Classification of Pringgasela Typical Songket Using Multi Texton Co-occurrence Descriptor and K-Nearest Neighbor

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Abstract. Songket is one of Indonesia's cultural heritages in traditional fabrics that are still preserved today. Pringgasela, a village located on Lombok Island has been producing Songket with distinct characteristics and various patterns. Generally, people are aware of the typical Pringgasela Songket pattern but the difference between one pattern and another is often unrecognized. Furthermore, information regarding the types of Pringgasela Songket has not been well documented. This study aims to build a model that can classify the Pringgalsela Songket patterns using Multi Texton Co-Occurrence Descriptor (MTCD) and K-Nearest Neighbor (KNN) methods. The data used in this study were 4700 images of Pringgasela's Songket, which were divided into training and test data. The highest accuracy obtained was 99.99, 100% precision, and 100% recall with k = 3, using manhattan distance calculation.

Keywords: Image Classification · *Pringgasela Songket* · Texton · MTCD · KNN

1 Introduction

Indonesia is a country with various types of cultural heritage, ranging from traditional clothes, cultures, dances, and languages that must be preserved [1]. Traditional fabrics have various types that can be distinguished based on the manufacturing methods, materials, and patterns. Songket, one of Indonesia's traditional fabrics, is woven traditionally by embroidering gold and silver threads in combination with other colored threads [2].

Lombok Island is famous for its traditional Songket. One of the villages that are actively producing Songket with distinctive design in Lombok is Pringgasela. Sri Menati Songket, for example, has a pattern dominated by small straight lines. Another example, the Pucuk Rebong Songket has a simple pattern representing the growing shoots of bamboo. Because of these characteristics, according to the manager of the Songket craft in Pringgasela, Songkets from the village have been exported and are in demand in the international market.

It is easy to recognize Songket designs from Lombok, however, as there are many types of Lombok Songket, especially in Pringgasela, a lot of people are unaware of the

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difference between each design. In this paper, we aim to classify the types of Pringgasela Songket using image classification techniques. In 2020, research was carried out for the classification of Lombok Songkets motif typical of Sukarare village using the *Gray Level Co-occurrence Matrix* (GLCM) method, Moment Invariant, and the classification method using the Linear Discriminant Analysis (LDA) method and it obtained the accuracy of 98.33%. The author classified ten types of Sukarare Songket using 100 images of each Songket [3].

The classification of Songket patterns can be done based on color and texture features. One method that can perform feature extraction is the *Multi Texton Co-occurrence Descriptor* (MTCD). MTCD is a method that during the process of extracting color and edge features, it is assisted by texton or a pattern in the form of a 2 × 2 matrix in the process of tracing an image and finding a pair of pixels with the same value. In previous studies, batik image classification was carried out with *Multi Texton Co-Occurrence Descriptor* and *Support Vector Machine* (SVM). In this research, the classification process using SVM proved that MTCD was better than MTH and GLCM with an accuracy of 100% [4].

K-Nearest Neighbor (KNN) is one of several methods for the classification process in pattern recognition. KNN aims to classify new data whose class is not yet known. In selecting a class at KNN, it is done by looking for group data with the closest distance (k) from the *training* data *object* that is closest to the new data that does not yet have that class. The KNN method has been used to identify Palembang Songket types with the highest accuracy of 91.67% [5]. There are also other experiments to carry out the Songket recognition process using the KNN method, namely the introduction of Balinese Songket cloth which in this study resulted in an accuracy of 77.3% [6]. Another experiment is the image classification process of batik cloth using KNN and *Artificial Neural Network* (ANN) which is invariant with scale and rotation using the MU2ECS-LBP algorithm. In this study, it was concluded that the KNN method was better used for the image classification process of batik cloth [7].

In this study, we built a Songket classification model that takes a case study on the typical Lombok Songket of Pringgasela. The *Multi Texton CoOccurrence Descriptor* (MTCD) method was used for the feature extraction process and the K-Nearest Neighbor (KNN) as the classification method. The organization of the paper is divided into Sect. 1 explains the motivation, purpose, and contribution of the paper and the organization of the paper; Sect. 2 explains the relationship of the research conducted with other studies that have been carried out; Sect. 3 explains the research method; Sect. 4 explains the results and discussions; and Sect. 5 discusses conclusions and opportunities for further research in the future.

