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Classification of Solo Batik patterns using deep learning convolutional neural networks algorithm

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ABSTRACT

The ideology of the Solo Batik pattern has not been conveyed to the public. In addition, a lot of people are unaware that batik contains particular patterns that are also used for particular activities. This study uses a convolutional neural network model to categorize 9 different Solo Batik patterns according to their use of elaborate geometric shapes, complicated symbols, patterns, dots, and natural designs. With 1 to 4 hidden layers, we aim to select the number of hidden layers that yields the highest accuracy. A 100×100 pixel image is used as the input. The feature extraction process then makes use of 3×3 feature maps from three convolution layers. The dropout regularization is then added, with settings ranging from 0.1 to 0.9. The Adam algorithm is also used in this model to perform optimization. The 3-layered convolutional neural networks (CNN) with a dropout value of 0.2, run in 20 epochs, produced accuracy results of 97.77%, which was the highest. Additionally, it can be inferred that applying a certain number of hidden layers and adding right dropout regularization values has an impact on raising the accuracy score.

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1. INTRODUCTION

Indonesia is an archipelagic country stretching from Sabang to Merauke, making it rich in ethnicity, culture, language, and ideology. The wealth of the Indonesian state is what makes Indonesia a pluralistic country. As a country rich in diversity, Indonesia has a characteristic that makes it a national identity and is known internationally. One of these characteristics is batik. On October 2nd, 2009, UNESCO designated batik as an Indonesian cultural heritage. Batik is the Indonesian nation's cultural heritage, designed by combining technology and art. The development of Indonesian batik, both in the process and in making the motifs, can reach the highest peak so that no one can compete with it [1]. Batik has a characteristic in the manufacture of motifs. A batik motif is an image pattern with a base or principal, a design image from the center or base so that the meaning of the symbol and the sign behind the motif can be understood [2].

Batik motifs have various patterns from various regions that are distinct. One of them is a batik from Solo. As one of the batik-producing areas, Solo does not only make batik a work of art but also poured his ideology into making batik; this is known from the existence of special patterns designed for certain activities. An example is the Babon Angrem batik motif, which has a pattern like a brooding chicken; this batik motif is usually used on a prospective mother who will give birth soon and reflects the love of a mother who will always care for her child. The Slobog batik pattern is used for mourning events, but by the community, it is used to attend thanksgiving events. This indicates that the ideology in batik has not been conveyed to the public. Also, many people do not know that batik has certain patterns that are also used for certain activities. These characteristics will be used to classify Solo Batik motifs [3].

Several academics have employed several classification approaches to categorize photographs based on batik patterns, all with the shared objective of accurately identifying images according to their batik motifs. One of the studies employed the feedforward neural networks (FNN) algorithm as well as treeval and treevit algorithm classification approach to effectively identify the type of batik pattern, with an accuracy level of around 55% and 65%, respectively [4]. The average accuracy of batik categorization, as determined through the application of artificial neural network (ANN), k-nearest neighbors (KNN), and decision tree (DT) techniques, is found to be 95% [5]. The accuracy achieved for four-class batik classifications using the invariance feature transform combined with support vector machine (SVM), resulted in 95% [6].

In previous studies, there were weaknesses in data collection of batik patterns where the batik patterns taken were universal so that people did not know the origin of the batik motifs in the area, and the results obtained were not maximized, so a convolutional neural network (CNN) classification method was needed for classifying Solo Batik patterns. CNN is a method for recognizing and detecting images with objects, which is one of the deep learning methods. CNN method has a higher level of accuracy than other classification methods. This is shown in a study entitled "wafer map defect pattern classification and image retrieval using convolutional neural network", which produces an accuracy value of 98.2% [7]. Further researchers also classify images as malware using CNN, where the accuracy rate can reach 98% [8]. The research entitled "heart diseases classification using convolutional neural network" obtained an accuracy of 99.46% [9]. Additionally, research in implementing the CNN method to detect the use of masks has an accuracy rate of more than 96% [10], while the classification of 10 CNN-based sports activities obtains an accuracy rate of 99.30% [11].

