Application of Contrast Enhancement Method on Hip X-ray Images as a Media for Detecting Hip Osteoarthritis

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***Abstract*—Image enhancement is one of the most important areas that is being developed in the field of image processing technology. Image contrast enhancement can significantly improve the perception of the digital image itself. X-ray images are crucial in assisting physicians in the formulation of treatment decisions based on diagnostic information. Contrast enhancement techniques, including Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and CLAHE with double Gamma Correction (CLAGAMTWO), have been utilized on 30 distinct image datasets. Among the three employed methods, the CLAGAMTWO approach yields the optimal values of SSIM = 0.850 and CNR = 0.773. CLAHE has superior performance with an Entropy value of 7.099. CLAGAMTWO is the superior approach overall, as evidenced by the average metric value, yielding optimal picture quality in visual structure (SSIM), information detail (Entropy), and crisp contrast with little noise (CNR).**

Keywords—X-ray; image enhancement; digital image; image processing; grayscale image

I. Introduction

Image enhancement is one of the most important areas that is being developed in the field of image processing technology. This effectively delivers visual picture enhancement effects and image clarity, both of which are beneficial for subsequent processing and analysis on the computer [1], [2]. Contrast enhancement is critical for improving visual quality in computer vision, pattern recognition, and digital image processing. Low contrast in digital or video images can be produced by a number of causes, including operator inexperience and inadequate imaging equipment. Reduced contrast quality can also be caused by unfavorable environmental variables in the filmed image, such as lack of sunlight or indoor lighting, among others [3]. Articular cartilage and the structures supporting it are vulnerable to deterioration in the degenerative joint condition known as osteoarthritis [4], [5]. X-ray images are crucial in assisting physicians in the formulation of treatment decisions based on diagnostic information [6]. Plain radiology images or X-ray images are one method of determining the condition of the bones. Changes in the skeleton, structure, density, bone deformities, and narrowing of the articular space between adjacent bones can be observed through the use of X-ray images [7], [8], [9]. The low contrast issues in X-ray images of certain intricate components hinder the complete representation of structural information [10]. Consequently, low contrast poses a challenge in discerning elements inside a network area [11]. A possible solution to this problem is to improve the image [12].

Research conducted by study [13] Improve the accuracy of chest X-ray diagnosis by employing DF-GAN (Deep Fusion-Generative Adversarial Networks) data augmentation that is based on text-to-image interaction. The results that were obtained were a sensitivity value of 2.1%, a specificity value of 1.9%, and an area under the curve (AUC) value of 1.4%. Additionally, during training, overfitting was reduced on both sets of data.

Other research concerning the enhancement of chest X-ray images through the use of white balance and CLAHE (Contrast Limited Adaptive Histogram Equalization). The objective of the research is to enhance the precision of pneumonia diagnosis by leveraging the effectiveness of MobileNetV2 and contrast enhancement. It is important to mention that the model achieved the highest accuracy and lowest loss in 50 epoch testing for three-class classification (91.17% accuracy, 35.0% loss) and two-class classification (99.76% accuracy, 7% loss) [14].

Augmented chest X-ray image executed by [15] via deep contrast diffusion learning. The original input image undergoes a multilayer contrast-limited adaptive histogram equalization (CLAHE) method. The low and required contrast are subsequently extracted using CLAHE and transmitted to a residual learning network founded on a convolutional neural network (CNN). The suggested model exhibits a superior structural similarity index measure (SSIM) compared to alternative techniques.

A class of fractional differential equations can be employed for X-ray picture enhancement [16]. This work determines picture pixel energy utilizing the general k differential equation, which is founded on the K-caputo fractional differential operator (K-CFDO), to enhance visual quality and delineate the problem clearly. The investigation yielded the Brisque, Niqe, and Piqe values for chest X-rays as follows: (Brisque = 23.25, Niqe = 2.8, Piqe = 21.58) and for oral X-rays as follows: (Brisque = 21.12, Niqe = 3.77, Piqe = 23.49).

A strategy for image enhancement involves the utilization of HOG (Histogram Oriented Gradients) [17]. Besides its application in image augmentation, HOG can also be utilized for feature extraction in tuberculosis (TB) chest X-ray pictures. The model applied to chest X-ray images yielded a true positive ratio (sensitivity) of 97.4% and a true negative ratio (specificity) of 97.2%. The results indicate that the model accurately identifies both positive and negative tuberculosis cases.

