Performance of Contrast Adjustment Techniques on The Face Recognition Method with Test Data Under Varying Lighting Conditions

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***Abstract*— In the face recognition process influenced by lighting, the application of the image enhancement process at the preprocessing stage plays an important role in normalizing image contrast so that the quality of the input image becomes better. This step is expected to improve face recognition performance. In this study, we implement a lighting-influenced face recognition method, namely Robust Regression, and test several image enhancement techniques in the preprocessing phase to determine their effects on face recognition performance under different image lighting conditions, including Contrast-limited Adaptive Histogram Equalization (CLAHE), Histogram Equalization (Histeq), and Image Intensity Adjustment (Imadjust). HE uses a global technique that adjusts the overall intensity of the image. CLAHE uses a local technique that adjusts the intensity of pixels based on their surrounding areas. Meanwhile, the Imadjust function adjusts the intensity of image pixels based on the specified minimum and maximum values. The experiment is conducted using the AR Face Database which contains images affected by lighting factors. Lighting conditions include several categories, namely low, medium, high, and very high (extreme) lighting conditions. The experimental scenario is carried out by comparing the results of face recognition using several preprocessing techniques on each test data. The experimental results show that image enhancement techniques improve the performance of face recognition. The face recognition approach that adds the CLAHE technique to the preprocessing shows the highest performance of 95.87%. Meanwhile, the face recognition approach that adds the Imadjust technique to the preprocessing shows the lowest performance of 84.38%.**

Keywords*— *face recognition; preprocessing; image enhancement; robust regression; lighting conditions

I. INTRODUCTION

In the process of identifying a person, one approach that is widely used today is biometric technology. Through this technology, the authentication process and setting access rights on an important service can be done automatically [1]. This is certainly very helpful to improve the level of security and ensure the use of important facilities by the right people. Currently, many buildings or important areas are equipped with biometric technology as a new security model for selecting people who enter and exit. Likewise, various personal devices, such as mobile phones, computers, and various types of gadgets are currently equipped with this technology to protect data from unauthorized access. Along with the increasing mobility of people and the need for fast transactions, the use of biometric technology is considered to be increasingly important because it offers speed and accuracy in identification and authentication than other means.

One of the biometric technologies developed by the researchers is face recognition, which is the most natural identification approach where people are visually recognized from their faces. The face is a unique body part that is different from each other and is most commonly used by someone to recognize other people. In its development, face recognition techniques have an important role in various applications, related to video surveillance and human-computer interaction [2]. Technically, the process of recognizing faces is done by matching the characteristics of a face object with the templates available in the face image database [3]. In another study, face recognition process was also carried out by matching between face images and sketches [4]. One of the advantages of face recognition is the ease of taking face objects. The acquisition of face images can be done using the camera, from near or far, without requiring the activity of the person. This certainly provides an advantage over other biometric approaches, especially in the surveillance process in certain areas for security and monitoring purposes.

A lot of research has been done on the problem of face recognition, which is still ongoing today because it has a high level of difficulty and complexity. This is caused by many factors that can lead to variations in face images that affect the performance of face recognition. These factors can be grouped into 2 categories, namely intrinsic and extrinsic factors [5]. Intrinsic factors are factors that affect face changes physically. Meanwhile, extrinsic factors affect face image variations not due to physical changes in the face, but caused by the interaction of light that leads to the face. Some intrinsic factors include including facial expressions, ethnic differences, gender, and accessories that cover some areas of the face (hair on the face, glasses, cosmetics, and so on). Changes in age are also important factors that affect facial physical changes significantly [6]. In addition, plastic surgery can also cause the face to change physically [7]. Meanwhile, some extrinsic factors include lighting conditions, face position, and noise (changed or contaminated original image pixels). These various factors then affect the performance of the face recognition system automatically [8].

Among the various conditions that affect the performance of face recognition systems, a lot of research focuses on pose, illumination, and expression factors [9]. This is because these factors have a very significant influence on face recognition. Among these three factors, based on previous research, lighting variations have a greater impact on face recognition performance than position or expression variations. [10]. Pose variation is considered as one of the main problems affecting face recognition performance [11]. Several face images of a person with the same position and face expression, but different lighting conditions, may be recognized as different people [12]. Many problems related to illumination are difficult to solve, especially in complex lighting conditions. A lot of research has been developed to identify the problems that arise due to this illumination variation, especially under unconstrained lighting variations, to produce approaches that can improve face recognition performance [13].

