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Medical Image Enhancement Using Genetic Optimization Algorithm

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ABSTRACT: Visual interpretation of the damaged areas of the human body may not be possible using low-quality medical photographs. Therefore, adaptive histogram equalization, a novel adaptive picture improvement technique based on genetic algorithms, has been proposed in this research to enhance the image visions as well as to give computational support.The study made use of several fitness functions. The fitness function included image entropy, peak signal-to-noise ratio, energy, sharpness, structural similarity index, gray level co-occurrence matrix (GLCM), and Sobel edge feature extraction techniques.Modified probability density function (PDF), histogram sub-division, genetic algorithm are part of the suggested framework. Exposure as well as ideal threshold have been used for histogram subdivision technique to maintain the brightness and minimize information loss. Using the idea of genetic algorithm and suggested multi-objective fitness function, the threshold parameters are modified to make the suggested method more adaptive. To improve the image quality, PDF of each sub-histogram is modified. Findings of the trial demonstrate that proposed method performs better than the other enhancement methods.

Keywords: Medical imaging, image enhancement, histogram equalization, genetic algorithm.

Contents

1. Introduction

One important image processing method for improving quality of an image is the image enhancement. Image of good quality is required for additional processing and interpretation .Several systems for medical imaging , including magnetic resonance imaging (MRI), computed tomography (CT),X-ray ,mammography imaging, use it as preprocessing approach. Medical images at times have low contrast and extremely poor quality [1]. The presence of multiple overlapped objects makes medical imaging more complex. Geometric distortions and artifacts highlt affects the image's quality. Therefore, elimination of artifacts is essential in order to improve the diagnosis. In images with low contrast , identification of Region of Interest (ROI) is very difficult [2]. As a result, it is extremely hard to comprehend these images [3], and diagnosing process is severely hampered, leading to incorrect measurements [4]. Therefore, various techniques for image enhancement are employed in order to increase visual quality of the medical

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images, which will greatly aid in the identification of tumors, bleeding, fractures, diseases, and tissue segmentation [5]. One of the conventional methods for enhancing contrast of an image is the histogram equalization (HE) [6], which involves rescaling histogram distribution as well as dynamic range of image. However, images that are histogram-equalized have bothersome artifacts as well as noise amplification. This technique also considerably alters overall brightness of image. In order to maintain images' brightness and enhance their contrast, various procedures like brightness preserving bi-histogram equalization (BBHE) [7], dualistic sub-image histogram equalization (DSIHE) [8,9] have been developed.

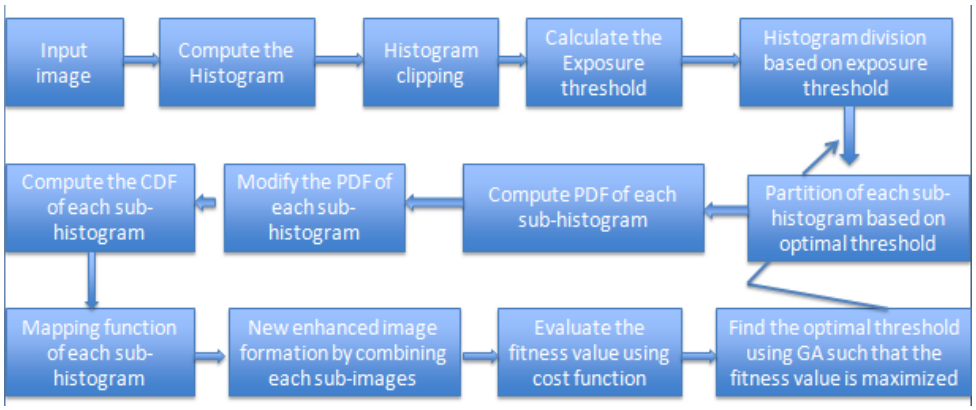

Figure 1: Proposed flowchart

However, the approaches mentioned above do not explain how the enhancement rate is controlled [10, 11]. The author of [10] presented a novel method for improving images with low contrast called recursively separated exposure based sub-image histogram equalization (RS-ESIHE). One of the difficult task in imaging applications is to enhance images that have wear edges. Thus, authors [12] suggested an intuitionistic fuzzy set-based method for image improvement. M. Agarwal et al. [13] have suggested an additional pipelined method for tumor detection that makes use of Wiener filtering, histogram equalization, optimum weighted constrained model, and adaptive gamma correction. Chen et al. [27] discussed an enhancement method that automatically improves contrast for the brain MR images in 2015.

This technique generates a correlation histogram based on the grayscale distribution, which helps in improving contrast for the specific items. Further a novel denoising method was introduced by [15] for the de-noising of MR image employing a bilateral filter (BF). [16] presented an fuzzy based adaptive histogram equalization approach in order to enhance the contrast of MRI brain pictures while maintaining the brightness. Dominant Orientation-based Texture Histogram (DOTHE) was introduced by [17] to improves the image's contrast. This technique uses texture region-based histogram equalization to reduce artifacts and improve contrast. Numerous algorithms [18–22] focused to improve quality of an image; however, the majority of these techniques are not appropriate for improving medical images with inadequate lighting because they produce artifacts in the improved images. Few methods improve the image's brightness without successfully separating the object from the background. Entropy maximization, contrast enhancement, artifact reduction, PSNR ,brightness preservation, preserving feature as well as structure similarity are the primary issues seen in medical images. To enhance quality of the medical image having low contrast, adaptive histogram equalization (AHE) method using exposure threshold and adaptive threshold parameters is presented in this study. To increase the adaptability of the improvement process, a genetic algorithm is employed. The following summarizes this work's primary contribution.

