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Bima Script Handwriting Pattern Recognition using Histogram of Oriented Gradients and Backpropagation Classification Method

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Abstract. The Bima script is one of the cultural heritage of the archipelago that needs to be preserved. Based on the results of a questionnaire conducted by the author online to 81 respondents from Bima, 48.1% had never studied the Bima script; moreover, 45.7% of people do not even know the existence of the Bima script. The dataset is collected from 20 respondents, which each responcent write 22 letters of the Bima script 12 times. The purpose of this research is to build a machine learning model that can recognize the handwriting pattern of the Bima script using the Histogram of Oriented Gradient (HOG) feature extraction and the Backpropagation classification method. This research results get 97.70% accuracy, 97.72% precision, and 97.65% recall, which used 1 hidden layer, 128 neurons, 0.5 dropouts, 1500 epochs, and a learning rate of 0.001 with an image size of 64x64 pixels.

INTRODUCTION

Indonesia has many cultures, traditions, and rituals. One of the cultural heritages owned by Indonesia that needs to be preserved is the traditional script in the Bimanese, namely the Bima script or known as the Mbojo script. Script is a visual symbol printed on a medium (paper, cloth) to express expressive elements in a language[1]. The shape or pattern of the basic syllables of the script has a different shape from writing in general, so that the script is still not used by the public. Based on the results of a questionnaire to 81 respondents from the Bima community, with 17 to 38 years age range, 45.7% of respondents still do not know about the existence of the Bima script. Moreover, at least 48.1% of respondents have never studied the Bima script. Based on these data, it can be said that there are still many Bima people who are not familiar with the use of the Bima script[2]. The difficulty in understanding the Bima script is the ability to write symbols and interpret the meaning of punctuation marks[3]. People with diverse ethnicities can cause various linguistic phenomena, such as bilingualism (or even multilingualism). Language contact can also result in a language shift, which is a permanent change in one's language selection[4]. Therefore, to overcome the extinction of a language, it is necessary to make a smart and serious effort. Language shifts can be avoided by the way the language speakers maintain the use of their regional language so that it does not lead to language extinction.[4].

Pattern recognition is the automatic grouping and processing of numerical data by machines. The purpose of pattern recognition is to recognize objects in digital images. Humans can recognize an object that is seen because the human brain has learned to process a similar object. Unlike computers that can only accept input image data objects then processed to get output in the form of information or description of an image object[5].

According to the author's observations, research on pattern recognition in the case of the Bima script does not currently exist. However, several similar studies have been carried out, namely the introduction of Javanese characters using the Histogram of Oriented Gradient (HOG) and Support Vector Machine (SVM) methods with an accuracy rate of 93.3%.[6]. Other studies that related to our research are [7] and [8]. In [7], the author proposed a method to recognize of Arabic script using the Discrete Cosine Transform (DCT), HOG and SVM methods, where the accuracy rate is 96.317%[7]. Meanwhile, in [8], the author proposed handwriting recognition using the HOG method and Deep-Learning Feedforward-Backpropagation Neural Network (DFBNN), where the accuracy rate is 99.08% for Thai script, 97.40% for Bengali numerals, and 80.00% for Devanagari Angsa[8]. Other similar studies that use pattern recognition are signature identification using the HOG method, Principle Component Analysis (PCA) to perform feature reduction, and Generalized Regression Neural Networks (GRNN) classifier with an accuracy rate of up to 98.33%.[9].

Based on several studies that have been described above, the authors propose a study to design a machine learning model to recognize the Bima character pattern using the HOG method for feature extraction and character classification using the Backpropagation Artificial Neural Network method. From the research, we obtain the optimal parameter of machine learning model using the HOG and backpropagation methods to recognize the Bima script. By doing so, we expect to help the public study the shape or pattern of the script. Consequently, we hope it can increase interest in preserving the Bima culture, especially the traditional writing of the Bima script.

