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Weather Forecasting Analysis using Bayesian Regularization Algorithms

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Abstract
Weather forecasting has become very urgent in various fields of human life, including in big cities. The need for weather forecasting accuracy will be effective and efficient in managing the quality of civilization flexibly. Bayesian regularization is one of the techniques used to obtain accurate results and development of artificial neural networks. The training process achieves the smallest epoch using a general processing unit to solve big data and high resolution. Scenarios performed via dataset partitioning and MSE enhancement. The addition of training data will improve system performance which indicates a significant increasing accuracy. Likewise, the decrease in MSE can increase the system accuracy to achieve a convergence stability point. Weather forecasting can recommend work units within the city and its surroundings, even between provinces or countries.

Keywords:
Weather-forecasting, Bayesian-regularization, Neural-network, Performance

1. Introduction

Weather data plays a significant role in agriculture, transportation, the food industry, systems at airports, mining, power generation, the search for renewable energy, prediction of forest fires [1]. The presentation of research results on weather forecasting is an exciting study during developing artificial intelligent computing.

The city area becomes one of the objects that is quite interesting because there are often cases in the same city that still have significant differences. It is raining heavily in the west, while the east is still cloudy. Accurate weather forecasting is a challenge, and the conveyed information is accurate and reliable because it is helpful for all citizens of the city and its surroundings, both national and international. The problems faced in weather forecasting include the unstable changing atmospheric conditions, measurement errors, too large data, and incomplete understanding of the performance of the weather forecast results.

Weather determination is essential because it is a collaborative process between science and technology to determine the earth's atmosphere [2] to present data [3]. The significant factors influence the weather, including temperature (maximum-minimum), average humidity, dew point, wind speed, average atmospheric pressure, radiation, and the likelihood of precipitation at locations around the world [1][4]. As a result, weather forecasts in periodic information daily, weekly, monthly, and even yearly scale, used in effective decision making. In exceptional cases, the weather forecasting accuracy helps prevent floods and droughts [5] and optimizes irrigation of agricultural land [6].

The techniques used in weather forecasting also vary greatly depending on past and present science and technology, including numerical techniques [7], [8], which use large-

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scale computers [9], then developed using machine learning techniques with linear regression [4], artificial neural networks [10]–[17] and deep learning [5][18]–[21]. The disadvantage of using linear regression in weather forecasting is that linear regression as a high variation model is because it is not stable for outliers so that to improve it, more data is needed. While functional regression has poor predictive results because the data interval in two days is too short, this technique requires much data, but the computation time is also longer.

From previous studies, it becomes a challenge for researchers that weather forecasting is a problem that continues to develop from time to time with the revolution in science and technology it adapts. The rapid development of internet of things technology, wireless sensor networks, cloud computing, and artificial intelligence has become the era of Big Data progress. Large amounts of data presented can generate more accurate information using machine learning or neural networks. The neural network will extract and identify patterns from a set of weather data through the learning system.

Research conducted by Putra [22] concluded that Bayesian Regularization could forecast well with the best performance on the neural net3 model (neurons 36, 12, and 6) even though it requires more repetitions net2 model converges with more iterations, more minor using the number of neurons 24, 12, and 6.

Similar to research Purba et al., Mohsin [23] has proven that Bayesian Regularization provides the best performance compared to several other methods. The performance includes the smallest MSE and good computing speed. Zhao [24] corroborated the results, who conducted training on BP neural networks to effectively improve the network structure, avoid the overfitting phenomenon, and have better prediction precision and generalization ability.

Several methods used previously still require high accuracy improvements, including overcoming the parameters of large data quantities, speed, prediction accuracy, and forecasting periods on a scale of 3 hours a day and a narrower urban area scale. In this case, the study of weather forecasting still requires different research contributions. For this reason, the author focuses on processing weather data presented every three hours using the Bayesian Regularization neural network method. This study investigates the effect of data and target error on system performance, including forecasting accuracy and speed. The method used is a recommendation for development in machine learning through comparison with other methods.