This study will boost the contrast of X-ray hip images, utilizing the most effective way as a medium for identifying hip osteoarthritis (OA). The acquired X-ray image is in PNG format. Subsequently, the PNG image is transformed into grayscale, followed by an enhancement of the image contrast utilizing Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and a hybrid approach combining the CLAHE model with two Gamma Corrections. The CLAHE method with two Gamma Corrections will hereafter be designated as CLAGAMTWO. The efficacy of enhancing picture contrast through the three techniques will be assessed utilizing SSIM (Structured Similarity Index Measure), Entropy, and CNR (Contrast-to-Noise Ratio).

II. Literature Review

Currently, digital images are frequently subjected to image contrast enhancement techniques. The perception of the digital image's visual quality can be considerably enhanced through the use of image contrast enhancement [18]. Currently, there are numerous methods of enhancing image contrast, including HE (Histogram Equalization), CLAHE (Contrast Limited Adaptive Histogram Equalization) and Gamma Correction.

A. HE (Histogram Equalization)

An effective histogram encompasses the complete spectrum of values on the gray scale. Histogram equalization is a well-established method for enhancing visual contrast, recognized for its simplicity and effectiveness [19], [20]. The horizontal axis of the histogram denotes the pixel count, while the vertical axis indicates the gray value. The histogram values are derived by quantifying the number of pixels corresponding to each grayscale value present in the image [21]. The fundamental objective of HE is to turn the global histogram equalization into a uniform distribution. Nonetheless, while each image possesses a distinct histogram, following histogram equalization, the pixel values are typically centralized within the midrange of the grayscale, resulting in considerable variations in the average brightness of the image. The typical solution to this issue involves dividing the histogram into two segments and individually equalizing the divided histograms [22].

Conventional histogram equalization can enhance visual contrast by extending the histogram to a specified range. For a given image, the image histogram $H(i)$ for intensity level i is obtained from the number of pixels n_i with intensity level i, which is defined as follows:

$$H(i) = ni \quad for\ i = 0,1,2, \dots (L-1) \tag{1}$$

Where L is the maximum range of gray levels (for 8-bit images it is 256, 0-255) [23]. Based on equation (1), the histogram is divided according to the number of pixels with a certain intensity (the total number of pixels in the image $n = \sum_{i=0}^{L-1} H(i)$) [23], [24]. This result is then used to calculate the probability $p_x(i)$ of pixel i (Eq. (2)) [25], which is then used to calculate the cumulative distribution function (CDF) at [Eq. (3)]. The CDF has a range of values 0-255, as the histogram distribution of the equalization [Eq. (4)] [24].

$$p_x(i) = p(x = i) = n_i/n \tag{2}$$

$$cdf_x(i) = \sum_{j=0}^{i} p_x\,(x = j) \tag{3}$$

$$h(v) = \text{round}\left(\frac{cdf(v) - cdf_{min}}{n - cdf_{min}}\right) \tag{4}$$

B. CLAHE (Contrast Limited Adaptive Histogram Equalization)

Contrast Limited Adaptive Histogram Equalization is a method employed for enhancing contrast in images, particularly in grayscale images [26]. This method's benefit is that it can boost the original image quality, particularly for grayscale photos which medical practitioners regularly apply for high-noise or interference-filled CT or X-ray shots. The CLAHE method concentrates on small segments of the image, referred to as tiles. The contrast of each tile is modified to ensure that the generated histogram for that area matches the specified histogram's shape. Bilinear interpolation links neighboring tiles. This approach is employed to enhance the visual smoothness of the tile combination [27]. The Contrast limited adaptive histogram equalization method can be defined as follows:

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{max} - 1)\right) \tag{5}$$

In Eq. (5) it is explained that β represents the limit value, then the variable M represents the area size, N represents the grey-level or grayscale value (256), α represents the clip factor which states the addition of the histogram limit with a value of 1 to 100. S_{max} is the maximum slope permitted.

