Received: October 12, 2022. Revised: November 26, 2022.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

MRI Image Enhancement Based Fuzzy C-Mean Segment and Modified Adapted Histogram Equalization

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Abstract: A powerful magnetic field and high-frequency radio waves are used in magnetic resonance imaging (MRI) to create highly detailed images. By examining anomalies in the brain, spinal cord, muscles and liver, MRI can be utilised to identify specifics about soft tissues. MRI is very helpful in finding cancers in these tissues. Brain images from MRI often suffer from insufficient detail and contrast. This study focused on improving brain images from MRI by relying on c-mean fuzzy segmentation to enhance and preserve the detail of the images and applying adaptive histogram equalisation with the introduction of a smoothing median filter for reducing blurring and increasing contrast using the sigmoid function. The method was compared with several methods, such as local fractional entropy, Riesz fractional, dual illumination estimation, fuzzy logic based on the sigmoid membership function, fuzzy and spline based dynamic histogram equalisation and modified colour histogram equalisation, by calculating quality standards, namely, NIQE and BRISQUE. Results show that the method obtained the best results, namely, 5.4003 (NIQE) and 36.614 (BRISQUE) values.

Keywords: Medical image enhancement, Brain MRI, Adaptive histogram equalisation, Fuzzy c-mean clustering, sigmoid function.

1. Introduction

Image enhancement is one of the most important and popular processing steps in the digital image processing field [1, 2] that reduces image noise, eliminates artifacts and preserves details [3]. Image enhancement processes specific image characteristics for analysis, diagnosis [4] and visual information with great clarity [5]. The processed image is more suitable than the original image for the purpose or required task [6]. In the medical field, digital image processing is used in many procedures [7], such as PET scans, magnetic resonance imaging (MRI), X-ray imaging computed tomography (CT), radiology imaging and imaging cancer cells, and many other activities in clinical medicine for diagnosing and distinguishing different types of diseases [8][9]. Where the surgeon needs to obtain improved medical images for accurate diagnosis and interpretation because the quality of medical images is degraded by noise, other data acquisition processing and lighting conditions. Solving the issues of low contrast and high-level noise in medical images is the primary objective of medical image enhancement [10].

Poor brightness and contrast are common degradations in MR images, and they have a significant impact on the visible quality. Numerous limitations in the real world cause these degradations. In the world of digital image processing, dynamic range limiting is also a well-known cause of these degradations. MR images are therefore classified as having a low dynamic range [11]. Interest in the field of image enhancement has increased significantly. Many great overview articles, journal papers and textbooks on image enhancement and identification have been published. A. Parihar et al. [12] presented a method that does not require any parameters to be specified or optimised to improve the contrast of images on the basis of fuzzy contextual contrast enhancement. This algorithm was tested on different types of low-contrast images, and the results show that it provides a good contrast enhancement and preserves the natural visual quality of images. K. Singh et al. [13] suggested two methods of exposure based on recursive histogram equalisation to improve image contrast, namely, recursive exposure and recursively divided exposure. Their methods achieve good visual quality for low-contrast images. H. G. Daway et al. [14] introduced a method for enhancing the contrast and illumination of colour images using fuzzy logic based on the sigmoid membership function (FLSMF). This suggested algorithm achieves better quality assessment of coloured images than other enhancement method, But the whiteness is high in the enhanced images .The fuzzy-based histogram equation was proposed by S. Saravanan and R. Karthigaivel. [15] to implement medical image contrast enhancement. The proposed method divides the image into connected regions according to a fuzzy membership function and spline-based dynamic histogram equalization (FSBDHE). The proposed model was tested with a T1-weighed MRI-brain dataset and significantly enhanced the contrast of the given dataset, but the image was extremely white since brightness enhancement wasn't good sufficiently. Wei-Yen Hsu and Ching-Yao Chou [16] used modified colour histogram equalisation (MCHE). This method improves retinal images, achieving good contrast enhancement but poor results in terms of information in colour. For images with bright and dark regions, A. Al-Shamasneh et al. [17] proposed a local fractional entropy (LFE) model to enhance MRI kidney images. This algorithm is based on the pixel probability of the neighbouring pixels. At the edges, the LFE provides good image details, and the smooth texture does not provide fine details. Depending on the change in intensity values, this model improves contrast and provides fine detail to entire MRI kidney images. Another algorithm used on the Riesz Fractional (RF) operator was proposed by K. Raghunandan et al. [18] to increase the characteristics of the edge information in license plate photos and improve the efficiency of text detection and identification procedures. The suggested method enhances each input image’s edge strength before applying Riesz fractional derivative convolution to it. The results from enhancement experiments illustrate that the model outperforms the current baseline enhancement strategies in terms of quality assessment. As a result of the image typically appearing dark, illumination did not significantly improve. Q. Zhang et al. [19] introduced a cutting-edge automatic exposure correction technology that can consistently produce results of the highest calibre for images with various exposure situations. The under- and over-exposure corrections were independently cast as the trivial lightness determinate of the input image and inverted in the proposed dual lightness estimation (DIE). Using a multi of the image fusion-based exposure algorithm, the two intermediate exposure correction images and the input image are adaptively combined into a good, exposed image. Several challenging images demonstrate the effectiveness of the suggested approach and how it outperforms state-of-the-art methods and well-liked automatic exposure correction solutions, but the results show that the image's brightness has not significantly improved. R. Ibrahim et al. [20] presented an algorithm that depends on the differential equations used fractional that were used to improve the low contrast in the presented enhancement operator using fractional. The presented method can significantly enhance the details of medical images and the medical diagnosis. X. Fu et al. [21] presented a method to improve the poor illumination of colour images based on an efficient fusion using an illumination estimating algorithm and a sigmoid function with adaptive histogram equalisation. This method enhances images under different low illumination conditions and preserves the natural feel of images.

