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Automated Recognition of Batik Aceh Patterns Using Machine Learning Techniques

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ABSTRACT

This research focuses on the automatic recognition of Aceh batik patterns using machine learning techniques. Utilizing a Convolutional Neural Network (CNN) model based on EfficientNet, a dataset consisting of 1,200 Aceh batik images was processed through various stages, from data collection to model training and evaluation. The images are divided into three main classes: Bungong Jeumpa, Ceplok, and Kerawang. The data processing steps include normalization, resizing, and data augmentation to ensure better variation. The model was trained using 75% of the data as a training set and 25% as a testing set. The results indicate that the model performed excellently, achieving an accuracy rate of 98%. According to the classification report, the model achieved an average precision, recall, and F1-score of 0.98. The Kerawang category achieved the highest precision at 100%, while the Bungong Jeumpa and Ceplok categories had F1-scores of 0.98 and 0.97, respectively. These findings demonstrate the potential of machine learning methods in recognizing Aceh batik patterns with high accuracy, supporting the preservation of local culture through technology.

INTRODUCTION

Aceh batik is a unique cultural art form from the Aceh region in Indonesia, bearing deep historical and symbolic meanings. The motifs and patterns in Aceh batik represent cultural heritage, blending elements of religion, nature, and philosophy. The creation process of Aceh batik motifs involves several stages, including the Pre-design Stage, Design Stage, Realization Stage, and Presentation Stage (Dahlia, Izzati, & Br Sembiring, 2023). This approach helps us understand that these motifs not only serve as visual decoration but also act as a significant medium for conveying the traditions and customs of the Acehnese people(Sembiring, Fauziana Izzati, & Putri Dahlia, 2024).

As Indonesia continues its efforts to preserve and promote its cultural heritage, the digital preservation and automatic recognition of Aceh batik motifs have become pressing issues, especially with advancements in image processing and machine learning technologies. Automating the recognition of Aceh batik motifs offers various benefits, including improved cultural documentation, support for the local textile industry, and the creation of digital archives. However, despite its artistic richness, manually identifying and categorizing these patterns is not easy, particularly for those unfamiliar with batik art. Machine learning (ML) offers a solution by automating this process through advanced image recognition techniques (M, 2024).

This research aims to explore the application of machine learning methods to automatically recognize and classify Aceh batik motifs. We also applied fine-tuning techniques to optimize the machine learning model for identifying Aceh batik motifs from digital images.

LITERATURE REVIEW

The field of automatic image recognition has advanced rapidly, especially with the development of machine learning algorithms, particularly in the realm of cultural heritage. Several studies have focused on the recognition of traditional batik patterns (Malika, M., & Widodo, 2022; Rizal, F., Hasyim, F., Malik, K., & Yudistira, 2022).

Pattern recognition in batik often involves digital image processing techniques aimed at extracting key features from batik images. According to (Sulistiyanti, Sri & Setyawan, Fx Arinto & Komarudin, 2016), image processing involves several stages, such as pre-processing, feature extraction, and classification Traditional image processing methods, such as wavelet transform and Fourier transform, have been widely used to analyze patterns in batik images. However, these methods have limitations when faced with the complexity and geometric variability of traditional batik motifs.

With the advancements in machine learning (ML), various techniques have been employed to improve the accuracy of batik pattern recognition. For example, a study by (Wiryadinata, R., Adli, M. R., Fahrizal, R., & Alfanz, 2019) used the Support Vector Machine (SVM) method for batik motif classification and achieved relatively high accuracy. However, this study highlighted that traditional machine learning models require manual feature extraction, which is time-consuming and prone to inaccuracies if the image quality is poor.

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Recent studies have begun using deep learning algorithms to automate feature extraction and batik pattern classification. For instance, the use of Convolutional Neural Networks (CNN) has been proven effective in classifying batik motifs with better accuracy compared to traditional methods (Gunawan & Setiawan, 2022). CNN can directly recognize batik patterns from raw images without the need for complex feature pre-processing. However, according to (Fahcruroji, Madona Yunita Wijaya, & Irma Fauziah, 2024), CNN still has limitations when predicting nearly similar shapes or images with many objects, increasing the likelihood of errors in predictions.