2 Literature Review

2.1 Related Research

In previous studies, batik images were classified using the Multi Texton Co-Occurrence Descriptor (MTCD) and SVM methods. The results obtained from the classification process have an accuracy of 100% [4]. The next research is batik and Corel image retrieval using the MTCD method. In this study, the performance of the feature extraction process was improved using the multi-texton histogram (MTH) method using the MTCD method. The results of this study showed an increase in precision of 2.86% for batik data, 2.40% for 5000 Corel data, and 3.06% for 10000 Corel data [8]. Similar research has also been conducted that discusses the redesign of the image retrieval process using the MTCD and K-Nearest Neighbor (KNN) methods using batik and Corel data. The results of the study showed an increase in the precision of the classification results by 0.8% for batik data and 9% for Corel data [9]. This study shows that MTCD is very well used for processing color and texture extraction for fabric images. The next research is the detection of macronutrient definitions in coffee plants based on visual symptom characteristics using Artificial Neural Networks (ANN) for the classification process and MTCD for the feature extraction process. The accuracy obtained from this study was 70.6% [10].

In another study, the classification of traditional textile images was carried out using the KNN method. The results of this study indicated the success of overcoming the KNN method with an average accuracy of 88.03% [11]. Similarly, research introducing Balinese traditional Songket cloth using the KNN method resulted in an accuracy of 77.3% [6]. Other research that supports the classification process using the KNN method is the recognition of Palembang Songket Motifs Using the Canny Edge Detection method, PCA and KNN gave 91.67% accuracy using 52 typical Palembang Songket data [5]. Furthermore, research on the implementation of the K-Nearest Neighbor (KNN) Classification Method for Lampung Batik Pattern Recognition has been successfully carried out, where the level of accuracy obtained is 98.12% [12]. Subsequent research using the KNN method, namely the grouping of wood texture types resulted in an accuracy of 91% with 150 training data and 100 test data [13]. The results of the accuracy of this research indicate that the KNN classification method gives excellent results as a method for the classification process.

2.2 Songket

Songket comes from the words prick and cut which is shortened to *suk-kit* usually becomes *sungkit*, and eventually turns into Songket [2]. Lombok is one of the regions in Indonesia that produces Songket which is known for its distinctive designs and sacred values [3]. Songkets made specifically for traditional events will be different from those made for purposes of worship and self-decoration. The pattern of Songket that are made for traditional purposes usually contains philosophical meanings, believed to be able to maintain and bring goods to its users. Pringgasela's typical Songket has several types of patterns including Pijet Manuk, Pucuk Rebong, Ragi Byanan, Ragi Dodot, Ragi Montor, Ragi Sama Indah, Sri Menanti, and Sundara. Some of these have their functions and meanings. Bayanan yeast, Sri Menanti, Sundawa, and Ragi Dodot, for instance, are used more in traditional events and ceremonies, while the Pijet Manuk, Ragi Montor, and Ragi Samar Indah are used for religious purposes.

2.3 Texture

Texture in the image is a characteristic of an area in the image. The area is large enough so that naturally these characteristics can be repeated in the area [14]. Other studies stated

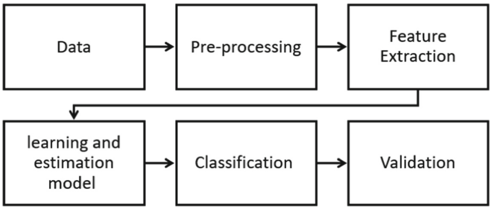

Fig. 1. Pattern recognition model

that texture is the shape of the surface of an image. An image can be rough, smooth, hard, or soft, texture can be said to be the surface of an object or image that can be felt as real or imaginary [15]. The definition of texture in the image in this case is a collection of pixels that regularly form certain patterns in a digital image.

