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Enhanced Medical Image Segmentation Using Firefly Algorithm and Bee Colony Optimization

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Abstract— **MRI and Mammogram is one of the best technologies currently being used for diagnosing breast cancer and brain tumour. Breast cancer and brain tumour is diagnosed at advanced stages with the help of the mammogram and MRI image. In this thesis an intelligent system is designed to diagnose tumour through mammograms, using image processing techniques along with intelligent optimization tools, such as Fire Fly Algorithm (FFA), Enhanced BEE Colony Optimization (EBCO) and Artificial Neural Network. The detection of tumour is performed in two phases: preprocessing and segmentation in the first phase and feature extraction, selection and classification in the second phase. 350 MRI images obtained from KMCH Hospital Coimbatore and 161 pairs of digitized mammograms obtained from the Mammography Image Analysis Society (MIAS) database is used to design the proposed diagnosing system. Initially, the film artifacts and X-ray labels are removed from the images and median filter is applied to remove the high frequency components from the image. The suspicious region is segmented using Markov Random Field (MRF) hybrid with EBCO and FFA algorithm for MRI and mammogram images. The MRF and EBCO and FFA algorithm based image segmentation method is a process seeking the optimal labeling of the pixels. The optimum label is that which minimizes the Maximizing a Posterior (MAP) estimate. EBCO and FFA metaheuristic algorithm is implemented to compute the optimum label, which is to be treated as an optimum threshold for segmentation.**

Keywords— **MRI, mammogram, Enhancement, Feature Extraction, Receiver Operating Characteristics.**

I. INTRODUCTION

The segmentation of an image entails the division or separation of the image into regions of similar attribute. The ultimate aim in a large number of image processing applications is to extract important features from the image data, from which a description, interpretation, or understanding of the scene can be provided by the machine.The segmentation of brain tumor from Magnetic Resonance Images is an important but time-consuming task performed by medical experts.

Mammography amd MRI images are used to detect tumor formation within breast and brain tissues. A new nature inspired metaheuristic algorithms remains untouched. The suspicious region or tumors are segmented using Markov Random Field hybrid with Enchanced Artificial Bee Colony Algorithm (EABC) and Fire Fly Algorithm (FFA) (Sahoo, A. ; Chandra 2013) for mammogram and MRI image (Karaboga.D, Bahriye Akay 2009).

Firefly algorithm proposed by Yang is a new intelligent optimization algorithm developed in recent years, Firefly algorithm is considered as an unconventional swarm-based heuristic algorithm for constrained optimization tasks inspired by the flashing behavior of fireflies (Du Xiaogang et.al 2013).

Fire Fly Algorithm (FFA) is a recent population-based approach inspired by the observation of real firefly and based upon their brightness behaviour. In FFA, solutions of the problem are constructed within an iterative process, by adding solution components to partial solutions. Each individual FireFly constructs a part of the solution using a brightness and distance, which reflects its experience accumulated while solving the problem, and heuristic information dependent on the problem. (Krishnamoorthi Murugasamy et.al.,2016).

Recently, many researchers have focused their attention on a new class of Algorithms called metaheuristics. A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems. In other words, a metaheuristic can be seen as a general-purpose heuristic method designed to guide an underlying problem specific heuristic toward promising regions of the search space containing high-quality solutions. (Thuy Xuan Pham, Patrick Siarry, Hamouche Oulhadj et.al.,2020).

A metaheuristic therefore a general algorithmic framework, which can be applied to different optimization problems with relatively few modifications to make them, adapted to a specific problem. The use of metaheuristics has significantly increased the ability of finding very high-quality solutions to hard, practically relevant combinatorial optimization problems in a reasonable time. This is particularly true for large and poorly understood problems. Several meta-heuristics, such as GA, Ant Colony Optimization (ACO), PSO, Tabu Search and Simulated Annealing, have been proposed to deal with the computationally intractable problems. FFA is a new meta-heuristic developed for composing approximate solutions.

A detailed study on methods of various stages of automatic detection of microcalcification and brain tumours in digital mammogram and MRIs. It is to be noted that researchers have not used Fire Fly Algorithm to analyse the mammogram and MRI in the recent past. In this work, the metaheuristic algorithms such as FFA and EABC are implemented to extract the suspicious region based on texture image segmentation.

In the mammogram and MRI image segmentation process, a pioneering method, viz., Markov Random Field hybrid with Enchanced Artificial Bee colony algorithm and Fire Fly Algorithm is used to segment the tumour from the mammogram and MRI image.

