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Batik Classification using Deep Learning

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Abstract: Batik is one of the Indonesian cultural heritages that has been recognized by the global community. Indonesian batik has a vast diversity in motifs that illustrate the philosophy of life, the ancestral heritage and also reflects the origin of batik itself. Because of the manybatik motifs, problems arise in determining the type of batik itself. Therefore, we need a classification method that can classify various batik motifs automatically based on the batik images. The technique of image classification that is used widely now is deep learning method. This technique has been proven of its capacity in identifying images in high accuracy. Architecture that is widely used for the image data analysis is Convolutional Neural Network (CNN) because this architecture is able to detect and recognize objects in an image. This workproposes to use the method of CNN and VGG architecture that have been modified to overcome the problems of classification of the batik motifs. Experiments of using 2.448 batik images from 5 classes of batik motifs showed that the proposed model has successfully achieved an accuracy of 96.30%.

***Keywords**: Batik Classification, Deep Learning, Convolutional Neural Network, Transfer Learning.*

I. INTRODUCTION

Batik is one of Indonesia's cultural heritage that has been recognized by the worldand even been defined by UNESCO as a Representative List of the Intangible Cultural Heritage of Humanity on October 2, 2009. Recently, batik has been progressing very rapidly in Indonesian society so as to create a lot of batik motifs.Their differencesare generally located on the component of colors and patterns.

Evidence of the development of batik in Indonesia can be seen not only by adults who use it, but almost all ages have used it. Even, civil servants and some companies in Indonesia have made a special day for wearing batik. However,inversely proportional to its development, batik is still confusing to be identified due to its immense number of its variations. Many Indonesian people have difficulties in identifying certain type of batik.They cannotdifferentiate between one motif and the others.Currently, only people who are knowledgeable and experienced can determine the type of batik. And yet, it would require a relatively long time in deciding the type of batik and even there is still a possibility of error in the determination of the type of batik itself.

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Related works on the classification of batik has been carried out lately.These works generally can be divided into two groups: (1)Classification using handcrafted features[1] - [12], and (2)Classification using deep learning approaches [13] - [14]. Along with its many new method developments, so in this work we will conduct an evaluation of several deep learning models. Then we make modification to the model that has the best performance in the evaluation result. Therefore, we can get the best model for our problem. The dataset used in this work is also a new dataset that is of our own making. Broadly speaking, this paper has the following structure: (1)background topics and issues are discussed;(2)discuss the latest works with the topics that are on the same domain with this work;(3)describe the framework that is carried out, as well as illustrates clearly theproposed method to overcome the problems encountered; (4)showed the results that have been found from various experiments carried out and also the interpretation of the results; and(5)the conclusion of the whole paper and also the possibility of the work that can be done in the future.

II. RELATED WORK

In recent years, there have been some studies on the classification of batik that has shown good results. Using several methods such as [1] using CDH and edge detection methods combined with GLCM method. Researchers [2] conducted a study in which the classification process will be based on the extraction result by using SIFT method combined with BOF, for the extraction process, itwas conducted by using SIFT method. Work conducted by [3] classified Indonesian batik by extracting the texture features and shape using GLCMmethod, while the classification process was conducted by using Artificial Neural. Work by [4] conducted a study in which the classification process will be based on the extraction of the similarity of textures, shapes and colors. For the extraction process of the texture similarity, this work used GLCM method, for the similarity of colors, itwas usedthe color moment, for the similarity of shape,it was used the invariant moment, and the classification by using the K-NN. Workconducted by [5] classified the Indonesian batik by extracting the texture features with GLCM method, while the classification process was conducted by using LVQ method. Workconducted by [6] classified Indonesian batik by extracting features with the Multi Texton Histogram and classification by using K-NN and SVM. Currently, Convolutional Neural Network (CNN) is a method that has the best performance in the field of image classification than the methods of using handcrafted features such as [2] SIFT and [1] CDH. In ImageNet Large ScaleVisual Recognition Challenge (ILSVRC), the majority of the winners used CNN as the base [15] – [22].

Work conducted by [13] classified Indonesian batik by using CNN with new network architecture, which is a merging with GoogLeNet with Residual Network (IncRes). Work conducted by [14] used CNN method with VGG16architecture [23] in addressing the problems of classification of batik.

