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Contrast Enhancement for MRI Image Using Hybrid Optimization Technique

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Abstract

The contrast enhancement in MRI image is a wide application in many real world applications like medical application areas and photographic images. The main key problem medical image processing is the poor contrast level enhancement. The nature of poor contrast enhancement is improved using the contrast nature of MR image is improved using a Binary Flower Pollination Algorithm and Binary Particle Swarm Optimization (BFPA-BPSO). The level of contrast nature in Magnetic Resonance Image (MRI) is improved to eliminate the degradation in images at the time of image acquisition process. By improving the contrast of the medical MRI image by taking the four different images as lung, breast, brain and thyroid MRI images. And also in this study presents to recognize spatial information for image enhancement. The cost function is integrated with contrast measure based on few metrics to create a newer transformation function. The timing complexity can be reduced using soft-computing approaches and it increases the search pattern using a transformation function in spatial domain. This method improves the pixel intensity to increase the resolution of an image. The performance evaluation of this method is estimated by using three different parameter as PSNR, SSIM and accuracy.

Keyword: Contrast Enhancement, Magnetic Resonance Image (MRI), Particle Swarm Optimization, and Flower Pollination Algorithm

1 Introduction

The modern world of today allows the digital images to be downloaded and stored. In order to achieve better results, it is occasionally essential to make some enhancements to these images. These amendments have three key objectives: encoding, interpretation and image comprehension. For this purpose, image processing schemes have been built to allow these activities to be carried out more quickly and precisely [1]. There are four main processes in these systems: pre-processing, image quality enhancement, image transfer, and image categorization and analysis. Contrast enhancement of the input image is one of the most important tasks for image processing and computer vision. The aim of this series of

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processes is solely to improve and enhance the clarity of the image so that a better understanding of the images can be achieved. The main reason for this is that if the input image is of low quality and contrast, the next processing steps, such as image segmentation, feature extraction and image classification, would fail. For example, the performance of pre-processing methods, such as image enhancement, will have a direct influence on any processing in the next steps [2-4]. High-resolution imaging techniques can also dramatically increase the overall performance of the system.

The most useful applications for Image Contrast Enhancement is its use in medical imaging. The contrast enhancement in MRI image is a wide application in many real world applications like medical application areas and photographic images. The main problem behind increasing the contrast level of an image is the poor quality, poor contrast, illumination and high noise during image acquisition. Hence, the objective of contrast enhancement in an image is to enhance its contrast level. Furthermore, due to its simplicity of function and mobility, it can be used as a portable system for medical applications[3-6]. However, due to the low contrast of the images captured from mobile phones, the image quality is usually low. Image enhancement can be used to improve the visual aspects of this condition.

The first step in the analysis of medical pictures is generally the image enhancement. A number of types of medical image enhancement are currently in progress [7-9]. Gamma correction is widely used to improve the contrast of medical images, which is mainly due to its ability to maintain light. Other waves, histogram (HE), de-correlation stretching methods, PDE-based and median filter-based methods include other methods for improving medical imagery. Most of these processes do not provide high-quality pictures, particularly hard core cases like satellite images and night-vision captures. For example, wavelet enhancement cannot improve all of the image parts simultaneously, and the image enhancement process is also difficult to automate. HE procedures have the issue of missing the input image histogram information [10]. Histogram equalizations also include numerous kinds of image artifacts.

2 Literature survey

In this section, we discussed about some recent existing techniques of medical image contrast enhancement, it may helpful for our proposed research method.

Wang and Pan (2017) presented an enhancement system to reduce the complexity of the image processor, which is dependent on histogram equalization algorithm using the neighbourhood concept. The image is divided into three sub-squares based on angle based distance measurement. This method avoids the effects associated with over-enhancement. The sub-squares 12 histograms is modified using adjacent sub-squares. Finally, complexity of image details is enhanced by storing the brightness levels these sub-squares.

Chen et al. (2018) presented an image contrast enhancement technique using Artificial Bee Colony (ABC) algorithm finds the optimal solution required to improve the contrast nature of an image. This is modelled as an enhancement problem. Initially, the fitness function assesses the nature of the contrast improved image. Secondly, the image transformation function is a key tool for the creation of new pixel elements for the improved image from the first image; all the more critically, it manages the developments of the artificial bees. A parametric image transformation is used with the goal that uses the optimal parameters that are searched by ABC algorithm in image transformation function. This is as opposed to that the entire space

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of power levels in an image, which is utilized in the regular ABC-based enhancement approaches.

