Feature Extraction using Histogram of Oriented Gradients and Moments with Random Forest Classification for Batik Pattern Detection

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***Abstract*— The preservation of traditional batik patterns, often transmitted orally and through direct practice across generations, faces significant challenges in the modern era. Globalization introduces the risk of cultural homogenization, potentially diminishing the uniqueness and diversity of these patterns. Furthermore, the manual recognition of batik motifs is labor-intensive, time-consuming, and requires specialized expertise, rendering it unsuitable for large-scale preservation initiatives. Consequently, the development of technology-based solutions capable of documenting, analyzing, and recognizing batik patterns with efficiency and precision is imperative for safeguarding this cultural heritage. This study aims to address these challenges by developing an automated system for recognizing batik patterns, focusing on Javanese batik motifs—Kawung, Megamendung, and Parang—which serve as foundational designs for the evolution of batik in other regions. The proposed methodology integrates two feature extraction techniques, Histogram of Oriented Gradients (HOG) and Texture Moments, with the Random Forest machine learning algorithm. The research process encompasses four key stages: pre-processing, feature extraction, classification, and system evaluation, where the accuracy of individual and combined feature extraction methods is analyzed. Experimental results reveal that the HOG method achieves an accuracy of 78.99%, while the Texture Moments method yields 81.88%. Notably, the combination of these two methods enhances system performance, achieving the highest accuracy of 86.23%, representing a 4.65% improvement over the single methods. These findings underscore the efficacy of integrating HOG and Texture Moments with the Random Forest algorithm for automated batik pattern recognition.**

***Keywords*— Classification, Batik, HOG (Histogram of Oriented Gradients), Texture Moments, Random Forest**

I. INTRODUCTION

Batik is one of Indonesia's cultural heritages, recognized globally as a symbol of diversity and the beauty of textile art. Each batik pattern carries profound philosophical values, reflecting local wisdom and traditions that have evolved over centuries [1]. With the advancement of technology, the use of computer-based methods has become increasingly important for automatically recognizing and classifying batik patterns. Image processing technology enables the efficient analysis of patterns and textures in batik designs [2, 3].

Despite its cultural significance, batik faces several challenges in preservation and innovation. One of the main challenges in batik image detection is the high complexity of patterns and the similarity between motifs, which often leads to identification errors. External factors such as variations in lighting, image rotation, and scale further complicate accurate recognition. According to previous studies [4], conventional techniques without specific texture feature extraction methods often fail to capture the intricate details of batik patterns. This limitation hinders the classification process, reducing the efficiency of production in the modern batik industry and the digital documentation of batik as cultural heritage.

To address these challenges, this study focuses on three widely recognized motifs: Kawung batik from Surakarta, Megamendung batik from Cirebon, and Parang batik from Yogyakarta. These motifs not only hold unique philosophical values but are also commonly used as foundational designs in modern batik creations. The accurate recognition of these motifs is critical to supporting their preservation and enabling their integration into contemporary batik production.

In the field of image processing, the Histogram of Oriented Gradients (HOG) method has been widely adopted for extracting directional and edge-based features from images [5]. HOG has demonstrated its effectiveness in detecting texture features and patterns in various applications, including batik motifs [6]. Additionally, Texture Moments provide complementary information by capturing the texture distribution and smoothness of patterns [7]. Combining these two feature extraction methods can enhance the ability to differentiate complex and similar batik patterns [8].

For the classification task, the Random Forest (RF) algorithm is particularly suitable due to its robustness in handling large datasets, managing noisy data, and producing high accuracy [9, 10]. Prior studies have shown the success of integrating HOG features with Random Forest classification in applications such as plant identification, facial recognition, and object detection [11].

This study aims to combine HOG and Texture Moments as feature extraction methods with the Random Forest algorithm to classify Indonesian batik patterns. By utilizing a processed batik image dataset, the research evaluates the effectiveness of

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the proposed approach in recognizing batik motifs, particularly Kawung, Megamendung, and Parang. The outcomes of this study are expected to contribute to the preservation of Indonesia's cultural heritage by providing an efficient, accurate, and automated solution for batik pattern recognition.

