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Implementation of deep learning based on convolution neural network for batik pattern recognition

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Abstract

Batik as a cultural heritage is one of the heritages that needs to be preserved so that it continues to be recognized from generation to generation. Efforts to preserve batik can be made by using technology that can recognize batik motifs. Pattern recognition is a branch of science related to the identification, classification, and interpretation of patterns. Deep learning is one of the technologies that can be used very well for pattern recognition, especially for syllable and image recognition. Convolutional neural network (CNN) is one of the most popular deep learning methods and the most established algorithm for deep learning models. The main advantage of CNN over the preceding methods is its ability to automatically detect features, making the feature extraction and classification process highly organized. This study aims to apply CNN for batik pattern recognition. The batik patterns used were geometric patterns, divided into 7 batik classes. Experiments were conducted on 3100 data, consisting of 3000 for training set and 100 for testing set. At the preprocessing stage, the batik image was resized to 28x28, and the color was changed to grayscale. Training was carried out on 100, 200, and 300 epochs. The classification results prove that CNN can recognize batik patterns well with an accuracy rate of 95%.

1. Introduction

Batik is a cultural heritage of the Indonesian nation as well as an intangible cultural heritage that has been recognized by the United National Educational, Science, and Cultural Organisation (UNESCO) [1][2]. As the work of the Indonesian people, batik is a combination of art and technology from the nation's ancestors. The patterns of batik become the basic framework comprising the combination of lines, shapes, and contents that become a unity to create batik as a whole. In general, batik patterns are divided into two main patterns, namely: geometric and non-geometric. Geometric batik patterns describe the symmetry of the pattern and the repetition of directions horizontally, vertically, and diagonally which form angles between shapes, while non-geometric patterns do not describe the symmetry [3][4]. Some geometric batik patterns that are often used include: kawung, banji, pilin, ceplok, parang, lereng, and nitik. Non-geometric patterns include lung lungan, semen, pagersari, and taplak meja. As the nation's cultural heritage, of course, the batik pattern needs to be preserved so that this cultural heritage will continue to be recognized from generation to generation [1].

Efforts to preserve batik patterns can be made by using technology that can recognize batik patterns automatically, one of the technologies that can be used is pattern recognition [1]. Pattern recognition is a branch of science related to the identification, classification, and interpretation of patterns. The pattern can be complex information in the form of images, sounds, text, or other data [5]. One of the main challenges in pattern recognition is how to develop an algorithm that can recognize and understand these patterns automatically. Batik patterns have a large variety of patterns, and one another might have almost similar pattern, increasing the complexity in the pattern recognition process. Thus, deep learning can play an important role [1]. Deep Learning is a technique in machine learning in the area of artificial intelligence. Research on deep learning continues to grow with various machine learning algorithms up to recently and very useful for syllable and image recognition [6][7][8][9][10][11]. Two important reasons for the increasing popularity of deep learning are the significant lower cost of computing hardware and the drastically increased processing capabilities of chips [8][12].

Convolutional neural network (CNN) is one of the most popular deep learning methods, because of this CNN deep learning is becoming a very popular and most established algorithm for deep learning models. The main advantage of CNN over previous methods is its ability to automatically detect features, making the process of feature extraction and classification highly organized [7][13][14]. CNNs utilize the convolution operation, which is a fundamental concept in image processing, to identify distinct patterns in the data. This allows the network to automatically extract important features from images in a hierarchical manner. CNNs usually consist of several layers, including a convolution layer, activation layer, pooling layer, and fully connected layer [15][16][17][18]. Although many studies mention that the weakness of CNN is the long training process, it has very good accuracy for pattern recognition. Therefore, this study aims to propose the application of the Convolutional neural network (CNN) method for the process of recognizing batik patterns in geometric types.

