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Detection of Palembang Jumputan Cloth Motifs Using Canny Edge Detection Method and Rule-Based Classifier

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ABSTRACT
Palembang jumputan cloth has a distinctive motif, which is part of the heritage culture of Indonesia. However, process identification motif is still done manually, requiring high accuracy and being prone to errors. This study aims to build an automatic detection system for Jumputan fabric motifs using the Canny Edge Detection method to extract borders and a Rule-Based Classifier for motif classification based on the number, area, and contour density features. This study uses 750 fabric images from five types of motifs: Tiga Negeri, Titik Tujuh, Tabur, Lereng, and Ecoprint. The images are processed through grayscale conversion, histogram smoothing, and Canny edge detection. The results of feature extraction are used to classify motifs using logical rules. Based range, mark each feature. Evaluation done with a confusion matrix and produces an accuracy rate of 54%, which shows that this method is quite Good as an approach, beginning, however, still needs improvement so that More accurate classification results. The system has also been implemented in a GUI interface for practical use.

Keywords: Palembang Jumputan Cloth, Canny Edge Detection, Rule-Based Classifier, Motif Classification, Digital Image Processing.

I. Introduction

Cloth Jumputan is a typical inheritance culture typical of Indonesia, which came from Palembang, South Sumatra. Cloth. This is known as the technique of coloring tie dip, which produces unique patterns and has high beauty. Motive on cloth jumputan has its own characteristics that reflect local cultural values and is often used in various traditional ceremonies and daily community activities. Palembang. As it develops technology, preservation and introduction of motif cloth traditional motifs as jumputan, can be assisted by digital-based approaches, one of which is digital image processing. However, in reality, recognizing and distinguishing jumputan fabric motifs is still often done manually. This process relies heavily on skill. Observer man, this is certainly still limited in terms of accuracy and consistent results each time, especially if the motifs are similar or have complex details. This presents a unique problem, particularly in terms of documentation, promotion, and digitalization. Motif as part of preservation culture. Study. This uses Canny edge detection is a method for classifying objects based on data, which is most similar (neighbor nearest) with amount k, which has been determined, and classifies them into new classes. (Imelda 2021)

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Therefore, a system is needed to help people learn more about the types of fabrics and their patterns. The system was developed using image processing using the Canny edge detection method (Fatani and Abdi 1973). Several previous studies have discussed fabric pattern recognition using methods based on texture, like LBP (Local Binary Pattern), GLCM (Gray Level Co-occurrence Matrix), as well as classification methods such as Artificial Neural Networks (ANN) and SVM (Support Vector Machine). Although the method was quite successful, the detection-based edge approach on an image, like Canny Edge Detection, is still seldom used, special for traditional motif cloth. Whereas, method Canny is known to be capable of producing a line edge which is more precise and accurate, and is useful in highlighting the pattern form that is the basis of a motif. This research focuses on the use of the Canny Edge Detection method to detect edge patterns that are characteristic of each Palembang jumputan cloth motif. The detection results are then analyzed using a rule-based classifier, which groups motifs based on the number, area, and density of lines. This approach is expected to be an initial solution in automating the process of digital jumputan cloth motif recognition.

II. Literature Review and Hypothesis Development

2.1. Jumputan

Cloth jumputan, also known as cloth rainbow, is a traditional Palembang textile product made using the tie-dye technique. This technique differs from batik, which uses wax as a color barrier. In the tie-dye process, certain sections of the fabric are tied tightly with a string and then dipped in a dye solution. This process is a tie-dye resistance technique, which aims to prevent color absorption in certain areas, creating distinctive and attractive motifs (Wuryani and Putri 2022) (Nova Ari Pangesti et al. 2024). The most common raw material used in making jumputan cloth is silk, known for its smooth, soft, and cool-to-wear patterns. The silk used is typically white and can be processed on a loom. Jumputan cloth not only has aesthetic value but also possesses a strong cultural dimension. As a result, work creation man, which became part of the rich culture of Palembang. Tie-dye cloth is one of Palembang's original cultural products, along with songket cloth, although the technique used to make it is relatively simple, namely by tying and dipping the cloth in dye to produce the desired motif (Nurhayati 2018; Tawulo and Anhusadar 2022). The history of tie-dye cloth can be traced back to the golden age of the Sriwijaya Kingdom, when Sumatra and Java were known for cloth patola made from silk. At the beginning 16th century, the entry of Javanese culture into the palace of Palembang through the nobility also encouraged the increased use of jumputan cloth, along with the development of the trade in woven cloth from Java to the Palembang region (Nurhayati 2018) (Riset et al. 2020). Figure 2.1 is an example of Palembang jumputan cloth.

2.2. Digital Image

An image describes two dimensions of an object in the world, which can be reviewed from various disciplines like art, perception, visual man (human vision), astronomy, engineering, and others and so on. In a general way, an image is a group of pixels or dots, dot, dot-colored objects arranged in a two-dimensional form and forming a certain visual appearance (Jumadi, Yupianti, and Sartika 2021) (Adhinata et al. 2020). An image in digital form represents an image in a format discrete Which can be processed by a computer. This image is obtained from the analog image digitization process, namely, through a sampling process that divides a continuous image into several discrete elements. This process produces a two-dimensional image composed of N rows and M columns of pixels (picture elements), each of which has position coordinates (x, y) and brightness values.

f (x, y). Coordinate (x, y) shows location pixels in the field image, while the f (x, y) value indicates the level of color intensity or brightness in that pixel (Munantri, Sofyan, and Florestiyanto 2020) (Pujianto 2021). Because an image is digitally converted into data in numerical form, namely numbers that indicate the intensity of light in each pixel, this image can be processed, and the process of checking can be performed

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using software or computer systems. The ability to digitally process images allows for wide applications in various fields such as recognition patterns, medical analysis, video processing, and system vision machine (Munantri, Sofyan, and Florestiyanto 2020) (Jumadi, Yupianti, and Sartika 2021).

2.3. Image Preprocessing

Preprocessing the image is a stage that begins in the process of processing an image digitally, which aims to improve image quality before further analysis or processing. This process transforms the input image into the best possible image, both in terms of visual quality and the information it contains. The main goal of preprocessing is to reduce or eliminate disturbances such as noise, improve contrast, as well as prepare the image so that more easily recognized and processed in the next stages (Rio Subandi, Herman, and Anton Yudhana 2023) (Widyaya and Budi 2021). According to Bahri and Maliki, preprocessing is a process of removing unnecessary parts of an input image, thus making the image cleaner and more focused on the main object being analyzed. Generally, in this stage, the image is converted to a grayscale format to simplify it while still retaining important information. Furthermore, preprocessing can also include other manipulation processes such as intensity normalization and histogram smoothing, depending on the purpose and needs of the image application (Munantri, Sofyan, and Florestiyanto 2020) (Rexion Alondeo Boimau and Yampi R. Kaesmetan 2024). With the advancement of technology in digital image processing, preprocessing techniques have become increasingly sophisticated and rapid. This has had a significant impact on various fields, as preprocessed images have superior performance for various applications such as object detection, segmentation, pattern recognition, and image classification (Munantri, Sofyan, and Florestiyanto 2020; Sanjaya et al. 2023).