The purpose of this study is to classify Solo Batik patterns using the CNN algorithm to earn the maximum accuracy value. This study provides benefits in educating the public about Solo Batik motifs and the ideology contained therein. The novel finding in this study is that we determime the best number of hidden layers in the CNN architecture – along with the best value for dropout regularization – which produces the highest accuracy. Hence, Indonesian people can use batik appropriately according to the pattern and know the accuracy of the CNN algorithm in classifying Solo Batik motifs. The output produced in this study is an algorithm generated to get the maximum accuracy value using CNN in implementing the Solo Batik pattern.

2. METHODS

2.1. Data collection

The first step in this research is data collection. Data collection is collecting information from the variables to be studied so that researchers can answer questions and the research results [12]. The collected data in this study were sourced from the Danar Hadi Solo Museum in the form of images of Solo Batik motifs in ".jpg format". This dataset will be used as training data in research to identify Solo Batik motifs. There are 450 datasets divided into 9 classes. The 9 batik motifs that will be used in the study are depicted in Figure 1. The motif of Babon Angrem is depicted in Figure 1(a), while Gurdo is illustrated in Figure 1(b), Figure 1(c) showcases the Kawung motif, followed by the Parang Barong pattern in Figure 1(d). The Satriya Manah motif is represented in Figure 1(e), while Figure 1(f) displays the Satriya Wibowo motif, Figure 1(g) exhibits the Semen Rante motif, while Figure 1(h) portrays the Slobog motif. Lastly, the Ceplok Kembang motif is depicted in Figure 1(i). The features used in the dataset to recognize the batik pattern include ornate geometric shapes, intricate symbols, patterns, dots, nature designs.

Image features extraction was conducted on batik image, which will identify the features. It is important to determine the pattern properly so that the feature extraction process gives significant features to be used in image classification This feature must be reliable, which requires the same consistency of in each image. On a batik image, image characteristics were extracted for identifying the features. It is crucial to correctly identify the pattern in order for the feature extraction procedure to produce significant characteristics that can be applied to image classification. This feature needs to be dependable, therefore each image needs to be consistent [13].

2.2. Data preprocessing

Image data must be adjusted before entering data processing to reduce system load and provide smooth processing. The dataset used has different pixel sizes, so it is necessary to have an equal size in the data [14]. Therefore, the collected dataset is resized to 100×100 pixels, and the results of the resized dataset will go through various stages, both data preprocessing and data processing, which is analyzed with the Python programming language, will be processed using the Google Colab software.