2.4 Pattern Recognition

Pattern recognition is a science that aims to group objects into many categories or classes. In general, pattern recognition has a model design that is usually depicted using a flow chart as shown in Fig. 1.

In picture 1 there are several stages in the pattern recognition process, starting from data acquisition which is the process of determining physical variables from the data to be used. The pre-processing stage is a process to clean noise from image data, then the feature extraction process aims to find representations of special features or characteristics of objects or images. The learning and estimation model is a mapping stage between categories or classes of features of an object or image. Consequently, the results of the mapping process will enter the classification process, which at this stage is a process for classifying an object or image according to its features. Then the next stage is postprocessing or the validation stage of the classification results [16].

2.5 Multi Texton Co-occurrence Descriptor (MTCD)

Multi Texton Co-Occurrence Descriptor (MTCD) is an image processing method based on color features and shape features of an image. MTCD has been developed from the *Multi Texton Histogram* (MTH) method [17]. In its representation, the processing of R, G, and B channels from the image uses a *color feature*, then *edge features* to detect textures and shapes locally which are then quantized using the Sobel operator. Finally, GLCM detects texture and shape features globally.

Color Quantization. Color generally differentiates one object and another and provides very useful information for detecting an object. RGB is the basic color space that can be used for digital processing. In previous studies, the RGB color space can provide optimal performance [18]. So, the color quantization extraction process in image research was divided into three basic colors, namely Red (R), Green (G), and Blue (B) [10]. Then the image will be quantized to reduce the range of color level values from the image to facilitate the processing of taking features from the image to be processed. Each component of the color space will be quantized into 4 color intensity bins, R =

4, G = 4, and B = 4 so that the index ranges from 0 to 63 for each color. As result, 64 features of the color quantization process were obtained.

Edge Quantity. *Edge* feature is a method to get the texture features of an image to find out the elements that become details in the image [10]. Several methods can be used for edge feature detection, in one study, the Sobel operator was used. The Sobel operator can reduce *noise* in the image before calculating the edge feature detection process compared to the gradient operator or other edge feature detection methods so that it is considered more efficient and simple [19].

The Sobel operator works by calculating the gradient estimate from the sharpness of an image. The Sobel operator applies 2 3 × 3 dimensional kernels which are convoluted through the actual image to perform derivative calculations. One for horizontal changes and one for vertical changes which are then calculated by the magnitude of the gradient using the formula.

$$\mathrm{G(x, y)} = \sqrt{g_x^2 + g_y^2} \tag{1}$$

Consequently, the gradient is the result of measuring changes in an intensity function, and an image can be viewed as a collection of several continuous intensity functions of the image. The Sobel operator uses the f(x,y) function for red, green, and blue image colors. Gradients x and y are defined by two vectors an (Rx, Gx, Bx) and b (Ry, Gy, By) where Rx is denoted as a gradient at the horizontal position R [19, 20].

$$|\mathrm{a}| = \sqrt{(\mathrm{R}x)^2 + (\mathrm{G}x)^2 + (\mathrm{B}x)^2} \tag{2}$$

$$|\mathrm{b}| = \sqrt{(\mathrm{R}y)^2 + (\mathrm{G}y)^2 + (\mathrm{B}y)^2} \tag{3}$$

$$\mathrm{a.b} = \mathrm{R}_x.\mathrm{R}_y + \mathrm{G}_x.\mathrm{G}_y + \mathrm{B}_x.\mathrm{B}_y \tag{4}$$

The angle between a and b:

$$\cos(\widehat{a, b}) = \frac{a.b}{|a|.|b|} \tag{5}$$

$$\theta = arc\cos[\cos(\widehat{a, b})] = arc\cos\left[\frac{a \cdot b}{|a| \cdot |b|}\right] \tag{6}$$

The results of the Sobel operator are then quantized into 18 bins to represent the orientation of the texton edges using 1–180° which then after quantization performs the MTCD feature texton detection.