III. METHODOLOGY

Overall, the proposed system to solve the problems of classification of batik in this workisdivided into two stages: (1) Data Acquisition and Preprocessing and (2) Classification Model. The system that was designed to solve this problem would be use Convolutional Neural Network and can be described in Fig. 1.

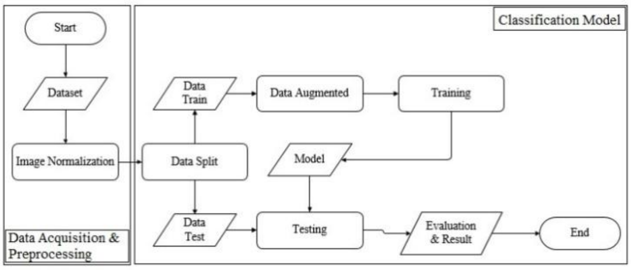

Fig. 1. The whole of proposed system

Classification problems can be solved by using a complex architecture, one of them by piling up several different layers. In CNN, there are four types of layers which are common, among others:

- Convolution Layer: In a convolutional network, it can be argued that thisconvolutional layer is a major building block which has the most important role in computation of heavy lifting.
- Pooling or Subsampling Layers: In a convolutional network architecture, generally between convolutional layer will be included a pooling layer successively, this is done to minimize the spatial space that is represented so as to minimize the parameters and computational processes that occur within the network.
- Non-Linear Layers: In aconvolutional network architecture, the function of "trigger" of non-linear in particular, is a thing that cannot be released to mark the identification of different features on each hidden layer.
- Fully Connected layers: This layer is usually in the last layer in the architecture of convolutional network, which this layer will determine the best combination to achieve the target that has been set

A. Dataset Collection

Image dataset used in this work is the result of automatic crawling of https://images.google.com/by using python. This data consists of 2448 images which are divided into 5 types of motifs. Details of dataset can be seen in Table- I.

Table-I: Details of dataset

Class Name	Sample Image	Number of Images
Kawung		626
Mega Mendung		390
Parang		804
Sekar Jagat		339
Truntum		289
Total		2448

B. Data Acquisition and Preprocessing

This stage started from performing first processing on the obtained data.This is done to facilitate the classification of batik at a later stage, as well as to obtain more accurate results. In this work, the data processing was done with the following steps: (1)ImageFiltering, datasets image owned will be filtered back manually, because the owned data is the data of the process of crawling in which the data is only based on keywords that we enter in Google image, there are no accurate filtering in the process;(2)Image Labeling, images obtained from the result of crawling and have gone through the previous stage is still fairly raw data, where such data are not labeled properly, therefore it is necessary to process the image labeling;(3) Image Resizing, images that are already labeled then be done using the resizing process by using library PIL on Python to change the image size to 224*224, this is done in order to support the process of transfer learning; and(4) Image Normalization, based on study results conducted by [6] the normalization process can improve the accuracy of 8%, then from this work, it will be normalized prior to the image dataset.

C. Classification Model

This stage is generally divided into two parts, the first is the training phase, this phase is the phase in which we conduct training on the proposed system. In this phase we do Augmented Data to the owned data, this is done to increase the amount of data used and minimize the overfitting, so that we can get the best model in classifying the batik images. The second phase is testing phase, this phase is the phase where we perform testing of the model we have with the new data that is different from the training data.

- VGG16: VGG16 is a very deep convolutional model invented by VGG (Visual Geometry Group) from University of Oxford, this architecture is composed of 16 convolutional layer and 5 MaxPool. Architectural detail can be seen in Fig. 2. This architecture has been trained to use Imagenet dataset.

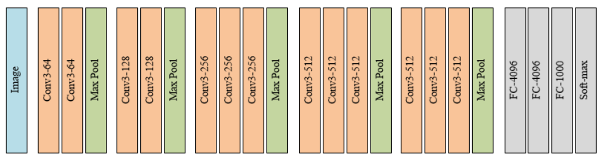

Fig. 2. Details of the VGG16 architecture

- VGG16 + Global Average Pooling: This architecture is not much different from VGG16 architecture. What distinguishes this architecture with the VGG16 architecture is only on the top layer. Where in this architecture,the part ofits previous fullyconnected layer that was contained two layers of dense 4096 were replaced with a Global Average Pooling. This architecture consisted of 14 convolutional layers and 5 MaxPool
- VGG19: This architecture is the development of VGG16, the initial idea of this architecture is to add the number of layers to improve the accuracy. This architecture has 19 convolutional layers and 5 MaxPool. Architectural detail can be seen in Fig. 3. This architecture has more 3 convolutional layer compared to VGG16.