Wang and Chen (2017) presented a novel histogram modification method for image contrast enhancement. To begin with, entirety of the input histogram and its standard deviation are figured. At that point, gamma correction is connected on the output sum to produce an altered histogram. Lastly, the conventional histogram equalization is connected on the adjusted histogram to create the mapping capacity. Notwithstanding saving the mean brightness, the developed technique can enhance an image consistently with lower complexity in computation.

Lewin (2018) presented the sensitivity of various contrast enhanced mammography for recognition of breast cancer is comparable to that of MR Imaging, at any rate in demonstrative populaces. The specificity of contrast enhanced mammography is by and large better than that of MR Imaging in clinical investigations. Contrast enhanced mammography utilizes iodinated differentiation and a mammography unit altered to perform double vitality imaging. Contrast enhanced mammography permits imaging of the two breasts in different projections. Contrast enhanced mammography has favorable circumstances over MR Imaging as far as expense and accommodation, yet is moderately restricted in its capacity to image the chest divider and axilla.

Pawar and Talbar (2018) present Discrete Wavelet Transform (DWT) coefficient combination dependent on neighbourhood entropy amplification algorithm for difference enhancement. In this algorithm, the first image and Contrast Limited Adaptive Histogram Equalization (CLAHE) contrast enhanced image are disintegrated for three levels utilizing Haar wavelet. At each level of disintegration, inexact coefficients are melded 15 utilizing averaging task and nitty gritty coefficients are combined by figuring entropy of 5x5 sliding window and picking pixel esteem comparing to most extreme entropy. At long last, the mammogram image is remade by joining rough and point by point coefficients. The developed algorithm is assessed with execution measurements.

Cao et al. (2018) developed an effective image Contrast Enhancement (CE) device, Adaptive Gamma Redress (AGR) was recently developed by relating gamma parameter with aggregate conveyance work Cumulative Distribution Function (CDF) of the pixel dim levels inside a image. Auto-Color-Correlogram (ACC) bargains well with most diminished images, however fizzles for comprehensively splendid images and the darkened images with nearby brilliant locales. Notwithstanding, such two classes of brightness mutilated images are widespread in genuine situations, for example, those brought about by ill-advised presentation and white items. With the end objective to constrict such insufficiencies, in this technique we propose an enhanced AGR procedure. The epic procedure of negative images is utilized to acknowledge CE of the brilliant images, and the gamma amendment tweaked by truncated CDF is utilized to improve the darkened ones. All things considered, neighbourhood over-enhancement and structure contortion can be reduced adequately.

3 Proposed Image Enhancement Model

In this proposed model, the contrast nature of MR image is improved using a Binary Flower Pollination Algorithm and Binary Particle Swarm Optimization (BFPA-BPSO). The level of contrast nature in Magnetic Resonance Image (MRI) is improved to eliminate the degradation in images at the time of image acquisition process. The image contrast

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enhancement in MRI image is considered as an optimization task that aims at producing optimal solution using BFPA-BPSO algorithm. The proposed model architecture is shown in figure 1.This study presents a newer objective function that estimates the quality level of image during the process of image contrast enhancement. The generation of newer pixel intensities is carried out with the help of an image transformation function over an enhanced reference image. This helps in guiding the movement of artificial bees in BFPA algorithm. The parametric transformation function ensures that BFPA algorithm searches optimal parameters. The image intensity levels are further enhanced using the proposed technique using Binary Particle Swarm Optimization (BPSO). The proposed technique uses two fold hybrid algorithms to enhance the contrast nature of an image with higher quality. The procedure of the proposed system uses hybrid BFPABPSO algorithm to address the problems while improving the contrast level of image. The optimization problem related to image contrast enhancement is regarded as a hybrid process of BFPA-BPSO algorithm. The position of flowers based on inputs from BPSO denotes the best possible solution to enhance the image contrast level. The quality of image is based on fitness value of pollens. The main advantage of this hybrid algorithm uses both local and global searches in BPSO and local or global search in BFPA algorithm in each iteration step. This helps to find the solution in an optimal way to improve the image quality.

