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Classification Of Batik Images Using Multilayer Perceptron With Histogram Of Oriented Gradient Feature Extraction

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Abstract. Batik is one of the hereditary cultural heritages which has a high aesthetic value and a deep philosophy. Batik is one of the cultural icons from Indonesia which was awarded as a cultural heritage from UNESCO on October 2, 2009. Currently, Indonesian batik has various types of motifs and different patterns, which are scattered in Indonesia with their names and meanings. The many batik patterns in Indonesia make it difficult to identify batik motifs, especially for the common people. To overcome this problem, it is necessary to have a batik classification system with a high level of accuracy, so that everyone can recognize the batik pattern easily. In this study, the Histogram Of Oriented Gradient method **was** used as a feature extraction process to obtain batik density and Multilayer Perceptron as a classification method to determine the level of accuracy. The result of the level of accuracy obtained for each batik motif has a different level of accuracy. This is because the batik motifs have unique patterns and shapes that are not specific. The level of income obtained was 83.4 %. From the results of the study concluded that the use of the Histogram Of Oriented Gradient method as a feature extraction method, the Multilayer Perceptron as a classifier can be applied for image classification on batik.

Keywords: Batik, Image, Histogram Of Oriented Gradient, Multilayer Perceptron.

Abbreviations: UNESCO (United Nations Educational, Scientific and Cultural Organization), BOF (Bag of Features), SIFT (Scale-invariant Feature Transform) SVM (Support Vector Machine), MLP (Multilayer perceptron), ANN (Artificial Neural Network), HOG (Histogram Of Oriented Gradient).

Running title: Classification Of Batik Images Using Multilayer Perceptron.

INTRODUCTION

Batik is one of the artistic heritage of the ancestors that have been established by UNESCO as a cultural heritage of the Indonesian nation internationally on October 2, 2009 (Steelyana, 2012)**.** Based on the field of art, batik is a two-dimensional painting, where the cloth is the medium of painting. Batik has high value and charisma. Various kinds of batik motifs have been produced from generation to generation, where these motifs contain the meaning of the ancestors of animism and dynamism (Muwafiq & Pamungkas, 2020). Currently, there are hundreds of batik cloth motifs spread across Indonesia which sometimes have their names and meanings. The motifs of batik are based on the shapes and patterns of the paintings depicted. A large number of batik patterns in Indonesia make it difficult to identify motifs, especially for ordinary people (Mawan, 2020).

Based on its development, Indonesian batik is centered on the island of Java, especially Jogja, Solo, and Pekalongan which then spreads to all regions in Indonesia with their characteristics. In its development, batik has a historical value that is still maintained today as a tradition and national culture that is invaluable (Efendi & M, 2016).

The growth of batik motifs in Indonesia is also increasing. Even today, not only written batik is available but there is also digital batik (*print*) which is popular. The many batik patterns in Indonesia make it difficult to identify the pattern (Kasim & Harjoko, 2017). Various batik textures, for example, thick line border patterns with high contrast values or thin line edges that have low contrast values. The size of the edge of the line, there is thick and thin as well as the main batik ornaments large, medium, and small.

Several studies have been conducted using methods that have been applied to batik image classification research, such as SIFT features and support vector machines (Azhar, et al., 2015), wavelet transform and fuzzy neural networks (Rangkuti, 2014), and Deep Convolutional Network Transfer Learning (Gultom, et al., 2018). In the study discusses the classification of batik by using SIFT Feature Extraction, Bag of Features, and Support Vector Machine shows that the Combination of Bag of Features (BOF) extracted using Scale-invariant Feature Transform (SIFT) and Support Vector Machine (SVM) classifier roommates had been successfully implemented in various classification tasks such as hand gesture, natural images, vehicle images, is applied to batik image classification in this study. The experimental results show that the average accuracy of this method reaches 97.67%, 95.47%, and 79% in a normal image, rotated image, and scaled image, respectively.

In a study (Yohannes & Rivan, 2020) which discusses the Use of Global Contrast Saliency and the Histogram of Oriented Gradient as Features for Classification of Mammal Animals, it was found that the saliency-based HOG method was able to extract features on the faces of mammals on the front view well. The k-NN method as a classification method can classify the types of mammals for each k with different levels of precision, recall, and accuracy. The k-NN method with city block distance is better than the euclidean distance in the classification of mammal species with k = 9. Mammals that can be recognized well are tigers. While mammals that cannot be recognized properly are sheep.

