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Research Article

Influence of gray level co-occurrence matrix for texture feature extraction on identification of batik motifs using k-nearest neighbor

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Abstract

Batik is one type of fabric that is unique because it has a special motif, in Indonesia itself batik is unique because it has certain motifs that are made based on the culture from which batik was made. This study aims to examine the effect of the texture feature extraction method on the identification of batik motifs from five major islands in Indonesia. The method used in this study is the Gray Level Co-occurrence Matrix as the texture feature extraction of batik motifs to obtain good batik motif identification accuracy results and to determine the value of the proximity of the training data and image testing of batik motifs, the K-Nearest Neighbor classification method will be used based on texture feature extraction value obtained. In this experiment, 5 experiments will be carried out based on angles 0°, 45°, 90°, 135°, and 180° using the values of k=1, 3, 5, and 7. The confusion matrix will be used to calculate the accuracy level of the K-Nearest Neighbor classification. From the results of experiments carried out using training data as many as 607 images and testing as many as 344 images in five classes used with angles of 0°, 45°, 90°, 135°, 180°, and values of k=1, 3, 5, and 7, getting the highest accuracy results is at an angle of 135°and 180° with a value of k=1 of 89.24% and the lowest is at an angle of 90° with a value of k=3 of 67.44%. This shows that the gray level co-occurrence matrix method is good for extracting the texture features of batik motifs from five major islands in Indonesia, it is evidenced by the results of the average accuracy of the classification obtained.

Keywords: Gray Level Co-Occurrence Matrix; K-Nearest Neighbor; Confusion Matrix; Feature Extraction; Identification of batik motif.

Introduction

Batik is an Indonesian cultural heritage that is now worldwide and has even become a fashion trend in several countries in ASEAN. Indonesia is also a country that has cultural diversity, one of Indonesia's cultural wealth which is widely known is the art of Batik. Batik is the ancestral cultural heritage of the Indonesian people that cannot be separated from the life of the Indonesian people, especially the people on the island of Java. In Indonesia, batik has become a trend in people's lives, with many batik enthusiasts making batik craftsmen continue to innovate in the creativity of making batik motifs that are adapted to fashion developments, especially in Indonesia.

Further developments, when batik as a tradition that has a symbolic meaning and the value of local cultural wisdom that must continue to be present in the era of globalization which incidentally is very complex with a mass culture that is struggling with information and communication technology is so extensive that it makes information about the art of batik widely spread by so fast [1]. Currently, batik is not only used at certain events and used by certain circles but has been transformed into Indonesian fashion. Patterns on batik are arranged repeatedly to describe the basic motif on a cloth as a whole, repetition of motifs on batik cloth can be arranged either regularly or irregularly [2]. Very diverse batik motifs make it difficult to recognize each pattern of batik imagery so that this is what makes batik interesting and has its own uniqueness to be studied.

Previously, research on the identification of batik motifs by, A.A. Kasim and A. Harjoko [3] examined the classification of batik images by utilizing Gray Level Co-Occurrence Matrices (GLMC) as feature extraction of batik images and backpropagation of artificial neural networks as classification methods. Yhoda and A.W. Kurniawan [4]

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in the study of batik motif recognition by utilizing canny edge detection and K-Nearest Neighbor as a classification. H. Wijayanto [5] researched the classification of batik using the K-nearest neighbor method based on the gray level co-occurrence matrix. N.L Wiwik and Sri Rahayu [6] who researched the detection of machete batik, in their research the geometric moment invariant and occurrence matrix were used as image feature extraction and used K-Nearest Neighbor as a classification method. Because batik craftsmen in Indonesia have spread across various regions and islands, so that the batik motifs made vary based on regional characteristics, that is one reason why batik is difficult to identify based on the area where batik is made. Batik can be classified based on its motifs, namely special motifs, non-geometric motifs, and geometric motifs [7].

