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Optimization of Residual Network 50 using Boosted Anisotropic Diffusion Filter and Contrast Limited Adaptive Histogram Equalization for Fingerprint Classification

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Abstract. Biometrics itself can be interpreted as a computerized method that uses aspects of biology, especially unique characteristics possessed by humans. Unique characteristics that can be used include fingerprints, geometric shapes of the hand, sound frequency keys, iris patterns, and retinas that generally differ from one individual to another. Fingerprints are the result of reproduction of the palm of the finger, either intentionally taken, stamped with ink, or marks left on objects because they have been touched by the skin of the palms of the hands or feet. Fingerprints are used as identification and verification as a means for security. So, there is a tool used to carry out this task, namely AFIS (Automatic Fingerprint Identification System). The purpose of this system is to strive for strong and fast detection. So, a fingerprint grouping or classification is needed, so that the identification process takes place faster. The algorithm used to classify fingerprints is ResNet-50. The data used came from the National Institute of Standards and Technology in 2000 (NIST-DB4 in 2000). In this dataset, there are 4000 data with each number per class is 800 data. There are five classes in this dataset including arch. right loop, left loop, tended arch, and whorl. In the training process, data processing is carried out first. This is done to optimize the accuracy produced during the training process. This research used preprocessing Boosted Anisotropic Diffusion Filter (BADF) and Contrast Limited Adaptive Histogram Equalization (CLAHE). The BADF method is used to reduce the noise present in the image. Whereas, CLAHE is used to adjust the contrast of the image. The accuracy produced using the two preprocessing was 94.5%.
Purpose: This research aims to optimize fingerprint classification using ResNet-50 combined with Boosted Anisotropic Diffusion Filter (BADF) and Contrast Limited Adaptive Equalization (CLAHE) methods.
Methods: This research uses the ResNet-50 method combined with the Boosted Anisotropic Diffusion Filter (BADF) and Contrast Limited Adaptive Histogram Equalization techniques CLAHE) methods.
Result: This research has four experiments, including an experiment using the ResNet-50 model without using preprocessing to obtain an accuracy of 92.5%. When BADF preprocessing was applied in the data training process, the accuracy increased to 93.5%. Meanwhile, the experiment using the ResNet-50 model using preprocessing obtained an accuracy of 94%. This accuracy can still be improved by combining BADF and CLAHE preprocessing which gets an accuracy of 94.5%.
Novelty: This research uses the ResNet-50 model with a preprocessing method that is combined to obtain higher accuracy. The update in this research is to apply the BADF and CLAHE methods as image preprocessing. The BADF method aims to reduce the noise present in the scattered image, while the CLAHE method is used to adjust the contrast in the image itself.

Keywords: Image Classification, ResNet-50, Boosted Anisotropic Diffusion Filter (BADF), Contrast Limited Adaptive Equalization (CLAHE)
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INTRODUCTION

Biometrics is a computerized method that uses biological aspects, especially unique characteristics possessed by humans. Unique characteristics that can be used include fingerprint patterns, geometric shapes of the hand, sound frequency keys, iris patterns, and retinas that are generally different from one individual to another and have their own uniqueness [1][2]. One example of biometrics is fingerprints. Fingerprints are used as identification and verification as a means for security. So, there is a tool used to

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carry out this task, namely AFIS (Automatic Fingerprint Identification System). The purpose of this system is to strive for strong and fast detection. AFIS performs matching and feature checks using a person's identity fingerprint information because fingerprint attributes cannot be changed [3]. In addition, fingerprints that are personal and unique in nature require a very extensive comparison process and generally a very large dataset size [4]. There have been many methods or techniques used to classify fingerprints. One of them is using deep learning. In several previous studies, such as the study conducted by Zeleňák et al. (2021) using the Convolutional Neural Networks (CNNs) method with 4 convolutional layers and 3 max-pooling layers followed by a fully connected layer [5]. The study shows that CNN has an important role in classifying fingerprints. Then, in the research of Rim et al. (2021) using a deep learning approach. The methods used in this research include: classic CNN, AlexNet, VGG-16, Yolo-v2, and ResNet-50 [4].

In the research conducted, it is tried to use CNN with a certain architecture. The CNN method is an algorithm designed to process two-dimensional data developed based on (MLP). CNNs are also part of deep neural networks because they have high deep layers and are often applied to data in the form of images [6]. CNNs work by moving the convolution kernel into an image in order to obtain new representative information from the result of multiplication of the image part with the filter used [7]. One of the architectures of CNN is ResNet-50. The use of ResNet-50 is considered good in classifying fingerprints. As in the research conducted by Zia et al. (2019) carried out fingerprint classification using several algorithms, one of which is using ResNet-50 [8].

