

Performance Analysis of Feature Extraction and Selection of Region of Interest by Segmentation in Mammogram Images between the Existing Meta-heuristic Algorithms and Monkey Search Optimization (MSO)

S.KANIMOZHI SUGUNA¹, DR.S.UMA MAHESWARI²

¹.Teaching Assistant, Department of Computer Applications,
Anna University Regional Centre – Coimbatore, Coimbatore -641 047
TAMIL NADU, INDIA

+91 9941968423, kani_suguna@yahoo.com

². Associate Professor, Department of Electronics and Communications Engineering,
Coimbatore Institute of Technology, Coimbatore – 641 014
TAMIL NADU, INDIA

+91 9944756014,umamaheswari@cit.edu.in

Abstract: In medical image processing, feature selection and extraction is an important task for performing image classification and recognition which is performed through the image segmentation process. This paper proposes a different approach; Monkey Search Optimization (MSO) which is based on Metaheuristic Algorithm is presented for selecting region of interest in mammogram image. Monkey Search Optimization (MSO) algorithm is considered as a new algorithm searching for optimum solution based on the foraging behavior of monkeys. Pectoral region removed image is given as input for feature extraction. The proposed algorithm can be implemented for various applications as the time consumption for the process is reduced greatly. In this paper the proposed algorithm is compared with few other meta-heuristics algorithms such as Ant Colony Optimization (ACO), Artificial Bee Colony Optimization (ABC) and Particle Swarm Optimization (PSO); from the results that the proposed approach can be considered to be an appropriate algorithm for image segmentation. Results are presented based on simulation made with the implementation in MATLAB which is tested on the images of MIAS database.

Key-Words: MSO, ACO, ABC, PSO, Climb, Watch – Jump and Co-operation.

1 Introduction

Breast Cancer is where cancerous (Malignant) cells are found in the breast tissue. Radiograph of the breast tissue is called mammogram. Getting a mammogram is an effective way to detect breast cancer in its early stages. Breast Cancer is the second leading cancer next to Cervical Cancer.

Breast Cancer is most common in women than men worldwide. The early symptoms of breast cancer is often not recognized or perceived by the patient. The only way to avoid breast cancer in women is early detection either through self – examination or approaching the doctor.

X-ray mammography is the most common investigation technique used by radiologists in

the screening, and diagnosis of breast cancer they could help the radiologists in the interpretation of the mammograms and could be useful for an accurate diagnosis. To perform a semi-automated tracking of the breast cancer, it is necessary to detect the presence or absence of lesions from the mammograms.

1.1 Related Works

The preprocessing technique is also known as background suppression. Before getting into the presence or absence of lesions preprocessing is done to remove the pectoral region, as it is not in need of the whole image [5]. In most conditions any of the filter is used as in [8, 9]. Next to the preprocessing is selecting the Region of Interest or Feature Extraction and Feature Selection

through segmentation process. It focuses on the relevant feature extraction and possible removal of irrelevant features [6]. The advantage of doing feature extraction is to compress the input space for classification which reduces the overhead of the classifier.

1.2 Overview of Metaheuristic Algorithms

This paper explains a new algorithm called Monkey Search Optimization for extracting the feature in mammogram image. This MSO is a Nature-Inspired Evolutionary Algorithm. Rest of the paper is organized as follow. Overview of the problem is explained in Section 2. Basic of the Monkey Search Optimization is focused in Section 3. Monkey Search Optimization for the problem (selecting the region of interest) is presented in Section 4. Experimental Results are performed in Section 5. Conclusion is drawn in Section 6.

2 Overview of the Problem

In this paper we focus on the selection of region of interest also known as feature extraction in image processing is the last stage in preprocessing of mammogram images [2]. Feature extraction refers to the presence of the parts of an object within the image in terms of appearance, structure and arrangement. The region which contains label and other detail regarding the mammogram image in X-ray image of the breast is the pectoral muscle region. Preprocessing technique involves background removal, noise removal and enhancing the image. The preprocessed and pectoral region removed image is given as input to the process of feature extraction.