In this study, MRI brain images were enhanced utilizing fuzzy segmentation methods, AHE optimization, and the sigmoid function to enhance contrast. One of this method's advantages was that it used segmentation and enhancement techniques to significantly improve brightness and contrast.

2. Proposed method

In this study, we investigated c-means fuzzy segmentation to enhance and preserve the details of brain images from MRI, using the segmentation method and applying adaptive histogram equalisation to each era, combining images after the segment process and introducing a smoothing median filter to reduce blurring and increase contrast using the sigmoid function. In c-means segmentation by fast and robust fuzzy (CMFRF), the image is segmented by dividing an image into multiple regions to locate the object of interest. Then, segmentation is performed using the CMFRF approach and morphological reconstruction (MR).

2.1 Fuzzy segmentation

The CMFRF approach is used to enhance the image quality without using any filters. CMFRF can remove various types of noise [22, 23].

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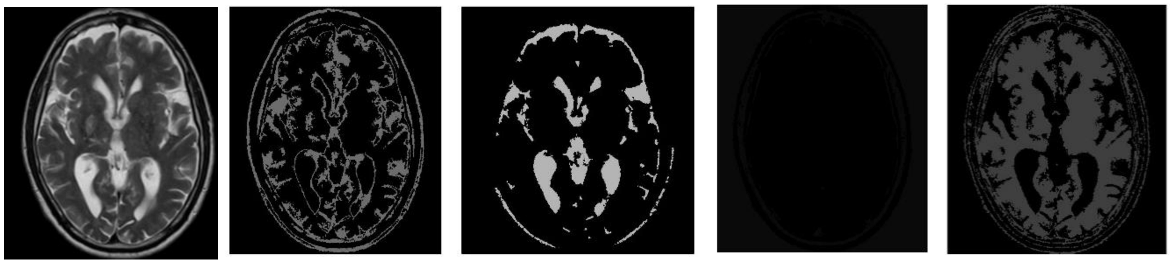
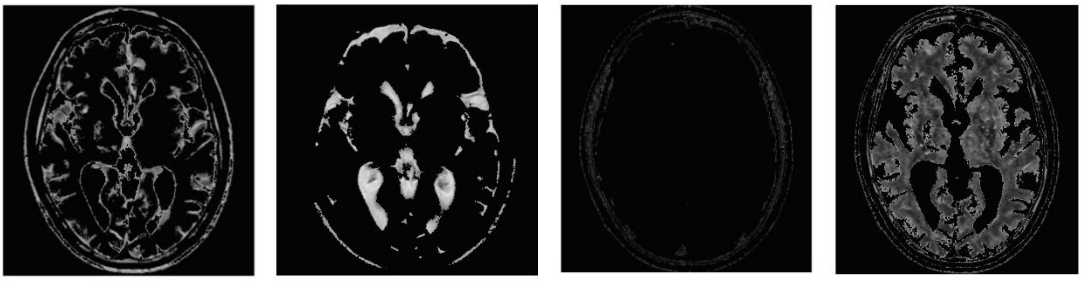


