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Prediction of flood events in the city of Bandar Lampung using the artificial neural network

Ramadhan Nurpambudi[1,*], Eka Suci Puspita Wulandari[2], RZ. Abdul Aziz[3]
[1,2,3]Darmajaya Lampung Institute of Informatics and Business
[1,2]Meteorological, Climatological, and Geophysical Agency of Lampung
[1,2,3]ZA. Pagar Alam Street No. 93, Bandar Lampung City, Lampung 35141, Indonesia
[1,2]Radin Inten II Airport, Branti Raya Street, South Lampung Regency, Lampung 35362, Indonesia
[*]Corresponding email: ramadhan92.2121211010@mail.darmajaya.ac.id

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Abstract — The city of Bandar Lampung, Indonesia, is recently experiencing seasonal flooding, which occurs almost every year and results in significant losses. In the last 10 years, floods event recorded by the National Agency for Disaster Countermeasure (BNPB) in the Bandar Lampung area is 16 incidents of flooding. More than 14,000 people suffered, more than 500 people had to be evacuated, more than 900 houses were damaged, and four public facilities were damaged. To study the pattern of flood events in the past, the Artificial Neural Network Backpropagation learning method will be used which will utilize its non-linear variable learning abilities. The configuration settings for the Artificial Neural Network were carried out experimentally without any basis for assigning values, especially for the parameters of the number of hidden layers, number of neurons, and epochs used in training and variable testing. The results obtained from this study are the results of training and testing of datasets that have been carried out by ANN backpropagation and can properly study patterns of flood events and also non-flood events in the dataset, this is evidenced by the results of high model configuration accuracy and also the results of predictive tables that able to describe actual conditions, setting the configuration model experimentally can produce an accuracy value of 90 %-100 %, an average training correlation value of 0.96 and an average test correlation value of 0.89, and an average error value of 0.0089 out of 20 model configuration, and the flood prediction table are made based on the 1 best configuration with a training and testing accuracy rate of 100 % with an error value of 0.00134, namely configuration model 20, the prediction table uses an average air temperature of 27°C with 80 % humidity. The prediction table can produce excellent flood potential results which can represent flood events as well as non-flood events based on the results of the dataset learning.

Keywords – Artificial neural network, early warning, flood, prediction

I. Introduction

The World Meteorological Agency (WMO) stated that disasters originating from weather and climate over the past 50 years claimed an average of 150 lives each year with material losses reaching US$ 202 million each day. The number of these disasters has almost tripled over the last 50-year period. There are more than 11,000 disasters reported related to this threat globally, with more than 2 million deaths at a cost of US$ 3.64 trillion. Of the total 11,000 disasters, hydrometeorological disasters accounted for 50 % of the incidents, of the 2 million deaths, 45 % were from hydrometeorological disasters, and 74 % of the total losses were caused by hydrometeorological disasters [1].

The most felt impact of climate change is the increase in the frequency of hydrometeorological disasters and their damage. This not only has an impact on environmental damage but also has an impact on the spread of disease, environmental quality, and also the level of social welfare in the community. Apart from that, another impact of climate change is the occurrence of land fires due to drought. Land fires can cause soil conditions to become unstable and can eventually cause landslides when it rains with heavy intensity [2].

Floods are one of the direct effects of extreme weather, namely heavy rains. With the increasing frequency of extreme weather, flood problems will also increase in the future. However, the current flood problem is still an annual routine in various regions, including Bandar Lampung. The problem of flooding still needs special attention from the local government. Floods can occur due to rain with high intensity for a long or short time, and accompanied by piles of garbage, lack of water catchment areas, or floods sent from higher areas [3].

According to Kurniadi *et al.* [4], the city of Bandar Lampung currently has frequent seasonal floods which occur almost every year, resulting in significant losses. Areas with flood-prone status do need special attention, not only for the people who live in the area, but the local government must also be responsive so that it does not continue to recur. Floods recorded by BNPB in the last 10 years there were 16 incidents of flooding in the Bandar Lampung area. More than 14,000 people suffered, more than 500 people had to be evacuated, more than 900 houses were damaged, and 4 public facilities were damaged. To prevent casualties from occurring in flood management, early warning information is needed before the flood arrives.

Until now, the BMKG has products that can be used by the public in the form of 3 daily extreme weather early warnings, 2–3-hour extreme weather early warnings, and 2-3 hour extreme weather early warnings. This still needs to be done with innovation to complement existing products. The prediction of the potential for flooding tomorrow will be very useful information for the community and the local government in carrying out the mitigation and evacuation processes. Current flood predictions at the BMKG are far from accurate, current flood predictions are only based on predictions of daily rainfall in an area without any prior research on which to base them. For this reason, before stepping into making flood event predictions, a collection of past flood events was first carried out and analyzed using an Artificial Neural Network (ANN).

The ANN algorithms are able to learn independently from the data input into them and then provide responses, ANN are very adept at handling nonlinear data and produce very accurate findings and predictions [5]. Use of Artificial Neural Networks in [5]–[10] able to provide a correlation value and a high accuracy value in predicting flood events and a small error value. Research that has been conducted by [11]–[13] is not up to making a prediction table for flood events even though the results of training and testing the learning process for past flood events were quite good. Likewise, research conducted by [14]–[19] also still has the same shortcomings in the research he does, namely not carrying out a simulation of making a flood prediction table as an illustration for future conditions.

Based on these deficiencies, in this study, after obtaining the best training and testing accuracy values, it will be continued with the process of making flood prediction tables. In addition, it is also based on research [20] and [21], mapping flood-prone areas is a condition that is climatological in nature, for those that are nowcasting or short-range forecasting it will be difficult to use mapping that is climatological in nature, especially in flood prediction. Research conducted by [22] have carried out simulations related to flood events but the variables used are only rainfall, water levels, and runoff so that areas far from rivers will have little or no flood probability values. Based on the background above, this research will be a reference for the community as well as the government and other agencies to take anticipatory and evacuation steps when a flood occurs in the future, especially for BMKG forecasters in providing early warning.

