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Development of a Method for Classifying Convective and Stratiform Rains from Micro Rain Radar (MRR) Observation Data Using Artificial Neural Network

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ABSTRACT

This study examined the performance of Artificial Neural Network (ANN)-backpropagation to classify rain types from observations of Micro Rain Radar (MRR) in Serpong (6.359oSL; 106.673oEL). The inputs of ANN are radar reflectivity, Doppler velocity, and Liquid Water Content (LWC). Rain events on January 5, 2017; at 16.28 – 21.21 local time were used as training data. The ANN results were validated with rain classified by the Bright Band (BB) and Countour Frequency by Altitude Diagram (CFAD) methods. The most appropriate ANN-backpropagation architecture is the 3-6-1 architecture (input layer-hidden layer-output layer), with an activation-transfer function being competitive and a learning rate of 0.9. The Mean Square Error (MSE) of the training step was 0.0098735, and the average percentage of accuracy for the test step was 94%. A rain event with a single type of rain can be classified accurately by ANN and gives the same results as the CFAD method. Thus, the ANN can be a solution to the shortcomings of the BB method, which sometimes classification results of a single type of rain events is interspersed with another type, which is physically impossible.

1. Introduction

The classifying of convective-stratiform rain is useful in various fields of meteorology and climatology, including making it easier to study the nature of atmospheric circulation [1]. Atmospheric circulation is influenced by the latent heat profile, which is the energy released or absorbed by the atmosphere [2] and is related to phase changes between liquids, gases, and solids during the process of forming rain. Horizontal and vertical analysis of latent heat is very important to understand large-scale circulation, cloud-rain formation, and aerosol-cloud-rain interaction [3]. The very different latent heat profiles of convective and stratiform systems cause diverse atmospheric circulation patterns [4]. Rainfall data that has been separated between convective and stratiform can be used to evaluate climate models [5].

There are several methods for classifying convective and stratiform rains. The first method is classifying using surface rainfall data from rain gauge observations [6,7]. This method is the oldest and simplest method. Rainfall intensity that exceeds the specified threshold is classified as a convective type. This technique is generally only able to classify rainfall from the convective core. The second method is a combination of surface rainfall data with horizontal radar observation coverage. The convective core is observed with a threshold value of rainfall intensity, then the convective influence radius is taken to determine the convective rain area [8]. This method uses a fixed threshold value for the convective area and is a weakness of the method because the coverage area of the convective area varies [9,10].

Classifying rain can also be done by observing the atmosphere in the vertical direction. Differences in physical processes that occur between convective and stratiform will be observed from the radar observation data in the vertical direction. Stratiform rain, whose formation involves a phase change from ice to liquid, will be indicated by the presence of a Melting Layer (ML) on the radar image. Rain classification will be more accurate if it is equipped with vertical structure data from radar reflectivity (Z) and Doppler velocity [11]. These variables describe the physical properties of raindrops and turbulence. Convective rains usually have a stronger updraft (turbulence) above the ML than stratiform rains. Convective and stratiform rains can also be classified based on raindrop data [12] because these two showers of rain have different raindrop characteristics. This technique has disadvantages, namely that most of the rain classifying will give ambiguous results, especially for low rainfall intensity (<5 mm/h).

MRR is a Doppler radar that operates vertically and utilizes the working principle of a continuous wave with a modulated frequency (Frequency Modulated Continuous Wave, FM-CW) at 24.1 GHz. The height measured by the MRR varies depending on the altitude resolution. The classifying of rain from MRR has been carried out by several researchers [13, 14]. The obstacle faced in this classification is a large amount of rain data that is not classified.

Foth et al. [15] have conducted research using Probability Density Functions (PDF) and Artificial Neural Network (ANN) methods, both methods obtained equally good results. ANN is a computerized system as an information processor that has a character similar to biological, meteorological, and oceanographic phenomena whose behavior is very complex. ANN-backpropagation algorithm is a flexible type of ANN, with comprehensive analytical capabilities, so it is appropriate to be applied to the classification of non-linear atmospheric phenomena (remote sensing data) [16, 17], to obtain more accurate results [18].