2.4. Edge Detection

Edge detection is a technique in digital image processing. Which aims for the mark boundaries object in an image. The edge or side of an object is described as an area where changes in the level of color intensity occur sharply or important. This change in strength level usually indicates a difference in visual structure, so that the process involves important edge detection to take the important features of objects in the image (Saluky 2019; Supriyatin 2020). In a general way, the detection edge will change the mark intensity pixels in a particular number into two different values, usually in binary form, such as 0 and 1. A high value (e.g., 1) indicates the presence of an edge, while a low value (e.g., 0) indicates its absence. Existence edge. Objective of the process. This is for clarifying the details object, which may be blurred due to image acquisition errors or other disturbances (Saluky 2019) (Ghozali and Sumarti 2020).

Detection edge, including in field analysis image And plays an important role in Various applications such as object segmentation, pattern recognition, and object tracking. Various techniques and operators can be used to detect edges, such as the Sobel, Prewitt, Roberts, Laplacian, and Canny operators. Each operator has its own characteristics. In detecting change intensity, the election must be customized with the type and characteristics image used. However, not all operators are capable of providing accurate edge information, especially if the image contains a lot of noise or low contrast (Herawati and Kardian 2018). In image digital processing, edges can be categorized become three main types, namely (Herawati and Kardian 2018) (Supiyandi et al. 2024) :

a. Edge Steep

Edge steeply marked with change intensity, which is very sharp and happens over a very short distance. Direction of change. This intensity usually forms an angle close to 90°. Type: This is generally easily recognized and produces a line edge Which clear. Figure 1 shows the detection edge type “edge steep".

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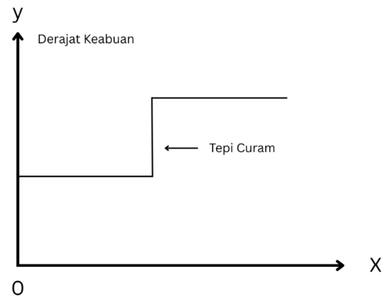

Figure 1. Steep Edge

b. Edge Sloping

A gentle edge is a gradual or gradual change in intensity. The edge direction has a small angle and typically consists of a collection of adjacent local edges. Detecting this type of edge requires more sensitive techniques because the transition is not as clear as a steep edge. Figure 2 shows the detection of a gentle edge.

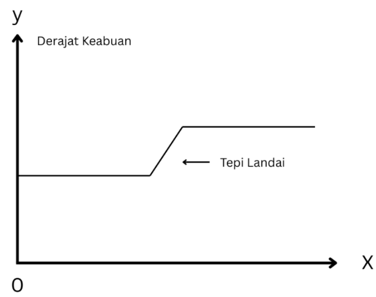

Figure 2. Sloping Edge

c. Edge Steep

In many cases, especially in computer vision applications, the images used contain noise that can interfere with the edge detection process. Therefore, it is necessary to process an improved quality image (image enhancement), like smoothing or filtering, before performing edge detection to make the results more accurate. Figure 3 shows the "noisy edge" type edge detection.

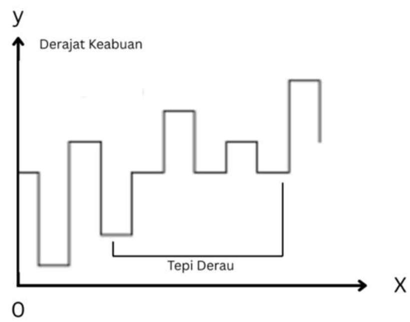

Figure 3. Steep edge with noise

2.5. Histogram Equalization

Histogram Equalization (HE) is a technique for adjusting image intensity to increase overall contrast. This process is carried out by leveling the histogram distribution on each color axis so that no color is too dominant, so that the distribution of gray values from the darkest to the lightest becomes more even (Ikhsan

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and Wiranda Hakiki 2024). The basic principle of HE is to equalize the cumulative distribution of gray values to form an X = Y relationship (Mahfuzh, Yuliantari, and Fatkhurrozi 2022). With this approach, the gray range in areas with a small number of pixels will be narrowed, while areas with a large number of pixels will obtain a wider gray range (Hasan & Liliana, 2020; Dwi Marisa Midyanti, 2020).

2.6. Method Canny

Method Canny, which put forward by John Canny on year 1986, is famous as an edge detection operator that is optimal. This algorithm provides an error rate that low, localizes edge points, and only provides one response for one edge (Supriyatin 2020) . The Canny operator has several advantages in extracting edges, with the freedom to choose the parameters used. (Batubara 2020) . The Canny method is an optimal edge detector and has excess over operator detectors, Which others (Alam et al. 2023) (Syarif et al., 2021). Detection Edge Canny has the following steps (Hasan and Liliana 2020) :

a. Smoothing

The first step in edge detection using the Canny operator is to smooth the image to reduce the system's response to noise and control the details that appear at the edges of the image. Smoothing is done by applying an image filter with the Gaussian operator (x,y). Convolution itself is the multiplication of two images. Function f(x,y) and g(x,y). In the Gaussian filter, mark intensity of every pixels replaced with average from mark weighting for each of its neighboring pixels and the pixel itself. Neighboring pixels are pixels that are located in around pixels Which intended. The amount neighbor Which involved depends on the designed filter.

b. Finding Gradients

Canny Edge Detection algorithm essentially finds the edge with the highest intensity change in an image. This region is found by determining the gradient of the image. The gradient at each pixel in the image is smoothed by applying operator Canny.

c. Non Maximus Suppression

This step aims to remove potential gradients at a pixel from the edge candidate if the pixel is not a local maximum in the edge direction at that pixel position.

d. Connection

This stage is the grouping of each pixel whether it is included in the edge pixel category or not. Apply double threshold (specify threshold lower and threshold on).

2.7. Rule-based classifier

A rule-based classifier is a classification method that works based on a set of manually designed logical rules (if-then) to group data into specific classes. Unlike machine learning algorithms, which require training from data, a rule-based classifier determines classification decisions based on feature values that meet certain predetermined criteria (Sidik et al. 2020). In the context of image processing, rule-based classifiers are often used when the resulting features are explicit and have logically identifiable patterns. For example, an object is classified into a particular class if it meets the criteria of having a number of edges exceeding a certain value, an average contour area within a certain range, or a contour density that matches certain visual characteristics (Darnita and Toyib 2021).