Texton Detect. Texton is a very useful process for texture analysis. Generally, a texton is defined as a set of emergent blobs or patterns that share a common property across the image [21]. After the image is quantized by color and edge quantization, the next step is texton detection. Research conducted by Liu, used 4 textons as shown in Fig. 2 for texture detection. The results of the 4 textons are then represented in the form of a histogram [19].

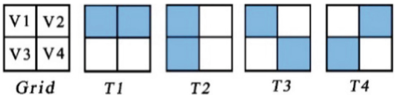

Fig. 2. Grid dan MTH Texton, *Grid* (left), MTH texton (right)

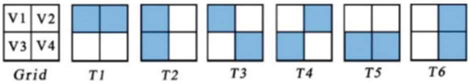

Fig. 3. MTCD texton

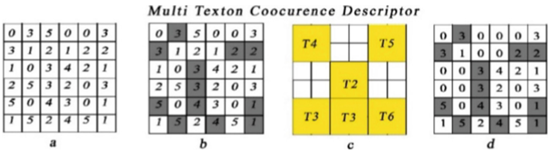

Fig. 4. Texton detection in MTCD

Then in the research conducted by Agus Eko, adding 2 textons which are textons from the representation of the MTCD method aims to prevent loss of information, then the textons will work below the horizontal and right vertical [8]. The textons used in MTCD can be seen in Fig. 3 where T1, T2, T3, and T4 are MTH textons, and T5 and T6 are additional textons.

In the feature extraction process that uses 6 *textons*, the image will be quantized on the color quantization and edge quantization of the image. The convolution process will be carried out using a 2 × 2 pixel grid identified by v1, v2, v3, and v4 starting from left to right, then from bottom to top. If the same value is found in the convolution grid, the grid will be read as *texton*. The calculation of *texton* is based on the quantization value, the total number of each component with a certain value is stored as a histogram and used as a *texton* feature. To clarify, it can be seen in the illustration of texton detection in Fig. 4.

Gray-Level Co-occurrence matrix (GLCM). A co-occurrence matrix is a statistical method that can be used for texture analysis. The co-occurrence matrix is formed from an image by looking at the paired pixel that has certain intensity within a certain distance d and orientation direction θ with a certain angle in an image [3, 22]. Distance is expressed in pixels, usually 1, 2, 3, and so on. Angle orientation is expressed in degrees, namely 0°, 45°, 90°, and 135°. To clarify the explanation of the GLCM angle, it can be seen in the illustration of the GLCM matrix in picture 5 (Fig. 5).

From the 4 GLCM matrices formed, the value of each feature is taken using the feature formula from GLCM itself. This feature The feature extraction process in GLCM, the image will be a feature of an image texture. The 5 most relevant features used are [3, 23, 24]. The features of GLCM are as follows [25]:

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \{\sum\nolimits_{j=0}^{G} P(i,j)\} \tag{7}$$

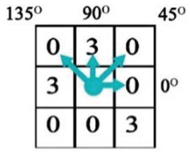

Fig. 5. GLCM matrix angle

$$\mathrm{IDM} = \sum_{i=1}^{G-1}\sum_{j=1}^{G-1}\frac{1}{1+(i-j)^2}P(i,j) \tag{8}$$

$$\mathrm{Entropy} = -\sum_{i=1}^{G-1}\sum_{j=1}^{G-1}P(i,j)\times\log(P(i,j)) \tag{9}$$

$$\mathrm{Energy} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)^2 \tag{10}$$

$$\mathrm{Correlation} = \sum_{i,j=0}^{N-1}P(i,j)\frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{11}$$

where P_{ij} is the element of each pixel of the GLCM matrix, μ is the average of the GLCM matrix, dan σ^2 is the variance of each GLCM matrix.