The scope of this study is related to the influence of lighting factors on face recognition. In order to reduce the effect of lighting variations on the image, the illumination normalization process using image enhancement techniques is often performed in the face recognition preprocessing stage. However, in most cases, this process remains a difficult problem to achieve face recognition performance optimally [14].

In this study, we carry out experiments to determine the performance of several image enhancement techniques on the face recognition approach under each test data condition. The test data represents the face object in the environment where the face will be detected. The lighting variations in the test data are divided into 4 conditions, namely low, medium, high, and extreme lighting conditions. We apply a method called Robust Regression for classifying faces. We choose the method because of its excellent ability to solve the problem of face classification affected by illumination factors. The method is the state of the art in the scope of this problem in an experimental environment using a small-sized and small number of facial image dataset. Through this study, it will be known which image enhancement approach is most appropriate to use for face recognition in every lighting condition.

II. Materials and Methods

This section describes the face recognition method used for the face classification process, the image enhancement technique which is the focus of this study, the image dataset for the experimental process, and the experimental scenario used. The process of face recognition using the Robust Regression method with image enhancement at the preprocessing stage is shown through flowcharts as shown in Figure 1. In the training phase, as shown in Figure 1(a), a predictor is generated for each class. Whereas, in the testing phase, as shown in Figure 1(b), class prediction is performed. In both stages, image enhancement is performed in the preprocessing phase.

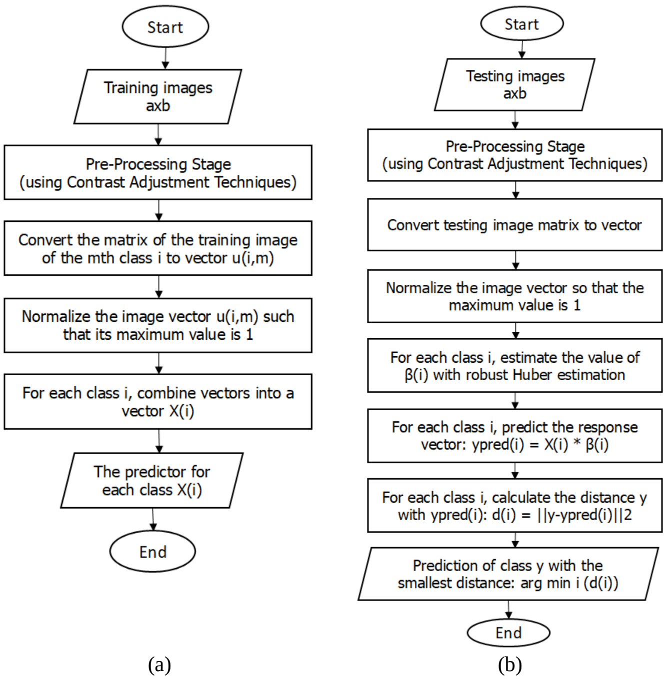


Fig. 1. The process of face recognition using the Robust Regression method with image enhancement in preprocessing: training stage (a) dan testing stage (b).

In this study, we use a standard dataset, the AR Face Database, which contains face images under several lighting conditions to evaluate the face recognition method affected by lighting factors. The images are generated in a specially designed lighting environment under 4 lighting conditions, namely low, medium, high, and extreme conditions. Each lighting condition uses 2 images. The number of individuals is 100 people, consisting of 50 men and 50 women. Thus, the total number of images is 800, consisting of 600 training images and 200 test images. The test images are based on the lighting conditions tested. Meanwhile, the training images are based on other lighting conditions. Overall, the number of images in this dataset is quite small. Likewise, the size of each image is 100x100 pixels. Thus, based on the small number of images and small image sizes, we use a conventional method, namely robust regression, that show very good performance in the scope of this study. We do not use deep learning-based methods considering the characteristics of the standard dataset we use. The use of deep learning-based methods would be more appropriate and would produce optimal performance on a large number of images and large image sizes.

