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THE SYSTEM TO PREDICT VOLCANIC ERUPTIONS WITH BACKPROPAGATION METHOD

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Abstract: This system for predicting volcanic eruptions will produce information that can help BMKG in making decisions to provide warnings to residents around the mountain. This will also help in mitigating volcanic eruptions, evacuating residents in volcanic eruptions. By using artificial neural networks with the backpropagation method, it can be used to predict volcanic eruptions. To conduct this test, criteria and factors that influence this volcanic eruption are needed. This method is tested using Matlab 6.1 software. In this test, various patterns will be carried out to compare the results of the network. From the various patterns tested, it can be seen that the number of epochs used affects the test results and will achieve the desired goal. The more epochs used, the faster the goal will be achieved. Where in the 4-2-1 pattern the goal was found in the 7th epoch with an error value of 0.0987135. This 4-2-1 pattern states that this network is tested with 4 input layers, 2 hidden layers and 1 output layer. The α value (α = learning rate) used is the Default value of 0.1. With this backpropagation method, you get more accurate results by getting smaller error values.

Keywords: backpropagation, matlab 6.1, layer, epoch, goal

Abstrak: Sistem untuk memprediksi gunung meletus ini akan menghasilkan informasi yang bisa membantu BMKG dalam mengambil keputusan untuk memberikan peringatan kepada warga sekitar gunung. Hal ini juga akan membantu dalam mitigasi bencana gunung meletus , evakuasi warga sekitar dalam bencana gunung meletus. Dengan menggunakan jaringan saraf tiruan dengan metode backpropagation bisa digunakan untuk memprediksi gunung meletus. Untuk melakukan pengujian ini dibutuhkan kriteria dan faktor yang mempengaruhi gunung meletus ini. Metode ini diuji dengan menggunakan software Matlab 6.1. Pada pengujian ini akan dilakukan dengan berbagai pola untuk membandingkan hasil dari jaringan tersebut. Dari berbagai pola yang diuji dapat dilihat bahwa jumlah epoch yang dipakai mempengaruhi hasil pengujian dan akan mencapai goal yang diinginkan. Semakin banyak epoch yang dipakai maka akan semakin cepat goal tersebut dicapai. Dimana pada pola 4-2-1 goal ditemukan pada epoch ke 7 dengan nilai eror 0,0987135. Pola 4-2-1 ini menyatakan bahwa jaringan ini diuji dengan 4 jumlah input layer, 2 hidden layer dan 1 output layer. Nilai α (α = learning rate) yang digunakan adalah nilai Default yaitu 0.1. Dengan metode backpropagation ini mendapatkan hasil yang lebih akurat dengan mendapatkan nilai eror yang lebih kecil .

Kata kunci: backpropagation ; epoch ; goal ; layer ; matlab 6.1

INTRODUCTION

Today's technology has developed greatly and is very helpful in various ways. One of them is in predicting volcanic eruptions.

Earlier studies have examined volcanic eruptions, with a focus on analyzing the substantial effects of Mount Merapi's eruptions on the five districts in

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its vicinity.[1] Testing on the system built for training and validation produces training accuracy of 93,92% with validation of 73,04%.[2]The researc hers used Artificial Neural Networks in the research.

Propagation method have two parts, backward and forward.[3] Back propagation Artificial Neural Networks consist of several layers and are the most widely used Artificial Neural Networ ks.[4] A learning process with the back propagation algorithm will build an Artificial Neural Network model. [5] Backpropagation, which is often used in neural network training, usually requires a long time to find an acceptable solution.[6]

A supervised training method, known as a Backpropagation Neural Network, operates by measuring the difference between the network's output and the desired outcome, which is then used to calculate the error.[7] This error is then backpropagated to adjust the network's weights to minimize the error.[8] The backpropagation method is used in predicting volcanic eruptions because of its ability to process complex and non-linear data.

Backpropagation networks consi st of several layers, with each unit in one layer fully connected to each unit in the layer above or below, except for the bias which is only fully connected to the units in the layer above.[9] Volcanic eruption data was taken from the BMKG geology office located in Bukittinggi city. The architecture of the Artificial Neural Network will determine the success of the target to be achieved because not all problems can be solved with the existing architecture.[10]

The purpose of this study is to predict future volcanic eruptions that will help in mitigating volcanic eruption disasters. In this research, the problem that will be raised is how to predict volcanic eruptions using backpropaga tion. After a volcanic eruption prediction is made, the accuracy of the results will be seen.

METHOD

Field research, library research, and laboratory research are the primary methods used for data collection.

The research will be continued with a field study involving the Center for Volcanology and Geological Disaster Mitigation of BMKG. To obtain direct information about volcanic eruptions, interviews were conducted with 2 experts, namely the Head of the Center for Volcanology and Geological Disaster Mitigation of BMKG and the office staff.

