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Batik Image Representation using Multi Texton Co-occurrence Histogram

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***Abstract*—This paper introduces a novel approach to batik image representation using the texton-based and statistical Multi Texton Co-occurrence Histogram (MTCH). The MTCH framework is leveraged as a robust batik image descriptor, capable of encapsulating a comprehensive range of visual features, including the intricate interplay of color, texture, shape, and statistical attributes. The research extensively evaluates the effectiveness of MTCH through its application on two well-established public batik datasets, namely Batik 300 and Batik Nitik 960. These datasets serve as benchmarks for assessing the performance of MTCH in both classification and image retrieval tasks. In the classification domain, four distinct scenarios were explored, employing various classifiers: the K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), Decision Tree (DT), and Naïve Bayes (NB). Each classifier was rigorously tested to determine its efficacy in correctly identifying batik patterns based on the MTCH descriptors. On the other hand, the image retrieval tasks were conducted using several distance metrics, including the Euclidean distance, City Block, Bray Curtis, and Canberra, to gauge the retrieval accuracy and the robustness of the MTCH framework in matching similar batik images. The empirical results derived from this study underscore the superior performance of the MTCH descriptor across all tested scenarios. The evaluation metrics, including accuracy, precision, and recall, indicate that MTCH not only achieves high classification performance but also excels in retrieving images with high similarity to the query. These findings suggest that MTCH is a highly effective tool for batik image analysis, offering significant potential for applications in cultural heritage preservation, textile pattern recognition, and automated batik classification systems.**

***Keywords*— Batik; texton descriptor; GLCM; classification; image retrieval.**

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I. INTRODUCTION

Batik has been long acknowledged as one of the cultural reflections symbolically in Indonesia and worldwide. UNESCO established the existence and uniqueness of Batik on October 2, 2009, as Masterpiece of the Oral and Intangible Heritage of Humanity [1]. Study on batik has been promising due to its unique characteristics and diverse motifs resulting from acculturation. The diversity of Batik motifs embodies certain characteristics of batik in each region, despite challenging for Batik researchers to identify, classify and search depending on motifs and regions [2]. However, the ability of artificial intelligence has currently assisted archeologists in searching for types of motifs and classifying certain batik motifs. Several studies on the utilization of machine learning through datasets of archaeological artifacts have been reported by researchers. Studies on batik were conducted by classification and image retrieval implementing painted pottery images [3], ceramic profile in archeological sketch implementing deep neural net [4], automated classification of petroglyphs [5], and Batik Nitik 960 [6].

Furthermore, other studies were conducted by utilizing deep learning approaches, particularly Convolutional Neural Networks (CNN), as a promising method for automatically adjusting image features without relying on manually created methods [7], [8], [9], [10]. However, CNN relies heavily on training datasets, which is challenging due to computational complexity and data storage requirements. Additionally, selecting appropriate images to build a training set requires significant human effort, making it less than ideal. According to another prior study [11], the texture features extracted from the fully connected (FC) layer on CNN were not suitable to represent textures because non-ordered approaches (such as the FC layer) could not capture the regularity of texture patterns.

One of the most important parts of image representation includes the feature extraction stage. At this stage, the features of an image are converted into vector form, enabling the classification and retrieval process. The most utilized image features by researchers include color, texture, and shape. The color histogram is the most widely used due to its effective feature for differentiating images. However, the weakness of color features lies in the absence of spatial distribution information. Meanwhile, texture features provide essential information related to spatial distribution [12].

Image features are divided into global features and local features [13], [14]. Global features provide an accumulative image, such as the Gray Level Co-occurrence Matrix (GLCM) [15], [16], while local features provide information from the micro-structure descriptor commonly recognized as texton. The theory of texton has been successfully applied in many studies on classification [17], [18], [19], [20] and on image retrieval [21], [22], [23], [12], [24], [25], [26], [27], [28].

Texture descriptors do not always produce optimal results; therefore, combining them with other descriptors for an effective CBIR is considered the most effective way. Combining color and texture in a single descriptor is common by combining feature vectors into one feature vector to extract two or more features into a single image representation vector.

A prior study [12] developed the Multi Texton Histogram (MTH) feature extraction method previously proposed by Liu et al. however, Khaldi presented by adding a new type of texton from 4 textons to 11 textons. The addition of texton was claimed to improve image retrieval and classification performance. However, [12] only performed local feature extraction without paying attention to global features. Likewise, local features such as color, texture, and shape do not always give the best results; therefore, this study proposes to combine local features and global features in order to get the best descriptor composition.

This study proposes a descriptor consisting of local features and global features. The proposed local feature is based on MTH modified by adding a new Texton type, while the proposed global feature applies GLCM. The combination of these two features is termed the Multi Texton Co-occurrence Histogram (MTCH). The contributions of this study are summarized as follows: (a) MTCH is an effective method used for batik image representation, (b) MTCH takes advantage of local features using texton-based and global features in GLCM as a descriptor for batik images, (c) MTCH has more detailed features about color, texture, and shape, as well as global GLCM features.

This paper is organized as follows: Section 1 presents research that is relevant to this research; Section 2 discusses the proposed MTCH method; Section 3 depicts the evaluation results and discussion of the test results; and the last section provides conclusions based on the test results at the end of this paper.

