



RESEARCH ARTICLE

Region Entropy–Based Histogram Equalization for Medical Image Contrast Enhancement

J. Hajiram Beevi^{1*}, O. A. Mohamed Jafar², A. R. Mohamed Shanavas²

Abstract

Contrast enhancement is applied in image processing and visualization as a preprocessing step to improve image clarity prior to visual inspection, object detection, and image segmentation. In medical imaging, contrast enhancement plays an important role in emphasizing regions of interest. However, existing algorithms often scatter pixel intensities in a histogram, leading to noise amplification, over-saturation, and poor human perception. To overcome these limitations, Region Entropy-based Histogram Equalization (REHE) was introduced as a preprocessing algorithm to enhance the local contrast while preserving structural integrity and texture information. The proposed algorithm is evaluated on publicly available multimodal medical images and benchmarked against multiple state-of-the-art enhancement algorithms. Results show that the proposed approach improves image quality and structural preservation, leading to better visual and diagnostic outcomes.

Keywords: Contrast Enhancement, Entropy Analysis, REHE, Performance Metrics, Medical Image Processing.

Introduction

Image contrast plays an important role in deciding the perceptual quality and readability of visual data. In many image processing applications, enhancing contrast is necessary for improving feature visibility and extracting meaningful information. With the fast growth of research in domains such as computer vision, remote sensing, biomedical imaging, and fault detection, there is an increasing demand for images with high brightness, contrast, and structural detail. In real-world scenarios,

images often appear with low contrast due to factors such as inadequate lighting, sensor constraints, and acquisition conditions. Factors such as improper exposure, environmental conditions, and hardware constraints can lead to degraded image quality, including blurring and reduced visibility of important features. These complications are especially critical in applications such as surveillance, forensic analysis, and medical imaging, where accurate interpretation is required.

Despite advancements in imaging technologies, captured images are still affected by various natural and artificial artifacts that degrade their quality (Kim, 1997). Therefore, efficient contrast enhancement techniques are required to improve image quality and ensure reliable analysis in real-world applications. Medical imaging plays a pivotal role in healthcare, as it is important for assisting clinical decision-making. Medical images are important due to their significance and accuracy in identifying a variety of medical conditions. Most tumors can now be detected at early stages through medical imaging, which enables earlier and more effective treatment. Medical images display contrast difference between different tissue types (Zhou et al., 2019). There are few medical images in certain applications that have sufficient quality for processing. However, the contrast available is typically quite low.

Therefore, one of the most important aspects of image preprocessing is to improve the quality of the original images. By emphasizing concealed or blurry attributes

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and enhancing contrast and brightness, low-light image enhancement technology attempts to improve the visual impact of images. This is an extremely challenging issue that has recently become notable as a research topic and has been extensively explored by researchers. An initial important step in medical image evaluation is basically image enhancement. The main objective of this paper is to implement an efficient contrast enhancement algorithm for medical images.

Transform domain and spatial enhancements are the two kinds of contrast enhancement approaches presently used. Logarithmic transformation, gamma function, histogram-based technology, and non-linear secondary filtering are some spatial contrast enhancement techniques (Zhang et al., 2023). Filtering techniques are direct way to enhance contrast in the transform domain. Numerous image enhancement techniques have been periodically proposed to improve image quality, contrast, and preserve fine details. The most widely used image enhancement methods are histogram-based ones as they are simple to use and yield acceptable results. Histogram-based methods really stand out because they blend so effortlessly with other processing techniques.

Histogram-based methods are simple and work excellent in many cases, but they are not without issues. When global histogram equalization is used, it can produce over-enhancement and may fail to preserve brightness, especially when the image has unbalanced intensity levels (Chen & Ramli, 2003). To deal with this, methods like Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) were introduced. These techniques process the image in smaller regions and improve contrast locally, which also helps in limiting noise (Ibrahim & Kong, 2007).

Even so, applying CLAHE to the whole image does not always give good results. In some cases, it can create artifacts or make certain regions appear overly enhanced (Abdullah-Al-Wadud et al., 2007). Because of this, recent work has started to concentrate on enhancing only specific parts of the image based on their local properties. Thus, contrast can be improved where it matters, while the rest of the image remains unaffected.

Contrast enhancement increases the visibility of intensity variations between anatomical structures and tissue regions. Image segmentation is based on pixel intensity, edge information, and local texture. When contrast is low, boundaries are weak and regions are more likely to merge, which can hide clinically relevant details. Higher contrast supports thresholding, clustering, and region-based segmentation, particularly in medical images with overlapping tissue intensities.

