Combination of Pre-Trained CNN Model and Machine Learning Algorithm on Pekalongan Batik Motif Classification

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Combination of Pre-Trained CNN Model and Machine Learning Algorithm on Pekalongan Batik Motif Classification

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***Abstract*—Pekalongan is a region in Indonesia well-known for its batik production. The Pekalongan batik is rich in varieties of motifs, such as the Jlamprang, Liong, Terang Bulan, and Tujuh Rupa. The difficulty of distinguishing Pekalongan batik motifs for ordinary people causes the need for a model that can help recognize these motifs automatically based on input from digital images. This research aims to classify the Pekalongan batik motifs using a pre-trained Convolutional Neural Network (CNN), the Inception V3, and machine learning, the K-Nearest Neighbors (K-NN) algorithm. First, we extract the features from the digital image using the Inception V3 model, resulting in m x 2048 features, where m is the number of images. The extracted features generated from the Inception V3 model will be used as the dataset for the motif classification. We build models to classify the features using the K-Nearest Neighbors (KNN) with a K value of 5. In the classification process, we employ two distance metrics, the Euclidean and Manhattan distance, and analyze their performance using the 10-fold and 20-fold cross-validation. The results of this study are the highest overall performace of accuracy (0.987), precision (0.987), and recall (0.987) produced by the Euclidean model.**

***Keywords*—batik classification, euclidean distance, inception v3, k-nearest neighbor, manhattan distance**

I. INTRODUCTION

One of Indonesia's internationally renowned cultural legacies is batik, which is particularly well-known on Java island [1]. Pekalongan, one of the famous batik-producing areas, has four popular motifs: Jlamprang, Liong, Terang Bulan, and Tujuh Rupa [2]. Ordinary people may have difficulty distinguishing these Pekalongan batik motifs, so we need a model that can automatically recognize Pekalongan batik motifs from a digital image medium. In this research, we employ machine learning to recognize the Pekalongan batik motifs using an image-based classification.

Some studies have proven the performance of machine learning in image-based batik classification: the Parang, Kawung, Ceplok Nitik, and Lereng motifs classification using Deep Convolutional Network, with the highest accuracy values of 89.7% [3]; the Pekalongan batik classification using Neural Network method, with the highest accuracy of 98.33% [4]; using a Convolutional Neural Network to classify the Riau batik, with an accuracy value between 65% [5]; the Karawang's batik identification using the CNN algorithm, with 73.33% [6] and the multi-label batik classification using the CNN algorithm, with an accuracy of 91.41% [7].

Feature extraction is a crucial step in digital image-based object recognition since the extracted features serve as the data for machine learning algorithms to recognize the digital image's object. In this research, we use a pre-trained model-based feature extraction to extract features in the image of Hanacaraka letters to be used as a dataset in the classification process using machine learning algorithms. A pre-trained model is a model that has been trained in advance using a large amount of data so it can classify using fewer data.

Inception V3 is a transfer learning method with excellent feature extraction capabilities compared to pre-training models, with recognition accuracy and generalization capabilities that use kernels to improve its performance [8]. Several studies used this model in their research, such as the Covid-19 detection in chest images with an average accuracy of 97.1% [9], multiclass skin cancer detection with an accuracy of 72.4% [10], an intelligent gender classification system with an accuracy of 98.75% [11], age and gender prediction on human face images with an accuracy of 93.61% [12], and malware images classification with an accuracy of 99.24% [13]. Based on the compatibility shown by these studies, we choose Inception V3 for the Pekalongan batik image's feature extraction and then transfer the results to the K-NN algorithm as classification datasets.

K-Nearest Neighbor (K-NN) is a machine learning algorithm that finds and evaluates the closest distance between the data and its neighbors in the classification process [14]. In classification research, In classification research, K-NN is a commonly used method, as demonstrated in the study about determining majors in vocational schools, with 84% accuracy [15]; the stroke disease detection with the highest accuracy value of 95.93% [16]; the flood prediction in Bangladesh city with an accuracy of 94.91% [17]; the non-performing loan prediction with an accuracy of 89.41% [18]; and the rice varieties classification with an accuracy value of 97.15% [19]. We choose the K-NN algorithm combined with the Inception

V3 model to classify the Pekalongan batik motifs from the extracted dataset.

