International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-3, February 2020

Brain MR Image Enhancement using Average Intensity Replacement Based on GWOHE Algorithm

Vidyasaraswathi H. N., Hanumantharaju M. C.

***Abstract:** The most important task in MR Image Enhancement is to obtain a high resolution optimized visual image using advanced image processing techniques. Most of the life photographs and various images such as aerial, medical and satellite are associated with noise and low grade intensity. To improve the quality for better visual appearance, noise has to be suppressed and contrast has to be enhanced. Traditional contrast improvement techniques do best for various images. But for MRI of brain images, there are chances of misrecognization of WMH (White Matter Hyperintensities) as Cerebrospinal fluid (CSF) in traditional enhancement techniques. To overcome this ambiguity and enhance WMH regions of MRI brain images, a novel algorithm has been proposed in this paper. This algorithm is called as Mean Intensity replacement based on Grey Wolf Optimization Histogram Equalization (GWOHE). This technique is applied on FLAIR images and comparison is tabulated along with existing technique for parameters such as PSNR, AMBE.*

***Keywords:** Image Enhancement, FLAIR Images, PSNR, Average Gradient.*

I. INTRODUCTION

The key function of an image enhancement is to upgrade the low contrast image and to find hidden parts in an image. High resolution images with sharp features can be obtained by applying spatial and frequency analysis. Fourier transform for image is obtained using frequency analysis while spatial analysis provides direct manipulation of pixels. Medical imaging of human body is usually obtained using MRI and CT scan [1,2]. These images help in identifying medical disorders such as stroke, tumour in bones and brains, spinal infection, shoulder injuries and multiple diseases.

MRI (Magnetic Resonance Imaging) of brain is also crucial in neuroimaging workflows. Therefore, enhancement of MRI images is essential to identify inflamed areas in the tissues, tumours and stream of the blood for proper diagnosis of diseases. Further non-invasive nature of MRI has made a resolution in diagnosis of neurological injury like ischemic stroke and other neurodegenerative pathologies like WML (White Matter Lesions) [3].

WMH observed in FLAIR (Fluid attenuated inversion recovery) images as well as T2-WI (T2-weighted imaging) of MRI, can be defined as variation in size and intensity of cerebral white matter [4]. High volume of WMH will lead to cardio vascular risk [5]. To differentiate WMH hyper intensities, it is essential to effectively examine the CSF tissue, white and gray matter division by using different hyper-intense sore analysis. Primarily, digital image processing was utilized to process three significant regions of brain cells (CSF, WM and GM) and it keeps processing WM defiled with WMH sores [6]. This work targets at improving the contrast enhancement algorithm, so that best enhancement result should be obtain to provide best segmentation accuracy.

II. LITERATURE SURVEY

In literature, a number of definitions exits for contrast. In general, each explanation defines the contrast as a rate of change of the luminance to the average background luminance value. Along with the numerous techniques of contrast enhancement, the Histogram Equalization (HE) based method is one of the most preferable techniques used by most researchers to enhance the image contrast [7][8][9]. In Senthilkumaran et.al [10], compare different enhancement algorithms based on HE such as GHE, LHE, BPDHE and Adaptive HE. The outcome of all the comparison methods has depicted certain amount of enhancement. Also in Kandhway et al. [8], they compare different enhancement approaches such as HE, RSIHE, BBHE.DSIHE, QDHE, ICEPMB, ESIHE, ACHME, DOTHE and ETHE. But these methods are applied to some general images.

Chiao Min Chen et.al [11] has proposed a progressive correlation histogram analysis depending on grayscale distribution level of pixel values by which improves adaptive contrast for recommended objects. The result has exposed that this technique is proper only for Parkinson disease patient. Gandhamal et.al [12] explained a LGS-Curve method, but in this method clarity of the small details is reducing and also block effects. Bhandari Ashish et.al [13] has introduced 'Cuckoo search algorithm' or 'meta-heuristic algorithm' to optimize brightness and to enhance image contrast by the process of image enhancement. Isa I.S, Sulaiman et.al [14] implemented AIR-AHE method to enhance the MRI images.