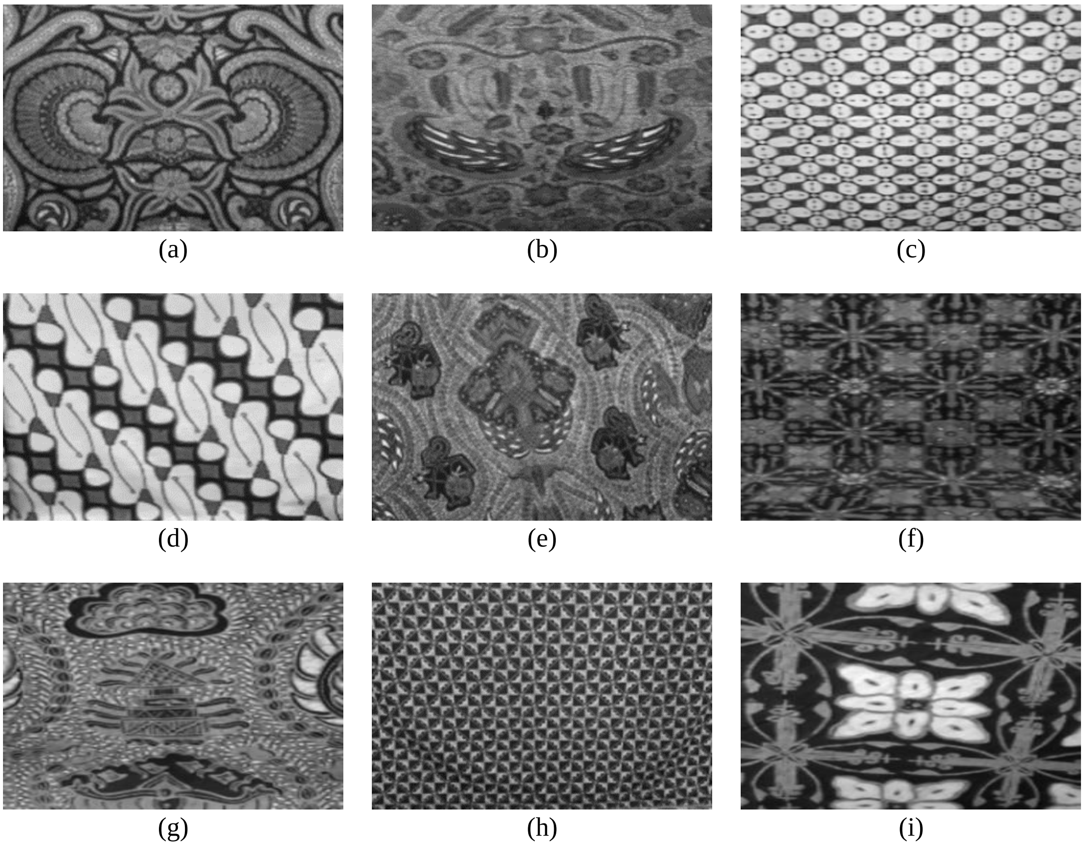


Figure 1. Solo Batik image dataset: (a) Babon Angrem, (b) Gurdo, (c) Kuwung, (d) Parang Barong, (e) Satriya Manah, (f) Satriya Wibowo, (g) Semen Rante, (h) Slobog, and (i) Ceplok Kembang

The next stage is colour image processing. The colour image has 3 matrix layers, namely R-layer, G-layer, and B-layer, so for the following process, it must pass through these three layers by doing the same three calculations. Therefore, the process design is changed to 1 layer matrix greyscale, which produces a greyscale image. Changes in the conversion of colour images to greyscale will simplify the image model. A greyscale image is a digital image with only one channel value for each pixel, the red, green, and blue parts have the same colour: black, grey, and white. The number of possible shades of grey depends on the image's bit depth. While black is a value that is close to 0, and for white, it is close to the final number displayed, according to the bit depth obtained. The value is to show the level of intensity [15]. Intensity levels can be calculated using (1).

$$K_0 = (R_j + G_j + B_i) \div 3 \quad (1)$$

Where:
- K_0 is the intensity value of the primary grey colour
- R_j is the value of the colour red
- G_j is the value of the colour green
- B_i is the value of the colour blue

After going through the greyscale process, the image will be flipped. Flip on an image is a method for flipping an image across the x-axis or y-axis so that multiple datasets can be better recognized. The results of the image dataset are grouped and labelled according to the category of batik motifs, which will be the training data and processed in the next stage.

2.3. Data processing
2.3.1. Convolutional neural network

After the data is preprocessed, the dataset will be processed using the CNN algorithm to identify and classify Solo Batik patterns. CNN is based on the artificial neural networks (ANN) architecture. The main objective of designing and training a neural network model is to identify, modify, and optimize parameters in order to minimize objective functions and generate precise predictions for incoming inputs [16].

CNN is the best algorithm to recognize and classify an image object. CNN has several layers that will be used in data processing to filter the dataset for this study. This layer has several stages, namely the convolutional layer, pooling layer, and fully connected layer, as illustrated in Figure 2. Since CNN applies ANN and contains several layers, this method can be categorized as deep learning [17].

As shown in Figure 2, the convolutional layer is the first stage in processing data using the CNN algorithm. A convolutional layer – where the feature extraction process occurs – is a layer that performs the convolution process of the first input image repeatedly. The convolutional layer forms a filter with pixels' length, height, and thickness. A convolution layer performs feature extraction, typically consisting of linear and nonlinear operations [18]. In this research, we use a 100×100 pixel image size as input. We then use three convolution layers: (i) Conv2D with 32 feature maps at size 3×3; (ii) Conv2D with 64 feature maps at size 3×3; and (iii) Conv2D with 128 feature maps at size 3×3 for the feature extraction process. The layer convolution process can be formulated in (2).

