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*Article*

# MRI Image Enhancement Using UNet Segmentation Based on AHE and Unsharp Mask

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**Abstract:** MRI image enhancement is an important and useful field for diagnosis, helping physicians identify diseases and determine the appropriate treatment. However, it is a delicate process, as the essential image information must be preserved unchanged. In other words, enhancement should not alter the basic image details but rather improve the quality and clarity of the MRI image. The most significant challenges in MRI image enhancement are preserving the essential image information and balancing noise removal with this information preservation. This research explores MRI image enhancement using the U-Net segmentation technique based on AHE and unsharp mask. The results were good compared to previous studies that used the same data: AG = 5.32, CEM = 0.76, SSIM = 0.83, PIQE = 57.94. This clearly demonstrates the success of the method in improving the image.

**Keywords:** MRI Image, AHE, Unsharp Mask, Image Enhancement and SSIM

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## 1. Introduction

Magnetic resonance imaging (MRI) is a well-known medical diagnostic tool that lets doctors see inside the body without having to cut it open. This method uses radio waves and magnetic fields to make three-dimensional images, which helps doctors figure out if someone has a neurological disorder or a brain tumor. Using image processing in diagnosing diseases is a useful and beneficial step [1].

Even so, MRI scans can have technical problems that make them less accurate when they are taken, which makes it harder to make an accurate diagnosis [2]. Therefore, increasing the clarity of medical images improves the results of medical examinations and disease diagnosis. This perspective underlines the need to establish approaches to enhance the quality of MRI images [3], particularly by using the artificial intelligence and deep learning algorithms [4]. Even though the MRIs are highly resolved, they have numerous problems. As an example, when scanning, the signal change noise may cause distortion of pictures and decreased contrast. The variations in tissue might not be apparent in certain instances, thus, it becomes difficult to diagnose. The reasons that may cause the distortions are the movement of the patient during the treatment or the malfunction of the imaging device [5]. It is possible that some of the pictures are blurred as this camera does not have a lot of spatial resolution. The UNET model that is a convolutional neural network developed to address the medical image segmentation issues can be used to improve the quality of MRI pictures. The UNET network is specifically developed that consists of encoder path that eliminates the features and the decoder path that reconstructs pictures correctly [6]. The U-Net is applicable to the quality improvement of MRI images, eliminating noise, and distortion. Training this many-layered neural network on a massive set of the distorted MRI images and their bright counterparts makes it learn these patterns and features which it must suppress in order to obtain artifact-free outputs. Diagnosing diseases using artificial intelligence technology helps doctors to achieve better results [7]. This enables the model to give more detailed images that are more clear and are easy to diagnose. U-Net has shown a lot of potential in various tasks of improving images [8]. U-Net is able to learn to remove noise automatically based on the association between noisy and clean images with MRI, e.g. U-Net, moreover, can enhance contrast in poorly defined areas using special loss functions [9]. With techniques such as super-resolution to enhance spatial resolution, we are able to come up with sharper and more detailed images. Many recent investigations have advanced this area. suggested a technique that uses multilayer thresholding to divide MRI images into important areas, then CLAHE for localized enhancement [10]. After merging and further refining the improved areas, no-reference measures are used to evaluate their quality. centered on improving lung CT scans by employing U-Net for segmentation, Dark Channel Prior and Adaptive Histogram Equalization for contrast enhancement, and nonlinear mapping for brightness control [11]. SSIM and average gradient were among the performance indicators used in their evaluation. In another study, improved MRI pictures of the brain by first utilizing Otsu's approach to isolate the region of interest and then using nonlinear enhancement techniques [12]. Additionally, presented a brand-new method known as Fuzzy and Spline-based Dynamic Histogram Equalization (FSDHE), which divides the picture into fuzzy-classified areas to improve contrast [13]. Dynamic histogram equalization is applied independently to each zone. However, integrating the equalized sub-histograms produces an inconsistent global histogram since this approach handles intensity ranges differently among areas. The suggested approach uses spline-based histogram smoothing to overcome this. Here, spline interpolation creates a smooth intensity translation using the equalized intensity mappings as control points for a polynomial curve. The MRI-brain imaging dataset with 3,064 images including both benign and malignant cases is used to assess the FSDHE model. Its contrast enhancement performance is assessed using multiple metrics: Peak Signal-to-Noise Ratio (PSNR), Absolute Mean Brightness Error (AMBE), Weber Contrast (WC), Entropy, Contrast (C), Texture Preservation (TP) and Hausdorff Distance (HD). proposed a lightweight version of the U-Net architecture. In addition to enabling real-time segmentation of MRI scans, the designed model requires only a limited amount of training data [14]. Moreover, it eliminates the need for additional data augmentation procedures. Promising results have been achieved on the BITE dataset. Brain tumor segmentation is simplified by employing three orthogonal perspective planes instead of three-dimensional volumetric pictures. In this study, a modified U-Net architecture has been developed within a deep learning framework for the purpose of brain tumor detection and segmentation from MRI images [15]. The suggested model was assessed utilizing actual MRI data sourced from the Medical Image Computing and Computer-Assisted Interventions (MICCAI) BRATS 2020 dataset. This research presents a fully automated method based on a 2D U-Net architecture applied to the BraTS2020 dataset for the segmentation of tumor regions from normal brain tissue [16]. The model is evaluated across all MRI sequences to identify which sequence yields the best segmentation performance. This study employs a fully convolutional network with a novel architecture, termed UNet-VGG16, to classify regions of interest (ROI) and non-ROI [17]. The suggested model amalgamates the U-Net architecture with VGG16 using transfer learning, intending to optimize and elevate the segmentation process. The Correct Classification Ratio (CCR) is used to check the accuracy of the model by comparing it to the ground truth.

