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UTILIZATION OF MULWIN-LBP ALGORITHM TO SUPPORT BATIK IMAGE CLASSIFICATION

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ABSTRACT

The variety of Batik motifs is always increasing in every year so that it is increasingly difficult to identify them. Based on these facts, Batik pattern recognition becomes important to help people to know Batik patterns. By Doing the research could improve reliability in recognizing and understanding Batik patterns originating from several regions in Indonesia by using the Mulwin-LBP algorithm to support image classification. This algorithm carried out 3 and 4 different types of windows to get optimal feature extraction results. With this algorithm, the resulting classification accuracy is reliable and optimal. Basically, this algorithm uses multi-windows such as 6x6, 9x9, 12x12, and 15x15 or a combination of 3 or 4 windows to get optimal image features. Some experiment were conducted to determine the reliability of the algorithm. Among them, the number of training images is more than the test image, but the accuracy and precision of classification can reach more than 76%. However, if the test is carried out by adding image classes, including the number of training images, and test images, the resulting classification accuracy reaches more than 82%. Even in other experiments with more training images than test images, the image conditions have the same rotation but different scales, for classification accuracy can reach more than 98% with the number of classes between 10 to 12 classes.

Keywords: *Mulwin-LBP, Rotation, Classification, Batik, Pattern, Reliable, Optimal, Scales*

1. INTRODUCTION

In general, Batik is one of the most famous traditional clothes from Indonesia. With various patterns and patterns, Batik has become very well known to foreign countries. Even the world community has also recognized the beauty of the patterns that exist in Batik so that it is widely used both at formal and informal events [1]. With the existence of Batik like this, it is felt necessary to conduct continuous research on all patterns of Batik fabrics which are already in great demand by many countries. Hence, continuous research on understanding it is necessary to preserve it. Despite being one of the most common research tasks, Batik's pattern automatic classification still requires some improvement especially in regards to the invariance dilemma [2][3]. Based on the types of basic motifs and regular patterns are owned they becomes the basis for the origin of the Batik cloth. The problem is that not all data or information about Batik motifs in each region can be well documented which is the cultural heritage of the Indonesian nation. Attention to Indonesian Batik motifs needs to be done so that they are not lost as the cultural heritage of the Indonesian people. Even though the Name of Batik is derived from Javanese language, namely ngembat (throw) and dots (writing some dots on fabric or other materials) [4]. The Indonesian government to promote Batik Clothing as the traditional clothing of the Indonesian nation has carried out some activities. At several international meetings attended by foreign countries, the government began to explain the existence of Batik cloth belonging to the Indonesian nation [5]. This study identifies various Batik motifs and divides them into several classes of Batik motifs so that they are easy to identify [6]. For that, we need information about Batik motifs or traditional clothing owned by each region so that documentation can be carried out properly and accurately. The documentation process need to maintain the cultural heritage of the Indonesian nation which has begun to be recognized by neighboring countries. [8]. Thus, Batik has a variety of motifs and is the main identity of Indonesian culture that must be preserved. However, the image of the Batik has motif characteristics that do not match the rotation and scale of the same image. Because taking pictures will change the zoom in or zoom out on the camera. Thus the image pattern looks bigger or smaller than the original image [7]. The problem is that it is still difficult to recognize Batik patterns even though certain feature extraction algorithms had been used to support their classification [9]. This study aims to develop a reliable feature extraction algorithm to support image classification with very diverse patterns while also changing rotation and scale. So that this algorithm can improve reliability performance to support the invariant dilemma in classifying them. Batik's pattern automatic classification still requires some improvement especially in regards to Batik images that experience multiple scale changes and rotations simultaneously for each image. Mulwin-LBP Algorithm is the feature extraction to solve the invariance dilemma in image Batik classification. Types of Batik motifs, can be seen in Figure 1.0 :

Figure 1. Types of Batik's Pattern

2. THE PROPOSED METHOD

A feature extraction method is required to support the classification of images rotated at various angles and scaled by a few percent of the original image. Because the system must recognize images from various sources [11]. In testing the classification accuracy of Batik images that experience changes in image rotation, it reaches an accuracy of between 65 - 85% with the feature extraction method using a complete robust local binary pattern [8]. There are two combinations of feature extraction methods, namely Speeded Up Robust Feature (SURF) and Scale Invariant Feature Transform (SIFT) apart from being supported by the classification method using the Deep convolution method [15].