In [1] comparison is made based on the behaviors of three different monkey species such as Howler, Spider, and Squirrel Monkeys. The behaviors of monkeys differ from each other based on the food type, movement, searching for food, resting, watching, and doing other activities. Types of food are leaf, fruits, and insects. Howler monkey depends on leaves, Spider monkey focuses on leaves and fruits, whereas Squirrel monkeys have both fruits and insects. Mammogram image is considered as forest. Forest will have both edible and non-

edible foods. This paper presumes the region of interest part as the edible food for monkeys, which is available in abundant. Hence the feature is selected and extracted.

3 Basic of the MSO

MSO focuses on the foraging behavior of monkey. Monkeys go in search of foods available in the branches of the trees. Each branch is considered as feasible solution. Selection of the branch is based on the probability mechanism. The process of MSO is organized in three processes such as climb, watch-jump and somersault processes. Climb process is further classified as climb up and climb down along with either long or short step climb process [3, 4, 5, 10, 11].

3.1 Climb Process

Let assume the concept by having the decision variable vector $R_i = (r_1, r_2, r_3, \dots, r_n)^T$ and the objective function for minimization as $f(R)$. $\Delta R = (\Delta r_1, \Delta r_2, \Delta r_3, \dots, \Delta r_n)^T$ is a randomly generated vector. The pseudo-gradient of function $f(R)$ at the point R can be expressed as $(f'_1(R), f'_2(R), \dots, f'_n(R))^T$, where

$$f'_j(R) = \frac{f(R+\Delta R) - f(R-\Delta R)}{2\Delta r_j} \quad j \in \{1, 2, \dots, n\} \quad (1)$$

As the generations of ΔR are repeated, local optimum is found by the decrease in the objective function $f(R)$ based on the sign caused as a result of slow replacement of R with $R + \Delta R$ or $R - \Delta R$.

3.2 Watch-Jump Process

This process is made once the monkey reaches the tip of the tree. Since the monkey has to move on to find availability of any other feasible solution in the forest. Besides searching for food the monkey has to be aware of the presence of enemies. If there is any feasible solution, then it is replaced with the current solution [3, 4, 5, 10, 11].

3.3 Cooperation Process

This process focuses on the cooperation among monkeys. Hence the monkeys at better solution will communicate with monkeys at poor solution and make them to climb to the better of the area [10].

3.4 Somersault Process

In this phase monkeys will move from one position to another position to find the availability of new solution [10] in the given forest area. Figure 1 depicts the MSO for feature extraction in mammogram image.

4 Implementation of MSO to the Problem

Given the details of the image, removal of pectoral muscle region in the mammogram image problem can be defined as:

Energy of Monkeys is represented as

$$\|RE\|_2 = \sqrt{\int_{-\infty}^{\infty} f(r)e^{-ihw} dr} \quad (2)$$

$$\text{Where } f(r) = (hw)_{ij} \quad (3)$$

Where hw is the energy required by each monkey for moving from one place to another.

Total energy is calculated based on

$$T(r) = \|RE\|_2 (hw)_{ij} = \|RE\|_2 \sum_{i=1, j=1}^M (hw)_{ij} \quad (4)$$

With the following conditions:

$$RI_m RI_v = RI_a - RI_d \quad (5)$$

$$-RI_l^M \leq RI_l \leq RI_l^M, l \in L \cup L' \quad (6)$$

$$0 \leq r_j \leq r_j^M, j \in \{1, 2, \dots, n\} \quad (7)$$

Solution Representation:

The solution for the problem is represented in the following equation.

$$R_i = (r_{i,1}, r_{i,2}, r_{i,3}, \dots, r_{i,n})^T$$

Objective function:

The objective function is modified as follows:

$$\min f(r) = \left\{ \begin{array}{l} RE \sum_{i=1, j=1}^M (hw)_{ij} + \\ G_0 \sum_{l \in L \cup L'} \max\{0, |RI_l| - RI_l^M\} \\ G_l \end{array} \right.$$

Generate initial population for M monkeys
 $r_i = (r_1, r_2, r_3, \dots, r_n)^T$

While (t < MaxGeneration) or (segmentation completed).

