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Recognition of Korean Alphabet (*Hangul*) Handwriting into Latin Characters Using Backpropagation Method

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ABSTRACT

The popularity of Korean culture today attracts many people to learn everything about Korea, especially in learning the Korean language. To learn Korean, you must first know Korean letters (*Hangul*), which are non-Latin characters. Therefore, a digital approach is needed to recognize handwritten Korean (*Hangul*) words easily. Handwritten character recognition has a vital role in pattern recognition and image processing for handwritten Character Recognition (HCR). The backpropagation method trains the network to balance the network's ability to recognize the patterns used during training and the network's ability to respond correctly to input patterns that are similar but not the same as the patterns used during training. This principle is used for character recognition of Korean characters (*Hangul*), a sub-topic in fairly complex pattern recognition. The results of the calculation of the backpropagation artificial neural network with MATLAB in this study have succeeded in identifying 576 image training data and 384 Korean letter testing data (Hangul) quite well and obtaining a percentage result of 80.83% with an accuracy rate of all data testing carried out on letters. Korean (*Hangul*).

Keywords: Korea, *Hangul*, Backpropagation Method, Artificial Neural Network

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I. INTRODUCTION

Handwritten character recognition has a vital role in pattern recognition and image processing [1][2]. In practice, handwritten Character Recognition (HCR) has helped a lot in life activities, such as the development of reading aids for the blind, recognition of writing on bank checks, and applications for reading pin codes on automated postal mail. Many studies have been carried out on recognizing handwritten characters, but characters with Latin letters have been studied more than non-Latin characters [3].

Previous research used the Backpropagation method to convert sound into text through feature extraction [4] and find out a person's personality [5]. The backpropagation method is a learning algorithm to reduce the error rate by adjusting the weights based on two differences in output and target. Previously, there have been several studies that also used the backpropagation method in character recognition. Three-layer backpropagation neural network algorithms used the researchers investigated the creation of alphanumeric character recognition applications [6]. They discovered that a backpropagation neural network method may be used to recognize alphanumeric characters (letters and numbers) [6]. The research uses the backpropagation method for Character Pattern Recognition System Using Principal Component Analysis Methods and Artificial Neural Networks - Back Propagation" in an accuracy rate above 95% [7]. The backpropagation method is the development of a single layer ANN which has limitations in pattern recognition [8]. The additional layer in this method is called the hidden layer. With this layer, the backpropagation method can more quickly recognize patterns through the network training process. The backpropagation method trains the network to balance the network's ability to recognize the patterns used during training and the network's ability to respond correctly to input patterns that are similar but not the same as the patterns used during training [9].

This principle is used for character recognition of Korean characters (*Hangul*), a sub-topic in fairly complex pattern recognition. In the study, the minimum mean square error value with the backpropagation method is 0.00001, which is obtained from training by giving 1000 iterations and the rate of understanding [10]. The artificial neural network model consists of 2 input units, ten

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hidden nodes in 1 hidden layer, and four output units [10]. Other studies using the backpropagation method recognition resulted in high accuracy in car shape recognition with a percentage of 94%, there is an error ratio of 6% due to poor lighting [11]. In the backpropagation neural network algorithm for Javanese letter pattern recognition, in the experiments that have been carried out, image processing using edge detection produces binary value images, which are then used for data learning processes. In the experiments that have been carried out, the value of the learning rate (α) affects the number of iterations of an input pattern in the learning data process to reach the iteration stop condition. In experiments that have been carried out using the backpropagation method with alpha = 0.6, hidden layer = 3 error tolerance = 0.0001, and target = 0.9 resulted in a system with an accuracy rate of (76%) and an error rate of 24 % [12].

Based on the description above, this study will develop software to recognize the handwriting of *Hangul* characters using the backpropagation method as the recognition method. Recognition of handwritten *Hangul* characters using the backpropagation method is expected to achieve a high level of accuracy. The backpropagation method used in this study because, which in fact sometimes causes overfitting, but here the author wants to explain that the backpropagation method can be quite accurate in predicting Korean handwriting if it uses backpropagation parameters such as epoch, hidden layer, learning rate, bias, and the appropriate minimum error, plus In this study, the author wants to detect the different classifications of Korean handwriting, the data is taken from various models of Korean handwriting from other people so that the test data is more varied and increases the accuracy of predictions.