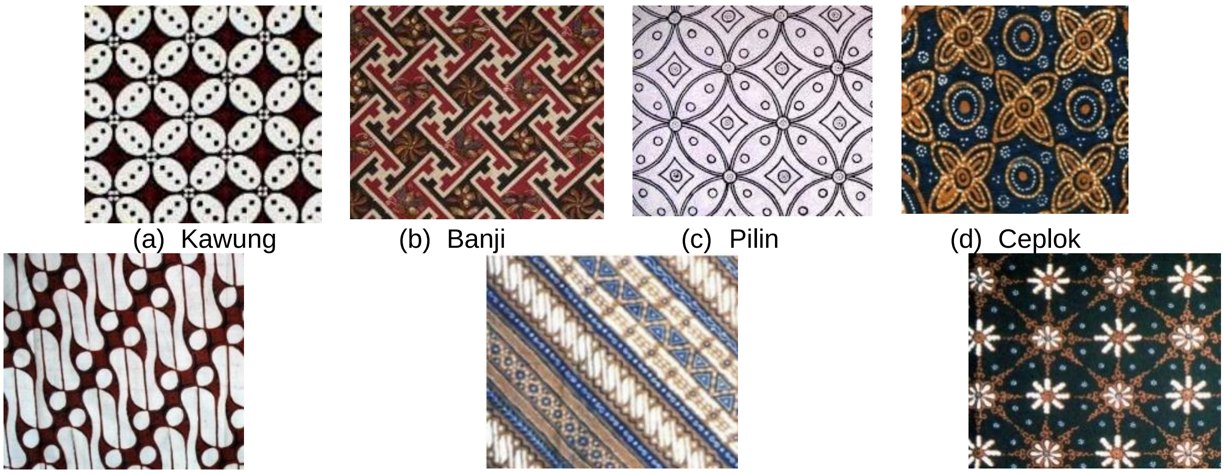
2. Research Method

2.1 Related Research

A number of research related to batik pattern recognition have been conducted. Edi Sugiarto conducted research on batik pattern recognition on geometric patterns by applying the SVM, DWT, PCA, and GLCM algorithms for feature enhancement, and found an increase in the accuracy of batik pattern classification using SVM method [1]. This research aimed to reduce features by determining the correlation between features and producing features with the best variance. They used 310 batik image data which were then divided into 240 for training data and 70 for testing data. The batik image was then resized to 160x160, the color was changed from RGB to grayscale, and edge detection was performed. During feature extraction stage, DWT method was used and has been optimized with GLCM and PCA, resulted 24 features reduced to 6 features for the classification stage. From the 6 features obtained, classification was then carried out and an accuracy rate of 93% was obtained. This result was 7% higher than the feature extraction using DWT method only, which was 86%. However, this research used only limited amount of data, while in a large amount of data, an appropriate algorithm is needed.

2.2 Batik

In Indonesian culture, Batik is one of the ancient art forms of high quality. Batik comes from the word "amba" which means to write, and "nitik" which means dot. These two words mean writing with wax when combined. The process of making batik on cloth uses canting which has small tip giving the impression that someone is writing dots [19]. The origin of batik in Indonesia is closely related to the history of the development of the Majapahit, Solo, and Yogyakarta sultanate. Many batik decorations in Indonesia can be broadly divided into two main batik motifs, namely: geometric and non-geomeric. Geometric batik patterns can be recognized because of the symmetry and repetition of horizontal, vertical, and diagonal directions that form angles between shapes, while non-geometric does not show these symmetrical patterns [3]. Some geometric patterns that are frequently used include kawung, banji, pilin, ceplok, parang, lereng, and nitik. Meanwhile, the non-geometric patterns that are frequently used include lung lungan, semen, pagersari and taplak meja.



(a) Kawung (b) Banji (c) Pilin (d) Ceplok

(e) Parang (f) Lereng (g) Nitik

Figure 1. Geometric Patterns

2.3 Convolutional Neural Network

Convolutional neural network or CNN is a supervised learning method that was first known to the public in 1998 under the name LeNet [12][20]. CNN is the development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the Deep Neural Network type because of the high depth of the network and is widely applied to image data[21][22]. The way CNN works has similarities to MLP, but in CNN each neuron is presented in two dimensions, unlike MLP where each neuron is only one dimension [23][24][25].