Revised Manuscript Received on February 24, 2020.
* Correspondence Author
Vidyasaraswathi H. N.*, Department of ECE, Bangalore Institute of Technology, Bangalore, India. E-mail: vidya.gowdaec@gmail.com
Hanumantharaju M. C., Department of ECE, BMS Institute of Technology and Management, Bangalore, India. E-mail: mchanumantharaju@bmsit.in

In this process, input images are partitioned into two sub-histograms and plateau limit concept has been applied, which help in brightness-preserving histogram. Optimization method is introduced to refine plateau limits. This paper produces better image by using GWOHE approach.

III. METHODOLOGY

The proposed work procedure for MRI brain Image Enhancement has been explained in this section.
This research implements an algorithm for MRI brain image called as the Average Intensity Replacement based on Grey Wolf Optimization HE (AIR-GWOHE). The implementation of this algorithm (AIR-GWOHE) on MR images at 1.5 Telsa indicates upgradation of WMH region.
The flow diagram represents the proposed algorithm is depicted in figure: 1

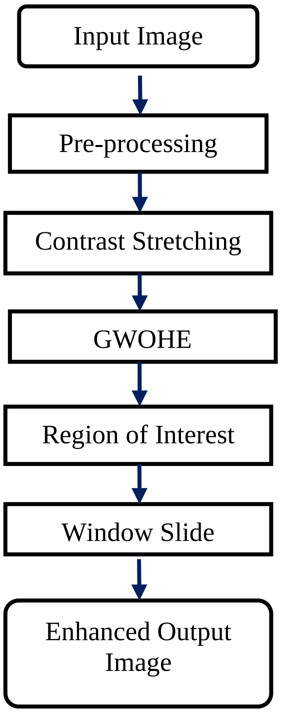


Figure: 1 Flow diagram of proposed model

Followings are the steps for image enhancement as

1. Load the input image.
2. Preprocessing to improve image data which suppresses unnecessary distortions and enhances some important image features for further processing.
3. The contrast of the pre-processed image will be improved by applying contrast stretching.
4. Apply the Grey wolf Optimization Histogram Equalization algorithm that, compresses and stretches the contrast for lower and higher histogram regions respectively.
5. Find the WMH regions with maximum intensity in the enhanced image.

A. Preprocessing

Image pre-processing is a significant task to enhance the features. Generally, MR image is available in DICOM format and converted to gray scale image as depicted in the figure:-2(a). MRI brain medical image has white matter lesions and outer head structures with similar hyperintensity values in FLAIR images [3]. MRI image also contains scattered attenuated signal (noise) as depicted in figure: 2(b). Therefore Skull-stripping is the most essential pre-processing stage [15][16][17].

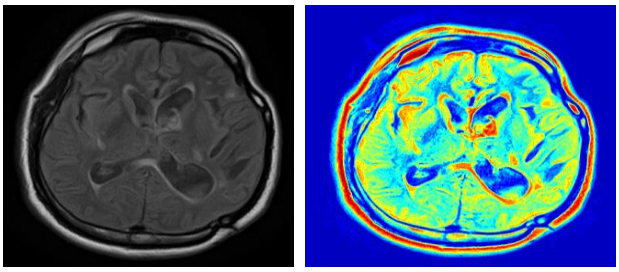


Figure:-2(a) Input image, (b) Image with scattered attenuated signal(noise) around skull.

Meanwhile, skull stripping is performed in pre-processing stage to remove noise and to retain essential parts of brain such as GM (gray matter), CSF (cerebrospinal fluid) and WM (white matter). The entire process involves morphological operations such as binarization, erosion followed by dilation and filling [18][19]. Binarization and erosion are used to isolate attached regions of the outer skull. The infinitesimal information in the eroded image will be preserved using dilation process. Then the final portion of the brain is obtained as a result of convolution of binary mask with input image .The overall process of morphological operations is as shown in the figure: - 3.

