J-COSINE (Journal of Computer Science and Informatics Engineering)
Vol. 10, No. 1, June 2026 E-ISSN:2541-0806
Accredited Sinta-4 by RISTEKDIKTI Decree No. 79/E/KPT/2023 P-ISSN:2540-8895

Data Augmentation Optimization for Indonesian Batik Motif Classification Using Transfer Learning on Convolutional Neural Network

Nazmi Wardiani, Baiq Anggita Arsya Rahmatin, Syarif Hidayatullah, I Gede Pasek Suta Wijaya
Master of Information Technology, Mataram University
Jl. Majapahit 62, Mataram, Lombok NTB, INDONESIA
Email: nazmiwardiani@gmail.com, baiqanggitaarsyarahmatin@gmail.com, syarifhidaya1945@gmail.com, gpsutawijaya@unram.ac.id

Corresponding Author

Abstract **Batik is an Indonesian cultural heritage that has various distinctive motifs from various regions. However, manual classification of batik motifs often requires special skills and considerable time.1 To overcome this, the Convolutional Neural Network (CNN)-based classification method with the help of transfer learning is a promising solution. This research uses a dataset of 500 batik images consisting of 10 different motif classes, each class containing 50 images. Data augmentation techniques are applied to expand the variety of training data with transformations such as rotation, zoom, and flipping to reduce overfitting and improve the generalization ability of the model. The MobileNetV2 model was selected as the base model of transfer learning due to its efficiency and ability to extract features from limited data. Experiments show that the MobileNetV2 model with fine-tuning produces the highest classification accuracy of 86%, which is superior to conventional CNNs that achieve accuracies between 59% and 65%. As a result, the combination of data augmentation and transfer learning in MobileNetV2 proved to be effective in improving the accuracy and efficiency of batik motif classification on small data.**

***Key words*: Batik Classification, Data Augmentation, CNN, Transfer Learning, MobileNetV2.**

I. Introduction

Batik is an Indonesian cultural heritage that has been recognized by UNESCO, so its popularity is increasing globally. As Indonesians, we have the responsibility to preserve it. Batik is not only a symbol of national identity, but also represents a wealth of cultural values through its colors, patterns, and textures. This traditional fabric is made with special techniques using canting and wax, resulting in motifs of high artistic value that are full of philosophical meaning [1]. Currently, there are more than 5,000 batik motifs that have developed in various regions in Indonesia, such as the Parang, Kawung, and Pataruman motifs [2]. Each region has a different typical motif, but it is often difficult to distinguish because the knowledge of batik classification that is passed down from generation to generation is not always passed on to the next generation. Therefore, the development of batik classification methods is important as an effort to preserve and understand culture [3].

Manual classification of batik motifs tends to be subjective, it needs special skills, and requires a lot of time. Along with the development of artificial intelligence technology, especially in the field of computer vision, the Convolutional Neural Network (CNN) method has proven effective in image classification tasks due to its ability to automatically extract spatial features from images without the need for manual feature design. As one of the leading deep learning algorithms in image processing, CNN is able to recognize objects in images and learn important features automatically without the need for explicit identification at the initial stage [4]. CNN have been widely used in various image classification research studies, including batik images, and produce quite high performance [5], [6].

While the CNN model has great potential, the accuracy of the CNN model built from scratch for batik classification still has limitations, mainly because it is highly dependent on the amount and diversity of training data. In the context of batik image classification, dataset limitations as well as variations in image conditions, such as lighting, orientation and background, can significantly affect classification performance. The challenge in batik classification comes not only from the diversity of motifs that exist, but also from the highly variable image conditions. This is mainly due to the diverse sources of batik images, ranging from the internet to individual shots. The variation in image conditions further emphasizes the need for a strategy that is able to perform batik classification accurately and efficiently, without being affected by differences in image quality or condition [3].

To solve this, data augmentation techniques become very important. Data augmentation is a very important regularization technique in machine learning that is used to improve the generalization ability of the model. The main purpose of data augmentation is to increase the amount, quality of representation, and variety of the original data so that the model can learn more effectively and not overfitting, especially when the original data is limited or unbalanced [7]. Data augmentation expands the variety of training data by means of artificial image transformation, such as rotation, zoom, or brightness change, which can enrich the dataset and reduce the risk of overfitting. With this augmentation, models can be trained to better recognize patterns under a wide variety of image conditions.

In addition to the use of data augmentation techniques, transfer learning has an important role in improving the accuracy of batik image classification. Transfer learning is a technique in deep learning that utilizes a model that has been trained on a problem (source domain) to help solve another similar problem (target domain). With this approach, the model does not need to be built from scratch, so the training time is shorter and the results can be more optimal, especially when the training data in the target domain is limited [8]. In the implementation of transfer learning, there are various CNN models that are often used as a basis, including MobileNetV2 [9], VGG16[10], ResNet[11], and Inception [12]. The selection of an appropriate CNN model in transfer learning is highly dependent on specific needs, such as the availability of computing resources, the size of the dataset, and the complexity of the batik image classification task. By using this trained model, the training process on a new domain becomes faster and the results are more accurate.

