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An Improved Okta-Net Convolutional Neural Network Framework for Automatic Batik Image Classification

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***Abstract*—Batik is one of Indonesia's most important cultural arts and has received recognition from UNESCO. Batik has high artistic and historical value with a variety of patterns. Currently, Indonesia has 5,849 batik motifs which are generally classified based on shape, color, motif and symbolic meaning. The diversity of batik motifs makes it difficult for ordinary people to fully recognize them. This paper intends to develop an automatic framework for classifying batik motifs as a solution to overcome this issue. To develop this classification automation framework, the paper proposes a new architecture based on deep learning, which is named Okta-net. The architecture consists of 8 convolutional layers with separate convolution operations (SeparableConv2D). The output of the last convolution block will be fed to the fully connected layer using global average pooling. Meanwhile, in developing a deep learning model to classify batik image patterns, a dataset of 5 batik classes (motifs) was organized, consisting of 4,284 batik images. Through a series of experiments carried out, the proposed Okta-Net architecture succeeded in achieving satisfactory results with a validation accuracy of 93.17%, Precision of 91.60%, Recall of 92.28%, F-1 Score of 91.54%, and a loss of just 0.12%. Thus, it can be concluded that Okta-Net architecture can help preserve Indonesia's batik cultural heritage by accurate batik motif's classification. Apart from that, based on a comparison of research outcomes, Okta-Net outperformed most of earlier studies, the majority of which had an accuracy of below 90%.**

***Keywords*—Batik motif; pattern; classification; accuracy.**

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I. Introduction

Batik is one of Indonesia's traditional arts of decorating cloth by drawing or printing certain patterns and motifs on cloth [1]. Batik has high artistic and historical value [2], [3]. Batik has various kinds of patterns [4], [5]. Today, Indonesia has 5,849 batik patterns [6]. Batik patterns can be classified based on their shapes, colors, motifs, and symbolic meanings [7]. Batik motifs can be thought of as the outline of the image in the batik created by the blending of lines, forms, and isen (variety of ornamental fillers in batik patterns) to create a whole pattern that represents batik [8]. Motif Batik patterns are known for their complexity, making it difficult to recognize and classify them into certain classes [5]. The knowledge to understand batik patterns is only possessed by certain people who have expertise in related fields such as batik painter [9] and all information about batik has not been well documented [7]. Recognizing and classifying batik patterns manually requires a lot of time and effort, therefore technological assistance is needed to automate the batik classification process to preserve the sustainability of Indonesia's cultural heritage [10].

Machine learning is one of the algorithms that has been used to classify batik patterns which provides high-accuracy results. Machine learning is a branch of science from artificial intelligence, which allows computers to become intelligent and behave like humans [11]. Machine learning, especially since the presence of deep learning, can learn on its own to make decisions without having to be repeatedly programmed by humans so that computers become increasingly intelligent, learning from the experience of the data they have, automatically [12].

Throughout the last 7 years, a lot of research has been carried out to assist in automatically classifying batik images based on the Convolutional Neural Network (CNN) algorithm. One of these studies was conducted by Wicaksono et al [13]. In this research, Wicaksono tries to classify batik images consisting of 11 classes and 7,112 images by proposing a novel CNN architecture called InCres. This architecture is proposed by combining 2 pre-trained CNN architectures, namely ResNet [13] and GoogleNet [13]. However, even though this research has made a major contribution to the creation of novel architecture, unfortunately, it has unsatisfactory performance with an accuracy rate of only 70.84%. Meanwhile, in 2018, three similar studies were conducted by Agastya and Setyanto [14], Trisanto et al [15] and Gultom et al [16]. Research conducted by Trisanto et al and Gultom et al utilized the VGGNet architecture [16] with an accuracy of 89%. Trisanto et al also proposed another novel architecture [15] instead of using the popular pre-trained architecture. Unfortunately, the performance of this research is far from satisfactory with an accuracy rate of just 56%. Rasyidi et al [17] conducted another research by utilizing several pre-trained architectures at once, namely ResNet, DenseNet [17] and VGGNet. The research succeeded in getting an accuracy of 85% using a very small dataset. Other research conducted by Arsa and Susila [18] and Khasanah [19] managed to obtain extraordinary performance with an accuracy of 97.58% and 98.96%, respectively. However, this research has limitations in terms of the application of a very small dataset.