In terms of improving the accuracy of fingerprint classification, this research uses the BADF (Boosted Anisotropic Diffusion Filter) method. This method is used to eliminate noise or noise in the image [9]. The selection of this method aims to maintain the details that exist in the image. Thus, the image can still look like the original image [10]. In addition to using the BADF method, this research also uses the CLAHE (Contrast-Limited Adaptive Histogram Equalization) method. This method is inspired by the human eye. The human eye infers the content of the image by adapting the local context to the image, so that the contrast of the local image is enhanced, so that the resulting image is sharper. The CLAHE method limits the slope of the grayscale accumulation histogram and cuts it into a histogram [11].

METHODS

This research uses a structured methodology that includes data collection, data preprocessing, ResNet-50 model development, and evaluation. Each stage is detailed to ensure clarity and replication on the research.

Data Collection

The dataset used in this research is the National Institute of Standards and Technology dataset in 2000 (NIST-DB4 2000). This dataset contains 8-bit grayscale images of randomly selected fingerprints. The database is distributed for use in the development and testing of automatic fingerprint classification systems on common image sets. This dataset contains 4000 (2000 pairs) of fingerprint data stored in PNG format. Each fingerprint print is 512×512×1 pixels with 32 lines of white space at the bottom of the print. These fingerprints are divided into five classes: left loop, whorl, right loop, tended arch, and arch. Each of these classes has 400 pairs or as many as 800 data. Each file name contains a reference to the hand number and digits so that the class can be converted to other classification techniques.

Data Preprocessing

In this research, two preprocessing methods were used, namely Boosted Anisotropic Diffusion Filter (BADF) and Contrast Limited Adaptive Equalization (CLAHE). Both methods are used to improve the quality of the image before the image enters the training process. This BADF method is used to efficiently preserve image details, such as image texture. The anisotropic diffusion equation is derived from the Partial Differential Equation (PDE). PDE is commonly used for noise removal, image edge detection, and detail preservation techniques [12]. PDE itself aims to overcome the trade-off between noise reduction and edge storage [9]. Noise in an image can not only be known through the naked eye, but noise in an image can also be measured quantitatively. The method used to quantitatively measure noise in images is the Signal to Noise Ratio (SNR) method. This method aims to measure the noise ratio of signal to noise in the original image with the image that has been processed. The larger the SNR value, the smaller the noise value in the image will be [13].

In addition to using the BADF method, the CLAHE method is also used in this research. The CLAHE method. Before CLAHE appeared, there was first an Adaptive Histogram Equalization (AHE) method that divided the image into small cells of 8 (8 pixels), after which the histogram of each cell was calculated. The best contrast is done by optimizing adjacent contrasts. However, the AHE increases the contrast too much, so there is noise. Therefore, CLAHE emerged to limit the increase in contrast to the same area. CLAHE can limit the slope of the grayscale accumulation histogram and cut the histogram. The gray scale is redistributed evenly across the histogram, although the histogram scale remains the same [11]. Image contrast can also be quantitatively measured, the method used to measure image contrast is Root Mean Square Contrast (RMS Contrast). Contrast describes the difference between brightness and darkness levels in an image [14].

Model Development

After the preprocessing process has been completed, it enters the modeling stage or training stage. The algorithm used in this research is the Convolutional Neural Network (CNN). CNN is a development of a multilayer perceptron (MLP) that aims to process two-dimensional data. CNNs are also included in Deep Neural Networks (DNNs), which are usually also used in images with high networks and are widely applied to research data in the form of images. CNN itself consists of an input layer, an output layer, and a hidden layer. The hidden layer itself is a layer that consists of a convolutional layer, a pooling layer, and a fully connected layer [15]. In this research, the architecture of CNN itself is used. The architecture used in this research is Residual Network-50 (ResNet-50).

ResNet as a whole consists of 5 stages of the convolution process which will then be continued with the average pooling process and ended with the fully connected layer as the layer used for prediction [16]. Meanwhile, ResNet-50 itself has two main focuses, namely the detection layer and the classification layer. The detection layer feature changes the image into a number and then the matrix is calculated. This feature displays three types of operations on all input data, including convolutional layer, pooling layer, and Rectified Linear Unit (ReLU). These three operations are performed repeatedly with each layer to detect different features. Meanwhile, the classification layer has a fully connected layer that outputs the output of the K dimension vector. Thus, this vector contains the probabilities for each class of the classified image [17]. The structure of ResNet-50 can be seen in Figure 1.

