Semarak International Journal of Electronic System Engineering

Journal homepage:
https://semarakilmu.com.my/journals/index.php/sijese/index
ISSN: 3030-5519

A Data-Driven Approach for Batik Pattern Classification Using Convolutional Neural Networks (CNN)

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ARTICLE INFO

Article history:
Received 5 November 2024
Received in revised form 19 November 2024
Accepted 2 December 2024
Available online 20 December 2024

Keywords:
Batik; Convolutional Neural Network; image classification; MobileNetV3; data driven

ABSTRACT

Batik is one of Indonesia's cultural heritages with complex and diverse patterns, high artistic value and deep philosophy. Manually classifying batik patterns takes time and depends on expert knowledge, making the process inefficient. It is very difficult to distinguish batik pattern motifs because of the similarity between one and the other. This research aims to develop a batik pattern classification model using a Convolutional Neural Network (CNN) with a data-based approach, allowing pattern recognition and classification to be carried out automatically and accurately. The data set used consisted of 4,284 batik images divided into five pattern classes: kawung, slope, ceplok, machet, and nitik. In this study, the CNN model was developed by utilizing transfer learning techniques with MobileNetV3 that had been trained previously on large datasets. The training process involves adding data to increase the robustness of the model against variations in batik patterns. Evaluation is carried out by measuring the accuracy and loss of the model. The results showed that the CNN model achieved an average accuracy of 93.42% on training data and 93.88% on test data. This study shows that a data-driven approach using CNN is effective for the classification of batik patterns, providing more accurate results compared to manual methods and offering an efficient solution for the digitization of the batik industry. Data driven helps produce a general model and is able to recognize batik motifs that have never been seen before. By using data-driven, larger, more diverse data allows the model to better understand variations in patterns and textures. The developed model can serve as the basis for wider applications in cultural preservation and technological advancement based on artificial intelligence.

1. Introduction

Batik according to Setyowati *et al.,* [1], Basiroen *et al.,* [2], Nurhaida *et al.,* [3], Elvitaria *et al.,* [4] is an Indonesian cultural heritage that has high artistic value and a variety of patterns typical of each region, with each pattern carrying a deep philosophical meaning that represents cultural identity.

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https://doi.org/10.37934/sijese.4.1.2230

However, the recognition and classification of batik patterns is a complex challenge due to the diversity and uniqueness of each motif, where it is estimated that there are more than 5,000 batik patterns throughout Indonesia by Dinata *et al.,* [5]. The manual classification process is often time-consuming and requires expert knowledge, which makes this process slow and inefficient, especially for large scales.

Along with the development of artificial intelligence technology, a data-driven approach that utilizes Convolutional Neural Networks (CNNs) has proven to be effective in image pattern recognition. CNN, as one of the deep learning models, allows the process of automatically extracting features from image data, making it particularly suitable for complex visual recognition tasks such as batik patterns. Various studies have tried to apply CNNs in pattern recognition, and the results are promising especially in applications such as facial recognition, object detection, and other visual pattern classification. For batik patterns, CNN offers great potential in automatic and efficient pattern recognition, but its implementation still faces some special challenges.

Previous studies in the classification of batik used several machine learning methods, such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN) has been carried out by Andrian *et al.,* [6], Wijaya *et al.,* [7], Irawan *et al.,* [8] and Random Forest by Fadlil *et al.,* [9], Arsa *et al.,* [10]. However, these methods generally require manual feature extraction and are less likely to be efficient for highly complex patterns such as batik by Chusna *et al.,* [11]. CNN according to Rasyidi, *et al.,* [12], Mawan [13], Prasetyo [14], offers automation solutions that can overcome these limitations, but their effectiveness for batik classification requires a diverse and high-quality dataset. The lack of a dataset that covers a complete variety of batik patterns and the limitations of batik-specific data augmentation techniques are obstacles in this data-driven approach. Therefore, more research is needed to maximize the potential of CNN which has been done by Tristanto *et al.*, [15], Fahri *et al.,* [16], Saputra *et al.,* [17], Bowo *et al.,* [18], Utari *et al.,* [19] in the classification of batik with a more focused data-driven approach.

