Classification of coastal batik and inland batik using three different models in machine learning

Ardha Ardea Prisilla[1], Yori Pusparani[2], Maftuhah Rahimah Rum[3]

[1]ardha.ardeaprisilla@lasallecollege.ac.id; [2]yori.pusparani@budiluhur.ac.id, [3]111125007@live.asia.edu.tw

[1]Department of Fashion Design, LaSalle College Jakarta, Jakarta, Indonesia,
[2]Department of Visual Communication Design, Budi Luhur University, Jakarta, Indonesia
[3]Department of Bioinformatics and Medical Engineering, Asia University, Taichung, Taiwan

Abstract

Through the generations, various batik motifs have been produced. Due to the difficulty of distinguishing batik patterns with the human eye, computer scientists have researched the classification of batik patterns. Image classification datasets are obtained from Google Images using keywords specific to distinguishing between inland and coastal batiks. The inland and coastal batik were then classified using three machine learning types: Resnet-50, Pretrained Resnet-50, and Pretrained Inception. Results showed that Pretrained ResNet-50 demonstrated the highest performance accuracy at 95%, Resnet-50 had a slightly lower performance accuracy at 93%, and Pretrained Inception had the lowest performance accuracy at 79%. In conclusion, this study successfully demonstrated that machine learning can classify inland and coastal batik with the highest accuracy using Pretrained ResNet-50.

I. Introduction

Batik is a technique of wax-resist dyeing applied to the entire piece of fabric [1]. In October 2009, UNESCO recognized batik as an internationally intangible cultural heritage of the Indonesian nation [1, 2]. Various batik motifs have been produced throughout the generations, reflecting the animism and dynamism of the ancestors [3].

The conservation of the batiks, one of Indonesia's cultural heritages, has entailed several efforts to collect and document batik data from all regions of the country [4]. Based on its development, Indonesian batik is primarily created in Java. The style is then spread throughout Indonesia with its characteristics.

According to their spread and development, batik Java is divided into inland and coastal regions [2, 5]. Inland Batik originates from the region of Yogyakarta and Surakarta. On the other hand, coastal Batik is developed along the coast of the northern islands of Java, such as Pekalongan and Cirebon, up to Madura [5]. The coastal and inland types can be distinguished by their coloring, motifs, and patterns. Batik in the inland region generally has a predominant brown color called Sogan or other natural colors drawn on a white or off-white background. In addition, the motifs of inland batik have formations and symbolic structures [2, 5]. In contrast, coastal batik from Java has a greater variety of colors, including red, green, blue, yellow, and purple, and the work motif is more freely expressed [2, 5].

At present, there are hundreds of batik cloth motifs that are found throughout Indonesia, each of which has its own name and significance. According to the book "Batik Spirits of Indonesia," there are at least 181 batik motifs in Indonesia, and the number is growing [6]. It is, therefore, difficult for ordinary people, especially those unfamiliar with batik patterns, to identify motifs in Indonesia because of the large number of batik patterns.

The difficulty of distinguishing batik patterns using the human eye has inspired computer scientists to research batik classification [7]. According to some studies, artificial intelligence, particularly machine learning, has been used to classify batik motifs based on their distinguishing characteristics [7, 8]. The concept of machine learning refers to creating programs that can learn from data and grow and adapt to new information when given new information [8]. As a result, it is expected that classification in machine learning will yield high-accuracy results. In spite of this, different machine learning models may produce different results during training. Therefore, this study proposes to compare three different machine learning models for the identification of inland batik and coastal batik.

II. Methods

2.1 Dataset and data acquisition

The dataset is obtained from Google images with keywords to distinguish the batik types. The keywords used for inland batik are *batik pedalaman, batik Yogyakarta, batik Solo, parang, semen,* and *kawung*. And the keywords used for coastal batik are *batik pesisir, batik Cirebon, batik Pekalongan,* and *mega mendung.* In this study, we compare coastal batik with inland batik based on their respective motives, colors, and structures (Figure 1). This study used 106 raw images divided into two classes, inland and coastal. We divided the used dataset from each class into 80% training and 20% validation (Figure 2).

