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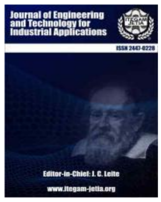

RESEARCH ARTICLE OPEN ACCESS

HYBRID UM-LT-AHE TECHNIQUE FOR CONTRAST ENHANCEMENT OF MEDICAL IMAGES

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ABSTRACT

This paper is concerned with combinations of un-sharp masking, logarithmic transformation and adaptive histogram equalization techniques to arrive at a hybrid method for enhancement different types of medical image' contrast. Motivation behind the hybridization is the need to have a contrast enhancement method that is not application specific and that can be deplored to several medical image enhancement. Four different types of medical images: X-ray, ultrasound, magnetic resonance and computer tomographic images are utilized in the evaluations of the proposed hybrid contrast enhancement method. As performance metrics, absolute mean brightness error, mean square error, peak signal to noise ratio and entropy are used. Comparative results both qualitative and quantitative, were conducted at the end of the research, and the proposed method out-perform other three (CLAHE, Fuzzy-based and Wavelet Transform-based) related selected methods in the field which used the same dataset in terms of testing accuracy. The enhancement quality of the proposed method was found to be satisfactory and can be used for any time of medical image, thus, the proposed hybrid technique produces better enhanced medical images from different medical image inputs.

I. INTRODUCTION

Image enhancement falls within the purview of computer vision with the aim of improving the visualization of asymmetric brightness level in images [1]. It is a technique widely utilized in medical image processing and analysis [2],[3] to modify a given picture such that desirable characteristics of the image are easier to recognize by automated image analysis systems [4] and aid accurate judgment from the image. Image enhancement represents one of the phases of digital image processing tasks, along with image detection, segmentation and classification [5]. The procedure of image enhancement encompasses a variety of approaches that geared towards improved image's aesthetic appeal, visual clarity and overall look of an image in order to facilitate easier extraction of its spatial characteristics [6]. In other word, through enhancement of an image, details of the image that are not readily visible in the original image right away become available. The need for the enhancement of an image may arise when the image data and the display system have different dynamic ranges, when the image is embedded with a lot of noise, or when the contrast is too low [4].

Image enhancement methods are divided into spatial domain-based and transformation domain-based approaches [5] - [6] Histogram Equalization (HE) is a frequently used spatial domain-based approach that produces a picture with a uniform distribution of intensity following equalization; however, if the histogram has high peaks, contrast is over-enhanced, resulting in a harsh and noisy image. Several other approaches have been used to address these shortcomings, including automatic image equalization using Gaussian mixture modeling [7], power-constraint contrast enhancements based on HE [8], and entropy maximization histogram modification for image enhancement [9], all of which were still deficient by causing a halo effect in high contrast areas [10]. In the transform-based approaches, one can find threshold transformation [11], log transformation [11], multi-scale retinex-based [12], image size dependent normalization [13], adaptive gamma correction-based algorithm [14], fractional order and directional derivatives [15], wavelet transform [16] and Non-

Subsampled Contourlet Transform (NSCT) [5]. Others are fuzzy logic-based and neuro-fuzzy method [11], [17].

A variety of apps provide a selection of photos with certain features, and the selection of augmentation techniques vary greatly based on particular requirements. The subject of this study is medical imaging. Globally, healthcare engineering is a significant and quickly growing field that includes illness prevention, diagnosis, treatment, and management as well as the maintenance and improvement of physical and mental health [18],[19]. In addition to diagnosing and treating diseases, medical imaging technologies are becoming more and more important for disease prevention, health screening, major disease screening, health management, early diagnosis, determining the severity of a disease, choosing a treatment plan, evaluating the effects of that plan, and rehabilitation [19]–[21]. As such, there has been a significant increase in the significance of medical imaging technology in healthcare delivery applications [19],[20].

Medical image enhancement has become standard practise due to its ability to improve different medical procedures, image-guided surgery, and illness detection and therapy [22]. Improving the clarity and quality of images is the goal of medical image enhancement, which also aims to improve the images' interpretability for human viewers. X-rays, Computed Tomography (CT), ultrasound, and Magnetic Resonance Imaging (MRI) are among the frequently used medical imaging [5]–[6], with the latter being especially helpful in the diagnosis of cerebrovascular diseases. The accuracy of doctors' diagnoses and treatments, where images of internal organs and human sub-systems are involved, is directly influenced by the quality of the images. This singular reason makes medical imaging an integral aspect of contemporary and modern medicine

II. THEORETICAL REFERENCE

Medical images are frequently bedeviled with effects of interference from sounds and electromagnetic sources, which often degrade the resultant image's quality. Furthermore, presence of noise and artifacts contribute uncertainty to the medical image in the form of ambiguous image segment homogeneity or ambiguous object-background contrast. These make segmentation and detection of contours and textures of the image very challenging [9].

