Iraqi Journal of Science, 2024, Vol. xx, No. x, pp: xx
DOI: 10.24996/ijs.2024.65.10.44

ISSN: 0067-2904

MRI Image Enhancement Using Multilevel Image Thresholds Based on Contrast-limited Adaptive Histogram Equalization

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Received: 4/6/2023 Accepted: 22/8/2023 Published: xx

Abstract

Magnetic resonance imaging (MRI) creates detailed images by combining a powerful magnetic field with high-frequency radio waves. MRI images need to increase brightness and contrast to facilitate distinguishing diseases. This study aims to improve the MRI images depending on the suggested algorithm, including three main stages. The first is to divide the image into three main areas using Multilevel image thresholds and then improve using CLAHE for each area separately. Finally, these images combine to form one image and improve it again. By analyzing the results and calculating non-referenced quality measures, the proposed method obtained the best quality results compared to the rest of the methods with quality rates of EN(6.14), AG(6.79), and CEM(0.84), which indicates excellent success in increasing clarity in those images.

Keywords: CLAHE, medical image, contrast enhancement, MRI Image, Multilevel image thresholds

تحسين صورة *MRI* باستخدام عتبات متعددة المستويات للصورة بالاعتماد على تسوية الهستوغرام المطورة ذات التباين الموقعي

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الخلاصة

التصوير بالرنين المغناطيسي (MRI) يستخدم مجال مغناطيسي قوي وموجات راديو ذات تردد عالي لإنتاج صور تحتوي على تفاصيل. تحتاج صور التصوير بالرنين المغناطيسي في الغالب إلى زيادة الاضاءة والتباين من أجل تسهيل عملية التميز بين الأمراض. الهدف هذه الدراسة هو تحسين صور الرنين المغناطيسي عن طريق اقتراح خوارزمية تعتمد على ثلاث مراحل رئيسية: الأولى هي تقسيم الصورة إلى ثلاث مناطق رئيسية باستخدام عتبات متعددة المستويات للصور ثم تحسينها باستخدام CLAHE لكل منطقة على حدة و اخيرا جمعها لتشكيل

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صورة واحدة يتم تحسينها مرة اخرى. من خلال تحليل النتائج وحساب مقاييس الجودة غير المرجعية، حصلت الطريقة المقترحة على أفضل نتائج جودة مقارنة بباقي الطرق بمعدلات جودة EN(6.14) و AG (6.79) و CEM(0.84) ، مما يدل على نجاحها الكبير في زيادة الوضوح في تلك الصور.

1. Introduction

Technology has permeated many facets of our lives, providing many solutions in health care and medical sciences.
Digital image processing in the medicine section is one example of such a solution since it allows doctors to adjust and enhance outcomes based on several factors [1].

Image enhancement is among the most crucial and often used operations in image processing. In doing so, artifacts are wiped out, details are boosted, and noise is reduced [2,3]. Clarifying and enhancing images [4,5] allows for better analysis, diagnosis, and observation [6]. The modified image is superior to the original in terms of suitability for the intended use or task [7]. Digital image processing has many medical applications [8], including diagnostic tests like PET scans, MRIs, X-rays, CT scans, radiology imaging, imaging cancer cells, and many other activities in clinical medicine [9,10]. Differentiation and categorization rely heavily on medical image enhancement [11,12]. Thresholding images is a common technique used to finish the segmentation process [13].

Wei-Yen Hsu and Ching-Yao Chou 2015 suggested a method of image enhancement that includes hue preservation. When applied to images of retinal and prostate cancer, the proposed method produced results that were superior in terms of mean squared error (MSE) of 5.85 and peak signal-to-noise ratio (PSNR) of 40.46 and 42.07 compared to the equalized image of each RGB color channel that was created using the conventional method. This can significantly assist medical professionals in arriving at the correct diagnosis [14].

K. S Raghunandan et al. 2018 a mathematical model presented to improve the details of edge information in photographs of license plates. The model was based on the Riesz fractional operator, which was used to create the model. This would make the methods for detecting and recognizing text function more effective. The proposed model uses the convolution operation of the Riesz fractional derivative to increase the edge strength of each image given. Tests were conducted to evaluate the proposed model's performance using standard license plate image databases such as the UCSD and ICDAR 2015-SR competition text image databases. The outcomes of the enhancement trials demonstrate that the proposed model performs a higher quality of work than the baseline enhancement strategies currently being utilized. According to research on text detection and recognition, text detection and recognition rates were much higher after enhancement. Also, experiments were shown that these rates are significantly higher [15].

TAla'a R. Al-Shamasneh et al. (2018) proposed model computes a local partial entropy by calculating, based on the Entropy, the probability that two neighboring pixels would constitute edges. A subtle difference in the intensity values indicates the presence of an edge in the image; the local partial Entropy can offer insights about the image. Similarly, the LFE does not reveal fine detail because there was no edge information when there was no change in the intensity values (which indicates a fuzzy texture). In order to prove that the results of the proposed model are reliable, the experiments were carried out using a massive data set consisting of photos of varying kidneys that were of low quality. The value of BRISQUE is 22.37, whereas the value of the Naturalness Image Quality Evaluator is 6.32 [16].

