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Pattern Recognition of Sarong Fabric Using Machine Learning Approach Based on Computer Vision for Cultural Preservation

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Abstract: Sarong is a traditional cloth typically worn during formal or religious events which conventionally woven using the traditional loom. Samarinda is one of Indonesia's regions with a sarong with a distinctive pattern. Nevertheless, the majority of indigenous people cannot distinguish the various motifs of Samarinda sarongs from those of other regions in Indonesia (non-Samarinda). Therefore, it is necessary to classify the motif of sarongs. This work proposed a pattern recognition method based on computer vision for sarongs motif classification. This method required adequate features to achieve the optimal results. Accordingly, the appropriate color and texture features were investigated to obtain the most discriminative ones. This work generated features using color moments, Gray Level Co-occurrence Matrix (GLCM), and Local Binary Pattern (LBP). The most discriminatory features were selected using the Correlation Based Feature Selection (CFS) and then fed into Artificial Neural Network (ANN). A total of 1000 images were used to evaluate the method and achieved the highest performance with an accuracy value of 100%.

Keywords: Features extraction, Color moments, GLCM, Local binary pattern, Features selection.

1. Introduction

The cultural heritage of each country is diverse in various forms, including historical documents [1, 2], stone carving [3], text [4-6], and traditional fabric [7-9]. Indonesia has the traditional fabric recognized as one of the country's cultural heritage in the form of batik and sarong fabric. Batik has various patterns and motifs which derive from several areas, such as Java [10, 11], central Sulawesi [9], and Madura [12]. Samarinda is one of the cities in East Kalimantan–Indonesia's largest province– has a distinctive sarong that residents typically wear for formal or religious occasions. Samarinda sarong is unrestricted in various patterns, motifs, and materials. Each sarong has a core motif in the form of a rectangular set presented with a combination of different colors. The combinations of motif, color, and material indicated the differences between the motif of Samarinda sarong and others (non-Samarinda sarong).

Regrettably, not all Indonesians, particularly the Samarinda, can distinguish them due to Samarinda sarongs being available in various types. Moreover, each kind of sarong could have similar motifs and colors. It indicates the necessity for raising awareness and the importance of cultural preservation. The previous work on computer vision related to sarong fabric classification is still limited. Meanwhile, batik classification has been developed more [8, 9, 13]. Generally, those works involved three main processes: preprocessing, feature extraction, and classification [8, 9, 14]. Pre-processing was commonly performed by resizing the original image into a square form [8, 9], converting the RGB image into grayscale [11], histogram equalization [15], edge detection [13], and Gaussian filter [3].

Three types of features were extracted throughout the feature extraction process: color [12, 16, 17], texture [10, 11], and shape [10, 12, 16, 17]. Color moments and histograms were used to generate the color features [12]. Meanwhile, GLCM [9, 11], LBP [8], and wavelet transform [13] were extracted as texture features. Furthermore, shape features were generated using moment Invariant [12] and area-based [7, 10]. The task of fabric classification was accomplished using machine learning. Several classifiers have been implemented, including K-Nearest Neighbor (KNN) [8, 12], Decision Tree [13], Support Vector Machine (SVM) [9, 14], and ANN [7, 8, 11].

Several prior works have made many efforts to classify traditional fabric patterns. Nonetheless, method adjustment was necessary to overcome the limitation imposed by previous work that resulted in misclassification. The work related to the sarong classification is challenging since the fabric type generally has a similar color combination with the dominance of the rectangle motif, which makes it difficult to differentiate. Therefore, this work aims to recognize and classify Samarinda sarong. There are six classes of sarong including non-Samarinda sarong and five types of Samarinda sarong, namely Belang Hatta, Belang Negara, Belang Pengantin, Garanso, and Kuningsau. The color and texture features were extracted to construct the feature sets. The color features were obtained by color moment on each channel of the RGB, HSV, HSI, YIQ, and YCbCr color spaces. Meanwhile, GLCM and LBP were applied to produce texture features. The feature selection process produced the essential features while discarding the remainder. Afterward, ANN was performed in the classification process. The proposed method classified all the types of sarong correctly and achieved high accuracy.

2. Related work

The previous work related to classifying traditional sarong fabric was limited. However, other prior works have been successfully performed to recognize the patterns of batik as a traditional fabric and appropriately used as a reference in this work.

A classification batik image utilizing treeval and treefit as decision tree functions suggested by Rangkuti et al. [13]. The coefficient's features were extracted using the two-level of wavelet transforms and invariant moments. There were five batik patterns: Lereng, Parang, Kawung, Nitik, and Truntum. The testing data consisted of 20 images on each pattern and achieved a similarity accuracy 80% – 85%. Two other patterns, Ceplok and Mega mendung consisted of 10 images on each pattern, yielding an accuracy of 30% – 40%. The main limitation of the proposed approach is the value of invariant moment derived from the resulting edge detection image. The invariant moment is in accordance applied against the resulting segmentation image based on the thresholding operation. It can affect the accuracy of the classifier proposed method.