A remapping technique called contrast enhancement modifies the image intensity distribution so that the entire image intensity range can be used [23]. This method has been used to improve the visual quality of photos, highlight important information, and highlight image aspects. For medical pictures, a variety of contrast enhancement techniques have been put forth. The Bihistogram Bezier curve contrast enhancement method was presented in [23], showing how well it works to emphasise important brain imaging features in low-resolution brain MR images [24]. A multimodal contrast enhancement strategy was proposed in [25] and successfully handled the problem of weak contrast in images of children's hand bones. In addition to the previously discussed techniques, the Hopfield Neural Network (HNN) is another way for image augmentation [26]. To ensure network stability throughout the training phase, this approach is said to have a few disadvantages [27], one of which is its propensity to converge to a fixed point [28]. Additionally, there could be a chance that the quality of the images decreases [29]. Notwithstanding these drawbacks, investigating various contrast enhancement techniques is still essential for developing the area of medical image enhancement and tackling particular problems related to various kinds of medical images.

NSCT technique introduced in [5] combined methods of adaptive thresholding and enhanced fuzzy set to meet the demands of medical image improvement. The fuzzy contrast function was improved through the adjustment of the normal inverse which was utilized in the creation of a new function for calculating the enhanced pixel gray membership. The new enhanced membership function together with the Laplace operator were used to improve the image details. The approach was able to boost the general contrast of an image, emphasize the features and contours of an image, and considerably improve the visual impression of an image; nevertheless, the algorithm's flexibility was ineffective. Other efforts to improve medical imaging include an approach to improving the visual look that makes use of the Bi-histogram Bezier Curve [23]. This technique focuses on improving MRI pictures that show a sudden leap in the knee. A different endeavour pertains to an altered iteration of the Hopfield Neural Network (HNN) methodology [30], which tackles the convergence issues linked to the conventional HNN approach. The goal of this update is to improve the HNN technique's overall efficacy in improving medical images. Additionally, a multimodal method has been investigated [6] that is intended for clinical imaging sensor applications. These varied methods demonstrate a dedication to honing procedures for a range of clinical settings and image types, and they highlight the continuous attempts to develop and improve in the field of medical image enhancement.

While those aforementioned methods and many others ensure improvement in the image contrast, there arises a problem of non-uniformity in enhancement and most importantly, over enhancement of certain portion of the image. There have been various modifications made to conventional histogram equalisation techniques in order to address the issue of over-enhancement. The contrast limited dynamic quadri-histogram equalisation [31], the minimum mean brightness error bi-histogram equalisation in contrast enhancement [32], the range limited weighted histogram equalisation (RLWHE) [33], the recursively separated weighted histogram equalisation (RSWHE) incorporating a normalised power law function [34], and the Recursive Mean-Separate Histogram Equalisation (RMSHE) intended for scalable brightness preservation [35] are noTab. among these techniques. The tendency towards over-enhancing in the final image remains a recurrent problem, even though these variations of the histogram equalisation (HE) technique have proven effective in producing high contrast enhancement and good brightness retention. Adaptive Gamma Correction with Weighted Distribution (AGCWD) is a revolutionary automated transformation approach that was developed [36] to solve the problems associated with RMSHE, RSWHE, and related techniques. To further address over-enhancement problems in medical image processing, the Triple Dynamic Clipped Histogram Equalisation based on Mean or Median (TDCHEM) approach [37] was put forth. The challenges presented by conventional histogram equalisation methods in medical image enhancement may be addressed by these creative approaches, which aim to achieve greater contrast while maintaining image quality. The two approaches AGCWD and TDCHEM are able to boost contrast and also prevent over-enhancement of images, however, none of them is able to retain brightness and preserve structures of images.

Several researches have been made in this area of contrast enhancements of medical images, various successes have been recorded and each technique with its identified shortcomings. Some of the shortcomings include the problem of over-enhancement, proper enhancement but brightness not preserved, some methods are not suiTab. for all types of medical images and so on. This study is primarily motivated by the shortcomings found in the previously described methods as well as the need for a low-complexity picture enhancing method. This work focuses on developing a hybrid algorithm for medical picture improvement that combines three different techniques: Un-sharp Masking (UM), Logarithm Transformation (LT), and Adaptive Histogram Equalisation (AHE). These three strategies were carefully chosen because they each have advantages over other alternatives in terms of robustness, low computational complexity, and short calculation times. By utilising the distinct benefits of each method, this hybrid strategy seeks to jointly address the issues raised by over-enhancing and computational complexity in medical picture enhancement.

III. MATERIALS AND METHODS

This study uses three different enhancing strategies in a cascaded manner. Un-sharp Masking (USM) is the first technique in this series, which is used to improve the image by sharpening edges and removing intrinsic blurring from the input medical image. Logarithm Transformation (LT) uses the output that is produced when USM is applied to the medical image. LT is specifically made to increase the brightness of the image's dark pixels, increasing its dynamic range. LT seeks to bring to light aspects that are buried inside the picture. The output is then passed into the Adaptive Histogram Equalisation (AHE) method after the LT step. AHE seeks to enhance the image's contrast even more. The planned tri-modal medical image enhancement strategy comes to a close with the final output of the AHE stage. The USM-LT-AHE medical image enhancement approach is the name given to this sequential process. These strategies were chosen because they have clear benefits over other approaches, such as being robust, efficient, and simple in terms of mathematical complexity.