Where RI_m , image matrix,

RI_v , pixel value,

RE , total energy,

RI_a , active pixels in the image,

G_0 , gravitational force when monkey jumps from one tree to another,

G_l , penalty if monkey is unreachable,

RI_l^M , maximum of how many pixels affected in the image,

RI_l , original image,

r_j , number of monkeys in correct position,

r_j^M , maximum number of monkeys,

L , set of existing path for movement, and

L' , set of new path for movement.

4.1 Climb Process

Initialize random position for M monkeys as $R_i = (r_{i,1}, r_{i,2}, r_{i,3}, \dots, r_{i,n})^T$ evaluate its current position to reach the border for which select either of large-step or small-step climb process:

- (a) The large-step climb process: Generate
 - (i) $\Delta R_i = (\Delta r_{i,1}, \Delta r_{i,2}, \Delta r_{i,3}, \dots, \Delta r_{i,n})^T$

Interval $[-r_L, r_L]$ where r_L is the length of large-step climb process.

- (ii) Calculate $f(R_i + \Delta R_i), f(R_i - \Delta R_i)$
- (iii) If $f(R_i + \Delta R_i) < f(R_i - \Delta R_i)$ and $f(R_i + \Delta R_i) < f(R_i)$

Then $R_i = R_i + \Delta R_i$

Else if $f(R_i + \Delta R_i) < f(R_i - \Delta R_i)$ and $f(R_i - \Delta R_i) < f(R_i)$

Then $R_i = R_i - \Delta R_i$

- (iv) Repeat (i) to (iii) of large-step climb until $N_{C,L}$ has been reached.

(b) The small-step climb process: Generate

- (i) $\Delta R_i = (0, \dots, 0, \Delta r_{i,j}, 0, \dots, 0)^T$

where $j \in \{1, 2, \dots, n\}$ and $\Delta r_{i,j}$ is a non-zero integer with an interval of $[-r_s, r_s]$ where r_s is the length of small-step climb process.

- (ii) and (iii) steps for small-step climb process is similar to the (ii) and (iii) steps in large-step climb process.

- (iv) Repeat (i) to (iii) of small-step climb process until $N_{C,S}$ has been reached.

4.2 Watch-Jump Process

Check whether there is higher position when compared to current position based on the eyesight b .

- (i) If higher position is available, Then generate an integer $r'_{i,j}$ for an interval of $[r_{i,j} - b, r_{i,j} + b]$ randomly, where $j \in \{1, 2, \dots, n\}$.

Let $R'_i = (r'_{i,1}, r'_{i,2}, \dots, r'_{i,n})^T$.

- (ii) If $f(R'_i) < f(R_i)$, let $R_i = R'_i$.
- (iii) Repeat (i) to (ii) until maximum allowable number N_w has been reached.

4.3 Co-operation Process

Assume optimal solution in one iteration as $R^* = (r_1^*, r_2^*, \dots, r_n^*)^T$.

Initial position is $R_i = (r_{i,1}, r_{i,2}, r_{i,3}, \dots, r_{i,n})^T$.

- (i) Generate real number β in $[0, 1]$ randomly.

- (ii) Calculate $r'''_{i,j} = \text{round}(\beta r_j^* + (1 - \beta)r_{i,j}), j \in \{1, 2, \dots, n\}$.

Let $R_i = (r_{i,1}, r_{i,2}, \dots, r_{i,n})^T$.

- (iii) Set $R_i = R'''_i$ and repeat the climb process.

4.4 Somersault Process

- (i) Generate the real number α in $[c, d]$.

- (ii) Calculate $u_j = \frac{1}{M} \sum_{i=1}^M r_{i,j}, j \in \{1, 2, \dots, n\}$, where $\tilde{U} = (u_1, u_2, \dots, u_n)^T$ as pivot of Somersault process.

- (iii) For $\forall i \in \{1, 2, \dots, M\}, \forall j \in \{1, 2, \dots, n\}$, Calculate $r'''_{i,j} = r_{i,j} + \text{round}(|u_j - r_{i,j}|)$ Let $R'''_i = (r'''_{i,1}, r'''_{i,2}, \dots, r'''_{i,n})^T$.

- (iv) Set $R_i = R'''_i$ and repeat climb process.

