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Multi-Layer Convolutional Neural Networks for Batik Image Classification

Daurat Sinaga[1*], Cahaya Jatmoko[2], Suprayogi[3], Novi Hendriyanto[4]
[1,2,3,4]Department of Informatics Engineering, Universitas Dian Nuswantoro, Indonesia

Abstract.
Purpose: The purpose of this study is to enhance the classification of batik motifs through the implementation of a novel approach utilizing Multi-Layer Convolutional Neural Networks (CNN). Batik, a traditional Indonesian textile art form, boasts intricate motifs reflecting rich cultural heritage. However, the diverse designs often pose challenges in accurate classification. Leveraging advancements in deep learning, this research proposes a methodological framework employing Multi-Layer CNN to improve classification accuracy.
Methods: The methodology integrates Multi-Layer CNN architecture with an image dataset comprising various batik motifs, meticulously collected and preprocessed for uniformity. The CNN architecture incorporates convolutional layers of different sizes (3x3, 5x5, and 7x7) to extract unique features from batik images. Training options, including the Adam optimizer and validation frequency, are optimized based on parameters to enhance model efficiency and effectiveness.
Result: Results from the experimentation demonstrate significant improvements in classification accuracy, with an overall accuracy rate of 90.88%. Notably, precision and recall scores for individual batik motifs, such as Motif Cual Bangka and Motif Rumah Adat Belitung, reached remarkable levels, showcasing the efficacy of the proposed approach.
Novelty: This study contributes novelty through the integration of Multi-Layer CNN in batik classification, offering a robust and efficient method for identifying intricate batik motifs. Additionally, the research presents a pioneering application of deep learning techniques in preserving and promoting traditional cultural heritage, thereby bridging the gap between tradition and modern technology.

Keywords: Batik, Classification, Multi-Layers, CNN, Confusion matrix
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INTRODUCTION

Batik is a traditional Indonesian art form that combines skilled craftsmanship and creative elements to produce unique and valuable textile artworks [1]. Renowned for its intricate and diverse motifs, batik not only showcases visual beauty but also embodies a rich cultural and historical heritage from the archipelago. The process of creating batik involves a specialized dyeing technique using wax as a resist on certain parts of the fabric, thus creating beautiful and structured patterns during the dyeing process. Besides serving as a symbol of Indonesia's national identity, batik has received international recognition as a UNESCO Intangible Cultural Heritage in 2009, underscoring the significance of this textile art in bridging generations and promoting the nation's cultural wealth [2]. Each region in Indonesia possesses its own unique batik design characteristics, resulting in a vast array of motifs that sometimes perplex the public in identifying specific regional types of batik [3]. This diversity serves as tangible evidence of Indonesia's cultural richness, which continues to be preserved and enriched from generation to generation.

Classification of batik types has become increasingly easier and more accurate due to advancements in the field of machine learning and deep learning, particularly through the utilization of Convolutional Neural Networks (CNN) algorithms [3], [4], [5], [6], [7], [8], [9]. Through the integration of artificial intelligence and data analysis, CNN algorithms are capable of processing and recognizing the unique characteristics of each batik motif with high precision [10], [11]. With this approach, the identification issues that often confuse the public due to the diversity of batik designs from various regions can be efficiently addressed. These algorithms are not only able to identify the distinctive patterns and textures of each type of batik but

*Corresponding author.
Email addresses: dauratsinaga@dsn.dinus.ac.id (Sinaga)*, jatmoko@dsn.dinus.ac.id (Jatmoko), suptayogi@dsn.dinus.ac.id (Suprayogi), nvhendriyanto@dsn.dinus.ac.id (Hendriyanto)
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also can differentiate between similar motifs with different nuances [12], [13]. Consequently, the implementation of machine learning and deep learning technologies in the classification of batik types through CNN not only facilitates accurate recognition but also appreciates and promotes the cultural heritage richness of Indonesia in the current digital era.

In this study, the primary approach utilized is the Convolutional Neural Networks (CNN) method, leveraging a dataset sourced from West Sumatra. The dataset employed is obtained from relevant public sources, enabling in-depth analysis of the various types of batik specific to the region. As a standardization measure in the research, each batik image within the dataset maintains uniform dimensions, specifically 512x512 pixels with three color channels (RGB). This uniform size facilitates the training and evaluation processes of the CNN model, ensuring consistency and accuracy in batik type classification. By utilizing a specific dataset from West Sumatra and maintaining uniform image dimensions, this study aims to optimize the performance of the CNN model in accurately and efficiently identifying and classifying batik motifs.