A thorough block diagram is used in Fig. 1 to graphically represent the suggested hybrid UM-LT-AHE contrast enhancement technique. As shown in figure 1, the methodology is divided into five main stages: pre-processing (colour conversion), post-processing (colour conversion), Adaptive Histogram Equalisation (AHE), Logarithm Transformation (LT), and Un-sharp Masking (UM). The primary goals of this image processing approach are contrast enhancement and image de-blurring. The input image is specially de-blurred by the UM stage, and the contrast of the image is improved by the LT and AHE stages. We then emphasise each step of the proposed UM-LT-AHE medical image enhancement strategy, starting with the first image colour conversion. This methodical technique aims to solve issues with image quality and enhance both clarity and contrast in medical images.

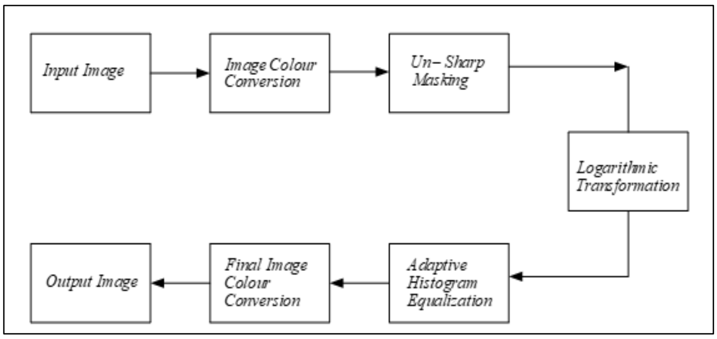

Figure 1: Block diagram of the proposed hybrid UM-LT-AHE method.
Source: Authors, (2024).

III.1 IMAGE COLOR CONVERSION

For the suggested hybrid UM-LT-AHE enhancement approach to be compatible and provide accurate colour rendering, two colour conversion stages must be included. Colour conversions are not required before the first processing steps or after the final output stages when the input is a grayscale image. However, colour conversion becomes an essential step when dealing with a colour image input. Prior to the Un-sharp Masking (UM) algorithm processing, the Red, Green, and Blue (RGB) components of the image are mapped into their equivalent Hue-Saturation-Value (HSV) on the input side. The output stage involves converting the processed image from the HSV mapping back to RGB equivalent using the Adaptive Histogram Equalisation (AHE) technique. The MATLAB environment facilitates the smooth execution of colour conversions for pre-processing and post-processing, with the rgb2hsv and hsv2rgb functions, respectively. Through these colour conversion steps, the suggested improvement method is made sufficiently flexible to handle both colour and grayscale images, offering a unified and uniform approach across many input conditions.

III.2 UN-SHARP MASKING

The Un-sharp Masking (UM) algorithm sharpens edges and areas with plenty of detail in a picture to highlight details that are otherwise hidden. This is accomplished by creating a corrective signal, which is basically an enlarged version of the input image's signal representation. A Laplacian filter, which has a negative centre coefficient, is used to generate the corrective signal. To recover the image's lost grey tones, this correction signal is then deducted from the original input image signal. Mathematically, the expression for the Un-sharp Masked input image at a pixel location (x, y) is represented as:

$$UM(x, y) = Original\ Image\ (x, y) Correction\ Signal(x, y) \quad (1)$$

In this equation, $UM(x, y)$ denotes the Un-sharp Masked pixel value at location (x, y), which is obtained by subtracting the Correction Signal at the same location from the corresponding pixel value in the original input image. This process results in an image that emphasizes fine details and enhances the overall sharpness of the edges within the original image.

The output image from UM stage that is fed into the input of LT stage is expressed as:

$$Y_{UM}(x, y) = I_o(x, y) + KI(x, y) \quad (2)$$

where $Y_{UM}(x, y)$ is the output image from the UM stage and K is a positive scaling factor that controls the level of achievable image de-blurring or sharpness level. The values for K is such that $0.2 \leq K \leq 0.9$ [38].

USM involves the following steps:

i. Get the input image that requires enhancement
ii. Generation of a blur copy of the input image using Laplacian of Gaussian (LoG) filter.
iii. Subtract blur copy from the input to give un-sharp masking image
iv. Multiplications of the un-sharp masking image by a fractional value "K"

Addition of the result in (iv) to the original image in (i).

III.3 LOGARITHMIC TRANSFORMATION

In the suggested enhancement scheme, the main goal of the Logarithm Transformation (LT) technique is to transfer the image's dark (or low) intensity values to brighter (or higher) values, increasing the visibility of features. Higher-intensity pixels are little impacted by the LT algorithm's application; instead, low-intensity pixels are mapped to high-intensity pixels. The expression for the logarithm transformation can be expressed mathematically as follows:

$$LT(x, y) = c.\log(1 + Original\ Image\ (x, y)) \quad (3)$$

Here, $LT(x, y)$ denotes the pixel value after the Logarithm Transformation at location (x, y) and c is a scaling factor. The logarithmic function $\log(1 + Original\ Image\ (x, y))$ is applied to the pixel values of the original image at the corresponding location. The addition of 1 in the logarithmic function helps avoid the issue of taking the logarithm of zero.