The main advantages of this method are its simplicity, rule transparency, and the lack of training data required. However, its drawbacks are its limited adaptability to complex data variations and its high dependence on the accuracy of the rule formulation. In this study, a rule-based classifier is used to classify

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Palembang jumputan cloth motifs based on the extracted features from the Canny method, namely the number of contours, contour area, and contour density resulting from the edge detection process. One example of the application of rule-based classifiers in the field of image processing is the classification of objects based on morphological features such as the number, area, and density of segmented objects. For example, in the process of identifying motifs on traditional cloth, such as jumputan cloth motifs, an image that has gone through the edge detection stage will produce edge objects (contours) whose number, average area, and density level can be calculated in the image (Gantini et al. 2025).

2.8. Confusion Matrix

A confusion matrix is a table used to illustrate the performance of a clustering system by showing the number of test data correctly or incorrectly classified. (Putri et al. 2024) . The use of a confusion matrix allows for a more in-depth analysis of the classification results, as it not only displays the overall accuracy but also shows where the clustering errors occurred. (Nurhidayat and Dewi 2023) (Dwitifani Hermanto and Susilawati 2023). As a simple yet effective evaluation technique, the confusion matrix helps in assessing the performance of a classification model in more detail. (Saputra, Atina, and Nastiti 2024) . Its main purpose is to measure how good the model is in classifying test data into the appropriate class (Nurhidayat and Dewi 2023) . Table 1 shows general view from a confusion matrix.

Table 1. General View of the Confusion Matrix

Predicted	Actual	
	True	False
True	TP (True Positive)	FP (False Positive)
False	TN (True Negative)	FN (False Negative)

In the confusion matrix, there are four main components that represent the classification results:

a. True Positive (TP): Actual positive data that was correctly predicted as positive.
b. True Negative (TN): Data is current negative Which succeed predicted with Correct as negative.
c. False Positive (FP) : Type I error, where actual negative data is predicted as positive.
d. False Negative (FN): Type II error, where actual data positive predicted as negative.

A confusion matrix is not only useful for displaying classification results, but also used for count metric evaluation like accuracy, precision, and recall, each of which has an important role in measuring model performance (Romadloni et al., 2022)

a. Accuracy shows how much big proportion prediction Which Correct against the entire test data.
b. Precision describes how much accurate prediction positive Which produced by model against truly positive data.
c. Recall (Sensitivity) measures the extent to which the model successfully finds all positive data in the test data.

By using the confusion matrix and these metrics, we can make a more objective assessment of the performance of a clustering step, as well as understand the strengths and weaknesses of the model developed.

III. Literature Review and Hypothesis Development

Research on detecting Palembang jumputan cloth motifs using the Canny Edge Detection and Rule-Based Classifier methods. Data Collection, namely collecting images of Palembang jumputan cloth with

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various motifs. These images are prepared in the Image Data stage, which is then used in the detection system process. The acquired image data is processed in the Pre-processing stage, which includes conversion to grayscale and image quality enhancement, such as histogram equalization. After pre-processing, the image enters the Edge Detection stage using the Canny method, which aims to extract edge or contour features from fabric motifs. The results of edge detection are used in the evaluation process, which is the classification of motifs using a rule-based classifier based on numerical features such as the number of contours, average contour area, and density. The evaluation also includes calculating accuracy, precision, recall, and F1 - score to measure system performance.

Next, system testing is performed using a user interface (GUI) application to assess practical performance against test data. The final stage is the report, which documents the entire research process, evaluation results, and conclusions of the system developed. This research focuses on the use of the Canny Edge Detection method to detect edge patterns that are characteristic of each Palembang jumputan cloth motif. The results of the edge detection are then analyzed using a rule-based classifier, which groups motifs based on the number, area, and density of lines, so that it can be an initial solution in automating the digital motif recognition process. The data collection process was carried out directly at the center of Palembang's traditional jumputan cloth production, namely at KC Haris Jaya, which is one of the craft centers that still actively produces various traditional jumputan motifs, namely the Tiga Negeri, Titik Tujuh, Tabur, Lereng, and Ecoprint motifs. Each motif was photographed separately to maintain the clarity of the visual characteristics of each pattern.

After the data collection process was completed, a total of 150 images were obtained for each motif type, resulting in a total of 750 image data sets representing the five Jumputan motifs that were the object of the study. The five motifs include Tiga Negeri, Titik Tujuh, Tabur, Lereng, and Ecoprint, each of which has distinct pattern and contour characteristics.


(a)

(b)

(c)

(d)

(e)

Figure 4. Research Data Samples for Jumputan Cloth Motifs (a) Tiga Negri Motif, (b) Titik Tujuh Motif, (c) Tabur Motif, (d) Lereng Motif, (e) Ecoprint Motif

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Data preprocessing is a process that aims to prepare the captured image for better use in the pattern detection process. This step is very important because the raw images obtained from the shooting process often have variations in lighting, contrast, and background that can affect detection accuracy. By performing preprocessing, the system will have input data that describes and does not change. The stages carried out in this pre-processing process include:

a. Grayscale Conversion

Converting a color image (RGB) to grayscale is the initial stage in preprocessing, which aims to simplify color information into brightness levels based on pixel intensities. This process reduces the complexity of the data without eliminating important features of the motif, thus facilitating further examination, such as edge detection and image segmentation. Figure 5 illustrates the process of converting the original image to grayscale.

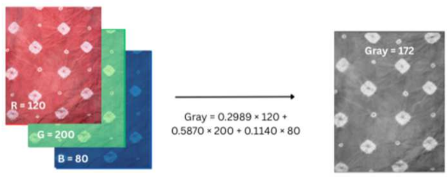


Figure 5. Illustration of the Process of Converting the Original Image to Grayscale

b. Light Equalization (Histogram Equalization)

Histogram equalization, or light leveling, is performed to improve the contrast of grayscale images. This technique distributes pixel brightness levels more evenly, making dark areas brighter and vice versa. This is especially helpful in conditions of uneven lighting in the original image, as well as improving the clarity of previously less visible patterns. Figure 6: Illustration of the Light Leveling Process of a Grayscale Image.