Gray level co-occurrence matrix is one of the best texture feature extraction methods used for feature extraction in images, that's why in this study it is used as a feature extraction method on batik motif images from five major islands in Indonesia, namely the islands of Kalimantan, Papua, Sumatra, Sulawesi, and Java. Meanwhile, K-Nearest neighbor is used for the classification of the feature extraction results of batik motif images and the confusion matrix is used as an evaluation to calculate the accurate value of the batik motif identification results. (Times 10pt)

Method

In this study, we will use the Gray Level Co-Occurrence Matrix as a feature extraction method, while K-Nearest Neighbor in this study will be used as a classification of batik motifs based on the results of feature extraction of the gray level co-occurrence matrix on the image of batik motifs, and the confusion matrix will be used as an evaluation to calculate the accuracy of the K-Nearest Neighbor classification based on angles 0°, 45°, 90°, 135°, and 180° at values of k=1, 3, 5, and 7. **Figure 1** is a method model that explains the stages of the batik motif image data processing process.

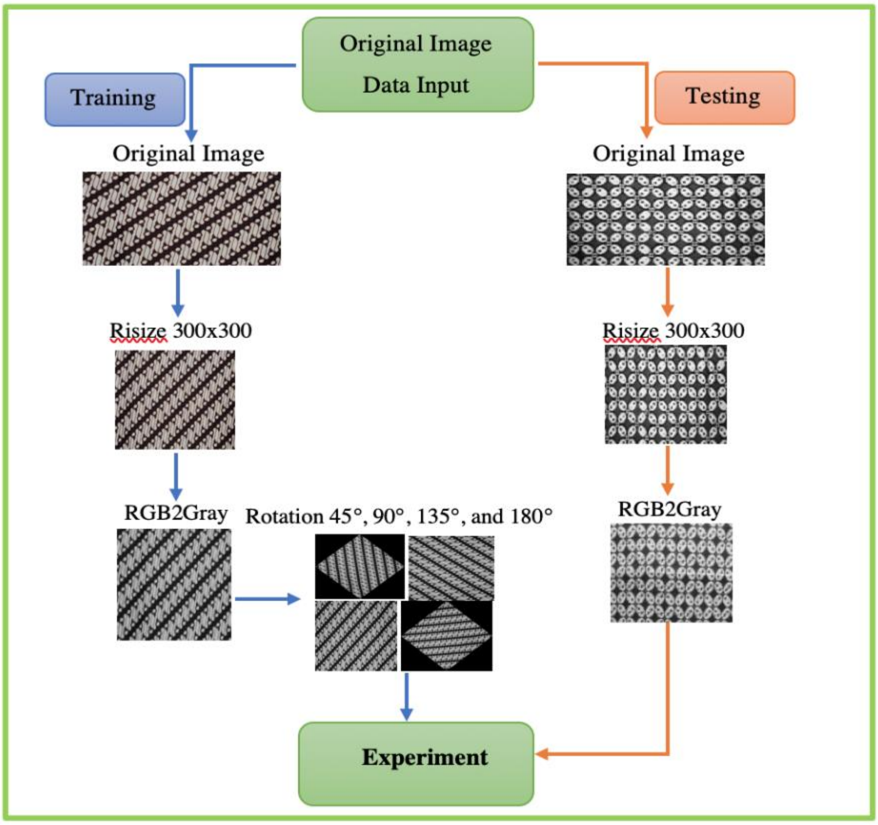


Figure 1. Image Data Processing Framework

A. Gray Level Co-Occurrence Matrix

The gray level co-occurrence matrix is a texture feature extraction method that works based on statistical calculations that refer to the original pixel value with the neighboring relationship between two pixels at a certain distance [8] [9]. The initial step to calculate the Gray Level Co-Occurrence Matrix feature is to create a co-occurrence matrix after which it is continued by determining the spatial relationship between neighboring pixels and frequency pixels based on 0° [7] [8] [9]. GLCM is calculated based on how often a Gray Level *i* pixel appears horizontally, vertically, or diagonally in pairs with a Gray Level *j* pixel [10].

The features extracted from GLCM are correlation, homogeneity, contrast, and energy. Homogeneity is the distribution of elements in GLCM, correlation is used to calculate the probability that pairs of pixels appear simultaneously, contrast is used for local variations in GLCM, and energy is used to calculate each element to the power of two [7] [9] [11]. **Figure 2**, is the angular direction of the Gray Level Co-Occurrence Matrix that will be used in this study.

