GENERATION JOURNAL

Vol. 10 No. 2 Tahun 2026
e-ISSN: 2549-2233 / p-ISSN: 2580-4952
DOI : https://doi.org/10.29407/gj.v10i2.28290

Classification Of Cirebon Typical Batik Motifs Using The Convolutional Neural Network (CNN) Algorithm

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Article Info

Received	2026-01-23
Revised	2026-02-02
Accepted	2026-02-09

Keywords:* *batik classification; convolutional neural network; cultural heritage preservation; image processing.

Abstract

The visual identification of traditional Cirebon batik motifs frequently relies on subjective observation, leading to inconsistent recognition results. To resolve this issue, this study implements a Convolutional Neural Network (CNN) with a four-layer convolutional architecture as an automated classification system. The dataset used in this research contains 1,492 images of Cirebon batik motifs, which are partitioned into a scheme of 80% for training and 20% for validation. Data augmentation is applied during the preprocessing phase to improve the variety and quality of the information processed by the model. The results show that the CNN model achieves an overall accuracy of 92%. Furthermore, the Area Under the Curve (AUC) values ranging from 0.98 to 1.00 confirm the model's strong capability in distinguishing between different motif classes, even though minor challenges persist in identifying motifs with high visual similarities, such as Singa Barong and Paksi Naga Liman.

INTRODUCTION

Batik is an Indonesian cultural heritage steeped in philosophical, aesthetic, and historical values. Each region has distinctive patterns that reflect the identity and local wisdom of its people. One region with unique characteristics is Cirebon, with batik motifs such as Mega Mendung, Singa Barong, Paksi Naga Liman, and Sawat Pengantin. These four motifs not only showcase artistic beauty but also reflect the blend of Javanese, Sundanese, and Chinese cultures that are deeply embedded in the lives of coastal communities [1].

Over time, digitalization has become a crucial step in preserving batik culture. However, the classification of batik motifs still relies heavily on human judgment in matching the patterns to each image. This dependence often leads to differences in classification results, especially as the number of images increases and the visual patterns between motifs show high similarities. As a result, consistency of results is difficult to maintain, and the data processing process becomes less structured. This situation indicates that visual observation-based approaches do not fully support large-scale batik data management, necessitating the need for an automated system capable of recognizing visual patterns consistently and measurably [2].

The main challenge in automatic batik classification is the complexity of the patterns and the high color variations within each motif. Conventional methods such as k-Nearest Neighbor (k-NN) and Support Vector Machine (SVM) are often unstable to changes in lighting, rotation, and shape deformation [3]. Therefore, an approach capable of recognizing visual patterns more adaptively and accurately is needed.

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Developments in artificial intelligence (AI), particularly in digital image processing, provide a solution through CNN technique is very reliable in recognizing complex patterns thanks to its ability to extract important features from an image automatically, so that the manual feature design process is no longer necessary [4].

Several studies have demonstrated the superiority of CNNs in classifying batik motifs. [1] achieved 70% accuracy in batik recognition using CNNs, while [2] achieved 95% with a simple CNN model. [4] reported 82.5% accuracy with the EfficientNetB0 architecture, demonstrating the stability of CNNs in image classification. [5] also successfully classified Riau batik motifs with 88.50% accuracy, demonstrating the flexibility of CNNs for diverse patterns. Furthermore, [6] demonstrated that CNN has advantages in accuracy and stability compared to traditional methods, and [7] confirmed the efficiency of CNN in accurately recognizing Indonesian batik patterns. However, most of these previous studies primarily focused on simple accuracy metrics, which may not fully capture the model's performance in handling class imbalances or distinguishing between visually similar motifs.

Although these studies demonstrated good performance, most of them still focused on batik motifs from other regions such as Pekalongan, Yogyakarta, and Riau. Cirebon batik motifs have not been studied in depth despite their unique and complex visual characteristics. Furthermore, a notable methodological gap exists in the current literature because most previous research relies exclusively on basic accuracy metrics and lacks detailed Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) analysis. Therefore, this study was conducted to analyze the performance of a Convolutional Neural Network (CNN) in classifying images of Cirebon batik motifs, namely Singa Barong, Mega Mendung, Paksi Naga Liman, and Sawat Pengantin. By incorporating ROC-AUC evaluation, this research provides a more robust and granular assessment of the model's discrimination capability . This approach ensures higher reliability in recognizing complex cultural patterns as a first step towards digitizing and preserving Cirebon batik culture in the modern era.

