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Data-driven approach for batik pattern classification using convolutional neural network (CNN)

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ABSTRACT

Batik is one of Indonesia's cultural heritages with complex and diverse patterns, possessing high artistic value and deep philosophy. Manual classification of batik patterns requires time and depends on expert knowledge, making the process inefficient. This study aims to develop a batik pattern classification model using Convolutional Neural Network (CNN) with a data-driven approach, enabling automatic and accurate pattern recognition. The dataset used consists of 4,284 batik images divided into five pattern classes: Kawung, Lereng, Ceplok, Parang, and Nitik. In this research, the CNN model was developed by using transfer learning techniques with MobileNetV3 pre-trained on a large dataset. The training process involved data augmentation to enhance the model's robustness against variations in batik patterns. The evaluation was conducted by measuring the model's accuracy and loss. The results show that the CNN model achieved an average accuracy of 93.42% on the training data and 93.88% on the testing data. This research demonstrates that the data-driven approach using CNN is effective for batik pattern classification, providing more accurate results compared to manual methods and offering an efficient solution for the digitalization of the batik industry. The developed model can serve as a foundation for broader applications in cultural preservation and the advancement of artificial intelligence-based technology.

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1. INTRODUCTION

Batik is one of Indonesia's cultural heritages that has high artistic value and various patterns that are typical of each region (Saputra et al., 2021). Each batik pattern has a deep philosophical meaning and is a symbol of cultural identity. However, the recognition and classification of batik patterns is often a challenge due to the complexity and uniqueness of each motif. It is estimated that there are more than 5,000 batik patterns that have been identified in various regions in Indonesia (Regine et al., 2023). Manual classification can be time-consuming and relies on expert knowledge, so a more efficient and automated approach is needed (Athira & Herlina, 2022).

Along with the development of technology in the field of machine learning and artificial intelligence, Convolutional Neural Network (CNN) has become one of the most effective methods in image pattern recognition and classification (Devega, 2019). CNN is a type of artificial neural network designed to process image data by extracting important features from images through convolutional layers. This method has proven to excel in various image recognition tasks such as face recognition, object recognition, and also complex visual patterns (Rizal et al., 2021). Batik classification research has used various methods, such as Support Vector Machine (SVM), K-

Nearest Neighbor (KNN), and Random Forest (Muawanah et al., 2023). SVM is effective for high-dimensional patterns but requires manual feature extraction, while KNN is simpler but less efficient for large datasets (Andrian et al., 2019). Random Forest offers good accuracy but requires intensive parameter tuning. Recently CNN has been widely applied because of its ability to automate feature extraction from images, making it very effective in recognizing complex batik patterns (Chusna et al., 2024). However, previous studies with CNNs face challenges such as the need for large and diverse datasets, and the risk of overfitting if data is limited. These shortcomings suggest that data-driven approaches require larger and higher-quality datasets. This opens up opportunities for more innovative data collection and augmentation techniques to improve model performance in classifying complex batik diversity (Ihdal, 2021).

The urgency of this research is driven by the need to improve accuracy and efficiency in image data analysis, especially in real-world applications such as surveillance, object detection, and pattern recognition. With the increasing complexity of the data at hand, approaches such as CNNs are becoming increasingly relevant and necessary. This research realizes that cultural preservation through digitization is a strategic step in maintaining cultural heritage, including batik. The implementation of technologies such as CNN offers an innovative solution that not only supports efficiency but also helps in cultural preservation. The technical challenges and uniqueness of batik patterns were identified based on literature sources and dataset analysis (Wona et al., 2023). Some previous research that shows the success or failure of CNN in batik classification: a) CNN Success in batik classification: Research showing the success of CNN with 91.24% accuracy in classifying various types of batik on a test dataset developed to recognize patterns, colors, and shapes (Wona et al. 2023). Research showing the CNN model achieved 80% accuracy in the classification of Sasambo Batik motifs from West Nusa Tenggara, which have a certain uniqueness (Malika and Widodo 2022). Another study using the Tanah Liat batik dataset with 400 images showed high accuracy on the training data (98.75%) but lower on the test data (62.5%), indicating potential overfitting (Azmi et al., 2023); b) CNN failures or challenges: Research that shows CNN accuracy for batik classification is only 52.63%, influenced by the small dataset size, image quality, and pattern complexity. A common problem encountered is the risk of overfitting, especially if the dataset does not include enough pattern variation, as seen in the case of the research on Tanah Liat batik (Dewi et al., 2024).