LITERATURE REVIEW

Research using the Histogram of Oriented Gradient (HOG) as a feature extraction method has been carried out previously. In [7], the authors try to recognize Arabic handwriting. That research includes Arabic handwriting feature extraction, where the process begins by doing Text Segmentation to get each character. Then they conduct the pre-processing image thresholding and normalization of the image. The last step is to perform feature extraction using HOG, Discrete Cosine Transform (DCT), and classification using the Support Vector Machine (SVM) on 2,940 data with 70% data sharing for training data and 30% for testing data and producing an accuracy of 96.317%. In [6], the authors try to recognize Javanese characters consisting of 20 basic characters. The process begins with segmenting characters in the image. Then it performs feature extraction using HOG, while doing classification using the Support Vector Machine (SVM). The accuracy is 93.3%. The next step is to identify the signature where the process begins by pre-processing the conversion into a binary image. The next steip is reducing noise, cropping and resizing the image to 80*150 pixels. In [6], the authors perform feature extraction using HOG, where before classification, feature reduction is performed using Principal Component Analysis (PCA). The total dataset used is 600 signatures with a total of 15 classes, and the classification used is Generalized Regression Neural Networks (GRNN) with an accuracy of 98.33%.

Several studies have used research using the Backpropagation Artificial Neural Network method as a classification method. For example, handwriting recognition of the first 5 consonants in Hindi with a total data of 1000 (each letter 200 data) [10]. This research conduct pre-processing noise reduction to reduce noise generated not important in the image. Then, it uses binarization to convert the image into binary form. That research also uses normalization to change the image size to 7x7 and uses thinning to streamline the characters in the image. The accuracy obtained is 93%. Meanwhile, in [11], recognition of uppercase and lowercase characters and printed numerals is conducted. With a total of 558 images for 62 characters, that research produces an accuracy of 99% for numeric, 97% for uppercase characters, and 96% for lowercase characters. In [12], handwriting recognition of numbers with a total of 70000 data written by 700 different people is conducted. It uses 60.000 data for training data and 10.000 for testing data. Before feature extraction and classification, a pre-processing normalization process is carried out on the image. The accuracy results obtained are 98.26%.

Based on what has been described above, the HOG feature extraction method and Backpropagation classification have a high level of accuracy in handwriting pattern recognition. The authors propose research to design a machine learning model to recognize the bima character pattern using the HOG method for feature extraction and classification using the Backpropagation Artificial Neural Network method.

Histogram of Oriented Gradient

Histogram of Oriented Gradient (HOG) is an object that appears in the image which is described by the edge gradient direction. The image will be divided into small areas called interconnected blocks. Inside the block, there are cells. For each pixel in the cell, each cell will be arranged in a histogram of the edge gradient direction or edge orientation [13]. Several stages of the Histogram of Oriented Gradient (HOG) method[14]:

1. Define blocks and cells

According to Navnet research written in the journal Risva et al, it was explained that the image size used was 64x128 pixels, then divided into 16x16 blocks with 50% overlap. Each block consists of 2x2 cells with a size of 8x8 pixels.

2. Calculating the Gradient value
   The process of calculating the gradient value is used to get the borderline value of the image object. Before calculating the gradient, the image will be converted to grayscale so that you don't have to pay attention to the color intensity of the image. The method used to calculate the gradient value is 1-D centered, with the matrix [−1,0,1] applied to the vertical and horizontal directions of a pixel using Eq. (1) and (2).

$$Ix(x,c)= (I(r,c+1)-I(r,c-1))/2 \tag{1}$$
$$Iy(x,c)= (I(r+1,c)-I(r-1,c))/2 \tag{2}$$

   Where x is the row of the matrix and y is the column of the matrix. Then the values of Ix and Iy are obtained, which are used to calculate the gradient value using Eq. (3) and (4).
   Magnitude (gradient):

(3)

   Orientation (large angle):

(4)

3. Orientation *Binning*
   Orientation Binning is the process of dividing an image into smaller areas called cells. The histogram orientation will divide the various angles in the value of the bin. The value of bins will be distributed by 9 bins with multiple angles of 20° in each bin.
4. Block normalization
   Block normalization is the last step in HOG to avoid significant value variations in the image. Block formation is useful for avoiding changes in intensity and contrast in an image. There are several block-level histogram normalization schemes and one of the methods used to perform block normalization is L1-sqrt, which can be calculated using Eq. (5).

(5)

Backpropagation Neural Network

An artificial neural network is a mathematical model derived from human cognition which is based on the following assumptions [15]:
1. The processing of information occurs in the neuron elements.
2. Information will flow between nerve cells/neurons through a link.
3. Each link has an appropriate weight.
4. Each nerve cell will be an activation function of the weighted summation information that enters it to determine its output information.

Artificial Neural Networks that use a single screen will have limitations in pattern recognition. This weakness can be overcome by adding one or more hidden layers between the input layer and the output layer. The backpropagation neural network trains a network to recognize the patterns used during training[15]. In simple terms, the architecture of BPNN is shown in Figure 1.