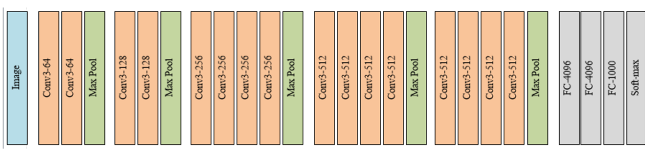

Fig. 3. Details of the VGG16 architecture

- VGG19 + Global Average Pooling: Just asVGG16 and VGG16 + Global Average Poolingarchitecture, what distinguishes this architecture with the VGG19 architecture is only on the top layer. Where in this architecture the part of its fully connected was replaced with a Global Average Pooling. This architecture consisted of 17convolution layers and 5 MaxPool.
- Inception V3: This architecture is the development of GoogLeNet.The idea of renewal of this architecture is the use of factorization. The purpose of this factorization is to reduce the number of parameters without reducing network efficiency. This architecture has 22 layers (equivalent to>100 Layers). Details of this architecture can be seen in Fig. 4. This architecture consisted of convolutional layer 32 (7x7, s=2), MaxPool, convolutional 32(1x1, s=1), convolutional 32(3x3, s=1), MaxPool, 4x Inception Module, output 1, 3x Inception Model, output 2, 2x Inception Module, Global Average Pooling, Dense 1000.

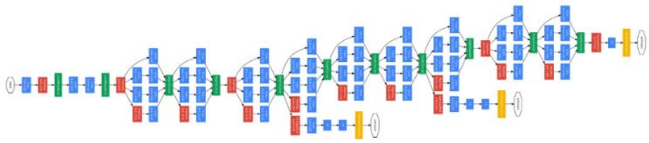

Fig. 4. Details of the Inception V3 architecture

- Proposed Method 1: The proposedmethod in this work is a modification to the VGG architecture by reducing the number of layers and then replaced parts of fully connected layer with Global average Pooling [24]. This is done to reduce the number of parameters.It can reduce processing time and is expected to improve the accuracy of classification.Details of the proposed Architecture can be seen in Fig. 5. This architecture consisted of 11 convolutional layer and 4 MaxPool.

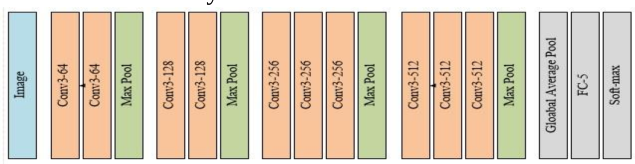

Fig. 5. Details of the proposed architecture

- Proposed Method 2: This architecture outlines have similarity with the proposed method 1. However, in the architecture, there is any reduction in the number of layer that is used. Layer used in this architecture is only just the first 7layer of fig. 5. Then it was added of Global Average Pooling up to Soft max. This architecture consisted of 8 convolutional layer and 3 MaxPool.

IV. RESULT AND DISCUSSION

In this work,the owned dataset is divided into 3 parts, namely: training, validation, and testing with a composition of 60% (1961 + Augmented), 20% (487) and 20% (487). This work will compare the results of multiple architectures from VGG16, VGG16 + Global average Pooling, VGG19, VGG19 + Global Average Pooling, Inception V3, and several variations of the proposed architecture model. The parameter considered is the accuracy of testing and training time per epoch. The entire process of experimentation in this workwere implemented by using Keras 2.2.4, Python 3.7.4 and the desktop computer with the specifications of Windows 10 (64 bit), 16GB RAM, 240GB SSD, AMD Ryzen 7 1700x and GPU Nvidia GTX 1060 6GB. The entire process of training in this experiment carried out with the epoch of 250, optimizer Adam, learning rate 0.0001, decay 1e-6. The best model selected by using the check pointer method with patience by 10 and the observed parameters is validation loss. Where this method will take the best model by considering thevalidation loss generated at every epoch, when on the 10 epoch, there is no improvement on the validation loss, then that model to be selected as the best model.