II. Materials and Method

A. Gray Level Co-occurrence Matrix (GLCM)

Texture is a key characteristic in identifying objects in images, providing information about the image's surface. Previously, GLCM (Gray Level Co-occurrence Matrix) was proposed by [29], discussing the theory of the probability of the occurrence of neighboring pixels with similar color intensity (co-occurrence). This probability is determined based on orientation angles (0°, 45°, 90°, and 135°) and varying distances, typically using a distance of 1. GLCM formulates 14 features, including energy, entropy, contrast, and correlation. Illustrations of GLCM feature extraction and GLCM edge orientation are shown in Fig. 1.

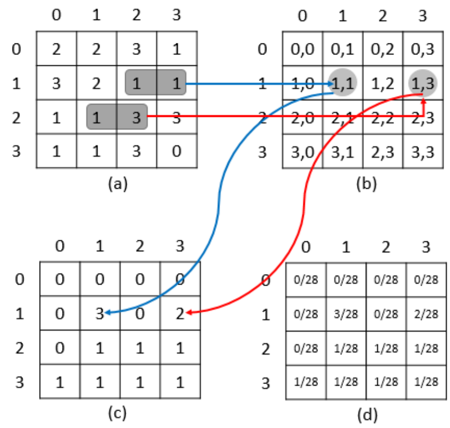

Fig. 1 Illustration of GLCM feature extraction (a) grayscale image; (b) definition of reference matrix; (c) reference matrix; (d) matrix normalization

B. Multi Texton Histogram (MTH)

The idea of MTH was proposed by a previous study [30], confirming that the Texton theory was introduced by Julesz. MTH uses four types of textons to detect the microstructure of an image, as shown in Fig. 2. This approach is chosen without involving segmentation and data training processes. MTH extracts image features using a color histogram in the RGB color space and detects edge orientation of the image by applying the Sobel operator.

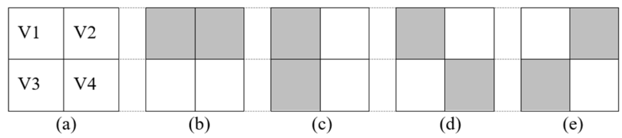

Fig. 2 Four types of texton on MTH. (a) 2x2 Grids; (b) T1; (c)T2; (d) T3; (e) T4

C. Complete Multi-Texton Histogram (CMTM)

A study by Khaldi et al. [12] introduces the Complete Multi-Texton Histogram (CMTH) method to represent visual content in images, focusing on texture and non-texture color images. CMTH incorporates color, edge orientation, and Texton distribution information. The results show that CMTH outperforms state-of-the-art methods in image classification and retrieval tasks. Khaldi proposed 11 types of textons for feature extraction, illustrated in Fig. 3.

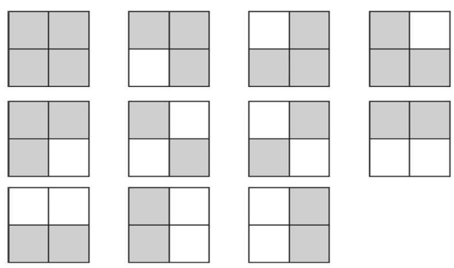

Fig. 3 Eleven types of text as descriptors of CMTH

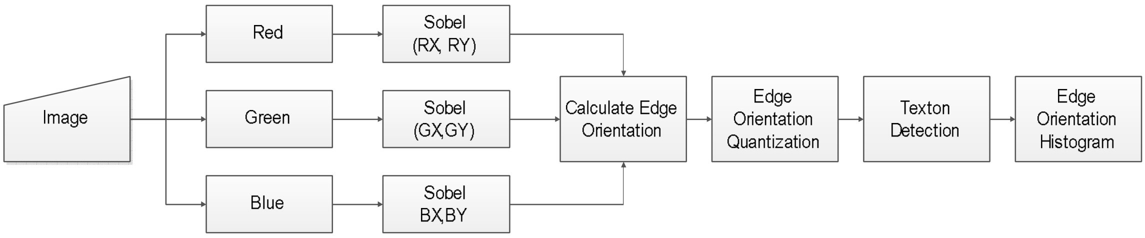

Fig. 4 Illustration of edge features extraction

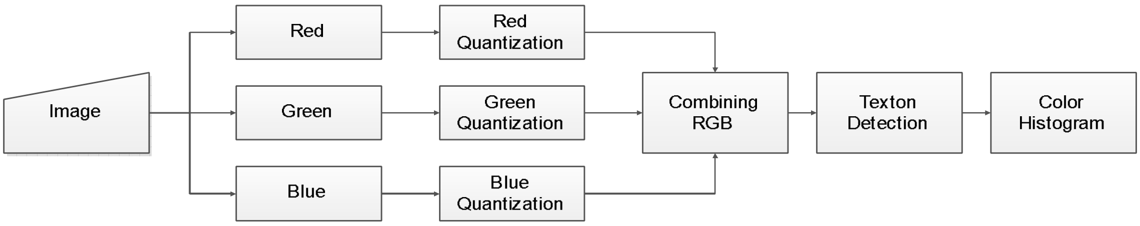

Fig. 5 Illustration of color features extraction

TABLE I
AVERAGE CLASSIFICATION RESULT ON BATIK NITIK 960 DATASET

FE	Time (s)	Accuracy							
		KNN					SVM	DT	NB
		1	3	5	7	9			
FE1	0.0262	0.51	0.53	0.49	0.50	0.49	0.71	0.69	0.88
FE2	0.0312	0.51	0.53	0.49	0.50	0.48	0.71	0.64	0.89
FE3	0.0300	0.50	0.51	0.48	0.50	0.48	0.67	0.68	0.88
FE4	0.0349	0.50	0.51	0.48	0.50	0.48	0.68	0.68	0.89