In a study (Wulansari, et al., 2016) which discusses the classification of EEG signals using Power Spectral Density and Multilayer Perceptron, it was found that this study produced a system that can classify EEG signals against sound stimulation. This system has been tested using the learning rate parameters 0.01 and 0.1. For accuracy using a learning rate of 0.01 of 54.16% for test data and 58.33% for training data, while learning rate of 0.1 results in an accuracy of 62.5% for test data and 75% for training data.

In a previous study, no researcher discusses the use of Multilayer Perceptron and Histogram Of Oriented Gradient (HOG) as its extraction .M aka with the researchers want to research the classification of batik using Multilayer Perceptron and extraction of features from Histogram Of Oriented Gradient (HOG) is expected to be able to assist and introduce the types of batik based on the respective class of batik patterns so that they can be easily recognized by its features through simple and easy-to-use technology.

MATERIALS AND METHODS

Study Area

1. Batik

Batik is one of the cultural heritages in Indonesia. There are various batik patterns found in Indonesia. Batik has also been recognized by the world as a cultural heritage of Indonesia that has been established by UNESCO. As a cultural heritage, various efforts have been made to preserve batik from its extinction. Traditionally, batik patterns were developed manually. On the other hand, batik patterns are developed with computational techniques that can improve batik processing with new pattern designs that are made faster and more diverse (KUSUMA, 2017).

A batik is a form of fine art in textiles that are produced using traditional drawing techniques originating from Indonesia. For the Javanese, batik is a traditional dress that is inseparable from their cultural identity. The visual form of batik cloth describes the expressions and values of life that underlie people's lives (Tresnadi & Sachari, 2015).

Batik is a type of clothing product that has grown rapidly in Java for several hundred years ago. Most Indonesian people have analyzed batik in both its traditional and modern patterns. The history of batik in Indonesia is closely related to the development of the Majapahit kingdom and the spread of Islamic teachings in Java. The word batik itself in Javanese means writing. Batik is a term used to describe a patterned cloth made with a resist technique using wax material. The batik technique itself has been known for thousands of years (Nurainun, et al., 2008).

2. Multilayer Perceptron.

The concept of artificial neural networks was founded in 1943. Then, in 1958, the first artificial neural network was introduced with the name perceptron. In 1986, Neural Networks became more widely known (Agirre-Basurko, et al., 2006) (Santoso, et al., 2020). Multilayer perceptron (MLP) is an artificial neural network (ANN) that is best used to resolve cases of non-linear and non-deterministic, k ethics given input high dimension than the output of real value (the result of human-readable). MLP can also reduce the negative impact of data errors (LI, et al., 2019). Therefore, compared to deterministic models or general linear statistical methods, the MLP model has excellent nonlinear mapping capabilities to perform LSP (Huanga, et al., 2017) (Huang, et al., 2017).

MLP has been implemented successfully to solve difficult and varied problems using the Error Back Propagation (EBP) algorithm. MLP is a multilayer feed-forward network model with one-way error propagation, and it is one of the most widely used ANNs. MLP can solve the problem of pattern recognition, time series prediction, and so on (Fortin, et al., 2014). The MLP model contains multiple perceptron layers which are connected in a feed-forward manner. The output of the last layer ends with a soft-max function to use it as a classifier (GAIKWAD, et al., 2019).

The MLP model consists of the input, hidden, and output layers, all of which are composed of similar neurons. The relationships between the input and hidden layers and between the hidden and output layers are all processed by weight values. By training and testing these weight values, the neural network forms an orderly and stable structure with decision-making capabilities. Because MLP with one hidden layer can approach nonlinear systems with arbitrary accuracy, this MLP model is a single hidden layer (Guo, et al., 2015).

