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Performance Comparison Between LeNet And MobileNet In Convolutional Neural Network for Lampung Batik Image Identification

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Abstract.
Purpose: The rich cultural heritage of Indonesia includes the intricate art of batik, which varies across regions with unique patterns and motifs. This study focuses on Lampung batik, a distinctive type of batik, representing Lampung Province, Indonesia. Leveraging Convolutional Neural Network (CNN) architectures, namely LeNet-5 and MobileNet, the research compares their effectiveness in recognizing and classifying Lampung batik motifs. Data augmentation techniques, including rotation, brightness, and zoom, were employed to enhance the dataset and improve model performance.
Methods: The study collected 500 Lampung batik images categorized into 10 classes which were then augmented and divided into training, validation, and testing sets. The model was created using a Deep Learning approach, LeNet And MobileNet. Both models were trained using identical hyperparameters and evaluated based on their accuracy in classifying Lampung batik motifs.
Results: The results demonstrate an accuracy of 99.33% for LeNet-5 and 98.00% for MobileNet, outperforming previous studies. LeNet-5, particularly with augmentation, exhibited superior precision and recall in classifying Lampung batik motifs. This research underscores the efficacy of CNN architectures, coupled with data augmentation techniques, in accurately identifying intricate cultural artifacts like Lampung batik.
Novelty: The Dharmagita learning model using a mobile application is a new model that has not existed before.

Keywords: Lampung batik, Convolutional neural network, LeNet, MobileNet
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INTRODUCTION

Indonesia, as a country rich in cultural heritage, boasts a diverse cultural wealth, including the art of batik [1]–[6]. Indonesian batik features various motifs that reflect the cultural richness of different regions in the country [7]–[12]. Each region has its uniqueness in terms of patterns, colors, and motifs, which serve as distinctive identities. One of the intriguing types of batik is Lampung batik, which symbolizes the richness of batik motifs that represent the distinctive identity of Lampung Province [13], [14]. To further introduce and identify this cultural wealth, it is essential to employ technology capable of efficiently and accurately processing batik images. Augmentation techniques are employed in the research to increase the quantity of datasets used in the study and achieve better results [15]–[17] as the goal.

There are several past research addressing the same problem of batik patterns classification, for example Deep Learning approach [18]. Deep Learning(DL)as AI technology (Artificial Intelligence) which became a hot topic, and many creating a detection of objects, faces, and several other types of health innovation development [19]. In this context, Convolutional Neural Network (CNN) has garnered attention for its ability to recognize patterns in visual images such as pictures [20]. Convolutional Neural Network (CNN) is the most widely used approach in various studies for the task of detecting and classifying [21]. CNN has been successfully applied in various fields, including pattern recognition in batik motifs [22]–[24]. Deep learning CNN is considered a promising approach to cirrhosis detection due to its ability to outperform traditional methods and provide accurate predictions [25]. CNN architectures, such as LeNet and MobileNet, have proven effective in recognizing complex patterns in visual data. LeNet architecture, first developed in the late 1990s, has made significant contributions to pattern recognition,

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while MobileNet, designed specifically for mobile devices, offers high efficiency and speed in image processing [26].

Figure 1. Lampung batik

Several previous studies have revealed the potential of LeNet and MobileNet architectures in object recognition in various domains, ranging from doodle recognition and wood species identification to leaf disease detection in rice plants. However, their implementation in identifying batik motifs, particularly Lampung batik, remains an intriguing area for investigation. Therefore, this study aims to compare the performance of both CNN architectures in recognizing and classifying Lampung batik motifs, with the hope of providing a clear understanding of the accuracy and efficiency levels of each architecture in identifying this unique Indonesian cultural heritage [27]. The image of Lampung batik can be seen in Figure 1.

METHODS

This research applies the research methodology shown in Figure 2.