In this research, MobileNetV2 was chosen as the transfer learning model due to its efficiency and training speed, suitable for the batik dataset which only contains about 500 images. MobileNetV2 uses depthwise separable convolution to reduce parameters without sacrificing accuracy. This pre-trained model on ImageNet is adapted through fine-tuning to suit the characteristics of batik datasets that vary in size and quality [9]. In addition, in this research, data augmentation techniques are used to artificially increase the variety of training data. The goal is for the model to learn from more examples despite the limited amount of original data, so that the risk of overfitting can be reduced. This research aims to optimize the use of data augmentation in batik motif classification with CNN and transfer learning methods using MobileNetV2. In this way, the model can better extract important features from limited and imbalanced data, making the training process more efficient and improving classification accuracy.

II. Literature Review and Basic Theory

A. Related Research

There have been many previous studies on batik classification. D. I. Mulyana and A. Akbar [13] f focused on Betawi batik, using K-Nearest Neighbors (KNN) and the Gray-Level Co-occurrence Matrix (GLCM) to classify 1,020 images into 12 classes, achieving an accuracy of 96%. Similarly, C. Irawan et al. [1] proposed a distinct approach by combining KNN with GLCM-based statistical and texture feature extraction for the classification of 300 batik motifs into 5 classes, also achieving an accuracy of 96%.

The above methods cannot automatically select features, but researchers who develop batik motif extraction features. To overcome this weakness, CNN can be a solution because it has the ability to determine features automatically. Batik classification using CNN has been done by Suthami et al. [14] conducted research on Lombok Songket and Sasambo Batik motifs using Convolutional Neural Networks (CNN) on 500 images, consisting of 20 songket motifs and 5 Sasambo batik motifs. Their results showed an accuracy of 83.85% in testing songket motifs and 93.66% in testing batik motifs. explored the effect of data augmentation in batik classification using techniques such as random noise, rotation, and flip on CNN and K-Nearest Neighbor (KNN) algorithms. They used 1,443 batik images divided into 4 classes, and the results showed that CNN produced higher accuracy (96.92%) compared to KNN (81.36%). C.U Khasanah et al. [2] applied advanced data augmentation techniques, such as Random Erasing and GridMask, in the use of VGG16 pre-trained CNN for the classification of five batik motifs using 550 images divided into 5 classes. This augmentation resulted in an accuracy of 96.88%. M. M. A. Wona et al. [15] developed a CNN model on 3,880 batik images divided into 14 classes. They augmented the image with techniques such as rotation (up to 45°), width shift, height shift, shear, zoom, horizontal flip, and fill mode, which resulted in an accuracy of 91.24%. Finally, Alya et al. [3] used transfer learning with pre-trained models such as VGG16 and Xception for the classification of five batik motifs. They achieved 91.23% accuracy, emphasizing the advantages of transfer learning in reducing training time and improving classification performance.

To highlight the novelty contribution of this research, a comparison with previous studies that classify batik motifs using CNN and transfer learning methods is made. The table I summarizes information related to the methods used, datasets, augmentation techniques, accuracy achieved, as well as the advantages and disadvantages of each study. The comparison results show that this study offers a more efficient approach with MobileNetV2 and diverse augmentation on small batik datasets, which has not been explored much in previous studies.

TABLE I. Table State of The Art

Ref	Method + Dataset	Accuracy	Key Strength / Novelty
[13]	KNN+GLCM, 1,020 images, 12 classes	96%	Simple method, high accuracy
[1]	KNN+GLCM, 300 images, 5 classes	96%	Combined statistical-texture features
[14]	CNN, 500 images, 25 motifs	93.66%	CNN feature extraction
[4]	CNN+KNN, 1,443 images, 4 classes	96.92%	Comparison between CNN and KNN
[2]	VGG16, 550 images, 5 classes	96.88%	Advanced augmentation with VGG16
[15]	CNN, 3,880 images, 14 classes	91.24%	Large dataset, extensive augmentation
[3]	VGG16 & Xception, 500 images, 5 classes	91.23%	Fast training using transfer learning

Ref	Method + Dataset	Accuracy	Key Strength / Novelty
This Study	MobileNetV2, 500 images, 10 classes	86%	Lightweight model, effective on small datasets

Based on these studies, the uniqueness of this research lies in the application of MobileNetV2, a lightweight convolutional neural network specifically designed to classify Indonesian batik motifs under limited data conditions. Unlike previous studies, which primarily utilized deeper architectures such as VGG16 or ResNet on large-scale datasets, this research highlights the effectiveness of MobileNetV2 in scenarios with limited and imbalanced training data conditions commonly encountered in local cultural datasets. By combining data augmentation techniques with transfer learning, this approach provides an efficient computational solution while maintaining competitive classification performance. To the best of our knowledge, few previous studies have systematically explored this combination for traditional pattern recognition, especially in the context of small-scale and culturally specific datasets.

B. Supporting Theory

B.1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a neural network architecture that is widely used in image processing due to its ability to extract features automatically without the need for manual feature engineering. CNN consists of several main layers such as convolutional, activation, pooling, fully connected, and output layer. Through convolution filters, CNNs can recognize local patterns such as edges and textures in images. Non-linear activation and pooling help reduce dimensionality and prevent overfitting. With the concept of weight sharing and efficient parameters such as stride and padding, CNNs become very effective for tasks such as image classification, object detection, and image segmentation [16].

B.2. Data Augmentation

Data augmentation is a technique to enlarge and enrich a dataset by generating synthetic data variations from existing samples without changing the original labels. This technique helps to overcome data limitations and improve the generalization ability of the model, as well as prevent overfitting [17]. Augmentation can be done at the single-sample level, techniques include single-sample methods (e.g., rotation, noise addition), multi-sample approaches (e.g., Mixup, CutMix), and dataset-level methods (e.g., GANs for generating realistic samples) [18].

