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# *COMPARATIVE ANALYSIS OF CONTRAST ENHANCEMENT METHODS FOR CLASSIFICATION OF PEKALONGAN BATIK MOTIFS USING CONVOLUTIONAL NEURAL NETWORK*

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***Abstract***

*Batik artists in Pekalongan have freedom in determining motifs, creating a diversity of distinctive batik motifs. However, this diversity often makes it difficult for people to recognize the different motifs, as visual identification requires in-depth knowledge. The lack of understanding about Pekalongan batik is a challenge in recognizing these motifs. To overcome this challenge, an efficient and accurate method of motif identification is needed. This study aims to analyze the efficacy of contrast enhancement methods in improving the classification results of Pekalongan batik motifs using convolutional neural networks (CNN) with ResNet50 architecture. The dataset of 480 images was collected directly from Museum Batik Pekalongan and split into three distinct categories: 15% for validation, 15% for testing, and 70% for training. Two contrast enhancement methods: contrast limited adaptive histogram equalization (CLAHE) and histogram equalization (HE), were applied to create additional datasets. The Adam optimizer was used to train the model over 50 epochs at a learning rate of 0.001. The test results show that the original dataset contrast-enhanced with CLAHE reaches the best accuracy of 83%, followed by the original dataset contrast-enhanced with HE at 81%, and the original dataset at 76%. This finding shows that the application of contrast enhancement methods, especially CLAHE, can increase the model's accuracy in classifying batik motifs.*

**Keywords**: *classification, contrast enhancement, contrast-limited adaptive histogram equalization, convolutional neural networks, histogram equalization, Pekalongan batik motifs*

## 1. INTRODUCTION

Batik is a distinctive Indonesian culture that has been recognized by UNESCO as the Masterpieces of the Oral and Intangible Heritage of Humanity on October 2, 2009 [1]. As a country rich in culture and natural beauty, Indonesia has a variety of batik motifs that are different in each region. Each batik motif contains high artistic value and philosophical meaning that reflects the animism and dynamism beliefs of the ancestors [2]. The uniqueness and diversity of batik motifs are influenced by the surrounding environment, including flora and fauna, as well as the lifestyle and livelihood of the local community [3]. Currently, Indonesia has hundreds of batik motifs scattered throughout the country, each with its own story, meaning, and beauty that gives a distinctive identity to each region [4]. In addition, batik has become a symbol of national pride and is often used in various events, both formal and non-formal, at home and abroad. Pekalongan is one of the cities famous for the beauty of its batik and is known as one of the largest batik production centers in Indonesia.

Pekalongan City, located in Central Java, province is famous as a producer of quality batik in Indonesia. The development of batik in Pekalongan gives its own characteristics to Indonesian batik because it has a long and complex history and characteristics that are different from batik from other regions [5]. Batik artists in Pekalongan have freedom in determining motifs, thus creating a variety of batik motifs. Batik production in Pekalongan is mostly carried out by home industries, so the batik tradition is very close to the lives of local people. From this tradition, a variety of typical Pekalongan batik motifs emerged. The diversity of batik motifs in Pekalongan often makes it difficult for people to recognize different motifs. Visual identification of batik motifs requires in-depth knowledge of the unique patterns of each motif. The lack of understanding and information about Pekalongan batik is a challenge for the recognition of these motifs. To overcome this challenge, an efficient and accurate method of motif identification is needed. Artificial intelligence (AI) and deep learning can help overcome this challenge by detecting and classifying Pekalongan batik motifs quickly and accurately.

Deep learning utilizes artificial neural networks to model patterns in data [6]. Convolutional neural networks (CNN) are a well-known deep learning architecture for image classification and are particularly effective for two-dimensional data such as images [7]. CNNs have been successfully used in various fields with accuracy rates reaching more than 90%, including in batik motif classification [8], plant disease identification [9], face recognition [10], and medical image analysis [11]. Research in batik motif classification shows that CNN is effectively used, such as research [12], which used CNN for the classification of Sasambo and Songket Lombok batik motifs. With 350 training data points, CNN achieved 99.43% accuracy. Tests showed the recognition of Songket Lombok motifs averaged 83.85% and Sasambo batik 93.66%. However, data outside the dataset led to an average recognition of 86.15%, but unrecognized motifs reached 52.23%. CNN was used in a different study [13] to categorize Solo batik motifs. CNN models with 1 to 4 convolutional layers were tested with a dropout of 0 to 0.9. A model with three convolutional layers and a dropout of 0.2 produced the best results, with an accuracy of 97.77%.