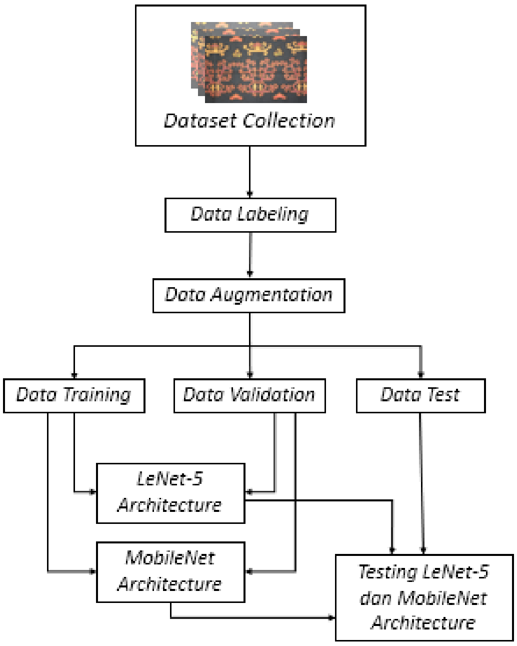


Figure 2. Research methods

The first stage conducted in the research involved the collection of a dataset for the study. A total of 500 Lampung batik images were gathered, and categorized into 10 classes. The images were stored in Google Drive to facilitate easy access and usage of data in Google Colab. Additionally, the Lampung batik images were also stored on the Tesla computer. Each Lampung batik image was stored in separate folders, each labeled according to the respective class of the dataset, as indicated in the folder names. At the beginning of the process, the machine would read both the Lampung batik images and the class names specified in each folder.

Data labeling is a crucial phase in the development of deep learning models. Data must be appropriately labeled or annotated to enable the model to comprehend and learn existing patterns. Data labeling involves the process of tagging or categorizing each data element, such as images, text, or sound, with labels that reflect the information the model needs to learn.

Data augmentation is employed to prevent overfitting and introduce diversity in the training data. This study used rotation, brightness, and zoom techniques, resulting in 500 additional images. Lampung Batik images were augmented using a rotation technique with a range of 90 degrees. This technique aims to generate new data variations by rotating objects within the images, intending to train or enhance the model's performance in object recognition or image processing. Lampung Batik images were augmented using the brightness technique with a range of 0.05 to 2.0. The primary objective is to enhance the visual quality or adjust the image lighting to align with user preferences. Lampung Batik images were augmented using the zoom technique with a range of 10%. The purpose is to modify the relative size of objects in the image without altering proportions or other essential aspects.

The images were resized to 224 x 224 pixels to maintain a balance between computational load and information retention. The augmented images were integrated with the original dataset, totaling 1000 images for model training and testing can be seen in Table 1. While three common augmentation techniques were applied, using too many could escalate computational complexity.

Table 1. Total dataset with augmentation data

No.	Class Name	Number of Datasets
1	Batik Granitan	100
2	Batik Jung Agung	100
3	Batik Kembang Cengkih	100
4	Batik Sekar Jagat	100
5	Batik Sembagi	100
6	Batik Siger Ratu Agung	100
7	Batik Kambil Sicukil	100
8	Batik Tambal	100
9	Batik Sinaran	100
10	Batik Abstrak	100
	Total	1000

The data was divided into three main parts: training data, validation data, and test data, with a split of 70% for training, 15% for validation, and 15% for testing. The primary objective of this division was to ensure sufficient data for effective training, adequate validation for model tuning, and reliable testing to measure final performance.

The training process involved the utilization of two main models, namely LeNet-5 and MobileNet, with a dataset comprising 500 Lampung batik images. The data training process was conducted using the Google Colab tool, the Tesla K80 machine, and several hyperparameters, including epoch, batch size, optimizer, and learning rate. Both models were set to use the same hyperparameters to ensure a comparable evaluation. The specific values of the employed hyperparameters can be found in Table 2.

Table 2. Hyperparameters

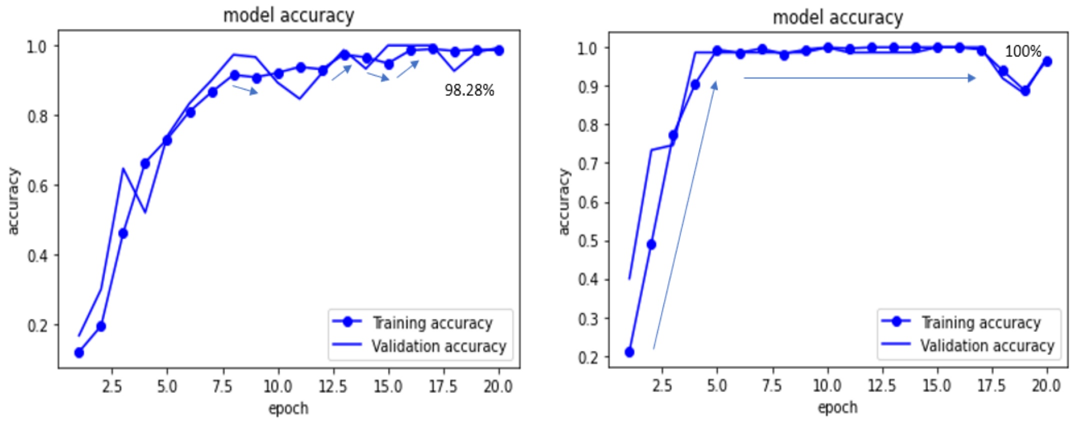
Hyperparameters	Value
Epoch	20
Batch-size	32
Optimizer	Adam
Learning-rate	0,001

