Image Classification on Garutan Batik Using Convolutional Neural Network with Data Augmentation

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Abstract - In Indonesia, Batik is one of the cultural assets in the field of textiles with various styles. There are many types of batik in Indonesia, one of which is Batik Garutan. Batik Garutan has different motifs that show the characteristics of Batik Garutan itself. Therefore, to distinguish the features of Batik Garutan from another batik, a system is needed to classify the types of batik patterns. Classification of batik patterns can be done using image classification. In image classification, there are methods to increase the size and quality of the limited training dataset by performing data augmentation. This study aims to obtain an image classification model by applying data augmentation. The image classification process is carried out using the Deep Learning method with the Convolutional Neural Network algorithm, which is expected to be helpful as a reference for research and can be applied to software development related to image classification. This study generated models from several experiments with different epoch parameters and dataset proportions. A system obtained the investigation with the best performance with a data proportion of 9:1, resulting in an accuracy value of 91 percent.

Keywords: Batik Garutan, CNN, data augmentation, image classification

I. INTRODUCTION

Batik Garutan originating from the Garut Regency area, is a written batik craft that contains the values of the philosophy of life and customs of the Sundanese people. Batik Garut is synonymous with a light brown color with a slight yellowish tint, which is the hallmark of Garutan Batik [1]-[2]. It isn't easy to distinguish the Garutan Batik motif from other batik motifs because the patterns have several similarities. To determine ways that have these similarities, it is possible to classify the types of batik patterns, especially Garutan Batik, by performing image classification using a Convolutional Neural Network (CNN) [3].

CNN is an algorithm that can be used to process and classify data in the form of images or images [4][5]. There are many architectures in CNN, some of which are AlexNet, VGG, and ResNet. Alexnet and VGG architectures have a better impact on representing input data than shallow structures, but such architectures often have instability in error gradients during the model training process. To solve this problem, the Residual Networks or ResNet architecture aims to represent better input data with a change in error gradient in the data training process which has higher stability [6]- [8].

In image classification, a pre-training process can be carried out with data augmentation to increase the size and quality of the limited training dataset. Especially for data types in the form of images, several augmentation methods can be considered [9]-[10]. Data augmentation can be implemented in several ways, including cropping, flipping, and rotating [11]-[12].

Previously, several studies were used as references in this study. Including research conducted by khasanah et al., Testing models with 500 batik images total, broken down into five classes: Ceplok, Kawung, Lereng, Nitik, and Parang. By choosing data augmentation, batik classification accuracy was successfully raised by 3.13%, from 95.83% (without data augmentation) to 98.96%. (by selecting data augmentation) [13]. Furthermore, there is research by Rasyidi et al. In this study, the six batik patterns Banji, Ceplok, Kawung, Mega Mendung, Parang, and Sekar Jagad were identified using the convolutional neural network (CNN). 994 photos from the six categories were gathered and split in half, 8:2, into training and test data. Additionally, image augmentation was done to add variety to the training data and avoid overfitting. Using the DenseNet network architecture, experimental results on the test data showed that CNN achieved an excellent performance as evidenced by accuracy of 94% and top-2 accuracy of 99% [14]. Subsequent research by Meranggi et al. Automate the classification of batik motifs using deep learning based on a Convolutional Neural Network

(CNN). In this investigation, two datasets were employed. The old dataset has 598 data with five different sorts of motifs and is taken from a public repository. In the meantime, the new dataset updates the previous dataset by substituting 621 data with five different types of motifs for the anomalous data in the old dataset. Due to the difficulty in getting the lereng motif, it is altered to pisanbali. Original, balance patch, and patch were the three categories into which each dataset was split. Employed the ResNet-18 architecture, which sped up training by using a pre-trained model. The new dataset's patch method of 88.88% 0.88 yielded the best test results [15]. Then there is also research conducted by Agastya et al.. This study describes convolutional neural networks (CNNs) called VGG-16 and VGG-19 to classify batik patterns in order to automatically recognize the patterns, and able to predict classification accuracy of about 90%. However, due to the variations in batik photos, such as images that have been resized and rotated, the classifier is unable to accurately identify the type of batik pattern. For instance, after it has classified a batik pattern that is scaled 2.0, the accuracy of batik classification drops to less than 56%. Then, in order to increase accuracy, train the CNN using augmented data. After all, the accuracy can be increased by 10% for rotated or scaled images using the augmented data technique [16]. The latest research as a reference was carried out by Rasyidi et al., which gathered a total of 120 photos, 40 for each form of batik. We used transfer learning with three fundamental CNN model architectures, namely ResNet, DenseNet, and VGG with batch normalization, to accelerate and streamline the model development process. Additionally, we tried creating a new dataset by slicing each image into 30 separate ones. Additionally, image augmentation was employed to add variety to the training data and avoid overfitting. According to the experimental results using 5-fold cross validation, vgg13 bn performs best on the modified dataset with an accuracy of 87.61%, whereas densenet169 performs best on the original dataset with an accuracy of 79.17% [17].