Qing Zhang et al. (2019) mentioned that the automatic exposure correction method can reliably produce high-quality results in various lighting settings (including underexposed, overexposed, and partially underexposed and overexposed images). Predicting the lighting conditions of two photos, one inverted, is the crux of our approach, centered on a proposed dual illumination estimation that makes correcting under and over-exposure as easy as predicting the lighting conditions of two photographs. By doing dual illumination estimation, abling obtaining two intermediate exposure corrections for the input photo. One of the corrections brought back the overexposure, and the other corrected the underexposure. After that, to create a single image that is correctly exposed, a multi-exposure image fusion method was employed to fuse the visually best-exposed regions of the input image adaptively, the two intermediate exposure correction images and the output image. Experiments performed on various challenging photographs showed that the proposed strategy is effective [17].

S. Saravanan R. Karthigaivel.2020 suggested a method (FSDHE), which stands for Fuzzy Spline-based Histogram Equalization, to enhance contrast in medical images. The image was segmented into connected subregions for the proposed FSDHE approach, which classifies various image components using a fuzzy membership function. The dynamic histogram normalization is applied in a manner that is independent of each factor's processing. Because dynamic histogram equalization handled the intensity range for each linked component differently, the global histogram was inconsistent because a combination of the equalized sub-histograms drives it. As a consequence of this finding, the research suggested utilizing splines to obtain a more consistent distribution of histogram values. After obtaining polynomial curve control points from the normalized intensity mapping, a spline interpolated a smooth shift in intensity. The suggested FSDHE model was evaluated using all 3064 images in the MRI-brain dataset; this model considers both normal and malignant instances. Absolute Mean-Brightness Error (AMBE), Peak Signal-to-Noise Ratio (PSNR), Contrast (C), Weber Contrast (WC), Entropy, Hausdorff Distance (HD), and Texture Preservation (TP) are just a few of the metrics that were utilized to quantify the contrast enhancement performance of the suggested FSDHE approach. The FSDHE strategy was demonstrated to perform better across a range of criteria when compared to alternative histogram equalization strategies. These metrics included quality measures of 3.1401, 30.5499, 21.5486, 0.7779, 4.0252, 0.2777, and 0.7836 [18].

The Fuzzy Logic Based-on Sigmoid Membership Function, abbreviated as FLBSMF, is a tool that was developed to improve the levels of brightness and contrast in color photographs Hazim G. Daway et al. (2020). The FLBSMF algorithm was used to adjust the brightness component, and the YIQ color space was the only color space used. The color compounds themselves were not changed in any way. The suggested approach was evaluated against several other algorithms, such as fuzzy logic enhancement utilizing membership function modification based on square operation, fuzzy logic based on histogram, histogram equalization, and multiscale retinex with color restoration. These and other algorithms were judged based on several different criteria. Because the FLBSMF was so successful in improving the quality of color photographs, its average values for Entropy (7.44), mean square error in saturation (2.2E-08) and hue (8.11E-08), nature image quality (2.97), and luminance order error (0.90) were all deemed suitable [19].

2. Proposed methods

The enhancement of medical MRI images using the suggested method was broken down into three primary steps. The first step was to improve each of the three main sections of the image using CLAHE individually before combining them into a single image. This was done by first dividing the image into three primary areas using Multilevel image thresholds. After that, the image should be improved once more with CLAHE, and a Mean filter and Non leaner mapping should be applied so that the contrast can be increased and noise can be removed.

2.1 Image segmentation based on Multilevel image thresholds

In image processing, separating objects from their backgrounds requires choosing a threshold of gray level.

Let the grayscale of the image's pixels be represented by the number L {1,2,...L}. The gray level histogram was normalized and represented as a probability distribution, where the number of pixels at level z is given by n z and the total number of pixels by N = n 1 + n 2 +....+n L:

$$p_z = n_z / N \quad , P_z \geq 0, \sum_{z=1}^{L} p_z = 1 \tag{1}$$

pixel G_0 and G_1 by threshold

Now, let us divide through cutoff, pretending to segment the into k levels, where G_o indicates pixels with a level of [1,... .k] at the G1 level (k+1). L]. Then the average levels and probability were provided by [20]

$$\omega_0 = \Pr(G_0) = \sum_{z=1}^{4} P_z = \omega(k) \tag{2}$$

$$\omega_1 = \Pr(G_1) = \sum_{z=k+1}^{4} P_z = 1 - \omega(k) \tag{3}$$

and

$$\mu_0 = \sum_{z=1}^{4} \Pr(z/g_0)\, z = \sum_{z=1}^{4} \frac{zP_z}{\omega_0} = \mu(k)/\omega(k) \tag{4}$$

$$\mu_1 = \sum_{z=k+1}^{4} z\Pr(z/g_1) = \sum_{z=k+1}^{L} \frac{zP_z}{\omega_1} = \mu_T - \mu(k)/1 - \omega(k) \tag{5}$$

where,

$$\omega(k) = \sum_{z=1}^{k} P_z \tag{6}$$

and

$$\mu(k) = \sum_{z=1}^{k} z p_z \tag{7}$$

differences between groups were calculated by:

$$\alpha_0^2 = \sum_{z=1}^{k} (z - \mu_0)^2 \Pr\left(\frac{z}{g_0}\right) = \sum_{z=1}^{k} (z - \mu_0)^2 P_z / \omega_0 \tag{8}$$

$$\alpha_1^2 = \sum_{z=k+1}^{L} (z - \mu_1)^2 \Pr\left(\frac{z}{g_1}\right) = \sum_{z=k+1}^{L} (z - \mu_1)^2 P_z / \omega_1 \tag{9}$$