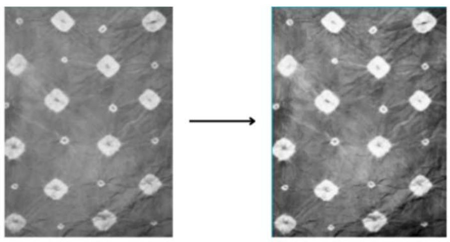
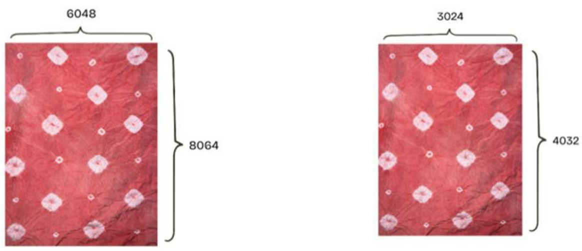


Figure 6. Illustration of Light Alignment from Grayscale Image

c. Image Resizing

To ensure consistency in processing and comparison between images, all images can be resized to a uniform size. This is especially important if the detection model relies on pixel size or number as a parameter. For image resizing, the image size is set to 3024 x 4032 pixels. Figure 7 shows the image sizes.



(a) (b)

Figure 7. Image Resize: a. Before resizing, b. After resizing

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The Canny Edge Detection method is used to detect edges or lines of motifs in Jumputan cloth images. This method was chosen because it has good capabilities in capturing fine and complex edges, as well as being resistant to noise interference that often appears in real images. Edge detection is a crucial part of the process of recognizing patterns or shapes, because these edges are later used as the basis for extracting features. Edge detection process using the Canny method. Edge Detection consists of several stages, that is:

a. Smoothing

The first step in the edge detection process using the Canny method is smoothing the image. This smoothing process is performed by convolving the image using a filter. Gaussian. Convolution itself is a mathematical process involving the combination of two functions, in this case, the image intensity function with the Gaussian function. g(x,y) . Filter Gaussian filters work by replacing a pixel's intensity value with a weighted average of the pixel's values and those of its surroundings. This filter produces a smooth smoothing effect, preserving important contours while significantly reducing unnecessary noise. The kernel used is 5x5 in size based on the default Filter. Gaussian, following Table 2, is an illustration of the kernel used with a result of 1/159.

Table 2. Kernel 5x5 Gaussian Filter

2	4	5	4	2
4	9	12	9	4
5	12	15	12	5
4	9	12	9	4
2	4	5	4	2

After obtaining a kernel with a value of 1/159, a dot product operation will be carried out to obtain the midpoint value of the pixels of an image. The following is an example of a dot product operation with a vector value from pixel extraction in a jumputan image, and Table 8, Table 8, and Figure 9 present the results of smoothing an image.

$$G(x,y) = \frac{1}{159}.$$

Table 8. Illustration of Dot Product Operation for Smoothing

132	135	137	137	138
133	135	135	136	136
133	133	133	133	133
133	132	131	133	132
130	130	130	130	132

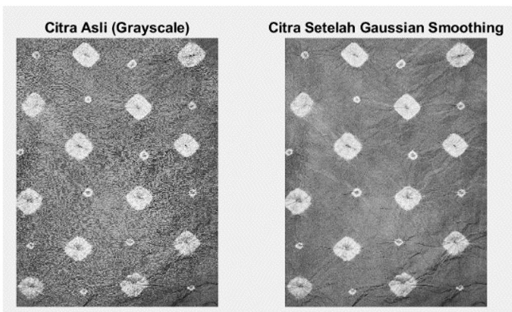

Figure 9. Smoothing Results

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b. Finding Gradients

This process begins by smoothing the image using the Canny operator to estimate the gradient value at each pixel, both in the horizontal (x) and vertical (y) directions, with the help of a special kernel. The following figure shows that 10 is the result of finding the gradient.

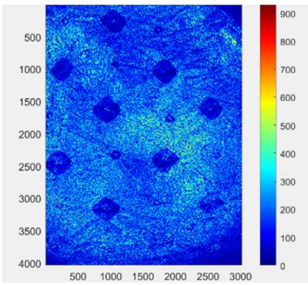

Figure 10. Results of Finding Gradients with Canny

c. Non-maximum Suppression

The next step is non-maximum suppression. This stage aims to filter only the sharpest or most important edges. It does this by comparing the intensity value of a pixel with that of its neighbors in the gradient direction. If the pixel's value is the highest compared to its neighbors, it is retained. However, if not, its value is set to zero to exclude it from consideration as an edge.

Figure 11. Non-maximum Suppression Results

d. Connection

This process removes broken lines at the edges of image objects. This stage applies Otsu thresholding automatically to the gray level of the histogram through discriminant analysis. Grouping the data is expected to maximize the separation of objects (foreground) and background.

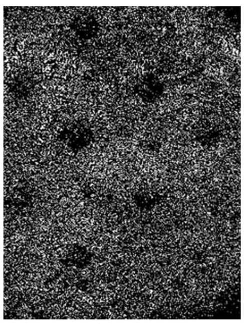

Figure 12. Connection Result Image

e. Rule-Base-Classifier

The classification of Jumputan cloth motifs in this study uses a rule-based classifier approach, namely a method based on numerical logic rules that is explicit, transparent, and does not require training like

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machine learning. The classifier is implemented using the MATLAB ruleBasedClassifier function, with three input parameters: the number of contours, the average contour area, and the contour density. This process produces numerical data that represents the visual characteristics of each motif. The results of this analysis are presented in a summary table (Table 3) containing the minimum, maximum, and average values of the three features in each class, as well as a visualization of the feature distribution using a boxplot (Figure 13). From the table and visualization, it can be seen that each motif class has a unique value distribution pattern that can be distinguished from the others.

Table 3. Feature Extraction Statistics per Motif

Class	Number of Contours (Min - Max)	Mean Contour Count	Contour Area (Min - Max)	Mean Contour Area	Contour Density (Min - Max)	Mean Contour Density
Ecoprint	36279 - 61749	48701,1667	48.5396 - 103.9776	70,3961	0.003 - 0.0051	0.004
Slope	46630 - 55903	50746.4333	44.7443 - 60.1968 49825.6	53,6334	0.0038 - 0.0046	0.0042
Country	34903 - 54479	44339.4	43.6442 - 89.2463	65,4123	0.0029 - 0.0045	0.0036
Sow	30387 - 53301	38703.4	48,0241 - 124,8026	85,7408	0.0025 - 0.0044	0.0032
Point	32308 74877	49825.6	49.2834 - 116.9445	78,8712	0.0026 - 0.0061	0.0041

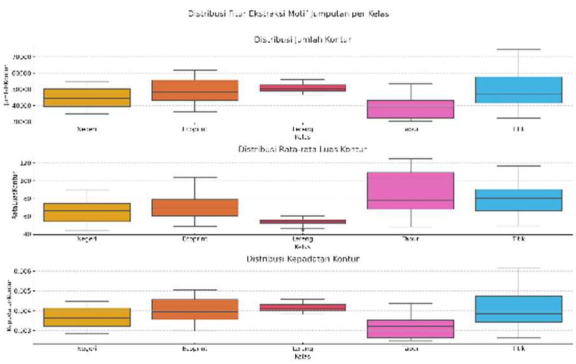

Figure 13. Visualization of Feature Distribution per Motif

Based on the analysis results, the range of feature values used in the classification rules is determined. For example, for the Point motif class, images with several contours between 43,437 and 58,431, an average area between 61.23 and 85.59 pixels, and a density between 0.00356 and 0.00479 will be classified as a Point motif. This logic is structured in the form of an if-else conditional structure in the MATLAB program code. Each if block reflects the classification rule for one type of motif. This approach allows for rapid classification and traceability of the decision flow. However, this method also has limitations, such as high sensitivity to image variation and a heavy dependence on the precision of threshold values within each rule. To check the performance of Canny Edge Detection, a rule-based classifier is used, which is done by comparing the class labels generated by the rule with the actual class labels (ground truth) that have been previously determined. Each motif image data has been equipped with its original class label, so the evaluation process can be carried out without the need to divide the training and testing data as in the machine learning approach.

