Classification of Basurek Batik Using Pre-Trained VGG-16and Support Vector Machine

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Classification of Basurek Batik Using Pre-Trained VGG-16 and Support Vector Machine

Meli Handayani[1], Rika Rosnelly[2], Hartono[3]

[1,2,3] *Magister of Computer Science, Potensi Utama University*
JL. KL. Yos Sudarso Km. 6,5 No. 3-A, Medan

[1]melihandayani0105@gmail.com

[2]rikarosnelly@gmail.com

[3]hartonoibbi@gmail.com

***Abstract*— By introducing Indonesian batik motifs, we know that the island of Sumatra, especially Bengkulu and Jambi provinces, has a distinctive batik called Basurek batik. This research aims to classify the two batik motifs using the Support Vector Machine (SVM) algorithm. First, we extract the image of the batik motif with a pre-trained VGG-16 model and then use them as a dataset for the SVM classification process. The classification process itself uses linear, polynomial, and sigmoid kernels. We divided the data 90:10 and used 10-fold cross-validation to analyze each training and testing data classification result. The results of this study are the highest values of accuracy, precision, and recall of 76.4%, 76.5%, and 76.4% produced by the linear kernel for the training data classification. For the testing data classification, both the linear and polynomial kernels generate the best accuracy, precision, and recall values of 87.5%, 90%, and 85.5%. On average, incorporating the training and testing classification results, we found that the linear kernel is the best function for classifying the Basurek batik motif using the collected images from the internet.**

***Keywords*— classification, batik basurek, support vector machine, transfer learning, vgg-16**

I. INTRODUCTION

Batik is one of Indonesia's cultural heritages recognized by the world [1]. However, not many people are familiar with Basurek batik, a distinctive batik art from Bengkulu and Jambi provinces [2]. In batik Basurek, Arabic calligraphy is the prime motif, combined with bright color patterns and a blend of Rafflesia flowers with a touch of animal character [3]. This research aims to show the difference between Bengkulu's and Jambi's batik Basurek through a classification using a machine learning algorithm.

Some research has shown the use of machine learning in batik motif classification, such as in the Javanese batik motifs classification using Convolutional Neural Network (CNN) and grayscale image [4]; Pekalongan batik identification using the Gray Level Co-Occurrence Matrix (GLCM) [5], and Batik motif classification using Deep Convolutional Neural Network method and Data Augmentation [6]. From these studies, we found that feature extraction is essential in the batik motif classification, as it is the source dataset for the classification algorithms.

In this research, we employ a pre-trained CNN, namely VGG-16, in the feature extraction process and transfer the result as the dataset. As references, we found some studies about the VGG-16 and other machine-learning algorithms combinations: in oil rig classification with combinations of the logistic regression, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors, Decision Tree (DT), Naive Bayes (NB), Neural Networks (NN), and AdaBoost [7]; in pediatric pneumonia detection with the combination of RF, AdaBoost, K-NN algorithms [8], and in fruit ripeness detection with Multilayer Perceptron (MLP) combination [9].

The Support Vector Machine (SVM) is chosen as the combination of VGG-16 since this algorithm has good performance, highly flexible configuration, and support from many data mining tools, such as the Orange data mining application, Rapidminer, and WEKA [10]. In this research, we employ the SVM algorithm as the classifier of the extracted feature dataset to classify a collection of batik Basurek motif images into two classes: Bengkulu and Jambi.

Some studies have combined the VGG 16 with the SVM algorithm in classifying image-based datasets. In the remote sensing image classification research, the combination of the VGG 16 and the SVM algorithm using a linear kernel managed to obtain an average accuracy of 96.63% for the UC Merced Land dataset and 91.41% for the RSSCN7 dataset [11]. Another research on face recognition stated that using the linear kernel, the combination of the VGG 16 and the SVM algorithm produced a classification accuracy of 97.47% on the LFW dataset [12]. Finally, research on Content-Based Image Retrieval (CBIR) shows that a combination of the VGG 16 as a feature extractor and the SVM algorithm using the linear kernel as a classifier yield the highest accuracy value of 96% [13]. In this research, we also try the VGG 16-SVM combination on the Basurek batik classification using the linear kernel with an addition of the polynomial and sigmoid.

To evaluate the classification result, we use 10-fold cross-validation to obtain accuracy, precision, and recall values from each model. The final result is which model performs the best in classifying the batik Basurek's image and which kernel function has the best overall performance.

II. METHODS

A. *Dataset*

We collect batik Basurek's images from the internet and found 160 images to use as the data. Figure 1 and Figure 2 show the sample images from each Bengkulu and Jambi batik Basurek.

Fig. 1 Bengkulu's Batik Basurek

Figure 1 shows samples from the 80 images of Bengkulu's Basurek batik motifs that we collected from the internet. From these 80 images, we use 90% as training and 10% as testing data.

Fig. 2 Jambi's Batik Basurek

Figure 2 shows samples from the 80 images of Jambi's Basurek batik motifs that we collected from the internet. From these 80 images, we use 90% as training and 10% as testing data. We use VGG-16 to extract the features from the images, resulting in a dataset containing 160 data with 4096 labels and one target. Table I show the samples of the dataset used in this research.