A. Inland Batik **B. Coastal Batik**

Figure1. An example of Inland batik, *Parang Tuding* motif in *Sogan* (brown) color (A), and an example of coastal batik, *Mega Mendung* motif in red and gradients of blue colors (B).

To ensure the uniformity of the dataset, we only selected the jpg/jpeg image format. And then, we separate the inland and coastal batik based on the motifs, colors, and structures [9]. We divided the 106 raw images into inland and coastal classes, with 80% training (85 images) and 20% validation (21 images) in each class. The class details and the training and validation image numbers are described in Table 1.

Table 1. Dataset for classification

Class	Training	Validation
Coastal Batik	85	21
Inland Batik	85	21

2.2 Methods procedures

We then classify the inland and coastal batik using three machine learning types: Resnet-50, Pretrained Resnet-50, and Pretrained Inception (Figure 2). We used 10 epoch and 32 batch size to train the dataset. The performance of the three models is compared after the training.

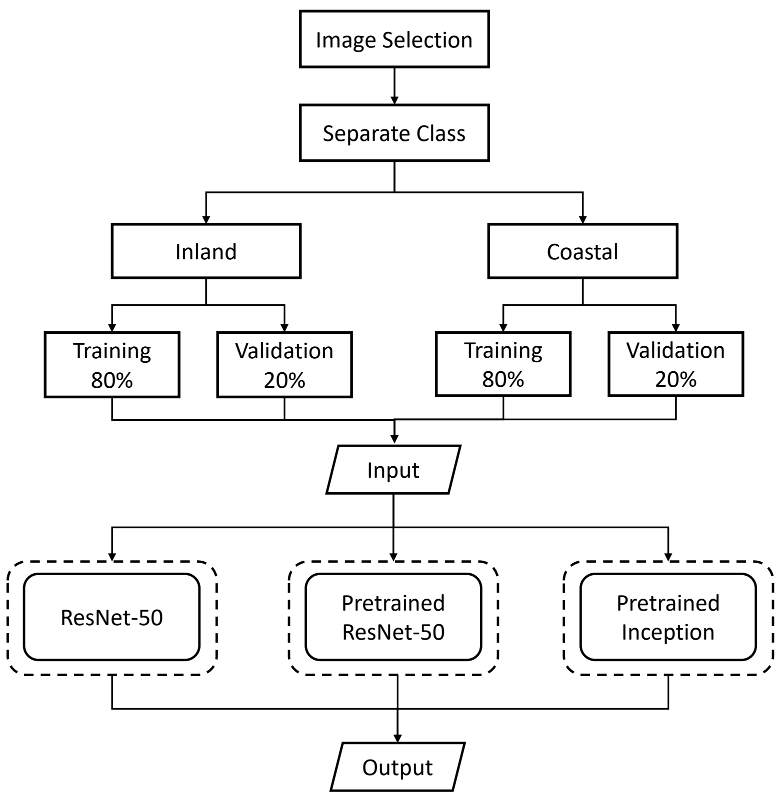

Figure 2. Flowchart of data processing

2.3 Machine learning models

In this study, we used three different machine learning models, namely ResNet-50, Pretrained ResNet-50, and Pretrained-Inception, to classify inland and coastal batik. The three models used 224x224 pixel image resolution, loss function with cross entropy error, optimization function adam and learning parameters such as Recall, Precision, F-1 Score, and Accuracy. The performance is compared based on the metric performance of each model.

ResNet-50

ResNet-50 is one of the deep learning models proven to be very efficient in batik classification [10]. ResNet-50 architecture is the 1st rank in ILSVRC and Common objects in Context (COCO) in 2015 for the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation. ResNet-50 architecture can classify images on the ImageNet dataset with a high degree of accuracy [11].