Class reparability is a metric used in discriminant analysis that allows assessing the threshold quality at level k.

$$\lambda = \alpha_B^2 / \alpha_W^2 \;,\; k = \alpha_T^2 / \alpha_W^2 \quad , \quad \eta = \alpha_B^2 / \alpha_T^2 \tag{10}$$

where

$$\alpha_W^2 = \omega_0\, \alpha_0^2 + \omega_1\, \alpha_1^2 \tag{11}$$

$$\alpha_B^2 = \omega_0 (\mu_0 - \mu_T)^2 + \omega_1 (\mu_1 - \mu_T)^2 \tag{12}$$

$$\text{so:} \quad \alpha_T^2 = \sum_{z=1}^{L} (z - \mu_T)^2 P_z \tag{13}$$

utilizing the straightforward cumulative quantities at the optimum threshold k* was to maximize Ƞ.

$$\alpha_B^2(k^*) = \max_{1 \leq k < L} \alpha_B^2(k) \tag{14}$$

2.2 Contrast Limited AHE (CLAHE)

This strategy is based on the idea that a picture may be partitioned into many non-overlapping areas of about similar size. Tile calls are the unit of operation for CLAHE instead of the complete picture. To modify the contrast color of each tile, an adaptive approach was used to determine the function of the current state of the histogram. The histogram of the approximated value of an area grows with the number of contrasted tiles. To prevent artificial barriers from forming, adjacent tiles were blended. The contrast will be reduced primarily in homogenous areas to prevent the amplification of any noise in the picture. Gray scale histogram equalization on picture x, where z is a grayscale value between 0 and 256. How to seek probabilities at pixel image from level z in a picture as[21].:

$$P_x(z) = P_{(x-z)} = n_z / n_0 \rightarrow 0 \leq z < V \tag{15}$$

The V value represents the whole intensity range of the picture (256), n represents the collection's total number of picture pixels, and P x (z) is an index representing the pixel's picture histogram. Tiles (of size 8x8) were utilized to partition the picture into smaller halves, and the histogram equalization process was applied to every pair of adjacent tiles. The findings that accumulate in a concentrated area to form the histogram would apply to that area. Limiting the contrast to cut down on the noise was essential. Before using histogram equalization, any bins whose contrast is more than the threshold were removed and redistributed evenly to other bins; after that, bilinear interpolation was used to eliminate artifacts in the tile's border. After applying the optimization technique to each segmentation image, three images (I_n, $n = 1,2$ and 3) were produced and combined to form one image according to the relationship.

$$I_T(x,y) = CLAHE\big(I_1(x,y)\big) + CLAHE\big(I_2(x,y)\big) + CLAHE\big(I_3(x,y)\big) \quad (16)$$

Technique CLAHE was applied again to the image. This process allows increasing contrast by

$$I_{Te}(x,y) = CLAHE(I_T(x,y)) \quad (17)$$

2.3 Mean filter and Non leaner mapping

Sharp edges appear because of the cutting rationing, so using the filter to eliminate these edges is preferable, as follows.

$$I\_Tem\ (x,y) = 1/(\ 1 + 0.4136(1 - I_{Te}(x,y))/[I_{Te}(x,y)]^{0.9}) \quad (18)$$

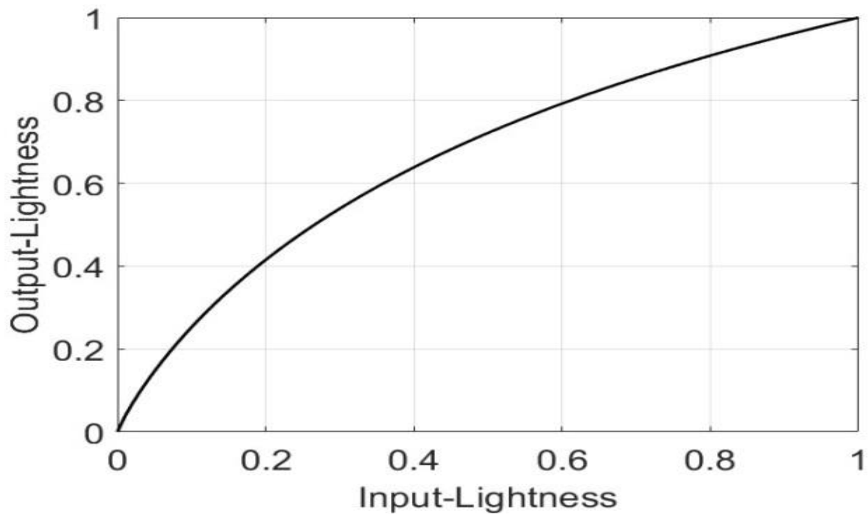

Figure 1: Non leaner Mapping Function for the gray image.