The K-NN algorithm used in this research produces two models, where each model uses different distance metrics: Euclidean and Manhattan distance. Using the extracted features from the Inception V3 models, we analyze the performance of these models' classification using the 10-fold and 20-fold cross-validation to generate the accuracy, precision, and recall values. Based on these values, we determine the best model for classifying the Pekalongan batik motifs based on the dataset generated from the feature extraction process using the Inception V3 model.

II. METHODS

A. *Dataset*

The dataset used in this research consists of 576 images, divided into four class targets: Jlamprang, Liong, Terang Bulan, and Tujuh Rupa, each with a dimension of 100x100. We collected the images from the internet, with Figure 1 displaying the sample from the Jlamprang motif, Figure 2 the Liong motif, Figure 3 the Terang Bulan motif, and Figure 4 the Tujuh Rupa motif.

Fig. 1 Jlamprang Motif Sample

Fig. 2 Liong Motif Sample

Fig. 3 Terang Bulan Motif Sample

Fig. 4 Tujuh Rupa Motif Sample

B. *Inception V3*

In image classification research, using the Inception V3 model as the feature extractor of an image dataset shows how this model can transfer the learning result to optimize the classification process, such as in food image recognition [20], pulmonary image classification [21], and the dynasty-based classification of ancient murals [22].

The architecture of Inception V3 uses the Inception module, with 22 convolutional layers spread over 9 Inception modules. For convolution layers with kernel filters (55, 33, and 11) and pooling layers with 33 filters, the Inception module provides three distinct sizes [23]. Figure 5 shows the architecture of Inception V3 in feature extraction [24].

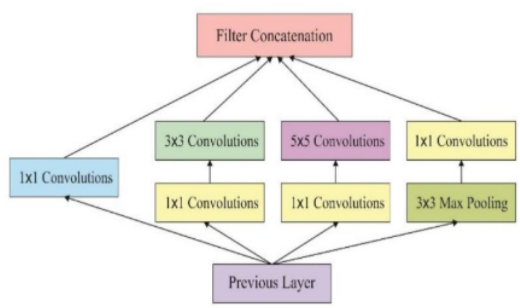

Fig. 5 Inception V3 Architecture

In this study, we use the Inception V3 architecture to extract the Pekalongan batik pictures and generate a dataset of 2048 characteristics. Figure 6 displays the architecture of the feature extractor used in this research, while Table I display the extracted feature samples from the extracted images.