(a) (b) (c) (d) (e)

Figure. 1 In (a) original images and in (b,c,d,& e) are Comparison of MRI brain segmentation results



(a) (b) (c) (d)

Figure. 2 the images in fgure1 (b,c,d,& e) are enhanced by AHE

Stages of the CMFRF technique [23]:

a. Determination of the minimal error threshold (ή), the filtering window size (w), the fuzzification parameter (m) and the cluster prototype value (c).
b. estimate the new image ξ by using the following equation and calculate the histogram of ξ

$$\xi = R^C(f) \tag{1}$$

Where R^C denotes morphological closing reconstruction and f represents original image
c. Random determination of the start of the iteration and the membership partition matrix $U^{(0)}$.
d. Setting of the loop count values to 0.
e. Use of the following equation to update the clustering center v_k.

$$u_{kl} = \frac{\|\xi_l - v_k\|^{-2/(m-1)}}{\sum_{j=1}^{c} \|\xi_l - v_j\|^{-2/(m-1)}} \tag{2}$$

$$v_k = \frac{\sum_{i=1}^{q} \gamma_l \mu_{kl}^{m_l}}{\sum_{i=1}^{q} \gamma_l \mu_{kl}^{m}} \tag{3}$$

μ_{kl} denotes the fuzzy membership for a lightness component l with regard to cluster K.
q denotes the number of the gray levels in ξ.

$$\sum_{l=1}^{q} \gamma l = N \tag{4}$$

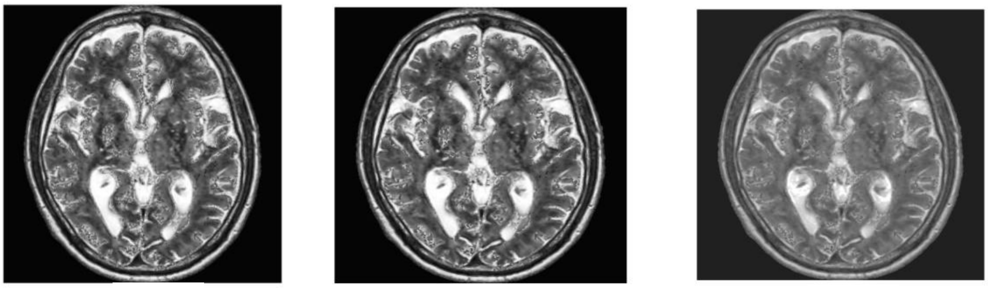
γl is the pixel number, N is the number of total pixels in the image.
f. Update of membership partition matrix $U^{(t+1)}$ using Eq. 2.
g. If $max\{U^{(t)} - U^{(t+1)}\} < \eta$, then stop; otherwise, t = t + 1 and perform Step 5.
h. Median filtering using the following equation on membership partition matrix U'

$$U'' = \text{med}\,\{U'\} \tag{5}$$

The image is segmented after using the CMFRF approach, and the noise is also removed. The segmentation yields four MRI regions, as illustrated in Fig. 1.

2.2 Modified AHE

A computer image processing method called adaptive histogram equalisation (AHE) is used to restore contrast in images [24]. This adaptive technique may be different from traditional histogram equalisation in that it uses many histograms, each representing a different area of the image, to reorder the image's brightness values. This technique is appropriate for enhancing an



(a) (b) (c)

Figure. 3 Simulation results of the MRI Brain image: (a) Collected output image in Fig. 2, (b) image filtered by median filter, and (c) image enhanced by sigmoid function