Based on literature review, numerous studies have implemented CNN methods for classifying types of batik based on image datasets. Study by Fonda et al. (2020) [9] indicates that the utilization of CNN in classifying Riau batik yields intriguing results. Through a deep learning approach employing CNN, Fonda successfully developed a model capable of distinguishing Riau batik images from others. Despite achieving a classification accuracy of 65%, these findings showcase the algorithm's potential to recognize the unique characteristics of Riau batik, particularly differences in color nuances. Mawan et al. (2020) [7] underscores the importance of exploring CNN methods in analyzing batik motifs with the aim of identification and preservation. It is noted that CNN, as one of the techniques stemming from Multi-Layer Perceptron (MLP) development, is specifically designed to handle two-dimensional data and is an integral part of Deep Neural Networks, particularly in the context of image data. Experiments conducted using a dataset of 120 batik photo samples divided into 3 classes yielded intriguing results. Models relying solely on CNN achieved an average accuracy of 65%. However, when CNN was combined with Grayscale techniques, a significant improvement was observed, with average accuracy increasing to 70%. Azmi et al. (2023) [3] demonstrates that the use of CNN in classifying West Sumatra clay batik yields highly promising results. By leveraging 400 batik images divided into four classes, this study successfully allocated 320 images as training data and 80 images as testing data. The results obtained after training and testing processes with CNN show an accuracy rate reaching 98.75% for the training data, indicating the model's capability to recognize and classify batik very effectively. However, the accuracy rate for the testing data reached 62.5%, suggesting potential challenges or variations that need further attention in subsequent research. Bariyah et al. (2021) [8] emphasizes that the application of CNN holds significant potential in multi-label classification of batik motif images. By utilizing CNN architecture, which is an evolution from multi-layer perceptron (MLP) in deep learning, this research achieved an impressive accuracy rate of 91.41% in identifying 15 different batik motifs. The use of 100 epochs in the training process also supports the efficiency and accuracy of the model, demonstrating CNN's capability in handling the complexity and variation of batik images.

This research introduces a novel approach by combining multi-layer CNN in transfer learning processed through deep learning CNN. This innovative method aims to enhance the classification accuracy of batik motifs by leveraging the capabilities of both multi-layer CNN and transfer learning. Through the integration of these techniques, the model can effectively extract intricate features from batik images and generalize well to new data, ultimately improving the overall performance of batik classification systems.

METHODS

In the proposed method, the process commences with the collection of the requisite dataset for model training and testing. Subsequently, the gathered images are utilized as inputs for analysis. Following this, data preprocessing is conducted, wherein each image is resized to 512 x 512 pixels with three color channels (RGB) to ensure data consistency and uniformity, as depicted in Figure 1.

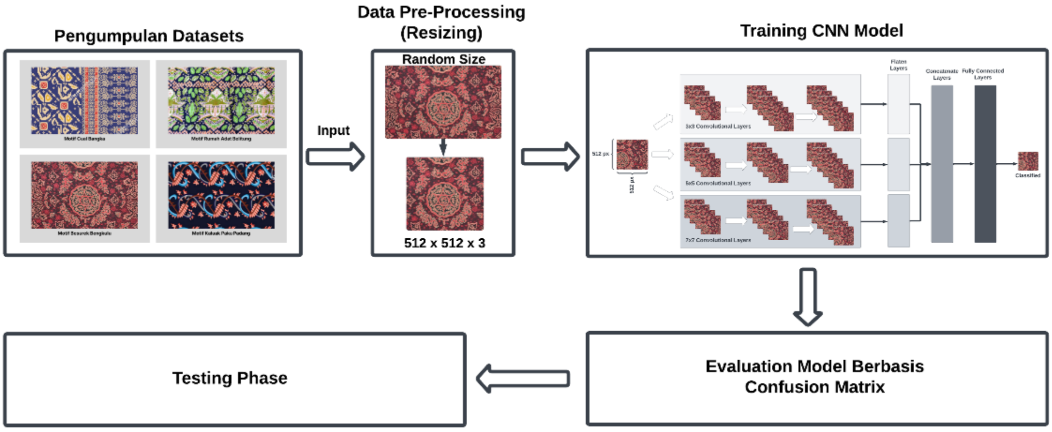

Figure 1. Proposed scheme

Once the data is prepared, the model is evaluated using a confusion matrix, an evaluation method that allows the analysis of the model's performance in classifying existing classes. Finally, after the evaluation process, the model undergoes testing phase to measure its accuracy and effectiveness in identifying and classifying various types of data based on predetermined parameters.

