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Identification of Papua Cenderawasih Batik Motifs using Local Binary Pattern and K-Nearest Neighbor

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Abstrak

Papua Island has natural and cultural richness wich is reflected in its batik motifs, such as the Cenderawasih and Tifa motifs. Although batik recognition technology has developed, systems capable of automatically identifying Papua batik motifs are still limited. This research aims to develop a texture recognition system using the Local Binary Pattern (LBP) feature extraction method and K-Nearest Neighbor (KNN) classification. The Cenderawasih motif dataset consists of 115 images, and the Tifa motif dataset consists of 120 images with an 80:20 composition for training and testing data. We tested the KNN model with various k values and found that k = 7 yielded the best results, with accuracy of 97.16%, precision of 97.10%, and F1-score of 97.10%. The developed GUI interface facilitates users in identifying batik motifs, providing prediction results, and texture visualization. The results of this study show that image processing technology could help protect Papuan batik. Future research could improve model accuracy by utilizing larger data sets and classification algorithms to make the models more accurate.

Keywords: papuan batik motifs, local binary pattern, k-nearest neighbor, image processing, classification

1 Introduction

Papua Island is known as one of the regions with extraordinary biodiversity and culture wealth, encompassing unique flora, fauna, and traditions that have thrived across land, sea, and air [1]. Among its culturals treasures, traditional arts such as batik play a significant role in Indonesia's heritage, reflecting the country's status as an archipelagic nation rich in traditions and diversity [2],[3]. Batik, acknowledged by UNESCO as an intangible cultural heritage in October 2009, holds profound historical and philosophical values, making it a symbol of national pride on a global scale [4],[5],[6].

Each region in Indonesia has distinct batik motifs that reflect its local identity, and while batik is commonly associated with Java, Papua possesses unique motifs that showcase its rich cultural and natural heritage. Highlighting not only artistic beauty but also deep philosophical values that convey stories, traditions, and local wisdom passed down through generations [7], Papuan batik is characterized by asymmetrical patterns, vibrant backgrounds, and striking colors, mirroring the region's biodiversity and traditional artistry [5]. The Cenderawasih motif, depicting Papua's iconic bird of paradise, and the Tifa motif, inspired by its traditional musical instrument, are among the most prominent representations of Papuan culture.

With the rapid advancement of digital technology, opportunities have emerged to preserve and promote traditional cultures, including batik. One effective approach involves digital image processing technology, which enables the automatic identification of batik motifs. This method not only accelerates motif recognition but also facilitates broader documentation and cultural promotion. Howefer, existing research on batik recognition primarily focuses on Javanese motif, with limited studies dedicated to Papuan batik motif identification.

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To address this gap, this study applies Local Binary Pattern (LBP) for texture feature extraction and K-Nearest Neighbor (KNN) for motif classification. LBP effectively captures local texture patterns, making it well-suited for batik motif analysis. Meanwhile, KNN is chosen for its simplicity and efficiency in handling diverse datasets. The combination of these two methods aims to develop a robust system capable of accurately recognizing Papua's Cenderawasih and Tifa motifs.

This research aims to produce a reliable system for identifying Cenderawasih and Tifa Papua batik motifs using the LBP and KNN methods. Through this texture-based approach, the research is expected to contribute to the development of a more accurate system for identifying Papuan batik motifs and to support the preservation and wider recognition of Cenderawasih and Tifa batik culture.

2 Literature Review

Advancements in image processing technology have brought significant innovations to the classification of batik motifs. Although many studies have been conducted, the majority still focus on motifs from the regions of Java and Sumatra, with limitations in the scale and types of motifs covered. This research aims to address that gap by developing a system capable of identifying typical Papua motifs, such as Cenderawasih and Tifa, using the Local Binary Pattern (LBP) method for feature extraction and K-Nearest Neighbor (KNN) for the classification process.

The GLCM, LBP, and HSV Color Moment-based approaches have been applied to a dataset consisting of 10 classes of batik motifs. This study shows that the accuracy drastically decreases by up to 29% as the number of classes increases, indicating that the method has limitations in handling the diversity of textures and patterns in batik motifs [8]. Another study used the KNN method for Karawang batik motifs with four classes, achieving an accuracy of up to 95%. However, the research faced challenges with the limited number of classes and the small dataset [9].

