Lampung Batik Classification Using AlexNet, EfficientNet, LeNet and MobileNet Architecture

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***Abstract*—This study explores the application of image recognition technology based on Convolutional Neural Network (CNN) to classify Lampung batik motifs. Four CNN architectures are employed, namely AlexNet, EfficientNet, LeNet, and MobileNet. The dataset consist of ten motif classes, including Siger Ratu Agung, Sembagi, Jung Agung, Kembang Cengkih, Granitan, Abstract, Sinaran, Tambal, Kambil Sicukil, and Sekar Jagat. It comprises a total of 1000 images of Lampung Batik motifs, which were enhanced using preprocessing techniques such as rotation, shifting, brightness adjustment, and zooming. The classification results show that AlexNet achieves an accuracy of 95.33%, EfficientNet achieves 98.00%, LeNet achieves 99.33%, and MobileNet achieves 98.00%. The best accuracy result was achieved by the LeNet architecture, attributed to its suitability for small datasets. While some classification errors occurred due to similarities in patterns and variations in image positions, employing more advanced methods to better distinguish between similar motifs could address these challenges. This study highlights the effectiveness of CNN architectures in supporting the recognition of Lampung Batik motifs, contributing to the understanding and preservation of Indonesia's cultural heritage.**

***Keywords*—Lampung Batik; image classification; convolutionl neural network; AlexNet; EfficientNet; LeNet; MobileNet**

I. Introduction

Batik is a fundamental part of Indonesia's cultural identity and has been officially recognized by UNESCO as part of the nation's rich cultural heritage. This traditional art form is created through a unique process involving the application of wax and canting to produce intricate patterns on cloth, resulting in works of art with high aesthetic and cultural value [1]. Each region in Indonesia presents its cultural philosophy through different batik motifs, including Lampung Batik. Lampung Batik motifs include images of people, animals, sea creatures, buffaloes, elephants, ships, houses, trees of life and supporting elements such as coffee leaves, cloves, pepper and betel leaves, representing Lampung's cultural identity [2].

However, despite its cultural significance, recognizing Lampung Batik motifs based on their colour, pattern, and texture remains challenging for the human eye, especially when motifs share similar visual elements. This difficulty underscores the importance of employing technology to simplify identification, enabling broader public access to knowledge about Lampung Batik motifs and aiding in their preservation.

In recent years, advancements in computer vision, particularly Convolutional Neural Networks (CNN), have offered robust solutions for image classification tasks. CNN use artificial neural networks to process and analyze images, producing significant results in digital image recognition [3][4]. Numerous CNN architectures have been developed, such as AlexNet, EfficientNet, LeNet, and MobileNet, each with unique advantages [5]. AlexNet is a breakthrough that has combined ConvsNet and dropout regularization techniques [6]. Another architecture is EfficientNet, a CNN model developed by Google in 2019, specifically for object recognition or image classification. EfficientNet currently has eight models, from EfficientNet-B0 to EfficientNet-B7, with increasingly higher levels of accuracy [7] [8]. LeNet is a convolutional neural network (CNN) architecture initially developed for image processing tasks. The architecture comprises six layers: three convolutional layers, two pooling layers, and one fully connected layer [9]. MobileNet uses a technique called separable convolution to reduce the number of model parameters [10].

Previous studies on regional batik image recognition have applied machine learning and deep learning techniques to identify distinct motifs from various regions in Indonesia. One approach used the AlexNet architecture to classify Lamongan batik motifs, achieving an accuracy of 98% on a dataset of 790 images divided into three categories [11]. The EfficientNet-B2 architecture, fine-tuned for optimal performance, was applied to classify Papuan batik motifs [12]. The dataset consisted of 213 images divided into four classes: Raja Ampat, Cendrawasih, Asmat, and Tifa Honai. This approach achieved an accuracy of 72%. Research on Lampung Batik classification has also explored machine learning approaches. One study employed the K-Nearest Neighbor (KNN) algorithm combined with the Gray Level Co-occurrence Matrix (GLCM) for feature extraction [13]. Using a dataset of 100 images divided into four categories with 25 images per class, the method achieved the highest accuracy of 97.96% with an orientation angle of 135° and k = 7. Another study expanded the dataset by including non-Lampung motifs, specifically Parang Kusumo and Parang Rusak, and utilized a backpropagation artificial neural network, achieving an accuracy of 92% [14].

