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Implementation of backpropagation artificial neural network for early detection of vitamin and mineral deficiency

Implementation of backpropagation artificial neural network for early detection of vitamin and mineral deficiency

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Abstract. Basic Health Research data in 2018 show that around 95.5 percent of Indonesian people less consumption of fruit and vegetables. This condition then leads to the suspicion of vitamin and mineral deficiency in Indonesia people. Several methods have been used to detect vitamin and mineral deficiency, such as convolutional rule-based and certainty factor method. However, these methods are less adaptive to adapt to the changes in symptoms when detecting vitamin and mineral deficiencies. This paper proposes an artificial neural network (ANN) using backpropagation (BPN) to detect the vitamin and mineral deficiencies in the human body. Using 107 input of physical symptoms and 17 output of the type of vitamin and mineral, the architecture of the ANN consist of 107-50-17 neurons for the input layer, hidden layer, and output layer respectively. Based on some trial and error experiments, can be determined the epoch, the learning rate, and the error rate to produce the optimal result of the detection. This experiment using 623 epochs, 0.0517 error rate, and 0.1 for the learning rate. The performance measurement conducted using precision, recall, and F-score, for each class output. The experiment shows the proposed ANN using BPN reaches an accuracy level of 73%.
Keywords: Artificial Neural Network; Backpropagation; Deficiency Vitamin and mineral; Health Informatics.

1. Introduction

Vitamins and minerals are organic nutrients that are needed in the human body in small amounts. Usually vitamins and minerals can be obtained from outside human bodies by eating vegetables and fruit. However, based on Basic Health Research data 2018 [1], around 95.5 percent of Indonesian people with more than 5 years of age eat fewer vegetables and fruit, so Indonesian people were susceptible to vitamin and mineral deficiency which at the end can cause various diseases.

Some methods have been used for detection deficiencies vitamin and mineral such as rule-based and Certainty Factor methods. Rule-based methods can be used for the detection of vitamin deficiency [2] and detection of mineral deficiencies [3]. The Certainty Factor method can also be used for the detection of vitamin and mineral deficiencies [4,5]. These studies are included in the AI branch called the expert system. However, the expert system is an AI branch that doesn't have the learning process so it is less adaptive to change of symptoms in detecting vitamin and mineral deficiencies [6]. Due to it less adaptive to changes in the symptoms, then the problem here is difficult to determine the most dominant type of deficiency suffered by the patients.

One of the adaptive methods that have the learning process is an artificial neural network [6]. Backpropagation is one of the learning methods that can be used on artificial neural network and has better accuracy compared to other learning methods [7,8]. Based on several studies that has been published, accuracy of backpropagation can reach above 90 percent [9,10,11,12,13,14,15,16,17]. The backpropagation learning process is done through some iterations to adjust the weight in all layers to produce the output with a minimum error value. The goal of this research is to detect vitamin and mineral deficiencies with backpropagation artificial neural network using the proposed architecture in this study.

2. Methods

Vitamin and mineral datasets will be used to detect vitamin and mineral deficiencies with backpropagation. The dataset is composed of 107 features and 17 classes. 107 features are 107 symptoms of vitamin and mineral deficiency and 17 classes are 17 types of vitamins and minerals that can be detected. Examples of the 107 symptoms as the input variables for the ANN and the 17 types of the deficiency as the output variables can be seen in table 1. The dataset was obtained based on previous studies [2,3,4,5].

Table 1. Examples of the input and output variables

Examples of Input Variables	Output Variables
Double vision; Panting; Lack of concentration; Brittle nails; Hair loss; Decreased endurance; Lack of appetite; Muscle and joint pain; Rough and dull skin; Dental caries; Easily tired; Unstable emotions; Diarrhea; Often cramps in the legs; Pain like rheumatism	Fe; F; I; Zn; A; B1; B2; B3; B5; B6; B7; B9; B12; C; D; E; K

The backpropagation has three phases in the learning process which are the feedforward phase, the backpropagation of error phase, and the weight adjustment phase and can be seen in figure 1 [18].
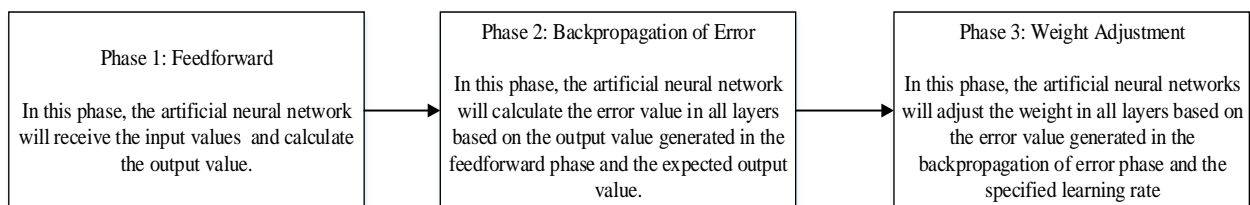
Figure 1. Phases in backpropagation