Nugrowati et al. [17] designed the searching system for batik patterns using color and shape features. The color feature was extracted using 3D-Vector Quantization. This technique might depict color distribution in various ways while simultaneously reducing the image's color complexity. The Hu moment approach was applied to extract the shape features. The extraction of shape features resulted in orthogonal invariant moments through the scaled, positioned, and rotated. The system was evaluated using 210 batik images classified into three types: Kawung, Parang, and Mega Mendung. The testing results showed the accuracy value of 50% for images based on color features, 80% for images based on shape features, and 60%, 50%, and 60% for images based on color and shape features. The drawback of the method is the color features are only extracted based on RGB color spaces. Whereas, other color spaces may have the opportunity to produce more discriminatory features to improve the performance of the classification method.

An Indonesian batik classification was proposed by Kasim et al. [10] using an ANN classifier. The work combined the features of texture and shapes' ornament in batik to classify images using ANN. The shape features included compactness, eccentricity, rectangularity, and solidity. Subsequently, these features were used to classify the batik images with ANN. The evaluation showed the shape feature obtained the lowest accuracy rate of 80.95%, while the combination of texture and shape features produced a higher accuracy value of 90.48%. The drawback of the method is no feature selection is applied. Therefore, the implementation of inappropriate features causes a decrease in the performance method.

A model for classifying Bomba traditional textiles was developed by Nuraedah et al. [9] using a Quadratic Support Vector Machine (QSVM). The GLCM approach was applied to extracting the texture features, including correlation, contrast, energy, and homogeneity, based on four angles of 0°, 45°, 90°, and 135°. The single texture feature with 90° angles achieved an accuracy of 90.3%. The classification model's accuracy improved by incorporating texture features and involving all features at all angles. The method developed a pattern classification model for the Bomba textile, with a classification accuracy of 94.6% and 5.4% error rate. The limitation of the method is that the GLCM features did not implement based on a similar angle. Even though the important features can be derived from the combination of

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several angles, the features should be generated from the combination of different angles and followed by the feature selection process to obtain the most discriminatory features.

Septiarini et al. [14] analyzed Samarinda sarongs' color and texture features to classify the motif. The goal of the work is to find out the appropriate features for obtaining the optimal classification results. The color moment was used on the RGB and HSV color spaces as the color features. Meanwhile, the GLCM was extracted to get the values of texture features, including contrast, correlation, energy, and homogeneity. CFS was applied to select these features, followed by SVM as the classifier. The dataset consisted of 150 images with three classes: Kuningan, Belang Hatta, and Belang Negara. Since the sarong was made from the same material, the experiment results showed the selected color features achieved an accuracy of 100%. The drawback of this work is that it does not use cross-validation to verify the results of the method evaluation.

3. Materials and methods

The proposed method was developed based on [14]. Previously, three classes were used: Belang Hata, Belang Negara, and Kuningsau. The color feature independently optimized the method's performance because the sarongs were made of the same material. Meanwhile, the combination of color and texture features was performed to accomplish the optimal performance in this work. These features were required since the superb variety of sarong types, including six classes: Belang Hatta, Belang Negara, Kuningsau, Belang Pengantin, Garanso, and non-Samarinda also; the sarongs have been made with various materials. The proposed method has consisted of two phases: training and testing; hence the dataset was divided into the training and testing set. Both phases involved three processes: pre-processing, feature extraction, and classification. The training phase applied the feature selection, whereas the testing phase only extracted the selected features. In the final step, the proposed method was evaluated. Fig. 1 depicts the process sequence of the proposed method. Meanwhile, the following subsection explains the detail of each process.

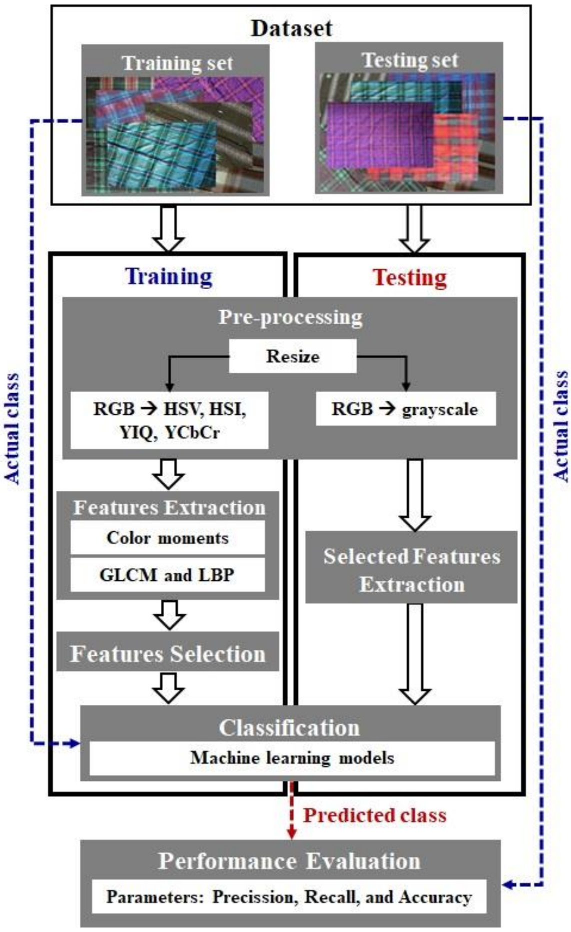

Figure. 1 The overview of all processes applied in the proposed method of sarong classification

