A Performance Comparison of Backpropagation Neural Networks and Learning Vector Quantization Techniques for Sundanese Characters Recognition

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Summary
This article aims to compare the accuracy of the Backpropagation Neural Network (BPNN) and Learning Vector Quantization (LVQ) approaches in recognizing Sundanese characters. Based on experiments, the level of accuracy that has been obtained by the BPNN technique is 95.23% and the LVQ technique is 66.66%. Meanwhile, the learning time that has been required by the BPNN technique is 2 minutes 45 seconds and then the LVQ method is 17 minutes 22 seconds. The results indicated that the BPNN technique was better than the LVQ technique in recognizing Sundanese characters in accuracy and learning time.
Keywords:
Sundanese characters, BPN, LVQ, Accuracy, MSE.

1. Introduction

The Republic of Indonesia as a large country and has many unique cultures in each region including the writing of ancient characters. Where, it continues to be used as a communication tool in oral and written languages. The Republic of Indonesia has 726 then 706 regional languages spread throughout its territory and are still being counted by researchers [1], [2]. One of the regional languages is the Sundanese characters, which is used in West Java. In order to maintain the ancient character writing (based on Indonesian Act. 24/2009, Clause 41), the technology approach is used. One technology that can be used in characters recognition is artificial intelligence (AI).

In general, characters recognition called pattern recognition is the science of classifying or describing an object based on quantitative measurements of features or main attributes of its object [3]–[5]. Numerous AI approaches are widely used by researchers in characters recognizing. Zamora (2014) has conducted research recognizing handwriting patterns using the Neural networks (NNs) method, Neural network language models (NN LM), Bidirectional long short-term neural networks (BLSTM) Hybrid HMM / ANN with ROVER combination. The studied showed that the hybrid HMM / ANN system was better (low error rate) than the BLSTM NN system [6]. Also, has performed on recognizing Chinese handwritten texts using LMs neural networks (NNLMs), feedforward neural networks LMs (FNNLMs), recurrent neural networks LMs (RNNLMs), and back-off N-gram LMs (BLMs). Researchers have been conducted with the CASIA-HWDB Chinese handwriting database. This study has demonstrated that the artificial intelligence method is capable of producing the character-level accurate rate (AR) and correct rate (CR) achieving 95.88% and 95.95% [7]. Afterwards, The Learning Vector Quantization (LVQ) processing stage in order to recognize The Buginese Lontara script from Makassar have been implemented. However, studied showed that LVQ method has not been able to provide good recognition [8]. Researchers also used the artificial neural network (ANN) approached to analyze Hanacaraka's handwriting [9], [10].

We demonstrate in this paper the applicability of BPNN and LVQ techniques for handwriting Sundanese characters recognition. This paper consists of four sections. First, the motivation of this research. Second, to explain the BPNN and LVQ. Third, to explain the experimental approaches. Finally, a comparative conclusion from the two approaches and further research.

2. Methodology

In this section, we will explain briefly about Sundanese characters, image processing as well as the BPNN and LVQ techniques implemented.

2.1 Image Processing

An image processing is a process of converting images to be better quality for a certain purpose. Image processing has two main reasons, including (1) improving image quality so that it can display information clearly; (2) extracting prominent feature information so that numeric image information is obtained. In general, image processing

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consists of image acquisition, size normalization, grayscale, sharpening, segmentation, and thinning [11]–[13].

2.2. Backpropagation Neural Network (BPNN)

The backpropagation neural network (BPNN) algorithm was originally introduced in the 1970s, and then popularized in 1986 by David Rumelhart, Geoffrey Hinton, and Ronald Williams. Rumelhart describes that BPNN works far faster than earlier approaches to neural networks learning to solve. The BPNN is a supervised learning algorithm used by perceptron with many layers to change the weights in the hidden layer. BPNN is a training that uses a weight adjustment pattern to achieve the minimum error value between the predicted and actual results. In BPNN, the activation function used must meet several conditions, namely continuous, deferred, and not derived functions such as binary sigmoid functions that have a range of values [0..1]. Today, the BPNN algorithm is one of the neural networks algorithms used in many areas such as engineering, financial, hydrology and so forth. In principle, the BPNN algorithm consists of three phases training, including feedforward, backward, and weight updates [14]–[17].

Stage one (feed forward): Each propagation input signal is computed forward by using an activation function that is determined from the input to the hidden layers and to the output layer. Stage two (Backward): Errors (the difference between the network output and the desired target) that occur in back propagation starting from the line that is directly related to the units in the output layer. In order to find errors between input and output units during training, each output unit compares activation with a predetermined output target. Stage three (Weight Update): Weights are modified to reduce errors. The error obtained in stage two is used to change the weight between the output and the hidden layers [16], [18]–[21].

2.3. Learning Vector Quantization (LVQ)

Learning Vector Quantization (LVQ) technique is a technique in ANN to conduct supervised learning. In recognizing patterns, LVQ technique classifies patterns with each output unit representing a particular class or category using a reference vector or codebook. Where, the weight vector of the output unit is the reference for the class or category represented by the output. The approach taken is to group input vectors based on the proximity of the input vector distance to the weights [22], [23]. LVQ architecture consists of an input layer (input layer), a competitive layer (a competition in the input to enter a class based on the proximity of its distance) and the output layer. The input layer is connected to the competitive layer by weights. In the competitive layer, the learning process is supervised. Input competes to be able to enter into a class. Then, the stages of LVQ are explained as follows [8], [24].