This research aims to overcome these limitations by developing an effective data-driven approach, which includes more diverse datasets, customized augmentation techniques, and implementations that allow automatic and efficient classification of batik patterns. This is expected to not only contribute to the development of science but also to the digitalization and preservation of the batik industry through advanced technology.

Based on a review of related research, it is clear that further investigation to develop an automatic batik image classification system is very feasible. This area remains challenging because of many of the problems identified in previous research. In summary, this study aims to address at least three major gaps to improve the effectiveness of automatic batik image classification using CNNs by Agus *et al.,* [21] with a data-driven approach, as illustrated in Figure 1 below.

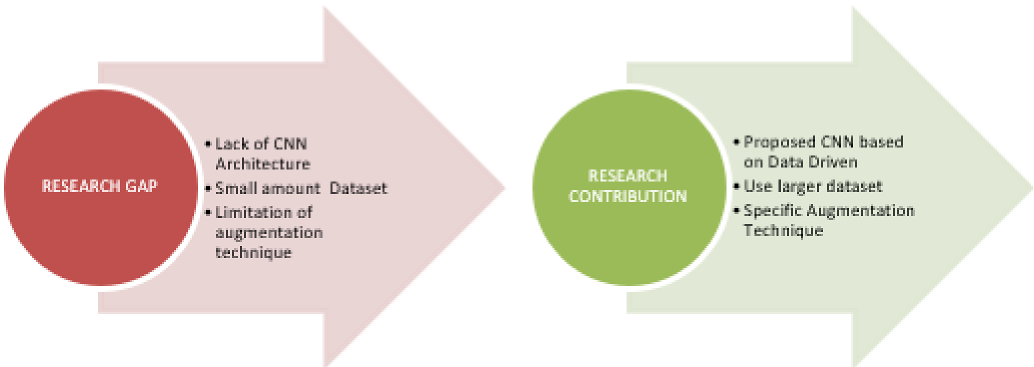

Fig. 1. Research gap and contribution

Based on the research gap presented in Figure 1, this study proposes a CNN architecture that is expected to be a model that can have good performance with a wider variety of patterns so that it can distinguish batik patterns often have visual similarities. In addition, this proposed model will be tested on a representative dataset containing more batik images. The gap subsequently requires data augmentation techniques designed specifically for batik patterns, which can help improve the performance of the CNN model without altering the essential elements of the batik pattern so that its performance can be legitimized because it has been tested on many batik images. Furthermore, through these three contributions, it is hoped that the goal of developing a reliable and strong batik image classification system will be achieved.

By using CNN, this research has the potential to produce a classification model that is able to recognize batik patterns with high precision, even on motifs that have complex details and color variations, which are difficult to capture by conventional methods.

This research is anticipated to make a substantial contribution to the field of pattern recognition, particularly in batik image classification. Additionally, it is expected to offer alternative solutions that improve the accuracy and efficiency of batik image classification.

2. Dataset and Methodology

2.1 Dataset

The dataset used in this research is a combination of datasets sourced from public datasets such as batik classification resnet [4] and deep learning batik classification [6]. Furthermore, the dataset used consists of five classes of batik motifs such as lereng, parang, nitik, kawung and ceplok batik, which are illustrated in Figure 2.

Fig. 2. Batik dataset

The collected batik dataset consists of 5 classes with a total of 4.284 images, which are then divided into three types of data: training and testing. To allocate the data for training, testing, and validation, the dataset was split using a ratio of 80:10. The final data for training, and testing is presented in Table 1.