II. RESEARCH METHOD

This section discusses the method for collecting data, research time period, research site, research data, and data analysis method.

A. Method of Collecting Data

The data collection carried out is as follows:

1) Collect data on flood events in Bandar Lampung City based on historical data from the National Disaster Management Agency (BNPB) and also online media,
2) Collect data on rainfall, air temperature, air humidity, surface winds, monsoon winds, and accumulated rainfall over the past week before the flood event in the Bandar Lampung City area based on BMKG observation data.

The amount of data used in this study amounted to 350 data consisting of 280 training data and 70 testing data. Of the 280-training data, 240 are training data and 40 data are training targets. Then from 70 test data it is divided into 60 test data and 10 test targets.

B. Research Time Period

The research time period taken in this study is the period 2010-2020. Flood events are collected based on this time period and for training and testing data variables such as rainfall data, air temperature data, air humidity data, surface winds, monsoon winds, and accumulated rainfall over the past week before the flood event also follows from the flood event.

C. Research Sites

The location of this research is focused on the city of Bandar Lampung, which has an astronomical location of 50º20’-50º30’ South Latitude and 105º28’-105º37’ East Longitude. For the boundaries of the City of Bandar Lampung as follows:

1) Northern Boundary: Natar District, South Lampung Regency,
2) Southern Boundary: Districts of Padang Cermin, Ketibung and Teluk Lampung, South Lampung Regency,

3) Eastern Boundary: Tanjung Bintang District, South Lampung Regency,
4) West Boundary: Gedong Tataan and Padang Cermin Districts, South Lampung Regency.

D. Research Data

There are several research data used in this study, namely:

1) Flood incident data for the 2010-2020 period obtained from BNPB which can be accessed through the website https://dibi.bnpb.go.id/.
2) Rainfall data in the Bandar Lampung City area, air temperature data, air humidity data, surface winds, monsoon winds, and accumulated rainfall over the past week before the flood event obtained from the data archive owned by BMKG Lampung.
3) Data on flood events and their supporting variables can also be obtained via kaggle [23].

E. Data Analysis Method

Analysis of predictions of flood events in this study using Matlab software. Before the data is input into Matlab, the data is collected in Excel. The data collected is in the form of data on flood events, rainfall, air temperature, air humidity, surface winds, monsoon winds, and accumulated rainfall over the past week before the flood occurred. This is useful to see whether there is an effect of soil saturation due to rainfall 1 week before the flood incident in the Bandar Lampung City area.

There are several important points in the analysis of this data, namely:

1) Rainfall data per day is the total amount of rainfall for one day.
2) Air temperature and humidity data are the average for one day.
3) Surface wind is the average surface direction in one day.
4) Monsoon wind is a wind direction that represents the direction of the Asian monsoon (360) and the Australian monsoon (130).
5) Data on flood events and whether there was rain one week before the flood event is denoted by 1 is a flood occurred and there was rain one week before the flood occurred, 0 is no flood and no rain fell one week before the flood occurred.

The data that has been collected in 1 table is divided into 80 % as training data and 20 % as testing data. Each of these training data and test data has training target data and test target data, these data are flood event data which are made in separate data columns. The data that has been divided is then transposed from the previous data in vertical form and then changed to horizontal so that it can be read in Matlab.

The next step is to add the transposed data into an excel database to then become training data, test data, and training targets. After the data is in the Matlab database, the next step is to conduct training through a backpropagation neural network. Furthermore, training functions use TRAINGD and adaptation learning functions use LEARNGD, this setting is an activation function (see Fig. 1). Then for the performance function, MSE is used. For the number of layers, number of neurons, and transfer function an experiment was carried out to get the best results, where the training target was R = > 0.9.

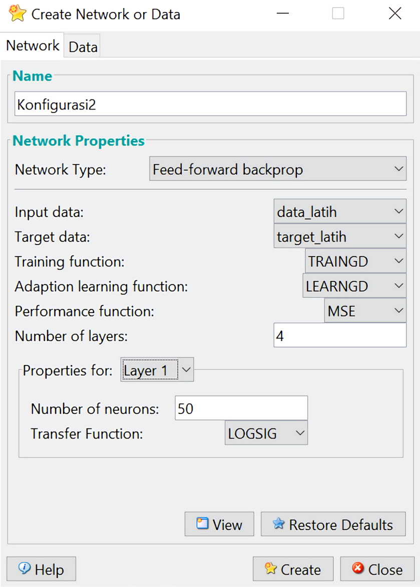

Fig. 1. Training data configuration in Matlab.

The next setting is to configure the epoch and max_fail values, the epoch value is set the same as max_fail. When the epoch is set to 10000, max_fail is also set to 10000. For other settings, it is set in default mode. After epoch and max_fail are set, the next step is to conduct training using the train network menu.

The data training process on the epoch menu will start running from 0 to the specified epoch value. To see the R value, you can use the regression menu, so it will look like in Fig. 2. If the R value is still below 0.9 then the training process continues to be repeated until the result is more than 0.9. If it is felt that the results have been maximized, the training process can be stopped.

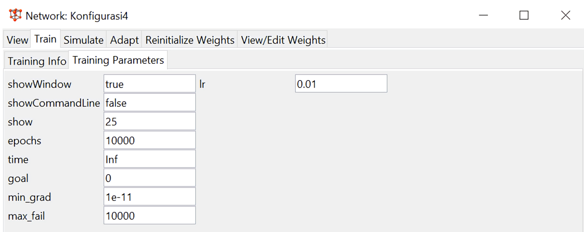

Fig. 2. Setting training parameters.

After obtaining the best R results, training on data testing is carried out which is 20 % of the total data that has been prepared. After that, the output results were verified with the flood event data. If the results are above 90 % then the training formula can be used for flood prediction testing, if it is not above 90 % then the experiment is repeated to get the best formula for flood prediction. After the best scheme is obtained, the next step is to make a flood classification table in the Bandar Lampung City area with various variations in the parameter element values to obtain the percentage of each element variation. This classification table will be used as a Decision Support System for BMKG forecasters to determine how big the chance of flooding tomorrow is. This can then be forwarded as flood early warning information to the community and also the local government for the mitigation and evacuation process.

