Batik Classification using Texture Analysis and Multiclass Support Vector Machine

Wahyu Tri Puspitasari, Dian C. R. Novitasari and Wika Dianita Utami
Departement of Mathematics UIN Sunan Ample Surabaya, Ahmad Yani Street, Surabaya, Indonesia

Keywords: Batik Image, Analysis Texture, Feature Extraction, GLCM, DWT Multiclass SVM.

Abstract: Batik is one of the cultural heritage has become an Indonesian identity and recognized by the Organization of Education, Science and Cultural Organization (UNESCO). Every region in Indonesia has very diverse batik motifs. There are 38 batik motifs based on the area of origin. It will be difficult to recognize each of these patterns while batik began to be liked by many local and foreign tourists. Therefore, a system is needed that can recognize every pattern of batik to facilitate people in recognizing batik motifs. Support Vector Machine (SVM) has excellent performance in classification and can also be used to recognize patterns of batik motif. We use the Gray Level Co-occurrence Matrix (GLCM) for feature extraction and SVM for batik classification. The result show that batik motif can be classified using SVM with 96% accuracy for two types of batik motifs, 88.89% for three types of batik motifs and 77.14% for four types of batik motifs.

1 INTRODUCTION

Batik is Indonesia's cultural heritage that has been worldwide. Batik is a fabric with patterns, motifs, or certain themed images according to the philosophy that exist in the regions of Indonesia (Wulandari, 2012). Batik motif in Indonesia is very diverse because the Indonesian nation has a diversity of ethnic and cultures. Motif consists of elements proportion and composition. Indonesia has more than 181 batik motifs (Achjadi, 1999). The types of batik can be classified by method of manufacture, area of origin and motif.

(a) (b) (c)

Figure 1: (a) Lereng Madura batik image, (b) Ceplok Indramayu batik image, (c) Sidomukti Yogyakarta batik Image.

Some examples of batik motifs in Figure 1 are batik motifs based on area of origin. Batik motifs in Indonesia are difficult to differentiate because the amount are very diverse. To recognize batik motifs, a classification process is needed. Classification is used to recognize the characteristics of the objects contained in the database and classed into different class (Moertini & Sitohang, 2005). The process of batik classification is the division of the image of batik into the classes in accordance with the pattern of the motive, it makes more easily recognizable based on the pattern.

Texture classification can be done using texture analysis results. Texture analysis in the image is an observation about a characteristic in the image. To get the characteristics of the image be done by extracting the image feature that serves to take the features of each image. The feature extraction methods include Cardinal Spline Curve Representation (Fanani, Yuniarti, & Suciati, 2014), FPGA (Babasaheb et al., 2012), Gray Level Co-occurrence Matrix (GLCM) (Öztürk & Akdemir, 2018), Wavelet (Putra, Suciati, & Wijaya, 2011).

GLCM is a feature extraction method used to obtain features in the image by calculating the *Angular Second Moment* (ASM), contrast, *Inverse Difference Moment* (IDM), energy, correlation of co-occurrence matrix(Mohanaiah, Sathyanarayana, & GuruKumar, 2013). Based on previous research used the GLCM method as feature extraction of brain tumor images for brain tumor classification (Zulpe & Pawar, 2012) and feature extraction of glaucoma images for the diagnosis of glaucoma (Karthikeyan

Puspitasari, W., Novitasari, D. and Utami, W.
Batik Classification using Texture Analysis and Multiclass Support Vector Machine.
DOI: 10.5220/0008517300650071
In *Proceedings of the International Conference on Mathematics and Islam (ICMIs 2018)*, pages 65-71
ISBN: 978-989-758-407-7

&Rengarajan, 2013). Feature extraction using the GLCM method has faster calculation and then GLCM used to recognize the pattern (Mohanaiah, Sathyanarayana, & Gurukumar, 2013).

