IMPROVED DUCK AND TRAVELER OPTIMIZATION (IDTO) ALGORITHM: A TWO- WAY EFFICIENT APPROACH FOR BREAST TUMOR SEGMENTATION USING MULTILEVEL THRESHOLDING

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Abstract: The merely human being who can accumulate yourself is you only. The pathologist is the caretaker who can help you to protect yourself from breast cancer. Invasive breast cancer of US women is approximately 281,550 in 2021. Objective: Early diagnosis of breast cancer using computer aided system is needed to create novel methods for fighting against the diseases. Methods: In this research a new Meta heuristic Duck Traveler Optimization algorithm is introduced for mammogram image segmentation. Automatic selection of threshold values is help to optimize the segmentation process in an efficient manner. IDTO calculation is utilized to amplify the Kapur's and Otsu's goal capacities. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) of swarm intelligence algorithms are efficiently used for validating the performance of IDTO. Datasets: MIAS Dataset consists of 322 mammogram images are taken for experimentation. Findings: The results of PSNR values proved that the proposed IDTO leads the optimum threshold values better than PSO and GA. The execution season of IDTO division technique is assessed and contrasted with GSA. The best average time of IDTO has been declared the proposed method has the high efficiency with minimum time.

Keywords Bio-Inspired Computing (BIC), Improved Duck Traveler Optimization (IDTO), Image segmentation, Kapur's entropy, Multilevel Thresholding (MTH), Otsu's between class variance.

1. Introduction

Cancer originating in the mammary gland is the most common type of cancer in women. It is a major public health problem worldwide and is the second leading cause of death in the United States. In United States estimation by 2021 new deaths of breast cancer in both cases are 281,550 and diagnosed in both cases are 284,200 [1]. Medical care specialists put a ton of endeavors to conquer this savage infection. One of these endeavors is screening. By screening the breast malignancy can be recognized in beginning phases and accordingly the treatment can be more viable. It is conceivable to recognize breast disease by various types of screening strategies, for example, mammography, ultrasound, CT and MR. Mammography is the most broadly utilized screening technique. Bosom disease is the most well-known non-skin malignant growth of American ladies; however it can likewise happen in men. Consistently in the US, there are more than 266,000 new conclusions of bosom disease. A lady has a danger of 1 of every 8 for creating bosom malignant growth sooner or later during her lifetime.



Figure 1: Breast tumor (resource: http://www.medicinenet.com/breast_cancer/article.htm)

Breast disease side effects and signs incorporate

- A knot in the bosom or armpit,
- Bloody areola release,
- inverted areola,
- Orange-strip surface or dimpling of the bosom's skin,
- Breast agony or sore areola,
- Swollen lymph hubs in the neck or armpit, and
- A change in the size or state of the bosom or areola.

• Breast malignant growth can likewise be without manifestation, which makes following public screening suggestions a significant practice.

In Image processing, image segmentation plays a vital role which has several applications in different areas such as; agriculture, medicine, satellite processing, industry etc. This process is classifying the pixel in the image depending on its intensity value. In image segmentation thresholding plays a crucial role which separates an image into foreground and background image. In image thresholding the different types are used for segmentation are single threshold, two-level threshold and multilevel threshold. Specific threshold values of different pixels in same class are available in multilevel thresholding. To specifying optimal threshold parametric and non parametric methods are used for obtained. Kapur entropy method and Otsu between class variance methods are helpful to achieve the optimal thresholds values.