Based on the problems mentioned in the background, Image Classification is carried out on Batik Garutan, which aims to implement data augmentation in the pre-processing process and use the CNN algorithm to produce better accuracy values. So based on the background described above, the formulation of the problem is obtained as follows: How to implement data augmentation in image classification?, How to do image classification of the Garutan Batik image using a Convolutional Neural Network (CNN).

II. METHOD

The process that will be carried out during the research is described by a work breakdown structure (WBS) [18]-[22] by explaining the research objectives and the stages of the research according to the system development method and the activities to be carried out at each of these stages. Fig. 1 as WBS in this study.

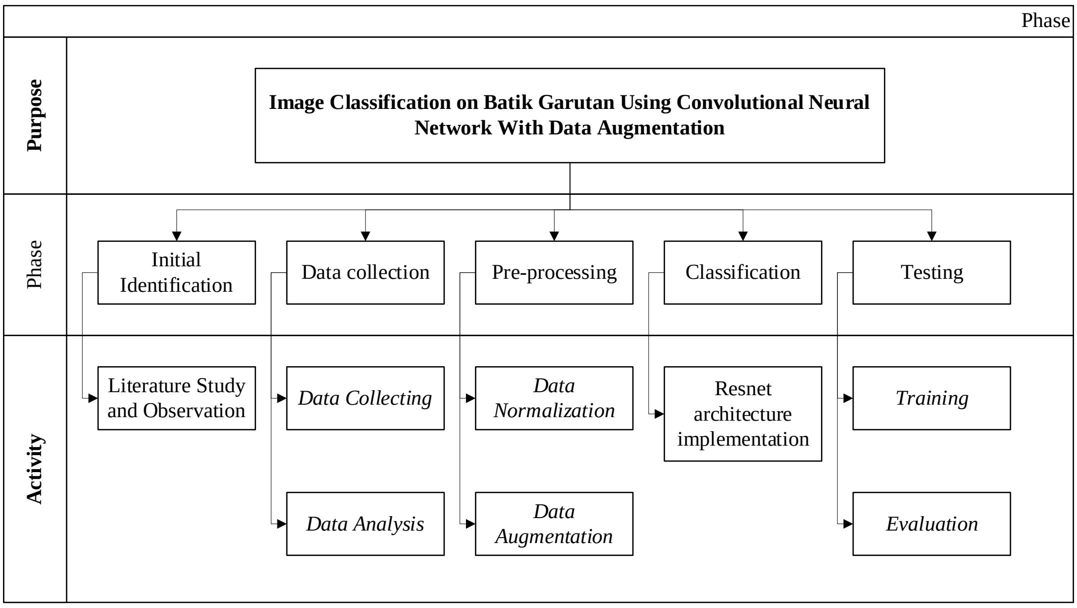

Fig. 1 Work breakdown structure

The stages of the work breakdown structure based on the framework, the following explanation:

- Initial Identification, the researcher conducted a literature study and observed several previous journals that discussed Garutan Batik and image classification.
- Data collection, researchers, collect data related to research and analyze the datasets that have been collected so that they can be classified. The image data for Garutan Batik used in this study were obtained from the dataset available on the Kaggle website (www.kaggle.com/datasets/ionisiusdh/indonesian-batik-motifs) labeled batik-garutan, which totals 50 images, as shown in Fig. 2.
- Pre-processing [23], after going through the data analysis stage, the uploaded dataset will then go through the pre-processing stage which consists of data normalization and data augmentation to simplify the classification process. Before the data goes through various image processing processes, the first step is to fetch/load the dataset that has been uploaded to Google Drive using the drive library from Google Colab.
- Classification, the Classification stage is the core stage of this research, which will determine the performance of the Resnet architecture used to classify the batik image dataset. The first thing to do is to initiate the Resnet architecture before conducting model training. The module used in this initiation process was obtained from Keras, namely Resnet50. The resnet50 architecture used can be seen in Fig. 3.

Overall ResNet-50 consists of 5 stages of the convolution process which is then continued by average pooling and ends with the fully connected layer as the classification layer.

Testing, at this stage using the Confusion Matrix as a method to measure the performance of a classification model is the accuracy value of a model. Some terms that are the basis for finding accuracy values are true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