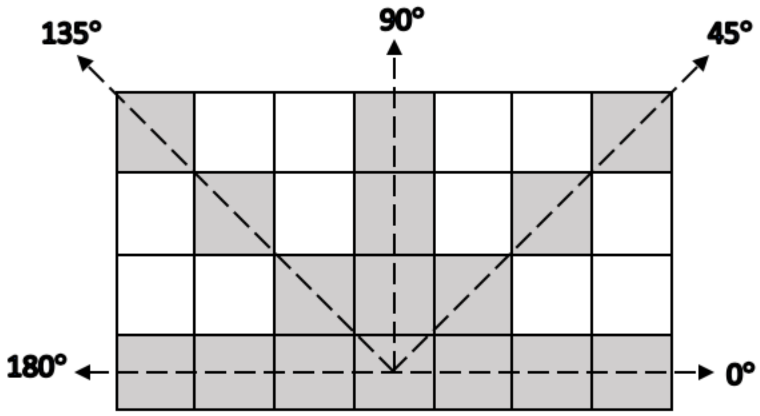


Figure 2. GLCM Angle Direction Used

What is shown in figure 2, describes the selection of neighboring pixels starting from the right. The 1,0 relationship is the relationship of 2 pixels with a value of 1 followed by a pixel with a value of 0. **Figure 3** is a sample calculation of the Gray Level Co-Occurrence Matrix in a pair of 2 pixels of the GLCM matrix.

0	4	6	6	6	4
3	4	5	5	4	3
5	4	4	4	3	1
5	3	4	4	2	0
3	3	2	2	1	1
3	1	1	0	1	2

(a) Original Image

0,0	0,1	0,2	0,3	0,4	0,5	0,6
1,0	1,1	1,2	1,3	1,4	1,5	1,6
2,0	2,1	2,2	2,3	2,4	2,5	2,6
3,0	3,1	3,2	3,3	3,4	3,5	3,6
4,0	4,1	4,2	4,3	4,4	4,5	4,6
5,0	5,1	5,2	5,3	5,4	5,5	5,6
6,0	6,1	6,2	6,3	6,4	6,5	6,6

(b) Pixel Composition

0	1	0	0	1	0	0
1	2	1	0	0	0	0
1	1	1	0	0	0	0
0	2	1	1	2	0	0
0	0	1	2	3	1	1
0	0	0	1	2	1	0
0	0	0	0	1	0	2

(c) Number of Pixel Pairs

Figure 3. GLCM matrix pixel pairs

After calculating the pair of 2 pixels of the Gray Level Co-Occurrence Matrix, the matrix will be processed into a symmetrical matrix by adding the transpose value as shown in **Figure 4**.

Symmetrical Matrix Formation																						
0	1	0	0	1	0	0		0	1	1	0	0	0	0		0	2	1	0	1	0	0
1	2	1	0	0	0	0		1	2	1	2	0	0	0		2	4	2	2	0	0	0
1	1	1	0	0	0	0		0	1	1	1	1	0	0		1	2	2	1	1	0	0
0	2	1	1	2	0	0	+	0	0	0	1	2	1	0	=	0	2	1	2	4	1	0
0	0	1	2	3	1	1		1	0	0	2	3	2	1		1	0	1	4	6	3	2
0	0	0	1	2	1	0		0	0	0	0	1	1	0		0	0	0	1	3	2	0
0	0	0	0	1	0	2		0	0	0	0	1	0	2		0	0	0	0	2	0	4

Figure 4. Symmetrical Matrix Formation

Furthermore, after the symmetric matrix is formed, the matrix normalization of the image will be carried out to eliminate the dependence on the image size. This is necessary to normalize the value of the Gray Level Co-occurrence Matrix so that the sum is worth 1 as shown in **Figure 5**.