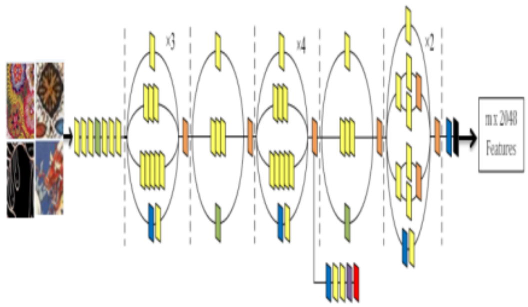

Fig. 6 Feature Extractor Architecture

TABLE I
EXTRACTED FEATURE SAMPLES

N2043	N2044	N2045	N2046	N2047	Motif
0	0.0633	0.6524	1.4208	0.4768	Jlamprang
0	0.0127	0.9320	1.5144	0.1478	Jlamprang
0	0.8492	0.8230	0.7005	0.3573	Jlamprang
0.0395	0.7180	1.1799	0.6942	0.3502	Jlamprang
0.0582	0.6586	1.4862	0.5306	0.1628	Jlamprang
0.0157	0.7416	0.7126	0.3137	0.8931	Liong
0.0004	0.5169	0.9781	0.1711	0.6085	Liong
0.0354	1.1584	0.7794	0.1062	0.3435	Liong
0.0150	0.8896	1.0507	0.2885	0.2842	Liong
0.0228	0.7893	0.8200	0.4093	0.5484	Liong
1.1803	0.9927	0.4852	0.4115	0.3395	Terang Bulan
1.2765	0.1332	0.3733	0.9428	0.0864	Terang Bulan
0.0733	0.0695	0.1030	2.1918	0.1220	Terang Bulan
0.5054	0.4035	0.2440	1.4717	0.2386	Terang Bulan
0.9544	0.1512	0.3557	0.9118	0.0498	Terang Bulan
0.6370	0.6969	0.1511	0.5264	0.1458	Tujuh Rupa
0.8425	1.8475	0.9139	1.3768	0.1759	Tujuh Rupa
0.6688	1.4571	1.0683	0.8011	0.2623	Tujuh Rupa
1.0757	1.1418	0.3067	1.3587	0.2061	Tujuh Rupa
0.6019	1.4143	0.6656	1.6122	0.2888	Tujuh Rupa

From Table I above, the feature extraction with the Inception V3 produces N0, N1, ..., and N2047 attributes with four target classes: Jlamprang, Liong, Terang Bulan, and Tujuh Rupa. With 576 images used in this research, the dataset contains 576 X 2048 = 1179648 records.

C. Classification Model

Combining the K-NN algorithm as a classifier and feature-extracting methods in image-based classification, such as the Grey Level Co-occurrence Matrix (GLCM) in the batik patterns classification [25], the Convolutional Neural Network (CNN) in 10 different image categories [26] and the GLCM in the grape image [27] shows promising results with above-decent performance. By first extracting the image feature and using it as the dataset in the classification process, this combination improves the performance of the traditional K-NN algorithm.

We use the K-NN algorithm as the classifier and the dataset obtained from Inception V3's feature extraction process in the classification process. We employ two distance metrics in the classification process, the Euclidean and the Manhattan distance. We use both distance metrics to build two models with a K value of 5. Each model will be responsible for classifying the extracted features dataset to classify each image into the Jlamprang, Liong, Terang Bulan, and Tujuh Rupa classes. Table II shows the configuration for each model used in this research.

TABLE II
CLASSIFICATION MODEL CONFIGURATION

Model	Distance Metric	K Value
KNN-E	Euclidean Distance	5
KNN-M	Manhattan Distance	5

We build the KNN-E model using the K-NN algorithm with the Euclidean distance metric and a K value of 5, while the KNN-M used the Manhattan distance metric. Both distance metrics will calculate the distance between each data and classify them using equations (1) and (2) [28].

$$Euclidean\ Distance = \sqrt{\sum_{j=1}^{N}|x-y|^2} \quad (1)$$

$$Manhattan\ Distance = \sum_{j=1}^{N}|x-y| \quad (2)$$

D. Evaluation

We use the 10-fold and 20-fold cross-validation to evaluate each model's performance in classifying the Pekalongan batik's motif. The accuracy, precision, and recall values gained using equations (1) to (3) will be the reference in ranking the models from best to worst [29].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

For overall performance measurement, we calculate the average accuracy, precision, and recall from each k-fold. We determine the best and worst models using the highest and lowest overall performance value.

III. RESULTS

We classify the dataset using the developed model and the feature derived from the Pekalongan batik pictures, which gave a prediction result in a confusion matrix table form. Table III and Table IV show the confusion matrix result for the 10-fold and 20-fold cross-validation evaluation.

TABLE III
CONFUSION MATRIX FOR 10-FOLD CROSS VALIDATION

Model	Actual	Predicted			
		Jlamprang	Liong	Terang Bulan	Tujuh Rupa
KNN-E	Jlamprang	143	0	0	1
	Liong	0	142	0	2
	Terang Bulan	0	0	140	4
	Tujuh Rupa	0	0	1	143
KNN-M	Jlamprang	143	0	1	0
	Liong	0	142	0	2
	Terang Bulan	0	1	139	4
	Tujuh Rupa	0	0	0	144

Table III shows that the KNN-E model correctly predicted 143 out of 144 Jlamprang motifs; incorrectly predicted 2 Liong motifs as Tujuh Rupa motifs; correctly predicted 140 out of 144 Terang Bulan motif; and failed to predict one Tujuh Rupa motif correctly.