In this work, a Region Entropy-based Histogram Equalization (REHE) approach is used to improve the contrast

of medical images prior to segmentation. The approach applies entropy analysis to locate regions with higher intensity variation and then enhances only those regions using Contrast Limited Adaptive Histogram Equalization (CLAHE). Regions with low entropy are left unchanged so that the original brightness distribution is preserved. Only regions with high entropy are enhanced, which increases local contrast and reduces noise amplification. The output images show clearer tissue boundaries, which helps improve segmentation accuracy.

Literature Review

Medical image enhancement plays a critical role in disease detection and diagnosis, thus making it an important area of research in the field of image processing. Therefore, a lot of research has been done to implement algorithms that can enhance the quality of medical images. Some popular approaches presented by different authors for medical image enhancement are reviewed as follows:

Dabass et al. (2019) have introduced a novel image enhancement method which applies CLAHE and entropy based intuitionistic fuzzy methods. The proposed method is applicable for various breast image categories, including dense mammograms. It retains the image's contrast, shape, information content and brightness without increasing noise. The paper does not provide an in-depth discussion of the approach's scalability.

Ganesan and Rabbani (2019) introduced the COUDSHE technique to improve images captured under challenging lighting conditions, particularly those affected by heavy shadows or uneven illumination. COUDSHE superior to Partially Overlapped Sub-Block Histogram Equalization (POSHE) in shadowed images with respect to histogram flatness and AMBE values, signifying improved brightness preservation.

Kandhway et al. (2019) proposed a Krill Herd (KH)-based image enhancement algorithm for medical imaging applications. The algorithm used histogram clipping with a plateau limit and provides residual pixels over the available histogram bins. A fitness function is used for parameter selection, and the algorithm is evaluated through comparison with SSA-based optimization techniques.

Stimper et al. (2019) proposed MCLAHE, a multidimensional variant of the CLAHE algorithm, to improve visualization in spectroscopy datasets. However, because of the exponential growth of interpolation kernels, it becomes difficult for datasets with over ten dimensions and requires loading entire datasets into RAM, restricting scalability.

Al-Ameen (2020) has proposed a simple algorithm that integrates statistical methods with image processing concepts. It was developed particularly to improve the contrast of low-quality medical images. It is evaluated

using a dataset of real-degraded low-contrast images and is assessed with a specialized no-reference metric. The algorithm is suitable for devices with low hardware specification.

Lucknavalai and Schulze (2020) introduced a real-time 3D Contrast Limited Adaptive Histogram Equalization (CLAHE) technique to improve 3D medical image stacks for better visualization, especially in virtual reality (VR) headsets with limited dynamic range. It proposed Focused CLAHE and Masked CLAHE, which enable users to improve specific regions or organs interactively.

Saravanan and Karthigaivel (2020) introduced a Fuzzy-Spline-based Histogram Equalization (FSDHE) algorithm. It divides the image into linked components, and each component is processed separately using dynamic histogram equalization. It is used to make sure easy integration over the improved regions.

Veluchamy and Subramani (2020) proposed an image contrast enhancement algorithm called FDAHE-GC. It uses a fuzzy dissimilarity histogram for intensity mapping, trailed by gamma correction to improve darker regions. It is designed to improve visual quality while ignoring over-enhancement.

H N and M C (2021) have proposed a new image enhancement method, Gradient computations and Texture Driven based Dynamic Histogram Equalization (GTDDHE). It applies a mapping function as a cumulative distribution function to generate the histogram in an ideal shape by adjusting both the dynamic range and contrast phases. It improves visual perception while retaining biomedical patterns and addresses distortions from over enhancement during enhancement.

Naidu et al. (2021) have introduced a method for medical image enhancement by means of statistical and histogram-based algorithms. Gaussian filtering and CLAHE are applied to enhance brightness, contrast, and image detail while reducing noise.

Rao and Srikrishna (2021) proposed an Enhanced Multi-Histogram Equalization (EMHE) technique that partitions the image histogram and applies controlled enhancement to prevent over-enhancement. It has displayed greater performance in improving low-light satellite and medical images, increasing pixel intensity while reducing mean square error.

Afghan and Samadzadehaghdam (2022) have given an approach for medical image enhancement using Gaussian model-based histogram equalization technique. The following histogram equalization methods have been evaluated and examined on breast thermography images: Histogram Equalization (HE), Equal Area Dualistic Sub-Image Histogram Equalization (DSIHE), Brightness Preserving Bi Histogram Equalization (BBHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Local

Histogram Equalization (LHE), Adaptive Gamma Correction with Weighted Distribution (AGCWD) and Gaussian Model-Based Histogram Equalization (GMHE). The proposed approach's computing efficiency is not discussed.