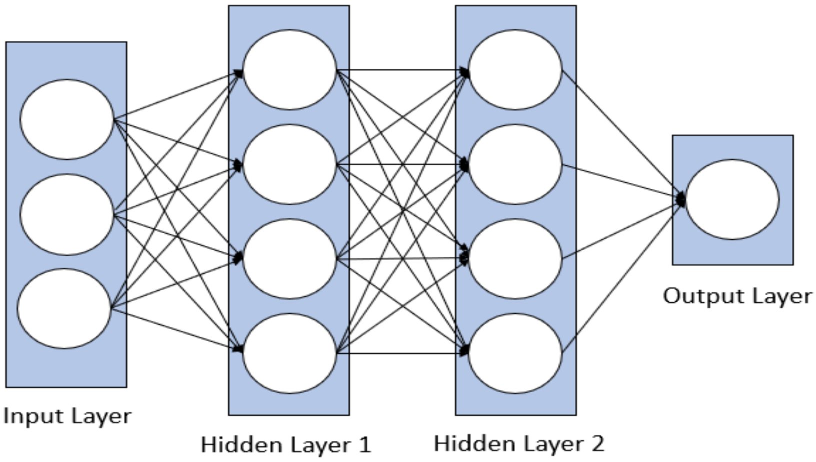


Figure 2. MLP Architecture

In CNN, the data propagated on the network is two-dimensional data, so the linear operation and weight parameters in CNN are different. In CNN, linear operations use convolution operations, while the weights are no longer one-dimensional, but in the form of four dimensions which are a collection of convolution kernels, namely:

input neuron x output neuron x height x width

Due to the nature of the convolution process, CNN can only be used on data that has a two-dimensional structure such as images and sound.

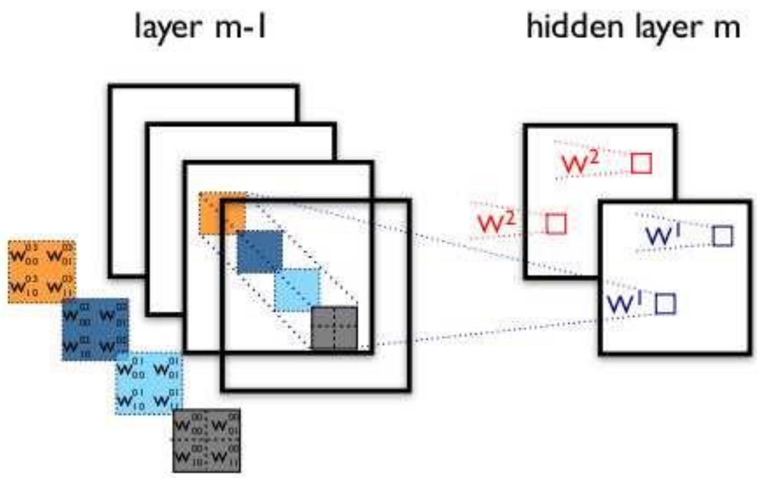


Figure 3. Convolution process in CNN

2.4 Pattern Recognition Process

This stage started from data collection, preprocessing, and classification using CNN. The data of batik images were collected in 7 motifs, namely: kawung, banji, pilin, ceplok, parang, lereng, and nitik. 3100 batik images were obtained during data collection process. This data then became a dataset with a composition of 3000 for training data and 100 for testing data. After collecting the data, the next step was preprocessing, namely rearranging the images by determining the specified resolution. Furthermore, classification was carried out using CNN. This research method is depicted in Figure 4.

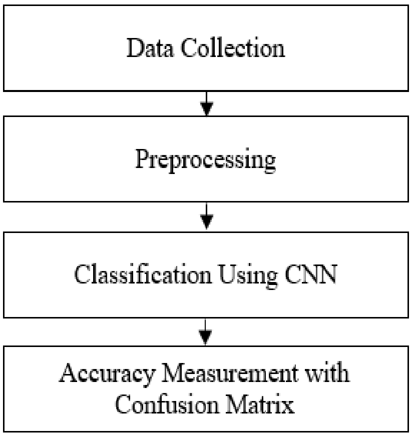


Figure 4. Research method

2.4.1 Preprocessing

This stage was performed to change the size of the image resolution in order to make the standard size of all images obtained and also to increase the training process time on CNN method. At this stage all of the images collected was set to 28x28 resolution. Furthermore, the batik image in RGB was converted to grayscale.