Matrix Normalization						
0/24	2/24	1/24	0/24	1/24	0/24	0/24
2/24	4/24	2/24	2/24	0/24	0/24	0/24
1/24	2/24	2/24	1/24	1/24	0/24	0/24
0/24	2/24	1/24	2/24	4/24	1/24	0/24
1/24	0/24	1/24	4/24	6/24	3/24	2/24
0/24	0/24	0/24	1/24	3/24	2/24	0/24
0/24	0/24	0/24	0/24	2/24	0/24	4/24

Figure 5. Matrix Normalization from Image

Matrix Normalization Result Value						
0.00	0.08	0.04	0.00	0.04	0.00	0.00
0.08	0.17	0.08	0.08	0.00	0.00	0.00
0.04	0.08	0.08	0.04	0.04	0.00	0.00
0.00	0.08	0.04	0.08	0.17	0.04	0.00
0.04	0.00	0.04	0.17	0.25	0.13	0.08
0.00	0.00	0.00	0.04	0.13	0.08	0.00
0.00	0.00	0.00	0.00	0.08	0.00	0.17

Figure 6. Matrix Normalization Results

From the normalization of the matrix, the results of the normalization of the matrix are obtained as shown in **Figure 6**. Based on the results of the normalization of the matrix obtained, the calculation of Angular Second Moment (ASM), Contras, Inverse Different Moment (IDM), Entropy, and Correlation will be carried out [7] [9] [12].

1. ASM is a measure of homogeneity calculated by the formula (1):
   $$ASM = \sum_{i=1}^{L} \sum_{j=1}^{L} (GLCM(i,j)^2 \quad (1)$$
   Where SN represents the number of levels used for computation, and (*i, j*) is the value in row *i* and column *j* in the normalized matrix.
2. Contrast Shows the size of the Grayscale variation obtained based on the formula (2):
   $$Kontras = \sum_{n=1}^{L} n^2 \left\{ \sum_{|i-j|=n} GLCM(i,j) \right\} \quad (2)$$
   Where i is the value in the row and j is the value in the column.
3. IDM is used to measure homogeneity based on the formula (3):
   $$IDM = \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{(GLCM(i,j)^2}{1+(i-j)^2} \quad (3)$$

Where (i, j) is the value in row 1 and column j, divided by the number 1 and then added by the squared value of i-j.

4. Entropy is an irregular measure of the gray level in an image. Entropy is calculated based on the formula (4):
$$Entropi = -\sum_{i=1}^{L}\sum_{j=1}^{L}(GLCM(i,j)\log\,(GLCM(i,j) \quad (4)$$
Where (i,j) is the value in a row and column j multiplied by log2 on the value (i,j).
5. Correlation is a linear dependence between the gray level values in an image, to calculate it using the formula (5):
$$Korelasi = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}(ij)(GLCM(i,j) - \mu_i{}'\mu_j{}'}{\sigma_i{}'\sigma_j{}'} \quad (5)$$
Where i is the row value and j is the column value, is the sum of the values of i or j.

B. K-Nearest Neighbor

K-NN is a classification method that works based on the Supervised algorithm and the results of the Querynstance are classified based on most of the K-Nearest Neighbor categories. K-Nearest Neighbor is a classification method that determines categories based on the majority of categories in the k-nearest neighbors, near or far neighbors are usually calculated based on the Euclidean distance. K-Nearest Neighbor works very simply, that's because K-NN works based on the shortest distance from the query instance to the training sample to find its K. Near or far neighbors are usually calculated based on Euclidean Distance. Euclidean distance serves to test a measure that can be used as an interpretation of the proximity of the distance between two objects [13] [14] [15]. Which is presented as formula (6):

$$d(x - y) = \sqrt{\sum_{j=1}^{i}\ (x_j - y_j)^2} \quad (6)$$

Information:

d = distance of test data to learning data

x_j = test data to-j, with j = 1, 2, . . . n

$y_{j=}$ learning data to-j with j = 1, 2, . . .n.

