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Comparison of Edge Detection Method in Case of Blood Pattern Recognition Using Backpropagation Algorithm

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***Abstract*—There are 4 types of blood: A, B, O, and AB. So far, the process of checking blood type depends on the officer's work accuracy. To keep the validity of the results, a system is needed to help humans to recognize the blood types. This recognition can be done by computers by applying the method of blood pattern recognition through an image. The data domain of this study is a scan of blood type checks obtained from PMI Yogyakarta City. A total of 54 images were used in the training and recognition process. The image used in .bmp extension with a size of 400 x 200 pixels. Before the recognition process, first execute the preprocessing image, that is convert the image to grayscale image. The next process is edge detection with a Sobel operator or Prewitt operator. The use of these two operators aim to determine the optimal operator for recognition of blood type case. After the edge detection process, the image is converted to binary so it can be processed by feature extraction. The last step is the implementation of artificial neural network backpropagation algorithm with bipolar sigmoid activation function for hidden layer and linear activation for output. As a result, the optimal neural network architecture is three hidden layers with each hidden layer having three nodes. The optimal value for the mean squared error parameter is 1e-1 or 0.1, epoch 1000 and learning rate 0.01. In this study, Sobel operator was better than Prewitt operator in introducing blood type types. When viewed from the difference in processing time, the Prewitt operator is slightly faster than the Sobel operator with a difference of 0.000052 seconds. From 39 training data and 14 test data, the percentage of success in the recognition of blood type was 92.86%.**

Keywords-Backpropagation; Blood Type; Edge Detection Prewitt; Sobel

I. INTRODUCTION

Image is a vital thing and an integral part of everyday life. On certain interests, image is used as a tool to express reason, interpretation, illustration, representation, memory, education, communication, evaluation, navigation, survey, entertainment, and so on.

In the medical, when you are going to do blood transfusion a person needs to know their blood type. Each blood type has a special image pattern. For medical officers who are used to checking blood types, it is very easy to distinguish whether the test results show blood types A, B, AB or O. The process of checking blood type depends on how accurate the blood type checking officers are. To keep the checking results valid, a system is needed to help humans recognize the type of blood type. The recognition of the type of blood type can be done by computer, one of them is the method of pattern recognition and training of each characteristic of the blood type through the image.

With the development of computers and digital imaging tools, the identification of blood types using computers is easier to do. With the approach of artificial intelligence, human blood classification can be done by utilizing artificial neural networks that have been developed as a generalization of mathematical models of human learning. One method that can be used is edge detection in the image. Image edge detection is a process that produces edges of image objects that aim to mark parts that are detailed images and improve blurred image details.

There are several operators in pattern recognition that can be used to identify certain types of blood types with a framework of artificial neural networks, including Sobel and Prewitt operators. The Sobel operator places emphasis or weight on the pixels closer to the center of the matrix. Thus the influence of neighboring pixels will differ according to their location to the point where the gradient is calculated [1]. Meanwhile, The Prewitt operator does not place emphasis or weight on the pixels closer to the center of the matrix [1]. This study will examine both of them to analyze which operators are the most accurate in determining blood type.

II. METHODS

A. Preliminary studies

A preliminary study was carried out in this study to examine what operators could be used and related to edge detection in pattern recognition. From these operators, the most relevant operators will be studied and selected.

1) Data Collection

The process of collecting data in this study was carried out through several methods, including:

i. Library Study

Library study is a method of collecting data or materials from the literature relating to edge detection, pattern recognition, and backpropagation through books, scientific journals, final assignments, and the internet.

ii. Interview

The interview method is a method of collecting data by holding a direct dialogue with the object of research. Interviews were carried out to PMI officers tasked with checking the blood type.

iii. Taking Pictures

Blood type checking test images were taken from blood donor activities by PMI Yogyakarta City in four places with details of the place and time as follows:

a) Kauman Grand Mosque on 12 August 2012: 10 data collected.

b) The Office of the People's Sovereignty on September 21, 2012: 9 data collected.

c) The south square of the city of Yogyakarta on September 23, 2012: 20 data collected.

d) All Season Hotel on October 2, 2012: 10 data collected.