This study is expected to find out how to detect the handwriting pattern of Korean letters (*Hangul*) using the backpropagation method and its accuracy. In this study, handwriting recognition of *hangul* was only used in the formation of the basic Korean alphabet, which includes vowels and consonants of simple vowels and simple consonants, and data were obtained from random respondents to know the diversity of Korean handwriting letters (*hangul*).

II. METHOD

It is necessary to have a system algorithm stage to recognize patterns in handwritten letters using backpropagation artificial neural network extraction. Fig. 1 is flow of the pattern recognition algorithm system on handwritten letters will be built.

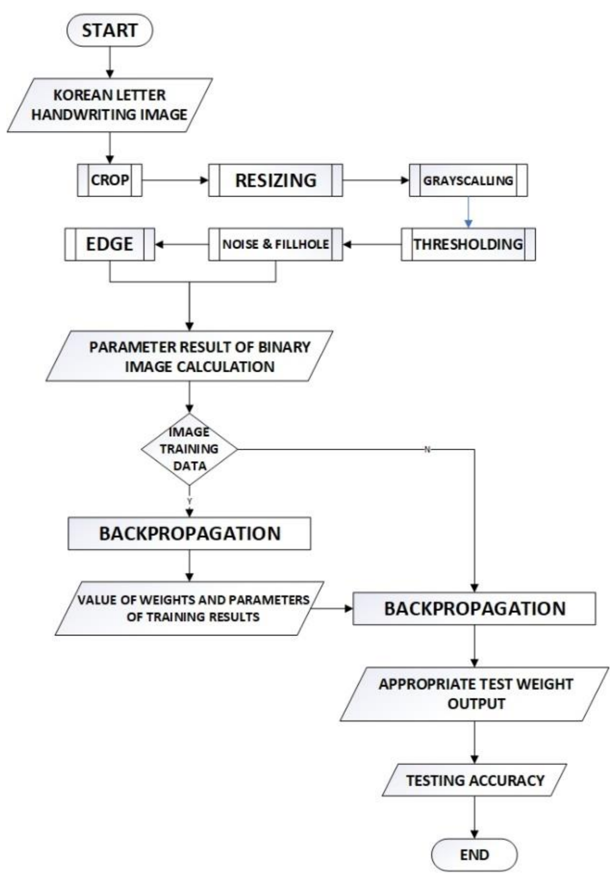

Fig.1. System Flowchart

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Input in the form of a handwritten image. The image is an RGB image in *.jpg* format. Before being processed, the image must go through several stages, such as cropping, resizing, grey scaling, thresholding, and noise fill hole. The first stage is cropping and resizing. After the image is cropped using the bounding box, each image has a different pixel. This resizes function converts the test image/image into a predetermined pixel of 300 x 300 pixels. The process changes the color image with the respective matrix values of r, g, and b into a grayscale image at the gray scaling or black-white stage. In the next stage, namely thresholding, the function of this stage is to change the conversion from black-and-white images to binary images by floating operations. The next stage, noise and fill hole, aims to eliminate the noise around the object after thresholding.

To identify the shape of the outline of each image, the results of the noise and fill hole computations are used to estimate the outline of each image. The use of binary pictures to recognize image characters in handwritten letter patterns with artificial neural networks is based on the use of metric, eccentricity, and quantitative pixel count data to recognize image characters in handwritten letter patterns. It starts with the data generated by noise and fills gaps, then moves on to border area data generated by binary pictures generated by outlines, which is then processed by calculating the artificial neural network. At this stage, 576 training images or images that have been processed previously will be trained on a test image of 384 data. Backpropagation calculation parameters such as epoch, bias, minimum error, and learning rate are determined based on previous studies and from data conducted by independent experiments by the author to find the best results. In this study, 1000 epochs were used, the learning rate was 0.1, the bias was 0.1, and the hidden layer was 70. The artificial neural network will recognize the output of the image that has been identified as a type of Korean letter (*hangul*) that is following its class or not. Accuracy is calculated by calculating the correct amount of data from all existing data.