Challenges in obtaining a representative dataset for Indonesian batik: Diversity of batik motifs; Indonesia has more than 5,000 batik patterns from different regions, each with unique philosophical meanings, colors, and designs. Creating a dataset that covers all these variations is very difficult. Availability of digital datasets; many batik motifs have not been digitally documented or have limited documentation. Existing datasets are often dominated by popular motifs, such as Parang or Kawung, making them less representative for rarer batik variations. Image quality; captured batik images often have quality issues, such as noise, poor lighting, or low resolution, which affect the model's ability to recognize patterns. Uneven class distribution; in this research dataset, classes such as Lereng (405 images) are much less than Parang (1,197 images), so the model tends to be biased towards classes with a larger amount of data. Data augmentation and processing; to overcome the limitations of the dataset, extensive data augmentation is required. However, augmentation cannot completely replace the natural variation of patterns present in the real world (Aprianingrum et al., 2021).

In this study, CNN is used as a data-driven approach for batik pattern classification (Mawan, 2020). This process involves collecting batik image data, training a CNN model with the dataset, and evaluating the model's performance in classifying different batik patterns (Kaswan et al., 2023). By utilizing the power of CNN, it is expected that the process of recognizing and classifying batik patterns can be done more accurately and efficiently compared to manual methods (Jansen et al., 2022).

This research sees great potential in combining modern technology with cultural heritage, as well as opportunities to create innovative solutions for the batik industry (Time, 2019). It is expected to not only contribute to the development of science, but also provide a real impact in accelerating the digitalization of the batik industry, increasing public appreciation of batik, and preserving Indonesia's cultural wealth through advanced technology (Meri & Perdana, 2023).

2. RESEARCH METHOD

The research method used through several stages that form a systematic flow. The initial steps taken are problem identification, data collection, data analysis, system analysis, design, and testing. The next step is to validate data and analysis and draw conclusions (Kersen & Widhiarso, 2023). Figure 1 is a form of research framework.

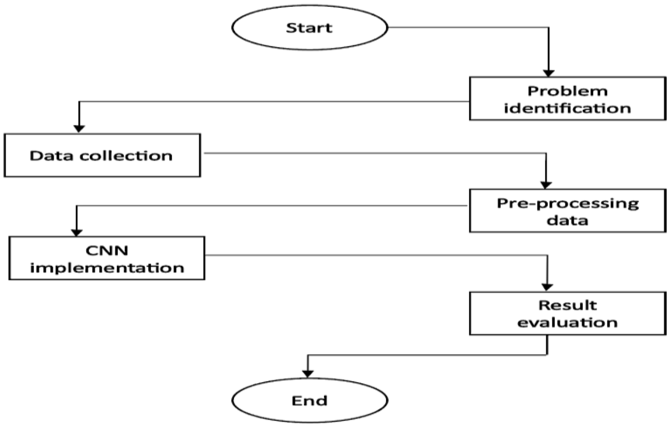

Figure 1. Research framework

Identification of Problems

Identification as an affirmation of the boundaries of the problem, so that the scope of the research does not deviate from the objectives. The results of the problem identification become the background in formulating the problem that will become the object of the research. The identified problemHow to apply the CNN model for classification techniques on batik pattern images digunakan (Novac et al., 2022). This research is based on a literature study on a number of previous studies on batik classification using different methods, such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and other algorithms. Some studies show limitations in terms of accuracy and manual requirements for feature extraction. The study results showed that CNN proved to be more effective in the classification of complex image patterns than traditional methods, with higher average accuracy.

Data collection

The dataset used in this study is a collecting dataset from Kaggle, containing various batik pattern images that have various patterns. The collected data then goes through preprocessing to adjust the image for the next step, such as resizing and downscaling the image. Dataset This study uses a dataset containing a total of 4284 batik images. With the number of classes divided into 5 different classes, which represent variations in batik motifs. Each class consists of Kawung: 747, Lereng: 405, Ceplok: 1053, Parang: 1197, Nitik: 882 batik images, so the total number of data used in the study is 4284 images.

