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Using Backpropagation to Predict Drought Factor in Keetch-Byram Drought Index

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Abstract:

Forest fires continue to rise during the dry season and they are difficult to stop. In this case, high temperatures in the dry season can cause an increase in drought index that could potentially burn the forest every time. Thus, the government should conduct surveillance throughout the dry season. Continuous surveillance without the focus on a particular time becomes ineffective and inefficient because of preventive measures carried out without the knowledge of potential fire risk. Based on the Keetch-Byram Drought Index (KBDI), formulation of Drought Factor is used just for calculating the drought today based on current weather conditions, and yesterday's drought index. However, to find out the factors of drought a day after, the data is needed about the weather. Therefore, we need an algorithm that can predict the dryness factor. So, the most significant fire potential can be predicted during the dry season. Moreover, daily prediction of the dry season is needed each day to conduct the best action then a qualified preventive measure can be carried out. The method used in this study is the backpropagation algorithm which has functions for calculating, testing and training the drought factors. By using empirical data, some data are trained and then tested until it can be concluded that 100% of the data already well recognized. Furthermore, some other data tested without training, then the result is 60% of the data match. In general, this algorithm shows promising results and can be applied more to complete several variables supporters.

Key words: Backpropagation, Drought Factor, Drought Index, Keetch-Byram, Neural Network Toolbox.

Introduction:

Some research suggests that forest fires changed since 1960 with the main activity because of human activities that cut down trees for agriculture, fields, plantations, and settlements (1). Humans cause forest fires does not depend on the season. Whenever they open up land, they will cut down trees and burn it when dry. In August and September concluded that there are a tendency all forest drought increases (2). Furthermore, the method can refine predictions are more focused time to oversee the forest without having to supervise all the time. Forest fires can occur anytime during the dry season. The potential of forest fires increases and difficult to stop because of the hot weather and reduced water content in the soil (3). Forest monitoring takes a long time, energy, and costs. Therefore, efforts are needed to stop forest fires by predicting when the potential for fires often occurs, so that anticipatory actions can be carried out effectively and efficiently.

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Measure to determine the risk of fire using a calculation commonly known as a drought index calculated by considering the level of rainfall average annual (3). KBDI calculates the index by involving the index the previous day, plus the current drought factor (4).

Today's data is only used to calculate today's drought factor. Today's data is only used to calculate the current drought factor. KBDI technique was used from 1968 until now because it can estimate the increasing lack of moisture in the lower layers and upper layers (5). The formulations used in the KBDI drought index calculation does not require many parameters, only requires the highest air temperature data and the maximum rainfall (4). Other methods require more detailed input with almost the same results. KBDI calculation technique selection is as responsive to changes in precipitation every day (6). Rapid response to changes is needed to predict the potential of daily forest fires. In KBDI techniques, drought is a very dominant factor because if the location to be measured has been determined and drought factors have been determined, the drought index calculation will be easier to do (3).

BP algorithm is used to predict the drought factor because it has two advantages. Namely, inputs made in the network can produce more accurate output, and architectures that calculate through advanced propagation, and more static backward propagation are used (7). To monitor the state of the forest from fire hazards, not only the current drought factor is needed. However, there needs to be a method that can predict tomorrow's conditions based on today's weather conditions. Backpropagation is a method of an artificial neural network that can be used to predict.

In this paper, the study aims to provide solutions to reduce fatal forest fires. This research is predicting the drought factor Keetch-Byram drought index using the BP algorithm. With accurate predictions, this will save more time and costs in monitoring forests from the danger of forest fires. The government as the forest supervisor can anticipate in advance given when increased fire potential based on the prediction.

Keetch-Byram Drought Index (KBDI)

KBDI calculation is used based on daily rainfall, daily maximum temperature, and annual average rainfall (3). The KBDI can be used as a daily drought index calculation method by using some inputs from daily data. The focus of determining the drought index in the KBDI is the change in soil moisture as an indicator of ecosystem development (4). Furthermore,the pattern of changes in soilmisture can be known through monitoring daily air temperature and rainfall that carried out.