This paper's remaining sections are organized as follows. The specifics of the suggested approach are explained in Section 2. The next section, section 3 shows results and discussions of the experiment. Lastly, section 4 draws the paper's final conclusion.

2. Proposed Methodology

Steps involved in the implementation of the proposed algorithm are discussed in this section. The primary goal of this technique is to improve low contrast image's visibility, regulate enhancement rate,

minimize information loss, and to maintain brightness of the enhanced image to offer a natural appearance. Here, the suggested method's flow chart is shown in Figure2. It involves the below mentioned actions.
Step 1: To compute histogram of the image taken.
Step 2: Clipping threshold is determined by averaging intensity value's mean and median. Original histogram is clipped by threshold value to create a new histogram.
Step 3: To split original histogram into sub-histograms, exposure threshold (E_t) is calculated. High as well as low exposure portions of image are represented by the sub histograms.

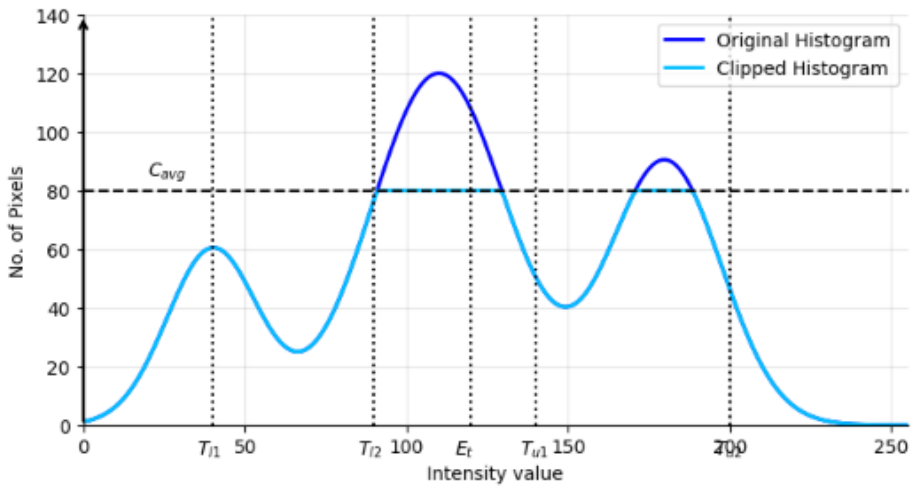

Figure 2: Histogram Division

Step 4: Next, using the ideal threshold parameters E_{tl} and E_{tu},the sub-histogram splits into two sub-histograms.
Step 5: Current PDF has been used to modify PDF in the sub-histogram and the sum of the PDF values.
Step 6: To maximize fitness function in relation to iterations, threshold utilized to create the sub-histograms is optimized. The thresholds are optimized using a genetic algorithm due to the complexity of medical imagery.
Step 7: Each sub-histogram's cumulative density function (CDF) is computed with the help of modified PDF value. CDF value of each sub-histogram is then used to calculate mapping function of every sub-histogram.
Step 8: Lastly, each equalized sub-picture is combined to create a new, improved image.
Step 9: Next, each image's fitness value is calculated. This process is carried out repeatedly until the fitness curve converges or the termination criteria are met.

2.1. Histogram Equalization Method

The histogram is clipped by computing (C_{avg}). To control enhancement rate and to prevent over-enhancement are primary goals of histogram clipping. Mean , median of image intensity values are averaged to determine this clipping threshold.

$$C_{median} = \text{median}(h(k)) \tag{2.1}$$

$$C_{mean} = \text{mean}(h(k)) \tag{2.2}$$

$$C_{avg} = \frac{C_{median} + C_{mean}}{2} \tag{2.3}$$

Exposure threshold is computed in order to split histogram into two sub-histograms and two sub-images. The subimages obtained are both overexposed and underexposed. The exposure's normalized

value lies in the interval [0,1]. Image's exposure value is computed as

$$Exposure = \frac{1}{L}\frac{\sum_{k=1}^{L} h(k)k}{\sum_{k=1}^{L} h(k)} \tag{2.4}$$

Max gray level is represented by L , h(k) represents image's histogram in Eq. (4). Below equation, Eq. (5) calculates exposure threshold.

$$E_t = L(1 - Exposure) \tag{2.5}$$

E_t, exposure threshold represents boundary of separation between two sub-histograms I_l and I_u, as shown in Figure 2.

Some algorithms use the technique of histogram sub-division to maintain brightness and minimize information loss [7–11]. For the purpose of subdividing the histogram, the authors of these articles employed standard parameters like median,mean, exposure threshold, and standard deviation. These algorithms aren't functioning correctly in some of the pictures. Few algorithms increase the image's contrast at an expense of more information loss. Image becomes strange in certain algorithms. Therefore, it is necessary to automatically choose the threshold parameter based on a few criteria in order to make the method more adaptive. In light of this, the thresholds (E_{tl} and E_{tu}), that was used to split sub-histogram should be chosen automatically with the help of genetic algorithm in accordance with suggested fitness function, that increases system's adaptability. There should be no human involvement in this threshold selection procedure. Subsections 2.2 and 2.3, respectively, provide information on the suggested fitness function and genetic algorithm.