B. Research Flow

Broadly speaking, the stages of research on the recognition of blood type patterns in this study consisted of:

1) Inputting the Image

The image to be processed is obtained from the results of a blood checking test. Then, scanning is done to get a digital image. The digital image is an array that contains real and complex values that are represented by a certain row of bits [2]. To eliminate noise in the image, cropping the image will be done.

2) Preprocessing

Preprocessing is the initial processing of images with the aim of getting images with patterns that can be processed, the preprocessing that is done is to convert the image to grayscale. It is called the grayscale because in general, the color used is between black as a minimum color and white as the maximum color, so the color between the two is gray [3].

3) Edge Detection

Edge Detection in an image will produce edges of the image object. The purpose of this edge detection process is: To mark the part that becomes the detail of the image and fix the details of the blurred image that occurs because of an error or the effect of the image acquisition process.

4) Changing image to binary

Image results from edge detection are converted into binary imagery for the next process. If the pixel value is less than 127 it will be changed to 0 and if the pixel value is more than or equal to 127 then it is changed to 255.

5) Texture Feature Extraction

Texture feature extraction can be represented in seven formulas [4]: contrast, energy, correlation, Inverse difference moment, homogeneity, maximum probability, and entropy. Energy and entropy are just the opposite, so the only entropy formula used is the uniformity of pixels in the image. Correlation is not used because of its application correlation when grayscale imagery. Whereas in this study, feature extraction was performed on binary imagery. Based on these reasons, extraction of texture characteristics is only represented in five formulas, namely contrast, Inverse difference moment, homogeneity, maximum probability, and entropy.

6) Training and pattern recognition

The pattern recognition process is carried out to determine the type of blood type whether A, B, O or AB based on edge detection of the image. The method used is backpropagation which produces certain codes according to the color of the pixels [5]. From several existing activation functions, bipolar and linear sigmoid activation functions are selected. This is based on [6] which states that work results using bipolar activation functions are better than binary activation functions. While the use of the linear activation function is intended so the results of the recognition are fixed.

7) Display Output

Blood type determination refers to a predetermined target. In learning using artificial neural networks, data must be numerical or numeric. Thus, the Output target in the form of a blood type must be initialized in the form of numbers as in Table I.

TABLE I. OUTPUT TARGET

Blood Type	Value
O	0
A	0,33
B	0,67
AB	1

In general, the whole process of the system can be seen in Figure 1.

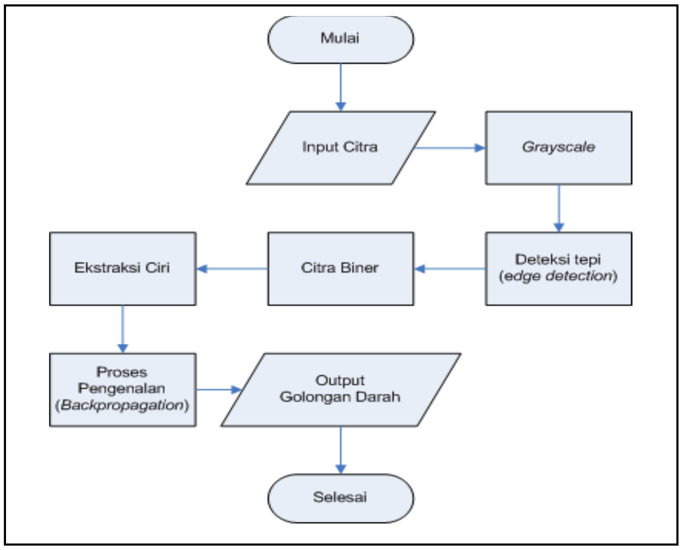


Figure 1. Overall System Flow Charts

III. RESULT AND DISCUSSION

In general, the system can receive input data from the user in the form of blood type checking images. It will be processed by edge detection and feature extraction and resulting in output in the form of a blood type. The details of the process and the results are explained as follows:

A. Input Blood Type Check Test Image

The image to be entered is in the form of a blood type checking test done by PMI Yogyakarta City officials during a blood donor activity. Scanning results using Canon Pixma MP287 in the form of a digital image with a .bmp extension (figure 2.). The noise outside the checking area will make the results of the recognition process with edge detection less than optimal. Therefore, empty space outside the checking area is removed by cropping. This process is done with the help of the Corel X5 application. The results of cropping can be seen in Figure 3.

Figure 2. Checking Blood Type Samples

From Figure 2, there are three colors, namely blue, yellow and white. Blue is the color of anti-A. reagent solution. Yellow is the color of anti-solution B reagent and white is the color of anti-rhesus reagent solution.

Figure 3. Overall System Flow Charts

After cropped, the data must be converted into data that can be processed by the program through preprocessing.

B. Preprocessing

Before an image undergoes further processing, it is necessary to do the initial process (preprocessing) first with the aim of getting images with patterns that can be processed, including changing the image to grayscale.

For the edge detection process, the color image is first converted into a grayscale image and then becomes a binary image for the edge calculation process and texture feature extraction. The result in Figure 3 is then converted into a gray or grayscale image, so it will be like Figure 4.

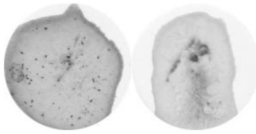


Figure 4. Blood Type Checking Samples

C. Edge Detection

The edge detection process is carried out with two operators, namely Operator Sobel and Prewitt. The results of both can be seen in Figure 5. and Figure 6.

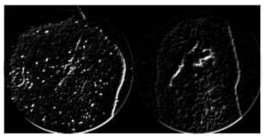


Figure 5. Detecting the Edge of the Sobel Operator

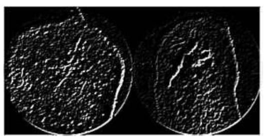


Figure 6. Detecting the Edge of the Prewitt Operator

D. Changing image to binary

The image from edge detection is converted into a binary image for the next process, namely texture feature extraction. Changing to binary imagery is done because binary imagery has the following advantages [1]:

1) Small memory needs because the gray degree value only requires a 1-bit representation.

2) Processing time is faster than black and white images because many operations in binary imagery are performed as logical (AND, OR, NOT) operations compared to integer arithmetic operations.

3) If the pixel value is less than 127, it will be changed to 0 and if the pixel value is more than or equal to 127 it is converted to 255.

The conversion results to binary for the Sobel operator as in Figure 7 while for the Prewitt operator as in Figure 8.

Figure 7. Binary Conversion of Sobel Operators

Figure 8. Binary Conversion of Prewitt Operators

E. Feature Extraction

Feature extraction consists of making vector maps of observation into the characteristic field [7]. Of the three types of feature extraction available, feature extraction used in this study is texture feature extraction. The first step of texture feature extraction is to convert the RGB image into a grayscale image then calculate the value of co-occurrence matrix in four directions, 00, 450, 900 and 1350 respectively [8]. Table I is an example of feature extraction training data with a Sobel operator and Table III is an example of feature extraction training data with a Prewitt operator.