In the study of Sumatra batik motifs, the GLCM-based Naïve Bayes approach achieved an accuracy of 96.66%. However, this method only focuses on the global texture without considering more detailed local patterns [10]. On the other hand, CNN has shown great potential in classifying batik motifs with an accuracy of 70% after preprocessing, such as conversion to grayscale, although this study used a limited dataset [11].

The latest methods, such as the Multiwindow and Multiscale Extended Center Symmetric Local Binary Patterns (MU2ECS-LBP) algorithm, are designed to address scale and rotation changes in batik motif patterns. This algorithm utilizes a combination of window sizes, such as 6x6, 9x9, 12x12, and 15x15, to capture texture more deeply. With the KNN approach, the accuracy achieved reaches 99.91%, while the ANN with a 64-240-12 architecture can achieve an accuracy of 98.43%. Although very effective in handling texture variations, this method has not yet been applied to Papuan batik motifs [12].

Another study using an Android-based CNN for the classification of Karawang batik motifs achieved an accuracy of 70%. However, the research has not yet developed a more interactive interface to facilitate direct motif identification by users [13].

However, there are several significant differences between the previous research and this study. In this study, the images used have a higher resolution, namely 300x300 pixels, allowing for sharper and more precise capture of motif details [14]. Additionally, the method applied is LBP for feature extraction and KNN for classification, which differs from the GLCM method used in previous research. LBP offers the advantage of capturing the texture of batik motifs more deeply, while KNN is known for its efficient ability to classify complex patterns. The combination of these two methods is expected to improve accuracy in identifying batik motifs, especially on larger and more diverse datasets such as the Cenderawasih and Tifa motifs from Papua.

This research uses a dataset consisting of 115 images of Cenderawasih motifs and 120 images of Tifa motifs with a resolution of 300x300 pixels. The composition of the training and testing data was 80:20, allowing for a more thorough evaluation of the model. By using LBP as the feature extraction method and KNN for classification, this research successfully achieved an accuracy of 97.16%, precision of 97.10%, and an F1-score of 97.10% at k=7. Unlike previous research, this study not only achieved high accuracy but also included the development of a GUI interface that allows for real-time motif identification, complete with generated texture visualizations.

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Although the results obtained are quite promising, this research acknowledges that there is still room for improvement, such as expanding the dataset to include motifs from various regions, exploring more complex classification algorithms like CNN, or combining other feature extraction methods to capture richer patterns. The main focus of this research is on the identification of Papua motifs, making an important contribution to the field of digital image processing while also supporting the preservation of batik culture.

3 Research Method

This section outlines the research methodology applied in the identification of Papuan batik motifs. The methodology encompasses several key stages, including data collection, preprocessing, feature extraction, classification, and evaluation. Each stage is systematically structured to develop a precise and dependable batik motif recognition system. The research adopts an organized approach, beginning with data acquisition from multiple sources, followed by essential preprocessing steps such as grayscale conversion and noise reduction. Feature extraction is carried out using the Local Binary Pattern (LBP) method, which transforms texture patterns into numerical representations, while classification is conducted using the K-Nearest Neighbor (KNN) algorithm. Finally, the system's performance is assessed based on accuracy, precision, and F1-score.

3.1 Data

The data collection phase begins with the search and retrieval of batik datasets from various sources, including the internet and websites that provide batik images, such as Kaggle, Lazada, Github, Shopee, and Tokopedia. The data set collected includes the Cenderawasih and Tifa batik motifs from Papua, which are the focus of this research.

(a)

(b)

Figure 1. Example dataset from (a) cenderawasih motif, (b) tifa motif

Figure 1(a) represents one of the 115 images from the Cenderawasih batik motif dataset, and Figure 1(b) represents one of the 120 images from the Tifa batik motif dataset. The sizes and resolutions of each taken image vary. We convert each image into the appropriate format and store it in a special folder for the model training and evaluation process. The research will then use this data set as the basis for the identification and classification process.

