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HEGMP: IMPROVING SIBI HAND GESTURE IMAGE QUALITY COMPARED TO AHE AND CLAHE USING CNN

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Abstract

Image visibility with low lighting can cause loss of visual detail in the image, which can obscure information. The research aims to increase the visibility of hand gesture images by contributing to increasing the accuracy of CNN recognition methods. To obtain the best method, the performance of the HE-GMP evaluation method (Histogram Equalization, Gaussian Filter, Median Filter, and Prewitt Edge Detection) is compared with the AHE and CLAHE methods. The HE-GMP method produces more effective image visibility to improve the quality of SIBI hand gesture information, clarity, sharpness, contrast, brightness. provides detail preservation in areas with high contrast and reduces noise in homogeneous areas, the high increase in color saturation means that hand gesture objects displaying the letters according to SIBI can be recognized easily when compared to the AHE-GMP and CLAHE-GMP methods. The improvement in visual quality of the HE-GMP method with MSE, PSNR, AMBE and Entropy measurement metrics is more significant than the AHE-GMP and CLAHE-GMP methods. Increasing the visibility of hand gesture images with low lighting involves 5 classes, each class consisting of 520 visual data, The HE-GMP method has contributed to increasing accuracy by 62.89% which is more significant compared to the AHE-GMP method of 12.48%, and CLAHE-GMP 20.54%. This research contributes to increasing the accuracy of the CNN method for visual data input in extreme lighting.

Keywords: HE, Gaussian, Prewitt, Median Filter, Normalization, CNN

INTRODUCTION

Improving the visual quality of images in visual data processing can increase accuracy and effectiveness in making reliable predictions. However, a pattern recognition system tends not to tolerate visual data input with poor visibility [1][2][3].

The CNN method includes machine learning with a more complex neural network architecture [4]. This method can complete the task of recognizing visual input by providing the method with the opportunity to learn to recognize visual patterns on its own [5]. Based on this experience, the performance of CNN (Convolutional Neural Networks) has provided real work achievements with undoubted pattern recognition performance [6][7].

A system needs input with good visibility to help the recognition model complete the task more successfully [8]. This research improves the visual quality of hand gesture images in very low-lighting situations so that they have adequate visibility to be accepted by the CNN method. Therefore, this research compares the robustness of optimization methods, which can promise a positive impact on the performance of CNN methods.

Literature Review

Research aimed at improving the visual quality of images based on the histogram equalization algorithm has been widely used. Research efforts by explaining the advantages and disadvantages of excessive

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contrast. The results of methods developed using visual image processing can provide an increase in the visual quality of images regardless of their classification and characteristics [9].

Research that investigates methods of increasing the visibility of most input images accurate facial recognition system. The research aims to improve the performance of biometric systems for degraded facial images. Experiments with applying nine image enhancement methods to a face database with results showing that several of the selected enhancement methods can improve the performance of the facial recognition system [10].

Research that provides a systematic literature review of the application of image enhancement algorithms to assess their impact on classification performance on input medical images. The algorithms listed in this study have different characteristics. However, the results provide information that not all efforts are successful in improving classification performance with situations of increased visibility showing worse performance than the original image [11].

Research investigating the effect of normalization on CNN model performance by adjusting IQA (Image Quality Assessment). The method comparison was found to be statistically significant with the basic scaling method. Normalization of the input is sometimes recommended and sometimes not, although it improves model training and helps learn important features but may result in loss of information such as contrast, color and lighting [12].

Research aimed at improving the quality of iris images with low quality such as poor resolution, low contrast and poor lighting. The method proposed at the normalization stage uses standard data, namely the Chinese Academy of Science Institute of Automation (CASIA) and Unconstrained Biometric Iris (UBIRIS). The research results show that the method developed has an accuracy of 96.3% [13].

Based on the research survey that has been carried out, this research aims to create an image processing method to increase input visibility in the normalization stage. This method is created with a filtering model for evaluation work by computing each pixel to increase visual detail with potentially important information or reduce it in homogeneous areas. This model can overcome the problem of blurred information in visual hand gesture input with low lighting. Assessment of the processing method that has the best impact on the performance of the CNN method in hand gesture recognition in low light using comparative research on processing methods.