$$\mu = \sum_{i,j=0}^{N-1}iP(i,j) \tag{12}$$

$$\sigma = \sum_{i,j=0}^{N-1}iP(i,j)(i-\mu)^2 \tag{13}$$

2.6 K-Nearest Neighbor (KNN)

KNN is a supervised learning algorithm where the output of new data is classified based on the majority group of k nearest neighbors. The purpose of this algorithm is to classify new data based on attributes and data mining [20]. KNN performs classification based on the proximity of the location (distance) of data to other data [26]. The KNN algorithm works based on the shortest distance from the training input object to get the number of k-neighbors. After getting the k value, the majority of the k values are taken to be used as predictions from a data object. The object will then be calculated at the distance from each training sample and then the closest number of k values to the object is taken. The distance calculation process will be carried out using Euclidean Distance. To define the distance between two points, namely the point on the training data (x) and the point on

Table 1. Confusion matrix

		Prediction	
		Positive	Negative
Actual	Positive	TP	TN
	Negative	FN	FN

the testing data (y), the Euclidean formula is used, as shown in the following equation [27]:

$$D(x, y) = \sqrt{\sum_{k-1}^{n} (x_k - y_k)^2} \tag{14}$$

where D is the distance between the points in the training data x and the testing data points y to be classified, where x = x1, x2,…, xi and y = y1, y2,…,yi and I represents the attribute values and n is the attribute dimension.

2.7 Classification Evaluation

In this research, the evaluation process of the classification results will be carried out by calculating the values of *True Positive, True Negative, False Positive, and False Negative*. Furthermore, these four values can be calculated with the *confusion matrix* in Table 1 [3]. These values will then be used to calculate the evaluation parameters for the classification results.

From the *confusion matrix*, the calculation of accuracy, recall, and precision values can be obtained. The following is an equation to calculate the accuracy value.

$$Akurasi = \frac{TP + TN}{TP + FN + FP + TN} \tag{15}$$

The recall is the proportion of correctly classified positives classes.

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

Precision is the proportion of the positive class that is classified as true positive compared to the overall result that is classified as positive.

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

3 Research Methods

3.1 Data

In this research, data collection was carried out by taking images directly to Pringgasela village in one of the weaver's houses. Image data were taken from as many as 8 types of Songket images, where each Songket image will be taken 50 images. So the images taken in the image retrieval process are 400 images. Figure 6 shows the example of the images.

The image was then preprocessed by *cropping them* into 6 parts, before being augmented to increase the number of images (Fig. 7).

Furthermore, the images were resized to 64 × 64, 128 × 128, and 256 × 256 pixels. Finally, the images were converted into *grayscale* (Fig. 8).

3.2 System Design

The system is built through the processes shown in Fig. 9.

3.3 Testing Scenario

In this research, we tested the model with the following scenarios:

- Finding the most optimum parameter for classification. In this testing scenario, we tried to find the most optimum k in the range of 3–15 using several distance calculation