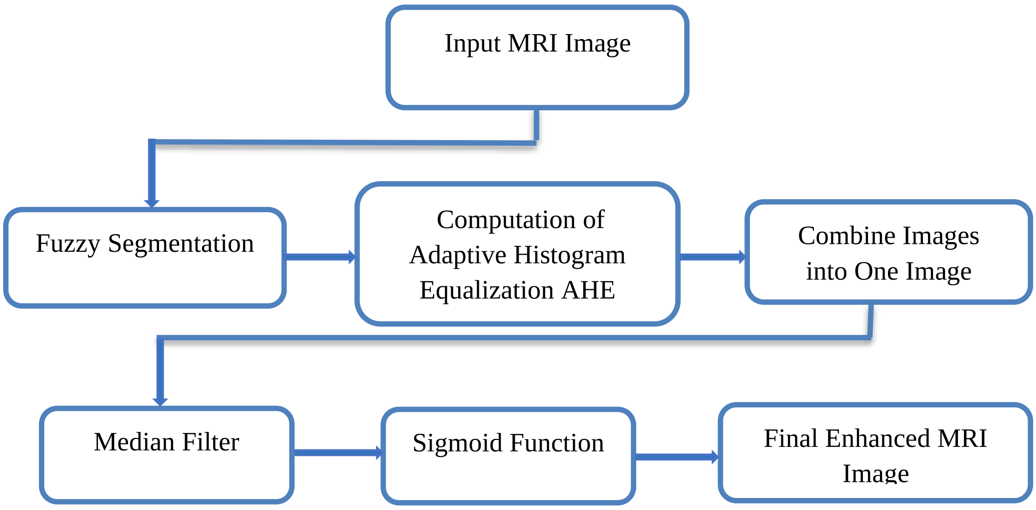


Figure. 4 A scheme for MRI image enhancement by suggested algorithm

image's local contrast and producing a detailed image [25]. Each segmented image was processed by using the AHE technique, as shown in Fig. 2.

2.3 Median filter

The median filter, which is the most popular order statistics filter, replaces grey pixel values with the median value in its immediate vicinity. The median is calculated considering the pixel's original value. Given their great denoising capabilities for some types of random noise and significant deblurring compared with the linear smoothing of comparable size [26], four MRI segment images were collected into one enhanced image (see Fig. 3 (a)) according to

$$\in = \sum_{i=n}^{n} AHE_i \tag{6}$$

To remove blurring and preserve the edge, a smoothing median filter was applied to the four MRI segment images to create one enhanced image as shown in Fig. 3 (b).

2.4 Sigmoid Mapping

The sigmoid function was used for the contrast enhancement of the image according to [14]:

$$\mu_{ij} = 1/\left(1 + \left(\sqrt{(1 - X_{ij})/X_{ij}}\right)\right) \tag{7}$$

Where X_{ij} is the input intensity value, and μ_{ij} is the output intensity value. This function also increases the contrast.

According to Fig. 3 (c), the intensity levels increase in areas with low illumination or less than 0.5, remain the same in areas with medium illumination or above 0.5 and remain low in areas with high illumination. The Fig. 4 shows the steps of the proposed method.

3. Quality assessment

NIQE is a completely blind quality analyser that focuses entirely on quantifiable derivations from the statistical regularities observed in real-world images, without any exposure to or training on distorted

