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RESEARCH ARTICLE OPEN ACCESS

A BIMODAL TECHNIQUE FOR ENHANCEMENT OF PICTURE QUALITY OF MEDICAL IMAGES

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ABSTRACT

Medical images are useful for diagnosis of medical disorder in human body. Image enhancement has received significant attention in the literature in a bid to help medical personnel in ascertaining the cause of ailment in human body. Conventional techniques for enhancing medical images suffer from over contrast enhancement, noise and poor picture quality. As a result, this work proposes a bimodal technique that combines Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) for improving the picture quality of medical images. The performance of the proposed model in enhancing the picture quality of gray scale X-ray, Computed Tomography (CT) and Magnetic Resonance Image (MRI) images is compared with HE and CLAHE. It is observed that the proposed bimodal technique performs better than HE and CLAHE in all images used as candidates of investigation. It produces better picture quality and better structural quality than HE and CLAHE. It is found that the proposed model exhibits 59% picture quality while HE and CLAHE, respectively, exhibit 11% and 30% picture qualities.

I. INTRODUCTION

In medical profession, medical images assist health personnel in disease diagnosis with a view to providing comprehensive report about an ailment in the human body. Poor quality medical image may be difficult to examine by the medical person and may lead to wrong diagnosis of the ailment in the internal structure of the body. The presence of noise in medical images hides the essential features which may cause inaccurate diagnosis of medical disorder [1]. In essence, a clear image devoid of noise and artefact is the foundation upon which an accurate diagnosis of medical ailment is built. Image enhancement concerns with increasing the visual appeal of an image by heightening the contrast or brightness and the picture quality of the image [2]. Various traditional methods have been proposed in the literature for improving the contrast content, increasing the picture quality and removing the noise in medical images in a bid to improve their visual representation. These methods include Histogram Equalization (HE) [3] and its variations [4-7], Adaptive Histogram Equalization (AHE) and its variations [8], Contrast Limited Adaptive Histogram Equalization (CLAHE) [9].

Others are Unsharp Masking (UM), sigma filtering, Logarithmic Transformation (LT), wavelet transform and discrete wavelet transform [10], [11], spatial domain methods such as Median filter, Weiner filter [12], fuzzy logic and Fuzzy inference models, Compressed Sensing (CS) methods and machine learning techniques etc. These techniques have been deployed by researchers with mixed performance and varying degree of success. Zhu et al. [13] proposed wavelet transform for enhancing contrast of X-ray images. Zaafouri et al. [14] proposed UM for brightening the dark area of human facial image where high pass filter was used to reduce the noise. Bilcu and Vehvilainen [15] combined UM and sigma filtering for contrast enhancement and removal of noise. Qiu et al. [2] introduced a method based on convolution neural network and frequency band broadening for enhancement of quality of medical images. Mirza et al. [7] utilized different versions of HE for increasing the quality of CoVID-19 Computed Tomography (CT) images. Sarath and Sreejiths [16] employed Fuzzy logic and homographic filtering for enhancement of visual quality of medical image. Agarkar [17] employed Fuzzy logic to enhance the picture quality of image in submarines and sea while Sharma and Bhatia [18] deployed Fuzzy logic for contrast enhancement in common images. These methods have inherent drawbacks which limit their performance. Though HE and UM enhance the brightness level of the images, the noise in the image is also increased in the process. HE produces images with too much lightening (over contrast) effect while AHE suffers from slow speed and noise. Though CLAHE limits noise level in the image, its contrast level is low. Fuzzy logic is poor when it is deployed to enhance images taken from crowded area. Convolution neutral network enhancement of image may lead to deterioration or distortion in the quality of the image.

Moreover, a number of hybrid models have also been presented by researchers [19],[20] that combined the characteristics of conventional enhancement techniques. These hybrid models require greater amount of computational effort for implementation. Hence, this work introduces a bimodal technique that requires less computational time. It combines the features of HE and CLAHE for enhancing the visual appeal of medical images. While HE is utilized to increase the contrast level in images, CLAHE on the other hand limits the noise level in the image and overly high contrast effect of HE.