Research [14] aims to improve the classification of batik patterns using CNN with oversampling and augmentation techniques. According to the findings, DenseNet169's accuracy went from 66.67% to 84.62%, while VGG-16 went from 69.76% to 82.56%. Research [15] used CNN for batik classification based on three methods of making. Transfer learning with ResNet, VGG, and DenseNet showed an increase in accuracy, with VGG13_bn increasing from 59.17% to 87.61%. In addition, research [16] utilized CNN with VGG16 architecture and data augmentation, which improved the accuracy from 95.83% to 98.96%. Although the accuracy is already high, CNNs can achieve more optimal performance after going through proper preprocessing stages, such as using contrast enhancement methods [17]. Contrast enhancement involves adjusting the range of pixel brightness levels to improve visual quality, which is very important in digital imaging techniques, pattern detection, and computer vision [18]. Low contrast or unusually bright images are often caused by device quality and lighting conditions. Low contrast can hinder image analysis, object recognition, and digital printing. Therefore, an important step before further processing is to improve the image's contrast. Frequently employed techniques for contrast enhancement include adaptive contrast limited adaptive histogram equalization (CLAHE) and histogram equalization (HE), among others.

Histogram equalization (HE) is a method that distributes image intensity evenly to improve contrast [19]. According to research [20], an emotion recognition system with CNN that used HE and data augmentation saw an increase in accuracy from 64.62% to 78.52%. Another study by [17] compared the use of HE, CLAHE, and a combination of both methods for medical image segmentation. The results show an increase in HE accuracy of 2.82% on the lung CT-Scan dataset and 0.91% on the chest X-rays dataset. CLAHE is a contrast enhancement technique that limits contrast to avoid an excessive rise in noise while dividing the image into small blocks and applying histogram equalization to each block [21]. Research [22] used CLAHE, ESRGAN, and Inception-V3 for diabetic retinopathy classification, improving the accuracy from 80.87% to 98.7%. Research conducted by [23] applied SUCK and CLAHE to improve image quality in animal skin image classification using CNN. According to the findings, ResNet50V2 averaged accuracy of 67.73% and 73.78%, InceptionV3 achieved 82.13% and 74.76%, and DenseNet121 achieved 87.64% and 87.46%. These studies show that contrast enhancement methods can boost the performance of CNN models in classifying various types of objects.

This study aims to analyze and compare the contrast limited adaptive histogram equalization (CLAHE) and histogram equalization (HE) methods in classifying Pekalongan batik motifs, utilizing the convolutional neural networks (CNN) with a ResNet50 architecture. The goal is to determine the most effective contrast enhancement method for improving the accuracy of batik motif classification. The findings of this study are anticipated to play a crucial role in advancing batik motif recognition systems, which could be extensively utilized within the creative and cultural sectors.

## 2. RESEARCH METHODS

This research uses a series of step-by-step procedures, starting with direct data collection at Museum Batik Pekalongan, preprocessing the data before it is put into the model or algorithm for further analysis, conducting training, validation, and testing with ResNet50 architecture, and evaluating the model. The research flow is depicted in Figure 1.