B.3. Transfer Learning

Transfer learning is a machine learning approach in which knowledge gained from training a model in one domain—for example, a large dataset such as ImageNet is transferred for use in another domain that contains limited data, such as batik motif classification. This approach is particularly useful when the target domain, such as batik motif images, has a limited number of samples, making it difficult to train a model from scratch without overfitting. Transfer learning allows the utilization of initial features such as edge patterns, textures, and shapes that have been learned from large and general data (source domain), in order to accelerate and improve accuracy in a more specific domain (target domain) [19].

B.4. MobileNetV2

MobileNetV2 is a lightweight convolutional neural network architecture optimized for image classification and feature extraction. It combines convolution layers, inverted residual blocks, and depthwise separable convolutions to achieve high efficiency with minimal parameters. Its key innovation is the inverted residual structure, where input features are expanded, processed for spatial information, and then compressed, effectively reducing computational cost without sacrificing accuracy [20].

III. RESEARCH METHODOLOGY

A. Research Flow

The following is a flowchart that explains the flow of this research:

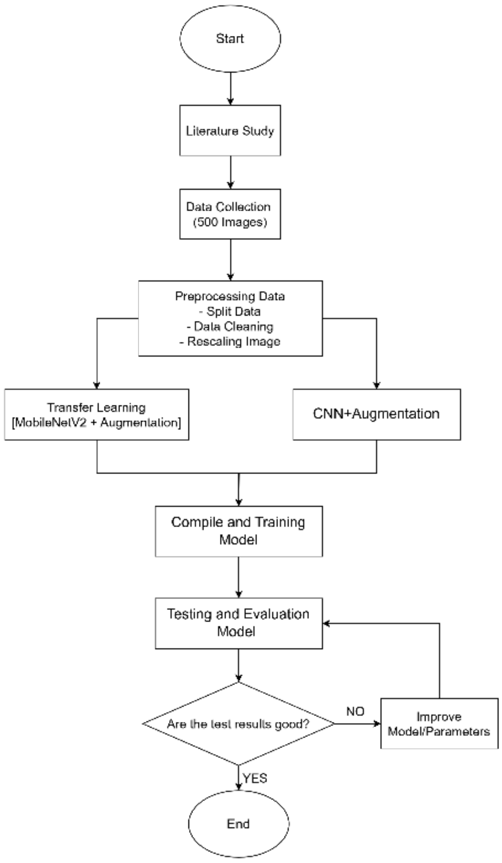

Fig. 1. System Flow

In Figure 1, the first stage in this research is a literature study, which aims to study various methods that have been used in similar research and compare the advantages and disadvantages of each approach.

The second stage is Data Collection, which is the process of collecting batik image datasets consisting of 10 classes of motifs representing various regions in Indonesia. The motifs are: Megamendung (West Java), Kawung and Keraton (Yogyakarta), Parang (Solo), Pala (Maluku), Boraspati (North Sumatra), Cendrawasih (Papua), Dayak (Kalimantan), Lumbung (NTB), and Lontara (South Sulawesi). Each class consists of 50 images in JPG format, resulting in a total of 500 images.

The third stage is Data Preprocessing, which is an initial processing stage that includes: separating data into training data and test data, cleaning data from duplication or invalid formats, and rescaling images to a uniform resolution to match the input layer in the CNN or transfer learning model.

The fourth stage of modeling is divided into two main approaches, the first approach is to build a custom CNN model from scratch by adding augmentation to determine initial performance, then the second approach is to use the Transfer Learning method with MobileNetV2 equipped with augmentation techniques as a performance comparison.

The fifth stage is Compile and Training Model, which is the process of compiling the network architecture and training the model using the training data. The model will be trained for a number of epochs to get the best weight based on accuracy and loss.

The sixth stage is Model Testing and Evaluation, which measures the performance of the model on test data that has never been seen before. Evaluation is done using metrics such as accuracy, precision, recall, and f1-score, as well as visualization of confusion matrix and prediction results. The last stage is the documentation stage, which takes documentation of the entire research from the beginning of the research to completion and is collected in the form of a report.

B. Model Building

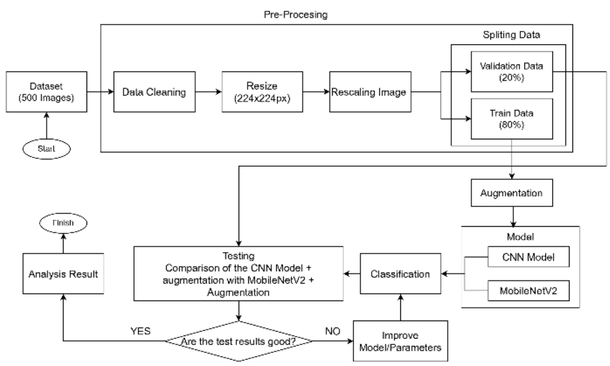

Fig. 2. Modeling Flow

Figure 2 is the flow of the model that will be made in this study which will be explained in the following points.