In this study, the development of the method that has been carried out by Foth et al. [15] will be carried out to produce a precise, simple, and accurate method for classifying stratiform and convective rains. In addition to using different ANN methods, this study also uses different input data. Foth et al. [15] used convective core data [15], while this study did not use these data. The data used are radar reflectivity (Z), Doppler velocity, and Liquid Water Content (LWC). The results of the ANN method will also be validated with the Bright Band (BB) and Contour Frequency by Altitude Diagrams (CFAD) methods. The BB method classes rain based on the presence of a Melting Layer (ML). Rain events occur when the rainfall value exceeds 0.1 mm/h. Convective rain is declared if no ML is observed and stratiform rain is declared if ML is observed. The lower layer of ML is calculated based on the maximum value of Gradient Fall Velocity (GFV) and the upper ML is calculated based on the maximum vale of the reflectivity radar gradient [13]. CFAD method is a statistical method that summarizes information on the frequency distribution of a variable based on altitude, especially from radar parameters [19]. Research Foth et al. [15] classify rain only on two types of rain, namely convective and stratiform rains. This study will also expand the classification of rain types, namely stratiform, mixed, deep convective, shallow convective, and no type.

2. Method

We used data recorded by MRR in Serpong, South Tangerang (6.359ºSL; 106.673ºEL; 40 m above sea level), Indonesia. Several rain events from December 2016 to February 2017 (Table 1) were analyzed. The resolution of the observation time of the MRR is 1 minute and the resolution of the height is 250 m with the highest observation range of 7750 m (31 gates). The rain event on January 5, 2017; from 16.28 – 12.11 local time had the longest duration of 294 minutes (the 3rd rain period). Training using ANN-backpropagation requires more data for accurate results, therefore the rain event in the third period on January 5, 2017; was used as training data. The ANN-backpropagation testing process is carried out using several other rain data, as shown in Table 1.

The MRR data used are rainfall/rain rate (R), radar reflectivity (Z), Doppler velocity, and Liquid Water Content (LWC). Only minutes with an R-value that exceed 0.1 mm/h at an altitude of 750 m are used in classification. All variables were normalized using the following equation:

$$x' = \frac{0.8\,(x-b)}{(a-b)} = 0.1 \quad (1)$$

where: x' is the result of normalization, x is the initial data, b is the minimum value of the initial data and a is the maximum value of the initial data. Determination of target data obtained from the results of the modified version of Williams et al.'s method [11], which will then also be used in the validation process of the ANN method.

Rainfall data is classified into five types, namely stratiform, mixed, deep convective, shallow convective, and no type. Rain is declared as deep convective and shallow convective if ML is not identified, while rain is declared as stratiform and mixed if ML is identified. The difference between deep convective and shallow convective rain types is that there are rain particles (hydrometeor) above ML for deep convective rain and no rain particles above ML for shallow convective rain. The characteristics of stratiform and mixed rains are also characterized by the absence of increased turbulence above ML for stratiform rain and the presence of increased turbulence above ML for mixed rain. Mixed rain is rain that is formed due to a combination of stratiform and convective rain. Other types of rain and in addition to the four types of rain above are called no types.

Table 1. Rain events in Serpong are from MRR data from December 2016 to February 2017

Nu.	List	Year	Month	Date	Start time	End time	Period	Duration (minute)
1.	20161205	2016	December	5	02.39	05.35	I	177
2.	20161214			14	07.04	10.20	I	197
3.					14.48	15.22	I	35
4.	20170105	2017	January	5	15.32	16.11	II	40
5.					16.28	21.21	III	294
6.	20170114			14	00.50	04.22	I	213
7.	20170221		February	21	00.00	03.39	I	220

The architecture (model) and training of the designed ANN-backpropagation algorithm are an architecture consisting of 3 input nodes (Z, Doppler velocity, and LWC), two hidden layers consisting of 6 nodes, and 1 output node to produce a rain classification that actually. This model is trained with several epochs (iterations) of 300 and with a maximum number of errors of 0.001. The optimization of the model is done by using a variation of the learning rate which is then evaluated based on the smallest Mean Square Error (MSE) value.