TABLE I
SAMPLES OF DATASET

n0	n1	n2	n3	n4	n5	Motif
0	0.184	0.936	0.163	1.09	0.151	Bengkulu
0	0.279	0.929	0.141	0.983	0.064	Bengkulu
0	0.563	1.245	0.042	1.188	0.002	Bengkulu
0	0.149	1.159	0.179	0.999	0	Bengkulu
0	0.167	0.891	0.069	0.944	0.084	Bengkulu
0	0.352	0.923	0.248	0.893	0.274	Jambi
0	0.995	0.885	0.097	0.826	0	Jambi
0.023	0.492	0.776	0.255	1.186	0.183	Jambi
0	0.807	0.966	0	1.097	0	Jambi
0	0.03	1.714	0	1.395	0	Jambi

B. *VGG-16*

VGG-19 (Visual Geometry Group-19) is a transfer learning network equipped with data augmentation and balancing, able to change the model architecture to suit the dataset and tackle imbalanced data for each class [14]. As a successor of the VGG-16 model, VGG-19 uses the same input size for an image, a dimension of 224 x 224 [15]. VGG-19 architecture, shown in Figure 3, consists of 19 connection layers, comprising 16 convolutional layers and three fully connected layers, thus making the VGG-19 a deep-learning neural network [16].

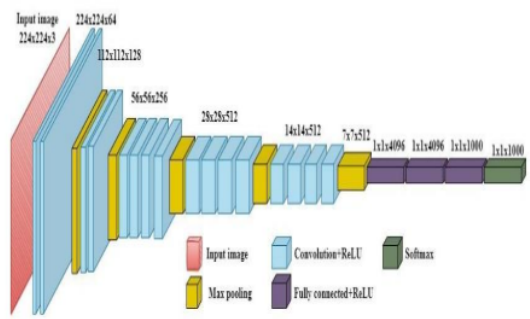

Fig. 3 Architecture of VGG-19

One of the advantages of using VGG 16 as a feature extractor in image classification is its ability to extract low-level image features such as edges, lines, and blobs [17]. Using VGG 16 in the image features extraction and transferring the results to other classifiers also reduces the possibility of overfitting as it uses the max pooling layers to reduce the dimensionality of the features [18]. As demonstrated in the MRI-based glioma classification, where the VGG 16 provides greater accuracy in categorizing the same dataset, the VGG 16 model is more successful in image classification than a pure CNN model [19].

C. *Support Vector Machine*

An approach called the support vector machine (SVM) divides the data into positive and negative classes using a hyperplane as a boundary [20]. This approach employs a kernel function (kernel trick) to map the data into a high-dimensional feature space to get a hyperplane that divides the data into two classes for tackling classification problems using non-linearly separable datasets [21]. Some of the more popular kernel functions often used in SVM are the linear, polynomial, and RBF sigmoid functions; these kernel functions use equations (1) to (3) to generate a hyperplane in the classification process [22].

$$Linear = (x * y) \tag{1}$$

$$Polynomial = (g * x * y + c)^d \tag{2}$$

$$Sigmoid = tanh(g * x * y + c) \tag{3}$$

Comparing these three kernels has been an intriguing case in classification studies. One study about cloud environment detection shows that the sigmoid kernel performs better (88.2%) than the linear (87.89%) and polynomial (52.58%) in terms of accuracy [23]. The industry's sustainability classification shows a different outcome where the polynomial kernel, with an accuracy of 100%, is the best kernel function compared to the linear (99.08%) and the sigmoid (89.89%) [24]. In the classification of two different datasets (the breast cancer and Iris flower), the linear kernel shows a higher performance with an average accuracy of 97.805%, followed by the polynomial kernel with an average accuracy value of 91.315%, and the sigmoid kernel with an average accuracy of 41.58% [25]. We combine, evaluate, and finally analyze the impact of these kernels on SVM classification performance.

D. Model

In this study, we construct three classification models using the linear, polynomial, and RBF kernel functions, as shown in Table II. In building these models, we use various parameter settings, such as cost value (C), gamma constant in the kernel function (g), c0 constant in the kernel function (c), and degree of the kernel (d).

TABLE II
CONFIGURATION OF MODEL

Model	Kernel Function	Parameters
Linear	Linear	C = 0.1
Polynomial	Polynomial	g = 0.5 c = 1 d = 1.9 C = 0.1
Sigmoid	Sigmoid	g = 0.1 c = 0.46 C = 0.1

E. Evaluation

In this work, we examine the performance of the models using the 10-fold. Using the calculations in equations (4) to (6), we rate each model using the accuracy, precision, and recall values [26].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

Where [27]:

TP (True Positive)	=	The proportion of accurately predicted positive-class data
FP (False positive)	=	The entire quantity of successfully predicted positive-class data
TN (True Negative)	=	All correctly predicted negative-class data
FN (False Negative)	=	The number of erroneously predicted negative-class data.

III. RESULTS

The VGG-16 feature extraction produces 4096 features with labels N0 to N4095 for the analyzed 160 images. From the feature extraction result, we summarize the average statistic for each Basurek batik motif using the mean, median, and dispersion values, as shown in Table III.