The rule-based model was tested using 150 motif image data (30 images each for 5 types of motifs), and the classification results were compared with the original labels to obtain an overview of the extent to which the designed rules can correctly recognize jumputan motif patterns based on the number of lines, average line area, and line density. Figure 13 is a confusion matrix from canny edge detection, and Figure 14 is a confusion matrix from canny edge detection and Figure 16 is a confusion matrix from canny edge detection and Figure 16 is a confusion matrix from canny edge detection and Figure 17 is a confusion matrix from canny edge detection and Figure 18 ... 15 views of accuracy, precision, and recall.

Figure 14. Canny Edge Detection's Confusion Matrix

Akurasi Total: 41.33%

Kelas Ecoprint | Precision: 0.50 | Recall: 0.20
Kelas Lereng | Precision: 0.58 | Recall: 0.70
Kelas Negeri | Precision: 0.23 | Recall: 0.60
Kelas Tabur | Precision: 0.62 | Recall: 0.33
Kelas Titik | Precision: 0.78 | Recall: 0.23

Figure 15. Evaluation Results of the Rule-Based Classifier

Conducting system testing using a Graphical User Interface (GUI). This GUI has been specifically designed as a user interface to automatically detect the type of Palembang jumputan cloth motif. The system interface design can be seen in Figure 16.

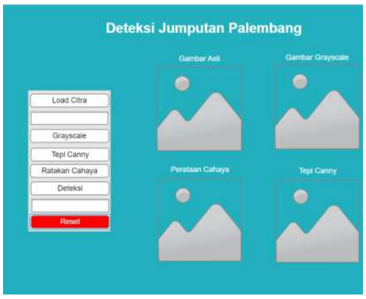

Figure 16. Graphical User Interface (GUI) Design Display

The final step in this research is the preparation of a research report that documents the entire process, from design to system evaluation. This report is based on the results of observations, experiments, and data analysis obtained during the research. The report preparation process begins with an introduction, which includes the background of the problem, problem formulation, objectives, scope, and benefits of the research.

IV. Results and Discussion

4.1. Grayscale Conversion

$$Gray=(0.2989\times120)+(0.5870\times200)+(0.1140\times80)=162.388\approx172$$

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These results are used as a representation of the brightness level in the grayscale image and form the basis for the next stage of image analysis. The final value of 172 has been rounded or adjusted in the figure. The following code is used to read a cloth image, convert it to grayscale, and then take a small 5×5 pixel snapshot from a specific position. These pixel values are displayed and converted into 1-dimensional vectors for further analysis purposes. The code output shows the pixel intensity values in a 5×5 grayscale patch taken from the image. These values are displayed as a matrix and also as a 1-dimensional vector (25 elements), representing the brightness level of a small area of the image. These results can be used for analyzing local patterns in the image.

Grayscale Vector (25 dimensions):

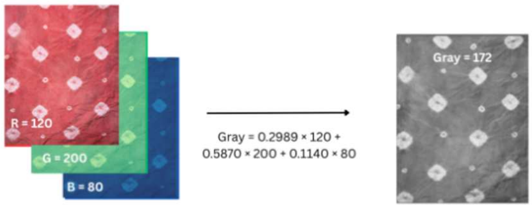
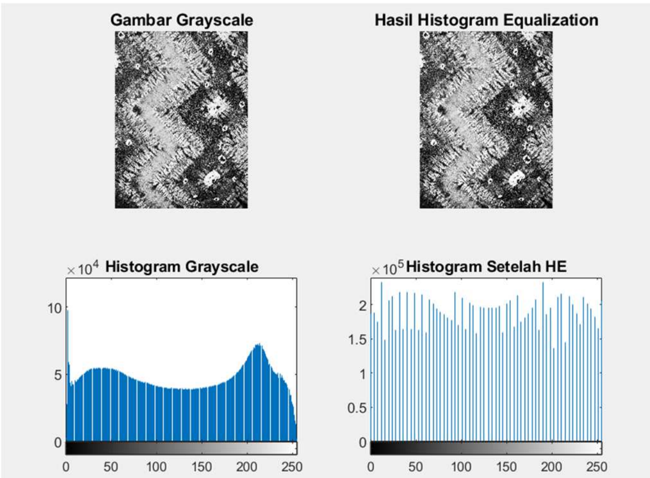


Figure 17. Illustration of the Process of Converting an Original Image to Grayscale

4.2. Histogram Equalization

Histogram equalization is used to even out lighting and increase image contrast. This technique helps clarify lines that may have previously appeared faint, especially in images with uneven lighting.

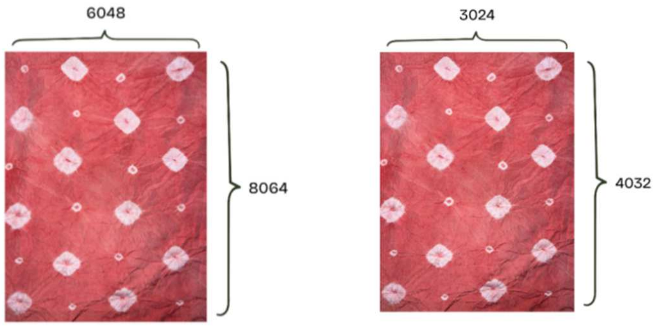


(a) (b)

Figure 18. Illustration of Light Equalization from Grayscale Image (a) Before Equalization, (b) After Equalization

4.3. Resizing

The image is resized to a standard size of 3024 x 4032 pixels to maintain consistent processing results. Resizing doesn't alter the image's proportions, but it helps the algorithm run faster and more accurately.



(a) (b)

Figure 19. Image Resize: a. Before resizing, b. After resizing

4.4. Canny Edge Detection

The Canny method is implemented in several stages: smoothing (using a Gaussian filter), gradient calculation (using the Canny operator), non-maximum suppression, and thresholding (Otsu threshold). The edge detection results in an image that displays distinct lines from the pattern. Each pattern exhibits different line characteristics.