If $r'''_{i,j}$ is new position $>$ upper limit r_j^M ,

Then

$$r'''_{i,j} = r_j^M$$

Else if $r'''_{i,j} < 0$

Then

$$r'''_{i,j} = 0$$

4.5 Stochastic Perturbation Mechanism

When $r_{i,j}$ is same for all monkeys,

Then,

$u_j = r_{i,j}$ and hence $r'''_{i,j} = r_{i,j}$ for monkey $k, k \in \{1, 2, \dots, M\}$,

Let $r_{k,j} = e$, where e is a uniformly distributed integer from is $[0, r_i^M]$

5 Experimental Results

MSO algorithm is carried out for MIAS database of 322 images for removing the pectoral muscle

region in the mammogram image. Figures 3 and 4 represents the pectoral region removed image and the Region of Interest segmented image by the algorithms respectively. Table 1, 2, 3, 4, 5 and 6 focuses on the details regarding the image dataset. The graphical figures made for the Tables 1, 2, 3 and 4 shows the variations in the values of the datasets based on the algorithms: MSO, PSO, ACO and ABC.

Among the sample image datasets shown in tables and graphs, region of interest for all the abnormal images are identified only by MSO algorithms, whereas the other algorithms has failed to identify it. As the algorithms are unable to identify the region of interest, the values of

mean and entropy are zero, whereas Skewness and Kurtosis has resulted in NaN, besides having the higher CPU Time. For the image mdb241, MSO was unable to obtain the values for the parameter Skewness and Kurtosis besides segmenting the image as abnormal. Table 5 focuses on the time taken by CPU for Feature Selection, Extraction and Segmentation of the image. For all the images it is observed that MSO takes less time when compared to other algorithms. The graphical representation of Table 5 is represented in Fig 7. As the algorithms PSO, ACO and ABC has not identified the region of interest, there is no pixels to be displayed, hence the values are represented as 0 (Table 6).

6 Conclusion and Future Enhancement

In this paper, a novel approach for extracting region of interest in mammogram image is proposed with Monkey Search Algorithm. The segmented image is given as input for classification. From the results it is observed that besides the segmented region is similar in all the techniques, the proposed MSO covers larger area of the image that are likely to contain masses, which is comparatively higher than the algorithms of PSO, ACO and ABC. In 95.6% of the cases, the region segmented by the Monkey Search Optimization (MSO), contains the actual mass which is 1% higher than the other algorithms. The main conclusion is that, accuracy rate can be increased if the proposed algorithm is trained more.

7 References

- [1] Amato Katherine R, Onen Dunya, Emel Sarah L, and Christina H, Comparison of Foraging Behavior Between Howler Monkeys, Spider Monkeys, and Squirrel Monkeys, *Ecology*, 2007; 28-31.
- [2] Moussa H.Abdallah, Ayman A.AbuBaker, Rami S.Qahwaji, and Mohammed H. Saleh, Efficient Technique to Detect the Region of Interests in Mammogram Images, *Journal of Computer Science*, Vol. 4, No.8, 2008, pp. 652-662.
- [3] Mucherino Antonio, and Seref Onur, Monkey Search: a novel metaheuristic search for global optimization.
- [4] Mucherino.A, Seref.O, and Pardalos.P.M, Simulating Protein Conformations through Global Optimization, *Optimization and Control (math.OC)* 2013, arXiv:0811.3094 [math.OC].
- [5] Ramirez – Villegas Juan F., Lam-Espinosa Eric, and Ramirez-Moreno David.F, Microcalcification Detection in Mammograms Using Difference of Gaussians Filters and a Hybrid Feedforward – Kohonen Neural Network, *SIBGRAPI'09 Proceedings of the 2009 XXII Brazilian Symposium on Computer Graphics and Image Processing*, 186-193
- [6] Roselin.R, Thangavel.K, and Velayutham.C, Fuzzy-Rough Feature Selection for Mammogram Classification, *Journal of Electronic Science & Technology*, Vol. 9, No. 2, 2011.pp. 124-132.
- [7] Serra Pablo, Stanton Aaron F., and Kais Sabre. Pivot Method for Global Optimization. *Physical Review E* 1997; 55(1).