The MRF based image segmentation method is a process of seeking the optimal labeling of the pixels. The optimum label is that which minimizes the Maximizing a Posterior estimate. Initially, a unique label is assigned for similar patterns to the mammogram and MRI images. The Enchanced Artificial Bee colony algorithm and Fire Fly Algorithm algorithm is applied to obtain the optimum label, which is to be considered an optimum threshold for segmentation. Figure1 shows the Flow Diagrams for the Medical Image segmentation.

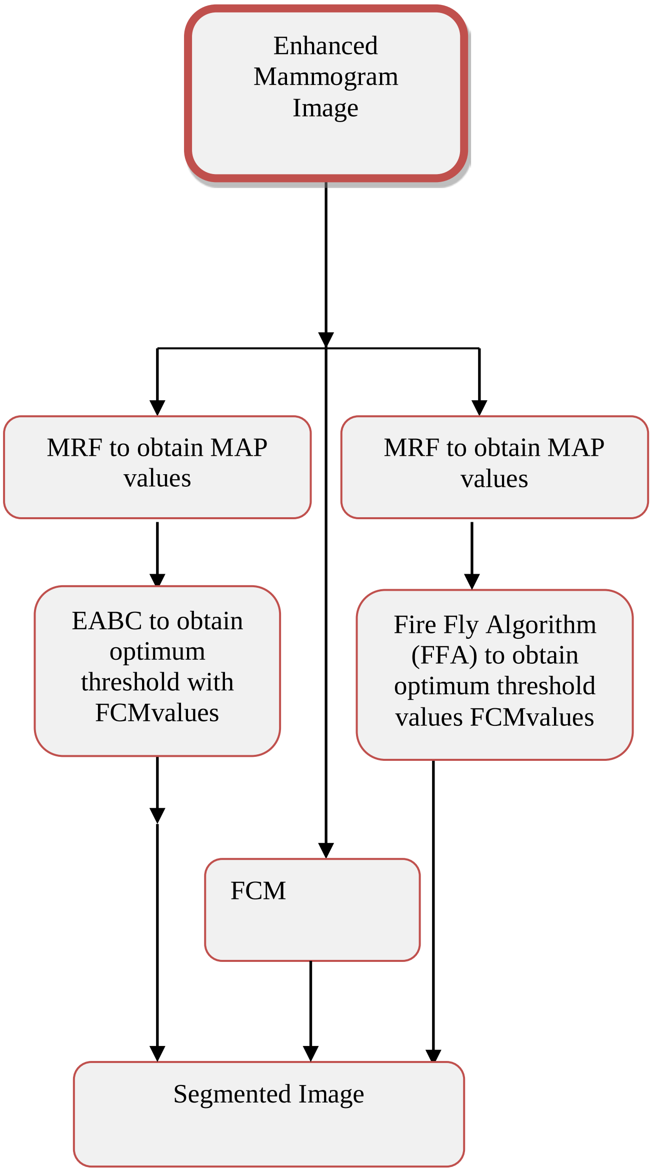

Fig 1 Flow Diagrams For The Medical Image segmentation.

2 Markov Random Filed

The image is stored in a two-dimensional matrix and a kernel is extracted for each pixel. A unique label is assigned to the kernels having similar patterns. In the labeling process, a label matrix is initialized with zeros. The size of the label matrix is equal to the size of the image. For each pixel in the image, the label value is stored in the label matrix at the location corresponding to its central pixel coordinates in the gray level image. (Chen M, Yan Q, Qin M et.al.,2017)

A pattern matrix is maintained to store the dissimilar patterns in the image. For each pixel, a kernel is extracted and the kernel is compared with the patterns available in the pattern matrix. Once it finds any matches the same label value is assigned to the currently extracted kernel. Otherwise the next label value is assigned to the kernel and the kernel is added to the pattern matrix. The labels are assigned integer values starting with one and incremented by one whenever a new pattern occurs. Finally the pattern matrix contains all the dissimilar patterns in the image and the corresponding label values are also extracted from the label matrix. For each pattern in the pattern matrix, the posterior energy function value is calculated using the formula

$$U(x)=\{\sum_{i=1}^{9}([(y_i-\mu)^2/(2*\sigma^2)]+\log(\sigma))+V(x)\}$$

The challenge of finding the MAP estimate of the segmentation is to search for the optimum label which minimizes the posterior energy function U(x). In this section a new effective approach, Enchanced Artificial Bee colony algorithm and Fire Fly Algorithm is proposed for the minimization of MAP estimation.