The development of an automatic system for batik recognition involves several key aspects, including optimal image processing and selecting the appropriate machine learning model that can adapt to the unique characteristics of Aceh batik motifs. This research proposes the use of data augmentation as a solution to improve CNN performance in classifying Aceh batik motifs.

METHOD

This study consists of several stages, as illustrated in Figure 1. The process begins with data collection and pre-processing, which includes normalization, resizing, and data augmentation. After pre-processing, the model is selected. The selected model is then trained and evaluated to assess its performance in recognizing batik patterns automatically.

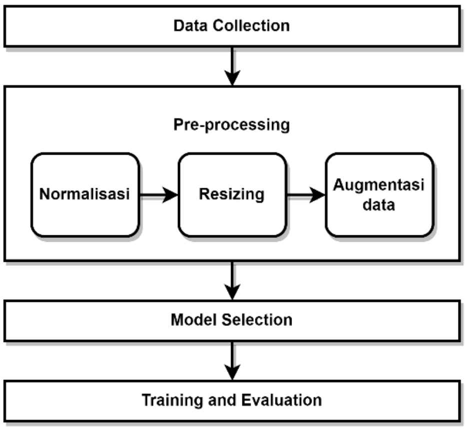

Figure 1. Research methods

Data Collection

The first step in this research involves collecting a dataset of Aceh batik images. These images are labeled based on motif type, considering variations in color and pattern structure. The dataset is divided into three subsets: training set (for training the model), validation set (for validating performance during training), and test set (for final model performance evaluation). Although there are various types of distinctive Aceh batik motifs, this research only focuses on three types: Kerawang, Ceplok Gayo, and Bungong Jeumpa. Other motifs, such as Pintu Aceh, Rencong, and Tolak Angin, are not used in this research because these motifs lack specific characteristics in batik. Symbols like Pintu Aceh, Rencong, and Tolak Angin frequently appear in nearly all types of batik, even with proportions that almost match the fundamental batik motifs.

Pre-processing

Before training the machine learning model, the images are pre-processed to enhance their quality and ensure uniformity. Pre-processing steps include:

1) Normalization: Pixel values of the images are normalized to a range of [0, 1] or [-1, 1] to accelerate convergence during training.
2) Resizing: Images are resized to fit the expected input of the CNN. Many CNN architectures accept input images of a fixed resolution (e.g., 224x224).
3) Data Augmentation: Data augmentation is used to create variations of the existing images. This technique helps increase the dataset size, allowing for optimal training and improving the model's performance in recognizing and classifying Aceh batik motifs.

Model Selection

This research utilizes the Convolutional Neural Networks (CNN) model, which is highly suited for image classification tasks as it automatically learns the spatial hierarchy of patterns in input images. The model is designed with several layers, including convolutional layers, pooling layers, and fully connected layers. The CNN is trained using the Aceh batik image dataset and evaluated based on accuracy and loss. The CNN architecture used is EfficientNet, known for its efficiency and high accuracy. The advantages of EfficientNet include: (1) Efficient scalability with

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compound scaling that increases the network proportionally (Tan, M., & Le, 2019)(Tan, 2023), (2) High performance with a top-1 accuracy of 84.4% and top-5 accuracy of 97.1% on ImageNet (Tan, M., & Le, 2019), (3) Fewer parameters and FLOPS, (4) Good transfer learning capabilities (Tan, M., & Le, 2019), and (5) Optimized architecture through MBConv and Squeeze-and-Excitation layers for performance improvement (Potrimba, 2023).