This transformation improves the contrast of the image overall by making details in the dark areas of the image more visible. The logarithmic function is a good choice since it preserves information in higher-intensity regions while extending the dynamic range of low-intensity values.

III.4 ADAPTIVE HISTOGRAM EQUALIZATION

The plot of the number of pixels n_k in an image against the intensity value k describes the image histogram, where $0 \leq k \leq 2^x - 1$ and x is the class unit of the image. In the context of this paper, 256 intensity levels are considered, resulting in a class unit of 8. This corresponds to an intensity value range between 0 (representing black) and 255 (representing white). For an image with a total number of pixels N the associated probability density function (PDF) is given:

$$P(k) = \frac{n_k}{N} \quad (4)$$

$P(k)$ is the probability density function at intensity value k
n_k is the number of pixels at intensity value k,
N is the total number of pixels in the image

The probability density function illustrates the possibility of coming across a pixel in the image with a certain intensity value. With 256 intensity levels in the provided context, the function characterises the distribution of pixel intensities throughout the image, offering important details about contrast, brightness, and general tonal qualities.

III.5 SUMMARY OF STEPS INVOLVED IN THE IMPLEMENTATION

The steps involved in the implementation of the proposed hybrid UM-LT-AHE contrast enhancement scheme for medical images:

1. Select the Type of Image:
   - Ascertain whether the input image is grayscale or colour.
2. Read Grayscale Pixel Values:
   - If the image is in grayscale, read each pixel's value.
3. Convert the RGB colour space to the HSV colour space if the image is coloured.
   - Examine the HSV's value component.
4. Sharp Masking Absence (UM):
   - As necessary, apply the Un-sharp Masking method to the results of steps (ii) or (iii).
5. Logarithm Transformation (LT):
   - Map the step (iv) output using a Logarithm Transformation mapping function.
6. Adaptive Histogram Equalisation (AHE):
   - Apply step (v)'s output to the Adaptive Histogram Equalisation with clipping.
7. Store Output (Grayscale):
   - Store the step (vi) output and move on to step (x) if the input image is grayscale.
8. Modify the Colour Image Value Component:
   - If the input image is coloured, use step (vi)'s result as the image's new V (value).
9. Combine H, S, and New V:
   - Combine the H and S components of the input image with the newly acquired V component from the previous step to create a new HSV colour space for the image.
10. RGB conversion:
    - Return the newly created HSV colour space from step (viii) to RGB colour space.
    - Keep the result stored.
11. Output Enhanced Image:

This is a version of the original input image that has been enhanced.

The developed hybrid UM-LT-AHE medical image enhancement approach was implemented using the MATLAB R2018a environment, which was set up on an HP EliteBook running Windows 10 with a core i5 processor, 64-bit architecture, and 4 GHz RAM. During implementation, a number of functions from the image processing toolbox were used, including rgb2hsv, hsv2rgb, imfilter, adapthisteq, and others.

A collection of sixteen test medical photos was used to assess how well the suggested UM-LT-AHE medical image enhancement method performed. These photographs cover a range of medical imaging modalities, such as ultrasound, X-ray, MRI, and CT scan images as shown in Table 1 and were taken from publicly accessible online databases. Both colour and grayscale photographs are included in the collection; each image format contributes four images.

Table 1: Descripption of images used for experiment.

Images	Ultrasound	X-ray	MRI scan	CT scan
(i)	multiple gestation	human elbow	cervical spine	gray scale abdominalcavity
(ii)	human kidney	human knee	human knee	healthy human heart
(iii)	human liver with gall bladder	human leg	human lung	brain tumor
(iv)	human liver	human toes	multiple fetal	color abdominal cavity

Source: Authors, (2024).

III.6 PERFORMANCE METRICS

By comparing its outcomes with existing methods from the literature, the suggested technique's performance in contrast enhancement is assessed using objective assessment criteria. For this, Absolute Mean Brightness Error (AMBE), Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and entropy are the four essential performance indicators used. When compared to the outputs of various contrast enhancement techniques in the literature, the suggested method is deemed superior if it produces an output image with the lowest AMBE, lowest MSE, highest PSNR, and highest entropy values.

Absolute Mean Brightness Error (MBE); the difference between the brightness level of the enhanced image and original image.

$$\boldsymbol{AMBE} = \mid E(y) - E(x) \mid \quad (7)$$

Where: $\boldsymbol{E(x)}$ = average intensity of input image; $\boldsymbol{E(y)}$ = average intensity of output image.

The output of this research was compared with those of other works using AMBE, the method yielding the least numerical value is adjudged best in performance in terms of brightness preservation.

Peak-Signal-to-Noise-Ratio (PSNR): is the evaluation standard of the reconstructed image quality, and is an important measurement feature. PSNR is measured in decibels. The higher the PSNR, the better the method.

$$PSNR = 10log_{10}\frac{R^2}{MSE} \quad (8)$$

Where $\boldsymbol{R} = \boldsymbol{2^{xbits}}$ which depends on image class

Entropy: This is a statistical measure of randomness that can be used to characterize the texture of an image. It is the measure of the content of an image. The higher the entropy, the better the method.

$$\boldsymbol{Entropy} = iP_i log_2 P_i \quad (9)$$

Where $\boldsymbol{P_i}$ is the probability that the difference between adjacent pixels is equal to $\boldsymbol{i}$.