Table 1
Dataset

Batik Class	Data	Training	Testing
Lereng	405	324	81
Parang	1,197	958	239
Ceplok	1,053	843	210
Kawung	747	598	149
Nitik	882	706	176
TOTAL	4.284	3429	855

The preprocessing process begins by resizing the batik image dataset so that it produces an output with dimensions of 224 x 224 pixels with a batch size of 32. The Augmentation techniques used are rotating with a maximum of 30 degrees, shifting the image with a maximum of 20% of the width and height of the image, zooming the image with a maximum of 20% zoom in and out, and flipping the image horizontally. All of these preprocessing components are randomly selected for each batik image dataset image so that it can be used for further processing in Figure 3.

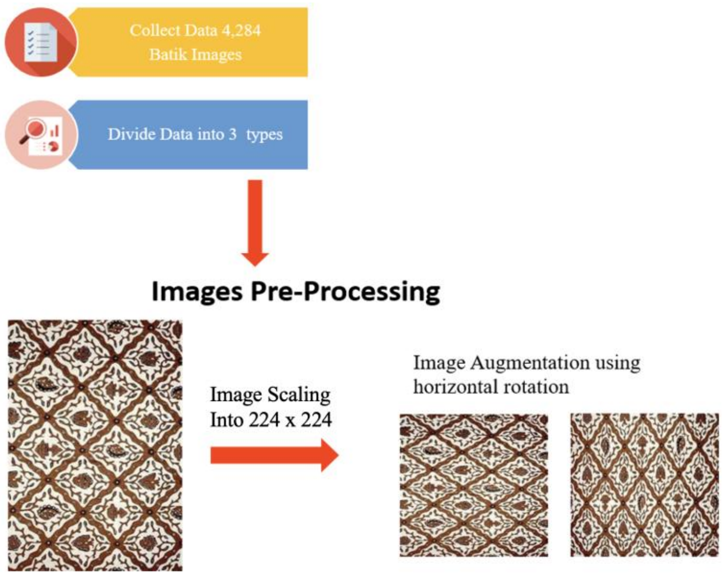

Fig. 3. Batik dataset

2.2 Implementasi CNN

The implementation of CNN begins by conducting transfer learning using MobileNetV3 [20], [21] with pre-trained ImageNet weights. Transfer learning is used to facilitate the training process of the CNN model because it contains weights that have been trained beforehand. Then, the model is frozen so that the training process does not affect the MobileNetV3 model as a result of transfer learning.

Then the specifications of the CNN model that will be applied in the batik classification can be seen in Figure 4. In Figure 4, you can see that the components of the CNN model consist of a foundation in the form of a pre-loaded MobileNetV3Large model, a GlobalAveragePooling2D layer that functions to reduce the dimensions of the image by taking the mean from each image data column, an initial Dense layer assisted by the ReLU activation function that functions to help the model recognize complex patterns, a Dropout layer that functions to reduce overfit, and a final Dense layer with a softmax activation function to produce an output in the form of probability.