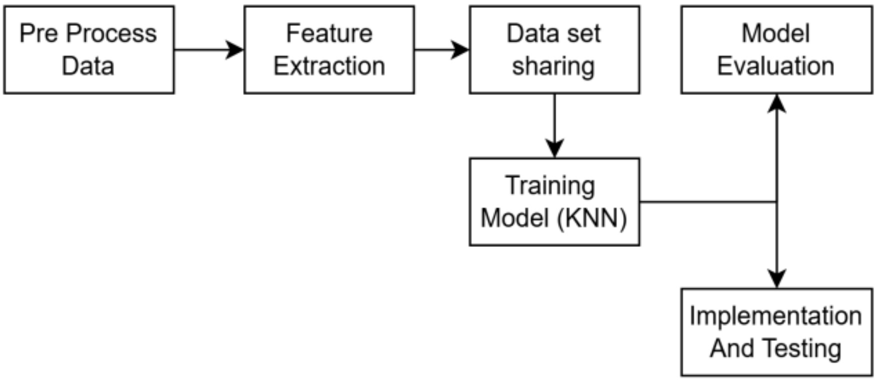

Figure 2. Research methodology flow

Figure 2 illustrates the research method flow, commencing with the data preprocessing stage that encompasses resizing, grayscale conversion, normalization, and segmentation. Next, we perform feature extraction using LBP, divide the dataset into training and testing data, train the model using

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KNN, and evaluate it using metrics like accuracy and F1-score. The final stage includes the implementation and testing of the model in the batik motif identification system.

3.2 Data preprocessing

At the data preprocessing stage, the collected images undergo a resizing process to ensure uniform image size, 300x300 pixels. This size was chosen so that the batik motifs are clearer and details can be extracted maximally. After that, the image is converted to grayscale to reduce data complexity without losing important information from the image texture. Then, normalization is performed to adjust the pixel scale of the image to make it easier for the model to process. Removing noise is done to clean the image from disturbances that could affect the extracted feature results.The final stage of this pre-processing is image segmentation, which aims to separate the main object of the batik motif from the background so that the features of the motif can be extracted accurately.

3.3 Feature Extraction

Local Binary Pattern (LBP) is an effective method for analyzing texture by converting the patterns around each pixel into binary values that indicate the intensity relationships between pixels in the image. Timo Ojala, Mati Pietikäinen, and David Harwood first developed this technique at the University of Oulu, Finland, in 1994 [13]. In the context of this research, feature extraction becomes an important process to capture unique patterns in batik motifs. We use the LBP method to break down pixel intensities in grayscale images and save them in a file format for later use in training classification models. Each image of a batik motif will produce a distinctive value that reflects the texture of the motif. Feature extraction in this research was carried out using the LBP formula, as shown in equation (1) :

$$\text{LBP}(x_c + y_c) = \sum_{p=0}^{p-1} \{s(1_p\} - 1_c) \,.\, 2^p \qquad (1)$$

Explation :
I_c *is the intensity of the central pixel*
I_p *is the intensity of neighboring pixel*
$S(X)$ *is a threshold function that takes the value* 1 if $x \geq 0$ and 0 if $x < 0$
P is the number of neighboring pixels considered
2^p is the binary weight assigned to each neighboring pixel position

The initial intensity matrix is a representation of the intensity or brightness values in a grayscale image. In this matrix, each element represents the intensity value of each pixel. In Figure 3.The midpoint value (4) is used as a reference or threshold in the next stage.

$$\begin{matrix} 8 & 10 & 0 \\ 8 & 4 & 2 \\ 8 & 8 & 6 \end{matrix}$$

Figure 3. Matriks intensitas awal

We obtain the binary matrix by comparing each pixel around the central pixel with the threshold value (the middle value). We change each pixel to if its value is equal to or greater than the threshold, and to 0 if its value is smaller. The formula for conversion can be seen in equation (2) :

$$\text{B(x, y)} = \text{f(x)} = \begin{cases} 1 If I, (x,y) \geq T \\ 0 If I, (x,y) < 0 \end{cases} \qquad (2)$$

The intensity value at the pixel coordinates is represented by I(x,y), and the threshold value is doneted by T.