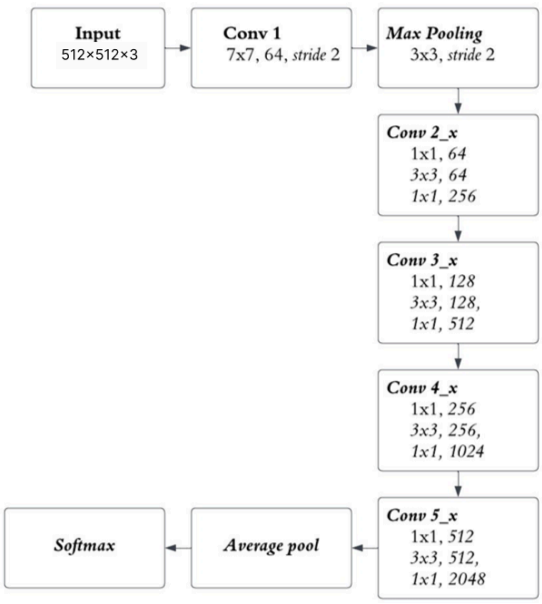


Figure 1. Block diagram of the ResNet-50 architecture CNN [18]

In Figure 1, it is known that the ResNet-50 architecture consists of an input layer, a convolutional layer, a residual block, global average pooling, and a fully connected layer. In the input layer, there is an image process that is inserted with a size of 512×512×3. So, the inserted image has a size of 512×512 pixels and should be an RGB image. After entering the input layer, the next step is to enter the convolution process. This process aims to process the edges of the image, texture, rotation and so on. In this process there is a layer with kernels 7×7, 64 which is useful for capturing the global features of the large image structure when the image enters the input process. Then, enter the residual block consisting of 5 bottlenecks. In this layer there is a kernel size of 3×3, 1×1, in each residual block there is a different filter size depending on the depth level. The 1×1 kernel size is used to reduce or change the dimensions of a feature channel, combining information from various feature channels. Whereas the 3×3 kernel is used to win local features and minor details [17].

After the image is completed, the preprocessing process is carried out, then the next stage is the training process using ResNet-50. In the training process, it was carried out four times according to the focus of the research in Table 1.

Table 1. Research focus

Metode	Dataset
ResNet-50	NIST-DB4 2000
ResNet-50 + BADF	NIST-DB4 2000
ResNet-50 + CLAHE	NIST-DB4 2000
ResNet-50 + BADF + CLAHE	NIST-DB4 2000

Based on the focus of the research in Table 1, the experimental flowchart can be seen in Figure 2 and Figure 3.

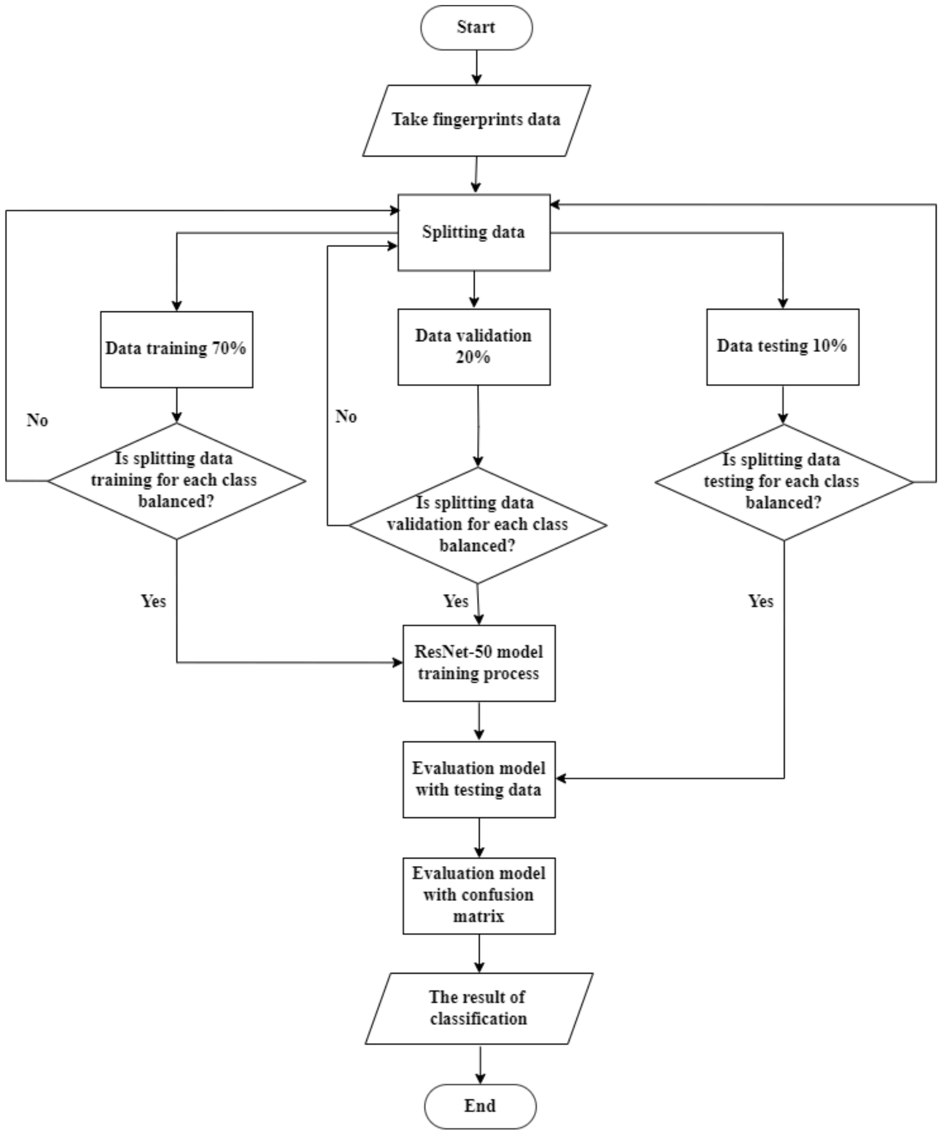


Figure 2. Flowchart Experiment of the ResNet-50 algorithm without using preprocessing