This learning process for ANN has a substantial effect on its efficiency. The feed-forward neural network has a specially supervised form. They consist of a set of processing elements called "neurons". These neurons are distributed in many stacked layers where each layer is fully connected with the next layer. The MLP architecture can be described as follows: the first layer that feeds the network with input variables is denoted as the input layer, the last layer is called the output layer, and all layers between the input and output layers are called the hidden layer (Basheer & Hajmeer, 2000). The multilayer perceptron neural network is one of the most commonly applied forward-feed neural networks. Neurons in the MLP are interconnected in a one-way manner. The connections between neurons are represented by weights which are the actual numbers that lie in the interval. The basic architecture of the MLP neural network can be described. Each layer in the MLP can be described mathematically, as illustrated in the following equation :

$$f_i^l = \emptyset\left(u_i^{(l)}\right) = \emptyset\left(\sum_{j=1}^{n_l} O_j^{(l-1)} w_{j,i}^{(l)} + w_{0,i}^{(l)}\right), 1 \leq l \leq L$$

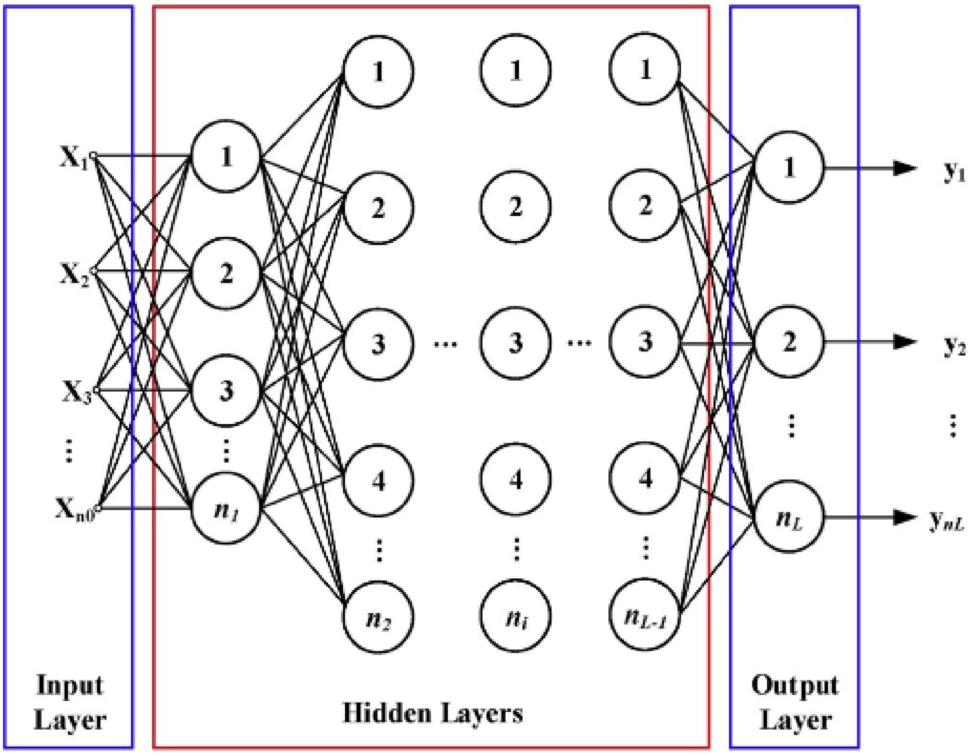


Figure 1. Arsi texture basic neural network Multilayer Perceptron.
Source: (Ewees, et al., 2020).

Where $\emptyset()$ is the activation function of that layer. Usually configured as a nonlinear tangent hyperbolic function for the intermediate layer, which is also known as the hidden layer, and a linear function for generating the output layer. The index ℓ identifies the real layer in the non-input layer network L, nℓ represents the number of neurons of the layer ℓ $\emptyset_i^l$ represents the output of neuron i in the real layer ℓ, $w_{j,i}^{(l)}, 1 \leq l \leq n_{l-1}$ is the weight associated for the connection of neuron i from layer ℓ with neurons from the previous layer ℓ-1, $w_{0,i}^{(l)}$ and is bias neuron i from a real layer. Vectors to outer layer with $l = 0$ length n_0 corresponding to the vector characteristics input, $O^0 = x$.. Furthermore, the vector output of the last layer ℓ = L length n_L, which is the output layer of the network, coinciding den gan network results, $O^L = y$ (Ewees, et al., 2020).