Pre-processing data

The image that is considered suitable as a sample is an image that clearly shows the batik motif (Palanisamy, 2024). After performing data acquisition and sorting, the next step is to perform data pre-processing. Not specifically removing noise, but using image augmentation such as rotation, shift, zoom, and flipping that can help the model be more resistant to noise. In addition, all images are automatically resized to 224x224 pixels to be uniform before entering the model. Image augmentation is also done through ImageDataGenerator, which normalizes pixel values to 0 to 1, rotation to 10 degrees, shift, 10% zoom, and horizontal flipping. The model is trained with augmented images to be more robust and can better understand a wider variety of images (Wona et al., 2023).

The addition of data through augmentation techniques such as rotation, zoom, and flip is done randomly using the Python library's built-in image augmentation method, ImageDataGenerator. The details of the augmentation techniques performed are Augmentation Parameters: Random rotation: the image is rotated by a maximum of 30 degrees. Random zoom: zoom is performed up to a maximum of 20% (zoom in and zoom out). Horizontal flipping: the image is flipped horizontally in a random manner. Random shift: the image is shifted up to a maximum of 20% of the image width and height.

CNN Implementation

Implementation of batik dataset using CNN method with pre-training approach using MobileNet model (Marinda et al., 2023). Data that has gone through pre-processing stage will be analyzed further according to the stages in CNN architecture. Data-driven approach is applied in every stage of this process, by continuously monitoring model performance through metrics such as accuracy and loss on training and validation data (Azmi et al., 2023). This allows in-depth analysis of the effectiveness of the model in recognizing batik motifs in real-time, providing feedback that underlies hyperparameter tuning decisions and model architecture (Werth et al., 2022). MobileNet pre-training to utilize the capabilities of models that have been previously trained on common image datasets, so as to speed up the training process and increase accuracy in batik motif classification. By utilizing the pre-trained MobileNet model, the system can extract image features more efficiently and produce more accurate classification results compared to training from scratch (More & Mishra, 2023). Data generated from the training process is used to continuously evaluate model performance and help identify overfitting or underfitting by utilizing visualization of accuracy and loss data. This stage allows the model to focus more on recognizing specific patterns in batik motifs after going through convolutional layers in the CNN architecture that will be created using the Python programming language running on TensorFlow (Li et al., 2021). With this data-driven approach, every decision in the model training process is based on measurable and visualized performance evidence, so that the model development process becomes more efficient and accurate (Keshary Shah et al., 2023).

MobileNet was chosen for its advantages in computational efficiency, flexibility of transfer learning, and balance between accuracy and required resources. It is particularly suitable for research involving batik datasets of moderate size and limited computing resources.

Evaluation of Results

At this stage, the CNN algorithm will be evaluated and relevant data will be described. Parameters measured from training accuracy data and quantitative validation accuracy and testing is carried out to ensure that the research objectives have been achieved.

3. RESULTS AND DISCUSSIONS

The problem that is used as the background of the research conducted is the complexity of the process of recognizing and classifying batik patterns due to the variation and uniqueness of each motif with the research object being the Ceplok, Kawung, Lereng, Nitik, and Parang batik patterns. Therefore, the Data Driven approach of the CNN algorithm is applied to carry out the classification process of batik patterns.

Data Collection

System analysis is a research stage on the running system and aims to find out all the problems that occur and facilitate the next stage, namely the interface design stage (Indah Purnama Sari, 2021). System analysis aims to find out more clearly how the system works, in addition to knowing the system that is running. This analysis aims to define and evaluate problems, opportunities, obstacles that occur and needs that are expected to be able to propose improvements.

Figure 2. Batik image dataset

The dataset used in this study is a collecting dataset containing 4284 batik images. This dataset is divided into 5 different classes that represent variations of batik motifs, consisting of: a) Kawung motif: 747 images; b) Lereng Motif: 405 images; c) Ceplok Motif: 1053 images; d) Parang Motif: 1197 images; e) Nitik Motif: 882 images.

Figure 3. Batik dataset graph

Data Preprocessing

Before processing data using the CNN algorithm, preprocessing is first carried out to determine suitable image samples. Figure 4 shows the preprocessing flow for the batik image dataset using the ImageDataGenerator object with the prepcoessing_function function, including various preprocessing components that can be used for data sorting and augmentation to reduce the model's vulnerability to noise. Applied to the training and testing datasets, the functions used are to rotate by a maximum of 30 degrees, shift the image by a maximum of 20% of the image width and height, zoom the image by a maximum of 20% zoom in or zoom out, and flip the image horizontally. All of these preprocessing components are randomly selected for each image of the batik image dataset so that they can be used for further processing. The resize process on the batik image dataset produces an output with dimensions of 224 x 224 pixels with a batch size of 32.

```
# Preprocessing and Augmentation
train_datagen = ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

test_datagen = ImageDataGenerator(preprocessing_function=preprocess_input)
```