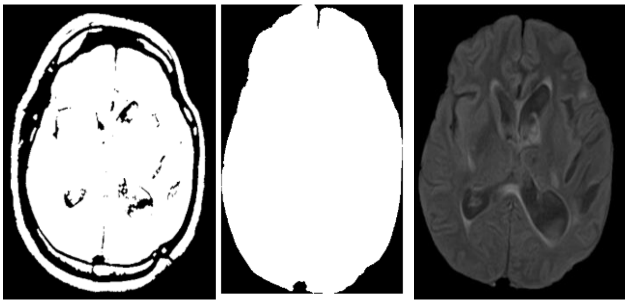


Figure:-3: Morphological Operations on Input Image (i) Image after erosion and dilation (ii) Filled Image (iii) Final image

B. Contrast stretching

In order to change the intensity values of image for specific range, contrast stretching is performed on FLAIR images. In this section stretchlim and imadjust functions are used. Stretchlim function returns the lower and upper gray values. Then the imadjust function increases the image contrast by using gray values returned. This stage will enhance the contrast of preprocessed image.

C. GWOHE based algorithm

Flow diagram depicted in figure:-4 is showing the procedure of GWOHE for image enhancement.

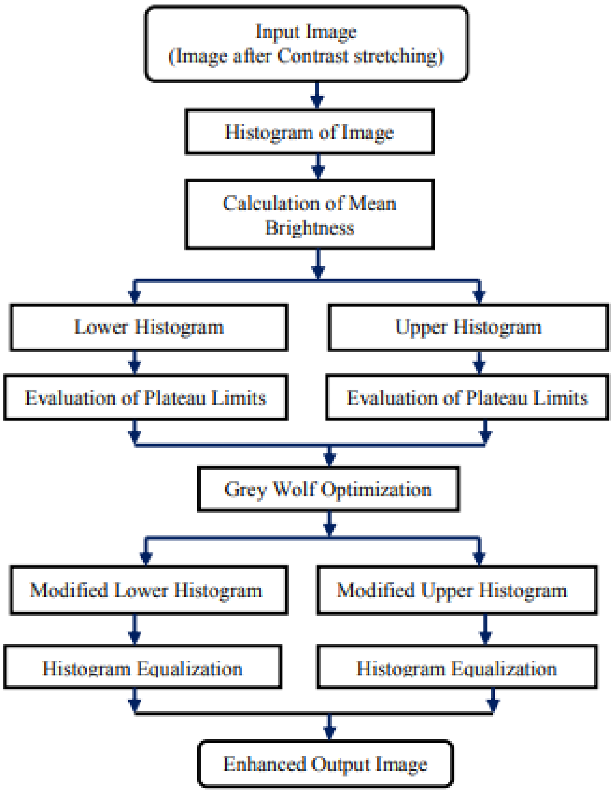


Figure:-4: Flowchart of the proposed grey wolf optimization based algorithm.

Detailed procedure of GWOHE for Image Enhancement:-

1) An input image after contrast stretching with low contrast is taken for processing whose size may be M x N.
2) Histogram of that image will be evaluated.
3) Histogram is segmented into lower histogram and upper histogram depending on average value of input image.

$$m_i = \frac{\sum_{j=0}^{Z-1} l_j * n_j}{M} \qquad (1)$$

where l_j is j_{th} gray level intensity and n_j is total sum of pixels with corresponding gray level, M indicates the sum of all the pixels.

With this average value, histogram of the input image is separated as lower histogram (H_{IL}) and higher histogram (H_{IH}). The range of the H_{IL} is from minimal non-zero gray level $l_{\min}$ to m_i and the range of H_{IH} ranges from $m_i + 1$ to maximal non-zero gray level value $l_{\max}$.