$$S(t) = (X \times W)(t) \tag{2}$$

Where $S(t)$ describes a single output, X is the input, and W is a kernel or filter. If the input is a two-dimensional image, then t as a pixel will be changed to i and j, which are pixels from the image. Therefore, the layer convolution process for inputs with more than one dimension can be written in (3).

$$S(i,j) = (w \times x)(i,j) = \sum_m \sum_n X(i-m, j-n)W(m,n) \tag{3}$$

After going through the convolution layer process, the value obtained will be normalized by rectified linear unit (ReLU). ReLU activation is an activation layer that normalizes the value generated by the convolutional layer by replacing the negative value in the image with a value of 0 using the max (0, x) function. In the equation for the value of ReLU with the input matrix x, that can be written in (4).

$$f(x) = max(0,x) \tag{4}$$

This means this function performs thresholding with a 0 to the pixel value in the input image. Then the second stage is the pooling layer. The pooling layer is the process of reducing the size of an image to enhance the feature position in variation. Max pooling is the method most CNNs use. The way max-pooling works is that the output received from the convolutional layer is divided into several grids where each filter shift takes the maximum value to plan the reduced matrix. Average pooling will determine the average value.

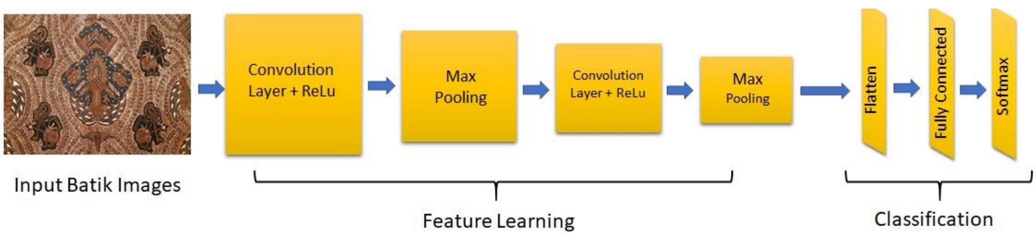


Figure 2. The stages of convolution neural network for input batik images

The last stage of using the CNN algorithm is the fully connected layer. A fully connected layer is where all activity neurons from the previous layer are connected with neurons in the next layer. The fully connected layer has neurons that are connected as a whole. Before entering the fully connected layer, each previous activity needs to be converted into one-dimensional data using flatten operations. Flatten is an operation that converts the matrix into a one-dimensional vector obtained from the previous layer to be classified with fully connected layers and softmax. A fully connected layer aims to process data so that it can be classified. This classifier process will get the dataset accuracy value with the output generated through Softmax activation.

Softmax is a function that takes a real vector K as input and is normalized to a probability distribution consisting of K probabilities. Before using softmax, some vector components can be negative or greater than one, but after using softmax, each component will be in the interval zero to one, and the components add up to one, so it can be interpreted as a probability. Mathematically, the softmax activation function is as written in (5).

$$S(x) = \frac{e^x}{\sum_{k=1}^{k} e^x} \quad (5)$$

Where S is the result of the function for each x element in the class output vector, where x indicates the hypothesis given by the training model so that the softmax function can classify it.

2.3.2. Dropout

Overfitting is a common problem often encountered [19], but overfitting remains a major challenge when training large neural networks or very small amounts of data. It is difficult to adequately address these challenges, such as classification [20], which makes the model too suitable for the training data so that the model's predictive ability becomes less than optimal. Dropout is a regularization method applied to avoid overfitting [21]. The dropout function is to prevent the dependence of neurons on the network by removing a neuron randomly and temporarily not being used during training. Each neuron will be assigned a probability that is between 0 and 1.