Convolutional neural networks (CNN)

CNN is a type of neural network architecture specifically designed to process data in the form of images and visual data [4]. By composing layers based on convolution, CNN can effectively extract hierarchical features from visual data in a manner similar to how the human brain identifies patterns in visuals. The convolutional layers in CNN function to scan input images using small filters, producing feature maps that highlight specific aspects of the images. Subsequently, subsequent layers such as activation, pooling, and fully connected layers are used to process and interpret these features, enabling the network to learn and understand the hierarchy of information from the images [14]. With its ability for automated feature extraction and classification, CNN have become highly efficient and popular tools in various applications such as object recognition, face detection, image classification, and many more.

In the context of batik type classification, CNN play a crucial role in identifying and distinguishing various batik motifs. The CNN architecture implemented in this research is designed with different convolutional layers, namely 3x3, 5x5, and 7x7, each aimed at extracting unique features from batik images [15], [16]. After the convolution process, specialized Flatten layers are configured for each convolution size, transforming matrix representations into vectors. Then, the vector outputs from the three Flatten layers are combined through a Concatenate layer, allowing the merging of feature information from various convolution sizes. Finally, using Fully Connected Layers, the CNN model can perform final classification based on the extracted features, ensuring accuracy and precision in recognizing and categorizing batik types based on their visual characteristics. Based on Multi-layer CNN can be seen in Figure 2.

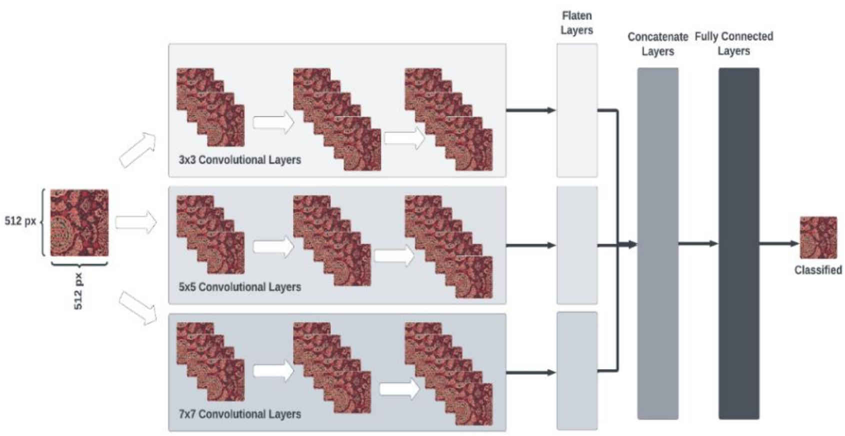

Figure 2. Multi-Layers CNN

In Figure 2, the Multi-layer CNN, featuring convolutional layers of sizes 3x3, 5x5, and 7x7, represents a deep approach in image analysis allowing for the extraction of more complex and hierarchical features [6]. Each convolutional layer possesses the ability to capture visual information at different scales, ranging from fine details to broader patterns. By combining these various sizes of convolutional layers, the multi-layer CNN architecture can comprehend and interpret images in a more comprehensive manner [18]. For instance, the 3x3 convolutional layer can handle fine details, whereas the 7x7 layer can recognize broader and more complex patterns [17].

Training options

Training options include a maximum of 100 epochs for optimization, the utilization of the Adam optimizer for adaptive learning rate, and a validation frequency of 30 to prevent overfitting. The learning rate is set at 0.0001, ensuring stable and efficient training, and yielding a CNN model with optimal performance in classifying batik types. Table I represents the utilization of parameters up to hyperparameters processed in this research.