However, existing studies on Lampung Batik motifs are limited by small and less diverse datasets and a need for more exploration into more advanced architectures or methods. This study explores the application of image recognition techniques using CNN architectures, including AlexNet, EfficientNet, LeNet, and MobileNet, for classifying Lampung Batik motifs. The dataset includes ten motif classes: Siger Ratu Agung, Sembagi, Jung Agung, Kembang Cengkih, Granitan, Abstract, Sinaran, Tambal, Kambil Sicukil, and Sekar Jagat. The study aims to investigate the potential of CNN-based image recognition in identifying Lampung Batik motifs, contributing to the understanding and preserving Indonesia's cultural heritage.

II. Research Method

This study uses the AlexNet, EfficientNet-B4, LeNet, and MobileNet architectures to classify Lampung Batik images with a dataset generated through augmentation techniques. The research process is detailed in Fig. 1.

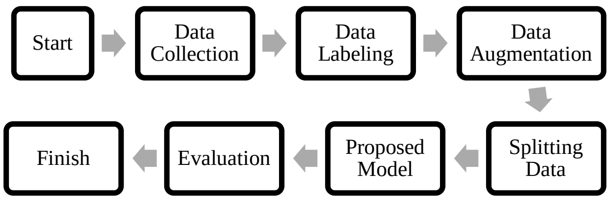

Fig. 1. Research method.

A. Dataset Collection

The dataset used is 1000 images of Lampung Batik motifs with ten classes. Images for each class are separated and saved in a folder named according to each class. The machine will then read the dataset at the beginning of the process, the images of Lampung Batik motifs, and the class names in each folder.

B. Data Labeling

Data labelling in a dataset is the process of adding information or labels to each example of data. This labelling functions to identify or categorize data so that machine learning or deep learning models can understand and process information more effectively. Labelling data in a dataset can involve different tasks, depending on the data analysis goals to be achieved [15].

C. Data Augmentation

This study employs data augmentation techniques such as rotation, shifting [16], and zooming, with the image size adjusted to 224 x 224 pixels. [17]. These augmentation techniques were selected to enhance dataset diversity by generating new variations of the existing dataset and altering objects' position, scale, and orientation [18].

D. Split Data

Data division is carried out by dividing the data into three primary subsets, namely training data, validation data, and test data. Training data is needed as the primary material for training data [19]. The training data itself takes up about 70% of the entire image. Data validation uses data equal to 15% of the whole picture. Test data is used to test a model's performance and success rate. The test data equals 15% of the entire image [20].

E. AlexNet, EfficientNet, LeNet, and MobileNet Architecture Training

The training model uses four architectures, namely AlexNet, EfficientNet, LeNet, and MobileNet, with a dataset of 100 images for each type of Lampung batik motif. Model training using hyperparameters such as epoch, batch size, and learning rate. The hyperparameter values used are in Table I.

TABLE I. Hyperparameters

Hyperparameter	AlexNet	EfficientNet	LeNet	MobileNet
Epoch	10	10	20	20
Batch-size	8	8	32	32
Optimizer	Adam	Adam	Adam	Adam
Learning-rate	0.0001	0.0001	0,001	0,001

Table I contains the hyperparameter values applied in this research. The hyperparameters in this study were determined through experimentation using various advanced callback libraries, including ReduceLROnPlateau and EarlyStopping [21]. ReduceLROnPlateau is a technique that reduces the learning rate when there is a stagnation or slowdown in performance improvement during the training process [22].