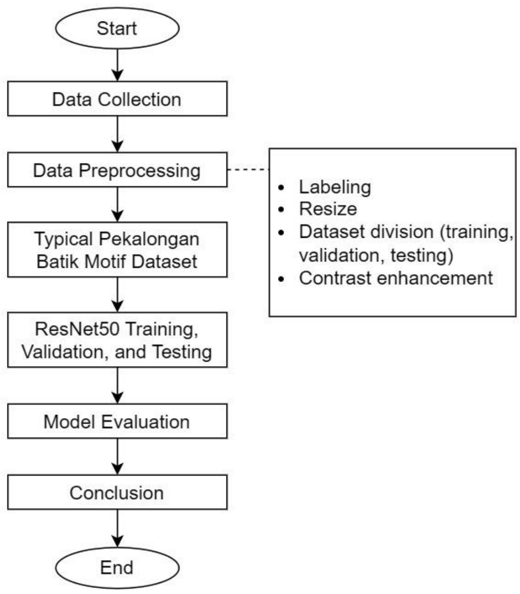


Figure 1. Workflow of the research

### 2.1 Data Collection

This research data was collected by taking pictures of Pekalongan batik motifs directly at the Pekalongan Batik Museum using a Fujifilm X-T20 camera. The images were taken from various angles, paying attention to the lighting and details of the batik motifs to ensure data quality. The dataset comprises 480 images, each with a resolution of 4000x4000 pixels and saved in .jpg format. The batik motifs included in this study include the Kelengan Variasi Semen motif, the Mega Mendung motif, the Tokwi motif, the Seekor Binatang Khayalan motif, the Boketan motif, the Boket Byur Tanahan motif, the Boket Ayam Alas Latar Banji motif, and the Sekar Jagad Ceplok Boketan motif. Figure 2 displays an example of a standard Pekalongan batik motif found in the dataset.

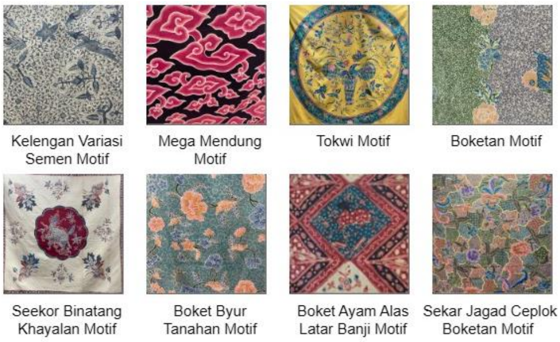


Figure 2. Examples of Pekalongan batik motifs

### 2.2 Data Preprocessing

After collecting image data of typical Pekalongan batik motifs, researchers performed several preprocessing steps before applying the contrast enhancement method and starting model training. First, each image is labeled according to the type of batik motif to facilitate the classification process during model training. Then, the size of all images is adjusted to 224x224 pixels so that the input given to the ResNet50 architecture is consistent. The dataset is segmented into three parts: 70% allocated for training, 15% for validation, and 15% for testing the model. After these steps, the initial dataset is referred to as the original dataset. The original dataset is then used to generate two additional datasets through advanced preprocessing methods, namely the application of contrast limited adaptive histogram equalization and histogram equalization.

### 2.3 Histogram Equalization

Histogram equalization (HE) is a technique for enhancing image contrast by flattening the pixel intensity distribution [19]. This procedure consists of distributing the input image's pixel intensity values to make the output image's histogram more even. By doing this, important details and features in the image become more visible and clear. When the original histogram of an image features numerous peaks and valleys, histogram equalization will alter the positions of these peaks and valleys shifted.

The HE process is performed in several steps, as described by [24]:

- Histogram formation: The initial step in the process involves calculating the histogram to illustrate the distribution of pixel intensities in the image.
- Probability density function (PDF): The PDF quantifies the likelihood of each intensity level in the image.

$$PDF(X_k) = \frac{n^k}{n} \quad (1)$$

- Cumulative distribution function (CDF): The CDF represents the running total of the likelihood of each intensity level appearing in the image.

$$CDF(X) = \sum_{j=0}^{k} PDF(X_j) \quad (2)$$

Where, $X_k = X$, for k = 0, 1…, $L$ – 1. By definition, $CDF(X_{L-1})$ = 1, where $L$ is the number of intensity levels in the image.