Beside GLCM method, there is a Wavelet Transform method to use features extraction. Chen et al. (2002) have successfully classified breast tumors using feature extraction of Wavelet Transformation and ANN classification. In addition, Rangkuti (2014) has done research on batik classification using Discrete Wavelet Transform with duabechies 2 type, where a type of duabechies 2 is better than other types. Angelos Tzotos shows that the Support Vector Machine (SVM) is excellent for object-based image analysis (Tzotsos & Argialas, 2008). SVM can only perform binary classification. However, currently, there is a multiclass SVM approach to solve many class classification problems. Multiclass SVM with ECOC approach has been implemented to diagnose the erythromotropic-squamous disease with high accuracy results (Prasetyo, 2014). Based on previous research, batik classification will be performed using feature extraction with GLCM and feature extraction results with DWT where classification using multiclass SVM.

2 LITERATURE REVIEW

2.1 Batik

The batik is a fabric patterned / special motif made by applying a *Malam* on the fabric and processed by a particular process (Musman & Arini, 2011). The types of batik can be classified based on the method of manufacture, origin area, and motif (Wulandari, 2012). Batik motif is formed from point, line, and the plane then becomes an abstract pattern, natural (natural), geometric and another pattern. Each pattern of batik has its own philosophical meaning. This makes batik as a craft that has high artistic value. Sometimes, some motifs are designed for important events such as engagements, weddings party, uniforms, etc.

2.2 Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is a feature extraction method that uses second-order grey level histogram (Embaugh, 2017). Capture features based on two parameters, that is distance and angle. Distance is the pixel difference used for second-order statistics, an angle formed between pixel pairs. In the GLCM method, angle orientation is expressed in degrees. The angular orientation is divided into 4 different angle directions with the 45 ° interval, which is 0°, 45°, 90°, 135° (Shi & Jeon, 2006). Co-occurrence direction can be seen in Figure 2. Let $f(x, y)$ represent images of size Nx and Ny that have pixels with L levels and r is the direction vector of spatial offset. $GLCM(i,j)$ defined by the number of pixels (j) occurring at offset r to pixel (i) which can be expressed as follows

$$GLCM(i,j) = \{(x_1,y_1),(x_2,y_2)\} \tag{1}$$

where the offset r can be an angle or distance, $i \in 1,2,..,L$ and $j \in 1,2,..,L$. A co-occurrence matrix is used to get the feature from the image. Harlick's suggested features include both angle (ASM) moments, contrast, inverse difference moment (IDM), energy, correlation(Mohanaiah, Sathyanarayana, & GuruKumar, 2013).

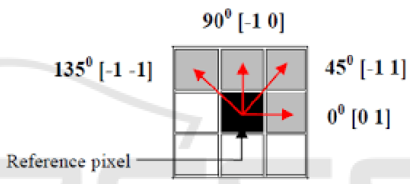

Figure 2: Co-occurrence Matrix direction for extracting texture features.

2.2.1 Angular Second Moment (ASM)

ASM is also known as uniformity ASM is related to energy, where energy is the sum of squares of second moment GLCM(Suresh, 2012). The highest value is achieved when the image has excellent homogeneity when the GLCM elements are all the same (Mohanaiah, Sathyanarayana, & Gurukumar, 2013). ASM is calculated using the following formula (2). Range energy value between [0,1].

$$ASM = \sum_i \sum_j (GLCM(i,j))^2 \tag{2}$$

where $GLCM(i,j)$is matriks co-occurrence, $i \in 1,2,..,L$ and $j \in 1,2,..,L$.

2.2.2 Contrast

Contrast is a measure of the presence of variations in the pixel grey level of the image. Contrast is calculated using the following formula (3).

$$Contrast = \sum_i \sum_j (i-j)^2 GLCM(i,j). \tag{3}$$

2.2.3 Inverse Difference Moment (IDM)

IDM is a local homogeneity. IDM has a high value when the same local gray level and the inverse of the high GLCM. IDM is obtained from the following formula (4).

$$IDM = \sum_i \sum_j \frac{GLCM(i,j)}{1+(i,j)^2}. \tag{4}$$

2.2.4 Entropy

Entropy is a measure of the randomness of the grey in the image. Entropy reaches the highest value when GLCM elements have relatively equal amounts and have a low cost when the GLCM elements are close to 0 or 1. Entropy is calculated using the following formula (5) (Thamaraichelvi & Yamuna, 2016).