Division assumes a basic part in picture preparing. It parts the picture into independent items. Each item uncovers data as force, shading or surface. Division procedures contrast from picture to picture contingent on the difficult examination of the picture. Biomedical pictures are dim level pictures in which the force of pixels changes for each article present in it. Limit is applied on biomedical pictures to separate the bizarre districts where the pixel esteem is high. Two level limit segments a picture into two classes, though staggered edge segments a picture into numerous classes relying on the edge level. Robotized determination of limit is as yet a troublesome errand. Preprocessing or post preparing of a picture improves the nature of picture by eliminating the commotion present in it. Improved Duck Traveler Optimization (IDTO) Algorithm is another Meta heuristic enhancement technique to locate the best ideal answer for an issue. In this work, another way to deal with fragment anomalous areas of mammogram picture is completed utilizing IDTO technique with staggered edge. The preprocessed picture is utilized for division. The preprocessing is finished utilizing morphology and middle channel. The preprocessed picture is applied as contribution to Duck voyager calculation alongside limit level. The pixels in the picture are bunched dependent on the best worth acquired from IDTO. The execution season of IDTO division technique is assessed and contrasted with GSA.

Specialists have applied a few nature-motivated calculations to picture division effectively. Feng-Ping An et al utilized Convolutional Neural Networks (CNNs) with viable criticism, component count models, and activity frameworks for medicinal picture division. Tianbao Ren et al proposed an improved fluffy grouping calculation for cerebrum picture division. A.S. Shamsaldin et al propose a novel calculation called Donkey and Smuggler Optimization Algorithm for way discovering. Crow Search Algorithm (CSA) is proposed by Alireza Askarzadeh and applied to enhance six compelled building plan issues which have various natures of target capacities, limitations, and choice factors. Ashraf M. Hemeida et al build up the electromagnetic improvement (EMO) calculation dependent on demand work, EMO-demand, to upgrade the EMO execution for deciding the ideal staggered thresholding for picture division. Eva Tuba et al balanced late elephant crowding improvement calculation to decide the ideal staggered edges for picture division and utilizing Otsu as the target work . K.P.Baby Resma presented a novel staggered thresholding calculation utilizing a metaheuristic Krill Herd Optimization (KHO) calculation for taking care of the picture division issue. Shen'ao Yan et al, by contemplating the scavenging conduct of ducks, another bionic bunching astute calculation – duck pack calculation (DPA) is proposed and applied to course arranging. Three principle classifications of NIC are described in reference. Motivation for this paper from

metaheuristics (Maniezzo et al. 2009), and the Base Optimization algorithm (Salem 2012) based on Computational Intelligence, which is the root of bio inspired computing.

Nonetheless, customary models face a few constraints, for example, computational time. As of late, Meta heuristic (MH) techniques have been generally applied to take care of different advancement issues, including picture division [1]. Different sorts of meta-heuristic calculations have been utilized in the field of picture division up until this point, presenting new Meta heuristic calculation is required [2]. Division of clinical pictures is famous as of late as it is useful for investigation of a specific piece of the body [3]. As of late, swarm knowledge strategies have been utilized in MLT, which is viewed as a NPdifficult issue [4]. The fundamental issue of thresholding is the way to discover consequently the ideal estimation of threshold(s), which prompts deciding the quantity of groups (classes) effectively. For parallel thresholding, we recognize two procedures. The first is presented by Otsu in that expected to augment the difference between classes. The subsequent procedure is given by Kapur that utilized the entropy rules as a measure to augment the homogeneity between classes [5]. In any case, the customary models that have been utilized to locate the ideal limit esteem require more computational time. To address these restrictions, meta-heuristic (MH) approaches have been utilized [6]. K-implies Clustering estimation using a meta-heuristic Duck Cluster Optimization (DCO) figuring has been proposed for dealing with picture division issue [7]. It is generally founded on the heuristic and meta heuristic calculations by following the technique "experimentation.". The Bio-Inspired Algorithms had been additionally grouped into the accompanying classifications, for example, Evolutionary Algorithm and Artificial Immune System (AIS), Bacterial Foraging and numerous others. The Evolutionary Algorithm comprises of Genetic Algorithm, Evolution methodologies, Genetic Programming, Evolutionary programming, Differential Evolution and Social calculations. Multitude knowledge incorporates Ant Colony Optimization, Cat Swarm Optimization, Cuckoo Search, Firefly and Bat Algorithm. Recreated Annealing and amicability Search calculations go under the actual based calculations [8]. As of late, there are a few methodologies have been applied for picture division, including histogram preparing, grouping, limit, and district developing techniques [9]. Redone robotized seed point figuring for featuring tumor area is improved in an effective manner [10].