2. Related Works

Abhishek in his research [17], non-linear data on weather data requires non-linear statistics and determines non-linear models before estimating it. It is difficult because the weather data follows a very irregular trend, so the solution makes it possible to use an artificial neural network by comparing and testing the performance of the developed models using different transfer functions. The advantages of the artificial neural network model based on the study [17] can reduce the process cost when reading raw data modeled in 10 inputs, five hidden layers using 10 or 16 neurons. Other weather factors include humidity and wind speed to extend forecasting the concentration of long-term weather trends in a small area at a maximum temperature.

Research based on deep learning [19] overcomes high-resolution computers because it already uses a general processing unit. It facilitates the research process by using the appropriate library because it uses a globally distributed network. A deep learning model through scaling using an artificial neural network can automatically receive input weather features. The learning system is based on supervised learning.

Hewage et al. [25] which made a model using ten weather parameters with a forecast range of 12 hours. This model outperforms Weather Research and Forecasting by up to 12 hours. The advantage of the model is that it can run on a stand-alone computer and for short to medium-term weather prediction geographic areas. The model can also overcome many challenges of WRF, such as understanding the model and its installation and model execution and probabilities.

Using Bayesian Regularization and Levenberg, Marquardt succeeded in accelerating the achievement of maximum epochs with better accuracy and a reduced amount of data [12]. To overcome the problem of overfitting, [26] increased the learning rate followed by stopping training during validation with a minimum error.

BESN has an accuracy that meets the operational requirements of electricity supply feasibility of more than 90% [27], which is in line with [28], which also results in the overall performance of the Levenberg Marquardt and Bayesian Regularization neural network models in a different time and input intervals showing the best trade-off performance in estimating the power.

In line with the results of previous studies, [29] found that forecasting performance has an RMSE of around 0.0753-0.0706 with 23-28 hidden layers on the same learning input, both real-time and offline. Overall, according to [30] that the results of Bayesian Regularization-Backpropagation Neural Networks have better all-around performance and have the ability to select automatic regulatory parameters, and can ensure good adaptability and reliability.

3. Proposed Method

In this experiment, we used Bayesian regularization to overcome significant output changes so that the network response is softer at smaller weight values. BR provides a modification of the addition of the final pattern, which is the square of all network weights, to reduce the tendency of a model to experience overfitting noise in training [31].

Bayesian optimization of the regularization parameter requires the computation of the Hessian matrix at minimum points. Foresce and Hagan in [31] proposed a Gauss-Newton approximation to a Hessian matrix, which is available if the Levernber-Marquardt optimization algorithm is used to locate the minimum points.

Hidayat et al. [32] and Muslim et al. [33] states that the Levenberg-Marquardt algorithm is a development of a standard backpropagation algorithm. In the backpropagation algorithm, the weight and bias update process use negative gradient descent directly, while the Levenberg-Marquardt algorithm combines the stability of the steepest descent method and the speed advantage of the Gauss-Newton algorithm in reducing the number of squared errors by using different values in solving:

$$(J^T J + \lambda I)\delta = J^T E \tag{1}$$

Which is Jacobian (J) matrix, reduction (λ) dan update weights (δ) to provide the best performance. The matrix J^T*E is equivalent to Hessian, which considers errors in its output. Weight update in Eq. (2) and Eq. (3) [33].

MSE calculation resulted from the difference between the output value and the network target. The number of signal outputs then updated the bias and weights. If the network reaches error and epoch threshold, the iterations stop. The network will continue the iteration process until providing the smallest value in the convergent region.

$$\Delta X = [J^T J + \mu I] - J^T e \tag{2}$$

$$X = X + \Delta X \tag{3}$$

The network provides the best weights and bias at the convergence area, an indicator to reach limited epoch and error. Mean Square Error (MSE) as a formula to measure forecasting error [15] as in Eq. (4).

$$\sum_{t=1}^{n} \frac{(X_t - F_t)^2}{n} \tag{4}$$

Therefore, the training stage obtains the bias value and the update weight. The network will use this value to carry out the testing process on several data. We compare the value of testing and training as a validation process in this stage.