Step 0: Initialize
Initial Reference Vectors
Initial Learning Rate alpha = 0
Step 1: If the stop condition is incorrect, do steps 2-6
Step 2: For each training vector, do steps 3-4
Step 3: Get the value of j such that $\| x-w_j \|$ minimum value
Step 4: Update the weight value of w_j
If T = J then $w_j(new)=w_j(old) + \alpha (x-w_j(old))$
If T $\neq$ J then $w_j(new)=w_j(old) - \alpha (x-w_j(old))$
Step 5: Update the learning rate value
Step 6: Test the stop condition

2.4. Performance of Accuracy

Some methods in statistics to measure the accuracy of an algorithm are mean absolute error (MAE), Mean square error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). The measurement algorithm aims at attaining the best value [25]–[28]. In this study, the MSE method was chosen to measure accuracy. Meanwhile, MSE used (1).

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(x_t - \hat{x}_t)^2 \quad (1)$$

Where, x_t is a data value; x_t-$\hat{x}_t$ is a result value; N is a number of sample dataset.

2.5. Sundanese Scripts

The Ngalagena script has been used from the 14th century AD by the Sundanese. Kawali Inscription or called Astaga Gede Inscription is one of the Sundanese script relics. The inscription was made in memory of King Niskala Wastukancana who at that time ruled Kawali, Ciamis in 1271-1475 [29]–[32]. Where, the Sundanese characters including Swara letters (independent vowels) and letters Ngalagena (consonants).

In this study, the data obtained by taking pictures in the form of 15 people's handwriting, then each person wrote seven vowels of Sundanese characters. In addition the data will be used to conduct training programs and as a system test data. Here is a sample of Sundanese characters vowel data can be seen in Figure 1.

Figure 1. Sundanese characters of vowels

3. Results and Discussion

This section has explained the results of image processing, feature extraction followed by testing using Backpropagation Neural Network (BPNN) and Learning Vector Quantization (LVQ) techniques.

3.1. Image Processing Results

In this experiment, based on the image processing process, the first stage is image acquisition; cropping process to crop the image in the required area has been done. The second step, size normalization, with a scale multiplied by 0.2 from the initial image measuring 226 x 195 pixels to 46 x 39 pixels has been obtained. The third stage, has changed RGB to grayscale image. The fourth stage, has carried out image sharpening which aims to clarify the image. The fifth stage, segmentation to obtain binary images using the threshold method has also been determined. Lastly, image depletion to extract important information from an image has been obtained. Meanwhile, the results of image processing can be viewed in Figure 2.

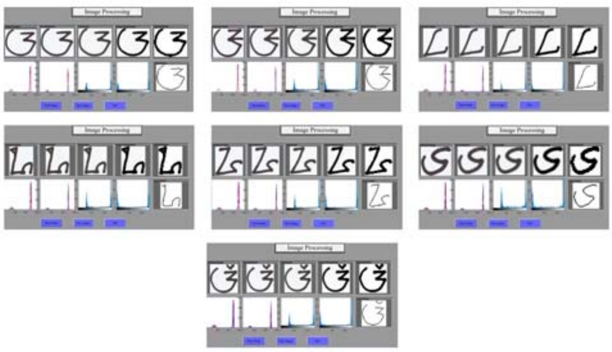

Figure 2. Image processing results

Afterward, the feature extraction stages. In this experiment, the character intensity algorithm and directional signs were exploited. The character intensity has to calculate the black pixels values in an image. Then, directional markings have been consumed to calculate how many pixels meet the horizontal, vertical, diagonal left and right masking of all images. In this study, the image has been divided into nine segments, 14x14 pixels. The segments divided has used the Chessboard method, which divided the image into objects such as chess boards. The results of image extraction can be seen in Figure 3.

Next, characterizing the image in each segment using directional markings to calculate vertical, horizontal, diagonal left and right masking has been achieved. Then, characterizing the character intensity to calculate the black value in each segment has been completed. After that, six feature combinations were made so that the obtained image characters were included Feature 1, contains the black variable; Feature 2, contains diagonal 1; Feature 3, contains the variables black and diagonal 1; Feature 4, contains the variables black and diagonal 2; Feature 5, contains diagonal variables 1 and 2; Feature 6, contains the variables black, diagonal 1 and 2, horizontal and vertical.

Then, an image character value of 112 data has been obtained. Based on the rules of artificial intelligence, the data has been determined into two parts consisting of 70 as training data and 42 as testing data. These data will be used for BPNN and LVQ algorithms.