4) *Calculation of plateau limits values for each histogram.* In [13], the plateau limit values are determined depending upon the information available in the partitioned histograms. This plateau limits are evaluated on the base of gray level criterion (GLCs) as shown below:

$$T_{L1} = GLC_{L1} X P_L \qquad (2)$$
$$T_{L2} = GLC_{L2} X P_L \qquad (3)$$
$$T_{L3} = GLC_{L3} X P_L \qquad (4)$$
$$T_{H1} = GLC_{H1} X P_H \qquad (5)$$
$$T_{H2} = GLC_{H2} X P_H \qquad (6)$$
$$T_{H3} = GLC_{H3} X P_H \qquad (7)$$

Where P_H is the peak value in the upper *and similarly* P_L corresponds to the lower sub-histogram. GLC_{Hl} is the GLC of l_{th} plateau limit in the upper and GLC_{Ll} is corresponds to lower sub-histograms. The value of GLCs is obtainable as

$$GLC_{L1} = GLC_{L2} - D_{LH} \qquad (8)$$
$$GLC_{L2} = \frac{mi - miL}{mi - lmin} \qquad (9)$$
$$GLC_{L3} = GLC_{L2} + D_{LH} \qquad (10)$$
$$GLC_{L3} = GLC_{L2} - D_{HH} \qquad (11)$$
$$GLC_{L2} = \frac{lmax - miH}{lmax - mi} \qquad (12)$$
$$GLC_{H3} = GLC_{L2} + D_{HH} \qquad (13)$$

Where m_{iH} and m_{iL} are the average values of the H_{IH} and H_{IL}. D_{HH} and D_{LH} is the GLC difference of H_{IH} and H_{IL} respectively. The D_{HH} and D_{LH} values are determined by equations (14) and (15).

$$D_{HH} = \begin{cases} \frac{1-GLC_{H2}}{2} & if \quad GLC_{H2} > 0.5 \\ \frac{GLC_{H2}}{2} & if \quad GLC_{H_2} \le 0.5 \end{cases} \qquad (14)$$

$$D_{LH} = \begin{cases} \frac{1-GLC_{L2}}{2} & if \quad GLC_{L_2} > 0.5 \\ \frac{GLC_{L2}}{2} & if \quad GLC_{L2} \le 0.5 \end{cases}$$

(15)

The histogram clipping is performed based on this plateau limits

$$HI_L = \begin{cases} TL1 & if\ HIL(j) \le TL1 \\ TL2 & if\ TL1 < HIL(j) \le TL3 \\ TL3 & if\ HIL(j) > TL3 \end{cases} \qquad (16)$$

$$HI_H = \begin{cases} TH1 & if\ HIH(j) \le TH1 \\ TH2 & if\ TH1 < HIH(j) \le TH3 \\ TH3 & if\ TH(j) > TH3 \end{cases} \qquad (17)$$

5) Grey Wolf Optimization Algorithm

The optimization algorithm by Mirjalali et al.[22] is inspired from Grey wolf searching and hunting process.In this model, there are four parameters as beta, alpha, omega and delta. Alpha(α) is first fitting solution, beta(β) is second and best fitting solution and delta (δ) is third best fitting solution. And Remaining fittings will be consider as omegas(ω).

The steps to summarize the GWOHE algorithm is shown below

i. The grey wolves population will be initialized.

ii. Initialize a, A, C.

The vector "$\vec{a}$" is linearly decreased from 2 → 0 , to give emphasis to explorations. When $|\vec{A}|$> 1 solutions tends to diverge and$|\vec{A}|$< 1 avoid stagnation in local solutions. The components of $\vec{A}$ and $\vec{C}$ are the combination controlling parameter *a* and random numbers as $\vec{r}_1$ and $\vec{r}_2$.

$$\vec{A} = 2a\vec{r}_1 - \vec{a} \quad and \quad \vec{C} = 2\vec{r}_2$$

iii. Determine the fitness value of each search agents α, β and δ, is estimating approximate possible position of prey. $\vec{D}\alpha$, $\vec{D}_{\beta}$ and $\vec{D\delta}$ are three coefficents of optimization and given in form of equations as below,

$$\vec{D} = \left|\vec{C} \cdot \vec{P_p}(n) - \vec{P}(n)\right| \quad (18)$$

$$\vec{P}(n+1) = \vec{P_P}(\mathrm{n}) - \vec{A} \cdot \vec{D} \quad (19)$$

Where, $\vec{P_P}$ and $\vec{P}$ are prey and wolf position vectors, respectivily.

iv. Find best search agents X_α, X_β and X_δ

v.

while (n < maximum number of iterations)

- For each of search agent
  - o Current search agent position is updated.
- End for
- The values of a, A, C are updated
- Revise $X_\alpha, X_\beta, X_\delta$ by computing the fitness value of all search agent
- $n = n + 1$

end while

vi. Give the value of X_α.