3 Segmentation Of Mammogram And Mri Image Using Fire Fly Algorithm (FFA)

The Firefly algorithm was developed by Xin-She Yang, on the basis of flashing light behavior of fireflies in nature (Ming-Huwi Horng ; Ting-WeiJiang2010 ; Goutam Das2013).

3.1 Fire Fly Metaheuristic

The fundamental function of the glowing light is to attract mate during mating session, where male firefly uses a brief signal pattern and female firefly respond in certain time interval for the same species. The pattern of flashes is often unique for a particular species of fireflies. A three rule base of firefly was established,

- ✓ All fireflies are unisex, so that one firefly is attracted to other fireflies regardless of their sex.
- ✓ The less bright one will move towards the brighter one. The value of brightness is proportional to brightness, which is reverse proportional to their distances.
- ✓ Brightness of each firefly is determined by evaluating fitness value. If there is no brighter one than a particular firefly, it will move randomly.

The brightness of a firefly is affected or determined by the landscape of the fitness value to be optimized. For a maximization problem, the brightness is simply proportional to the value of the fitness value.

The algorithm itself proposes some initializations that include:

γ- the light absorption coefficient (range 0 to 1)

r: the particular distance from the light source

d: the domain space.

The Figure 2 shows the FFA Algorithms

The general algorithm of firefly:
Define the fitness function of f(x), where $x=(x_1... x_d)$ T
Generate the initial population of fireflies or x_i (i=1, 2,.., n)
Determine the light intensity of Ii at x_i via $f(x_i)$
While (t<MaxGen)
For i = 1 to n (all n fireflies);
For j=1 to n (n fireflies)
if (Ij > Ii), move firefly i towards j;
end if
Attractiveness varies with distance r via Exp [-γr2];
Evaluate new solutions and update light intensity;
End for j;
End for i;
Rank the fireflies and find the current best;
End while;
Postprocess results and visualisation;
End procedure;

Fig: 2 FFA Algorithms

Alpha determines random percentage in firefly moving. It includes value between zeros to one. Absorption coefficient is named gamma. The constraint varies between zeros to extreme. If Coefficient is close to zero, then ß=ß0 and this corresponds to a special case of particle swarm optimization. Besides, if absorption coefficient is close particularly, this is the case where the fireflies fly in a very foggy region randomly. Finally ß0 is maximum Attractiveness value.

Each firefly i can move toward another more attractive (brighter) firefly j by equation

$X_i = x_i + ß0eγr2\ ij\ (X_j - X_i) + α(rand -1/2)$

r is the distance

ß0 is attractiveness

γ is light absorption coefficient

- ✓ Initial population: Total number of image pixels (3*3 window).
- ✓ MaxGen: intensity variation through iteration.
- ✓ If the previous pixel value is greater than of current pixel value after considering the fitness evaluation, which depends upon the global intensity values of the image, it should be replaced.
- ✓ As attractiveness varies with distance, the boundary value of the window size, that is 3x3 in this case, is considered. Any value that crosses the boundary, it was ignored.
- ✓ After each iteration, the global best in consideration in accordance to the window size was updated and the highest intensity value of that iteration was considered for the previous update. The rank of the firefly was updated.

The algorithm constitutes a population-based iterative procedure with numerous agents (perceived as fire flies) concurrently solving a considered optimization problem. Agents communicate with each other via bioluminescent glowing which enables them to explore cost function space more effectively than in standard distributed random search.

Intelligence optimization technique is based on the assumption that solution of an optimization problem can be perceived as agent (fire fly) which glows proportionally to its quality in a considered problem setting. Consequently each brighter fire fly attracts its partners (regardless of their sex), which makes the search space being explored more efficiently. The firefly algorithm has three particular idealized rules which are based on some of the basic flashing characteristics of real fireflies. They are the following:

- ✓ All fireflies are unisex and they will move towards more attractive and brighter ones regardless of their sex.
- ✓ The degree of attractiveness of a firefly is proportional to its brightness. Also the brightness may decrease as the distance from the other fire flies increases due to the fact that the air absorbs light. If there is not a brighter or more attractive fire fly than a particular one it will then move randomly.
- ✓ The brightness or light intensity of a fire fly is determined by the value of the objective function of a given problem.