As a final comment, MRI pictures have been significantly improvedwith the help of deep learning or the U-Net model [18]. It is a major breakthrough in the field of medical imaging. Such techniques enhance the quality of images and simplify the making of correct diagnoses and treating the patients in a short time.

## 2. Methodology

### *2.1 AHE Enhancement Based On Otsu Segmentation*

Digital image processing plays a significant role in the field of medicine, in particular, to enhance the quality of MRI and CT scans as unclear data cannot be properly diagnosed. Adaptive Histogram Equalization (AHE) is important in performing the local contrast enhancement of an image. However, whole image AHE may increase noise in insignificant regions. The Otsu segmentation technique is applied in order to locate areas of interest before they are improved.

#### 2.1.1 Otsu Segmentation Algorithm

Otsu method is effective in that it determines the optimal threshold amount to cut the image into two or more. This limit is self-determined by reducing the contrast in certain areas and increasing it between areas. This simplifies the visualization of the brain region in MRI images since it is isolated by the background hence minimizing the impact of additional artifacts.

#### *2.1.2 Enhancement Using AHE*

Otsu identifies the area of interest in the picture and then applies the AHE technique on the picture. This technique splits the image in small sections and histogram modifications are then applied to the sections. This reveals features of the image that are difficult to see using conventional image-enhancing methods, such as tissue or small tumors.

#### *2.1.3 Merging and Reconstruction*

Once the area of interest is enhanced by AHE, it is reassembled with the other parts of the image. This action enhances the image in terms of displaying more details without compromising on the quality of other portions of the image. Otsu segmentation coupled with AHE is selective in enhancing contrast in areas of interest, minimizing the side effects of the global enhancement and raising awareness of complex facts that are significant to medical diagnosis. Improving medical images with Otsu segmentation and Adaptive Histogram Equalization (AHE) is an excellent method since it allows addressing and refining certain areas of interest. This combination facilitates the clarity of details and enhances both medical diagnosis and scientific research of image processing.