RESEARCH METHOD

This research was conducted through several main stages systematically structured: data collection, data preprocessing, Convolutional Neural Network (CNN) model development and training, and model performance evaluation. The research flow was designed to ensure the Cirebon batik image classification process runs in a structured and replicable manner.

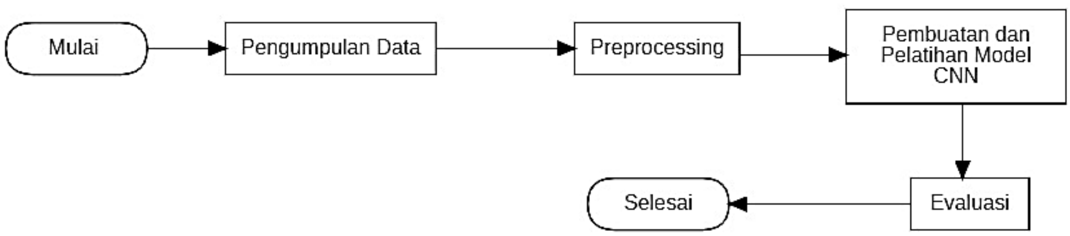

Figure 1. Research Flow Diagram

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2.1 Data Collection

Data collection for this study was performed using the Cirebon Batik dataset from Kaggle, which includes a total of 1,492 images. The dataset is distributed across four distinct motifs with 300 images for Mega Mendung, 355 for Paksi Naga Liman, 450 for Sawat Pengantin, and 387 for Singa Barong. In the model development stage, 80% of the total data was allocated for the training set to enable the CNN model to learn various visual features effectively. The remaining 20% was used as the validation set to monitor the model's performance and support the early stopping mechanism during the training process.

2.2 *Preprocessing*

In the preprocessing stage, the dataset is prepared through several steps, including image quality checks, removing corrupted files, standardizing image sizes, recognizing patterns, dividing the dataset into training and validation data, and applying augmentation to increase data variation. This stage is crucial for ensuring the CNN model receives clean, consistent, and visually diverse data.

2.3 Model Creation and Training

The Convolutional Neural Network (CNN) architecture in this study is specifically designed with four convolutional layers to effectively extract features from Cirebon batik images. Each convolutional layer utilizes a 3x3 kernel size with a progressively increasing number of filters, starting from 32, 64, 128, to 256, to capture hierarchical visual patterns. Following each convolution, a Max Pooling layer with a 2x2 pool size is applied to reduce feature dimensionality and improve computational efficiency. This CNN approach is widely adopted in batik image classification because it can effectively recognize complex and varied visual patterns [8]. After the feature extraction stage, the architecture transitions into a flattening process before passing the data through a fully connected layer containing 128 neurons and a 0.2 Dropout rate to minimize overfitting. The final output layer employs the Softmax activation function to generate probabilities for each batik motif class [9].

The model implementation was carried out using the TensorFlow framework and Keras API in a Python environment. The model was trained for 50 epochs with a batch size of 32 while monitoring the accuracy and loss curves. Optimization was performed using the Adam optimizer with a learning rate of 0.0001 to accelerate convergence and maintain weight stability [10]. Training was conducted using 80% of the dataset, while the remaining 20% served as validation data to assess the model's generalization ability. To ensure optimal training, an EarlyStopping technique was applied to stop the process if the validation loss did not improve for five consecutive epochs.

2.4 Evaluasi

The evaluation phase was conducted to assess the optimal performance of the CNN model after undergoing training. Testing was conducted using validation data to measure the model's ability to recognize and classify batik motif images that had not been used during training. This process provided an overview of the model's generalization level to new data.

The evaluation method used in this study was the Confusion Matrix, a matrix that displays the comparison between the actual classes and the model's predictions. In this matrix, the vertical axis represents the actual classes, while the horizontal axis shows the predictions. Analysis of the Confusion Matrix provides information on the model's success rate in recognizing each class and helps identify batik motifs that are still misclassified [11].

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

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

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

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{(4)}$$

Where:

a. True Positive (TP) is a condition where positive data is correctly classified as positive by the algorithm.
b. True Negative (TN) is achieved when negative data is accurately identified as negative.
c. False Positive (FP) is recorded when negative data is incorrectly predicted as part of the positive class.
d. False Negative (FN) is found when positive data is incorrectly assigned to the negative category.