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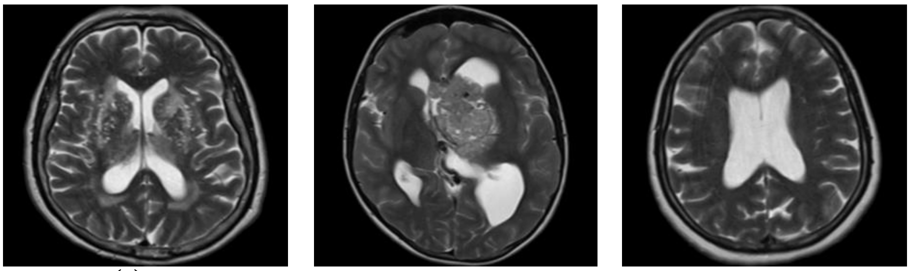
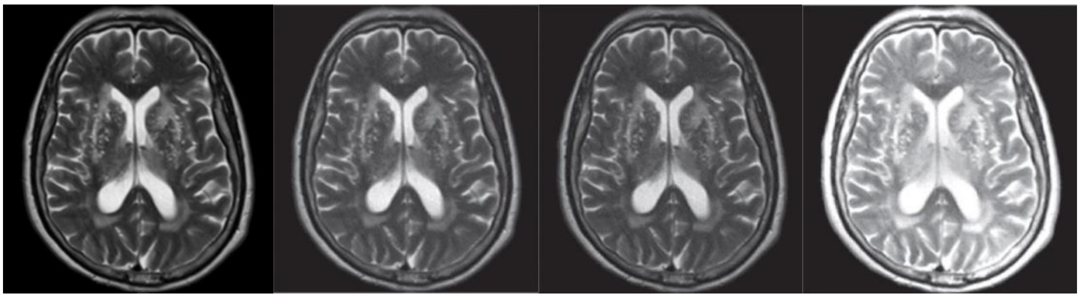
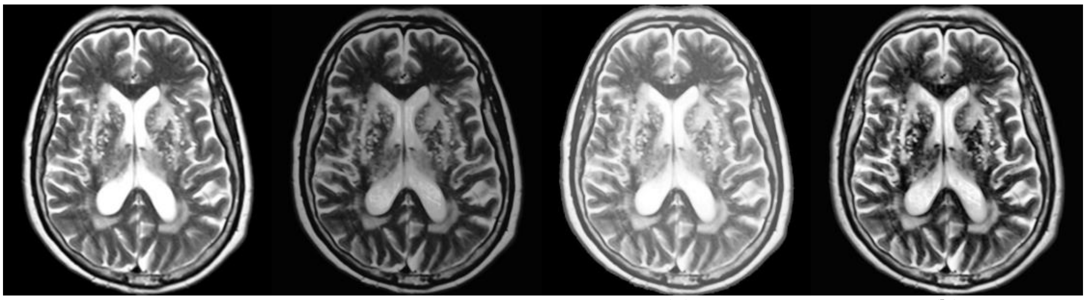


(a) (b) (c)

Figure. 5 Images selected: (a) label_13, (b) label_37, and (c) label_46



(a) (b) (c) (d)



(e) (f) (g) (h)

Figure. 6 MRI brain Images 13 enhanced by using several algorithm: (a) original, (b) LFE[17], (c) RF[18], (d) DIE[19], (e) FLSMF[14], (f) FSBDHE[15], (g) MCHE[16], and (h) Sug

images that have been graded by humans. Based on a straightforward and efficient space domain natural scene statistic algorithm, it builds a quality-aware collection of static features. These characteristics are generated from a collection of accurate, natural images. The NIQE descriptor calculates an image's quality score; a low number suggests a high perceived quality [27]. The no reference image quality assessment of images is used, that is, blind-referenceless is image spatial quality evaluator (BRISQUE) [28].

4. Result and discussion

In this study, a new method is suggested to enhance brain images from MRI. All programmes were developed using Matlab (r2021a). A dataset (154 MRI) of images was used in this study (with size of 512 × 512 and JPG type) [29]. Brain images are enhanced using several algorithms LFE, RF, DIE, FLSMF, FSBDHE, MCHE and the suggested algorithm (sug.). NIQE and BRISQUE are quality measures were employed to determine the effectiveness of enhancing these images. Table 1. Present the rate of the quality assessment for the enhanced MRI brain images (154 images). The lowest value (NIQE and BRISQUE) was obtained by the proposed method, followed by the following methods: LFE for NIQE and FSBDHE for BRISQUE and the other algorithm. In Fig. 5, three images (a, b and c) from the dataset with respective labels of (a) label_13, (b) label_37, and (c) label_46 were selected for subjective quality assessment and histogram distribution. Increased details, information and illumination value were achieved by the proposed method and preserved the details of brain images

Using subjective observations, Fig. 6 shows that 13 images were improved using various enhancement techniques. The proposed method produced the best enhancement (increase in contrast). The histogram distribution in Fig. 7 shows the same enhancement characteristics. The best wide histogram ranges were obtained by the suggested method, indicating the proposed algorithm was successful in increasing the lightness and contrast of the enhanced images. Figs. 8 and 9 show enlarged portions of an improved image (37 and 46) with more information and details. The sug. Methodology produced the greatest increase in illumination value.

5. Conclusion

This study attempted to enhance low contrast and non-uniform lighting brain images from MRI by implementing a new algorithm. By employing quality measurement techniques, like NIQE and BRISQUE, the proposed method was compared with the LFE, RF, DIE, FLSMF, FSBDHE and MCHE algorithms. The analysis of the data reveals that the suggested algorithm can successfully improve brain images from MRI and exhibit good performance on those obtained using alternative techniques. The proposed method obtained the best averages for the NIQE (5.4003) and BRISQUE (36.614) values. Future studies can employ the suggested technique to enhance CT images.