### *2.2 Un Sharp Mask Enhancement*

Image processing is a crucial component of digital image processing, and the tools used to augment the quality of images are image augmentation techniques. The first process is the technique of Unsharp Masking (USM), which is commonly used in medicine, technology, and photography. This is based on the principle of edge sharpening in an image to enhance the clarity of complex details in an image. The principle of USM: This technique, despite the name, is meant to sharpen a picture, or, to be more precise, it is called unsharp because it is intended to remove the blurred image of the original one and only leave the edges. The original picture is obtained by capturing an image, which is then sharpened. The fundamental procedures of USM are as follows: before the edge information is added back into the original picture, it is first blurred using a Gaussian Blur filter to remove the complex detail and edge in question. The edge information is then reintroduced into the original image, which increases sharpness and detail. Though it is extremely basic, it finds application in fields such as medical imaging, digital image processing, and professional photography. This technique is adequately utilized to improve the quality of the image and minimize the negative effects.

### 2.3 Composed Between Background And Un Sharp Mask

Image enhancement using digital technology is a fundamental operation in various sectors such as the health sector, engineering, and photography. Unsharp Masking (USM) is a popular method in this sphere that enhances the edges and increases the level of detail. Nevertheless, it is possible that direct application can cause an increase in noise or even negative results. A compositing technique is utilized between the background image and the output of the Unsharp Mask filter to produce an enhanced image that integrates sharpness with visual harmony. The concept of compositing is based on the integration of: the original image (background), which provides fundamental information devoid of any enhancement; and the Unsharp Mask picture, which is the product of the sharpening process that subtracts the blurred version of the original image to accentuate the edges. Blending these two images in specific ratios (sometimes known as the Blending Factor) produces an enhanced image with clear details without losing the overall balance or increasing noise. How it works: blurring the original image by applying a Gaussian Blur filter to produce a smooth version; calculating the Unsharp Mask by subtracting the blurred version from the original image to highlight the edge components; and blending with the background, where the original image (background) is combined with the USM mask to produce the final enhanced image. This approach reduces artifacts such as over-sharpening, controls the degree of enhancement by changing the blending parameter ($\alpha$), and maintains the visual balance between the natural background and enhanced details. It enhances medical images to highlight diagnostic details without losing less important areas. Medical images: enhancing radiology and MRI images while reducing noise. Photography: enhancing image details while preserving naturalness. Computer vision: enhancing the output of image and pattern recognition systems. Blending the background with the Unsharp Mask strikes a balance between increasing sharpness and preserving the original image quality. This strategy provides researchers and professionals with an effective tool for obtaining high-resolution images while minimizing the negative effects that may result from direct enhancement processes, see Figure 1.

### 2.4 Mathematical Details of Image Enhancement Algorithm

#### 2.4.1 Input Image: Load the original grayscale image.

$$I(x, y) \in [0,255] \tag{1}$$

It's a 2D intensity matrix where x, y denote spatial coordinates.

If originally in RGB, convert using:

$$I(x, y) = 0.299R + 0.587G + 0.114B \tag{2}$$

#### 2.4.2 DCP Dehazing: Enhance image using Dark Channel Prior.

At this stage it is based on the assumption that in the non-light areas of the image there is at least one channel in which the intensity is very low. The DCP method is one of the most popular methods used to remove haze from images. It relies on a simple and effective statistical hypothesis known as the "dark channel prior." It can be adapted and applied to MRI images to improve contrast and remove haze and noise resulting from factors such as light and poor illumination. The general idea when applying DCP to MRI images. The result on MRI images: Increased contrast, highlighting fine details within brain tissue and other organs. Improved scanning accuracy and automated analysis using artificial intelligence.

#### 2.4.3 Dark channel

$$Ie = 255 - J_{dark(x,y)} \tag{3}$$

#### 2.4.4 Transmission map

Because the single-channel image becomes the equation

$$t(x, y) = 1 - \omega . J_{dark}(x, y) \tag{4}$$

where ω constant

#### *2.4.5 Restore original image*

Using the following substitution equation:

$$J(x,y) = \frac{I(x,y) - A}{\max\left(t(x,y), t0\right)} + A \tag{5}$$

Where to A very small value such as 0.1 to avoid division by zero.