In Figure 2, it is known that the experiment without using preprocessing was carried out directly in the training process without the implementation of the BADF or CLAHE method. The next flowchart is an experiment with the implementation of preprocessing can be seen in Figure 3.

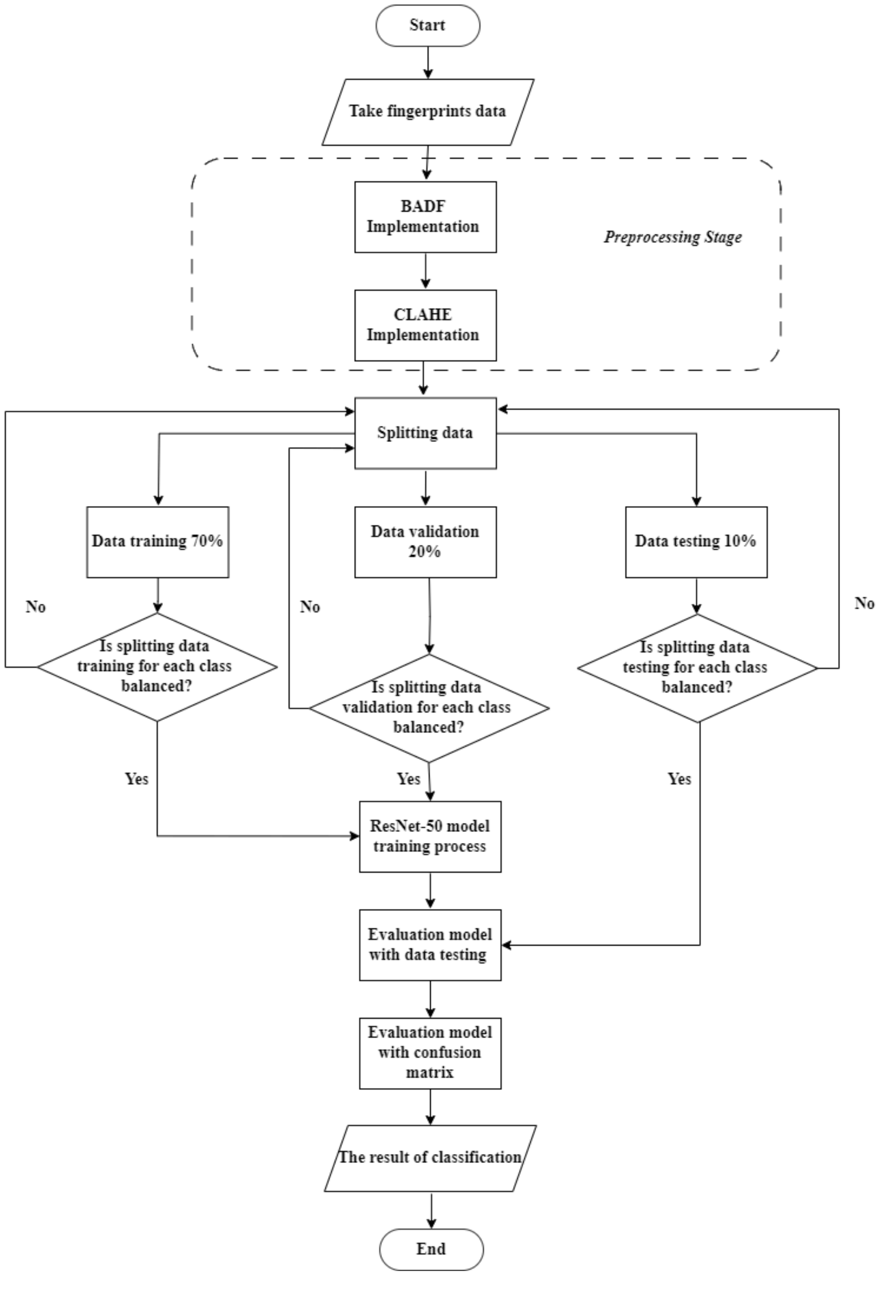


Figure 3. Flowchart Experiment of the ResNet-50 algorithm using BADF and CLAHE preprocessing

In Figure 3, it is known that the experiment by applying BADF and CLAHE preprocessing. The BADF method aims to reduce the noise present in the image. Furthermore, after the noise in the image is reduced, the contrast level of the image will be adjusted using the CLAHE method.