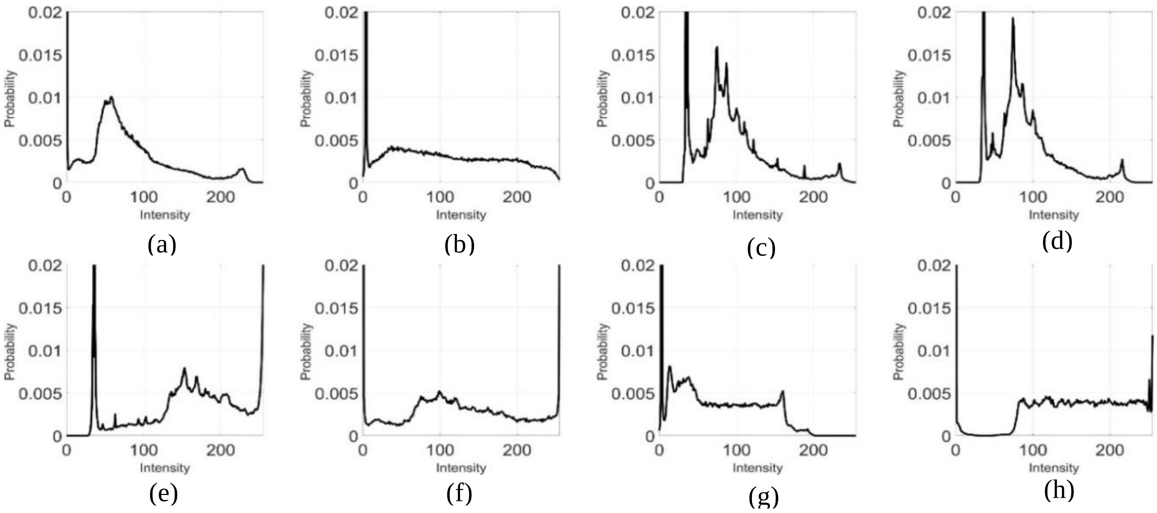


Figure. 7 Histograms of MRI brain Images 13 enhanced by using several algorithms: (a) original, (b) LFE[17], (c) RF[18], (d) DIE[19], (e) FLSMF[14], (f) FSBDHE[15], (g) MCHE[16], and (h) Sug