Mainly uses real random numbers and is based on the global communication among the firefly, hence more effective in multi objective optimization. Now we can idealize some of the flashing characteristics of fireflies so as to develop firefly-inspired algorithms. For simplicity in describing our new Fireflire Algorithm (FA), we now use the following three idealized rules:

- ✓ all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
- ✓ Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly;
- ✓ The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function.

Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms. Based on these three rules, the basic steps of the Fire Fly Algorithm (FFA) can be summarized as the pseudo code shown in Fig. 3.

Objective function f(x), x = (x1, ..., xd)T
Generate initial population of fireflies xi (i = 1, 2, ..., n)
Light intensity Ii at xi is determined by f(xi)
Define light absorption coefficient
while (t <MaxGeneration)
for i = 1 : n all n fireflies
for j = 1 : i all n fireflies
if (Ij > Ii), Move firefly i towards j in d-dimension; end if
Attractiveness varies with distance r via exp[−r]
Evaluate new solutions and update light intensity
end for j;end for i
Rank the fireflies and find the current best
end while
Postprocess results and visualization

Figure 3: Pseudo code of the Fire Fly Algorithm

3.2 Attractiveness

In the firefly algorithm, there are two important issues: the variation of light intensity and formulation of the attractiveness. Assume that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function. In the simplest case for maximum optimization problems, the brightness If a firefly at a particular location x can be chosen as I(x) / f(x).

However, the attractiveness is relative, it should be seen in the eyes of the beholder or judged by the other fireflies. Thus, it will vary with the distance rij between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption.

In the simplest form, the light intensity I(r) varies according to the inverse square law I(r) = Is/r2 where Is is the intensity at the source. For a given medium with a fixed light absorption coefficient , the light intensity I varies with the distance r. That is I = I0e−r, where I0 is the original light intensity. In order to avoid the singularity at r = 0 in the expression Is/r2, the combined effect of both tinverse square law and absorption can be approximated using the Gaussian form.

3.3 Distance and Movement
Euclidean distance

In the Euclidean plane, if **p** = (p_1, p_2) and **q** = (q_1, q_2) then the distance is given by

$$\mathrm{d}(\mathbf{p},\mathbf{q}) = \sqrt{(p_1-q_1)^2+(p_2-q_2)^2}.$$

This is equivalent to the Pythagorean theorem.

Alternatively, it follows from (*2*) that if the polar coordinates of the point **p** are (r_1, θ_1) and those of **q** are (r_2, θ_2), then the distance between the points is

$$\sqrt{r_1^2+r_2^2-2r_1r_2\cos(\theta_1-\theta_2)}.$$

The distance between any two fireflies i and j at xi and xj, respectively, is the

Cartesian distance

rij = ||xi − xj || = vuutdX

k=1 (xi, k − xj, k)^2, where xi,k is the kth component of the spatial coordinate xi of ith firefly. In2-D image, we have rij = q(xi − xj)^2 + (yi − yj)^2.

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined byxi = xi + 0e−r2: ij (xj − xi) + _ (rand −12), where the second term is due to the attraction while the third term is random-ization with being the randomization parameter. rand is a random number generator uniformly distributed in [0, 1].

3.4 Extacting Suspicious Region from Image Using Fire Fly Algorithm

Fire Fly Algorithm is applied to find the optimum label from the pattern matrix. Initially, the dissimilar patterns, the corresponding labels and the MAP values are stored in a solution matrix and the parameters such as number of iterations (NI), number of firefly (NF), γ- the light absorption coefficient r: the particular distance from the light source d: the domain space are assigned the values of 1, 10 and 0.001 respectively. Also the solution matrix contains separate columns for absorption, distance and flag values of each firefly.

The flag value is used to indicate whether the kernel has been selected previously or not. Initially all the flag values are set to zero and the absorption, distance values are assigned d0. At the initial step, all the fireflies are assigned random kernels and the pheromone values are updated. The posterior energy function value for all the selected kernels from each firefly is extracted from the solution matrix. Compare the posterior energy function value for all the selected kernels from each firefly, to select the minimum value from the set, which is known as ‘Local Minimum’ (Lmin) or ‘Iterations best’ solution. This local minimum value is again compared with the ‘Global Minimum’ (Gmin). If the local minimum is less than the global minimum, then the local minimum is assigned with the current global minimum. Then the kernel that generates this local minimum value is selected and its brightness is updated.

The brightness value for the remaining kernels is updated. Thus the brightness and distance values are updated globally. This procedure is repeated for all the image pixels. At the final iteration, the Gmin has the optimum label of the image. The corresponding kernel is selected from the pattern matrix. The intensity value of the center pixel in the kernel is selected as optimum threshold value for segmentation. In the MRI image, the pixels having lower intensity values than the threshold value are changed to zero. The entire procedure is repeated for any number of times to obtain the more approximated value.