METHOD

CNN methods are often given the task of pattern recognition with the potential to be able to learn on their own to recognize visual data features, such as edges, textures, and shapes [14]. This method is classified as complex machine learning to carry out feature extraction operations on each layer whose dimensions will be reduced by pooling, and predicting with fully connected layers [15][16]. The performance achievements of the CNN method are no longer in doubt with the accuracy of its experience with visual input processing [6][7]. The CNN method architecture consists of complex layer processing as follows [4].

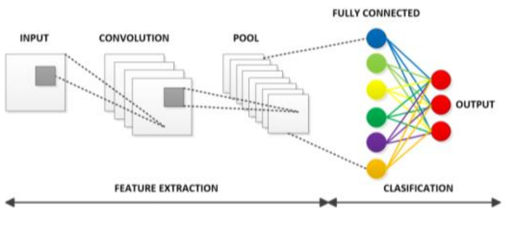

Figure 1 Convolution neural network

Visual input with decent visibility can show the performance of the CNN method for pattern recognition accurate [17]. So, in the case of visual input with poor lighting, a visual normalization stage is required to increase visual detail [18]. The following are the normalization stages in pattern recognition [12].

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Figure 2. Stages of increasing input visibility for pattern recognition processing

Methods for improving the visual quality of images based on histogram processing include HE, AHE and CLAHE [19][20][21]. Mathematical review of the Histogram Equalization (HE) method with the basic idea of smoothing the histogram more uniformly with the following formulation [22].

$$S_k = \frac{(n_G - 1)}{n} \sum_{j}^{k} n_{rj} \tag{1}$$

Where S_k is the number of gray levels in the image, n is the total number of pixels in the image, (0, 1,…, n_G– 1) and $n_{rj}$is the number of pixels that have rj - gray level. Generalization of the histogram equalization (HE) method to become more adaptive (AHE) by redistributing the image surface partition to obtain new image brightness values [23] with the following formulation.

$$s = T(r) = \int_0^r P_r\,(In)dw \tag{2}$$

If the variable (r) represents a degree of gray that requires contrast enhancement, then (T) is the transformation function and (s) is the transformation value. Whereas P_r And P_s represents the probability density function r And s. For P_s can be obtained with the following formulation:

$$P_s(S) = P_r(r)\left|\frac{dr}{ds}\right| \tag{3}$$

Transformation function $T(r)$ in the formulation to obtain P_s, so that $P_s(S)$ produces an even distribution of image histograms. Limited adaptive contrast histogram equalization (CLAHE) is a modification of the adaptive histogram equalization (AHE) method that uses excessive contrast enhancement control with clipping limits in homogeneous regions. This method uses variables (M) states the size of the region, (N) expresses the gray scale value (256), and (α) is a clip factor for adding histograms between 0 and 100 [24] which is formulated as follows.

$$b = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{max} - 1)\right) \tag{4}$$

Based on improving the visual quality of hand gesture images showing the letter A with low lighting (1 lux) using the HE, AHE and CLAHE methods provides the following visual output information.

Input 1 lux | Output HE | Output AHE | Output CLAHE

Figure 3. Comparison of HE, AHE and CLAHE output

Observation of the comparative output of the HE, AHE and CLAHE visual image quality improvement methods provides visual information regarding the image quality improvement situation. The output of the HE and CLAHE methods experienced a better increase in brightness, but the homogeneous region experienced an increase in noise [25][19]. Meanwhile, the output of the AHE method contains the most realistic color transformation to approximate actual colors [26]. In contrast to the HE and CLAHE methods, color saturation experiences changes with green, purple and blue being dominant over the actual colors [27][25]. A comparison of the HE, AHE, and CLAHE methods has output characteristics other than increasing contrast and increasing noise in homogeneous areas which can obscure important information [28]. By understanding these visual symptoms, the HE, AHE, and CLAHE methods are not sufficient for normalizing visual input with a method perspective that explains how easy it is to differentiate hand gesture objects and the background. Meanwhile, an important problem that must be solved is increasing visual detail that is free from noise interference by evaluating areas that have the potential for important information to be maintained or reduced if they have the potential to degrade

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visual information. Thus, low lighting input if it does not have good visibility can cause machine learning (CNN) accuracy to be too heavy to provide tolerance [2].