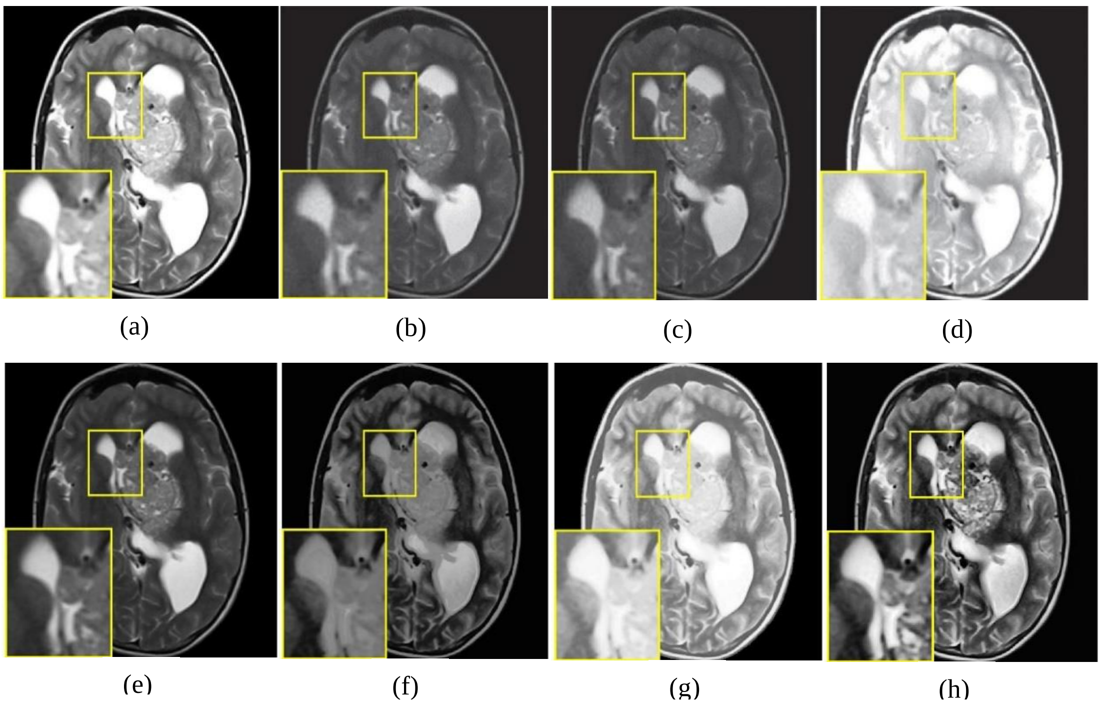


Figure. 8 MRI brain Images 37 enhanced by using several algorithms: (a) original , (b) LFE[17], (c) RF[18], (d) DIE[19], (e) FLSMF[14], (f) FSBDHE[15], (g) MCHE[16], and (h) Sug

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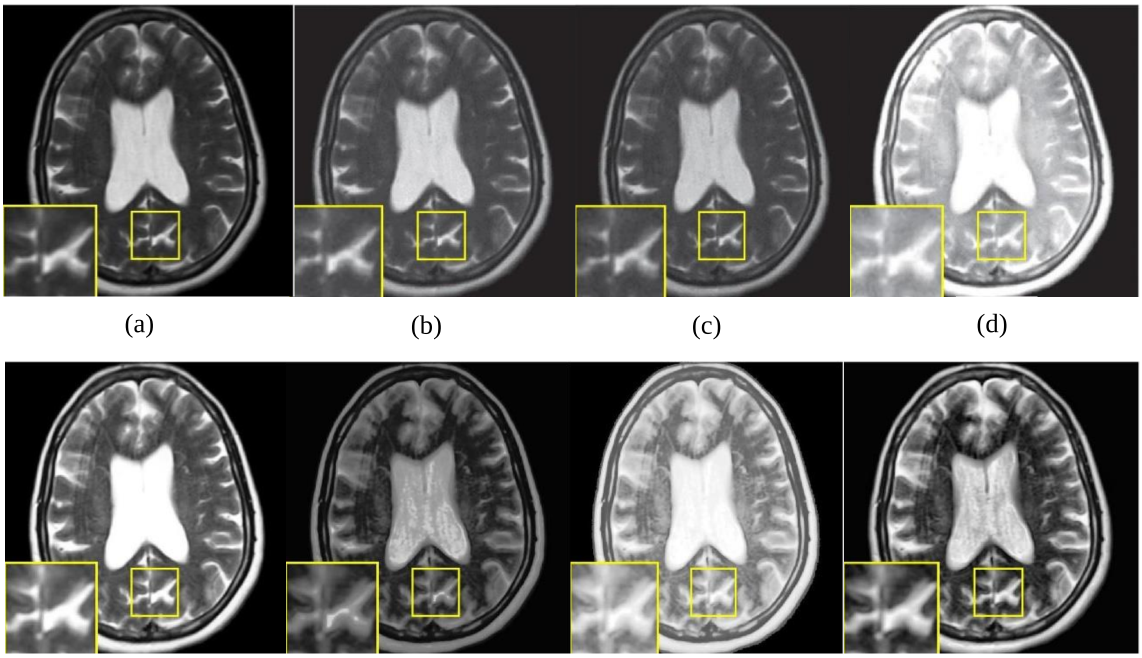

Figure. 9 The MRI brain Images 46 enhanced by using several algorithms: (a) original, (b) LFE[17], (c) RF[18], (d) DIE[19], (e) FLSMF[14], (f) FSBDHE[15], (g) MCHE[16], and (h) Sug

Table 1. Average of quality enhancement MRI brain images

Method	BRISQE	NIQE
Sug.	**36.614**	**5.400**
LFE[17]	51.372	5.516
RF [18]	49.501	5.749
DIE[19]	43.017	5.559
FLSMF [14]	42.158	6.151
FSBDHE [15]	41.156	5.947
MCHE [16]	41.541	6.196

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Hazim G. Daway has contributed to the design and implementation of the research by using Matlab. Alaa H. Sheer have supervised the written paper and providing the necessary data. All authors approved the final version.

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