2.4.2 Classification Using CNN

After the preprocessing stage, the data were classified using CNN. The features extraction in this method was carried out in two parts, namely the convolutional layer and the pooling layer. The features were formed in a feature map which was the result of the convolution process. The classification stage was performed by creating the architecture depicted in Figure 5.

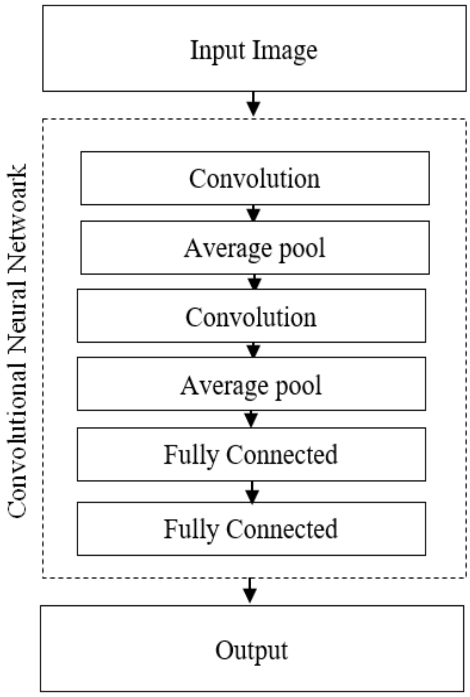


Figure 5. Classification Using CNN

The input image before processing on CNN is resized to 28x28 size and the RGB image is converted to grayscale, in the 1st convolution with 9x9x10 parameters, for the 1st average pool with 2x2 parameters, in the 2nd convolution the dimensions are reduced to 3x3, in the 2nd average pool with 2x2 parameters, in this CNN architecture using 2 fully connected with the number of hidden layers in the 1st fully connected as many as 150 and the 2nd fully connected as many as 7.

3. Results and Discussion

3.1 Experiments and Results

To measure the accuracy of CNN, experiments were carried out using 3100 batik images which were divided into 3000 for training and 100 for testing. At the preprocessing stage, the batik image was resized to 28x28, the color was changed to grayscale, and the batik images that had been resized became the input image on CNN. The training process was carried out using 3000 data in the form of images. At the training stage, experiments were carried out using 100, 200, and 300 epochs and the computer device with specifications: 11th generation Intel (R) Core (TM) i7 2.80Ghz (8CPUs) processor, with 16Gb of RAM. The result of this training stage is a model. This model contains important information such as map features for each batik class which will later be used for classification in the testing stage. The testing stage was carried out using 100 batik images to determine the level of accuracy. The level of accuracy was measured by using a confusion matrix at the training stage and the testing stage. The results of the accuracy measurement can be seen in Table 1.

Table 1. Accuracy Measurement Table

Epoch	Method	True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)	Over All Accuracy (AC)
100	CNN - Training	97	3	0	0	0.97
	CNN - Testing	94	6	0	0	0.94
200	CNN - Training	98	2	0	0	0.98
	CNN- Testing	95	5	0	0	0.95
300	CNN- Training	98	2	0	0	0.98
	CNN- Testing	95	5	0	0	0.95

From the results of measuring the accuracy using a confusion matrix, it can be seen that the highest accuracy was achieved at epoch 200, and it did not change even though the epoch was increased to 300 during training and testing stage, 98% and 95% respectively.

4. Conclusion

From the experiments that have been carried out on this CNN method using 3000 training data and 100 testing data with the number of epochs ranging from 100, 200, and 300, the highest accuracy was found when the convolution occurred at epoch 200, 98% for training and 95% for testing. From the experimental results, the accuracy for the classification of batik patterns did not change even though the epoch increased. It is proven that the accuracy remained the same when the epoch reached 300. Improving accuracy for this CNN method can be done by improving the architecture, either by using algorithms for preprocessing to help extract important features, or experimenting with a soft voting approach by combining other feature extraction and classification algorithms.

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