B.1. Dataset Collection

Capturing image datasets in this research is essential to provide the data needed in the training, testing, and evaluation process of the model. The model will learn from the available image data to automatically perform classification based on the recognized visual patterns. This research uses 500 batik images divided into 10 motif classes, where each motif represents a specific region in Indonesia, namely Megamendung (West Java), Kawung and Keraton (Yogyakarta), Parang (Solo), Pala (Maluku), Boraspati (North Sumatra), Cendrawasih (Papua), Dayak (Kalimantan), Lumbung (West Nusa Tenggara), and Lontara (South Sulawesi). Each class consists of 50 images in JPG format, resulting in a total dataset of 500 images. All of these datasets were obtained from the Hugging Face public repository, which is a community-based open-source platform for sharing datasets and models in the field of machine learning.

B.2. Dataset Preprocessing

B.2.1. Data Cleaning

The first data processing is data cleaning, data cleaning is done to ensure that all images in the dataset can be used in the training process without causing errors. This process involves checking and removing corrupted or unreadable image files. Images that are in error or out of format will be detected and removed from the dataset directory so as not to interfere with the model training process.

B.2.2. Resize

Resizing is applied to equalize image dimensions to 224×224 pixels to ensure input consistency, reduce computational and memory load, speed up the training process, and allow the model to efficiently handle images. Smaller image sizes help reduce noise and unimportant details, enabling the model to focus more on the most relevant features.

B.2.3. Rescaling Image

Rescaling is done with the aim of normalizing the image pixel values into a scale of 0 to 1. This is done using ImageDataGenerator. This process is important to speed up convergence during model training, avoid too large pixel values that can cause gradient exploding, and improve the stability of model performance during the training and validation process.

B.2.4. Spliting Data

The dataset was divided into two subsets, namely training data and validation data with a ratio of 80:20 using the splitfolders library. This division was done randomly and equally to ensure each class was proportionally distributed in both subsets.

B.3. Dataset Augmentation

Data augmentation is performed to increase the variety of training data without having to manually increase the amount of data. This augmentation technique helps the model learn better and avoid overfitting, especially when the dataset is small. This technique will generate new image variations that still represent the original class, such as rotating, enlarging, shifting, or reflecting the image horizontally. All augmentations are applied randomly during the model training process.

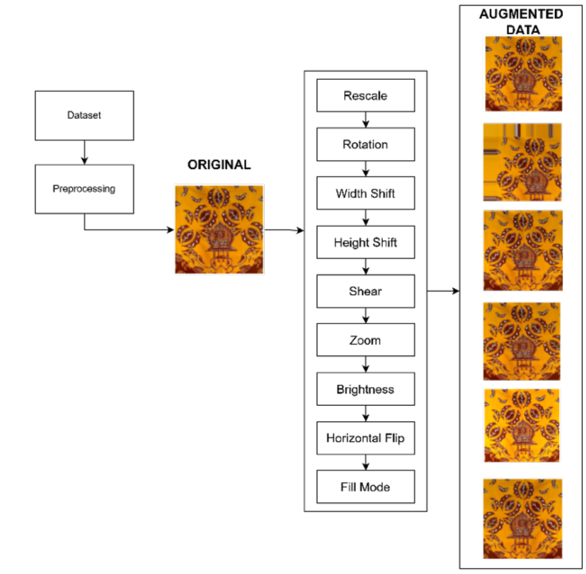

Fig. 3. Augmented Data

B.4. Classification

In the classification stage, the batik motif classification process is carried out based on the features that have been extracted through the deep learning model used. The two main models applied in this research are CNN (Convolutional Neural Network) and MobileNetV2.

B.4.1. CNN Model

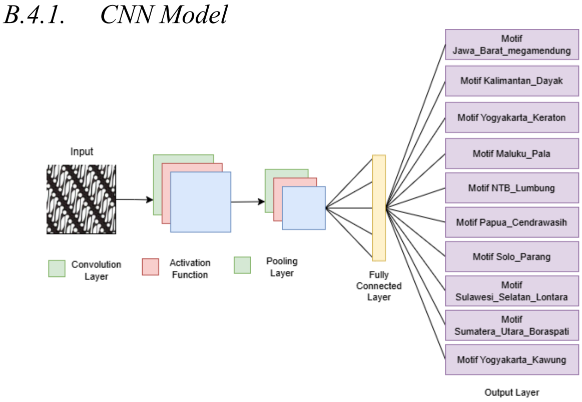

Fig. 4. Arsitektur CNN

The CNN model used has a multi-layered architecture consisting of several convolutional blocks followed by an activation function and a pooling layer. Figure 4 shows the overall CNN architecture, starting from an input image of a batik motif, then passing through a series of convolution layers in charge of extracting local features from the image. Each convolution layer is followed by an activation function that uses the LeakyReLU activation function to add non-linearity to the model so that it can recognize complex patterns. The pooling layer is then used to reduce the dimensionality of the features while preserving the important features obtained from the previous layer. After several layers of feature extraction, the results are processed in the fully connected layer which converts the features into output in the form of batik motif classes.