The process of calculating the accuracy value is obtained based on calculating the number of correct predictions divided by the total data multiplied by 100 %. The magnitude of the predicted value is expressed in percentages. Accuracy value calculations are carried out both during training and during testing. This is done to see how the performance and also the stability of the configuration model. After calculating the accuracy of the training and subsequent testing, it will be collected into one table for analysis. In addition to performing the manual accuracy calculation process, accuracy value calculations are also carried out using the hyperparameter feature. To see whether the dataset variables used are suitable for use, use the hyperparameter feature. This feature will look for the highest accuracy value based on the dataset variables entered the model. However, this feature has the disadvantage of not always matching the entire dataset used, but the advantage is computational time efficiency and minimizing the opportunity for model overfitting.

Hyperparameters work to find the best pattern from the dataset with the existing configuration so that a good accuracy value is obtained. There are no standard rules for setting parameters such as layers, neurons, to epochs. Each setting will produce different results on each set of datasets [24]. The use of hyperparameters in a neural network will not always match the entire dataset variable, this is still a drawback in this feature [25]. Research conducted by [26] focus on making settings in the hyperparameter to find the best settings for the entire dataset used in the study because these features are not good for all datasets used.

III. Result

Before training and testing of a dataset totaling 350 data have been carried out by training (train) and also testing (test) using 20 different model configurations. From a total of 350 data, it is divided into 80 % for training data and 20 % for testing data. The amount of training data is 280 consisting of 240 training data and 40 training targets, and 70 testing data consisting of 60 test data and 10 test targets. The variables used as training data and test data are average air temperature, average humidity, average surface wind, monsoon wind (season), amount of rainfall, and accumulated rainfall over the past week before the date used.

As for the training targets and test targets, flood event data are used which are defined as floods (1) and no floods (0). The number of non-flooding events in the dataset is 29 events while the number of flood events is 21 events. First, the dataset is trained using the backpropagation ANN and also the distribution ANN to get the error value of each ANN. Then, a large difference in error values is compared to prove that backpropagation ANN works by reducing error values to get good predictive results. After that, it is continued by analyzing the training result data and test results using backpropagation ANN to see how the correlation changes between the training result data and the test result data and measuring the results of accuracy to see the performance of the model. Before determining the best model, an analysis is also carried out regarding how the backpropagation ANN performs using the hyperparameter feature or without using the hyperparameter. Hyperparameter is a feature provided by the model to find the best accuracy value in the configuration settings that are made. To test how the performance of the hyperparameter is tested regarding its error value, rmse value, and also its accuracy both in the training process and also in testing in various divisions of the dataset, namely 50:50, 60:40, 70:30, 80:20 and 90:10.

A. Comparison of Backpropagation ANN and Distribution ANN Error Values

Comparative analysis of error values between backpropagation ANN and distribution ANN has been carried out through 20 different configuration models regarding the number of hidden layers, number of neurons, and also epochs or iterations. The results obtained by the backpropagation ANN have a smaller error value of 85 % when compared to the error value of the distribution ANN. Of the 20 configuration models that have been tested, there is no error value from the distribution ANN which is smaller than the error value from the backpropagation ANN. This is done to prove that the backpropagation ANN works to reduce the error value so that the accuracy results obtained are better. The smallest percentage of error values occurs in the 13th model configuration with a value of 31 %. The rest is the percentage of error values above 50 % in 19 other configurations. Whereas the largest percentage occurs in the 8th model configuration with a percentage reaching 100 % smaller backpropagation ANN error value compared to the distribution ANN error value. Based on the average error value, the backpropagation ANN has a value of 0.009 while the distribution ANN has a value of 0.089 out of 20 model configurations. There is no backpropagation ANN error value that has a value of more than 0.05, while in distribution ANN there is no configuration that has a value less than 0.05. Based on the results of experiments that have been carried out from 20 model configurations, backpropagation ANN can be proven to have a smaller error value, especially in research conducted using flood event datasets.

The largest error value of the distribution ANN is 0.22 while the largest error value of the backpropagation ANN is 0.04. For the best error value of the distribution ANN, a value of 0.05 was obtained, while for the back-propagation ANN, a value of 0.00004 was obtained. The error value gets better when it is getting smaller or closer to the value 0 while for accuracy the greater or closer to 1 the better. Then an analysis was carried out based on the number of hidden layers used, first for the number of hidden layers 2, the average error value for the distribution ANN was 0.159 while for the backpropagation ANN was 0.007. Backpropagation ANN has a better or smaller error value of 93 %. The average difference in the error values of the two ANNs is 0.152, where the backpropagation ANN always has a smaller error value. The best distribution ANN error value is 0.052 while for backpropagation ANN is 0.00004, from each of the best values the backpropagation ANN value has a difference in error values of almost 100 %. For the configuration model with 3 layers, the average error difference between the backpropagation ANN and the distribution ANN is 0.054 or in percentage terms the backpropagation ANN with layers 3 has an error value of 91 % smaller than the distribution ANN. Then for the average distribution ANN error value of 0.059 and for backpropagation ANN of 0.005. In layer 3 there is not even a backpropagation ANN error value that reaches an error value of 0.1, this further strengthens the theory of backpropagation ANN which seeks to reduce the error value in order to obtain a better accuracy value. The largest backpropagation ANN error value is only 0.008 while the distribution ANN reaches 0.069. The difference between each of the smallest error values between the backpropagation ANN and the distribution ANN is 0.052 or the percentage reaches 97 %.