Model performance was further evaluated using the Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) metrics. The ROC curve visualizes the correlation between True Positive Rate and False Positive Rate at various classification decision thresholds. Meanwhile, the AUC value serves as an indicator of the model's ability to effectively distinguish between batik motif categories. An AUC score approaching 1 reflects a higher level of accuracy and stability of the model in performing accurate classification [12].

RESULTS AND DISCUSSION

3.1 Data Collection

In this study, the dataset used consists of images of typical Cirebon batik motifs grouped into four motif categories: Mega Mendung, Paksi Naga Liman, Sawat Pengantin, and Singa Barong. The number of images in each category is not entirely equal, with 300 images for the Mega Mendung motif, 355 for the Paksi Naga Liman motif, 450 for the Sawat Pengantin motif, and 387 for Singa Barong motif. Figure 2, displays example images from each category of batik motifs used in this study.

Figure 2. Mega Mendung, Singa Barong, Paksi Naga Liman, Sawat Pengantin

3.2 Preprocessing

The preprocessing stage in this study encompasses several image processing steps, including resizing, rotation, flipping, zooming, and adjusting contrast and lighting levels. This series of processes aims to standardize image dimensions, minimize irrelevant visual noise, and enrich the training data.

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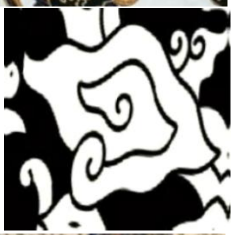
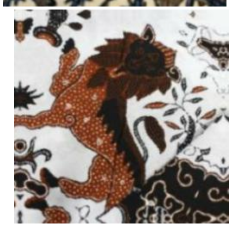
Through this stage, key visual characteristics such as patterns, lines, and textures of batik motifs can be more optimally highlighted. Thus, the CNN model is expected to be able to learn more consistent visual patterns and improve accuracy in distinguishing each category of batik motifs. The results of this preprocessing stage are presented in Table 3.1.

Table 1. Preprocessing Results

Preprocessing	Results
Resize	 
Flipping	 
Rotation	 
Contrast	 
Translation	 
Zooming	 

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3.3 Model Creation and Training

The designed Convolutional Neural Network (CNN) model was then trained using training data and evaluated against validation data on the Cirebon batik motif dataset. The training process was terminated using an early stopping mechanism when performance on the validation data no longer showed improvement, ensuring the model with the best weights was used and preventing overfitting.

Training Accuracy and Loss Graphs: During the training process, accuracy and loss metrics for the training and validation data were monitored at each epoch. The results were visualized to observe the model's learning behavior.

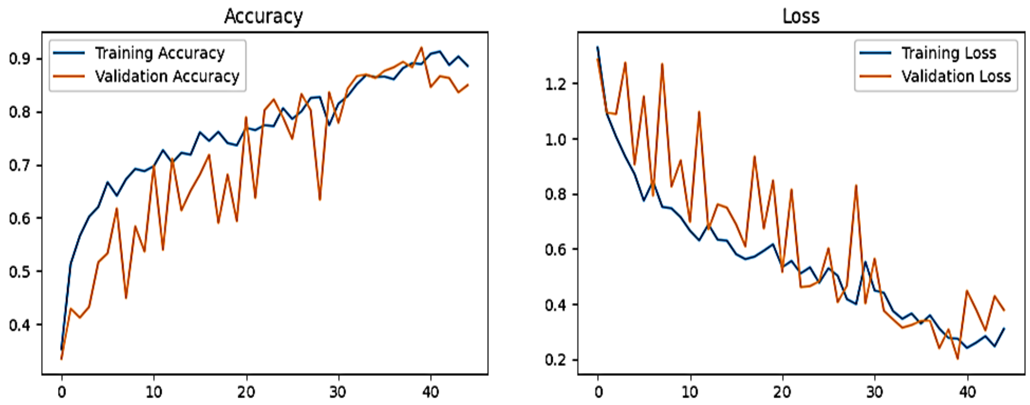

Figure 3. Results of Model Creation and Training

Based on Figure 3, the accuracy value on the training data gradually increased as the number of epochs increased, indicating that the model was able to progressively learn the visual patterns in the batik motif images. The accuracy of the validation data also showed an increasing trend and followed a pattern that was relatively consistent with the accuracy of the training data, although fluctuations occurred in the first few epochs. These fluctuations indicate the model is adapting to data variations, but do not indicate a significant decline in performance.

In the loss graph, the loss value on the training data decreased consistently throughout the training process, indicating a reduction in the model's prediction error on the training data. Meanwhile, the loss value on the validation data increased in certain epochs, but overall, it showed a downward trend and eventually stabilized. This indicates that the model was able to learn patterns from the training data well and maintain consistent performance on the validation data.