Table 1. Parameter of training options

Parameter / Hiperparameter	Value
Optimizer	Adam
Max Epoch	100
Initial Learning Rate	0.0001
Validation Freq	30

Performance analysis based on confusion matrix

Performance evaluation of the model is based on the confusion matrix, an evaluation tool that enables the measurement of accuracy, precision, recall, and F1-score [18], [19], [20]. In the context of batik type classification, accuracy measures the proportion of overall correct predictions. Precision assesses the model's ability to correctly identify positive classes, while recall indicates how well the model detects all actual positive instances [5]. The F1-score is the harmonic mean metric of precision and recall, providing a comprehensive overview of the model's performance by considering both. By analyzing the confusion matrix, this research can provide a deep understanding of the CNN model's effectiveness in classifying batik types by incorporating various critical evaluation metrics. The formula of the confusion matrix can be seen in equations (1) – (4).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \tag{4}$$

RESULTS AND DISCUSSIONS

Before the multi-layer CNN training phase, dataset initialization is performed, consisting of four classes of batik motifs: Motif Cual Bangka, Motif Rumah Adat Belitung, Motif Besurek Bengkulu, and Motif Kaluak Paku Padang. This dataset encompasses characteristic batik motifs from various regions, ensuring comprehensive representation for subsequent batik type classification. Sample dataset can be seen in Figure 3.

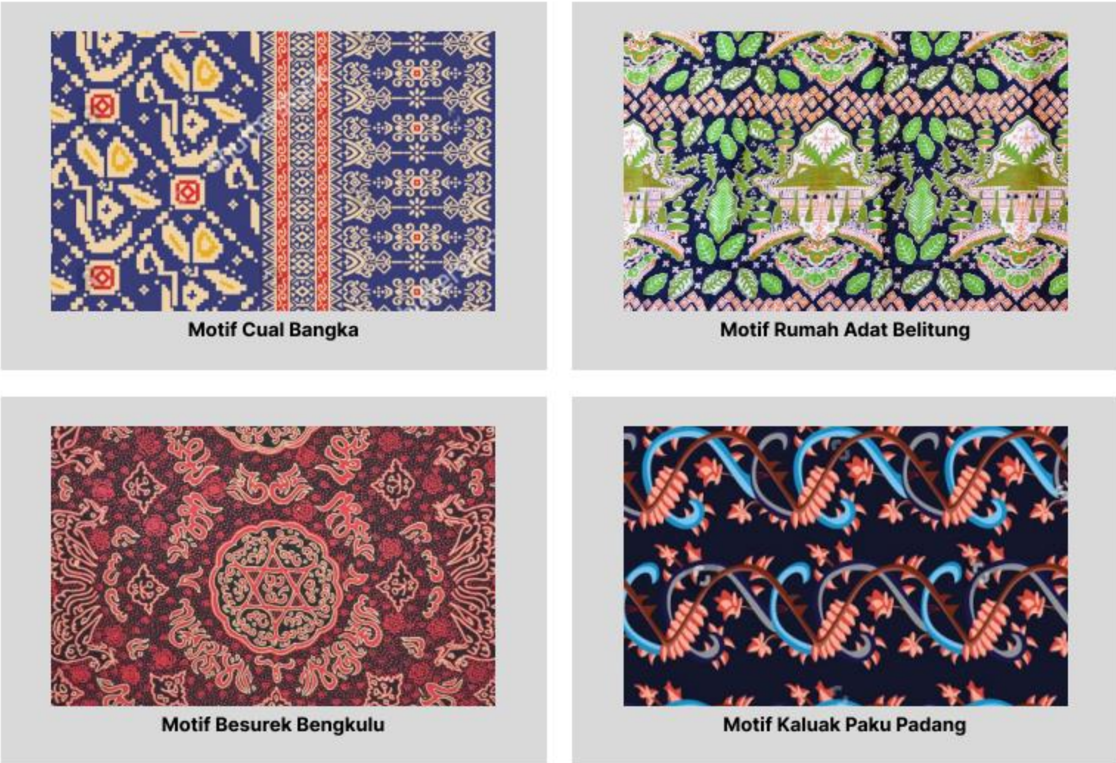

Figure 3. Sample of Batik Datasets

After initializing the dataset separated based on each batik motif class, the next step is to initialize the multi-layer CNN algorithm. In this context, Table 2 presents the detailed specifications of the multi-layer CNN algorithm used, including the configuration of convolutional layers, filter sizes, and other network architectures. Furthermore, to ensure efficient and optimal model training.