4. Experimental Setup

The research method used in this study (Fig 1) is experimental research to compare backpropagation and Bayesian regularization algorithms, and both algorithms are classifiers to forecast weather. The stages of this study are data collection, experimentation, testing, and evaluation of research results.

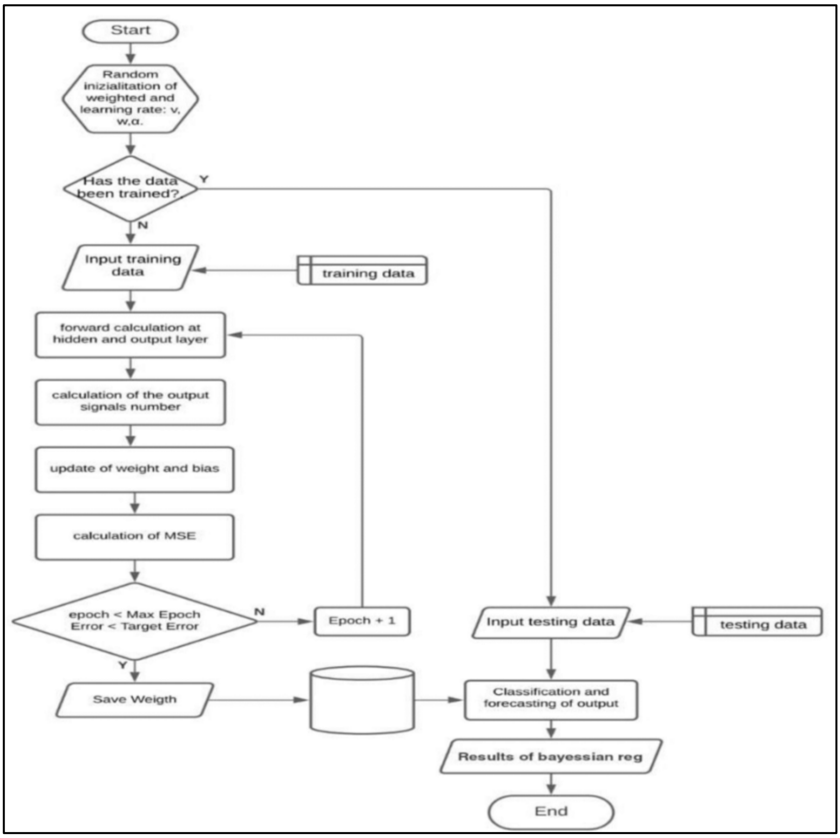

Fig.1: Weather forecasting algorithms

1. Collection

This data is sourced from the website rp5.ru (Reliable Prognosis), which presents data for Class I Hasanuddin Makassar Meteorological Station Balai Besar Region IV Makassar located at Sultan Hasanuddin Airport Makassar, which has an optimal weather forecast distance of only about 100 meters from the observation point and data in the form of comma-separated vector (*.csv).

The data in this study consisted of two seasons, namely the rainy season and the dry season. Weather samples taken include sunny, cloudy, light rain, and heavy rain. In Indonesia, the rainy season occurs in October-March, while the dry season occurs in April-September. There are 4,311 data in the rainy season and 4,345 data in the dry season.

The input variables are air temperature (x_1), air pressure (x_2), humidity (x_3), cloud hood (x_4), wind speed (x_5) and precipitation (x_6), and weather classification as target values (y).

Table 1: Clustering of Data

Weather	Rainy Season			Dry Season		
	30%	60%	100%	30%	60%	100%
Sunny	349	569	905	682	1097	2028
Cloudy	589	1250	2027	460	1171	1767
Light rain	220	506	897	98	229	373
Heavy rain	135	261	481	64	109	176
Total	1293	2587	4311	1304	2607	4345

2. Experimentation
   It is conducting experiments on data sets, both on training data and on testing data. The tool used is Python using the Numpy library, and the method used is the Bayesian Regularization method for time series data. It carried out three scenarios: training data scenarios of 30%, 60%, and 100%, which aims to see the effect of training data on MSE, Accuracy, and duration of prediction time (Table 1).