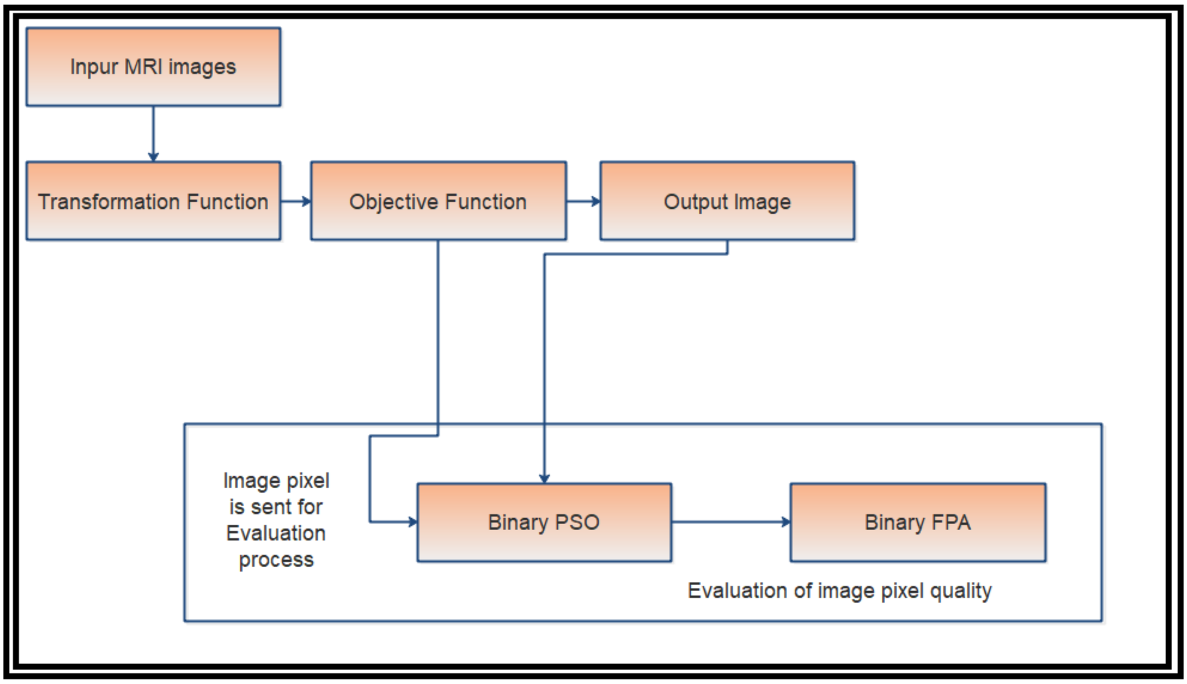

Figure 1: Proposed architecture for contrast enhancement in MRI

The proposed method is used to enhance the contrast level of an image with the help of a global intensity transformation. This method utilizes lookup tables in order to capture the intensity levels of an image that maps the older gray level of an image into newer gray levels. This method enables the contrast levels of a reference image. The lookup table in global intensity transformation function improves the contrast nature of an input image using relevant parameters. The image enhancement is carried out by the mapping of older pixel intensity level into newer pixel intensity levels. This is usually carried out in both reference and noisy images. The main aim of the proposed method is to use an objective function to optimize the image quality enhancement.

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3.1 Transformation Function

The reference image is improved through a transformation function in spatial domain that generates newer intensity values of pixels in an image and this generates the enhanced version of the reference images. Thus if the spatial relationship between each pixel in an image is enhanced using the transformation function. This increases the timing complexity of the process, when the image size increases. To reduce this, an incomplete beta function is used for improving the contrast nature of an image. The transformation function used in the proposed system is designed to serve the BPSO algorithm for improving the contrast nature of an image and this is defined using the following expression,

$$F(u) = B^{-1}(\alpha,\beta)\int_0^u t^{a-1}(1-t)^{\beta-1}dt \tag{1}$$

$$B(\alpha,\beta) = \int_0^1 t^{a-1}(1-t)^{\beta-1}dt \tag{2}$$

Where,

$B(\alpha,\beta)$ is signified as the beta function

u is defined as the normalized gray level of a reference image

$\alpha\, and\, \beta$ is defined as the parameters to generate larger fitness value and this produces the enhanced reference image.

