Architectural Models for Predicting the Amount of Natural Disasters and their Effects Using Batch Training

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Abstract. The Batch Training method is one of the methods of Artificial Neural Networks that can be used to make predictions, especially in times series data. This method is able to make predictions by learning from data that has never happened before by forming the right network architecture model. Therefore, this research will discuss the best network architecture model that is appropriate for making predictions using the Batch Training method. The data used in this study is the data of Natural Disasters in Indonesia, sourced from the National Disaster Management Agency. There are 12 variables used, namely Time of disaster, Number of disasters, Death and missing victims, injured victims, victims suffering and displaced, seriously damaged houses, lightly damaged homes, submerged houses, damage to health facilities, damage to worship facilities, and damage to facilities education. Based on this data will be formed and determined the network architecture model used, including 4-5-1, 4-10-1 and 4-15-1. From these 3 models after training and testing, the best architectural model is obtained 4-10-1 with an accuracy level of 91% with MSE Training and testing values of 0.0245532940 and 0.0579265906.

1. Introducing
Natural disasters are disasters caused by events or a series of events caused by nature such as earthquakes, tsunamis, volcanic eruptions, floods, droughts, hurricanes, and landslides. In general, natural disasters occur because of changes in nature, both slowly and in the extreme. However, some natural disasters occur because of human intervention, for example, the felling of trees in the forest which causes landslides. Until now scientists have made various efforts to detect disasters. However, not all natural disasters can be detected early because it is still a mystery until now. Natural disasters cause losses and damage and can affect subjective expectations about the prevalence and severity of future disasters [1]. Natural disasters can also affect social life in society [2]. Some researchers and experts also claim that natural disasters also have a negative effect on politics in a country [3]. Some natural disasters in the world have caused serious damage to social construction and economic development, such as the 2004 Indonesian tsunami, Gempa Wenchuan 2008 [4], freezing rain disaster in southern China in 2008, 2011 earthquake disaster in Japan, flood disaster in India in 2013 and hail...
in Yancheng in 2016, Jiangsu. Especially in July 2016, heavy rains continued to strike northern China, with severe flooding in southern China at the same time [5].

In Indonesia, in the last few decades, according to the National Disaster Management Agency, the number of natural disasters in Indonesia from 2008 to 2018 has increased, but in 2019 the number of natural disasters in Indonesia has decreased significantly, from which 3,406 natural disasters began to become 1,999 natural disasters or down 1,407 natural disasters. However, this is because, at the time of data collection, 2019 was still incomplete, because the authors took data in October 2019. Overall, based on data from the National Disaster Management Agency, 2018 was the biggest natural disaster compared to previous years when viewed from the Number of natural disasters, dead and missing victims, suffering and displaced, and moderate damaged homes. Whereas based on heavily damaged houses, lightly damaged homes, damage to health facilities, damage to worship facilities and damage to the worst educational facilities occurred in 2009 [6].

There are several previous studies that discuss natural disasters, among others, research to predict fatalities who died, injured, lost or displaced due to natural disasters. This study produces predictions with an accuracy rate of 80% [7]. Furthermore, the research was conducted using the DWT, ARIMA and ANN methods to predict and visualize the risk of disasters that occur in the Philippines. Of the three methods, the ARIMA method is the best method for predicting victims affected by natural disasters, house damage or property damage with an accuracy of 53.72%, while the other two methods only produce an accuracy of 36.72% and 26.36 %. However, based on the impact of natural disasters that occur as a whole, the DWT model is the best with an accuracy of 62.81%, while the ARIMA accuracy rate is only 39.84% and ANN accuracy is 33.33%. The conclusion of this research is that there is not a too big difference between the predicted data obtained from the actual data [8]. Based on this background, research will be carried out to determine the best architectural model that can later be used to assist further research in terms of predicting the number of natural disasters and their consequences using batch training. The way these method works is almost the same as the Backpropagation algorithm, it's just that the parameters used in this algorithm are more complex to obtain the desired results. This method is also one of the methods of Artificial Neural Networks which is often used to make predictions, this is because this method is able to predict data based on previous data, so we get prediction results after learning and training based on data that has already happened [9 - 14].

### 2. Methodology

#### 2.1. Research Methods

Data collection uses quantitative methods. While the research method used is Batch training (trainb). This method is able to make predictions based on data (times series). In this method, each weight and bias will be updated according to the learning function. The training that has been conducted will stop if one of these conditions is met: Performance has been minimized to the destination, Maximum amount of time has been exceeded, Maximum number of history (repetitions) has been reached, Validation performance has increased beyond the max_fail time when the last time was rejected (validation use).