3.5 Fire Fly Algorithm (FFA) With FCM

After completing all the process by Fire Fly Algorithm the generated output is given to the FCM as input. The optimal value of FFA through mammogram or MRI Brain Image is given as an input for FCM. The aim of FCM is to find cluster centers (centroids) that minimize dissimilarity function.

The membership matrix (U) is randomly initialized as

$$\sum_{i=1}^{c} U_{ij} = 1;$$

where i is the number of cluster

j is the image data point

The dissimilarity function can be calculated with this equation

$$C_i = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} U_{ij}{}^{n} d_{ij}{}^{2}$$

where U_{ij} is between 0 and 1

C_i is the centroid of cluster i

d_{ij} is the Euclidean distance between i_{th} and centriod (C_i) and j_{th} data point

M is a weighiting exponent.

To calculate Euclidean distance (d_{ij})
Euclidean distance (d_{ij}) = Cluster center pixels - current neuron

$D_{ij} = CC_p - C_n$

where CCp is the Cluster center pixels

C_n is the current neuron

i.e. Number of clusters is computed as

C = (N/2)1/2

N= no. of pixels in image

To find the Minimum dissimilarity function can be computed as

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}}$$

where $d_{ij}=\| x_i - c_j\|$ and $d_{kj}=\| x_i - c_k\|$

x_i is the i_{th} of d- dimensional data

c_j is the d-dimensional center of the cluster

||**|| is the similarity between any measured data and center

so these iteration will stop when the condition

$\text{Max}_{ij} \{ | U_{ij}^{(k+1)} - U_{ij}^{k} | \} < €$ is satisfied

where € is a termination criterion between 0 and 1

K is the iteration step

The step of the FCM Algorithm has been listed

Step 1: Initialise $U = U_{ij}$ matrix

Step 2: At K step initialize centre vector $C^{(k)} = C_j$ taken from FF Algorithm

Step 3: Update $U^{(k)}$, $U^{(k+1)}$, then compute the dissimilarity function

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}}$$

If $\| U^{(k+1)} - U^{(k)} \| < €$ then stop. Otherwise return to step3.

In the first step, the algorithm selects the initial cluster from FFA Algorithm. Then, in later step after several iteration of the algorithm, the final result converges to actual cluster of FFA with FCM. The Maximum Adaptive threshold is used to compare the current neuron value,If the current value is less than the Adaptive Thresholds neglects the region set to black and the suspicious region is look like bright. The aim of FFA with FCM is to detect the suspicious region from the background region in the mammogram or MRI brain Image.

Input: mammogram or MRI Brain Image

Output: Segmented Image contains only Tumor (suspicious reign)

Step 1. Read the brain image or the stored in a two dimensional matrix

Step 2. Divide the image to 3x3 sub image (cells)

Step 3. For each label in the image, calculate the posterior energy U (x) value

$U(x) = \{\Sigma[(y-\mu)^2/(2*\sigma^2)]+\Sigma \log(\sigma)+\Sigma V(x)\}$

where

y = intensity value of Pixels in the kernel,

μ = mean value of the kernel,

σ = standard deviation of the kernel,

V = potential function of the kernel, and

x = center Pixel of the label. If x1 is equal to x2 in a kernel, then

V(x) = β, otherwise 0, where β is visibility relative parameter (β≥0)

Step 4. The posterior energy values of all the labels are stored in a separate matrix

Step 5. *FFA* is used to minimize the posterior energy function.

The procedure is as follows:

Step 6. Initialize the values of number of iterations (N), number of fireflies (K),

Step 7. Create a solution matrix (S) to store the labels of all the Pixels, posterior energy values of all the Pixels, initial brightness values for all the fireflies at each pixels , and a flag column to mention whether the pixels is selected by the firefly or not

Step 8. Store the labels and the energy function values in S

Step 9. Initialize the light obsorbtion coefficient and distance values,

Step 10. Initialize all the flag values for the entire firefly with 0, it means that pixels is not selected yet, if it is set to 1 means selected

Step 11. Select a random pixel for each Ant, which is not selected previously

Step 12. Update the pheromone values for the selected pixels by all the firefly

Step 13. Select the minimum value from the set, assign as local minimum (Lmin)