The results of training and testing of the ANN-backpropagation method were then validated with the results of the modified version of William et al.'s (Bright Band/BB) and CFAD methods. The final stage of this research is the process of analyzing the calculation of the error value (MSE) using a comparison of values between truth and prediction. The percentage of accuracy will be high if there are more and more values that are the same between prediction and truth when validation is carried out with the data test process. The label or output value for the probability of stratiform rain is marked with a value of 5, mixed with a value of 4, deep convective with a value of 3, shallow convective with a value of 2, and no type with a value of 1.

3. Results and Discussion

3.1 ANN-Backpropagation Architecture for Rain Classifying

The architecture of ANN-backpropagation that has been designed is the 3-6-1 architecture (input layer-hidden layer-output layer). The best activation and transfer function in the training process with an initial learning rate value of 0.1 for rain classifying is competitive-competitive (compet-compet). The results of the variation of the function are shown in Table 3. The competitive function which is applied to the training data (for rain events on January 5, 2017; for the 3rd period in Table 2) gives the smallest Mean Square Error (MSE) value of 0.0099822. The order of activation and transfer function with the smallest to the next largest MSE value is satlin, logsig, poslin, hardlim, satlins, tansig, hardlism, and purelin. The purelin function is linear and has the largest MSE value in this train classifying training process. The rain phenomenon has no-linear characteristics between variables or causal factors, therefore the purelin function is a function that gives very inaccurate results for rain classifying [16,17].

The poslin function has the largest number of iterations, namely, its stops at the 45th epoch (iteration). The function with the least iteration is the purelin function which stops at the 6th iteration. The number of iterations only affects the duration of the training process and does not reduce the accuracy of the results. The largest number of iterations results in a training process with a long duration, and vice versa and each function or pattern have a different number of iteration characteristics. The iteration process will stop when the set error threshold is reached, which is 0.001.

More accurate training results (smallest training MSE value) in the train classifying process with competitive function were obtained from the learning rate value of 0.9. The MSE value of the training was 0.0098735 which stopped at the 11th epoch (iteration). The variation of the learning rate value in the classifying process with the competitive function is shown in Table 3. Another order of the learning rate values with the highest MSE training to the lowest in the learning rate 0.3; 0.5; 0.6; 0.1; 0.7; 0.8; 0.2; and 0.4. The maximum number of iterations is 26 obtained from a learning rate of 0.1 and the minimum number of iterations is 11 obtained from a learning rate of 0.9.

Table 2. Activation and transfer function for classifying rain using ANN-backpropagation

Activation function	Transfer function	Maximum Epoch	MSE training
purelin	Purelin	6	0.0292330
satlin	Satlin	34	0.0100920
satlins	Satlins	39	0.0108010
logsig	Logsig	40	0.0104240
tansig	Tansig	41	0.0114030
poslin	Poslin	45	0.0104950
compet	Compet	26	0.0099822
hardlim	Hardlim	34	0.0106290
hardlims	Hardlims	35	0.0134670

Table 3. The results of the rain classifying learning-rate variation training using ANN-backpropagation competitive function

Learning rate	MSE training	Maximum Epoch
0,1	0.0099822	26
0,2	0.0099192	16
0,3	0.0104100	14
0,4	0.0099138	24

0,5	0.0102930	17
0,6	0.0102640	12
0,7	0.0099444	24
0,8	0.0099377	18
0,9	0.0098735	11

3.2 Rain Classifying Test with ANN Method and Validation with BB method

The training process for the ANN-backpropagation method has been carried out for rain data on January 5, 207; at 16.28 – 21.21 local time. The results of classifying in that period based on the ANN and BB methods mostly obtained stratiform rain types (Figure 1E). The exceptions for different types of rain by the BB method are no-type rain (at 16.54 – 15.55 local time), deep convective (at 16.56 local time), mixed (at 16.57 - 17.08 local time), and shallow convective (at 17.54 – 17.56 local time). The next step is the training process using several other rain events, as shown in Table 1. The test results were compared with the classifying of rain using the Bright Band (BB) method. The BB method is commonly used in classifying rain types from radar data.