3. Testing and Evaluation
   Testing the data set by validating the training and testing data. This section serves to measure the accuracy or performance of the two methods used. The highest accuracy indicates that the method is more accurate than the others.
   The measurement using Mean Squared Error (MSE) is another method for evaluating forecasting methods. Each error or residual is squared, and this approach regulates significant forecasting errors because they are squared.
   The method results in moderate errors that are likely better for small mistakes but sometimes make a big difference. MSE is the second way to measure overall forecasting errors, and MSE is the average squared difference between the predicted and observed values. The downside of MSE use is that MSE tends to accentuate large deviations due to the squad rating [15]. The formula for calculating MSE is as follows.

$$\sum_{t=1}^{n} \frac{(X_t\text{-}F_t)^2}{n} \tag{5}$$

   with Xt is the actual data in the t period, Ft is the forecasting value in the period t, and n is the amount of data.
   The initial stages of inputting weather features consist of the input variables are air temperature (x_1), air pressure (x_2), humidity (x_3), cloud hood (x_4), wind speed (x_5) and precipitation (x_6), and weather classification as target values (y), learning rate and weights. Furthermore, the hidden and output layers would carry on the training process to compute their variables.
   The calculation of the number of output signals then updates the bias and weights in calculating the mean square error to see between the error and the target epoch. If the error and epoch thresholds have fulfilled the target, algorithms will stop and provide update weights, and the biases are training results. If otherwise, it will continue the epoch process to reach the threshold value. It will compare the probe data and training data suitable error and epoch threshold. Its results are output classification such as sunny, cloudy, light rain, and heavy rain.

5. Result & Analysis

The weather forecasting process produces output classification are sunny, cloudy, light rain, and heavy rain. The investigation results describe the entire process with the following results.

1. Initialization of Input in the form of Weight and Learning Rate

   The results obtained from this stage are in the form of interpretation of weather features into the input of the Bayesian Regularization algorithm. The six weather features are then converted to six input nodes and have one hidden layer using five nodes because, in this epoch, the network shows the best performance where the error rate is relatively low and execution time is speedy compared to other nodes (in the form of error 0.00995 and learning rate 0.001).

The experiment obtained the lowest learning rate and MSE using 200 weather data and 1000 maximum epochs (Table 2) during the 19th epoch. BR simulation uses 200 pieces of weather data cleaned and put into a hidden layer system. It will test weights and biases into training data and testing data to get an efficient network value. The results are the number of hidden neurons between 3 to 5 nodes with a maximum epoch of 1000.

Table 2: Searching epoch of hidden neuron

NO	Learning rate	Hidden Neuron	Error (%)	Time (minutes)
1	0.001	3	0.0237	0.067
2	0.002	3	0.0249	0.016
3	0.003	3	0.0378	0.016
4	0.004	3	0.0389	0.016
5	0.005	3	0.0459	0.000
6	0.006	3	0.0427	0.000
7	0.007	3	0.0483	0.000
8	0.008	3	0.0427	0.033
9	0.009	3	0.0467	0.000
10	0.001	4	0.0234	0.016
11	0.002	4	0.0477	0.000
12	0.003	4	0.045	0.000
13	0.004	4	0.0446	0.016
14	0.005	4	0.0402	0.016
15	0.006	4	0.0402	0.016
16	0.007	4	0.0436	0.000
17	0.008	4	0.0312	0.000
18	0.009	4	0.0227	0.016
19	0.001	5	0.00995	0.000
20	0.002	5	0.0379	0.016
21	0.003	5	0.0203	0.016
22	0.004	5	0.0303	0.016
23	0.005	5	0.0262	0.016
24	0.006	5	0.0383	0.016
25	0.007	5	0.0391	0.000
26	0.008	5	0.0364	0.000
27	0.009	5	0.0165	0.000

Based on the search results, then the other parameters are initialized as mentioned in Table 3.