Evaluation

The evaluation looked at the results obtained from the ResNet-50 model using the BADF and CLAHE methods. This stage looks at the accuracy of the data testing using a confusion matrix. The evaluation stages are as follows.

1. Enter the test results in the confusion matrix as shown in Table 2.

Table 2. Accuracy calculation mechanism using confusion

		actual	
		correct	***incorrect***
predict	***correct***	*correct prediction*	*incorrect prediction*
	incorrect	*incorrect prediction*	*correct prediction*

2. Calculating the accuracy value with the calculation formula that can be seen in Equation 3.1 [19].

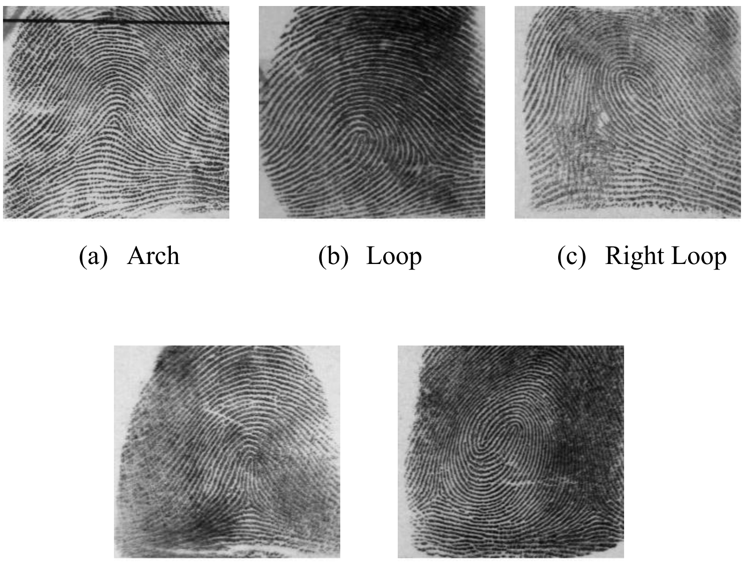
RESULT AND DISCUSSION
Result
Data Collection

The data used in this research was taken from NIST (National Institute of Standards and Technology). The name of this dataset is NIST Database 4 (2000). This dataset consists of five folders so there are five classes. These folders include A (Arch), L (Left Loop), R (Right Loop), T (Tended Arch), and W (Whorl). Each of the one-letter folder names refers to the initials of the existing class name. The existing dataset is an 8-bit grayscale image in PNG format. Each print is 512×512 pixels in size with a total of 4000 data. Each file in this dataset has its name, number, and class format. The original data division obtained from the NIST-DB4 dataset (2000) can be seen in Table 3.

Table 3. Distribution of Data from the source

Class	Label	Total Data
Left loop	*L*	800
Whorl	*W*	800
Right loop	*R*	800
Tended Arch	*T*	800
Arch	*A*	800
Total	5	4000
Ratio	100%	100%

Each sample in the data can be seen in Figure 4.



(a) Arch (b) Loop (c) Right Loop

(d) Double Loop (e) Whorl

Figure 4. Dataset sample [20]

Data Preprocessing

BADF Implementation

The process carried out after knowing that the amount of data used is appropriate is the implementation of BADF. The BADF implementation is used for noise removal by retaining fine details in the image. By applying this method, it makes the image appear more detailed. The output of the BADF implementation can be seen in Figure 5.

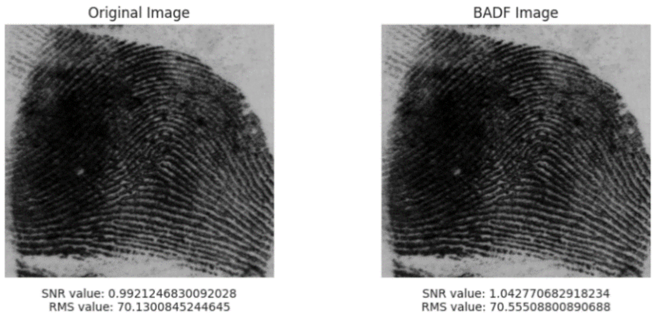


Figure 5. Comparison of the original image with the image that has been implemented by BADF

In Figure 5, it can be seen that the image quality before and after the BADF method is carried out looks different. The image that has been implemented by BADF is more visible with reduced noise. Then it also looks smoother and clearer. In addition, the degree of difference between the two images can be seen in the SNR and RMS values. The SNR value is used to measure the noise in the image. The higher the SNR value, the lower the noise level in the image itself. While the RMS value is used to measure the contrast in an image. The higher the RMS value, the higher the contrast in the image. In Figure 5, it is known that the SNR and RMS values in the image that has been implemented by BADF are larger when compared to the values in the original image. Thus, it can be seen that the noise in the image that has been implemented by BADF is less noise level and the contrast is higher.