The nonlinear transformation was adopted to improve illumination consistently; Figure-1 shows the nonlinear transformation function. This transformation increases the illumination in the low and medium areas and remains almost constant in the high areas. Figure 2 represents the general outline of the proposed algorithm for improving MRI images. In contrast, Figure 3 shows the details of the proposed method supported by images of the most critical stages.

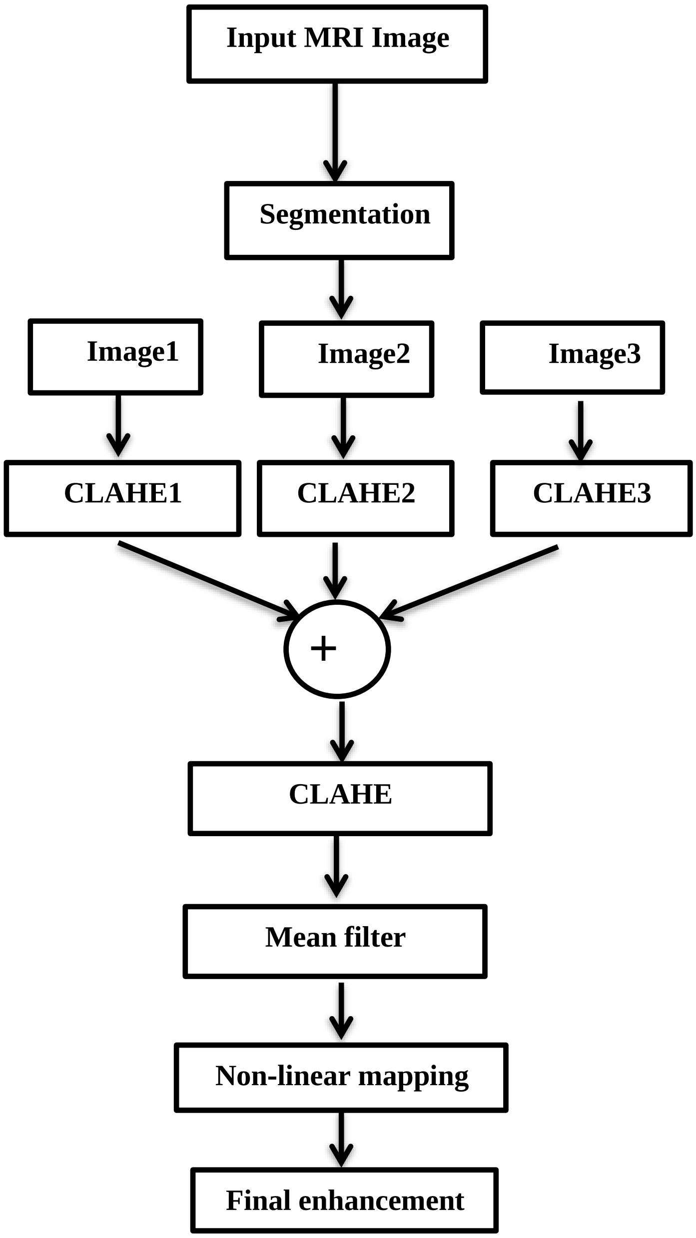

Figure 2: Diagram of the proposed method

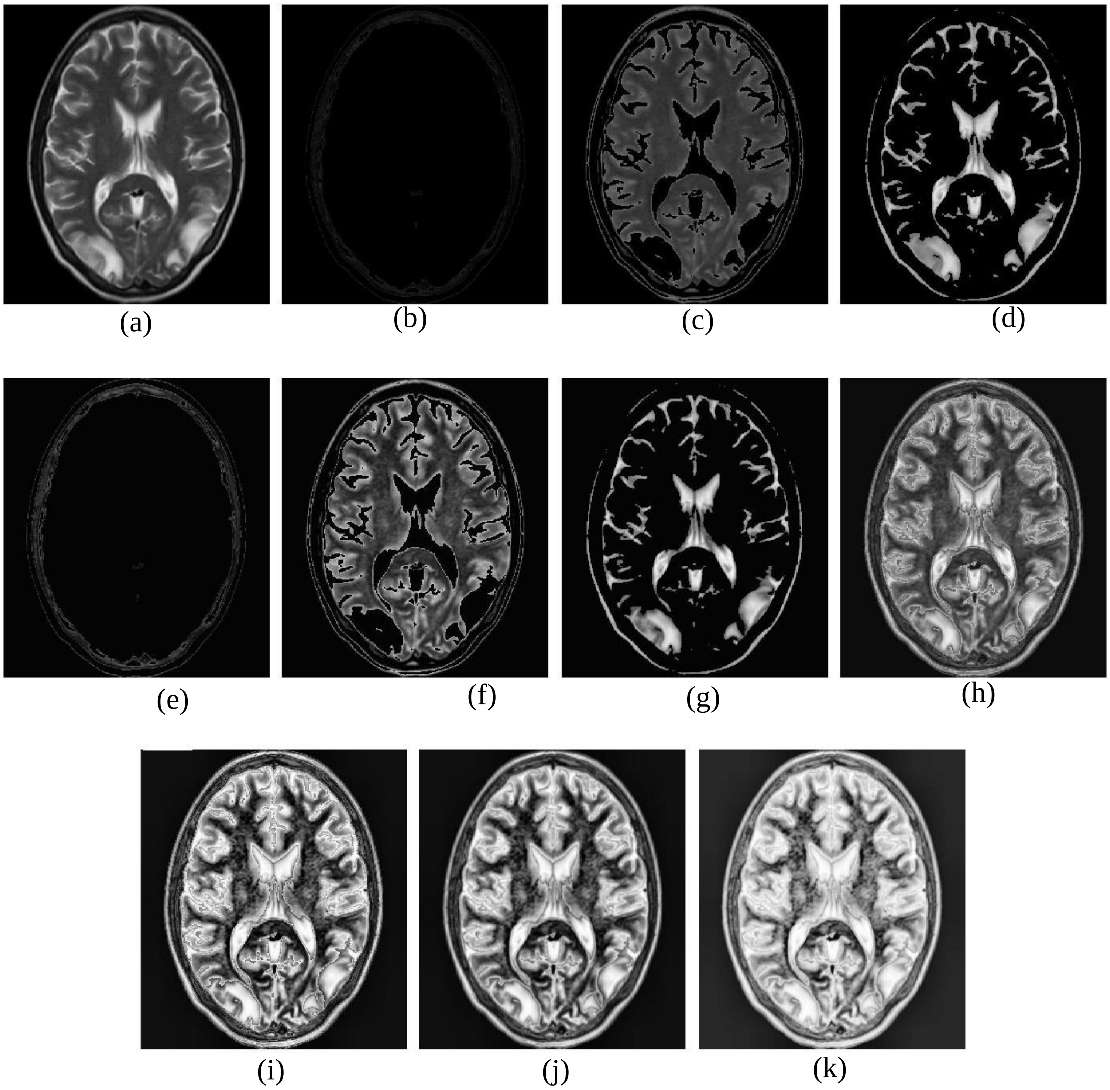

Figure 3: The original image in (a), the first, second, and third segmented images in (b, c, and d), respectively, in (e, f, and g), the enhanced image for (b, c, and d) respectively by using (CLAHE), in (h) the overall image resulting from the summation of images (e, f, and g), in (i) CLAHE for (h) image, in (j) the application of the mean filter to the overall image in (i), and (k) the final enhanced image after applying the nonlinear image transformation for (j) image

3. Results and analysis

MRI images were improved in this study based on several algorithms like MCLAHE, AHE, FCCE, FLSMF, FSBDHE, MCHE, and MSR. Data were used [22] containing 154 of type bmp and size of 512×512. All algorithms used in this study were done using MATLAB programs