- [8] Thangavel.K, Karnan.M, and Pethalakshmi.A, Performance Analysis of RoughReduct Algorithms in Mammogram, *International Journal on Global Vision and Image Processing*, Vol. 5, No.8, 2005, pp. 13-21.
- [9] Vijaya Kumar.S, Naveen Lazarus.M, and Nagaraju.C., A Novel Method for the Detection of Microcalcifications Based on Multi-Scale Morphological Gradient Watershed Segmentation, *International Journal of Engineering Science and Technology*, Vol. 2, No. 7, 2010, pp. 2616-2622.
- [10] Wang Jingran, and Yu Yixin, Discrete Monkey Algorithm and its Application in Transmission Network Expansion Planning, *IEEE Power and Energy Society General Meeting (Conference)*, 2010, pp. 1-5.
- [11] Zhao Ruiqing, and Tang Wansheng, Monkey Algorithm for Global Numerical Optimization, *Journal of Uncertain Systems*, Vol. 2, No. 3, 2008; pp. 165-176.

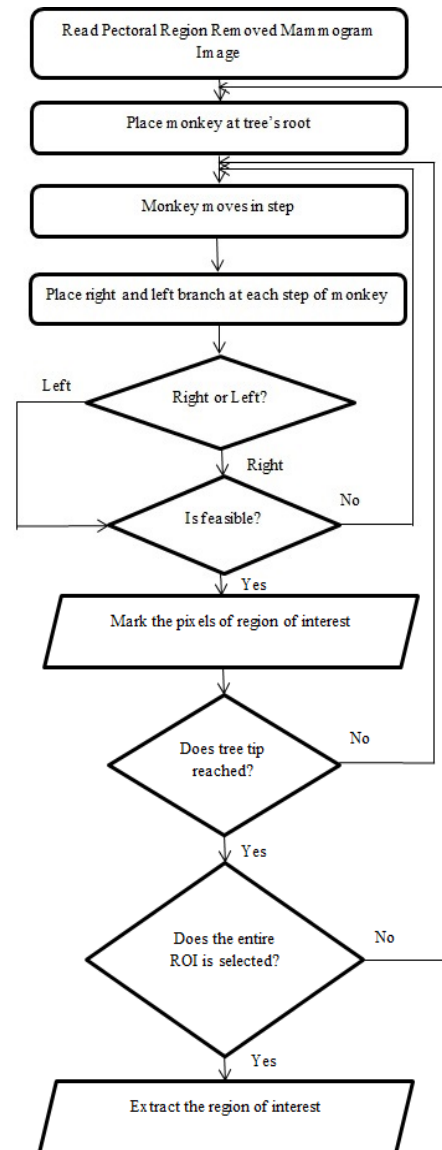


Figure 1: Flowchart for extracting region of interest using MSO

```

1  Set parameters:  $M, R_i, \Delta R_i$ 
2  Randomly generate monkey population  $M$ 
3    for  $i = 1$  to  $M$ 
4      initialize monkey's position at tree's root
5       $R_i = (r_1, r_2, r_3, \dots, r_n)$ 
6      if change in position
7        then  $\Delta R = (\Delta r_1, \Delta r_2, \Delta r_3, \dots, \Delta r_n)$ 
8      end if
9    end for
10   for each monkey  $i$  do  $f(R + \Delta R)$ 
11     generate right and left branches for each step
12     using probability mechanism choose either right or left branch
13     if the distance is small
14       then choose  $\Delta R_i = (0, \dots, 0, \Delta r_{i,j}, 0, \dots, 0)^T$ 
15     else if distance is large
16       then choose  $\Delta R_i = (\Delta r_{i,1}, \Delta r_{i,2}, \Delta r_{i,3}, \dots, \Delta r_{i,n})^T$ 
17     end if
18   end if
19   if the branch has the unwanted pixel
20     mark as feasible solution  $R_i$ 
21   else
22     move next step (repeat from step 1)
23   end if
24   continue the process from step 10 until the monkey reaches the tree tip
25 end for
26 while tree tip is reached by monkey do
27   for each monkey  $i$  do  $f(R - \Delta R)$ 
28     move to next tree
29     repeat the process from step 4
30     if local feasible solution is obtained
31       then cooperate the monkeys,  $R_i''$ 
32     end if
33   end for
34 end while
35 while local optimum is obtained
36   move on to new domain  $u_j$  in search of better solution
37   find  $R_i'''$ 
38   update with monkeys initial position  $R_i$ 
39   move all monkeys to  $R_i'''$ 
40 end while
41 if the entire region of interest is marked
42   then extract the pixels and terminate the process
43 end if