- Transform function (FT): This technique modifies the pixel values from the source image to generate new intensity values in the resulting image. FT $f$(x) based on CDF is defined as:

$$f(x) = X_0 + (X_{L-1} - X_0)CDF(x) \quad (3)$$

The resulting image from HE, Y = {Y $(i,j)$}, can be described as:

$$Y = f(\mathbf{X}) \quad (4)$$

$$\{f(X(i,j)) \mid \forall X(i,j) \in \boldsymbol{X}\} \quad (5)$$

HE improves image contrast by expanding the dynamic range and equalizing the histogram, which has an effect on image entropy. Image entropy reaches its peak value when the pixel intensity distribution is close to uniform.

### 2.4 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is an advancement of the adaptive histogram equalization method that adaptively improves image contrast without sacrificing important details or increasing unwanted noise [21]. CLAHE performs histogram equalization on each image block individually by applying clipping to the histogram to limit contrast enhancement to homogeneous or noisy image regions, thus overcoming significant noise enhancement.

The steps of CLAHE [25] can be explained as follows:

- Divide the input image into small continuous and non-overlapping blocks, with the block size typically 8×8 pixels or customized according to the configuration.
- Calculates a histogram for each image block and uses a threshold to truncate the histogram before calculating the PDF and CDF, restricting the gradient of the transformation function.

- Redistribute pixel values by evenly allocating the adjusted pixel values across the histogram.
- Performs local histogram equalization on each block.
- Uses linear interpolation to reconstruct pixel values based on mapping the intensity levels of surrounding sample points.

### 2.5 Convolutional Neural Networks (CNN)

CNN is an efficient deep learning algorithm for processing two-dimensional structured data such as images [26]. With their hierarchical approach, CNNs are able to analyze information from the initial to the final convolutional layer, which makes it possible to perform classification with high accuracy, such as in the context of Pekalongan batik motif classification. Each convolutional layer uses the output from the preceding layer as its input, allowing it to extract progressively more intricate features as the network depth increases. The use of fully connected layers and activation functions such as ReLU (Rectified Linear Unit) plays a role in processing these features to ultimately produce a prediction of the image class or label [27]. An illustration of the CNN process, as shown in Figure 3, provides a clear visual representation of how CNN works in this context, from the initial processing of the image to the final classification result.

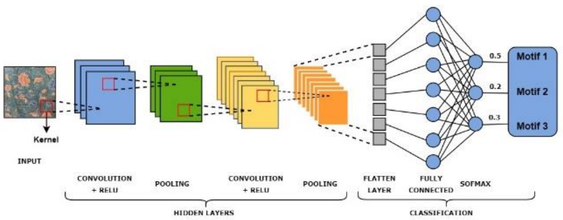


Figure 3. CNN Process

### 2.6 ResNet50

ResNet50 is a CNN architecture developed by Microsoft Research and won the ImageNet Large Scale Visual Recognition Competition (ILSVRC) competition in 2015 [28]. The architecture consists of 50 layers that include convolution blocks, residual blocks, and fully connected layers. One of the key innovations is the use of residual blocks, which allows for deeper training of the network without running into performance degradation (vanishing gradient) issues [29]. ResNet50 accepts images with a size of 224x224 pixels as input and can classify images into various categories. The output is a probability vector for each class generated by the fully connected layer using the Softmax function. The architecture uses convolution blocks with 7x7 filters in the initial layer, followed by a pooling layer and a series of residual blocks consisting of convolution layers with 3x3 filters to extract detailed features from the image. A ReLU activation function is applied following each convolutional layer to incorporate non-linearity into the model. The data then passes through a global average pooling layer, flattened into a one-dimensional vector before entering the fully connected layers and ending with a Softmax layer for classification purposes. An illustration of the ResNet50 architecture can be seen in Figure 4.