3.1 Sarong dataset

The dataset for this work was obtained through the image acquisition process. The sarong images were recorded in an indoor location with even lighting using an integrated camera on the smartphone (iPhone 6s). The distance between the camera and the object should be approximately 30–60 cm, with the camera perpendicular to the object. During image acquisition, various perspectives of the sarong were acquired by rotating the sarong position. The images were saved in JPEG format and had a 3024×4032 pixels resolution. The dataset consisted of six classes, including five classes for the Samarinda sarong pattern: Belang Hatta, Belang Negara, Belang Perngantin, Garanso, and Kuningsau, also a class for non-Samarinda sarong, which contains several types of patterns. Each Samarinda sarong pattern consists of 100 images, whereas the non-Samarinda sarong motif consists of 500 images; hence, the total image acquisition consists of 1000 images. Fig. 2 presents the example of the dataset used in this work.

3.2 Pre-processing

The first step in pre-processing was scaling the original Sarong images of 3024×4032 pixels into 256×256 pixels was the first step in pre-processing [17]. The scaling step was employed to reduce the computation time and optimize the result of the

Figure. 2 The example of sarong images is divided into six classes: a class of non-Samarinda sarong and five classes of Samarinda sarong: (a) Belang Hatta, (b) Belang Negara, (c) Belang Pengantin, (d) Garanso, and (e) Kuningsau

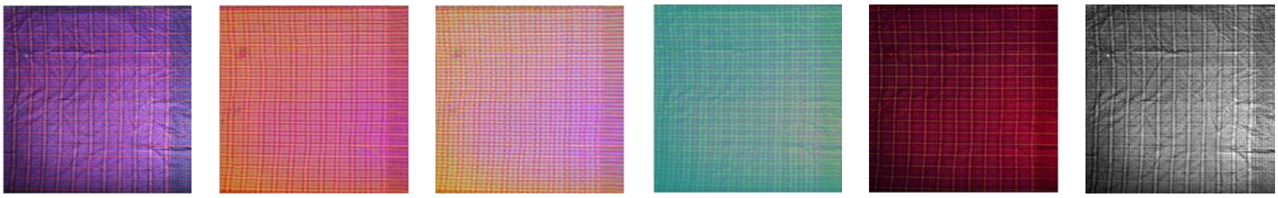

Figure. 3 The resulting of pre-processing: (a) resize, (b) HSV, (c) HSI, (d)YcbCr, (e) YIQ, and (f) Grayscale

subsequence process. Afterward, the RGB color space was converted into the HSV, HSI, YIQ, and YCbCr color spaces, also grayscale. Those five color spaces were required to obtain the color features. Meanwhile, the grayscale image was needed to extract the texture features. The conversion of RGB HSV, HSI, YIQ, and YCbCr color spaces as in [18]. The resulting images of each step in this process is depicted in Fig. 3.

3.3 Features extraction

This process generated the feature value to distinguish between the several types of Samarinda sarongs and non-Samarinda sarongs. Color and texture were the two features used to obtain the feature values. Color features were applied due to has discriminating capabilities against several types of sarong. Color moments were performed to extract the color features based on RGB, HSV, HSI, YIQ, and YCbCr color spaces. Meanwhile, texture features were required due to the sarong was made with different materials. These features were produced with GLCM and LBP method against the grayscale images. The following subsections discuss the detail of features extraction methods.

3.3.1. Color moments

Color moments were successfully used to obtain the color features [17, 19]. Most of the color distribution information was found in the low-order moments. This work used five types of color moments to extract the features. The first through fifth orders represented the color distribution indicated by the value of mean (μ), the standard deviation (σ), median (m), the minimum (min), and maximum (max). Those values were computed using Eqs. (1) to (5). These features were extracted in each channel of RGB, HSV, HSI, YIQ, and YCbCr color spaces; hence 75 color features were obtained.

$$\mu = \sum_{j=1}^{N} \frac{1}{N} P_{ij} \tag{1}$$

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - \mu_i\right)^2\right)} \quad (2)$$

Here, N is the number of pixels in the image, and P_{ij} is the value of pixel j at color component i.

$$m = x + \left(\frac{\frac{f}{2} - f_{ii}}{f_i}\right)p \quad (3)$$

Here, x is the lower limit of the assumed median as defined by the equation N/2, f is total of frequency, f_{ii} is the cumulative frequency immediately below the assumed median, f_i is the corresponding frequency, and p is the class interval.

$$min = min(I) \quad (4)$$

$$max = max(I) \quad (5)$$

Here, I is the intensity value of all pixels in an image.