A. Image Processing and Feature Extraction

After obtaining the *Hangul* handwritten data, the following step is to process the information received. Processing the data entails several processes, one of which is scanning the completed form through a scanner. Because of this process, digital data from handwritten data gathered on the questionnaire form will be generated when the handwriting data is converted to digital format. The very first plant data is in digital format. This is accomplished by completing a form that may be used to retrieve the letter data from which the cropping is performed. Then comes gray scaling, which begins with grayscale, a technique used to convert a color image to a grayscale or gray level image (from black to white). The luminance approach is used to create the grayscale image, which is composed of the RGB value multiplied by a value computed based on the eye's sensitivity to color. In terms of color, green is the most dominant, followed by red and finally blue.

The final output of this operation, shown in Fig. 2, is a gray value (8 bits) with a range of values ranging from black (0) to white (1). (255). Finally, thresholding, the stage of producing a binary picture in which the grayscale image is turned into a binary image, i.e., an image with only two colors, black and white, which is the beginning of the threshold process, is performed. An example of an RGB image that has been grayscale and transformed into a binary image can be seen here: Images are floated by performing an image floating operation, which divides the gray level value of each pixel into two classes: black and white. A floating function is used to transfer each pixel in the image into one of two values, namely 1 or 0, using a floating function that can be seen in the image binarize equation and image complement to alter the background color to black. After obtaining a binary image from the thresholding results, the image is cleaned through a morphological and fill hole process to eliminate small shapes that appear around the image shape and fill holes to make it easier on the image, followed by a morphological and fill hole process. Shape homogeneity is important for later feature extraction. Finally, the outline, the final step in the picture preparation process, is the procedure by which the handwritten word object is transformed into a boundary, and its large content is removed.

Fig. 2. Image Processing

After the image preprocessing stage, the next stage is the feature extraction stage. At this stage, the sample data (image) is extracted using a metric value: the comparison value between the area and the perimeter of the image, the eccentricity value of the image, the circumference value obtained from the image border area, and also the image area value.

B. Backpropagation

The backpropagation method is learning that reduces error rates by modifying weights based on how far an algorithm has progressed from the starting point. Backpropagation is also a methodical method for training multilayer artificial neural networks (ANNs). When it comes to training, the backpropagation method is referred to as a multilayer training algorithm because it involves three layers in total: the input layer, the hidden layer, and the output layer. This backpropagation is developing a single-layer network (Single Screen Network), which has two layers: the input layer and the output layer, which is why it is called a multilayer training algorithm of the hidden layer in the backpropagation method, the error rate in backpropagation can be lower than the error rate in a single layer network, which is advantageous. Since the hidden layer in backpropagation is used to update and adjust the weights, a new weight value is obtained that can be directed closer to the intended output target as a result of this update and adjustment. In this backpropagation process, the activation function is a binary sigmoid function because the predicted output is in the range of 0 to 1.

The backpropagation algorithm is an algorithm to reduce the error rate by adjusting the weights based on the difference between the output and the desired target. The parameters generated by the above stages are inserted into the neural network using the backpropagation learning method. The network training process flowchart can be seen in Fig. 3.

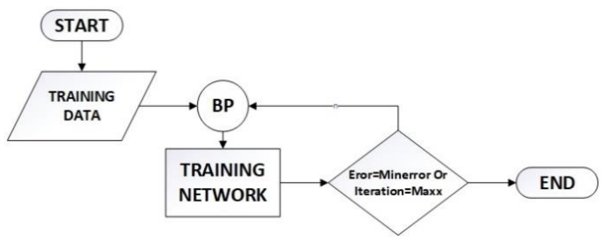

Fig.3. Flowchart Backpropagation

Prior to considering any data, the weights must be established. After that, they must be fed into the backpropagation process algorithm, which includes advanced computations to track the degree of the error and reverse computations to update and alter the weights. Updating the weights can be accomplished in two ways: either without momentum or with momentum, depending on the situation. However, the procedure described below for updating the weights is carried out without reference to the magnitude of the momentum applied to the system. Therefore, to properly implement the backpropagation method, it is important to perform several steps, including initializing weights, computing feedforward and backpropagation, and initializing stopping conditions based on either an error limit value or a number of epoch limits. In artificial neural network learning, an epoch is a series of steps that must be completed before training the network. One epoch of artificial neural networks is defined as a single instance of learning [13].

