Advance Sustainable Science, Engineering and Technology (ASSET)
Vol. 6, No.4, October 2024, pp. 0240406-01 ~ 0240406-09
ISSN: 2715-4211 DOI: https://doi.org/10.26877/asset.v6i4.771

A Web-Based for Demak Batik Classification Using VGG16 Convolutional Neural Network

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Abstract. The diversity of Demak batik motifs presents challenges in classification and identification. This research aims to develop a Demak batik motif classification system using deep learning and VGG16 convolutional network. A dataset of Demak batik images is collected and processed to train the model. The VGG16 architecture is modified by fine-tuning to optimize the classification performance. Results show that the modified VGG16 model achieved a classification accuracy of 98.72% on the test dataset, demonstrating its potential application in preserving and digitizing Demak batik cultural heritage.

Keywords: Batik Demak, Deep Learning, Convolutional Neural Network, Classification, VGG16, Cultural Preservation

(Received 2024-07-02, Accepted 2024-08-08, Available Online by 2024-08-16)

1. Introduction

Demak batik motifs are generally inspired by the religious history of the Demak Kingdom, such as the ornaments in the Great Mosque of Demak, including Bledheg (lightning), Bulus, Belimbing, and Jambu motifs. To recognize a motif requires a pattern of characters in the image that requires special characteristics [1]. The different characteristics of each character will become the identity of the Demak Regency batik culture. However, the variety of batik motifs in Indonesia, especially in Demak Regency, makes it difficult to recognize batik image patterns.

They are seeing the many batik motifs that have been found as well as in Karangmlati Village, Wedung Village, Mangunjiwan Village, Kauman, Bintoro Village, Kadilangu Village, Dempet Village, Gajah District, and Bonang Village, a digital approach is needed [2] to facilitate and speed up the classification process. Classification is a technique used to distinguish objects based on their visual characteristics [3], and can be realized by deep learning methods, such as deep learning convolutional neural networks (CNN) that can process image classification [4]. The VGG16 CNN architecture, with 16 convolutional layers and 3 fully connected layers, has proven to be effective in classifying images [5]. It includes the basic structure of each VGG model pre-trained in TensorFlow[6] including the number and type of layers used. This is expected to make a significant contribution to preserving, developing, and promoting Demak batik through the utilization og artificial intelligence technology.

Research conducted by Azmi, Defit, et al [7], has produced a CNN configuration and architecture with the parameters obtained and implemented through Python. The test simulation uses 80 of test data. An entire 50 out of 80 images get an accuracy result of 62.5%. In the train data training results, an accuracy of 98.75% was obtained, while the test data training stage obtained an accuracy of 62.5%. This accuracy proves that CNN can classify West Sumatra Clay Batik well.

Research conducted by Santosa, Iskandar, et al [8], based on the developed sequential model, the training data reached the highest accuracy value at the 19th and 20th epochs of 1,000, an average accuracy of 1.15, and an average loss value of 5.8. In addition, the VGG16 on-top model with a total of 20 epochs was tested and showed an average accuracy value of 2.7 and an average loss value of 1.6. So it can be concluded that the deep learning model with the CNN algorithm implemented in the research classifies Balinese batik motifs quite well.

2. Methods

2.1. Dataset Collection Phase

Data collection is done using primary data [9]. Primary data is taken directly without going through intermediaries. This data was obtained by interviewing and asking permission to photograph images of Demak batik motifs directly from one of the Demak batik collectors to wit Mrs. Aniek Shaubichati as in Figure 1.