Figure 4. Batik dataset preprocessing

CNN Implementation

Start by performing transfer learning using MobileNetV3 with pre-trained ImageNet weights. In Figure 5, the specifications of the CNN model that will be applied in the classification of batik images. The components of this CNN model consist of a foundation in the form of a previously loaded MobileNetV3Large model, a GlobalAveragePooling2D layer that functions to reduce image dimensions by taking the mean of each column of image data, 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 output in the form of probability. The CNN model will be compiled using the Adam optimizer and categorical cross-entropy loss used in multi-class classification. The metric value to be measured is defined as model accuracy. The training process is carried out iteratively for 50 epochs and validation is carried out in parallel, then the accuracy evaluation function and loss value of the CNN model used are also defined.

```
# Load MobileNetV3 model with pre-trained ImageNet weights
base_model = MobileNetV3Large(weights='imagenet', include_top=False,
                              input_shape=(224, 224, 3))

# Freeze the base model
base_model.trainable = False
```

Figure 5. Transfer learning mmodel mobilenetv3large

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 model performance can be evaluated objectively on new data. The flow of the graphical appearance will display the values to be measured (metrics) from the CNN training process, namely the loss value and model accuracy. The values are displayed in the form of a graph with horizontal columns representing epochs and vertical columns representing values. The testing process is carried out iteratively for 50 epochs. Then, the accuracy evaluation function and the CNN model loss value used after the testing process is complete are also defined.

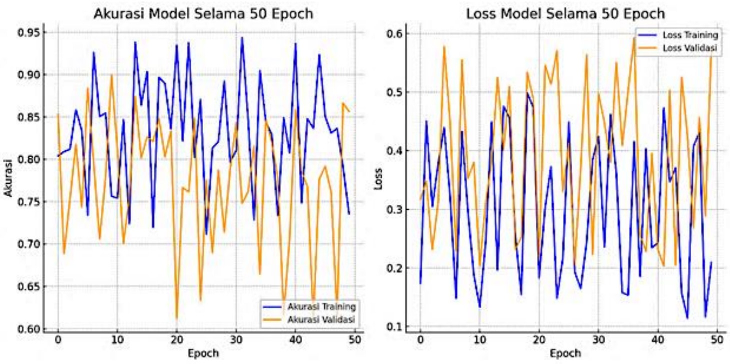

Figure 6. Example appearance of CNN model testing values

Figure 6 shows the results that will display the values that will be measured from the CNN testing process, namely the loss value and model accuracy. The values are displayed in the form of a graph with horizontal columns representing epochs and vertical columns representing values. The data-driven approach implements a CNN model to utilize large and representative datasets to improve accuracy and performance in batik image classification. Through the use of extensive data, the CNN model can extract specific patterns such as shape, texture, and edges in batik motifs more efficiently. By utilizing the data-driven approach, every decision in the model training process, such as hyperparameter tuning and performance evaluation, is based on measured data. This allows the model to generalize better to new data and reduce the risk of overfitting, so that the results of batik motif classification become more accurate and reliable.

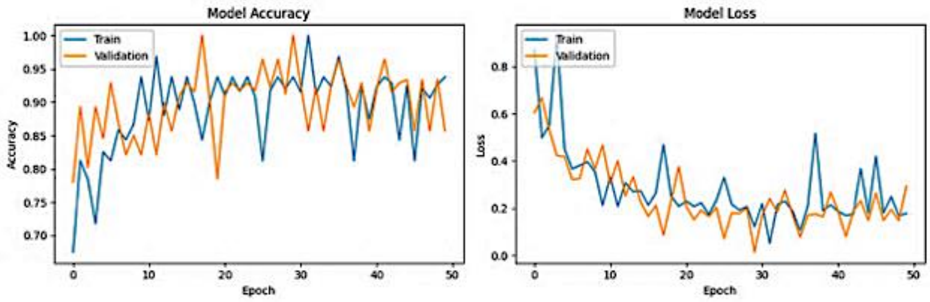

Figure 7. CNN model training accuracy and loss graph

Figure 7 shows the graph produced from the CNN model training process containing the model accuracy value and the model loss value. The graph is divided into 2, the accuracy graph and the loss graph which consist of 2 components, namely the value in the training process (blue line) and the value in the validation process (orange line). The mean accuracy was obtained at 93.42% and the mean loss was 1.3%.