Formulated calculations drought factor (dQ) in S.I. unit equation (Eq. (1)) as an important component in the calculation of the drought index (Eq. (2)) using KBDI (8):

$$dQ = \frac{(203.2 - Q)\left(0.968exp^{(0.0875T+1.5552)} - 8.30\right)d\tau}{1 + 10.88e^{(-0.001736R)}}x10^{-3} \quad (1)$$

$$KBDI^t = KBDI^{t-1} + dQ - RF^t \quad (2)$$

The correction using the English unit equation to calculate the drought factor KBDI (Eq. (3)) and unit equaition (Table 1) (9). Based on table 1 shows that to measure drought factor requires moisture deficiency, daily maximum temperature, and mean annual precipitation calculated based on daily data.

$$dQ = \frac{(800 - Q)\left(0.968exp^{(0.0486T)} - 8.30\right)d\tau}{1 + 10.88exp^{(-0.0441R)}}x10^{-3} \quad (3)$$

Table 1. Unit Equation

Symbol	Quantity	English units	S.I. units
	Drought factor		
dQ	Moisture deficiency	0.01 in	Mm
Q	Daily maximum	0.01 in	mm
T	temperature	ºF	ºC
R	Mean annual	In	mm
dτ	precipitation	= 1 day	= 1 day
	Time Increment		

It can be categorized, specially for rainfall, into three parts depending on the daily rain conditions (Eq. (4)) (10):

$$RF^t = \begin{cases} (R^t - 5.1),\ R^t \geq 5.1\ mm/day, 1st\ rainy\ day \\ R^t, R^{t-1} \geq 5.1\ mm/day, 2nd\ and\ the\ next\ rainy\ day \\ 0, R^t < 5.1\ mm/day \end{cases} \quad (4)$$

The drought index is measured by using a metric system between 0 - 203 that reflects conditions ranging from average to the states with the highest maximum drought causing the fire (10). Table 2 presents the KBDI drought index also defined with a value of 0 to 800 to show increasing soil moisture, with 0 referring to maximum soil saturation and 800 as the highest soil moisture deficiency (4). In general, the output from the calculation of the drought index is divided into six scales: very low, low, moderate, high, very high, and extreme.

Table 2. KBDI Fire Risk Levels.

KBDI	Risk Levels
<99	Very Low
100-199	Low
200-299	Moderate
300-399	High
400-599	Very High
600+	Extreme

Forest area owners should start think about the integration of several sources of information relating to the local climate, soil characteristics, and hydrological conditions to produce better predictions about forest fires (10). The combination of using KBDI techniques with technology needs to be considered in research so that it can produce significant changes (11).

Backpropagation (BP) Algorithm

BP algorithms are used to predict inventory (12), Predicting the Water Level Fluctuation (13), A Study of Image Classification of Remote Sensing Based (14), local rainfall prediction (15), face recognition (16), security situation prediction (17), plate recognition (18), and others. Those studies show that BP is very well used to predict patterns and data series, so it needs to be tried to predict the drought factor in this study.

BP algorithm is a mathematical approach to operate functions and data using multiple layers (12). In this study, the BP algorithm uses three layers consisting of an input layer, output layer, and hidden layers. Moreover sequence, the input layer is filled with three cells comprising count variables (Q, R, and T), and the output layer is only one cell, drought factor.

BP Algorithm has the advantage of reducing slow learning problems by changing inputs from values 0 and 1 to values 0.1 to 0.9 (14). That is an essential step because in computing each input value must be calculated for the Appropriate of the calculation.

In this situation, each cell in the layer will receive input from the cell in the previous layer (or it can also come from bias) (19), then creates rules of learning between layers that connect between cells on each layer, then calculate information errors with the help of the activation function (20). The accuracy in determining the number of cells in a hidden layer and the amount of learning rate is a challenge for each study to get the smallest iteration.

The activation function is an essential component in determining the value of information errors so that the selection of the type of activation function must be ensured according to computing needs (21). Many types of activation functions are used sigmoid, pureline, hardlimit, threshold, saturating linear, and so on depending on the suitability of the data to be trained. The indicator of success in using the BP algorithm depends on the quality of the data being trained (17).