TABLE II
AVERAGE CLASSIFICATION RESULT BY UTILIZING K-FOLD=6 ON BATIK 300 DATASET

FE	Time (s)	Accuracy							
		KNN					SVM	DT	NB
		1	3	5	7	9			
FE1	0.0261	0.97	0.93	0.91	0.86	0.82	0.98	0.83	0.97
FE2	0.0313	0.97	0.93	0.91	0.86	0.82	0.98	0.86	0.98
FE3	0.0285	0.96	0.91	0.87	0.79	0.76	0.97	0.84	0.98
FE4	0.0337	0.96	0.91	0.87	0.79	0.76	0.97	0.85	0.98

D. Multi Texton Co-occurrence Histogram (MTCH)

Upon accomplishing a detailed analysis of the GLCM, MTH, and CMTH studies, each of which is advantageous in the feature extraction process. GLCM has an advantage in identifying textures globally with statistical features, while MTH has simple feature extraction capabilities with 4 textons indicating high accuracy, and CMTH improves MTH by increasing texton detection utilizing 11 types of textons which are claimed to be better than MTH.

However, in the feature extraction process using 4 textons on MTH, a lot of information is lost when using a non-overlapping stride scheme. Meanwhile, the addition of 11 textons, as reported in a prior study [12], presents an increasing computation time. This study proposes the combination of MTH with GLCM, termed the Multi Texton Co-occurrence Histogram (MTCH). MTCH proposes the application of 6 types of texton and 6 GLCM features (energy, entropy, contrast, correlation, dissimilarity, and homogeneity) to improve performance. The stages of feature extraction in MTCH are as follows:

- Step 1. Edge orientation extraction, which calculates edge orientation features adopted from research using the Sobel operator applied to each R, G, and B channel and quantized to 18 bins.
- Step 2. Texton detection on the results from step 1; the convolution results are stored in a vector with 18 features.
- Step 3. Color quantization on the R, G, and B channels into 4 bins each, totaling 64 bins.
- Step 4. Texton detection on the results from step 3; the convolution results are stored in a vector with 64 features.
- Step 5. GLCM feature extraction (energy, entropy, contrast, correlation, homogeneity, and dissimilarity) with 4 orientations (0, 45, 90, and 135 degrees), totaling 24 features.
- Step 6. Combining 18 edge features, 64 color features, and 24 GLCM features into the MTCH histogram.

1) Edge Orientation Extraction:

Edge orientation plays a crucial role in human visual perception, providing an overview of object boundaries and texture structures containing semantic information. Additionally, edge orientation simultaneously provides shape and texture feature information. In this study, edge orientation detection uses components from the RGB color space. Another study reported that using grayscale images results in the loss of chromatic information [30]. Fig. 4 illustrates the edge orientation feature extraction process.

The maximum change in direction on the gradient is obtained by using Equation 1:

$$\theta = arccos\frac{a.b}{|a|.|b|} \tag{1}$$

The gradients along the x and y directions can then be denoted by two vectors $a(Rx\,, Gx\,, Bx)$ and $b(Ry\,, Gy\,, By)$ where Rx denotes the gradient in R channel along the horizontal direction, Ry denotes the gradient in R channel along the vertical direction and so on. Their norm |a, |b|, and dot product can be defined as Equations 2, 3, and 4.

$$|a| = \sqrt{(Rx)^2 + (Gx)^2 + (Bx)^2} \tag{2}$$

$$|b| = \sqrt{(Ry)^2 + (Gy)^2 + (By)^2} \tag{3}$$

$$a.b = Rx.Ry + Gx.Gy + Bx.By \tag{4}$$

2) Color Extraction:

Color features are crucial for image retrieval and classification. The RGB color space is widely used due to its ease of processing. MTCH quantizes the RGB color space into 64 colors based on prior studies [30]. For an image of size M x N, each R, G, and B channel is quantized into 4 bins, producing 64 colors. These colors form the color features of MTCH in vector form. Fig. 5 illustrates the color feature extraction process.

3) Texton Detection:

Texton detection is performed after color quantization and edge orientation detection. In earlier research, [30] applied the four different types of texton to form a histogram on MTH. For MTCH, this approach adds 2 Textons to detect the presence of the same pixel in one texton, thereby obtaining 6 types of Textons. The added Texton types are horizontal bottom and vertical right. The purpose of adding this texton is to prevent pixel co-occurrence information from missing during feature extraction. The texton used on MTCD is illustrated in Fig. 6, indicating the types of Texton which are T1, T2, T3, T4, T5, and T6. The illustration of Texton detection using MTH vs MTCH is presented in Figs. 7 and 8, indicating that there is a missing pixel pair information when utilizing only the 4 types of texton; meanwhile, the application of the 6 types of texton will enrich the feature and prevent pixel pair information from missing.