C. Confusion Matrix

The confusion matrix performs tests to estimate true and false objects. Each cell contains a number that shows how many actual cases of the observed class are predicted, here is the confusion matrix model shown in **Table 1** [13]:

Table 1. Confusion matrix model

True \ Pred	Jawa	Kalimantan	Papua	Sulawesi	Sumatera
Jawa	***True Jawa***	False Kalimantan	False Papua	False Sulawesi	False Sumatera
Kalimantan	False Jawa	***True Kalimantan***	False Papua	False Sulawesi	False Sumatera
Papua	False Jawa	False Kalimantan	***True Papua***	False Sulawesi	False Sumatera
Sulawesi	False Jawa	False Kalimantan	False Papua	***True Sulawesi***	False Sumatera
Sumatera	False Jawa	False Kalimantan	False Papua	False Sulawesi	***True Jawa***

Note: TP = positive tuple which is classified as positive
TN = negative tuple which is classified as negative
FP = positive tuple which is classified as negative
FN = negative tuple that is classified as positive

D. Dataset

In this study, batik data used is batik data from five major islands in Indonesia, namely, Papua, Kalimantan, Sumatra, Sulawesi, and Java. In **Table 2**, is the total amount of data used in each class, both training image data and testing image data.

Table 2. Total Training and Testing Data

CLASS	Training Data Amount	Testing Data Amount
Batik Papua	127	72

CLASS	Training Data Amount	Testing Data Amount
Batik Kalimantan	120	68
Batik Sumatera	113	64
Batik Sulawesi	106	60
Batik Jawa	141	80
Total	607	344

Figures 7 and **Figure 8** are sample training and testing data used.

Figure 7. Sample Data Training

The training data will be resized to a size of 300 x 300 pixels, and then rotated with angles of 0°, 45°, 90°, 135°, dan 180° as shown in **Figure 7**. While the testing data will only be rotated with a size of 300 x 300 pixels as shown in **Figure 8**.

Figure 8. Sample Data Testing

Results and Discussion

This study aims to measure the accuracy of batik motif identification using K-Nearest Neighbor based on the effect of feature extraction on the Gray Level Co-Occurrence Matrix on batik motifs from five major islands in Indonesia. The test was carried out with 5 angles, namely 0°, 45°, 90°, 135°, 180° and 5 classes, namely Java, Kalimantan, Papua, Sulawesi, and Sumatra, classification is done with k values of 1, 3, 5, and 7. From the results of experiments conducted at angles of 0°, 45°, and 90°, it shows different results for the 5 angles of and the value of k used, while the results of accuracy carried out at angles of 135° and 180° have high accuracy results. the same for each value of k used.

The results of experiments carried out on all angles of and the value of k get different highest accuracy results and there are also those with the same accuracy values as shown in **Table 3**.

Table 3. highest accuracy results at all angles and *k* values

Highest Accuracy		
Angle θ	**Value *k***	**Accuracy %**
0	1	83,43023265
45	1	88,37209302
90	3	67,44186047
135	1	89,24418605
180	1	8924418605

Figure 9 is a graphic image of the highest accuracy results at all angles and values of.

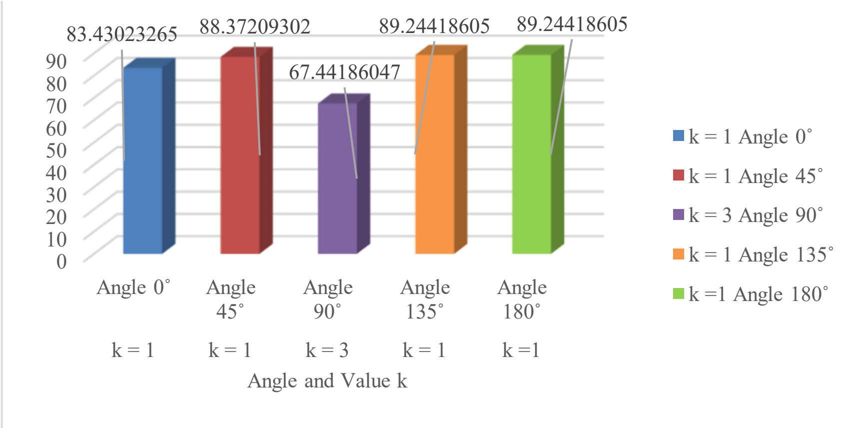


Figure 9. Highest accuracy chart

Figure 9 is explained that the accuracy results from the experiments carried out, the lowest accuracy results are at an angle of 90°, and the highest accuracy results are at an angle of 135°, and 180°. From the experimental results, the highest average percentage of accuracy is at an angle of 45° for each *k* value used. Below is a graphic image of the experiment carried out at angles 0°, 45°, 90°, 135°, 180° and for all *k* values used, namely *k*=1, 3, 5, and 7.