Research Method:

Study Area

A case study is selected at Bukit Suharto's forest. This forest is in Province of East Kalimantan, Indonesia. The area's range is ± 61,850 hectares located in Kutai Kartanegara Regency and Penajam Paser Utara Regency. The purpose of this area is as a the first fores for preserving sustainability and ensuring potential utilization of the area for the sake of research, knowledge, education, cultivation aims,and tourism.

The Bukit Suharto's forest is chosen as a case study. Because it is a conservation area, furthermore, it is the ecosystem of wet tropical rainforest that represent the characteristics of Kalimantan's forest (22). However, current forest conditions have been partially degraded due to forest fires, illegal mining, and community settlements (23).

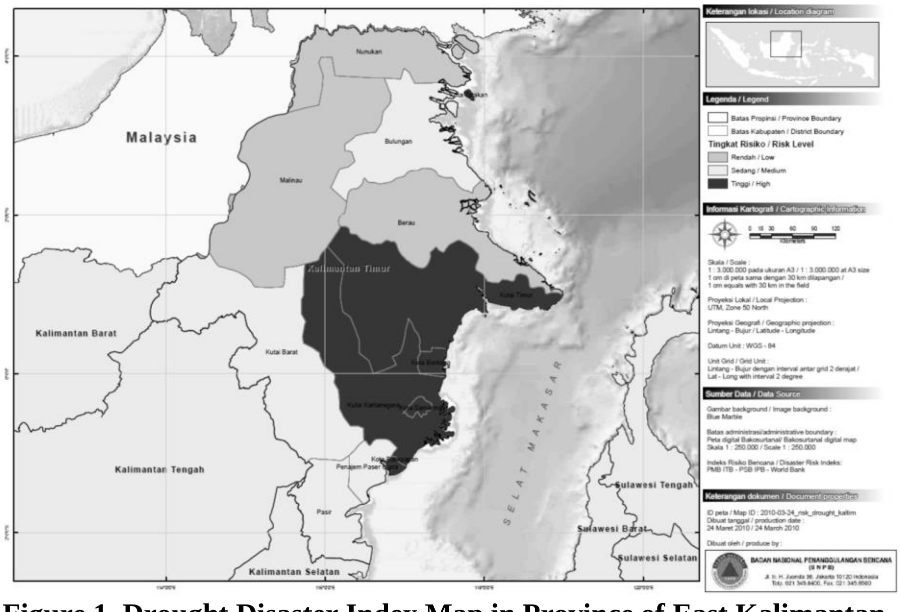

Figure 1. Drought Disaster Index Map in Province of East Kalimantan.

Data released by the National Disaster Management Agency in 2010 explained that parts of East Kalimantan Province were at a high-risk level. Figure 1 shows that the Kutai Kartanegara region, parts of East East Kutai, Samarinda, and Bontang areas are indicated in black spot.

Dataset Used

The data consist of three variables: moisture deficiency (mm), daily maximum temperature (°C), and mean annual precipitation (mm). The data collection time is taken for 50 days. From the whole data, 40 data will be trained and tested, while only10 data that will be assessed.

Stages

The study completion uses five stages. The stages are from calculating drought index to comparing the result. Firstly, the KBDI's method is used for calculating the drought index. Secondly, BP algorithm is used for training the data into the neural network toolbox. Next, testing the result of second step. Then, testing the untrained data for determining the network validity for recognizing new data. Finally, comparing the testing result of backpropagation method with using KBDI data calculation.

