Utilization of the Batch Training Method for Predicting Natural Disasters and Their Impacts

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Abstract. Indonesia is one of the countries that often experiences natural disasters, including earthquakes, floods, tsunamis, etc. All of this causes losses, both casualties, Broken, and Anguishing for the population. Based on this, this paper is proposed, which aims to predict natural disasters in the coming years in Indonesia, casualties, Broken, and their consequences. This paper is an extension of previous research, which is still an architectural model to predict Indonesia's natural disasters and their impacts. Model 4-10-1 is the best in this study, which produces 91% accuracy. Based on this architectural model, this paper will predict natural disasters that occur and their impacts for the years to come in Indonesia. The research dataset and algorithms used remain the same, namely the natural disaster dataset for 2008-2019. Resourced from its National Emergency Management Department and the Batch Training algorithm. Specifically, the results of this proposed paper are in the form of a prediction of natural disasters that will occur, dead and disappear, injured, Anguishing and displaced, houses severely Broken, moderately Broken, lightly Broken to submerged, and Broken to facilities and infrastructure such as health facilities, facilities. worship and educational facilities.

1. Introduction
The occurrence of natural disasters is usually triggered by a condition or series of natural events such as floods, tsunamis, earthquakes, volcanic eruptions, landslides, hurricanes, drought and others. In general, natural disasters arise due to changes in nature, both gradual and extreme. But there are also natural disasters that arise because of human activity, such as logging that can cause landslides. Many researchers and scientists to date have tried various ways so that natural disasters can be detected. However, in reality, natural disasters are always a mystery because identification and detection are quite difficult. Almost every natural disaster that occurs is bound to cause loss, damage to casualties. In addition, natural disasters can influence subjective perceptions about the seriousness of potential disasters and their prevalence [1]. The impact of natural disasters also has implications for people's lives, especially in the social sector [2]. Experts and analysts also argue that the occurrence of natural disasters has a very negative effect on state policy [3]. Some of the world's natural disasters have caused significant harm to the social building and economic growth, including the 2004 Indonesian tsunami and the 2008 Wenchuan earthquake [4], Southern China's freezing rain disaster in 2008, Japan's earthquake disaster in 2011, India's flood disaster in 2013 and Jiangsu hail in Yancheng in
2016. Continues to hit Heavy rains in July 2016 in North China, along with major floods that hit South China [5].

According to the National Emergency Management Department of Republic Indonesia, natural disasters in 2008-2018 in the last decade have increased quite a bit, but in 2019 this number decreased as recorded from 3,406 to 1,999 alone. Based on statistics from the National Emergency Management Department, natural disasters in 2018 were the biggest disasters compared to previous years, due to the large number of natural disasters, depression and loss of homes, dead and missing victims, and broken moderate houses [6].

Table 1. Natural Disasters Data in Indonesia

| Times | Total | Dead & Disappear | Injuries | Anguish & Evacuate | Broken Severe | Broken Moderate | Broken Lightly | Submerged | Facility Medical | Facility Worship | Facility Educational |
|-------|-------|------------------|----------|-------------------|---------------|----------------|---------------|-----------|-----------------|-----------------|---------------------|
| 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                 |
| 2012  | 1.781 | 320              | 1198     | 954.241           | 10.686        | 8.018          | 35.356        | 187.601   | 89              | 219             | 473                 |
| 2013  | 1.666 | 512              | 3.410    | 3.892.986         | 17.727        | 12.590         | 59.401        | 470.756   | 321             | 684             | 1.902               |
| 2014  | 1.963 | 604              | 2.104    | 2.814.265         | 20.079        | 6.067          | 29.350        | 525.434   | 63              | 355             | 766                 |
| 2015  | 1.694 | 276              | 370      | 1.277.929         | 5.217         | 3.871          | 16.444        | 180.319   | 33              | 159             | 309                 |
| 2016  | 2.308 | 578              | 2.675    | 3.162.491         | 9.029         | 9.979          | 28.790        | 334.606   | 232             | 601             | 1.484               |
| 2017  | 2.868 | 378              | 1.042    | 3.674.369         | 10.452        | 10.648         | 28.631        | 376.373   | 117             | 715             | 1.326               |
| 2018  | 3.406 | 2.046            | 12.96010| 354.764           | 117.655       | 70.303         | 182.195       | 313.653   | 287             | 1.176           | 2.984               |
| 2019  | 1.999 | 367              | 1.431    | 651.095           | 4.047         | 4.181          | 16.857        | 153.025   | 102             | 281             | 452                 |

