Evolutionary Computing Model for Finding Breast Cancer Masses using Image Enhancement Procedures with Artificial Intelligent Algorithms

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Abstract: *In this research, Particle Swarm Optimization (PSO) based image equalization is projected to enhance the contrast of different breast cancer images. Breast cancer is the highest and another important root of tumor disease in females worldwide. Mass and microcalcification clusters are a significant early signs of breast cancer. The mortality rate can effectively be decreased by early diagnosis and treatment. Most practical approach for the early detection and identification of breast cancer diseases is mammography. Mammographic images contaminated by noise usually involve image enhancement techniques to aid interpretation. Contrast enhancement is divided into two categories: development of direct contrast and enhancement of indirect contrast. Indirect contrast improvement is used in the image histogram update. Histogram Equalization (HE) is the modest enhancement of the indirect contrast approach usually used for contrast enhancement. The proposed method's average entropy is 5.3251 with the highest structural similarity index 0.99725. The best contrast improvement of this method is 1.0404 and Peak Signal to Noise Ratio (PSNR) is 46.3803. The MSE value is 2157.08. This paper recommends an innovative method of enhancing digital mammogram image contrast based on different HE approaches. The performance of the projected method has been related to other prevailing techniques using the parameters, namely, discrete entropy, contrast improvement index, structural similarity index measure, mean square error, and peak signal-to-noise ratio. Investigational findings indicate that the projected strategy is efficient and robust and shows better results than others.*

Keywords: *Image enhancement, breast cancer, histogram equalization, particle swarm optimization, analysis.*

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1. Introduction

Breast cancer is the abnormal growth of the cells lining the breast lobules or the vessels. Such cells are hysterically developing and can disseminate to further parts of the body. Breast cancer begins once cells instigate to grow out of control in the breast. Typically, these cells form a swelling that can sometimes appear as a lump on an x-ray or sensed. The tumor is malicious if the cells will grow into surrounding tissues or spread to the remaining portions of the body. At its initial level, mammography is still the finest tool for detecting breast cancer. The issue with mammography images is that they are difficult. Image analysis and extraction procedures are also used to support radiologists in the identification of tumors [9]. So far, there is no successful way to avoid the existence of breast cancer. Hence, it is renowned that, the first crucial step in the detection and therapy of breast cancer is the initial finding. Owing to its cost-effective and simplicity, X-ray mammography is probably the general method used in clinical procedures with respect to medical imaging analysis and testing techniques [14].The clinical evaluation of breast cancer is not special, but the lack of accurate initial diagnosis methods is a problem [2].

Introspection by touch is insufficient to facilitate initial diagnosis of breast cancer: the convenience of imaging tests, procedures is critical in some cases; it takes around ten years for tumors to convert palpable [16]. Skilled radiologist exercise plays a crucial part in detecting and elucidating medical data and establishing the correct diagnosis due to the relevance breast imaging procedures. Due to the large changeability of examples, where several does not match precisely in conventional models and descriptions, this is an especially multifarious task [18]. A number of important breast cancer signs that radiologists are looking for are clusters of micro calcifications, lumps, and structural deformations. Lump identification is another complicated task, since it is also identical from neighboring tissues [6]. In particular, the understanding of lumps in noisy images, similarly particulars generated by mammography accession, is very difficult.

Artificial intelligence testing is very helpful in this scenario for physicians to advance both the susceptibility of diagnosis and selectivity of diagnosis. The development of appropriate computing analysis that can focus the attention of the doctor on suspicious image areas in order to prevent misidentification and for cancer, finding at an initial stage, the measurable image explanation is significant [28].

Cai *et al.* [4] recommends a novel computerized technique for breast cancers analyzed in mammogram images by Convolutional Neural Network (CNN) and advanced thermal exchange optimization algorithm. The outcomes display that the accurateness of analyzing cancer cases for this technique is 93.79%, and sensitivity and specificity are found 96.89% and 67.7%, correspondingly. Liu *et al.* [21] investigated computer assisted breast cancer analysis based on image segmentation and interval analysis. The authors developed the traditional Laplacian of Gaussian filter based on interval analysis to contemplate the intensity uncertainties. Investigational outcomes showed that this technique contributes a hopeful performance than the paralleled approaches.

Guo and Razmjooy [13] investigated and presented a strong picture segmentation approach for breast cancer image diagnosis based on interval uncertainty. The goal is to use interval analysis to improve the ordinary Sobel filter by taking intensity uncertainty into account. The proposed approach is compared against LoG, Prewitt, and canny filters in simulation. The final findings revealed that by taking into account specific types of uncertainties such as Gaussian noise and salt and pepper noise.

For image feature improvement, several techniques have been suggested. Several investigators have concentrated their work on growing the microcalcification divergence in evaluation also nearby regular tissue; although a few research schools focus on eliminating contextual noise [12, 20, 25, 32, 36].

A Computer Aided Diagnosis (CAD) method for mass segmentation in mammography images, charted through a competent indexing the image into a malignant or benign one, is proposed by Menon *et al.* [23]. This technique is evaluated on various images and has been found to be very operational with an accuracy of 95.7% with inflated precision and progressive analytical assessment. Dheeba *et al.* [7] projected abnormality finding procedure is centered on removing Law's Texture Energy Measures in the mammography images and organizing with doubtful areas by using a pattern classifier. The outcome demonstrates that the region of the suggested procedure's Receiver Operating Characteristic curve (ROC) is 0.96853 with 94.167 % susceptibility and 92.105 % selectivity.

Al-Najdawi *et al.* [1] examined linking numerous image enhancement procedures to improve the enactment of the breast area partitioning. The results attained in tumor categorizing precision values of 90.7%. Furthermore, the outcomes showed a susceptibility of 96.2% and a selectivity of 94.4% for the mass categorizing procedure.