F. Evaluation

Performance evaluation in this study is a crucial stage to assess the effectiveness and accuracy of the developed model or algorithm [23]. This process evaluates how effectively the model can accurately predict unseen test data. Metrics such as F1-score, precision, accuracy, and recall are used to measure its performance [24].

III. Result and Discussion

This section presents the results and analysis of Lampung Batik image classification using CNN and explains the evaluation and implementation of the classification process. This section reviews the model's accuracy and evaluation metrics for Lampung Batik image recognition.

A. Dataset Collection

The dataset used in this research consists of 10 classes, each containing 100 images. The batik motifs can be seen in Fig. 2, and the diversity of each motif can be seen in Fig. 3.

B. Dataset Augmentation

The original dataset, consisting of 50 images per class stored in Google Drive, was expanded through augmentation techniques, including rotation, shifting, brightness adjustment, and zooming. These augmentations were applied with specific parameters: a 100° rotation, a 0.1 shift, brightness ranging from 0.05 to 2.0, and a 20% zoom. As a result, the dataset increased to 100 images per class. The final number of images for each class after augmentation is presented in Table II.

Fig. 2. Lampung Batik motifs.

Fig. 3. Lampung Batik motifs diversity.

TABLE II. DATASET AUGMENTATION LAMPUNG BATIK

Name Class	Amout Dataset
Batik Sembagi	100
Batik Granitan	100
Batik Jung Agung	100
Batik Sekar Jagat	100
Batik Siger Ratu Agung	100
Batik Kambil Sicukil	100
Batik Kembang Cengkih	100
Batik Sinaran	100
Batik Tambal	100
Batik Abstrak	100

C. AlexNet Achitecture Model

The AlexNet architectural model has 11 layers, consisting of five convolution layers, three max-pooling layers, two fully connected layers, and one output layer [25]. AlexNet is a CNN architecture that emphasizes the depth of its model, with training parameters reaching 70 million [26]. The dataset is fed to the first layer and read by the model. Multiple image samples are processed in a convolutional layer. The convolution layer functions to retrieve and help the model understand the characteristics of Lampung Batik motifs by using filters and the ReLu activation function. The filters in the convolution layer are matrix arrays that help adjust the image pixel values to fit the model. The ReLU activation function converts negative pixel values to zero while leaving positive pixel values unchanged. The pooling layer in this model is tasked with extracting essential features from the previous layer (convolution layer) [27]. AlexNet uses max-pooling as the pooling layer type. The fully connected layer in this model connects one feature to another of the Lampung Batik motif image. The connected features will be arranged to form a pattern that matches the arrangement of the features. Subsequently, the resulting output will be processed using softmax activation to determine the prediction of the image to one of the ten classes of Lampung Batik motifs.

D. EfficientNet Architecture Model

The EfficientNet-B4 architecture has a different type and number of layers than AlexNet, with only about 17 million parameters. The layers in EfficientNet-B4 consist of MBConv, an advancement of the layers used in the MobileNet architecture. The EfficientNet-B4 architecture consists of 10 blocks forming its primary structure, which includes fully connected, where this block is responsible for extracting abstract features in images [28]. The output from the previous block process will be processed and added with average pooling and flattening, which then results in a one-dimensional array or allows the model to recognize objects and patterns so that classification of Lampung Batik images is obtained in the form of classes of Lampung Batik motifs.

E. LeNet Architecture Model

LeNet-5 is a CNN-based multilayer network that represents an advancement over earlier versions of LeNet. It features additional layers and more adjustable parameters compared to its predecessors, enhancing its capacity for feature extraction and learning [29]. LeNet-5 has six layers: the input layer that receives the image, two convolutional layers for extracting features in the image, two pooling or subsampling layers for reducing image dimensions by half, and fully-connected layers. LeNet-5 is often used in more complex pattern recognition, such as facial or object recognition.