Step 14. Compare this local minimum (Lmin) with the global minimum (Gmin),

if Lmin is less than Gmin, assign Gmin=Lmin

Step 15. Select the Ant, whose solution is equal to local minimum, to update its Brightness and distance globally

Step 16. Perform the steps (13) to (15) till all the Image Pixels have been selected

Step 17. Perform the steps (7) to (16) for M times

Step 18. The Gmin has the optimum label which minimizes the posterior energy function

Step 19. Gmin (Global optimal value) has the optimum is taken from center (3x3) value of optimal label

Step 20. Give a center cluster value is a Gmin

In the image, the pixels having lower intensity values than the threshold value are changed to zero. The entire procedure is repeated for any number of times to obtain the more approximated value.

Step 1: The optimal value FFA is used to select the initial cluster point.

FFA-FCM Algorithm is the following:

Step 2: Calculate the cluster centers.

C = (N/2)1/2

Step 3: Compute the Euclidean distances

$D_{ij} = CC_p - Cn$

Step 4: Update the partition matrix

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}}$$

(Repeat the step 4)

Until Max[│U_{ij}(k+1)-U_{ij}k│] <€ is satisfied

Step 5: Calculate the average clustering points.

$$C_i = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} U_{ij}{}^{n} d_{ij}{}^{2}$$

Step 6: Compute the adaptive threshold

Adaptive threshold =max (Adaptive threshold, c_i) i=1...n

In the MRI image, the pixels having lower intensity values than the adaptive threshold value are changed to zero. The entire procedure is repeated for any number of times to obtain the more approximated value.

Fig: 5 Algorithm of FFA with FCM

In the mammogram and MRI image segmentation process, a swarm intelligence method, viz., FFA and EABC is used to segment the tumour from the mammogram and MRI image. The figure 4.6 shows the segmented Mammogram image using FF Optimization algorithm. The figure 4.7 shows the segmented MRI image using FF Optimization algorithm.

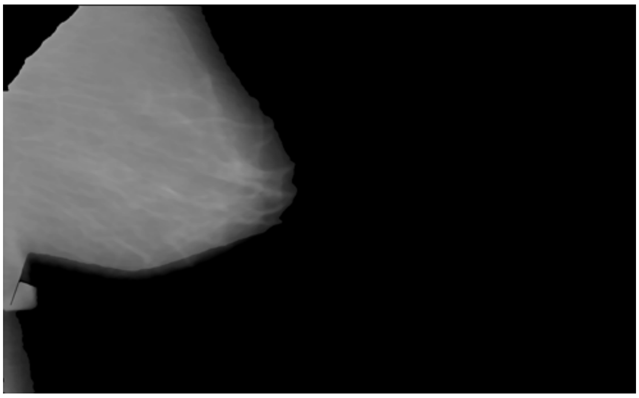

Figure: 6 segmented mammogram Image using the FF Algorithm

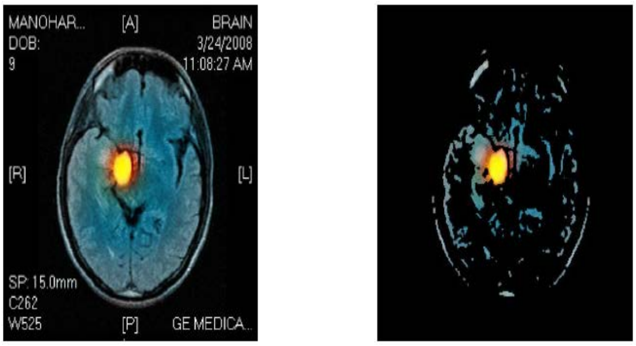

Figure: 7 Segmented MRI Image using the FF Algorithm

4 SEGMENTATION OF MAMMOGRAM AND MRI IMAGE USING HYBRID MRF- ENCHANCED ARTIFICIAL BEE COLONY

Image segmentation has been approached from a wide variety of perspectives such as region-based approach, morphological operation, multi-scale analysis and fuzzy approaches and stochastic approaches are discussed earlier. In this section, MRF hybrid with Enchanced Artificial Bee Colony (EABC) is implemented for mammogram and MRI image segmentation.