Table 2. Multi-Layers algorithm

1st Algorithm: Three-Layers CNN
Inisialisasi: Input layer (ukuran gambar $512x512x3$) **Convolutional Layers:** a. $3x3$ Convolutional Layer: - Operasi Convolution dengan filter $3x3$ - Aktivasi dengan fungsi ReLU b. $5x5$ Convolutional Layer: - Operasi Convolution dengan filter $5x5$ - Aktivasi dengan fungsi ReLU c. $7x7$ Convolutional Layer: - Operasi Convolution dengan filter $7x7$ - Aktivasi dengan fungsi ReLU **Flaten Layers:** a. Flaten Layer untuk $3x3$ $Convolutional\ Layer$ b. Flaten Layer untuk $5x5$ $Convolutional\ Layer$ c. Flaten Layer untuk $7x7$ $Convolutional\ Layer$ **Concatenate Layers:** - Menggabungkan output dari ketiga Flaten Layers **Fully Connected Layers:** - Hidden layer dengan 4 $neuron$ - Aktivasi dengan fungsi ReLU - Output layer untuk klasifikasi: 4 $Class$

The results of the training options in Tables 1 and 2 for the multi-layer CNN can be observed in the training outcome graph documented in Figure 4. This graph represents the dynamics of the CNN model's performance during the training process, indicating changes in the values of the loss function or accuracy over the number of iterations or epochs.

(a) Training and Loss graph (b) Table of Confusion Matrix Analysis

Figure 4. Training and loss graph and table of confusion matrix

Following the completion of the training graph process in Figure 4 (a), the final evaluation of the model is conducted by analyzing the confusion matrix table, which is then represented in Figure 4 (b). This confusion matrix provides a clear overview of the model's performance in classifying the existing batik classes. The evaluation results based on accuracy, precision, recall, and F1-score metrics of the classification model are recorded and documented in Table 3. This table provides a comprehensive summary of the model's performance in classifying each batik motif class. With an accuracy rate reaching 90.88%, the final step of this research involves comparing the results with relevant studies existing in the literature. This is done to position the performance of the developed model within the context of overall relevant research. The comparison table is documented in Table 4.

Table 3. Matrix evaluation based on multi-layers CNN

Class	Accuracy	Precision	Recall	F1-Svore
Motif Cual Bangka	90.88%	100%	96%	97%
Motif Rumah Adat Belitung		98%	95.5%	97%
Motif Besurek Bengkulu		88%	91.2%	92.7%
Motif Kaluak Paku Padang		92%	93.4%	94.7%

Table 4. Comparison with other studies

Research	Model	Akurasi
Fonda [9]	CNN	65%
Mawan [7]	CNN+MLP	70%
Azmi [3]	CNN	62.5%
Proposed	**Multi-Layer CNN**	**90.88%**

CONCLUSION

Based on evaluation results using multi-layer CNN with convolutional layers of sizes 3x3, 5x5, and 7x7, it can be concluded that the model has demonstrated excellent performance in classifying various types of batik motifs. With an overall accuracy of 90.88%, this model is capable of recognizing Motif Cual Bangka with 100% precision and recall, indicating very high accuracy in classification. Meanwhile, good performance is also found in Motif Rumah Adat Belitung with 98% precision and 95.5% recall. Although there is a slight decrease in precision and recall for Motif Besurek Bengkulu and Motif Kaluak Paku Padang, they still maintain very good scores above 88%. Overall, the utilization of convolutional layers of various sizes in this CNN architecture has resulted in a reliable and efficient model in identifying and classifying batik types, validating the effectiveness of this approach for image classification applications.

For future research, the next progressive step will involve the application of transfer learning techniques, particularly leveraging proven effective model architectures such as ResNet and LeNet. By harnessing the accumulated knowledge from existing architectures, transfer learning allows us to utilize features learned on extensive previous datasets and apply them to our batik classification task. With this approach, computational efforts and training time can be optimized while maintaining or even improving the quality and accuracy of the model. Through the utilization of transfer learning, it is expected that future research can provide deeper insights into the potential and applications of this method in the context of batik motif classification, as well as identifying the benefits and challenges that may arise in its implementation.

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