```

Figure 2: Algorithm for MSO

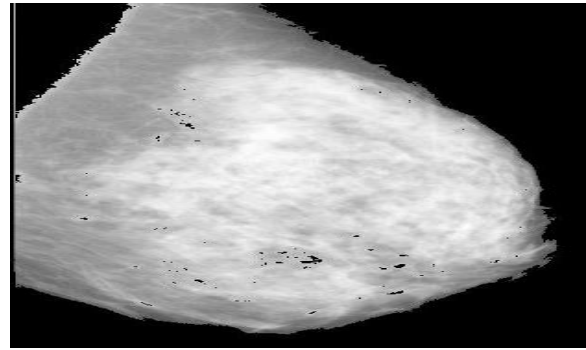


Fig 3: Pectoral Region removed mammogram image mdb240.png

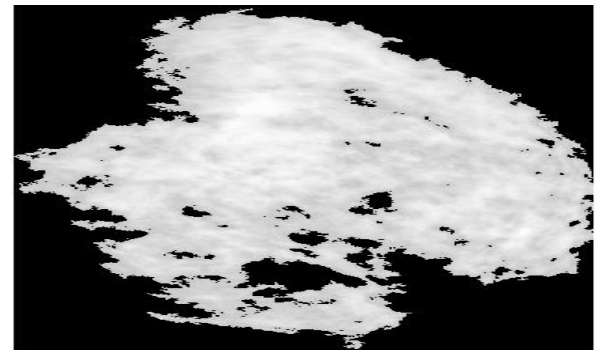


Fig 4: Region of Interest for the mammogram image mdb240.png

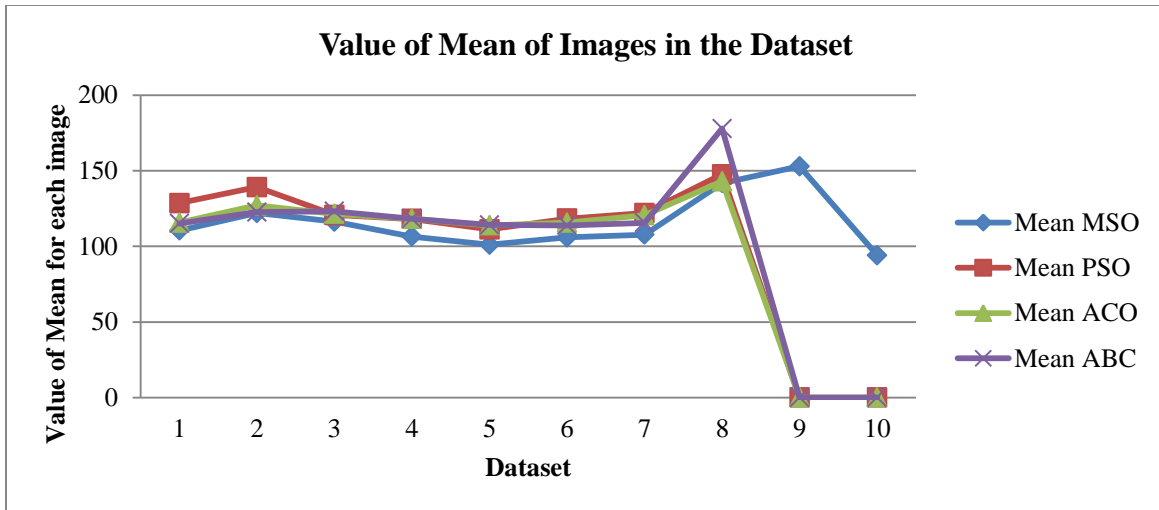