3.3.2. Gray level co-occurrence matrix

The gray level co-occurrence matrix (GLCM) is a method for determining the gray level that frequently occurs in paired pixels with a value at a specific distance (d) and angle orientation (θ) by doing a single-pixel analysis against the image. The most θ widely utilized is 0°, 45°, 90°, and 135° [9,11,20]. The $(i,j)th$ entry in the GLCM matrix (P) refers to the frequency with which the gray level i is followed by the gray level j with distance d and angle θ. There were eight features extracted in this work, including Contrast (G1), Correlation (G2), Energy (G3), Homogeneity (G4), Dissimilarity (G5), Entropy (G6), Rows mean (G7), and Columns mean (G8). Therefore, the number of texture features produced was 32 features. Those features are defined using Eqs. (6) to (13) [21].

$$G1 = \sum_{i,j=0}^{n-1} P_{ij} * (i-j)^2 \quad (6)$$

$$G2 = \sum_{i,j=0}^{n-1} P_{ij}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \quad (7)$$

$$G3 = \sum_{i,j=0}^{n-1}\left(P_{ij}\right)^2 \quad (8)$$

$$G4 = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2} \quad (9)$$

$$G5 = \sum_{i,j=0}^{n-1} P_{ij}|i-j| \quad (10)$$

$$G6 = \sum_{i,j=0}^{n-1}(P_{ij})\log(P_{ij}) \quad (11)$$

$$G7 = \sum_{i,j=0}^{n-1} i(P_{ij}) \quad (12)$$

$$G8 = \sum_{i,j=0}^{n-1} j(P_{ij}) \quad (13)$$

where μ_i and σ_i^2 represent the mean and variance of $\sum_{i=0}^{n-1} P_{ij}$, μ_j and σ_j^2 represent the mean and variance of $\sum_{j=0}^{n-1} P_{ij}$.

3.3.3. Local binary pattern

A local binary pattern (LBP) is a technique for capturing the textural features of an area that develops based on binary descriptors [22]. The extraction of texture features from the normalized image $\tilde{I}(u,v)$. According to the observations, the degree of texture patterns varies with the image noise level. It indicates that texture features are susceptive to differences in the image's noise occurrence [23].

Consider the normalized image $\tilde{I}(u,v)$ with the size U × V, and let $\tilde{I}(u,v)$ represent a single central pixel in the normalized image. Specifically, the surrounding pixels were generated from the neighborhoods of 3×3 pixels of the center pixel $\tilde{I}(u,v)$. The radius (R) of the center pixel $I(u, v)$ was set to 1 in order to determine the local binary descriptor of the center pixel $\tilde{I}(u,v)$. The disparity between the center and surrounding pixels are defined in Eq. (14) [23].

$$\Gamma\left(\mathfrak{I}_{\mathfrak{R}t}(u,v) - \mathfrak{I}_c(u,v)\right) = \begin{cases} 000001, \mathfrak{I}_{\mathfrak{R}t}(u,v) \geq \mathfrak{I}_c(u,v) \\ 0, \; otherwise \end{cases} \quad (14)$$

The variable Γ (.) indicates the difference between pixels with a radius of the variable t and $\mathfrak{R}$=1, which denotes the pixel index. The limit of t is 1 to N, where N is the number of neighboring pixels (in this case, N = 8). For example, if the value of $\mathfrak{R}$=1 and t=1, the neighboring pixel $\mathfrak{I}_{\mathfrak{R}t}(u,v) = \mathfrak{I}_{11}(u,v)$. It indicates the index 1-pixel value among the N(8) other pixel values with a radius $\mathfrak{R}$=1. The difference between the center pixel $\mathfrak{I}_c(u,v)$ and the surrounding pixels is computed by multiplying this result by the binary count to obtain the LBP. LBP is calculated by utilizing the difference calculation in (x) and multiplying it by the binary descriptor for the center pixel x, which is represented by the following Eq. (15) [23].

$$LBP_{\mathfrak{I},\mathfrak{R}}(u,v) = \sum_{t=1}^{N} \Gamma\left(\mathfrak{I}_{\mathfrak{R}t}(u,v)\right) - \mathfrak{I}_c(u,v)2^{t-1} \quad (15)$$

Table 1. The feature sets extracted using different methods

Feature type	Method	Number of features	Feature set
Color	Color moments	75	**RBG:** μR, μG, μB, σR, σG, σB, mR, mG, mB, maxR, maxG, maxB, minR, minG, minB, **HSV:** μH, μS, μV, σH, σS, σV, mH, mS, mV, maxH, maxS, maxV, minH, minS, minV, **HSI:** μH, μS, μI, σH, σS, σI, mH, mS, mI, maxH, maxS, maxI, minH, minS, minI, **YIQ:** μY, μI, μQ, σY, σI, σQ, mY, mI, mQ, maxY, maxI, maxQ, minY, minI, minQ, **YCbCr:** μY, μCb, μCr, σY, σCb, σCr, mY, mCb, mCr, maxY, maxCb, maxCr, minY, minCb, minCr
Texture	GLCM	32	$G1_0$, $G1_{45}$, $G1_{90}$, $G1_{135}$, $G2_0$, $G2_{45}$, $G2_{90}$, $G2_{135}$, $G3_0$, $G3_{45}$, $G3_{90}$, $G3_{135}$, $G4_0$, $G4_{45}$, $G4_{90}$, $G4_{135}$, $G5_0$, $G5_{45}$, $G5_{90}$, $G5_{135}$, $G6_0$, $G6_{45}$, $G6_{90}$, $G6_{135}$, $G7_0$, $G7_{45}$, $G7_{90}$, $G7_{135}$, $G8_0$, $G8_{45}$, $G8_{90}$, $G8_{135}$
	LBP	10	L1, L2, L3, L4, L5, L6, L7, L8, L9, L10

There are 117 features generated using color moment, GLCM, and LBP with 75 features, 32 features, and 10 features, respectively. All the resulting features are summarized in Table 1.