Alshamrani et al. (2022) have discussed enhancement of mammographic images using histogram-based contrast algorithms in order to increase the efficiency of computer aided detection systems. The proposed approach enhances specific regions of interest by mapping intensity values to improve contrast, facilitating better tissue differentiation.

Gamara et al. (2022) have proposed an upgraded X-ray image enhancement hybrid algorithm that uses and contains Contrast Limited Adaptive Histogram Equalization (CLAHE) method combined with the Wiener filter. It assists to enhance the images by improving contrast and minimizing noise, which are important for better diagnostic outcomes. The approach has been implemented on a dataset of 6000 X-ray images significantly increasing the validation accuracy of deep learning classification models from 50% to 78%.

Saroj (2022) have proposed a hybrid enhancement approach based on Principal Component Analysis, Multi-Scale Switching Morphological Operator and CLAHE. The approach has been implemented on a large dataset comprising various medical image modalities, including MRI, ultrasound and retina images. Very few medical images have been used to assess the method.

Sunitha et al. (2022) proposed a fuzzy-based dynamic histogram equalization (FEDHE) algorithm used with multi-scale singular value decomposition (MSVD) to improve the quality of registered medical images. It improves contrast while preserving complementary information during registration, thereby producing higher quality images that support more accurate medical diagnosis.

Halder et al. (2023) have introduced a combined approach which uses two innovative image enhancement techniques AHE and Adaptive Gamma with CDF-based Geometric Transformation that enhance medical images without requiring manual parameter adjustments or training datasets. The enhancement process is conducted in two phases: background pixel removal followed by brain histogram incorporation, utilizing Adaptive Power-law and CDF-based Geometric Transformation.

Haddadi et al. (2024) proposed a medical image enhancement method that integrates contrast adaptive histogram equalization with the pelican optimization algorithm (POA) to greatly enhance image contrast and visual perception. It outperformed several state-of-the-art methods, enhancing the quality of various medical images.

Mansour et al. (2024) improved radiographs using histogram-based techniques, specially HE and CLAHE, to enhance visual quality for diagnostic purposes. CLAHE outperformed HE by maintaining finer details necessary for accurate diagnosis.

Nia and Shih (2024) introduced the G-CLAHE method to considerably improve the contrast and quality of X-ray images, in order to improve diagnostic accuracy.

R and Mahajan (2024) proposed the COA-SCSO method for efficient contrast enhancement in MRI images. It addresses common restrictions in medical image contrast enhancement by using a cost function optimized using multiple evaluation metrics.

In order to enhance various kinds of medical images, Ilori *et al.* (2024) have proposed the Hybrid approach UM-LT-AHE which includes un-sharp masking, logarithmic transformation and adaptive histogram equalization techniques. The proposed approach is limited to medical images drawn from CT scan, MRI images, Ultrasound scan and X-rays. Other sources of medical images were not considered. Both grayscale and colour medical images can be dealt with by it.

Proposed Algorithm

Contrast enhancement techniques are used in medical imaging to improve brightness. But employing these methods to an entire image can introduce noise and lead to over-enhancement, especially in uniform regions. It reduces visual quality and might even hide important diagnostic details. To handle this issue, an entropy-based selective enhancement approach is used. The proposed algorithm concentrates on improving only the regions with more useful information instead of whole image. It combines entropy-based region selection with CLAHE so that enhancement is applied only where needed, while the rest of the image remains unchanged. As a result, contrast is improved in important regions without changing the overall appearance of the image.

Entropy helps measure local intensity changes, pinpointing areas that hold significant structural and textural details. By choosing the top 10% of high-entropy regions, the algorithm focuses on an image’s most informative parts. It avoids nonessential enhancement of uniform areas. Unlike

applying CLAHE everywhere, the proposed algorithm reduces noise amplification and keeps over-enhancement in check. Figure 1 represents the complete methodology of the proposed algorithm.