II. RESEARCH METHODOLOGY

This research is designed to recognize batik types based on their motifs. The batik motifs studied are Kawung, Megamendung, and Parang. The research is conducted in several stages. The first stage is pre-processing, which simplifies the image to reduce computational costs. The second stage involves feature extraction, where two methods are applied: Histogram of Oriented Gradients (HOG) and texture feature extraction using moments. These extracted features are then classified using the Random Forest algorithm to identify the batik types. The final stage is system testing, where evaluation is performed using a confusion matrix. The research stages are illustrated in Figure 1.

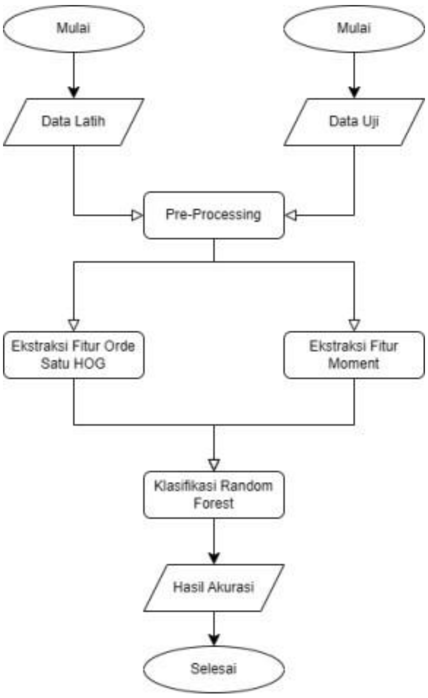

Fig. 1. Flowchart of the Batik Identification System Accuracy

A. *Pre-Processing*

This stage involves cropping and scaling to reduce the image size, which helps minimize computational load during processing. Once the images are resized uniformly, they are converted from RGB to grayscale.

B. *Feature Extraction*

The feature extraction process begins with preparing the batik image dataset, consisting of three main motifs: Parang, Kawung, and Megamendung. Each batik image is processed using two feature extraction methods: HOG and texture moments.

a. Texture Moments

The texture moments used in this study include statistical measures such as *mean, entropy, standard deviation, skewness, and kurtosis,* which can be mathematically defined as follows:

- *Mean*

  In Equation (1), the mean is obtained using xi to calculate the pixel intensity values, where N represents the total number of pixels in the image.

$$\mu = \frac{\sum x_i}{N} \quad (5)$$

- *Entopy*

  In Equation (2), p(xi) represents the probability of the pixel intensity xi.

$$H = -\sum p(x_i) log_2\, p(x_i) \quad (6)$$

- *Standard Deviation*

  In Equation (3), the standard deviation is calculated based on the values of each data point (xi) and the Mean (μ).

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}} \quad (7)$$

- *Skewness dan Kurtosis*

  Skewness and kurtosis are calculated using standard statistical formulas, which measure the asymmetry of the distribution in Equation (4) and the sharpness of the distribution's peak in Equation (5).

$$Skewness = \left(\frac{x_i - \mu}{\sigma}\right)^3 \quad (8)$$

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$$Kurtosis = \left(\frac{x_i - \mu}{\sigma}\right)^4 \qquad (9)$$

b. Histogram of Oriented Gradients (HOG)

HOG is a highly effective feature extraction method for identifying patterns and textures in images. The HOG features capture the orientation and gradient magnitude information within an image, enabling the system to recognize the texture structure of batik images [12, 13, 14]. Mathematically, HOG can be explained through the following steps:

- ***Image Division****: The batik image is divided into several small grid cells (e.g., 8x8 pixels).*
- ***Gradient Calculation:*** *For each cell, the magnitude and orientation of the gradient are calculated using the Sobel operator, where Gx and Gy represent the image gradients in the horizontal and vertical directions, respectively.*

$$Gx = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad (1)$$

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$$Gy = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (2)$$