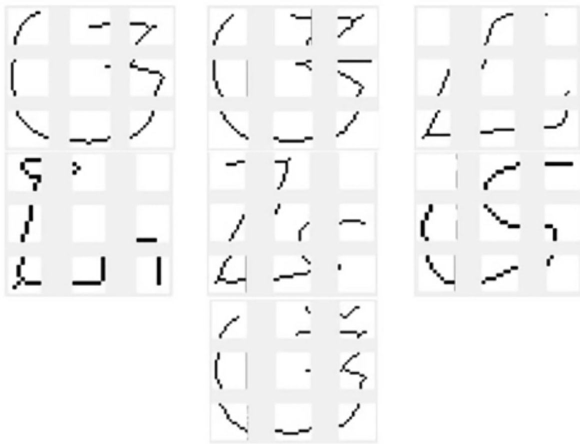

Figure 3. The feature extraction results with nine segments of Sundanese Vowels

3.2. Backpropagation Neural Network Results

In this experiment, the BPNN testing parameters technique with six network architecture variations, six the learning rate (LR) values variations, and 10 the number of hidden layer neurons variations have been established.

Thus, in each variation the LR value has been verified to two different number of hidden layer neurons. Learning function of *trainlm*, and activation function of *logsig*, *tansig*, and epochs of 1000 have been applied for BPNN learning. Meanwhile, the results of the experiment can be seen in Table 1.

Table 1. BPNN results

Learning Rate (α)	*Number of hidden layer*	*Learning Function*	*Activation Function*	*Results*				
				Best Epoch	*MSE*	*Time*	*Match*	*Accuracy*
0,01	90	trainlm	tansig, logsig	20	0.0186	2’ 48”	37	88,09%
	100			18	0.0585	2’ 54”	38	90,47%
0,02	90			21	0.0499	2’ 45”	40	95,23%*
	100			21	0.0123	3’ 19”	38	90,47%
0,05	90			20	0.0186	2’ 24”	37	88,09%
	100			22	0.0941	3’ 21”	38	90,47%
0,1	90			21	0.0237	2’ 46”	37	88,09%
	100			24	0.0017	4’ 10”	37	88,09%
0,5	90			30	0.0156	4’ 2”	38	90,47%
	100			23	0.0528	3’ 42”	38	90,47%
1	90			23	0.0848	2’ 55”	37	88,09%
	100			27	0.0848	6’ 34”	37	88,09%

3.3. Learning Vector Quantization Results

In this experiment, the LVQ testing parameters technique with six network architecture variations, six the learning rate (LR) values variations, and 10 the number of hidden layer neurons variations have been established.

Thus, in each variation the LR value has been verified to two different number of hidden layer neurons. Learning function of *learnlv1* and epochs of 1000 have been operated for LVQ learning. Meanwhile, the results of the experiment can be seen in Table 2. Then, the performance of comparison of these algorithms can be viewed in Figure 4.

Table 2. LVQ results

Learning rate (α)	**Number of hidden layer**	**Activation Function**	**Results**				
			Best Epoch	**MSE**	**Time**	**Match**	**Accuracy**
0,01	90	learnlv1	241	0.0408	17’22”	28	66,66%*
	100		643	0.0449	18’34”	24	57,14%
0,02	90		161	0.0490	18’25”	25	59,52%
	100		26	0.0490	18’42”	23	54,76%
0,05	90		422	0.0449	18’43”	27	64,28%
	100		206	0.0449	18’14”	17	40,47%
0,1	90		881	0.3670	17’43”	19	45,28%
	100		98	0.0490	16’56”	22	52,38%
0,5	90		77	0.1430	18’11”	6	14,28%
	100		127	0.1430	18’8”	6	14,28%
1	90		2	0.1760	16’59”	6	14,28%
	100		109	0.1430	20’	6	14,28%

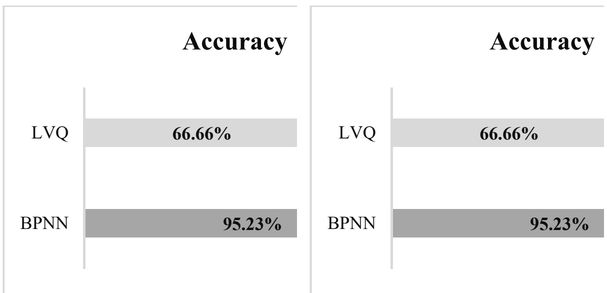

Figure 4. Comparison of BPNN and LVQ

4. Conclusions

The backpropagation neural network (BPNN) and learning vector quantization (LVQ) techniques in recognizing Sundanese character have been performed. Based on experiments, the BPNN architecture consist of learning rate (LR) of 0.02 and hidden layers of 90, then the LVQ architecture consist of learning rate (LR) of 0.01 and hidden layers of 90 has been utilized. The results show that the BPNN technique can recognize 40 out of 42 characters, with an accuracy of 95.23%, and MSE of 0.0499. Meanwhile, the LVQ technique can recognize 28 out of 42 characters, with an accuracy of 66.66%, and MSE of 0.0408. In time process, the BPNN technique has a short-time learning of 2 minutes 45 seconds compared to 17 minutes 22 seconds. This study shows that the BPNN technique is quite good at recognizing Sundanese characters compared to the LVQ technique. In the near future, in order to get more accurate coupled combination techniques will be investigated.

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