#### 2.2. Data Source

Data on Natural Disasters in Indonesia by Time, from 2010-2019 taken from the National Disaster Management Agency[6].

| Years | Amount | Victim (jiwa) | Home (unit) | Damage (unit) |
|-------|--------|---------------|-------------|---------------|
|       |        | Died & Lost | Suffer & Evacuate | Severely damaged | Moderately damaged | Damaged lightly | Submerged | Medical Facility | Worship Facility | Educational Facilities |
| 2010  | 1,947  | 1,907 | 35,730 | 1,663,103 | 20,084 | 3,709 | 35,708 | 686,523 | 367 | 628 | 1,557 |
| 2011  | 1,622  | 428 | 692 | 475,529 | 13,549 | 3,358 | 56,736 | 194,785 | 106 | 457 | 566 |
2.3. Research Stages

The first thing to do in this research stage is the collection of datasets. The dataset used is natural disaster data in Indonesia according to the time taken in 2010-2019. Then pre-processing and dividing the data are divided into several parts, namely the data used for training (training) and the data used for testing. Then determine the network architecture model that will be used for the training process and the testing process, after all, is done will be obtained based on the architectural model used. Furthermore, from the several architectural models used, the best is chosen.

2.4. Research Variable

There are 12 variables used, namely Time of disaster, Number of disasters, Death and missing victims, injured victims, victims suffering and displaced, seriously damaged houses, lightly damaged houses, submerged houses, damage to health facilities, damage to worship facilities, and damage to facilities education.

2.5. Normalization

Before the data in table 1 is used as input data in ANN, the data must be normalized first because in training the author uses the sigmoid (binary) activation function, the existing data must be normalized to the output range of the sigmoid activation function (between 0 and 1). Normalization is done by simplifying the computational process. After that, the data is divided into 2 parts. The data for 2010-2013 with the 2014 target is used as training data, while the 2015-2018 data with the 2019 target are used as test data.

3. Results and Discussion

3.1. Results of Normalization Data

Table 2 is the result of data normalization using the sigmoid function based on the data contained in table 1.

| Years | Amount | Died & Lost | Injuries | Suffer & Evacuate | Severely damaged | Moderately damaged | Damaged lightly | Submerged | Medical Facility | Worship Facility | Educational Facilities |
|-------|--------|-------------|----------|-------------------|------------------|-------------------|----------------|-----------|----------------|----------------|---------------------|
| 2010  | 0.00125| 0.01020     | 0.01026  | 0.00010           | 0.01015          | 0.01002          | 0.01027        | 0.015299  | 0.00003        | 0.00005        | 0.00002             |
| 2011  | 0.0011 | 0.01003     | 0.01005  | 0.01067           | 0.01010          | 0.01002          | 0.01043        | 0.011503   | 0.01001        | 0.01003        | 0.01004             |
| 2012  | 0.0013  | 0.01002     | 0.01009  | 0.01736           | 0.01008          | 0.01006          | 0.01027        | 0.011448   | 0.01000        | 0.01001        | 0.01003             |
| 2013  | 0.0013  | 0.01004     | 0.01026  | 0.00004           | 0.01013          | 0.01009          | 0.01045        | 0.13633    | 0.01002        | 0.01005        | 0.01014             |
| 2014  | 0.0015  | 0.01004     | 0.01016  | 0.01722           | 0.01015          | 0.01004          | 0.01022        | 0.14055    | 0.01000        | 0.01002        | 0.01006             |
| 2015  | 0.0013  | 0.01002     | 0.01003  | 0.19477           | 0.01040          | 0.01030          | 0.10127        | 0.11392    | 0.01000        | 0.01001        | 0.01002             |
| 2016  | 0.0018  | 0.01004     | 0.01020  | 0.04409           | 0.01069          | 0.01007          | 0.10222        | 0.12582    | 0.01002        | 0.01004        | 0.01011             |
| 2017  | 0.0022  | 0.01003     | 0.01008  | 0.38360           | 0.01080          | 0.01082          | 0.10221        | 0.12905    | 0.01001        | 0.01005        | 0.01010             |
| 2018  | 0.0026  | 0.01016     | 0.10151  | 0.90000           | 0.10908          | 0.10542          | 0.11406        | 0.12421    | 0.01002        | 0.01009        | 0.01023             |
| 2019  | 0.0015  | 0.01003     | 0.10011  | 0.15025           | 0.10231          | 0.10032          | 0.10130        | 0.11181    | 0.01001        | 0.01002        | 0.01003             |