CLAHE Implementation

After the image is subject to BADF implementation, the next stage is implementation using the CLAHE method. This method is used to increase the contrast of the image. The results of the CLAHE implementation can be seen in Figure 6.

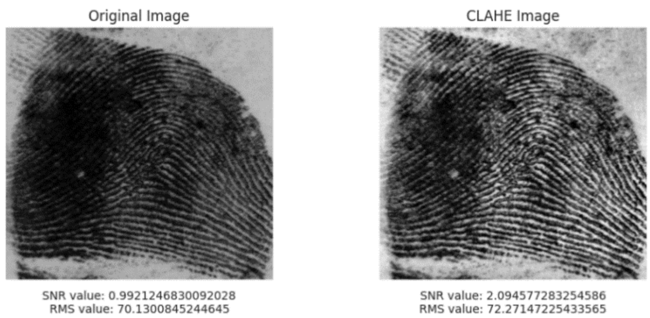


Figure 6. Comparison of the original image with the image that has been implemented by CLAHE

In Figure 6, it can be seen that the image before applying the CLAHE method and having implemented the CLAHE method there is a difference. The difference that can be seen is that the image that has been subjected to the CLAHE method tends to have a clearer contrast. There is a striking part, the level of contrast is that in the dark and light parts, the details can be identified more clearly. Figure 6 shows that the SNR and RMS values in the CLAHE implemented image are larger than the values in the original image. Thus, it can be seen that in the image that has been implemented, CLAHE has a smaller noise level and higher contrast.

BADF and CLAHE Implementation

After the implementation of the image using the BADF method and the CLAHE method. The next step is the imposition of imagery by applying two methods at once. The step taken is to apply the BADF method first, then apply the CLAHE method. This is done to reduce the noise in the image first. Then, after the image has been reduced by the amount of noise, the next step is to adjust the brightness or contrast level in the image. The output on the BADF and CLAHE implementations can be seen in the figure. The implementation of BADF and CLAHE can be seen in Figure 7.

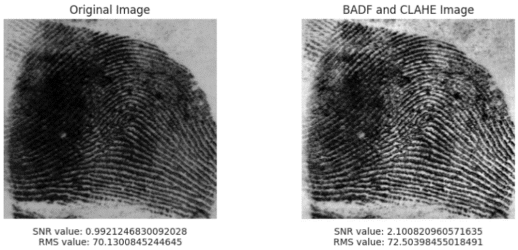
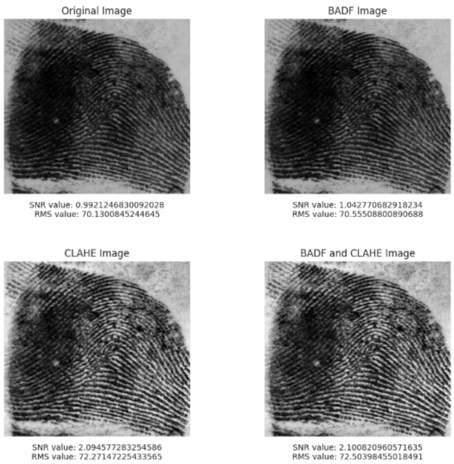


Figure 7. Comparison image with the image that has been implemented by BADF and CLAHE

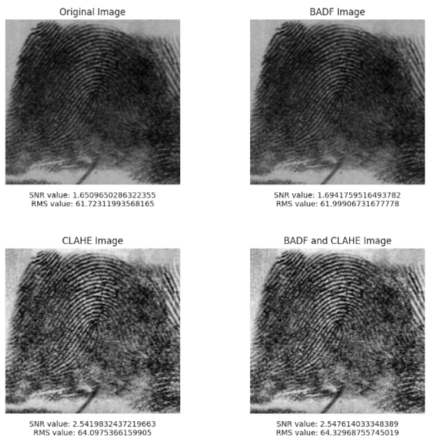
Figure 7 shows that the SNR and RMS values in the images that have been implemented by BADF and CLAHE are larger when compared to the values in the original images. Thus, it can be seen that the noise in the images that have been implemented by BADF and CLAHE is smaller and the contrast is higher.

Compare All Class on Preprocessing

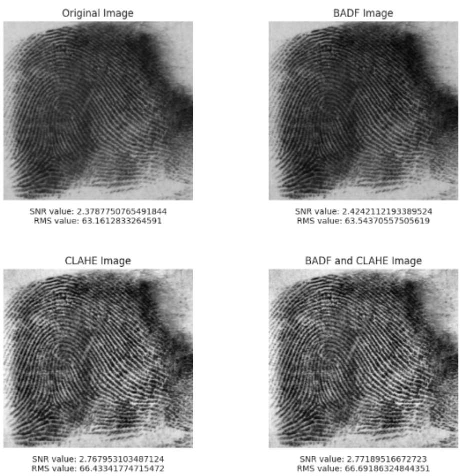
The image of each class that implements preprocessing can be seen in Figure 8.