- ***Histogram Formation:*** *A gradient direction histogram is generated within each cell, indicating the distribution of orientation angles across the image. The magnitude and orientation are calculated using the following formulas:*

$$M = |Gx| + |Gy| \quad (3)$$

$$\theta = \arctan\left(\frac{Gy}{Gx}\right) \quad (4)$$

- ***HOG Feature Calculation:*** *After obtaining the HOG image, statistical values such as mean, standard deviation, skewness, and kurtosis are calculated to serve as the features derived from HOG.*

C. Random Forest Algorithm

After the feature extraction process, the next step is the classification of batik motifs using the Random Forest (RF) algorithm. Random Forest is an ensemble method that uses multiple decision trees to classify data [15, 16]. Each decision tree in RF is built using a random subset of the training data, and the final classification decision is made based on the majority decision from all the trees [17, 18].

Mathematically, Random Forest can be explained as follows:

1. ***Decision Tree Formation****: Each decision tree is created by selecting a random subset of the data and features.*
2. ***Classification Prediction****: For an input image with feature x, the following formula is used:*

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} h_i(x) \quad (10)$$

This equation illustrates the basic principle of Random Forest in making predictions. By using multiple decision trees trained on random data subsets, Random Forest generates the final prediction by combining (averaging or majority voting) the results from all trees in the ensemble. This approach improves the accuracy and robustness of the model against overfitting, making it suitable for batik image data, which tends to have high variation.

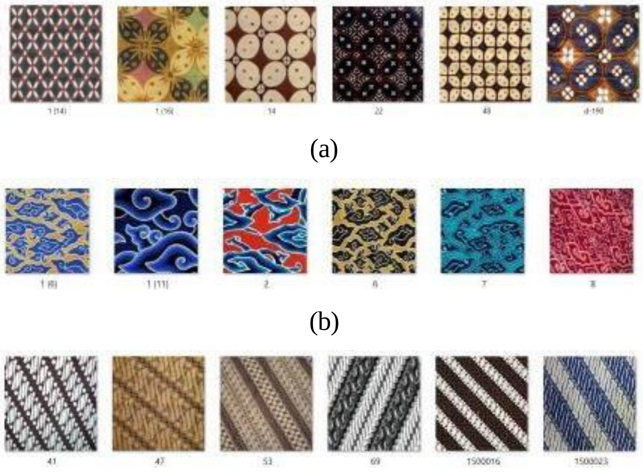
D. System Evaluation

The classification results from Random Forest will be compared with the true class labels to determine the accuracy of the results using the following formula:

$$\text{Accuracy} = \frac{\textit{Number of Correct Predictions}}{\textit{Total Number of Data}} \times 100\%$$

III. RESULTS AND DISCUSSION

The testing conducted in this study involves comparing the classification results from Random Forest using texture features, HOG, and the combination of both. The batik image dataset used in this research was sourced from the website https://www.kaggle.com/search?q=batik, with data collected from three main motifs: Parang, Kawung, and Megamendung. A total of 690 images were used in this study, divided into three classes: Parang (230 images), Kawung (230 images), and Megamendung (230 images), as shown in Figure 2 which devide into training data = 184 and testing data = 46.

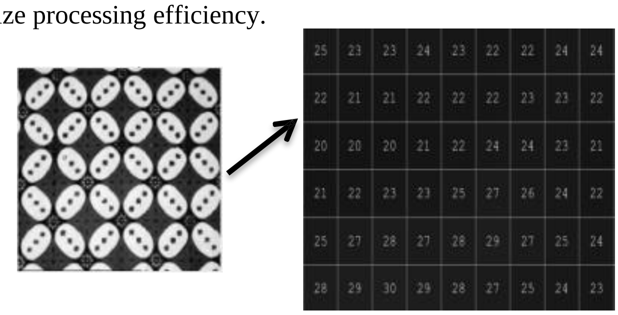


(a) (b) (c)

Fig. 2. Citra Data (a) Kawung (b) Megamendung (c) Parang

A. Pre-prosessing Stage

The dataset comprises images with varying dimensions, necessitating uniformity in size. This stage significantly reduces the image dimensions while standardizing them. Each image is resized to 244×244 pixels and subsequently converted to grayscale, as illustrated in Fig. 3. The grayscale conversion is performed to simplify computational complexity and optimize processing efficiency.



