Implementation of The Backpropagation Method and The Kohonen Network to Predict Blood Availability: Case Study in PMI Kota Magelang

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ABSTRACT

The availability of blood stock at the Indonesian Red Cross (PMI) is a must and absolute for institutions that carry out the procurement and distribution of blood for medical purposes. The problem is, blood stock at PMI Magelang City Branch is not ideally available for every blood type, especially AB blood type which in recent years has been very minimal and difficult to obtain. The aim of this research is to predict blood stock for type AB with software based on backpropagation neural network and Kohonen Network. Backpropagation Artificial Neural Network (BANN) is used to predict stock availability for blood type AB. While Kohonen is a network that is used to divide input patterns into several groups. The application has a network structure consisting of 3 input neurons, 10 neurons in the hidden layer, and 1 neuron in the output layer. The total amount of data is taken from AB blood group stock data for 3 years, 2 years data is used for training data, and 1 year data is used for testing data. The engine predicts using a maximum iteration of 3,000 epochs, a learning constant of 0.01, momentum of 0.5, and a minimum error rate of 0.001. By varying the value of the backpropagation component, BANN is able to predict the availability of AB blood stock per month based on information from the previous 3 months' data, with an average error (MSE) < 0.0038. Meanwhile, the weights generated by the Kohonen Network can accelerate BANN in the network learning process and reduce the prediction error by an average of 26%.

Keywords: Prediction, Blood Stock, Backpropagation, Kohonen Network

INTRODUCTION

The Indonesian Red Cross Institute (PMI) is an organization of national associations in Indonesia engaged in the social and humanitarian sector. In recent years, PMI organizations have experienced difficulties in determining the exact amount of blood stocks in a period of time per month and per year. The supply of blood stocks is difficult to predict, especially for blood type AB, because this group is still relatively small and people who have blood type AB are very few and rare so that in the application of blood stock collection, especially blood stock AB, must be more precise in determining the blood stock to be taken so that between taking and removing can be controlled and controlled. Starting from this problem, by utilizing computer technology, the artificial intelligence system, namely the Artificial Neural Network (JST). Backpropagation and Kohonen networks methods were used for the prediction process based on AB blood stock data from 2015 to 2017. The backpropagation method is a method that has a learning system similar to artificial neural networks [1]–[5]. Artificial neural networks are used to recognize and study existing data patterns, while in the backpropagation method there is a change in weight to improve the weight of the synapse so that the weight will continue to be corrected (directed) so that the error is produced to be as small as possible. The Kohonen network method is used for such grouping of data that data adjacent to each other will be in the same group. Self-organizing map is a generation of competitive networks. Both are unsupervised networks [3]. Neuron will compete to be the winner of the vector input given. Given the importance of the continuity of the PMI Institution, which in this case is experiencing problems in determining the number of stocks, it is necessary to conduct research to examine things that will later be overcome using computer technology. With this prediction of blood expenditure, it is hoped that in the future it can play a role in reducing the level of blood deficiency, as well as a solution and effort to develop information technology for the wider interest.

The implementation of Artificial Neural Networks is widely seen as a way of storing knowledge in certain fields in computer programs so that decisions can make reasoning intelligently [6], [7]. Artificial neural networks have been trained to perform complex functions in a variety of application areas that include best pattern recognition, identification, sound processing and control systems [2]. Using the Artificial Neural Network of the Kohonen Method", which states that consuming electrical power has an important role in the implementation of development for the improvement of welfare and economic activities [8]. Thus, electricity load forecasting is needed to carry out an effort to provide an even amount of electricity day [9], [10]. The amount of electricity consumption by the community in kWh units greatly affects the calculation of electricity supply. Drawing conclusions from the 3rd study above and the middle line of the two previous studies, from 365 data, 250 training data, and 115 test data will be used, as well as using the trial error method in determining the best network architecture by changing the amount of training data, learning rate and hidden layer at the time of the experiment. The difference between the three studies above and the ongoing research is in the method. The backpropagation method is used for the blood stock prediction process, while the Kohonen tissue method is used as a grouping of data displayed through SOM [11].

METHOD

The following is the flow of research methods from testing made to make it easier to predict AB blood stocks in PMI Magelang City Branch.