C. Gamma Correction

Gamma correction [28] is frequently utilized in diverse image processing applications. The process necessitates a fixed parameter, typically represented by the symbol γ, which varies from 0 to 3 to enhance the input image. Gamma correction redistributes the gray levels of the image worldwide based on the set parameter. This solution is effective for underexposed or overexposed photographs, but may not be suitable for images affected by both issues [29]. The classical gamma correction is stated as follows:

$$L = 255 \left[\frac{I(x,y)}{255}\right]^{\gamma} \quad (6)$$

In Eq. (6), γ control the degree of image stretching. If $\gamma < 1$, then the overall brightness of the image increases, whereas if $\gamma > 1$, then the image becomes darker than the original image. In this investigation, researchers attempted to apply two Gamma corrections subsequent to the execution of CLAHE on the original image. This was done to enhance image contrast quality.

III. Material and Methods

The PC utilized in this study is a laptop including an Intel Core i7-12700H Processor, NVIDIA GeForce RTX 3070Ti 8GB GDDR6 Graphics with a TGP of 150W, and 16GB of memory configured as 2 x 8GB SO-DIMM DDR5-4800. The programming language employed for computing is Python. X-ray images of the hip joint were acquired from Kariadi Hospital Semarang following the procurement of a research permit with Ethical Clearance No: 535/EC/KEPK/FK-UNDIP/X/2023.

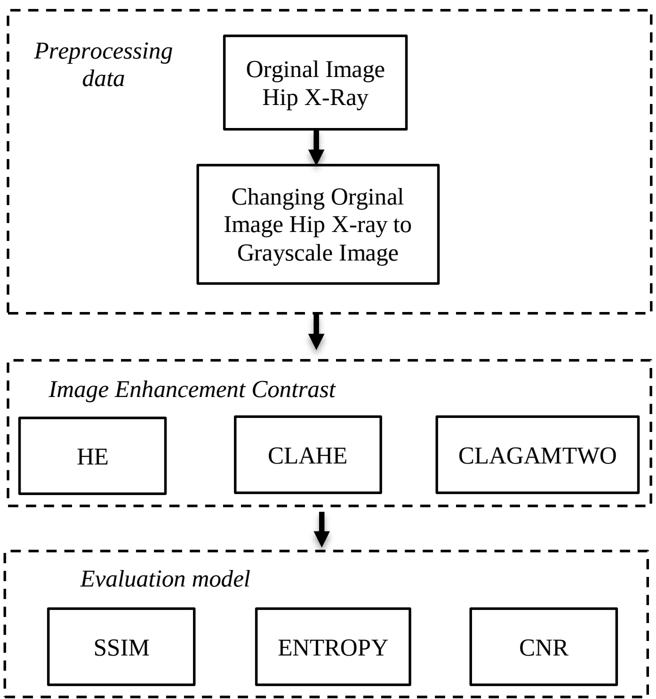
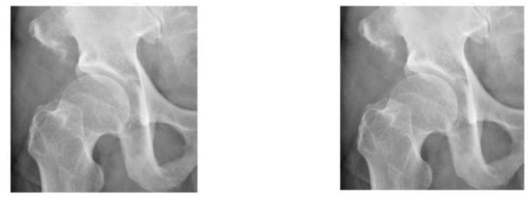


Fig. 1. Research process flow.

Fig. 1, illustrates the research methodology, which comprises multiple stages, beginning with data preprocessing that involves converting the original hip X-ray image to a grayscale format. Subsequently, the process advanced to the picture enhancement contrast phase employing three distinct techniques: HE (Histogram Equalization), CLAHE (Contrast Limited Adaptive Histogram Equalization), and CLAHE with dual Gamma Corrections (CLAGAMTWO). The final phase involves assessing the outcomes of enhanced picture contrast using the three ways utilizing SSIM (Structured Similarity Index Measure), Entropy, and CNR (Contrast-to-Noise Ratio). A comprehensive explanation will be provided in the subsequent sub-chapter:

A. Preprocessing Data

At this juncture, the original hip X-ray image acquired from the hospital is stored in PNG format [15] with dimensions of 1024 × 1024 pixels. After that the original hip X-ray image will be converted into a gray image so that it can be processed in the next stage. Subsequent to acquiring the hip X-ray image, the next step is to transform it into a grayscale image, as illustrated in Fig. 2. A grayscale image consists of a single color channel representing light intensity on a scale from black (minimum value) to white (maximum value). This procedure is conducted to streamline the data, decrease the information size, and remove color components that are typically unnecessary in medical image analysis.