The PDF of each sub-images I_1, I_2, I_3, I_4 is calculated using Eqs. (2.6)–(2.9),

$$P_{li}(k) = \frac{h_{cl}(k)}{N_{li}}, \text{for} \quad 0 \le k \le E_{tl} \tag{2.6}$$

$$P_{lj}(k) = \frac{h_{cl}(k)}{N_{lj}}, \text{for} \quad E_{tl} + 1 \le k \le E_t \tag{2.7}$$

$$P_{ui}(k) = \frac{h_{cl}(k)}{N_{ui}}, \text{for} \quad E_t + 1 \le k \le E_{tu} \tag{2.8}$$

$$P_{uj}(k) = \frac{h_{cl}(k)}{N_{uj}}, \text{for} \quad E_{tu} + 1 \le k \le L - 1 \tag{2.9}$$

Here, $N_{li}, N_{lj}, N_{ui}, N_{uj}$, for $i = 1, j = 2$,are numbers of pixels present in the sub-images I_a, I_b, I_c, I_d respectively. The sub-histograms' PDFs were modified in [27]. The similar change was used in this investigation as well because the findings showed modest improvement. Equations (2.6), (2.7), (2.8), and (2.9) were used to calculate the updated PDFs. The four sub-images' updated PDFs (Eqs. 2.10–2.13) are described as follows:

$$P_{li}^{m}(k) = \left(\frac{P_{li}(k)}{\sum_{s=0}^{E_{ti}} P_{li}(s)} + P_{li}(k)\right), \quad 0 \le k \le E_{tl} \tag{2.10}$$

$$P_{lj}^{m}(k) = \left(\frac{P_{lj}(k)}{\sum_{s=E_{tl}+1}^{E_t} P_{lj}(s)} + P_{lj}(k)\right), \quad E_{tl} + 1 \le k \le E_t \tag{2.11}$$

$$P_{ui}^{m}(k) = \left(\frac{P_{ui}(k)}{\sum_{s=E_t+1}^{E_{tu}} P_{ui}(s)} + P_{ui}(k)\right), \quad E_t + 1 \le k \le E_{tu} \tag{2.12}$$

$$P_{uj}^{m}(k) = \left(\frac{P_{uj}(k)}{\sum_{s=E_{tu}+1}^{L-1} P_{uj}(s)} + P_{uj}(k)\right), \quad E_{tu} + 1 \le k \le L - 1. \tag{2.13}$$

where $i = 1, j = 2$. CDFs are computed for each modified PDF using Eqs. 2.14–2.17:

$$C_{li}(k) = \sum_{s=0}^{k} P_{li}^{m}(s), \quad 0 \leq k \leq E_{tl}, \tag{2.14}$$

$$C_{lj}(k) = \sum_{s=E_{tl}+1}^{k} P_{lj}^{m}(s), \quad E_{tl}+1 \leq k \leq E_{t}, \tag{2.15}$$

$$C_{ui}(k) = \sum_{s=E_{t}+1}^{k} P_{ui}^{m}(i), \quad E_{t}+1 \leq k \leq E_{tu}, \tag{2.16}$$

$$C_{uj}(k) = \sum_{s=E_{tu}+1}^{k} P_{uj}^{m}(s), \quad E_{tu}+1 \leq k \leq L-1. \tag{2.17}$$

with $i = 1, j = 2$. Each sub-histogram is equalized independently following the computation of the CDF. Each sub-histogram uses a different transfer function in order to conduct histogram equalization. Equations (2.18-2.21) are used to calculate the transfer function for each sub-histogram.

$$T_{li} = (E_{tl})C_{li} \tag{2.18}$$

$$T_{lj} = (E_{tl}+1) + (E_{t} - (E_{tl}+1))C_{lj} \tag{2.19}$$

$$T_{ui} = (E_{t}+1) + (E_{tu} - (E_{t}+1))C_{ui} \tag{2.20}$$

$$T_{uj} = (E_{tu}+1) + (L - (E_{tu}+1))C_{uj} \tag{2.21}$$

Here, $T_{li}, T_{lj}, T_{ui}, T_{uj}$, where $i = 1, j = 2$ represents transfer functions that are used for the equalization of the individual sub-histogram.

2.2. Fitness Function

Medical images have poor contrast and are noisy. Also, much information is lost while enhancing images. Maintaining visual feature after the improvement is exceedingly challenging. So, in order to overcome this issue, novel fitness function is developed here using characteristics such as contrast, energy, PSNR, information contents (entropy), SSIM and edge contents. Thus, the suggested fitness function has been represented as multi-objective function in this study. Every fitness function is given equal weight. In contrast, the first objective function is described as

$$cf_{a} = \log\left(\frac{I_{contrast} \times \exp(I_{entropy})}{I_{energy}}\right) \tag{2.22}$$

The GLCM has been used in order to calculate both energy and contrast. The GLCM functions describe an image's texture. Total number of times a pixel having i value appeared in designated spatial relationship to a pixel having value j in input image is used to represent element (i, j) in resulting GLCM.Cooccurrence matrix element is shown as

$$g(i,j) = \sum_{k=0}^{H-1}\sum_{l=0}^{V-1} d(k,l) \tag{2.23}$$

$$\partial(k,l) = \begin{cases} 1, & \text{if } I_{e}(k,l) = i \text{ and } I_{e}(k,l+1) = j \\ & \text{or } I_{e}(k,l) = i \text{ and } I_{e}(k+1,l) = j \\ 0, & \text{otherwise} \end{cases} \tag{2.24}$$

In the Equation (2.23), H is the number of pixels that are present in image's horizontal direction, V is the pixel's count in image's vertical direction. Term I_{energy} in Equation (2.25) shows the energy that

indicates image's homogeneity. It shows image's pixel pair repetition. Parameter GL(i, j) is computed by using Equation (2.26).

$$I_{energy} = \sum (GL(i,j)^2) \tag{2.25}$$

$$GL(i,j) = \frac{g(i,j)}{\sum_{i=0}^{H-1} \sum_{j=0}^{V-1} g(i,j)} \tag{2.26}$$

Contrast parameters of Equation (2.27) helps in measuring local variations of gray levels.Image's is high if the neighboring gray level differences is more.