II. MATERIAL AND METHODS

II.1 DATASETS

The dataset employed in this study consists of several X-ray, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI) images which are sourced from the public repositories. The sourced images are preprocessed by resizing them to 255×255 pixels in order make them compatible with the models considered as candidate examples of enhancement.

II.2 HISTOGRAM EQUALIZATION (HE)

Histogram equalization is usually employed to increase the brightness or contrast of image. It transforms the pixel value of image into image of uniform distribution. It is useful in images with overly dark area by uncovering the hidden details.. The grayscale distribution of an image assumes expression of the form

$$h(f_n) = d_n \tag{1}$$

where f_n is the nth gray level with $0\leq n \leq L-1$, in which, L is the total number of gray levels in the image, d_n represents the number of pixels in the image with a grayscale value of f_n. Thus, the probability density of the histogram equalized image can be expressed by

$$P(f_n) = \frac{d_n}{N} \tag{2}$$

in which N represents the total number of pixels in the image, and $P(f_n)$ denotes the proportion of the total number of pixels in the image that has n-th grayscale level. Histogram equalization produces an enhanced image by applying histogram to the entire image via cumulative distribution function expressed by

$$T(f_i) = \sum_{i=1}^{n} P(f_i) = \sum_{i=1}^{n} \frac{d_i}{N} \tag{3}$$

In eq. (3), the input image is mapped into entire range given by $[f_0, f_1, \ldots, f_{L-1}]$ for which cumulative distribution function serves as a transform function [4].

II.3 CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Unlike HE that works on the entire image, CLAHE divides the original image into a number of non-overlapping images of equal sizes. It operates on these non -overlapping small portions, otherwise known as tiles. The brightness of each tile is enhanced and adjacent tiles are combined using bilinear interpolation to prevent the creation of artificial boundaries. CLAHE limits the contrast level in homogeneous regions and in such a manner avoids increasing the noise level in the image. The following steps are implemented when using CLAHE to enhance medical images.

Step 1: Start

Step 2: Input X-ray, CT scan, and MRI images

Step 3: Determine the number of regions in images, dynamic range and clip limit

Step 4: Split the images into regions after padding

Step 5: Process each mapped region, and create gray level mapping

Step 6: Carry out interpolation of gray level mapping in order to aggregate CLAHE images

Step 7: Output enhanced image

Step 8: Stop

II.4 PROPOSED BIMODAL TECHNIQUE

The proposed method integrates the concept of HE and CLAHE for improving the visual appeal of medical images. It enhances medical image quality by leveraging on the strength of both techniques. Specifically, the proposed model utilizes HE to enhance brightness level of medical image while CLAHE is used to remove noise and reduce over contrast effect of HE. Thus, the overall visibility and quality are improved without the adverse effect of noise amplification. The steps followed when implementing the proposed technique are as follows:

Step 1: Input X-ray, CT scan, and MRI images

Step 2: Convert the input X-ray, CT scan, and MRI images into Gray level image.

Step 3: Apply HE on the input images to enhance the contrast of the image.

Step 4: Apply CLAHE on the Histogram Equalized images to reduce noise and over contrast enhancement resulting from HE.

Step 5: Output enhanced images.