A. *The Classification Approaches*

A lot of research has been done to solve the problem of lighting conditions to produce many face recognition methods. In general, the various methods that have been developed for recognizing faces are grouped into 3 approaches, namely approaches based on model, approaches based on features, and approaches with preprocessing. Examples of model-based techniques to lessen the impact of illumination on face images include the Spherical Harmonic [16], the Illumination Cone [15], and a number of additional techniques created based on low-dimensional linear sub-spaces. In this approach, the linear space that is built requires many face images, so handling the large database is often difficult. On the other hand, features based approaches use illumination invariant features for face recognition, for example the 2D Gabor-like Filters method [17], Discrete Cosine Transform [18], Local Binary Pattern [19], and so on. Meanwhile, in the preprocessing approaches, a preprocessing stage before the classification process is needed to normalize the illumination of face images to reduce lighting effects [20]. Several methods of this approach include the Quotient Image method, Self-Quotient Image, and so on.

In this study, a method called Robust Regression [21] is used in the classification process which empirically has a very good face recognition performance. This method uses a pre-processing approach. The process of illumination normalization of face images use an image enhancement technique. This method is developed based on linear regression technique [22]. Furthermore, this method is further developed to decrease the impact of noise on face images.

The training process of this method needs to be carried out to produce regressors/predictors for each class/individual, which will later be used as a classifier machine model to identify the test image. Predictors of each class are generated by combining vectors from the matrix of training images in each class. The image vector has dimension that are smaller than the original matrix with a maximum value 1.

At the testing process for the face classification process, each image matrix is converted into a smaller vector with a maximum value 1, then the value β of each class is estimated with the robust huber estimation. Furthermore, the prediction of the response vector is carried out in each of these classes (1) and each class is calculated the distance from the prediction results of the response vector (2). Then, each class is predicted with the smallest distance.

$$ypred(i) = X(i) * \beta(i) \quad (1)$$

$$d(i) = ||y\text{-}ypred(i)||2 \quad (2)$$

Both in the training and testing process, the preprocessing process is carried out on all images of faces. The preprocessing process uses a image enhancement technique. In previous study, the image enhancement technique used in this method is histogram equalization. In this study, several image enhancement techniques were used to analyze their performance on face recognition.

B. Image Enhancement

In order to improve face recognition performance, which is impacted by lighting conditions, illumination normalization employing image enhancement techniques is frequently done during the preprocessing stage. Several image enhancement approaches are histogram equalization [23], contrast-limited adaptive histogram equalization (CLAHE) [24], and Imadjust. Each of these techniques certainly has a different influence on the performance of the method to recognizing faces.

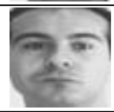
In this study, we test the image enhancement techniques empirically to determine their effect on each lighting condition on the test data. Theoretically, the implementation of the image enhancement technique in the proprocessing process is able to normalize all images due to illumination variations into images with neutral lighting conditions or have relatively the same contrast level, thereby improving face recognition performance. However, each image enhancement technique will certainly produce a different performance. We will test each of these techniques to determine their measurable performance. Each of these techniques will also be compared with preprocessing without using image enhancement, to find out whether each image enhancement technique is able to improve face recognition performance in each lighting condition of the test image.

C. The Dataset

Face recognition performance needs to be tested using a standar dataset in the form of a representative collection of images, so that the experiment produces accurate and precise conclusions. In the study, experiments are performed using a collection of facial images in one of the standard face image databases, namely AR Face Database [25]. Every individual whose face is photographed in this database has a variety of lighting conditions. Every image is captured under carefully regulated circumstances utilizing a data collecting approach.

The focus of the study is testing the performance of face recognition test images with lighting variations. Thus, the results of this study can provide important information related to face recognition performance by preprocessing using image enhancement techniques in each lighting condition from the test images data.

TABLE I. EXAMPLE OF FACE IMAGE OF ONE PERSON WITH 4 LIGHTING CONDITIONS IN AR FACE DATABASE

Lighting Condition	**Session 1**		**Session 2**	
	Image Number	***Image View***	***Image Number***	***Image View***
Low	01		14	
Medium	05		18	
High	06		19	
Extreme	07		20	

In this experiment, face images used 100 people, consisting of 50 men and 50 women, with variations in face images in neutral expressions, frontal views, and several lighting conditions. The size of each image used is 100x100 pixels. Each person in the dataset has 2 sessions. Each session shows the results of image acquisition in the same position with several variations of lighting. Each session consists of 4 lighting conditions, namely low condition (face image generated from a face object that receives low-intensity lighting from the front), medium condition (face image generated from a face object that receives moderate-intensity lighting from the side), high condition (face image generated from a face object that receives high-intensity lighting from the side) and extreme condition (face image generated from a face object that receives very high-intensity lighting from the front).