3.4 Feature selection

The total number of features should be analyzed to determine which features are most useful or have the most robust discriminatory capabilities against the dataset utilized. This work used Correlation-Based Feature Selection (CFS) and Principal Component Analysis (PCA) to perform feature selection. The following subsections describe the selection features in detail.

3.4.1. Correlation-based feature selection

Feature selection is a method of selecting an important feature subset from a larger collection of candidates. In contrast to other filter algorithms, correlation-based feature selection (CFS) is a straightforward algorithm that ranks feature subsets according to the correlation-based heuristic evaluation function. A subset of unique features should have a feature that is substantially associated with the class label, but it should not contain features that are highly correlated with each other. CFS eliminates attributes without affecting the quality of vital signals contained within the data. CFS is determined operating Eq. (16) [24].

$$Ms = \frac{kr_{\overline{cf}}}{\sqrt{k+k(k-1)\overline{rff}}} \tag{16}$$

Merit (Ms) indicates the S feature's worthiness, while k and c are the number of features and classes. At the same time, r_{cf} is the average correlation between each feature with its class, and r_{ff} is the average pair correlation between the two features.

3.4.2. Principal component analysis

The principal component analysis (PCA) is classical feature extraction and data representation method widely applied in pattern recognition and computer vision to identify and detect the object. It is a statistical technique to reduce the size of high-dimensional data to improve the performance of object recognition [25]. PCA determined with the Eqs. (17) to (21) [26].

- Step 1: A column or row vector of size N2 denotes a set of M images (B1, B2, B3...BM) with the resolution N×N.
- Step 2: The training set image average (μ) is defined using Eq. (17).

$$\mu = \frac{1}{m}\sum_{n=1}^{M} B_n \tag{17}$$

- Step 3: The average image produced by the vector (W) varies for each training using Eq. image (18).

$$W_i = B_i - \mu \tag{18}$$

- Step 4: Total scatter matrix or covariance matrix is computed from ϕ using Eq. (19).

$$C = \sum_{n=1}^{M} wnwnt = AAT \tag{19}$$

where A = [$W1W2W3...Wn$]

- Step 5: Determine the covariance matrix C's eigen vectors UL and eigen values λL.
- Step 6: This feature space can be used to classify images. Utilize Eqs. (20) and (21) to determine the weight vectors.

Table 2. Comparison of feature sets generated

Feature selection	Number of features	Features	
		Color	Texture
None	117	μR, μG, μB, σR, σG, σB, mR, mG, mB, maxR, maxG, maxB, minR, minG, minB, μH, μS, μV, σH, σS, σV, mH, mS, mV, maxH, maxS, maxV, minH, minS, minV,μH, μS, μI, σH, σS, σI, mH, mS, mI, maxH, maxS, maxI, minH, minS, minI, μY, μI, μQ, σY, σI, σQ, mY, mI, mQ, maxY, maxI, maxQ, minY, minI, minQ, μY, μCb, μCr, σY, σCb, σCr, mY, mCb, mCr, maxY, maxCb, maxCr, minY, minCb, minCr	$G1_0$, $G1_{45}$, $G1_{90}$, $G1_{135}$, $G2_0$, $G2_{45}$, $G2_{90}$, $G2_{135}$, $G3_0$, $G3_{45}$, $G3_{90}$, $G3_{135}$, $G4_0$, $G4_{45}$, $G4_{90}$, $G4_{135}$, $G5_0$, $G5_{45}$, $G5_{90}$, $G5_{135}$, $G6_0$, $G6_{45}$, $G6_{90}$, $G6_{135}$, $G7_0$, $G7_{45}$, $G7_{90}$, $G7_{135}$, $G8_0$, $G8_{45}$, $G8_{90}$, $G8_{135}$, L1, L2, L3, L4, L5, L6, L7, L8, L9, L10
CFS	20	σG, minH, σS, mH, maxS, μQ, σQ, maxQ, minY, minI, minQ, μCb, μCr, σCb, maxCb, minCb, minCr	$G3_{90}$, L3, L7
PCA	48	μR, μB, σG, σB, mR, mG, mB, maxG, maxB, minR, minG, μV, σH, σS, σV, mH, mV, maxH, μH, σS, σI, mH, maxH, maxI, minH, μI, minY, minQ, σY, maxCb, maxCr, minY, minCb	$G1_0$, $G2_0$, $G3_{45}$, $G4_{45}$, $G4_{135}$, $G5_0$, $G7_{45}$, $G7_{135}$, L1, L2, L4, L5, L6, L7, L8, L10

$$\Omega T = [w1, w2, \ldots, wM'] \tag{20}$$

where,

$$Hk = UkT(B - \mu), K = 1,2, \ldots, M' \tag{21}$$

The implementation of the CFS and PCA feature selection methods yielded different feature sets based on the number of features and features selected. CFS and PCA reduced the features number from a total of 117 features to 20 features and 48 features, respectively. The comparison of all the various feature sets, including feature sets obtained without the implementation of features selection (none), is presented in Table 2.