B.4.2. MobileNetV2 Model

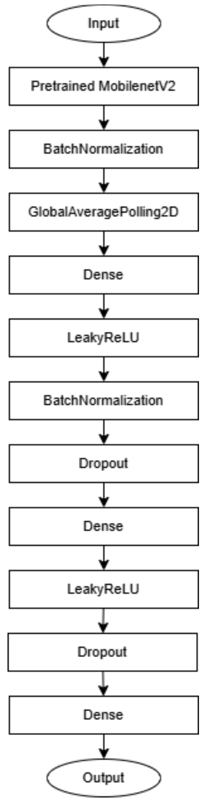

Fig. 5. Arsitektur MobileNetV2

The model utilizes the pretrained MobileNetV2 architecture as a backbone for feature extraction from a 224x224 pixel input image with three color channels. The output of this backbone is then normalized using BatchNormalization to make the feature distribution more stable. Next, GlobalAveragePooling2D is used to summarize spatial features into a more compact global feature vector. This vector is then processed through two consecutive fully connected layers with LeakyReLU activation, batch normalization, and dropout to improve the representation ability while preventing overfitting. Finally, a dense output layer with softmax activation function generates classification probabilities for the 10 target classes. This architecture effectively combines the feature extraction power of MobileNetV2 with a flexible classification layer that is resistant to overfitting.

B.5. Testing Model

The testing process is performed by running the evaluation method on the test data, so as to obtain key evaluation metrics such as loss and accuracy. The model was tested on two different architectures, namely custom CNN and transfer learning using MobileNetV2. The evaluation was performed using accuracy metrics, and visualization of the prediction results through loss and accuracy per epoch graphs, as well as visual prediction of some test images were shown. The MobileNetV2 model showed more stable and accurate results than the custom CNN, especially in terms of faster convergence and generalization to new data.

B.6. Analysis Result

The last stage in this process is result analysis, where researchers evaluate the performance of the classification model that has been built and tested previously. The evaluation is done by looking at the accuracy value generated from the testing process and analyzing it using the confusion matrix. Confusion matrix is used because it is able to present prediction results in a structured form, making it easier to interpret how well the model recognizes each batik motif class. From the resulting confusion matrix, it can be seen to what extent the model is able to distinguish between one class of motif and another, as well as identify patterns of misclassification that occur.

IV. Result and Discussion

This chapter presents the training and evaluation results of four batik motif classification models using CNN and transfer learning with MobileNetV2 architecture. Two CNN models are built from scratch, while two MobileNetV2 models use a fine-tuning approach. Evaluation is done using accuracy, loss, and F1-score metrics. Data augmentation techniques were also applied to increase data variety and overcome the limited number of datasets. The discussion focuses on the influence of model architecture, the effectiveness of transfer learning, and the role of augmentation, organized in stages from the description of the experiments to the comparative analysis between models.

A. Data Augmentation

In this research, we implemented nine data augmentations, namely rescale, rotation, width shift, height shift, shear, zoom, brightness, horizontal flip, and fill mode as shown in Figure 6. In Table II, we specify the value of each data augmentation.

TABLE II. Data Augmentation

Parameter	Value
rescale	1./255
rotation_range	10
width_shift_range	0.2
height_shift_range	0.2
shear_range	0.15
zoom_range	0.1
brightness_range	[0.7, 1.3]
horizontal_flip	True
fill_mode	'nearest'

Fig. 6. Augmentation Results

B. CNN

In this section, two conventional CNN models with different architectures are tested for batik motif classification. The first model has a simple structure with two convolution layers, while the second model uses three deeper convolution layers. The evaluation is done to see the effect of depth and complexity of the architecture on the classification performance on the batik motif dataset.

B.1. Architecture 1

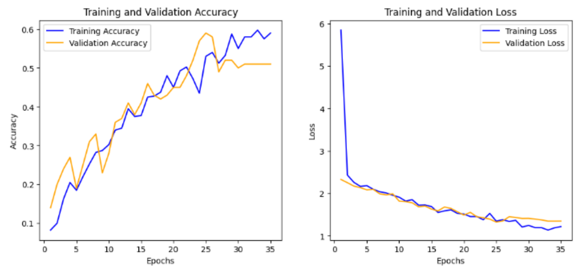

Fig. 7. Training and Validation Curves on CNN Architecture 1 Using 2 Conv Layers

CNN Architecture 1 has a simple structure with two convolution layers (16 and 32 filters) followed by LeakyReLU and MaxPooling activations, respectively. After that, the feature results are compacted through Flatten and passed to a dense layer with 128 neurons and a dropout of 0.5 to prevent overfitting, then ended with a softmax output layer for 10-class classification. The model obtained an accuracy of about 59%, which shows a basic ability to recognize batik motif patterns, but is still limited due to the depth and complexity of the simple architecture.

B.2. Architecture 2

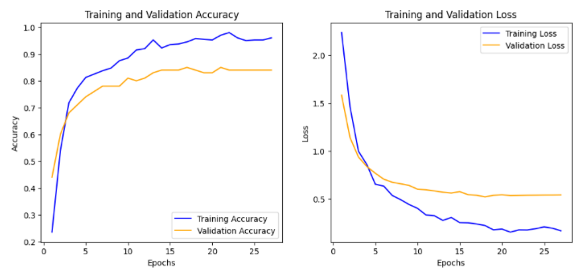

Fig. 8. Training and Validation Curves on CNN Architecture 2 Using 3 Conv Layers

CNN Architecture 2 uses three convolution layers with a larger number of filters (32, 64, and 128), along with LeakyReLU and MaxPooling activations. This structure allows for richer and more complex feature extraction. After the flatten process, the model proceeded to the dense layer with 128 neurons and dropouts, and a 10-class softmax output. The model managed to increase accuracy to around 65%, showing that increasing the depth and capacity of the model has a positive impact on classification performance.