F. MobileNet Architecture Model

MobileNet Architecture is designed to provide high performance with limited power sources [30]. This architecture uses Depthwise Separable Convolution to reduce the parameters and calculations required to train and run the model. MobileNet can provide comparable or even more performance in some tasks with small model sizes and slight complexity. MobileNet architecture comprises an input layer, a standard convolutional layer, depthwise separable convolutional layers, a fully connected layer, and an output layer.

G. Model Evaluation

Evaluation of the AlexNet, EfficientNet, LeNet, and MobileNet architectural models to classify Lampung Batik images using precision, recall, accuracy and F1-score values.

Table III presents the precision, recall, and f1-score values for the AlexNet architecture. Each class has an excellent precision value, namely reaching 100%, except for the Kembang Cengkih, Batik Tambal, Batik Jung Agung, and Batik Kambil Sicukil classes; the Kembang Cengkih Batik class has the lowest precision value, namely 62.00%. The recall value reached 100% in each class, except for the Kembang Cengkih Batik, Garnitan Batik and Sekar Jagat Batik classes. The Kembang Cengkih Batik class has the lowest recall value, 62.00%.

Table IV presents the EfficientNet performance, where all batik classes achieved a precision score of 100%, except for the Batik Kambil Sicukil and Batik Jung Agung classes. The Jung Agung Batik class has the lowest precision value, 80.00%. The Kambil Sicukil Batik class has the lowest recall value, 93.00%. The Kambil Sicukil Batik class has a precision value of 92.86%. This was caused by 1 FP value occurring in the Kambil Sicukil Batik class, which should have been included in the Jung Agung Batik class. The model predicts incorrectly because there are similarities in the Jung motif pattern found in Batik Kambil Sicukil and Batik Jung Agung.

TABLE III. CONFUSION MATRIX ALEXNET ARCHITECTURE

Batik Motif Class	Results Model		
	Precision	Recall	F1-score
Batik Sembagi	100%	100%	100%
Batik Siger Ratu Agung	100%	100%	100%
Batik Granitan	100%	96.00%	98.00%
Batik Kambil Sicukil	94.00%	100%	97.00%
Batik Tambal	82.00%	100%	90.00%
Batik Sinaran	100%	100%	100%
Batik Jung Agung	93.00%	100%	97.00%
Batik Kembang Cengkih	62.00%	62.00%	62.00%
Batik Abstrak	100%	100%	100%
Batik Sekar Jagat	100%	80.00%	89.00%
Accuracy		95.33%	
Error		4.67%	

TABLE IV. CONFUSION MATRIX EFFICIENTNET ARCHITECTURE

Batik Motif Class	Results Model		
	Precision	Recall	F1-score
Batik Sembagi	100%	100%	100%
Batik Siger Ratu Agung	100%	100%	100%
Batik Granitan	100%	94.74%	97.30%
Batik Kambil Sicukil	92.86%	93.00%	92.93%
Batik Tambal	100%	100%	100%
Batik Sinaran	100%	100%	100%
Batik Jung Agung	80.00%	100%	88.89%
Batik Kembang Cengkih	100%	93.75%	96.67%
Batik Abstrak	100%	100%	100%
Batik Sekar Jagat	100%	80.00%	89.00%
Accuracy		98.00%	
Error		2.00%	

TABLE V. CONFUSION MATRIX LENET ARCHITECTURE

Batik Motif Class	Results Model		
	Precision	Recall	F1-score
Batik Sembagi	100%	100%	100%
Batik Siger Ratu Agung	100%	100%	100%
Batik Granitan	100%	100%	100%
Batik Kambil Sicukil	100%	100%	100%
Batik Tambal	100%	100%	100%
Batik Sinaran	100%	100%	100%
Batik Jung Agung	94.00%	100%	97.00%
Batik Kembang Cengkih	100%	100%	100%
Batik Abstrak	100%	100%	100%
Batik Sekar Jagat	100%	93.00%	97.00%
Accuracy		99.33%	
Error		0.67%	

Table V presents the LeNet performance, where Batik Jung Agung has the lowest precision value of 94.00%, and the other classes achieve a precision value of 100%. The recall value for the Batik Sekar Jagat class has the lowest recall value, 93.00%, while the other classes get a recall value of 100%.