4) GLCM features:

The addition of the Gray Level Co-Occurrence Matrix (GLCM) feature to the MTCD is implemented using 6 features: energy, entropy, contrast, correlation, homogeneity, and dissimilarity. The first step is converting the RGB image to grayscale. Second, a co-occurrence matrix is created. Third, the spatial relationship between the reference and neighboring pixels is determined using angle (θ) and distance (d) parameters. Fourth, the matrix is symmetrized by adding the co-occurrence matrix and its transpose. Fifth, the matrix is normalized by calculating the probability of each matrix element. Finally, the GLCM features are calculated. Each

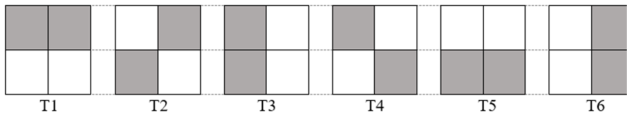

Fig. 6 Six types of Texton of MTCH

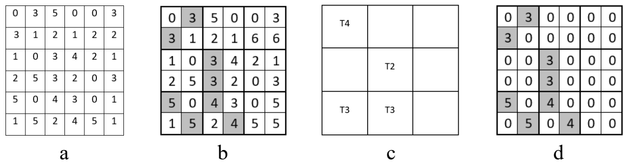

Fig. 7 Illustration of text detection by utilizing MTH

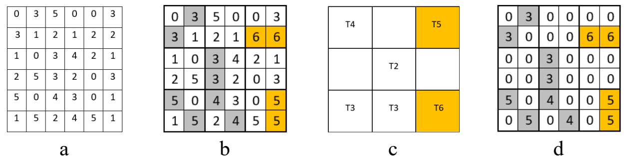

Fig. 8 Illustration of text detection by utilizing MTCH

feature uses a distance of 1 pixel and 4 directions (0°, 45°, 90°, 135°) to detect co-occurrence. Figure 9 provides an overview of the feature extraction process using GLCM. If the GLCM has a matrix of size L x L, where (L) denotes the number of gray levels in the original image, and if the probability (P) of one pixel being adjacent to another pixel at distance (d) and angle (θ) occurs simultaneously, then the energy, entropy, contrast, correlation, homogeneity, and dissimilarity features can be calculated using Equations 5-10.

$$Energy = \sum_{i,j=0}^{L-1} P^2(i,j,d,\theta) \tag{5}$$

$$Ent = \sum_{i,j=0}^{L-1} P(i,j,d,\theta).\log P(i,j,d,\theta) \tag{6}$$

$$Cont = \sum_{i,j=0}^{L-1} (i-j)^2.P(i,j,d,\theta) \tag{7}$$

$$Corr = \sum_{i,j=0}^{L-1} \frac{(i-\mu_x)(j-\mu_y)P(i,j,d,\theta)}{\sigma_x\sigma_y} \tag{8}$$

$$Hom = \sum_{i,j=0}^{L-1} \frac{P^2(i,j,d,\theta)}{1+(i-j)^2} \tag{9}$$

$$Dis = \sum_{i,j=0}^{L-1} P^2(i,j,d,\theta)|i-j| \tag{10}$$

5) Feature Representation:

MTCH consists of two main features, local features and global features. Local features are represented by utilizing Texton-based, while global features are represented by implementing GLCM. Each feature has advantages and disadvantages, from which local features only describe the micro-structure of an image, while GLCM provides global statistical information from an image; thus, the combination of the two capabilities of each of these features underlies MTCH. Fig. 10 presents an illustration of the representation of a batik image by utilizing MTCH.

Texton-based features consist of color feature extraction and edge orientation feature extraction. The color feature map is generated from the Texton convolution on the color quantization results to sixty-four color feature maps, while the edge feature map is generated from the Texton convolution results to the 18 bins quantization results. Global features