2.3.3. Adam optimizer

In this study, Adam's method was used as the optimizer. Adam optimizer was used, and it was observed that it adapts faster [22] and performs better than other optimizers [23]. The formulation of the Adam optimizer is shown in (6).

$$w_{(n+1)} = w_{(n)} - \frac{Lr}{\sqrt{\widehat{v_n}} + \in} \widehat{m_n} \quad (6)$$

Estimation of the gradients' first moment (the mean), shown in (7).

$$\widehat{m_n} = \frac{\beta_1 m_{n-1} + (1-\beta_1)\widehat{g_n}}{1-\beta_1^n} \quad (7)$$

The gradients' second moment (the uncentered variance) is shown in (8).

$$\widehat{v_n} = \frac{\beta_2 v_{n-1} + (1-\beta_2)\widehat{g_n}^2}{1-\beta_2^n} \quad (8)$$

Where $w_{(n)}$ is the updated variable at time n, n is iteration, Lr is the learning rate, $\in$ is the epsilon constant value of 10^{-8}, $\hat{g}$ is a gradient vector, $\widehat{m_n}$ is the first moment of the gradients, $\widehat{v_n}$ is the second moment of the gradients, and β_1, β_2 are constant values of 0.9 and 0.999.

2.4. Evaluation

For the evaluation, we use an accuracy value of an algorithm obtained from the results and evaluation process. The classification of the accuracy value is a presentation of the accuracy of the data record after testing the classification results [24]. The method used to calculate the accuracy value is formulated in (9).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (9)$$

Where, TP: true positive, TN: true negative, FP: false positive, and FN: false negative.

3. RESULTS AND DISCUSSION

This section provides both an extensive discussion and an explanation of the research's findings. Results can be presented in ways that are simple for the reader to understand, such as figures, graphs, and tables [25], [26]. In this study, the dataset used was 450 batik images that had been preprocessed with 9 classes, divided into 70% training data with 315 images, 20% validation data with 90 images, and 10%

testing data with 45 images. Then the dataset that has gone through the preprocessing stage will be processed using the CNN algorithm with the TensorFlow library model to get the level of accuracy of the data that has been obtained. TensorFlow is an artificial library developed by Google to classify data sets and is one of the most popular deep learning libraries [27].

The initial stage is a feature extraction phase using the Conv2D algorithm. The calculation to get the weight value is to enter the convolution layer with different filter sizes depending on the number of layers used, the number of kernels in the matrix is (3×3) and use the ReLU activation function. ReLU activation is an operation to represent nonlinearity and improve the representation of the model. ReLU has a simple calculation by changing the negative value to 0 so that ReLU can significantly reduce training and testing time [28]. At the convolution stage, there is also input with (100×100×1), meaning the image pixel is 100×100 with dimension 1, namely greyscale.

The subsequent step is a pooling layer. In this stage, we apply the max-pooling layer (2×2) with a shift of 2 steps by taking the largest value and then proceed with flattening, which changes the output of the convulsion process in the form of a matrix into a vector, also at this stage the dropout regulation function is used to reduce the occurrence of overfitting which will be continued by the classification process using softmax activation where softmax is used for the number of classes which is more than or equal to three.

The next process is calculating the accuracy value. In calculating the accuracy value, an optimization algorithm is needed, namely Adam. Adam has the advantages of efficient computing, easy implementation a small memory requirement, and the use of Adam's method more often produces the highest accuracy. As the use of Adam, epoch is also used to get the accuracy value. An epoch is an algorithm cycle that learns the entire training data set, to achieve the maximum weight value, it takes repeated data learning. Therefore, the epoch quantity is needed, and the epoch value is determined from the research conducted because the epoch value cannot be ascertained [29]. For this study, the number of epochs used is 20 with a batch size value of 100 and a dropout from 0 to 0.9 with a 4-layer category.

Table 1 presents the mean accuracy value obtained by employing an epoch value of 20 and a batch size of 100, while considering criteria per layer. The utilization of a 4-layer categorization system is also employed as a means of comparison in order to achieve elevated levels of accuracy in the classification of batik images. This study used a hierarchical categorization system consisting of four layers, specifically referred to as the first layer, second layer, third layer, and fourth layer. The level of detail in picture processing within the convolutional layer increases proportionally with the number of layers employed. Each layer is assigned a distinct dropout rate, which is indicative of its accuracy. Various dropout levels are employed as a means of mitigating overfitting. Dropout entails the removal of neurons inside both hidden and visible layers of the network. The findings of this study indicate that the inclusion of dropout has an impact on the overall accuracy levels. Specifically, as the dropout value increases, there is a corresponding decrease in the accuracy level. This finding demonstrates that the use of dropout has a significant impact on the amount of accuracy achieved.