Fig. 6. Songket dataset

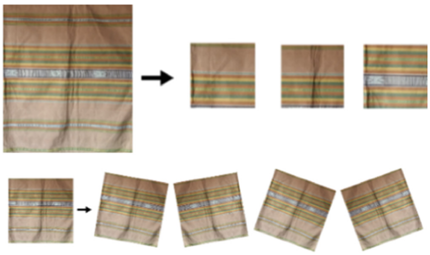

Fig. 7. Cropping and augmentation process

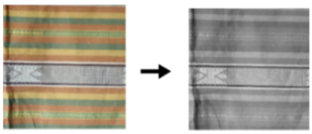

Fig. 8. Grayscale Image

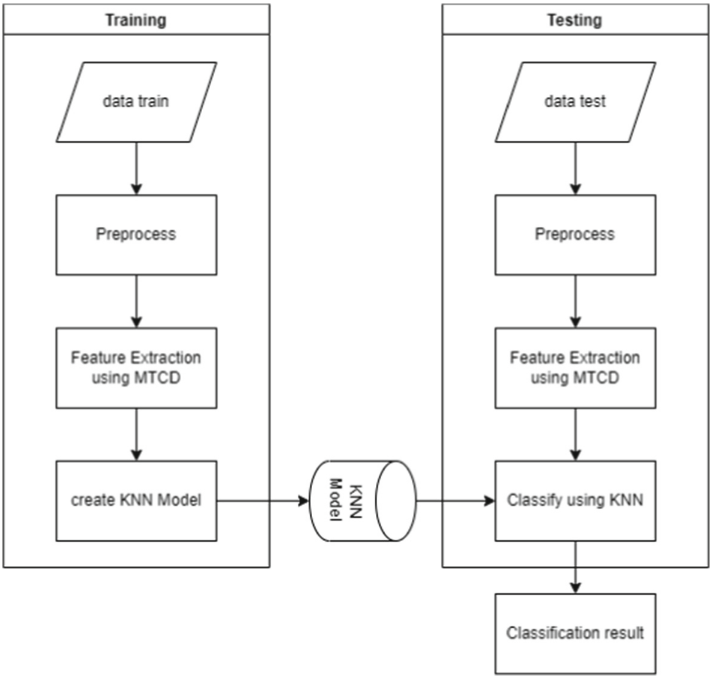

Fig. 9. System Design

methods including *euclidean, manhattan, Chebyshev, and Minkowski.* We also looked for the best image resolution.

- The second scenario is comparing the performance between RGB and HSV color channels.
- Thirdly, we tested the model using new images which did not belong to any of the 8 classes.
- The last scenario is testing the model with k-fold cross validation.

The evaluation metrics we used in this research were accuracy, precision, and recall.

4 Results and Discussion

4.1 The Most Optimal Model Parameters

During this first testing scenario, we tried to find the most optimum number of k. Table 2 shows that as the number of k increased, the KNN performance consistently decreased and the best accuracy was obtained with k = 3 and k = 4 with 99.80% of accuracy and 100% recall.

Furthermore, Table 3 shows the evaluation metrics with different distance computation methods using 128 × 128 image resolution and $k = 3$. We found out that Manhattan Distance resulted in the best performance for the KNN classifier, with the accuracy of 99.90 and 100% for both recall and precision.

Table 2. EVALUATION METRICS WITH DIFFERENT NUMBERS OF K

k	Data test without noise			Data test with noise		
	Accuracy	Presisi	Recall	Accuracy	Presisi	Recall
3	99.80%	100%	100%	99.50%	100%	100%
4	99.80%	100%	100%	99.50%	100%	100%
5	99.60%	100%	100%	99.60%	100%	100%
6	99.60%	100%	100%	99.60%	100%	100%
7	99.60%	100%	100%	99.70%	100%	100%
8	99.60%	100%	100%	99.70%	100%	100%
9	99.60%	100%	100%	100%	99%	99%
10	99.60%	100%	100%	100%	99%	99%
11	99.50%	100%	100%	100%	99%	99%
12	99.50%	100%	100%	100%	99%	99%
13	99.40%	99%	99%	99.87%	99%	99%
14	99.40%	99%	99%	99.87%	99%	99%
15	99.40%	99%	99%	99.83%	99%	99%

Table 3. PERFORMANCE METRICS WITH DIFFERENT ALGORITHMS

Distance	Data test without noise			Data test with noise		
	Accuracy	Presisi	Recall	Accuracy	Presisi	Recall
Euclidean	99.80%	100%	100%	99.50%	100%	99%
Minko	99.80%	100%	100%	99.50%	100%	99%
Manhattan	99.90%	100%	100%	100%	100%	100%
Chebys	99.80%	100%	100%	97.50%	98.00%	98%

We also tested the model with different image resolutions using $k = 3$ and Manhattan distance. Table 4 shows the result, and the best accuracy was obtained using an image size of 128 × 128 pixels, with an accuracy of 99.90 and 100% of recall and precision.

4.2 Finding the Best Color Space

In this test, tried to compare the RGB and HSV color spaces to find which one obtains the better performance. Figure 10 shows that the HSV color space performed better than the RGB with the accuracy, recall, and precision of 100%.