The following are the steps in the calculation process using the Backpropagation method:

1) Step 0: Initialize all weights with a small random number. The binary sigmoid function is used, which is an asymptotic function (never reaches 0 or 1), so the data transformation is carried out at smaller intervals, namely [0.1; 0.9], shown in Equation (1).

$$X' = \frac{0.8\,(x-a)}{b-a} + 0.1 \tag{1}$$

where X' variable is normalized data values, X variable is n^{th} data, a variable is lowest data, and b variable is highest data

2) Step 1 : If the termination conditions are not met, perform steps 2-9.
3) Step 2 : For each pair of training data, do step 3-8.

Phase 1: Forward Propagation

4) Step 3 : Each input layer receives the signal and passes it on to the hidden layer above it.
5) Step 4 : Count all output in the hidden layer, Zj (j = 1,2,…, p) use Equation (2).

$$z\_net_j = v_{j0} + \sum_{i=1}^{n} x_i v_{ji} \tag{2}$$

and using the specified sigmoid activation function to calculate the output signal from the hidden layer in Equation (3),

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$$z_j = f\left(z_{netj}\right) = \frac{1}{1+e^{-z\_netj}} \tag{3}$$

Then send the output signal to all layers in the output layer where z_netj variable is *input signal* on hidden *layer* j^th^, vjo variable is biased to j^{th} hidden layer, vji variable is the weight between the i^{th} *input layer* and the j^{th} hidden *layer*, xi variable is i^{th} input layer, zj variable is j^{th} hidden layer, i variable is input layer order, j variable is hidden layer order, and p variable is the maximum number of units in the hidden layer,

6) Step 5 : Calculate all network outputs in the output layer ,k = 1,2,3,… ,m) using Equation (4)

$$y\_net_k = w_{k0} + \sum_{i=1}^{n} z_j w_{kj} \tag{4}$$

And use the specified activation function to calculate the output signal of the corresponding output layer used Equation (5).

$$y_k = f\left(y_{netk}\right) = \frac{1}{1+e^{-y\_netk}} \tag{5}$$

Where, y_netk variable is k^{th} *output* input signal, and $wk0$ variable is biased k^{th} variable hidden layer is k^{th} output and j^{th} variable hidden layer is j^{th} variable hidden layer.

Phase 2: Back Propagation

7) Step 6 : Calculate the factor of each output layer from the error of each output layer (yk, k=1,2,3,…,m) using Equation (6).

$$\begin{aligned}\delta_k &= (t_k - y_k)f'(ynet_k) \\ &= (t_k - y_k)\, y_k\, (1 - y_k)\end{aligned} \tag{6}$$

δk is the unit of error used in changing the weight of the layer below it (step 7). The factor is used to calculate the error correction (Δwkj), which is used to update the acceleration rate with Equation (7)

$$\Delta wkj = \alpha\delta kzj \tag{7}$$

This δk factor is then sent to the *front layer*. Where, δk variable is wjk weight error correction factor, tk variable is k^{th} *output* target, yk variable is k^{th} *output* activation, Δwkj variable is wkj weight error correction value, and zj variable is j^{th} *hidden* layer activation,

8) Step 7 : Calculate the hidden layer factor based on the error in each hidden layer (Zj, 1,2,3,…,) using Equation (8),

$$\delta\_netj = \sum mk{=}1\ \delta kwkj \tag{8}$$

hidden layer factor using Equation (9),

$$\delta j = \delta\_netjf'(znetj) = \delta netjzj(1 - zj) \tag{9}$$

Calculate the weight change rate that will be used for the weight change process using Equation (10),

$$\Delta vji = \alpha\delta jxi \tag{10}$$

where $\_netj$ variable is j^{th} *hidden layer* weight, δk variable is wkj weight error correction factor, wkj variable weights between the k^{th} output and j^{th} hidden layer, δj variable is vij weight correction factor, zj variable is j^{th} hidden layer, vji variable is vji weight error correction value, α variable is learning rate, δi variable is vji weight error correction factor, and xi variable is i^{th} input unit

Phase 3: Weight Change

9) Step 8 : Each output unit (yk,k = 1,2,3,… ,m) will update its bias and weight with each hidden unit using Equation (11).

$$wkj(\text{new}) = wkj(\text{old}) + \Delta wkj \tag{11}$$

Likewise, each hidden unit will update its bias and weight with each input unit using Equation (12).

$$vji(\text{new}) = vji(\text{old}) + \Delta vji \tag{12}$$

where, wkj(new) variable is new weight from hidden layer to output layer, Δwkj(old) variable is old weight from hidden layer to output layer, Δvji(new) variable is new weight from hidden layer to the output layer, and Δvji(old) variable is old weight from hidden layer to output layer

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10) Step 9 : Checking the stop conditions. If the stop conditions have been met, the network training can be stopped [14].