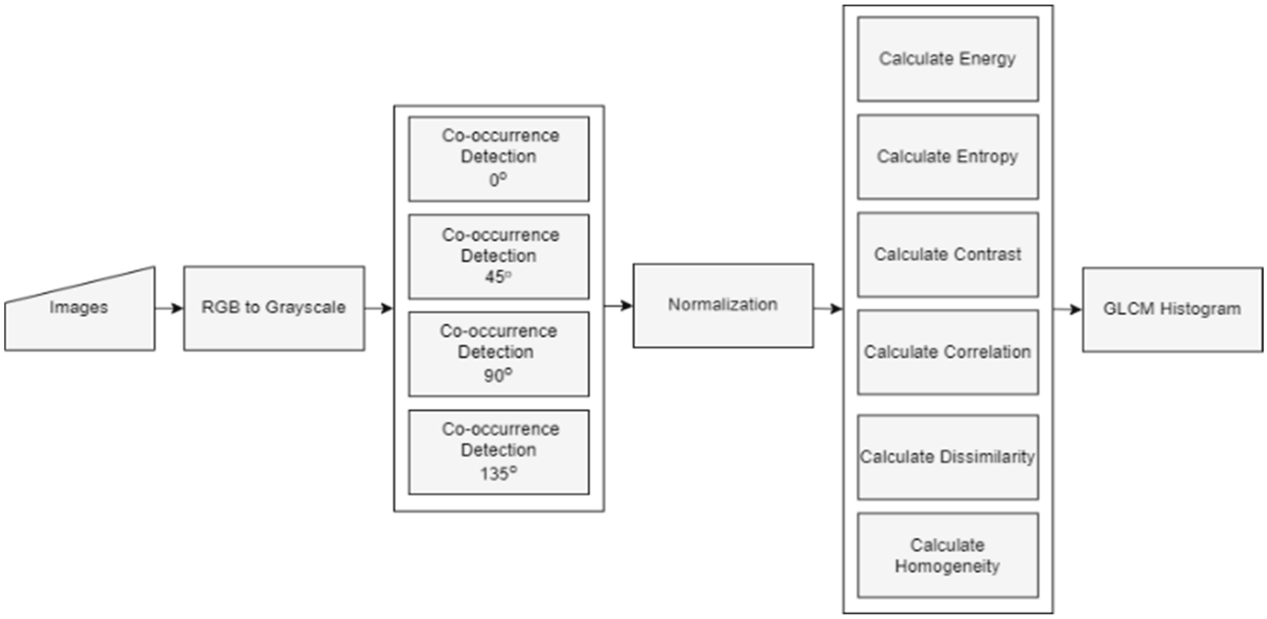

Fig. 9 Illustration of GLCM features extraction.

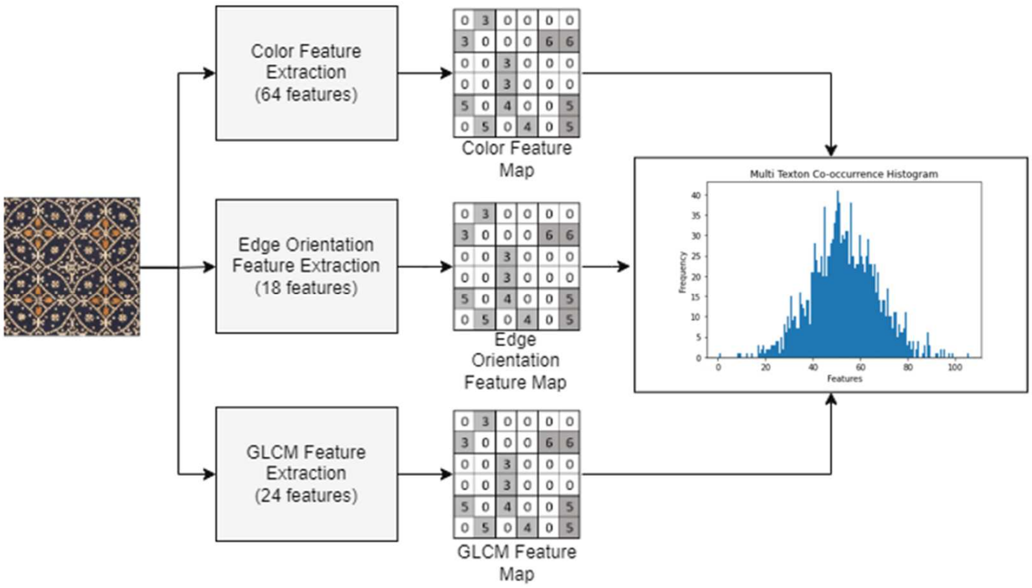

Fig. 10 Illustration of MTCH features a representation

apply GLCM with 6 features, each of which has 4 corners, generating 24 GLCM features. The total features that MTCH has are 64+18+24, equal to 106 features.

III. Results and Discussion

A. Datasets

Batik is regarded as a traditional cultural heritage of Indonesia. This study utilizes the two Batik datasets with different characters to test the capabilities of the proposed feature descriptor. The dataset used is the Batik 300 dataset [31] and Batik Nitik 960 [6]. Batik 300 consists of 50 categories, each category has 6 images, generating a total data of 300 images.

B. Experimental Evaluation

The authors of this study utilized the 4 scenarios to test MTCH and compare it with the state of the arts. The scenario that we compiled is a combination of the use of 6 Textons and 11 Textons. Besides, the present authors conducted an evaluation to determine the effect of using the 4 and 6 GLCM features. The following is the compiled scenario aimed to evaluate the classification and image retrieval.

1) Feature extraction 1 (FE1): Texton: 6 types of texton; GLCM features: energy, entropy, contrast, correlation.

2) Feature extraction 2 (FE2): Texton: 6 types of texton; GLCM features: energy, entropy, contrast, correlation, dissimilarity, homogeneity.

3) Feature extraction 3 (FE3): Texton: 11 types of texton; GLCM features: energy, entropy, contrast, correlation.