4.5. Smoothing Using a Gaussian Filter

The first step in the Canny algorithm is image smoothing. The goal is to reduce noise that can affect the edge detection process and maintain the important features of the motif so that they can still be captured accurately. The smoothing process is smoothed with a Gaussian filter to make it smoother. The Gaussian filter works by replacing the intensity value of a pixel with a weighted average of the values of surrounding pixels. This convolution uses a 5×5 kernel as the weighting matrix, which is a standard configuration in the Canny method.

Smoothing or smoothing process in this study was carried out using a 5x5 Gaussian filter to reduce noise that can interfere with the edge detection stage. The smoothing process was carried out using MATLAB with the following steps. First, the image of the jumputan cloth motif was read using the imread function, and then checked whether the image was colored (RGB) or not. If the image was colored, the image was first converted to grayscale format with the rgb2gray function so that processing was easier and only focused on the pixel brightness level. After that, a 5x5 Gaussian kernel was created that had been normalized by dividing each matrix element by a total weight of 159. This kernel was used to weight the pixels during the image filtering process. Based on the appearance of the image results, the smoothing process successfully reduces noise clearly without damaging the shape of the main pattern, so it is very helpful for the edge detection stage using the Canny method.

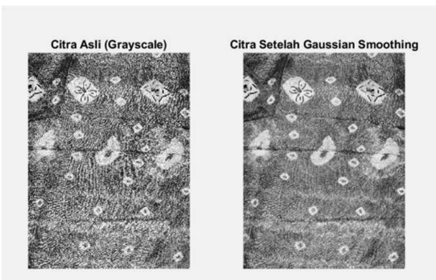


Figure 20. Smoothing Results

In Figure 20, when the Gaussian kernel matrix is applied via the dot product operation to the pixel values above, a weighted average value is obtained that represents the smoothing results at the center pixel.

4.6. finding gradients

The next step in the edge detection process using the Canny method is finding gradients, which aim to identify areas in the image that experience the sharpest changes in intensity. Gradients are used to indicate how much brightness changes in an image in a specific direction, namely horizontally (the x-axis) and vertically (the y-axis). Gradient magnitude visualization image. The Canny map above shows the results of calculating the magnitude of the intensity change in each pixel of the image after going through the smoothing stage. The colors in the image represent the strength of the gradient, where blue indicates a low intensity change (flat area or background), while yellow to red indicate a high intensity change, which is generally the edge lines of the jumputan cloth motif. This process is carried out by calculating the horizontal and vertical gradient values using the Canny operator, then the results are combined using the gradient magnitude formula. This visualization result is very helpful in recognizing parts of the image that have a strong pattern structure, which will later be processed further in the non-maximum suppression and thresholding stages. Thus, this gradient map becomes an important basis in determining the location of the main edges of the motif to be detected.

The Gradient search process in this study was carried out using the Canny operator, which consists of two kernels, namely, for the horizontal and vertical directions. The results of the horizontal and vertical convolution are stored as the gradient value of each pixel. Next, these values are combined to produce the gradient magnitude, which is a measure of how much intensity changes in each pixel. These results are then visualized in the form of a color map using a colormap jet, which shows low values in blue and high values in red. This visualization is useful for displaying areas with sharp intensity changes, which are usually the edges or boundaries of jumputan fabric motifs. This stage is very important for recognizing the main pattern before the edge detection process is carried out.

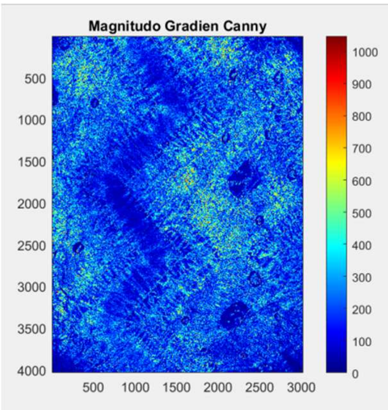


Figure 21. Results of Finding Gradients with Canny

Figure 21 below shows the results of the finding gradients process, which shows that areas with high intensity changes (edges) are more prominent than flat areas. Based on these results, the finding gradients process has proven successful in highlighting the main lines of the motif.

4.7. Non-Maximum Suppression

This stage is very important because it aims to sharpen the edges by filtering and retaining only the pixels that are truly part of the object's edge. This process is done by comparing the gradient magnitude value of a pixel with the values of its two neighboring pixels that are in the same direction as the gradient direction. If the gradient value of a pixel is the highest compared to its two neighbors, it is retained as part of the edge. Conversely, if it is not the highest, its value is reduced to zero to exclude it from being considered an edge. This ensures that only clear and important edge lines remain, while unimportant or noisy parts are removed.

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This helps produce thinner, sharper, and more accurate edges, which are crucial in forming the visual pattern of tie-dye motifs.

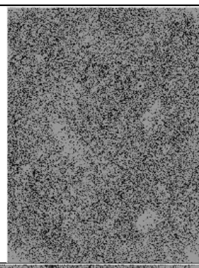
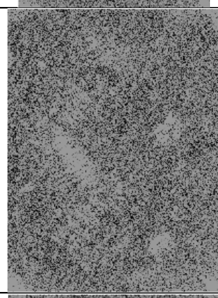
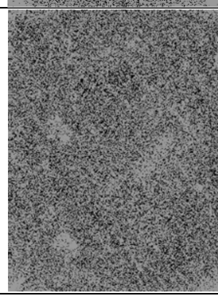
Figure 22 Non-maximum Suppression Results

This can be seen in Figure 22, which shows that the resulting edge lines are cleaner and more focused compared to the previous results, which still contained many double lines or blurred edge areas. The non-maximum suppression process is very helpful in clarifying the edge detection results, so that the motif lines become clearer and easier to recognize in the subsequent motif classification process.

4.8. Thresholding and Edge Connections

Thresholding and edge connection, which function to ensure that the resulting edge lines truly form a complete pattern and represent the structure of the motif object.