Based on this related research, it can be concluded that further research on the topic of developing an automatic batik image classification model is still feasible. This research area is very much challenging due to the issues from previous research as above and extended patterns of batik motif being produced over time. Finally, there are at least three research gaps that this study aims to fill in producing a better automatic batik image classification framework, as illustrated in Figure 1.

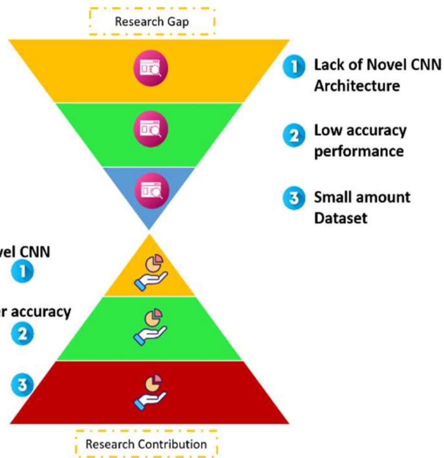

Fig. 1 Research Gap and Contribution

Consequently, this paper proposes an improved CNN framework that is expected to have good performance. In addition, this proposed architecture will be trained and tested on a representative dataset that contains significantly more batik images.

II. Material and Method

A. Dataset

The dataset used in this research is a combination of datasets sourced from public datasets such as batik classification resnet [4] and deep learning batik classification [6]. Furthermore, the dataset used consists of five classes of batik motifs such as *lereng*, *parang*, *nitik*, *kawung* and *ceplok* batik, which are illustrated in Figure 2.

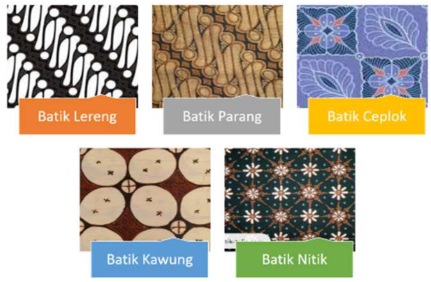

Fig. 2 Batik Dataset

The batik dataset that has been collected consists of 5 classes of 4,284 images and is then separated into three types of data, such as training, testing, and validation data. To assemble data for training, testing, and validation, the dataset was separated by applying a ratio of 70:20:10. The final data for training, testing, and validation can be seen in Table 1.

TABLE I
DATASET

Batik Class	Data	Training	Testing	Validation
Lereng	405	284	81	41
Parang	1,197	838	239	120
Ceplok	1,053	737	211	105
Kawung	747	523	149	75
Nitik	882	617	176	88
TOTAL	**4,284**	**2,999**	**857**	**428**

The next step is image preparation from raw data to ready-to-use data, known as the image pre-processing stage. At this image pre-processing stage, two activities are carried out, namely size adjustment and image dataset augmentation. In the image adjustment activity, customization is carried out so that all batik images have a uniform size of 150 x 150 pixels. After that, data augmentation is carried out on the rescaled image using the horizontal rotation method. The overall results of the data collection and pre-processing stages are described in Figure 3.