Because disaster information is so important as an Early Warning step for the people of Indonesia, it is necessary to predict the number of disasters in the following year as well as an estimate of casualties (Death and Missing, Injured, Anguish and Displaced), Houses / Units (Severely Broken, Moderately Broken), slightly Broken and submerged) and Broken / unit (health facilities, worship facilities and educational facilities). One of the good algorithms used to make predictions is the batch training algorithm. This algorithm is one of the Algorithms of the ANN. Artificial Neural Networks are widely used for solving problems related to estimation (prediction), pattern recognition, data analysis, control and grouping [7]–[12].

This research was conducted as a development of previous research conducted by Ginantra, et al (2020). As it should be noted that the results of this study are still in the form of a network architecture model to predict natural disasters and their impact using Batch training, not yet at the stage of the resulting predictive value [13]. Therefore in this paper, a calculation process will be carried out to obtain a prediction result in the form of the number of disasters, casualties (Death and Disappear, Injuries, Anguishing, and Evacuate), Houses/Units (Broken Severe, Broken Moderate, Broken lightly and submerged) or Broken/unit (Facility Medical, Facility Worship, and Facility Educational). The next research was conducted by Wanto, et al. (2019) to analyze the Batch Training method's accuracy in seeing the development of Indonesian aquaculture companies. The result is that the accuracy of this method reaches 75%, which means it is good enough to use [14].

Based on this background, a study was conducted to predict natural disasters and their impacts using a batch training algorithm. This study's results are expected to be input and reference for the government to determine policies or make appropriate strategic steps to respond to disasters that will occur in Indonesia for the coming years to minimize casualties and Broken.
2. Methodology

2.1. Techniques and Methods
Collecting data uses quantitative techniques. While the method used is batch training (trainb). This approach will render data-based predictions (times series). The weighting and bias processes in accordance with the learning function with this method will be modified.

2.2. Techniques and Methods
The stages carried out in this study can be seen in Figure 1.

![Figure 1. Research Stages](image)

2.3. Variables
The twelve variables of this analysis are the time of catastrophe, the total of disasters, dead and Disappear, Injuries, Anguishing and Evacuate, seriously Broken houses, lightly Broken houses, Submerged, Broken facility medical, Broken facility worship, and Broken facility educational.

3. Results and Discussion

3.1. Normalization
Based on the data in Table 1, first normalization will be carried out using equations (1) berikut: [15]–[18].

\[ x' = \frac{0.8(x - a)}{b - a} + 0.1 \]  

(1)