Table 4. Threshold Table

No	Low Threshold	High Threshold	Results
1	50	50	
2	90	60	
3	35	45	

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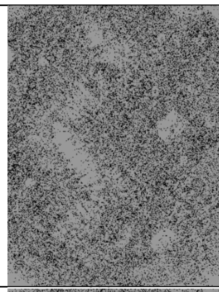
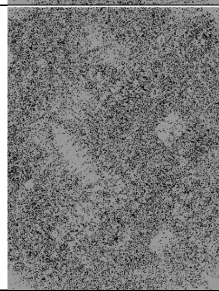
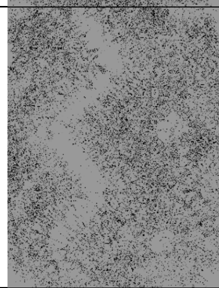
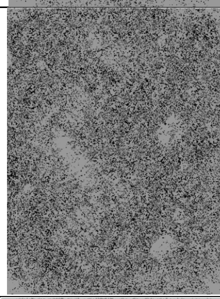
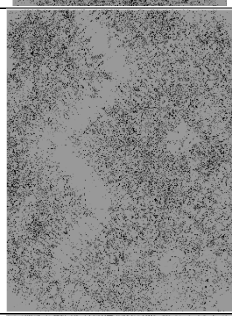
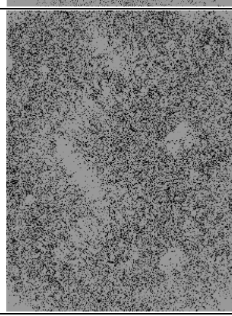
4	5	95	
5	65	70	
6	100	150	
7	55	65	
8	125	145	
9	75	80	

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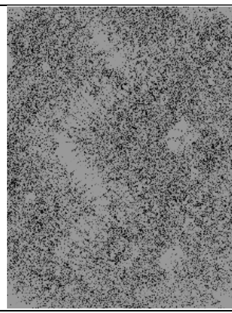
10	80	90	

In the Canny method, the hysteresis thresholding stage determines how strongly the edges are retained, using two threshold values: lowThreshold and highThreshold. Experiments with various combinations of values show that the detection results are highly dependent on the choice of threshold. Too low values (e.g., 5 and 95) produce a lot of noise, while too high values (e.g., 200 and 450) actually remove many important details in the pattern. A balanced threshold combination that isn't too far apart, such as 35 and 45 or 70 and 150, produces more optimal edge detection—the pattern lines are clearly visible and noise is minimized.

From this test, it can be concluded that selecting the right threshold value significantly affects detection results. The value needs to be adjusted to the image characteristics so that the main pattern can be detected properly without interference. In the excerpt, the pixel gradient direction is checked, namely the vertical direction (90 degrees) and the upper left diagonal (135 degrees). For each direction, two neighboring pixels along the direction line are compared with the current pixel gradient value. If the pixel gradient value is greater than or equal to both of its neighbors, then its value is retained. Otherwise, its value is removed by setting it to zero. With this approach, only the edges that are truly at the peak of the intensity change are retained, resulting in thinner, cleaner detection results that focus on the main contours of the motif.

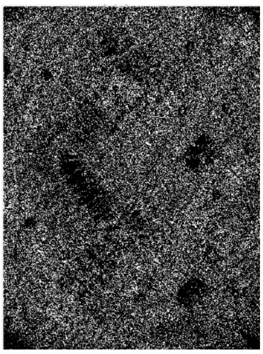


Figure 23. Connection Result Image

In the context of digital image processing, a contour refers to a closed line that forms the outer boundary of an object in a binary image. Contours are used to represent the visual form of a pattern that emerges after the edge segmentation process is complete.

Based on the contours that were successfully detected, several features were calculated, namely :

a. Number of contours: the number of contours or closed shapes detected edge detection results.
b. Contour area: the average area (in pixels) of each contour identified.
c. Contour density: the ratio between the number of contours to the image area, which describes how densely the motifs are arranged in one image.

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Table 5. Rule-Based-Classifier Table

No	File Name	Number of Contours	Contour Area	Contour Density	Prediction
1	Sprinkle__15.jpg	46324	65.01	0.003799	Point
2	Slope__150.jpg	51513	39.76	0.004225	Country
3	Negeri__84.jpg	38623	75.96	0.003168	Sow
4	Ecoprint__54.jpg	50944	47.88	0.004178	Country
5	Ecoprint__99.jpg	40299	77.56	0.003305	Sow

Classification is performed using a rule-based classifier, which is a set of logical rules based on features. Example rules:

a. If the number of contours is in the range of 43,437 to 58,431, the average contour area is between 61.23 to 85.59, and the density is between 0.00356 to 0.00479, then the image is classified as "Point Seven" In addition, if the number of contours is more than 58,000, the average area is less than 65, and the density is more than 0.0044, it is also classified as “Point Seven” (additional correction rule)
b. If the number of contours is in the range of 33,984 to 45,747, the average contour area is between 62.65 to 101.05, and the density is between 0.00278 to 0.00375, then it is classified as "Sown" If the number of contours is less than 43,000, the average area is more than 90, and the density is less than 0.0033, then it is also considered as “Tabur” (additional correction rule)
c. If the number of contours is in the range of 44,498 to 49,965, the average contour area is between 39.67 to 44.34, and the density is between 0.00364 to 0.00409, then it is classified as “Slope”. If the number of contours is less than 46,000, the average area is less than 50, and the density is less than 0.0036, then it is also classified as Slope (additional correction rule).
d. If the average contour area is in the range of 56 to 78, the density is between 0.0033 to 0.0042, and the number of contours is between 41,000 to 50,500, then the motif is classified as “ Ecoprint”. Also, if the number of contours is between 46,000 to 50,000, the area is between 60 to 80, and the density is between 0.0036 to 0.0042, then the result is “ Ecoprint” (additional correction rules)
e. If the number of contours is in the range of 48,464 to 53,575, the average contour area is between 41.29 to 54.15, and a density between 0.00397 to 0.00439, then it is classified as “State”. In addition, if the area is less than 55 and the density is more than 0.0043, it is also classified as a “Country” (additional correction rule).

If no rule matches, then the default class fallback will be returned as “Country”.

4.9. Detection Results

Detection of jumputan fabric motif types using the Canny Edge Detection method is carried out through several systematic stages, starting from image pre-processing to motif classification based on the visual characteristics of the edge detection results. The first step is to convert the image to grayscale format to simplify visual information by only focusing on brightness intensity, then a smoothing process is carried out using a 5x5 Gaussian filter to reduce noise without eliminating the main contours of the motif. After that, Canny is used to detect image edges through the stages of finding gradients, non-maximum suppression, as well as thresholding, and edge connection. This process produces a binary image that only displays the edges of the motif pattern.

From the edge detection results, features are extracted that represent the visual form of the motif, such as the number of edge pixels, the area of the edge, and the density of the edge lines. These features reflect the characteristics of certain motifs—for example, dot motifs tend to have a small number of edges that are scattered, while sprinkled or slope motifs will display denser and connected edges. Based on these feature values, a classification process is carried out using a rule-based classifier approach that determines the

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type of motif based on logical rules from feature combinations. Thus, the Canny method plays an important role in extracting the pattern structure of jumputan fabric, which is then used to recognize the type of motif visually and systematically.