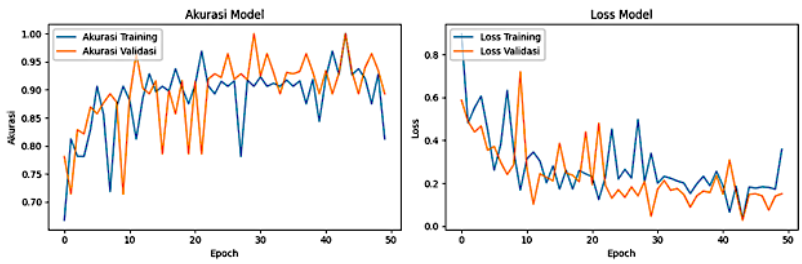

Figure 8. Accuracy and loss graph of CNN model testing

Figure 8 shows the graph produced from the CNN model testing process for batik image classification. The measured values are the accuracy (blue line) and loss (orange line) values of the CNN model used, which produced a mean accuracy of 93.88% and a mean loss of 1.2%.

Table 1. Batik image classification metric values

Mark	*Average*Training	*Testing Average*
Accuracy	93.42%	93.53%
Loss	1.2%	1.3%

Table 1 shows the measured values when performing the batik image classification process using the CNN method with a data-driven approach, namely the accuracy and loss values, two important metrics in evaluating the performance of machine learning models, including CNN. Accuracy measures the percentage of correct predictions from the total predictions made by the model, reflecting how well the model correctly classifies data; the higher the accuracy, the better the model performance. Conversely, Loss measures how far the model's predictions are from the actual values, with lower loss values indicating fewer errors. The results of the training and testing processes produced an average accuracy value of 93.42% for training and 93.53% for testing. Then also produced an average loss value of 1.2% for training and 1.3% for testing.

4. CONCLUSION

A batik pattern classification model that is able to recognize and classify various types of batik patterns effectively has been successfully built using the CNN method. Batik pattern classification was successfully carried out on batik image testing data using the pretrained TensorFlow and MobileNetV3 models. The implementation of this model produced an accuracy value of 93.42% and a loss value of 1.2%. The use of the MobileNetV3 architecture allows the model to extract image features efficiently, so that batik motif classification can be carried out accurately, and the resulting error is below average. The use of data Driven itself in the development of the CNN model 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, so that it can provide more accurate and reliable predictions.

The main contribution of this research is the use of CNN for batik pattern classification which not only improves efficiency and accuracy, but also has great potential in batik culture preservation and technology development in the creative industry. The implications of this research are vast, ranging from the development of e-commerce, education, to the empowerment of the Indonesian batik industry in the global market.This research can support the preservation of batik culture in Indonesia because it enables more systematic documentation, facilitates the preservation of batik motifs that may be in danger of being lost, an accurate automated system can help the younger generation and the global community understand the uniqueness of batik patterns, batik classification technology can be integrated into e-commerce platforms to help consumers recognize authentic products, encourage purchases, and support the sustainability of the batik industry. Recommendations for further model development are: Adding a more representative dataset that includes rare batik patterns from various regions in Indonesia. The dataset should be validated by batik experts to ensure the accuracy of the labels. Then use a more complex architecture, trying models such as EfficientNet or Vision Transformers (ViT) that are capable of producing higher accuracy, albeit with greater resource requirements. Then adding the extraction of metadata contextual features, such as regional origin or time of batik making, to make the model more contextual and informative. Also applying ensemble learning by combining multiple CNN models with ensemble methods to improve robustness and classification accuracy. Discussion for practical implementation: a) Implementation for education: A CNN-based application can be developed for schools or museums, allowing users to scan batik images and get information about their patterns, meanings, and history; b) E-commerce platform for batik: This technology can be used to recognize batik patterns on products uploaded by sellers, assisting in automatic categorization on local e-commerce platforms; c) Automated detection system for cultural archiving: The government or cultural institutions can implement this system to document batik collections in museums or national archives, so that batik patterns are not lost to time or physical damage; d) Use in the creative industry: Batik designers can use this model to get inspiration for new patterns by combining features of traditional patterns; e) Utilization for product certification: With its pattern identification capabilities, this technology can help detect the authenticity of hand-drawn versus printed batik, supporting the certification of genuine products.

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