III. RESULT AND DISCUSSION

Fig. 4 is the initial view of the program for handwriting recognition of Korean letters (*Hangul*) using the backpropagation method. This initial view is a means of connecting users and applications. This system has several buttons that will make it easier for users to run the program, including Open Image, Segmentation, Edges, Feature Extraction, Classification, and Reset.

Fig. 4. The initial view of the *MatLab*-GUI

Fig. 5. Open Image Button

Fig. 5 is the result of the button that takes Picture to clicked, will be directed to select an RGB image file, inputting it into the axes1 box on the program display, which then enters the following process.

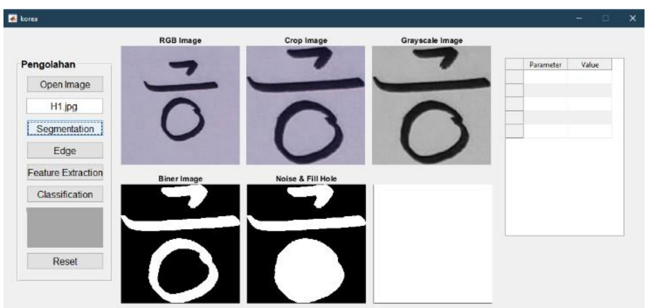

Fig. 6. Segmentation

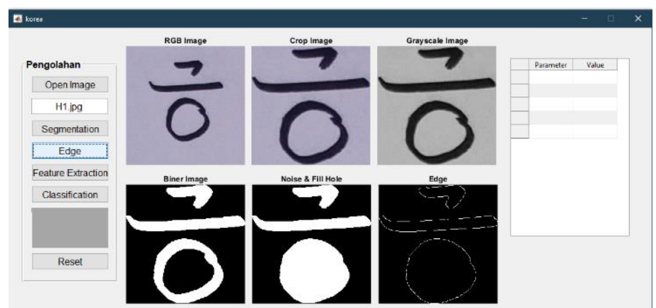

Fig. 7. Edge

Fig. 6 is the result of the Segmentation button. When clicked, the RGB image file in the axes1 box will be cropped, then converted into a grayscale image, from grayscale to a binary image, then noise and fill hole. This conversion will be displayed in axes2, axes3, axes4 box, and axes5, and in Fig. 7 is the result of the Border button. When clicked, the Noise & Fill hole image file in the axes4 box will be changed to a border-image.

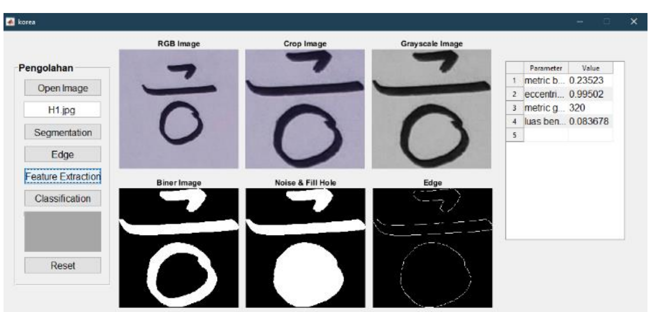

Fig. 8. Feature Extraction

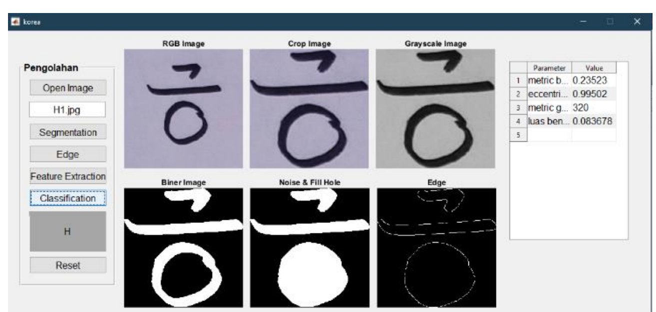

Fig. 9. Classification

Fig. 8 is the result of the Feature Extraction button. When clicked, it will display the parameter values in the table box in the application, and Fig. 9 is the result of the Classification button. When clicked, it will display the classification results from the image file that has been processed earlier into the text edit box under the Classification button. The results in Table I of the trials carried out, for testing the image training data as much as 576 with image testing data as much as 384, then the calculation of the percentage of success is carried out to determine the level of accuracy the application made.