3.5 Classification

Classification is a process to determine the class of data. Currently, machine learning has been widely applied for pattern recognition of various objects [3, 20, 26]. Machine learning is a field of automated processes that investigates the function and structure of algorithms that allow and make predictions based on the provided data. Instead of strictly following instruction sets, such algorithms develop a model to make data-driven estimations and choices using sample inputs. The mathematical and statistical models are used to derive inferences from existing training data to derive class predictions about the unknown from testing data based on these inferences.

The sarong pattern classification was accomplished with machine learning in this work. Various machine learning algorithms were employed, including ANN, C.45, Decision Tree, KNN, Naive Bayes, and SVM. These methods have been carried out in several previous studies on different objects [9, 16, 23, 24]. Cross-validation was performed with k-folds of 2, 5, and 10 to divide the training and testing data [27]. The method combination of feature selection, and classification were used to develop the proposed method.

3.6 Evaluation methods

The classification method's performance was evaluated using three indicators: precision, recall, and accuracy [10] based on the confusion matrix multiclass. These parameters are defined using Eqs. (22) to (24) [28]:

$$Precision = \frac{\sum_{k=1}^{n} N_{ki}}{N_{ii}} \times 100, \tag{22}$$

$$Recall = \frac{\sum_{k=1}^{n} N_{ik}}{N_{ii}} \times 100, \tag{23}$$

$$Accuracy = \frac{\sum_{i=1}^{n} N_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} N_{ij}} \times 100. \tag{24}$$

In this work, the number of data consisting of (k-1)/k and 1/k is utilized as training and testing data, respectively [28]. Subsequently, the procedure is repeated several times (k−times). Finally, the rate estimation is made using the validation result of the average k-time, which is chosen as the last point. Cross-validation is used to evaluate the performance with k-fold values of 2, 5, and 10.

4. Experimental results

The color and texture features were extracted using color moment, LBP, and GLCM. Hence, the

Table 3. Performance comparison of the classifier with various feature sets based on k-fold 2

Classifier	None (%)			CFS (%)			PCA (%)		
	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.
ANN	100	100	100	100	100	100	100	100	100
C.45	98.7	98.6	98.6	98.7	98.6	98.6	98.0	98.0	98.0
Decision Tree	98.0	97.9	97.9	98.0	97.9	97.9	96.8	96.7	96.7
KNN	100	100	100	100	100	100	99.5	99.5	99.5
Naïve Bayes	100	100	100	98.4	98.4	98.4	98.4	98.4	98.4
SVM	99.9	99.9	99.9	100	100	100	98.4	98.4	98.4

Table 4. Performance comparison of the classifier with various feature sets based on k-fold 5

Classifier	None (%)			CFS (%)			PCA (%)		
	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.
ANN	100	100	100	100	100	100	100	100	100
C.45	99.8	99.8	99.8	99.8	99.8	99.8	99.3	99.3	99.3
Decision Tree	99.8	99.8	99.8	99.8	99.8	99.8	97.5	97.5	97.5
KNN	100	100	100	100	100	100	100	100	100
Naïve Bayes	99.9	99.9	99.9	98.4	98.3	98.3	98.1	98.0	98.0
SVM	100	100	100	100	100	100	98.7	98.7	98.7

Table 5. Performance comparison of the classifier with various feature sets based on k-fold 10

Classifier	None (%)			CFS (%)			PCA (%)		
	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.
ANN	100	100	100	100	100	100	100	100	100
C.45	99.9	99.9	99.9	99.9	99.9	99.9	99.5	99.5	99.5
Decision Tree	98.4	98.3	98.3	98.4	98.3	98.3	98.4	98.3	98.3
KNN	100	100	100	100	100	100	100	100	100
Naïve Bayes	99.0	99.0	99.0	99.0	99.0	99.0	98.6	98.6	98.6
SVM	100	100	100	100	100	100	99.1	99.1	99.1

total number of features produced was 117 features. The high performance of the proposed method was achieved with a minimum number of features. Therefore, feature selection was implemented using CFS and PCA approaches; since the number of features was reduced to 20 and 48, respectively. Those features fed into six classifiers, including ANN, C.45, Decision Tree, KNN, Naive Bayes, and SVM. The classification was carried out by dividing training and testing data using cross-validation with k-fold values consisting of 2, 5, and 10. The experiment was conducted using by combining the different methods of feature extraction, feature selection, classification, and k-fold values. It aimed to justify the appropriate method against the dataset used in this work. The dataset consisted of 1000 images and was divided into six classes (Belang Hatta, Belang Negara, Belang Pengantin, Garanso, Kuningsau, and non-Samarinda). The method performance was indicated by the parameters: precision, recall, and accuracy. The test result for each classifier using various feature sets obtained without (none) and with two feature selection methods was indicated using three parameters: precision (Prec.), recall (Rec.), and accuracy (Acc.). Those result are summarized in Table 3 to 5.