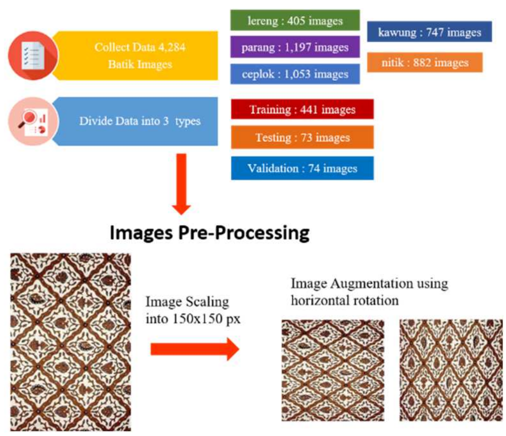

Fig. 3 Image Pre-Processing Stage

B. Proposed Method

The main component of this automatic batik classification framework is the newly proposed architecture, called Okta-net. Most of the previous research used transfer learning techniques and popular pre-trained architectures such as Inception [20], ResNet [21], EfficientNet [22], [23], [24] and so on. Meranggi et al [25] used a transfer learning technique with a pre-trained ResNet architecture, which achieved an accuracy of up to 88.88%. Even though it has achieved performance with accuracy above 80%, as previously mentioned, this research only applies the pre-trained ResNet-18 architecture directly without trying to modify the architecture or propose new CNN architecture. To overcome this dependency on existing pre-trained architecture, this paper proposes a new architecture called Okta-net as depicted in Figure 4.

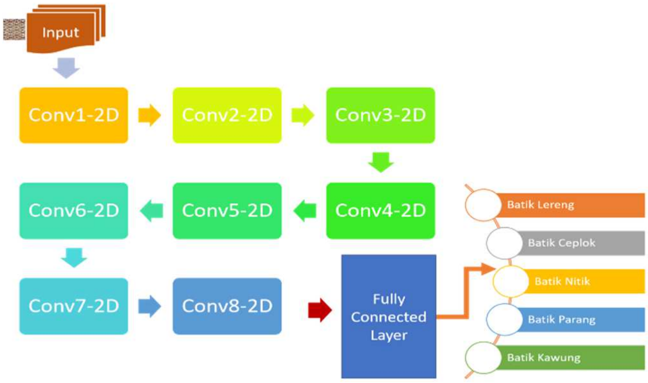

Fig. 4 Proposed Okto-Net Architecture

The proposed Okta-net architecture applies sequential convnet (CNN), which is expected to be able to classify batik images with better performance than previous research. The proposed architecture consists of 8 convolutional layers with separate (SeparableConv2D) [26], [27] and 1 fully connected layer. The model is given an RGB image of dimensions (150 × 150 × 3). The convolutional layer uses a kernel of size 3 [28]× 3 pixels and a stride of 2 pixels without padding. The output of the convolution block is batch-normalized and passes through a ReLU activation function [29]. Apart from that, the ReLU activation function is also used to enable the model to solve nonlinear problems. The output of the last convolution block will be fed to the fully connected layer using global average pooling [30]. The proposed Okta-Net architecture is trained using Adam Optimizer [28] with a learning rate of 0.001. In addition, the paper uses categorical Cross-Entropy [7] to calculate the loss.

III. Results and Discussion

The performance of the automatic batik classification framework based on the proposed Okta-Net architecture was evaluated in terms of accuracy and loss level. Accuracy is a simple and easy-to-understand evaluation metric. It is calculated by comparing the number of correct predictions with the total number of observations. Accuracy provides an intuitive understanding of the extent to which a model can classify images correctly. Apart from that, evaluation metric based on accuracy has other advantages in terms of simplicity and ease of understanding. In terms of loss function measurements, this measurement is a very important element in training image classification models. Measuring the loss function can extract the extent of the difference between the predicted results and the actual labels. Additionally, the use of an appropriate loss function can help reduce the risk of overfitting. The performance of the automatic batik image classification framework in terms of accuracy and loss is shown in Figures 5 and 6, respectively.