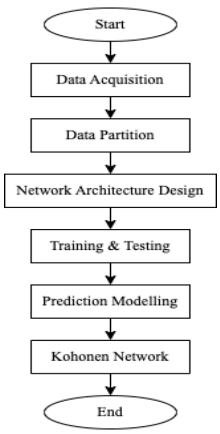

Figure 1. Research Flow

Figure 1 explains that the research flow starts from collecting blood stock data and then separating the data for training using the backpropagation method. If the design of the artificial neural network is appropriate, it will be continued with data testing using an artificial neural network and blood stock predictions will come out, then on a cluster basis using the Kohonen network to get the initial network weight values.

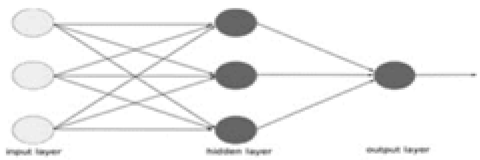

Figure 2. Backpropagation Method

For the development of a prediction engine that will be made using the backpropagation method where this algorithm is widely used in applications because the training process is simple, that is, if the output gives an incorrect result, the weight will be corrected so that the next network response is expected to be closer to the correct result, this network can be seen in figure 2. Meanwhile, the Kohonen network structure for obtaining initial network weight values is shown in Figure 3.

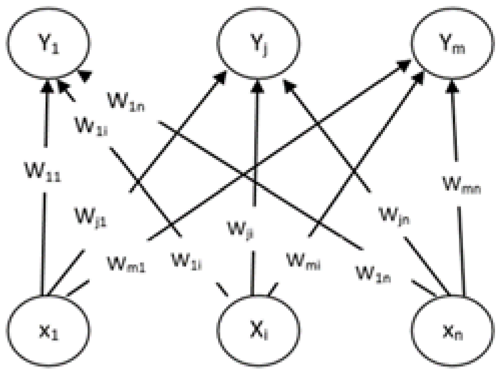

Figure 3. Kohonen Network Method

After the prediction results are known, the w weight data will be retrained with the Kohonen network which will later be modified or corrected by the Kohonen model, so that it will form a group of neurons that will be the main focus of prediction of blood stocks per month. After all processes are completed, ANN will form a network architecture according to ANN training and testing data as shown in figure 4. The network architecture formed has 3 input neurons, 10 hidden layer neurons and 1 output neuron. The neuron output represents the predicted results of blood stocks in the nth month (*Xn*) based on information from input blood stock data in the previous 3 months (*Xn-1*, *Xn-2* and *Xn-1*).

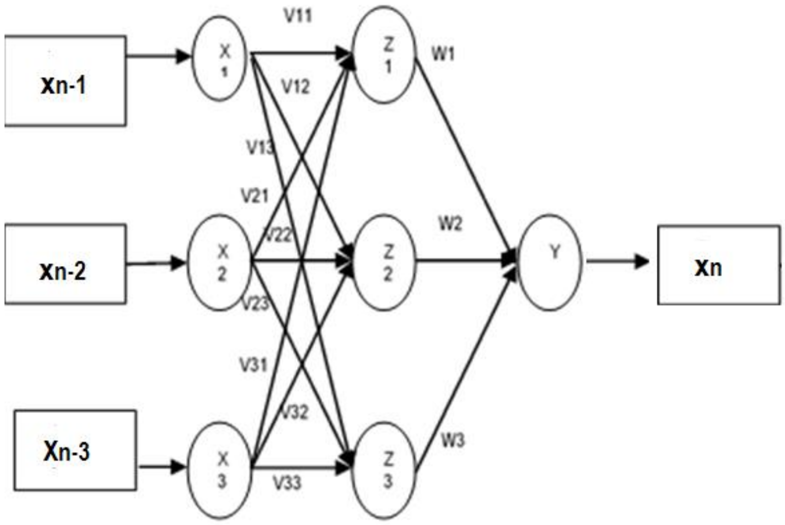

Figure 4. AB Blood Stock Prediction Network Architecture

Table 1. shows the training data that will be used to train an artificial neural network. This data is the result of processing AB blood stock data for 3 years at PMI Magelang City, as shown in table 2.