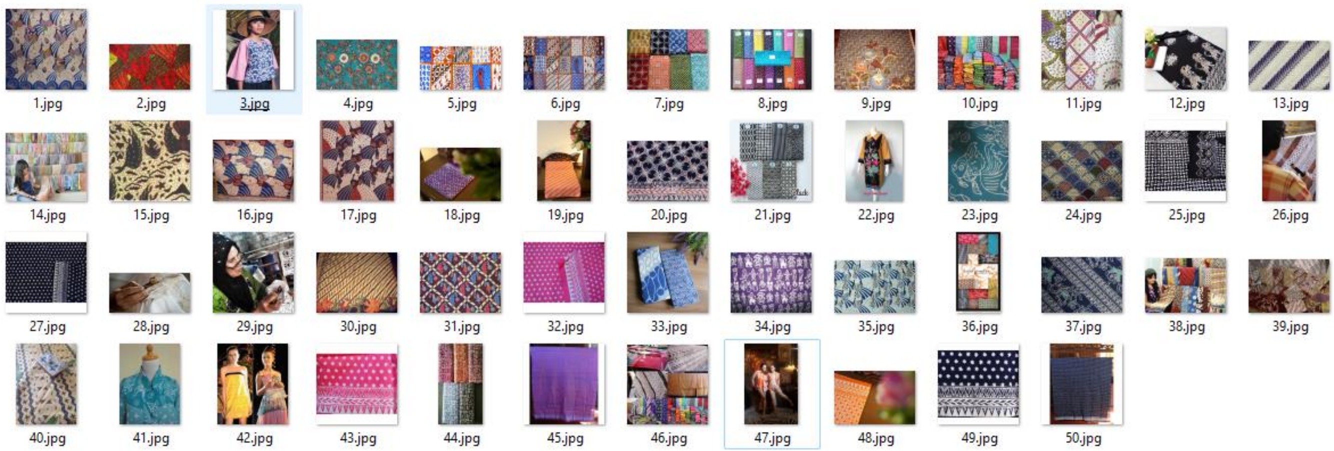

Fig. 2 Image of Garutan Batik

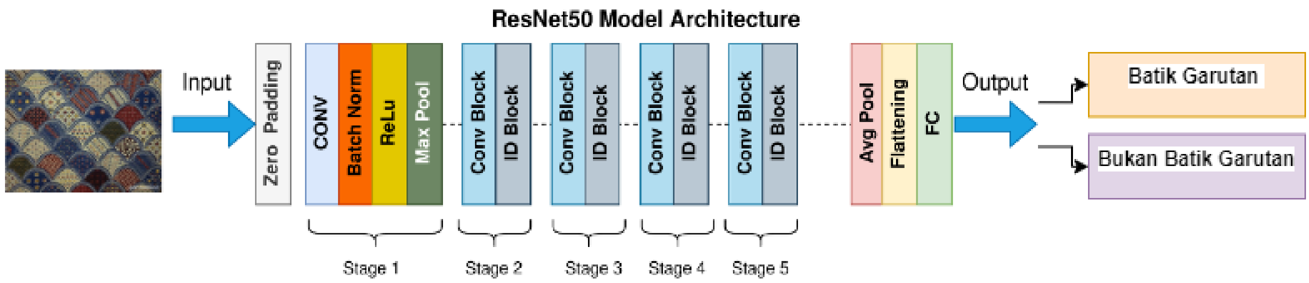

Fig. 3 ResNet50 model architecture

III. RESULT AND DISCUSSION

A. Initial Identification

At the initial identification stage, literature studies and observations were carried out by conducting visits and interviews with one of the companies producing Garutan Batik. These interviews found that Garutan Batik also had 55 kinds of motifs.

B. Data Collection

In Data Collecting, the next step is collecting data after carrying out the initial Identification. The data stage is carried out to identify the Garutan Batik motifs by using objects in the form of images or photos of batik motifs to identify the differences using the image classification process. Batik motifs that will be used as data objects in the image classification this time include:

1) *Batik Garutan*
2) *Other Batik (not Garutan Batik)*

Garutan Batik photos were taken at Garutan Batik producing companies in Garut Regency, Garutan Batik RM. Figure 4 shows some images of Batik Garutan that have been obtained.

This dataset has 20 classes/labels and contains 983 files in .jpg format. One of the classes has the Garutan Batik label, which can be used as a different class. The following are details of all data obtained in the Data Collecting process (Table I).

TABLE 1
DATA COLLECTING RESULTS

No.	Source	Total
1	Batik Garutan RM	125
2	*Kaggle*	983
	Total	1108

At the data analysis stage, the data that has been obtained will be sorted, where the 19 labels (excluding Garutan Batik) will be grouped into a label with the name Batik Lain. The data obtained for the training and validation process is as in Table II.

C. Pre-Processing

After going through the data analysis stage, the uploaded dataset will then go through the pre-processing stage which consists of data normalization and data augmentation to simplify the classification process.