$$Entropy = -\sum_i \sum_j GLCM(i,j) \log GLCM(i,j). \tag{5}$$

2.2.5 Correlation

Correlation is used to calculate the gray linear dependence of the neighboring pixel. To obtain correlation values can use the following formula (6).

$$Corelation = \frac{\sum_i \sum_j (i,j)GLCM(i,j) - \mu_i{}'\mu_j{}'}{\sigma_i{}'\sigma_j{}'} \tag{6}$$

where :

$$\mu_i' = \sum_i i \sum_j GLCM(i,j), \tag{7}$$

$$\mu_j' = \sum_j j \sum_i GLCM(i,j), \tag{8}$$

$$\sigma_i{}' = \sum_i (i-\mu_i')^2 \sum_j GLCM(i,j), \tag{9}$$

$$\sigma_j' = \sum_j (j-\mu_j')^2 \sum_i GLCM(i,j). \tag{10}$$

2.3 Discrete Wavelet Transform

Wavelet Transform method is very influential in the field of signal analysis, especially in analysis and image compression. Wavelet is a dangerous method of image and video compression because of hasprofessive character in reconstruction. The wavelet transform is divided into two versions, there are Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). From the perspective of computing, the DWT method better than the CWT method (Embaugh, 2017). DWT method works multiraisonally and provides information about the frequency and timing of the signal. In DWT-2D image processing used wavelet filter horizontally then vertically to produce four sub-bands that contain wavelet coefficient value. The type of wavelet filter is the Low Pass Filter (LPF) and High Pass Filter (HPF) that evolved from the mother wavelet. Wavelets develop into several types, there are haar / db1, duabechies (db2,3,4 .., n), coiflets, symlets, discrete major, and bioerthogonal) (Jayaraman, Esakkirajan, & Veerakuma, 2011). Here's the filtering scheme shown by Figure 3.

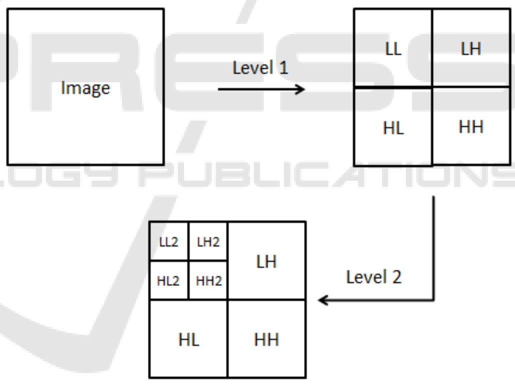

Figure 3: Decomposition level 2.

The LL, LH, HL, HH are the result of decomposition level 1. Lowpasslowpass (LL) contains the original image approximation coefficient, *lowpasshighpass* (LH) contains the horizontal subband edge coefficient, *highpass-lowpass* (HL) contains the vertical subband edge image coefficient, and*highpasshighpass*(HH) contains the vertical edge coefficient information. When decomposition of two levels is done, then the subband that can be decomposed only sub only, because LL contains information about the image.

From the wavelet decomposition can be calculated several statistical characteristics by using the following formula

$$Energy = \sum_{i,j} P(i,j)^2, \quad (11)$$

$$Entropy = -\sum_{i,j} P(i,j) \log P(i,j), \quad (12)$$

$$Standard\ Deviation = \frac{1}{n-1}\sum_{i,j}^{n} (x_{i,j} - \bar{x})^2, \quad (13)$$

$$Mean = \frac{\sum_{i,j}^{n} P(i,j)}{n}. \quad (14)$$

2.4 Support Vector Machine

SVM is a binary classification method by dividing two different classes using the best hyperplane (He, Wang, Jin, Zheng, & Xue, 2012). But in the real world problems are often classified into more than two classes. To resolve these problems can use SVM multiclass approach. There are two types of data sets that can be classified using SVM, there are linear data and non-linear data.