The remainder of the paper is composed as follows: Section 2 displays a writing survey of swarm intelligence techniques, Kapur's and Otsu's methods. Section 3 outlines the formulation used for making DTO. In section 4, the new algorithm is explained in detail. In Section 5, the results and discussion of performance evaluation are presented. To end with, Section 6 concludes the effort and recommends a few directions for future studies.

2. Literature Review

The most well-known and utilized calculation is molecule swarm improvement, which was begat by both Kennedy and Eberhart in 1995. Marriage in Honey Bees Optimization (MBO) was recommended in 2001. Fake fish-swarm calculation (AFSA), which was created in 2003 (Li, 2003), is viewed as extraordinary compared to other improvement approaches inside the class of swarm insight calculations. Monkey Search (Mucherino and Seref, 2007) was proposed in 2007 as a worldwide looking through calculation motivated by the practices of monkeys. The cuckoo search calculation is another advancement calculation instituted by Xin-she Yang and Suash Deb in 2009 (Yang and Deb, 2009). Another significant calculation that is generally utilized by the specialists is called counterfeit honey bee state; (Karaboga, 2010). Bat calculation is roused by the bats' practices. (Yang, 2010). In 2012, a Krill Herd (KH) calculation created and recommended to handle enhancement issues. Another calculation was created in 2014. From (Eesa et al., 2015) utilizing cuttlefish. Moreover, a Gray Wolf Optimizer (GWO) as a novel metaheuristic proposed in 2014 (Mirjalili and Lewis, 2014) for taking care of improvement issues. In 2016, an imaginative hunt calculation named fluffy congruity search (FHS) was presented by Peraza et al., (2016) for taking care of enhancement issues. Besides, in 2017, the presentation of the dim wolf streamlining agent (GWO) calculation when a progressive administrator is presented in the calculation was analyzed (Rodríguez et al., 2017). In 2018, another meta-heuristic calculation was proposed, which is another bio-enlivened streamlining calculation dependent on the self-defense mechanics of plants (Caraveo, Valdez, and Castillo, 2018). Another calculation presented in 2018 is known as another metaheuristic motivated by the fume fluid harmony for ceaseless improvement (Cortés-Toro et al., 2018). At long last, in 2019, a strategy for powerfully altering parameters in meta-heuristics that depend on the vital sort 2 fluffy rationale was presented (Olivas et al., 2019). In the field of image processing, which was considered as one of the primary analyses in bio-inspired computing in the referenced paper [44], multi-thresholding, which is a significant image segmentation system to locating the tissue in medical images. This research work propels us to figure another model that copies the social conduct of ducks.

Kapur's method (Entropy criterion method)

The target of an advancement issue is to locate the variable quality that improves a goal/wellness work and simultaneously fulfill the imperatives. Right now, the target capacities for the IDTO calculation for multilevel thresholding have been planned dependent on the entropy foundation and furthermore dependent on between class differences.

Kapur's entropy model strategy finds the optimal qualities for the thresholds dependent on the amplification of entropy (Kapur et al., 1985). Leave L alone the number of grey levels in a given picture with the goal that the force esteems are in the range [0, L-1]. We would then be able to characterize $p_r=b(r)/N$, where b(r) indicates the number of pixels with grey level worth *r* and *N* speaks to the all out number of pixels in the picture. Here the point is to amplify the target work.

$$f_k(t) = G^a + G^a_{,a} = \begin{cases} 1 & \text{if Grey image} \\ 1,2,3 & \text{if RGB image} \end{cases}$$
(1)

here, G_1 and G_2 are the entropies.