(a) (b)

Fig. 3. (a) Grayscale Citra Batik (b) Nilai Piksel Citra Batik

B. Feature Extraction Stage

a. Texture Feature Extraction

Texture feature extraction is calculated on the grayscale image. The texture values used are: Mean, Entropy, Standard Deviation, Skewness, and Kurtosis, calculated using equations (5 - 9). The extracted texture feature values are presented in Table 1.

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TABLE I. Texture Feature Extraction

FILE_NAME	Mean	Entropy	Std_Dev	Skewness	Kurtosis	Class
1 (14).png	112.62	6.78	60.17	1.17	-0.21	1
1 (16).png	125.62	7.23	45.22	-0.26	-1.01	1
1 (18).png	131.45	7.31	88.05	0.01	-1.78	1
1 (11).png	66.39	7.38	57.88	1.07	0.26	2
1 (6).png	128.04	6.97	53.25	0.26	-1.40	2
10.png	98.41	7.59	53.83	0.44	-0.81	2
1500016.png	103.47	7.05	93.24	0.65	-1.27	3
1500023.png	116.08	7.29	68.95	-0.03	116.08	3
1500028.png	125.87	7.33	45.17	0.21	125.87	3

The results of this analysis are derived from several batik images that have been processed through texture moment feature extraction. This extraction process provides a deeper insight into the characteristics of the patterns and textures of each batik motif, allowing for a better understanding of the complexity and variation present in the batik images. Images with a high mean brightness, high entropy, large standard deviation, as well as skewness and kurtosis indicating sharp variations in pixel intensity, generally represent more complex and diverse patterns

b. Histogram of Oriented Gradients (HOG) Feature Extraction

HOG feature extraction begins by calculating the intensity changes between adjacent pixels, resulting in two main components: magnitude and orientation. Magnitude measures the degree of brightness change between pixels, while orientation indicates the direction of that change. After calculating the magnitude and orientation, the gradient orientation values in degrees are obtained and used to compute HOG features for the image, such as Mean, Standard Deviation, Skewness, and Kurtosis. The method for calculating the batik image is demonstrated using an example of a grayscale image snippet from the Kawung batik, as shown in Fig. 4.

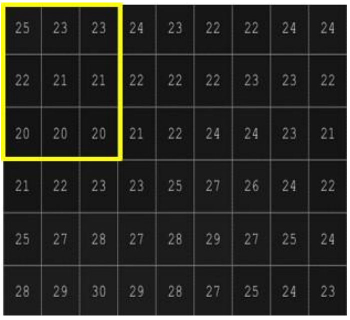

Fig. 4. Grayscale Batik Image

The area within the yellow box is a sub-matrix (kernel) of the main image. This sub-matrix is typically selected for local operation applications, such as edge detection, using equations (1) and (2). This can be seen in Fig. 5.

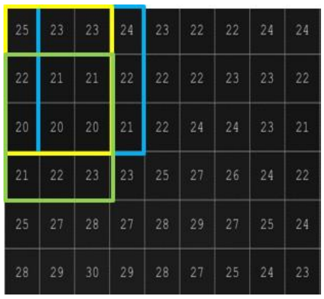

Fig. 5. Convolution Operation

The convolution operation is performed by sliding the Sobel kernel over the entire image, involving the multiplication of kernel elements with the corresponding sub-matrix pixel elements, and then summing the results. Below is the calculation for Gx (horizontal direction):

Matrix (1,1) = $(-1\times25) + (0\times23) + (1\times23) + (-2\times22) + (0\times21) + (2\times21) + (-1\times20) + (0\times20) + (1\times20) = -4$

Matrix (1,2) = $(-1\times23) + (0\times23) + (1\times24) + (-2\times21) + (0\times21) + (2\times22) + (-1\times20) + (0\times20) + (1\times21) = 4$

…..