Algorithm: Region Entropy-based Histogram Equalization (REHE)

Input: DICOM image Img_{dicom}

Output: Enhanced grayscale image $Img_{combined}$

Begin

Read the input DICOM image Img_{dicom}

Convert Img_{dicom} into pixel array representation

Normalize pixel intensity values to the range [0,255]

If the image is RGB then convert to grayscale using:

$$Img_{gray} = 0.299 * r + 0.587 * g + 0.114 * b$$

Else

Set $Img_{gray} = Img_{dicom}$

End if

Compute histogram of Img_{gray}

Calculate probability distribution $p(i)$ for intensity levels $i \in [0,255]$:

Compute entropy of the image:

$$H = - \sum_{i=0}^{255} [P(i) \cdot \log_2(P(i))] \text{ for each } p(i) > 0$$

Compute entropy map $Entropy_{img}(x,y)$

Determine threshold using 90th percentile:

$$Threshold_{High_Entropy} = P_{90} (Entropy_{img})$$

Generate high entropy mask $Mask_{High_Entropy}(x,y)$

$$Mask_{High_Entropy}(x,y) = \begin{cases} 1 & \text{if } Entropy_{img}(x,y) > Threshold_{High_Entropy} \\ 0 & \text{Otherwise} \end{cases}$$

Apply CLAHE to obtain enhanced image:

$$Img_{enhanced} = CLAHE(Img_{gray})$$

Combine images using mask:

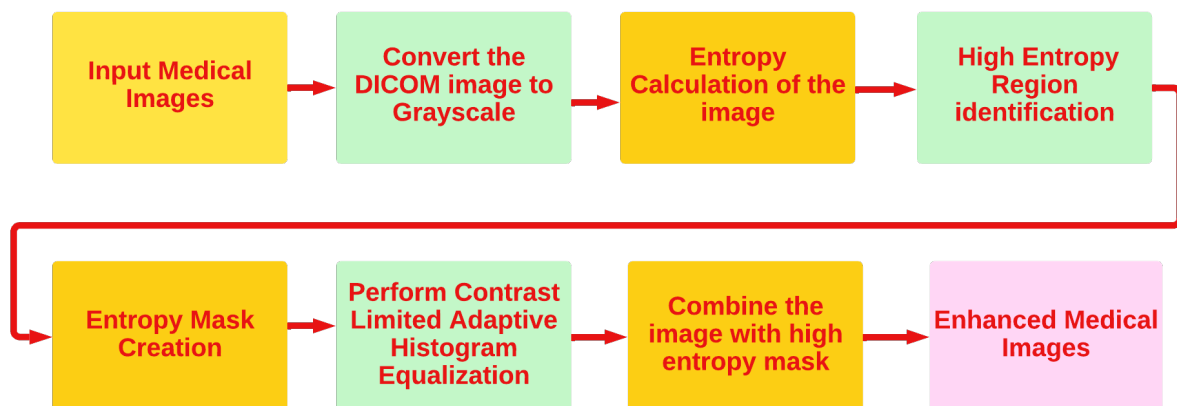


Figure 1: Block diagram of the Proposed Algorithm

$$\text{Img}_{\text{Combined}}(x,y) = \begin{cases} \text{Img}_{\text{enhanced}}(x,y) & \text{if } \text{Mask}_{\text{High_Entropy}}(x,y) = 1 \\ \text{Img}_{\text{gray}}(x,y) & \text{if } \text{Mask}_{\text{High_Entropy}}(x,y) = 0 \end{cases}$$

Return $\text{Img}_{\text{combined}}$

End

Image Quality Assessment Metrics

To assess the effectiveness of the image enhancement method, several standard image quality metrics were used. This section discusses four widely used metrics—Absolute Mean Brightness Error (AMBE), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Entropy—and their relevance in assessing contrast improvement.

AMBE

AMBE is an objective metric used in image processing to evaluate an image enhancement algorithm's ability to preserve the original image's mean brightness. It is evaluated as the absolute difference between the mean intensity of the original input image and the mean intensity of the processed output image. A lower AMBE value exhibits better brightness preservation, as it signifies a smaller change between the mean brightness of the original and the enhanced image.

$$\text{AMBE} = |I_m - I_e|$$

I_m and I_e denote the mean intensity of the original and enhanced image, respectively (Selvam & Sundaram, 2025).

MSE

MSE is the average of the variation in pixel values between the original image and contrast enhanced image. A higher MSE indicates greater variance between the original and enhanced image.

$$\text{MSE} = \left(\frac{\sum_{x,y} [\text{Img1}(x,y) - \text{Enh1}(x,y)]^2}{X,Y} \right)$$

where x and y are the image's respective height and width. Img1 is the original image, Enh1 is the contrast enhanced image. The MSE should be low when manipulating an image through enhancement, reconstruction and compression (Selvam & Sundaram, 2025).