$$G_{1}^{a} = \sum_{i=1}^{L_{1}} \frac{pr_{i}^{a}}{x_{0}^{a}} \ln \left(\frac{pr_{i}^{a}}{x_{0}^{a}} \right), \quad G_{2}^{a} = \sum_{i=t+1}^{L_{1}} \frac{pr_{i}^{a}}{x_{1}^{a}} \ln \left(\frac{pr_{i}^{a}}{x_{1}^{a}} \right)$$
(2)

 x_0^a and x_1^a are probability dispersions.

$$f_{k\sim}(T) = \sum_{i=1}^{j} G_i^a \quad a = \begin{cases} 1 & \text{if Grey image} \\ 1,2,3 & \text{if RGB image} \end{cases} (3)$$

here, different threshold values are used for obtaining the target work in an efficient manner.

$$G_{1}^{a} = \sum_{i=t_{k}+1}^{t_{1}} \frac{p\overline{r}_{i}^{a}}{p\overline{r}_{i}^{a}} \ln\left(\frac{pr_{i}^{a}}{a}\right)$$

$$G_{2}^{a} = \sum_{i=t_{k}+1}^{t_{2}} \frac{p\overline{r}_{i}^{a}}{1} \ln\left(\frac{pr_{i}^{a}}{x}\right)$$

$$G_{j}^{a} = \sum_{i=t_{k}+1}^{L} \frac{pr_{i}^{a}}{x^{a}} \ln\left(\frac{pr_{i}^{a}}{x^{a}}\right)$$

$$(4)$$

Otsu's method (between- class variance method)

Otsu's between-class fluctuation strategy (Otsu, 1979) finds the optimal threshold esteems dependent on the between-class difference augmentation. The Otsu's technique would then be able to be characterized as expanding the accompanying target work.

$$f(t)_{otsu} = \max(\sigma_c^{2^{\circ}}(t))$$
(5)

where, $0 \le t \le L - 1$

The enhancement issue is diminished to show signs of improvement intensity level (threshold) that amplifies (5). The past target work is utilized for the grey level picture since it contains one limit (t). In any case, condition (5) can be changed to be utilized to account for RGB pictures as;

$$f(T)_{otsu} = \max(\sigma_c^2(T))$$
(6)

where, $0 \le T_i \le L - l = l, \dots, j$

 $T = (T_1, T_2, ..., T_{j-1})$ and j is the number of class

$$\sigma_A^{2^s} = \sum_{i=1}^j \sigma_i^s$$

$$\sigma_i^s = x_i^s (mn_i^s - mn_i^s)^2$$
(7)

where *i* and *j* are used to mention the particular and total number of classes, respectively. If s = I (grey image). The variance σ_i^s , and mn_i^s respectively. and mean value of all the classes are calculated by using $t_i = \frac{1}{2}$

$$mp^{s} = \sum_{i=1}^{t_{i}} \frac{ip r_{i}^{s}}{x_{r(t)}^{r}}$$

where x_l^s Occurrence probability

$$x_{1}^{s}(t) = \sum_{i=1}^{I_{1}} pr_{i}^{s}$$

$$x_{2}^{s}(t) = \sum_{i=t_{1}+1}^{I_{1}} pr_{i}^{s}$$

$$x_{j-1}^{s}(t) = \sum_{i=t_{j}+1}^{L} pr_{i}^{s}$$

$$r_{i}^{s} = \frac{r_{i}^{s}}{M}, \quad s = \begin{cases} 1 & \text{in grey image} \\ 1,2,3 & \text{in RGB image} \end{cases}$$
(11)

Here, pr_i^s is the probability distribution for calculating the r_i^s histogram distribution values in M (Image).

$$\sum_{i=1} pr_i^s = 1 \tag{12}$$

Maximize $f(T)_{otsu}$ Subject to $T \in x$, $T=(t_1, t_2, \dots, t_q)$ *Here q refers to different threshold values.* The objective of the planned method is that maximizing Kapur's or Otsu's objective function to find out the optimal thresholds.