Step 6: End

Figure 1 illustrates the block diagram for implementing the proposed model

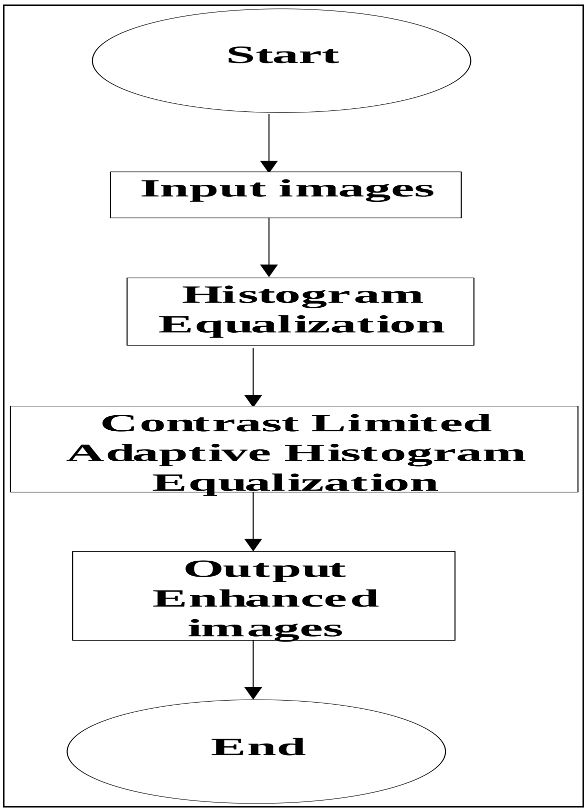


Figure 1: Illustration of steps for implementing the proposed hybrid model.
Source: Authors (2025)

III. RESULTS AND DISCUSSION

Here, simulation results were presented using HE, CLAHE and bimodal technique to enhance the quality of X-ray images showing bone femur with tumour, chest and knee, CT images depicting human kidney, human chest and human brain with tumor, and MRI images showing human lumber spine, human brain and human spine. The results were generated via simulation code written with python and implemented on Intel ® Corre ™ i5-6300U CPU @2.40GHz.. Figures. 2-4 illustrated the results of enhancement of X-ray images via HE, CLAHE and proposed (bimodal) method.

(a)

(b)

(c)

(d)

Figures 2: Simulation results for X-ray image showing bone femur with tumour, (a) original image (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors (2025)

(a)

(b)

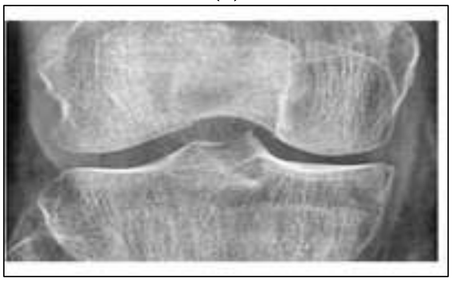
(c)

(d)

Figure 3: Simulation results for X-ray image showing Human chest, (a) original image, (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

(a)

(b)



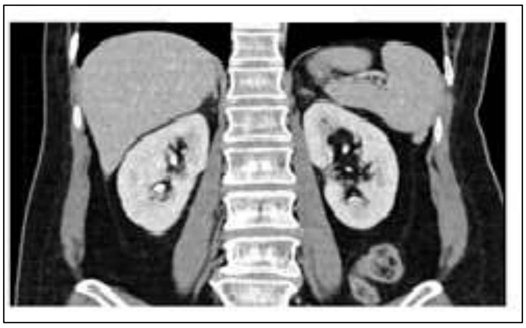
(c)

(d)

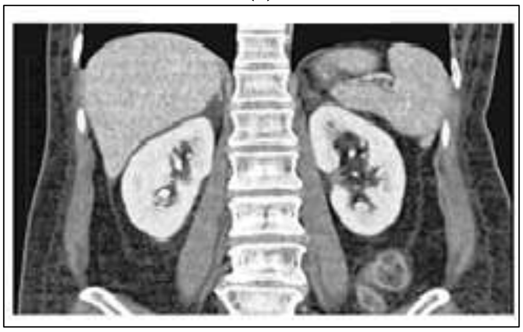
Figure 4: Simulation results for X-ray image illustrating Human knee, (a) original image, (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

It was found in Figures 2(b) and 4(b) that the brightness level of HE was higher than CLAHE and the proposed model. This was expected as HE has specific application in improving the contrast or brightness of an image. It was found in these images that HE produced images with too much light effect which covered internal structures of the images and which may hinder accurate clinical diagnosis. It was seen also that CLAHE images were a bit darker as seen in Fig 2-4(c). It was however observed that the proposed bimodal technique performed better than HE and CLAHE in enhancing the picture quality of X-ray images as seen in Figures 2-4(d), producing images with little light effect and moderate brightness that maintained important details of the image.