| Years | Total   | Dead & Disappear | Toll (Soul) | Input | Testing | Training (Change update weight) | Selecting Learning Algorithms | Determining the Network Structure | Data Separation for Training and Testing | Implementation of Artificial Neural Networks | Data collection |
|-------|---------|-----------------|-------------|-------|---------|---------------------------------|------------------------------|----------------------------------|-----------------------------------|---------------------------------------|----------------|
| 2010  | 0.10015 | 0.10014         | 0.10276     | 0.22836 | 0.10155 | 0.10028                         | 0.10275                     | 0.15299                         | 0.10003                         | 0.10005                         | 0.10012       |
| 2011  | 0.10002 | 0.10003         | 0.10005     | 0.13670 | 0.10104 | 0.10026                         | 0.10438                     | 0.11503                         | 0.10001                         | 0.10003                         | 0.10004       |
| 2012  | 0.10013 | 0.10002         | 0.10099     | 0.17365 | 0.10082 | 0.10062                         | 0.10273                     | 0.11448                         | 0.10000                         | 0.10001                         | 0.10003       |
| 2013  | 0.10013 | 0.10004         | 0.10026     | 0.40048 | 0.10137 | 0.10097                         | 0.10458                     | 0.13633                         | 0.10002                         | 0.10005                         | 0.10014       |
| 2014  | 0.10015 | 0.10004         | 0.10016     | 0.31722 | 0.10155 | 0.10047                         | 0.10226                     | 0.14055                         | 0.10000                         | 0.10002                         | 0.10006       |
| 2015  | 0.10013 | 0.10002         | 0.10003     | 0.19477 | 0.10040 | 0.10030                         | 0.10127                     | 0.11392                         | 0.10000                         | 0.10001                         | 0.10002       |
| 2016  | 0.10018 | 0.10004         | 0.10020     | 0.34409 | 0.10069 | 0.10077                         | 0.10222                     | 0.12582                         | 0.10002                         | 0.10004                         | 0.10011       |
| 2017  | 0.10022 | 0.10003         | 0.10008     | 0.38360 | 0.10080 | 0.10082                         | 0.10221                     | 0.12905                         | 0.10001                         | 0.10005                         | 0.10010       |

Table 2. Normalization Results
3.2. Results of Training and Testing

Based on previous research [13], there are 3 architectural models used: 4-5-1, 4-10-1, and 4-15-1. Model 4-10-1 is the best because of its 91% accuracy rate (higher than other architectural models). The parameters used are also the same as the study. The analysis process uses Matlab and Microsoft Excel tools. The training and testing results of the three models used can be seen in Table 3, Table 4, Table 5, Table 6, Table 7, and Table 8.

| Table 3. Training with Model 4-5-1 |
|-----------------------------------|
| P      | T     | O     | E     | SSE   |
| P1 0.10015 | 0.12560 | 0.02545 | 0.0006477551 |
| P2 0.10004 | 0.12620 | 0.02616 | 0.0006841325 |
| P3 0.10016 | 0.12830 | 0.02814 | 0.0007918681 |
| P4 0.31722 | 0.73840 | 0.42118 | 0.1773959463 |
| P5 0.10155 | 0.12150 | 0.01995 | 0.0003981123 |
| P6 0.10047 | 0.12410 | 0.02363 | 0.0005585786 |
| P7 0.10226 | 0.10720 | 0.00494 | 0.000243757 |
| P8 0.14055 | 0.30540 | 0.16485 | 0.0271745377 |
| P9 0.10000 | 0.12620 | 0.02620 | 0.0006863187 |
| P10 0.10002 | 0.12610 | 0.02608 | 0.0006799133 |
| P11 0.10006 | 0.12610 | 0.02604 | 0.0006782599 |

MSE 0.209719782

| Table 4. Testing with Model 4-5-1 |
|-----------------------------------|
| P      | T     | O     | E     | SSE   | Results |
| P1 0.10015 | 0.12520 | 0.02505 | 0.0006274151 | 0 |
| P2 0.10003 | 0.12600 | 0.02597 | 0.0006746601 | 0 |
| P3 0.10011 | 0.12480 | 0.02469 | 0.0006096996 | 0 |
| P4 0.15025 | 0.90700 | 0.75675 | 0.5726673694 | 0 |
| P5 0.10031 | 0.11960 | 0.01929 | 0.0003721110 | 1 |
| P6 0.10032 | 0.12020 | 0.01988 | 0.0003952079 | 1 |
| P7 0.10130 | 0.11160 | 0.01030 | 0.0001061197 | 1 |
| P8 0.11181 | 0.47510 | 0.36329 | 0.1319805966 | 0 |
| P9 0.10001 | 0.12610 | 0.02609 | 0.0006809320 | 0 |
| P10 0.10002 | 0.12600 | 0.02598 | 0.000675050 | 0 |
| P11 0.10003 | 0.12560 | 0.02557 | 0.0006537052 | 0 |