Table 1. Training Data for Blood Stock Prediction

	Data:	1	2	3	4	5	6	7	…	21
Input	Xn-3	98	59	81	98	80	90	78	…	86
	Xn-2	59	81	98	80	90	78	82	…	104
	Xn-1	81	98	80	90	78	82	84	…	68
Target	Xn	98	80	90	78	82	84	71	…	135

Xn : Month n

Table 2. AB Blood Stocks Table

Blood Stock Data type AB PMI Magelang City

No	YEAR	JAN	FEB	MAR	APR	MEI	JUNI	JUL	AGU	SEP	OKT	NOV	DES
1	2015	98	59	81	98	80	90	78	82	84	71	55	136
2	2016	98	59	81	93	72	87	98	86	86	104	68	136
3	2017	138	86	119	94	51	63	105	100	102	110	88	138

Table 2. shows AB blood stocks from 2015-2017 where the training data uses data for 2015-2016 and test data using data in 2017.

RESULTS AND DISCUSSION

Based on research conducted at PMI Magelang City, PMI is still unable to predict AB blood stock because AB blood stock is difficult to obtain while the need continues to increase. The test results are obtained by experiment to test whether the test data as in table 1 has functioned as desired. This study aims to test the data to make it easier to predict type AB blood stock. The test uses the existing tools in Matlab as shown in Figure 5.

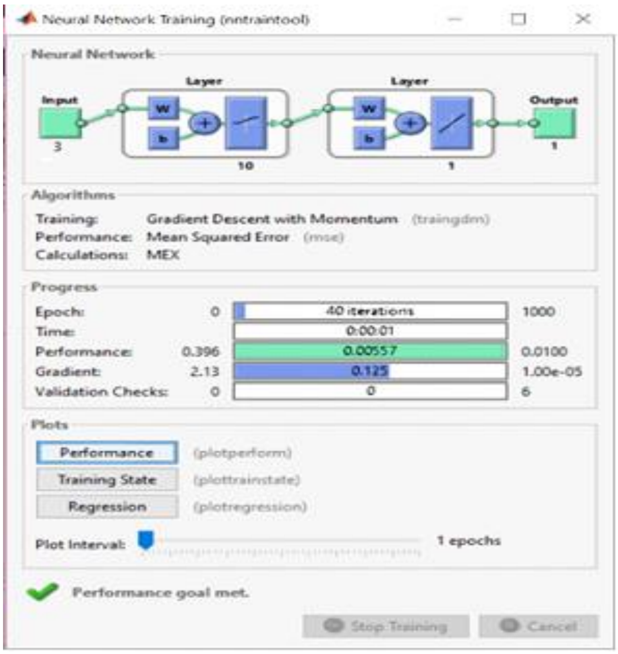

Figure 5. Training Nntool Matlab 8.3

Figure 5. is a Matlab view of the training data taken from the normalization results of table 1. The structure of the Matlab tool consists of input, initial weight of the input layer, hidden layer. From here you can also find out the iterations emitted and the performance and gradients generated during the training process.

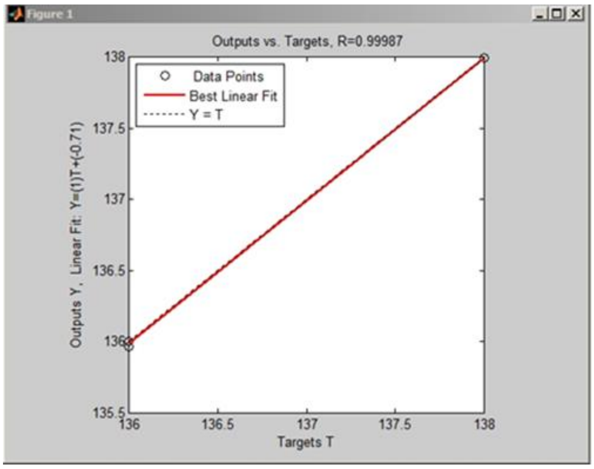

Figure 6. Linear Regression Analysis of Training Data

Figure 6 is a linear regression graph, where there are blue lines, nodes and dashed lines. Basically, training is said to be successful if the three elements are combined into one. The results of the training process carried out show this.

After the training process has been carried out for 3000 epochs using normalized training data, the BANN network structure created is able to generalize the training data well as shown in figure 7. The output data pattern from BANN is able to follow the output pattern of the expected target data even though there are still differences in the values (errors) of the output data and the target data. With an average error value or MSE of 0.0036, the BANN is capable of predicting blood stocks with an average prediction error rate of around 0.0036.