Matrix (1,8) = $(-1\times22) + (0\times21) + (1\times21) + (-2\times20) + (0\times20) + (2\times20) + (-1\times21) + (0\times22) + (1\times23) = 1$

….

After obtaining the values for Gx and Gy, the next step is to compute the magnitude, as seen in equation (3), the orientation in equation (4), and the calculation for the orientation angle $\theta'(x,y)$ for each pixel based on the gradient direction $\theta'(x, y)$derived from the orientation values. The degree of orientation is calculated using the following formula:

$$\theta'(x,y) = \begin{cases} \theta(x,y) + 180\,, & \text{jika } \theta\,(x,y) < 0 \\ \theta\,(x,y), & \text{jika } \theta\,(x,y) \geq 0 \end{cases}$$

This formula ensures that all gradient orientation values fall within the range of $0°$ to $180°$ (for unsigned gradients). If $\theta'(x, y)$ is negative, 180 is added to convert it to a positive value. If $\theta'(x,y)$) is already positive, no change is made to the orientation value, as presented in Table II.

TABLE II. Degree Orientation Results

99	108	112	108	84	59	45
72	56	45	63	69	108	156
75	84	77	61	81	130	144
70	88	0	63	153	8	0

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99	108	112	108	84	59	45

This gradient orientation represents the direction of pixel intensity changes in an image, with higher values indicating sharp changes and lower values reflecting smooth transitions. The process of converting negative values into positive ones is done by adding 180°, ensuring all orientations fall within the 0° to 180° range.

Higher orientation values, such as 153° and 156°, indicate patterns with fine details or sharp transitions, while lower values, such as 45° and 56°, signify more regular textures. Gradient orientation plays a crucial role in detecting different batik patterns or textures, assisting in distinguishing between complex and simple motifs. Images with sharp gradients tend to have more intricate patterns, while low gradients indicate simpler patterns.

After obtaining the values for the Orientation Angle, the next step is to calculate the HOG features, which include Mean, Standard Deviation, Skewness, and Kurtosis, as outlined in equations (5), (7), (8), and (9).

TABLE III. HOG Feature Extraction

FILE_NAME	HOG Mean	HOG Std Dev	HOG Skewness	HOG Kurtosis	Class
1 (14).png	0.12	0.11	0.81	2.37	1
1 (16).png	0.14	0.08	0.34	1.97	1
1 (18).png	0.12	0.10	0.79	2.63	1
1 (11).png	0.11	0.12	0.88	2.40	2
1 (6).png	0.11	0.12	0.89	2.49	2
10.png	0.12	0.11	0.60	1.94	2
1500016.png	0.14	0.07	-0.07	2.15	3
1500023.png	0.12	0.11	0.38	1.59	3
1500028.png	0.14	0.09	0.18	1.78	3

Table III shows the results of HOG feature extraction, including Mean, Standard Deviation, Skewness, and Kurtosis of the batik images. The HOG Mean values range from 0.11 to 0.14, reflecting the average gradient intensity in the images, while the Standard Deviation indicates the variation in gradient distribution, ranging from 0.07 to 0.12. Skewness and Kurtosis reveal how the gradient distribution is skewed and sharp; most images have positive skewness, indicating a dominance of gradients in a specific direction, and high kurtosis, indicating a more concentrated gradient distribution.

The results indicate challenges in establishing direct thresholds between classes due to overlapping feature values across different classes, such as Mean, Standard Deviation, Skewness, and Kurtosis. To address this limitation, the Random Forest algorithm employs a decision tree approach that uses the average (mean) value of each class as the root of the decision tree.

This approach enables the algorithm to perform classification decisions in a more structured and balanced manner, effectively accommodating variations in feature values between classes. By using the mean value as the foundation for tree construction, Random Forest optimizes the classification process, even when direct thresholds between classes are difficult to determine.