(a) (b)

Fig. 2. Hip X-ray: (a) Original image and (b) Grayscale image.

B. Image Enhancement Contrast

In Fig. 3, the preprocessed picture will undergo contrast enhancement with HE (Histogram Equalization), CLAHE (Contrast Limited Adaptive Histogram Equalization), and CLAGAMTWO (CLAHE with two Gamma Corrections).

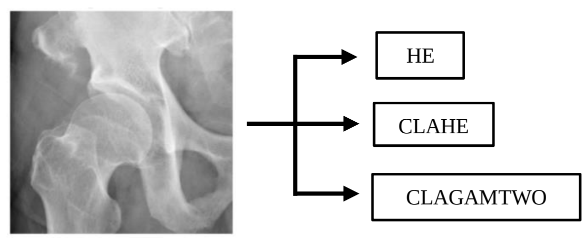


Fig. 3. Contrast enhancement of the original image using HE, CLAHE and CLAGAMTWO.

C. Evaluation Model

The contrast-enhanced image will be assessed using SSIM (Structured Similarity Index Measure), Entropy, and CNR (Contrast-to-Noise Ratio). SSIM [30] is a metric evaluated based on three primary components: brightness, contrast, and structure, as seen in Eq. (7).

$$SSIM\ (x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \quad (7)$$

In Eq. (7), l represents the luminance employed to assess the brightness comparison between two images. c is the contrast utilized to differentiate the spectrum between the most luminous and the most obscure areas of the two photographs. s is the framework employed to analyze the local luminance patterns of the two images in order to identify their similarities and differences. Consequently, α, β and γ are positive constants. The luminance, contrast, and structure of the image can be delineated individually by Eq. (8), Eq. (9), and Eq. (10).

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \quad (8)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \quad (9)$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\,\sigma_y + C_3} \quad (10)$$

Where μ_x and μ_y denote the local means, σ_x and σ_y represent the standard deviations, and σ_{xy} indicates the cross-covariances for images x and y, respectively. When $\alpha = \beta = \gamma = 1$, the index can be simplified utilizing Eq. (8)- Eq. (10), with the outcomes presented in Eq. (11).

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)\,(2\sigma_x\sigma_y + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)\,(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (11)$$

Entropy quantifies the complexity or diversity of information within an image. A greater entropy number indicates increased complexity and diversity of information inside the image. Entropy is determined by the distribution of pixel intensities in an image and is utilized to evaluate image quality or for pattern detection and segmentation [31]. The subsequent formula pertains to entropy:

$$H = -\sum_{i=1}^{n} p(i) log p(i) \quad (12)$$

In Eq. (12), H represents the entropy. $p(i)$ represents the probability of the occurrence of a pixel intensity i. n represents the quantity of intensity levels in the image.

CNR is a metric utilized to assess the discernibility of the contrast between high and low areas in an image, despite the interference of noise. In image processing, CNR assesses the clarity of a feature or detail in an image, free from interference by noise. A greater CNR signifies that the feature in the image exhibits increased contrast with the background, facilitating visibility [32]. The fundamental equation for CNR is as follows:

$$CNR = \frac{|S1 - S2|}{\sigma} \quad (13)$$

In Eq. (13), $S1$ dan $S2$ represent the average intensities in two distinct regions, with $S1$ denoting the feature of interest and $S2$ indicating the background area. Meanwhile, σ represents the standard deviation of noise inside the image.

IV. Result and Discussion

In the following section, we will show a comparison of the experimental data obtained from the various methods of picture contrast enhancement that were discussed earlier.