Table 4. PERFORMANCE METRICS WITH DIFFERENT IMAGE RESOLUTIONS

Image Size	Data test without noise			Data test with noise		
	Accuracy	Presisi	Recall	Accuracy	Presisi	Recall
64 × 64	99.9%	100%	100%	94.0%	94.0%	94.0%
128 × 128	99.9%	100%	100%	100%	100%	100%
256 × 256	100%	100%	100%	99.8%	100%	100%

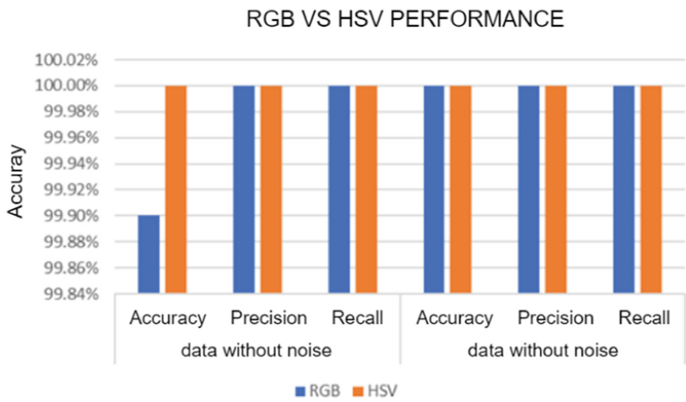

Fig. 10. Comparison Value RGB and HSV

4.3 Testing a Most Optimal Model with Images that Did Not Belong to Any Class

We tested our model with 19 new images that did not belong to any of the classes that were trained. The result (Fig. 11), shows that 11 images were classified into one of the classes with a probability of 66.67%. The remaining 8 images were classified into another category with a probability of 100%. We calculated the average of these probabilities which is 80.10%, and we used this value as our threshold for identifying whether or not an image is a Songket from Pringgasela.

4.4 Testing Model with k-Fold Cross-Validation

In this last test, we tested the model using k-fold cross-validation to determine the maximum accuracy of the model. We tested the model with the number of k ranging from 3 to 10 folds, the result is shown in Table 5.

We found out that the value of precision and recall increased along with the increase of K. However, the accuracy slightly decreased from K = 9 to K = 10. We can see from the table that the values of each metric changed below 1% with a different number of K, hence we conclude that the model is not under fitted nor overfitted.

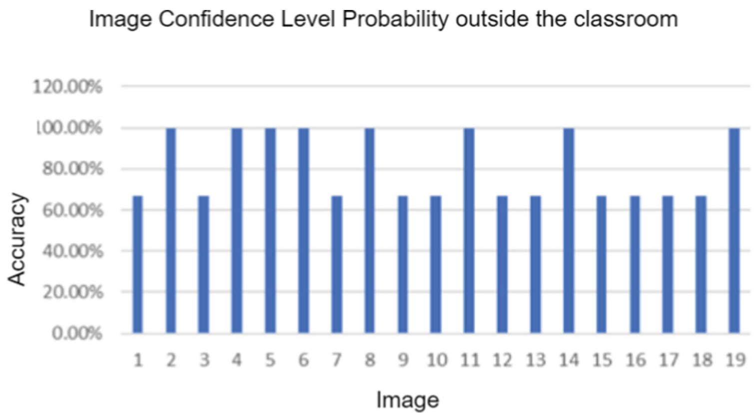

Fig. 11. Test comparison chart with new images

Table 5. Test Results With K-Fold Cross-Validation

k	Accuracy	Precision	Recall
3	99.68%	99.69%	99.68%
4	99.66%	99.67%	99.66%
5	99.77%	99.77%	99.77%
6	99.79%	99.79%	99.79%
7	99.81%	99.81%	99.81%
8	99.79%	99.79%	99.79%
9	99.83%	99.83%	99.83%
10	99.81%	99.82%	99.81%

5 Conclusion

The experiment showed that our model obtained its most optimized performance using the image resolution of 128 $\times$ 128 pixels. Furthermore, the Manhattan distance with k-neighbor = 3 obtained the best accuracy among the others. We also found that the model obtained 0.99, 1.00, and 1.00 accuracy, recall, and precision respectively using the HSV color space. We also tested the model with k-fold cross-validation and the values of evaluation metrics were stable in each fold.

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