A. Angle 0° Experiment Results

The results of the 0° angle experiment show different accuracy results at each angle and the k value, the test is carried out 4 times according to the k value, namely 1, 3, 5, and 7. the highest value is at *k*=1 which is 83.43% and the lowest is at the value of *k*=7 which is 59.59%.

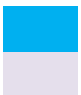
Table 4 is the calculation of the highest accuracy at an angle of 0° with a value of k=1 using a confusion matrix.

Table 4. Confusion Matrix Calculation on Value *k*=1 Angle 0°

Kelas	Confusion Matrix Evaluation *k*=1 Angle 0°				
	Papua	**Kalimantan**	**Papua**	**Sulawesi**	**Sumatera**
Jawa	68	1	5	1	5
Kalimantan	1	59	5	1	2
Papua	2	4	60	2	4
Sulawesi	3	1	1	53	2
Sumatera	4	4	6	3	47

$$Accuracy = \frac{68+59+60+53+47}{344} = 83,43\%$$

Color Explanation:



True Test Data

Incorrect Test Data

Figure 10 shows the results of the 0° angle accuracy at the values of k = 1, 3 5, and 7.

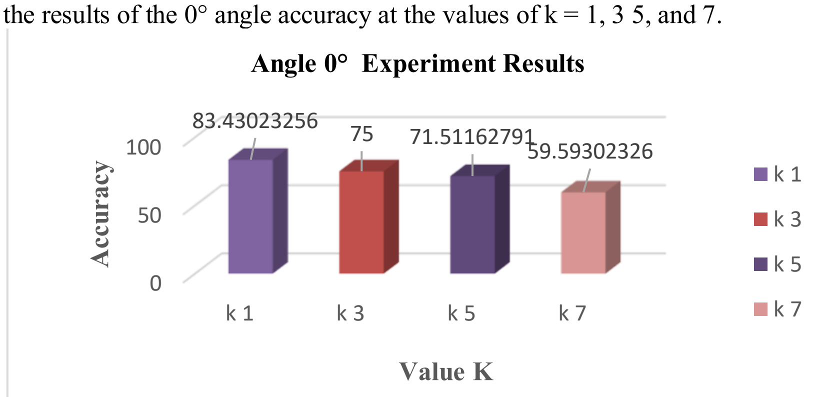


Figure 10. Angle 0° Experiment Results graphic

B. *Angle 45° Experiment Result*

The results of experiments conducted at an angle of 45° using the values of k = 1, 3, 5, and 7, it shows different results. The highest accuracy results are at a value of k = 1, which is 88.37% while the lowest is at a value of k = 7, which is 68.02%.

Table 5 is the calculation of the highest accuracy results at the value of k = 1 with a confusion matrix.

Table 5. Confusion Matrix Calculation on Value k=1 Angle 45°

Kelas	Confusion Matrix Evaluation k=1 Angle 45°				
	Papua	Kalimantan	Papua	Sulawesi	Sumatera
Jawa	73	2	1	4	0
Kalimantan	1	59	3	4	1
Papua	3	2	60	2	5
Sulawesi	2	2	0	56	0
Sumatera	2	4	1	1	56

$$Accuracy\ \frac{73+59+60+56+56}{344} = 88{,}37\%$$

Color Explanation:

True Test Data

Incorrect Test Data

Figure 11 describes the results of the 45° angle accuracy at the values of k = 1, 3, 5, and 7.