6) Again that optimized image is segmented into modified lower histogram and upper histogram and after that equalization of that image will take place.

7) Finally, get the enhanced image.

D. Maximum Intensity Region

MATLAB function of imregionalmax is used to locate maximum intensity region in the white matter. This function returns pixel value 1 for regional maxima and remaining pixel values as 0, representing binary image. Figure: 5 show the process of enhancing the contrast of the WMH area.

E. WMH Mapping (Window Sliding)

The sequence of MRI FLAIR images used for segmentation, have lower contrast. After enhancing the quality of an image using proposed hybrid model, region of high intense will be determined in order to represent potential WMH area. A sliding neighbourhood operation is applied to obtain mean intensity value of pixels neighbourhood. The algorithm performs sliding of 3*3 pixel center to the neighbourhood pixel, resulting in enlargement of region of interest. This way WMH region will be determined. Figure:-6 is showing WMH mapped image.

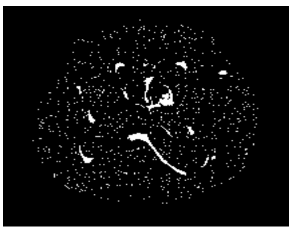
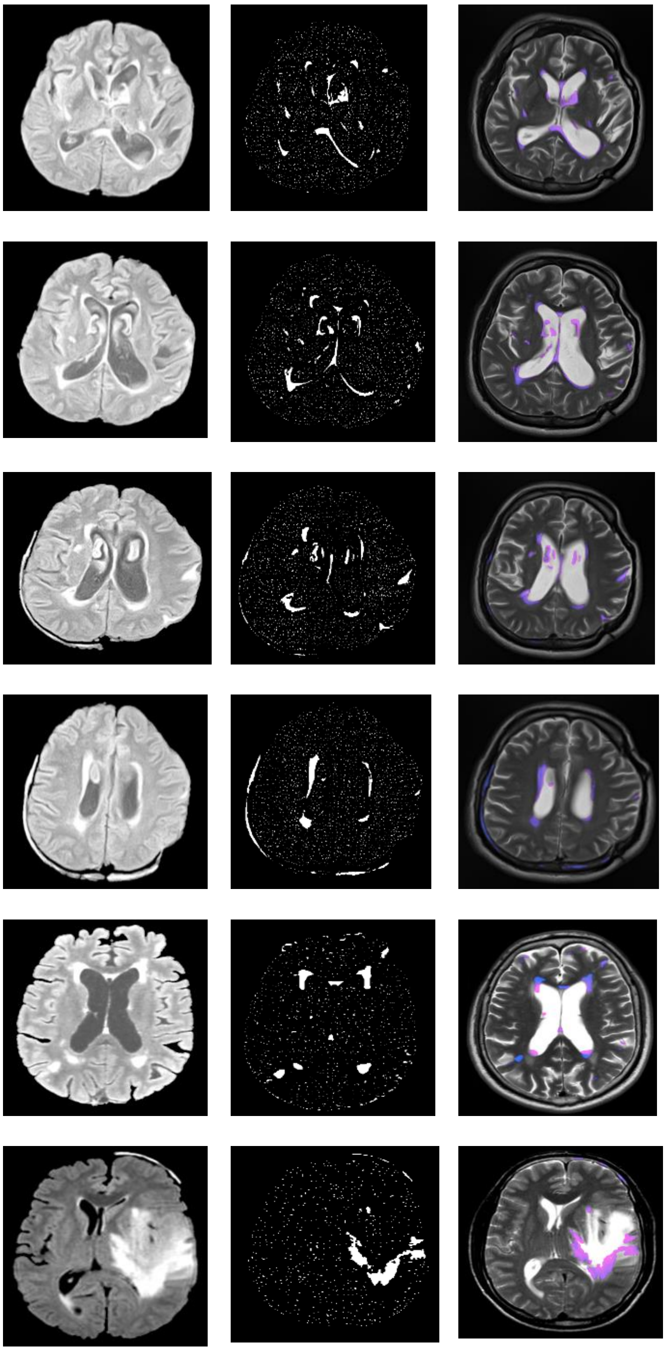