One example of a face image in this dataset with 4 lighting conditions is shown in Table I. Sessions 1 and 2 for each person are used for experiments in each lighting condition, whether they show consistent results or not.

D. Experiment Scenario

The experimental scenario was conducted to determine the impact of every image enhancement technique on the performance of face recognition in each test image condition, as shown through Table II. This experiment is carried out using 4 scenarios. In each scenario, testing is carried out on Histeq, CLAHE, and Imadjust techniques. The results of the performance of some of these techniques are also compared to the approach without pre-processing (no image enhancement). So, the results will show which techniques that produce better performance.

TABLE II. EXPERIMENT SCENARIO

Sce-nario	**Ses-sion**	**Image Number**		Accuracy (%)
		Training	***Testing***	
1	1	05, 06, 07	01	Histeq, CLAHE, Imadjust, No image enhancement
	2	05, 06, 07	14	
2	1	01, 06, 07	05	
	2	01, 06, 07	18	
3	1	01, 05, 07	06	
	2	01, 05, 07	19	
4	1	01, 05, 06	07	
	2	01, 05, 06	20	

In each experimental scenario, testing is carried out on each session. The first scenario is carried out using the test images in low lighting conditions (Image Number 01 and 14). The second scenario is carried out using test images in medium lighting conditions (Image Number 05 and 18). The third scenario is done using test images in high lighting conditions (Image Number 06 and 19). While the fourth scenario is done by using the test images in extreme lighting conditions (image number 07 and 20).

III. EXPERIMENT RESULTS

This chapter explains the results of study that has been obtained based on the experimental scenario that has been performed. In detail, the experimental results are displayed through Tables III-VI and Fig. 1-4.

TABLE III. EXPERIMENT RESULTS ON SESSIONS 1

Lighting Condition of Testing Image	**Image Enhancement Techniques**			
	Histeq	***CLAHE***	***Imadjust***	***No Contrast Adjustment***
Low	89.33 %	94.33 %	88.00 %	85.33 %
Medium	83.33 %	97.00 %	79.67 %	76.67 %
High	81.67 %	97.33 %	81.67 %	80.00 %
Extreme	93.67 %	97.67 %	86.33 %	87.33 %

Based on the experimental results on the session 1, as shown in Table 3, the accuracy of Histeq, CLAHE, Imadjust, and No image enhancement approaches on low lighting condition respectively are 89.33%, 94.33%, 88.00%, and 85.33%. The accuracy of the approaches on medium lighting condition respectively are 83.33%, 97.00%, 79.67%, and 76.67%. The accuracy of the approaches on high lighting condition respectively are 81.67%, 97.33%, 81.67%, and 80.00%. While the accuracy of the approaches on extreme lighting condition respectively are 93.67%, 97.67%, 86.33%, and 87.33%.

At the session 1, the experimental results indicate that Clahe techniques produce the best performance on all Lighting Conditions, as shown in Figure 2. In the three tested techniques, the imadjust technique shows the worst results on all lighting conditions. Nonetheless, the imadjust technique shows better performance than no contract adjustment approach in the conditions of low, medium, and high lighting.

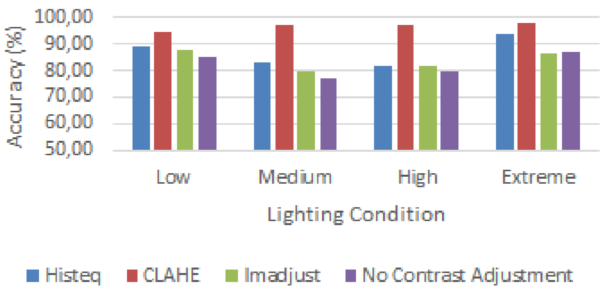


Fig. 2. Chart of accuracy of image enhancement techniques at each Lighting Condition on Session 1

Based on the experimental results on the session 2, as shown in Table 4, the accuracy of Histeq, CLAHE, Imadjust, and No image enhancement approaches on low lighting condition respectively are 88.33 %, 92.33 %, 87.00 %, 85.33 %. The accuracy of the approaches on medium lighting condition respectively are 82.00 %, 97.67 %, 78.67 %, 79.33

%. The accuracy of the approaches on high lighting condition respectively are 84.00 %, 95.33 %, 85.67 %, 78.33 %. While the accuracy of the approaches on extreme lighting condition respectively are 94.67 %, 95.33 %, 88.00 %, 81.33 %.