The Batik image classification research would carry out one of Convolutional Neural Network architecture with the 70.84% accuracy. The system can be used to classify the Batik image motif accurately [14]. In addition, Batik images research used the machine learning development by using fuzzy neural network algorithm. Meanwhile In feature extraction process used the wavelet transform method. With the classification accuracy of the trained image reached more than 95% [19]. In another study, we carried out classification accuracy value of neural networks in Batik class with their texture features, their shape, and the combination of texture and shape features. The result was obtained using shape feature had the lowest accuracy rate of 80.95% but the combination of texture and shape features produced a greater value of accuracy by 90.48% [21]. In the implementation of this research, it was hoped that would be able to improve the ability to perform the classification process on batik images that have changed rotation and image scale simultaneously. With the development of feature extraction algorithms hoped that it can support batik classification .

In supporting the Batik image classification process with several conditions, an appropriate and reliable feature extraction algorithm is needed to be able to recognize Batik images from various sources such as on the internet, magazines, direct retrieval of Batik image motifs through digital cameras. In Development this new feature extraction algorithm is called Mulwin-LBP Algorithm. Basically, this algorithm combines the advantages of the Multiscale block local binary pattern, which can describe in detail the feature structure on a wider scale, so that it is not only a micro pattern structure but also a macro pattern [16]. In another study of images that have texture and shape characteristics, one of which is the refinement of the complete local binary pattern (CLBP) algorithm. Basically, this algorithm is the development of the local binary pattern algorithm in supporting the Batik image recognition process which changes in rotation and slightly changes in scale. Basically the CRLBP algorithm is perfecting the complete local binary pattern (CLBP) method, by adding a feature of the magnitude value for the difference between the center pixel and neighboring pixels (CLBP_M) and the characteristics of the center pixel of the overall image intensity value (CLBP_C) [17]. The Robust Local Binary Pattern algorithm was improved and developed, especially on the central pixel value which would affect the LBP value, this algorithm was called Completed Robust Local Binary Pattern. This algorithm was carried out to extract more complete texture and shape characteristics [18]. However, the MulWin-LBP algorithm is a development of the extended center symmetric local binary pattern (XCS-LBP) algorithm which is very suitable and precise for images that are dominant in micro-feature structures, including being able to increase the speed in determining frequency values, when compared to LBP in determining the number of frequencies. The XCS-LBP algorithm is quite suitable to reduce noise in the local image description and produce a shorter histogram, without ignoring the local characteristics of the image pattern structure [12].

Basically In the Mulwin-LBP algorithm implemented multi-windows with sizes 6×6, 9×9, 12×12 and 15×15 pixel where the window will be divided into sub windows to get an optimal feature extract. In every window would be divided into 9 sub-windows without overlapping like a 6x6 window will be processed into 9 sub-windows of 2 × 2 size, a 9x9 window would be processed with 3x3 sub-windows, a 12×12 sized window would be processed with sub-sized windows 4x4 windows and 15x15 windows with 5x5 sub-windows. With a variety of window sizes, this will be able to adopt the problem if the image is scaled up to 200 percent of the original image, besides being able to solve the problem of rotation. Every sub-window process will be sent to a 1 (one) dimensional array to parameter g between arrays g [0] to g [8], then it will then be calculated using the XCS-LBP formula. Every time you finish processing 1 window, the system will move 1 pixel to the right and carry out the process as above. The process steps will be continued to get the accumulated value for each window. You can see the research method diagram in Figure 2.