Table III also shows that the KNN-M model correctly predicted 143 out of 144 Jlamprang motifs; incorrectly predicted 2 Liong motifs as Tujuh Rupa motifs; correctly predicted 139 out of 144 Terang Bulan motifs; and correctly predicted all Tujuh Rupa motifs.

TABLE IV
CONFUSION MATRIX FOR 20-FOLD CROSS VALIDATION

Model	Actual	Predicted			
		Jlamprang	Liong	Terang Bulan	Tujuh Rupa
KNN-E	Jlamprang	143	0	0	1
	Liong	0	142	0	2
	Terang Bulan	0	1	140	3
	Tujuh Rupa	0	0	1	143
KNN-M	Jlamprang	143	0	1	0
	Liong	0	142	0	2
	Terang Bulan	0	1	140	3
	Tujuh Rupa	0	0	0	144

Table IV shows that the KNN-E model correctly predicted 143 out of 144 Jlamprang motifs; incorrectly predicted 2 Liong motifs as Tujuh Rupa motifs; correctly predicted 140 out of 144 Terang Bulan motif; and failed to predict one Tujuh Rupa motif correctly.

Table IV also shows that the KNN-M model failed to predict one Jlamprang motif correctly; incorrectly predicted 2 Liong motifs as Tujuh Rupa motifs; correctly predicted 140 out of 144 Terang Bulan motifs; and correctly predicted all Tujuh Rupa motifs.

From the confusion matrix shown in Table III and Table IV, we calculate the performance values of accuracy, precision, and recall using equations (1) to (3). The result shown in Table V displays the performance comparison of each model in classifying the Pekalongan batik images.

TABLE V
PERFORMANCE EVALUATION

Model	Fold	Accuracy	Precision	Recall
KNN-E	10	0.986	0.986	0.986
	20	0.988	0.988	0.988
KNN-M	10	0.986	0.987	0.986
	20	0.986	0.986	0.986

From Table V, we get the highest performance value of accuracy (0.988), precision (0.988), and recall (0.988) from the KNN-E model with the 20-fold cross-validation. We also get the lowest accuracy (0.986), precision (0.986), and recall (0.986) values from the KNN-E with the 10-fold cross-validation and the KNN-M with the 20-fold cross-validation models.

Next, we calculate the average performance value from each 10-fold and 20-fold cross-validation evaluation, resulting in data shown in Table VI.

TABLE VI
OVERALL PERFORMANCE EVALUATION

Model	Accuracy	Precision	Recall
KNN-E	0.987	0.987	0.987
KNN-M	0.986	0.9865	0.986

From the overall performance result, we found that the KNN-E model has the best overall performance with an average accuracy of 0.987, an average precision of 0.987, and an average recall of 0.987.

IV. CONCLUSIONS

We conclude from this study that the pre-trained Inception V3 model accelerates feature extraction. The generated features, which total 2048, may be used as the dataset for the Pekalongan batik categorization by various machine learning algorithms, in this example, the K-NN. From the 10-fold cross-validation evaluation, we found that the Manhattan distance metric performs better than the Euclidean, proven by the accuracy (0.986), precision (0.987), and recall (0.986) values generated from this model. Meanwhile, the 20-fold cross-validation evaluation shows that the Euclidean distance metric performs better than the Manhattan, judging by the accuracy (0.988), precision (0.988), and recall (0.988) value produced from this model. Overall, the Euclidean distance metric performs the best compared to the Manhattan, shown in the average accuracy, precision, and recall values of 0987, 0.987, and 0.987, respectively. This research also proves the feasibility of combining the pre-trained CNN model, especially the Inception V3, with machine learning, in this case, the K-NN algorithm. For future research development, Pekalongan batik motifs can be compared with other batik motifs, such as Solo or Yogyakarta batik, to see how similar the motifs from the three regions are.

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6