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TABLE I
TESTING RESULT

No.	Letter	Test	Succeed	Fail	Percentage
1	ㅇ	16	13	3	81.25%
2	ㅏ	16	12	4	75.00%
3	ㅂ	16	11	5	68.75%
4	ㅊ	16	14	2	87.50%
5	ㄷ	16	12	4	75.00%
6	ㅓ	16	13	3	81.25%
7	ㅡ	16	15	1	93.75%
8	ㄱ	16	9	7	56.25%
9	ㅎ	16	11	5	68.75%
10	ㅣ	16	15	1	93.75%
11	ㅈ	16	13	3	81.25%
12	ㅋ	16	13	3	81.25%
13	ㅁ	16	13	3	81.25%
14	ㄴ	16	16	0	100.00%
15	ㅗ	16	13	3	81.25%
16	ㅍ	16	14	2	87.50%
17	ㄹ	16	13	3	81.25%
18	ㅅ	16	13	3	81.25%
19	ㅌ	16	14	2	87.50%
20	ㅜ	16	13	3	81.25%
21	ㅑ	16	11	5	68.75%
22	ㅕ	16	14	2	87.50%
23	ㅛ	16	13	3	81.25%
24	ㅠ	16	13	3	81.25%
Total		384	311	73	80.83%

Based on the results of trials that have been conducted on 24 Korean letters (*Hangul*), the percentage details begin with the lowest, which is 56.25 percent on the letter G, and work their way up to the highest (1). A total of 68.75 percent of the next order contains the letters B, H, and the word YES in the percentage value (3). Seventy-five percent of the letters A and D are capitalized (2). The percentages for the letters -/-NG, EO, J, G, M, O, R/L, S, U, YO, and YU are 81.25 percent, respectively (11). The percentages for the letters CH, P, T, and YEO are 87.5 percent, respectively (4). The letters EU and I have a 93.75 percent success rate, respectively (2). The letter N is the owner of the greatest percentage, which is 100 percent (1).

As a consequence of the findings, it can be stated that the average success rate for all testing letters is 73.6 %, with the maximum percentage value of 100 % for one letter being the highest and the lowest percentage value of 56.25 % for one letter being the lowest. 86.0417 % training accuracy will be achieved by the employment of 24 classes and 576 training data sets, each of which will be retrained using the same training data set. The accuracy of the test was 80.833 % in the testing stage, which was conducted with 24 classes and 384 test data to be tested from the previous training data.

IV. CONCLUSION

The MATLAB application was used to implement the backpropagation method in the handwriting recognition of Korean letters (*Hangul*). Beginning with the input image or image and progressing to the output text, represented by the Korean letters (*Hangul*) that are inputted, the built process is described below. The training data consisted of 576 picture data, and the test data consisted of 384 image data. The application of the backpropagation method is extremely effective in deciphering the meaning of each character in the Korean alphabet (*Hangul*) with great accuracy. It is possible to correctly modify the capacities of the human brain using this strategy in numerous areas. This has been demonstrated in the pattern recognition process, where patterns can be detected correctly. It can be concluded that the backpropagation neural network has performed admirably in detecting Korean letter pattern recognition (*Hangul*), achieving an accuracy rate of 80.83 percent with a percentage result of 80.83 percent for all data testing performed on Korean letters (*Hangul*). This has demonstrated that the backpropagation Neural Network is extremely effective and efficient in the process of developing and executing the application in question. This application was developed with the goal of increasing public awareness of the meaning of Korean letters (*Hangul*) through the use of a system that has been designed to be more easily comprehended by a broader range of people. Based on previous citation studies that used other methods or backpropagation methods that were accompanied by other methods, as well as sources from previous studies and repeated experiments to find the appropriate backpropagation parameters, the backpropagation method is quite good at classifying each data point and produces reasonably good results, and it is quite efficient when compared to the quotes in the table. In the future, this application will be able to determine the meaning of the Korean word (*Hangul*), allowing individuals to recognize Korean letters as well as the meaning of the Korean word (*Hangul*). The backpropagation method of pattern recognition was re-developed because it has the potential to improve the precision with which Korean letters can be identified in the future (*Hangul*).

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