The combination of hyperparameters employed in this study was derived from experiments utilizing several techniques from the Keras callbacks library, such as ReduceLROnPlateau and EarlyStopping. ReduceLROnPlateau is a deep learning technique used to decrease the learning rate when the model's training experiences stagnation or a slowdown in performance improvement, while EarlyStopping is a technique used to automatically halt the training when there is no performance improvement over the validation data for several epochs (training iterations). ReduceLROnPlateau and EarlyStopping were used to assist in determining the learning rate and the number of epochs, whereas the batch size was determined based on experiments yielding the best performance.

After training the LeNet and MobileNet models with the specified hyperparameters, the next step is testing the models. The evaluation stage of the architecture involved using the acquired test data and was conducted after the model training on the training and validation data was completed. The classification results were recorded and subsequently compared in the following stage.

RESULTS AND DISCUSSIONS

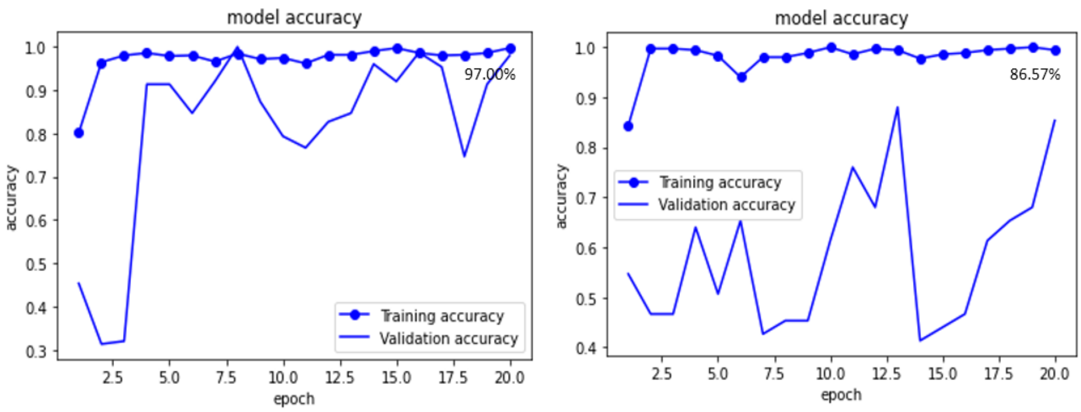
This section outlines the results and discussion of the motif classification process in Lampung batik using the CNN architectures LeNet-5 and MobileNet. The analysis and evaluation results of the classification process and implementation are elucidated in this section. The main focus of this chapter is the accuracy results and model evaluation for each Lampung batik motif.



(a) **(b)**

Figure 2. Graph comparing the accuracy levels of the LeNet-5 architecture

Figure 2 illustrates the accuracy graph during the training of the LeNet-5 model with and without augmentation categories. Figure 2a depicts a steadily increasing accuracy level in the LeNet-5 model with augmentation, with a slight decrease and subsequent rise. The training data achieved an accuracy rate of 98.28%. In contrast, Figure 2b shows a significant increase in accuracy in the LeNet-5 model without augmentation, indicating overfitting during the training process, with the training data reaching an accuracy rate of 100%.



(a) **(b)**

Figure 3. Graph comparing the accuracy levels of the MobileNet architecture.

Figure 3 displays the accuracy graph during the training of the MobileNet model with and without augmentation categories. In Figure 3a, the accuracy level is shown to be unstable in the MobileNet model with augmentation, with training data achieving an accuracy rate of 97.00%. Meanwhile, Figure 3b depicts the accuracy level of MobileNet without augmentation, where the training data attained an accuracy rate of 86.57%.