t is defined as the integration variable and

3.2 Objective Function

The proposed method uses an objective function to enhance the quality of a reference image and this is attained using impartial estimation of image quality. The multi-objective function in the proposed system consists of total number of edges, image entropy and summation of intensity levels of each edge. Thus the quality of an image is improved with increased contrast range in edges and further the intensity is increased than original reference image. The estimation of enhanced reference image is improved using multi-objective function and this is given by.

$$F = \log(Log(Log(E(I_s)))\frac{n(I_s)}{M\times N}H(I_e) \tag{3}$$

Where, M is defined as the total number of columns,

N is defined as the total number of rows,

n is defined as the total number of pixels associated with higher value of threshold intensity levels,

I_s is defined as the sum of image pixels intensity and

I_e is defined as the entropy of enhanced reference image.

The convergence rate is considered as slower one using the above method and hence a statistical variable is used in the multi-objective function. This representation is independent of its conditions and its observers but this can be applied on newer test image to improve its quality.

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4. BFPA-BPSO ALGORITHM

This section provides the details of preludes of both BPSO algorithm and BFPA algorithm. The detailed discussions are given in following sub-sections:

4.1 Binary Flower Pollination Algorithm (BFPA)

The Flower Pollination Algorithm (FPA) operates based on the process of pollination by bees that help in exchanging the pollen grains. This is carried out between the flowering plants through biotic and abiotic pollination. The pollinators are used to transfer the pollens to longer distance at the time of global pollination process and this process has four rules, which are given below:

1. The Levy flights distribution is performed by the external pollinators in cross and self-pollination that carries the pollen grains between various flowers, which is referred as global pollination process. 2. The self-pollination and abiotic pollination helps to operate the local pollination process.

3. The flower constancy concept is used when the similarity between two different flowers is proportional to the reproduction probability.

4. Finally, the local pollination and global pollination is controlled by the switching probability and this lies in the range between $p \in [0, 1]$.

The process of global pollination is thus defined by,

$$x_1^{t+1} = x_i^1 + \gamma^1 L(\lambda)(x_i^t - g^*) \tag{4}$$

Where, x_i^1 is defined as the pollen i and this is a solution vector at an iteration t

$\gamma$is defined as the scaling parameter and

$L(\lambda)$ is defined as the Levy flight step size.

$(g^*)$is defined as the best solution

The step size (L) is then found using Levy flight distribution, which is given by,

$$L(\lambda) = \frac{\lambda\Gamma(\lambda)\sin(\lambda)}{\pi}\frac{1}{S^{1+\lambda}}, S > 0 \tag{5}$$

Where, $\Gamma(\lambda)$ is defined as the Standard gamma function, where the value of λ is set as 1.5

Finally, the process of local pollination is defined by following expression,

$$x_1^{t+1} = x_i^1 + \epsilon(x_j^1 - x_k^1) \tag{6}$$

Step 1. Define the fitness function $max\ f\ (x), where\ x = (x1, x2, \ldots, xd)$

Step 2. Parameter of PSO is initialized: size of flowers and pollens, total number of iterations. **Step 3.** Determine the best solution in initial population.

Step 4. Define the switch probability $p \in [0, 1]$

Step 5. Set maximum number of iterations.

Step 6. While (t< maximum generations)

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Step 7. For i = 1:n(all n flowers in the population)

Step 8. If $rand < p$

Step 9. Else

Step 10. End If Step 11. Find new pollens or solutions

Step 12. If new solutions is better than old solution, a. update the population with new solution

Step 13. End for a. Check the current best solution or current pollens g*

Step 14. End while

Step 15. Output the final best solution

4.2 BPSO Algorithm

The PSO algorithm helps in driving the candidate solution or particles from swarms and this helps in establishing communication depending on its evolutions. It utilizes a group of candidate solution or particles that moves in its search or swarm area and this helps the solution to move in its global optimum region. The objective of BPSO algorithm is to speed up the movement of position along its best and global solution. The BPSO algorithm effectively finds the particles or candidate solution and moves it effectively into the region of optimal solution