A comprehensive literature review and thorough data collection will be conducted to achieve the research objectives. This data will be used to develop a better understanding of the research problem and generate relevant findings.The equipment available in the laboratory is indispensable for this research.

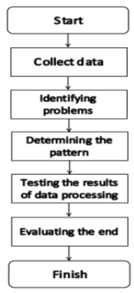

Image 1. Research framework

In this study, it begins by collecting data. After the data is collected, problem identification is carried out. After that, determine the pattern that will be used for training and testing. After the pattern is obtained, data testing will be carried out. And after that, an evaluation

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of the tests carried out is carried out.

Table 1. Eruption data Gunung Merapi 2022.

Mounth / Year	Eruption frequency Gunung Marapi
January / 2022	85
February / 2022	64
March / 2022	39
April / 2022	21
May / 2022	34
June / 2022	10
July / 2022	19
August / 2022	10
September / 2022	11
October / 2022	2
November / 2022	6
December / 2022	3

After the data is collected, the data is normalized to have the same scale. The normalized data is separated into two groups of data, namely training data and testing data. The linear transformation used to transform the data to the interval [0.1 , 0.9] is:

$$X' = \frac{0{,}8\ (x-a)}{b-a} + 0{,}1$$

Description:
x' = transformation result to x'
X = initial data
a = minimum data value
b = maximum data value

The steps in solving problems using the backpropagation method are:
Step 0: Initialize weights (preferably using small random numbers).
Step 1: If the condition is not met, do steps 2-9.
Step 2: For training pairs, do steps 3-8.

Phase 1: Forward Propagation

Step 3: Each input unit receives a signal xi and sends this signal to all units in the layer above it (hidden layer). To calculate it, use the formula below:

$$Z\_net_j = Vo_j + \sum_{i=1}^{n} X_I\ V_{ij}$$

Step 4: Calculate the output on the hidden layer using the formula:

$$y\_net_k = w_{k0} + \sum_{j=1}^{2} z_j w_{kj}$$

Step 5: Calculate all output values in unit yk.

Phase 2: Back Propagation

Step 6: Each output unit receives a target that is related to the input of the training pattern, calculate its information error.
Step 7: Calculate the hidden factor δ based on the error in each hidden unit zj (i = 1,2,3,….,p) with the formula:

$$\delta k = (tk - yk)\ f'\ (y\_net_k)$$

Step 8: Calculate the weight change term Vj (which is used to change the weight Vj) with a training rate of α = 0.1 using the formula:

$$\Delta W_{kj} = \alpha\ \delta_k\ z_j$$

Step 9: Calculate the hidden factor δ based on the error in each hidden unit zj (i = 1,2,3,….,p) with the formula:

$$\delta_{net_j} = \sum_{k=1}^{m} \delta_k w_{kj}$$

Step 10: Calculate the error factor in the hidden unit using the formula:

$$\delta_j = \delta_{net_j} f'\left(z_{net_j}\right) = \delta_{net_j} z_j\ (1 - z_j)$$

Step 11: Calculate the weight change term Vji (which is used to change the weight Vj) using the formula below and the value α = 0.1:

$$\Delta\ v_{ji} = a\ \delta_j j_i$$

Step 12: Change the line weight leading to the output unit with the formula:

$$W_{kj}\ (new) = w_{kj}\ (old)\ + \Delta\ w_{kj}$$

Step 13: Change the line weight towards the hidden unit using the formula:

$$V_{kj}\ (new) = v_{kj}\ (old)\ + \Delta\ v_{kj}$$

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RESULT AND DISCUSSION

Providing initial values for the input data (Xi) that the network will process, the weights (Wi) that represent the strength of connections between neurons, the expected output that the network should aim for, and the learning rate that determines how quickly the backpropagation. This function produces a value between 0 and 1. The process is repeated iteratively to minimize the error and converge towards the desired output. Using the backpropagation algorithm, the network will process this data and produce an output that aligns with the desired outcome.

The activation function, which is a key component of an Artificial Neural Network, determines the output of each neuron. In this case, we're using the sigmoid function, which produces outputs between 0 and 1. The maximum value for Gunung Marapi eruption data is 85, while the minimum is 1. Applying formula (1) to these raw data will yield a transformed dataset:

$$x_1 = \frac{0{,}8\ (85-1)}{85-1} + 0{,}1 = 0{,}9000$$

$$x_2 = \frac{0{,}8\ (64-1)}{85-1} + 0{,}1 = 0{,}7000$$

By applying the aforementioned calculations to the entire dataset of volcanic eruptions from January 2022 to December 2022, the transformed data, as presented in Table 1, will be updated to match the values in Table 2:

Table 2. Transformed Eruption Data Gunung Merapi 2022

Bulan / Tahun	Frekuensi Letusan Gunung Marapi
January / 2022	0,9000
February / 2022	0,7000
March / 2022	0,4619
April / 2022	0,2905
May / 2022	0,4143
June / 2022	0,1857
July / 2022	0,2714
August / 2022	0,1857
September/ 2022	0,1952
October / 2022	0,1095
November / 2022	0,1476
December / 2022	0,1190

The transformed data will be used to create training and testing sets for a backpropagation neural network. Each set will consist of 4 patterns: January 2022 to April 2022 as input and May 2022 as the target output. In total, 12 patterns will be generated, with 10 for training and 2 for testing. A detailed breakdown is provided in Table 3:

Table 3. Patterns of Transformed Eruption Data Gunung Marapi 2022

	X1	X2	X3	X4	TARGET
Pola 1	0,9000	0,7000	0,4619	0,2905	0,4143
Pola 2	0,7000	0,4619	0,2905	0,4143	0,1857
Pola 3	0,4619	0,2905	0,4143	0,1857	0,2714
Pola 4	0,2905	0,4143	0,1857	0,2714	0,1857
Pola 5	0,4143	0,1857	0,2714	0,1857	0,1952
Pola 6	0,1857	0,2714	0,1857	0,1952	0,1095
Pola 7	0,2714	0,1857	0,1952	0,1095	0,1476
Pola 8	0,1857	0,1952	0,1095	0,1476	0,1190
Pola 9	0,1952	0,1095	0,1476	0,1190	0,1190
Pola 10	0,1095	0,1476	0,1190	0,1190	0,1286
Pola 11	0,1476	0,1190	0,1190	0,1286	0,1190
Pola 12	0,1190	0,1190	0,1286	0,1190	0,1000

The following network architecture is designed to predict volcanic eruptions. This model is a network consisting of many layers and has one or more hidden layers located between the input layer and the output layer.[11] In this research, the Artificial Neural Network architecture used is a multilayer neural network with a backpropagation algorithm consisting of:

1. Input layer consisting of 4 neurons, namely x1, x2, x3, and x4.

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2. Hidden layer consisting of 2 neurons.
3. Output layer consisting of 1 neuron.

Processing unit consisting of three layers of processing units. Each relationship has a relationship strength (weight) which is symbolized by v(n) and w(n).[12] The Artificial Neural Network to be built is the backpropagation algorithm with a sigmoid activation function.

The training procedure is a series of steps taken to train the network so that the network can easily recognize data patterns designed during testing.[13] The training procedure consists of several steps: Step 0: Initialize weights (preferably small random numbers).
Step 1: If the condition is not met, perform steps 2-9.
Step 2: For each training pair, perform steps 3-8. Phase 1: Forward Propagation
Step 3: Each input unit receives a signal xi and sends this signal to all units in the layer above it (hidden layer). To calculate it, use formula (2) and the results can be seen below:
z_net1 = v1+x1*v11+x2*v21+x3*v31+x4*v41 = 1,8232
z_net2 = v2+x1*v12+x2*v22+x3*v32+x4*v42 = -3,9357
z1 = sigmoid [1,8232] = $\frac{1}{1+e^{-z\_net_j}}$ = 0,8609
z2 = sigmoid [-3,9357] = $\frac{1}{1+e^{-z\_net_j}}$ = 0,0192

Step 4: Compute the activation of the hidden layer neurons using the specified formula. :
y_net_k = 0,7822
f(y_net) = sigmoid [0,7822] = $\frac{1}{1+e^{-y\_net_k}}$ = 0,6862
Step 5: Calculate all output values at unit yk.

Phase 2: Backpropagation
Step 6: Each output unit receives the target that is related to the input training pattern, calculate its error information.
Step 7: Calculate the hidden layer factor δ based on the error at each hidden unit zj (i = 1, 2, 3, ..., p) using the formula (4) :

δ1 = (t1 – y1) f` (y_net1) = (t1 – y1) y1 (1-y1) = (0,4143 – 0,6862) * 0,6862 (1 - 0,6862) = -0,0585
Step 8: Calculate the weight change term Vji (used to modify the weight Vj) with a learning rate α = 0.1, referring to Figure 2.9. :

ΔW10 = α δk zj
= -0,00585
ΔW11 = α δk zj
= -0,00504
ΔW12 = α δk zj
= -0,00011

Step 9: Calculate the hidden layer factor δ based on the error at each hidden unit zj (i = 1,2,3,….,p) using the formula (6) :

δ_net_1 = -0,0376
δ_net_2 = 0,0065

Step 10: Calculate the error factor at the hidden unit using the formula (7) :

$\delta 1 =$ -0,0045
$\delta 2 =$ 0,0001

Calculate the weight change term Vji (used to modify the weight Vj) using formula (8) and the value is $\alpha = 0{,}1$:

$\Delta v_{11} = \alpha\, \delta_1 j_1$
= -0,000405

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$\Delta v_{12} = a\,\delta_1 j_2$
$= -0{,}000315$

Perform this step for all data in all hidden layers. From the overall calculation, the following data will be obtained:

Table 4. Weight Changes of Hidden Units per Iteration (Δv)

	x1	x2	x3	x4
z1	-0,000405	-0,000315	-0,000208	-0,000131
z2	0,000011	0,000009	0,000006	0,000004

Step 11: Update the weights of the connections leading to the output unit using the formula (9) :

W1 (new) = w1(old) + Δw_1
= 0,6378

W2 (new) = w2(old) + Δw_2
= -0,1107

Wo (bias baru) = w0(lama) + Δw_0 = 0,2250

Calculate the bias correction for the hidden neuron which will be used to update the value using the formula (10) :V[oj]:

$$\Delta V_{[o,j]} = \alpha * \delta_j$$

$\Delta V_{[o,1]}$ =0,1*-0,0045= -0,00045

$\Delta V_{[o,2]}$=0,1* 0,0001 = 0,00001

Calculate the new bias value for the hidden neuron using the formula (11) :

$$V_{[o,j]}(baru) = V_{[o,j]}(lama) + \Delta V_{[o,j]}$$

$V_{[o,1]}$ = -10,3515

$V_{[o,2]}$= 0,8412

Step 12: Update the weights of the connections leading to the hidden units using the formula (12) :

V11 (new) = v11(old) + Δv_{11} = 6,24189

V12 (new) = v11(old) + Δv_{11} = -3,70859

Perform the same calculations as described above for all input data going into the hidden layer.[14]

Table 5. Changes in Weights to the Hidden Layer

	x1	x2	x3	x4
z1	6,24189	1,98318	12,17229	-1,56583
z2	-3,70859	-0,25879	8,10971	-17,22500

Step 13: Test the stopping condition.

The stopping condition is met if the training error is smaller than the error tolerance.[15] The number of neurons in the hidden layer affects the training of the artificial neural network.[16]

After the training process is complete, the values obtained from the network output must be returned (denormalized) to their original. From the denormalization results above, the real data obtained is 72.631. The desired target is the volcanic eruption data in May 2023, which is 34.

Based on the manual training iteration P = 1 with a network architecture of 4-2-1, it can be seen that the accuracy of predicting beef cattle supply is 21%.Testing the Neural Network with an architecture of 4-20-1. The test was conducted with an epoch value of 5000 with a target error value of 0.01.

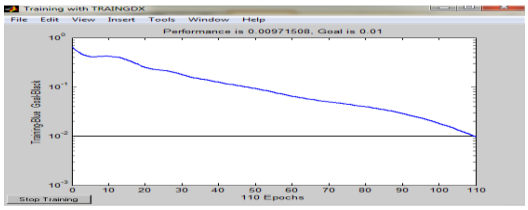

Image 2. Training Progress of the 4-20-1 Network

From the figure 2, it can be seen that the goal will be achieved at the 110th epoch with an error value of

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0.00971508. The results of the Neural Network test after training with the desired target error of 0.01 can be seen in the table.

Table 6. Training Results for Different Neural Network Architectures 4-20-1

	X1	X2	X3	X4	TARGET	JST Pola 4-20-1	
						Act	Error
Pola 1	0,9000	0,7024	0,4671	0,2976	0,4200	0,3430	0,0713
Pola 2	0,7024	0,4671	0,2976	0,4200	0,1941	0,2856	-0,0999
Pola 3	0,4671	0,2976	0,4200	0,1941	0,2788	0,2689	0,0025
Pola 4	0,2976	0,4200	0,1941	0,2788	0,1941	0,0737	0,1120
Pola 5	0,4200	0,1941	0,2788	0,1941	0,2035	0,1516	0,0436
Pola 6	0,1941	0,2788	0,1941	0,2035	0,1188	0,2871	-0,1776
Pola 7	0,2788	0,1941	0,2035	0,1188	0,1565	0,2334	-0,0858
Pola 8	0,1941	0,2035	0,1188	0,1565	0,1282	0,0099	0,1091
Pola 9	0,2035	0,1188	0,1565	0,1282	0,1282	0,1979	-0,0789
Pola 10	0,1188	0,1565	0,1282	0,1282	0,1376	0,0255	0,1031

CONCLUSION

The conclusion that can be drawn from the use of Neural Network with the backpropagation method to predict volcanic eruptions is that in this study it can be seen that the 4-20-1 model has the highest accuracy and this architectural model is used for system testing. With the 4-5-1 architectural model, the goal was achieved at epoch 63. With the 4-20-1 architectural model, the goal was achieved at epoch 110.

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