TABLE II. CHARACTERISTICS OF BLOOD TYPE IMAGE EXTRACTION WITH SOBEL OPERATORS

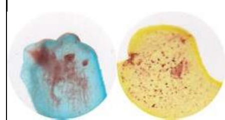
Image	Time	Feature Extraction		Blood Type
	0,016	ASM	3,6808915093	B
		CON	0,0535558445	
		IDM	1,9732220777	
		ENT	1,3762429245	
		MP	1,9179799753	
		ASM	3,4936778430	
		CON	0,0762824006	
		IDM	1,9618587997	
		ENT	1,0899480918	
		MP	1,8675142639	

TABLE III. CHARACTERISTICS OF BLOOD TYPE IMAGE EXTRACTION WITH PREWITT OPERATORS

Image	Time	Feature Extraction		Blood Type
	0,016	ASM	3,7507806204	B
		CON	0,0420157319	
		IDM	1,9789921340	
		ENT	1,4921634502	
		MP	1,9363444105	
		ASM	3,6045797439	
		CON	0,0584908823	
		IDM	1,9707545588	
		ENT	1,2577476976	
		MP	1,8976149381	

From the experiment, the recognition of blood types obtained data from the processing time of each operator. From the comparison graph of the two operators (figure 9.), it is known that the average processing time is 0.024462 seconds, while the graph of the processing time using the Prewitt operator is 0.024410 seconds. Based on the comparison of the time, the operator that is more optimal at the time of feature extraction seen from the processing time is the Prewitt operator whose processing average is to recognize the type of blood type for 0.024410 seconds for each image.

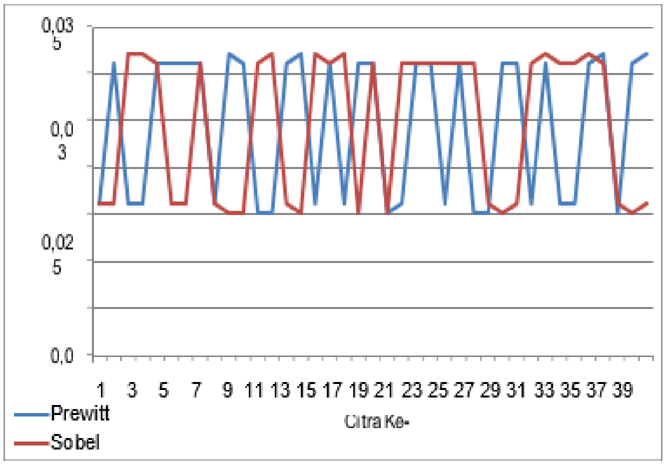


Figure 9. Comparison Graph of Edge Detection Process Time

F. Experiment with Matlab

1) Determination of Input Nodes

In this study, the number of input nodes that will be applied to the prototype for the identification of blood types is the same as the results of the experiments conducted in Matlab. This is done to be able to get the optimal comparison results. In determining this input node, the experiment is conducted with epoch 5000, goal or Mean Squared Error (MSE) 0.001, learning rate 0.02 and momentum 0.3. In determining the number of input nodes there are three choices: 5 nodes from one image, 10 nodes from one image, and 10 nodes from two images.

Good experimental results will get the R-value (Correlation Coefficient) which is close to 1. Experimental data from all three shows that the optimal number of nodes for input nodes is 10 nodes from one image, with an R-value of 0.992 for Sobel operators and 0.814 for Prewitt operators. The R-value of the 10 nodes of one image that best meets the requirements of a good trial result. The results of this experiment will be used to determine the number of input nodes during the training process and blood type identification.

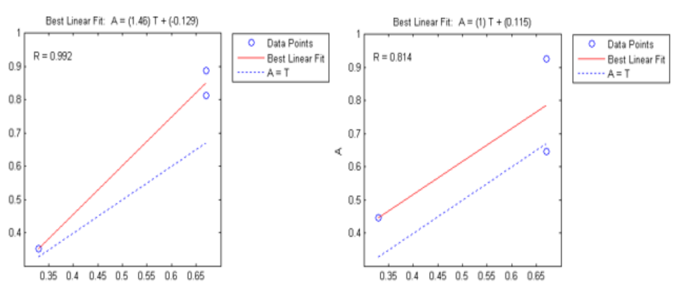


Figure 10. Experiment Results Recognition of 10 nodes from one image with Prewitt Operator (a) and Sobel Operator (b)

2) Determination of Artificial Neural Network (ANN) Architecture and Edge Detection Operators

Based on experiments to determine the number of input nodes, the optimal input node is obtained from 10 input nodes. So, the experiment to determine the optimal artificial neural network architecture uses 10 node input nodes, epoch 20,000, goal or MSE 0.3, learning rate 0.01, and momentum 0.5. Graph comparison of ANN architecture for each edge detection operator can be seen in Figure 11.