### *2.5 Segmentation:*

Segment the brain area from the background

Apply Otsu's method to divide the brain into low and high-intensity regions.

$$\sigma_b^2(t) = \omega_0(t)\omega_1(t)[\mu o(t) - \mu_1(t)]^2 \tag{6}$$

### *2.6 Enhancement:*

#### *2.6.1 Adaptive Histogram Equalization:*

(AHE) The image is divided into small squares or regions, and then the histogram is applied locally to each region.

Histogram: h(i)

$$PDF\!: p(i) = h(i)/(N \times N) \tag{7}$$

Where PDF probability density function . Represents the probability of pixels with the same gray value appearing in an image or in a local tile

$$CDF(i) = \sum p(i) from\ j = 0\ to\ i \tag{8}$$

Where CDF cumulative distribution function. Represents the cumulative sum of the probabilities from level 0 to level i.

$$Output\!: I(x,y) = round\big(CDF\big(I(x,y)\big) * 255\big) \tag{9}$$

#### *2.6.2 Merging and Unsharp Masking:*

It is a sharpening filter that is based on the idea of increasing the contrast of the edges, which makes the details in the image appear clearer.

$$I_{enh}(x,y) = Ilow\ if\ < T^*, else\ I\ high \tag{10}$$

$$I_{sharp}(x,y) = I_{enh}(x,y) + \lambda^* \left(I_{enh}(x,y) - Gaussian(I_{enh}(x,y))\right) \tag{11}$$

### *2.7 Output: Save enhanced image and compute quality metrics.*

$$I_{enh}(x,y) = f(I(x,y)) \tag{12}$$

Where I(x,y) is Original image , f is The function that represents all the processing and optimization steps (AHE, DCP, Unsharp Mask).

$I_{enh}(x,y)$is Enhanced image .

### *2.8 Quality metrics*

#### *2.8.1 Mean Squared Error (MSE)*

$$MSE = \frac{1}{min} \sum_{x=1}^{n} \sum_{y=1}^{n} \left[I_{enh}(x,y) - I_{ref}(x,y)\right]^2 \tag{13}$$

Where I_ref (x,y) is Reference image (Ground Truth).

m×n is Image dimensions.

#### *2.8.2 Peak Signal-to-Noise Ratio (PSNR)*

$$PSNR = 10log_{10}\left(\frac{MAXi}{MSE}\right) \tag{14}$$

The image's maximum value is denoted by MAXi.(usually 255 for a grayscale image) . The higher the PSNR value, the higher the quality. SSIM (Structural Similarity Index Measure) is a quality measure used to evaluate the enhancement of MRI images. It is used to compare the original image with the enhanced image. If the SSIM between the two images is large, this indicates that the enhanced image has preserved the basic structure of the original medical image, which is very important in medical applications.

### *2.8.3 Contrast Enhancement Measure (CEM)*

It is a numerical measure used to evaluate the improvement in image contrast between the original image and the enhanced image19.

$$CEM = \frac{I\ max - I\ min}{I\ max + I\ min} \tag{15}$$

### *2.8.4 Average Gradient (AG)*

It is a quantitative measure used to show the sharpness of detail in enhanced images and it depends on the value of the spatial gradient. The higher its value, the greater the change in edge density.

$$AG = \left(\frac{1}{M\ N}\right) \sum (|I(x+1, y) - I(x, y)| + |I(x, y+1) - I(x, y)|) \tag{16}$$

### *2.8.5 Structural Similarity Index (SSIM):*

It is a measure that indicates image quality by comparing two images20. It relies on the structure of the images being compared (the original or reference image and the enhanced or distorted image) and on the contrast, lighting, and equation of this measure used in the research.

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{17}$$

where x,y are two images. μ_(x ) μ_y are the mean intensity σ_(x )^2,σ_y^2variance , σ_xycovariance C_(1 ),C_2 are Small constants so that we do not divide by zero.