4.1 Enchanced Artificial Bee Colony

Enchanced Artificial Bee Colony (EABC) algorithm is a new swarm intelligence method which simulates intelligent foraging behavior of honey bees. Artificial Bee Colony (ABC) system is a novel optimization algorithm inspired of the natural behavior of honey bees in their search process for the best food sources, which proposed by Karaboga and Basturk in 2006. ABC consists of three groups of bees: **employed, onlooker and scout bees** (Karaboga, D, Basturk, .B. 2006, 2007)

Firstly, half of the colony consists of the employed bees and the second half consist of onlookers. Employed bees go to the food sources, and then they share the nectar and the position information of the food sources with the onlooker bees which are waiting on the dance area determine to choose a food source. The employed bee whose food source has been abandoned by the bees becomes a scout bee that carries out random search in the simulating model. The goal of bees in the EABC model is to find the best solution, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. These three groups are applied to successive string populations to create new string populations. Employed bees carry with them information about their food sources, its distance and direction from the nest, and the nectar amount of the source; scout bees are searching the environment surrounding the nest for finding new food sources; and onlooker bees waiting in the hive and finding a food source through the information shared by employed bees.

In mammogram and MRI Image segmentation, the Production Mechanism is a process that selects the members from the population for employed bee operation. The intensity values are considered population strings for

ABC. The corresponding Values are extracted from gray level mammogram and MRI image using spatial coordinate points and the $1/1+x_i$ intensity values are considered as the nectar value or fitness value.

After identifying the initial population and the nectar value, the employed bee and onlooker bee can be applied to generate the new population. Employed bee operation produces a new string for onlooker bee operation. Stochastic selection process is implemented as linear search through roulette wheel with slots weighted in proportion to kernel fitness values. In this function, a random number multiplies the sum of the population fitness called as the stopping point.

The partial sum of the fitness value is accumulated in a real variable until it is greater than or equal to the stopping point. The location where the iteration stops is noted and the corresponding value is selected for onlooker bee operation. Next, the onlooker bee operation, flipping bits at random carries it out, with some small probability values. When onlooker bee sharing the valuable information. The Fig 8 shows sharing the

G1	0	1	0	1	0	1	0	0
G2	1	0	1	0	1	0	1	0
G1	1	1	1	1	1	1	1	0
G1	1	1	1	1	1	1	1	0

Fig 8: Sharing the Information

After sharing the information, the values are considered a new population. This Scout bee procedure is performed until the size of the new population is equal to the initial population. Then the old population is assigned the new population value and the same procedure is performed again to generate the next population. Finally, the scout bee gives optimal threshold value from latest population. The Figure 4.9 shows Algorithm for Segmentation using MRF-Enhanced Artificial Bee Colony algorithm.

4.2 Algorithm: Segmentation using Enchanced Artificial Bee Colony

O_{ij} ← Original Image;
X_{ij} ← segmented image;
[m n] ← size of O_{ij}
for each pixel in O_{ij}
G_i← Population ←intensity of the Original pixel from O_{ij}, converted to binary string, i ←1 to n
F← Nectar (or)fitness value; computed by MAP
Pop1 ← initial population contains G
End
(Employed bee Operation- production mechanism)
p ← 1
repeat for N times (N=300)
for each string in Population1
g1, g2 ← select two strings for stochastic selection process.
(Onlooker bee Operation)
For the selection of two strings roulette wheel is implemented as follows:r = random() * sum_of_Nectar or fitness
[Hint: random() function returns a random number between 0 and 1]
(i) Fsum = 0, i=0, m → size of the population
(ii) F → contains the population strings
(iii) Fsum = Fsum +F(i) → nectar value 0 to 1
(iv) i = i + 1
(v) if ((i <= m) and (Fsum < r)) Goto Step: (iv)
(vi) return i
g3, g4 ←sharing the valuable information.
Pop2(p) ← g3;
p ← p+1; Pop2(p) ←g4;
end
(Scout bee Operation)
min ← Min(Pop2); Pop1 ← Pop2;
pos ← where the X(i,j) = min;
end

Fig 9: Algorithm for Segmentation using MRF-Enchanced Artificial Bee Colony algorithm.