C. Transfer Learning (MobileNetV2)

In the transfer learning part, a pretrained MobileNetV2 model trained on the ImageNet dataset was used. Two architectural variants are tested, namely with a frozen base model and the addition of a simple head layer and a model with a more complex head and fine-tuning at the top layer. This approach is expected to improve the accuracy of batik motif classification by utilizing the prior knowledge of the pretrained model.

C.1. Architecture 1

Fig. 9. Training and Validation Curves on MobileNetV2 Architecture 1 Using Base Model Frozen

MobileNetV2 Frozen is a pretrained MobileNetV2 model with initial weights from the ImageNet dataset, without retraining the base weights (frozen). On top of this base model, several layers are added such as BatchNormalization, GlobalAveragePooling, dense layer of 128 neurons with LeakyReLU activation, dropout, and softmax output. This transfer learning approach was able to significantly improve accuracy to around 85%, signifying the ability of the pretrained model to extract important features despite the limited training dataset.

C.2. Architecture 2

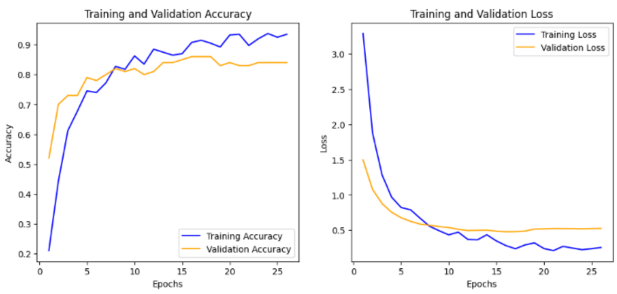

Fig. 10. Training and Validation Curves on MobileNetV2 Architecture 2 Using Head Model Fine-Tuning

MobileNetV2 Fine-Tuned uses a similar architecture as in mobileNet1, but with the addition of more and larger dense layers (512 and 128 neurons) with batch normalization and more intensive dropout. Although the base weights of MobileNetV2 remain frozen, this architecture provides more learning capacity in the upper layers so that the model is able to adapt better to the batik motif dataset. The model achieved the highest accuracy of around 86%, slightly better than the frozen version, demonstrating the effectiveness of fine-tuning the upper layers to improve classification performance. Of the four models tested, this architecture shows the best performance in batik motif classification, both in terms of accuracy and generalization ability of the model.

The dataset consists of 100 validation data with 10 batik motif classes, each with about 10 samples. The confusion matrix in Figure 11 shows the classification performance of the model. Motifs such as Jawa_Barat_Megamendung, Solo_Parang, and Maluku_Pala were predicted correctly or almost without error. In contrast, motifs such as Kalimantan_Dayak and Sulawesi_South_Lontara have quite a lot of prediction errors, mainly confused with each other. In general, the model works well but needs improvement for motifs that are similar to each other. It should be noted that the classification results are highly dependent on the quality and distribution of the dataset used. Some motifs that are less well classified could be due to the limited amount of data or the similarity of patterns between motifs in the dataset.

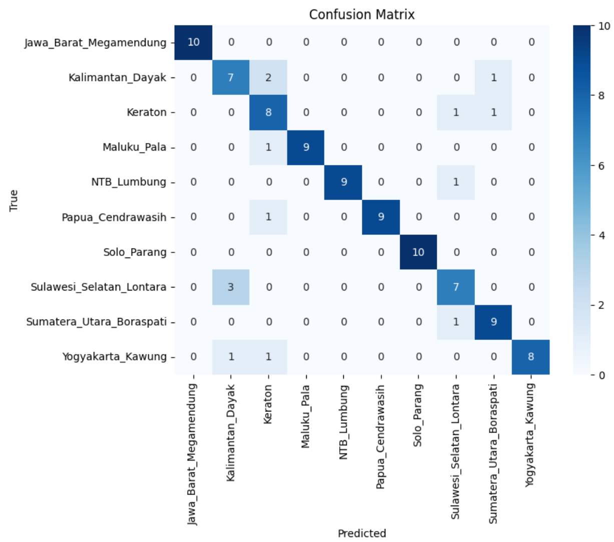

Fig. 11. Confusion Matrix of Batik Motif Classification Results Using MobileNetV2 Model with Fine-Tuning

The classification report results in Figure 12 show the model's performance in classifying various batik motif classes. The model achieved an overall accuracy of 86%. Some classes such as Jawa_Barat_Megamendung, Maluku_Pala, NTB_Lumbung, Papua_Cendrawasih, Solo_Parang, and Yogyakarta_Kawung have very high precision and recall values, even reaching perfect scores. However, there are some classes such as Kalimantan_Dayak and Keraton that have lower performance, indicating that the model still has difficulty in classifying motifs in these classes. The macro and weighted average f1-score values are around 0.87, indicating that the model's performance is quite consistent across classes. Thus, although the model is able to recognize most motifs well, specific improvements are still needed to increase accuracy in sub-optimal classes.

```
Classification Report:
                           precision    recall  f1-score   support

  Jawa_Barat_Megamendung       1.00      1.00      1.00        10
        Kalimantan_Dayak       0.64      0.70      0.67        10
                 Keraton       0.62      0.80      0.70        10
             Maluku_Pala       1.00      0.90      0.95        10
             NTB_Lumbung       1.00      0.90      0.95        10
       Papua_Cendrawasih       1.00      0.90      0.95        10
             Solo_Parang       1.00      1.00      1.00        10
Sulawesi_Selatan_Lontara       0.70      0.70      0.70        10
 Sumatera_Utara_Boraspati       0.82      0.90      0.86        10
       Yogyakarta_Kawung       1.00      0.80      0.89        10

                accuracy                           0.86       100
               macro avg       0.88      0.86      0.87       100
            weighted avg       0.88      0.86      0.87       100
```