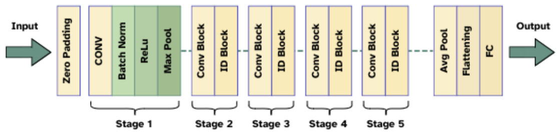


Figure 4. ResNet50 Architecture

### 2.7 Model Evaluation

The last step involves evaluating the model by calculating accuracy, precision, recall, and F1-score using a confusion matrix. A confusion matrix is a method employed to assess the effectiveness of a classification method by contrasting the system's classification outcomes with the expected results. The confusion matrix provides information about four conditions of classification results: False Positive (FP), False Negative (FN), True Positive (TP), and True Negative (TN). Using these values, different metrics can be calculated to assess the performance of a model [30], including:

- Accuracy: (TP+TN) / (TP+TN+FP+FN) (9)
- Precision: TP / (TP + FP) (10)
- Recall: TP / (TP + FN) (11)
- F1-score: $2 \text{ x } \frac{Precisionx\ Recall}{Precision+\ Recall}$ (12)

### 2.8 Experimental Environment

We conducted experiments on a 64-bit Windows 11 platform equipped with an Intel Core i5 processor, 8 GB RAM, and a 4 GB Graphic Processing Unit (GPU). Model training was performed using the GPU to take advantage of the high computational speed. The model implementation uses the TensorFlow framework and Keras library version 2.15.0, which runs on Google Colab. This platform provides a robust infrastructure for the development and evaluation of CNN models with ResNet50 architecture for batik motif classification. Comprehensive details regarding the experimental parameters are presented in Table 1.

Table 1. Detailed information of the experimental environment

| Name | Parameter |
|---|---|
| Operating System | Windows 11 Home 64-bit |
| CPU | Intel Core i5-8250U CPU, up to 3.4GHz |
| GPU | NVIDIA GeForce MX150 4 GB |
| RAM | 8 GB |
| Hard Disk | 1 TB |
| Environment | Google Colab, TensorFlow, Keras 2.15.0 |
| Language | Python |

## 3. RESULTS

The experimental results will be described in this section. This study uses the ResNet50 model with Adam's optimization algorithm. The dataset is split into three sections: 15% for validation, 70% for training, and 15% for testing. During the training phase, the learning rate is set to 0.001 and the model is trained for 50 epochs. We will compare the performance of CLAHE and HE methods based on experimental results to evaluate their effectiveness in improving the classification accuracy of Pekalongan batik motifs.

### 3.1. Dataset

After the preprocessing process, a dataset consisting of 480 images measuring 224x224 pixels is prepared for the validation, training, and testing stages of the Pekalongan batik motif classification model. Besides using the original dataset in scenario 1, two additional datasets were generated by applying contrast enhancement methods to the original dataset: histogram equalization (HE) for scenario 2 and contrast-limited adaptive histogram equalization (CLAHE) for scenario 3. Each of these additional datasets has the same number of images as the original dataset. These contrast-enhanced datasets are utilized to assess how contrast enhancement methods affect classification accuracy and to compare the outcomes.

### 3.2. Scenario 1

In scenario 1, the model was trained and validated on the original dataset, with performance assessed using test data. Figure 5 visualizes training and validation accuracy and losses, while Table 2 presents the classification results for the ResNet50 model.

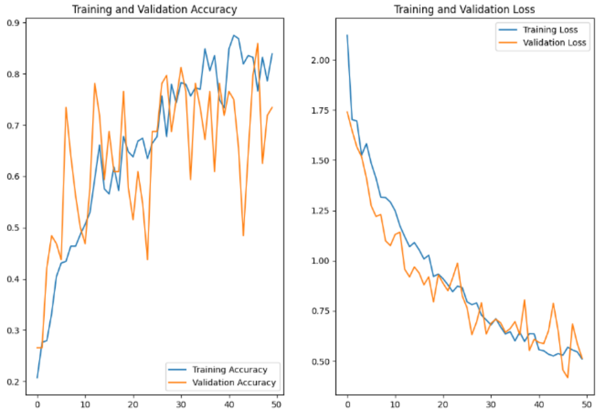


Figure 5. Plots of training and validation accuracy and loss in scenario 1

Figure 5 in scenario 1 shows improved accuracy and reduced losses across epochs. Initially, training and validation losses were 2.12 and 1.73, with accuracies of 0.20 and 0.26. By the 25th epoch, training loss dropped to 0.86 with an accuracy of 0.66, while validation loss decreased to 0.82 with an accuracy of 0.68. The model peaked at the 42nd epoch with a training accuracy of 0.87 and a loss of 0.55. The best validation result occurred at the 47th epoch, with a loss of 0.41 and an accuracy of 0.85.