Backpropagation training includes 3 stages: the forward stage, the backward propagation stage, and the weight change stage. The following is an example of a backpropagation training algorithm.

Step 0: Initialize the values of all weights with small random numbers
Step 1: If the termination condition is not met, then do steps 2-8
Step 2: For each training data, do steps 3-8
Stage I: Forward Propagation
Step 3: Each input unit receives the signal and forwards it to the hidden unit above it
Step 4: Counting all outputs in hidden units, using Eq. (6) and (7),

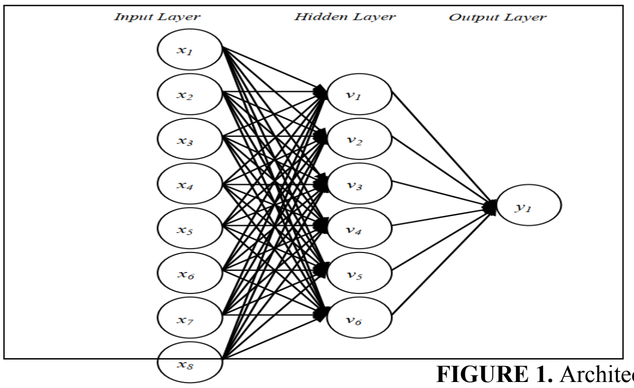

FIGURE 1. Architecture of BPNN

(6)
(7)

Step 5: Calculate all network outputs in the unit, using Eq. (8) and (9),

(8)
(9)

Stage II: Backpropagation
Step 6: Calculate the output unit factor based on the error in each output unit, using Eq. (10)

(10)

is the error unit that will be used in changing the weight of the layer below it (step 7) calculate the rate of change of weight (which will be used later to change the weight) with the acceleration rate(Eq. 11)

(11)

Step 7 : Calculate factor of hidden units based on the error in each hidden unit. Eq. (12)

(12)

Factor hidden units, Eq. (13):

(13)

Calculate the weight change rate (which will be used later to change the weight), can be calculated by Eq. (14)

(14)

Stage III: Changes in weight
Step 8: Calculate all changes in weight Change in weight of the line leading to the output unit, using Eq. 15:

(15)

Change the weight of the line leading to the hidden unit, using Eq. 16:

(16)

Step 9: Checking the stop condition (end of iteration)

Performance

To determine the performance of the applied method, the author uses a confusion matrix as a performance measurement tool for the applied method. Confusion Matrix is used in grouping the classification data into four parts and will be used to calculate the accuracy of the test[16]. The confusion matrix table can be seen in Table 1.

True Positives (TP) indicates that the prediction is true according to the condition that it is true. False Positives (FP) show predictions that are true where in actual conditions, they are false. True Negatives (TN) indicate the prediction is wrong according to the wrong condition. False Negatives (FN) indicate that the prediction is wrong, in which the actual condition is true. From the Confusion Matrix results, the values of accuracy, precision, and recall are obtained[17].

TABLE 1. Confusion Matrix

		True value	
		Right	**Wrong**
Prediction	Right	*True Positive*	*False Positive*
	Wrong	*False Negative*	*True Negative*

Accuracy is the ratio of correct predictions (positive and negative) to the overall data. The calculation of accuracy can be seen in Eq. (17).

(17)

Precision is the ratio of positive correct predictions to the overall positive predicted outcome. The precision calculation can be seen in Eq. (18).

(18)

A recall is the ratio of true positive predictions to the total number of true positive data. The recall calculation can be seen in Eq. (19) [18].

(19)

RESEARCH METHOD

Research Stages

In the implementation of this research, there are several stages. The first stage is conducting a literature study. Literature studies carried out were reading journals, books, and pattern recognition research related to handwriting characters. Next, the dataset was collected. The dataset will be used as training data and test data. After that, the Backpropagation model was made for the recognition of the Bima script handwriting pattern. After the model is completed, it is continued by testing the scenario using HOG. After successfully testing the scenario, the accuracy value of the Bima character pattern recognition using HOG and the Backpropagation model will be obtained. The research flow chart can be seen in Figure 2.