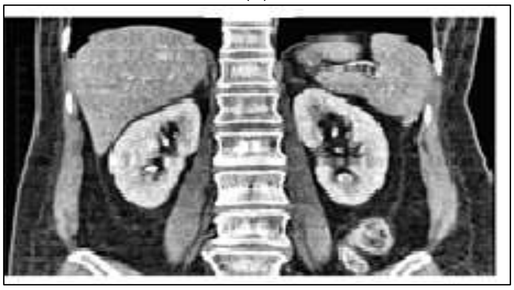
Figsures 5-7 illustrated the results of enhancement of CT images via HE, CLAHE and the proposed model.



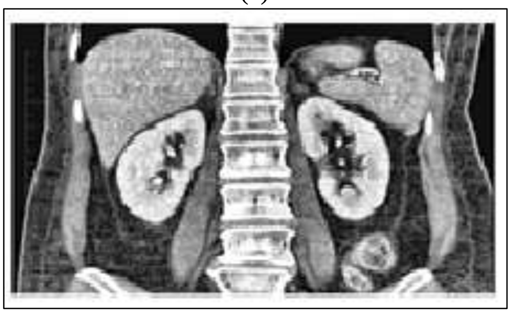
(a)



(b)



(c)

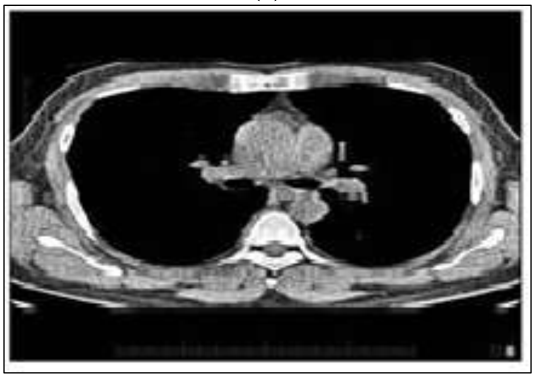


(d)

Figure 5: Simulation results for CT scan of human kidney, (a) original image (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

(a)

(b)



(c)

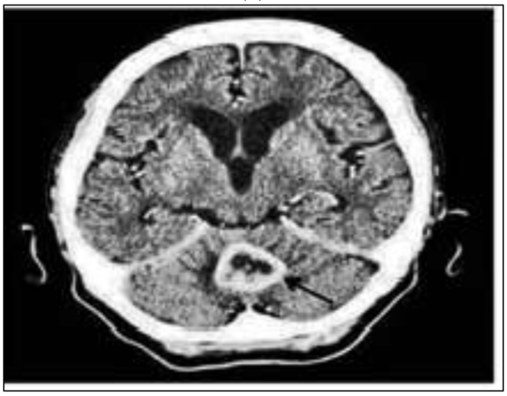
(d)

Figure 6: Simulation results for CT scan of Human chest, (a) original image (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

(a)

(b)

(c)



(d)

Figure 7: Simulation results for CT scan of human brain with tumor, (a) original image, (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

It was observed in Figures 5-7 that the proposed bimodal technique produced better CT images than other models considered. It revealed internal features and structures of CT images better than HE and CLAHE which made it a better technique for clinical diagnosis. In addition, Figures 8-10 compared the performance of the proposed model with HE and CLAHE for enhancing MRI images.

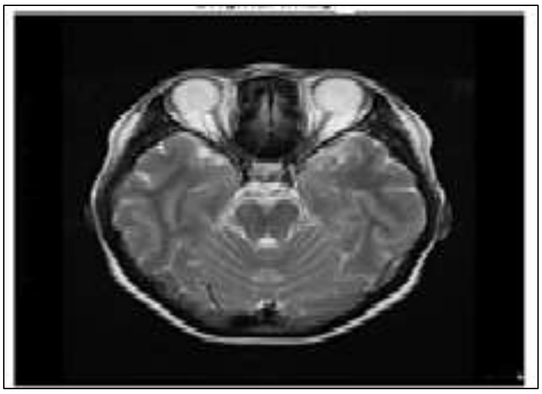
(a)

(b)

(c)