R2022a. Figure 4 shows four images selected as an enhancement model to find out the efficiency of improvement, and several quality measures were used Entropy (EN) [23], Average Gradient (AG) [24], and contrast enhancement measurement (CEM) [25].

Table 1 shows the improvement quality average for all images. Noticing that the best improvement quality was for the proposed method followed by AHE and MSR, where the MCLAHE has the highest quality values and which indicates the success of the proposed method in increasing the contrast and detail of the MRI images; this can be seen through macroscopic observation of the improvement in the Figures (5 and 6) which contains an enlarged area to know the contrast quality of the two images (37 and 38). The two Figures (8 and 10) represent the histogram distribution of the images (39 and 40) in Figures (7 and 9). Through it, noticing that the best distribution ranges were for the proposed method MCLAHE, followed by the modalities (FSBDHE and AHE).

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

Method	EN	AG	CEM
MCLAHE	6.14	6.79	0.84
AHE	6.14	5.78	0.84
FCCE	5.83	4.30	0.81
FLSMF	5.39	5.23	0.79
FSBDHE	5.32	3.62	0.82
MCHE	4.50	4.60	0.72
MSR	5.43	6.19	0.81

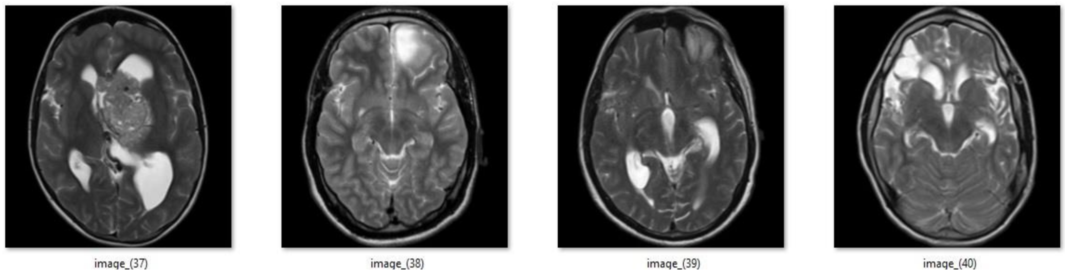

Figure 4: Four images were chosen as models to illustrate the quality of the improvement