In linear SVM, two different classes are separated by the best divisor function (hyperplane). Hyperplane best obtained from the most optimal margin. While the non-linear data used kernel trick that can map the training data into a feature vector that has a higher dimension. There are several kernels that can be used such as linear kernels, polynomial kernels, and Gaussian kernels (Shigeo, 2010). Below are some kernel formulas:

a. Linear Kernel

$$K(x,x') = x^T x',$$

b. Polynomial Kernel

$$K(x,x') = (x^T x' + 1)^d,$$

c. Gaussian Kernel

$$K(x,x') = \frac{\exp(||x^T x'||)^2}{2\sigma^2},$$

where $x^T x'$is a pair of two data from all parts of the training data, parameter σ dan d is a constant.

2.4.1 Binary Classification

Two-class classification is done by dividing the data into two different classes using hyperplane best. Hyperplane best obtained from the most optimal margin. The margin is the distance between the hyperplane with the closest data to the hyperplane of each class. The data is called a support vector.

2.4.2 Multiclass Classification

Multiclass SVM is used to solve classification problems of more than two classes. There are three multiclass approaches, which is one-against-one, one-against-one and ECOC approaches (Prasetyo, 2014). The one-against-all approach, making binary classifiers as much as K is then trained to separate the y_i class vector from the others, for each $y_i \in Y$. Then each data object is classified into the class where the greatest decision value is determined (Chih-Wei Hsu, 2002). The second approach, which is one-against-one with classification binary form as K (K-1) / 2. The vectors are not the member of the class y_i or $y_j$are ignored when the formation of a binary classifier (y_i,y_j). The last approach, the ECOC approach works by providing a string of bits called codewords of length n, where n denotes the number of classes. Then created a binary classification of $in$to predict every bit codeword. To calculate the predicted result, look for the closest distance between the codeword and the classifier by using the Hamming distance (Prasetyo, 2014).

3 METHODS

Stages of batik classification using the result of texture analysis with SVM multiclass classification method shown in Figure 3.

Some stages of batik classification are, datasets, preprocessing, feature extraction, and classifiers: the first stage, data collection batik image. The data is divided into two groups which is training data and testing data. The information is stored in one file with the format .jpg.

The second stage, which will be pre-processing for all data by changing all the image of batik into gray scales that when extracting features does not get the effect of RGB / HSV colors. The third stage is feature extraction. In this research, used two feature extraction methods, there are Gray Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transform (DWT). For the GLCM method with a default degree orientation or 0 degrees and a distance of 1 pixel can be calculated the frequency of gray pairs appears between pixels in the direction and distance that has been determined. After kookuren matrix formed can be calculated statistical characteristics of the image that is energy, in contrast, homogeneity, correlation using Equations (2), (3), (4), (6). While the DWT method using Daubechies 2, level 3 can be calculated several statistical characteristics there are energy, entropy, standard deviation, and mean using Equation (11), (12), (13) and (14). The feature will be used for classification stages. In the classification process used the multi mile SVM method with the ecoc approach. The stages in the multiclass SVM classification determines the characteristic parameter, select the kernel that fits the data, training data, and the test data to obtain classification results. In this research using Gaussian Kernel, The Gaussian Kernel was obtained through Equation (9). The data will be divided into two, three and four classes.

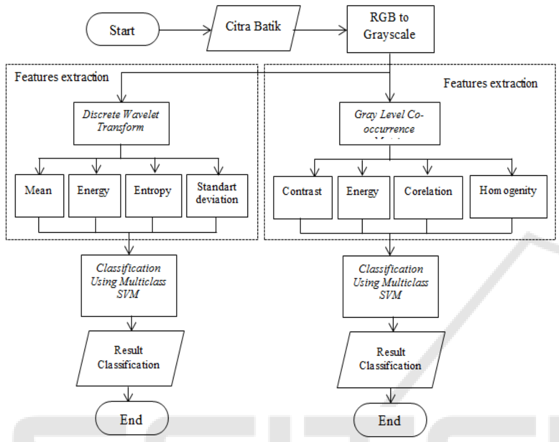

Figure 4: Flowchart Batik Classification.