Pereira *et al.* [26] presents a cluster of artificial intelligence mechanisms to assist segregation and finding of mammograms that confined the lump. First, an object removal procedure is implemented and tracked by a system of image denoising and enrichment of gray scale based on wavelet conversion and Wiener filter. The authors established an artificial intelligence technique to spot and segregate areas in breast tumor images with genetic algorithm and multi resolution methods.

The aim of this research is to find the best methodology and also to compare the various methodologies that exist in mammography images to detect cancer. Compared to multimodal images, very few researchers recognize similar limits for different modalities of images. This study allows the radiologist in the initial stage to consider and avoid the seriousness of illnesses. Various methods of Histogram Equalization (HE) and PSO-based optimization algorithms are modest methods of optimization and are adapted to improve images for several medical imaging procedures. Enhancement parameters like discrete entropy, SSIM, CII, PSNR, and MSE are used to validate the enactment of various HE procedures and Particle Swarm Optimization (PSO) based optimization algorithm. This research also compares the accuracy and computational time with different HE methods and PSO based optimization algorithm, and proved that PSO based optimization is suitable for enhancing the breast images.

The structure of this paper is as follows: The "Introduction" section highlights the main ideas of the suggested strategy and addresses the difficulties related to breast cancer as well as applications of image analysis techniques, specifically the HE and PSO for feature enhancement. The specifics of the data sets used for the inquiry are provided in the "Materials and techniques" section. The HE and PSO Algorithm are described in the "Methods" section. The strategy and model utilized for the proposed method are described in detail in the section titled "Breast Cancer Image Enhancement Using PSO: Proposed Scheme." Information about the picture quality evaluation performance used to look into the results of the enhancement is provided in the Measures of Performance section. The quantitative and qualitative evaluations as well as the findings of the comparative inquiry between various methodologies are presented in the sections titled "Experimental outcomes and discussions." The section titled "Conclusion and Future Work" summarizes the work done for the paper and offers some ideas for new directions.

2. Materials and Techniques

This part explains the methods applied for breast cancer image enhancement mammogram masses using HE and PSO based enhancement.

2.1. Histogram Equalization (HE)

HE is a technique for altering the strength of the image to increase contrast. Consider an original image $F(x,y)$ built of different gray scales in the active collection of [0, Z-1], the conversion function $M(r_t)$ is explained as:

$$D_t = M(r_t) = \sum_{i=0}^{t} P(r_i) = \sum_{i=0}^{t} \frac{n_i}{n} \quad (1)$$

When $0 \leq D_t \leq 1$ and $t=0,1,2,\ldots,Z-1$, n_i denotes the quantity of gray scale pixels r_t , n is the total quantity of pixels in the input image and $P(r_t)$ denotes the Probability Density Function (PDF) of the original gray scale r_t. The Cumulative Density Function (CDF) is derived from the PDF as $M(r_t)$. Histogram Linearization or Global HE is represented in Equation (1). Here, D_t is plotted in the active range of [0, Z-1] by reproducing it by (Z-1). By means of the level plotting calculation, HE transforms an input level t towards an output level S_t from the achieved CDF values (2).

$$\mathrm{S_t} = (\mathrm{Z} - 1)\mathrm{M}(\mathrm{r_t}) \quad (2)$$

The raise in the output level S_t for the conventional GHE described above is given by:

$$\mathrm{S_t} = \mathrm{S}_t - \mathrm{S_{t-1}} = (\mathrm{Z} - 1)\mathrm{P}(\mathrm{r}_t) \quad (3)$$

In the original picture, the increase in level St is comparable to the likelihood of its matching level t. A plotting structure like this will flawlessly fit the histogram in principle for images with constant strength levels and PDFs. But, in reality, the exposure levels and PDFs of medical images are different. In this instance, conventional HE plotting is imperfect and results in unintended effects where high probability levels often develop over enriched and low probability levels become less enriched and their frequency in the resulting image is either reduced or even eradicated.

HE is widely used contrast improvement method owing to its easiness and affluence of implementation [10]. HE levels the dissemination of likelihood and increases the complex form of gray intensities, thus increasing the whole picture contrast [19]. For low exposure images Singh *et al*. [33] studied the equalization of recursive histogram procedure. The authors appealed that the proposed approaches are positive for capturing images in a dim light situation, for example immersed arrangements or dark visualization pictures.

Singh *et al*. [34] developed a new histogram clipping for improvement of lower illumination retinal pictures for primary observation of damage to the small blood vessels due to diabetics. The authors proposed RIHE-RVE and RIHE-RRVE to report heterogeneous brightness in retinal pictures to do the pictures well suitable for CAD. Quality metrics indicate the procedures expected outweigh much of the avant-garde procedures. A model for image contrast and colour enhancement was created by Veluchamy and Subramani [37] with Adaptive Gamma Correction and Weighted Histogram Equalization (AGCWHD). This approach is suggested to enhance dissimilarity, even though retains usual colour and comfortable particulars in pictures.

Suradi *et al*. [30] suggested a new Fuzzy Anisotropic Diffusion Histogram Equalization Contrast Adaptive Limited (FADHECAL) approach for reducing mammography picture noise while maintaining contrast and brightness. The results demonstrated that FADHECAL outperforms other enhancement approaches, with AMBE values of 6.502 ±1.855, SSIM value of 0.934± 0.034, MAE values of 15.742 ±1.217, PSNR values of 26.843± 2.541, UIQI values of 0.969± 0.021, and RMSE values of 1.151± 0.147.