Table 4 shows the result and accuracy of classifying rain types. The dominant type of stratiform rain based on the ANN and BB methods occurred in the rain events of December 5, 2016; December 14, 206; January 6, 2017; for the third period; and February 21, 2017. The Melting Layer (ML), which is the main indicator of the formation of stratiform rain, was observed during this period at an altitude of about 4500 m (Figure 1A, Figure 1B, Figure 1F, and Figure 1G). Most of the deep convective rains were classified on January 5, 2017; for the first and second periods by the ANN and BB methods. The reflectivity contour of the radar shows that in these two rain events there is no ML which is a requirement for deep convective rain (Figure 1C and Figure 1D). The classifying of rain into mixed types from the ANN and BB methods was observed on January 14, 2017. In Figure 1F it is shown that ML was observed and this is a supporting factor in the process of forming mixed rain. Based on the reflectivity radar contour which indicates the presence or absence of the ML, then the classifying of rain by ANN-backpropagation which only produces one type of rain is more acceptable than the BB method. The average of the ANN method classifying accuracy from the above test is 94%. This value indicates that the ANN-backpropagation method of competitive function and learning rate of 0.9 is a simple method that is accurate and precise for classifying rain from MRR data.

Table 4. The results of the rain event test using the ANN and BB method

Rain events	Percentage of classifying accuracy (%)	Rain type
20161205	97.2811	stratiform
20161214	91.5937	stratiform
20170105 for 1st period	96.9792	deep convective
20170105 for 2nd period	92.2623	deep convective
20170114	88.4148	mixed
20170221	97.0194	stratiform