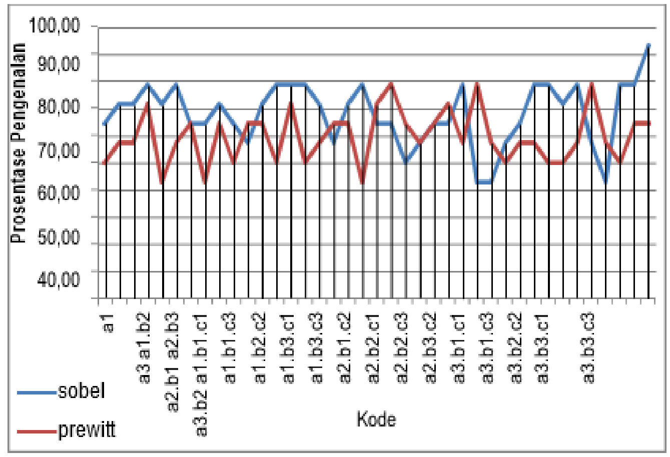


Figure 11. Comparison Graph of Percentage of Recognition

The code on the graph shows the number of hidden layers and nodes in the hidden layer. The letter 'a' shows the first layer, 'b' shows the second layer and 'c' shows the third layer. The numbers behind each letter indicate the number of nodes on that layer. For example, the code ‘a3.b2.c1’ means that it consists of three hidden layers with three nodes on the first layer, two nodes on the second layer and one node on the third layer. From the 39 training data, the optimal results were obtained with a percentage of 82.05% in the a3b2c2 and a3b3c3 architectures. Whereas from the 14 test data the optimal results were obtained with a percentage of 92.86%.

From the results of the experiment, it was found that the optimal neural network architecture was 3 layers of 3 nodes each. Optimal ANN architecture as shown in Figure 12.

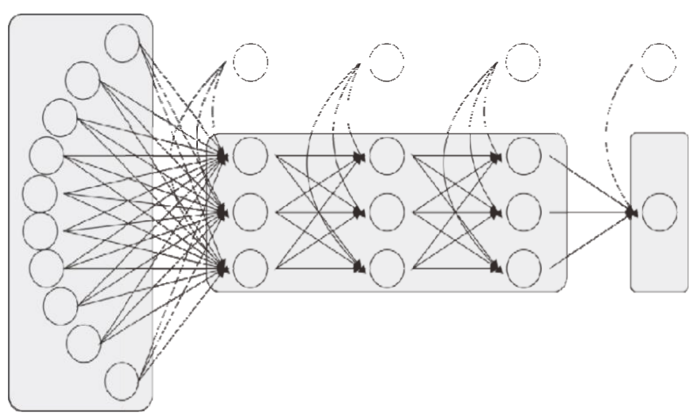


Figure 12. Comparison Graph of Percentage of Recognition

3) Determination of Mean Squared Error (MSE)

From the experiment of determining the hidden layer, the optimal result is 3 hidden layers. Referring to the experiment for determining MSE (Mean Squared Error), the hidden layer used is 3 hidden layers as shown in Figure 11. MSE or goal performance is the target value of the performance function. Iteration will stop if the performance function value is less than or equal to the goal performance. In this study, three experiments were conducted with variations in the value of MSE, namely 0.1, 0.2, and 0.3. The results of the comparison of the three experiments as in Table IV.