Data processing, both in the form of training and testing, will be assisted using the Matlab 2011b application in determining the best architectural model. This study was analyzed using 3 Architectural
models, namely: 4-5-1, 4-10-1 and 4-15-1. The way to determine the best architectural model is to use the Batch training method (trainb), to determine the minimum error of the training and testing process conducted. The error rate used is 0.02. The parameters used with this method are generally standard parameters that have been determined by Matlab, including: Epochs =1000, Goal = 0, max_fail = 6, min_grad = 1e-6, show = 25, showCommandLine = false, showWindow = true, time = inf [22].

3.2. Best Model Training and Testing
From 3 network models analyzed, the 4-10-1 is the best.

Figure 1. Training network model 4-10-1.

Table 3. Training Network Model 4-10-1.

| Pattern | Targ  | Op   | Err  | SSE       |
|---------|-------|------|------|-----------|
| 1       | 0.10015 | 0.10170 | 0.00155 | 0.00000242057 |
| 2       | 0.10004 | 0.10110 | 0.00106 | 0.0000011150 |
| 3       | 0.10106 | 0.09740 | -0.00276 | 0.0000076168 |
| 4       | 0.31722 | 0.83600 | 0.51878 | 0.2691368195 |
| 5       | 0.10155 | 0.10530 | 0.00375 | 0.00001040832 |
| 6       | 0.10047 | 0.10280 | 0.00233 | 0.0000054488 |
| 7       | 0.10226 | 0.11600 | 0.01374 | 0.0000187099 |
| 8       | 0.14555 | 0.16750 | 0.02695 | 0.0007261415 |
| 9       | 0.10000 | 0.10110 | 0.00110 | 0.0000012049 |
| 10      | 0.10002 | 0.10120 | 0.00118 | 0.0000013810 |
| 11      | 0.10006 | 0.10120 | 0.00114 | 0.0000013074 |

$\text{MSE} = 0.2700862337$

Table 4. Testing Network Model 4-10-1.

| Pattern | Targ  | Op   | Err  | SSE       | Results |
|---------|-------|------|------|-----------|---------|
| 1       | 0.10015 | 0.10220 | 0.00205 | 0.0000041953 | 1       |
| 2       | 0.10003 | 0.10140 | 0.00137 | 0.0000018885 | 1       |
| 3       | 0.10011 | 0.10240 | 0.00229 | 0.0000052537 | 1       |
| 4       | 0.15025 | 0.94830 | 0.79805 | 0.6368804351 | 0       |
| 5       | 0.10031 | 0.10550 | 0.00519 | 0.0000269380 | 1       |
| 6       | 0.10032 | 0.10610 | 0.00578 | 0.0000334065 | 1       |
| 7       | 0.10130 | 0.11460 | 0.01330 | 0.0001769284 | 1       |
| 8       | 0.11162 | 0.10340 | -0.00751 | 0.0000056380 | 1       |
| 9       | 0.10001 | 0.10130 | 0.00129 | 0.0000016762 | 1       |
| 10      | 0.10002 | 0.10140 | 0.00138 | 0.0000019068 | 1       |
| 11      | 0.10003 | 0.10190 | 0.00187 | 0.0000034882 | 1       |

$\text{MSE} = 0.6371924966$ 91%

3.3. Prediction results
In table 5 below, we will see a comparison of the 3 architectural models.
**Table 5.** Comparison of Architectural Models.

| Model   | Epoch | Times | MSE Training       | MSE Testing       | Accuracy |
|---------|-------|-------|--------------------|-------------------|----------|
| 5-5-1   | 1000  | 00:05 | 0,0190654362       | 0,0644948020      | 27%      |
| 5-10-1  | 1000  | 00:05 | 0,0245532940       | 0,0579265906      | 91%      |
| 5-15-1  | 1000  | 00:06 | 0,0017735481       | 0,0542400885      | 82%      |

4. Conclusion

The Batch (trainb) method can be used to predict the number of natural disasters in Indonesia and their impacts, due to good accuracy. Based on the analysis of 3 architectural models used in this study (4-5-1, 4-10-1 and 4-15-1), the best architectural model is obtained 4-10-1 with prediction accuracy of 91%. MSE training of this model is 0,0245532940 and MSE testing is 0,0579265906.

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