A. Evaluation Result of Existing Architecture

The architecture tested in this work amounted to 5 pieces. Each of these architectures will be tested to determine the accuracy of the test results.

- VGG16: The test results using VGG16 architecture can be seen in fig. 6. From the test results we can see that the best model is onthe 10thepoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 10thmodel,it was obtained the result: Training loss: 0.1327 – Training accuracy: 0.9578, Validation loss: 0.3830 – Validation accuracy: 0.8961 and for its testing showed: Testing loss = 0.168 and Testing accuracy = 0.959.

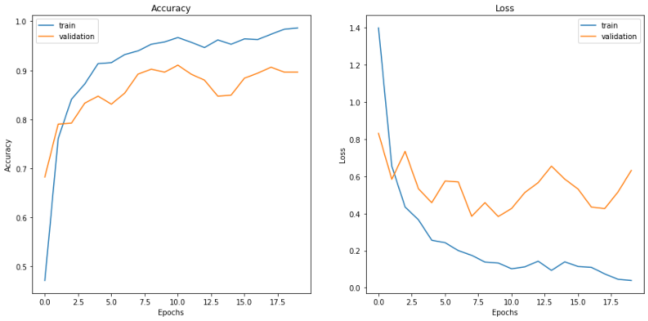

Fig.6. Results of the batik classification experiments by using VGG16 architecture

- VGG16 + Global Average Pooling: The test results using VGG16 + Global Average Pooling architecture can be seen in fig. 7. From the test results we can see that the best model is onthe 15thepoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 15thmodel,it was obtained the result: Training loss: 0.1012 – Training accuracy: 0.9619, Validation loss: 0.2535 – Validation accuracy: 0.9389and for its testing showed: Testing loss = 0.125 and Testing accuracy = 0.963.

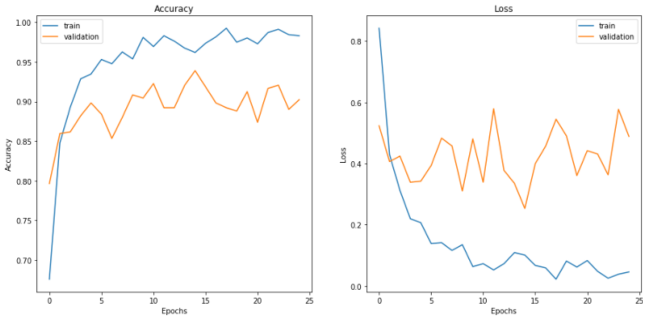

Fig.7. The results of the batik classification experiments by using VGG16 + Global Average Poolingarchitecture

- VGG19: The test results using VGG19 architecture can be seen in fig. 8. From the test results we can see that the best model is onthe 23thepoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 23thmodel,it was obtained the result: Training loss: 0.0741 – Training accuracy: 0.9776, Validation loss: 0.2435 – Validation accuracy: 0.9328and for its testing showed: Testing loss = 0.177 and Testing accuracy = 0.953.

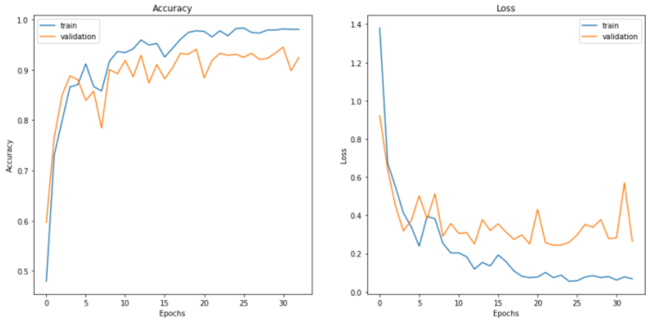

Fig.8. Results of the batik classification experiments by using VGG19 architecture

- VGG19 + Global Average Pooling: The test results using VGG19 + Global Average Pooling architecture can be seen in fig. 9. From the test results we can see that the best model is onthe 19thepoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 19thmodel,it was obtained the result: Training loss: 0.1446 – Training accuracy: 0.9497, Validation loss: 0.2242 – Validation accuracy: 0.9308and for its testing showed: Testing loss = 0.139 and Testing accuracy = 0.955.