Furthermore, the configuration model that uses layers 4 is used and the average error value of the distribution ANN is 0.086 while for the back-propagation ANN is 0.013. The average difference is 0.073 or 75 times smaller than the backpropagation ANN error value compared to the distribution ANN. The smallest error value for backpropagation ANN is 0.001 while for ANN the most error value distribution is 0.052. From each of the smallest error values, the two ANNs have a difference of 0.050 or 97 smaller the value of the backpropagation ANN to the distribution ANN. The performance of the backpropagation ANN in reducing the error value, especially in this study that uses a flood event dataset, is very good. Next is an analysis of the configuration model using layers 5 where the average error value for the distribution ANN is 0.056 while for the backpropagation ANN is 0.010. The average error difference between backpropagation ANN and distribution ANN is 0.046 or 81 % smaller than the distribution ANN error value of backpropagation ANN. The best backpropagation ANN error value is 0.002 while the best distribution ANN error value is 0.053. Starting from the configuration model that uses layers 2 to layers 5, there is no error value from the distribution ANN which is smaller than the backpropagation ANN error value. So based on the research that was carried out using the backpropagation ANN flood event dataset it was successful in reducing the error value of each model configuration that was run.

B. Backpropagation ANN Training Results

Based on the 20 training model configuration results, the best correlation value was 0.99 for model configurations 2 and 12. As for the model configuration that had the lowest correlation value, the configuration model 3, 6 and 8 was 0.92. All model configurations during training are defaulted to 0.9. If during the training process the correlation does not reach 0.9 then the configuration settings will be replaced by parameters. As seen on Table 2, the greater the number of hidden layers, the greater the correlation results obtained. When the number of hidden layers used is 2 the highest correlation results are 0.95, out of 5 configuration attempts 4 of them have a configuration of 0.92. Whereas when using hidden layers 5 the lowest correlation result was 0.94, from 6 experiments using hidden layers 5 the correlation results were 0.99, 0.98, 0.97, 0.97, 0.96, and 0.94. Based on the parameter number of neurons, the greater the value of the parameter, it turns out that it doesn't really affect the correlation results. That the more neurons used does not guarantee the better the correlation results. Model 19 configuration that uses 10 neurons has better correlation results than model 18 configuration that uses 50 neurons, 0.94 compared to 0.93. Then for the epoch or iteration parameters, it is the same as the number of neurons parameter, the greater the epoch used, the greater the correlation does not result.

The model 15 configuration using epoch 3000 has better correlation results than the model 4 configuration using epoch 1000, the result is 0.97 compared to 0.94. The number of configuration settings was carried out randomly, not based on any guidelines, the configuration settings were carried out experimentally to find the best correlation results in as many as 20 trials with different configurations. The next analysis is to look at the performance of the configuration model by separating the number of hidden layers used. The first is an analysis related to the use of hidden layers 2 which obtains an average training correlation value of 0.93 with an average error value of 0.0073.

Table 1. Comparison of Backpropagation ANN and Distribution ANN Error Values

Config	Layers	Neurons	Epoch	Diff	Average Error	Backprop Error	Percentage of Error (%)
1	3	40	5000	-0.052	0.054	0.002	97
2	4	50	10000	-0.048	0.052	0.004	92
3	2	30	3000	-0.135	0.156	0.021	86
4	3	20	10000	-0.051	0.056	0.005	92
5	4	40	5000	-0.041	0.052	0.010	80
6	2	30	5000	-0.191	0.192	0.001	99
7	3	30	5000	-0.060	0.069	0.008	88
8	2	20	5000	-0.176	0.176	0.00004	100
9	5	50	10000	-0.052	0.054	0.002	96
10	5	20	10000	-0.045	0.054	0.009	83
11	2	50	10000	-0.216	0.222	0.006	97
12	5	30	10000	-0.042	0.054	0.012	78
13	4	50	10000	-0.016	0.052	0.036	31
14	3	50	5000	-0.053	0.059	0.006	90
15	5	50	3000	-0.050	0.060	0.010	84
16	5	20	3000	-0.060	0.062	0.002	97
17	5	20	5000	-0.038	0.054	0.016	71
18	2	50	5000	-0.043	0.052	0.008	84
19	5	10	10000	-0.033	0.053	0.020	61
20	4	30	10000	-0.188	0.189	0.001	99
						Average	85

The best correlation value obtained in the model with hidden layers 3 is 0.95 with the best error value of 0.00004. The lowest correlation value is 0.92 and the largest error value is 0.0214. In the configuration model with hidden layers 2, no one is able to achieve a value of 0.99 or even a perfect score of 1. Of all the configuration models, even the value is below the total average which has an average value of 0.96. Furthermore, for the model that uses hidden layers 3, the average training correlation value is 0.96 with the largest correlation value of 0.97 and the smallest 0.94. For the error values generated from several configuration models using layers 3, an average error of 0.0052 is obtained. The best error value is 0.0018 and the biggest error value is 0.0084. The average configuration model that uses layers 3 has an average training correlation value and also a better error value than the average configuration model that uses layers 2.

Table 2. Model Training Results

Config	Layers	Neurons	Corr	Error
1	3	40	0.97	0.00181
2	4	50	0.99	0.00439
3	2	30	0.92	0.02140
4	3	20	0.94	0.00476
5	4	40	0.97	0.01037
6	2	30	0.92	0.00099
7	3	30	0.97	0.00838
8	2	20	0.92	0.00004
9	5	50	0.97	0.00193
10	5	20	0.98	0.00898
11	2	50	0.95	0.00571
12	5	30	0.99	0.01166
13	4	50	0.95	0.03586
14	3	50	0.97	0.00585
15	5	50	0.97	0.00951
16	5	20	0.96	0.00202
17	5	20	0.98	0.01589
18	2	50	0.93	0.00820
19	5	10	0.94	0.02036
20	4	30	0.98	0.00134

Next is the training correlation analysis of the configuration model with the number of layers 4. For the average training correlation, a value of 0.97 is obtained with the best correlation value of 0.99 and the lowest correlation of 0.95. The average error value is 0.0130 with the best error value of 0.0013 and the largest error value is 0.0359. With an average training of 0.97, the model with layers 4 has an average training correlation that is better than layers 2 and 3. However, for the average error value, the configuration model with layer 3 is still the best. Furthermore, the configuration model that uses layers 5 has an average training correlation of 0.97 with an average error value of 0.0101. The best training correlation value is 0.99 and the lowest is 0.94. The best error value is 0.0019 and the largest error value is 0.0204. The average correlation value of the configuration model with layers 5 is as good as the configuration model with layers 4, which is 0.97. The best error value still belongs to the configuration model with layers 3, namely 0.0052.