Contrast is important information in image visibility [8]. Meanwhile, in a homogeneous area it is not permitted to have details with high contrast [12]. Evaluate each pixel $f(x, y)$with contrast information potential with edge detection to assess regions with detailed information that must be retained or reduced. The Prewitt Edge Detection Method is a development of Robert's method for detecting edges which uses a High Pass Filter (HPF) with one number and zero as a buffer [29] in the following equation.

$$G_x = |-1\ 0\ 1\ \ -1\ 0\ 1\ \ -1\ 0\ 1\,|\ And\ G_{and} = |-1\ \ -1\ \ -1\ 0\ 0\ 0\ 1\ 1\ 1\,| \quad (5)$$

Filter implications G_x And G_{and} in processing with convolution to obtain two gradient components, the horizontal and vertical components needed to calculate the magnitude of the combined gradient G with the following formulation [30]:

$$G = \sqrt{G_x^2 + G_{and}^2} \quad (6)$$

The next image processing method required is processing to smooth the image surface using the Gaussian Filter Method which uses weighting of pixel intensity values with the following formulation [31].

$$h(x, y) = c.e - \frac{(x-u)+(y-v)}{2} \quad (7)$$

Where c and e are constants, $h(x, y)$ is a filter located on coordinates (x, y), whereas (u, v) is the index on the filter, $(x, y)$are height and width. The visual details of the image that are maintained can use the median filter method by employing a median value filter mask to determine the ordering of pixel intensities at the middle value with the following formulation [32].

$$m(x, y) = G(x, y)\,min, G(x, y)\,max \quad (8)$$

Where $m(x, y)$is the resulting pixel intensity, whereas $G(x, y)min$ is the minimum pixel value and $G(x, y)max$ is the maximum pixel value. Thus, a formulation that combines the Gaussian Filter, Median Filter, Prewitt Edge Detection methods is used to improve the visibility of poor images. Evaluate pixel based Prewitt edge detection filtering to find high contrast regions as visual details with Median Filter output surface sources. Meanwhile, the low contrast region is reduced with a Gaussian Filter output surface source. A pixel $f(x, y)$ generate visibility $P(x, y)$ by formulating an evaluation method using the GMP filtering model (Gaussian Filter, Median Filter, Prewitt Edge Detection) with the following formulation.

$$\begin{gathered} if\ G(x, y) = 1 \\ then\ P(x, y) = h(x, y) \\ otherwise\ P(x, y) = m(x, y) \end{gathered} \quad (8)$$

Where $m(x, y)$ is the result of processing median filtering and $h(x, y)$ The results of the Gaussian Filter processing, both processing uses input dimensions of the intensity array, output of HE, AHE and CLAHE histogram equalization processing in the RGB channel. Whereas $G(x, y)$ is prewitt edge detection processing with pixel intensity array dimension input $m(x, y)$ in the grayscale channel. Pixel intensity on $G(x, y)$ used to evaluate the potential for visual surface detail of images with the GMP filtering model with edge areas or not. The method of improving the visual quality of images using the GMP filtering model needs to be compared with the evaluation of the HE, AHE and CLAHE histogram equalization methods to obtain better visibility.

Test Data

Visual gestural language according to the Indonesian Language Sign System (TO HIMSELF) often used to communicate with hands that demonstrate the alphabet in the poses found in https://pmpk.kemdikbud.go.id/sibi/ [33]. Creating a dataset involving low lighting with a detailed visual situation that is lost is generalized in the class 1 lux to 18 lux. The measuring instrument required is a

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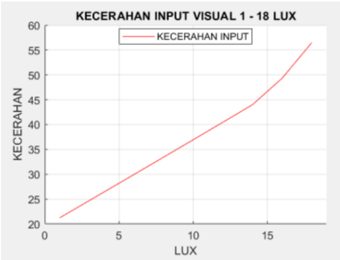
lux meter with light units lux (lx) which is a unit of light intensity received by one square meter of illuminated surface [34]. The visual data of hand gesture images used in the following test shows the letters A to Z according to SIBI. The following are examples of hand gestures for the letters A, G, I, V, and X from visual data used in testing with various lux.

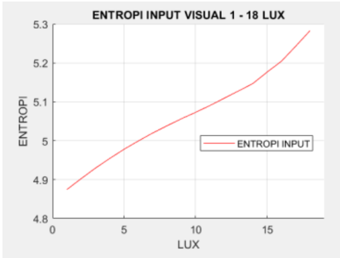
1 Lux 5 lux 10 lux 15 lux 18 lux

Figure 4. Input hand gesture images A, G, I, V, and X with various lux

Measurement of diversity in color combinations on the visual surface of the test image from 1 lux to 18 lux with the following brightness and entropy.