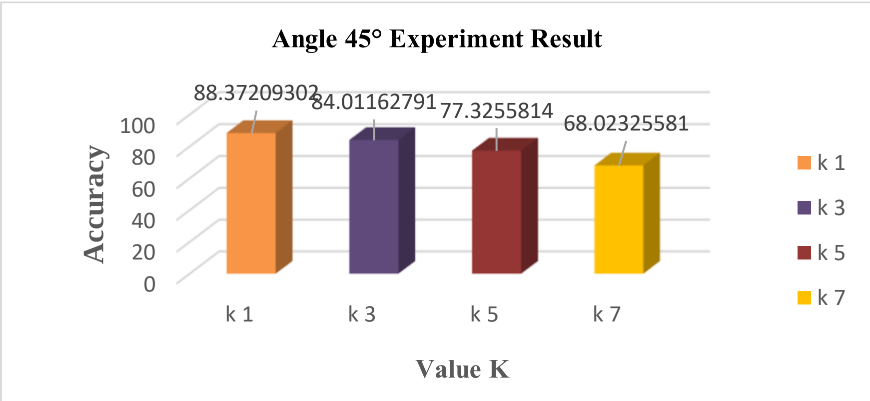


Figure 11. Angle 45° Experiment Results graphic

C. *Angle 90° Experiment Result*

Experiments carried out at an angle of 90° get the highest accuracy at a value of k = 3, which is 67.44%, and the lowest accuracy is at a value of k = 7, which is 52.90%. **Table 6** is the result of calculating accuracy using a confusion matrix at a value of k = 3.

Table 6. Confusion Matrix Calculation on Value k=1 Angle 90°

Kelas	Confusion Matrix Evaluation k=1 Angle 90°				
	Papua	Kalimantan	Papua	Sulawesi	Sumatera
Jawa	59	3	8	2	8
Kalimantan	8	45	7	4	4
Papua	10	2	50	2	8
Sulawesi	3	5	10	36	6
Sumatera	8	3	6	5	42

$$Accuracy\ \frac{59+45+50+36+42}{344} = 67{,}44\%$$

Color Explanation:

True Test Data

Incorrect Test Data

Figure 12 describes the results of accuracy at an angle of 90° at values of k = 1, 3, 5, and 7.

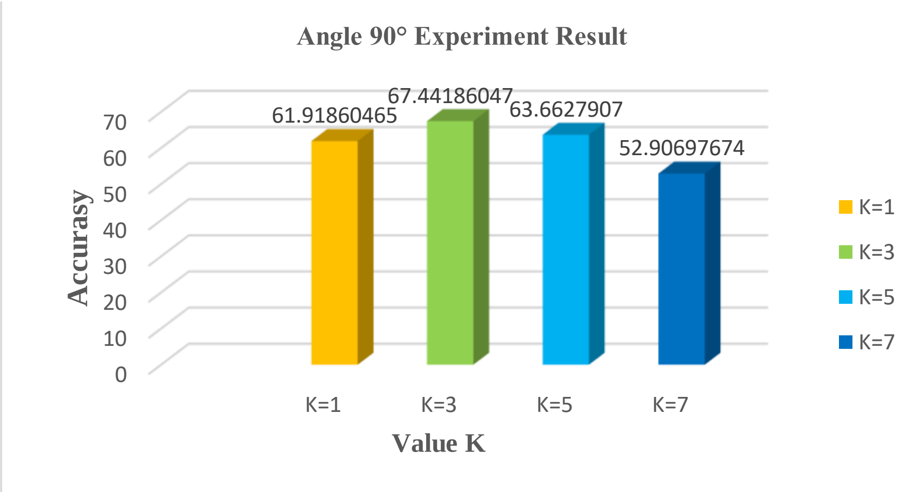


Figure 12. Angle 90° Experiment Results graphic

D. Angle 135° Experiment result

From the experimental results at an angle of 135°, the highest accuracy results are at a value of k = 1, which is 89.24%, while the lowest accuracy results are at a value of k = 7, which is 65.98%. **Table 7** is the result of calculating the accuracy of k = 1 using the confusion matrix.