The development of accuracy and loss values on the training and validation data indicates that the training process was stable and balanced. Thus, the resulting CNN model has sufficient generalization capabilities in classifying typical Cirebon batik motifs, making it suitable for use in further evaluation.

3.4 Evaluasi

The evaluation phase was conducted after the training process of the Convolutional Neural Network (CNN) model was completed, with the aim of assessing the model's performance in classifying batik motif images. This evaluation is used to determine the level of accuracy and consistency of the model in predicting batik motif classes. In this study, the model's performance was evaluated using the Confusion Matrix as well as the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) value. The CNN model, which was developed with four convolutional layers, achieved

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an overall accuracy of 92%, proving its strong capability in recognizing the complex patterns of Cirebon batik.

Table 2. Hasil dan Evaluasi

Motif Batik	Precision	Recall	F1-Score	Support
Mega Mendung	1.00	1.00	1.00	51
Paksi Naga Liman	0.84	0.93	0.88	88
Sawat Pengantin	0.95	1.00	0.98	79
Singa Barong	0.94	0.78	0.85	80
Accuracy			0.92	298
Macro Average	0.93	0.93	0.93	298
Weighted Average	0.92	0.92	0.92	298

The results presented in the classification report indicate high effectiveness across the different motifs, with an overall accuracy of 92%. The Mega Mendung and Sawat Pengantin classes achieved a perfect recall score of 1.00, which means the model successfully identified every image in these categories without any errors. This high success rate occurs because these two motifs have very clear and unique shapes, such as the cloud patterns in Mega Mendung and the symmetrical wing shapes in Sawat Pengantin, which allow the model to recognize their characteristics easily.

However, the analysis also reveals a specific challenge with the Singa Barong motif, which recorded the lowest recall score of 0.78. This situation happens because Singa Barong and Paksi Naga Liman look very similar since both use complex animal figures and dense line details that can sometimes confuse the model during the feature extraction process. Despite this, the high precision and F1-scores across all classes demonstrate that the four-layer convolutional architecture is highly capable of distinguishing the intricate details of Cirebon batik patterns.

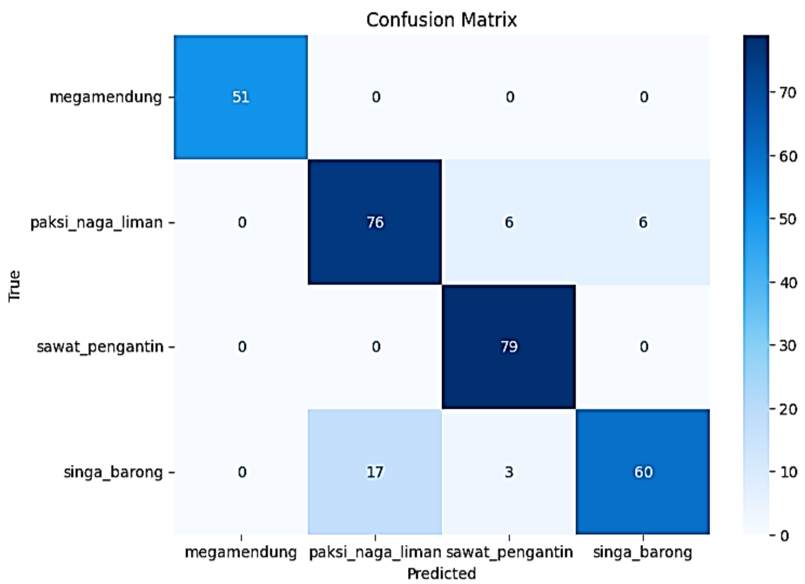

Figure 4. Evaluasi Confusion Matrix

Figure 4 presents the results of the CNN model evaluation using a Confusion Matrix, comparing the actual class and the model's predicted class for each batik motif. This evaluation provides a clear picture of the classification accuracy and prediction errors for each class. In the megamendung class,