4.10. Evaluation of Detection Results

Evaluation was performed using a rule-based classifier that assesses three key features of the edge detection results: the number of lines, the average line area, and the line density. The evaluation data were compared with ground truth labels and organized into a confusion matrix.

4.11. Confusion Matrix

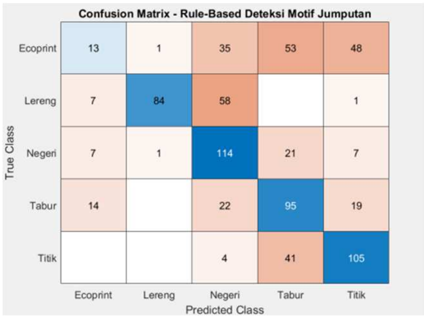

Figure 24. Confusion Matrix of Canny Edge Detection

4.12. Evaluation Results

The experimental results show a total accuracy of 54.80%, with an average precision of 56.40% and recall of 54.80%. These findings indicate that the Canny edge detection method performs fairly well in capturing object edges; however, its ability to recognize and differentiate complex patterns remains limited when not supported by additional feature extraction or classification techniques.

4.13. Testing Through GUI

The GUI application is designed to automatically detect patterns. GUI features include image upload, detection process, edge detection results, and pattern prediction. Testing the GUI using 25 test images demonstrated consistent results with initial testing.

Table 6. GUI Testing Table

No	Name	Original Class	Prediction
1	Three Countries__3	Three Countries	Country
2	Three Countries__8	Three Countries	Country
3	Three Countries__14	Three Countries	Country
4	Three Countries__22	Three Countries	Country
5	Three Countries__25	Three Countries	Country
6	Point Seven__3	Point Seven	Point
7	Point Seven__20	Point Seven	Sow
8	Point Seven__100	Point Seven	Point
9	Point Seven__105	Point Seven	Point
10	Point Seven__110	Point Seven	Point
11	Sprinkle__3	Sow	Sow
12	Sprinkle__8	Sow	Sow
13	Sprinkle__14	Sow	Point
14	Sprinkle__20	Sow	Sow

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15	Sprinkle__25	Sow	Sow
16	Slope__3	Slope	Ecoprint
17	Slope__8	Slope	Slope
18	Slope__14	Slope	Country
19	Slope__20	Slope	Country
20	Slope__110	Slope	Slope
21	Ecoprint__3	Ecoprint	Point
22	Ecoprint__8	Ecoprint	Point
23	Ecoprint__14	Ecoprint	Sow
24	Ecoprint__20	Ecoprint	Point
25	Ecoprint__128	Ecoprint	Ecoprint

Testing was conducted on 25 image samples consisting of five motif classes: Tiga Negri, Titik Tujuh, Tabur, Lereng, and Ecoprint. Based on the classification results, the system was able to correctly classify 17 images and misclassify the other 8 images. The Country Three Class achieved perfect results with all images being correctly classified as Countries. The Titik Tujuh and Tabur classes each had one misclassified image, classified as Titik and Titik. The system's performance on the Lereng class decreased slightly, with two out of five images misclassified as Ecoprint and Negeri. The class with the highest error rate was Ecoprint, where only one image was correctly classified, while the other four were incorrectly predicted as Tabur and Titik. Overall, the system produced an accuracy of 68%, which indicates that although the system is able to recognize some motif patterns well, there are still weaknesses in distinguishing motifs that have visual similarities.

4.14. Report

Based on the research conducted, the Canny Edge Detection method is capable of capturing the edge patterns of Palembang jumputan cloth motifs quite well. Each stage of this method, from pre-processing to thresholding and edge connection, contributes significantly to producing edge images that represent the main structure of each motif. In the pre-processing stage, grayscale conversion, histogram equalization, and a Gaussian filter are applied. It's proven to help clarify images before edge detection. Lighting equalization helps clarify patterns previously hidden by uneven lighting, while Gaussian filters successfully reduce noise without removing important pattern contours. This is a crucial foundation for ensuring the detection process is undisturbed by irrelevant visual elements.

In the edge detection process using Canny, the system is able to extract the main pattern well through the stages of finding gradients, non-maximum suppression, and thresholding. Visual results show that the main motif lines become clearer and more defined, thus simplifying the classification process. However, the evaluation results show that the system still has limitations in recognizing motifs accurately, especially for motifs with smooth or non-contrasting edges. From the evaluation using the confusion matrix, the total accuracy was 54.80%, with an average precision of 56.40% and a recall of 54.80%. These values indicate that although the system is quite successful in detecting edges, its classification capability is not optimal, especially when the motifs have similar shapes or line densities.

One of the main factors influencing these results is the classification approach, which still uses a rule-based classifier. This approach is static and relies heavily on certain constraint parameters (such as the number of lines, area, and density), making it less flexible in dealing with more complex motif variations. Furthermore, Jumputan motifs have a high degree of texture and shape diversity, making it difficult for rule-based models to generalize. However, the Graphical User Interface (GUI) provides added practicality. Through the GUI, users can directly test images and view the detection process and classification results in real time. This demonstrates that the system already has a viable prototype and can be further developed into a decision support system for motif identification.

Overall, the results of this study indicate that the Canny method can be used as an initial basis for fabric pattern detection, but it is not yet robust enough if it only relies on edge features. Combining it with

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texture features, such as Local Binary Pattern (LBP), GLCM, or even the use of machine learning- based classification methods (such as KNN, SVM, or CNN), are important options that need to be considered in further research to improve detection accuracy and make the system more adaptable to various pattern variations. Thus, this research can be a starting point for the development of a more sophisticated jumputan cloth motif identification system, which not only relies on line contours but also takes into account texture, color, and other visual contexts.

V. Conclusion

Based on the results of research on the detection of Palembang jumputan cloth motifs, it can be concluded that the first objective, namely applying the Canny Edge Detection and Rule-Based Classifier methods in the motif detection process, has been successfully achieved. The Canny method has proven to be quite good in extracting edges in cloth motif images, especially after the image has gone through pre-processing processes such as conversion to grayscale, histogram equalization, and smoothing using a Gaussian filter. These stages play an important role in improving image quality so that edge detection results become more optimal. Furthermore, the second objective, which was to determine the results of the application of the method, was also achieved. The developed detection system then classifies motifs using a rule-based classifier based on three main features: the number of contours, the contour area, and the contour density. The evaluation results showed that this system was able to achieve an accuracy of 54.80%, with an average precision of 56.40% and a recall of 54.80%. In addition, the system was tested through a Graphical User Interface (GUI) and can be used directly by users to automatically detect motifs. Although the accuracy obtained is not yet high and there are limitations, especially for motifs with faint or unclear edges, this research can be an initial step in developing a more precise and easy-to-use digital image processing-based jumputan cloth motif detection system in the future.

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