Pretrained ResNet-50

A pretrained neural network is capable of classifying images into 1000 different categories of objects. The neural network has therefore acquired rich feature representations for various images [11]. Pretrained models usually converge to a higher training loss but generalize significantly better than models with random initialization on test data [12].

Pretrained inception

Designed to maximize the utilization of computing resources within the network, Inception V3 CNN increases depth and width while maintaining computation operations. Inception modules are built as building blocks of this network and are termed by its designers as an optimized network structure with skipped connections. The inception module is repeated spatially by stacking with occasional max-pooling layers to reduce the degree of dimensionality to a manageable computation level [13, 14].

III. Results

In this study, we use three K-train models such as Resnet-50, Pretrained Resnet-50, and Pretrained inception, to classify coastal and inland batik. The metric performance comparison of the three models can be seen in the chart below. The result of ResNet-50 is shown in Figure 3, Pretrained ResNet50 is shown in Figure 4, and Pretrained Inception is shown in Figure 5.

Results Resnet-50

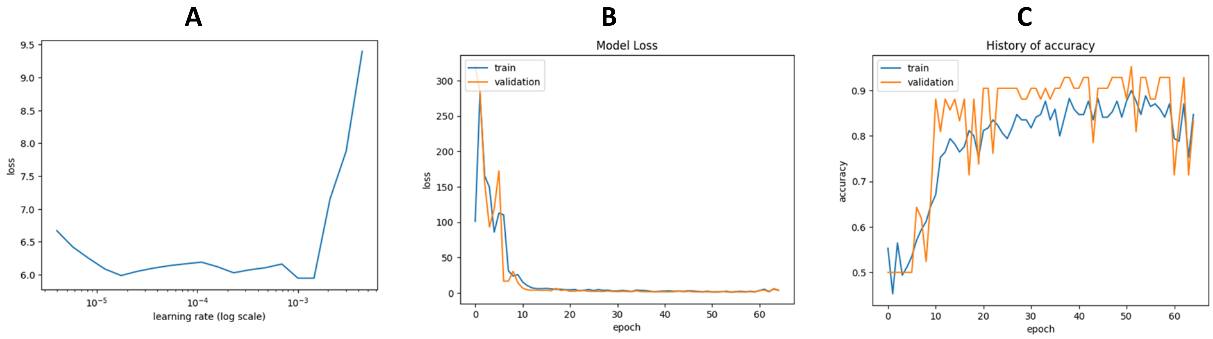

Figure 3. Result of ResNet-50 model. The learning rate (A), model loss during training and validation (B), the accuracy during the training and validation (C)

Result Pretrained ResNet-50

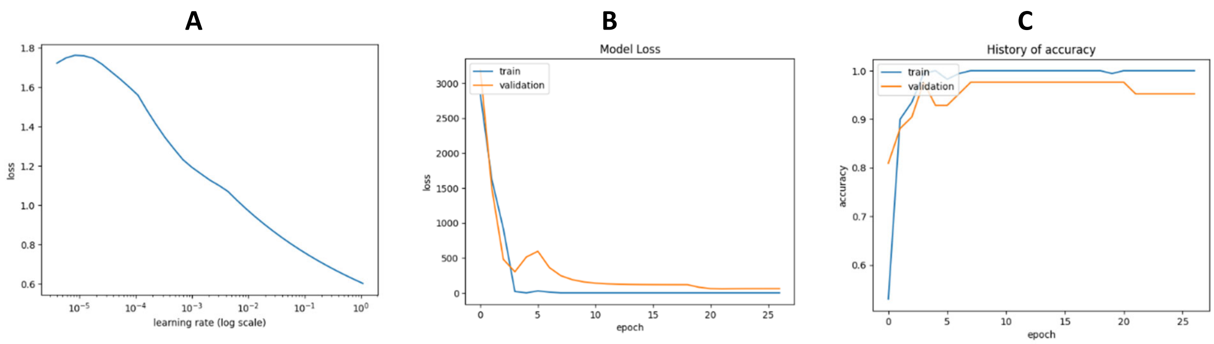

Figure 4. Result of Pretrained ResNet-50 model. The learning rate (A), model loss during training and validation (B), the accuracy during the training and validation (C)