TABLE II
DATA ANALYSIS RESULTS

No.	Label	*Training*	*Validation*	Total
1	Batik Garutan	140	35	175
2	Batik Lain	680	157	837
	Total	820	192	1012

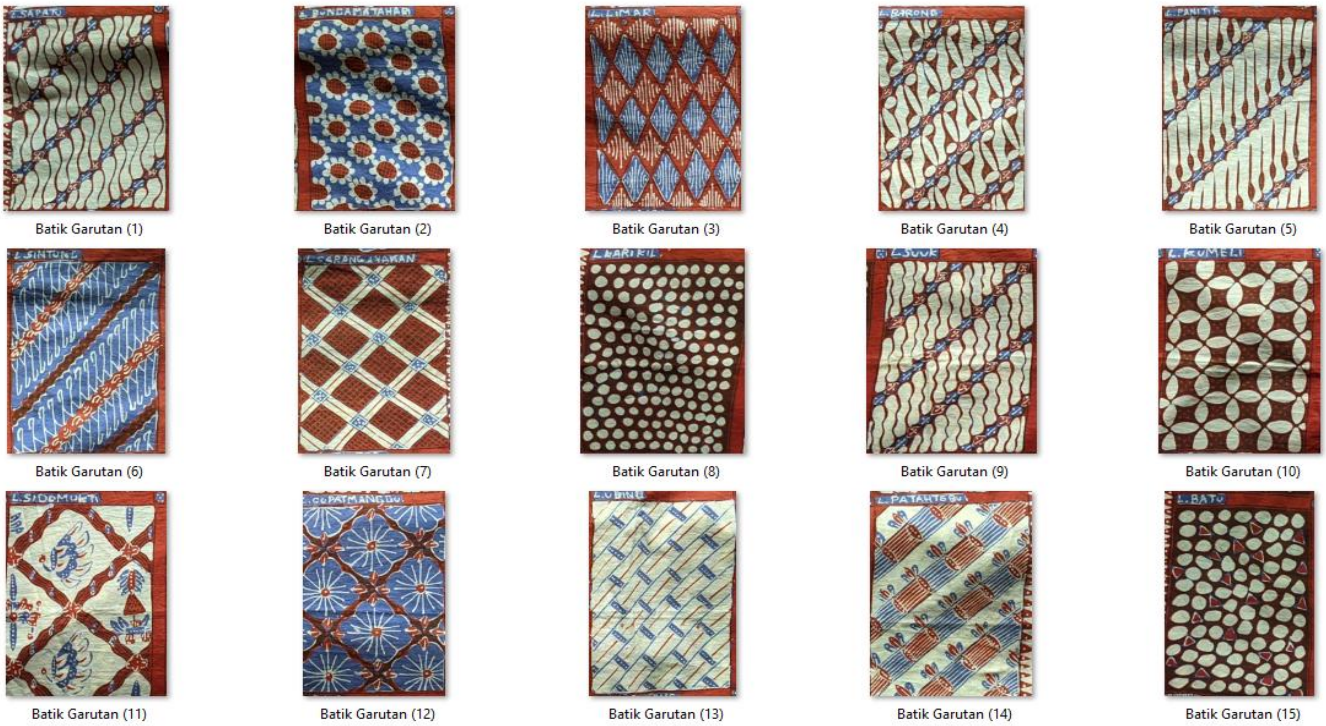

Fig. 4 Example of Garutan Batik data

1) Data Normalization is the first step of the Pre-Processing stage, where in Data Normalization datasets in the form of images will be extracted into an array or matrix with a size of 3x3. These matrices represent each of the images in the dataset used in this process. The contents of this matrix have a value range from 0 to 255, where the range will be simplified in this process. By doing Data Normalization or simplifying the value of this matrix, it will make the next process easier because the data values are smaller and consistent. Datasets that have gone through the Data Normalization stage will then undergo the Data Augmentation process.

2) Data Augmentation in this study includes zoom, flip, and rotate. Zoom is done to get data if the image used is enlarged. In the case of this study, the image will be enlarged with a scale of 0.3 or 30%. An example of zoom can be seen from Fig. 5 to 8.

The following augmentation is the flip, where this flip performs an inversion of the image horizontally and vertically. Flip is very helpful in identifying batik motifs which sometimes have irregular directions. Examples of horizontal and vertical flips can be seen in Fig. 6 and 7. Furthermore, the augmentation that is carried out is rotated where the image will be rotated with the maximum rotation amount that will be carried out is 90 degrees. An example of augmentation can be seen in Fig. 8.