TABLE VI. CONFUSION MATRIX MOBILENET ARCHITECTURE

Batik Motif Class	Results Model		
	Precision	Recall	F1-score
Batik Sembagi	100%	100%	100%
Batik Siger Ratu Agung	100%	100%	100%
Batik Granitan	100%	100%	100%
Batik Kambil Sicukil	100%	100%	100%
Batik Tambal	100%	100%	100%
Batik Sinaran	100%	94.00%	97.00%
Batik Jung Agung	89.00%	100%	94.00%
Batik Kembang Cengkih	100%	100%	100%
Batik Abstrak	96.00%	92.00%	94.00%
Batik Sekar Jagat	100%	100%	100%
Accuracy		98.00%	
Error		2.00%	

Table VI presents the MobileNet performance, where Batik Abstract gets a precision value of 96.00%, and Batik Jung Agung gets the lowest precision value of 89.00%. In comparison, the other classes get a precision value of 100%. For the recall value, the Batik Sinaran class gets 94.00%. Batik Abstract records the lowest recall value of 92.00%, except for Batik Sinaran and Batik Abstract, all classes get a recall value of 100%.

H. Performance Comparison Between Architectures

The differences among the four architectures can be seen in Table VII. AlexNet is an 11-layer architecture with 70 million parameters for processing complex features. EfficientNet, on the other hand, consists of 10 blocks that form its primary structure, with a total of 17 million parameters to ensure efficient computation. LeNet comprises 6 layers, including an input layer for receiving images, two convolutional layers for extracting features, two pooling layers for reducing image dimensions, and fully connected layers for classification. MobileNet includes input layers, convolutional layers, depth-separable convolutional layers, fully connected layers, and output layers to support lightweight computations. MobileNetV1 contains 28 layers, incorporating depth-separable convolutions, whereas MobileNetV2 improves upon this with 53 layers, introducing inverse residuals and linear bottlenecks to enhance efficiency and performance on mobile and embedded devices.

In addition, Table VII presents an accurate comparison between the four architectures. LeNet achieves the highest accuracy for Lampung Batik classification by effectively extracting essential features through convolution and pooling layers, which preserve the spatial information crucial for image recognition. In previous Lampung Batik studies, LeNet outperforms KNN and Backpropagation due to its efficiency in recognizing patterns and resistance to overfitting. Unlike KNN, which only measures distances in feature space, and Backpropagation, which flattens images and loses spatial information, LeNet delivers superior performance for image classification tasks. Therefore, this study addresses the limitations of smaller and less diverse datasets in previous research by exploring four CNN architectures and employing augmentation techniques to enhance dataset quantity and accuracy.

TABLE VII. RESULT COMPARISON BETWEEN ARCHITECTURES

Architecture	Layer	Parameters	Accuracy
AlexNet	11	70m	95.33%
EfficientNet	10	17m	98.00%
LeNet	6	60k	99.33%
MobileNet	53	3.4m	98.00%

IV. CONCLUSION

The study concludes that the AlexNet, EfficientNet, LeNet, and MobileNet architectures effectively classify ten Lampung Batik motif classes, including Siger Ratu Agung, Sembagi, Jung Agung, Kembang Cengkih, Granitan, Abstract, Sinaran, Tambal, Kambil Sicukil, and Sekar Jagat. The accuracy achieved by AlexNet is 95.33%, EfficientNet-B4 is 98.00%, MobileNet is 98.00%, and LeNet achieves the highest accuracy at 99.33%. The dataset was enhanced using augmentation techniques, including rotation, shifting, brightness adjustment, and zooming, to generate 1000 images to train and evaluate the models. However, the study is limited by the similarity of specific Lampung Batik motifs, occasionally leading to misclassification. Future research could leverage advanced architectures and methods to differentiate motifs with similar patterns better, further enhancing classification accuracy.

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