IV. RESULTS AND DISCUSSIONS

Obtained simulation results from the proposed hybrid UM-LT-AHE method are compared with those from three other methods (CLAHE, Fuzzy and WT) in the literature, for image contrast enhancement.

What follows are the simulation results beginning with those of ultrasound images. The images in (a) are the original images before they were subjected to various enhancement techniques, (b)-(e) are the images after they have been enhanced with different enhancement methods; the Hybrid UM-LT-AHE, CLAHE, AHE and Fuzzy-based methods respectively. The level of enhancement on the images can be visualized in the output as shown in the Figure 2 to 5.

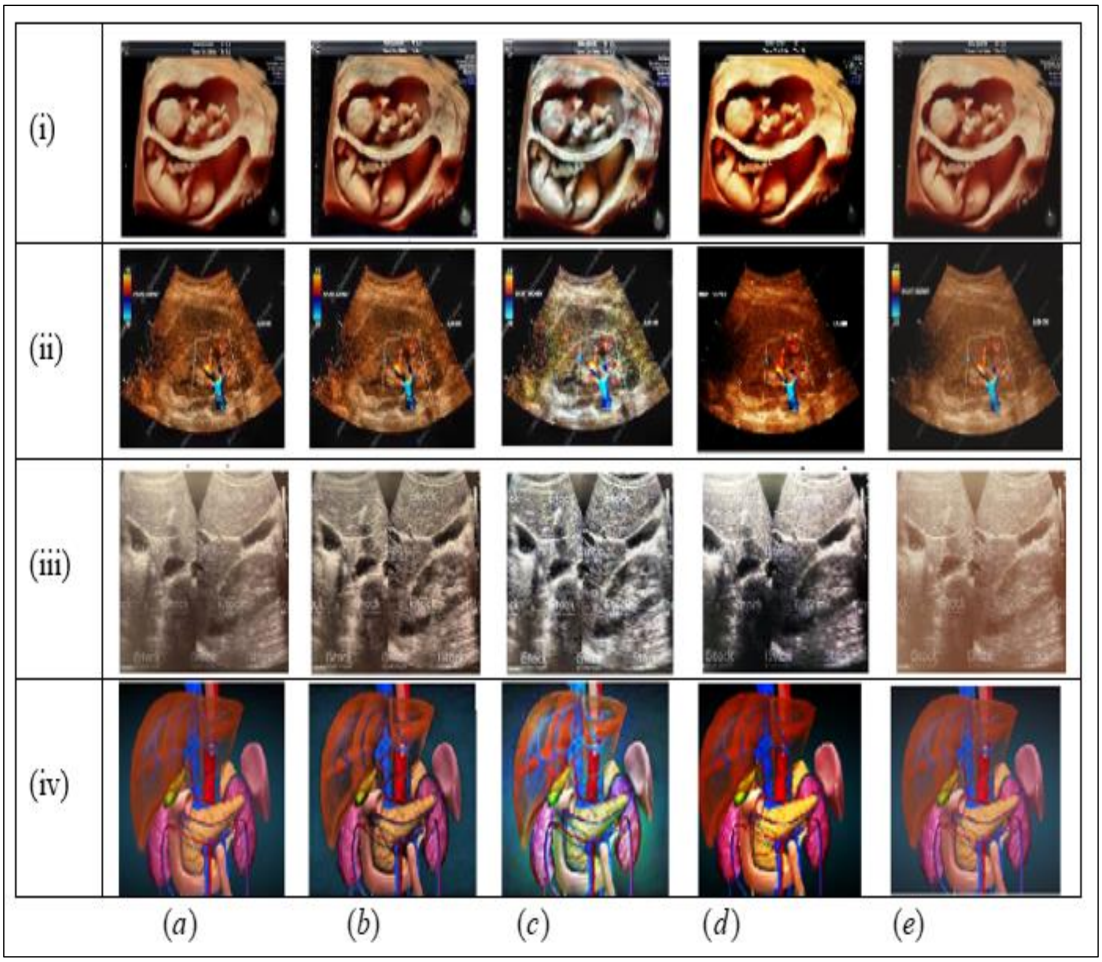

Figure 2: Simulation results using Ultrasound images (a)original image (b)UM-LT-AHE method (c)CLAHE method (d)Fuzzy-based method (e)WT method.

Source: Authors, (2024).