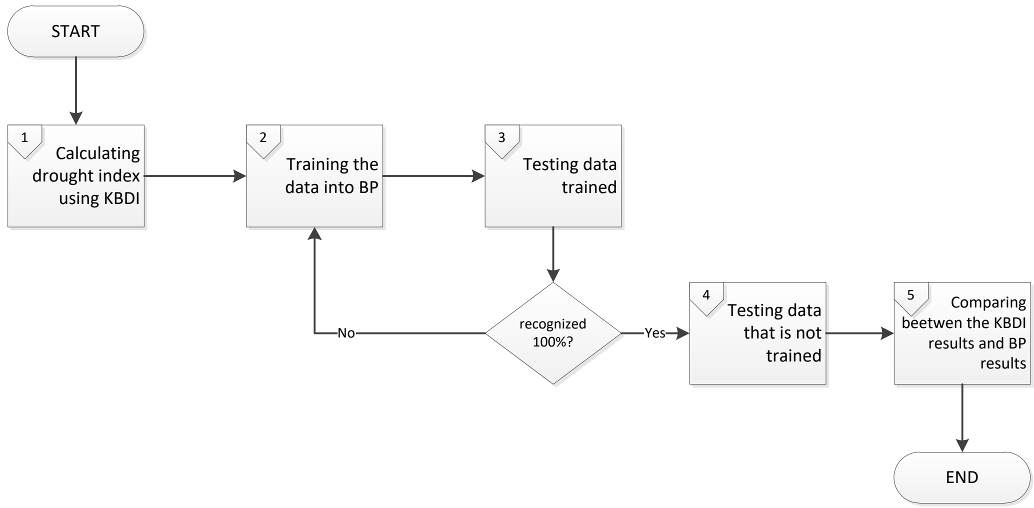

Figure 2. Stages of Study.

Figure 2 shows the first step is the initial one to calculate the drought index as a basis for comparison. The data used to calculate the drought factor in the KBDI method is included as the input layer in the training process using BP Algorithm. Testing of trained data is carried out after convergent tissue. After the tarained data are recognized 100% by network, the untrained data will be tested. The final step is to compare the results of both.

Software

Matlab is used for calculating KBDI's formula. Moreover, data training and data esting of backpropagation will use the neural network Toolbox in Matlab. The version of Matlab that used is R2016b.

Data training instructions is written in Matlab (format .m file) include the steps. Which are: (1) retrieving data from excel format files, (2) determining the range of data cells to be trained, some cells as input and other cells being output, (3) creationing the network with the "newff" command, (4) determiningthe goal value, epochs, learning rate, and other attributes, (5) training the data using "train" commands, and (6) saving network output after training success in .mat file.

Input data and output data are included in the excel format. Subsequently, the number of cells in the hidden layer is used as many as 3-1 cells with the activation function using 'logsig' and 'pureline'. Goal parameters are determined with an initial value of 0.001, and the learning rate is given an initial value of 0.1, where the values of the two variables can be changed after seeing the progress of the training results. An important part of the command to do data training is shown in the following syntax:

```
% network creation
net = newff(minmax(data_train),[3 1],{'logsig','purelin'},'traingdx');
% Provide value to influence the training process
net.performFcn = 'mse';
net.trainParam.goal = 0.001;
net.trainParam.show = 5;
net.trainParam.epochs = 1000;
net.trainParam.mc = 0.95;
net.trainParam.lr = 0.1;
% training
[net_output,tr,Y,E] = train(net,data_train,target_train);
```

The instructions to test the data are carried out by two stages, namely testing the data that has been trained and testing new data that has not been trained. Both of these tests are based on the training results data stored in the .mat format carried out in the previous stages. The instruction syntax for testing:

```
% result prediction
result = sim(net_output, data_test);
value_error = result-target_test;
 max_data = 100;
min_data = 0;
result = ((result-0.1)*(max_data-min_data)/max_data)+min_data;
% Performance of result
error_MSE = (1/n)*sum(nilai_error.^2);
```

Result and Discussion:

Figure 3 is a presentation of the data elements that used to calculate the drought factor using KBDI technique, such as, Q is a variable being moisture deficiency (mm), T is a daily maximum temperature (°C), and R is the mean annual precipitation (mm). The length of time for assessing in training stage is 40 days. The data presented is still in the original unit for calculation purposes.

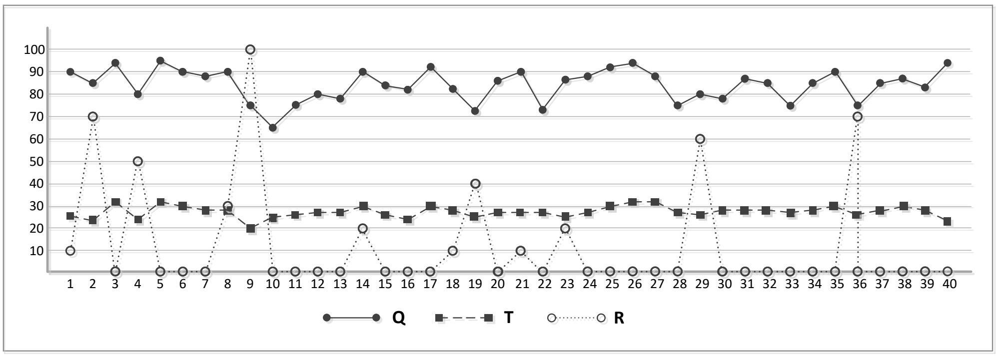

Figure 3. Variable of Training Data.