Graphic Input visual brightness 1 – 18 lux



Visual input Entropy graph ``1 – 18 lux

Figure 5. Graph of brightness and input entropy for lighting class 1 -18 lux

Based on the brightness and entropy measurement model, in an alphabetic class consisting of 18 image inputs, lighting from 1 lux to 18 lux is brighter and has more color combinations. Even though the visibility of the input visual data is classified as low lighting, the visibility of the hand gesture object still has difficulty distinguishing the hand gesture object and the background directly.

RESULT AND DISCUSSION

a. Result

Visual Inspection of HE-GMP Method Output

The following test is to assess the processing stages in order to achieve the goal of improving the visibility of effective hand gesture images. Inspection of HE-GMP output with hand gesture input showing the letter A with a lighting class of 1 lux.

Input 1 lux Output HE Output Gaussian Output Median Output Prewitt Output HE-GMP

Figure 6. Visibility of HE-GMP formulation class A with 1 lux light.

The visibility of HE-GMP output in the processing stage provides subjective information regarding detail, texture, contrast, brightness, sharpness and noise. HE output has improved contrast and sharpness, but noise and texture details introduce new artifacts that blur information. The Gaussian Filter method smooths visuals without exception giving the effect that important areas of detail are lost. Meanwhile, the Median Filtering method can strengthen contrast but is unable to overcome high contrast situations in homogeneous areas. The edge detection method has shown information classification of important and homogeneous contrast regions. The HE-GMP method processes to

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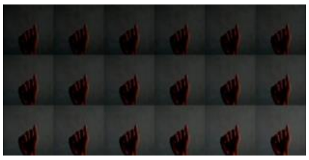
improve visibility with evaluations to enhance areas of important detail and refine homogeneous areas. Visibility The HE-GMP method provides output with effective consistency with input in the following illumination range of 1 to 18 lux.



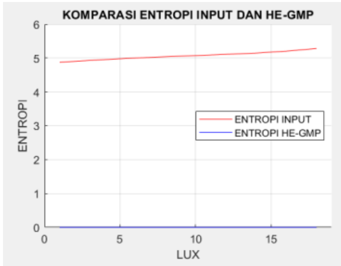
Input A with Lux 1 - 18 Lux

Output HE-GMP A with Lux 1 - 18 Lux

Figure 7 HE-GMP output in the range of 1 lux to 18 lux

The output provides statistical information on brightness and entropy through comparison of the visual input with the following graph.

Comparison Chart of Input Brightness and HE-GMP



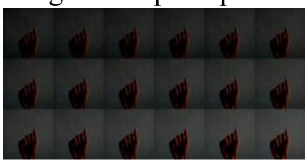
Comparative graph of input entropy and HE-GMP

Figure 8 Graph of HE-GMP brightness and entropy test results

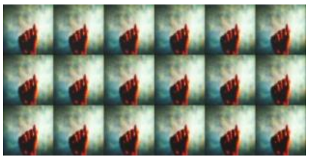
Thus, the performance of the HE-GMP method produces output with increased contrast, brightness, sharpness and visual clarity of hand gesture objects. In addition, noise in homogeneous areas is significantly reduced, detail and texture can be maintained to improve the visibility of hand gesture image data sets in low lighting situations of 1 lux to 18 lux.

Comparison results of HE-GMP, AHE and CLAHE

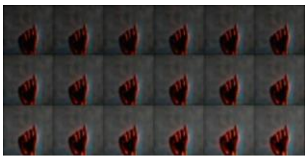
Refining the HE method with GMP evaluation has been able to provide solutions by increasing valuable area details and reducing noise areas. Testing how robust the visibility improvement of the HE-GMP method is by comparing the adaptive processing method with the AHE and CLAHE methods.