Table 3 to 5 shows the classification result based on the value of k-fold, classifier, and feature sets indicated decision tree classifier obtaining the lowest accuracy value. It occurs in all implementation of k-fold values. The decision tree generated the lowest value of 96.7% with k-fold = 2, where the feature set was derived using PCA, as shown in Table 3. It proved that PCA's feature set was not discriminatory enough to differentiate the sarong pattern. Meanwhile, the highest performance achieved of 100% accuracy value was obtained by the ANN, KNN, Naïve Bayes, and SVM classifier. However, ANN has been indicated as the most robust classifier because the optimal performance can be achieved in all experimental scenarios applied. Based on Table 3–Table 5, several classifiers are capable of achieving the maximum performance represented by the accuracy value of 100% even without feature selection. Those particular classifiers–ANN, KNN, and SVM–achieved optimal performance using PCA and CFS, excepting Naïve Bayes, which uses all features to get optimal results.

The number of features generated using PCA and CFS was reduced by more than 40% and 80%, respectively, and produced maximum method performance. The feature selected by the various

Table 6. The example of the feature extraction result

Images	Features	
 **Belang Hatta**	-σG = 0,19 -*min* H = 0 -σS = 0,11 -*m*H = 0,10 -*max*S = 0,63 -μQ = -0,03 -σQ = 0,01 -*max*Q = 0,02 -*min*Y = 0,04 -*min*I = -0,06	-*min*Q = -0,07 -μCb = 0,48 -μCr = 0,51 -σCb = 0,01 -*max*Cb = 0,41 -*min*Cb = 0,41 -*min*Cr = 0,46 -L3 = 0,08 -L7 = 0,15 -G3$_{90}$ = 0,05
 **Belang Negara**	-σG = 0,11 -*min*H = 0 -σS = 0,14 -*m*H = 0,80 -*max* S = 0,93 -μQ = 0,49 -σQ = 0,31 -*max*Q = 0,14 -*min*Y = -0,42 -*min*I = -0,42	-*min*Q = -0,32 -μCb = 0,12 -μCr = 0,55 -σCb = 0,51 -*max*Cb = 0,60 -*min*Cb = 0,46 -*min*Cr = 0,25 -L3 = 0,14 -L7 = 0,21 -G3$_{90}$ = 0,51
 **Belang Pengantin**	-σG = 0,81 -*min*H = 0,57 -σS = 0,96 -*m*H = 0,77 -*max*S = 0,69 -μQ = 0,13 -σQ = 0,53 -*max*Q = 0,75 -*min*Y = -0,18 -*min*I = 0,09	-*min*Q = 0,28 -μCb = 0,59 -μCr = 0,57 -σCb = 0,51 -*max*Cb = 0,50 -*min*Cb = 0,39 -*min*Cr = 0,50 -L3 = 0,19 -L7 = 0,27 -G3$_{90}$ = 0,38
 **Garanso**	-σG = 0,19 -*min*H = 0 -σS = 0,11 -*m*H = 0,43 -*max*S = 0,72 -μQ = -0,30 -σQ = 0,52 -*max*Q = 0,53 -*min*Y = -0,29 -*min*I = -0,19	-*min*Q = 0,13 -μCb = 0,49 -μCr = 0,47 -σCb = 0,05 -*max*Cb = 0,46 -*min*Cb = 0,24 -*min*Cr = 0,46 -L3 = 0,17 -L7 = 0,20 -G3$_{90}$ = 0,44
 **Kuningsau**	-σG = 0,18 -*min*H = 0 -σS = 0,23 -*m*H = 0,51 -*max*S = 1 -μQ = -0,33 -σQ = 0,28 -*max*Q = 0,62 -*min*Y = -0,54 -*min*I = -0,15	-*min*Q = 0,29 -μCb = 0,55 -μCr = 0,40 -σCb = 0,47 -*max*Cb = 0,46 -*min*Cb = 0,11 -*min*Cr = 0,46 -L3 = 0,15 -L7 = 0,23 -G3$_{90}$ = 0,54
 **Non-Samarinda**	-σG = 0,23 -*min*H = 0 -σS = 0,12 -*m*H = 0,68 -*max*S = 0,50 -μQ = -0,23 -σQ = -0,64 -*max*Q = 0,51 -*min*Y = -0,25 -*min*I = -0,12	-*min*Q = 0,11 -μCb = 0,43 -μCr = 0,42 -σCb = 0,01 -*max*Cb = 0,36 -*min*Cb = 0,21 -*min*Cr = 0,42 -L3 = 0,20 -L7 = 0,18 -G3$_{90}$ = 0,43

feature selection methods in different color spaces and textures is summarized in Table 1. Table 1 shows that CFS produces the least number of features (reduces more than 80%), followed by PCA. The experiments conducted show that not all color channels of each color space and texture features were selected. In addition, the similar feature selection method applied to different features shows the differences in selected channels from the color and texture. This case occurs in CFS implementation on color features of the RGB, HSV, HSI, YIQ, and YCbCr color spaces and texture features of LBP and GLCM. The example of the feature extraction result is shown in Table 6.