2.8.6 Contrast Enhancement Measure( CEM):This metric is used to determine the contrast in digital images after image enhancement21. It measures the difference between the lowest and highest light intensity, then calculates the average using the following equation.

$$CEM = 1/\mathrm{N} \sum_{i=1}^{N} \mathrm{C_i} \quad , \quad C_i = \frac{I_{max},i - I_{min},i}{I_{max},i + I_{min},i} \tag{18}$$

where I_maxiis The highest intensity value in the image. I_miniis Lowest intensity value in the image. N is number of image.

### *2.8.7 Perception-Based Image Quality Evaluator (PIQE)*

This measure is non-referenced; it does not require original images for comparison2223,. It is used only to measure the degree of distortion in the enhanced image (noise, blur, structural distortion). It has an equation that was used in the research, which is

$$PIQE = \frac{\sum_{i=1}^{N} \mathrm{D_i}}{N} \times 100 \tag{19}$$

where D_i is Degree of distortion in the image, N is number of images It is between (0-100), where on this scale the closer the value is to zero, the better the result.

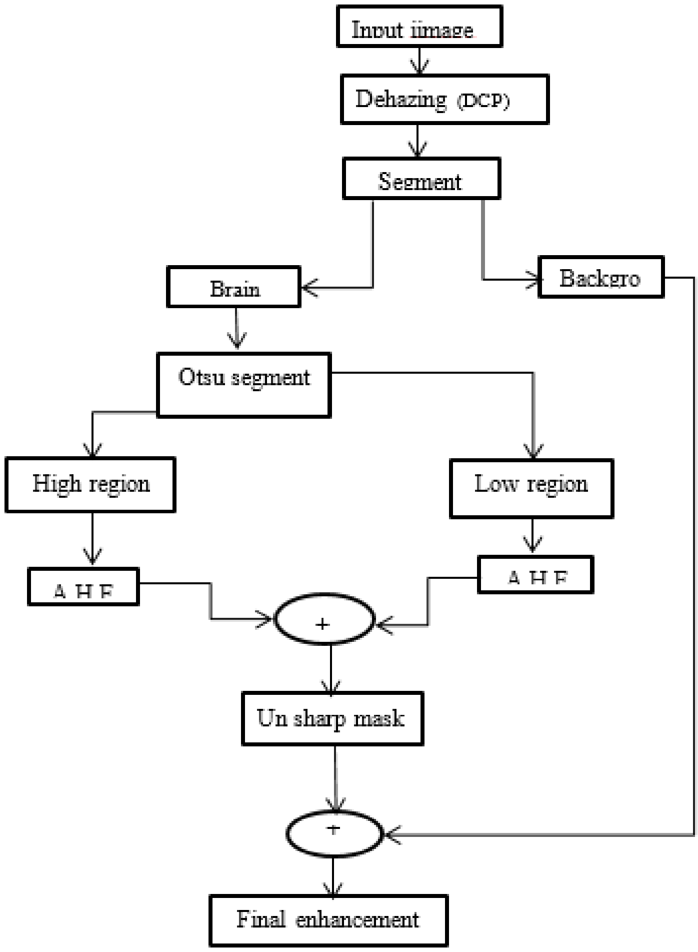


**Figure 1.** Proposed Method For Enhancement MRI Images.

## 3. Results and Discussion

In this research, the results shown in the table were obtained using a dataset of 154 BMP images24 and size of 512×512. The MRI images were enhanced using AHE and an unsharp mask. In this study, MATLAB R2022a was used to design all the algorithms. Several quality metrics were used: AG, CEM, SSIM, and PIQE. From Table (1), observe that the proposed method( SUG.) achieved the best improvement results compared to previous research. This demonstrates the success of the proposed method in improving the image by increasing detail and contrast, as can be seen in the attached enlarged region of the image. Analysis of the results showed that the AG scale had a high value compared to the results of previous studies. The AG scale measures edge clarity and detail, and the higher the value, the clearer the image and the more detail it provides. As for the CEM scale, it measures contrast improvement, and the higher the value, the better the image contrast. The research results indicate that the proposed method excels in this scale compared to other results, or at least closely matches the best. The SSIM scale measures the preservation of the original structure, and the closer its value is to one, the better the result. The proposed method achieved the best result compared to other results, closely matching the best. Finally, the PIQE scale measures perceptual quality, and the lower the value, the better the perceptual quality. The proposed method performed exceptionally well. By observing Figures (3, 4), we can see the microscopic enhancement. Both figures contain enlarged areas to increase the clarity and quality of the images (33, 66). Figure (6) represents the frequency distribution of image (105). Figures (2, 5) show that the second-best distribution range for the proposed method is NMAHE [10], found in images (16 and