Assume a search space of n-dimensions and consider a particle (i) that lies in the swarm space and this is characterized as $Yi = (yi1, yi2, \ldots, yin)$. The velocity of each particle is thus given as $Vi = (vi1, vi2, \ldots, vin)$. The local best position of a candidate solution or a particle is given as $Pibest = (pi1, pi2, \ldots, pin)$ and the global best position of a candidate solution or a particle is given by $Pgbest = (pg1, pg2, \ldots, pgn)$, respectively. The velocity and position of each particle is updated at regular instance until the objective function gets converged. The performance of premature convergence problem in PSO is avoided using BPSO that increases the convergence rate by combining the Linearly Decreasing Inertia Weight (LDIW) and convergence factor. The following expression derives the rule needed for BPSO algorithm to operate, which is given below,

$$V_{t+1} = \lambda W\ Pbest_t\big(V_t + C_1 rand(1,1)\big) - (CurrVlaue_t + C_2 rand\ (0,1)) \tag{7}$$

$$CurrVlaue_{t+1} = CurrVlaue_t + V_{t+1} \tag{8}$$

$$LDIW = (W_{start} - W_{end})\left(\frac{T_{max}^{-t}}{T_{max}}\right) + W_{end} \tag{9}$$

Where,

w is defined as the inertia weight,

$rand()$is defined as the random number,

Where the value lies between 0 and 1

c1 and c2 is defined as the acceleration parameter,

Step 1. Define the fitness function $maxf\ (x), where\ x = (x1, x2, \ldots, xd)$

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Step 2. Parameters of PSO are initialized: size of swarms, total number of iterations.

Step 3. Initially, assign random velocity and position to the particles in swarm.

Step 4. Find the personal best position of the particle.

Step 5. Estimate the particles‟ fitness function

Step 6. Determine best position of particle in swarm

Step 7. Loop

Step 8. Update the particle velocity as per Equation (7)

Step 9. Update the particle positions as per Equation (8)

Step 10. Find the personal best position in swarm

Step 11. Find the global best particle in swarm

Step 12. Stop criterion until maximum number of iterations.

4.3 BFPA-BPSO Contrast Enhancement

The quality of enhanced reference image is improved using contrast enhancement using BFPA-BPSO algorithm. The convergence rate is made easier using BPSO algorithm that attains local optimal solution at the time of convergence or complicated problem. The convergence problem is avoided using BFPA algorithm that helps in converging the problem to a global solution. However, this is achieved only at a slower rate but this problem is resolved with the help of Levy distribution and this generates faster convergence by generating a newer solution. This method avoids the solution tapped at local optimal points. 90 Further, the randomness associated with Levy flights distributes leads to reduced convergence rate and its associated search efficiency and this affects the method to attain optimal solution. The proposed BFPA-BPSO method helps in avoiding such limitations using BFPA. The faster convergence rate is thus improved using BPSO algorithm Levy Flight distribution process. The searching process is thus improved using this hybrid algorithm and this finds the optimal solution and attains a global optimal convergence. The pseudo code for proposed hybrid BFPA-BPSO algorithm is given below:

1. Initialize particles in PSO with random velocity and positions on the given search space.

2. For each particle, evaluate fitness value through classification accuracy.

3. Find pest and gbest value of each particle in entire swarm.

4. Find the overall previous best of particles using fitness evaluation.

5. Check if the present value is greater than gbest value, update the present particle with updated value.

6. Modify the position and velocity of particle in swarm as per Equation (7) and Equation (8).

7. Repeat the operation from step 2 until the maximum iterations are met.

8. The particle with best position using BPSO is sent as input to BFPA algorithm.

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9. The particles are expressed as flower in the form of vector $X = (x1, x2, \ldots, xd)$, with d set of features.

10. The switching probability (p) is to attain global or local pollination.

11. If rand value<p. Global pollination is carried out using Levy flights

12. Or else if rand value

13. Find new pollens with better solutions.

14. Update the new pollens in given population

15. Find the present best solution.

16. Return the best solution, after the total iteration conditions are met.

5 Results and Discussions

The proposed algorithm is implemented in MATLAB and processing of images requires high resolution processing of images. The implementation is carried out in a high end computing system with Intel Core i5 with 8 GB ram having a memory of 1 TB. This section provides a detailed evaluation of various performance metrics to test the proposed method and existing contrast enhancement soft-computing models over MR images. This study considers evaluation of the models like PSO, FPA and combination of BFPA-BPSO scheme. The proposed method is tested rigorously tested to acquire optimized contrast enhanced images.

5.1 Performance Measures

To make the testing process effective, the study uses various performance metrics and compared it over other soft computing algorithms. These performance metrics include Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and accuracy.