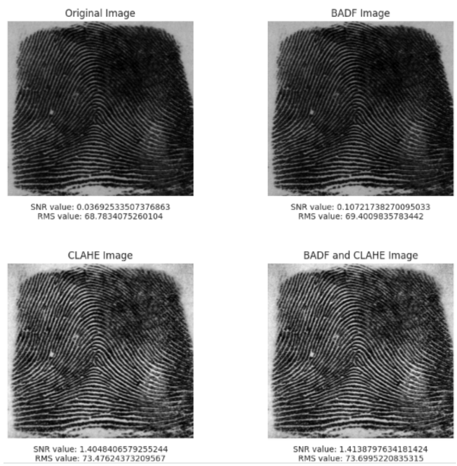
(a) Class A



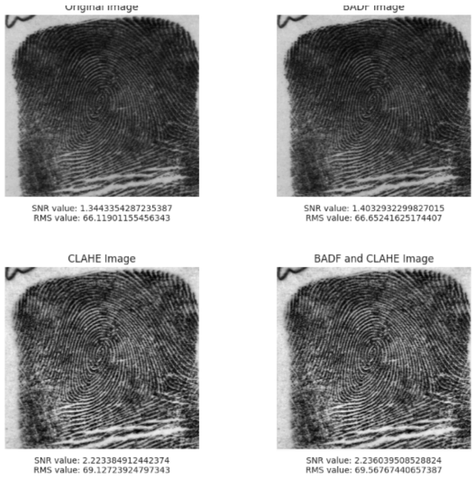
(b) Class L



(c) Class R



(d) Class T



(e) Class W

Figure 8. Comparison images with those that have been implemented preprocessing in each class

Splitting Data

After preprocessing, the next step is to split the data or the data sharing process. The data division used in this research was 70:20:10 or 70% for training data, 20% for validation data, and 10% for testing data. The process of data sharing starts from dividing the entire data into training data and data testing. Training data is 90% while testing data is 10%. Then, for validation data, 20% was taken from the training data. The results of data splitting can be seen in Table 4.

Table 4. Dataset split

Num.	Split Dataset	Number of Images
1	Training	2800
2	Validation	800
3	Testing	400

Model Training

After preprocessing, splitting data, generators, and framing data, the next step is the modeling process. The modeling process aims to determine the model to be used as a method or algorithm that is tasked with analyzing the data used. The data analysis used can be in the form of detection, classification, and so on.

In this research, the ResNet-50 architecture was used. The creation of this model is carried out by a transfer learning process from the ImageNet model. Some of the parameters used include top and weight. The weight parameter has the value of 'imageNet' as the initial weight so that the model can take advantage of the existing knowledge from ImageNet. Then, the include top parameter is given a false value so that it can adjust to the ResNet-50 architecture by adding a fully connected layer, pooling layer, or dropout. Furthermore, Global Average Pooling (GAP) is added which is used to calculate the average value of each feature map used.

In this research, there were four experiments carried out, including experiments without using preprocessing, experiments using BADF preprocessing, experiments using CLAHE preprocessing, and experiments combining BADF and CLAHE preprocessing.

Evaluation

The evaluation in this research uses the confusion matrix method with the formula in Equation 1. The following is the confusion matrix in each experiment carried out.