PSNR

PSNR is the ratio of the maximal possible power of a signal to the power of distorting noise that compromises the correctness of its representation. However, an elevated PSNR particularly implies that the reconstruction is of higher quality in image compression. The PSNR has been calculated based on the MSE by,

$$\text{PSNR} = 10 \log_{10} \left(\frac{R^2}{\text{MSE}} \right)$$

Maximal variation of input image data is denoted by R . If the data type is an 8-bit unsigned integer, the value of R is 255 (Selvam & Sundaram, 2025).

Entropy

Entropy is a quantitative measure of randomness that can characterize the texture of the input image. It is an effective way to assess the quality of the details in the resulting image (Selvam & Sundaram, 2025).

$$\text{Ent}[P] = - \sum_{i=0}^n [P(i) \cdot \log_2(P(i))]$$

Experimental Results

For a comprehensive evaluation, the proposed algorithm was compared with multiple state-of-the-art enhancement algorithms: Krill Herd Reformed Histogram Equalization (KH-RHE), Fuzzy Dissimilarity Adaptive Histogram Equalization with Gamma Correction (FDAHE-GC), Fuzzy and Spline based Histogram Equalization (FSDHE), Fuzzy Employed Dynamic Histogram Equalization (FEDHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Fuzzy based, Wavelet based and Unsharp Masking Logarithmic Transformation Adaptive Histogram Equalization (UM-LT-AHE). These abbreviations will be used throughout the paper for clarity and ease of reference. This comparison shows that the proposed algorithm has better performance than the recent algorithms on the evaluated datasets. Four performance metrics were used to evaluate the quality of the enhanced images, which are consistent with previous works. The results of existing algorithms were taken from their respective publications, without re-implementation. All experiments were conducted using a Python implementation of the proposed REHE algorithm on a machine with an Intel® Core™ i3-12100 processor (3.30 GHz), 16 GB RAM, and Windows 10 (64-bit).

It was evaluated using two datasets collected from publicly available online sources. Dataset 1 was taken from an open image database developed by Bavirisetti (2017), which includes images from remote sensing, visual surveillance, and medical imaging domains. In this study, we focused only on the medical images from this dataset. These images are multi-modal and were taken with various imaging devices. Representative medical images used for the analysis from this dataset are shown in Figure 2. It also includes the corresponding contrast enhanced images and the histograms of the original and enhanced images. Representative medical images from Dataset 2, adopted from Ilori et al. (2024), are presented in Figure 3. It comprises seven medical images obtained from online sources, including ultrasound, X-ray, MRI, and CT scan images. It also comprises the corresponding contrast enhanced images and the histograms of the original and enhanced images.