Training and Evaluation

The dataset is divided into two sets, the training set and the testing set, with a 75:25 ratio. The model is trained using the training set and evaluated using the testing set. Performance evaluation methods such as accuracy, precision, recall, and F1-score are used to assess the model's performance (M. Muhathir, N. Khairina, R. Karenina Isabella Barus, M. Ula, 2023). Here are some formulas for this method:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$F1 - Score = \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

A True Positive occurs when the model predicts a positive result, and the actual outcome is also positive, indicating a correct prediction for the positive class. Similarly, a True Negative happens when the model predicts a negative result, and the actual outcome is negative, signifying a correct prediction for the negative class. Conversely, a False Positive arises when the model incorrectly predicts a positive result, but the actual outcome is negative, which is also referred to as a Type I error. Lastly, a False Negative occurs when the model predicts a negative result, but the actual outcome is positive, representing an incorrect prediction for the negative class, commonly known as a Type II error

RESULT

In this research, we implemented machine learning techniques using the CNN EfficientNet architecture to automatically recognize Aceh batik patterns. The dataset used consists of 1,200 images representing three types of batik patterns: Bungong Jeumpa, Ceplok, and Kerawang Gayo. Figure 2 shows examples of these three patterns

Figure 2. Aceh Batik Motifs: (a) Bungong Jeumpa; (b) Ceplok; (c) Kerawang

The dataset of batik pattern images is divided into two subsets, with 75% used for training (900 images) and 25% for testing (300 images). During the training process, 10% of the training data, totaling 30 images, was used for validation.

Evaluation Results

Based on testing 300 images, consisting of 94 Bungong Jeumpa images, 62 Ceplok images, and 144 Kerawang Gayo images, the trained model demonstrated excellent performance. This can be seen from the classification results illustrated by the confusion matrix in Figure 3.

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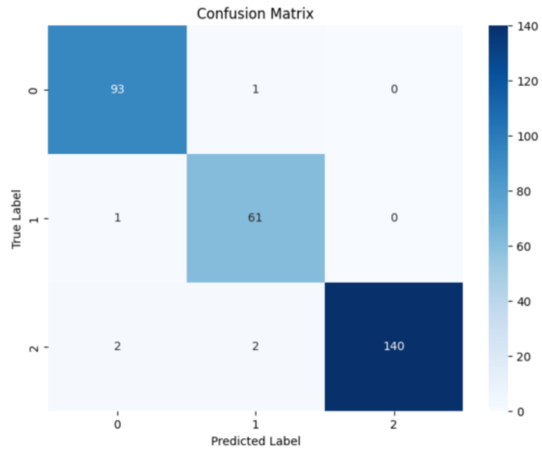

Figure 3. Matrix Confusion

There are 3 prediction classes: 0 for Bungong Jeumpa, 1 for Ceplok, and 2 for Kerawang Gayo. The CNN EfficientNet model successfully detected 93 out of 94 Bungong Jeumpa images, 61 out of 62 Ceplok images, and 140 out of 144 Kerawang Gayo images. Below are the calculated values of accuracy, precision, recall, and F1-score from the testing process of the CNN EfficientNet model in detecting Aceh batik types:

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

    BungongJ       0.97      0.99      0.98        94
      Ceplok       0.95      0.98      0.97        62
    Kerawang       1.00      0.97      0.99       144