C. Backpropagation ANN Test Results

After training the dataset, it was also tested using 20 model configurations. Of the 20 model configurations after going through the whole testing process, the correlation decreased. The largest model configuration correlation is 0.96 and the smallest is 0.77. The average configuration correlation during testing is 0.89 compared to the correlation during training of 0.96. Based on Table 3, it can be seen that there is no model configuration that has a better test correlation value than during training. The best results are in the model 19 configuration where the test correlation results are the same as the training results of 0.94. The biggest decrease in correlation is in the configuration of model 5, from 0.97 during training to 0.77 during testing. Only 60 % of the results of the dataset correlation test whose value is fixed at 0.9 or more and the other 40

% have decreased below 0.9. The configuration that has the best test correlation value (0.96) both has a training value of 0.98. Both of them use epoch 10000 and use hidden layers 4 and 5. For configurations with the number of hidden layers 2 it turns out that out of 5 model configurations 3 of them can achieve a test correlation value of 0.9 or more. To find out the performance of the configuration model in the following discussion, an accuracy test will be carried out.

The analysis is carried out by dividing the configuration model by the layers used, the first is the configuration model using layers 2 which has an average test value of 0.89 with the highest accuracy value of 0.91 and the lowest of 0.86. When compared to the average training correlation with the configuration model that uses layers 2 during training, there is a decrease in the accuracy value of 0.04. Then for the lowest correlation test value during training the value remains at 0.9 while during testing the value is below 0.9. When testing as much as 40 % the test correlation value is below 0.9. For the configuration model with layers 3 it has an average test correlation value of 0.87. The best test correlation value is 0.94 and the lowest is 0.80. The average correlation test value on layers 3 is lower than the correlation test value on layers 2. The average correlation decrease value is also greater than that on layers 2, where in layers 3 the correlation decrease value is 0.09. 50 % of the correlation test results on layers 3 are below 0.9. Even in the 7 configuration model, the accuracy value is only 0.8.

Table 3. Model Testing Results

Config	Layers	Neurons	Epoch	Train Corr	Test Corr	Diff Corr
1	3	40	5000	0.97	0.83	-0.14
2	4	50	10000	0.99	0.86	-0.13
3	2	30	3000	0.92	0.91	-0.01
4	3	20	10000	0.94	0.92	-0.02
5	4	40	5000	0.97	0.77	-0.20
6	2	30	5000	0.92	0.91	-0.01
7	3	30	5000	0.97	0.80	-0.17
8	2	20	5000	0.92	0.86	-0.06
9	5	50	10000	0.97	0.91	-0.06
10	5	20	10000	0.98	0.96	-0.03
11	2	50	10000	0.95	0.87	-0.08
12	5	30	10000	0.99	0.85	-0.15
13	4	50	10000	0.95	0.92	-0.04
14	3	50	5000	0.97	0.94	-0.03
15	5	50	3000	0.97	0.92	-0.05
16	5	20	3000	0.96	0.94	-0.03
17	5	20	5000	0.98	0.87	-0.11
18	2	50	5000	0.93	0.90	-0.03
19	5	10	10000	0.94	0.94	0
20	4	30	10000	0.98	0.96	-0.01

Next is an analysis of the configuration model with layers 4, the resulting average correlation value is 0.88 with the best test correlation value of 0.96 and the lowest is 0.77. The average value of the correlation is still better when compared to the average correlation in layers 3 but for the lowest test correlation value it becomes 0.77 even below 0.8. Up to the analysis of layers 4, there has been no result of layers that have managed to reach 0.9. The best correlation value of 0.96 is the highest test correlation value starting from layers 2 to layers 4. Next is analysis with layers 5, the average value obtained is 0.91. With this average value, layers 5 is the only set of test configuration models that have succeeded in achieving this value. The best test correlation value was obtained at 0.96 and for the lowest correlation at 0.85. With these results, layer 4 has the lowest test correlation value of 0.77 obtained from configuration model 5 which contains layers 4, neurons 40, and epoch parameters of 5000. The difference in the decrease in the average correlation value during testing and training is 0.06. Layers 5 is a collection of configuration models that have an average test correlation that can reach 0.9.

D. Backpropagation ANN Accuracy

After going through the training and testing process, then the configuration model is tested for accuracy to measure the performance of the model that has the best accuracy score. Based on Table 4, there are several configurations that have an accuracy score of 100 % during training, namely model configurations 1, 2, 4, 7, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20. Meanwhile during testing there are also several configuration models that have an accuracy score of 100 %, namely configuration models 3, 4, 6, 8, 10, 14, 16, 19, and 20. When training for accuracy beyond the perfect score of 100 %, namely 98 % occurs in configuration model 3, 5, 6, 8, 13. Meanwhile, when testing outside the perfect score of 100 %, there is a score of 90 % in the model configurations 1, 2, 5, 7, 9, 11, 12, 13, 15, 16, 17, and 18. Both when training and testing of dataset variables there is no accuracy score whose value is below 90 %.