Fig. 12. Classification Report Using MobileNetV2

The results of batik motif prediction using the MobileNetV2 model show a validation accuracy of 86%. Of the 16 batik motif images tested, most of the model predictions are correct (marked with green text), while there are some prediction errors (marked with red text). The errors occur in Papua_Cendrawasih and NTB_Lumbung motifs that are predicted to be misclassified. In general, the model is able to recognize batik motifs quite well based on the visual features of the images.

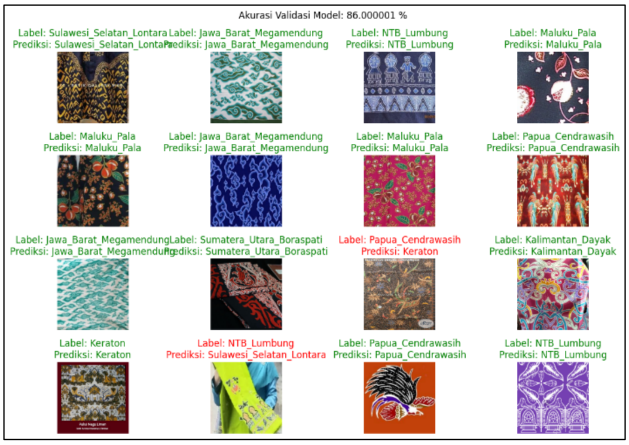

Fig. 13. Batik Motif Prediction Results Based on Architecture 2 Using the MobileNetV2 Model

D. Comparison of Overall Model

To provide a comprehensive overview of the performance of the models tested in this study, a comparison is made based on the main architecture, the accuracy obtained, and the specific characteristics of each model. The following table summarizes this information for the four batik motif classification models developed, including two conventional CNN models and two MobileNetV2-based transfer learning models with different configurations.

In the context of the dataset in this study, the use of Leaky ReLU activation functions in the convolutional and dense layers can help overcome the ReLU dying problem, so that the model is able to learn features better without losing gradients. In addition, the application of dropout in the dense layer plays an important role in preventing overfitting by randomly turning off a number of neurons during training, so that the model becomes more generalized and robust to new data. The combination of these two techniques supports the improvement of model stability and accuracy, especially on datasets with a limited amount of data and high motif complexity.

From this table, it can be seen how architectural complexity and the use of transfer learning techniques have an effect on improving the accuracy and efficiency of model training.

TABLE III. COMPARISON OF TABLE RESULT

Model	Main Architecture	Accuracy (%)	Description
CNN Architecture 1	2 Conv + MaxPooling + Dense 128 + Dropout	59	Simple structure, fast train
CNN Architecture 2	3 Conv + MaxPooling + Dense 128 + Dropout	65	Deeper, better accuracy
MobileNetV2 Frozen (mobileNet1)	Base MobileNetV2 frozen + BatchNorm + GAP + Dense 128 + Dropout	85	Transfer learning, frozen base
MobileNetV2 Fine-Tuned (mobileNet2)	Base MobileNetV2 frozen + BatchNorm + GAP + Dense 512 & 128 + Dropout	86	More complex head, fast trainning, best performance

V. CONCLUSION

This research was successful in developing and comparing four batik motif classification models using two main approaches, namely conventional CNN with different architectures and MobileNetV2-based transfer learning. The experimental results show that the MobileNetV2 model with fine-tuning in the upper layer provides the best performance with accuracy reaching around 86%, outperforming the conventional CNN model which only achieves 59% to 65% accuracy. Transfer learning is proven to be effective in utilizing knowledge from large datasets such as ImageNet to improve the feature extraction capability on the relatively small and complex batik dataset. In addition, the application of data augmentation techniques helps to enrich the variety of training data thereby reducing the risk of overfitting and improving model generalization. Therefore, the combination of MobileNetV2 transfer learning and data augmentation is a promising approach for the development of an accurate and efficient batik motif classification system.

VI. LIMITATION AND FUTURE WORK

Although this study has the advantage of efficient performance on limited datasets, it has several limitations. First, the dataset used is relatively small and limited in motif diversity, which may affect the model's generalization. Second, visual similarities between some motifs can lead to classification errors, as seen in the confusion matrix. For further development, we suggest testing this model on a larger and more diverse batik dataset, as well as exploring its application in real-time classification systems or digital preservation platforms.

REFERENCES

[1] C. Irawan, A. Winarno, H. Kusumodestoni, A. Sucipto, T. Tamrin, and M. Doheir, "A Combination of Statistical Extraction and Texture Features Based on KNN for Batik Classification," *Proceedings - 2021 International Seminar on Application for Technology of Information and Communication: IT Opportunities and Creativities for Digital Innovation and Communication within Global Pandemic, iSemantic 2021*, pp. 113–117, 2021, doi: 10.1109/iSemantic52711.2021.9573214.