Fig 5: Graph showing variation in Mean for the dataset

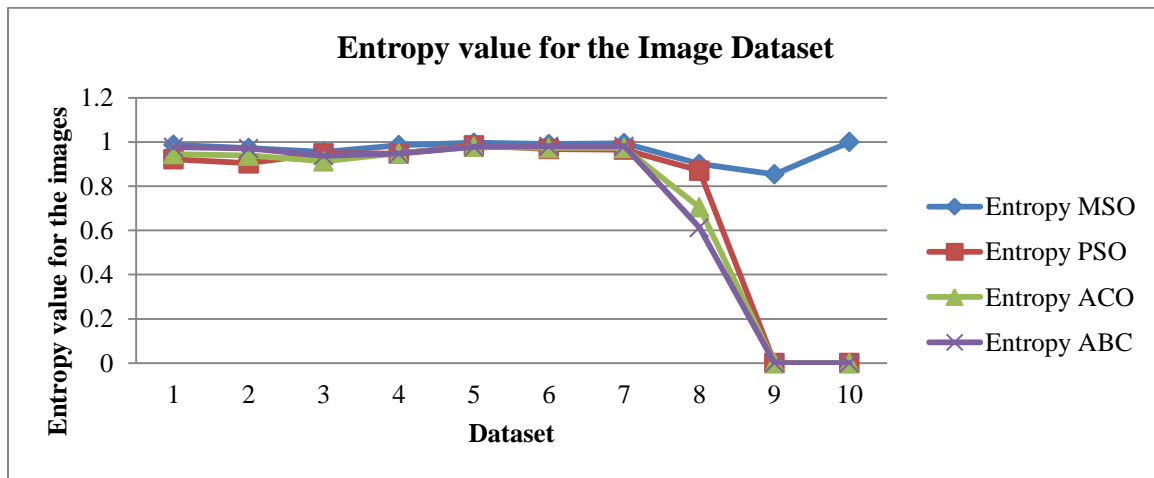


Fig 6: Graph showing variation in Entropy for the dataset

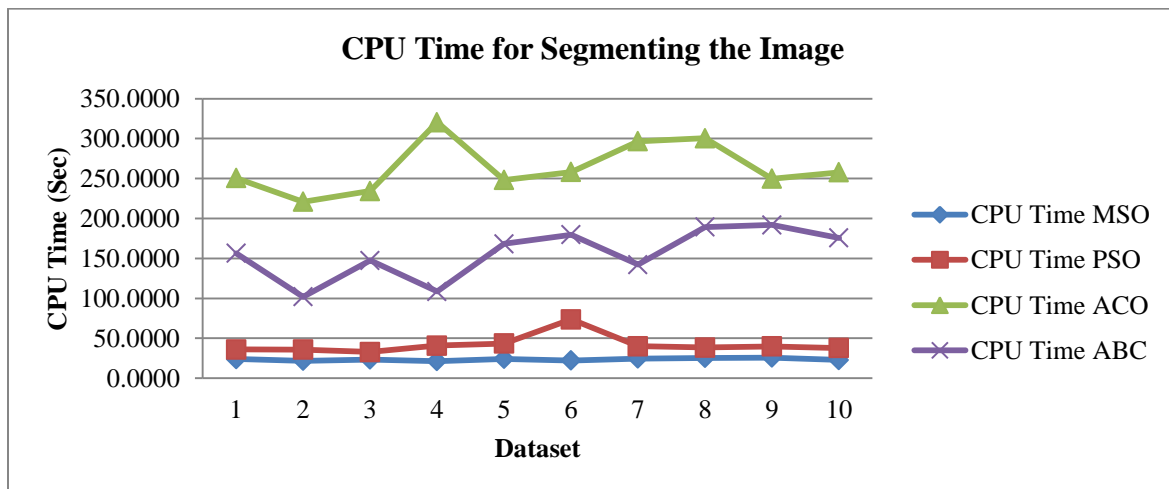


Fig 7: Graph showing variation in CPU Time for Feature Selection, Extraction and segmenting the image dataset