Pseudo Code of Histogram Equalization

```
Scan the image to calculate the Frequency [0…Z-1], i.e. histogram
From the Frequency [ ] array compute the cumulative frequency
        Array Cumulative_frequency [0…Z-1]:
        {
        Cumulative_frequency [0] = Frequency [0];
                For i = 1 to Z-1
Cumulative_frequency [i] = Cumulative_frequency [i-1]+Frequency[i];
                }
Determine the histogram equalization transformation lookup table
        For i = 0 to Z-1
        {
        j = round (Cumulative_frequency [i]*(Z-1)/N;
                R[i] = j;
                Inverse R[j] = i;
                }
Transform the image using lookup table R.
```

2.2. PSO Algorithm

PSO is population-based. It replicates bird clustering or shoal of fish performance to attain a self-evolution arrangement. Every result in the PSO is named a particle. The PSO is a set of rules that improves the particles inside the space under analysis. Over the time, the discrete particles existing in space range their position. In PSO, in a multi-dimensional examining space, particles move throughout. Every particle regulates its location through flight, according to its particular occurrence, and confirming to the occurrence of its adjacent particles.

Using localized contrast modification, Mohan and Mahesh [24] projected an enrichment method called Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the better details of mammographic pictures and PSO method for making improvements in the enrichment constraints. This planned technique offers the finest contrast enrichment even though maintaining the original mammogram image's confined particulars.

An image grouping procedure by means of PSO through two better objective functions is suggested by Wong *et al*. [39] research findings indicate that the PSO based image grouping strategy can achieve enhanced K-means by providing additional dense clusters and higher mean cluster segregation by means of better objective functions.

Beheshti *et al*. [3] studied the artificial neural network based training by means of centripetal enhanced PSO based enhancement for medical ailment's analysis. Method competence is assessed on the basis of MSE, correctness, susceptibility, accuracy, region in the functional features of the receiver curve and t-test and the signed rank test of Wilcoxon. The result shows that this method provides efficient implementation of other medical ailment analysis methods, especially with hidden data and high data loss values.

Vijayalakshmi *et al*. [38] proposed multi-modal prediction algorithm for breast cancer prediction. It includes k-nearest neighbour approach, rapid decision tree, and kernel density estimation, as well as PSO nondominating sorting, and multi-classifier algorithms. Finally, Bayes' theorem is used to revise the results to attain the highest level of accuracy in breast cancer prediction. When applied to the WBCD and WDCD data sets, this PSO-NDS model produced the best results (98.8% and 98.6%, respectively).

Janga and Sharma [17] studied a new approach for enhancement of satellite image, which is based on AHE-RWT with SVD and PSO-CS algorithm for quality improvement of the low brightness satellite images. The satellite image is ruined due to noise, so eliminating of noise is essential from the images for improved visualization. Sumathi *et al*. [35] studied with Kapur's entropy-derived from Cuckoo Search algorithm and structural rebuilding filters to remove cancers in brain and mammography image. It has been checked with the aid of PSNR and MSE results from segmentation shows that the projected analysis has strong exception to noise intervention. This method's precision rate is much greater than the FCM and PSO procedures. The drawback of this approach, however, lies in the implementation of comparable limitations for both conditions which are not currently in use.

Razmjooy *et al*. [27] presented thresholding based Breast Cancer findings in digital mammograms with world cup optimization algorithm. With respect to the goal function used by Kapur's technique, this method uses random samples as candidate solutions from the search space within the image histogram. The masses are totally segregated from other areas of the image in the proposed model, and their quality and brightness boost the precision of mass position recognition. The final results are compared with PSO algorithm and Imperialist Competitive Algorithm (ICA).

Garg and Juneja [8] proposed PSO based segmentation of cancer in multi-parametric prostate MRI. Subjective and objective trial results demonstrated that the suggested strategy provides better value than other existing approaches, implying that it can be used in clinical situations.

Selvarajan *et al.* [29] conducted a comparison of PSO and ACO-based feature selection methods for medical data conservation. The outcome is analyzed using machine learning algorithms built on the randomized dataset based on classification accuracy. The experimental findings demonstrate that the accuracy is preserved in the smaller affected datasets. Additionally, the findings indicate that ACO search-based feature selection is more accurate than PSO search-based selection.

Every particle has objective rules and those are calculated by the fitness function to be optimized, and need velocity that guides the particles flying. The particles travel all over the concern area by succeeding the personal best (pbest) and global best (gbest) particle. The swarm is organized by a selection of random particles and then searches for the best by learning by iterations. Every particle is reorganized in entire iterations, succeeding two "best" standards. For every particle attained earlier, the leading particle is the best result. This is identified as "pbest" result. The best result, followed through whichever particle in the entire population, is an additional one. This is identified as "gbest" result. The two leading values are answerable for driving the particles to travel to a different, better location.

Later detecting the two finest data, by using the subsequent Equations (4), and (5) a particle reforms its position and velocity.

$$\overrightarrow{X_i^{t+1}} = \overrightarrow{X_i^t} + \overrightarrow{V_i^{t+1}} \tag{4}$$

$$\overrightarrow{V_i^{t+1}} = w\overrightarrow{V_i^t} + c_1 r_1 \left(\overrightarrow{P_i^t} - \overrightarrow{X_i^t}\right) + c_2 r_2 (\overrightarrow{G^t} - \overrightarrow{X_i^t}) \tag{5}$$

When V_i^t and X_i^t specifies the velocity and position of particle *'i'* on the time occurrence 't', c_1 and c_2 are progressive hastening coefficients and w is termed as inertia load to attain the equilibrium among the global quest and local quest and r_1 and r_2 are arbitrary values produced in the span [0,1]. G_i^t is the global finest result and P_i^t is the finest result of the i^{th} particle attained up to now. In the Equation (5), the 1st segment signifies the particle's inertia speed, 2nd segment specifies the assessment taken by the particle from its own understanding and 3rd segment indicates the swarm understands societal. The Pseudo code of PSO as follows:

Pseudo Code of PSO

```
Begin
Load the governing constraints (Z, Wmin, Wmax, c1, c2, Vmax and Max iter)
Load the number of Z particles in population
do
        for every particle
                Compute the target of particle
                Upgrade PBEST if needed
                Upgrade GBEST if needed
        end
        Upgrade the inertia mass number
        for every particle
                Upgrade velocity (Vi)
                Upgrade position (Xi)
        end
```

while condition not fulfilled
Return GBEST is the good approximation of the global best

3. Projected Scheme for Breast Cancer Image Enhancement Using PSO

The projected PSO based Optimization combines the power of many HE procedures. The algorithmic explanation of this method is given here below:

1. Split the given image in two, based on its average.
2. Articulate lower and higher weighting limitations pertaining to bottom and top divided images.
3. Fix lower and higher limitations for the equivalent divided images.
4. Enhance the constraints through PSO.
5. Use HE technique on the divided images.
6. Merge the divided images to output image with the enrichment of contrast and preservation of brightness.

The procedure used for PSO based optimization of breast cancer image is shown below

Procedure

Input Breast Cancer image, F[a,b] using 'Z' pixels in the gray scale

span [X_0,X_{N-1}], r,s,t,u

Output F_0(a,b), enhanced with contrast and brightness preserved image

Start

1. Divide *F(a,b)* into bottom divided image $F_B(a,b)$ and top divided image $F_t(a,b)$ based on its average '*m*'
2. Calculate the Probability Density Function (PDF), $P_B(pdf)$ and $P_T(pdf)$ for the bottom and top divided images, separately.
3. Calculate the average PDF of bottom and top divided images as mB and mT, separately.
4. Apply the next limitations to the bottom divided image:

$$P_{BC}(pdf) =$$
$$T(P_B(pdf)) = \begin{cases} \alpha & if\ P_B(pdf) > \alpha \\ \left(\frac{P_B(pdf)-\beta}{\alpha-\beta}\right)^s \alpha, & if\ \ \beta \le P_B(pdf) \le \alpha \\ 0 & if\ P_B(pdf) < \beta \end{cases} \tag{6}$$

When α=s×max (P_B (pdf)), 0.1<s<1.0, 'r' is power factor when 0.1<r<1.0 and β=0.0001.

5. Calculate the average PDF of controlled lower divided image as m_{BC}.
6. Find the mean error meB as:

$$m_{eB}=m_{Bc}-m_B$$

7. Add meB to $P_{BC}(pdf)$.
8. Calculate the CDF, *CB(FB(i,j)* using $P_{BC}(pdf)$ and apply the HE procedure as:

$$\mathrm{F}'_\mathrm{B}(\mathrm{i},\mathrm{j}) = \mathrm{X}_0 + (\mathrm{m}-\mathrm{X}_0)\times \mathrm{C}_\mathrm{B}(\mathrm{F}_\mathrm{B}(\mathrm{i},\mathrm{j}) \tag{7}$$

9. Apply the following limitations to the top divided image:

$$\mathrm{P_{TC}(pdf) = T(P_T(pdf)}$$
$$= \begin{cases} \delta & \text{if } \mathrm{P_T(pdf)} > \delta \\ \left(\frac{\mathrm{P_T(pdf)}-\varphi}{\delta-\varphi}\right)^{\mathrm{u}}\delta, & \text{if } \ \varphi \le \mathrm{P_T(pdf)} \le \delta \\ \varphi & \text{if } \mathrm{P_T(pdf)} < \varphi \end{cases} \tag{8}$$

When δ=u×max (PT(pdf)), 0.1<u<1.0, 't' is the power factor when 0.1<t<1.0 and φ=mean (PT(pdf)).

5. Calculate the average PDF of the controlled better divided image as mTC.
6. Find mean error meT as:

$$m_{eT}=m_{Tc}-m_{T.}$$

7. Add m_{eT} to *(pdf)*.
8. Calculate the CDF, $C_T(F_T(i,j)$ using $P_{TC}(pdf)$. and apply the HE procedure as

$$F'_T(i,j) = (m+1) + (X_{N-1} - (m+1)) \times C_T(F_T(i,j) \tag{9}$$

9. Final output enhanced image is

$$F_0 \ = F'_B(i,j) U\ F'_T(i,j) \tag{10}$$

End

In a well-ordered and practical methodology, the limitations tested on the bottom and top divided images help to balance the images. The new divided image PDFs are fixed to the higher threshold *α and δ* and to the lesser threshold *β* and *φ*. The PDFs of the divided image is greater than the limit, based on the higher probability range. In this projected PSO based procedure, 4 main constraints namely *r*, *s*, *t* and u are documented. They are adaptable boundaries which resolve the grade of the enhancement process. Values may be set either physically or mechanically to these constraints, depending on need. In comparison with the brightness retained, the best values will enhance the result image. The ideal values of the constraints (*r*, *s*, *t*, and *u*) are seen inevitably by means of PSO wherein a fitness function is also used to maintain the brightness of the images, and also improve the contrast of the original images.

3.1. Objective Function

An objective function is desirable to measure the fitness to determine the output of image enhancement, i.e., the enhanced image function rather than the human interface, which can independently evaluate the image function to the degree feasible [5, 11, 22, 23, 40]. Gorai and Ghosh [11] defined a fitness function generated for evaluation by merging three performance metrics, such as entropy, number of edges, edge intensity, etc. The enhanced image has incorporated a sum of edges matched to the original image and the enhanced version must have greater edge strength. Sober edge detector has been used in this study due to its simplicity and also it makes a fair good evaluation of enhanced image. The entropy of the image also considered making the concentrations of the edges may be inclined to images that do not ensure a normal contrast.

$$Max.F(I_e) = log\left(log\left(E(I_S)\right)\right) \times \frac{n.edges(I_S)}{P \times Q} \times H(I_e) \quad (11)$$

Where I_e is the improved image of the grey level generated by the projected enhancement procedure, P represents the column numbers and Q represents row numbers of the initial image, *n.edges* is the number of pixels, (I_S) is the addition of P×Q pixel concentrations of Sober edge image and (I_e) is the entropy value of the enhanced image.