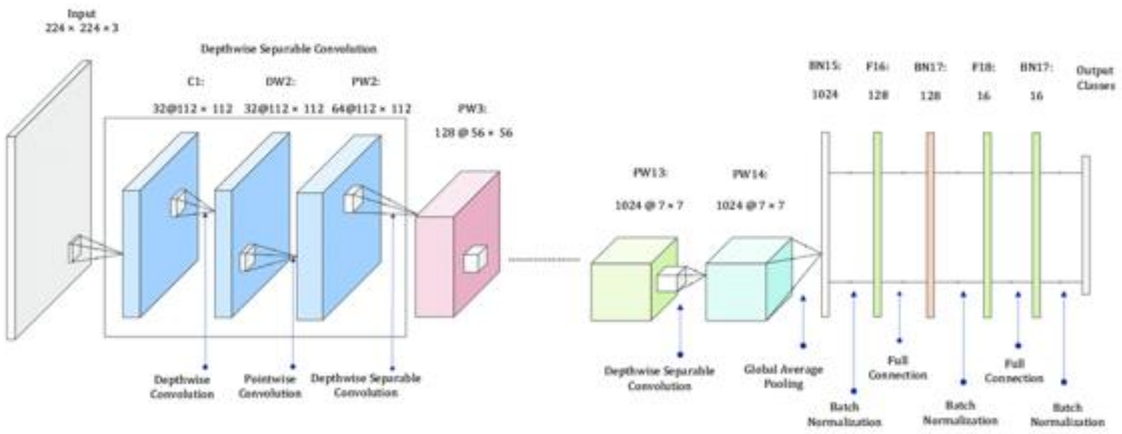

Fig. 4. CNN model batik image classification

Then, the CNN model will be compiled using the Adam optimizer and categorical cross-entropy loss used in the multi-class classification. The metric value to be measured is defined as the accuracy of the model. The training process is carried out in iterations of 50 epochs and validation is carried out in parallel. Then, the function of evaluating the accuracy and loss value of the CNN model used is also defined. The data division of 80% for training and 20% for testing is applied to ensure that the model is able to generalize well and avoid overfitting, so that the model's performance can be objectively evaluated on new data.

The loss value and accuracy of the model to be measured can be seen in the appearance of the graph in Figure 5. The values are displayed in the form of a graph with horizontal columns symbolizing epochs and vertical columns representing values. The testing process is carried out in iterations of 50 epochs Then, the function of evaluating the accuracy and loss value of the CNN model used after the testing process is completed is also defined.

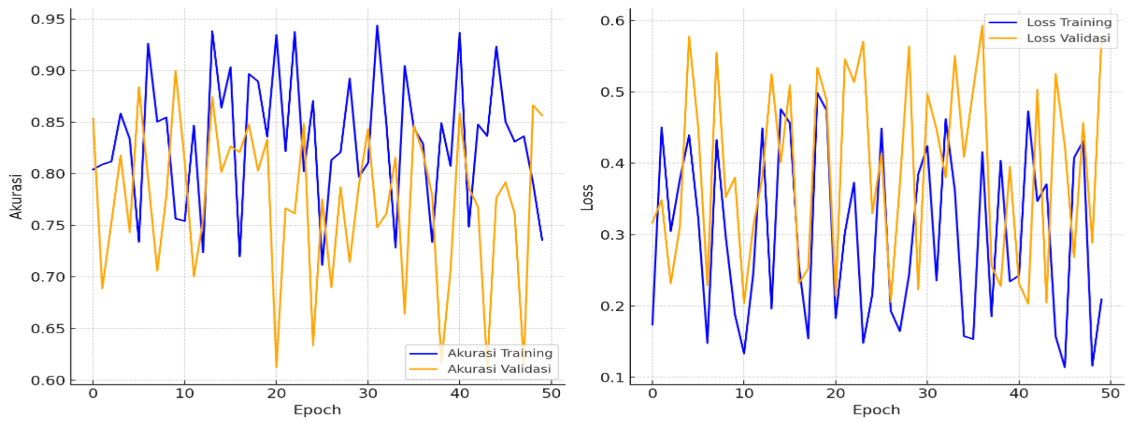

Fig. 5 Testing model CNN

The data-driven approach implements a Convolutional Neural Network (CNN) model to utilize large and representative datasets to improve accuracy and performance in batik image classification. Through the extensive use of data, the CNN model can extract specific patterns such as shapes, textures, and edges present in batik motifs more efficiently. By leveraging a data-driven approach, every decision in the model training process, such as hyperparameter tuning and performance evaluation, is based on measurable data. This allows the model to make better generalizations to new data and reduce the risk of overfitting, so that the results of the classification of batik motifs become more accurate and reliable.

3. Results

3.1 Evalution Model

At this stage, an evaluation of the performance of the batik classification model was carried out with three experiments, namely the CNN method, decision tree and randome forest. Model performance is measured by the accuracy value that the model produces.