The Figure: 10 shows the Algorithm of EABC with FCM

Step 1: The optimal value EABC is used to select the initial cluster point.
EABC -FCM Algorithm is the following:
Step 2: Calculate the cluster centers.
C = (N/2)1/2

Step 3: Compute the Euclidean distances
$D_{ij} = CC_p - Cn$
Step 4: Update the partition matrix

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$$

(Repeat the step 4)
Until Max[$|U_{ij}(k+1)-U_{ij}k|$] <€ is satisfied
Step 5: Calculate the average clustering points.

$$C_i = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} U_{ij}{}^{n} d_{ij}{}^{2}$$

Step 6: Compute the adaptive threshold

Fig: 10 Algorithm of EABC with FCM

In the mammogram and MRI image segmentation process, a pioneering method, viz., Markov Random Field hybrid with Artificial Bee Colony Optimization algorithm is used to segment the micro-calcifications from the mammogram and MRI image. Figure 4.11 shows the segmented image using the EABC algorithm

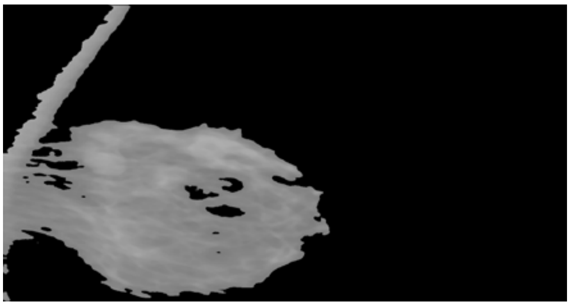

Figure: 11 segmented mammogram image using the EABC algorithm

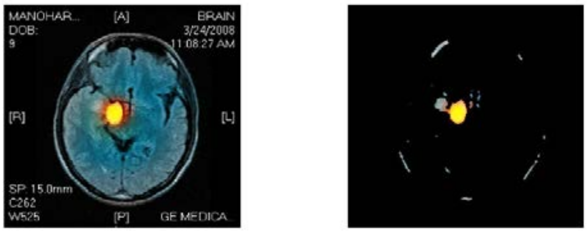

Figure:12 segmented MRI image using the EABC algorithm

5 EXPERIMENTS AND RESULTS

The effectiveness of the proposed technique is determined by extracting the suspicious region from the mammogram and MRI image using FFA and EABC. The true positive detection rate and the number of false positive detection rate at various thresholds of the segmented images are used to measure the algorithm's performance. These rates are represented using Receiver Operating Characteristic curves.

True Positive (TP) and False Positive (FP) rates are calculated at ten different thresholds selected on the segmented image to generate the ROC curve. Previous methods are taken an overlap region of only 40% as true positive. However, in the proposed method, the true positive is considered only at 80% of overlap. All other regions extracted by the algorithm are labeled false positives. Figure 13 shows the ROC curves generated on the full test set, using 10 operating points from FFA and EABC segmentation. If the threshold value is low true detections may become merged with false positive regions.

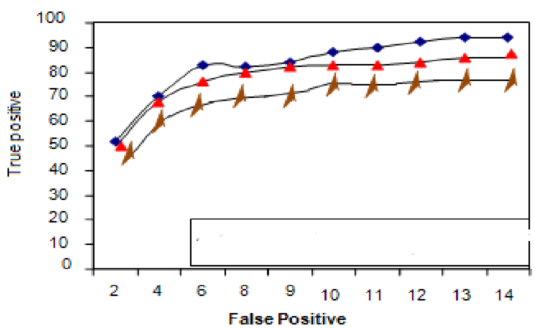

Fig 13: Combined results on all 161 normal and abnormal MIAS image pairs using FUZZY, FFAand

Classification Ratio*:* The area under the ROC curve (Az value) is an importFFA criterion for evaluating diagnostic performance. The ROC curve is in the range between zero and one. The value of Az is 1.0 when the diagnostic detection has perfect performance, which means that TP rate is 100% and FP rate is 0%. The Az value for the proposed algorithm is 0.99. Table 1 shows the comparison of detection rate between the previous works and the proposed method**.**

Table 1 Performance analysis

Sl. No	Author	Method	Result The tumor detection rate (Az value)
1	S. Murugavalli and V. Rajamani 2007	FUZZY	93.21
2	T. Logeswari and M.Karnan2010	HSOM	93.21
3	The Proposed approach	EABC	96.00
		FFA	99.13

6. CONCLUSION

The three different methods such as FFA and ABC segmentation techniques for mammogram and MRI image segmentation have been implemented. The suspicious region was extracted from the mammogram and MRI image based on the combination of Markov Random Field with FFA and Enhanced Artificial Bee Colony Optimization. In MRF the image pixels are labeled and their posterior function values were computed. FFA and EABC were used to find the optimum label that minimizes the Maximizing a Posterior estimate to segment the image. To evaluate the performance of the segmentation algorithms the ROC curve was generated. The experimental results show that the FFA with fuzzy produces 0.99 and the EABC with fuzzy method produces 0.96 as Az value. It was observed that the metaheuristic FFA hybrid with MRF performed well.

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