$$I_{contrast} = |i-j|^2 \times GL(i,j) \tag{2.27}$$

$I_{entropy}$ shows image's entropy in Equation (2.28). It displays average amount of information included in the picture. Uniform intensity distribution ensures equalization of histogram with high entropy. The variable n in Equation (2.28) stands for greatest intensity value of the image, pd_i is PDF at each gray level i.

$$I_{entropy} = -\sum_{i=0}^{n-1} pd_i \log_2 pd_i \tag{2.28}$$

Since maintaining the medical image's edge content is crucial, the image's edge contents are used as the second objective function. In Equation (2.29), it is denoted by cf2. The edges in the pictures have been identified using Sobel edge detection. Therefore, by taking these parameters into account, second fitness function is shown in Equation (2.29). I_{sobel} is the Sobel edge image, total intensity of edge pixels is shown by $E(I_{sobel})$, n_{edges} represents pixel's count in the edge in final image, $w \times x$ is image's size.

$$cf_b = \log(\log(E(I_{sobel}))) \times \frac{n_{edges}}{w \times x} \tag{2.29}$$

Another fitness function used here is to evaluate image's quality as well as anti noise performance namely peak signal to noise ratio (PSNR). MSE is used to evaluate this, shown in Equation (2.30).

$$cf_c = PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \tag{2.30}$$

Whereas the MSE is calculated as

$$MSE = \frac{1}{r \times c} \sum_{i=1}^{r} \sum_{j=1}^{c} (I_o(i,j) - I_e(i,j))^2 \tag{2.31}$$

Along with PSNR, Structural similarity index (SSIM) have been used in fitness function in order to evaluate image's quality. SSIM is given by the equation

$$cf_d = SSIM = \frac{(2\mu_x\mu_y + C_i)(2\sigma_{xy} + C_j)}{(\mu_x^2 + \mu_y^2 + C_i)(\sigma_x^2 + \sigma_y^2 + C_j)}; i = 1, j = 2 \tag{2.32}$$

Proposed fitness function is represented as,

$$cf = 0.25cf_a + 0.25cf_b + 0.25cf_c + 0.25cf_d \tag{2.33}$$

The enhancement problem is portrayed in this work as the maximization problem. So, the suggested algorithm's fitness value should be maximized. In terms of mathematics, it is expressed as

$$C = \arg\max(cf) \tag{2.34}$$

$$C = \arg\max(0.25 \times cf_a + 0.25 \times cf_b + 0.25 \times cf_c + 0.25 \times cf_d) \tag{2.35}$$

2.3. Genetic Algorithm

A sort of evolutionary computing approach called genetic algorithms is utilized to produce high-quality results while searching [19]. The population,that is a collection of solutions (represented by chromosomes), is where the algorithm starts. One population's solutions are utilized to create new population. The genetic algorithm has been executed using the following steps:
Step 1: Random population of n chromosomes is created.
Step 2: Assess each chromosome's fitness within the population.
Step 3: Repeat selection, crossover, mutation processes in order to create a new population. Next, fresh progeny are added to the new population.
Step 4: Run algorithm again using newly created population.
Step 5: If last criterion is satisfied, stop and provide the best answer in the current population.
Step 6: Repeat from step 2 if termination condition is not met.

Table 1: Parameter selection

Parameters	**Value**
Population Size	50
No of iteration	30
Dimension of the problem space	2
Mutation Probability	0.01
Cross over Probability	0.8
Lower Threshold parameter	$[0, E_t]$
Upper Threshold parameter	$[E_t + 1, 255]$

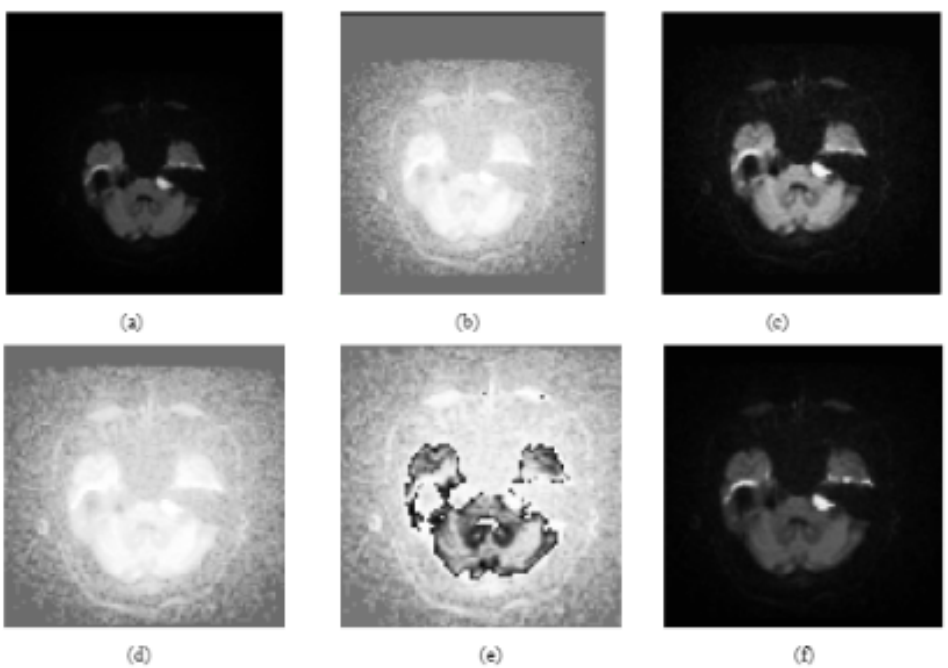

Figure 3: Enhanced image obtained for first medical image (Img i) (a) Input image (b) HE (c) CLAHE (d) BBHE (e) DOTHE (h) Proposed method