3.2. Performance Measures

The efficiency of our investigating methods is authenticated by different measures like Discrete Entropy (DE), Structural Similarity Index (SSIM), Mean Square Error (MSE), Contrast Improvement Index (CII) and Peak Signal to Noise Ratio (PSNR).

3.2.1. Discrete Entropy

Discrete entropy is used to measure the average amount of missing information and a lot of data in a later enhancement picture [31, 35]. It is explained as

$$Entropy = -\sum_{k=0}^{255} p(x_k) log_2(p(X_k)) \quad (12)$$

Ideally, the higher the entropy value, the higher the image's information, hence greater entropy is needed. If an enhanced image's entropy value is similar to that of the initial image, then it is said that the input image information are retained in the outcome image.

3.2.2. Structural Similarity Index Measure (SSIM)

The SSIM is a magnificent criterion that computes the deprivation of image feature induced by treating, like data density or data relocation losses. It is a fully recommended criterion that involves double images - an original image and a treated image-from the comparable image seizure.

$$SSIM = \frac{(2\mu_x\mu_y + C_1)((2\sigma_{x_y} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (13)$$

When x and y are the individual original images and the result images; σ_x and σ_y are the standard deviation of x and y. A distinct average of x and y is μ_x and μ_y. σ_{xy} is the square root of covariance of x and y, while C_1 and C_2 are coefficients. The value of the SSIM is 0 to 1 for two pictures. If $x=y$, then the SSIM is equal to 1 which suggests that the amount of structural comparison among the dual images are further.

3.2.3. Contrast Improvement Index (CII)

The contrast improvement index is a computable quantity of image contrast improvement that is characterized as:

$$CII = \frac{C_t}{C_i} \quad (14)$$

The value of the contrast improvement is treated and initial images are indicated as C_t and C_i correspondingly. The image contrast C is characterized as:

$$C = \frac{(G_f - G_B)}{(G_f + G_B)} \quad (15)$$

When G_f and G_B are the average intensities of the front and backdrop of the appearance. Higher index values mean the enhancement of the contrast in the improved image.

3.2.4. Peak Signal To Noise Ratio (PSNR)

The ratio among the highest probable signal power and the iniquitous noise power that disturbs the adherence of its illustration is the peak signal-to-noise ratio.

$$PSNR = 10 * log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \quad (16)$$

3.2.5. Mean Square Error (MSE)

The mean square error is used between the original image *F(a,b)* and the enhanced image *Y(a,b)* to calculate the cumulative square error,

$$MSE = \frac{1}{rc}\sum_{i=0}^{r-1}\sum_{j=0}^{c-1}[F(a,b) - Y(a,b)]^2 \quad (17)$$

The rows and columns of the original image are characterized by r and c.

3.3. Data Set

Data sets of mammogram screen/film digitized images were taken from the Digital Mammography Screening Database in this analysis (DDSM) [15]. DDSM is a joint project among Massachusetts General Hospital, Sandia National Laboratories and the Department of Computer Science and Engineering in University of South Florida. There are nearly 2,500 studies in the databank. For many papers on this field, it had been utilized as a yardstick, for cost free and owning a huge and distinct number of studies. All the studies involve dual pictures of both breasts, with several related patient data such as age in the period of testing, ACR breast solidity assessment, ACR abnormality keyword classification, sensitivity assessment for irregularities, and picture information such as four dimensional resoluteness, analyzer, etc. The identified images with a lumisys film scanner at 50µm, 1024x1024 pixels resolution and 8 bit accuracy. The mammogram selected for this research should contain at least one mass region which physically outlined by a qualified radiologist.

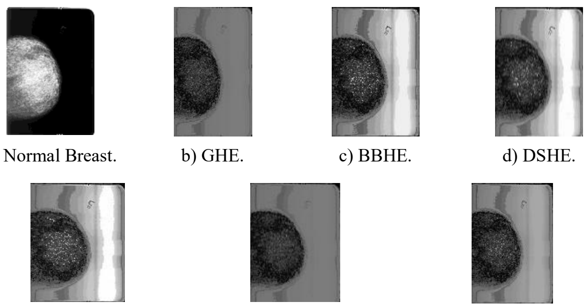
4. Results and Discussions

This part explains the outcomes attained in artificial intelligent computing procedures for the image improvement used for different breast cancer mammogram images. This technique is assessed in PC using Intel(R) Core™ i7-8700 CPU @3.20GHz, 3.19GHz, operating system with 64 bit and 16 GB RAM.

4.1. Subjective (Individual) Evaluation

To demonstrate examples of the programmed enhancement procedure conclusions, six cases are selected B 3659, B 3628, C 0160, B 3029, B 3401 and C 0307, from the 550 medical cases investigated. These terminologies are utilized from the page of the DDSM scheme, which uses a coding to distinguish all the current medical mammography cases via the digital scanner applied to digitally convert it (Upper case letter) and patient code (numeral). For additional info, the researcher may read the reference [15].

Visual examination of image enhancement is known as individual evaluation. Improved images sense the visual contact with the ordinary human perception in order to achieve individual assessment. Visual inspection aids, to accomplish a thorough check the additional artefacts, irregular appearance, and unnecessary development. The visual feature investigation is an operative constraint to evaluate the enactment of several approaches applied in image contrast improvement and average brightness conservation. The visual assessment findings of the proposed enhanced breast cancer images optimized by PSO and the different techniques for different images of breast cancer are demonstrated in Figures 1, 2, 3, 4, 5, and 6.