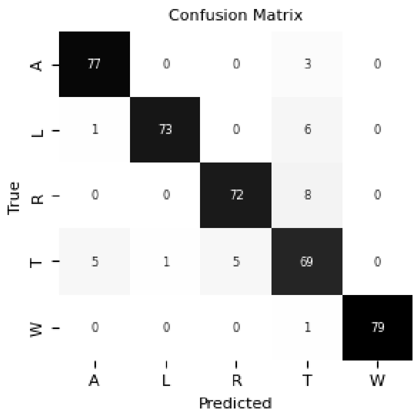


Figure 9. Confusion matrix ResNet-50

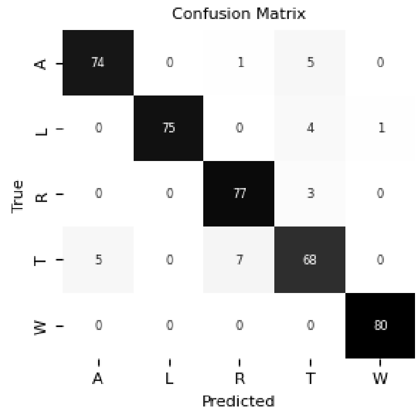


Figure 10. Confusion matrix ResNet-50 BADF method

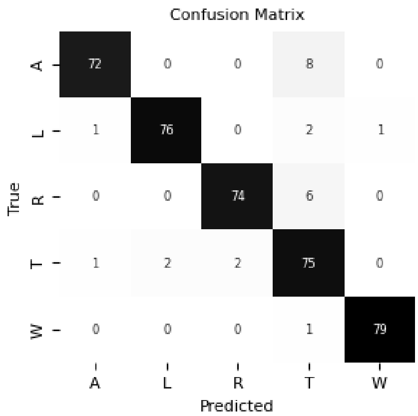


Figure 11. Confusion Matrix ResNet-50 CLAHE method

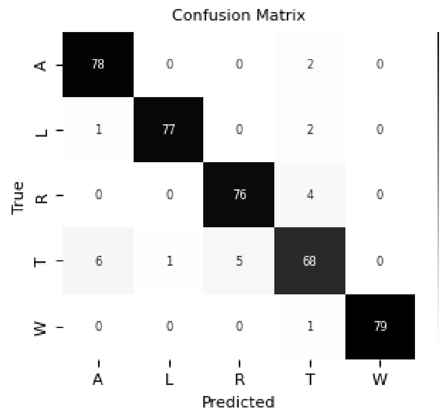


Figure 12. Confusion matrix ResNet-50 BADF dan CLAHE method

Figure 9 is the confusion matrix in the training using ResNet-50 without using preprocessing. Based on Equation 1, it can be seen that the accuracy obtained is 92.5%. This accuracy is the lowest when compared to experiments using BADF preprocessing, experiments using CLAHE preprocessing, and experiments using a combination of BADF and CLAHE preprocessing.

The next experiment is to use ResNet-50 with BADF preprocessing whose accuracy can be calculated using the confusion matrix in Figure 10. In the figure, the accuracy value can be calculated using Equation 1, the result is 93.5%. This accuracy was the third highest after the experiment using CLAHE preprocessing and the experiment using a combination of BADF and CLAHE preprocessing.

The third experiment is to use ResNet-50 with CLAHE preprocessing whose accuracy can be calculated using tin the confusion matrix Figure 11. In the figure, it can be seen that the accuracy value using equation 1 is 94%. This accuracy is the second highest after experiments using combined BADF and CLAHE preprocessing.

The last experiment was using a combination of BADF and CLAHE preprocessing. The accuracy of the experiment can be calculated using the confusion matrix in Figure 12. In the figure, it is known that the accuracy value using Equation 1 is 94.5%. This accumulation is the highest accuracy among experiments without preprocessing, experiments using BADF preprocessing, and experiments using CLAHE preprocessing.

Based on the experiments carried out, the accuracy results of each experiment can be seen in Table 5.

Table 5. Results of each experiment

Method	Accuracy
ResNet-50	92,5%
ResNet-50 + BADF	93,5%
ResNet-50 + CLAHE	94%
ResNet-50 + BADF + CLAHE	94,5%

Based on the table above, it is known that the accuracy value in ResNet-50 of the combined preprocessing method between BADF and CLAHE obtained an accuracy of 94.5%. This accuracy is the highest accuracy when compared to other experiments conducted. The preprocessing used supports noise reduction by implementing the BADF method. Next, after the noise is reduced, the next step is to increase the contrast in the image using the CLAHE method. The combination of these methods provides two conditions that can support the high accuracy obtained. It was different from the other three trials. Other experiments only support one or even some who do not use it at all. So, this condition affects the accuracy obtained.

Discussion

In this research, the preprocessing method used was systematically evaluated. The dataset used is NIST-DB4 in 2000. Based on the research conducted, preprocessing affects the accuracy obtained during the training process itself. The experiment using the ResNet-50 algorithm without using preprocessing obtained an accuracy of 92.5%. When the same algorithm implements the BADF method, the accuracy can increase to 93.5%. Meanwhile, when the ResNet-50 algorithm is only implemented using the CLAHE method, the accuracy obtained increases again to 94%. In addition, the ResNet-50 algorithm is implemented a combination of the BADF and CLAHE, the accuracy obtained from the combination of the two methods is 94.5%. The experiment using the BADF and CLAHE methods obtained the highest accuracy of 94.5% among other experiments. As for the ResNet-50 experiment using a combination of BADF and CLAHE methods compared to previous studies which can be seen in Table 6.

Table 6. Comparison with previous research

Method	Accuracy
ResNet-50 [20]	91,3%
ResNet-50 + BADF + CLAHE	94,5%

Based on the research of Zia et al. (2019) [20], it is known that the accuracy of the study is still superior to the proposed research, namely the ResNet-50 algorithm using BADF and CLAHE preprocessing.

CONCLUSION

Based on the research that has been conducted, the experiment using the resNet-50 algorithm combined with BADF and CLAHE preprocessing obtained an accuracy of 94.5%. The accuracy results are the highest of any other experiment that has been conducted. The accuracy achieved using the combined preprocessing of BADF and CLAHE has a tendency to reduce noise first. Then, the results of the image that has been implemented BADF are contrast-adjusted using the CLAHE method.

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