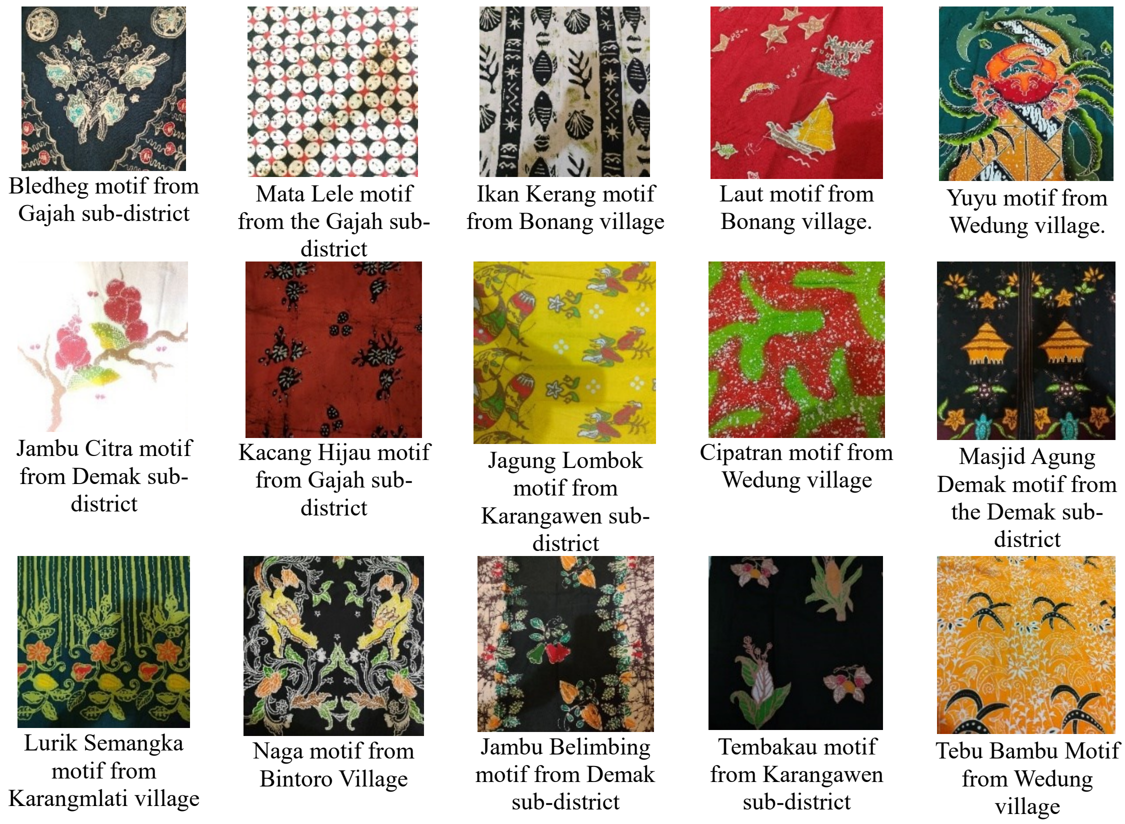

Figure 1. Sample Dataset for experiment

At this stage, two main steps need to be taken. The first is to collect data sources [10] and ensure that this is done with a strong and proper foundation. Second is the division of data into train data (70%), validation data (20%), and test data (10%) [11]. There are 15 types of batik models with the composition of Bledheg motif (45), Ikan Kerang motif (56), Jagung Lombok motif (53), Jambu Belimbing motif (55), Jambu Citra motif (72), Kacang Hijau motif (68), Laut motif (62), Lurik Semangka motif (63), Masjid

Agung Demak motif (82), Mata Lele motif (59), Naga motif (75), Tebu Bambu motif (66), Cipratan motif (57), Tembakau motif (60), and Yuyu motif (65).

2.2. Model Architecture Phase

Next comes the model architecture stage which includes a detailed description of how the sequential and VGG16 model [12] are built and organized, details of how each layer in the model is configured, and the hyperparameter settings to be used. Hyperparameters include values such as learning rate, number of epochs, batch size, and other parameters that affect model training [13]. The building part of the CNN model consists of several layers, namely the convolution layer (layer that extracts features from the image) [14], the pooling layer (layer that reduces the image dimension) [15], and the fully connected layer (layer that classifies the image) [16] as in Figure 2.