The calculation results based on the data in Fig. 3 describes the drought factor as same as show on Figure 4. Unlike the units in the input element, the units in the drought index are between 0 and 1. Nevertheless, the first results can be define as a basis of comparison.

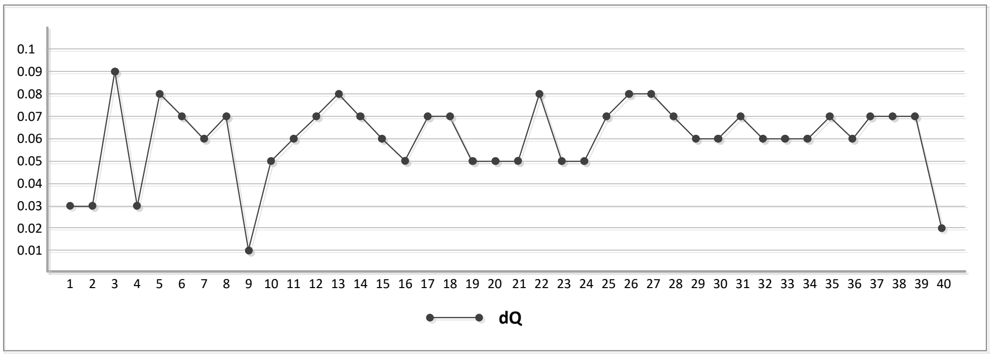

Figure 4. Drought Factor.

According to Fig. 3 and 4, the data is trained by the BP algorithm with columns Q, T, R as cells in the input layer, and drought factor as cells in the output layer. Then, Fig. 5 point it out that the input layer consists of three cells with variable Q is being the input of cell x1, R is being the input of cell x2, and T is being the input of cell x3. All data units are converted into values between 0 and 1. The number of hidden layers cannot be determined at the beginning of the training because it will be known after getting the smallest iteration after making several attempts.

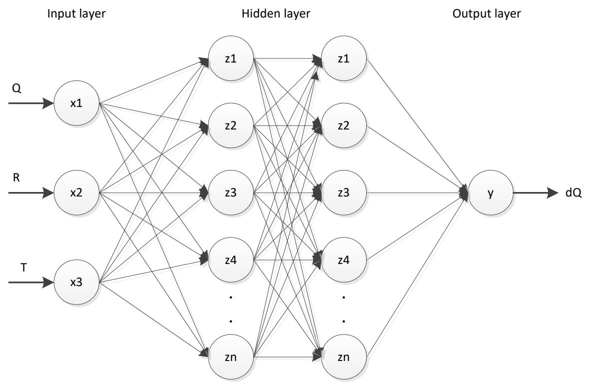

Figure 5. Initial BP Network Architecture with Three Input Cells and One Output Cell.

The right layer in Figure 5 is the output one which it is a drought factor data. In this study, drought factor is categorized into four types, namely: ‘0 0’ for the range of values 0 - 0.25, ‘0 1’ for the range 0.26 - 0.5, ‘1 0’ for the range 0.51 - 0.75, and ‘1 1’ for a range of 0.75 – 1.

This study uses specific data in small range because it is only whether test drought factors can be assed by BP algorithm. The results obtained from the training phase are converging networks at 187th iteration, with train parameter goal 0.001 and learning rate 0.1 (see coding). The network architecture is shown in Figure 6, the neural network is formed by the formation of an input layer consisting of three cells, which are: the hidden layers consists of a combination of three cells for the ‘logsig’ activation function and one cell for the ‘pureline’ activation function, and one cell in the output layer.