We assess the classification outcomes of each model using a 10-fold cross-validation and a 90:10 training-testing data ratio and provide the findings as a table of the confusion matrix. Table III and Table IV show the results of the model classification for the training and testing data in the confusion matrix.

TABLE III
CONFUSION MATRIX FOR TRAINING DATA

Statistics	Bengkulu	Jambi	Difference
Average Mean	0.436025	0.428649088	0.0073761
Average Median	0.132672	0.126348364	0.006323978
Average Dispersion	1.328649	1.3306215	0.0019725

The differences value displayed in Table III shows the divergence between the Bengkulu and Jambi motif features. The mean average of 0.0073761 for the 160 images utilized in this study demonstrates that the characteristics of both motifs are highly comparable. The average dispersion of 0.0019725 indicates that both motifs' features were uniformly distributed and had a lower deviation. From this statistic, we conclude that the images used in this research are closely similar and provide challenges for the models to classify them. This result also shows the advantage of using the VGG 16 model, where we can analyze the data used in image classification using their features' statistics.

Using these features as a dataset in the SVM algorithm produces a prediction outcome in a confusion matrix form, shown in Table IV for the training data and Table V for the testing data.

TABLE IV
CONFUSION MATRIX FOR TRAINING DATA

Model	Actual	Predicted	
		Bengkulu	Jambi
Linear	Bengkulu	56	16
	Jambi	17	55
Polynomial	Bengkulu	53	19
	Jambi	15	57
Sigmoid	Bengkulu	26	46
	Jambi	9	63

From the confusion matrix result in Table IV, we see that the linear kernel function is the best at predicting Bengkulu's Basurek motif, with 56 out of 86 data. While the sigmoid kernel function is the worst at predicting Bengkulu's Basurek motif, with 26 out of 86 data. From the confusion matrix result in Table IV, we also see that the sigmoid kernel function is the best at predicting Jambi's Basurek motif, with 63 out of 86 data. While the linear kernel function is the worst at predicting Jambi's Basurek motif, with 55 out of 86 data.

TABLE V
CONFUSION MATRIX FOR TESTING DATA

Model	Actual	Predicted	
		Bengkulu	Jambi
Linear	Bengkulu	6	2
	Jambi	0	8
Polynomial	Bengkulu	6	2
	Jambi	0	8
Sigmoid	Bengkulu	2	6
	Jambi	0	8

From the confusion matrix result in Table V, we see that the linear kernel and polynomial are the best functions for predicting Bengkulu's Basurek motif, with 6 out of 8 data, while the sigmoid kernel function is the worst with 2 out of 8 data. From the confusion matrix result in Table V, we also see that all kernel functions perfectly predicted the Jambi's Basurek motif.

We use equations (4) to (6) to generate the results of the 10-fold cross-validation assessment of the SVM models, such as the accuracy, precision, and recall values shown in Table IV and Table V. For a convenient comparison, we summarized the accuracy, precision, and recall values from each result in Table VI.

TABLE VI
PERFORMANCE EVALUATION

Model	Data	Accuracy	Precision	Recall
Linear	Training	77.1%	77.1%	77.1%
	Testing	87.5%	90%	87.5%
Polynomial	Training	76.4%	76.5%	76.4%
	Testing	87.5%	90%	87.5%
Sigmoid	Training	61.8%	66.0%	61.8%
	Testing	62.5%	78.6%	62.5%

Table VI shows that the Linear model yields the best performance for the training process, while the Sigmoid model performs the worst. The results in Table VI also show that the Linear and Polynomial models generate the best performance for the testing process, while the Sigmoid model yields the worst performance.

We calculate the average value of all the model assessment results for the final performance score, as shown in Table VI (from the training and testing process).

TABLE VII
AVERAGE PERFORMANCE

Model	Accuracy	Precision	Recall
Linear	82.3%	83.55%	82.3%
Polynomial	81.95%	83.25%	81.95%
Sigmoid	62.15%	72.3%	62.15%

We can determine how well each model has performed overall by looking at the results in Table VII. With an average accuracy value of 82.3%, an average precision value of 83.55%, and an average recall value of 82.3%, the Linear model stood out among the others. This finding demonstrates that the linear kernel SVM technique, on average, is the best model for categorizing the batik Basurek pattern.

IV. CONCLUSIONS

We conclude that, compared to the manual method, the VGG-16 model helps faster feature extraction from digital images. The batik Basurek classification using the SVM algorithm may use the 4096 features from the VGG-16 feature extraction as a dataset with excellent performance outcomes. The highest average performance value of 82.3% accuracies, 83.55% precisions, and 82.3% recalls shown in the evaluation of the classification process are solid proof of this statement. This research also shows the importance of choosing the appropriate kernel function. The three kernel functions employed in this study each performed differently, demonstrating how using the wrong kernel function will impact the model's overall performance.

In conclusion, the study's findings show that the VGG-16 algorithm and the SVM method, particularly utilizing the linear kernel function, are suitable for an image-based batik Basurek classification.

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