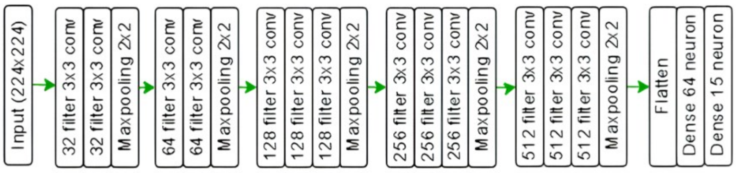

Figure 2. VGG16 Design Layers

2.3. Model Training Phase

The next step is the train model process, the data is loaded and preprocessed before being used for training (a division of the data set into training and validation sets, resizing, normalization, data augmentation, etc.) [17]. The architecture of the VGG16 model will be adjusted by layer or a special layer will be added. There is a selection of hyperparameters such as the number of epochs, learning rate, batch size, and optimizer used [18]. After that, the training process takes place at each epoch [19], including forward pass, backward pass, and update weights. Model evaluation on a validation dataset independent of the training dataset is essential to ensure model generalization. The evaluation of model test results is based on the calculation of accuracy values (correct model predictions and total predictions made) [20] and loss values (an indication of the model's bad predictions compared to the correct labels). Loss, also known as 'error', measures how far the model's predictions differ from the correct label [21]. The specific formula of Loss depends on the Loss function used. Cross-entropy loss is used for multi-class classification, where the predicted class probability is multiplied by the digital record of the actual class probability [22]. While Mean Squared error (MSE) for regression with actual and predicted values [23].

$$Accuracy = \frac{Correct\ Prediction}{Number\ of\ Predictions} \times 100\% \tag{1}$$

$$Cross - entropy\ Loss = \sum_{k=0}^{n} (\, \mathrm{p_i} * \log(q_i)) \tag{2}$$

The results of model performance on training and validation data for each epoch are shown in the form of graphs or tables of changes in accuracy and loss. Accuracy graphs usually show an increasing trend over time, while loss graphs show a decreasing trend. Analysis of model performance should consider whether there is overfitting or underfitting, whether accuracy increases over time, and how loss changes. Overfitting [24] occurs when the model memorizes the training data very well but still generalizes well to new data characterized by high training accuracy but low validation accuracy. Underfitting [25] occurs when the model does not learn enough from the training data characterized by low training and validation accuracy. The higher the accuracy, the better the model performance [26]. The lower the loss, the better the model performance [27].

3. Results and Discussion

3.1. Data Pre-Processing

Image data is preprocessed to ensure quality and consistency. The process includes resizing, normalization, data addition, data cleaning, and data validation. In resizing, all batik images are resized to 224×224 pixels using proportional resizing to maintain aspect ratio and image detail. In normalization to standardize pixel values, all batik images are normalized using standard normalization with a range of pixel values between 0 and 1. In the data augmentation process, the batik image is enlarged by random rotation between -15 degrees to 15 degrees, horizontal and vertical reversal, random cropping with an aspect ratio of 0.8, random enlargement with a factor between 0.8 and 1.2, and the addition of Gaussian noise with a mean of 0 and a standard deviation of 0.02. The next step is the data cleaning process, where damaged, blurry, or irrelevant batik images are identified and removed manually. A total of 10% of the batik images are removed in this process. The last is data validation with the data set divided into training (70%), validation (20%), and testing (10%) subsets. The validation subset is used to monitor the performance of the model during training and prevent overfitting.

3.2. CNN VGG16 Model Training

The VGG16 CNN model is trained using preprocessed image data. The model is correctly classified if the model prediction is equal to the actual label. Cross-entropy will be used for multi-class classification tasks. Mean squared error (MSE) will be used as a function for the regression task. Accuracy is calculated as the proportion of correct predictions to the total predictions made. In this case, there were 926 correct predictions out of 938 predictions. Cross-entropy Loss calculation for each wrong prediction in this case there are 4 predictions namely the Bledheg motif, Ikan Kerang motif, Jambu Belimbing motif, and Mata Lele motif. The model predicts the Bledheg motif, but the actual label is one of the other 3 motifs (Ikan Kerang, Jambu Belimbing, or Mata Lele). The probability of the model predicting each batik motif (p(Bledheg), p(Ikan Kerang), p(Jambu Belimbing), and p(Mata Lele)) must be known to calculate the cross-entropy loss. The total loss is then divided by the number of predictions to get the average cross-entropy loss. In practice, this probability can be obtained from the machine learning model output. A higher cross-entropy loss indicates that the model is more confident in its incorrect predictions. Centered on the prediction of the Bledheg motif. The actual labels are Bledheg Motif, Ikan Kerang Motif, Jambu Belimbing Motif or Mata Lele Motif.