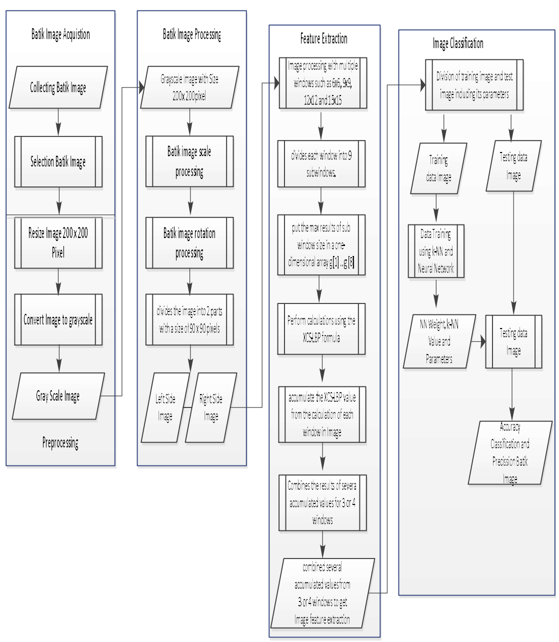

Figure 2. Research Method Diagram for Batik Image Classification

Figure 2 illustrates several processes that will be carried out starting from data collection, preprocessing, feature extraction, and image classification. However, to support the feature extraction process, the Mulwin-LBP algorithm will be used to support the classification accuracy performance to be more optimal and invariant to changes in rotation and scale. In the current study, there are several developments to support classification accuracy compared to previous studies. The first is for the calculation of the sub window used by the maximum value. In contrast to the previous one is the average value. So the frequency is large values at small values. But now by using the maximum value, for the frequency results the values are more evenly distributed for both small values and large values. Second, each image must undergo a rotation and scale process with a size of 200 x 200, followed by division into left and right images measuring 90 x 90. This is different from previous studies. Third. The image merging process only combines 3 types or 4 different window types. Merging process with the concatenation function. For feature extraction with a combination of 3 (three) windows with feature values between 1 to 48 and a combination of 4 (four) feature value windows 1 to 64. Even though feature extraction is carried out in different windows, the results will be combined for the frequency value of each window as an image feature value using the concatenation function. Merging 3 windows or 4 windows will result in a new feature extraction consisting of the frequency values of each image. The process stages can be seen in Figure 3.

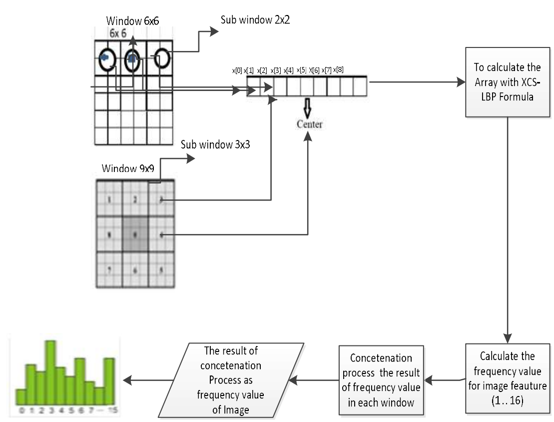

Figure 3. The Mulwin-LBP algorithm stages Used 6x6 window and 9x9 window to extract the image features

In figure 3.0 illustrates the feature image extraction using multiple windows. Each image is processed with a 6x6 window with a 2x2 sub window and a 9x9 window with a 3x3 sub window. The image extraction results in each window will be combined with the concatenation function. The combination of the results of image feature extraction with different windows will support the classification of Batik images.

3. RESEARCH METHOD

In determining the class on the batik pattern cloth to be studied are 9 and 12 classes / Batik motifs

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consisting of Kawung, Ceplok, Lereng, Parang, Nitik, Tambal, Sida drajat, Truntum, Sida Luhur, Sekar Jagat, Tambal and Mega motifs. . In this experiment, the research does not focus on color characteristics, because the basic philosophy of batik motifs in an area is based on texture and shape characteristics. The research scheme in developing a Batik image classification that is invariant to rotation and scaling is divided into 5 main stages, starting from :

1. Collection and Selection Batik image
2. Doing Preprocessing (Grayscale)
3. Batik image processing with scale and rotation differences
4. Doing Feature Extraction of Batik image with MulWin-LBP algorithm
5. Doing Measurement for Classification with using K-NN and ANN.

The stages process in the research scheme of Batik

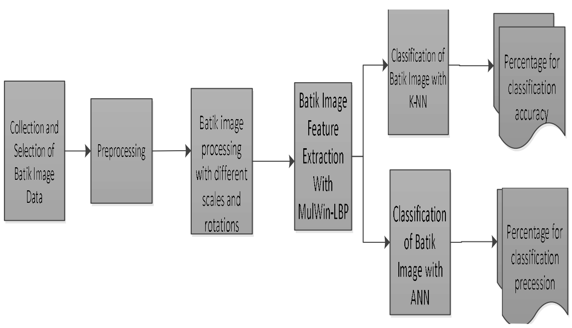

image classification are in Figure 2.

Figure 2. Research schemes for Batik image classification which invariant with scale and rotation

3.1 Batik image processing uses scale and rotation differences

The batik image has undergone a gray color change (grayscale) but the next step is processing the image. Than in the beginning of the batik image with a size of 200 x 200 pixels divided into 2 parts, namely:

1. The image left side is 90 x 90 pixels with overlapping 30, 40 and 50 pixels
2. The image right side is 90 x 90 pixels with overlapping 30, 40 and 50 pixels.