Based on the accuracy score of the configuration model test, which has a value of 100 %, there is no reference to setting parameters related to the number of hidden layers, number of neurons, and epochs that can be used as a standard. For the hidden layer parameter, an accuracy score of 100 % is obtained from the number of hidden layers starting from 2, 3, 4, and 5. For the parameter number of neurons, an accuracy score of 100 % when tested is obtained from neurons 10, 20, 30, and 50. As for the epoch parameter or iteration 100 % accuracy score obtained from epoch 3000, 5000, and 10000. All parameter representation almost gets representation except for neurons 40. In addition to having good training and testing accuracy scores, model performance based on error values can also be said to be good because the error values obtained when the training dataset is very small, the largest is only around 0.03586 which occurs during the configuration model training 13, in this condition also the value of the accuracy of training and testing does not reach a score of 100 %. Of the 3 model configurations using the epoch 3000, 2 of them managed to achieve a perfect 100 % accuracy.

Table 4. Model Testing Accuracy Results

Config	Layers	Neurons	Epoch	Error	Accu (%)	Result
1	3	40	5000	0.00181	90	Good
2	4	50	10000	0.00439	90	Good
3	2	30	3000	0.02140	100	Good
4	3	20	10000	0.00476	100	Good
5	4	40	5000	0.01037	90	Good
6	2	30	5000	0.00099	100	Good
7	3	30	5000	0.00838	90	Good
8	2	20	5000	0.00004	100	Good
9	5	50	10000	0.00193	90	Good
10	5	20	10000	0.00898	100	Good
11	2	50	10000	0.00571	90	Good
12	5	30	10000	0.01166	90	Good
13	4	50	10000	0.03586	90	Good
14	3	50	5000	0.00585	100	Good
15	5	50	3000	0.00951	90	Good
16	5	20	3000	0.00202	100	Good
17	5	20	5000	0.01589	90	Good
18	2	50	5000	0.00820	90	Good
19	5	10	10000	0.02036	100	Good
20	4	30	10000	0.00134	100	Good

Based on the results of the accuracy test, the average value obtained based on 20 configuration models is 94.5 %. 45 % of the total model configuration managed to achieve a perfect accuracy value while the remaining 55 % achieved an accuracy value of 90 %. There is no accuracy value that is below 90 %. For each configuration model that has a perfect accuracy value of 100 %, it has an average error value of 0.00730 with the best error value being 0.00004. Meanwhile, the configuration model, which is only able to achieve 90 % accuracy has an average error value of 0.01034 with the best error value of 0.00181. The underfitting configuration models are configuration models 5 and 13 where both during training and testing the value does not reach 100 %. For the overfitting configuration models, namely configuration models 1, 2, 7, 15, 17, and 18 where the training accuracy reaches 100% and the accuracy during testing drops to 90 %. While the best fitting configuration models are configuration models 4, 10, 14, 16, 19, and 20 where the configuration results during training and testing are both 100 % perfect.

E. Best Model Determination

After conducting an analysis of the results of the training and testing, an accuracy test analysis is then carried out on the results of the model configuration test. The 20 model configurations, there are 6 model configurations that have a perfect accuracy score of 100 % during training and also testing, namely model configurations 4, 10, 14, 16, 19, and 20. Meanwhile the other 14 models have the lowest accuracy score of 90 % during testing and 98 % during training. The overall accuracy of the configuration model is very good where there is no accuracy that scores less than 90 % so that the overall configuration model can study the dataset very well. Then the 6 configuration models that have a score of 100 % are separated to find the best value to be used as a model for making flood prediction tables using the prepared dataset. After separating the model configurations and narrowing them down into 6 models, the configuration model number 20 was chosen as the best model for various reasons including having the greatest training and testing correlation values (0.98 and 0.96). It has the smallest difference in the correlation value which indicates good model performance because the decrease in the correlation value is small, only 0.01. Another factor is because it has the smallest error value among the other 5 models, namely 0.00134. The next step is to test using the model 20 configuration against the prepared datasets. After obtaining the 1 best configuration model, a dataset arrangement will be tested which consists of an average air temperature ranging from 24-32 °C, an average humidity of 50 %-100 %, 130 and 330 monsoon winds where 130 means the Australian monsoon or the dry season while 330 means the Asian monsoon which means the rainy season is in progress. Then there are the average surface wind variables from 16 cardinal directions, north 360, north northeast 20, northeast 40, east northeast 60, east 90, east southeast 110, southeast 130, south southeast 160, south 180, south west southwest, 200, southwest 220, west southwest 250, west 270, west northwest 290, northwest 310, north northwest 330. The next variable is rainfall, rainfall is arranged from 2-152 mm in multiples of 6. Then the other variable that is compiled is total rainfall for 1 week from the date used. Total rainfall is used as a variable to see its relation to the level of soil vulnerability. The more total rainfall that has fallen in the last week, the level of vulnerability has not been stable. In the prediction table dataset compiled the total rainfall for 1 week starting from 0-200 mm with a multiple of 8. This is done so that the resulting prediction table is able to represent various conditions in the future and become one of the basics for BMKG forecasters in making decisions in determining flood opportunities.

F. Flood Prediction Table

In total there are 234 prediction tables prepared for the 1 best configuration model, namely configuration model number 20. The indicator of a good prediction table is that when there is additional rainfall, the potential for flooding events is also greater, if there is an increase in rainfall but the potential for flooding decreases, then the prediction model used needs to be revisited. In addition, what can be used as an indicator is when the average air humidity increases, the potential for flooding will increase. If the opposite occurs, configuration model number 20 needs to be reviewed. Flood prediction tables are prepared using various possible dataset variables to be used in the future. The configuration model 20 is used as a model to conduct training on the dataset that has been compiled to see how the best configuration model responds in the process of making flood prediction tables. This table can be used as a reference for BMKG forecasters who are working to be able to provide early warnings to the public 1 day before a flood occurs. Table 5 is the result of flood predictions using the 20 prediction models that have been studied. The potential for flooding is generated in units of percent (%) where each change in parameter means the probability or potential for flooding will also experience a change in magnitude.