4 RESULTS AND DISCUSSION

In this research, batik will be classified into two classes which is *Parang* and *Nitik*, three classes there are *Parang*, *Nitik*, and *Semen*, four classes there are *Parang*, *Nitik*, *Semen* and *Buketan*. The process of batik classification uses the GLCM and DWT methods for feature extraction and the SVM Multiclass with the ECOC approach to the classification process.

Before the feature extraction, pre-processing is required. In pre-processing, color images (RGB) are converted into grayscale images. This process is used to simplify the image model so that when extracting features does not get the effect of RGB / HSV colors. Image changes to grayscale images shown in Figure 5.

After obtaining a grayscale image, the next step is the feature extraction process. Feature extraction is used to get statistical features in the picture. There are two feature extraction methods used are GLCM and DWT. In this study using the GLCM method with an orientation of 0 degrees and a distance of 1 pixel.

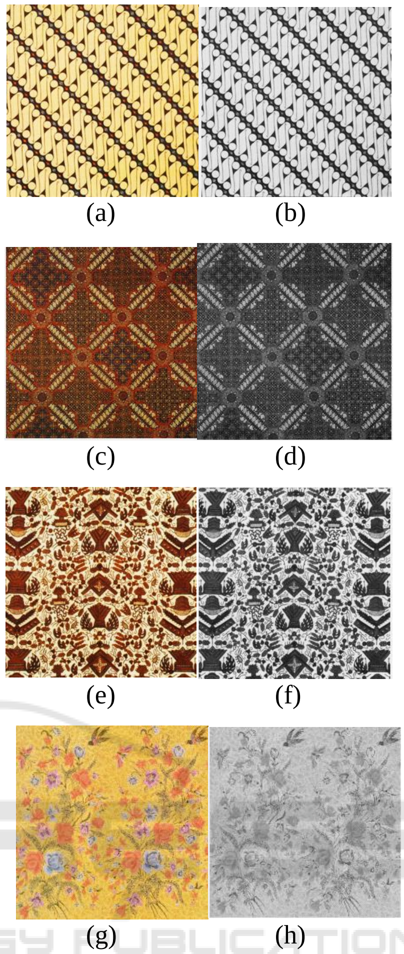

Figure 5: (a) Parang batik image, (b) gray scale image of Parang batik, (c) Nitik batik image, (d) grayscale image of Nitik batik, (e) Semen batik image, (f) grayscale image of Semen batik, (g) Buketan batik image, (h) gray scale image of Buketan.

After determining the direction, then make the co-occurrence matrix using Equation (1). From the matrix can be calculated statistical characteristics, there are energy, contrast, homogeneity and correlation using Equation (2), (3), (4) and (6). The samples from feature extraction using GLCM are shown in Table 1.

While the DWT method using duabechies 2 level 3. From the wavelet decomposition only from the approximation, coefficients can be calculated statistical features which is mean, standard deviation, energy and entropy using Equations (11), (12), (13), (14). The samples from feature extraction using DWT are shown in and Table 2.

Table 1: Sample data feature extraction result using GLCM.

Data	Contrast	Corela-tion	Energy	Homogeni ty
1	2.32750	0.55703	0.07465	0.59638
2	1.78760	0.73334	0.06928	0.67667
3	1.83738	0.68679	0.11120	0.65869
4	2.07442	0.75875	0.08655	0.66997
5	2.34345	0.59124	0.05418	0.6244
6	0.28138	0.93332	0.10911	0.86300
7	1.56753	0.81615	0.11668	0.69613
8	1.42406	0.82779	0.11793	0.71025
9	5.17642	0.42063	0.02992	0.50094
10	0.66446 6	0.930196	0.08059	0.775365

Table 2: Sample data feature extraction result using DWT.