TABLE IV. COMPARISON OF OPTIMAL MSE DETERMINATION

MSE Value	Corelational Coefficient		Recognized total	Percentage
	Training	Testing		
0.1	0,948	0,936	13,00	92,86%
0.2	0,892	0,846	12,00	85,71%
0.3	0,832	0,829	13,00	92,86%
Average			12,75	90,48%

Based on Table IV, it is known that the best MSE with a value of 0.1 success rate is 92.86%. So for the implementation of the prototype, the MSE is determined to be 0.1.

4) Determination of Learning rate

Learning rate is the rate of learning where the greater the value of the learning rate will have implications for the greater learning step. If the learning rate is set too large, the algorithm becomes unstable. Conversely, if the learning rate is too small, the algorithm will remain in a very long time. In this experiment, training was conducted with three learning rate values, namely 0.01, 0.05 and 0.1. In addition, from the results of the optimal MSE determination is 0.1, MSE used for determining the rate of likelihood is also 0.1. Comparison results from each learning rate value as in Table V.

TABLE V. COMPARISON OF OPTIMAL LEARNING RATE DETERMINATION

Learning Rate Value	Correlational Coefficient		Recognized total	Percentage
	Training	Testing		
0.01	0,948	0,936	13,00	92,68%
0.05	0,949	0,912	13,00	92,68%
0.1	0,947	0,932	13,00	92,68%
Average			13,00	92,68%

From Table V, it can be seen that the number recognized for each learning rate is the same, 13 data. However, the largest correlation coefficient at the learning rate is 0.01. So, the highest success rate is the use of a learning rate of 0.01 with a success rate of 92.86. So for the implementation of the prototype, the learning rate is determined to be 0.01.

5) Determination of Epoch

The maximum epoch is the number of epochs that can be done during the training process. The iteration will stop if the epoch value exceeds the epoch maximum. Referring to the experiment to determine the optimal MSE and learning rate, then the epoch determination is used MSE 0.1 and a learning rate of 0.01.

TABLE VI. COMPARISON OF OPTIMAL EPOCH DETERMINATION

Epoch Value	Corelational Coefficient		Recognized total	Percentage
	Training	Testing		
500	0,930	0,906	11,00	78,57%
1000	0,947	0,932	13,00	92,86%
5000	0,947	0,859	11,00	78,57%
Average			11,67	83,33%

From the optimal architectural results, experiments were conducted again with epoch variations. The experiment was conducted with 3 epoch variations, namely 500, 1000 and 5,000. Based on Table VI, it is known that the greatest success uses the value of epoch 1000 with a percentage of 92.86%.

G. Blood Type Recognition Result

Of all the experiments conducted to obtain optimal results, the implementation of the prototype was initiated as follows:

1) Edge detection operators use the Sobel operator
2) Input layer with 10 nodes
3) The number of layers is three pieces with each of the three nodes
4) The MSE value is 1e-1 or 0.1
5) Learning rate value of 0.01
6) Epoch value of 1000.

Figure 13 is the main form of blood type identification prototype. On the main form, an overview of the process carried out by the system can be used to recognize the type of blood type from the image inputted by the user.

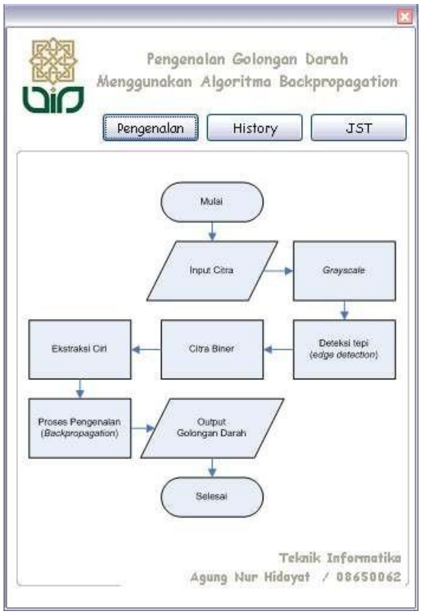


Figure 13. Prototype Main Form

To be able to carry out the recognition process, the user first presses the “Pengenalan” button. then the user can input the image by pressing the “Buka Citra” button as shown in Figure 14.