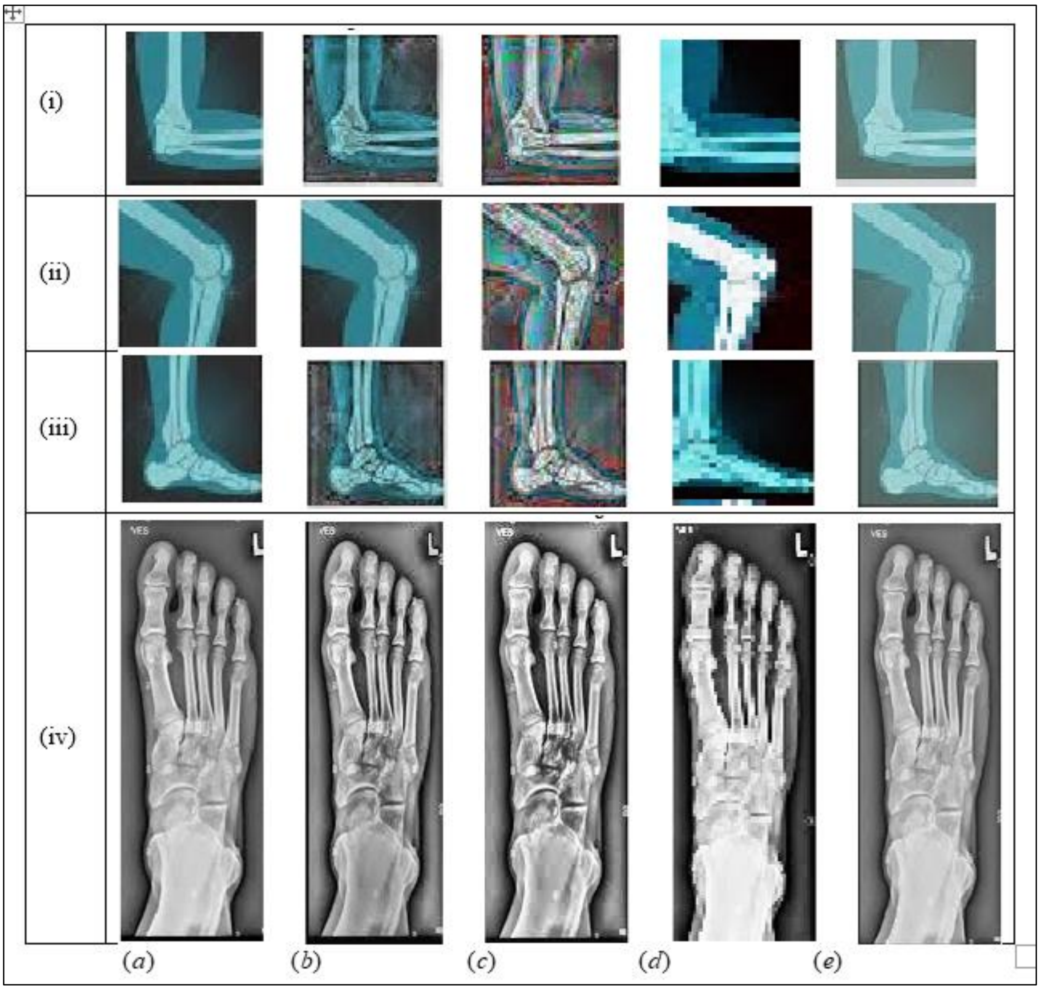

Figure 3: Simulation results using X-ray images (a)original image (b)UM-LT-AHE method (c)CLAHE method (d)Fuzzy-based method (e)WT method.
Source: Authors, (2024).

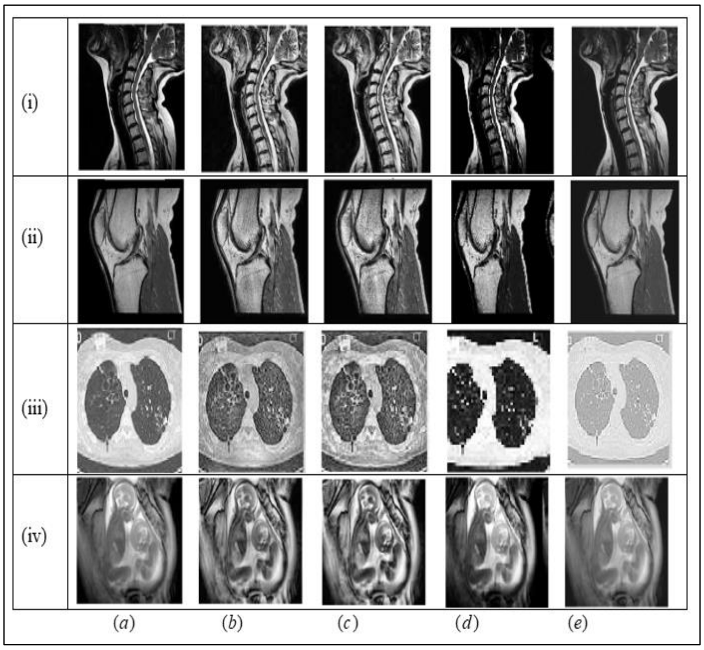

Figure 4: Simulation results using MRI scan images (a)original image (b)UM-LT-AHE method (c)CLAHE method (d)Fuzzy-based method (e)WT method.
Source: Authors, (2024).