TABLE IV. EXPERIMENT RESULTS ON SESSIONS 2

Lighting Condition of Testing Image	**Image Enhancement Techniques**			
	Histeq (%)	***CLAHE (%)***	***Imadjust (%)***	***No Contrast Adjustment (%)***
Low	88.33	92.33	87.00	85.33
Medium	82.00	97.67	78.67	79.33
High	84.00	95.33	85.67	78.33
Extreme	94.67	95.33	88.00	81.33

At this session 2, the same as the results of the session 1, the experimental results also indicate that the CLAHE technique produces the best performance on all lighting conditions, as shown in Figure 3. In the three techniques tested, the imadjust technique shows the worst results on low, medium, and extreme lighting conditions. In Medium Lighting Condition, imadjust techniques are also worse than contract adjustment. While the Histeq technique shows the worst results on the High Lighting Condition, but it is still better than the No image enhancement approach.

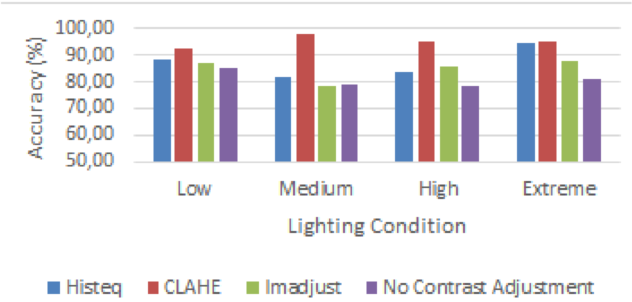


Fig. 3. Chart of the accuracy of image enhancement techniques at each Lighting Condition on Session 2

TABLE V. AVERAGE ACCURACY OF THE RESULTS IN SESSIONS 1 AND 2

Lighting Condition of Testing Image	**Image Enhancement Techniques**			
	Histeq	***CLAHE***	***Imadjust***	***No Contrast Adjustment***
Low	88.83 %	93.33 %	87.50 %	85.33 %
Medium	82.67 %	97.34 %	79.17 %	78.00 %
High	82.84 %	96.33 %	83.67 %	79.17 %
Extreme	94.17 %	96.50 %	87.17 %	84.33 %

Lighting Condition of Testing Image	**Image Enhancement Techniques**			
	Histeq	***CLAHE***	***Imadjust***	***No Contrast Adjustment***
Average	87.13 %	95.87 %	84.38 %	81.71 %
Gap with No Contrast Adjust-ment	5.42 %	14.17 %	2.67 %	0

Based on performance results on sessions 1 and 2, as shown in Table 5, the average accuracy of the Histeq technique, Clahe, Imadjust, and No image enhancement at the Low Lighting Condition respectively are 88.83%, 93.33%, 87.50%, 85.33%. The accuracy of these techniques in the Medium Lighting Condition respectively are 82.67%, 97.34%, 79.17%, 78.00%. The accuracy of these techniques at the High Lighting Condition respectively are 82.84%, 96.33%, 83.67%, 79.17%. While the accuracy of these techniques on the extreme lighting condition respectively are 94.17%, 96.50%, 87.17%, 84.33%.

The average accuracy of the sessions 1 and 2 show that CLAHE technique produce the best performance on all lighting conditions, as shown in Figure 4. In the three techniques tested, the imadjust technique shows the worst results on low, medium, and extreme lighting conditions. While the Histeq technique shows the worst results on the High Lighting Condition. However, the three techniques show better performance than No Contract Adjustment approach on all Lighting Conditions.

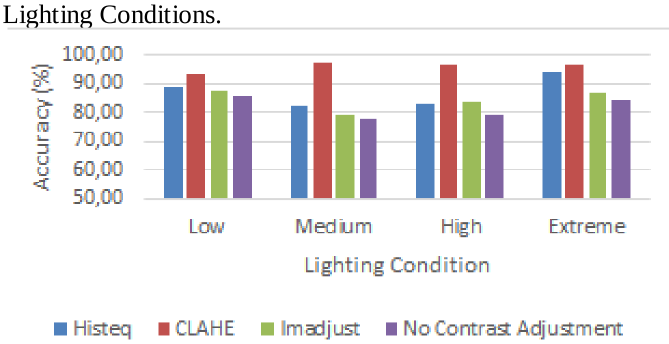


Fig. 4. Chart of the average accuracy of image enhancement techniques at each Lighting Condition

The chart in Figure 5 shows comparison of the accuracy of each image enhancement technique on all Lighting Conditions. The Histeq technique shows the best performance on extreme lighting condition and the worst performance on medium lighting condition. The CLAHE technique shows the best performance on medium lighting condition and the worst performance on low lighting condition. The Imadjust technique shows the best performance on low lighting condition and the worst performance on medium lighting condition. While the No image enhancement approach shows the best performance on low lighting condition and the worst performance on medium lighting condition.