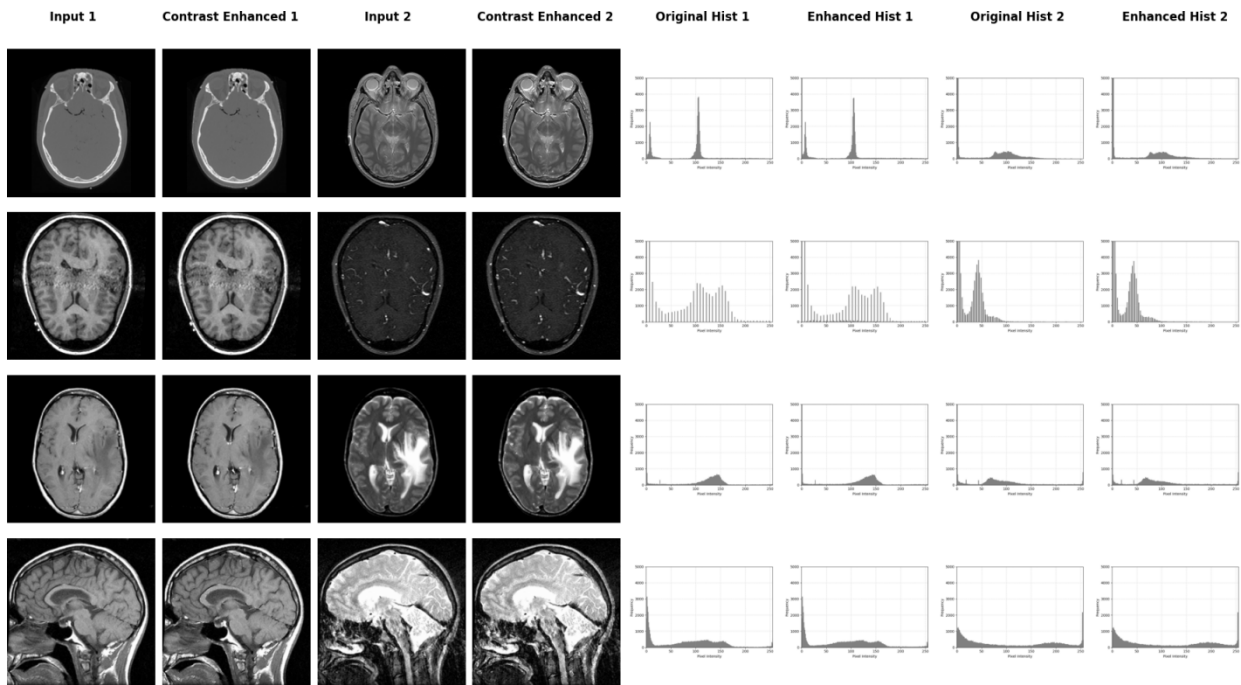


Figure 2: Comparison of original and contrast enhanced medical images

Table 1 presents a summary of the quantitative comparison of the average AMBE, PSNR, and entropy values between the FEDHE method and the proposed algorithm. Table 2 presents a summary of the quantitative comparison of the AMBE, MSE, PSNR, and entropy values between the UM-LT-AHE algorithm and the proposed REHE algorithm.

The quantitative results given in Tables evaluate the performance of the compared image enhancement methods in terms of brightness preservation, signal fidelity, and information content. AMBE, MSE, PSNR, and Entropy are used as objective measures to analyze how effectively each algorithm enhances contrast while controlling brightness deviation and distortion across different medical imaging modalities.

Table 1 shows the average performance of different histogram-based enhancement algorithms, comprising KH-RHE, FD-AHE-GC, FSDHE, FEDHE, and the proposed REHE algorithm. Among all the algorithms, REHE achieves the lowest AMBE value of 0.3126, showing better preservation of the original image brightness. It is just lower than that of FEDHE (0.3345) and considerably lower than those of KH-RHE, FD-AHE-GC, and FSDHE, which show higher brightness deviation.

With reference to image quality, REHE achieves the highest PSNR value of 36.39 dB, outperforming FEDHE (35.68 dB) as well as KH-RHE, FD-AHE-GC, and FSDHE. The higher PSNR value shows lower distortion after enhancement. Besides, REHE achieves the highest entropy value of 5.21, compared to 4.23 for FEDHE and lower values for the remaining algorithms, showing a broad gray-level

Table 1: Average performance comparison of state-of-the-art enhancement algorithms and the proposed (REHE) algorithm

Methods	AMBE	PSNR	Entropy
KH-RHE	0.625	24.89	2.56
FDAHE-GC	1.720	28.35	3.54
FSDHE	3.210	32.30	3.86
FEDHE	0.3345	35.68	4.23
Proposed (REHE)	0.3126	36.39	5.21

distribution and improved contrast representation. The results in Table 1 shows that REHE improves better contrast enhancement than the other algorithms, while maintaining brightness and reducing distortion.

Table 2 shows how CLAHE, Fuzzy-based, Wavelet-based, UM-LT-AHE, and REHE perform when applied to ultrasound, CT, and X-ray images. Each algorithm displays distinct behavior with regard to brightness preservation, noise control, and contrast enhancement.

For the multiple gestation ultrasound image, CLAHE and Wavelet-based methods produce high AMBE values, indicating noticeable brightness deviation, while the Fuzzy-based approach shows moderate improvement. UM-LT-AHE minimizes the brightness error further; however, REHE produces the lesser AMBE value (2.6725), which signifies better brightness consistency. In terms of PSNR, CLAHE and Fuzzy-based algorithms give relatively lower values, which signify higher distortion, while REHE produces the highest PSNR (32.3072 dB). The entropy value produced by REHE (7.6067) is also higher than those of the other algorithms,