To find out the stages of the original image which are divided into 2 parts but have undergone changes in rotation and scale simultaneously, it can be seen in Figure 3.

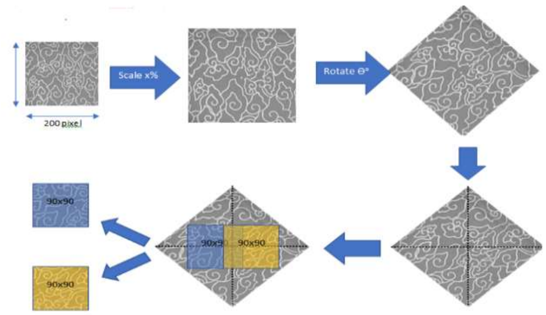

Figure 4 : The Batik images divided the original image into 2 parts that have undergone changes in scale and rotation [11].

In Figure 4 describes the stages of image processing are divided into two parts left and right images with a size of 90 x 90 pixels to obtain optimal feature extraction. It will be processed with several windows such as size 6x6, 9x9, 12x12 and 15x15. Where each window will be processed into 9 sub windows of different size.

3.2 Feature Extraction using MulWin-LBP Algorithm.

An illustration of the MulWin algorithm process in which the division of the left and right images with a size of 90 × 90 pixels using multi-window can be seen in Figure 5.

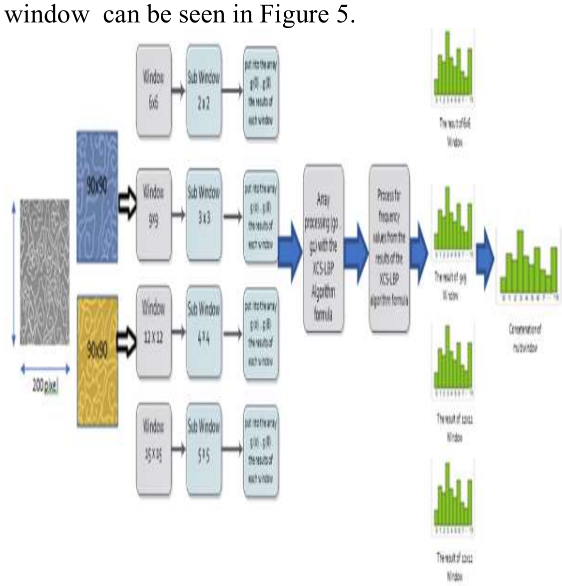

Figure 5. Step of feature extraction of Batik image Using Mulwin-LBP Algorithm

In Figure 5 is a chart process of the Batik image feature extraction process with the MulWin-LBP algorithm. The stages are as follows:

1. To divide of 200 x 200 pixel image into 2 parts with measuring of 90 x 90 pixels with an overlap of 30, 40, 50 pixel.

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2. To continue in processing the images with the size of are 90 x 90 pixels and have undergone a change in scale and rotation are processed with the 6x6, 9x9, 12x12 and 15 x15 windows.
3. In every window is divided into 9 sub windows without overlapping to get the maximum value
4. To deviate the maximum value in each sub window to a 1-dimensional array element with parameter g starting from g [0] to g [8].
5. To do calculation the 1-dimensional array value with the XCS-LBP formula and save it in parameter E.
6. To do calculation the frequency distribution of parameter values E
7. The window would shifts 1 pixel to the right, back to the sequence of process 3, until the rightmost window
8. The window would put down in 1 pixel and to start again to number 3 process.
9. The Window process would stop until the bottom right window.
10. To continue the feature extraction process for the 90 × 90 pixel right image with a different window.
11. To process of features image extraction with other windows such as 9 × 9 window, 12 × 12 window, and 15 × 15 window.
12. To combine between 3 and 4 window to get the optimal feature such as 6-9-12, 6-12-15, 6-9-15, 9-12-15 and 6-9-12-15.
13. After finishing all window process than would be merged with the concatenating function to get the feature value in every image.