FIGURE 2. Research flow chart

Dataset Collection

The dataset used in this study is the Bima script handwriting. Data were obtained from 20 volunteers, where volunteers were divided into two, namely volunteers from Bima and non-Bima, so the data was varied so that machine learning could be better. Data were collected using F4 size paper which was divided into 12 columns and handwritten using a 1.0 mm ballpoint. Each writes 12 characters for each character with a total number of 22 characters so that the data obtained is 5280 images. The Bima script's handwritten data is then scanned and cropped with the same size, which is 64x64 pixels.

Algorithm Design

There are several stages in model development using HOG feature extraction and Backpropagation classification. The model development flow chart can be seen in Figure 3

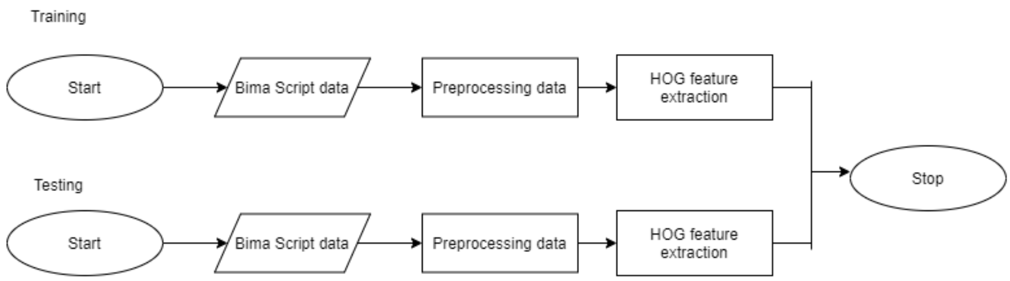

FIGURE 3. Flowchart of program algorithm

Pre-processing

The pre-processing stage is carried out to manipulate the image. The pre-processing stage on the original image is converted into a grayscale color space then resizes for all images with 32x32 pixels. The resizing process is carried out so that the size of the matrix and the features obtained are not too large to ease the computational process. The size of the 32x32 pixel image will produce 324 features with 50% overlap.

Testing Scenario

In the Bima character pattern recognition system, the backpropagation method will be used for the testing phase. Several parameters will be used in feature extraction and classification:

1. The number of bins used is 9 bins (0°,20°,40°,60°,80°,100°,120°,140°,160°) with a block size of 16x16 pixels, 2x2 cells with a size of 8x8 each pixel
2. The number of hidden layers used in the BPNN 1, 2, and 3 Hidden layer models
3. Learning rate as a test parameter used in BPNN is 0.1-0.5
4. The epoch limit as the test parameter used in the BPNN model is 1500 epoch
5. Dropout as test parameters used in the BPNN model are 0.2, 0.3, 0.4, and 0.5
6. Neuron hidden layer as a test parameter used in the BPNN model, namely: 16, 32, 64, 128, 256, and 512 neurons
7. The K-Fold Cross Validation approach is used to determine the combination of training data and test data where 10 K-Folds are used.
8. Feature reduction using correlation with threshold 0.9, 0.8, 0.7

RESULTS AND DISCUSSION

Effect of Number of Neurons, Hidden layer, and dropout

This test aims to determine the effect of the number of neurons, the number of hidden layers, and dropouts because the provisions for the value itself do not determine, so that testing must be carried out to produce the best model results. Tests were carried out using 1, 2, and 3 hidden layers, where each hidden layer was tested using 16,32, 64, 128, 256, and 512 neurons with dropout tests 0.2, 0.3, 0.4, and 0.5. The learning rate used is 0.001 and epoch 1500. In this test, only one scenario is used for the image features, the bin used is 9 Bin (0°,20°,40°,60°,80°,100°,120°, 140°,160°) with a block size of 16x16 pixels, 2x2 cells with a size of 8x8 pixels each, and an image with a size of 32x32 pixels. Test results can be seen in Table 2.

The highest results were obtained on 16 neurons with a value of 9 Bin (0°,20°,40°,60°,80°,100°,120°, 140°,160°), a block size of 16x16 pixels, 2x2 cells with each cell size of 8x8 pixels, and image size of 32x32 pixels are to use 1 hidden layer and dropout of 0.2, resulting in an accuracy of 94 .50%, the precision of 94.99%, recall of 94.18%, and computation time of 210.87 seconds. Test results can be seen in Table 3.