Fig. 11 Samples of Batik Nitik 960

TABLE III
AVERAGE RETRIEVAL RESULTS ON BATIK NITIK 960 DATASET

FE	Time (s)	Average Precision r=1-12				Average Recall r=1-12			
		Euclidean	City blocks	Euclidean	City blocks	Euclidean	City blocks	Euclidean	City blocks
FE1	0.0262	0.382	0.427	0.427	0.505	0.189	0.209	0.210	0.254
FE2	0.0321	0.382	0.432	0.431	0.558	0.189	0.211	0.212	0.281
FE3	0.0306	0.375	0.399	0.399	0.505	0.186	0.196	0.196	0.254
FE4	0.0353	0.375	0.403	0.404	0.558	0.186	0.198	0.198	0.281

TABLE IV
AVERAGE RETRIEVAL RESULTS ON BATIK 300 DATASET

FE	Time (s)	Average Precision r=1-12				Average Recall r=1-12			
		Euclidean	City blocks	Euclidean	City blocks	Euclidean	City blocks	Euclidean	City blocks
FE1	0.0257	0.929	0.953	0.954	0.991	0.568	0.585	0.586	0.616
FE2	0.0307	0.929	0.954	0.954	0.993	0.568	0.586	0.586	0.619
FE3	0.0288	0.919	0.929	0.933	0.991	0.558	0.564	0.568	0.616
FE4	0.0341	0.919	0.929	0.929	0.993	0.558	0.564	0.564	0.619

4) *Feature extraction 4 (FE4)*: Texton: 11 types of texton; GLCM features: energy, entropy, contrast, correlation, dissimilarity, homogeneity.

MTCH was tested on classification and image retrieval. The classifiers included k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Naïve Bayes (NB). For image retrieval, Euclidean distance, City block, Bray Curtis, and Canberra distances were used. Classification performance was measured by accuracy, while image retrieval used precision and recall.

For the Batik Nitik 960 dataset, we used 12 training sessions, 2 validation, and 2 test samples. KNN classifiers were tested with k values of 1, 3, 5, 7, and 9. For the Batik 300 dataset, K-fold cross-validation was applied due to the limited number of images per category. Feature extraction time was measured using 4 scenarios to compare 6 and 11 texton types. Table 1 shows the average classification results for Batik Nitik 960, and Table 2 for Batik 300. Results indicate no significant difference between 6 (FE1) and 11 textons (FE3), though FE3 had slightly longer computation time. Using 6 GLCM features (FE3, FE4) significantly improved accuracy compared to using 4 GLCM features (FE1, FE2).

For image retrieval, Batik Nitik 960 used retrieval 1 to 12, as the other 4 data were for testing and validation. Batik 300 used retrieval r = 1 to 4, with 2 data for testing. The same test scenarios (FE1-FE4) were applied to both datasets. Results in Table 3 and Table 4 show that combining local (Texton-based) and global (GLCM) features improves performance.

In this study, we evaluated the MTCH method against three established techniques (MTH, CMTH, and SCH), focusing on feature extraction time and classification accuracy using the Batik Nitik 960 dataset. Our results show that MTCH outperforms others, achieving superior classification accuracies with classifiers such as SVM, DT, and NB. Table 5 and Table 6 present the classification performance comparison, while Table 7 and Table 8 compare MTCH with state-of-the-art methods.

TABLE V
PERFORMANCE COMPARISON CLASSIFICATION RESULT ON BATIK NITIK 960 DATASET TO STATE OF THE ARTS

Datasets	FE	Time (s)	Accuracy		
			SVM	DT	NB
Batik Nitik 960	MTH [30]	0.0232	0.62	0.62	0.84
	CMTH [12]	0.0340	0.64	0.65	0.86
	SCH [25]	0.0470	0.66	0.67	0.88
	MTCH (Proposed)	0.0349	0.68	0.68	0.89

With scores of 0.68, 0.68, and 0.89, respectively, and a feature extraction time of 0.0349 seconds, MTCH demonstrates a balance between processing speed and

TABLE VI
PERFORMANCE COMPARISON CLASSIFICATION RESULT ON BATIK 300 DATASET TO STATE OF THE ARTS

Datasets	FE	Time (s)	Accuracy k-fold = 6		
			SVM	DT	NB
Batik 300	MTH [30]	0.0219	0.92	0.82	0.93
	CMTH [12]	0.0313	0.94	0.82	0.94
	SCH [25]	0.0465	0.96	0.83	0.96
	MTCH (Proposed)	0.0337	0.97	0.85	0.98

TABLE VII
PERFORMANCE COMPARISON OF IMAGE RETRIEVAL ON BATIK NITIK 960 DATASET TO STATE OF THE ARTS

Datasets	FE	Time (s)	Precision	Recall
Batik Nitik 960	MTH [30]	0.0314	0.50	0.24
	CMTH [12]	0.0337	0.52	0.25
	SCH [25]	0.0478	0.53	0.26
	MTCH (Proposed)	0.0353	0.55	0.28

TABLE VIII
PERFORMANCE COMPARISON OF IMAGE RETRIEVAL ON BATIK 300 DATASET TO STATE OF THE ARTS

Datasets	FE	Time (s)	Precision	Recall
Batik 300	MTH [30]	0.0308	0.96	0.57
	CMTH [12]	0.0335	0.97	0.58
	SCH [25]	0.0466	0.98	0.59
	MTCH (Proposed)	0.0341	0.99	0.61

accuracy, surpassing both CMTH's time efficiency and SCH's speed. This balance makes MTCH suitable for real-time systems and large-scale datasets requiring both precision and speed. In classification tests, MTCH consistently outperforms SVM, DT, and NB classifiers, proving its robustness. For image retrieval, MTCH boasts superior precision (0.55) and recall (0.28), highlighting its effectiveness in pinpointing relevant images. MTCH's combined efficiency and accuracy make it an excellent choice for applications needing fast and precise image retrieval. Overall, MTCH stands for a significant advancement in image processing and machine learning, offering a balanced approach to computational efficiency and performance accuracy.