3. Histogram Of Oriented Gradient (HOG).

Histogram of Oriented Gradients (HOG) is a method for discriminating features. This feature is a description of the histogram based on the edges and orientation that applies to object recognition. The appearance and shape of local objects can often be characterized quite well by the distribution of the gradient of local intensity or the direction of the edges, although it is not known exactly where the gradient or the edges will fit. The way HOG works are by calculating the gradient value of a certain image area. Each image has characteristics indicated by the gradient value obtained by dividing the image into the smallest area called cells (Muhathir, et al., 2020). The histogram of oriented gradient (HOG) descriptor is a representative feature extraction method (Tanjung & Muhathir, 2020).

The histogram of oriented gradient (HOG) descriptor is a representative feature extraction method. The HOG technique was developed by Dalal and Triggs (Dalal & Triggs, 2005) for human recognition. To implement the HOG, the image is first divided into cells and a gradient orientation histogram is calculated for the pixels in the cells. The resulting histograms are then combined to represent image descriptors (Tanjung & Muhathir, 2020).

The input image is extracted by using the HOG into a square cell. HOG main principle is that the object in the image display can be illustrated by the distribution of the intensity gradient, and descriptors can be implemented by dividing the image into cells or regions - the area is small. Furthermore, the histogram gradient direction in each cell is compiled, this histogram represents the descriptors. And also the histogram can be normalized by calculating the intensity through a wider image area, this area is called a block, and then normalizing all cells in the block (Devella, 2018).

Procedure

1. Dataset

The dataset used in this study is the sample taken from batik 300 datasets with 50 types and 6 pictures for each type. This study uses 7 types of samples which by adding changes in the rotation angle of -5^0, -15^0, -25^0, -35^0, -45^0, +5^0, +15^0, +25^0, +35^0, + 45^0. Total batik samples for each ma sing kind totaling 66 samples.

2. Research Steps

In general, the research steps modeled in this study are illustrated in the following figure:

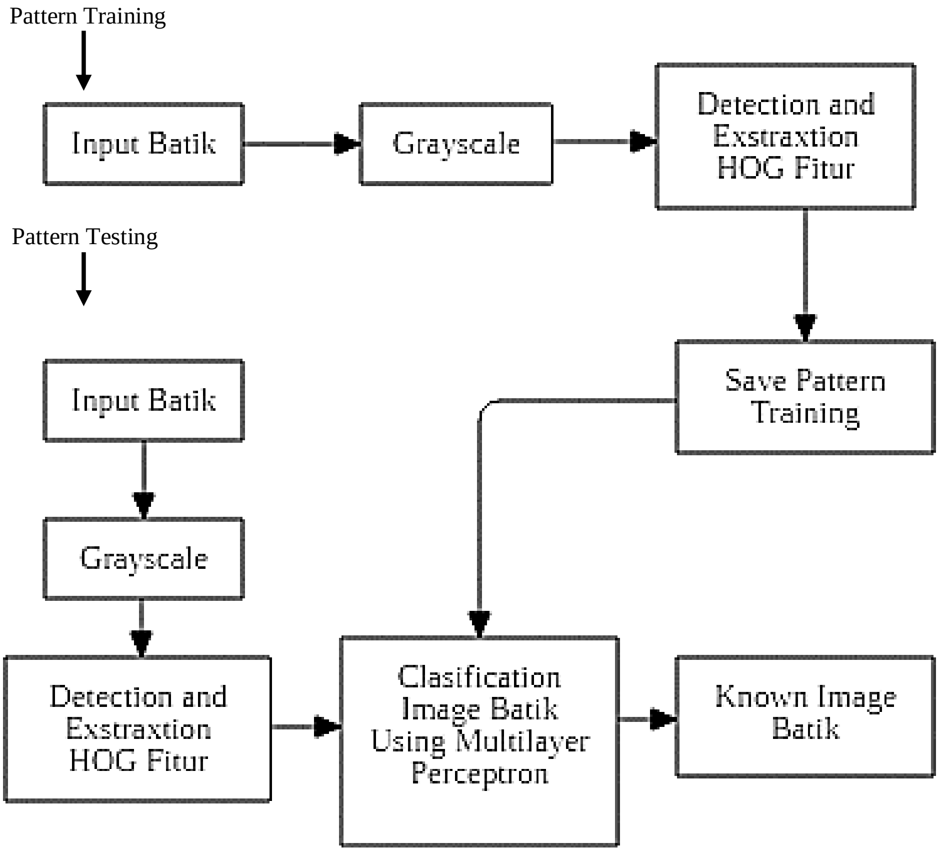


Figure 2. General Research Steps.
Source: (Muhathir, et al., 2017) (Muhathir, et al., 2019).