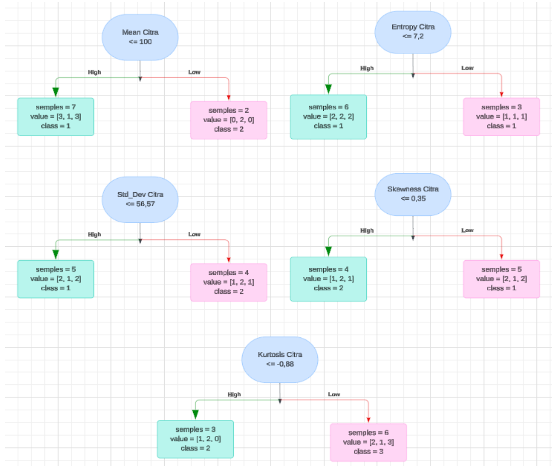
C. Random Forest Algorithm Classification Stage

Next, classification is performed using the Random Forest method to determine the correct and incorrect predictions as well as the precision [17]. In this stage, decision trees are created as follows:

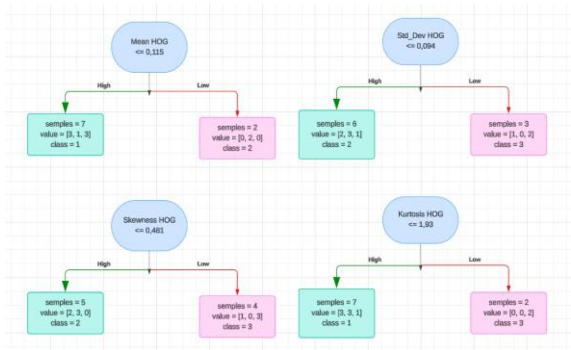
a. *Create thresholds based on the average of each feature value. If the value of a feature is lower than the average, it is categorized as "low," and if it is higher than the average, it is categorized as "high."*
b. *Performing the decision tree construction process to map classification results into more structured decisions. Each tree in the Random Forest performs classification and produces a class prediction.*

The predictions from all trees are then aggregated through a voting process, where the class with the highest number of predictions is selected as the final classification result [18]. This approach ensures that Random Forest can overcome the limitations of directly determining thresholds between classes while improving classification accuracy through the combined decisions of multiple trees.

Fig. 6 illustrate the results of the Random Forest construction.



(a)



(b)

Fig. 6. (a) Random Forest Results for Grayscale Image (b) Random Forest Results for HOG Image

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Since each class consists of three images, accuracy is calculated based on the number of correct predictions (high samples) for each class. A prediction is considered correct if the number 3 appears in the image, representing the number of samples in each class. This strategy helps evaluate the accuracy of the Random Forest algorithm in classifying batik images in a more systematic manner as shown in Table.

TABLE IV. Random Forest (RF) Results

No.	NAMA_FILE	Class	RF Predict
1	1 (14).png	1	1
2	1 (16).png	1	1
3	1 (18).png	1	1
1	1 (11).png	2	2
2	1 (6).png	2	2
3	10.png	2	2
1	1500016.png	3	3
2	1500023.png	3	3
3	1500028.png	3	3

D. System Evaluation Stage

The system evaluation is performed by calculating the number of test data correctly classified. based on the feature extraction values from Texture, HOG, and their combination. Table V shows the accuracy results for each experiment.

TABLE V. System Accuracy Results

Feature Extraction	Correct Prediction	Incorrect Prediction	Accuracy
Texture (Moment)	113	25	81,88%
HOG	109	29	78,99%
Combined	119	19	86,23%

Based on the feature extraction methods using Texture (Moment), HOG, and their combination with Random Forest classification, the system's performance yields the following results:

The system using *Texture (Moment)* feature extraction achieved an accuracy of 81.88%. Although this method is capable of capturing texture information, its effectiveness is limited in identifying more complex batik patterns, which restricts its classification performance. The system with *HOG feature extraction* produced a higher accuracy of 78,99%. HOG excels at capturing gradients and orientations, which are crucial for recognizing patterns and contours in batik motifs. Additionally, HOG is more effective in handling sharper and clearer texture variations in batik images.