Figure 5:- ROI Max Intensity

Figure 6:- WMH Mapping

IV. EXPERIMENTAL RESULTS

The experiment outcome of the proposed model has illustrated below. The first column images are obtained after proposed GWOHE method. Even though, images depict hyperintense signals on WM but raters neglect the visual rating scale. Thus this is followed by regional maxima function to obtain images with region of interest as shown in second column. For enhanced results on WMH localization, the WMH regions are mapped on to T2-WI image as shown in the third column of figure:-7.



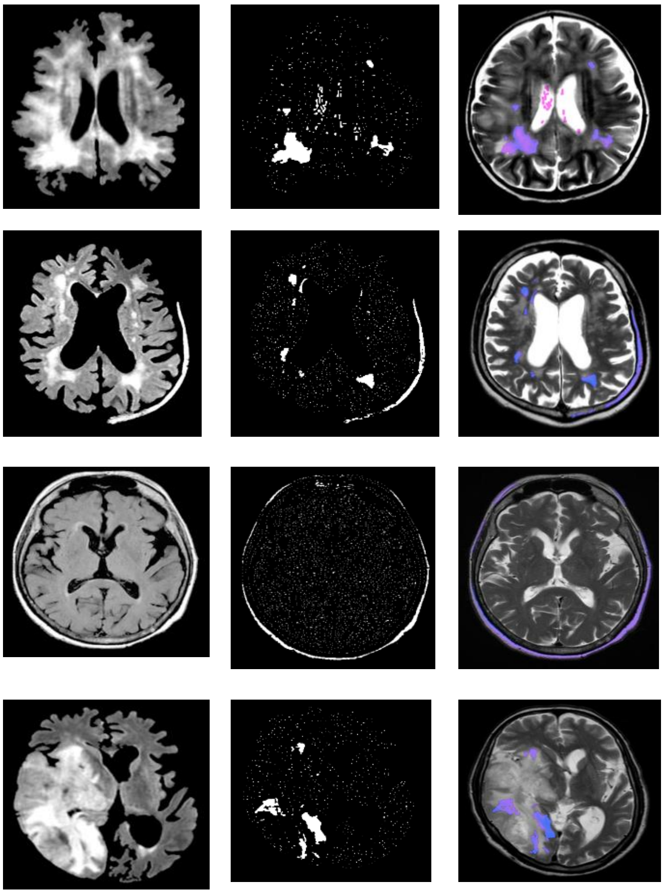


Figure:-7: FLAIR images after contrast enhancement by using proposed GWOHE algorithm, Region of interest and WMH mapped on T2-WI.

A. Experimental Discussion for Various Parameters

To measure the efficiency of the proposed algorithm, different parameters are used here and those are illustrated below.

1) *Mean Square Error (MSE)*

MSE determines the mean squared variation between estimated values and expected value, that is- mean of squared errors. This is given by using the Eq. (20).

$$MSE = \frac{1}{HG}\sum_{a=0}^{H-1}\sum_{b=0}^{G-1}[U(a,b) - V(a,b)]^2 \qquad (20)$$

Where U(a,b) is the enhanced image pixel at position (a,b), V(a,b) is the original image pixel value at position (a,b) and, H and G denotes an image dimension .

2) *Peak Signal to Noise Ratio (PSNR)*

It evaluates the image quality. The PSNR (in dB) is given by Eq. (21).

$$PSNR = 20.\log_{10}(\mathrm{MAX1}) - (10)\log_{10}(\mathrm{MSE}) \qquad (21)$$

$(MAX1)$ is maximum pixel value of an image.