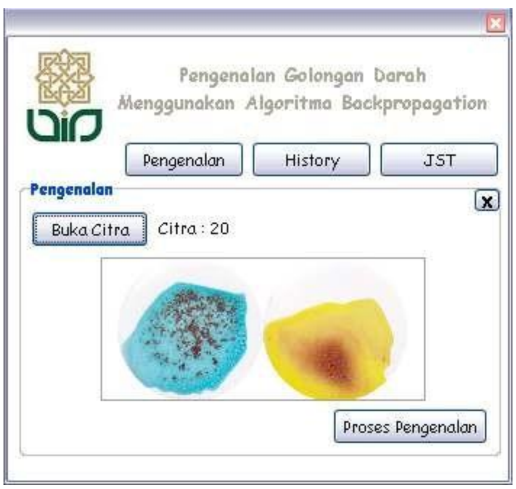


Figure 14. Recognition Image Input Form

After the image is inputted the user can press the 'Proses Pengenalan' button. The results of the recognition of blood type can be seen in Figure 15.

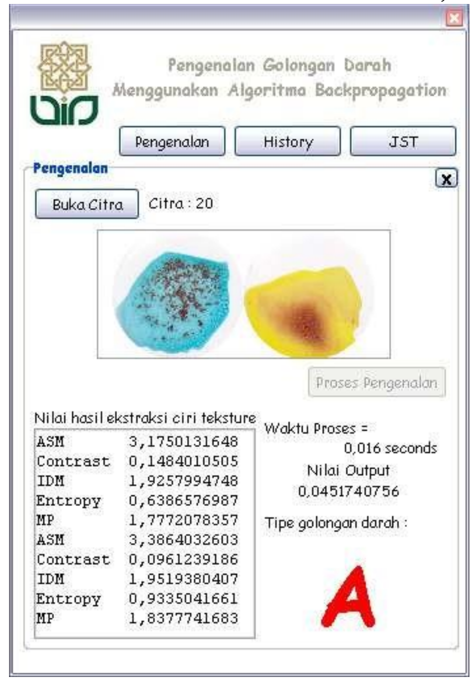


Figure 15. Recognition Result Form

From the images that have been inputted by the user and recognized by the system will be stored in history. To open it, the user can press the “History” button. To see the results of the recognition, then select the name of the image entered in the table and it will appear as in Figure 16. The results of the experiment using a system prototype get a success rate of 92.86%. compatibility with the results of the pattern recognition using Matlab is 100%.

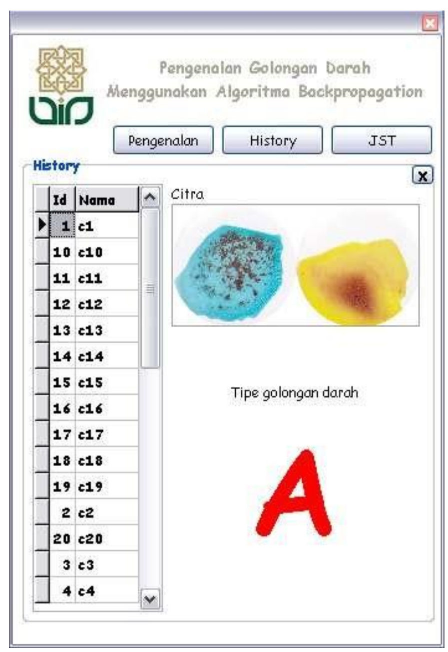


Figure 16. Form of View History

Besides the user can input the image to identify blood type, this system can also receive input from the user to conduct artificial neural network training. This menu is given so users can train when there is new data. In the "JST" menu, users can perform feature extraction and training. For feature extraction, the step that must be done by the user is to press the "Ekstraksi" button. Then the user can input the blood type checking image and determine the blood type target for training. The form and the results of feature extraction carried out by the user are as shown in Figure 17.