Figure 2 shows the research steps that will be carried out with two processes, first the training process, the training process is a process in extracting data (starting with minimizing the color space in the image from the three color spaces R, G, B into one color space, namely grayscale and extracting with utilizing extraction features HOG) and extract the results of i is stored as a model pattern to be used in the testing process, the testing process is the process of matching the model pattern that has been in training to utilize Multilayer Perceptron is a classification method.

RESULTS AND DISCUSSION

1. Batik Samples.

The batik training sample used in this study was taken from a 300 batik dataset with 50 types and 6 pictures for each type. In this study, 7 types of samples were used by adding changes in the rotation angle of -5^0, -15^0, -25^0, -35^0, -45^0, +5^0, +15^0, +25^0, +35^0, + 45^0. The total sample of batik for each type is 66 samples. Here are some batik samples:

Figure 3. Batik A.

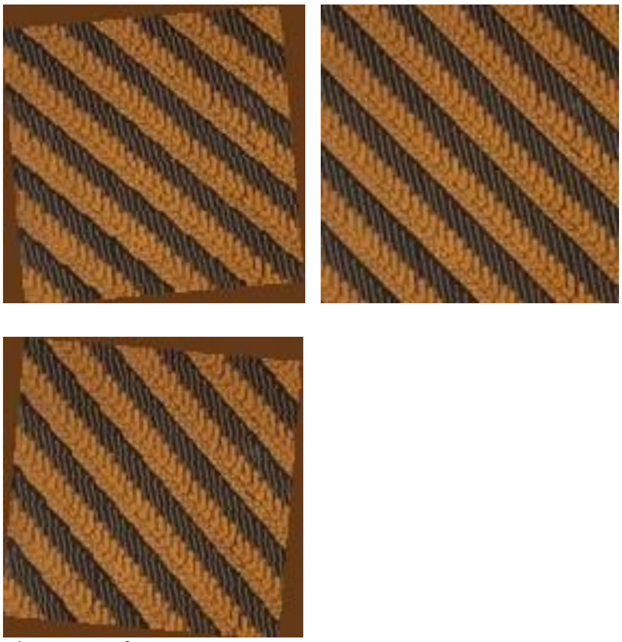
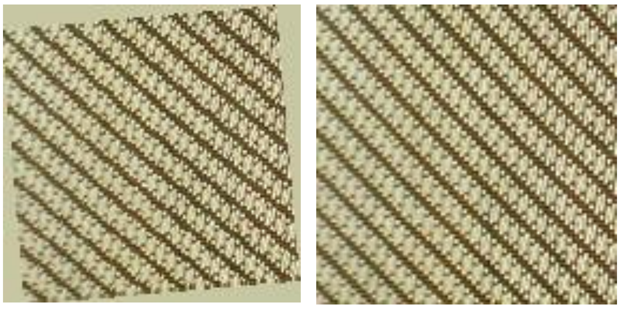


Figure 4. Batik B.



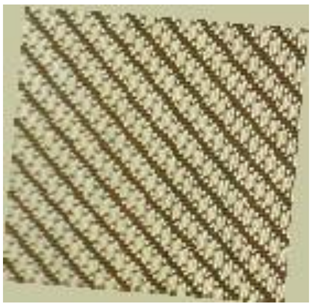


Figure 5. Batik C.

Figure 6. Batik D.

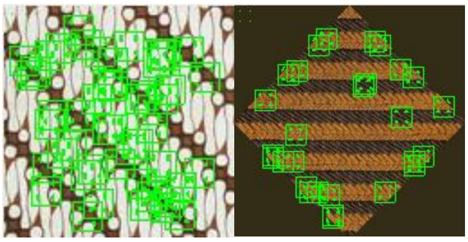
Figure 7. Batik E.