The *combination of Texture (Moment) and HOG* achieved the highest accuracy of 86.23%. This result demonstrates that combining the two methods significantly enhances classification accuracy. The combination leverages the strengths of both methods: Texture (Moment) captures fine pattern details, while HOG captures gradient orientations.

In addition to calculating the accuracy on the test data, this study also calculates the precision value of each class as presented in table VI. precision calculations are calculated as in the accuracy calculation but are carried out on each class of training data images.

TABLE VI. Precision Results

Class	Correct Prediction	Incorrect Prediction	Precision
1	41	5	89,13%
2	44	2	95,65%
3	33	13	71,74%

The table V presents the classification results for three batik image classes: class 1 (kawung batik image), class 2 (megamendung batik image), and class 3 (parang batik image). The "Class" column identifies the image categories, while the "Correct Predictions" and "Incorrect Predictions" columns record the number of correct and incorrect classifications. Precision is calculated by dividing the number of correct predictions by the total predictions for each class. Class 2 achieved the highest precision at 95.65%, indicating the most accurate classification. Class 1 recorded a precision of 89.13%, which is also relatively high. Class 3 had a lower precision of 71.74%, indicating a higher rate of misclassification. Overall, the system performed best on class 2 and worst on class 3.

And here are the results of the confusion matrix:

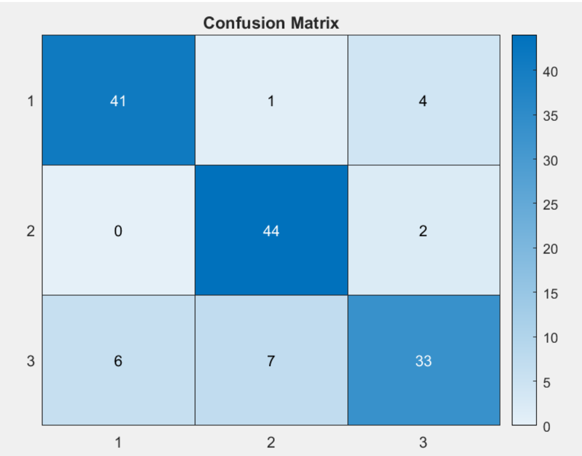

Fig. 7. (a) Confusion Matrix

The confusion matrix in the image above illustrates the model's performance in classifying three batik motifs: (1) Kawung, (2) Megamendung, and (3) Parang. The Kawung class has 41 data points correctly classified, but 1 data point was misclassified as Megamendung, and 4 data points were misclassified as Parang. The Megamendung class demonstrates the best performance with 44 data points correctly classified, while only 2 data points were misclassified as Parang, and none were misclassified as

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Kawung. On the other hand, the Parang class has 33 data points correctly classified, but 6 data points were misclassified as Kawung, and 7 were misclassified as Megamendung. Overall, the model is more accurate in recognizing the Megamendung class compared to the others; however, there are still notable misclassifications, especially in the Parang class.

IV. CONCLUSION

The conclusions of this study indicate that the combination of HOG and texture moment feature extraction, followed by classification using the Random Forest algorithm, can deliver good results in recognizing Indonesian batik motifs. In the test results, the HOG method achieved an accuracy of 78.99%, while the Texture Moment method reached an accuracy of 81.88%. The combination of both feature extraction methods improved the system performance, achieving the highest accuracy of 86.23%, an increase of 4.65% compared to the texture method and an 8% improvement over the HOG feature extraction method. This demonstrates that both texture feature extraction and HOG can effectively recognize Batik motifs such as Parang, Kawung, and Megamendung.

V. SUGGESTIONS FOR DEVELOPMENT

The research results provide quite high accuracy with an accuracy of 86.23%. However, this accuracy can be improved by eliminating the resizing step which can result in loss of object details. In addition, other developments that can be done are by extracting features with other methods such as Local Binary Pattern (LBP), Gabor filter, Wavelet and so on which are texture-based. Research in Batik recognition is still wide open because of the many types of batik that exist both in Indonesia and abroad. This provides challenges for the future, especially in the field of image processing and computer vision.

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