IV. CONCLUSION

In sum, the exponential growth of artificial intelligence, alongside technological advances, has aided in classifying batik motifs. However, the diversity and evolution of contemporary batik pose recognition challenges. Machine learning can serve as a decision support system for deeper analysis of batik motifs. This paper presents a descriptor for representing batik images with various motifs, using classification and image retrieval. MTCH was tested on two datasets, incorporating color, texture, and shape through a combination of local and global features. Results indicate that the correct type of texton can save computation while maintaining performance and adding dissimilarity and homogeneity features can enhance classification and image retrieval.

REFERENCES

[1] N. Setyawan, M. N. Achmadiah, C.-C. Sun, and W.-K. Kuo, “Multi-Stage Vision Transformer for Batik Classification,” 2024 International Electronics Symposium (IES), pp. 449–453, Aug. 2024, doi:10.1109/ies63037.2024.10665807.

[2] A. E. Minarno, I. Soesanti, and H. A. Nugroho, “Optimization of BatikGAN with Gradient Loss for Enhanced Batik Motif Generation,” 2024 IEEE 6th Symposium on Computers & Informatics (ISCI), pp. 305–310, Aug. 2024, doi:10.1109/isci62787.2024.10668317.

[3] X. Zhao, C. Shu, S. Jiang, and Y. Hu, “From classification to matching: A CNN-based approach for retrieving painted pottery images,” Digital Applications in Archaeology and Cultural Heritage, vol. 29, p. e00269, Jun. 2023, doi: 10.1016/j.daach.2023.e00269.

[4] A. Colmenero-Fernández and F. Feito, “Image processing for graphic normalisation of the ceramic profile in archaeological sketches making use of deep neuronal net (DNN),” Digital Applications in Archaeology and Cultural Heritage, vol. 22, p. e00196, Sep. 2021, doi:10.1016/j.daach.2021.e00196.

[5] M. Seidl, E. Wieser, and C. Alexander, “Automated classification of petroglyphs,” Digital Applications in Archaeology and Cultural Heritage, vol. 2, no. 2–3, pp. 196–212, 2015, doi:10.1016/j.daach.2015.03.001.

[6] A. E. Minarno, I. Soesanti, and H. A. Nugroho, “Batik Nitik 960 Dataset for Classification, Retrieval, and Generator,” Data, vol. 8, no. 4, p. 63, Mar. 2023, doi: 10.3390/data8040063.

[7] A. E. Minarno, I. Soesanti, and H. A. Nugroho, “Batik Image Retrieval using Convolutional Autoencoder,” 2024 IEEE 14th Symposium on Computer Applications & Industrial Electronics (ISCAIE), pp. 15–20, May 2024, doi: 10.1109/iscaie61308.2024.10576476.

[8] A. E. Minarno, I. Soesanti, and H. A. Nugroho, “A Convolutional Neural Network Model for Batik Image Retrieval,” 2024 IEEE 14th Symposium on Computer Applications & Industrial Electronics (ISCAIE), pp. 31–36, May 2024, doi:10.1109/iscaie61308.2024.10576422.

[9] “Batik image Retrieval based on Convolutional Neural Network | Code Ocean.” Accessed: Oct. 22, 2024. [Online]. Available: https://codeocean.com/capsule/1012598/tree/v1

[10] “Batik image Retrieval based on Autoencoder | Code Ocean.” Accessed: Oct. 22, 2024. [Online]. Available: https://codeocean.com/capsule/8881860/tree/v1

[11] X. Bu, Y. Wu, Z. Gao, and Y. Jia, “Deep convolutional network with locality and sparsity constraints for texture classification,” Pattern Recognition, vol. 91, pp. 34–46, Jul. 2019, doi:10.1016/j.patcog.2019.02.003.

[12] B. Khaldi, O. Aiadi, and K. M. Lamine, “Image representation using complete multi-texton histogram,” Multimedia Tools and Applications, vol. 79, no. 11–12, pp. 8267–8285, Jan. 2020, doi:10.1007/s11042-019-08350-1.

[13] A. E. Minarno, I. Soesanti, and H. A. Nugroho, “Batik Classification using Microstructure Co-occurrence Histogram,” JOIV : International Journal on Informatics Visualization, vol. 8, no. 1, p. 134, Mar. 2024, doi: 10.62527/joiv.8.1.2152.

[14] V. Ayumi, I. Nurhaida, and W. H. Haji, “Designing a Web Application for Detecting Indonesian Batik Motifs Based on Image Processing and Machine Learning,” *JSAI (Journal Scientific and Applied Informatics)*, vol. 6, no. 3, pp. 499–504, Nov. 2023, doi:10.36085/JSAI.V6I3.6240.