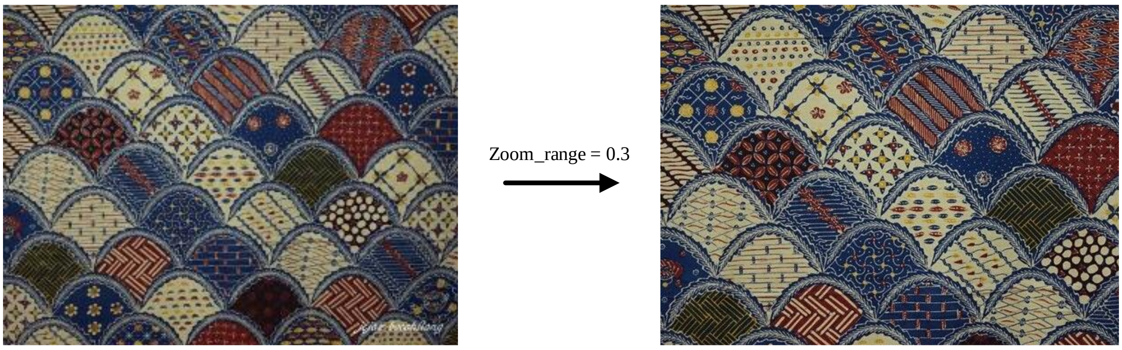

Fig. 5 Zoom

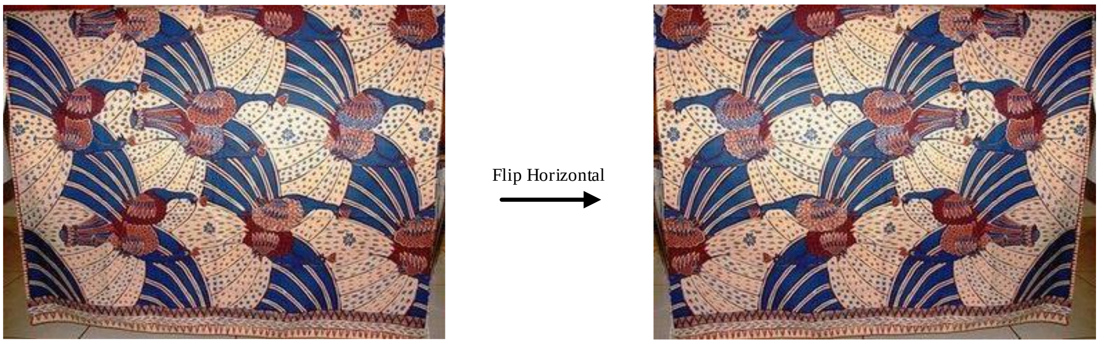

Fig. 6 Flip horizontal

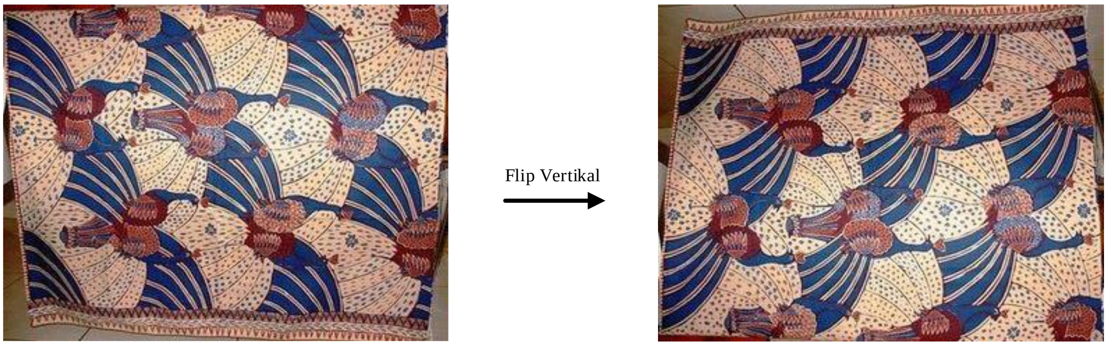

Fig. 7 Flip vertikal

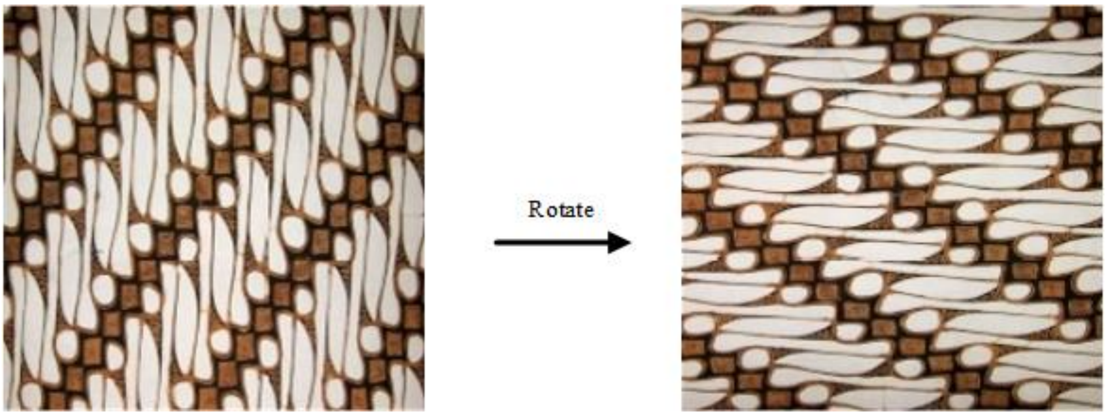

Fig. 8 Rotate

After the data augmentation process, each image in the dataset used has developed data from the zoom, flip and rotate methods so that the amount of data obtained is greater than the actual number of images in the dataset. This can add to the characteristics or identity of one existing batik image to further facilitate the subsequent classification process.

D. Classification

The Classification stage is the core stage of this research, which will determine the performance of the Resnet architecture used to classify the batik image dataset. The first thing to do is to initiate the Resnet architecture before conducting model training as in Fig. 9.