Using a binary scheme, the LBP weight matrix assign weights to each pixel at a specific position based on its distance from the center.

We obtain the resulting LBP matrix by multiplying each element in the binary matrix with the corresponding element in the LBP weight matrix, then summing all the results to obtain the final LBP value at the center pixel. The LBP outcome matrix can be calculated using the formula as shown in equation (3):

$$\text{f}(x) = a_0 + \sum_{i=1}^{p} S(I(x_i, y_i) - T \; x \; W \; (x_i, y_i) \qquad (3)$$

With :
$\text{S}(I(x_i, y_i) - T \; x \; W \; (x_i, y_i)$: the result of a binary function that converts pixel values to 1 or 0 depending on the threshold.

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$W(x_i, y_i)$: *The weighht at the corresponding pixel position in the LBP weight matrix*

3.4 Dataset Division

Following feature extraction, we divide the dataset into two parts : the training data and the test data. We use the training data to train the model to recognize batik patterns effectively, and use the test data to gaugle the model's ability to classify patterns in previously ussen imags. The ideal ratio for dataset splitting in the machine learning proccess is 80% for training data and 20% for test data. We also conducted data verification to confirm the accuracy of both datasets.

3.5 Model Training (KNN)

The KNN algorithm, which compares features from the test image with features from the training image to find the most similar patterns based on a certain distance, trains the classification model at the model training stage using features generated from the extraction proccess. KNN is a clasification algorthm that groups new data based on learning from previously classified data [4],[15]. In the process, this algorithm works by measuring the shortest distance between the query and the training samples projected in the dimensional space to describe the characteristics of the data [9],[16]. We conducted model training by splitting the training and testing data in an 80:20 ratio, testing the KNN hyperparameter with various k values from 1 to 19, and determining the best accuracy [17]. However, the main drawback of K-NN is its high computational cost due to the need to calculate the distance of each query instance in the dataset[18]. To train the KNN model, it can be calculated using the formula as shown in equation (4):

$$\sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{4}$$

Where p and q are two points in the feature space, and n is the number of features.

3.6 Model Evaluation

We conduct the evaluation stage to measure the model's performance using test data. We evaluate the performance using accuracy, precision, recall, and F1-score. We visualize the evaluation results to identify the optimal k value for classifying the Cendrawasih and Tifa motifs. To find the values of Accuracy, Precision, Recall and F1-Score they can be calculated using the formula as shown in equations (5), (6), (7) and (8):

3.6.1 Accuracy: The proportion of correct predictions to all predictions.

$$Accuracy = \frac{Number\ Of\ Correct\ Predictions}{Total\ Number\ Of\ Predictions} \tag{5}$$

3.6.2 Precision: The proportion of true positive predictions

$$Precission = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{6}$$

3.6.3 Recall : The proportion of actual positive data that is correctly predicted.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{7}$$

3.6.4 F1-Score: The harmonic mean of precision and recall.

$$F1 - Score = 2X\ \frac{Precission\ x\ Recall}{Precission + Recall} \tag{8}$$

3.7 Implementation and Testing

During g the system's implementation and testing phase, we built the desktop application using Python and a pre-trained KNN model. The LBP method extracts texture features, which KNN then uses to classify the Cenderawasih or Tifa batik motifs. Users can upload images, display prediction results, provide a brief motif description, and present a similarity table through the system's Graphical User Interface (GUI). Additionally, the system visualizes the LBP histogram as supplementary information.

4 Results and Analysis

We carried out a series of preprocessing steps at the data preprocessing stage to prepare the images of the Cendrawasih and Tifa batik motifs. Figure 4a displays the outcomes of the resizing process on the Cendrawasih and Tifa motifs, standardizing the images to a resolution of 300x300 pixels. Figure 4b shows the Cendrawasih and Tifa motifs after undergoing the grayscale process, which aims to eliminate color information and focus on texture patterns. Figure 4c displays the outcomes of the normalization and noise removal process, which standardizes pixel intensity values