IV. Discussion

The analysis process begins by determining the error value of the backpropagation ANN and also the distribution ANN as a comparison. This is done to test the performance of the backpropagation ANN which states that the way it works goes backwards to reduce the error value so that accuracy increases. After testing the error value, it was found that the backpropagation ANN has a much smaller error value when compared to the distribution ANN as a comparison. Even the error value is 85 % smaller, from 20 trials using different configuration models. There is no error value from the backpropagation ANN that is greater than the distribution ANN error value. The smallest error difference is 31 % and the largest reaches 100 %. After that, the next analysis is a discussion related to the results of training and testing of dataset variables. For dataset training, all model configurations have correlation results above 0.9 with an accuracy of at least 98 %. Of the 20 model configurations, only 5 configuration models have an accuracy beyond 100 %, namely configuration models 3, 5, 6, 8, and 13. These 5 configuration models both have an accuracy value of 98 %. For the configuration model that obtains a training accuracy value of 9 %, it has 60 % of layers 2 settings and those that use layers 4 of 40 %. The neuro settings vary from 20 to 50. As for the epochs used, they also vary from 3000 to 1000, 60 % of which use 5000 epochs.

For testing the dataset of 20 configuration models, there are still 12 configuration models that have a correlation value of 0.9 while the remaining 8 are in the range of 0.7-0.8. More than 50 % of the dataset testing accuracy results have a score of less than 100 %, which is 90 %. More than 50 % of the accuracy results when testing has decreased scores compared to during training. However, from the overall accuracy score both during training and testing, none of them has a value below 90 %. This is also followed by the error value during training where the average error is 0.00897 with the largest error value being 0.03586. In matlab there is a feature to maximize the search for the best accuracy results from a model configuration called hyperparameters. To test the ability of ANN with hyperparameter features, this study also conducted dataset experiments using hyperparameters and compared them with non-hyperparameters using the parameters rmse, r-squared, mse, and also mae. The results obtained showed that ANN with non-hyperparameters was still able to get better results where the r-squared value reached 0.95, the rmse value was 0.11456, the mse value was 0.013124, and the mae value was 0.0792. Of the 9 model configurations tested, the dominant r-squared value was greater with the non-hyperparameter ANN, while for the parameters rmse, mse, and mae the average obtained with the hyperparameter ANN was better where all three showed values that were smaller or closer to 0 compared to ANN is non-hyperparameter. With an average r-squared value of 0.89 for non-hyperparameter ANN compared to 0.68 for hyperparameter ANN, it means that the dataset variable used with 89 % non-hyperparameter ANN can explain flood or non-flood events so that non-hyperparameter ANN is still used in this study.

In addition to testing the error value and the relationship between variables on flood events using the hyperparameter feature, this feature is also carried out by a training and testing process to compare the accuracy values. This feature is considered to have good performance in finding the best accuracy value of a model configuration. However, after conducting experiments on 9 configuration models, better accuracy results were obtained for the ANN model without using the hyperparameter feature. In training, there is not even a hyperparameter model accuracy value that is greater than the model accuracy value without hyperparameters. When testing is slightly better out of 9 model trials, 2 times the test accuracy value with the hyperparameter model is greater than the model without hyperparameters. Based on this research, the hyperparameter feature does not immediately give the best results, without using this feature one can still find better accuracy results. The next analysis is to determine the best configuration model based on the accuracy results obtained during training and testing. Of the 20 configuration models that have been run, there are 6 configuration models that have 100 % training and testing accuracy results. The configuration of this model is the configuration of models 4, 10, 14, 16, 19, and also 20. Based on these 6 configuration models, the number of hidden layers used starts from 3-5, for the number of neurons used 10, 20, 30, 50, while for the number of epochs or iterations is used 3000, 5000, and 10000. The correlation between the training obtained is the greatest 0.98 and during the test of 0.96 occurs in the configuration of models 10 and 20. The smallest error value occurs in the configuration of model 20 with a value of 0.00134. Configuration model 20 has advantages over the other 5 model configurations including having a large correlation value during training and testing and having the smallest error value. It is because of this that the 20-configuration model was chosen to be the best model to be used as a model for testing datasets that have been compiled for various future possibilities. A flood prediction table using 20 configuration models has been successfully created.

Table 5. Flood Prediction based on Prediction Model 20 Average Temperature 27°C and Average Humidity 80 %

Temp. (°)	Humid. (%)	Wind	Monsoon	Rain (mm)	Total Rain 1 Week (mm)	Flood (%)
27.0	80	360	130	2	0	31
27.0	80	360	130	8	8	37
27.0	80	360	130	14	16	43
27.0	80	360	130	20	24	50
27.0	80	360	130	26	32	56
27.0	80	360	130	32	40	63
27.0	80	360	130	38	48	69
27.0	80	360	130	44	56	75
27.0	80	360	130	50	64	80
27.0	80	360	130	56	72	84
27.0	80	360	130	62	80	87
27.0	80	360	130	68	88	89
27.0	80	360	130	74	96	89
27.0	80	360	130	80	104	88
27.0	80	360	130	86	112	86
27.0	80	360	130	92	120	83
27.0	80	360	130	98	128	79
27.0	80	360	130	104	136	76
27.0	80	360	130	110	144	72
27.0	80	360	130	116	152	69
27.0	80	360	130	122	160	67
27.0	80	360	130	128	168	64
27.0	80	360	130	134	176	63
27.0	80	360	130	140	184	62
27.0	80	360	130	146	192	61
27.0	80	360	130	152	200	61
27.0	80	360	330	2	0	47
27.0	80	360	330	8	8	52
27.0	80	360	330	14	16	57
27.0	80	360	330	20	24	61
27.0	80	360	330	26	32	64
27.0	80	360	330	32	40	68
27.0	80	360	330	38	48	71
27.0	80	360	330	44	56	74
27.0	80	360	330	50	64	76
27.0	80	360	330	56	72	78
27.0	80	360	330	62	80	80
27.0	80	360	330	68	88	81
27.0	80	360	330	74	96	82
27.0	80	360	330	80	104	81
27.0	80	360	330	86	112	100
27.0	80	360	330	92	120	100
27.0	80	360	330	98	128	100
27.0	80	360	330	104	136	100
27.0	80	360	330	110	144	100
27.0	80	360	330	116	152	100
27.0	80	360	330	122	160	100
27.0	80	360	330	128	168	100
27.0	80	360	330	134	176	100
27.0	80	360	330	140	184	100
27.0	80	360	330	146	192	100
27.0	80	360	330	152	200	100
27.0	80	90	130	2	0	0
27.0	80	90	130	8	8	7
27.0	80	90	130	14	16	11
27.0	80	90	130	20	24	16
27.0	80	90	130	26	32	21
27.0	80	90	130	32	40	25
27.0	80	90	130	38	48	31
27.0	80	90	130	44	56	36
27.0	80	90	130	50	64	42
27.0	80	90	130	56	72	48
27.0	80	90	130	62	80	55
27.0	80	90	130	68	88	63
27.0	80	90	130	74	96	71
27.0	80	90	130	80	104	79
27.0	80	90	130	86	112	88
27.0	80	90	130	92	120	100
27.0	80	90	130	98	128	100
27.0	80	90	130	104	136	100
27.0	80	90	130	110	144	100
27.0	80	90	130	116	152	100
27.0	80	90	130	122	160	100