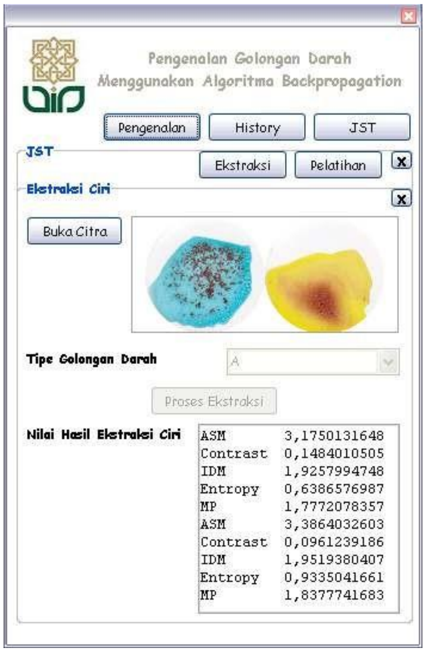


Figure 17. Form of Feature Extraction Results

For training, the step that the user must do is press the "Pelatihan" button. Then the user can specify epoch parameters, MSE, learning rate, and momentum. After the four parameters are entered, the user can press the "Proses Pelatihan" button and the training process is complete. To renew the new weight resulting from the training process, the user can do this by pressing the "Set Bobot" button then automatically, the new weight has changed as the weight during the training process. The training process and weight update can be seen in Figure 18 while the details of the artificial neural network architecture are used as shown in Figure 19.

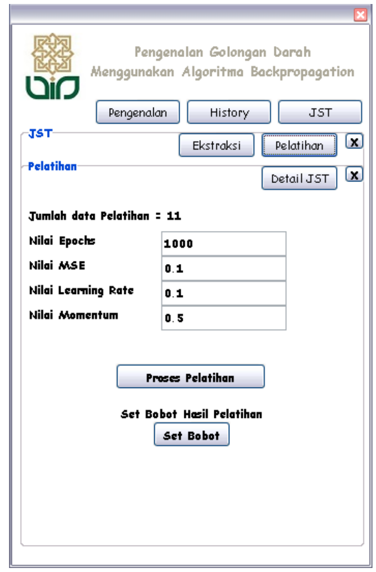


Figure 18. Artificial Neural Network Training Form

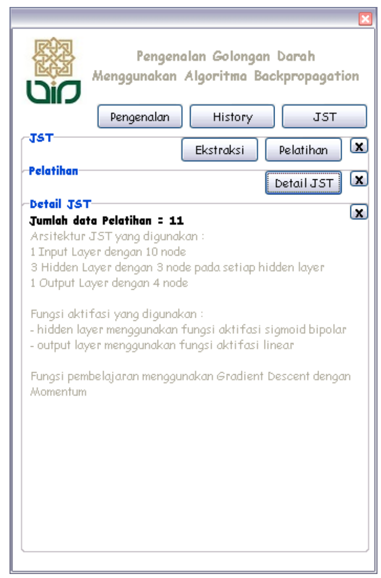


Figure 19. Form Details of Artificial Neural Network Architecture

IV. CONCLUSION

From the experiments conducted in this study, it can be concluded: The most optimal artificial neural network architecture is three hidden layers with each hidden layer having three nodes. The optimal value for the mean squared error parameter is 1e-1 or 0.1, epoch 1000 and learning rate 0.01. For each experiment, the results can change even though the values of the three parameters are the same because it depends on the randomly given of the initial weight value. The time needed for the edge detection process with Sobel operator averages 0.024462 seconds while for Prewitt operator 0.024410 seconds. In this study, Sobel operator was better than Prewitt operator in term of introducing blood type. From the training data, as many as 39 data and test data as many as

14 data obtained the percentage of success in the recognition of blood type of 92.86%.

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