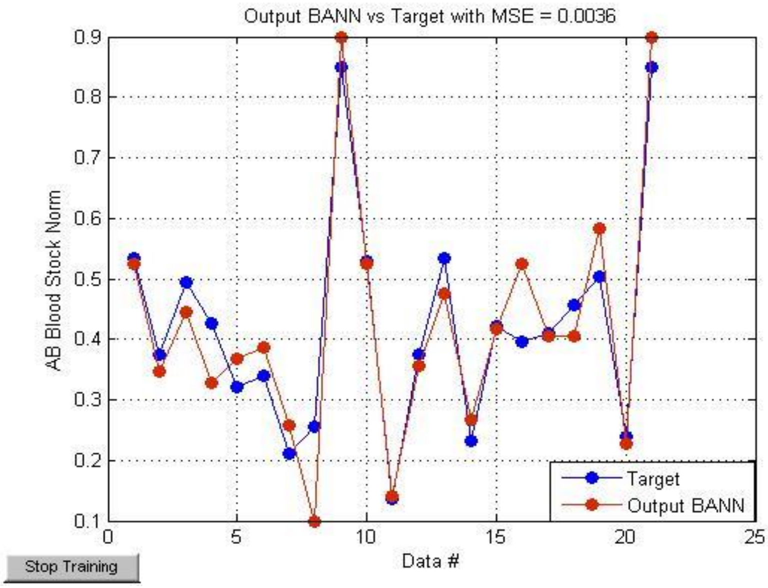

Figure 7. Comparison of Output to Target

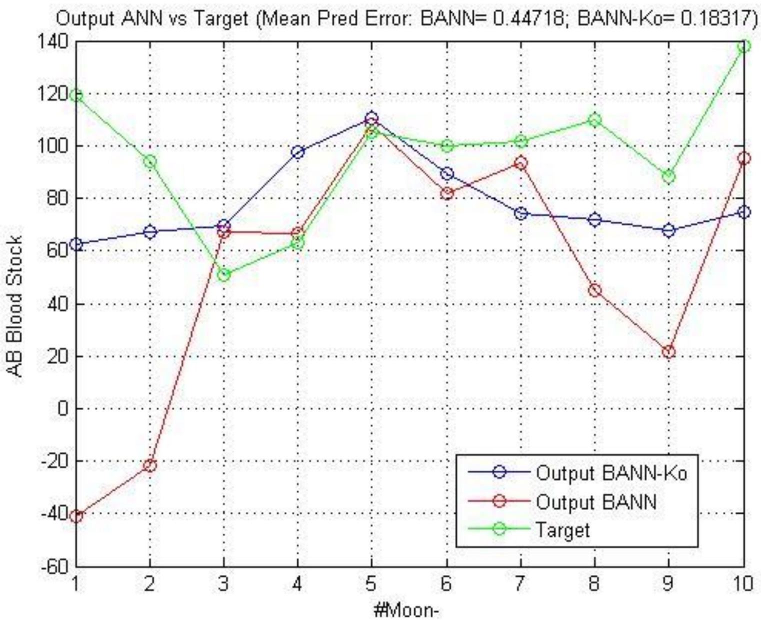

Figure 8. BANN Output Results with Test Data

While for the test results using test data, the BANN that was made shows improved output when using the initial value of the network weight obtained from the cluster results of the Kohonen method. This is as shown in figure 8 The weight value resulting from the Kohonen network cluster is used as the initial value of the network weight when training the BANN. The values of the other parameters of the learning process for the two BANNs are the same, namely:

using a maximum iteration of 3,000 epochs, a learning constant of 0.5, momentum of 0.9, and a minimum error rate of 0.001. Meanwhile, the initial value of the network weight is different, BANN-Ko uses the weight value resulting from the Kohonen network cluster and BANN uses a random value for the initial value of the network weight.

CONCLUSION

From the results of this study, it can be concluded that the prediction engine which is made using a learning constant of 0.5, momentum of 0.9, and is trained through a maximum iteration of 3,000 epochs, is able to predict the availability of AB blood stock per month based on information from data from the previous 3 months, with an average the mean error (MSE) is around 0.0036. Meanwhile, the weights generated by the Kohonen method can speed up the network learning process and reduce the prediction error by an average of 26%. Reducing learning constants and adding system training data can affect the accuracy of the system in making predictions.

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