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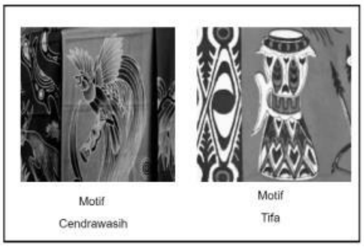
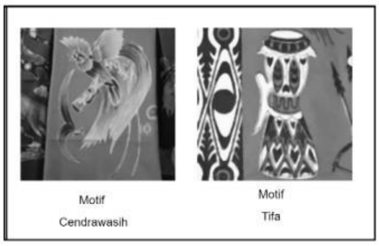
and enhances image quality to improve feature extraction accuracy. Meanwhile, Figure 4d displays the final segmentation result, separating the batik motifs from the background to analyze only the batik patterns.

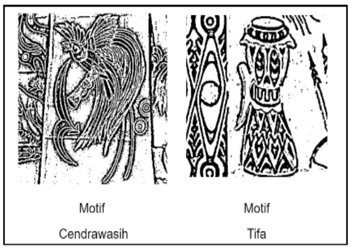
(a)



(b)



(c)



(d)

Figure 4. Data preprocessing (a) cendrawasih and tifa motifs that have undergone the resizing process (b) cendrawasih and tifa motifs that have undergone the grayscale process, (c) cendrawasih and tifa motifs that have undergone the noise removal process, (d) cendrawasih and tifa motifs that have undergone the segmentation

The next stage is feature extraction using LBP, which successfully displays texture patterns in the form of an initial matrix representing small areas of the original image. This process demonstrates how the LBP method analyses local patterns around each pixel in the grayscale image as a preliminary step to recognizing unique patterns of the image's texture, such as batik motifs. The initial matrix (pixel intensity) in Figure 5a represents a small area of the original image. We use this matrix as the basis for LBP calculations, comparing each central pixel with its neighboring pixels. Figure 5b: Binary Matrix. The matrix compares the intensity of each central pixel with that of its surrounding pixels. The system assigns a value of "1" (true) to the neighboring pixels if their intensity is greater than or equal to the central pixel, and a value of "0" if it is less (false). The result of this process is a unique binary pattern, representing the local relationships of the pixels around the central pixel. Figure 5c: Binary Weight Matrix. Once we form the binary matrix, we multiply each binary value by a specific binary weight. For instance, we arrange binary weights such as 128, 64, 32, and so on based on the positions of the pixels surrounding the central pixel. This result matrix shows the contribution of binary weights for each neighboring pixel in determining the LBP value. Figure 5d: LBP Result Matrix. The final matrix represents the LBP output, transforming each pixel in the original image into a distinct LBP value. We can use these values as characteristics or features to distinguish patterns or textures in images, like the Cendrawasih or Tifa batik motifs.

$$\begin{bmatrix} 8 & 10 & 0 \\ 8 & 4 & 2 \\ 8 & 8 & 6 \end{bmatrix} \quad \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \quad \begin{bmatrix} 128 & 64 & 32 \\ 1 & 16 & 0 \\ 2 & 4 & 8 \end{bmatrix} \quad \begin{bmatrix} 128 & 64 & 0 \\ 1 & 16 & 0 \\ 2 & 4 & 8 \end{bmatrix}$$

(a) (b) (c) (d)

Figure 5. Feature extraction matrix, (a) initial intensity matrix, (b) binary matrix, (c) LBP weight matrix, (d) final result matrix

Figure 6 is a line plot graph that illustrates the distribution of LBP features from images of the motifs of Cendrawasih and Tifa. Each line on the graph represents one image, with colors generated from the Viridis colormap used to differentiate between them. The colors on this graph do not have specific meanings other than to distinguish between different images.

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On the X-axis, there are LBP values that indicate various local texture patterns detected in the image. Meanwhile, the Y-axis shows the frequency of occurrence for each LBP value, which indicates how often a particular texture pattern appears in the image. The shape of each line represents the distribution of texture in the image. Images with similar texture patterns will produce lines with similar shapes, while images with different texture patterns will have lines with different shapes.