Fig. 4(a1) and 4(a2) depict the original photos alongside their corresponding histograms. Fig. 4(b1) and (b2) illustrate the outcomes of enhancing image contrast using histogram equalization [33]. The histogram's form reveals that the central region of the image exhibits an excessive brightness, while the edges display a pronounced darkness. The histogram illustrates a transformation in shape, initially centralized, now exhibiting an even distribution, with the dark blue hue confined to the right and left margins. Fig. 4(c1) and Fig. 4(c2) illustrate the outcomes of enhancing image contrast through Contrast Limited Adaptive Histogram Equalization [34]. The images exhibit increased contrast, uniformity, and prominence; however, they appear somewhat dark due to the significant enhancement in contrast, as evidenced by the histogram's shape. Fig. 4(d1) and 4(d2) illustrate the outcomes of augmenting picture contrast with CLAGAMTWO. In this part, the researcher employs a method that first applies contrast enhancement through CLAHE, followed by a further enhancement using gamma correction applied twice. The resulting image exhibits commendable contrast, appearing elevated internally and exhibiting a smoother upper surface.

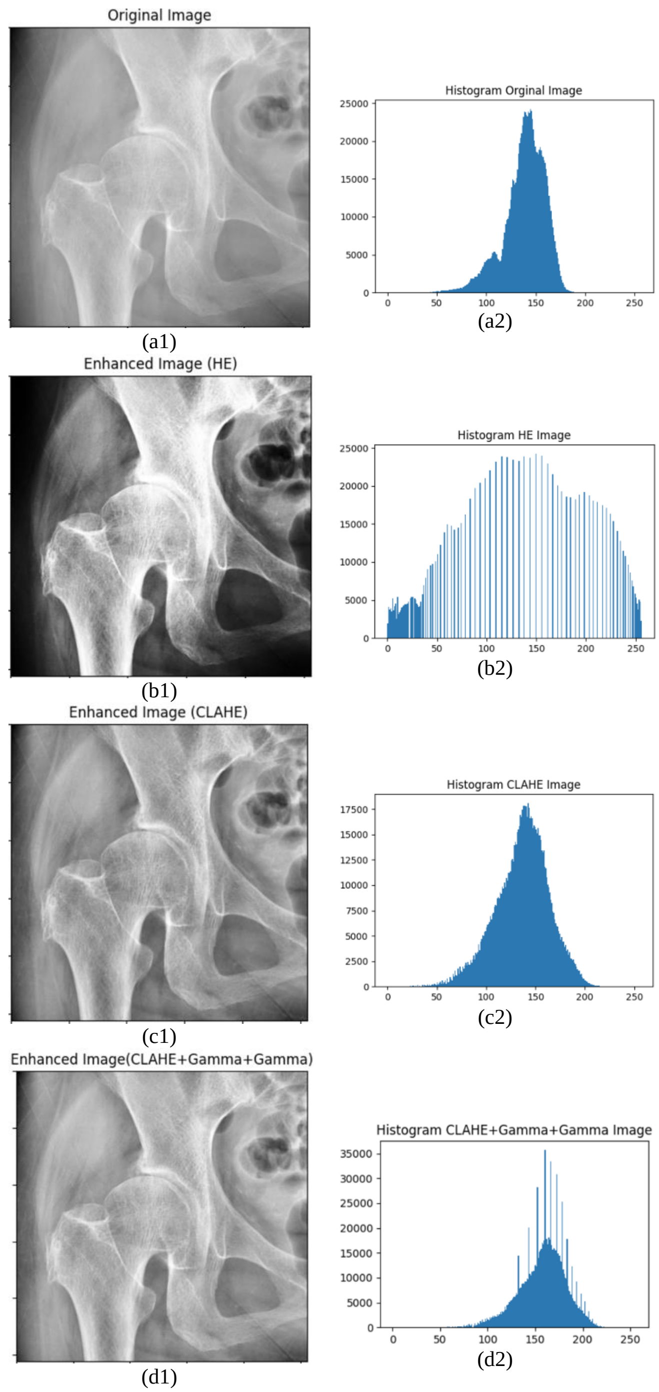


Fig. 4. Image contrast enhancement using HE, CLAHE and CLAGAMTWO.

Image quality evaluation is crucial in digital image processing applications. The researcher performed metric testing using SSIM (Structured Similarity Index Measure), Entropy, and CNR (Contrast-to-Noise Ratio) on several hip photos presented in Table I, notwithstanding the absence of observed and explained variance in visual quality in certain other photographs.