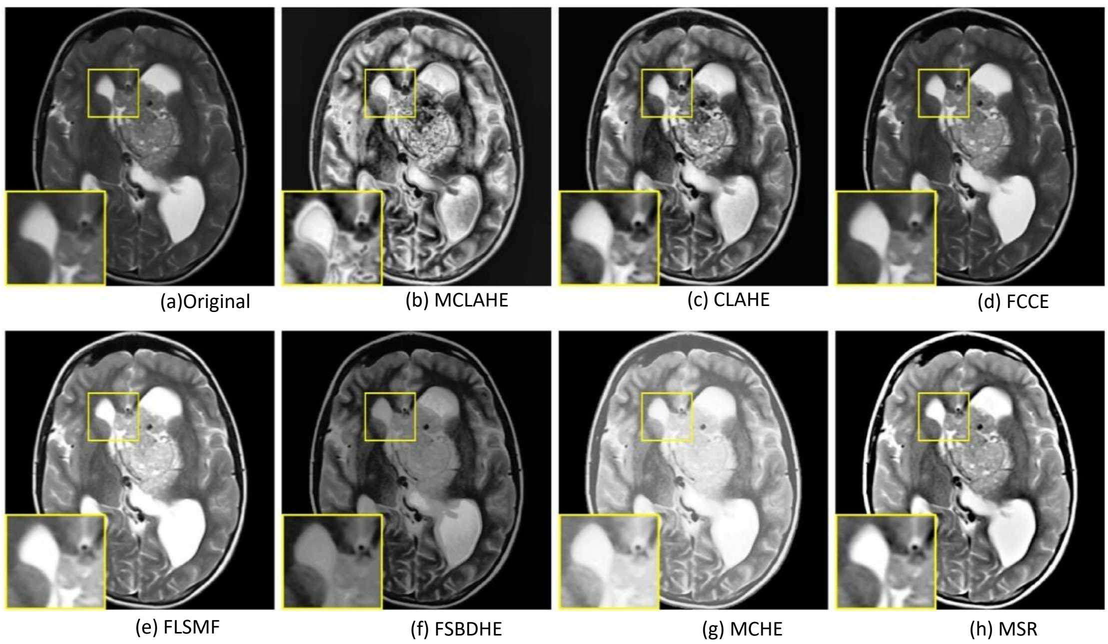

Figure 5: MRI image (37) with an enlarged area that was enhanced using various algorithms.

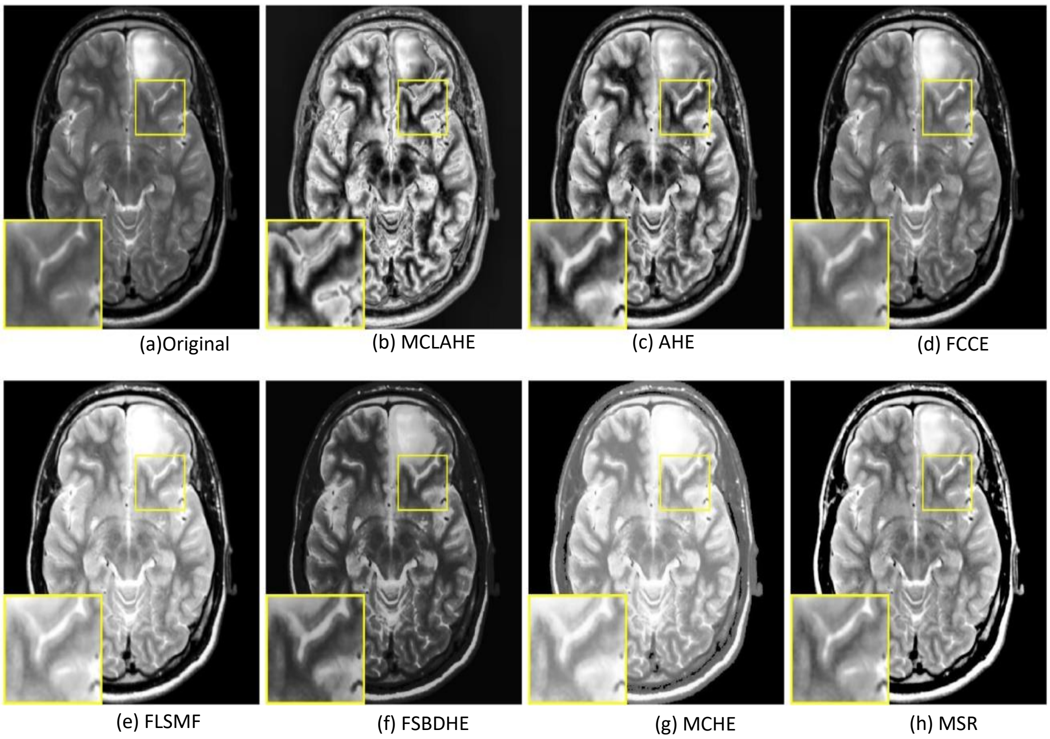

Figure 6: MRI image (38) with an enlarged area that was enhanced using various algorithms.