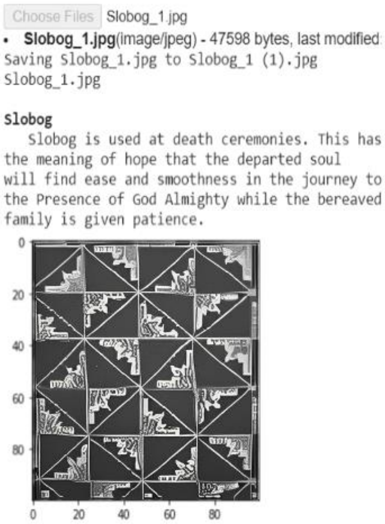
The accuracy values of the layer levels vary based on the number of layers employed. Among these levels, the first layer, featuring a dropout value of 0.2, exhibits the highest accuracy value of 91.11%. The second layer, also with a dropout of 0.2, achieves an accuracy value of 95.55%. In comparison, the third layer, incorporating a dropout of 0.2, attains the highest accuracy value of 97.77% among the other layers. Lastly, the fourth layer, with a dropout of 0.5, demonstrates an accuracy value of 80.00%.

After all the classifications in finding, the highest accuracy value has been obtained. Here are the results of several classifications of Solo Batik motifs that have been successfully classified, which can be seen in Figure 3. The classification test for the Slobog motif is depicted in Figure 3(a), the Babon Angrem motif is represented in Figure 3(b), and the Parang Barong motif is presented in Figure 3(c).

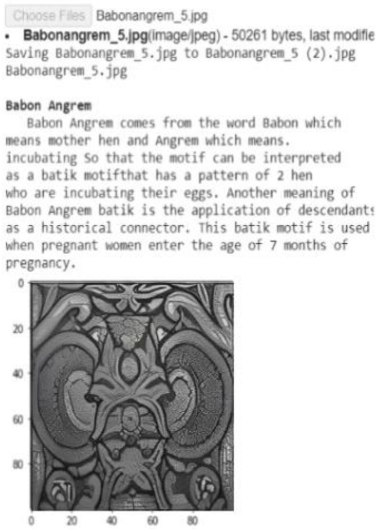
Table 1. The average value of convolutional neural network accuracy with an epoch of 20

Dropout	Layer 1	Layer 2	Layer 3	Layer 4
0	91.11	93.33	97.76	77.78
0.1	75.55	93.33	95.55	80.00
0.2	91.11	95.55	97.77	75.55
0.3	77.77	95.55	91.11	55.55
0.4	66.66	95.55	97.76	77.77
0.5	31.11	93.33	95.55	80.00
0.6	20.00	95.56	86.66	60.00
0.7	20.00	88.88	91.11	55.55
0.8	26.66	86.67	73.35	60.00
0.9	20.00	68.89	42.22	42.22

The result of the experimental result outperforms the result of preliminary research which classify image batik dataset, with an accuracy of 97.77%. The best result occurs when the model has 3-layered model with a dropout value of 0.2 and Adam optimization. The previous research classifying batik pattern using the FNN classification method perform accuracy of 55% to 65% [4]. The classification of batik based on the comparison of the ANN, KNN, and DT algorithms yields an average result of 95% [5].



(a)



(b)

(c)

Figure 3. Classification test: (a) Slobog motif, (b) Babon Angrem motif, and (c) Parang Barong motif

4. CONCLUSION

In light of previous studies conducted on the categorization of Solo Batik motifs, our objective is to ascertain the optimal accuracy rate by employing a 4-layer classification framework and incorporating dropout values spanning from 0 to 0.9. The 3-layered model, with a dropout value of 0.2 and Adam optimization, achieves the highest accuracy value of 97.77%. This investigation also yields the conclusion that the inclusion and utilization of additional hidden layers has a discernible impact on the augmentation of accuracy values. Similarly, when employing dropout in a model, various dropout rates can have an impact on both diminishing and augmenting the accuracy metric. In our future endeavors, we intend to explore the implementation of a higher number of layers and diverse tuning parameters in order to develop a more resilient model capable of effectively classifying a wider range of batik patterns.

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