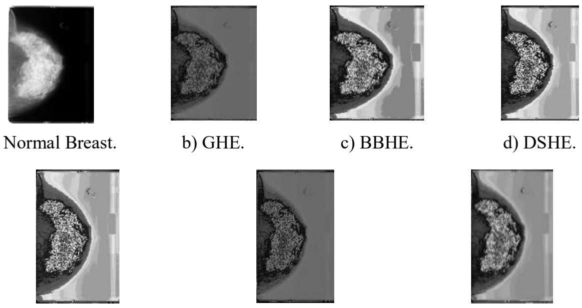


a) Normal Breast. b) GHE. c) BBHE. d) DSHE.

e)) HS. f) RMSHE. g) PSO.

Figure 1. Enhancement of breast cancer images (BC1).

Figure 1 displays the seeable outcome of the projected and current techniques for the 'normal breast' image. This is witnessed in Figure 1-b) and 1-c) that the outcomes of GHE and BBHE procedures are not perceptibly appealing and there are insufficient structural details in the output image, therefore it is not so ideal for enhancing the breast image. In the Figure 1-d), it is seen that optical effects of DSHE slightly good for brightness degradation problem. From Figure1-e) results of HS shows that the image suffers from concentration overload objects resulting in the ruin of the feature of the image. It is clearly presented in the Figure 1-f), results of RMSHE has a capacity to yield visually pleasing images with a higher degree of mean brightness conservation. From Figure 1-g) results of PSO optimized method produce greater grade of good illumination. By the projected PSO based procedure, the preservation of the brightness sensitive structures allows the radiologist to additional post-process for claims such as breast tissue classification, breast image removal features and cancer cell enhancement, etc. The pixel concentration standards are either accumulated in one component or moved inadequately when matching the histograms of all five existing techniques. The projected PSO based technique can resolve this difficult by extending the concentration values over the whole active span.

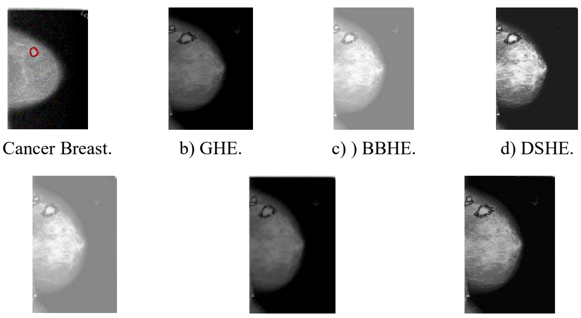


a) Normal Breast. b) GHE. c) BBHE. d) DSHE.

e) HS. f) RMSHE. g) PSO.

Figure 2. Enhancement of breast cancer images (BC2).

Figure 2 displays the normal breast image and contrast improvement outcomes by way of histograms made by GHE, BBHE, DSHE, HS, RMSHE and PSO based technique. In Figure 2-a) the original image is presented. The GHE process balances the histogram of the original image to produce an improved image wherein the original image missing certain intensity, as displayed in Figure 2-b). Mostly concentrations are higher than average illumination and having lower intensity error, improved image can be produced by both BBHE and DSHE, as shown in Figure 2-c) and 2-d). But, concentration is not enhanced by the HS method. The HS marginally leveled the input image to reserve intensity; however the dissimilarity of the resulting image, presented in Figure 2-e), is adequately improved. The RMSHE method is a HE growth, but some slight objects are shown in Figure 2-f) in the breast. The outcomes of the optimized approach based on PSO are shown in Figure 2-g) is that the image is retained with a satisfactory image brightness, resulting in appropriate contrast.



a) Cancer Breast. b) GHE. c)) BBHE. d) DSHE.

e) HS. f) RMSHE. g) PSO.

Figure 3. Enhancement outcomes of breast cancer images (BC3).

Figure 3 shows the contrast improved versions of breast cancer image. Because of its over-enhancement, the improved outcome of GHE Figure 3-b) presents a concentration overload issue in the image. Although the BBHE and DSHE Figure 3-c) and 3-d) procedures boost the image's brightness, the local visual quality information is concentrated in the processed image. From the Figure 3-e) and 3-f), the HS and RMSHE, methods are to conserve intensity and similarly certain areas in the picture are dim and the data is misplaced. Figure 3-g) clearly demonstrates that the visual representation of optimized image based on PSO is greater than other methods and free of unsolicited objects and unnecessary improvement. It is found that all the existing techniques have unregulated scattering of intensity. The optimized PSO based algorithm shows accurate dissemination of intensity, thus retaining average illumination and enlightening the contrast of the images.

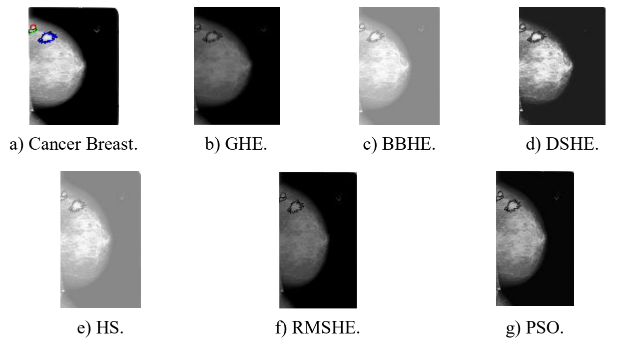


Figure 4. Enhancement outcomes of breast cancer images (BC4).