    accuracy                           0.98       300
   macro avg       0.97      0.98      0.98       300
weighted avg       0.98      0.98      0.98       300
```

The overall accuracy reached 98%, with macro averages of precision, recall, and F1-score at 0.97, 0.98, and 0.98, respectively. Additionally, the weighted average yielded similar results, indicating that the model is reliable in recognizing all types of batik patterns present in the dataset.

The results show that the CNN EfficientNet model is highly effective in classifying Aceh batik patterns. The high accuracy rate of 98%, along with a stable F1-score across various classes, indicates the model's ability to recognize complex visual patterns with high precision. The best performance was achieved in the Kerawang class, where precision reached 100%, indicating that no images were misclassified as Kerawang, although there was a slight reduction in recall to 97%. In the Bungong Jeumpa and Ceplok classes, although the precision was slightly lower compared to Kerawang, the model still demonstrated strong performance with F1-scores above 0.95. The imbalance in the number of images in each class may have contributed to this slight variation, as smaller classes like Ceplok are somewhat more challenging to consistently recognize.

Overall, the model exhibits good generalization and is capable of handling the complexity of varying batik patterns, making it highly promising for use in automated batik recognition applications in the textile industry. Further implementation could consider the use of data augmentation to enhance performance in less-represented classes.

DISCUSSION

The results show that the CNN EfficientNet model is highly effective in classifying Aceh batik patterns. The high accuracy rate of 98%, along with a stable F1-score across various classes, indicates the model's ability to recognize complex visual patterns with high precision. The best performance was achieved in the Kerawang class, where precision reached 100%, indicating that no images were misclassified as Kerawang, although there was a slight reduction in recall to 97%. In the Bungong Jeumpa and Ceplok classes, although the precision was slightly lower compared to Kerawang, the model still demonstrated strong performance with F1-scores above 0.95. The imbalance in the number of images in each class may have contributed to this slight variation, as smaller classes like Ceplok are somewhat more challenging to consistently recognize.

Overall, the model exhibits good generalization and is capable of handling the complexity of varying batik Aceh patterns. Comparing this result with other machine learning models such as Support Vector Machines (SVM) (ZAMAN & Khoirudin, 2021) or traditional image processing methods like Fourier and wavelet transforms (Novita, Haryono, & R, 2016; Rangkuti, 2014), CNN-based models like EfficientNet offer clear advantages. Unlike traditional methods that

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require manual feature extraction and are limited when handling complex patterns, CNNs can automatically learn features from raw data, which explains the significant improvement in classification accuracy. EfficientNet, with its advanced architecture and ability to scale effectively, outperformed models that rely on manual feature engineering, highlighting its suitability for tasks requiring intricate pattern recognition.

One notable challenge, however, is the class imbalance, particularly in the Bungong Jeumpa and Ceplok classes. These classes had slightly lower precision compared to Kerawang, likely due to fewer training examples for those patterns. This imbalance often leads to decreased model performance because the model is exposed to less variation and fewer instances in the smaller classes. This is a common issue in machine learning, where underrepresented classes can lead to biased results. To address this, future research could include more extensive data augmentation techniques to artificially increase the number of training samples in underrepresented classes, improving recognition performance in these classes.

The findings also suggest that this method is well-suited for practical applications in the textile industry, where automated batik pattern recognition could streamline processes such as quality control, design cataloging, and cultural preservation. Compared to manual classification, this method offers a scalable and efficient solution with high precision, which could be especially valuable for large-scale batik production.