Input A with Lux 1 - 18 Lux



Output HE-GMP A with Lux 1 - 18 Lux



Output AHE A dengan Lux 1 - 18 Lux

Output CLAHE A dengan Lux 1 - 18 Lux

Figure 9 Comparison of HE-GMP, AHE, and CLAHE output

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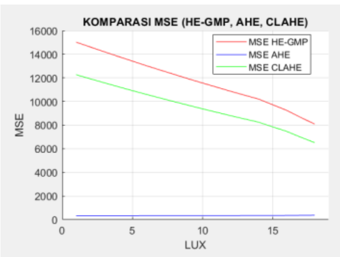
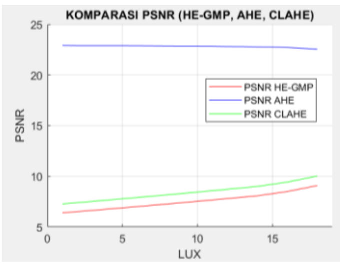
Visual analysis by producing a perception review of color transformation, area detail, contrast impact, brightness, noise and color sharpness to analyze hand gesture display information. There is a comparison of the HE-GMP, AHE and CLAHE methods with the following visual output analysis.

1. The color transformation in the HE-GMP method found color saturation in the input image which was originally without detail, dominated by black (dark) due to low light, the HE-GMP method has shown higher saturation with mostly blue, green and purple colors. The AHE method has not experienced color transformation with low saturation. Meanwhile, CLAHE color transformation increases saturation with most gray colors.
2. The impact of processing the HE-GMP method is an increase in the quality of alphabet information with positions demonstrated by clear hand gestures through detailed areas such as fingers, palms and hands. The AHE and CLAHE methods do not produce better details of the object area which causes the display details to not be captured properly.
3. Increased contrast and brightness can be used to directly differentiate hand gesture objects and the background. The HE-GMP method produces increased contrast and visuals that can be used to directly differentiate parts of an object and the background. Meanwhile, the AHE method does not increase the contrast and brightness enough to help distinguish parts of the object and the background directly. The CLAHE method increases contrast and brightness, especially in homogeneous areas such as the background, which occurs excessively, causing noise which interferes with distinguishing parts of the object area from the background.
4. The HE-GMP method is able to reduce noise in a homogeneous area without flattening the edge of the object as important information about the object. The AHE and CLAHE methods produce noise with the most severe impact of the CLAHE method in homogeneous areas.
5. The visual quality with color sharpness resulting from the HE-GMP method with preserved edge areas and noise reduction in homogeneous areas makes perception clearer for defining hand gesture object areas against the background.

Thus, the HE-GMP method has improved visibility through color saturation, increased detail of important regions, contrast and brightness, color sharpness, and noise reduction qualities to capture better information than the AHE and CLAHE methods. The edge area of the hand gesture object is maintained to facilitate visual perception to distinguish the hand gesture object from the background. Measurement metrics use Mean Squal Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Average Mean Brightness Error (AMBE), and Entropy to show the transformation of the statistical data collected [35][36][37][38]. The statistical measurement metrics for input comparison, HE-GMP, AHE, and CLAHE are as follows.



MSE HE-GMP, AHE, CLAHE measurements



HE-GMP, AHE, CLAHE PSNR measurements

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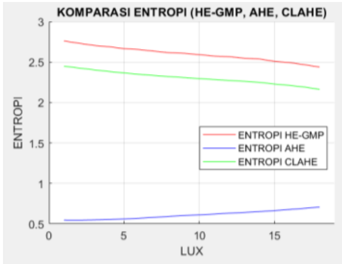
AMBE measurements of HE-GMP, AHE, CLAHE



HE-GMP, AHE, CLAHE ENTROPY Measurement

Figure 10 HE-GMP, AHE, and CLAHE statistical metrics

The analysis of measurement metrics in the performance comparison of the HE-GMP evaluation method with AHE and CLAHE is as follows.

1. The MSE measurement used to assess the difference between the input image and the processed image provides information on how much the visual quality of the hand gesture image has increased. The HE-GMP method has shown a more significant difference in improving the visibility of input images compared to the AHE and CLAHE methods.
2. PSNR measurements to assess distortion using the ratio between input and output images show that the HE-GMP method experiences more distortion than the AHE and CLAHE methods.
3. AMBE measurements to assess the increase in brightness of a visual image referring to grayscale level with the results of the HE-GMP method are better than the AHE and CLAHE methods.
4. Entropy measurements are used to assess visual image irregularities which provide information on the complexity of pixels with varying intensities that form regions in the visual image. The results obtained by the HE-GMP method are more complex, showing many variations in pixel intensity through more detail and texture when compared to the AHE and CLAHE methods.