2.1. Feedforward Phases

First, each neuron on the input layer (Xi) receives an input value and passes it to all neurons on the hidden layer (Yj). Then, each neuron on the hidden layer (Yj) calculates the output value of the hidden layer using equation (1) and using activation function such as in equation (2).

$$Y\_in\,j = \left(\sum_{i=1}^{p} X_i * V_{ij}\right) + V_{0j} \tag{1}$$
$$Y_j = f(Y\_in\,j) \tag{2}$$

Then, each neuron on the output layer (Zk) calculates the output value of the output layer using equation (3) and using activation function such as in equation (4).

$$Z\_in\,k = \left(\sum_{j=1}^{q} Y_j * W_{jk}\right) + W_{0k} \tag{3}$$

$$Z_k = f(Z\_in\ k) \tag{4}$$

2.2. Backpropagation of Error Phases

First, each neuron on the output layer (*Zk*) receives an expected target value (*Tk*) and calculates the error value in output layer using equation (5) and calculates the weight correction value for the weight that connects the output layer and the hidden layer using equation (6).

$$\delta_k = (T_k - Z_k) * f'(Z\_in\ k) \tag{5}$$
$$\Delta W_{jk} = \alpha * \delta_k * Y_j \tag{6}$$

Then, each neuron on the hidden layer calculates the error value in the hidden layer using equation (7) and equation (8). Then, calculates the weight correction value for the weight that connects the hidden layer and the input layer using equation (9).

$$\delta\_in\ j = \sum_{k=1}^{r} \delta_k * W_{jk} \tag{7}$$
$$\delta_j = \delta\_in\ j * f'(Y\_in\ j) \tag{8}$$
$$\Delta V_{ij} = \alpha * \delta_j * X_i \tag{9}$$

2.3. Weight Adjustment Phases

Each weight that connects the input layer and the hidden layer adjusts their value using equation (10) and each weight that connects the hidden layer and the output layer adjusts their value using equation (11).

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} \tag{10}$$
$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk} \tag{11}$$

Then, after reading all data in the dataset, the learning process will stop if the MSE calculated using equation (12) is smaller than the expected error value or the number of epoch has been reached the epoch limit.

$$MSE = \sum_{k=1}^{n} \frac{(Tk - Yk)^2}{n} \tag{12}$$

3. Result and Discussion

The architecture of artificial neural networks used in detecting vitamin and mineral deficiencies is 107-50-17 which the architecture can be seen in Figure 2 and obtained the smallest MSE on the trial and error listed in Table 2, marked with red square. The parameters of artificial neural networks are also determined by the trial and error process. The result of the trial and error process for each parameter can be seen in Table 3 to Table 6. In Table 3 is the result for the learning rate, Table 4 for the error limit, Table 5 for the epoch limit, and Table 6 for the activation function. Based on the trial and error process, the parameter of artificial neural networks used in detecting vitamin and mineral deficiencies is 10% for learning rate as seen in red square in Table 3, 0.0517 as error limit and 623 as epoch limit as seen in the last row in Table 4 and Table 5. The activation function is the Hyperbolic Tangent has smallest MSE as seen in red square in Table 6.
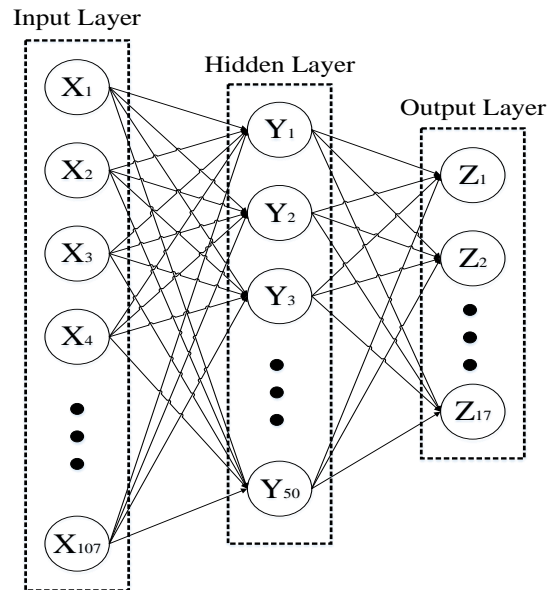
Figure 2. Architecture Artificial Neural Network