The decision tree method obtained a very low accuracy result of only 21% because the decision tree is suitable for simple datasets and when model interpretability is the top priority. However, these models are prone to overfitting and may not work well on larger and complex datasets.

Then the random forest method obtained an accuracy value of 72%, this is because random forests offer better performance in terms of accuracy, generalization, and resistance to overfitting, especially on large and complex datasets. However, this model is more complex and requires more computing resources.

As for the CNN method, the model performance results can be seen in Figure 6.

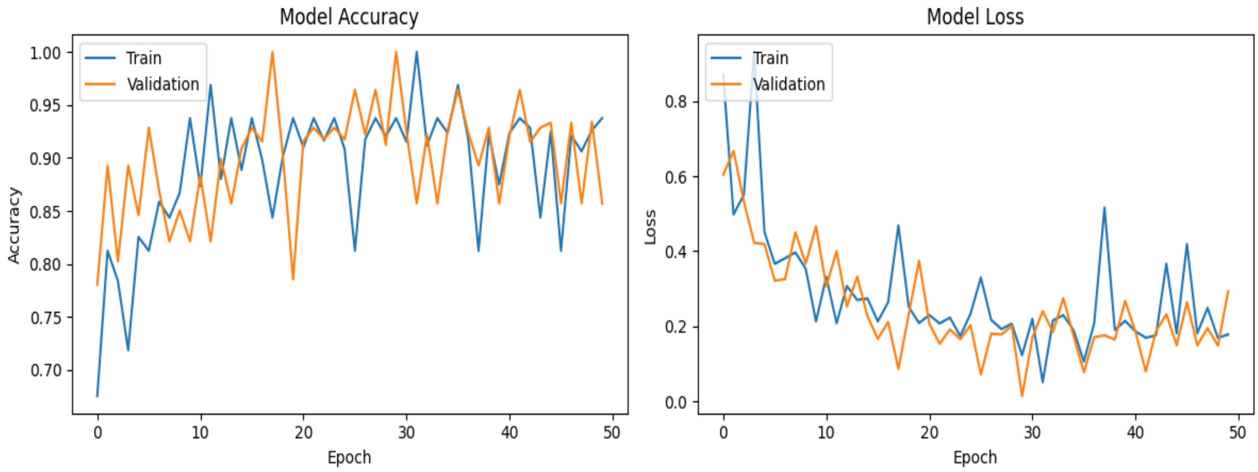

Fig. 6 Accuracy and loss training of CNN models

In Figure 6, you can see the graph generated from the CNN model training process which contains the model accuracy value and the model loss value. The graph is divided into 2, namely the accuracy graph and the loss graph which consists of 2 components, namely the value in the training process (marked with a blue line) and the value in the validation process (marked with an orange line). From this graph, the mean accuracy is 93.42% and the mean loss is 1.3%**.**

In Figure 7, the graph generated from the CNN model testing process for the classification of batik images. The values measured were the accuracy (blue line) and loss (orange line) values of the CNN model used, which resulted in a mean accuracy of 93.88% and a mean loss of 1.2%.