MSE 0.7094428217

| Table 5. Training with Model 4-10-1 |
|-----------------------------------|
| P      | T     | O     | E     | SSE   |
| P1 0.10015 | 0.10170 | 0.00155 | 0.0000024057 |
| P2 0.10004 | 0.10110 | 0.00106 | 0.0000011150 |
| P3 0.10016 | 0.09740 | -0.00276 | 0.0000076168 |
| P4 0.31722 | 0.83600 | 0.51878 | 0.2691368195 |
| P5 0.10155 | 0.10530 | 0.00375 | 0.0000140832 |
| P6 0.10047 | 0.10280 | 0.00233 | 0.0000054488 |
| P7 0.10226 | 0.11600 | 0.01374 | 0.0001887099 |
| P8 0.14055 | 0.16750 | 0.02695 | 0.0007264145 |
| P9 0.10000 | 0.10110 | 0.00110 | 0.0000012049 |
| P10 0.10002 | 0.10120 | 0.00118 | 0.0000013810 |
| P11 0.10006 | 0.10120 | 0.00114 | 0.0000013074 |

MSE 0.2700862337

| Table 6. Testing with Model 4-10-1 |
|-----------------------------------|
| P      | T     | O     | E     | SSE   | Results |
| P1 0.10015 | 0.10220 | 0.00205 | 0.0000041953 | 1 |
| P2 0.10003 | 0.10140 | 0.00137 | 0.0000018885 | 1 |
| P3 0.10011 | 0.10240 | 0.00229 | 0.0000052537 | 1 |
| P4 0.15025 | 0.94830 | 0.79805 | 0.6368804351 | 0 |
| P5 0.10031 | 0.10550 | 0.00519 | 0.0000269380 | 1 |
| P6 0.10032 | 0.10610 | 0.00578 | 0.0000334605 | 1 |
| P7 0.10130 | 0.11460 | 0.01330 | 0.0001769284 | 1 |
| P8 0.11181 | 0.10430 | -0.00751 | 0.0000563800 | 1 |
| P9 0.10000 | 0.10130 | 0.00129 | 0.0000016762 | 1 |
| P10 0.10002 | 0.10130 | 0.00138 | 0.0000019068 | 1 |
| P11 0.10003 | 0.10190 | 0.00187 | 0.0000034882 | 1 |

MSE 0.6371929496

| Table 7. Training with Model 4-15-1 |
|-----------------------------------|
| P      | T     | O     | E     | SSE   |
| P1 0.10015 | 0.10540 | 0.00525 | 0.0000275734 |
| P2 0.10004 | 0.10470 | 0.00466 | 0.0000216777 |
| P3 0.10016 | 0.10300 | 0.00284 | 0.0000080665 |
| P4 0.31722 | 0.18450 | -0.13272 | 0.0176135416 |

| Table 8. Testing with Model 4-15-1 |
|-----------------------------------|
| P      | T     | O     | E     | SSE   | Results |
| P1 0.10015 | 0.10590 | 0.00575 | 0.0000330424 | 1 |
| P2 0.10003 | 0.10480 | 0.00477 | 0.0000227932 | 1 |
| P3 0.10011 | 0.10520 | 0.00509 | 0.0000259294 | 1 |
| P4 0.15025 | 0.91380 | 0.76355 | 0.5830053807 | 0 |
Based on the data in Table 3, Table 4, Table 5, Table 6, Table 7, and Table 8, the results show that Model 4-10-1 is the best model chosen.