Peak signal to noise ratio

As per the pixel values, the PSNR reflects the quality of the image evaluated by the following two contrast images and the PSNR is considered as,

$$PSNR = 10 * Log_{10} \frac{n^2}{MSE} \tag{10}$$

Structural similarity index metric

For the purpose of finding the comparability (similarity) between two images (X, Y) the SSIM measure is defined as

$$SSIM = \frac{(2\mu_x \mu_y + a_1)(2sd_{XY} + a_2)}{(\mu x^2 + \mu y^2 + a1)(s, d_X^2, +, s, d_Y^2 + a2)} \tag{11}$$

Accuracy

The degree to which data in a computer database organises its actual values is called accuracy. The accuracy degree is close to the actual value and the true output proportion is processed as

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$$Accurarcy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Where, TP and TN are the true positive and negative of images. FP and FN are the false positive and negative of MRI images

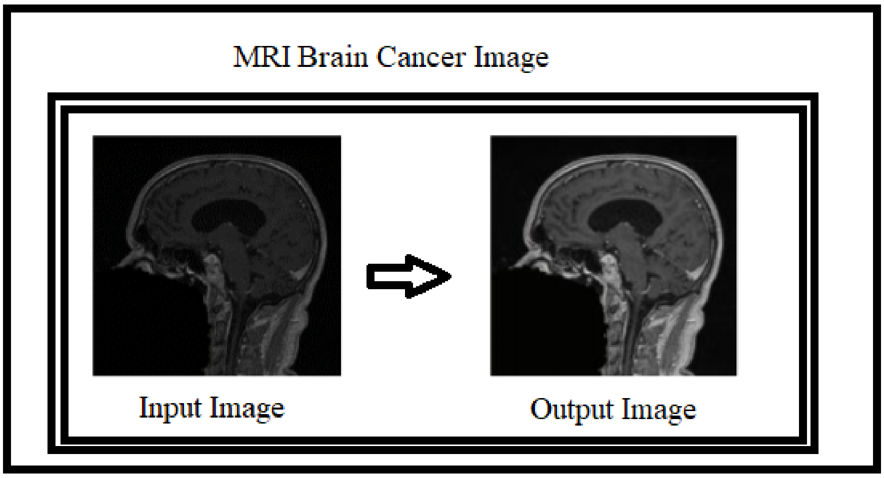

Figure 2: Simulation output of MRI brain cancer image

In figure 2 and table1 show as that the simulation results of proposed model with specific algorithm. By this comparison, proposed model reached the better performance than other two algorithm techniques.

Table 1: Performance evaluation of various methods against brain cancer images

Methods	PSNR	SSIM	Accuracy (%)
PSO	13.98	0.72	87.00
FPA	14.20	0.89	89.21
BFPA-BPSO	18.98	1.01	97.24

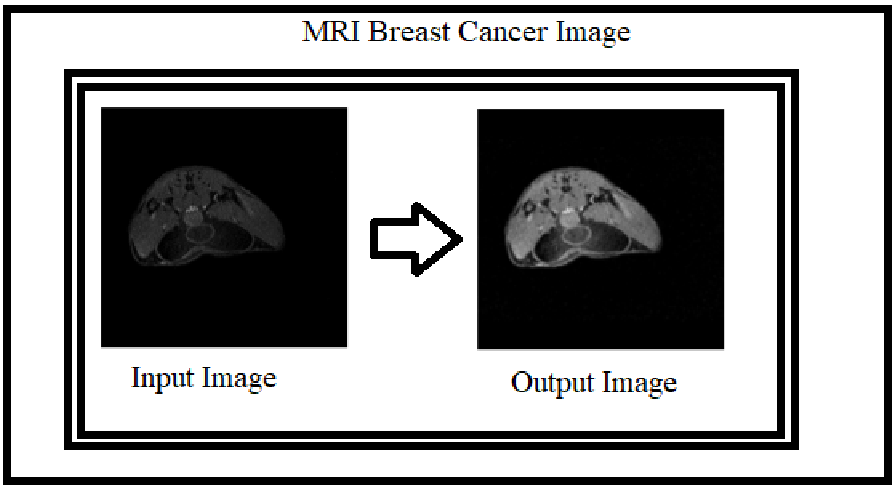

Figure 3: Simulation output of MRI breast cancer image

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In figure 3 signifies that the simulation output of breast cancer image with better contrast level. And also table 2 identified as the performance of proposed model, it attained the better accuracy value of 97.93%, which is better than other model.