Thus, statistical information on the results of MSE, PSNR, AMBE and Entropy measurements can provide an assessment of the HE-GMP method to improve visual quality more significantly and more effective when compared to the AHE and CLAHE methods for hand gesture image input with extreme lighting in the range of 1 to 18 lux. In terms of visual perception, the HE-GMP method has been able to provide important evaluation information on the edges of images with high contrast to maintain and reduce noise in homogeneous areas. Improving the visual quality of the HE-GMP method has improved the quality of information which gives good hope for machine learning to be captured better.

Comparison results of HE-GMP, AHE-GMP and CLAHE-GMP

The evaluation method using GMP (Gaussian Filter, Median Filter, and Prewitt Edge Detection) is considered to be able to improve the visibility of the HE method in low lighting. However, a comparative evaluation of visual quality improvement on other histogram-based methods such as AHE and CLAHE was used to validate the robustness of improving the visibility of the HE method with the GMP method with the following results.

Input (Lux 1)

HE-GMP (Lux 1)

AHE-GMP (Lux 1)

CLAHE-GMP (Lux 1)

Figure 11 Visual comparison of HE-GMP, AHE-GMP, and CLAHE-GMP

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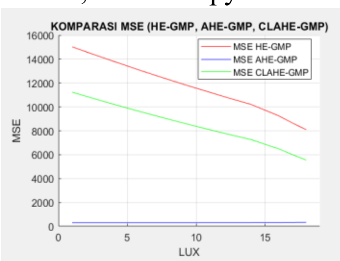
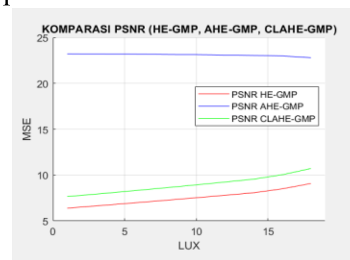
Comparative visual analysis of visual image quality improvement methods to assess the extent to which the HE-GMP method has succeeded in improving image quality. In addition, the effectiveness of visual image enhancement achieves its functional purpose of improving the quality of information.

1. Improving the visual quality of the HE-GMP method obtains fine details in a homogeneous area, the sharpness of the outline can be maintained which makes the object clearer, the contrast between the object and the background becomes more prominent, the visual brightness of the image can show more visual details. The visual enhancement of the GMP evaluation method is better in clarity, sharpness, contrast and brightness in improving the visibility of the HE method when compared to improving the AHE and CLAHE methods.
2. HE-GMP method pixel evaluation with preservation of detail in areas with high contrast, while noise reduction in homogeneous areas can provide a cleaner impact so as to avoid the appearance of new artifacts. The HE-GMP evaluation method improves visibility when compared to the AHE-GMP and CLAHE-GMP methods which cannot provide precise evaluations in the edge areas of objects.
3. The color balance of the HE-GMP method with high saturation means that hand gesture objects when displaying the alphabet according to SIBI can be recognized easily. Meanwhile, the AHE-GMP and CLAHE-GMP methods even with sufficient visibility, a lot of valuable information such as edges is lost.

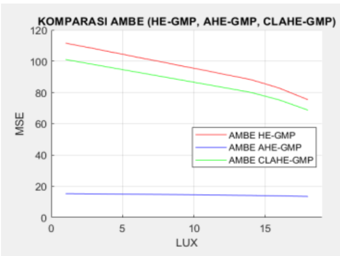
Thus, the GMP evaluation method is more effective in increasing the visibility the Histogram Equalization method achieves The aim is to improve the quality of information when compared with the AHE and CLAHE evaluation methods. However, quantitative analysis with measurement metrics MSE, PSNR, AMBE, and Entropy with the following comparison.