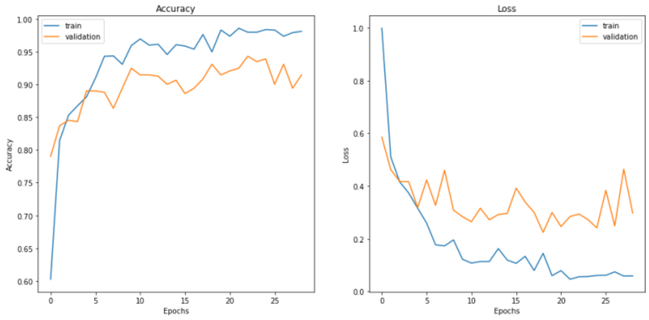

Fig.9. Results of the batik classification experiments by using VGG19 + Global Average Poolingarchitecture

- Inception V3: The test results using Inception V3 architecture can be seen in fig. 10. From the test results we can see that the best model is onthe 12thepoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 12thmodel,it was obtained the result: Training loss: 0.0479 – Training accuracy: 0.9864, Validation loss: 0.3352 – Validation accuracy: 0.8961and for its testing showed: Testing loss = 0.160 and Testing accuracy = 0.949.

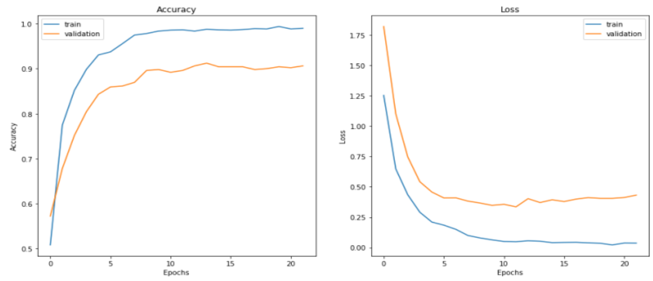

Fig.10. Results of the batik classification experiments by using Inception V3architecture

Details of experimental results in this test can be seen in Table- II. It can be seen that best accuracy be obtained by VGG16 + Global Average Poolingarchitecture with test accuracy reaches 96.30%. Make changes of fully connected layers with Global Average Pooling proven to increase accuracy.

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We can see and do a comparison of the test results of VGG16 with VGG16 + Global Average Pooling and VGG19 with VGG19 + Global Average Pooling. At the same time for a similar architecture (VGG16 with VGG19) the increasing of the number of layers will influence on the resulting accuracy.

Table-II: Details of experimental results

Architecture	No. of Parameters	Train Accuracy	Validation Accuracy	Test Accuracy
VGG16	65,075,013	95.78%	89.61%	95.90%
VGG16+GAP	14,717,253	96.19%	93.89%	96.30%
VGG19	70,384,709	97.76%	93.28%	95.30%
VGG19+GAP	20,026,949	94.97%	93.08%	95.50%
Inception V3	21,813,029	98.64%	89.61%	94.90%

Based on the experimental results, it can be seen that the more complex architectures used, the lower the accuracy value produced, overfit level becomes higher, therefore it is proposed to make changes to the architecture that have the value of the best accuracy (VGG16 + Global Average Pooling) by reducing multiple layers so that the parameters used to be much less, so that, it can reduce computational process, minimize the time of the training process, and it is also expected to improve the accuracy of testing. The reason for reducing the number of layers, among others: (1) Features extractedfrom batik can tend to be simpler and repetitive. (2) Based on the results of the three architectural tests above, it can be seen that the more complex and large the architecture used actually makes the model overfit and has poor accuracy.

B. Evaluation Result of ProposedArchitecture

In this work, there are two variations of the proposed method, the difference in each of these variants is the number of layers owned. The first variation has 11 layers and the second variation has 8 layers.

- Proposed Method 1 (VGG16 Modified: 11 Conv Layer + 4 MaxPool + Global Average Pooling): The test results using Proposed Method 1 architecture can be seen in fig. 11. From the test results we can see that the best model is onthe 26th epoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 26th model,it was obtained the result: Training loss: 0.0479 – Training accuracy: 0.9857, Validation loss: 0.3097 – Validation accuracy: 0.9369and for its testing showed: Testing loss = 0.187 and Testing accuracy = 0.963.