Furthermore, the features obtained with CFS indicated appropriate for implementation. These features were more robust than PCA because applying the least number of features to achieve maximum performance was implemented for all k-fold values and those classifiers. The feature selection

results presented that color features significantly influence texture. It was indicated by the 20 features selected, which included 17 color features and 3 texture features. The selected color and texture features are presented in Table 2.

Regarding color features, only several types of features and color channels are considered discriminatory in classifying the Samarinda Sarong. The *min* feature is most repeatedly selected, followed by *std*, *mean*, *max*, and *m*. Meanwhile, channels Q and Cb were the most frequently selected, followed by Cr, S, H, G, Y, and I. There were only three texture features selected: two LBP features (L3 and L7) that indicated applying in the 3 and 7 bins, also one GLCM feature, namely energy with a 90o angle. While color features are the most significant, it was revealed that texture features have the potential to improve the proposed method's performance to become optimal. Meanwhile, regarding the implementation of several classifiers, the most appropriate and robust was ANN for the dataset in this work. Even though KNN, SVM, and Naïve Bayes were able to achieve the maximum performance, ANN is competent to produce the maximum performance with all types of feature sets produced with or without features selection. In addition, this proposed method applied a combination of the color moment, GLCM, LBP, CFS, and ANN approach was robust because it has been tested using cross-validation with the different k-fold values of 2, 5, and 10. The results showed the highest accuracy value successfully achieved of 100%. These results

Table 7. A comparison of our proposed sarong fabric pattern recognition method and several related methods in terms of accuracy, feature extraction, and classification methods

Authors	Feature extraction method	Classifier	Dataset	Accuracy (%)
Nuraedah et al. [9]	GLCM	QSVM	Not reported	94.60
Kasim et al. [10]	- Compactness - Eccentricity - Rectangularity - Solidity	ANN	40 images from 7 classes: ceplok, grompol, gurda, kawung, mega mendung, parang, and sidoasih.	90.48
Rangkuti et al. [13]	Wavelet Transform	Decision Tree	225 images from 7 classes: lereng, parang, kawung, nitik, truntum, mega mendung, and ceplok	85
Septiarini et al. [14]	Color moments applied on RGB and HSV color spaces GLCM	SVM	150 sarong images (50 Belang Hata, 50 Belang Negara, and 50 Kuningsau)	100
Nugrowati et al. [17]	Hu's moment, Color Vector Quantization and Color Moment	The Cosine similarity distance metric	210 batik images from three classes: Kawung, Parang, and Mega Mendung	80
Our proposed method	Color moments, GLCM, and LBP	ANN	1000 sarong images from six classes: Belang Hatta, Belang Negara, Belang Perngantin, Garanso, Kuningsau, and non-Samarinda sarong	100

indicated the proposed method powerful to classify the Samarinda sarong successfully.

To further demonstrate the efficacy of the proposed method, a comparison is made with the most relevant work, as shown in Table.7. Due to there is no public sarong images dataset and one study related to sarong classification only with three classes [14], the comparison was performed with the classification of batik as another traditional fabric. As represented in Table. 7, the proposed pattern recognition of sarong fabric achieved optimal performance. That is due to the appropriate combination of feature selection methods to derive fewer features and the implementation of ANN as a classifier.

5. Conclusion

This work of recognizing patterns proposed a method for Samarinda sarong classification. The proposed method required several processes, including preprocessing, features extraction, features selection, and classification. The appropriate pre-processing and feature extraction techniques affect the classification results. Color features were applied based on five color spaces: RGB, HSV, HIS, YIQ, and YCbCr. The color moment was used to extract the color features, while GLCM and LBP were performed to obtain the texture features. These features were selected using CFS; therefore, a total of 117 features were reduced to 20 features. These selection features were fed into the ANN classifier. The classification was divided into six classes consisting of a class of non-Samarinda sarong and five classes of Samarinda sarong (Belang Hatta, Belang Negara, Belang Pengantin, Garanso, and Kuningsau). The dataset used to evaluate the proposed method performance consists of 1000 images. Furthermore, cross-validation with k-fold values of 2, 5, and 10 was applied to divide the dataset into training and testing sets. Three parameters were used to indicate the method performance, namely precision, recall, and accuracy, which managed to achieve the value of 100%. The result showed the proposed method successfully achieved maximum performance against the dataset used.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The authors' contributions are as follows: conceptualization, Anindita Septiarini; methodology, Anindita Septiarini; software, Rizqi Saputra; validation, Andi Tedjawati and Masna Wati; formal analysis, Hamdani Hamdani and Masna Wati; investigation, Andi Tedjawati; resources, Rizqi Saputra; data curation, Rizqi Saputra and Andi Tedjawati; writing—original draft preparation, Anindita Septiarini; writing—review and editing, Hamdani Hamdani and Masna Wati; visualization, Rizqi Saputra; supervision, Anindita Septiarini; project administration, Andi Tedjawati; funding acquisition, Anindita Septiarini.

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