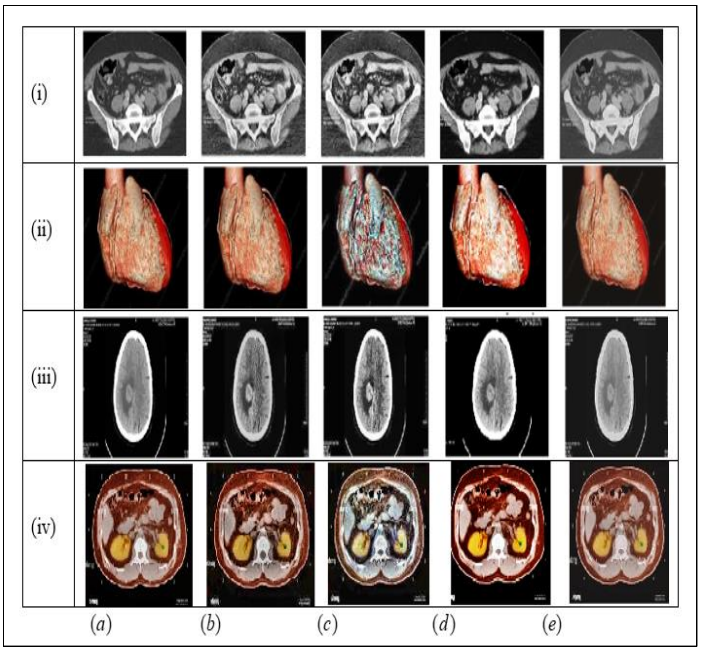

Figure 4: Simulation results using CT scan images (a)original image (b)UM-LT-AHE method (c)CLAHE method (d)Fuzzy-based method (e)WT method.
Source: Authors, (2024).

A cursory look at simulation results presented in Figure 2 to 5 for enhanced images of different types reveal that outputs of the proposed UM-LT-AHE medical image enhancement method fare better than other four methods employed in comparison. It is obvious that output images using the proposed UM-LT-AHE medical image enhancement method closely match the input test images than what obtains from other four methods used.

Next in the evaluation process is quantitative and objective evaluation of the performance of the UM-LT-AHE medical image enhancement method proposed in this work along with those of CLAHE, Fuzzy-based and Wavelet transform-based methods using those sixteen test images described in Table 1.

Table 2 to 4 present computed parametric results, starting with those of X-ray images.

Table 2: Evaluation results using X-ray images.

ELBOW				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	186583	10.3738	39.6560	18.528
MSE	0.0910	0.0853	0.11225	0.0678
PSNR	23.9670	24.6105	21.8702	26.9127
Entropy	7.7059	6.5089	6.8866	7.5612
KNEE				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	18.528	0.37373	36.446	1.0074
MSE	0.0866	0.0978	0.1040	0.0635
PSNR	24.4660	23.2496	22.6370	27.5704
Entropy	7.6671	6.6577	6.9027	7.4787
LEG				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	19.5594	20.2151	34.3872	4.6719
MSE	0.0917	0.0723	0.1060	0.0703
PSNR	23.8899	26.2699	22.4391	26.5479
Entropy	7.6073	6.7336	6.9859	7.5064
FOOT				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	5.0847	11.2024	15.1105	2.5408
MSE	0.0616	0.0775	0.0638	0.0553
PSNR	27.8784	25.5748	27.5273	28.9528
Entropy	6.2224	5.7115	5.5348	6.2548

Source: Authors, (2024).

Objective evaluation results involving X-ray images show that the proposed hybrid UM-LT-AHE contrast enhancement method performed better than each of CLAHE, fuzzy-based and wavelet transform-based methods. Specifically, the performance of the proposed method in this work surpasses those of others in terms of AMBE, MSE and PSNR Figures in all four images while it has entropy Figures that are slightly lower than those yielded by CLAHE in three of the test images

Table 3: Evaluation results using Ultrasound images.

MULTIPLE GESTATION				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	18.4466	7.2810	12.4194	3.6492
MSE	0.0714	0.0723	0.0570	0.0523
PSNR	26.3917	26.2662	28.6539	29.5030
Entropy	7.1841	6.3418	7.0386	7.2399
HEALTHY KIDNEY				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	27.5549	8.1986	17.7543	9.7369
MSE	0.0481	0.0228	0.0303	0.0287
PSNR	30.3426	37.8118	34.9762	35.5070
Entropy	6.9083	4.9430	6.2130	6.8636
HUMAN LIVER WITH GALL BLADDER				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	8.7964	6.4803	18.9987	8.8073
MSE	0.0995	0.0901	0.1029	0.0715
PSNR	23.0714	24.0728	22.7391	26.382
Entropy	7.8810	7.8152	7.4250	7.6415
NORMAL LIVER				
Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
AMBE	25.845	10.7739	14.7473	0.58036
MSE	0.0690	0.0443	0.0513	0.0400
PSNR	26.7381	31.1763	29.7004	32.1825
Entropy	7.7775	6.9439	7.3239	7.3812

Source: Authors, (2024).

Results shown in Table 3 for ultrasound test images reveal a different scenario from that of X-ray images. While Fig.s obtained from the proposed hybrid UM-LT-AHE method are generally not the best, they are however, compare favorably with those adjudged to be best for ultrasound images. In fact, the marginal difference in those parameters is small as can be inferred from results involving 'healthy kidney' image where fuzzy-based method appear better than others as well as those of entropies returned by CLAHE for 'human liver with gall bladder' and 'normal liver'.