Result Pretrained Inception

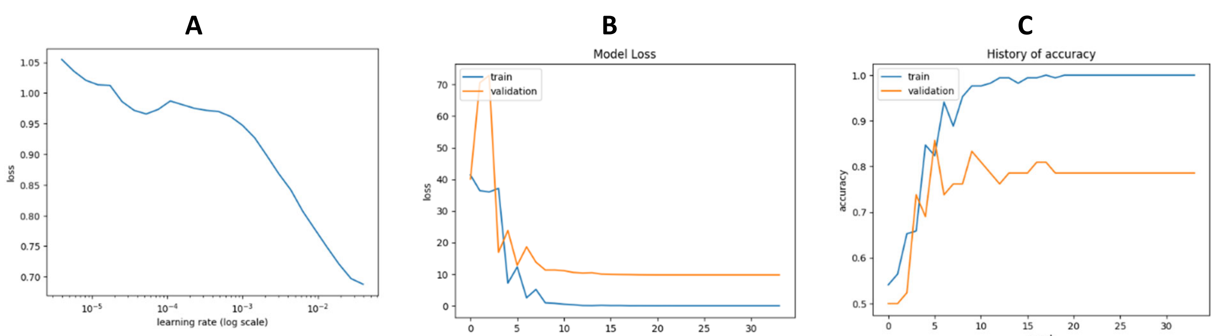

Figure 5. Result of Pretrained Inception model. The learning rate (A), model loss during training and validation (B), the accuracy during the training and validation (C)

The three models are able to classify the inland and coastal batik from 106 dataset. All models have performance accuracy above 75%. Pretrained ResNet-50 demonstrated the highest performance accuracy at 95%, Resnet-50 had slightly lower performance accuracy at 93%, and Pretrained Inception had the lowest performance accuracy at 79% (Table 2).

Table 2. Metric Performance comparison of Resnet-50, Pretrained ResNet-50, and Pretrained Inception

Model Performance Comparison	Resnet-50		Pretrained ResNet-50		Pretrained Inception	
	Coastal	Inland	Coastal	Inland	Coastal	Inland
Precision	95%	91%	95%	95%	80%	77%
Recall	90%	95%	95%	95%	76%	81%
F1-Score	93%	93%	95%	95%	78%	79%
Accuracy	93%		95%		79%	

Pretrained ResNet-50 had a stable performance on all metric performance parameters, with Precision, Recall, and F1-score at 95% on both Coastal and Inland classes. Resnet-50 showed the highest classification performance in the coastal class on the Precision at 95%, while in the Inland class on the Recall at 95%. However, the Recall for the coastal showed the lowest value at 90%. In addition, both classes shared the same performance on the F1-score. In contrast, Pretrained Inception showed the lowest result among all models. The highest value is inland class Recall at 81% and the lowest at coastal Recall at 76%.

IV. Discussion

This study provides several contributions to the design field related to artificial intelligence through the classification of inland batik and coastal batik. From the results, it can be concluded that the three models used have the potential to be used to classify inland batik and coastal batik, with the highest accuracy value acquired by the Pretrained ResNet-50 with 95%. The Pretrained ResNet-50 has a greater accuracy result because its architecture can create deeper networks, which positively impact the accuracy of the model, resulting in a more efficient training network [13]. On the other hand, The Pretrained Inception algorithm has been designed to create a balance, particularly when computational resources are limited. This method, however, utilized a variety of filter sizes within the same layer rather than deeper layers [14], which might be the reason it showed a lower accuracy in comparison to Pretrained ResNet-50 and ResNet-50

Additionally, this study demonstrated that machine learning can be used to differentiate between inland batik and coastal batik and to assist in more advanced transfer learning using artificial intelligence. Since there are many and varied motifs in inland and coastal batiks, the younger generation of Indonesians are unable to distinguish them properly, resulting in a lack of understanding of their meanings. Such an issue might be because there is no centralized repository of information about the traditional cloth of Indonesia, especially the traditional motifs [15].