The first layer added is flatten which functions to transform the resulting matrix from the pre-classification process into vector form. The next layer is dense, in this layer there are 2 activators used, namely relu and sigmoid. Relu activator uses a filter quantity of 512, while for sigmoid itself uses a filter quantity with a value of 1. Figure 9 represents the structure of the sequential model by applying the resnet50 architecture. The sequential model created is an algorithm ready to be used to classify the Garutan Batik and other Batik datasets through the testing phase.

A total of 1108 datasets that are entered for the system are loaded into the system one by one. Then the prediction process is carried out using the trained ResNet-50 system model. After experiencing the feature extraction process with the help of the convolutional layer and pooling layer, the extracted values are then changed in dimension using the flattening function so that they can be processed to the fully connected layer. In the fully connected layer, a prediction process is carried out which places an input image into a certain class category. The overall results of the process that is carried out are shown in Fig. 10.

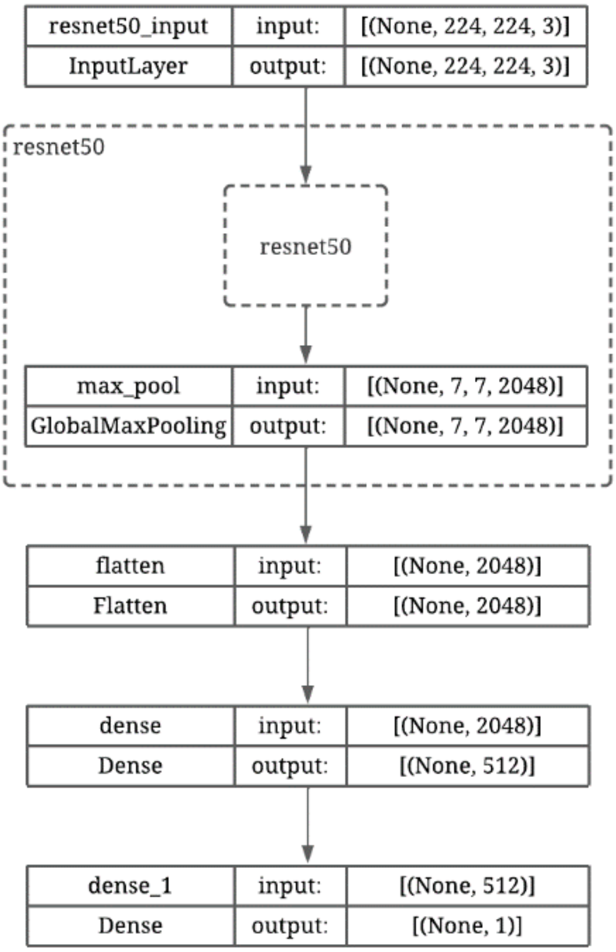

Fig. 9 Sequential model structure with resnet50 architecture

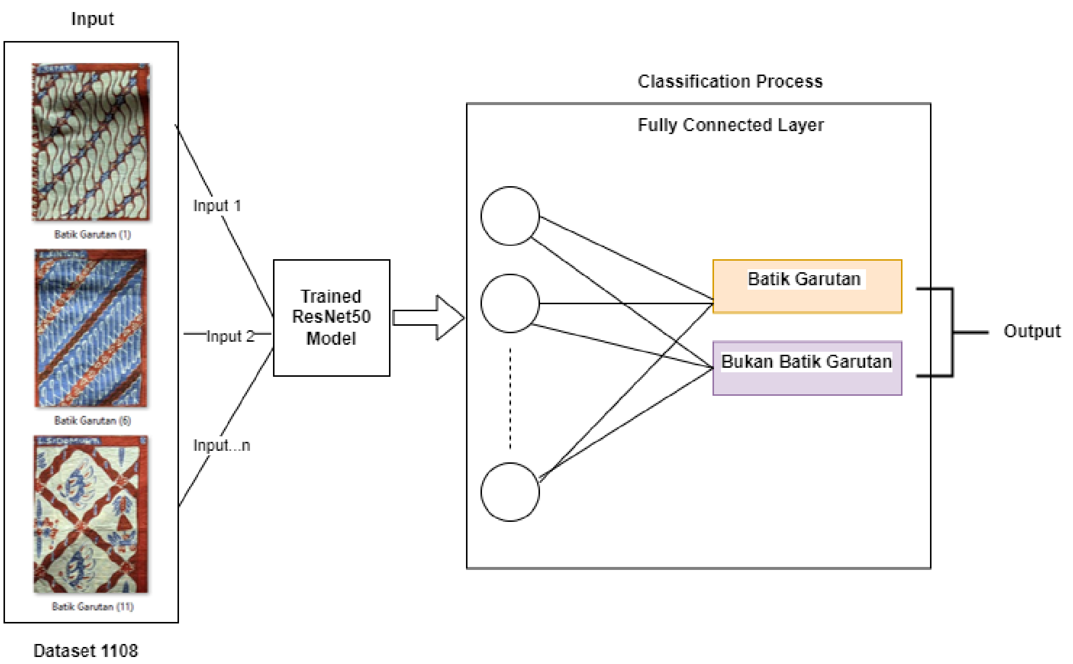

Fig. 10 Classification process

At the testing stage, the dataset will go through the data training process repeatedly according to the specified epoch to have a good accuracy level.