This graph illustrates the distribution of texture patterns in the batik motif image through the relationship between frequency and LBP value. Common or frequently occurring LBP patterns will have lower frequencies. In the context of motif identification, the differences in these graphic motifs can help distinguish between the motifs of cendrawasih batik and tifa, as different motifs will produce different texture distributions. This graph serves as a visual representation of the feature extraction process, where the system converts a grayscale image into LBP patterns, calculates the histogram of those patterns, and displays their distribution in the form of an image file in the specified directory.

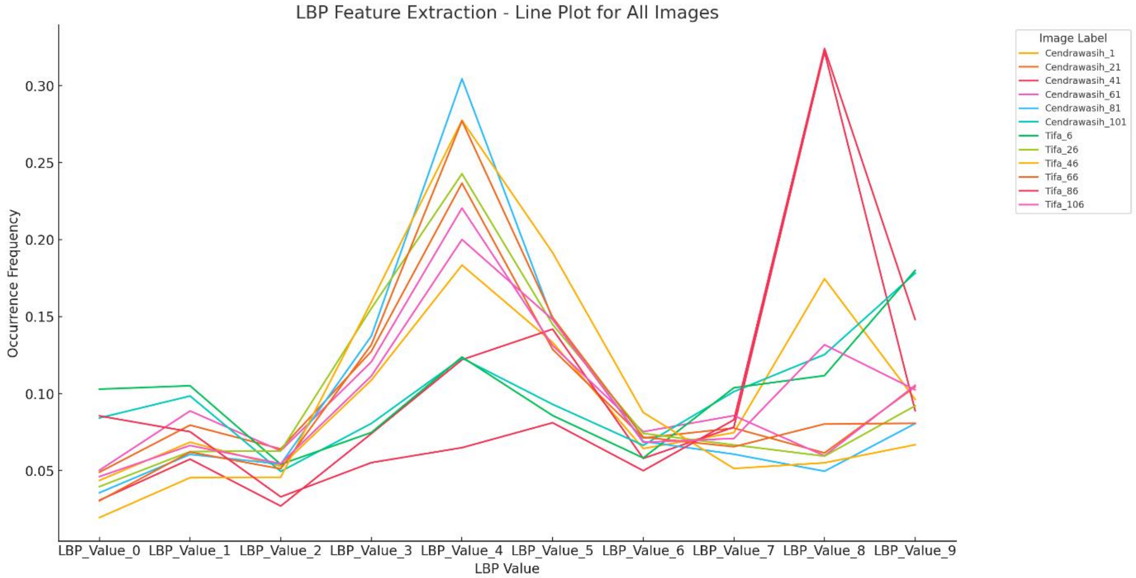

Figure 6. Line plot graph illustrating the distribution of LBP features

Figure 7 presents a graphical and line graph analysis of feature extraction using the LBP Method, offering significant insights into the distribution and characteristics of batik motif textures. The histogram shows the frequency distribution of LBP values in the image, reflecting how often certain texture patterns appear. Peaks in the histogram indicate the dominance of specific patterns, while a uniform distribution suggests a wider variety of textures. The line graph illustrates the spatial changes in LBP values, helping to visualize transitions or periodicity in the motifs. The interconnection of both analyses aids in understanding the spatial structure and distribution of batik motif textures by depicting local texture patterns. Understanding this distribution pattern is important to improve the quality of the generated features and the accuracy of the batik motif classification system.

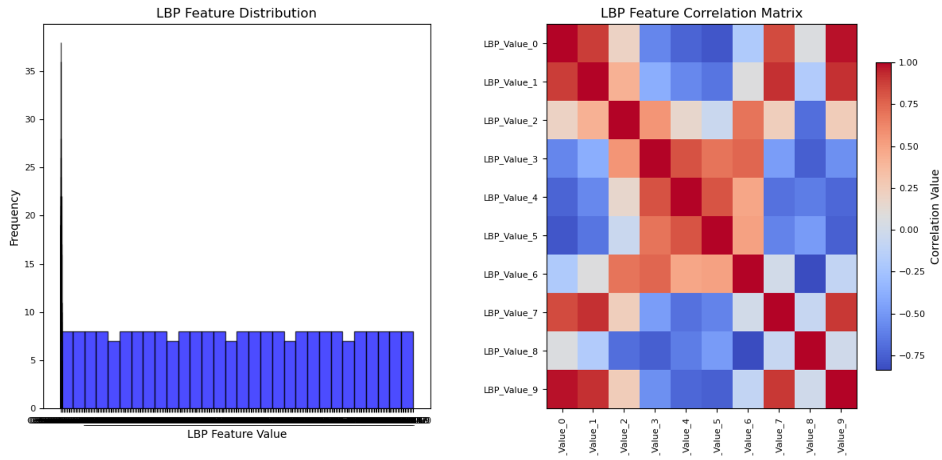

Figure 7. Graph analysis and line graphs in feature extraction using the LBP method