The model's success in handling varying complexities within batik motifs signifies a significant step forward in applying machine learning to cultural preservation. The ability of CNNs to generalize across different visual features opens new opportunities for extending this research to other types of cultural textiles or even to broader image recognition problems in various fields. In addition, further optimization of the model, such as exploring other CNN architectures like ResNet or MobileNet, could provide insights into even more efficient solutions, particularly for low-resource environments.

In conclusion, the research demonstrates that CNN EfficientNet can be a reliable tool for the automatic classification of Aceh batik patterns. Although there are minor challenges such as class imbalance, the overall performance is strong, with potential for further improvements through data augmentation and the exploration of other model architectures. The high accuracy and generalization capability make this approach highly promising for real-world applications in batik recognition and beyond.

CONCLUSION

This study shows that CNN with EfficientNet Model architecture is able to classify Acehnese batik patterns with high accuracy. This model is able to overcome the complexity of varying batik patterns and can be relied upon as a solution for automatic batik pattern recognition. Although there are minor challenges such as class imbalance, the overall performance is strong, with potential for further improvements through data augmentation and the exploration of other model architectures. The high accuracy and generalization capability make this approach highly promising for real-world applications in batik recognition and beyond.

REFERENCES

Dahlia, P., Izzati, F., & Br Sembiring, S. (2023). Tradisi Peusijuk Sebagai Inspirasi Penciptaan Desain Motif Aceh Pada Media Batik. *Gorga : Jurnal Seni Rupa*, *12*(2), 590. doi:10.24114/gr.v12i2.50782

Fahcruroji, A. R., Madona Yunita Wijaya, & Irma Fauziah. (2024). Implementasi Algoritma Cnn Mobilenet Untuk Klasifikasi Gambar Sampah Di Bank Sampah. *PROSISKO: Jurnal Pengembangan Riset Dan Observasi Sistem Komputer*, *11*(1), 45–51. doi:10.30656/prosisko.v11i1.8101

Gunawan, D., & Setiawan, H. (2022). Convolutional Neural Network dalam Citra Medis. *KONSTELASI: Konvergensi Teknologi Dan Sistem Informasi*, *2*(2), 376–390. doi:10.24002/konstelasi.v2i2.5367

M. Muhathir, N. Khairina, R. Karenina Isabella Barus, M. Ula, and I. S. (2023). "Preserving Cultural Heritage Through AI: Developing LeNet Architecture for Wayang Image Classification". *(IJACSA) International Journal of Advanced Computer Science and Applications*, *14*(9).

M, L. (2024). *Research on Textile Pattern Recognition Based on Artificial Intelligence*. In *2024 IEEE 7th Eurasian Conference on Educational Innovation (ECEI),* (pp. 335-338.).

Malika, M., & Widodo, E. (2022). *IMMPLEMENTASI DEEP LEARNING UNTUK KLASIFIKASI GAMBAR MENGGUNAKAN CONVOLUTIONAL NEURAL NETWORK (CNN) PADA BATIK SASAMBO*. In *Pattimura Proceeding: Conference of Science and Technology.*

Novita, V. D., Haryono, N. A., & R, I. D. E. K. (2016). Klasifikasi Motif Batik Semen Berdasarkan Ekstraksi Polar Fourier Transform Dan K-Nearest Neighbour, (November), 263–268.

Potrimba, P. (2023). What is EfficientNet? The Ultimate Guide.

Rangkuti, A. H. (2014). Klasifikasi Motif Batik Berbasis Kemiripan Ciri dengan Wavelet Transform dan Fuzzy Neural Network. *ComTech: Computer, Mathematics and Engineering Applications*, *5*(1), 361. doi:10.21512/comtech.v5i1.2630

Rizal, F., Hasyim, F., Malik, K., & Yudistira, Y. (2022). Implementasi Algoritma Convolutional Neural Networks

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https://doi.org/10.47709/brilliance.v4i2.4831

(CNN) Untuk Klasifikasi Batik. *COREAI: Jurnal Kecerdasan Buatan, Komputasi Dan Teknologi Informasi*.

Sembiring, S., Fauziana Izzati, & Putri Dahlia. (2024). Analisis Semiotik Motif Peusijuk Pada Karya Batik Aceh. *DESKOVI : Art and Design Journal*, *7*(1), 66–70. doi:10.51804/deskovi.v7i1.16574

Sulistiyanti, Sri & Setyawan, Fx Arinto & Komarudin, M. (2016). *PENGOLAHAN CITRA DASAR DAN CONTOH PENERAPANNYA*.

Tan, M., & Le, Q. (2019). *Efficientnet: Rethinking model scaling for convolutional neural networks.* In *International conference on machine learning* (pp. 6105-6114. PMLR).

Tan, M. (2023). efficientnet-improving-accuracy-and-efficiency-through-automl-and-model-scaling. Retrieved 11 October 2024, from https://research.google/blog/efficientnet-improving-accuracy-and-efficiency-through-automl-and-model-scaling/

Wiryadinata, R., Adli, M. R., Fahrizal, R., & Alfanz, R. (2019). Klasifikasi 12 Motif Batik Banten Menggunakan Support Vector Machine. *Jurnal EECCIS (Electrics, Electronics, Communications, Controls, Informatics, Systems)*, *13*(1), 60–64. doi:https://doi.org/10.21776/jeeccis.v13i1.570

ZAMAN, B., & Khoirudin, K. (2021). Klasifikasi Citra Batik Menggunakan Co-Occurrence Matrices Berbasis Wavelet Filter. *Jurnal Pengembangan Rekayasa Dan Teknologi*, *5*(2), 123. doi:10.26623/jprt.v17i2.4594