3) *Structural Similarity Index (SSIM)*

SSIM value is higher means better will be the performance. The SSIM is calculated as

$$SSIM(e,f) = \frac{(2\mu_e\mu_f + C_1)(2\sigma_{ef} + C_2)}{(\mu_e^2 + \mu_f^2 + C_1)(\sigma_e^2 + \sigma_f^2 + C_2)} \qquad (22)$$

4) *Absolute Mean Brightness Error (AMBE)*

AMBE represents the average intensity values of enhanced image subtracted by average intensity value of input image.

$$AMBE = \left| m_{\tilde{i}} - m_i \right| \qquad (23)$$

Where m_i represent the mean intensity of an image. As AMBE is smaller, input image intensity is preserved better.

B. Comparison and analysis

The proposed MR brain image enhancement algorithm is applied on input images of dimensions 512*512. The main intention of the AIR-GWOHE algorithm is the enhancement of low contrast images and also to preserve the mean brightness of an image. The mean brightness preserved is evaluated by using AMBE value. As shown in figure:-8 and table I, the AIR-GWOHE method shows better results. As shown in figure:-9 and table II, PSNR value is incremented by 4-5 % on an average after the application of proposed method. The sharpness of an image has slightly reduced as shown in figure:10 and table III. But it does not have an effect on WMH region in an image. The values of Structural similarity index (SSIM) as shown in figure:-11 and table IV, of proposed algorithm is higher than the AIR-AHE method [14].

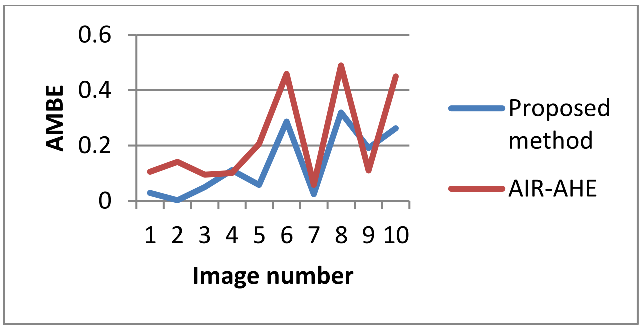


Figure:-8. AMBE performance graph for each test images.

Table- I: Comparison of AMBE values for each test images.

Test Image	AIR-AHE	Proposed method
1	0.10519	0.028339
2	0.14112	0.001925
3	0.093914	0.049476
4	0.099719	0.110553
5	0.20551	0.057369
6	0.45918	0.286095
7	0.057557	0.023892
8	0.48926	0.31911
9	0.10911	0.19008
10	0.44961	0.26173

Table- II: Comparison of PSNR values for each test images.

Test Image	AIR-AHE	Proposed method
1	39.23	43.03
2	38.25	41.63
3	38.67	42.11
4	44.23	47.32
5	37.68	40.21
6	33.86	36.53
7	40.50	44.98
8	41.33	47.66
9	40.45	45.21
10	42.79	43.82

Table- III: Comparison of AG values for each test images.

Test Image	AIR-AHE	Proposed method
1	9.42E-05	5.87E-05
2	9.69E-05	6.08E-05
3	9.37E-05	6.71E-05
4	8.33E-05	5.97E-05
5	9.29E-05	6.40E-05
6	9.30E-05	6.72E-05
7	5.68E-05	4.73E-05
8	9.81E-05	7.54E-05
9	1.29E-04	1.09E-04
10	8.87E-05	6.49E-05

Table- IV: Comparison of SSIM values for each test images.

Test Image	AIR-AHE	Proposed method
1	0.9848	0.9899
2	0.9818	0.9896
3	0.9811	0.9834
4	0.9852	0.9909
5	0.9827	0.9875
6	0.9815	0.9882
7	0.9851	0.9883
8	0.9846	0.9876
9	0.9876	0.9912
10	0.9801	0.9892