3.3 Dataset setup

In this study, 12 classes of Batik images have been processed, where each class consists of 10 Batik image classes so that there are a total of 220 Batik images. For each Batik image that has a scale changed from 90, 100, 120, 140, 150, 160, 180, and 200% of the original image. Furthermore, every change in scale will experience a change in slope starting from 0, 10, 15, 30, 45, 60, 75, 90, 105, 110, 120, 135, 150, 165, 180 degrees. For an illustration of the pattern of Batik images that experience changes in scale and rotation, see Figure 6.0

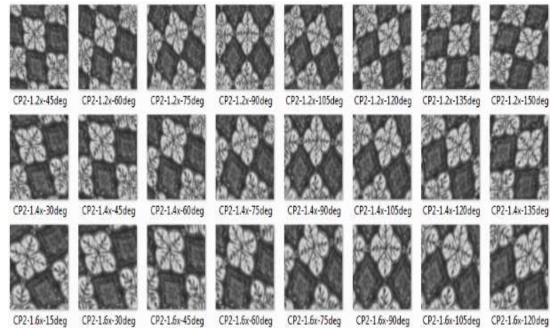

Figure 6. an example of a Batik pattern that has undergone a change in scale and subsequently has a change in slope.

3.4 Classification method using k-NN

In conducting experiments with the k-NN method are as follows:

1. Perform the feature extraction process on the test and training images that have undergone changes in rotation and scale
2. Classify with the kNN method on the test images and training images that have been extracted.
3. The results of the classification processing of the feature-extracted training image will become a classification model, which will be used by the feature-extracted test image to determine the accuracy and precision values.

4. RESULTS AND DISCUSSIONS

In this experiment Several parameters are also used to determine the accuracy of classification consisting of image rotation and image scale, combination of multiple windows (multi-window), number of training images, number of test images, number of image classes, overlap between left and right images, artificial neural network architecture, including the k value in kNN.

4.1 Effect of multi-window and variable k on kNN

In this experiment determine the effect of scale and image rotation, multi-window variation and variation of 3 (three) k values in KNN namely 1, 3 and 5 on the precision value using multi-window variations. The conditions of the image data are as follows:

1. The number of training image (1080 images)
   a Image scale is100, 150
   b image rotation is 0, 10, 110
2. The number of testing image (10800 images)
   a. Image scale is 90, 120, 140, 160, 180
   b. image rotation is 15,30,45,60, 5,90,105,120,135,150,165,180

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3. Image overlapping is 50 pixels and the number of classes is 9 classes.

The results of this experiment are attached in Figure 7.

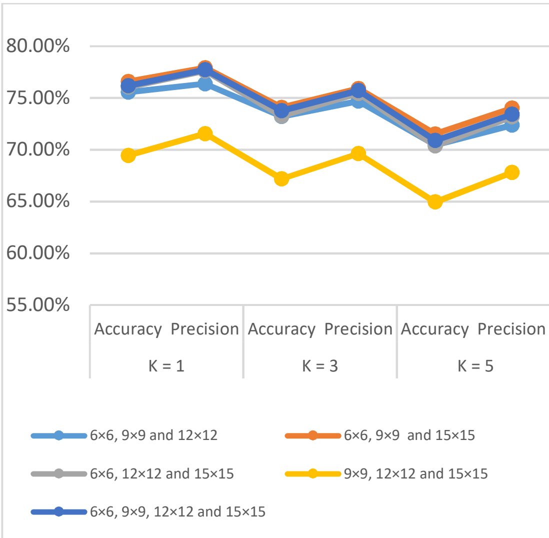

Figure 7.0 Accuracy and precession of image classification based on multi-windows and k on k-NN

In Figure 7 shows the highest accuracy and precision values for the combination of 3 windows, namely in multi-windows 6-9-15 and 6-12-15 with k on kNN = 1 are 76.59% and 77.92%, 76.05% and 77.62%. This experiment also shows the reliability where the ratio of the number of training images and test objectives is 1: 10. Base on this experiment can be concluded that the k value on kNN = 1 has a higher classification accuracy and precision value than the k value at kNN = 3 and 5 for all windows. For that, in the next experiment, we use the k value on kNN = 1.

4.2 Multi-window effect and image overlap

In this experiment determine the multi-window effect and image overlap, including the effect of scale and image rotation on the value of precision and accuracy in image classification using the KNN method. With the experimental image conditions as follows:

1. The number of training image (2160 images)
   a. Image scale is90, 100, 150
   b. image rotation is 0,10,30,110
2. The number of testing image (9900 images)
   a. Image scale is80, 120, 140, 160, 180
   b. image rotation is 15, 45,60,75,90,105, 120, 135, 150, 165, 180
3. Image Overlapping is 30, 40, and 50 pixel
4. The number of image classes is 12 classes ;
5. For k on kNN = 1.