Table I presents only 10 image values from a total of 30 evaluated. The bold values in the table represent the optimal results achieved through the employed methods. The average SSIM value indicates that the CLAGAMTWO method achieves the highest value at 0.850, followed by CLAHE at 0.826, and HE at 0.644. The CLAGAMTWO method consistently yields image quality that closely resembles the original image, demonstrating its effectiveness in preserving visual structure. CLAHE demonstrates satisfactory performance however, it remains marginally inferior to CLAGAMTWO. In contrast, HE exhibits the lowest SSIM performance, suggesting a diminished capacity to preserve the similarity of image structure.

TABLE I. SSIM, ENTROPY AND CNR VALUES OF 10 SAMPLE IMAGE FROM 30 TESTED DATASETS

Image	Method	Image Quality Assessment		
		SSIM	Entropy	CNR
Image1	HE	0.597	6.238	0.414
	CLAHE	0.885	**6.782**	0.104
	CLAGAMTWO	**0.911**	6.548	**0.944**
Image2	HE	0.664	6.796	0.216
	CLAHE	0.805	**7.221**	0.166
	CLAGAMTWO	**0.845**	7.016	**0.576**
Image3	HE	0.579	6.506	0.569
	CLAHE	0.774	**7.218**	0.264
	CLAGAMTWO	**0.779**	7.045	**0.956**
Image4	HE	0.762	7.032	0.105
	CLAHE	0.834	**7.296**	0.001
	CLAGAMTWO	**0.854**	7.108	**0.607**
Image5	HE	0.609	6.634	0.458
	CLAHE	0.809	**7.222**	0.219
	CLAGAMTWO	**0.855**	6.995	**0.547**
Image6	HE	0.599	6.507	0.623
	CLAHE	0.799	**6.996**	0.319
	CLAGAMTWO	**0.801**	6.822	**1.085**
Image7	HE	0.647	6.542	0.297
	CLAHE	0.849	**6.885**	0.039
	CLAGAMTWO	**0.865**	6.702	**0.909**
Image8	HE	0.663	6.660	0.054
	CLAHE	0.847	**7.132**	0.048
	CLAGAMTWO	**0.875**	6.927	**0.742**
Image9	HE	0.614	6.525	0.254
	CLAHE	0.813	**7.091**	0.170
	CLAGAMTWO	**0.854**	6.881	**0.753**
Image10	HE	0.713	6.738	0.056
	CLAHE	0.848	**7.154**	0.035
	CLAGAMTWO	**0.862**	6.941	**0.613**
Average		**0.850**	**7.009**	**0.773**

For the greatest average entropy value CLAHE (7,099) was obtained, followed by CLAGAMTWO (6,944) and HE (6,617). The CLAHE approach excels in keeping detailed information in the image, demonstrating that CLAHE is more effective in improving the amount of detail. CLAGAMTWO is in second place, displaying pretty high performance in keeping detail, although lower than CLAHE. HE displays the lowest entropy performance, indicating that this method is less able to keep picture detail optimally.

The CLAGAMTWO method once again demonstrates the highest performance in the average CNR measurement, with a value of (0.773), which significantly surpasses CLAHE (0.136) and HE (0.305). CLAGAMTWO is an optimal method for generating high-quality images, as it significantly enhances contrast with minimal noise. The efficacy of CLAHE in enhancing CNR is significantly lower, and HE is also not optimal in this regard, despite being slightly better than CLAHE.

V. CONCLUSION

The CLAGAMTWO method is the most effective method in terms of visual structure (SSIM), information detail (Entropy), and distinct contrast with low noise (CNR) based on the average of the metric values. The CLAHE method is superior in terms of maintaining information detail (Entropy), but it is less effective in terms of increasing CNR when compared to CLAGAMTWO. In contrast to CLAHE and CLAGAMTWO, HE is the method with the lowest performance in all metrics, and as a result, it is not as recommended for enhancing image quality. This demonstrates that the CLAGAMTWO method, as proposed by the researcher, is the most effective method for enhancing the quality of the overall image in terms of visual structure, information detail, and distinct contrast with low noise. The outcomes of this image contrast enhancement will be employed as a diagnostic tool for hip OA in the future. For future work, it may implement a novel deep learning-based methodology, incorporate additional evaluation metrics, and expand the dataset.

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