Table 2. Classification results for scenario 1

| Motif Name | Precision | Recall | F1-score |
|---|---|---|---|
| Boket Byur Tanahan | 1.00 | 0.11 | 0.20 |
| Boket Ayam Alas Latar Banji | 0.50 | 0.89 | 0.64 |
| Kelengan Variasi Semen | 0.47 | 0.89 | 0.62 |
| Mega Mendung | 1.00 | 1.00 | 1.00 |
| Boketan | 1.00 | 1.00 | 1.00 |
| Tokwi | 1.00 | 0.56 | 0.71 |
| Seekor Binatang Khayalan | 1.00 | 0.67 | 0.80 |
| Sekar Jagad Ceplok Boketan | 1.00 | 1.00 | 1.00 |
| Macro Avg | 0.87 | 0.76 | 0.75 |
| Weight Avg | 0.87 | 0.76 | 0.75 |

Table 2 presents the classification report for scenario 1, highlighting model performance across various batik motifs. Precision indicates correct positive predictions, recall measures the accurate identification of actual positives, and the F1-score balances between precision and recall [31]. While motifs like 'Boket Byur Tanahan' had a high precision of 1.00, its recall was only 0.11, resulting in an F1-score of 0.20. In contrast, 'Sekar Jagad Ceplok Boketan', 'Mega Mendung', and 'Boketan' achieved perfect scores of 1.00 across all metrics, indicating excellent classification. The overall average metrics were 0.87 for recall and 0.76 for precision and F1-score.

### 3.3. Scenario 2

In Scenario 2, the ResNet50 model was applied to the original dataset with histogram equalization (HE) for contrast enhancement. Figure 6 shows the accuracy and loss metrics, and Table 3 presents the classification report.

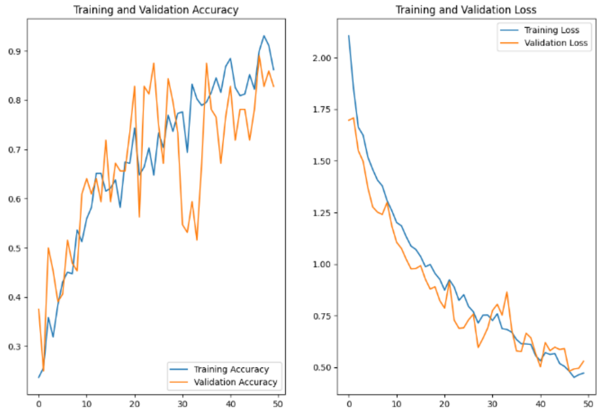


Figure 6. Graph showing training and validation accuracy along with loss metrics for scenario 2

Figure 6 shows the ResNet50 model's training progression over 50 epochs in scenario 2. The training loss decreased significantly from the initial 2.10 to 0.47 in the last epoch, indicating effective learning. Correspondingly, the training accuracy increased from 0.23 to 0.86, demonstrating enhanced performance in classifying the training data. For the validation set, the loss decreased from 1.69 to 0.52, while accuracy improved from 0.37 to 0.82, indicating strong generalization of the model to unseen data.

Table 3. Classification results for scenario 2

| Motif Name | Precision | Recall | F1-score |
|---|---|---|---|
| Boket Byur Tanahan | 0.71 | 0.56 | 0.63 |
| Boket Ayam Alas Latar Banji | 0.53 | 0.89 | 0.67 |
| Kelengan Variasi Semen | 0.62 | 0.89 | 0.73 |
| Mega Mendung | 1.00 | 1.00 | 1.00 |
| Boketan | 1.00 | 1.00 | 1.00 |
| Tokwi | 1.00 | 0.44 | 0.62 |
| Seekor Binatang Khayalan | 1.00 | 0.89 | 0.94 |
| Sekar Jagad Ceplok Boketan | 1.00 | 0.78 | 0.88 |
| Macro Avg | 0.86 | 0.81 | 0.81 |
| Weight Avg | 0.86 | 0.81 | 0.81 |