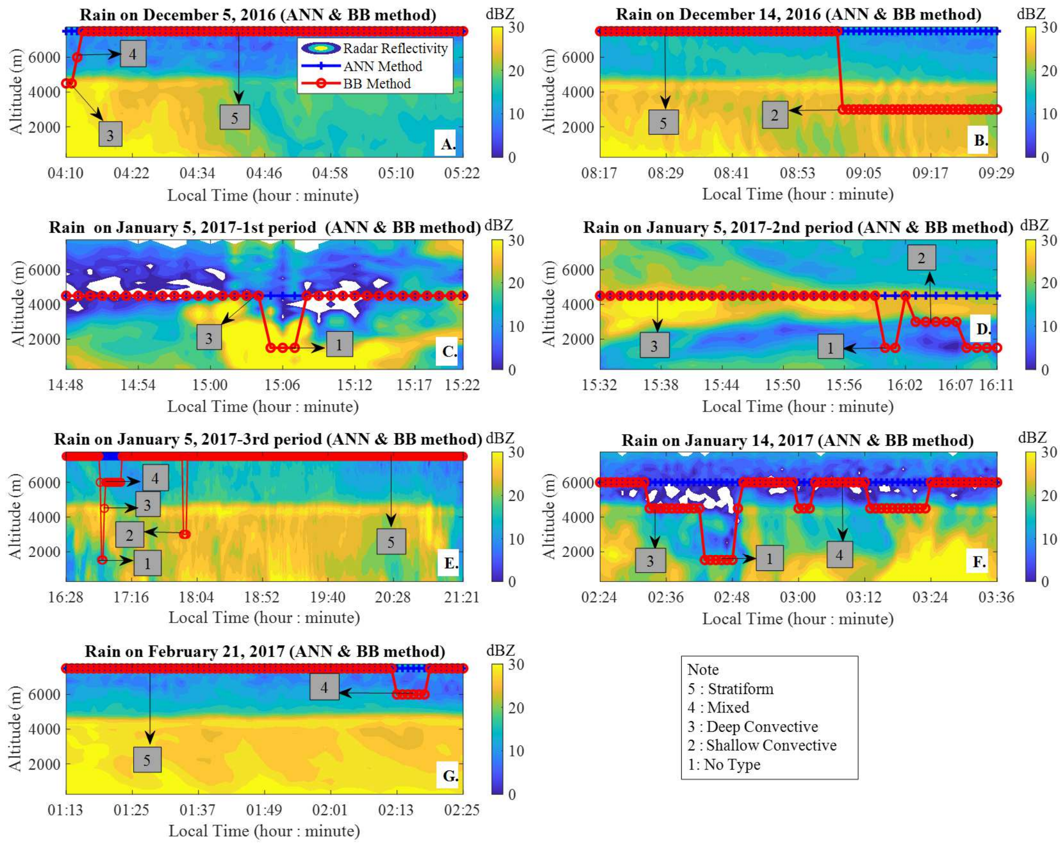

Figure 1. Comparison of rain classifying by ANN and BB methods

The difference in classifying results between the ANN and BB methods is stated as follows:

1. Rain events on December 5, 2016 (Figure 1A): the BB method also classifies the rain in this period into deep convective (at 04.10 – 04.11 local time) and mixed (at 04.12 local time) with an accuracy percentage of 97.2811% (Table 4).
2. Rain events on December 14, 2016 (Figure 1B): the BB method also classifies the rain in the period as shallow convective (at 09.01 – 09.29 local time) with an accuracy percentage of 97.5937% (Table 4).
3. Rain events on January 5, 2017; for the first period (Figure 1C): the BB method also classifies the rain in this period into no type (at 15.05 – 15.07 local time) with an accuracy percentage of 96.9792% (Table 4).
4. Rain events on January 5, 2017; for the second period (Figure 1D): the BB method also classifies the rain in this period into no type (at 16.00 – 16.01 local time and 16.08 – 16.11 local time) and shallow convective (at 16.03 – 16.07 local time) with an accuracy percentage of 92.2523% (Table 4).
5. Rain events on January 14, 2017 (Figure 1F): the BB method also classifies the rain in this period into deep convective (at 02.33 – 02.42 local time, 02.49 local time, 03.00 – 03.02 local time) and no type (at 02.43 – 02.48 local time) with an accuracy percentage of 88.4148% (Table 4).
6. Rain events on February 21, 2017 (Figure 1G): the BB method also classifies the rain in this period into mixed (at 02.13 – 02.18 local time) with an accuracy percentage of 97.0194% (Table 4).