$$Accuracy\ All\ Motif\ = \frac{926\ True\ prediction}{938\ Prediction} \times 100\% = \ 98.72\% \tag{3}$$

Bledheg Motif

$$Cross - entropy\ Loss\ = -log(p(Motif\ Bledheg)) \qquad \text{(Prediction 1)}$$
$$= -log(9/45)\ = 0.70$$

Ikan Kerang Motif

$$Cross - entropy\ Loss\ = -log(p(Motif\ Ikan\ Kerang)) \qquad \text{(Prediction 2)}$$
$$= -log(9/56)\ = 0.79$$

Jambu Belimbing Motif

$$Cross - entropy\ Loss\ = -log(p(Motif\ Jambu\ Belimbing)) \qquad \text{(Prediction 3)}$$
$$= -log(9/55)\ = 0.79$$

Mata Lele Motif

$$Cross - entropy\ Loss = -log(p(Motif\ Mata\ Lele)) \qquad \text{(Prediction 4)}$$
$$= -log(9/59)\ = 0.82$$

$$Cross-entropy\ Loss\ rata-rata = \frac{Cross-entropy\ loss\ total}{4} \tag{4}$$

$$= \frac{0.70 + 0.79 + 0.79 + 0.82}{4} = 0.77$$

Table 1. Sequential Model

Layer (type)	Output Shape	Parameter
conv2d_3 (Conv2D)	(None, 298, 298, 32)	896
max_pooling2d_2 (MaxPooling2D)	(None, 149, 149, 32)	0
convo2d_4 (Conv2D)	(None, 147, 147, 64)	18496
max_pooling2d_3 (MaxPooling2D)	(None, 73, 73, 64)	0
convo2d_5 (Conv2D)	(None, 71, 71, 64)	36928
flatten_3 (Flatten)	(None, 322624)	0
dense_2 (Dense)	(None, 64)	20648000
dense_3 (Dense)	(None, 15)	975

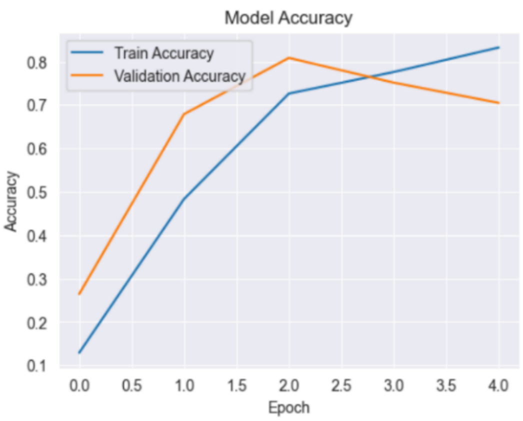

Figure 3. Training and Validation Accuracy Result Graph

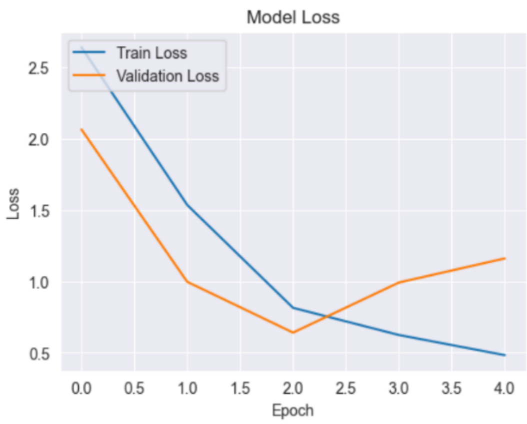

Figure 4. Training and Validation Loss Result Graph

Table 2. Trial Epoch

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/5	2,6390	0,1289	2,0635	0,2642
2/5	1,5343	0,4832	0,9959	0,6788
3/5	0,8137	0,7262	0,6402	0,8083
4/5	0,6235	0,7758	0,9909	0,7513
5/5	0,4823	0,8322	1,1597	0,7047