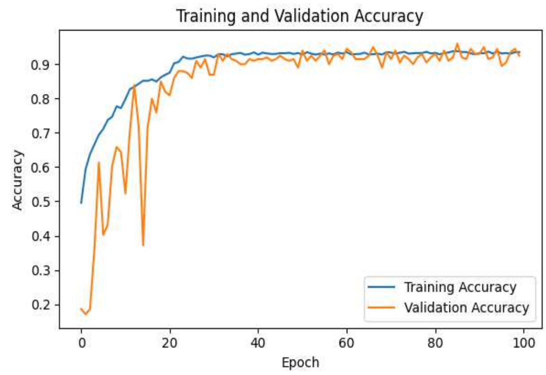

Fig. 5 Accuracy Level of Proposed Okta-Net Architecture

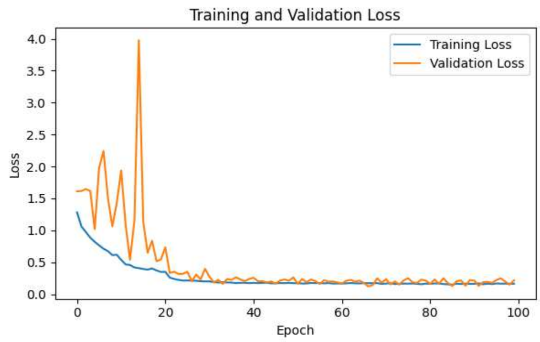

Fig. 6 Loss Level of Proposed Okto-Net Architecture

As seen in Figures 5 and 6, the proposed Okta-net architecture achieves promising results by achieving accuracy above 90% with a very small loss. The training accuracy for the proposed Okt architecture creeps up from the initial training until it peaks at 93.79%. While the performance for validation accuracy is not much different, with an output of 93.13%. In terms of other performance measurements such as Precision, Recall, and F1-Score, the Okta-net architecture also managed to achieve satisfactory results above 90%. The overall performance measurement results of the Okta-Net architecture are shown in Table 2 below.

TABLE III
PERFORMANCE MEASUREMENT RESULTS OF THE OKTA-NET ARCHITECTURE

Metric	Value (%)
Accuracy	93.13
Precision	91.60
Recall	92.28
F1-Score	91.54

Based on the results presented in Table 2, it can be concluded that the Okta-net architecture has succeeded in achieving good performance and can be used for automatic classification of batik images. This is evidenced by the almost absence of underfitting and overfitting in testing the batik images. In addition, this argument is also supported by the low loss obtained by the Okta-net architecture, which is precisely below 0.12%.

However, accuracy measurements have weaknesses in terms of their inability to provide information about the type of errors by the model, such as false positives or false negatives. This can make it difficult to identify and correct possible problems. To address this issue, this paper also involves a confusion matrix-based performance evaluation. Confusion matrix is used to describe the performance of a classification model by comparing the model prediction results with the actual labels from the data. It provides more detailed information about the performance of a classification model than using accuracy alone. Furthermore, the confusion matrix can provide a direct picture of the model's performance on the test dataset, helping in identifying the extent to which the model can make correct predictions and identify class patterns.