The results the experiment are attached in Figure 8.

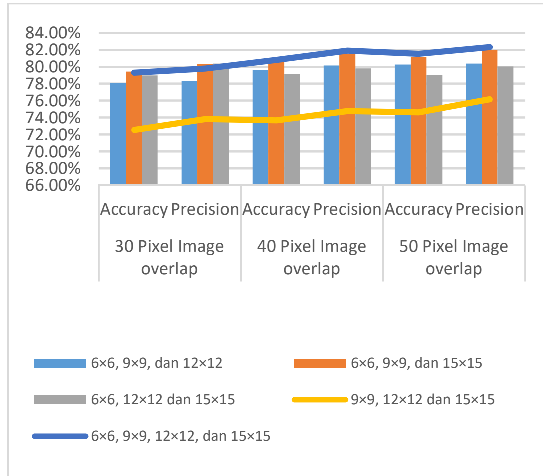

Figure 8 Accuracy and precision of image classification based on multi-windows and several Image overla

In Figure 8 shows the highest value of accuracy and precision using a combination of 3 (three) windows, namely the combination of 4 windows is 6-9-12-15 with an overlap of 40 pixel images is 80.81% and 81.91% and 50 pixels is 81.54% and 82.32%. In this experiment also shows the reliability where the ratio of the number of training images and test objectives is 1:4. However, the classification precision and accuracy can reach more than 82%.

4.3 Multi-window Effect and the number of image classes

In this experiment determine the multi-window effect and the type of image class, including the effect of image scale and image rotation on the value of accuracy and precision in image classification. Beside The image rotation is the same but different in scale to the training image and the test image. The image conditions are as follows:

1. The number of training images (13,440 images)
   a. Image scale is90, 100, 110, 120, 130, 140, 150, 200
   b. image rotation is 0, 15, 30, 45, 60, 90,120
2. The Number of testing images (8,400 images)
   a. Image scale is 80, 160, 170, 180, 190
   b image rotation is 0, 15, 30, 45, 60, 90, 120
3. Image Overlapping is 50 pixels ; k on kNN = 1

The results of experiment are attached in Figure 9.

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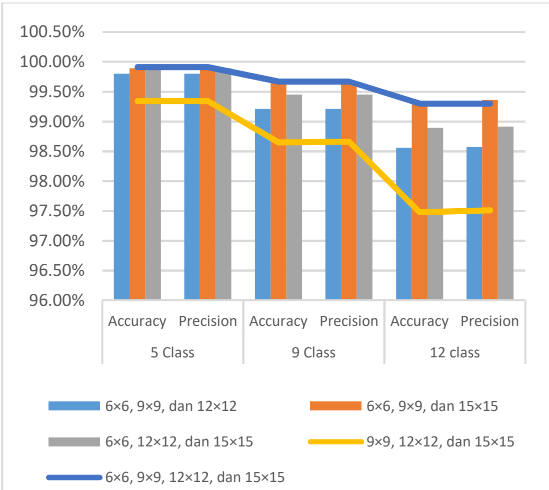

Figure 9 Accuracy and precision of image classification based on multi-window and the number of class

In Figure 9 shows the accuracy and precision values for multi-window types and image classes, namely 5 classes, 9 classes and 12 classes or Batik patterns, with 50 pixel overlap images. The value of accuracy and precision in the resulting classification, with the image conditions as above for all classes in some multi-windows can reach more than 99%. This is influenced by the kind of multi-window and the number of image classes, including the condition of the testing image and the training image have the same rotation but different image scales.

4.4 Multi-window effect and neural network architecture.

This experiment determine the multi-window effect and artificial neural network architecture on classification performance. For this reason, several experiments have been carried out to get the right artificial neural network architecture so as to produce maximum accuracy and precision values. The first layer will be inputted from the results of the image feature extraction processing using a combination of 2, 3 and 4 windows. For 2 windows it has a frequency value from 1 to 32, for 3 windows it has a frequency value from 1 to 48 and 4 windows have a frequency value from 1 to 64. The neural network architecture with the frequency value of the feature extraction can be seen in Figure 10

.