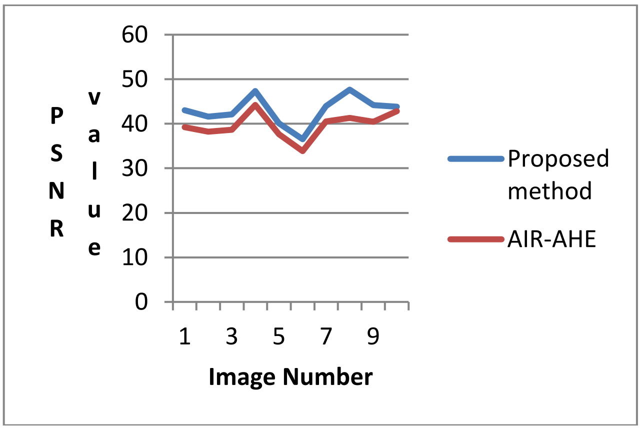


Figure:-9: PSNR performance graph for each test images.

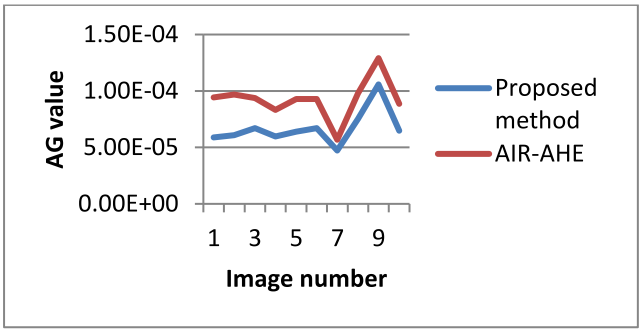


Figure:-10: Average gradient performance graph for each test images.

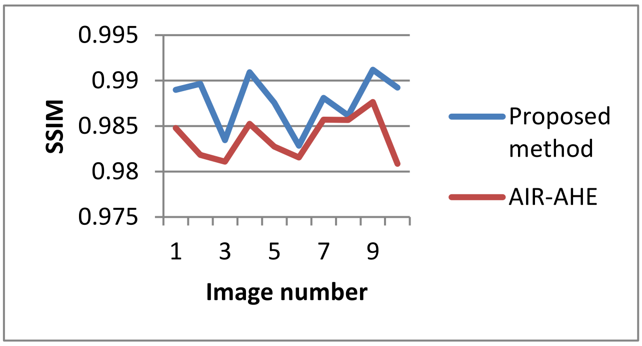


Figure:-11. SSIM performance graph for each test images.

V. CONCLUSIONS

The proposed MR brain medical image enhancement scheme incorporates GWO to enhance contrast of brain MR images by preserving brightness in an efficient manner. The performance of the proposed hybrid model has been tested on the FLAIR image dataset and results are shown. The method is simple, computationally effective and hence easy to implement. The proposed algorithm preserves the brightness of original image even after enhancement.

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AUTHORS PROFILE

Vidyasaraswathi H. N., graduated from Visvesvaraya Technological University (VTU), Belagavi in Electronics and Communication Engineering in the year 2011 and M. Tech (VLSI Design and Embedded Systems) degree from VTU, Belagaum in the year 2013, and pursuing Ph. D in VLSI Signal and Image Processing. She is presently working as an Assistant Professor in the Department of ECE at Bangalore Institute of Technology, Bengaluru, India. Her research interests include Design of hardware architectures for signal and image processing algorithms, FPGA/ASIC Design.

M. C. Hanumantharaju, received B. E (Electronics and Communication Engineering) degree from Bangalore University in 2001, M. Tech (Digital Communication and Network Engineering) degree from VTU, Belagavi in 2004, and Ph. D (VLSI Signal and Image Processing) degree from VTU, Belgaum, in the year, 2014. He is working as a Professor in the Department of ECE at BMSIT&M, Bengaluru, India. He has authored two books and 50 technical articles in refereed journals and proceedings such as IEEE etc. He is serving as a reviewer for IEEE Transaction on Industrial Electronics, Computers and Electrical Engineering Journal, Journal of Microscopy and Ultrastructure, etc. His research interests include Design of hardware architectures for signal and image processing algorithms, Register Transfer Level (RTL) Verilog coding, synthesis and optimization of Integrated Circuits (ICs), FPGA/ASIC Design.