Table 2: Performance evaluation of various methods against Breast Cancer images

Methods	PSNR	SSIM	Accuracy (%)
PSO	15.35	7.91	81.48
FPA	17.01	8.03	82.20
BFPA-BPSO	19.21	1.31	97.93

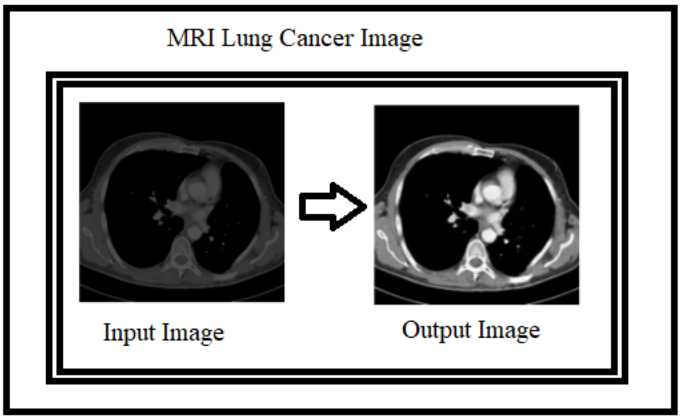

Figure 4: Simulation output of MRI lung cancer image

In figure 4 signifies that the simulation output of brain cancer image with better contrast level. And also table 3 identified as the performance of proposed model, reached accuracy of 98.01% and PSNR value of 18.90.

Table 3: Performance evaluation of various methods against Lung Cancer images

Methods	PSNR	SSIM	Accuracy (%)
PSO	15.72	0.97	84.53
FPA	14.99	0.99	86.78
BFPA-BPSO	18.90	1.01	98.01

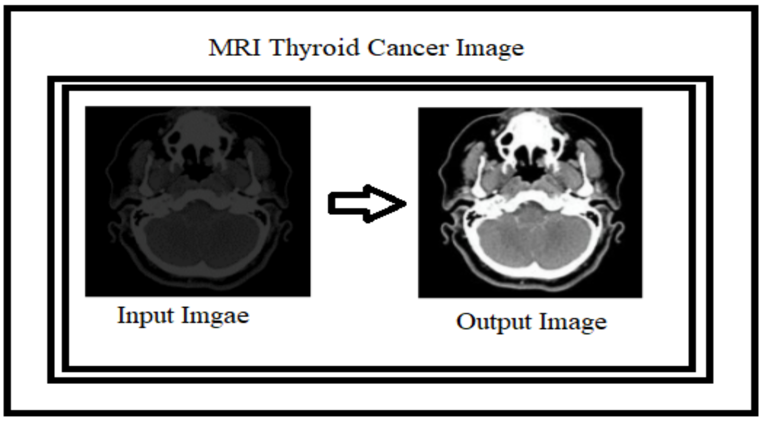

Figure 5: Simulation output of MRI thyroid cancer image

In figure 5 identified as the simulation output of MRI thyroid cancer image, output image contrast level is in high quality than input image, and also performance achieved by proposed model as accuracy of 98.31%, SSIM value of 1.05 and PSNR value of 19.01.

Table 4: Performance evaluation of various methods against thyroid Cancer images

Methods	PSNR	SSIM	Accuracy
PSO	17.89	0.89	91.58
FPA	18.22	0.93	89.35
BFPA-BPSO	19.01	1.05	98.31

By compared to other two specific algorithm, proposed model provide better results in image contrast enhancement process. Compared with original image pixel, the enhanced image pixel has improved edges with high contrast and high intensity using the proposed method.

6 Conclusion

This study presents the details of BFPABPSO algorithm to enhance the gray-level of cancer MRI images using adaptive transformation method. The proposed method is compared with contrast enhancement methods that uses PSO, and FPA. It could be inferred from the results that proposed BFPABPSO method enhances the contrast nature of MR images. The overall result shows that proposed method has improved its quality in enhancing the contrast nature of MR images than other existing algorithms. The results provide higher convergence rate than other existing algorithms. The improved contrast nature of image is due to the use of objective function that improves the pixels in MRI images to form an improved contrast enhanced MRI images. Hence, it is concluded from the above discussion that proposed method is considered as an effective, quick and stabilized method to improve the contrast nature of images.

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