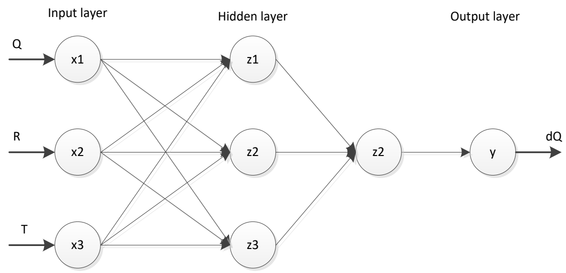

Figure 6. BP Network Architecture After Convergence.

The training results after converging on the Neural Network Training Toolbox in Matlab are shown in Figure 7. The information presented consists of four parts, they are: neural network architecture, algorithms used, progress, and plots that show a graph of error changes for each iteration. The algorithm is used to train data uses Gradient Descent with Momentum and Adaptive Learning with performance using Mean Squared Error. Furthemore, in Progress information, the network is declared convergent after going through 187 iterations with the time needed 0.3 seconds.

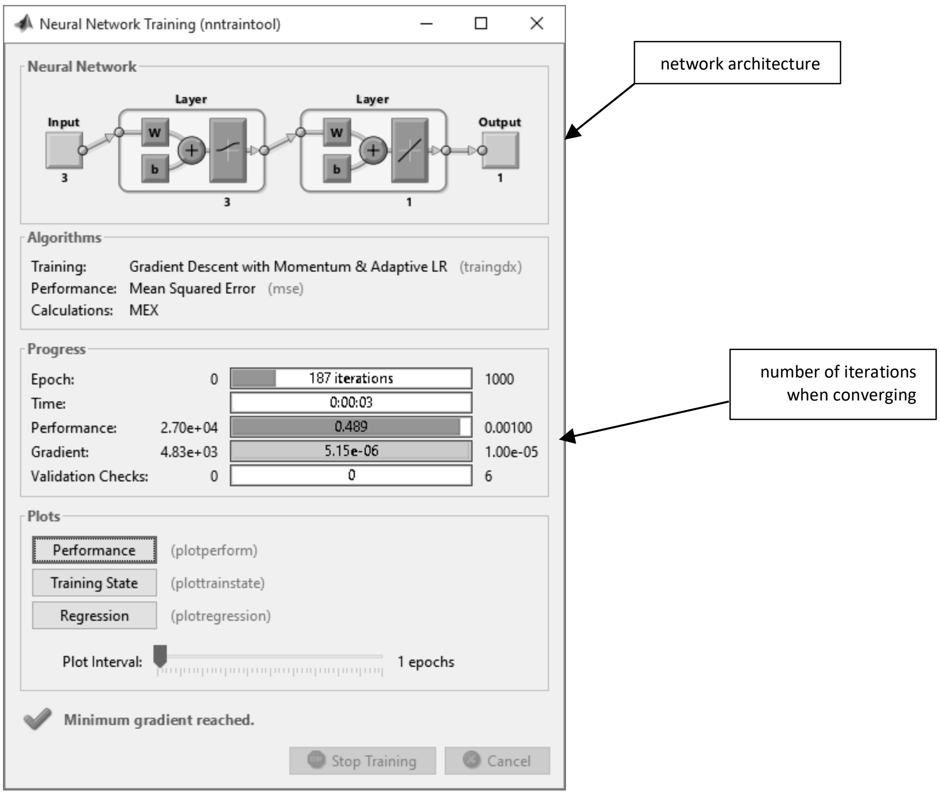

Figure 7. Neural Network Training.

Then all the same data is tested using a function in the neural network toolbox, indicating that the output of the test results is the same as the output being trained. That means that 100% of the trained data can be identified when tested (presented in Figure 8). In this result, OT means that the output issued by the calculation of the drought factor manually, while OB is the output produced by Backpropagation network.

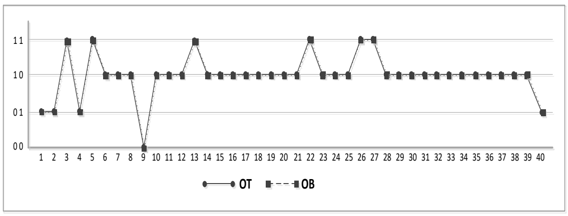

Figure 8. The Results of Testing Trained Data.