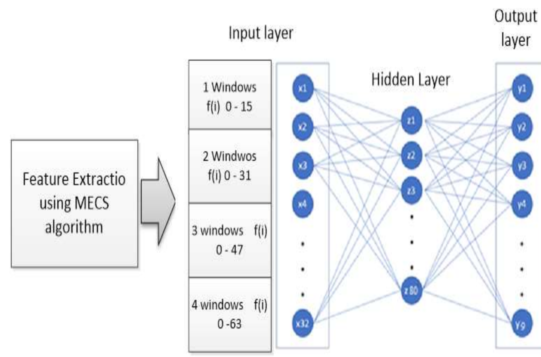

Figure 10 The neural network architecture with the Frequency Value of the feature extraction as input

The condition of the image data and some of the supporting parameters utilize the artificial neural network method as follows:

1. The number of training image(1080 Images)
   a Image scale is 100, 150
   b image rotation is 0, 10, 110
2. The number of testing image (10800 images)
   a Image scale is 90, 120, 140, 160, 180
   b image rotation is 15,30,45,60,75, 90,105, 120,135,150,165,180
3. Image overlapping is 30 pixels
4. The number of image classes is 9 classes

For conditions with Artificial Neural Networks are as follows:

5. Number of epochs used = 1500
6. MSE (mean square error) = 0.0001
7. Learning Rate = 0.01
8. Neural network method = backpropagation algorithm.

The results of experiment are attached in Figure 11.

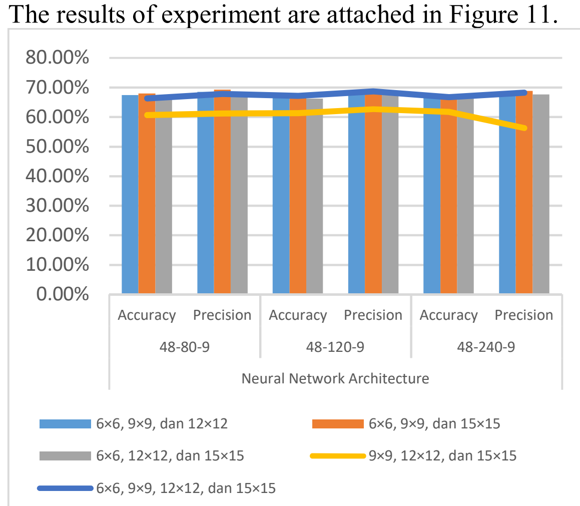

Figure 11 Accuracy And Precision Of Image Classification Based On Multi-Window And Neural Network Architecture

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In Figure 11 shows the effect of multi-window and artificial neural network architecture in supporting on the value of accuracy and precision in image classification. This experiment utilize 3 artificial neural network architectures, namely 48-120-9 (48 input layers, 120 hidden layers and 9 output layers). The results of this experiment show that the highest accuracy and precision values reach 67.98% and 69.25% at 6-9-15 multi-window.

4.5 Multi-window effect and image overlap

This experiment carry out the artificial neural network algorithm and with multi-window effect and several overlap images to determine the value of accuracy and precision in image classification. For image data conditions as follows:

1. The number of training image (10,800 images)
   a. Image scale is 90, 120,140, 160, 180
   b. image rotation is 15, 30, 45, 60, 75, 90, 105, 120, 135,150,165,180
2. The number of test image (1080 images)
   a. Image scale is 100, 150
   b. image rotation is 0, 10, 110

For conditions with artificial neural networks are as follows:

3. MSE = 0,0001; Learning Rate = 0,01 and number of Epoch = 1500
4. Neural network method = Backpropagation
5. Number of image classes = 9 classes
6. Neural network architecture for 3 windows = 48-240 -9 and 4 windows = 64-240-9.
7. overlapping images = 30, 40 and 50 pixel.

The result of experiment are attached in Figure 12.

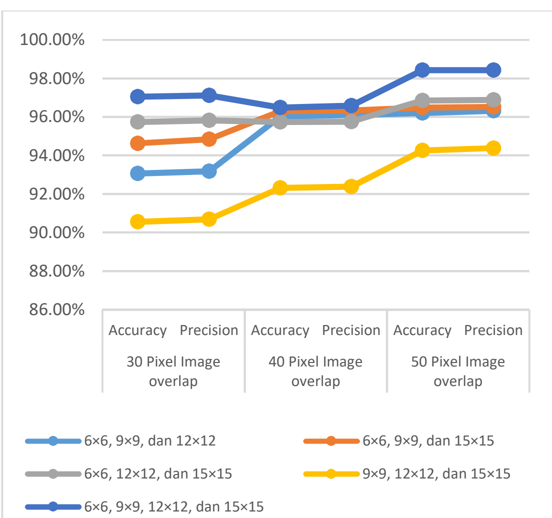

Figure 12 Accuracy and precision of image classification based on multi-window and Image Overlap

In Figure 12 shows the value of accuracy and precision influenced by 3 kinds of overlap images, also supported by the number of training images that are more than the test images, ANN architecture and other supporting parameters. For the highest accuracy and precision values in a combination of 3 windows for multi-windows 6-12-15 are 96.85% and 96.88% and multi-windows 6-9-15 are 96.48% and 96.52% with 50 pixel image overlapping, and a combination of 4 windows on the multi-window 6-9-12-15 with that reaches 98.43% and 98.43%.