TABLE 2. Test results with 16 neurons

Number of HL	***Dropout***	**Accuracy (%)**	**Precision (%)**	***Recall*** **(%)**	**Time(s)**
1	0.2	**94.50**	**94.99**	**94.18**	210.87
1	0.3	93.80	94.34	93.44	210.00
1	0.4	92.84	94.00	91.76	211.27
1	0.5	92.31	93.92	90.53	**205.52**
2	0.2	92.76	93.46	92.29	224.82
2	0.3	90.35	91.79	88.52	219.81
2	0.4	86.59	91.33	79.67	232.82
2	0.5	82.31	92.90	64.56	215.98
3	0.2	90.96	92.25	89.75	214.91
3	0.3	85.28	90.58	77.61	227.28
3	0.4	73.73	90.73	59.45	225.14
3	0.5	53.06	91.57	32.32	230.38

TABLE 3. Test results with 32 neurons

Number of HL	***Dropout***	**Accuracy (%)**	**Precision (%)**	***Recall*** **(%)**	**Time(s)**
1	0.2	**96.19**	**96.33**	**96, 04**	224.06
1	0.3	95.96	96.16	95.92	**222.96**
1	0.4	95.64	95.81	95.45	231.22
1	0.5	95.35	95.64	95.22	223.90
2	0.2	95.68	95.78	95.54	260.45
2	0.3	94.90	95.15	94.81	260.85
2	0.4	93.99	94.40	93.73	263.18
2	0.5	91.64	92.72	90.58	261.30
3	0.2	94.64	94.95	94.54	294.57
3	0.3	94.16	94.61	93.83	292.66
3	0.4	91.30	92.98	89.86	279.10
3	0.5	82.38	91.76	73.50	285.94

The highest results were obtained on 32 neurons using the same feature extraction value in testing the number of neurons 16. It uses 1 hidden layer and a dropout of 0.2, resulting in an accuracy of 96.19%, precision of 96.33%, recall of 96.04 %, and a computation time is 224.06 seconds. Test results can be seen in Table 4. The highest results obtained on 64 neurons using the same feature extraction value in testing the number of neurons 16, and 32 are using 1 hidden layer and a dropout of 0.4, resulting in an accuracy of 96.59%, precision of 96.73%, recall of 96.55%, and the computation time is 237.99 seconds. Test results can be seen in Table 5.

TABLE 4. Test results with 64 neurons

Number of HL	***Dropout***	**Accuracy (%)**	**Precision (%)**	***Recall*** **(%)**	**Time(s)**
1	0.2	96.43	96.52	96.36	229.61
1	0.3	96.49	96.60	96.47	**217.95**
1	0.4	**96.59**	**96.73**	**96.55**	237.99
1	0.5	96.45	96.56	96.38	259.63
2	0.2	96.19	96.19	96.17	292.76
2	0.3	96.45	96.51	96.38	274.61
2	0.4	95.85	96.03	95.79	306.04
2	0.5	95.71	95,80	95.68	277.67
3	0.2	95.89	95.92	95.85	349.10
3	0.3	96.07	96.17	96.06	336.71
3	0.4	95.79	95.93	95.71	361.04
3	0.5	94.84	95.23	94.58	327,70

The highest results obtained on 128 neurons using the same feature extraction value in testing the number of neurons 16, 32, and 64 are using 1 hidden layer, and a dropout of 0.5, resulting in an accuracy of 97.00%, precision of 97.13%, recall is 96.91%, and computation time is 284.57 seconds. Test results can be seen in Table 6.

The highest results obtained on 256 neurons using the same feature extraction value in testing the number of neurons 16, 32, 64, and 128 are using 2 hidden layers, and a dropout of 0.5, resulting in an accuracy of 97.00%, a precision of 97.06 %, recall is 96.93%, and computation time is 540.83 seconds. Test results can be seen in Table 7.

TABLE 5. Test results with 128 neurons

Number of HL	*Dropout*	Accuracy (%)	Precision (%)	*Recall* (%)	Time(s)
1	0.2	96.64	96.72	96.60	273.93
1	0.3	96.59	96.75	96.45	274.72
1	0.4	96.74	96.92	96.74	298.50
1	0.5	**97.00**	**97.13**	**96.91**	284.57
2	0.2	96.57	96.58	96.53	**255,80**
2	0.3	96.64	96.70	96.64	356.81
2	0.4	96.62	96.68	96.60	358,87
2	0.5	96.62	96.71	96.59	353.76
3	0.2	96.60	96.68	96.59	430.24
3	0.3	96.30	96.34	96.24	431.10
3	0.4	96.34	96.39	96.32	436.18
3	0.5	96.43	96.58	96.30	430.12