Figure 4 displays the cancer breast image and its contrast improved types attained through the projected technique and further five approaches. From the visual description, it is evident that the methods of DSHE and RMSHE produce an improved image quality, although certain areas have been most improved. The GHE and BBHE process results are dimmer and all the facts in the picture have been absent. The resulting improved images from HS method showed better dissimilarity, however, this technique failed to reserve the average luminosity. The proposed PSO based optimized image outclasses the other five procedures by refining intensity, conserving luminosity and holding a normal appearance.

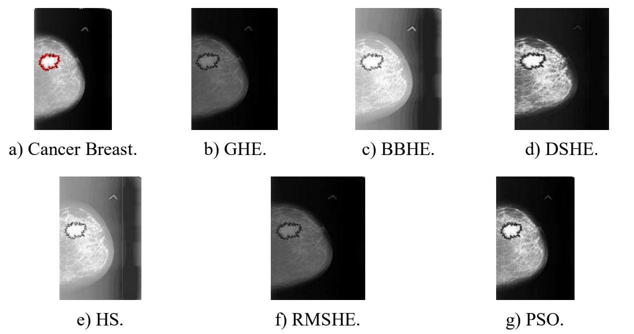


Figure 5. Enhancement outcomes of Breast Cancer Images (BC5).

The effects of image improvement pertained to the image of breast cancer and Benign Breast image are shown in the figure 5 and 6. The predicted PSO based optimized enhancement procedure is intended as the finest method for refining the dissimilarity of the images of breast cancer through destroying the issue of enhancement, confirming to the visual analysis of all the data, however existing procedures are originating to agonize due to surplus artifact's, clouding effect, most improvement, abnormal look etc. It is evident from the visual analysis of all outcomes that the predicted procedure enhances the visual excellence resourcefully devoid of producing any annoying objects and moreover recalls the best picture of breast cancer that simplifies successful diagnosis.

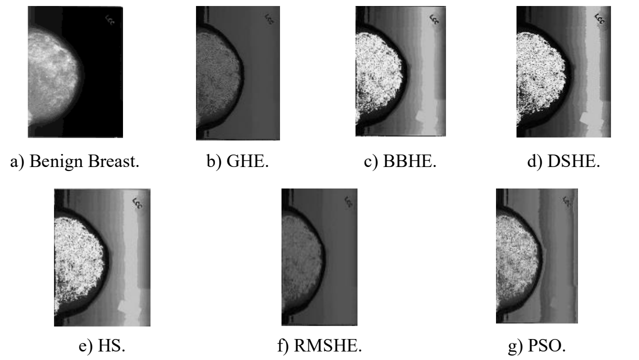


Figure 6. Enhancement outcomes of Breast Cancer Images (BC6).

4.2. Computable (Evident) Evaluation

The quality of the optimized enhancement system based on the PSO can be considered by quantifiable evaluation and is validated by the considerations specified in the section on performance methods.

Table 1 displays the discrete entropy details for all the enhancement methods used in this research. Discrete Entropy is the degree to which the accessible data in a breast cancer image are interpreted. It is used to measure the average amount of missing information and richness of data in after enhanced image. The fruitfulness of the knowledge provided in that picture corresponds to higher discrete entropy. Due to dropping data through its most improvement, the GHE method provides lower entropy value. It is considered that the predicted optimized enhancement technique based on PSO generates the value of entropy that is roughly equal to the entropy of input pictures and thus retains the unique data quality more efficiently while matched to every technique of contrast improvement.

Table 1. Comparison of the discrete entropy values of the image pattern obtained from various procedures.

Name	Original	GHE	BBHE	DSHE	HS	RMSHE	PSO
BC1	5.72	4.89	5.64	5.61	5.60	5.60	5.68
BC2	5.45	4.54	5.35	5.17	5.34	5.39	5.41
BC3	5.58	4.98	5.35	5.41	5.43	5.55	5.57
BC4	4.14	3.20	3.86	3.97	3.98	4.14	4.11
BC5	5.61	4.92	5.40	5.43	5.43	5.59	5.60
BC6	5.54	4.85	5.37	5.37	5.44	5.48	5.54

Table 2 provides the evident assessment outcomes for different breast cancer images using the metric SSIM. The higher value of SSIM indicates the less contrast deviation from the input image suggesting the best variety of preservation. It is perceived in all figures that, the projected PSO based technique attains high SSIM value while related to further techniques and it displays that image is not significantly modified without losing its data.

Table 2. Comparison of the SSIM values of the image pattern obtained from various procedures.

Name	Original Image	GHE	BBHE	DSHE	HS	RMSHE	PSO
BC1	1	0.80	0.79	0.78	0.79	0.95	0.99
BC2	1	0.67	0.67	0.62	0.67	0.79	0.99
BC3	1	0.22	0.43	0.62	0.22	0.75	0.99
BC4	1	0.26	0.29	0.37	0.26	0.48	0.99
BC5	1	0.25	0.43	0.67	0.25	0.79	0.99
BC6	1	0.60	0.58	0.58	0.61	0.73	0.98

Table 3 shows the CII values, it is obvious that the planned PSO based optimization and RMSHE methods have higher CII value relative to all other improvement approaches evaluated in this report. The contrast is usually upgraded in every study by the predicted approach while maintaining the outline of the whole function profile. In comparison, through other existing contrast improvement methods, it is considered that the projected approach has better CII performance. Greater CII numbers indicate the predicted PSO based approach besides improves an image's contrast, but moreover enhances the physical data or good information that is more suitable for analysis in the breast cancer image.

Table 3. Comparison of the CII values of the image pattern obtained from various procedures.