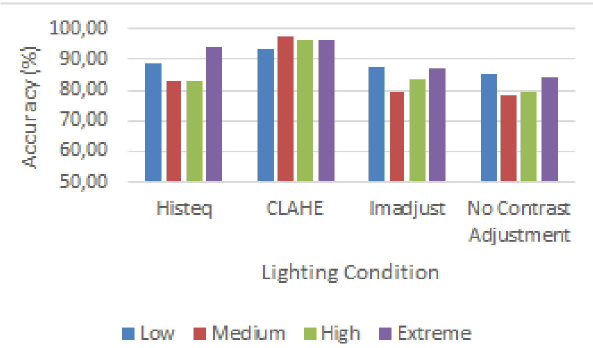


Fig. 5. Chart of the average accuracy of each image enhancement technique on all Lighting Conditions

Based on the result of the average accuracy of all lighting conditions, CLAHE technique shows the best performance than other techniques. Meanwhile, the imadjust technique shows the worst performance than other techniques, but it is still better than no image enhancement approach. Overall, CLAHE technique shows very significant effect, where performance gap between this technique with no image enhancement approach is 14.17%. Meanwhile, Histeq and Imadjust techniques show quite good performance gap respectively are 5.42% and 2.67%.

The CLAHE technique shows the highest effect in medium lighting conditions. Meanwhile, in low lighting conditions, this technique shows the lowest effect. In low lighting, this technique can help improve image contrast, but it cannot overcome noise associated with low lighting. In addition, in low-light images, the contrast between the object and the background can be low. This causes the effect of this technique on the performance of face recognition in low lighting conditions to be lower than in more lighting conditions.

To determine the significance of the influence of image enhancement techniques on face recognition performance, we measured the experimental results using statistical analysis using ANOVA. The results of the analysis are shown in Table VI. The F value (9.78) is greater than the F-Critical value (3.49), indicating that the image enhancement technique makes a significant difference to the overall performance.

TABLE VI. RESULTS OF STATISTICAL ANALYSIS USING ANOVA

SUMMARY						
Groups	Count	Sum	Average	Variance		
Histeq	4	3,485	0,8712	0,0030		
CLAHE	4	3,835	0,9587	0,0003		
Imadjust	4	3,375	0,8437	0,0015		
No Contrast Adjustment	4	3,268	0,8170	0,0013		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	0,045	3	0,0151	**9,78**	0,0015	**3,49**
Within Groups	0,018	12	0,0015			
Total	0,063	15				

IV. CONCLUSION AND FUTURE WORK

Based on the experiments that have been carried out, CLAHE technique shows better face performance than Histogram Equalization, Imajust, and preprocessing without image enhancement in all ligting conditions of testing data (low, medium, high, and very high). Meanwhile, the approach without the preprocessing (no image enhancement), face recognition performance is worse than the image enhancement techniques. The results of experiments in this study produce important information that the application of image enhancement techniques (HISTEQ, Clahe, and Imadjust) for the normalization of illumination on pre-processing has a positive influence on the performance of the method to recognizing faces that is influenced by lighting factors. The CLAHE technique performance shows the highest accuracy on the test data with medium lighting (i.e 97.34%). Meanwhile, the lowest accuracy is on test data with low lighting (i.e 93.33%). The findings produced in this study have practical implications in efforts to improve the performance of facial recognition by adding image enhancement to the preprocessing that has been proven to improve the quality of input images. In addition, these findings can be used to develop more effective security systems or AI-based devices, such as facial recognition for access control, surveillance, and identity verification.

For further development of study, experiments need to be continued using other preprocessing techniques, which results are compared to the results of this study. So, the study forward provides more alternative techniques to increase face recognition reliability. In addition, the standard dataset in this study has a small number of images and small image sizes. Thus, further research development can also be carried out on larger data sets to produce more comprehensive findings.

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