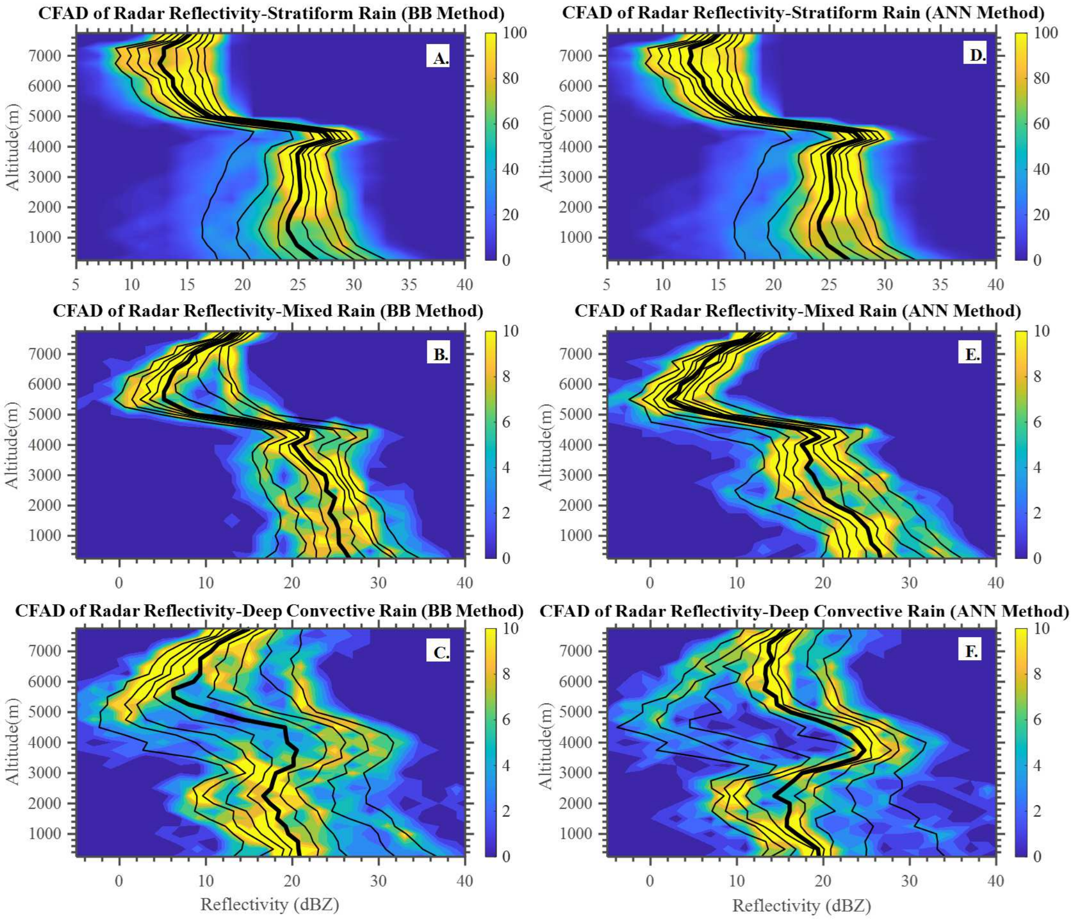

Figure 2. Contour Frequency by Altitude Diagrams (CFAD) of radar reflectivity for stratiform, mixed, and deep convective rains.

The comparison of Contour Frequency by Altitude Diagrams (CFAD) radar reflectivity profiles for stratiform, deep convective, and mixed rain types from the two methods (ANN and BB) is shown in Figure 2. Stratiform rain is rain with the largest frequency distribution value of radar reflectivity, while deep convective rain is rain with the smallest value of radar reflectivity frequency distribution. This profile states that the ANN and BB methods give the same results, namely:

1. The average value of the reflectivity radar frequency distribution of the stratiform rain formation process is about 27 dBZ. The stratiform CFAD profile has a narrower pattern so that the presence of ML is observed at an altitude of around 4000 – 5000 m (Figure 2A and Figure 2D).
2. The average value of the reflectivity radar frequency distribution of the mixed rain formation process is about 26 dBZ. The mixed CFAD profile has a wider pattern than stratiform rain and the presence of ML was also observed at an altitude of around 4000 – 5000 m (Figure 2B and Figure 2E).
3. The average value of the reflectivity distribution from the process of coming deep convective rain is about 20 dBZ. The deep convective CFAD profile is wider and randomly distributed so that ML is not observed (Figure 2C and Figure 2F).

4. Conclusion

The results of this show that ANN-backpropagation can classify the types of rain from MRR observations. The most appropriate ANN-backpropagation architecture is the 3-6-1 architecture (input layer-hidden layer-output layer) with an activation-transfer function that is competitive and a learning rate of 0.9. The training MSE value of this architecture is 0.0098735 and the average percentage of classifying accuracy for testing on six rain events is 94%. The ANN method can classify rain very well for rain that tends to be uniform (one type) and gives the same results as the CFAD method. This is can cover the shortcomings of the BB method, which often class several minutes of data between the dominant rain types into other types of rain, which is physically impossible. The accuracy of the ANN method for rain with several types is still lower than uniform rain (one type), therefore further research is needed to correct this weakness. It is possible to increase the results of the ANN method by increasing the number of cases and adding input data or other MRR variables such as raindrop size distribution because each type of rain has different grain characteristics.

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