### Table 7. Training with Model 4-15-1

| P   | T       | O       | E       | SSE     |
|-----|---------|---------|---------|---------|
| P5  | 0.10155 | 0.10990 | 0.00835 | 0.0000687685 |
| P6  | 0.10047 | 0.10710 | 0.00663 | 0.0000440135 |
| P7  | 0.10226 | 0.13160 | 0.02934 | 0.000860697 |
| P8  | 0.14055 | 0.11230 | -0.02825 | 0.0007982313 |
| P9  | 0.10000 | 0.10470 | 0.09470 | 0.0000220682 |
| P10 | 0.10002 | 0.10470 | 0.00468 | 0.0000218570 |
| P11 | 0.10006 | 0.10470 | 0.00464 | 0.0000215614 |
|     |         |         | 0.0195090286 |         |
| MSE | 0.0017735481 |   |         |         |

### Table 8. Testing with Model 4-15-1

| P   | T       | O       | E       | SSE     | Results |
|-----|---------|---------|---------|---------|---------|
| P5  | 0.10031 | 0.10680 | 0.00649 | 0.0000421224 | 1 |
| P6  | 0.10032 | 0.10850 | 0.00818 | 0.0000669097 | 1 |
| P7  | 0.10130 | 0.11600 | 0.01470 | 0.0002161324 | 1 |
| P8  | 0.11181 | 0.22650 | 0.11469 | 0.0131541031 | 0 |
| P9  | 0.10001 | 0.10480 | 0.00479 | 0.0000229889 | 1 |
| P10 | 0.10002 | 0.10490 | 0.00488 | 0.0000238228 | 1 |
| P11 | 0.10003 | 0.10530 | 0.00527 | 0.0000277482 | 1 |
|     |         |         | 0.0542400885 |         | 82%     |

Explanation: P = Pattern, T = Target, O = Output, E = Error

3.3. Prediction results

Then the prediction will be made using the 4-10-1 model using the formula to return the value:

\[
x_n = \frac{(x - \bar{b}) \times (b - a)}{a} + a
\]

Explanation:

- \(x_n\) = Prediction Results
- \(x\) = Predicted Target
- \(a\) = The smallest data from the dataset
- \(b\) = The largest data set from the dataset

For the prediction results in 2020 can be seen in Table 9.
Table 9. Results of Prediction of Natural Disasters in Indonesia (2020)

| Years | Total | Dead & Lost | Anguish & Evacuate | Severely Broken | Moderately Broken | Broken Lightly | Submerged | Medical Facility | Worship Facility | Educational Facilities |
|-------|-------|-------------|--------------------|-----------------|------------------|----------------|------------|-----------------|-----------------|------------------------|
| 2016  | 2.308 | 578         | 2.675              | 3.162.491       | 9.029            | 9.979         | 28.790     | 334.606         | 232             | 601                    | 1.484                 |
| 2017  | 2.868 | 378         | 1.042              | 3.674.369       | 10.452           | 10.648        | 28.631     | 376.375         | 117             | 715                    | 1.326                 |
| 2018  | 3.406 | 2046        | 19.610             | 10.364.764      | 117.655          | 70.303        | 182.195    | 313.653         | 287             | 1.176                  | 2.984                 |
| 2019  | 1.999 | 367         | 1.431              | 651.095         | 4.047            | 4.181         | 16.857     | 153.025         | 102             | 281                    | 452                   |
| 2020  | 223   | 138         | 232                | 176.860         | 1.361            | 481           | 1.943      | 331.102         | 104             | 122                    | 148                   |

4. Conclusion

The 4-10-1 architectural model with the Batch training method can be used to predict natural disasters in Indonesia with an accuracy rate of 91%. The architectural model and parameters used have an effect on the resulting level of accuracy. Based on the comparison between the Preliminary Data and the Prediction data (2020), the number of disasters and their consequences decreased quite significantly. However, in reality, until the end of 2020, natural disasters and their consequences has indeed decreased, but not significantly compared to the predicted data. Thus the results of this study need to be reviewed to obtain accurate results (even better).

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