[2] C. U. Khasanah, E. Utami, and S. Raharjo, "Implementation of Data Augmentation Using Convolutional Neural Network for Batik Classification," *2020 8th International Conference on Cyber and IT Service Management, CITSM 2020*, pp. 2–6, 2020, doi: 10.1109/CITSM50537.2020.9268890.

[3] R. F. Alya, M. Wibowo, and P. Paradise, "Classification of Batik Motif Using Transfer Learning on Convolutional Neural Network (Cnn)," *Jurnal Teknik Informatika (Jutif)*, vol. 4, no. 1, pp. 161–170, 2023, doi: 10.52436/1.jutif.2023.4.1.564.

[4] D. Trimakno and Kusrini, "Impact of Augmentation on Batik Classification using Convolution Neural Network and K-Neareast Neighbor," *ICOIACT 2021 - 4th International Conference on Information and Communications Technology: The Role of AI in Health and Social Revolution in Turbulence Era*, pp. 285–289, 2021, doi: 10.1109/ICOIACT53268.2021.9564000.

[5] S. Ariessaputra, V. H. Vidiasari, S. M. Al Sasongko, B. Darmawan, and S. Nababan, "Classification of Lombok Songket and Sasambo Batik Motifs Using the Convolution Neural Network (CNN) Algorithm," *International Journal on Informatics Visualization*, vol. 8, no. 1, pp. 38–44, 2024, doi: 10.62527/joiv.8.1.1386.

[6] M. M. A. Wona *et al.*, "Klasifikasi Batik Indonesia Menggunakan Convolutional Neural Network (CNN)," *Jurnal Rekayasa Teknologi Informasi (JURTI)*, vol. 7, no. 2, p. 172, 2023, doi: 10.30872/jurti.v7i2.13694.

[7] A. Mumuni and F. Mumuni, "Data augmentation with automated machine learning: approaches and performance comparison with classical data augmentation methods," *Knowl Inf Syst*, vol. 67, no. 5, pp. 4035–4085, 2024, doi: 10.1007/s10115-025-02349-x.

[8] P. Goel and A. Ganatra, "Handwritten Gujarati Numerals Classification Based on Deep Convolution Neural Networks Using Transfer Learning Scenarios," *IEEE Access*, vol. 11, no. January, pp. 20202–20215, 2023, doi: 10.1109/ACCESS.2023.3249787.

[9] M. H. P. S. Ikhya Ulummuddin, Anggraini Puspita Sari, "Jurnal Teknologi Terpadu WATERFALL," vol. 6, no. 22, pp. 72–78, 2020.

[10] R. Syafi'i and S. Khomsah, "Classification of Indonesian Batik: A Comparative Study of CNN and VGG16 with Canny Edge Detection," *COMNETSAT 2024 - IEEE International Conference on Communication, Networks and Satellite*, pp. 355–363, 2024, doi: 10.1109/COMNETSAT63286.2024.10862216.

[11] J. Algoritme *et al.*, "Pengenalan Motif Songket Palembang Menggunakan Convolutional Neural Network dengan Arsitektur ResNet-50," vol. 5, no. 1, pp. 78–87, 2024, doi: 10.35957/algoritme.xxxx.

[12] N. Putu, W. Yuniari, I. M. S. Kumara, I. K. Agus, and W. Raharja, "Analisis Unjuk Kerja Klasifikasi Citra Motif Kain Bali Menggunakan Model Inception Dan EfficientNet," pp. 49–62, 2023.

[13] Dadang Iskandar Mulyana and Ali Akbar, "Optimasi Klasifikasi Batik Betawi Menggunakan Data Augmentasi Dengan Metode Knn Dan Glcm," *Jurnal Aplikasi Teknologi Informasi dan Manajemen (JATIM)*, Oct. 2022.

[14] S. Ariessaputra, V. H. Vidiasari, S. Mariyanto, A. Sasongko, B. Darmawan, and S. Nababan, "Classification of Lombok Songket and Sasambo Batik Motifs Using the Convolution Neural Network (CNN) Algorithm," 2024. [Online]. Available: www.joiv.org/index.php/joiv

[15] M. Misela *et al.*, "Klasifikasi Batik Indonesia Menggunakan Convolutional Neural Network (CNN)," 2023. [Online]. Available: https://www.kaggle.com/datasets/dionisiusdh/indonesian batik-motifs.

[16] M. M. Taye, "Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions," Mar. 01, 2023, *MDPI*. doi: 10.3390/computation11030052.

[17] Z. Wang *et al.*, "A Comprehensive Survey on Data Augmentation," May 2024, [Online]. Available: http://arxiv.org/abs/2405.09591

[18] W. Zeng, "Image data augmentation techniques based on deep learning: A survey," 2024, *American Institute of Mathematical Sciences*. doi: 10.3934/mbe.2024272.

[19] M. Jindal and B. Singh, "Class imbalance-aware domain specific transfer learning approach for medical image classification: Application on COVID-19 detection," *Eng Appl Artif Intell*, vol. 150, Jun. 2025, doi: 10.1016/j.engappai.2025.110583.

[20] Y. Zou, L. Wu, C. Zuo, L. Chen, B. Zhou, and H. Zhang, "White blood cell classification network using MobileNetv2 with multiscale feature extraction module and attention mechanism," *Biomed Signal Process Control*, vol. 99, Jan. 2025, doi: 10.1016/j.bspc.2024.106820.