E. Testing

The resnet_model will undergo a compilation or training and evaluation process at this testing stage. At this stage, several parameters will be used as a reference to get a good accuracy value. The settings for these parameters are listed in Table III.

The results of training and evaluation will be obtained from 4 experiments with epochs of 25, 50, 75, and 100, respectively, as a comparison of which results are better. The following is an explanation of the training and evaluation process. Table IV is a comparison of the results of the training data process based on the epoch previously mentioned.

The last stage of this research is the evaluation stage. All the previous processes will be summarized into one of the evaluation methods, namely the confusion matrix with three evaluation calculations, including precision, recall, and f1-score. The following is calculating accuracy, precision, memory, and f1 score.

TABLE III
TEST PARAMETER SETTING

Learning Rate	*Loss*	*Epoch*
0.00001	binary_cross *entropy*	25, 50, 75, 100

TABLE IV
RESULTS OF MODEL TRAINING WITH EPOCH SETTINGS

Epoch	*Training*		*Validation*	
	Accuracy	*Loss*	*Accuracy*	*Loss*
25	0.8713	0.3368	0.8438	0.3950
50	0.8922	0.2937	0.8698	0.3823
75	0.8934	0.2917	0.8750	0.3711
100	0.9130	0.2495	0.8854	0.3692

Evaluation of Garutan Batik:

$$Precision = \frac{TP}{TP+FP} = \frac{16}{16+5} = 0.76$$

$$Recall = \frac{TP}{TP+FN} = \frac{16}{16+19} = 0.46$$

$$F1\ Score = \frac{2\ x\ (recall\ x\ precision)}{(recall + precision)} = \frac{2\ x\ (0.46\ x\ 0.76)}{(0.46+0.76)} = \frac{0.6992}{1.22}$$
$$= 0.57$$

Based on the picture above, the results obtained from the accuracy evaluation results are 0.73. Meanwhile, the precision, recall, and f1 scores for Batik Garutan were 0.76, 0.46, and 0.57, respectively.

IV. CONCLUSION

Based on the research results, the conclusions drawn by implementing data augmentation in the image classification process on Batik Garutan help increase the accuracy values obtained in the training process. This is because the unique value of an image can grow along with the application of data augmentation. In addition, the role of the epoch also significantly impacts the results of image classification. These things are supported by test results from the training process, which on average, has an accuracy value of more than 0.8, and the higher the epoch used, the higher the accuracy value obtained. The highest accuracy was obtained from 100 epoch trials with an accuracy value of 0.9130 for training data and 0.8854 for data validations.

This research contains a Deep Learning model for image classification problems on Batik Garutan images using the CNN algorithm. The study is limited only to the evaluation stage using the confusion matrix. It is hoped that further research can be developed for the image prediction process for Batik Garutan.

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REFERENCES

[1] S. Suhartini, N. A. Mahbubah, and M. Basjir, "MARKETING STRATEGY DESIGN BASED ON INFORMATION TECHNOLOGY IN BATIK SMALL AND MEDIUM-SIZED ENTERPRISES IN INDONESIA," *Eastern-European J. Enterp. Technol.*, vol. 6, no. 13–114, pp. 39–48, 2021, doi: 10.15587/1729-4061.2021.244137.

[2] Y. Y. Sunarya and B. Anas, "The priangan batik in the constellation of modern aesthetics," *J. Vis. Art Des.*, vol. 6, no. 1, pp. 9–16, Jan. 2014, doi: 10.5614/itbj.vad.2014.6.1.2.

[3] J. Qin, W. Pan, X. Xiang, Y. Tan, and G. Hou, "A biological image classification method based on improved CNN," *Ecol. Inform.*, vol. 58, p. 101093, 2020, doi: 10.1016/J.ECOINF.2020.101093.

[4] G. Zhou, W. Zhang, A. Chen, M. He, and X. Ma, "Rapid detection of rice disease based on FCM-KM and faster R-CNN fusion," *IEEE access*, vol. 7, pp. 143190–143206, 2019, doi: 10.1109/ACCESS.2019.2943454.

[5] X. Lei, H. Pan, and X. Huang, "A dilated CNN model for image classification," *IEEE Access*, vol. 7, pp. 124087–124095, 2019, doi: 10.1109/ACCESS.2019.2927169.

[6] S. Arya and R. Singh, "A Comparative Study of CNN and AlexNet for Detection of Disease in Potato and Mango leaf," *2019 Int. Conf. Issues Challenges Intell. Comput. Tech.*, vol. 1, pp. 1–6, 2019, doi: 10.1109/ICICT46931.2019.8977648.