[15] Y. Sari, M. Alkaff, and R. A. Pramunendar, “Classification of coastal and Inland Batik using GLCM and Canberra Distance,” AIP Conference Proceedings, vol. 1977, p. 020045, 2018, doi:10.1063/1.5042901.

[16] N. K. Hamzidah, A. Jariyah, A. R. Ramadhani, N. Nurhasni, M. M. Parenreng, and S. Suyuti, “Evaluation of image feature extraction using gray level co-occurrence matrix (GLCM) parameters and multilayer perceptron (MLP) algorithms in classifying typical batik motifs of South Sulawesi,” *AIP Conf Proc*, vol. 3140, no. 1, Jul. 2024, doi: 10.1063/5.0221156/3302835.

[17] A. Tarigan, D. Agushinta, A. Suhendra, and F. Budiman, “Determination of SVM-RBF Kernel Space Parameter to Optimize Accuracy Value of Indonesian Batik Images Classification,” Journal of Computer Science, vol. 13, no. 11, pp. 590–599, Nov. 2017, doi:10.3844/jcssp.2017.590.599.

[18] F. Budiman, “SVM-RBF Parameters Testing Optimization Using Cross Validation and Grid Search to Improve Multiclass Classification,” Scientific Visualization, vol. 11, no. 1, 2019, doi:10.26583/sv.11.1.07.

[19] A. E. Minarno, Y. Azhar, F. D. Setiawan Sumadi, and Y. Munarko, “A Robust Batik Image Classification using Multi Texton Co-Occurrence Descriptor and Support Vector Machine,” 2020 3rd International Conference on Intelligent Autonomous Systems

(ICoIAS), pp. 51–55, Feb. 2020, doi:10.1109/icoias49312.2020.9081833.
[20] A. H. Rangkuti, Z. E. Rasjid, and D. J. Santoso, “Batik Image Classification Using Treeval and Treefit as Decision Tree Function in Optimizing Content Based Batik Image Retrieval,” Procedia Computer Science, vol. 59, pp. 577–583, 2015, doi:10.1016/j.procs.2015.07.551.
[21] M. Fadhilla, D. Suryani, N. Syafitri, and H. Gunawan, “Image Retrieval of Indonesian Batik Clothing Based on Convolutional Neural Network,” 2022 3rd International Conference on Electrical Engineering and Informatics (ICon EEI), pp. 177–180, Oct. 2022, doi:10.1109/iconeei55709.2022.9972332.
[22] J.-M. Guo, A. W. Hari Prayuda, and H. Prasetyo, “Hashing-based Batik Image Retrieval using Progressive Multi-Stage Training,” 2022 1st International Conference on Smart Technology, Applied Informatics, and Engineering (APICS), pp. 21–26, Aug. 2022, doi: 10.1109/apics56469.2022.9918690.
[23] H. Prasetyo, W. Wiranto, and W. Winarno, “Statistical Modeling of Gabor Filtered Magnitude for Batik Image Retrieval | Journal of Telecommunication, Electronic and Computer Engineering (JTEC).” Accessed: Jun. 21, 2024. [Online]. Available: https://jtec.utem.edu.my/jtec/article/view/4322
[24] B. R. Lidiawaty, M. Isa Irawan, and R. V. Hari Ginardi, “Image Pattern Verification Based On Seller’s Batik Solo Product Name Using SURF As A Texture Based Image Retrieval,” 2020 International Electronics Symposium (IES), pp. 674–679, Sep. 2020, doi:10.1109/ies50839.2020.9231950.
[25] E. M. Martey, H. Lei, X. Li, and O. Appiah, “Image Representation Using Stacked Colour Histogram,” Algorithms, vol. 14, no. 8, p. 228, Jul. 2021, doi: 10.3390/a14080228.
[26] A. E. Minarno, M. Y. Hasanuddin, and Y. Azhar, “Batik Images Retrieval Using Pre-trained model and K-Nearest Neighbor,” JOIV : International Journal on Informatics Visualization, vol. 7, no. 1, p. 115, Feb. 2023, doi: 10.30630/joiv.7.1.1299.
[27] H. Prasetyo et al., “Batik Image Retrieval Using ODBTC Feature and Particle Swarm Optimization.” Accessed: Jun. 21, 2024. [Online]. Available: https://jtec.utem.edu.my/jtec/article/view/4319/3166
[28] H. Prasetyo and J. W. Simatupang, “Batik Image Retrieval Using Maximum Run Length LBP and Sine-Cosine Optimizer,” 2019 International Conference on Sustainable Engineering and Creative Computing (ICSECC), pp. 265–269, Aug. 2019, doi:10.1109/icsecc.2019.8907190.
[29] R. M. Haralick, K. Shanmugam, and I. Dinstein, “Textural Features for Image Classification,” IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, no. 6, pp. 610–621, Nov. 1973, doi:10.1109/tsmc.1973.4309314.
[30] G.-H. Liu, L. Zhang, Y.-K. Hou, Z.-Y. Li, and J.-Y. Yang, “Image retrieval based on multi-texton histogram,” Pattern Recognition, vol. 43, no. 7, pp. 2380–2389, Jul. 2010, doi:10.1016/j.patcog.2010.02.012.
[31] A. Minarno and N. Suciati, “Batik 300,” vol. 1, 2022, doi:10.17632/VZ7PZT2GRF.1.