105). The proposed method achieved a result comparable to the (CLAHEWF) 25 method according to the CEM scale.

**Table 1.** Average quality assessment for (154 images).

| Method | AG | CEM | SSIM | PIQE |
|---|---|---|---|---|
| SUG. | 5.323093 | 0.766516 | 0.832056 | 57.94754 |
| NMAHE | 5.881247 | 0.741951 | 0.806283 | 66.83036 |
| CLAHEWF | 4.882207751 | 0.774052055 | 0.628547158 | 86.51901906 |
| DCP | 3.933751953 | 0.77866832 | 0.858308847 | 54.11146533 |
| FCCE | 4.302380147 | 0.717042639 | 0.967705131 | 75.94148877 |
| PACR | 4.728771978 | 0.576639005 | 0.513558289 | 62.83837888 |
| MCHE | 4.60883 | 0.556837 | 0.715364 | 60.72695 |

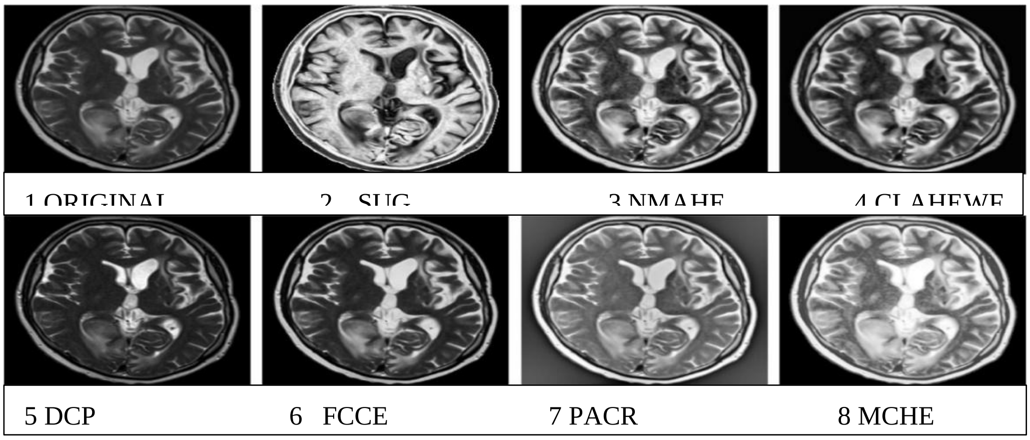


**Figure 2.** MRI Image (16) With An Enlarged Area That Was Enhanced Using Various Algorithms.

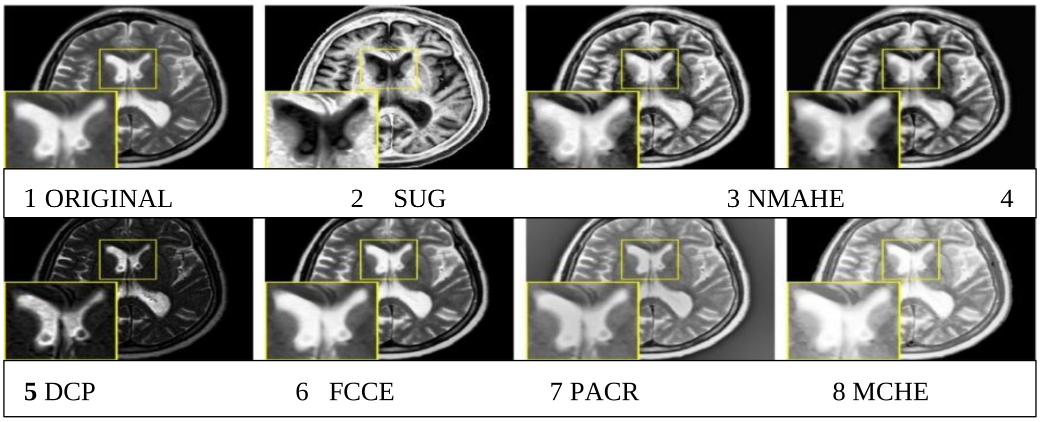


**Figure 3.** MRI Image (33) With An Enlarged Area That Was Enhanced Using Various Algorithms.

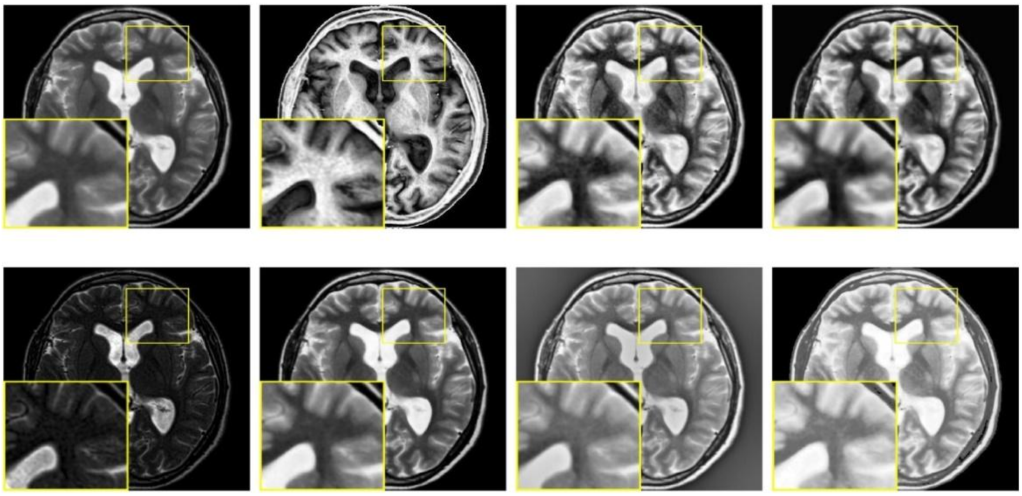

**Figure 4.** MRI Image (66) With An Enlarged Area That Was Enhanced Using Various Algorithms.

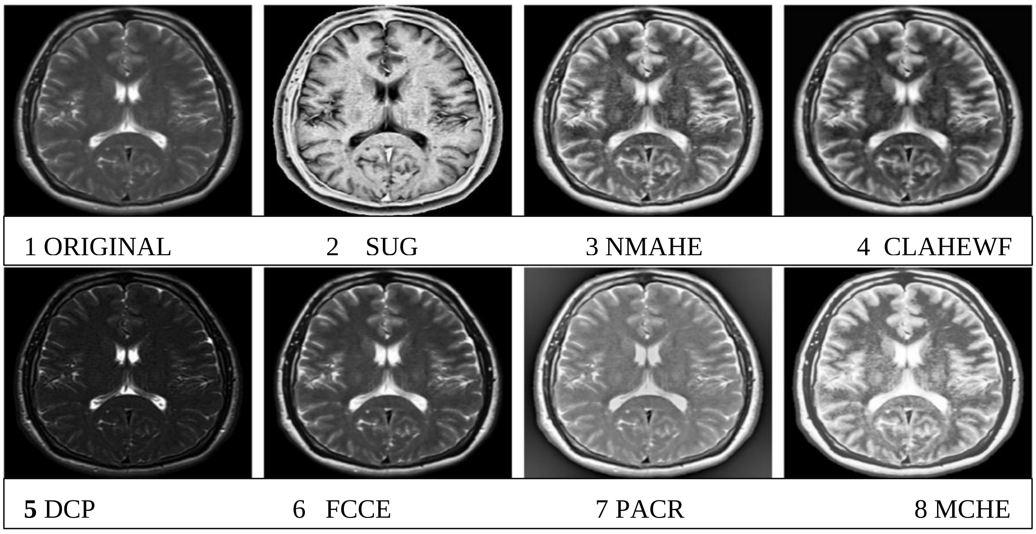