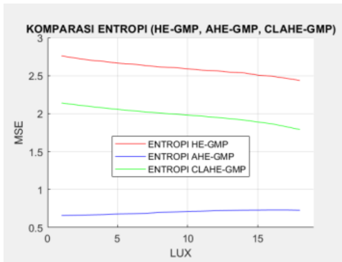
Grafik MSE HE-GMP, AHE-GMP, CLAHE-GMP



Grafik PSNR HE-GMP, AHE-GMP, CLAHE-GMP



Grafik AMBE HE-GMP, AHE-GMP, CLAHE-GMP



Graph Entropy HE-GMP, AHE-GMP, CLAHE-GMP

Figure 12 Comparison chart of measurement metrics

Based on a comparison of MSE, PSNR, AMBE and Entropy measurement metrics, it was found that the results of the GMP evaluation method using the HE (Histogram Equalization) method were more significant in improving the visual quality of hand gesture images with low lighting of 1 lux to 18 lux when compared with the AHE and CLAHE methods. The comparison results of these measurement metrics have supported visual analysis to determine the robustness of the HE-GMP method in improving

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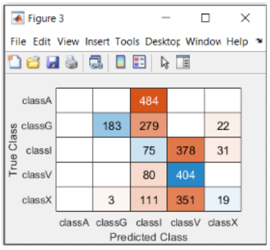
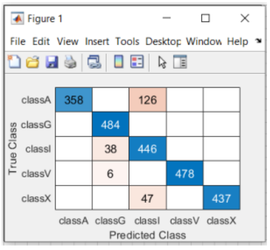
the visual quality of hand gesture images. It is hoped that this formulation will improve the performance of the CNN method in processing visual hand gesture input with low lighting.

The influence of the HE-GMP method on CNN performance

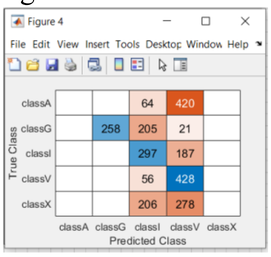
Testing to analyze the contribution of increasing visual image quality to CNN performance to complete hand gesture pattern recognition tasks. In this case, CNN performance uses option settings consisting of epoch 10, data validation 0.1, learning rate 0.2, sgdm model, 3 layers, fully connected 5 classes, and 5 classes of training data consisting of 520 visual data. Test scenario with comparison of visual input with low lighting, visual improvement of the HE-GMP, AHE-GMP, and CLAHE-GMP methods at lighting from 1 to 18 lux.



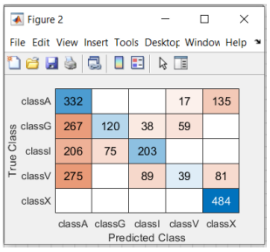
Lighting test data from 1 to 18 lux



Data test HE-GMP



Data test AHE-GMP



Data test CLAHE-GMP

Figure 13 Comparison of confusion metrics

Meanwhile, training progress shows model accuracy and loss in low lighting test scenarios, visual improvements of the HE-GMP, AHE-GMP, and CLAHE-GMP methods with visual lighting test data from 1 to 18 lux.

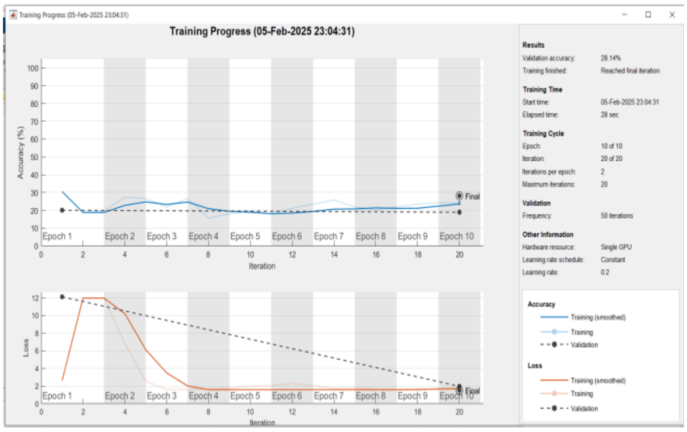


Figure 14 Training progress accuracy and loss of low lighting visual data input

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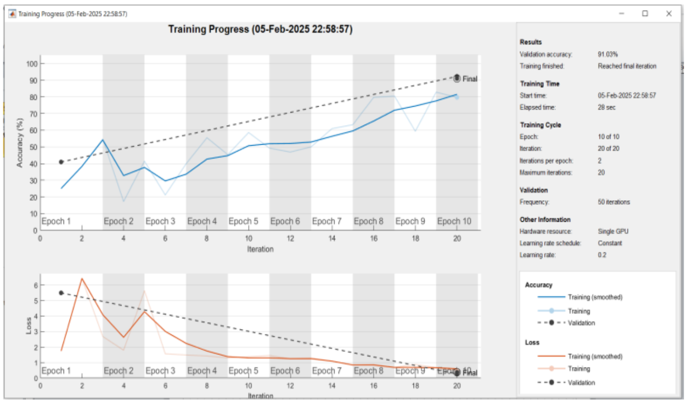