Data	Energy	Entropy	Mean	Standart Deviation
1	0.6538	-1.6E+08	-0.11388	4.200617
2	2.67966	-7.4E+08	-0.0668	5.263958
3	1.06521	-2.2E+08	-0.26316	3.304104
4	0.7446	-1.2E+08	0.04548	5.188262
5	4.02238	-5.1E+08	0.252135	5.116634
6	4.22896	-4.5E+08	0.037634	4.344027
7	0.31044	-1.8E+07	0.003963	1.700911
8	2.6412	-1.7E+08	-0.12314	3.307191
9	0.61473	-1.9E+08	-0.0126	3.976344
10	2.85036	-8.9E+08	-0.26698	7.125455

These features are used as parameters in the classification. There are two processes in the classification, the training process, and the testing process. The ratio of training data and testing data used were 70%:30%, 75%:25%, and 80%:20%. The classification process uses the ECOC Multiclass SVM approach with the Gaussian Kernel. SVM multiclass classificatory performance is measured using three measure of performance is the accuracy, precision, and recall. The result of an experiment with four different types of data sharing between the two methods stated in Table 3, Table 4 and Table 5.

Table 3: The results of the two-class classification.

Data	Method	Accuracy	Precision	Recall
70% : 30%	GLCM	92.3 %	91.87%	91.87%
	DWT	73.05%	84.78%	65%
75% : 25%	GLCM	96 %	95%	96.88%
	DWT	76 %	86.36%	66.67%
80% : 20%	GLCM	91.3%	88.89%	93.75%
	DWT	78.26%	88.1%	64.29%

Table 4: The results of the three-class classification.

Data	Method	Akurasi	Presisi	Recall
70% : 30%	GLCM	86.67%	84.04%	82.92%
	DWT	63.33%	46.33%	43.33%
75% : 25%	GLCM	88.89%	90.51%	82.64%
	DWT	66.67%	43.81%	43.75%
80% : 20%	GLCM	88.46%	89.58%	82.04%
	DWT	67.86%	43.13%	47.62%

Table 5: The results of the four-class classification.

Data	Method	Akurasi	Presisi	Recall
70% : 30%	GLCM	77.14%	82.50%	62.12%
	DWT	42.85%	27.78%	30.97%
75% : 25%	GLCM	75.00%	75.00%	67.19%
	DWT	53.13%	39.44%	34.90%
80% : 20%	GLCM	74.19%	77.03%	62.96%
	DWT	58.06%	46.18%	38.91%

Based on Table 3, the classification of batik into two-classes using GLCM based on the distribution of data sets shows the best results in 75%:25% with 96% accuracy, precision 95%, and 96.88% recall. From the experiments show that the GLCM method is perfect for recognizing each class. While the classification of batik using DWT showed the best results on the distribution of data sets 80%: 20% with an accuracy of 78.26%, precision of 88.1% and recall of 64.29%. From the experiment shows that the DWT method can only recognize one class.

Based on Table 4, the classification of batik into three-classes using GLCM based on the distribution of data sets shows the best results in 75%: 25% with an accuracy of 88.89%, precision of 90.51%, and recall of 82.64%. The experiment shows that the GLCM method is good for recognizing each class. While the classification of batik using DWT showed the best results on the distribution of data sets 80%:20% with an accuracy of 67.86%, precision of 43.13%, and recall 47.62%. The experiment shows that the DWT method is good enough for recognizing each class.

Based on Table 5, the classification of batik into four-classes using GLCM based on the distribution of data sets shows the best results in 70%: 30% with an accuracy of 77.14%, precision of 82.50% and recall of 62.12%. The experiment shows that the GLCM method is good enough to recognize each class. While the classification of batik using DWT showed the best results on the distribution of data sets 80%: 20% with an accuracy of 58.06%, precision of 46.18% and recall of 38.91%.

5 CONCLUSIONS

Based on, the experiment that has been performed, batik classification into two classes and three classes get the best results when using GLCM feature extraction method with an accuracy of 96% for two type of batik motifs, accuracy of 88.89% for three kinds of batik motifs and accuracy of 77.14% for four kinds of batik motifs. This indicates that the feature extraction using GLCM method is better than the DWT method to recognize batik pattern based on the pattern.

ACKNOWLEDGMENTS

A big thank you to Allah SWT for giving blessings and guidance in the life of the author, UINSA which has provided an opportunity for the author to seek knowledge.