Table 3 shows the classification report for Scenario 2. For instance, 'Boket Byur Tanahan' achieved a recall of 0.56, precision of 0.71, and an F1-score of 0.63, indicating balanced performance. Motifs like 'Boketan', 'Mega Mendung', and 'Seekor Binatang Khayalan' reached perfect scores (1.00) in precision, recall, and F1-score. 'Tokwi' had high precision (1.00) but lower recall (0.44), with an F1-score of 0.62, highlighting challenges in full recognition. Overall, the model showed strong performance with macro and weighted averages for precision, recall, and F1-score at 0.86 and 0.81, respectively.

### 3.4. Scenario 3

In Scenario 3, the ResNet50 model was applied to the original dataset enhanced with CLAHE for improved local contrast. Figure 7 displays the accuracy and loss metrics, while Table 4 provides the classification report.


Figure 7. Training and validation accuracy and loss plots for scenario 3

Figure 7 shows the ResNet50 model's training progression over 50 epochs in scenario 3. At epoch 1, the training loss was 2.01 with an accuracy of 0.20, while validation reported a loss of 1.76 and accuracy of 0.30. By the 25th epoch, training loss dropped to 0.83 with an accuracy of 0.69, and validation loss decreased to 0.71 with an accuracy of 0.70. The model reached its best performance at epoch 50, with a training loss of 0.45 and accuracy of 0.87, and a validation loss of 0.47 with accuracy of 0.84, showing strong generalization.

Table 4. Classification results for scenario 3

| Motif Name | Precision | Recall | F1-score |
|---|---|---|---|
| Boket Byur Tanahan | 0.80 | 0.44 | 0.57 |
| Boket Ayam Alas Latar Banji | 0.62 | 0.89 | 0.73 |
| Kelengan Variasi Semen | 0.57 | 0.89 | 0.70 |
| Mega Mendung | 1.00 | 1.00 | 1.00 |
| Boketan | 1.00 | 1.00 | 1.00 |
| Tokwi | 1.00 | 0.89 | 0.94 |
| Seekor Binatang Khayalan | 1.00 | 0.67 | 0.80 |
| Sekar Jagad Ceplok Boketan | 1.00 | 0.89 | 0.94 |
| Macro Avg | 0.87 | 0.83 | 0.83 |
| Weight Avg | 0.87 | 0.83 | 0.83 |

Table 4 shows the classification report for Scenario 3, evaluating the model's performance on Pekalongan batik motifs. The motif 'Boket Byur Tanahan' has a precision of 0.80, recall of 0.44, and an F1-score of 0.57, indicating adequate performance. The motifs 'Sekar Jagad Ceplok Boketan', 'Mega Mendung', and 'Boketan' achieved perfect scores in precision, recall, and F1-score, all at 1.00. The motif 'Tokwi' demonstrated high precision at 1.00 and recall at 0.89, with an F1-score of 0.94, showing strong identification ability. Overall, the macro and weighted averages for precision, recall, and F1-score were 0.87 and 0.83, respectively, reflecting the model's general effectiveness.

### 3.5. Comparison between Testing Scenarios

Comparison of the performance of each test scenario is done by training for 50 epochs on each scenario, which results in significant performance differences. The comparison results for each training scenario are presented in Table 5 and comparison results for each testing scenario are in Table 6.

Table 5. Performance results for training and validation

| Scenario | Training Loss | Training Acc | Validation Loss | Validation Acc |
|---|---|---|---|---|
| Scenario 1 | 0.51 | 0.83 | 0.51 | 0.73 |
| Scenario 2 | 0.47 | 0.86 | 0.52 | 0.82 |
| Scenario 3 | 0.45 | 0.87 | 0.47 | 0.84 |

Table 5 provides an overview of training performance across the three scenarios. Scenario 1 achieved a training loss of 0.51 and accuracy of 0.83, with validation loss and accuracy both at 0.51 and 0.73, respectively. Scenario 2 showed improved metrics with a training loss of 0.47 and accuracy of 0.86, while validation results were 0.52 loss and 0.82 accuracy. Scenario 3 had the best performance, with a training loss of 0.45 and accuracy of 0.87, and validation metrics of 0.47 loss and 0.84 accuracy. This scenario demonstrates the model's effectiveness in generalizing with high accuracy and low loss.