Figure 15 Training progress accuracy and loss of HE-GMP visual data input

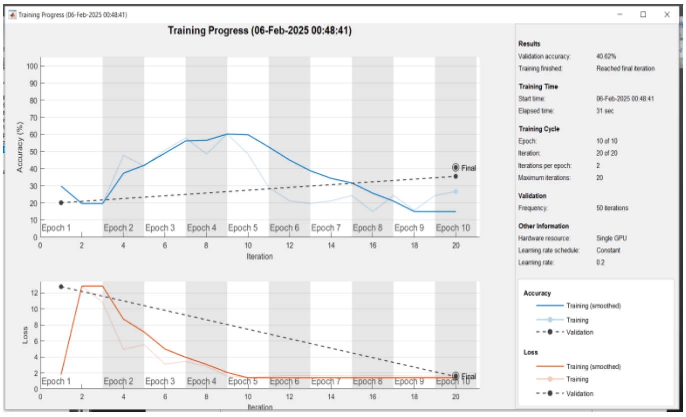

Figure 16 Training progress accuracy and loss of AHE-GMP visual data input

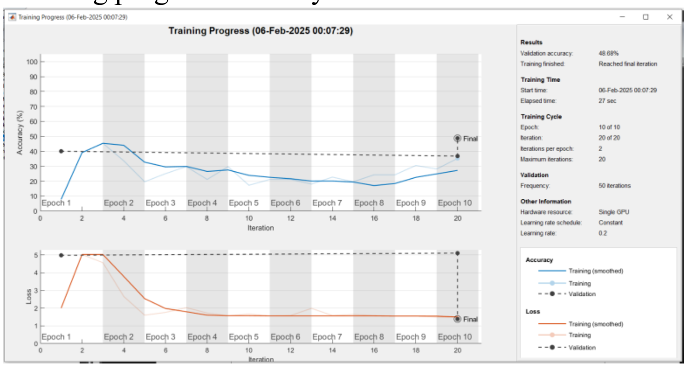

Figure 17 Training progress accuracy and loss of CLAHE-GMP visual data input

Comparison of CNN test processing accuracy with visual enhancement of low lighting data from 1 to 18 lux HE-GMP, AHE-GMP, and CLAHE-GMP methods.

Table 1 comparison of accuracy

Model	Accuracy	Low lighting - CNN	Improvement
HEGMP - CNN	91.03%	28.14 %	62.89 %
AHEGMP - CNN	40.62 %	28.14 %	12.48 %
CLAHEGMP - CNN	48.68 %	28.14 %	20.54 %

Based on increased accuracy with a contribution of HE-GMP of 62.89%, AHE-GMP of 12.48%, and CLAHE-GMP of 20.54%. Where, the most significant improvement is the HE-GMP method with better hand gesture image visibility which can provide clearer information, color transformation, area detail,

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contrast impact, brightness, noise and color sharpness thereby increasing CNN's ability to recognize objects more accurately.

b. Discussion

Improving visual quality using the HE-GMP method is more effective and significant in clarity, sharpness, contrast, and brightness when compared to improving the AHE-GMP and CLAHE-GMP methods. In addition, the pixel evaluation method HE-GMP provides detail preservation in areas with high contrast and reduces noise in homogeneous areas. The high color saturation of the HE-GMP method means that hand gesture objects displaying the alphabet according to SIBI can be easily recognized. However, in situations that may occur in reality with extreme lighting, not only low light can cause blurry information, high lighting can cause blurred information. Visual input with normal lighting does not require an evaluation of the increase in visual quality of the image which can be classified using grayscale level calculations. So, the functionality of the HE-GMP method can improve the visual quality of various lighting characters to improve the quality of information with extreme low and high lighting. Improved image visibility has contributed to more accurate CNN recognition.

CONCLUSION

The research which aims to increase the visibility of hand gesture images with low lighting involves 5 classes, each class consisting of 520 visual data. The test results show that the HE-GMP method has shown its contribution by increasing CNN accuracy by 62.89 %.

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