Table 3: Initialization result of weight and learning rate

Net Size	Parameter
Input Layer	6 nodes
Hidden Layer	5 nodes
Output Layer	1 node
Maximum Epoch	1000
Show Epoch	10
Mu	0,001
Goal	10^{-3}, 10^{-4}, dan 10^{-5}
Weights	-1 to 1
Neuron Function	
Hidden Layer	Sigmoid Biner
Output Layer	Linear

Fig 2 represents the initialization of the variables as a Bayesian regularization architecture. It shows the network architecture with one input layer xi, one hidden layer zi and one output layer y. The inputs are made up of 6 input features, x1, x2, x3, x4, x5, and x6. The hidden layer consists of 5 nodes z1, z2, z3, z4, and z5. The output layer will accumulate all the values from the hidden layer to a single output value.

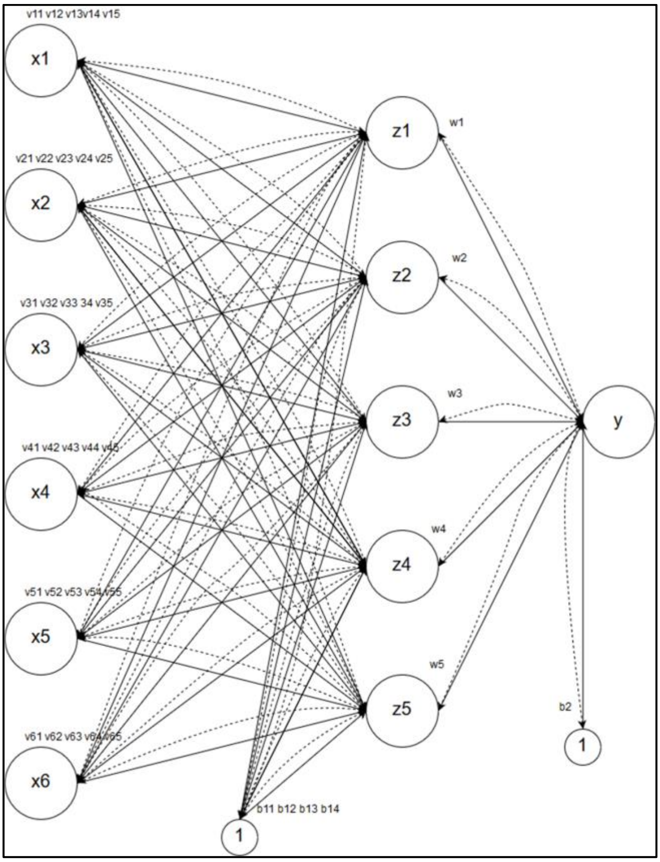

Fig 2: Bayessin Regularization Network Architecture

2. The Scenario of Experiment Results for Cluster Testing Data 30%, 60%, dan 100%

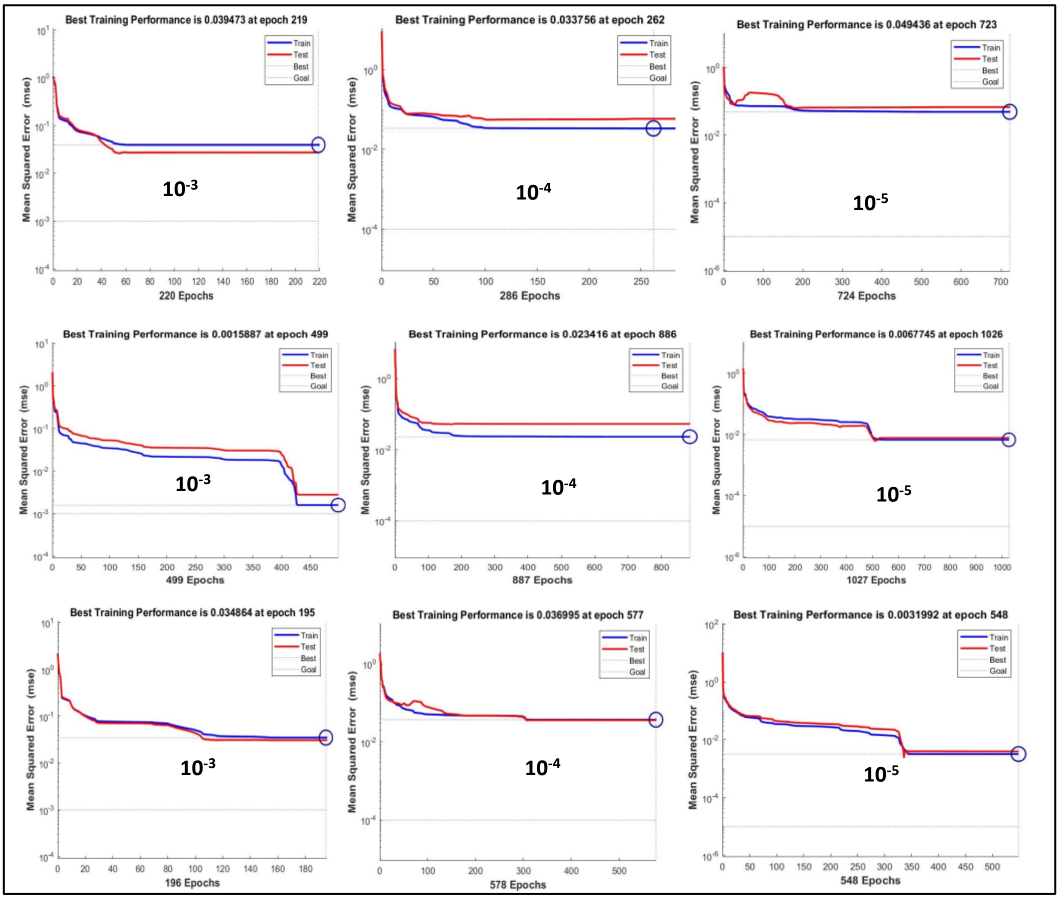

Fig 3: MSE Variance of Rainy Season at: a. 30% of total data; b. 60% of total data; c. 100% of total data.

Based on Fig 3a (30% of the data), it shows that the error reduction process, which is graphically visible fluctuating, on the graph with MSE targets 10^{-3} and 10^{-4}, then when MSE targets 10^{-5}, the training and testing graphs and targets almost coincide.

The same thing (Fig 3b) with 60% sample occurred from the MSE 10^{-3} -10^{-5} process, and the graph shows a significant decrease in error indicated by the linearity of the three target-training-testing lines that almost linearly coincide.

The decrease in graphic error is more significant when the sample data has reached 100%, the change in error from 10^{-3} - 10^{-5} has a very significant change from the two previous scenarios with an MSE result of 0.0031992 in the fastest iteration, epoch 548.

Fig 3c shows a small and stable error value in the convergent region, is the MSE 10^{-5}. The final results of the expected iteration process are: the three lines coincide with the target-training-testing; smallest MSE value; all three lines are stable and convergent.

Fig 4a shows the change from 10^{-3}-10^{-4} produces the smallest training targets, but the target-testing has a reasonably significant line difference. The training-testing process reached lower to 10^{-5}, then the result convergent value.