Table 4: Evaluation results using CT-scan images.

Parameters	**CLAHE**	**Fuzzy-based**	**Wavelet-based**	**Proposed**
GRAY SCALE ABDOMINAL CAVITY				
AMBE	17.3672	10.9913	11.4329	14.4132
MSE	0.0858	0.0666	0.0691	0.0783
PSNR	24.5553	27.0946	26.7278	25.4705
Entropy	7.6063	6.5047	6.8863	7.6202
HEALTHY HEART				
AMBE	2.7463	15.7666	13.4307	8.5005
MSE	0.0515	0.0789	0.0550	0.0348
PSNR	29.67	25.3993	29.0009	33.5753
Entropy	5.5869	4.9244	6.0456	5.7624
BRAIN TUMOR				
AMBE	4.5612	6.3451	16.7043	12.896
MSE	0.0407	0.0501	0.0403	0.0327
PSNR	32.0259	29.9346	32.1063	34.1945
Entropy	4.8102	30.751	44.571	4.8786
COLOR ABDOMINAL CAVITY				
AMBE	16.0203	24.185	14.8689	12.558
MSE	0.0695	0.0654	0.0593	0.0509
PSNR	26.6681	27.2683	28.2501	29.7763
Entropy	7.173	5.9548	6.7886	7.2027

Source: Authors, (2024).

Although parametric evaluation results CT scan of gray scale abdominal cavity image show that fuzzy-based method performed better than others in terms of AMBE, MSE and PSNR Figure, however, judging by the margin between corresponding values returned by the proposed hybrid UM-LT-AHE method, it can be safely said that the method compare well. Aside the results of gray scale CT scan of abdominal cavity, the proposed hybrid UM-LT-AHE method performed better than other methods, especially in terms of MSE and PSNR Figures. These observations are premised on results presented in Table 4.

Table 5: Evaluation results using MRI-scan images.

Parameters	CLAHE	Fuzzy-based	Wavelet-based	Proposed
CERVICAL SPINE				
AMBE	28.6652	**13.0575**	17.212	28.2196
MSE	0.0630	0.0937	**0.0406**	0.0604
PSNR	2.7654	23.6791	**32.0408**	28.0758
Entropy	6.8039	48.239	64.707	**68.113**
KNEE				
AMBE	13.0372	**96.004**	155.956	111.961
MSE	0.0638	0.1394	**0.0544**	0.0583
PSNR	27.5133	19.7026	**29.1072**	28.4297
Entropy	62.196	50.685	58.780	**62.251**
LUNG				
AMBE	20.2711	**18.5814**	37.828	24.3273
MSE	0.1279	0.1627	0.2150	**0.1150**
PSNR	20.563	18.1576	15.3711	**21.6259**
Entropy	**77.815**	65.790	64.779	76.419
MULTIPLE FETAL				
AMBE	13.4195	**7.2406**	12.6458	11.0239
MSE	0.0883	0.2131	0.0786	**0.0806**
PSNR	242.710	154.600	254.397	251.808
Entropy	78.333	71.747	74.522	77.251

Source: Authors, (2024).

Evaluation results using MRI scan images appear rather clumsy as mixed results are returned. One thing that is cleared from entries of Table 5, where MRI scan images results' are presented, is that the results of the proposed UM-LT-AHE method still compare well with those of other methods used for comparison.

IV.I. LIMITATION OF THE PROPOSED METHOD

The proposed method is limited to medical images drawn from CT scan, MRI images, Ultrasound scan and X-rays. Other medical images from other sources were not considered.

IV.II. FUTURE WORK

The method should be tested for its applicability in enhancement of many imaging applications such as underwater, astronomical, and consumer-based electronics.

V. CONCLUSIONS

We present a novel hybrid UM-LT-AHE technique in this work that is intended primarily to improve contrast in medical photos. This technique is noteworthy for its adaptability, as it can handle medical images in both grayscale and colour. Our assessment, carried out on a variety of test medical pictures including X-ray, ultrasound, CT, and MRI scan modalities, proved that the hybrid UM-LT-AHE contrast enhancement method that was suggested was effective. Its application to a variety of medical images was demonstrated by the results, which also showed that it produced accepTab. results for important assessment metrics like AMBE, MSE, PSNR, and entropy Figures. This highlights how well the technique works to improve contrast in a range of medical imaging situations, confirming its usefulness as a strong and adap table. instrument in the field of medical image processing. Furthermore, it was shown here that the proposed hybrid UM-LT-AHE method performed well than each of CLAHE, fuzzy-based and wavelet transform-based methods, on the average when deployed for contrast enhancement of the four aforementioned medical image types. Based on these findings, the proposed UM-LT-AHE method can be safely deployed for the enhancement of different types of medical images' contrast with satisfactory results for all types of images, something which was lacking in some other methods.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Kamoli A. Amusa and Olumayowa A. Idowu.
Methodology: Kamoli A. Amusa and Olumayowa A. Idowu.
Investigation: Olumayowa A. Idowu and Abolaji O. Ilori.
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