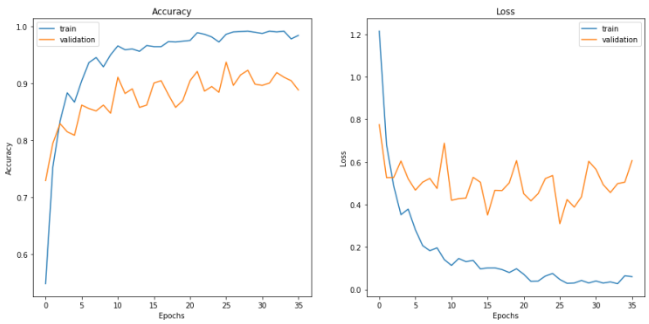

Fig.11. Results of the batik classification experiments by using proposed architecture 1

- Proposed Method 2 (VGG16 Modified: 8 Conv Layer + 3 MaxPool + Global Average Pooling): The test results using Proposed Method 2 architecture can be seen in fig. 12. From the test results we can see that the best model is onthe 29th epoch. For the next 10 epoch, there is no improvement on the partof validation loss. In this 29th model,it was obtained the result: Training loss: 0.1917 – Training accuracy: 0.9347, Validation loss: 0.4492 – Validation accuracy: 0.8635and for its testing showed: Testing loss = 0.206 and Testing accuracy = 0.926.

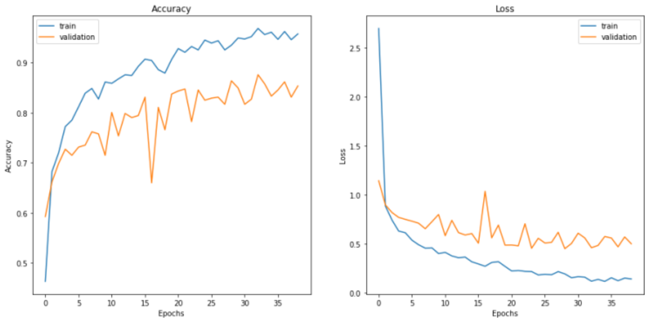

Fig.12. Results of the batik classification experiment by using proposed architecture 2

Details of the experimental results of the comparison between the proposed method with the best architecture in the previous experiment can be seen in Table- III. It can be seen that the proposed method one could achieve the same accuracy as the best architecture in earlier tests which amounted to 96.30%. Although it has the same accuracy results, but the proposed method 1 has several advantages, namely, it has far fewer parameters so as to make time of training and testing processes become more briefly also reduces the computational process burden during the training. Proposed method 2 is made as a barometer of whether the proposed method 1 is still too complex or not. It turned out that this architecture result in decreased accuracy becomes 92.60% for test accuracy. This showed that the proposed method 2 architecture is too simple in solving the problems of batik classification.

The proper use of architecture is very important to obtain maximum accuracy. A large architecture will has a weight parameter that much, so it will affect the process of computing the weight, a longer training time and tend to cause overfit. But of course, the large architecture has advantages such can learn large and complex datasets. While small architecture will have fewer weight parameters so that it will affect the computation process becomes lighter, faster training time, suitable for a training process that has the number of datasets that are not much and typical dataset that is not too complex. But of course, a small architecture has the disadvantage that tends to result in underfit.

Table-III: Details of experimental results of Proposed method

Architecture	No. of Parameters	Train Acc.	Val. Acc.	Test Acc.	Train Time	Test Time
VGG16 + GAP	14,717,253	96.19 %	93.89 %	96.30 %	14.6s /epoch	3s
Proposed Method 1	7,637,829	98.57 %	93.69 %	96.30 %	12.5s /epoch	2s
Proposed Method 2	1,736,773	93.47 %	86.35 %	92.60 %	10.8s /epoch	2s

V. CONCLUSION

Results from this work showed that the proposed method can handle the batik classification problems well. Performance of the proposed method is better than the general architecture. The obtained accuracy reached 96.30% with per-epoch training time by 12.5 seconds. The use of appropriate architecture has a very important role in order to obtain maximum accuracy. For the future work, this work will be developed with the use of more complex datasets (there are people who are using batik, batik motifs found on certain objects, etc.) and also the use of the transfer of learning and designing of a more optimal architecture.

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