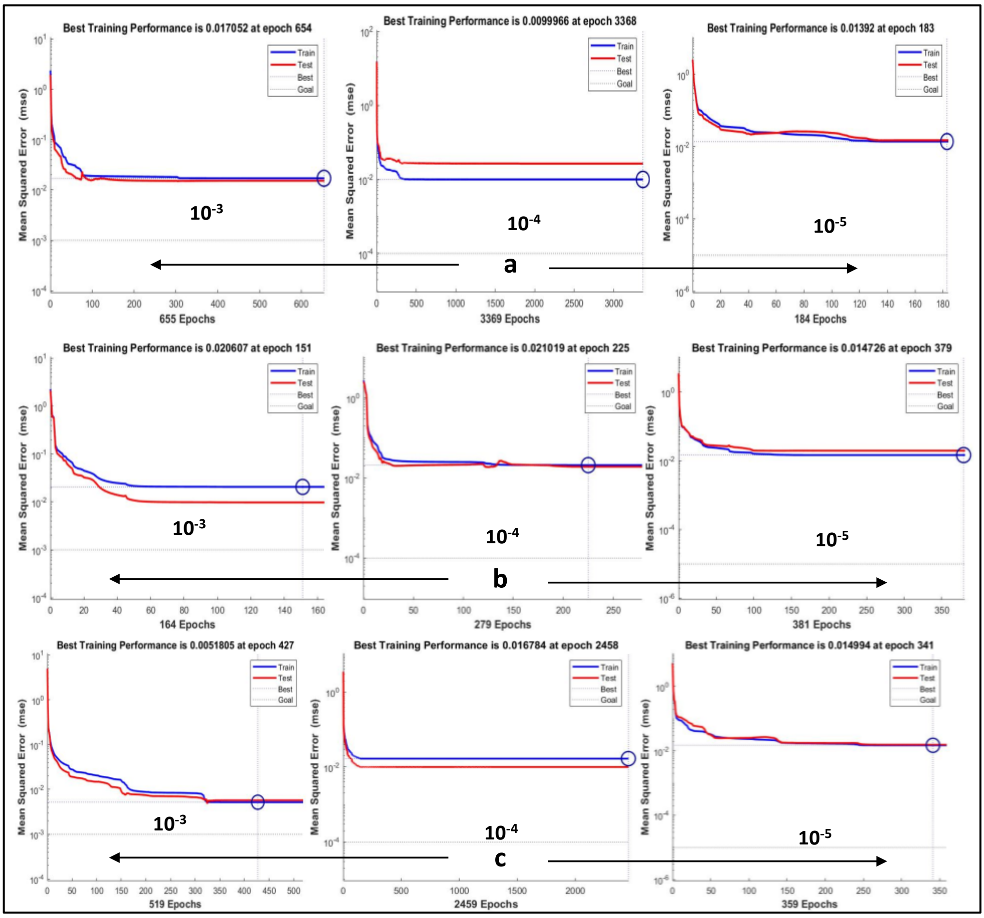

Fig 4: Variance of Dry Season at a. 30% of total data; b. 60% of total data; c. 100% of total data.

Fig 4b shows that at 10^{-3}-10^{-4} the line between target-training-testing is almost close; only at 10^{-5} does the training-target line coincide, but the testing line has a relatively large offset in the convergent area. Figure 4c shows that the stability is highest with the alignment of the three target-training-testing lines in the convergent region. Therefore, this stability area marks the best MSE performance obtained as the system's best performance. If we compared MSE in the rainy season and MSE in the dry season at a value of 10^{-5}, the stability of the rainy season is better, the smallest value of 0.0031992 compared to the value of the dry season with a value of 0.014994. The rainy season dataset is larger than the dry season.

3. System Performance

System performance will focus on accuracy and duration of time to obtain the value with the smallest MSE. The measured performance is the weather features in the rainy and dry seasons: sunny, cloudy, light rain, and heavy rain.

Based on table 4, it appears that the data cluster affects the number of epochs to achieve the lowest error according to the target at MSE < 10^{-3}, 10^{-4}, and 10^{-5}. At the max epoch and the best epoch, the characteristic is that the 30% data cluster will increase the number of epochs by 60%, which will experience a decrease in the number of epochs when the data cluster is 100%. The result indicates that when the data cluster is 30-60%, the stability condition still fluctuates and has not yet reached convergence. After reaching 100% cluster data, the number of epochs decreases and decreases the epoch time, indicating that Bayesian regularization achieved the best convergence under conditions of minimum time duration.

The table also shows that the accuracy of each data cluster fluctuates from low-up-down in the MSE interval of 10^{-3}-10^{-4}. After MSE 10^{-5}, the accuracy fluctuation became stable from low-medium-up, meaning that the model achieved with the MSE 10^{-5} target has a stable accuracy. This is also marked by the difference in the largest data cluster, with previously having the smallest value of 0.239 compared to the other two values of -2.559 and -0.967.