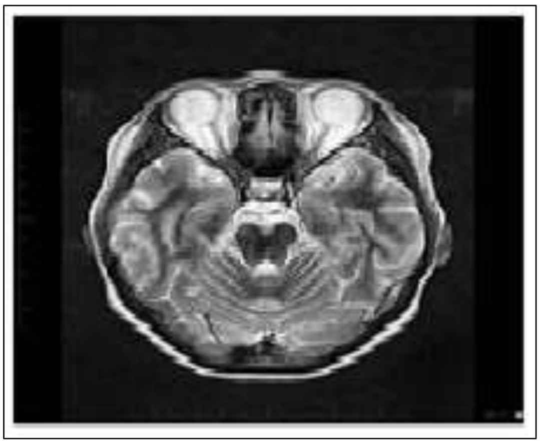
(d)

Figure 8: Simulation results for MRI image of a human lumbar spine, (a) original image, (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

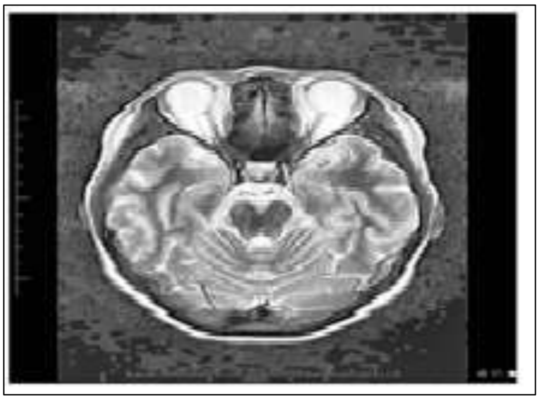


(a)

(b)



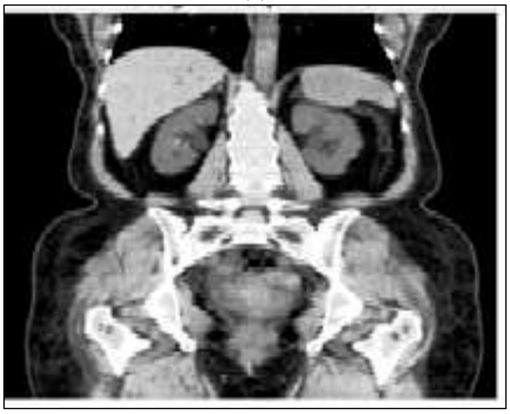
(c)



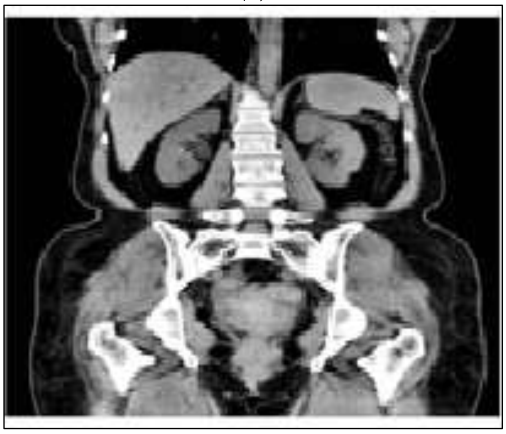
(d)

Figure 9**:** Simulation results for MRI image of human brain, (a) original image (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

(a)



(b)



(c)

(d)

Figure 10: Simulation results for MRI image of human spine, (a) original image, (b) HE, (c) CLAHE and (d) proposed (bimodal) model
Source: Authors, (2025)

It was observed in Figures 8-10 that HE produced images with too much light effect as revealed in Figure 8-10(b) which could obstruct important structural details of the image and consequently affect its performance for clinical diagnosis. In addition, it was found that CLAHE images were better than those produced by HE. It was however observed in Figures 8-10 that the proposed bimodal technique had the best picture quality as seen in Figures 8-10 (d).

Furthermore, nine medical personnel (radiologists) were contacted to assess the quality of enhanced images shown in Figs. 2-10 in terms of brightness level, structural quality and picture quality. The opinion results of this assessment were presented in Table 1.