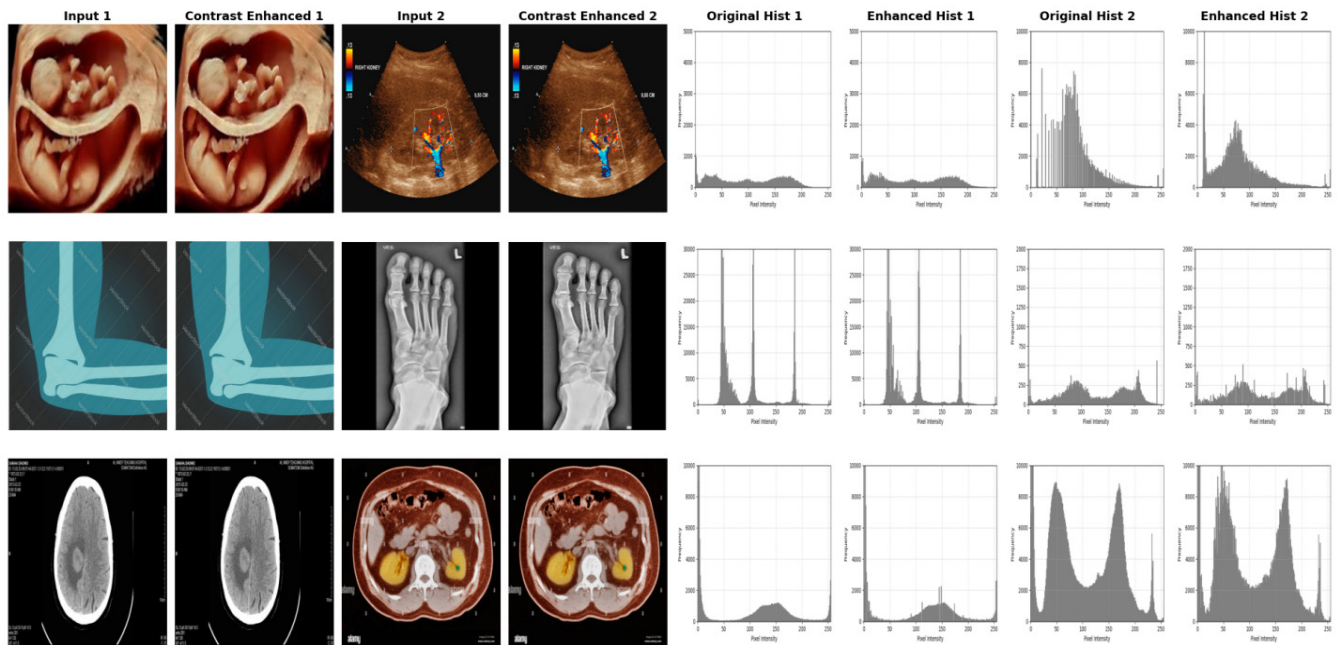


Figure 3: Comparison of original and contrast enhanced medical images

which signifies better contrast and gray-level information distribution.

A similar observation can be made in the healthy kidney ultrasound image. CLAHE and Wavelet-based methods exhibit higher AMBE values, indicating weaker brightness preservation. Although the Fuzzy-based approach enhances contrast, it causes intensity variations which affect entropy. UM-LT-AHE produces a higher PSNR, but REHE retains better brightness ($AMBE = 7.6687$) and higher entropy (6.0096), resulting in a more balanced enhancement.

In the abdominal CT scan image, CLAHE and Fuzzy-based algorithms have a significant change in brightness, which is specified by their higher AMBE values. The Wavelet-based approach improves contrast but gives lesser PSNR values than REHE. UM-LT-AHE provides moderate results; however, REHE significantly reduces the AMBE value to 10.0854 and increases the PSNR value to 34.6869 dB. The entropy values for algorithms are similar, and REHE showing a little advantage, showing effective contrast enhancement without changing the natural brightness characteristics of the CT image.

For the brain tumor CT scan, CLAHE and Fuzzy-based methods enhance contrast but at the cost of increased distortion, as indicated by lower PSNR values. The Wavelet-based method improves structural visibility but introduces brightness inconsistencies. On the other hand, REHE reduces the AMBE value to 9.2664 and increases the PSNR value to 37.3130 dB with an increase in entropy.

In the elbow and foot X-ray images, CLAHE often over-enhances bright regions, leading to brightness imbalance, whereas the Fuzzy-based and Wavelet-based methods

achieve only moderate contrast improvement and show limited intensity consistency. The performance of REHE is better compared to other algorithms as it obtains lower AMBE values (15.4388 for elbow and 1.2311 for foot) and higher PSNR values (29.8529 dB and 31.3790 dB, respectively), along with higher entropy values, indicating better visualization of the fine details of the skeletal structure.

It can be inferred from the comparison that although the contrast enhancement techniques such as CLAHE, Fuzzy-based, and Wavelet-based have been able to enhance contrast to some extent, they tend to have problems of brightness distortion or intensity irregularity. UM-LT-AHE provides better performance but does not have consistency in all aspects. On the other hand, REHE has a more stable and balanced enhancement pattern in all types of imaging modalities, providing better brightness preservation, reduced distortion, and improved contrast. The above findings indicate that the REHE technique is appropriate for medical imaging tasks that require proper intensity information and visibility of structures.

Histogram-Based Discussion

Evaluating image enhancement methods in medical imaging often requires combining numerical metrics with visual and histogram analysis. Although measures such as AMBE, MSE, PSNR, and entropy describe overall image quality, they do not always reflect local changes that influence visual interpretation.