Dataset	Image	MSO	PSO	ACO	ABC
1	mdb001	110.4654	128.617	115.689	115.1622
2	mdb002	121.9908	139.18	127.05	122.7012
3	mdb013	116.3493	120.791	121.439	123.2326
4	mdb023	106.4143	118.149	118.243	118.3571
5	mdb125	101.1022	111.21	113.87	114.1939
6	mdb126	105.9008	118.342	115.682	113.8459
7	mdb212	107.6895	122.043	120.538	115.609
8	mdb239	141.845	147.668	142.923	177.848
9	mdb240	152.86	0	0	0
10	mdb241	94.0688	0	0	0

Table 1: Mean Value of the Feature Extracted and Segmented Image

Dataset	Image	MSO	PSO	ACO	ABC
1	mdb001	0.9873	0.9218	0.9453	0.9764
2	mdb002	0.9726	0.9042	0.9389	0.9706
3	mdb013	0.9552	0.9484	0.9126	0.9377
4	mdb023	0.9856	0.9481	0.949	0.9472
5	mdb125	0.9962	0.9847	0.9786	0.9776
6	mdb126	0.9908	0.9681	0.9735	0.9806
7	mdb212	0.9946	0.9651	0.9731	0.9803
8	mdb239	0.9012	0.8705	0.7051	0.6128
9	mdb240	0.8541	0	0	0
10	mdb241	1	0	0	0

Table 2: Entropy Value of the Feature Extracted and Segmented Image

Dataset	Image	MSO	PSO	ACO	ABC
1	mdb001	-0.104	-1.055	-0.2619	-0.3799
2	mdb002	-1.4001	NaN	NaN	NaN
3	mdb013	-0.4357	-0.6029	NaN	-0.7215
4	mdb023	-0.609	NaN	NaN	-0.6212
5	mdb125	-0.0107	-0.442	-0.5517	-0.5721
6	mdb126	-0.0763	-0.552	-0.6782	NaN
7	mdb212	0.4283	NaN	NaN	NaN
8	mdb239	-1.2193	NaN	NaN	-2.6883
9	mdb240	-1.8427	NaN	NaN	NaN
10	mdb241	NaN	NaN	NaN	NaN

Table 3: Skewness Value of the Feature Extracted and Segmented Image

Dataset	Image	MSO	PSO	ACO	ABC
1	mdb001	4.465	5.0892	3.5612	2.8333
2	mdb002	9.5904	NaN	NaN	NaN
3	mdb013	2.9867	2.5668	NaN	2.3847
4	mdb023	1.9126	NaN	NaN	2.1246
5	mdb125	6.9713	6.8278	5.1398	6.4007
6	mdb126	5.6188	3.104	NaN	NaN
7	mdb212	12.3114	NaN	NaN	NaN
8	mdb239	6.4119	NaN	NaN	21.9027
9	mdb240	11.9459	NaN	NaN	NaN
10	mdb241	NaN	NaN	NaN	NaN

Table 4: Kurtosis Value of the Feature Extracted and Segmented Image

Dataset	Image	MSO	PSO	ACO	ABC
1	mdb001	23.9900	36.0713	250.6445	156.4445
2	mdb002	21.9097	35.9097	220.9097	101.9877
3	mdb013	23.3747	32.8611	234.3747	147.3737
4	mdb023	21.5101	40.8960	320.5101	108.5121
5	mdb125	24.2245	43.4184	248.2245	168.2245
6	mdb126	22.3154	73.7922	258.3154	179.7459
7	mdb212	24.6301	40.0419	296.6301	142.1649
8	mdb239	25.5000	38.5000	300.5000	189.3240
9	mdb240	25.9000	39.9000	249.9000	191.9030
10	mdb241	22.8000	37.8000	257.8000	175.7871

Table 5: CPU Time (sec) – Time Taken for Feature Selection, Extraction and Segmentation

Dataset	Image	MSO	PSO	ACO	ABC
1	mdb001	52513	52345	51194	51100
2	mdb002	83056	83000	82900	83032
3	mdb013	100533	99742	98510	100252
4	mdb023	123389	122118	122200	122621
5	mdb125	94195	93398	93205	93037
6	mdb126	171699	170666	170548	170787
7	mdb212	54498	54177	54160	54023
8	mdb239	218352	206104	205490	188165
9	mdb240	186946	0	0	0
10	mdb241	80515	0	0	0

Table 6: Number of Pixels obtained after Segmentation of Mammogram Images