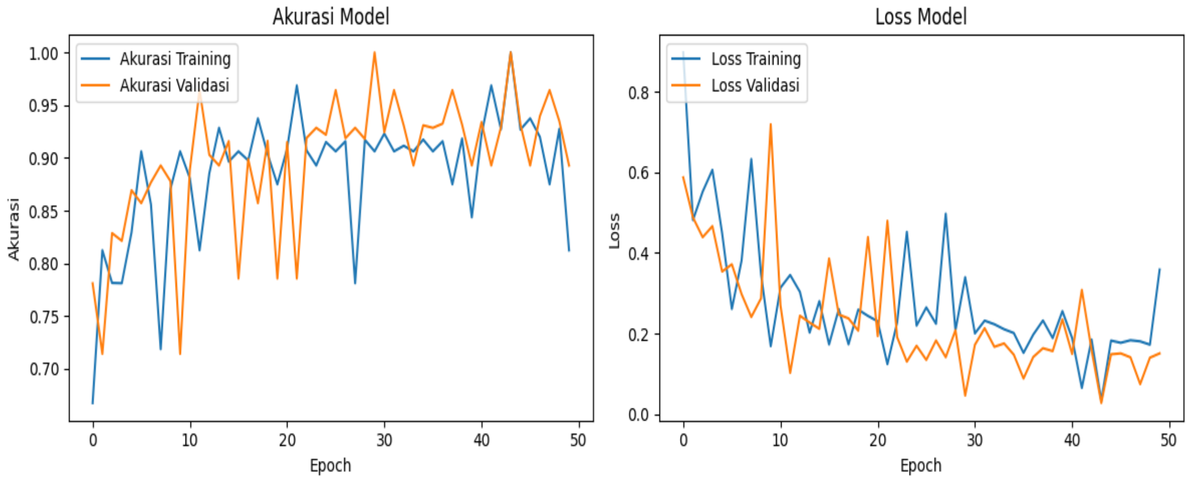

Fig. 7. Accuracy and Loss Testing of CNN Models

The results of the accuracy values of the three models can be seen in Table 2.

Table 2
Metric Values: CNN-MobileNET, Random Forest, dan decision tree

Method	Accuracy
Decision tree	21%
Randome forest	72%
CNN	93.42%

In Table 2 it can be seen that the CNN (Convolutional Neural Network) method shows the highest accuracy with a score of 93.42%, far superior to other methods. Random Forest came in second with an accuracy of 72%, which while quite good, is still significantly lower than CNN. On the other hand, the Decision Tree method has the lowest performance with an accuracy of only 21%, indicating that this model is less effective for the dataset or problem being tested. Overall, CNN proved to be the most superior in terms of accuracy compared to the Random Forest and Decision Tree methods. It can be seen that the values measured when classifying batik images using the CNN method with a data-driven approach, namely accuracy and loss values are two important metrics in evaluating the performance of machine learning models, including Convolutional Neural Network (CNN). Accuracy measures the percentage of correct predictions out of the total predictions the model makes, which reflects how well the model classifies data correctly; The higher the accuracy, the better the model's performance. In contrast, Loss measures how far the model predicts from the actual value, with a lower loss value indicating fewer errors. The results of the training and testing process resulted in an average accuracy score of 93.42% for training and 93.53% for testing. Then an average loss of 1.2% for training and 1.3% for testing was also produced.

4. Conclusions

Based on the research conducted, the following conclusions were obtained:

i) Classification of batik patterns was successfully carried out on batik image testing data using the TensorFlow and MobileNetV3 models that had been pretrained. The implementation of this model resulted in an accuracy value of 93.42% and a loss value of 1.2%. The use of the

MobileNetV3 architecture allows the model to efficiently extract image features, so that the classification of batik motifs can be carried out accurately, and the resulting errors are below average.

ii) The usefulness of Data Driven itself in the development of Convolutional Neural Network (CNN) models is very important to improve the accuracy and performance of the model. By using a large and representative dataset, the model can learn and extract features more effectively, thus providing a more accurate and reliable classification.

iii) Convolutional Neural Networks (CNNs) excel in image classification because of their ability to extract automatic features and provide high accuracy, although it requires more time and resources, while Decision Trees are faster and easier to interpret but prone to overfitting and less effective in complex image classification, whereas Random Forest offers a better balance in terms of accuracy and generalization by reducing overfitting through an ensemble of several decision trees, but still not as effective as CNN in handling image classification tasks.

Acknowledgement
The author expresses gratitude to the Faculty of Computer Science and Information Technology at Universiti Tun Hussein Onn Malaysia (UTHM) for their support, particularly to all of the instructors who helped them finish this essay. The Abdurrab Foundation, through the Institute of Research and Community Services at Universitas Abdurrab in Pekanbaru, Indonesia, has funded this research in order to produce satisfactory results.

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