As can be seen from the histograms presented in Figure 2 and Figure 3, it is clear that the original images tend to

Table 2: Performance comparison of state-of-the-art enhancement algorithms and the proposed (REHE) algorithm

Image	Metric	CLAHE	Fuzzy based	Wavelet based	UM-LT-AHE	Proposed (REHE)
Multiple Gestation (Ultrasound)	AMBE	18.4466	7.2810	12.4194	3.6492	2.6725
	MSE	0.0714	0.0723	0.0570	0.0523	0.0378
	PSNR	26.3917	26.7662	28.6539	29.5030	32.3072
	Entropy	7.1841	6.3418	7.0386	7.2399	7.6067
Healthy Kidney (Ultrasound)	AMBE	27.5549	8.1986	17.7543	9.7369	7.6687
	MSE	0.0481	0.0228	0.0303	0.0287	0.0521
	PSNR	30.3426	37.8118	34.9762	35.5070	29.0395
	Entropy	6.983	4.9430	6.2130	6.8636	6.0096
Color Abdominal Cavity (CT Scan)	AMBE	16.0203	24.185	14.8689	12.5580	10.0854
	MSE	0.0695	0.0654	0.0593	0.0509	0.0119
	PSNR	26.6681	27.2683	28.2501	29.7763	34.6869
	Entropy	7.173	5.9548	6.7886	7.2027	7.0137
Brain Tumor (CT Scan)	AMBE	4.5612	6.3451	16.7043	12.8960	9.2664
	MSE	0.0407	0.0501	0.0403	0.0327	0.0123
	PSNR	32.0259	29.9346	32.1063	34.1945	37.3130
	Entropy	4.8102	30.751	44.571	4.8786	4.9500
Elbow (X-ray)	AMBE	18.6583	10.3738	39.6560	18.5280	15.4388
	MSE	0.0910	0.0853	0.11225	0.0678	0.0113
	PSNR	23.9670	24.6105	21.8702	26.9127	29.8529
	Entropy	7.7059	6.5089	6.8866	7.5612	7.6235
Foot (X-ray)	AMBE	5.0847	11.2024	15.1105	2.5408	1.2311
	MSE	0.0616	0.0775	0.0638	0.0553	0.0103
	PSNR	27.8784	25.5748	27.5273	28.9528	31.3790
	Entropy	6.2224	5.7115	5.5348	6.2548	6.4421

have a narrow and irregular distribution of gray levels. This is more so in the case of ultrasound and CT scans, where the intensity levels tend to be concentrated in a small range due to certain limitations in their generation.

After enhancement, the histograms equivalent to the proposed REHE algorithm display a wider and more evenly spread distribution of gray levels. It shows the effective utilization of the available dynamic range, resulting to improved contrast across different regions of the image. Particularly, the histogram expansion achieved by REHE does not introduce excessive peaks or abrupt spikes, showing that the algorithm avoids over-enhancement and reduces unnecessary noise amplification.

The histogram patterns are consistent with the AMBE values, as the enhanced histograms remain close to those of the original images. This shows that REHE maintains mean brightness while redistributing pixel intensities. In addition, the smoother histogram shapes correspond to the observed increase in entropy, indicating that more gray-level information is preserved without affecting visual clarity.

Altogether, the analysis of the histogram supports the quantitative results in that it shows how REHE enhances contrast without affecting brightness. The broader range of gray levels is useful in highlighting details and boundaries of structures, which is particularly important in medical images that need to have uniform intensity.

Conclusion and Future Scope

Contrast enhancement is a crucial step in medical image preprocessing, as it helps disclose subtle details that are important for accurate diagnosis. This paper introduces an algorithm REHE to address issues found in existing histogram based techniques, such as uneven brightness or loss of subtle structural detail. The performance of REHE was compared with multiple state-of-the-art enhancement algorithms. Quantitative evaluation based on AMBE, MSE, PSNR, and Entropy metrics displayed that REHE achieved consistently lower error rates and superior perceptual quality. Visual inspection and histogram analysis showed that REHE improved local contrast effectively while avoiding

excessive brightness or amplified noise. The pixel values were adjusted to maintain fine anatomical structures while preserving the contrast and texture of the images. In general, the proposed algorithm focuses on keeping a proper balance between global and local contrast, to ensure that the visual content of medical images is given with greater clarity and realism. Future work may extend this algorithm to color and high-dimensional images and combine it with deep learning to assist in image reconstruction and segmentation.

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