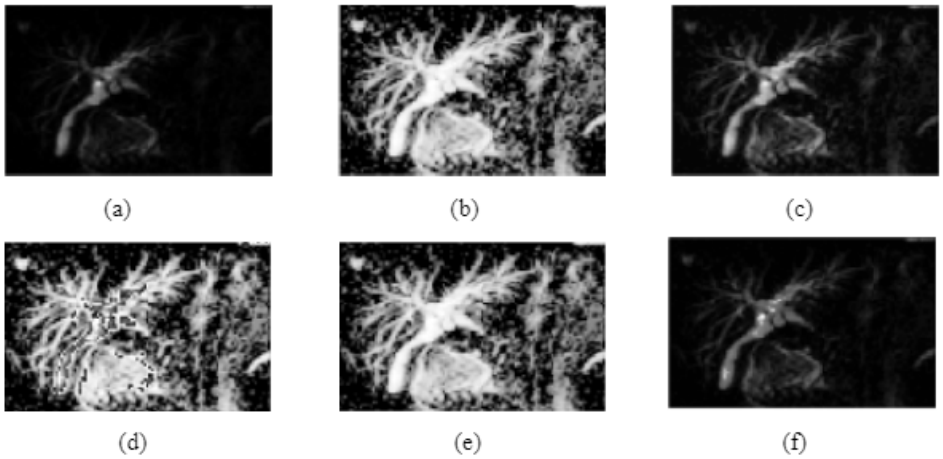

Figure 4: Enhanced image obtained for second medical image (Img ii) (a) Input image (b) HE (c) CLAHE (d) BBHE (e) DOTHE (h) Proposed GAAHE method

3. Results and Discussion

Here images from [23–25] are used to evaluate the performance of the suggested method and then compared with a few of the popular enhancing methods, such as HE [6], BBHE [7], CLAHE, and DOTHE [17]. Python programming and the Windows-7 operating system have been used for all the experimental work.

3.1. Parameter selection

Table 1 displays the characteristics used to successfully simulate our suggested work. Number of chromosomes in a single generation is indicated by the size of the population. Only a limited portion of the search area is examined and GA has few opportunities to accomplish crossover if each generation contains too few chromosomes. However, GA slows down if there are too many chromosomes. Thus, population of size fifty is used here in order to identify the best optimal solution more quickly without wasting resources. The goal of crossover is to make new chromosomes better by incorporating positive traits from old chromosomes. The frequency of the crossing is determined by the parameter crossover probability. All offspring are produced by crossover if the crossover probability is one. If it is zero, the entire new generation is created using exact replicas of the old population's chromosomes. Therefore, in this paper, the cross-over probability is set at 0.8. One or more chromosomal segments are altered when a mutation is carried out. The frequency of chromosomal mutations is determined by the mutation probability parameter. The entire chromosome is altered if the mutation probability is 1. Nothing is altered if it is 0. Therefore, in this paper, the mutation probability is assumed to be 0.01.Since two limitations parameters have been used, so 2 is taken as the dimension of problem space.

Effectiveness of image's enhancement methodology can then be assessed using the qualitative and quantitative methods discussed in sections 3.2 and 3.3, respectively.

3.2. Qualitative approach

The investigation of visual quality or look of the photographs serves as the foundation for the qualitative evaluation of the suggested approach. Examining excessive enhancement, bothersome artifacts, unnatural enhancement are all part of visual quality examination.

Figure 3–Figure7 present a comparative analysis based on visual quality between the proposed method and the existing methods. Input images of the various human organs are shown in Figure 3(a)–Figure7(a) in this paper. Figure 8 displays image-1 histograms that are produced using various enhancing methods. Enhanced MRI images generated by HE, CLAHE BBHE, DOTHE and the suggested approach are shown in Figure 3(b-f)–Figure7 (b-f), respectively. These graphs show that intensity shifting and the flattening

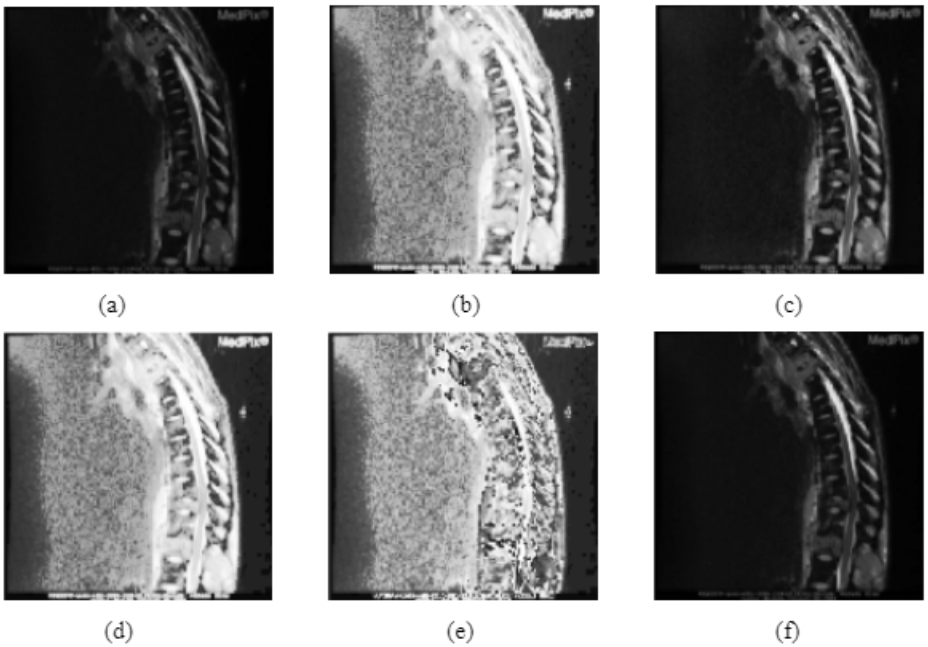

Figure 5: Enhanced image obtained for third medical image (Img iii) (a) Input image (b) HE (c) CLAHE (d) BBHE (e) DOTHE (h) Proposed method