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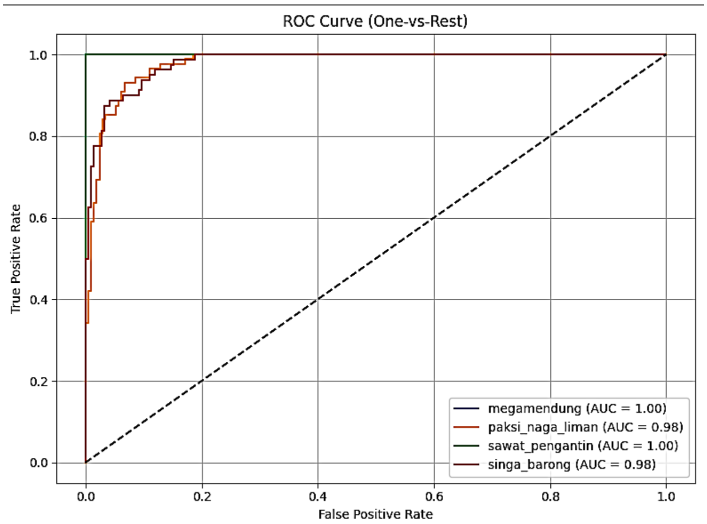
the model correctly classified all test data, with 51 images predicted to be in the actual class, with no misclassifications to other classes. These results indicate that the megamendung motif has visual characteristics that the model can recognize very well. For the paksi naga liman class, 76 images were correctly classified. However, 6 images were incorrectly predicted as the sawat pengantin class and 6 others as the singa barong class. These misclassifications indicate a similarity in visual characteristics between the paksi naga liman motif and both motifs. In the sawat pengantin class, the model demonstrated good classification performance, with 79 images correctly classified. No misclassifications to other classes were found for this motif, indicating that the visual pattern of the sawat pengantin is quite consistent and easily distinguishable. Meanwhile, in the singa barong class, 60 images were correctly classified. However, 17 images were still incorrectly predicted as the paksi naga liman class and 3 others as the sawat pengantin class. This indicates that the Singa Barong motif shares relatively similar visual characteristics with several other motifs, increasing the potential for misclassification.



Gambar 5. Evaluasi Kurva ROC dan AUC

Based on Figure 5, the Mega Mendung and Sawat Pengantin classes demonstrated perfect classification performance with an AUC value of 1.00. These results indicate that both motifs possess highly distinct visual characteristics, such as the cloud-like curves in Mega Mendung and the symmetrical wing patterns in Sawat Pengantin, which the CNN model can recognize consistently without error. Meanwhile, the Paksi Naga Liman and Singa Barong classes achieved an AUC of 0.98. Although slightly lower, these values still represent excellent discrimination ability, where the minor prediction errors are likely caused by the shared complexity of animal-inspired features and similar line textures between the two motifs.

The high performance achieved in this study, with AUC values ranging from 0.98 to 1.00, significantly outperforms the earlier CNN-based batik classification by [1], which reached 70% accuracy, and provides more stable results than the simple CNN model in [2]. This superior performance is attributed to the implementation of four convolutional layers, which allowed for deeper hierarchical feature extraction compared to shallower architectures used in previous works. Furthermore, the use of diverse data augmentation in the preprocessing stage successfully enriched the training variety, enabling the model to achieve a higher level of discrimination than the EfficientNetB0 approach in [4] and the

Vol. 10 No. 2 Tahun 2026
e-ISSN: 2549-2233 / p-ISSN: 2580-4952
DOI : https://doi.org/10.29407/gj.v10i2.28290

Riau batik classification in [5]. Overall, these results confirm that the integration of deep architectural layers and comprehensive ROC-AUC evaluation provides a more robust and reliable methodology for cultural heritage preservation compared to traditional accuracy-focused methods.

CONCLUSION

Based on the research findings, from problem formulation, method design, preprocessing, model training, and evaluation, the following conclusions can be drawn:

1. The Convolutional Neural Network (CNN) method can be used to classify images of Cirebon batik motifs into several motif classes. The classification process utilizes images as input data through preprocessing and model training, allowing the patterns and visual characteristics of each motif to be automatically recognized.
2. The performance evaluation results indicate that the CNN model has good classification performance, with a high level of accuracy on the test data. Evaluation using a Confusion Matrix demonstrated a high level of accuracy for most motif classes, while evaluation using the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) values yielded AUC values in the range of 0.97 to 1.00. These results indicate that the CNN model has excellent capabilities in distinguishing each class of batik motifs used in the study.

SUGGESTIONS

Based on the results obtained in this study, the following points can be considered for further development:

1. Increasing the number and variety of batik motif image datasets, particularly for classes with similar visual characteristics, has the potential to improve classification accuracy and reduce prediction errors in certain classes.
2. Improved model performance can be achieved by exploring more complex Convolutional Neural Network (CNN) architectures or by applying a transfer learning approach to obtain more optimal visual feature representations.