[7] S. Baranwal, S. Khandelwal, and A. Arora, "Deep learning convolutional neural network for apple leaves disease detection," *Proc. Int. Conf. Sustain. Comput. Sci. Technol. Manag. (SUSCOM), Amity Univ. Rajasthan, Jaipur-India.*, 2019, doi: 10.2139/ssrn.3351641.

[8] A. Ramcharan, K. Baranowski, P. McCloskey, J. Ahmed, B., Legg, and D. P. Hughes, "Deep learning for image-based cassava disease detection," *Front. Plant Sci.*, vol. 8, p. 1852, 2017, doi: 10.3389/fpls.2017.01852.

[9] J. Chaki and N. Dey, *A beginner's guide to image shape feature extraction techniques*. CRC Press Taylor & Francis Group, 2019.

[10] L. Perez and J. Wang, "The effectiveness of data augmentation in image classification using deep learning," *arXiv Prepr. arXiv1712.04621*, 2017, doi: 10.48550/arXiv.1712.04621.

[11] M. A. Khan, T. Akram, M. Sharif, K. Javed, M. Raza, and T. Saba, "An automated system for cucumber leaf diseased spot detection and classification using improved saliency method and deep features selection," *Multimed. Tools Appl.*, vol. 79, no. 25–26, pp. 18627–18656, Jul. 2020, doi: 10.1007/S11042-020-08726-8.

[12] M. Kashif *et al.*, "Detection of viruses in sweetpotato from Honduras and Guatemala augmented by deep-sequencing of small-RNAs," *Plant Dis.*, vol. 96, no. 10, pp. 1430–1437, 2012, doi: 10.1094/PDIS-03-12-0268-RE.

[13] C. Uswatun Khasanah, E. Utami, and S. Raharjo, "Implementation of Data Augmentation Using Convolutional Neural Network for Batik Classification," in *In 2020 8th International Conference on Cyber and IT Service Management (CITSM)*, Oct. 2020, pp. 1–5, doi: 10.1109/CITSM50537.2020.9268890.

[14] M. A. Rasyidi and T. Bariyah, "Batik pattern recognition using convolutional neural network," *Bull. Electr. Eng. Informatics*, vol. 9, no. 4, pp. 1430–1437, Aug. 2020, doi: 10.11591/eei.v9i4.2385.

[15] D. G. T. Meranggi, N. Yudistira, and Y. A. Sari, "Batik Classification Using Convolutional Neural Network with Data Improvements," *JOIV Int. J. Informatics Vis.*, vol. 6, no. 1, pp. 6–11, Mar. 2022, doi: 10.30630/joiv.6.1.716.

[16] I. M. A. Agastya and A. Setyanto, "Classification of Indonesian batik using deep learning techniques and data augmentation," in *In 2018 3rd international conference on information technology, information system and electrical engineering (ICITISEE)*, Nov. 2018, pp. 27–31, doi: 10.1109/ICITISEE.2018.8720990.

[17] M. A. Rasyidi, R. Handayani, and F. Aziz, "Identification of batik making method from images using convolutional neural network with limited amount of data," *Bull. Electr. Eng. Informatics*, vol. 10, no. 3, pp. 1300–1307, Jun. 2021, doi: 10.11591/eei.v10i3.3035.

[18] B. Pasaribu, Y. Latief, and S. Riantini L, "Development of Risk-Based Standardized Work Breakdown Structure (WBS) to Improve Quality Planning of Drainage Construction Work Development of Risk-Based

Standardized Work Breakdown Structure (WBS) to," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 258, no. 1, p. 12054, 2019, doi: 10.1088/1755-1315/258/1/012054.

[19] E. Siami-Irdemoosa, S. R. Dindarloo, and M. Sharifzadeh, "Work breakdown structure ({WBS}) development for underground construction," *Autom. Constr.*, vol. 58, pp. 85–94, 2015, doi: 10.1016/j.autcon.2015.07.016.

[20] R. C. Tausworthe, "The work breakdown structure in software project management," *J. Syst. Softw.*, vol. 1, pp. 181–186, 1979, doi: 10.1016/0164-1212(79)90018-9.

[21] L. Fitriani, P. Hakim, and R. M. Al Haq, "E-Commerce For Village Information System Using Agile Methodology," *J. Online Inform.*, vol. 7, no. 1, pp. 89–96, 2022, doi: 10.15575/join.v7i1.825.

[22] L. Fitriani, S. Dianti, D. Kurniadi, A. Mulyani, and R. Setiawan, "Mapping-Based Using Geographic Information Systems for Smart Transportation," in *in 2021 International Conference on ICT for Smart Society (ICISS)*, 2021, pp. 1–5, doi: 10.1109/ICISS53185.2021.9533202.

[23] D. I. Mulyana and V. V. Pramansah, "Gender Classification for Anime Character Face Image Using Random Forest Classifier Method and GLCM Feature Extraction," *JUITA J. Inform.*, vol. 10, no. 2, pp. 243–250, 2022, doi: 10.30595/juita.v10i2.13833.