Table 7. Confusion Matrix Calculation on Value k=1 Angle 135°

Kelas	Confusion Matrix Evaluation *k*=1 Angle 90°				
	Papua	Kalimantan	Papua	Sulawesi	Sumatera
Jawa	74	2	1	2	1
Kalimantan	3	57	3	2	3
Papua	2	2	65	2	1
Sulawesi	2	2	0	56	0
Sumatera	0	5	3	1	55

$$Accuracy\ \frac{74+57+65+56+55}{344} = 89{,}24\%$$

Color Explanation:

True Test Data

Incorrect Test Data

Figure 13 is a graphic image of the highest accuracy at an angle of 135° with values of k=1, 3, 5, and 7.

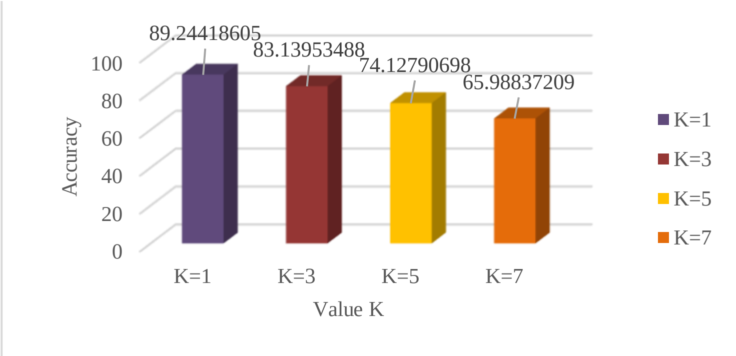


Figure 13. Angle 135° Experiment Results graphic

E. Angle 180° Experiment Result

Meanwhile, for the accuracy results from the experiment at an angle of 180°, the highest accuracy results at a value of k=1 which is 89.24%, while the lowest accuracy results are at a value of k=7 which is 65.98%. **Table 8** shows the results of the calculation of accuracy at the value of k=1 using the confusion matrix.

Table 8. Confusion Matrix Calculation on Value *k*=1 Angle 180°

Kelas	Confusion Matrix Evaluation *k*=1 Angle 90°				
	Papua	**Kalimantan**	**Papua**	**Sulawesi**	**Sumatera**
Jawa	74	2	1	2	1
Kalimantan	3	57	3	2	3
Papua	2	2	65	2	1
Sulawesi	2	2	0	56	0
Sumatera	0	5	3	1	55

$$Accuracy\ \frac{74+57+65+56+55}{344} = 89{,}24\%$$

Color Explanation:

True Test Data

Incorrect Test Data

Figure 14 shows the results of the 180° angle accuracy at the values of k=1, 3, 5, and 7.

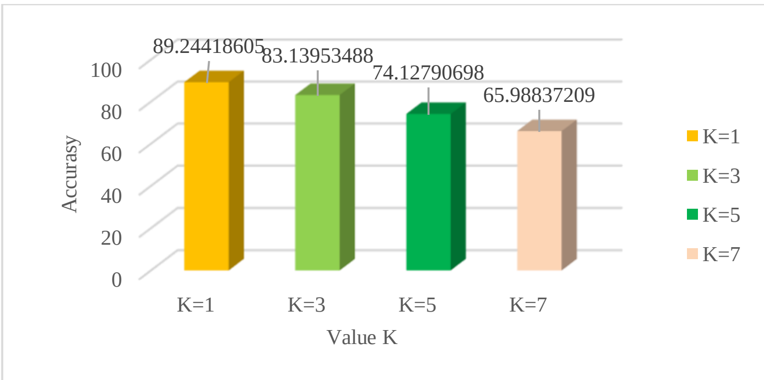


Figure 14. Angle 180° Experiment Results graphic

Conclusion

From the results of experiments conducted at angles of 0°, 45°, 90°, 135°, 180° and the values of k=1, 3, 5, and 7, it shows that the highest accuracy results are at angles of 135° and 180° where both angles. The result has the highest accuracy at the value of k = 1, which is 89.24%. Thus, it can be concluded that the effect of Gray Level Co-occurrence Matrix for texture feature extraction on the identification of batik motifs using K-Nearest Neighbor is optimal, so the Gray Level Co-Occurrence Matrix method is very well used to extract texture features on batik motifs.

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