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We divide the dataset into 188 training samples, distributing the test and training data in an 80:20 ratio. The distribution of data between the Cenderawasih and Tifa classes remains balanced before and after the division. We then trained the KNN model with training and test data, which yielded an accuracy of 53.19%, indicating that this model still requires improvement for better classification.

The model training process, the KNN algorithm is implemented to classify the Cenderawasih and Tifa batik motifs by testing various k parameters. The optimal k value for this classification is selected through evaluation using several metrics, namely accuracy, precision, recall, and F1- score. Each metric is evaluated at each iteration based on changes in the k value, and the results are comprehensively displayed in Table 1.

In the evaluation results, it is evident that the model's accuracy significantly increased along with the increase in the value of k up to the optimal point. This shows that a higher k value helps the algorithm to take into account more nearest neighbors, making it more accurate in recognizing patterns and variations in batik motifs. However, if the value of k is too large, the model's performance may actually decrease due to the influence of noise and information from different motifs. The visualization of the model's performance graph for various values of k is also shown in Figure 8. The graph helps in understanding which value of k provides the best performance for the KNN model in classifying batik motifs. In Figure 6, it shows that at k=1, the accuracy reaches 93.62% but the model is more sensitive to outliers. At k=7, the model performs optimally with an accuracy of 97.16%, precision of 97.10%, and an F1-score of 97.10%. The graph shows stability in performance as the value of k increases, but values that are too large cause a decrease in accuracy. Therefore, k=7 is chosen as the optimal parameter because it provides the best balance between model generalization and sensitivity.

Tabel 1. Results of KNN model training

K	Akurasi	Precision	Recall	F1-Score
1.	0.9362	0.9412	0.9275	0.9343
2.	0.9291	0.9275	0.9275	0.9275
3.	0.9149	0.9014	0.9275	0.9143
4.	0.9149	0.9130	0.9130	0.9143
5.	0.9362	0.9412	0.9275	0.9343
6.	0.9362	0.9286	0.9420	0.9353
7.	0.9710	0.9710	0.9710	0.9710
8.	0.9645	0.9706	0.9565	0.9635
9.	0.9504	0.9559	0.9420	0.9489
10.	0.9574	0.9701	0.9420	0.9559
11.	0.9504	0.9559	0.9420	0.9489
12.	0.9504	0.9559	0.9420	0.9489
13.	0.9645	0.9571	0.9710	0.9640
14.	0.9574	0.9565	0.9565	0.9565
15.	0.9433	0.9420	0.9420	0.9420
16.	0.9362	0.9412	0.9275	0.9420
17.	0.9078	0.8889	0.9275	0.9343
18.	0.9078	0.9000	0.9130	0.9065
19.	0.9007	0.8873	0.9130	0.9000

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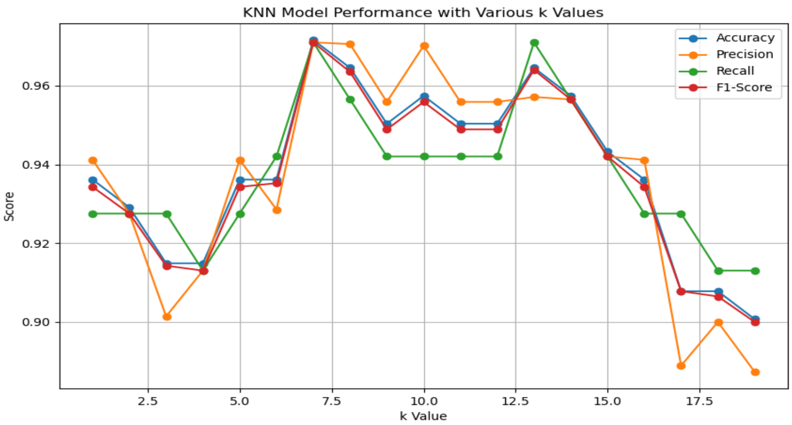