REFERENCES

Achjadi, J., 1999. *Batik Spirit of Indonesia*. Jakarta: PT. Buku Antar Bangsa.

Babasaheb G. P., Mane, N. N., and Subbaraman, S., 2012. IRIS Feature Extraction and Classification using FPGA. *International Journal of Electrical and Computer Engineering (IJECE)*, Vol 2, No 2, April 2012, 214–222.

Chen, D.-R., Chang, R.-F., Kuo, W.-J., Chen, M.-C., & Huang, Y. .-L., 2002. Diagnosis of breast tumors with sonographic texture analysis using wavelet transform and neural networks. *Ultrasound in Medicine & Biology*, 28(10), 1301–1310.

Chih-Wei Hsu, 2002. A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks*, 12(2), 425–547.

Embaugh, S. E., 2017. *Digital Image Processing and Analysis Applications with MATLAB and CVIPtools* (Third Edition). Boca Raton: CRC Press.

Fanani, A., Yuniarti, A., & Suciati, N., 2014. Geometric Feature Extraction of Batik Image Using Cardinal Spline Curve Representation. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *12*(2), 397.

He, X., Wang, Z., Jin, C., Zheng, Y., & Xue, X., 2012. A simplified multi-class support vector machine with reduced dual optimization. *Pattern Recognition Letters*, 33(1), 71–82.

Jayaraman, S., Esakkirajan, S., & Veerakuma, T., 2011. *Digital Image Processing*. New Delhi: Tata McGraw Hill Education Private Limited.

Karthikeyan, S., & Rengarajan, N., 2013. Performance analysis of gray level cooccurrence matrix texture features for glaucoma diagnosis. *American Journal of Applied Sciences*, 11(2), 248–257.

Moertini, V. S. & Sitohang, B., 2005. Algorithms of Clustering and Classifying Batik Images Based on Color, Contrast and Motif. *ITB Journal of Engineering Science*, 37(2), 141–160. https://doi.org/10.5614/itbj.eng.sci.2005.37.2.5

Mohanaiah, P., Sathyanarayana, P., & Gurukumar, L., 2013. Image Texture Feature Extraction Using GLCM Approach. *International Journal of Scientific & Research Publication*, 3(5), 1–5.

Musman, A., & Arini, A. B., 2011. *Batik Warisan Adhiluhung Nusantara*. Yogyakarta: G Media.

Öztürk, Ş., & Akdemir, B., 2018. Application of Feature Extraction and Classification Methods for Histopathological Image using GLCM, LBP, LBGLCM, GLRLM and SFTA. *Procedia Computer Science*, 132 (ICCIDS), 40–46.

Prasetyo, E., 2014. *Data Mining Mengolah Data Menjadi Informasi Menggunakan MATLAB*. Yogyakarta: Andi.

Putra, R. E., Suciati, N., & Wijaya, A. Y., 2011. Implementing Content Based Image Retrieval for Batik Using Rotated Wavelet Transform And Canberra Distance. *Bali International Seminar on Science and Technology*, 1–5.

Rangkuti, A. H., 2014. Content based batik image classification using wavelet transform and fuzzy neural network. *Journal of Computer Science*, 10(4), 604–613.

Shi, Y. Q., & Jeon, B., 2006. *Digital Watenarking*. Korea: Springer.

Suresh, A., 2012. Image Texture Classification using Gray Level Co-Occurrence Matrix Based Statistical Features. *European Journal of Scientific Research*, 75(4), 591–597.

Tzotsos, A., and Ardialas, D., 2008. Support vector machine classification for object-based image analysis. *Final Paper*. Retrieved from http://datascienceassn. org/sites/default/files/A%20Support%20Vector%20Machine%20Approach%20for%20Object%20Based%20Image%20Analysis.pdf, accessed on December 8, 2018.

Wulandari, A., 2012. *Batik Nusantara - Makna Filosofis, Cara Pembuatan & Industri Batik*. Yogyakarta: Andi.

Zulpe, N., & Pawar, V., 2012. GLCM textural features for Brain Tumor Classification. *International Journal of Computer Science*, *9*(3), 354–359.