Figure 8. Batik F.

Figure 9. Batik G.

2. HOG Detection Features

The results of the detection of HOG features are indicated by a cube mapping on the image,
Figure 10 shows the results of Hog feature detection on batik.



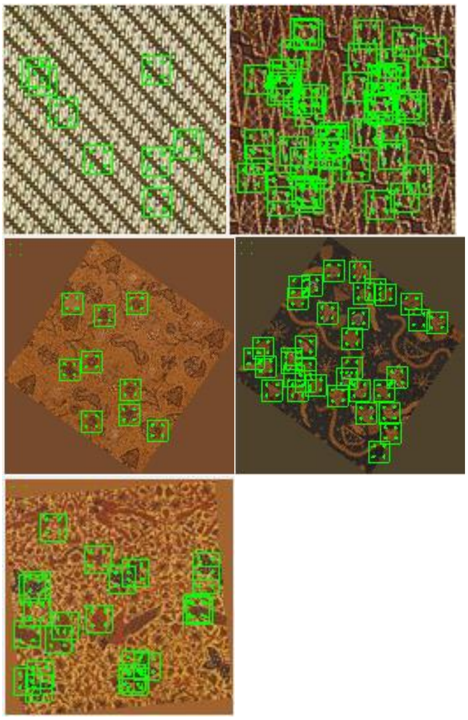


Figure 10. HOG Detection Results.

3. Classification Results.

The results of testing the classification of Batik by using Multilayer Perceptron and extraction of features from Histogram Of Oriented Gradient (HOG) with Cross-Validation 10 kFold can dil Ihat in Table 1.

Table 1. Result of classification of batik using MLP with Cross-Validation 10 kFold.

Batik Class	Accuracy	Precision	Recall	F-Measure	ROC Area
Batik A	0.954	0.984	0.954	0.969	1
Batik B	0.8	0.881	0.8	0.839	0.986
Batik C	0.907	0843	0.907	0.874	0.994
Batik D	0.923	0.8	0.923	0.857	0.984
Batik E	0.769	0.794	0.769	0.781	0.983
Batik F	0.692	0.763	0.692	0.726	0.79
Batik G	0.738	0.727	0.738	0.733	0816
Weighted Avg.	0826	0827	0826	0826	0.936

In table 1. Displays the classification results of batik using the Multilayer Perceptron and the extraction of the Histogram Of Oriented Gradient (HOG) feature with the number of samples, p there is a test of the results of batik classification using the Multilayer Perceptron with a Cross-Validation of 10 kFold the results of the classification of batik with an average accuracy value 0.826, precision 0.827, recall 0.826, F-Measure 0.826, and ROC Area 0.936.

Table 2. Result of classification of batik using MLP with Cross-Validation 5 kFold.

Batik Class	Accuracy	Precision	Recall	F-Measure	ROC Area
Batik A	0.985	0.955	0.985	0.97	0.999

Batik B	0846	0.887	0846	0866	0.986
Batik C	0.938	0.859	0.938	0897	0.992
Batik D	0.877	0.792	0.877	0832	0.984
Batik E	0.8	0.825	0.8	0813	0.981
Batik F	0.662	0.782	0.662	0.717	0.769
Batik G	0.785	0.785	0.785	0.785	0.859
Weighted Avg.	**0842**	0841	0842	0840	0.939

In table 2. Displays the results of the classification of batik using the Multilayer Perceptron and the extraction of the Histogram Of Oriented Gradient (HOG) feature with the number of samples , p there is a test of the results of batik classification using the Multilayer Perceptron with Cross-Validation 5 kFold the results of the batik classification with an average accuracy 0.842, precision 0.841, recall 0.842, F-Measure 0.840, and ROC Area 0.939.

CONCLUSIONS

The results showed that the classification of batik by using Multilayer Perceptron and extraction of features from Histogram Of Oriented Gradient (HOG) with Cross-Validation 5 kFold produce a higher level of accuracy when compared with the Cross-Validation 10 kFold .

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