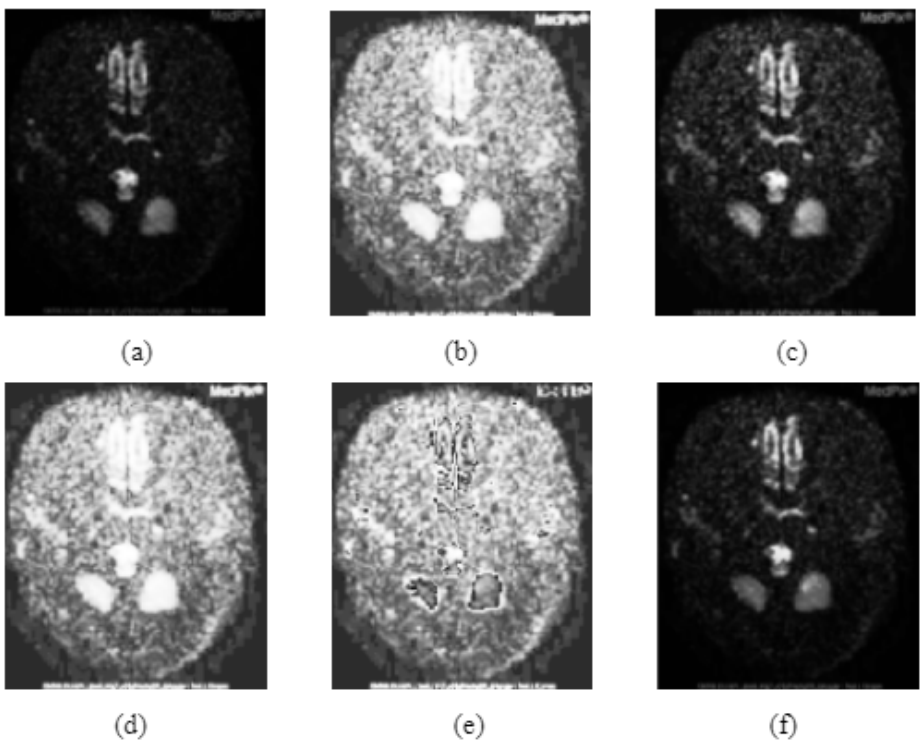

Figure 6: Enhanced image obtained for fourth medical image (Img iv) (a) Input image (b) HE (c) CLAHE (d) BBHE (e) DOTHE (h) Proposed method

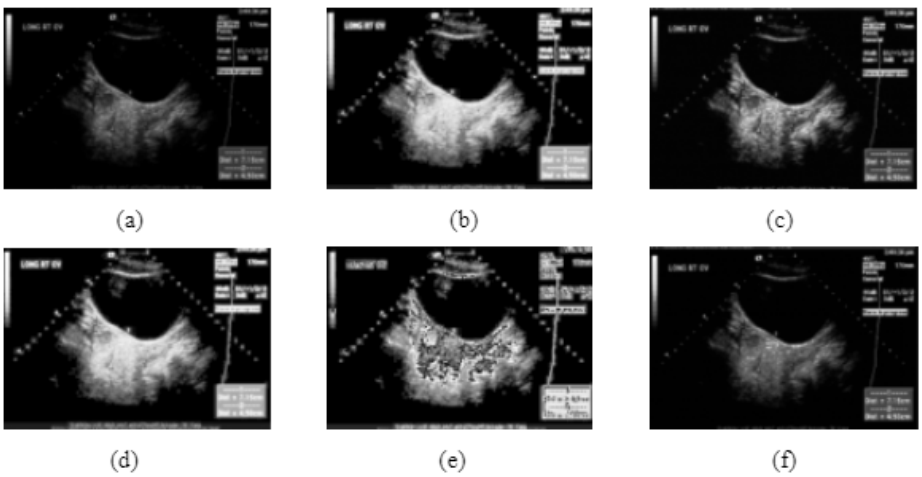

Figure 7: Enhanced image obtained for fifth medical image (Img v) (a) Input image (b) HE (c) CLAHE (d) BBHE (e) DOTHE (h) Proposed method

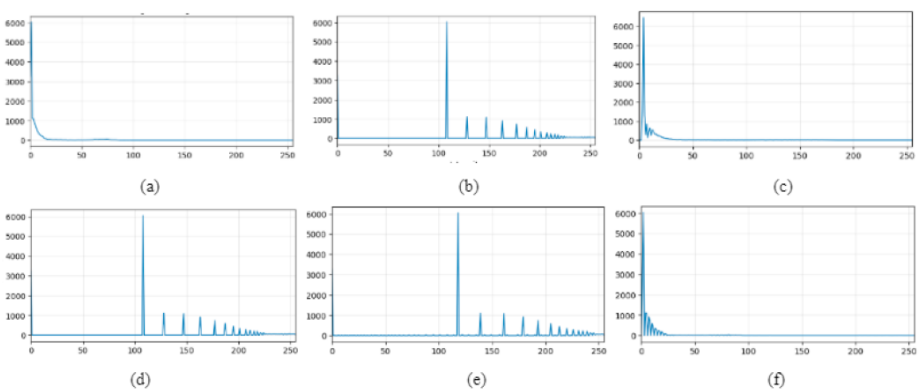

Figure 8: Histogram of first enhanced image (a) Input image (b) HE (c) CLAHE (d) BBHE (e) DOTHE (h) Proposed GAAHE method

Table 2: Performance based on entropy

Method/Image	**Original**	**HE**	**CLAHE**	**BBHE**	**DOTHE**	**GAAHE**
Img1	3.7393	3.5926	4.7028	3.5926	3.6753	3.7165
Img2	4.5691	4.4382	4.5106	4.432	4.4952	4.5365
Img3	5.3909	5.2288	5.3525	5.2288	5.2560	5.3670
Img4	5.1819	4.9720	5.1026	4.9720	5.0601	5.1426
Img5	4.0505	3.9354	4.0000	3.9354	3.9446	4.0065

impact of HE make the histogram-equalized enhanced image brighter than the other enhanced photos. These images, that are displayed in Figure 3(b)–Figure7(b), include artifacts, an image that is over enhanced with noise amplification.