Table 4: Performance at Rainy Season

Weather	Performance at Rainy Season (%)								
	MSE < 10^{-3}			MSE < 10^{-4}			MSE < 10^{-5}		
	30%	60%	100%	30%	60%	100%	30%	60%	100%
Max Epoch	220	499	196	286	887	578	724	1027	548
Best Epoch	219	499	195	262	886	577	723	1026	548
Time (s)	5.294	9.5	6.299	5.634	13.558	12.516	10.933	15.659	12.030
Best Accuracy	98.642 *2)	100.00 *2)	100.00 *3)	98.812 *2)	99.600 *2)	99.260 *2)	98.812 *2)	100.000 *2)	100.00 *2)
Mean accuracy (%)	96.906	99.845	97.286	96.210	98.879	97.912	95.360	99.459	99.698

Note: *1) = Sunny, *2)= Cloudy, *3)= Light Rain, *4) = Heavy Rain

Table 5: Performance at Dry Season

Weather	Performance at Dry Season (%)								
	MSE < 10^{-3}			MSE < 10^{-4}			MSE < 10^{-5}		
	30%	60%	100%	30%	60%	100%	30%	60%	100%
Max Epoch	655	164	519	3369	279	2459	184	381	359
Best Epoch	654	151	427	3368	225	2458	183	379	341
Time (s)	9.944	5.782	13.112	34.002	7.225	41.232	4.998	10.146	10.159
Best Accuracy	99.267 *1)	100.00 *2)	99.901 *1)	99.853 *1)	99.573 *2)	100.00 *3)	99.120 *1)	100.00 *3)	99.88 *2)
Mean accuracy (%)	98.390	98.542	99.402	98.696	97.699	98.688	98.466	99.233	99.056

Note: *1) = Sunny, *2)= Cloudy, *3)= Light Rain, *4) = Heavy Rain

Table 5 shows that the best fluctuations in the number of epochs are in the MSE 10^{-5} interval. The data will increase and then decrease steadily so that the time duration will also be shorter. In addition, the difference in mean Accuracy between MSE clusters has the smallest difference in MSE 10^{-5} worth -0.177 compared to the difference in the other two MSEs, respectively 0.86 (MSE 10^{-3}) and 0.98 (MSE 10^{-4}).
Table 6: Performance comparation of Backpropagation and Bayesian regularization

Performance Error dan Time	Winter		Summer	
	BP	BR	BP	BR
MSE	0.264606	0.00331	0.12484	0.01509
time (s)	186,9	12,030	152,154	10,146

The results obtained from table-6 show that BR has the smallest MSE to obtain the best accuracy than using BP [34]. Bayesian Regularization has an MSE value of 0.00331 with 12.030 seconds in the rainy season; MSE 0.01509 with a time of 10.146 seconds in the dry season. Comparing these results with Backpropagation which has an MSE of 0.26406 with 186.9 seconds in the rainy season; MSE 0.12484 with a time of 152.154 seconds in the dry season. This significant value proves that Bayesian Regularization has the best MSE and much better speed than Backpropagation.

Mohsin [23] also proved that Bayesian Neural Network has better speed than using Least Absolute Shrinkage and Selection Operator (LASSO). Purba [22] compared that the Bayesian Regularization speed of a few neurons (type-2) had the best computational time compared to that of a neuron with a more significant number (type-3), although the best accuracy was obtained for a large number of neurons.

Our study has a better significance with the smallest MSE value of 0.0033 than Zhao research [24] only 0.05. Several points resulted from this research, including:

a. Based on the figures and tables results, adding the number of datasets will affect the system accuracy level and reduce the mean square error.
b. Increasing the number of datasets will reduce the system speed in providing forecasting output because the system will require the epoch time also longer.
c. The graph shows that Bayesian regularization reduces overfitting, which increases the system accuracy, which is directly proportional to the decline in MSE.

6. Conclusion

Weather forecasting features of air pressure, humidity, cloud hood, wind speed, and precipitation using a Bayesian regularization neural network have better performance than backpropagation. They indicate that the use of this method provides high accuracy and good convergence speed. For the subsequent development, the model will implement deep learning recurrent for forecasting to compare with the results of previous studies. The number of datasets must increase the best performance.

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