This table uses the latest average air temperature in the City of Bandar Lampung, which is 27°C with an average humidity of 80 %. This condition is made to see how the configuration model 20 performs in predicting various flood opportunities with the prepared dataset arrangement. When the average surface wind direction is from the north (360) the potential for flooding is only 89 % when the Australian monsoon blows or during the dry season, but when it changes to the Asian monsoon or the rainy season the potential increases to 100 %. When the surface wind direction changes to north northeast (20) either during the rainy season or the dry season the potential for flooding is at most 100 % with rainfall of 90 mm during the dry season and 60 mm during the rainy season. When the average surface wind blows from the northeast (40) the potential for flooding is always greater during the rainy season or when the monsoon winds blow at 330. The potential for flooding is 60 % in the dry season when it rains 60 mm while in the rainy season when it rains decreased by 38 mm for the previous week's total rainfall of 48 mm compared to 80 mm. When the average surface wind blows from the east (90) 20 mm of rain falls during the dry season and the rainy season could cause flooding in the Bandar Lampung City area by 16 % and 20 %. During the dry season or the Australian monsoon blows in the Bandar Lampung City area and the average surface wind comes from the southeast (130) the potential for flooding is 50 % when the total rainfall is 62 mm with an accumulation of 1 week's rainfall of 80 mm. Conversely, when the average surface wind is from the southeast (130°) and occurs in the rainy season or Asian monsoon, there is a 50 % chance of flooding occurring when rainfall is 38 mm with an accumulation of 1 week's rainfall of 48 mm.

In the dataset, the minimum rainfall that caused flooding in the City of Bandar Lampung was recorded at 18 mm on 15 February 2011. February means that the Asian monsoon or rainy season is still in progress. When the average surface wind originates from the south (180) with 14 mm rainfall and the Asian monsoon is active, the chance of flooding in the Bandar Lampung City area is 11 %, while if the Australian monsoon is active, the potential is 17 %. A 100 % potential for flooding will only occur when rainfall amounts to 98 mm during the dry season and 62 mm during the rainy season. There is a difference of ±30 mm between the rainy season and the dry season to achieve 100 % rain potential. When the average surface wind blows from the southwest (220), the average rainfall that causes flooding is 67 mm. If it is adapted into the flood prediction Table 5, when it occurs during the dry season the potential for flooding is 69 % and during the rainy season it is 100 % with 68 mm of rainfall. The difference between the dry season and the rainy season is 31 % even though the amount of rainfall is the same, namely 68 mm. This illustrates that the backpropagation ANN is able to study the dataset properly so that it is able to distinguish between dry season and rainy season events. Furthermore, when the average surface wind blows from the west (270), using an average total rainfall of 1 week which causes flooding in the Bandar Lampung City area in a dataset of 80 mm. Referring to the prediction table, the potential for flooding during the dry season using the average of the total rainfall that causes flooding is 74 %, while if it occurs during the rainy season, the potential is 87 %. This again illustrates that floods will always have a greater potential when they occur in the rainy season than the dry season even with the same rainfall or with the same total rainfall for 1 week. Then when the average surface wind blows from the northwest (310) using minimum rainfall in the two seasons, the potential for flooding is quite large, with only 2 mm of rainfall the potential for flooding has reached 21 % during the dry season and 30 % during the rainy season. This is because the average wind used is close to the Asian monsoon (330) so the model reads this as an indication of a significant potential for flooding. If it refers to the total rainfall of 1 week minimum that causes flooding in the dataset is 3 mm, in the prediction table it is used 8 mm so the potential for flooding is 26 % during the dry season and 36 % during the rainy season.

From the various cardinal directions that were analyzed, the potential for flooding is always greater when it occurs during the rainy season compared to the dry season. The average difference is 10 %-20 %. This illustrates that the backpropagation ANN model can study the dataset very well, as well as the dataset used can represent various possibilities that can be studied by the backpropagation ANN so as to produce a good prediction table. This prediction table can be used as one of the tools in making decisions for a BMKG forecaster to determine how big the chance of flooding for tomorrow in the Bandar Lampung City area so that it is hoped that it can prevent fatalities in the future.

V. Conclusion

Based on the analysis and discussion that has been carried out, several important points can be drawn, including the results of training and dataset testing that has been carried out. the results of the prediction table are able to describe the actual conditions, setting the configuration model experimentally is able to produce an accuracy value of 90-100 %, the average training correlation value is 0.96 and the average test correlation value is 0.89, and the average error value is 0.0089 out of 20 model configurations, and a flood prediction table was made based on the 1 best configuration with a training and testing accuracy rate of 100 % with an error value of 0.00134, namely the 20 configuration model, the prediction table uses an average air temperature of 27°C with 80 % humidity. The prediction table is able to produce excellent flood potential results which are able to represent flood events as well as non-flood events based on the results of the dataset learning.

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