It suggests that the medical images are not sufficiently enhanced by these methods. Therefore, medical images are more complex. By maintaining brightness, the BBHE and method have created an improved image with a more realistic appearance, as seen in Figure 3(d) -Figure 7(d) . However, there is higher information loss in these kinds of pictures. It is evident from visual quality that the DOTHE technique improves the image's contrast more effectively than other methods currently in use. The DOTHE approach improves information content preservation, however these photos have greater noise. However, the improved image generated by our suggested method, displayed in Figure 3(f)– Figure 7(f), shows no such consequences as over-enhancement, artifacts, or noise amplification. Histogram of the initial medical image (Img i) is shown in Figure 8. It is clearly evident from Figure 8(a) that the input image's histogram has a narrow range. However, as Figure 8(b) illustrates, histogram equalization flattens, expands dynamic range of input image.To alter the image's overall brightness and produce an overly boosted artifacts image. Therefore, HE-based photos have a higher absolute mean brightness inaccuracy. The isolation in bins is indicated by the large gaps in the histogram.

The histogram's form differs from the original histogram, indicating that noise has been amplified.

3.3. Quantitative approach

In this part, additional similarity metrics are evaluated to gauge the effectiveness of proposed algorithm. Entropy, absolute mean brightness error (AMBE), PSNR, feature similarity index measure (FSIM) are all measured as part of the quantitative method. Additionally, these factors are crucial in the diagnosing procedure.

3.3.1. Entropy. The texture of the input image can be described using entropy, a statistical measure of randomness[13]. Maintaining information contents of medical images is just as important as improving contrast. An image with a higher entropy value has more information and greater details. Using the aforementioned Equation (2.28), average information contents of various images taken are calculated and displayed in Table2. This table shows that, in comparison to other approaches currently in use, our suggested solution has relatively little information loss. The average information contents of image taken and enhanced image produced by the suggested GAAHE approach are extremely similar. The histogram equalization method results in a greater loss of information.

3.3.2. AMBE. The primary metric for evaluating quality of enhanced image is AMBE [11]. Improved image retains more brightness when the AMBE is lower. AMBE is the difference between the input and output image's mean brightness. This parameter aids in determining the image's brightness preservation quality.

$$AMBE(I, Y) = |E(I)–E(Y)| \tag{3.1}$$

Here E(I) represents mean brightness of input image, E(Y) is mean brightness of enhanced image. Equation (3.1) is used to calculate AMBE. AMBE values are presented in Table3 .

Table 3: Performance based on AMBE

Method/Image	HE	CLAHE	BBHE	DOTHE	GAAHE
Img1	116.9079	10.3250	116.9079	118.9934	2.7027
Img2	88.3022	16.9084	88.3022	89.1635	6.8915
Img3	111.5430	16.1441	111.5430	112.7976	3.4669
Img4	118.0828	16.6687	118.0828	118.4406	5.6203
Img5	37.3739	11.3575	37.3739	38.0029	4.1176

3.3.3. PSNR. The performance of enhancement approaches is measured using a different metric called PSNR. This PSNR [13] is given in Equations (2.30) and (2.31), respectively. Table 4 shows PSNR values from several images that are obtained using different enhancement approaches. By computing PSNR, it is clear that the proposed approach gives greater PSNR values than the other traditional approaches. It demonstrates superior anti-noise performance of the suggested approach.

Table 4: Performance based on PSNR

Method/Image	HE	CLAHE	BBHE	DOTHE	GAAHE
Img1	5.6004	22.3074	5.6004	5.2442	34.6640
Img2	7.1595	20.7600	7.1595	6.7739	27.6029
Img3	6.1962	20.9250	6.1962	5.7876	32.7641
Img4	5.8891	21.1591	5.8891	5.6333	29.1126
Img5	12.6607	22.6025	12.6607	11.1111	30.6408

3.3.4. FSIM. There are two ways to measure the feature similarity index (FSIM) [16]. After the local similarity map has been calculated, it is combined into a single similarity core. FSIM is measured using the following elements. These are gradient magnitude and phase congruency. Equation (3.2) is used to calculate FSIM.

$$FSIM = \frac{\sum_{x \in X} S_L(x)\, PC_m(x)}{\sum_{x \in X} PC_m(x)} \tag{3.2}$$

Table 5 presents an analysis of the FSIM values. This table shows that, in comparison to other traditional methods, proposed method outperforms.

Table 5: Performance based on FSIM

Method/Image	HE	CLAHE	BBHE	DOTHE	GAAHE
Img i	0.1558	0.5667	0.1558	0.1214	0.8979
Img ii	0.0705	0.4518	0.0705	0.0288	0.7816
Img iii	0.1517	0.7724	0.1517	0.0598	0.9812
Img iv	0.0900	0.6092	0.0900	0.0445	0.9207
Img v	0.5596	0.6233	0.5596	0.4264	0.9186

The suggested method may be regarded as the appropriate enhancement methodology for medical images with low contrast in terms of entropy, that should be maximum, PSNR, decreasing AMBE, improving feature similarity measure, according to qualitative and quantitative evaluations. By maintaining the average brightness of the photographs, the natural appearance of the image can also be preserved. The improved image generated by the suggested method performs better than the other traditional methods in terms of the anti-noise performance. Brightness is preserved, artifacts are reduced, and contrast is improved with little information loss because to the innovative subdivision of the histogram and adjusted PDF. This algorithm's balanced and ideal performance is a result of the genetic algorithm's ideal parameter selection process, that is directed by suggested fitness function. Because of its adaptability, it performs better in the majority of medical imaging.