Still, there is a limitation in this study due to many motifs from both inland and coastal batik [5]. Some of the coastal batiks may contain motifs inspired by or combined with those of inland batik, which could hinder the learning process of the models [2, 10]. The future study may establish guidelines for each motif, arrange them based on specific regions of each inland and coastal batik before training, and separate the individual motif accordingly. Further study might also include the possibility of classifying prohibited motifs from the inland region [16]. For the inland region, the court established motifs exclusively used by the court and prohibited the use of these motifs by ordinary citizens. A further study may provide a basis for setting out prohibited motifs for ordinary citizens so that they do not violate any court's rules during a visitation.

V. Conclusion

In conclusion, this study has made significant contributions to the field of artificial intelligence in classifying inland and coastal batik The results indicate that all three models used in the study show potential for accurately classifying inland can coastal batik patterns, with the highest accuracy achieved by the Pretrained ResNet-50 model. This study provides a basis for more advanced transfer learning using artificial intelligence, thereby aiding in preserving and understanding traditional Indonesian cloth.

Reference

1. UNESCO, *Intangible Cultural Heritage of Humanity.* 2009.
2. Steelyana, W., *Batik, a beautiful cultural heritage that preserve culture and support economic development in Indonesia.* Binus Business Review, 2012. **3**(1): p. 116.
3. Muwafiq, A.u., D.P. PAMUNGKAS, and R. WULANNINGRUM, *Implementasi Metode Convolutional Neural Network Untuk Klasifikasi Motif Batik.* Prosiding Semnasinotek 2020, 2020.
4. Santosa, D., *Batik: Pengaruh Zaman dan Lingkungan.* Solo: Danar Hadi, 2002.
5. Tulistyantoro, L. and S.D. Yong, *Batik Java–A Prayer Behind Every Stroke*. 2019, Petra Christian University.
6. Achjadi, J., et al., *Batik: spirit of Indonesia.* 1999.
7. Riadi, I., A. Fadlil, and I.J.D.P. Putra, *Batik Pattern Classification using Naïve Bayes Method Based on Texture Feature Extraction.* Khazanah Informatika: Jurnal Ilmu Komputer dan Informatika, 2023. **9**(1).
8. Wicaksono, A.Y., et al., *Modified convolutional neural network architecture for batik motif image classification.* IPTEK Journal of Science, 2017. **2**(2).
9. Suciati, N., W.A. Pratomo, and D. Purwitasari. *Batik motif classification using color-texture-based feature extraction and backpropagation neural network*. in *2014 IIAI 3rd International Conference on Advanced Applied Informatics*. 2014. IEEE.
10. Negara, B.S., et al. *ResNet-50 for Classifying Indonesian Batik with Data Augmentation*. in *2021 International Congress of Advanced Technology and Engineering (ICOTEN)*. 2021. IEEE.
11. He, K., et al. *Deep residual learning for image recognition*. in *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.
12. Trinh, T.H., M.-T. Luong, and Q.V. Le, *Selfie: Self-supervised pretraining for image embedding.* arXiv preprint arXiv:1906.02940, 2019.
13. Horry, M.J., et al., *X-ray image based COVID-19 detection using pre-trained deep learning models.* 2020.
14. Szegedy, C., et al. *Rethinking the inception architecture for computer vision*. in *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.
15. Sari, Y., M. Alkaff, and R.A. Pramunendar, *Classification of coastal and inland Batik using GLCM and Canberra Distance.* AIP Conference Proceedings, 2018. **1977**(1).
16. Tozu, M., *Forming Process of Batik Indonesia One Type of Forming of National Culture in Indonesia.*