Figure 8. Results of KNN model performance evaluation

At the implementation and testing stage of the motif identification system, the model calculates the probability of an image belonging to the Cendrawasih or Tifa motif categories with a probability threshold of 10%. Figure 9a and Figure 9b illustrate the creation of a GUI that follows this implementation process. Figure 8a showcases the GUI interface, featuring a green button named "Masukkan Gambar" that facilitates the loading or input of images, including those with Cendrawasih or Tifa motifs. Additionally, the "Keluar" orange button allows you to either exit the GUI or close the system. In the main part of the interface, there is a table with two columns: the "Motif Batik" column, which displays the type of motif, and the "Similarity (%)" column, which shows the similarity achieved by the identification results.

When the prediction results appear, the similarity percentage sometimes shows a higher similarity value for the Tifa motif even though the input image is a Cenderawasih motif. This can happen because the Cenderawasih motif contains patterns similar to the Tifa motif, but the system still categorizes it as a Cenderawasih motif. After the user inputs an image, Figure 8b displays the prediction results, and the GUI provides a brief description of the recognized motif by the system. This description only recognizes the uploaded images as belonging to one of the two supported motifs, namely Cenderawasih and Tifa.

(a)

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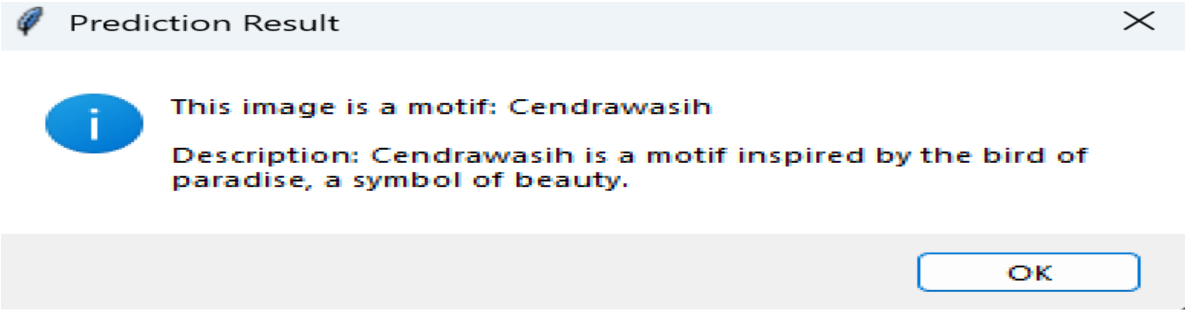

(b)

Figure 9. (a) Cendrawasih motif GUI display, (b) motif description display

5 Conclusion

This research successfully developed a system for identifying Papuan batik motifs, specifically the Cendrawasih and Tifa motifs, by utilizing LBP and the KNN algorithm for classification. This research draws its background from the natural and cultural wealth of Papua, evident in their batik motifs, and emphasizes the importance of preserving and maintaining culture through modern technology. The method used includes a series of data preprocessing processes, feature extraction using LBP and KNN methods to classify motifs based on the distribution of extracted texture patterns. The analysis results show that the KNN model with k = 7 provides the best performance with an accuracy of 97.16%, precision of 97.10%, and F1-score of 97.10%. Although the initial model's accuracy only reached 53.19%, adjusting the k value in the KNN model successfully improved its performance. The developed GUI makes it easier for users to identify the motifs of Cendrawasih and Tifa, as well as display the similarity and distribution of textures through LBP histogram visualization. Future research should increase the dataset size and apply other classification techniques, such as support vector machines (SVM) or artificial neural networks, to improve the model's accuracy. We can expand the research to encompass more Papuan batik motifs and develop a system that can detect batik motifs from various regions in Indonesia.

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