Table 2. Trial and error for architecture ANN

	Architecture	Epoch	MSE
1	107-10-17	1000	0.16004
2	107-20-17	601	0.060881
3	107-30-17	331	0.16206
4	107-40-17	529	0.062284
5	107-50-17	1000	0.046877
6	107-60-17		0.052332
7	107-70-17	153	0.05469
8	107-80-17	1000	0.050939
9	107-90-17	317	0.064988
10	107-100-17	165	0.061005
11	107-10-10-17	1000	0.12501
12	107-20-20-17	1000	0.1157
13	107-30-30-17	1000	0.059958
14	107-40-40-17	1000	0.089868
15	107-50-50-17	1000	0.05816
16	107-60-60-17	1000	0.05934
17	107-70-70-17	1000	0.057084
18	107-80-80-17	1000	0.055597
19	107-90-90-17	1000	0.058377
20	107-100-100-17	1000	0.056508
21	107-10-10-10-17	1000	0.17711

Table 2. Trial and error for architecture ANN

	Architecture	Epoch	MSE
22	107-20-20-20-17	1000	0.15109
23	107-30-30-30-17	1000	0.054816
24	107-40-40-40-17	1000	0.054335
25	107-50-50-50-17	1000	0.05629
26	107-60-60-60-17	1000	0.060677
27	107-70-70-70-17	1000	0.058659
28	107-80-80-80-17	1000	0.054402
29	107-90-90-90-17	1000	0.053259
30	107-100-100-100-17	1000	0.05239

Table 3. Trial and error for learning rate

	Learning Rate	Epoch	MSE
1	1%	1000	0.11893
2	2%	1000	0.056012
3	3%	1000	0.059579
4	4%	1000	0.16595
5	5%	1000	0.051815
6	6%	1000	0.061316
7	7%	1000	0.060127
8	8%	1000	0.051365
9	9%	1000	0.057172
10	10%	1000	0.049706

Table 4. Trial and error for error limit

	Epoch	MSE		Epoch	MSE
1	1000	0.058264	6	1000	0.052847
2	1000	0.059016	7	1000	0.044894
3	1000	0.04634	8	1000	0.050041
4	1000	0.051016	9	1000	0.054787
5	1000	0.051475	10	1000	0.049212
				Average	0.0517

Table 5. Trial and error for epoch limit

	MSE	Epoch		MSE	Epoch
1	0.0517	764	6	0.0517	502
2	0.0517	647	7	0.0517	687
3	0.0517	659	8	0.0517	563
4	0.0517	703	9	0.0517	627
5	0.0517	514	10	0.0517	568
				Average	623

Table 6. Trial and error for activation function

	Activation Function	Epoch	MSE
1	Hyperbolic Tangent	284	0.064902
2	Sigmoid Biner	1000	0.1578
3	Linear Transfer Function	1000	0.204128

Then, to determine the performance of the ANN that has been produced, a confusion matrix is used to obtain the value of precision, recall, f-score and accuracy in detecting vitamin and mineral deficiencies. The values of precision, recall, scores for each class and accuracy values in detecting vitamin and mineral deficiencies can be seen in table 7 as follows. The accuracy is 73% obtained from comparing the output of the ANN with the data testing. In this research, the dataset divided into 88 data training that used to produce the output and 30 data testing to test the performance. The accuracy measurement will counted based on the match and mismatch classification between the output of the ANN and the annotation data in the data testing. Table 7 also describes the value of precision, recall, and f-score for each class output as the result of the comparison between output of the ANN and the data testing. For recommendation in the next research, it is interesting to compare the selected input variables that related to the accuracy of output using feature selection method.

Table 7. Performance ANN

Class	Precision	Recall	F Score
Fe	1.00	0.75	0.85
F	0.00	0.00	0.00
I	0.00	0.00	0.00
Zn	0.00	0.00	0.00
A	1.00	1.00	1.00
B1	1.00	0.75	0.85
B2	0.67	0.67	0.67
B3	0.67	0.50	0.57
B5	0.50	1.00	0.67
B6	0.00	0.00	0.00
B7	0.20	1.00	0.40
B9	0.00	0.00	0.00
B12	0.50	1.00	0.67
C	1.00	1.00	1.00
D	1.00	1.00	1.00
E	0.00	0.00	0.00
K	0.00	0.00	0.00
		Accuracy	73%

4. Conclusion

Based on the analysis and testing that has been done, it can be concluded that backpropagation in artificial neural networks with architecture 107 neurons in the input layer, 50 neurons in the hidden layer, and 17 neurons in the output layer with 10% learning rate, 0.0517 error limit, 622 epoch limit, and Hyperbolic Tangent as an activation function can be implemented in detecting vitamin and mineral deficiencies and produce 73% accuracy rate. For the next research, the implementation of feature selection is needed to increase the accuracy rate and add more training data in the learning process in hopes of improving the error rate.

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