun 2010 http://sp2010.bps.go.id/
[4] Arora MK, Gupta ASD, Gupta RP 2004 An artificial neural network approach for landslide hazard zonation in the Bhagirathi (Ganga) Valley, Himalayas Int J Remote Sens 25(3): 559-572
[5] Ermini L, Catani F, Casagli N 2005 Artificial neural networks applied to landslide susceptibility assessment Geomorphology 66:327–343. 2005
[6] Pradhan B and Lee S 2010 Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia Landslides 7(1) 13-30.
[7] Haykin S 1994 Neural Networks: A Comprehensive Foundation (New York: Macmillan Publishing Company)
[8] Valencia MA, Ya–nes C, Sanchez LP 2006 Backpropagation Algorithm for Neural Networks: concepts and applications México: Instituto Politecnico Nacional Centro de
Investigacion en Computacion

[9] Pradhan, B and Lee S 2010 Landslide susceptibility assessment and factor effect analysis: backpropagation artificial neural networks and their comparison with frequency ratio and bivariate logistic regression modelling Environmental Modelling & Software 25(6): 747-759

[10] Varnes DJ 1978 Slope movement types and processes in Schuster RL, Krizek RJ (Eds), Landslides, Analysis and Control, Special Report 176: Transportation Research Board National Academy of Sciences, Washington DC 11–33

[11] Fausett L 1994 Fundamentals of Neural Network, Architecture, Algorithm And Application (London: Prentice-Hall. Inc)

[12] Irawan MI 2013 Dasar - Dasar Jaringan Saraf Tiruan Algoritma, Pemrograman dan Contoh Aplikasinya (Surabaya: ITS Press)

[13] Paola JD and Schowengerdt RA 1995 A review and analysis of back propagation neural networks for classification of remotely sensed multi-spectral imagery Int J Remote Sens 16(16): 3033–3058