Table 1: Results of subjective evaluation of HE, CLAHE and the proposed model

Image category	Performance indicators	HE	CLAHE	Proposed (Bimodal) model
Bone femur X-ray	Brightness	9	-	-
	Picture quality	-	6	3
	Structural similarity with original image	6	3	-
Chest X-ray	Brightness	3	3	3
	Picture quality	3	3	3
	Structural similarity with original image	3	3	3
Knee X-ray	Brightness	3	-	6
	Picture quality	-	6	3
	Similarity with original image	3	3	3
Human Kidney CT image	Brightness	9	-	-
	Picture quality	3	-	6
	Structural similarity with original image	3	6	-
Human chest CT image	Brightness	6	-	3
	Picture quality	-	3	6
	Structural similarity with original image	-	-	9
Human brain with tumor CT image	Brightness	-	6	3
	Picture quality	-	3	6
	Structural similarity with original image	3	-	6
Human lumber spine MRI image	Brightness	3	-	6
	Picture quality	-	3	6
	Structural similarity with original image	-	6	3
Human brain MRI image	Brightness	6	-	3
	Picture quality	-	-	9
	Structural similarity with original image age	-	-	9
Human spine MRI image	Brightness	6		3
	Picture quality	3	-	6
	Structural similarity with original image	-	3	6

Source: Authors, (2025)

It was seen in table 1 that 45 radiologists out of 81 possible outcomes, polled HE as producing the brightest image while 9 polled CLAHE as producing the brightest image. On the other hand, 27 out of 81 possible outcomes polled the proposed bimodal technique as generating the brightest image.

The corresponding percentage scores of the subjective evaluations by the medical personnel resulting from the analysis presented in table 1 were illustrated in Figure 11 which revealed the rating of the brighness level of all the models considered for investigation.

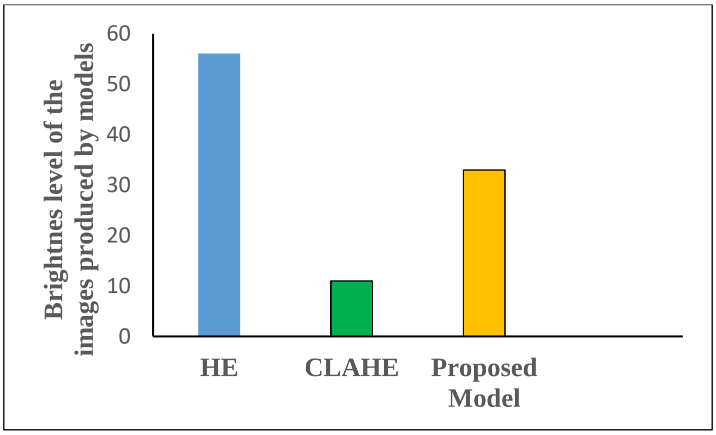


Figure 11: Comparison of brightness level of the models.
Source:Authors, (2025)

It was observed in Figure 11 that HE, CLAHE and the proposed model had the percentage scores of 56%, 11% and 33%, respectively. This implied that majority of the evaluators agreed that HE produced brighter images than others. This is in line with the expectation as the model has specific application in increasing the contrast or brightness level of images but suffer from over contrast enhancement [9]. Images in Figs 2(b), Fig. 8(b) and Fig. 9(b) supported this observation

It was observed in table 1 that the picture quality of the bimodal technique received highest poll with 48 medical personnel out of 81 preferring the model to other models. CLAHE received 24 polls while 9 medical personnel prefered HE to other models. Figure 12 presented the graphical representation of the rating of the picture quality of the images produced by different model.

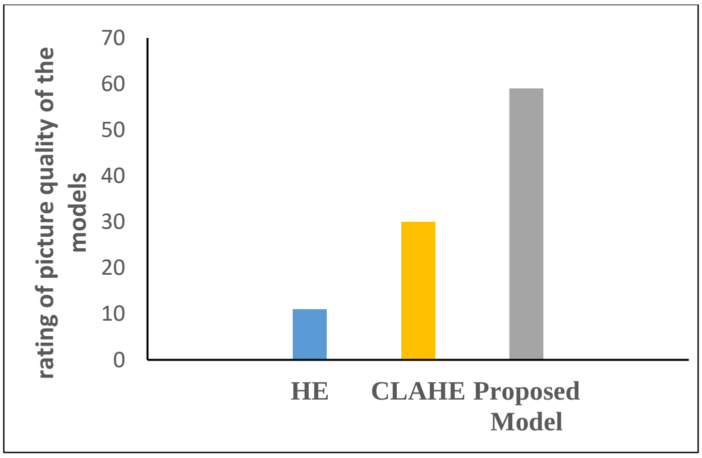


Figure 12**:** Comparison of picture quality of the models.
Source:Authors, (2025).