Name	Original Image	GHE	BBHE	DSHE	HS	RMSHE	PSO
BC1	1	0.9759	1.0138	0.9857	1.0047	1.0068	1.0588
BC2	1	0.9833	1.0304	1.0135	1.0304	1.0149	0.9657
BC3	1	1.1757	1.0600	0.9935	1.2917	1.0135	1.0588
BC4	1	1.4286	1.1464	1.0262	1.4286	1	1
BC5	1	1.0476	1.0039	0.8995	1.1583	1	1.0084
BC6	1	1.1095	1.1225	1.1225	1.1039	1.0421	1.1512

In Table 4, when equated with other current methods, it is clear that when equated through current techniques, the suggested PSO based approach provides a higher number in PSNR. In reducing noise modules in the improved image, the projected techniques with higher number of PSNR results and also possibilities to produce a maddening object free result. The highest number in PSNR produces a worthy improved image contrast. Here, this projected technique has relatively good number in PSNR, so with improved contrast; its resultant image has a pleasing feature.

Table 4. Comparison of the PSNR values of the image pattern obtained from various procedures.

Original Image	GHE	BBHE	DSHE	HS	RMSHE	PSO
BC1	13.125	12.1506	12.397	12.495	20.8369	46.0993
BC2	11.9859	11.1023	13.474	11.643	14.7708	43.3003
BC3	7.4208	13.2544	12.843	7.3723	14.4512	46.6144
BC4	5.7150	14.3198	15.120	5.9759	20.1152	59.5699
BC5	7.8176	14.7058	13.614	7.7186	15.4453	49.7423
BC6	9.7763	10.2643	10.264	9.7208	14.5229	32.9559

For all enhancement processes, Table 5 provides the MSE values. It is noted that the projected optimization approach based on PSO offers minimal MSE values for every image of breast cancer and therefore has good in contrast, minimum noise and other existing methods compared to them. It is found that of all strategies, the PSO based approach has the lowest time complication.

Table 5. Comparison of the MSE values of the image pattern obtained from various procedures.

Original Image	GHE	BBHE	DSHE	HS	RMSHE	PSO
BC1	3166	3962.9	3744.0	3660.42	3660.42	3660.42
BC2	4116	5044.8	2921.6	4454.27	3041.2	2167.69
BC3	11776	3073.5	3378.3	11908.41	1417.9	2333.23
BC4	17441	2404.9	2000.2	16424.45	718.0	633.22
BC5	10747	2200.3	2829.2	10955.65	690.0	1855.89
BC6	6846	6118.5	6118.5	6934.33	3292.23	2292.03

In this research, 360 file images were examined, and when compared to other recent methods, the average entropy of the recommended method is close to the original image.

Table 6. Average objective measures value for 360 breast cancer images.

	Performance Metrics				
Methods	Entropy	SSIM	CII	PSNR	MSE
Ori. Image	5.3389	1	1	29.68	--
GHE	4.6586	0.4698	1.1198	9.29565	9087.60
BBHE	5.2561	0.5412	1.0596	12.5437	3799.76
DSHE	5.1982	0.6109	1.0072	12.8634	3502.12
HS	5.1463	0.469	1.1728	9.09862	8987.36
RMSHE	5.3197	0.7531	1.0134	16.7098	2214.39
PSO (Proposed)	5.3291	0.9969	1.0398	46.4792	2046.18

An average of 360 database images is used to compute the computation time is shown in Table 7. The BBHE and DSHE algorithms produce the best results for the calculation time listed in Table 6 because of their low complexity. These techniques, however, provide outcomes that are excessively boosted while barely improving contrast.

Table 7. Computational time (Sec) of algorithms for an average of 360 Breast Cancer images.

Algorithm	HE	BBHE	DSHE	HS	RMSHE	ACO	GA	PSO
Avg. Computational time (Sec)	0.15	0.251	0.293	0.39	0.312	0.317	0.291	0.274

It has limited time involvedness; however, it does not ensure the excellence of the resulting improved image in visual examination. Hence, the achievement of the planned method developed most precise in cultivating dissimilarity and conserving good particulars and the outcomes assist the detail that the planned method by means of added keys are full-bodied in general and operative in treating several types of breast cancer or other medicinal pictures.

5. Conclusions

A competent and powerful image enhancement technique focused on the PSO with HE is projected in this research paper to improve the image contrast with virtually not any artifacts. In order to determine the efficiency of the projected process in terms of both subjective and computable indicators, experiments are carried out on different images of breast cancer. In addition, the verified findings on datasets for breast cancer have shown that the proposed approach is consistent with other existing enhancement methods. In a standard look with the best image contrast, the predicted procedure results where all areas are transparent and visible. Research findings have shown that, in line with the information quality and contrast enhancement, the projected approach outlines the other existing procedures. The projected optimization approach based on PSO is ideal for improving breast cancer images that could be employed to support medical examiners or doctors to accurately classify the breast tumor in the correct way. The following conclusions can be drawn from this study, which used the DDSM dataset for breast cancer mammograms and the image enhancement techniques with PSO:

1. To remove noise and improve breast cancer images, a powerful new PSO algorithm based HE method is utilized.
2. The diagnosis accuracy of the PSO model is comparable to the stated current medical imaging procedure, but it is quicker and less expensive.
3. Combined with HE, the PSO is a very successful method for improving breast cancer images.
4. It was shown that the PSO-based HE algorithms produced better visual and measurable results when evaluated on challenging breast cancer picture enhancement.
5. A visual examination demonstrates that the projected technique can deliver a more realistic-looking image.
6. The PSO approach has average entropy of 5.3251, a structural similarity index of 0.99725, a PSNR of 46.3803, a CII of 1.0404, and an MSE value of 2157.08 when compared to all other HEtechniques. It proves that this process produces better results and offers better contrast when compared to other approaches.

Future research will concentrate on using this approach on different datasets. For mammography images, additional benchmark datasets are accessible. It is also possible to use this PSO algorithm-based HEto other medical imaging, such as retinal and liver scans. Additionally, this approach aims to advance complete competency by reducing computational complexity.

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