TABLE 6. Test results with 256 neurons

Number of HL	*Dropout*	Accuracy (%)	Precision (%)	*Recall* (%)	Time(s)
1	0.2	96.45	96.60	96.40	**357.56**
1	0.3	96.49	96.64	96.49	369.59
1	0.4	96.72	96.90	96.70	386.42
1	0.5	96.87	97.00	96.79	404.19
2	0.2	96.62	96.72	96.59	523.23
2	0.3	96.72	96.81	96.68	516.08
2	0.4	96.89	96.91	96.89	557.22
2	0.5	**97.00**	**97.06**	**96.93**	540.83
3	0.2	96.60	96.66	96.59	717.64
3	0.3	96.93	96.93	96.93	722.21
3	0.4	96.89	96.96	96.83	722.83
3	0.5	96.85	96.92	96.85	721.73

The highest results obtained on 512 neurons using the same feature extraction value in testing the number of neurons 16, 32, 64, 128, and 256 are using 3 hidden layers, and a dropout of 0.5, resulting in an accuracy of 96.79%, a precision of 96 .89%, recall is 96.79%, and computation time is 1400.04 seconds.

TABLE 7. Test results with 512 neurons

Number of HL	*Dropout*	Accuracy (%)	Precision (%)	*Recall* (%)	Time(s)
1	0.2	96.30	96.39	96.26	542.06
1	0.3	96.66	96.84	96.60	548,88
1	0.4	96.45	96.62	96.42	545.39
1	0.5	96.66	96.75	96.66	**497.30**
2	0.2	96.43	96.52	96.38	977.55
2	0.3	96.66	96.79	96.66	986,80
2	0.4	96.55	96.58	96.51	997,40
2	0.5	96.81	96.89	**96.81**	987.54
3	0.2	96.32	96.35	96.24	1501.28
3	0.3	96.26	96.32	96.23	1453.78
3	0.4	96.76	96.83	96.74	1423, 25
3	0.5	96.79	96.89	96.79	1400.04

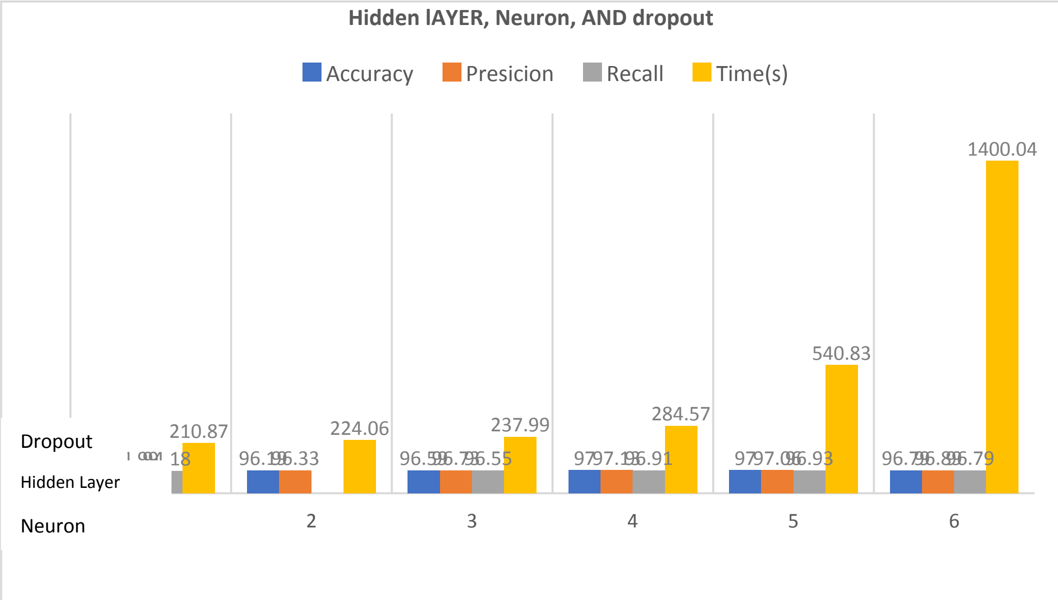

FIGURE 4. Graph of the effect of hidden layers, neurons, and dropouts

From the results of all the tests shown in Figure 4, the Backpropagation model obtained the highest results with 1 hidden layer, 128 neurons, and 0.5 dropouts. The result produces an accuracy of 97.00%, a precision of 97.13%, and a recall of 96.91%. This is because the more hidden layers and neurons in the model or network used, the better the learning process is. However, the computation time will be higher. These results will be used for further testing, testing the effect of the learning rate.