The testing accuracy of the LeNet-5 model for classifying Lampung batik motifs on the Tesla K80 machine is 99.33%. Testing the LeNet-5 model was done with data augmentation using rotation, brightness, and zoom techniques. Information regarding the confusion matrix values for the classification of Lampung batik motifs using LeNet-5 can be found in Table 3.

Table 3. LeNet-5 confusion matrix

No.	Batik Class	Results		
		Precision (%)	Recall (%)	F1-score (%)
1	Batik Sinaran	100	100	100
2	Batik Sembagi	100	100	100
3	Batik Abstrak	100	100	100
4	Batik Jung Agung	94.00	100	97.00
5	Batik Granitan	100	100	100
6	Batik Siger Ratu Agung	100	100	100
7	Batik Kembang Cengkih	100	100	100
8	Batik Kambil Sicukil	100	100	100
9	Batik Tambal	100	100	100
10	Batik Sekar Jagat	100	93.00	97.00
	Accuracy (%)		99.33	
	Error (%)		0.67	

Table 3 displays precision, recall, and f1-score values for the LeNet architecture utilizing augmentation on the Tesla K80 machine. Almost all classes exhibit excellent precision values, reaching 100%, except for the Batik Jung Agung class, which has the lowest precision at 94.00%. Precision indicates how reliable the model is in identifying samples correctly predicted as a positive class (TP) out of all samples predicted as the positive class (TP and FP). The recall values reach 100% for nearly all classes, except for the Batik Sekar Jagat class, which has the lowest recall at 93.00%. Recall depicts how reliable the model is in identifying samples correctly predicted as the positive class (TP) out of all actual positive samples (TP and FN).

The testing accuracy of the MobileNet model for classifying Lampung batik motifs on the Tesla K80 machine is 98.00%. Testing the MobileNet model was done with data augmentation using rotate, brightness, and zoom techniques. Information regarding the confusion matrix values for the classification of Lampung batik motifs using MobileNet can be found in Table 4.

Table 4. MobileNet confusion matrix

No.	Batik Class	Results		
		Precision (%)	Recall (%)	F1-score (%)
1	Batik Sinaran	100	94.00	97.00
2	Batik Sembagi	100	100	100
3	Batik Abstrak	96.00	92.00	94.00
4	Batik Jung Agung	89.00	100	94.00
5	Batik Granitan	100	100	100
6	Batik Siger Ratu Agung	100	100	100
7	Batik Kembang Cengkih	100	100	100
8	Batik Kambil Sicukil	100	100	100
9	Batik Tambal	100	100	100
10	Batik Sekar Jagat	100	100	100
	Accuracy (%)		98.00	
	Error (%)		2.00	

Table 4 presents precision, recall, and f1-score values for the MobileNet architecture with augmentation. All Batik classes, except for Batik Abstrak and Batik Jung Agung, achieve the highest precision values of 100%. Batik Abstrak and Batik Jung Agung have the lowest precision values at 96.00% and 89.00%, respectively. The Batik Sinaran and Batik Abstrak classes exhibit the lowest recall values, at 94.00% and 92.00%, respectively. Recall illustrates how reliable the model is in identifying samples correctly predicted as the positive class (TP) out of all actual positive samples (TP and FN).

The results of this research yield an accuracy of 99.33% with the LeNet-5 architecture and 98.00% with the MobileNet architecture. This proves that both architectures in this research produce better results than previous studies, which achieved batik detection using k-NN at 97.96% and batik detection using DenseNet at 94% [7], [28]. From the aforementioned points, it is evident that this research has advantages, namely producing more accurate accuracy with a larger number of dataset classes, specifically 10 compared to previous studies using 4 to 6 dataset classes.

CONCLUSION

The identification of Lampung batik using LeNet-5 and MobileNet architectures was successfully achieved with the addition of data augmentation techniques such as rotation, brightness, and zoom. LeNet-5 demonstrated the highest accuracy, reaching 99.33%, while MobileNet achieved an accuracy of 98.00% on the Tesla K80 machine. LeNet-5, with the application of augmentation techniques, particularly rotation, brightness, and zoom on the Tesla K80 machine, achieved the highest precision and recall in predicting Lampung batik classes accurately. The research results indicate an average recall value of 99.30% and an average precision value of 99.40%. Despite having more learning parameters than MobileNet, LeNet-5 exhibited superior accuracy with data augmentation, showcasing its performance efficiency for the Lampung batik dataset.

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