The standard VGG16 CNN Model architecture with 16 convolution layers, 5 pooling layers, and 3 fully connected layers is used. The ReLU activation function was used for all convolutional layers and fully connected layers, and pooling max was used for all pooling layers. A total of 20.705.295 parameters were obtained that could be trained and 0 parameters that could not be trained. This means that all models can be changed during the training process to improve model performance. The cross-entropy Loss function is used as it is suitable for multi-class classification tasks. Adam's optimizer is used as it has good stability and convergence. An initial learning rate of 0.001 was used and reduced by a factor of 0.1 every 10 epochs. Compile the model with the compile() function to determine the loss function, optimizer, and metrics that will be used to train the model. The model was trained for 5 epochs with a batch size of 32. The data was shuffled before each epoch. A validation subset was used to monitor the accuracy of the model during training. Early termination was applied if the validation accuracy did not improve for 5 consecutive epochs. The training results of the accuracy curve showed a steady improvement during training. The accuracy on the validation subset reached 95.4%, and the accuracy on the testing subset reached 96.3% as shown in Figures 17 and 18, the modified VGG16 model achieved an accuracy result of 98.72% and a loss result of 0.77 on the testing dataset.

Table 3. Trial Data

Motif Type	Motif Prediction	Actual Label	Retrieved
Bledheg	Bledheg	Bledheg, Ikan Kerang, Jambu Belimbing, Mata Lele	36/45
Ikan Kerang	Ikan Kerang	Ikan Kerang	56/56
Jagung Lombok	Jagung Lombok	Jagung Lombok	53/53
Jambu Belimbing	Jambu Belimbing	Jambu Belimbing	55/55
Jambu Citra	Jambu Citra	Jambu Citra	72/72
Kacang Hijau	Kacang Hijau	Kacang Hijau	68/68
Laut	Laut	Laut	62/62
Lurik Semangka	Lurik Semangka	Lurik Semangka	63/63
Masjid Agung Demak	Masjid Agung Demak	Masjid Agung Demak	82/82
Mata Lele	Mata Lele	Mata Lele	59/59
Naga	Naga	Naga, Ikan Kerang	72/75
Tebu Bambu	Tebu Bambu	Tebu Bambu	66/66
Cipratan	Cipratan	Cipratan	57/57
Tembakau	Tembakau	Tembakau	60/60
Yuyu	Yuyu	Yuyu	65/65

3.3. Performance Evaluation CNN VGG16 Model

The performance of the CNN VGG16 model is evaluated using image data that has never been seen before. In Figure 19 the Bledheg batik motif with blurred conditions but the results can still be detected according to the type of motif that can be predicted. Whereas Figures 20 and 21 show that there is an effect of resolution that can affect the performance of the CNN VGG16 model which should be predicted by the Bledheg motif causing the actual label to change to the Mata Lele and Jambu Belimbing motifs.

Figure 5. Types of Bledheg motifs with predictions of Bledheg motif models

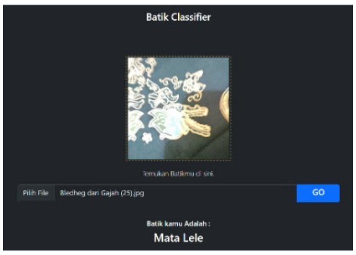

Figure 6. The type and prediction of the Bledheg motif with the actual label is the Mata Lele motif

Figure 7. The type and prediction of the Bledheg motif with the actual label is the Jambu Belimbing motif

4. Conclusion

The Demak batik classification method using deep learning with the VGG16 architecture CNN algorithm can be proven. With only 5 epochs, the modified VGG16 model achieved an accuracy result of 98.72% and a loss result of 0.77 on the test dataset. This result shows that VGG16 can capture the distinctive features of Demak batik motifs and classify them correctly. The ability of VGG16 to classify complex images makes it suitable for this task, compared to classic CNN calculations that require speed and efficiency.

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