4.6 Multi-window effect and number of training images

In this experiment determine multi-window effect and some number of training images which is more than the testing image. However, the image rotation is the same and the image scale is different for the training image and the testing image. The image data conditions are as follows:

1. Number of training images (13,440 images)
   a) Image scale is 90, 100, 110, 120, 130, 140, 150, 200
   b) image rotation is 0, 15, 30, 45, 60, 90, 120
2. Number of training images (11,760 images)
   a) Image scale is 90, 100, 110, 120, 130, 140, 150
   b) image rotation is 0, 15, 30, 45, 60, 90, 120
3. Number of training images (10,080 images)
   a) Image scale is 90, 100, 110, 120, 130, 140
   b) image rotation is 0, 15, 30, 45, 60, 90, 120
4. The number of test data (4,800 images)
   a) Image scale is80, 160, 170, 180, 190
   b) image rotation is 135, 150, 165, 180
5. Image overlapping = 30 pixels
6. Number of images in class = 12 classes.

For conditions with Artificial Neural Networks are as follows:

7. Number of epochs = 1000; MSE = 0.0001; LR = 0,01
8. Neural network method = Backpropagation
9. Neural network architecture for 3 windows = 48-240-12 and for 4 windows = 64-240-12

The result of experiment are attached in Figure 13.

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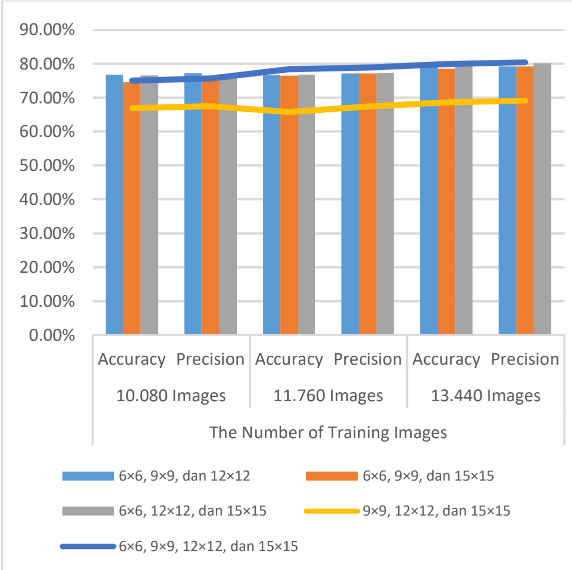

Figure 13 Accuracy and precision of image classification based on multi-window and number of training image

In Figure 13 shows accuracy and precision values in the combination of 3 windows, namely the 6-9-12 multi-window are 78.88% and 79.21% and the 6-12-15 multi-window are 79.63% and 80.13% in the number of training images 13,440 image and neural network architecture 48-240-12. For the highest accuracy and precision values are found in the multi-window 6-9-12-15, the number of training images is 11,760 images are 78.42% and 78.89%, while for the number of training images 13,440 images are 79.98% and 80, 44 with a 64-240-12 as neural network architecture.

5. CONCLUTION

Some of the results of the experiments had been carried out, it could be concluded as follows:

1. Some experiments have been carried out to determine the reliability of the Mulwin-LBP Algorithm in supporting the classification of Batik images that have invariant Dilemma.
2. The results of this study can provide an overview of the mulwin-LBP algorithm can produce optimal classification accuracy even though the test image is much more than the training image. The percentage of classification accuracy reaches more than 75%.
3. In this experiment, the classification accuracy can reach more than 98% using the k-NN method and artificial network system, with the condition that the training image data is more than the test image data, but the degree of rotation between the training image and the test image is the same and different for the scale.
4. The development of the Mulwin-LBP Algorithm will continue so that its reliability can be improved and developed, including to be able to recognize the patterns of traditional fabrics originating from various regions of Indonesia..

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