It was seen in Figure 12 that the picture quality scores of HE, CLAHE and the proposed model were 11%, 30% and 59%, respectively which indicated that the proposed bimodal technique had higher preference than other models. This implied that most evaluators prefered the picture quality of the model to others.

Also, in terms of structural quality when compared with the original image, 39 evaluators indicated that the proposed bimodal technique had the best structural quality while 24 and 18 prefered CLAHE and HE, respectively. Figure 13 therefore compared the evaluators' rating of the structural quality of all the models when compared with original image.

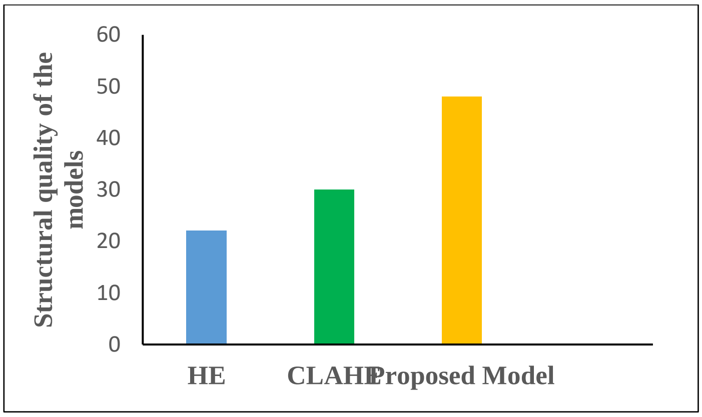


Figure 13: Comparison of the structural quality of the models
Source: Authors, (2025)

Figure 13 revealed that the proposed model had the percentage score of 48% while CLAHE and HE had 30% and 22%, respectively. This implied that majority of the evaluators chose the proposed model as having better structural quality than the other models.

IV. CONCLUSIONS

This work proposed a bimodal technique that combined Histogram Equalization (HE) and Contrast Limited Histogram Equalization (CLAHE) for enhancing the picture quality of medical images. The proposed method utilized the advantage of HE and CLAHE to enhance the picture quality and structural appearance of medical images by reducing the over contrast effect resulting from HE. Nine set of images comprising three modes of CT, X-ray and MRI images were sourced from different repositories and were used as candidates for enhancement.

The performance of the proposed model was compared with HE and CLAHE. It was found that the proposed model produced images with better picture qualities than the other models. Moreover, subjective assessment of the performance of these models by radiologists revealed that HE suffered from over enhancement which was in line with what has been previously reported in the literature. It was observed that the proposed model had better picture quality and better structural similarity with original image than other models considered for assessment and required less computational time when compared with hybrid models existing in the literature.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Akeem Abimbola Raji
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Investigation: Akeem Abimbola Raji, Oluwaseun Ibrahim Adebisi Olubunmi Adewale Akinola, and Ayoade Benson Ogundare

Discussion of results: Akeem Abimbola Raji, Oluwaseun Ibrahim Adebisi Olubunmi Adewale Akinola, and Ayoade Benson Ogundare
Writing – Original Draft: Akeem Abimbola Raji
Writing – Review and Editing: Oluwaseun Ibrahim Adebisi and Olubunmi Adewale Akinola
Resources: Akeem Abimbola Raji, Oluwaseun Ibrahim Adebisi, Olubunmi Adewale Akinola, and Ayoade Benson Ogundare
Supervision: Akeem Abimbola Raji, Oluwaseun Ibrahim Adebisi Olubunmi Adewale Akinola, and Ayoade Benson Ogundare
Approval of the final text: Akeem Abimbola Raji, Oluwaseun Ibrahim Adebisi Olubunmi Adewale Akinola, and Ayoade Benson Ogundare
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