Effect of Learning Rate

This test aims to determine the effect of the learning rate on a backpropagation model that will be built as a parameter to correct the weights in the training process. The learning rate used in this test is between 0.001-0.005. The model used for this test uses a hidden layer, 128 neurons, and 0.5 dropouts. The results obtained are shown in Table 8.

TABLE 8. The results of testing the effect of learning rate

Learning rate	**Accuracy (%)**	**Precision (%)**	***Recall* (%)**	**Time(s)**
0.001	**97.00**	**97.13**	**96.91**	284.57
0.002	96.79	96.89	96.78	275.06
0.003	96.79	96.81	96.78	275.39
0.004	96.72	96.74	96.70	**252.40**
0.005	96.49	96.49	96.47	261.43

The highest results obtained in testing the effect of learning rate using 1 hidden layer, 128 neurons, and 0.5 dropouts are using a learning rate of 0.001, resulting in an accuracy of 97.00%, precision of 97.13%, and recall is 96.91%. These results will be used to create the next test model.

Effect of Image Size

This test aims to determine the effect of image size on the accuracy that will be generated. In this study, the size of the image to be tested is an image with a size of 32x32, 64x64, and 128x128 pixels using1 hidden layer, 128 neurons, and 0.5 dropouts which are the best results from the previous test, namely testing the effect of learning rate.

TABLE 9. The results of testing the effect of learning rate

Image size **(pixel)**	**Accuracy (%)**	**Precision (%)**	***Recall*** **(%)**	**Time(s)**
32x32	97.00	97.13	96.91	284.57
64x64	**97.70**	**97.72**	**97.65**	**518.29**
128x128	96.49	96.62	96.43	1523.22

The highest results obtained in testing the effect of image size using 1 hidden layer, 128 neurons, and 0.5 dropouts, and learning rate of 0.001 is to use an image size of 64x64 pixels, resulting in an accuracy of 97.70%, precision of 97.72%, and recall is 97.65%.

Feature Reduction Using Correlation

This test aims to reduce the feature size by performing feature selection using the correlation method. We do this because, from the previous best test results, the computational time obtained is too long for it uses too many features. We use 1 hidden layer, 128 neurons, 0.5 dropouts, a learning rate of 0.001, and an image size of 64x64 pixels in that best test results. The results obtained are shown in Table 10.

From the results of the feature selection correlation test table, it is obtained that the accuracy is 97.61%, the precision is 97.63%, the recall is 97.55%, and the computation time is 558.92 seconds. From the results above, it can be concluded that the accuracy results after the feature is reduced are not too far from the results that have not been reduced. But the computational time obtained is also not too far away and even exceeds the computation time before the feature is reduced.

TABLE 10. Feature selection correlation test results

Threshold	**Number of features**	**Accuracy (%)**	**Precision (%)**	***Recall*** **(%)**	**Time(s)**
0.9	**1069**	**97.61**	**97.63**	**97.55**	**558.92**
0.8	762	97.08	97.19	97.04	492.25
0.7	545	96.51	96.56	96.43	439.53

CONCLUSIONS AND SUGGESTIONS

Based on the research that has been done, it can be concluded that the HOG method works quite well in classifying the Bima script handwriting using backpropagation. It is achieved by obtaining the best backpropagation model using 1 hidden layer, 128 neurons, 0.5 dropouts, 1500 epochs, and 0,001 learning rate with an image size of 64x64 pixels. The results obtained are 97.70% accuracy, 97.72% precision, and 97.65% recall. This result can be produced because the network or model will learn less if the hidden layer and neurons are used too little combined with dropout values. After all, the basic concept of dropout is to delete random neuron values so that the network for learning will decrease. Meanwhile, using a hidden layer and too many neurons will take a long time to compute even though the accuracy, precision, and recall values will consistently be of good value. The difference in image size affects the computation time because more features will be obtained, but the accuracy, precision, and recall values are not significantly different.

To develop the next Bima script handwriting classification research, the authors suggest combining the HOG method with a better feature reduction method to reduce computation time. Then, we suggest the next researchers try several combinations of bin, block, and cell values in HOG feature extraction to determine the value of the extraction combination which feature is better to use in the backpropagation model.

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