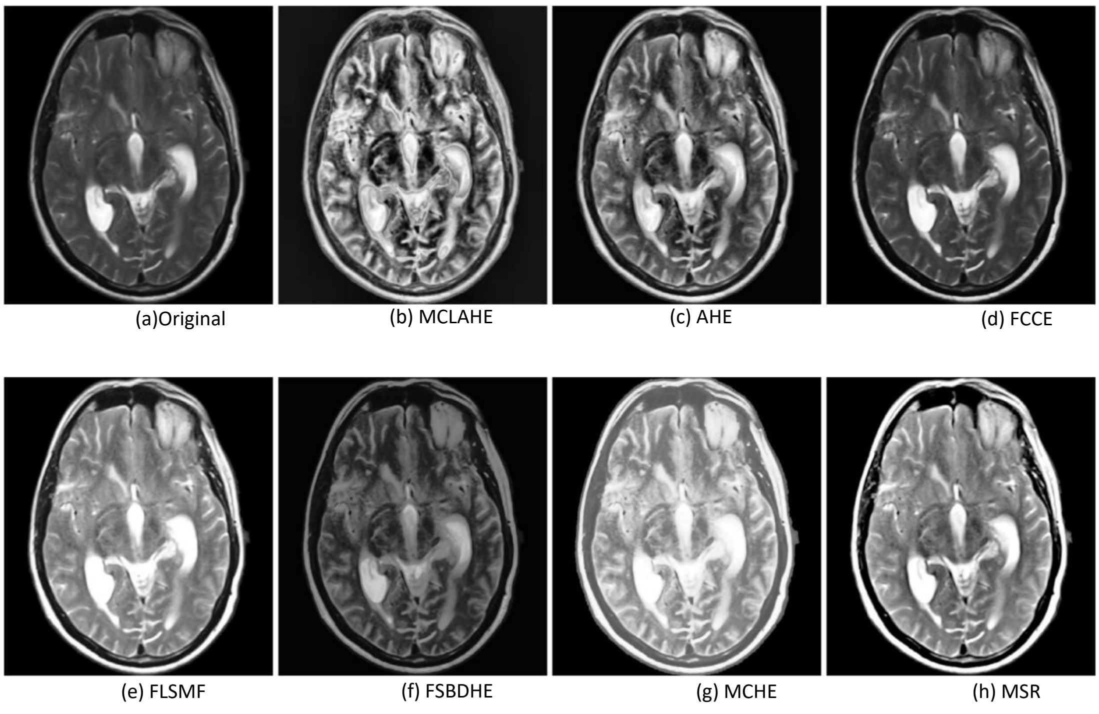

Figure 7: MRI image (39) that was enhanced using various algorithms.

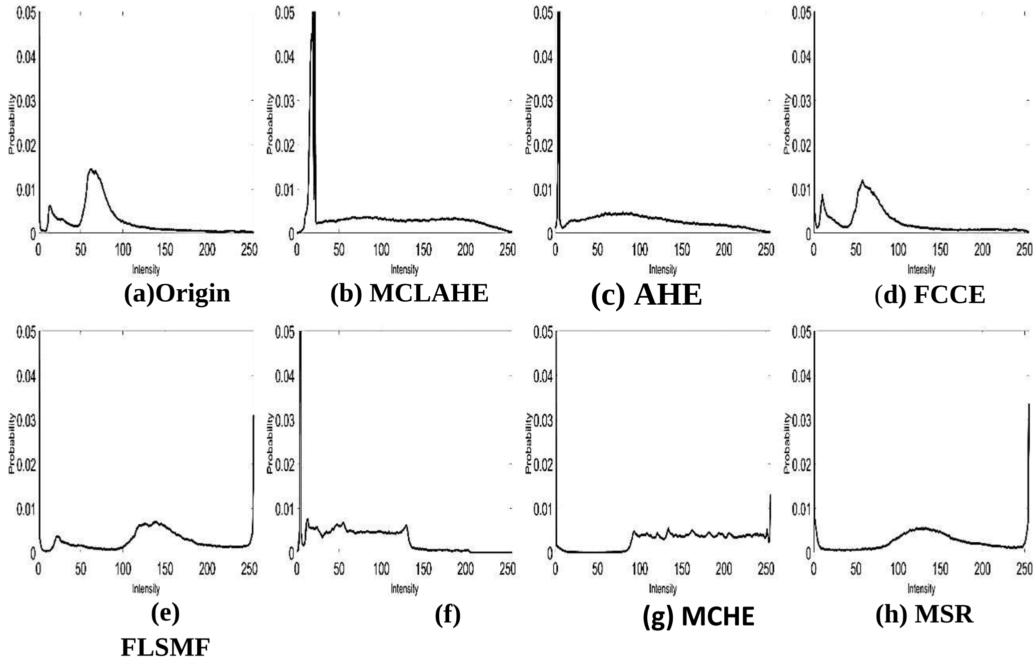

Figure 8: The histogram of the MRI image (39) was enhanced using various algorithms.