Table 6. Test results of each proposed scenario

| Scenario | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|
| Scenario 1 | 0.87 | 0.76 | 0.75 | 0.76 |
| Scenario 2 | 0.86 | 0.81 | 0.81 | 0.81 |
| Scenario 3 | 0.87 | 0.83 | 0.83 | **0.83** |

Table 5 and Table 6 reveal that applying contrast enhancement techniques has a notable impact on the performance of the ResNet50 model for classifying batik motifs. Specifically, Scenario 3, which utilized CLAHE to enhance the original dataset, achieved the highest accuracy of 83%. This indicates that CLAHE significantly improves image contrast, thereby enhancing the model's ability to classify batik motifs more accurately. In comparison, Scenario 2, which employed histogram equalization, achieved an accuracy of 81%. Although this accuracy is lower than that of Scenario 3, it still represents an improvement over Scenario 1, which used the original dataset without any contrast enhancement and resulted in the lowest accuracy of 76%. These results highlight the effectiveness of contrast enhancement techniques in optimizing model performance and demonstrate their critical role in improving classification accuracy.

## 4. DISCUSSION

Studies on batik classification with CNN also show promising results. Research by [13] used CNN with various convolution layers for Solo batik classification and achieved 97.77% accuracy. Research conducted by [14] improved batik pattern classification with CNN through oversampling and advanced augmentation, significantly improving accuracy from 66.67% to 84.62% for DenseNet169. Study by [16] used CNN and data augmentation for batik classification, with an increase in accuracy from 95.83% to 98.96% using VGG16. The study by [32] used ResNet-18 for batik motif classification with different datasets, achieving the highest accuracy of 88.88% with the patch method on the new dataset.

Studies on contrast enhancement with HE and CLAHE also show promising results. The study by [17] improved medical image segmentation accuracy with HE, showing improved accuracy on chest X-rays and lung CT-Scan datasets. Research by [23] used CLAHE and SUCK for animal skin image classification with CNN, achieving an average accuracy of 87.64% for DenseNet121. Research by [33] used HE to enhance the contrast of ship fire detection images with YOLOv8, achieving 99% detection accuracy. Research by [34] used CLAHE to improve retinal fundus image quality, showing significant accuracy improvement on CNN models such as VGG16, InceptionV3, and EfficientNet.

This finding is consistent with the studies conducted by [17], [20], and [35]-[36], which show that the use of contrast enhancement methods enhances the model's classification effectiveness. In this study, the test results showed an accuracy improvement of 5% with the use of the HE method and 7% with the use of the CLAHE method. Previous research, as reported in [17], found that the use of HE improved accuracy by 0.91% on the chest X-ray dataset and 2.82% on the lung CT-Scan dataset, while the use of CLAHE improved accuracy by 2.73% and 0.66% on the same dataset. Other studies, as reported in [35], also show that the use of CLAHE can improve accuracy by 0.1%.

## 5. CONCLUSION

Based on the outcomes from analyzing and testing with the Adam optimizer, running for 50 epochs, and using a learning rate of 0.001 for each scenario. The experimental results show that scenario 3, which uses the original dataset that is contrast enhanced with CLAHE, achieves an accuracy rate of 83%. Meanwhile, scenario 2 with the original dataset contrast enhanced using HE achieved an accuracy rate of 81%, while scenario 1 with the original dataset achieved an accuracy rate of 76%. The use of contrast enhancement methods such as CLAHE and HE proved to be effective in improving accuracy in the classification of Pekalongan batik motifs. In particular, CLAHE shows better performance in improving model accuracy compared to HE, making it a superior choice in this context for improving image contrast and the model classification performance.

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