3.4. Convergence Analysis

Figure 9 displays convergence performance of the suggested method for medical images Img i to Img v at each iteration. This convergence curve has shown that it can attain the global optimum and accomplish multiple objectives in a relatively small number of iterations.

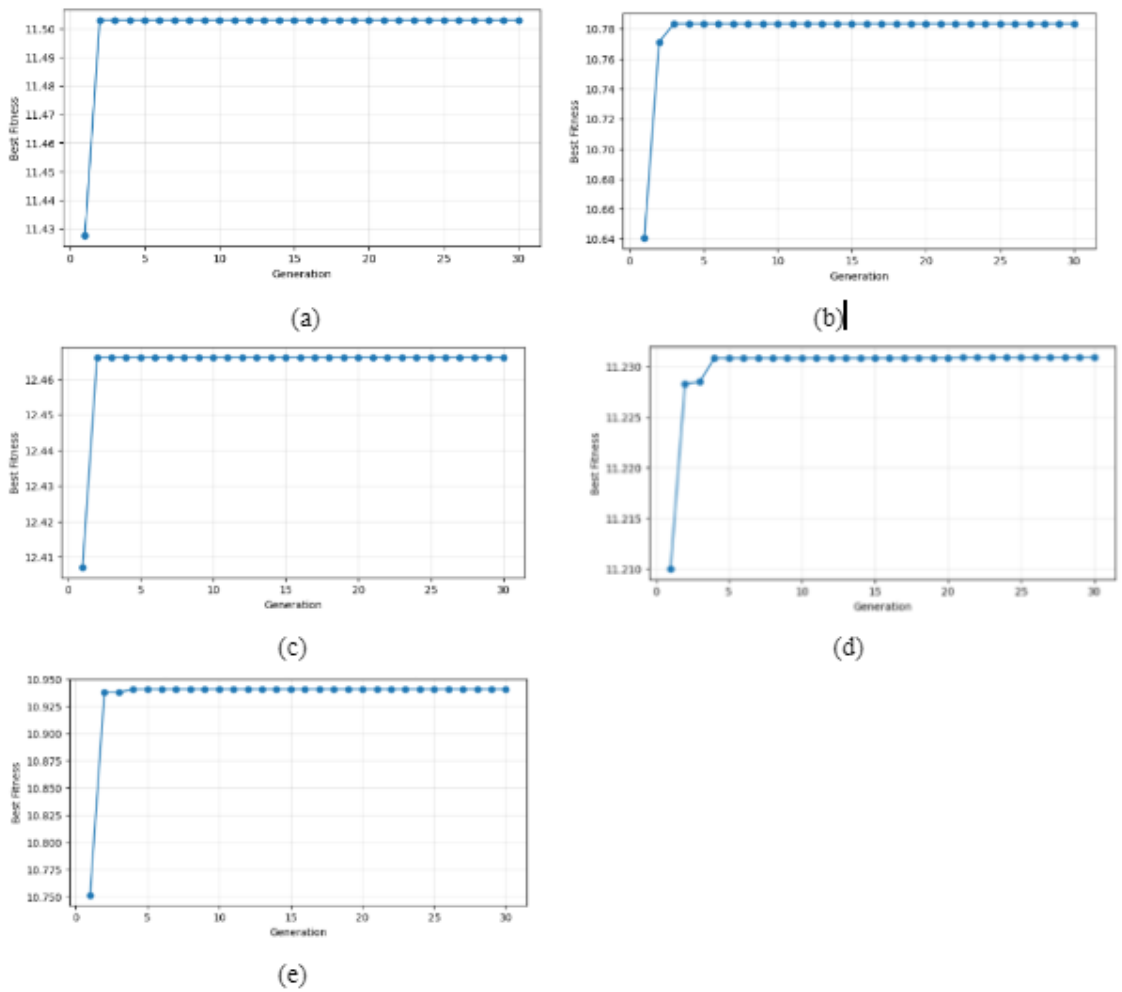

Figure 9: Convergence performance of proposed method (a) Img i (b) Img ii (c) Img iii (d) Img iv (e) Img v

Despite the complexity of medical imaging, it will provide the best possible outcome. Additionally. It demonstrates the suggested GAAHE algorithm's resilience and effective application.

4. Conclusion

In order to improve the quality of low contrast medical images, this research presents a novel adaptive image enhancement technique based on GA. This framework was created in order to automatically choose the threshold parameters for various photos without the need for human participation. Thus, the suggested method is more flexible. The suggested multi-objective fitness function and evolutionary algorithm determine how the parameters are automatically chosen. To optimize the fitness value, they are chosen. Thus, the suggested method produces a balanced improved image that has an improved quality, reduced loss of information, and increased anti-noise performance. In this study, the methods of histogram partitioning, PDF modification, and histogram equalization are crucial for improving image quality.

The suggested method's clipped methodology aids in preventing artifacts and over-enhancement. As a result, the suggested approach outperforms existing cutting-edge techniques in terms of entropy, AMBE, PSNR, feature similarity, and adaptability while producing aesthetically beautiful outcomes without any evident faults. In order for the suggested medical picture enhancing method to be useful in the diagnosis, monitoring, and interpretation of diseases in the human body.

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