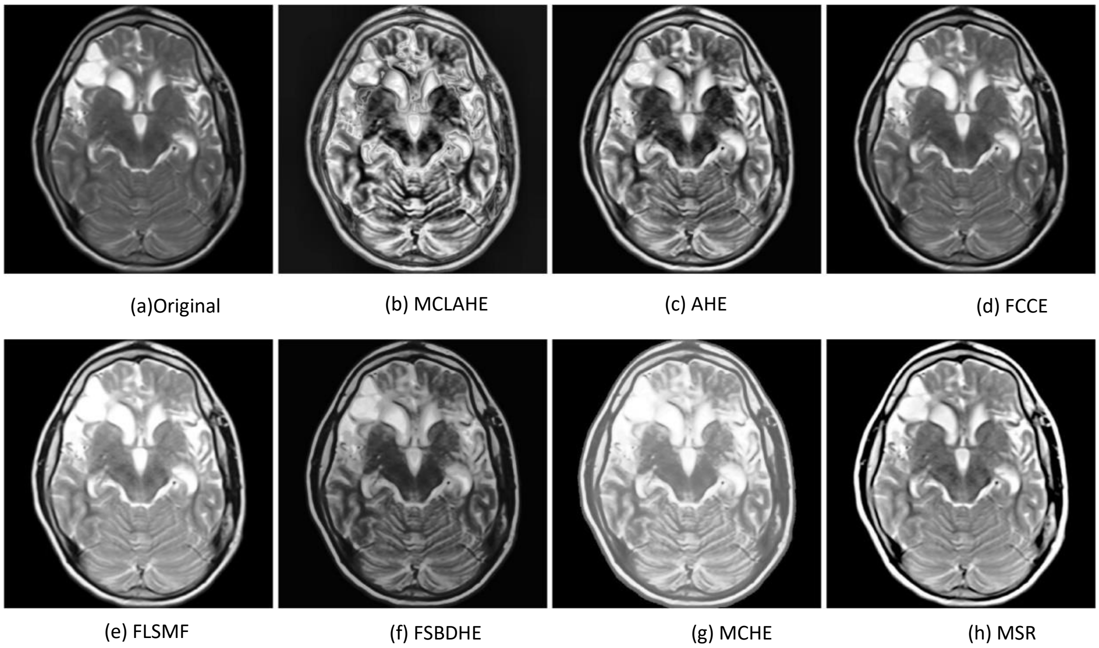

Figure 9: MRI image (40) that was enhanced using various algorithms.

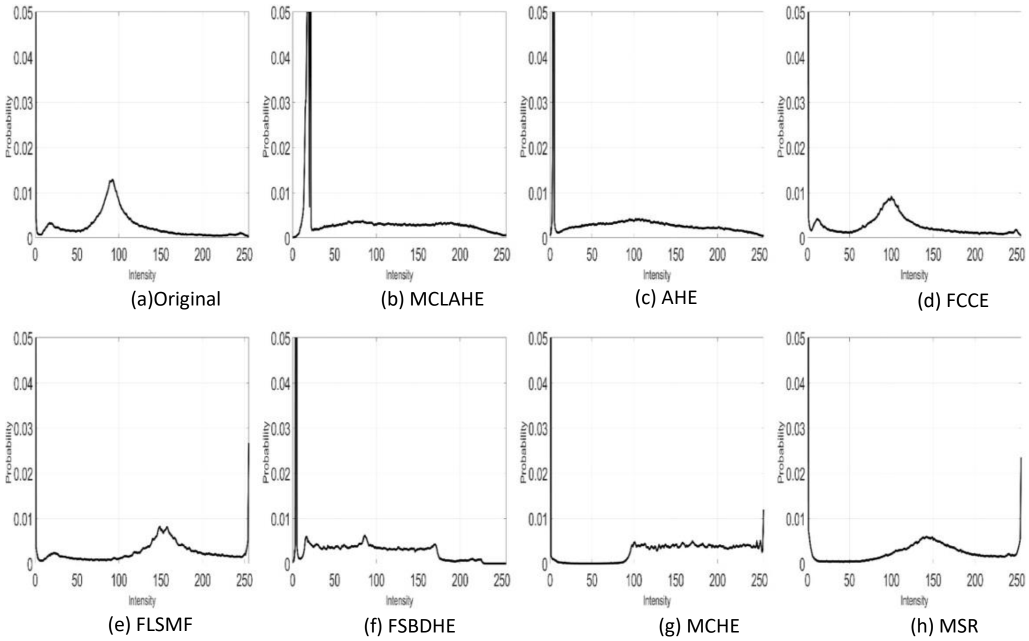

Figure 10: The histogram of the MRI image (a_40) was enhanced using various algorithms.

4. Conclusions

MRI images need to increase brightness and contrast to facilitate distinguishing diseases. This study aims to improve the MRI images depending on the suggested algorithm (MCLAHE) to improve contrast in MRI images. This proposed algorithm was compared with several algorithms using non-referenced quality measures, such as (AHE, FCCE, FLSMF, FSBDHE, MCHE, and MSR). By analyzing the results in which a large number of images (154) were used, the proposed method obtained the best quality rates EN(6.14), AG(6.79), and CEM(0.84), which indicates its great success in increasing clarity in those images.

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