**Figure 5.** MRI Image (105) With An Enlarged Area That Was Enhanced Using Various Algorithms.

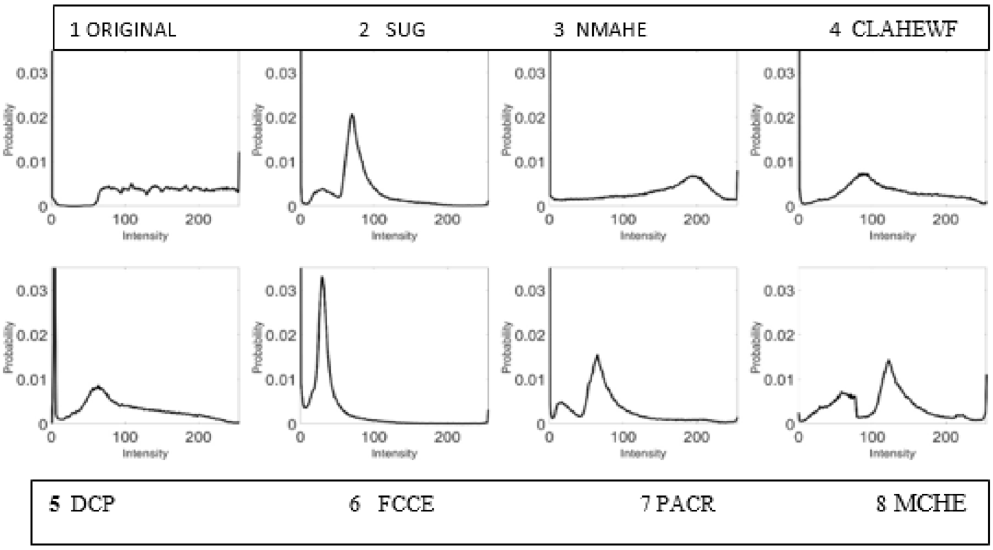


**Figure 6.** The Histogram Of The MRI Image (105) Was Enhanced Using Various Algorithms.

The intensity-probability distributions for eight different image versions or enhancement techniques are contrasted in the figure. While SUG exhibits a prominent peak in the mid-intensity range, indicating a larger concentration of gray levels, the original histogram seems comparatively flat with little contrast. With smoother, wider distributions, NMAHE and CLAHEWF shift probability toward higher intensities, indicating improved brightness and contrast balancing. While FCCE concentrates probability sharply at low intensities, indicating high contrast amplification in darker places, DCP creates a wider spread across intensities, suggesting enhanced dynamic range. MCHE displays a balanced distribution with a distinct mid-to-high intensity emphasis, while PACR shows several modest peaks, indicating redistributed tonal detail. Overall, the panels show how various enhancement methods alter contrast, brightness, and tonal spread by reshaping pixel intensity distributions.

## 4. Conclusion

The proposed method achieved a good balance between contrast and detail improvement while maintaining acceptable anatomical structure and quality. In MRI images, we must not only seek the highest contrast but also preserve structure, maintain edge clarity, and minimize noise. The aim of this study is to obtain a clear picture of pathological differentiation in magnetic resonance imaging (MRI) for 154 images. The proposed algorithm was compared with several algorithms that use different quality metrics, such as DCP, FCCE, PACR, and MCHE. By analyzing the results, the proposed method achieved AG = 5.32, CEM = 0.76, SSIM = 0.83, and PIQE = 57.94. MRI image enhancement using the U-Net segmentation technique based on AHE and the unsharp mask produced good results compared to previous studies that used the same data. This clearly demonstrates the success of the method in improving the image.

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