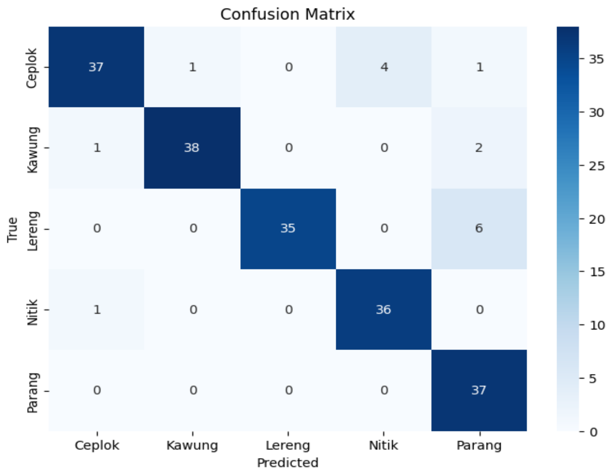

Fig. 6 Confusion Matrix of Proposed Okto-Net Architecture

Based on the Figure 7 depiction of the confusion matrix of the proposed model, of the five existing classes, the Okto-net architecture perfectly recognizes the batik image for the Parang class. As for the other two classes (nitik and kawung), only minor errors occur which are considered negligible because of only a few classification errors. Some difficulties occurred with the classification of lereng and ceplok classes due to the considerable error rate. The trained deep learning model failed to correctly classify the image for lereng class as the parang class. As for the ceplok class, there were several misidentifications, with one image identified as kawung class, four nitik class and one parang class. Based on the analysis, this misclassification can be caused by the unequal number of samples owned by each class, known as an imbalanced dataset. In future research, one solution that can be done is to homogenize the size of the dataset for each class to avoid such drawbacks. In addition, the application of different modes of pre-processing, data augmentation, and resampling can also be applied as another solution.

Following a discussion of the suggested Okta-net architecture's performance in terms of accuracy and confusion matrix, performance benchmarking will be conducted against relevant research. This benchmark will involve comparisons and analysis to establish whether the paper has succeeded in outperforming other current studies as a conclusion. The benchmarking results are compiled in Table 3.

TABLE III
THE BENCHMARKING RESULTS

Dataset	Class	Architecture	Accuracy (%)
900 images	5 classes	VGG-19 [14]	89.3
7,112 images	11 classes	Novel Architecture (IncRes) [13]	70.84
2,092 images	5 classes	VGG-16 [16]	89
967 images	11 classes	Novel Architecture [15]	56
120 images	3 classes	ResNet152 [17]	84.08
		DenseNet121 [17]	85
		VGG-16 [17]	85.50
300 images	50 classes	VGG-16 [18]	97.58
500 images	5 classes	VGG-16 [19]	98.96
4,284	5 classes	an improved Okta-Net	93.79

Based on the compiled results in Table 3, there are only two studies that propose new architectures. Unfortunately, these two studies have not managed to acquire satisfactory classification results. Research conducted by Wicaksono et al [13] managed to get only 70.84% accuracy. Meanwhile, Tristanto et al [15] obtained a much lower performance with an accuracy rate of 56%. Furthermore, other studies generally apply pre-trained CNN architectures such as VGGNet and ResNet. On the other hand, two studies obtained higher accuracy than the proposed Okta-net architecture. However, these studies, Arsa et al [18] and Hasanah et al [19], have limitations in terms of the use of images in their datasets (significantly smaller number of images). Such research requires to be tested on a larger number of images per dataset to ensure its robustness for a reliable automatic batik image classification. Therefore, it is almost conclusive (bare the minor modifications for future works) that the proposed Okta-net architecture is capable of an automatic classification for batik images.

IV. Conclusion

This paper demonstrated a state-of-the-art automatic batik image classification with a novel an improved CNN framework called Okta-Net. An automatic classification model of batik images is required because manually classifying batik patterns is time-consuming, laborious, and prone to human errors. Through a series of experiments, the proposed Okta-Net architecture has achieved satisfactory results with an accuracy of 93.17%, Precision of 91.60%, Recall of 92.28%, F-1 Score of 91.54% and a loss of 0.12%. In addition, based on the comparison of the benchmarking results, the performance of Okta-Net has outperformed most of the previous studies, the majority of which have an accuracy below 90%. However, even though this proposed architecture has obtained outstanding results, there are still some issues, mostly related to using imbalanced data. Of the five classes tested, there are two classes with considerable prediction errors. In the future, the application of appropriate pre-processing techniques, data augmentation, and resampling will be applied as another solution for a much more robust and reliable framework. In addition, the use of feature optimization algorithms such as Principal Component Analysis (PCA) [2], [31] and Artificial Bee Colony [32], [33] is worth investigating for their integration into the model, mainly to simplify the complexity of the data to speed up the training of classification models.

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