Data that not trained were tested in the network. It can be seen on Fig. 9. Moreover, new data as much as 10 are tested without training shown that six data matched on between standard calculation output and backpropagation output and four incompatible data and four data (day 1, 3, 8, and 9) do not match.

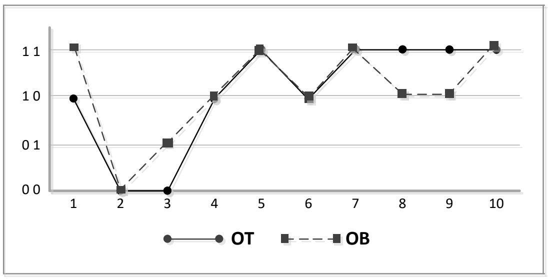

Figure 9. The Results Not Trained Data.

Conclusion:

The goal of the study has been achieved. Based on the result, it can be seen that 100% of trained data is recognized. Furthermore, in accordance from 10 data measures, it can be identified that with using KBDI, the drought factor appear 60% macth and the rest missmatch. In this case, it can be concluded that the backpropogation algorithm is usefull to predict future drougth factor based on daily weather data.

In this study, the results of daily drought factor calculations did not show a significant difference. It happens because of the data used is only 40 days. So, there is no established pattern for increasing and decreasing of the drought factor.

The study has promising result. For improving the result, future study should be conducted. For instance, increasing the amount of data that involved to find the better patter for increasing and decreasing daily darought factors, and combining the KBDI variables with others variables, such as, topology, sunlight, plant's type, and forest's density.

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Conflicts of Interest: None.

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استخدام خوارزمية الانتشار الخلفي للتنبؤ بعامل الجفاف في مؤشر للجفاف Keetch-Byram

هاديسويتو أ س **حسن ف هـ**

جامعة سينز ماليزيا ، ماليزيا.

الخلاصة:

تستمر حرائق الغابات في الارتفاع خلال موسم الجفاف ومن الصعب إيقافها. في هذه الحالة، يمكن أن تتسبب درجات الحرارة المرتفعة في موسم الجفاف في زيادة مؤشر الجفاف الذي يحتمل أن يحرق الأضرار في كل مرة. وبالتالي، ينبغي للحكومة إجراء المراقبة طوال موسم الجفاف. المراقبة المستمرة دون التركيز على وقت معين تصبح غير فعالة وغير فعالة بسبب التدابير الوقائية التي تتم دون معرفة مخاطر الحريق المحتملة. استنادًا إلى مؤشر Keetch-Byram للجفاف (KBDI) ، يتم استخدام صياغة عامل الجفاف فقط لحساب الجفاف اليوم استنادًا إلى الظروف الجوية الحالية ، ومؤشر الجفاف بالأمس. ومع ذلك ، لمعرفة عوامل الجفاف بعد يوم واحد ، هناك حاجة إلى بيانات حول الطقس. لذلك، نحن بحاجة إلى خوارزمية يمكنها التنبؤ بعامل الجفاف. لذلك ، يمكن التنبؤ بإمكانية الحريق الأكثر أهمية خلال موسم الجفاف. علاوة على ذلك، هناك حاجة إلى التنبؤ اليومي بموسم الجفاف يوميًا للقيام بأفضل عمل، ثم يمكن تنفيذ إجراء وقائي مؤهل. الطريقة المستخدمة في هذه الدراسة هي خوارزمية الانتشار الخلفي التي لها وظائف لحساب واختبار وتدريب عوامل الجفاف. باستخدام البيانات التجريبية، يتم تدريب بعض البيانات ومن ثم اختبارها حتى يمكن استنتاج أن 100 ٪ من البيانات معترف بها بالفعل بشكل جيد. علاوة على ذلك ، فإن بعض البيانات الأخرى التي تم اختبارها دون تدريب ، فإن النتيجة هي 60 ٪ من تطابق البيانات. بشكل عام، تُظهر هذه الخوارزمية نتائج واعدة ويمكن تطبيقها أكثر لإكمال العديد من مؤيدي المتغيرات.

الكلمات المفتاحية: Keetch-Byram ، مؤشر الجفاف، عامل الجفاف, الانتشار الخلفي، صندوق أدوات الشبكة العصبية.