REFERENCES

[1] I. Maulana, H. Sastypratiwi, H. Muhardi, N. Safriadi, and H. Sujaini, “Implementasi Convolutional Neural Network (CNN) untuk Klasifikasi Motif Batik pada Aplikasi Computer Vision Berbasis Android,” *J. Edukasi dan Penelit. Inform.*, vol. 9, no. 3, p. 384, 2023, doi: 10.26418/jp.v9i3.69496.

[2] M. M. A. Wona, S. A. Asyifa, R. Virgianti, M. N. Hamid, I. M. Handoko, and M. Lestari, “Klasifikasi Batik Parang Menggunakan Convolutional Neural Network (CNN),” *Pop. J. Penelit. Mhs.*, vol. 3, no. 1, pp. 62–69, 2023, doi: 10.58192/populer.v3i1.1666.

[3] D. Barhate, S. Pathak, B. K. Singh, A. Jain, and A. K. Dubey, “A systematic review of machine learning and deep learning approaches in plant species detection,” *Smart Agric. Technol.*, vol. 9, no. August, p. 100605, 2024, doi: 10.1016/j.atech.2024.100605.

GENERATION JOURNAL
Vol. 10 No. 2 Tahun 2026
e-ISSN: 2549-2233 / p-ISSN: 2580-4952
DOI : https://doi.org/10.29407/gj.v10i2.28290

[4] E. Budimansyah, D. Ariawan, R. D. Maulana, W. R. Yudha, and M. Munsarif, “Klasifikasi Motif Batik Indonesia Menggunakan Convolutional Neural Network (Cnn),” *J. Komput. Dan Teknol. Inf.*, vol. 3, no. 2, pp. 1–8, 2025, doi: 10.26714/jkti.v3i2.18627.

[5] D. A. Ramadhan, D. Ramadhani, and U. Riau, “Classification of Riau Batik Motifs Using the Convolutional Neural Network (CNN) Algorithm,” vol. 07, no. 03, pp. 201–211, 2024.

[6] F. Y. Tember, I. Najiyah, T. Informatika, F. T. Informasi, and J. Barat, “Klasifikasi Motif Batik Jawa Barat menggunakan Convolutional Neural Network Classification of West Java Batik Motifs Using Convolutional Neural Network,” vol. 12, pp. 282–292, 2023.

[7] K. H. Suradiradja and K. Nano, “Perbandingan Model Deep Learning Untuk Prediksi Klasifikasi Jenis Batik,” vol. 14, no. 2, pp. 97–105, 2024.

[8] Angginy Akhirunnisa Siregar, Citra Citra, Dechy Deswita Indriani.S, and Gifari Dhaffa Prawira Sianturi, “Klasifikasi Batik Parang Menggunakan Convolutional Neural Network (CNN),” *Pop. J. Penelit. Mhs.*, vol. 3, no. 1, pp. 62–69, 2023, doi: 10.58192/populer.v3i1.1666.

[9] S. Aisyah, R. Astuti, F. M. Basysyar, O. Nurdiawan, and I. Ali, “Convolutional Neural Networks for Classification Motives and the Effect of Image Dimensions,” *J. RESTI*, vol. 8, no. 1, pp. 181–188, 2024, doi: 10.29207/resti.v8i1.5623.

[10] T. Mufizar, A. Sudiarjo, E. S. Mulyani, A. A. Wakih, M. A. Kasyfurrahman, and L. A. Mahbub, “Classification of Tasikmalaya batik motifs using convolutional neural networks,” *IAES Int. J. Artif. Intell.*, vol. 14, no. 4, pp. 3287–3299, 2025, doi: 10.11591/ijai.v14.i4.pp3287-3299.

[11] S. Dewi, F. Ramadhani, and S. Djasmayena, “Klasifikasi Jenis Jerawat Berdasarkan Gambar Menggunakan Algoritma CNN (Convolutional Neural Network),” *Hello World J. Ilmu Komput.*, vol. 3, no. 2, pp. 68–73, 2024, doi: 10.56211/helloworld.v3i2.518.

[12] W. Bismi, D. Novianti, and M. Qomaruddin, “Analisis Perbandingan Klasifikasi Citra Genus Panthera dengan Pendekatan Deep learning Model MobileNet,” *J. Inform. dan Rekayasa Perangkat Lunak*, vol. 6, no. 1, pp. 1–9, 2024.