3. Formulation Using For Making IDTO Algorithm

The demand to find out/create the solution for the researcher to initiate/improve the existing/proposed innovative/research, either minimizing/maximizing the problem constraints with an appropriate algorithm, the expectation of the proposal is to achieving the optimal/feasible solutions in a particular given period within the highest quality and minimum cost.

$$D_i^{new} = D_i + \alpha \oplus Terrif(\mu)$$

(13)

here, α is a track dimension parameter. Terrif (μ) is the distribution parameter for position update. α is calculated by using the following formula:

(18)

(20)

(21)

$$\alpha \oplus Terrif(\mu) \sim 0.01 \frac{a}{|b|^{\frac{j}{\mu}}} \left(D_i^t - D_{best}^t \right)$$
(14)

here, variables α and *b* produced from a typical distribution where,

$$a \sim P(0, \phi_a^2), \quad b \sim P(0, \phi_b^2) \tag{15}$$
$$\left[\Gamma(1 + \mu) \times \sin(\pi \times \mu / 2) \right]^{1/\mu} \tag{16}$$
$$\phi_a = \left[\frac{\Gamma[(1 + \mu) / 2] \times \mu}{\Gamma[(1 + \mu) / 2] \times \mu} \right] \quad , \phi_b = 1 \tag{16}$$

where enriches the gamma corrected function. Here $0 \le \mu \le 2$. To the best search, the position (μ) is updated by using the height *Tag* (Q_{wg}):

$$\mathcal{D}_{best}^{new} = D_{best}^t \stackrel{\pm}{_{5}} I \times Q_{wg} \tag{17}$$

here, I_5 is the random number in [0,1]. Q_{wg} is the height tag.

 $Q_{wg} = Q_{\max} e^{(l \times m)}$

 (Q_{min}) In denote the smallest number and Q_{max} indicates the highest limits

$$l = \left(\frac{\ln\left(\frac{Q_{\text{max}}}{Q_{\text{max}}}\right)}{M_{\text{max}}}\right)$$
(19)

here, m is the present iteration and (M_{max}) is the greatest number of iterations.

The position of the duck concerned just limiting the separation of voyaging and boosting speed to discover the prey. Speed>Distance=Capturing the prey in minimum time. Therefore, the optimality can be achieved through minimizing the distance (travelling) and maximizing the speed of (find out the prey) by duck flock.

$$S > D = P$$

Where S stands for Speed and D represents the Distance used for achieving P that means Prey. Force concerned only for catching food.

$$F = m * a$$

Here, m is used to denote the duck weight and which is used to calculate the distance/time² for updating speed (a).



Figure 2: Searching the food source by duck flock

Let fs = 1, 2, ..., n is *n* food sources, which can be considered as the nodes of a graph. Let β_{jk} be the decision variable for connecting food source *j* to food source k (i.e., an edge in the graph from node *j* to node *k*) such that $\beta_{jk} = 1$ means the duck travel starts at *j* and ends at *k*. Otherwise, $\beta_{jk} = 0$ means no connection along this edge. Therefore, the cities form the set *V* of vertices and connections form the set *E* of edges. Let d_{ij} be the distance between food path *j* and food path *k*. Due to the symmetry, we know that $d_{jk} = d_{kj}$, which means the graph is undirected. The objective is to minimize

$$fs = j, k \in E, j = kd_{jk} \beta_{kj}$$

$$A = D^{s+1} = DTO(D^s, P(s), \in (s))$$

$$(22)$$

 D^{s+1} =new solution vector;

 D^{s} =current solution vector

P(s)=Parameters P=(P_1,...,P_u)

 \in (*s*)=random variables $\epsilon = (\epsilon_{1,...,k})$

s =Scheduled time

An algorithm IDTO tends to generate a new and better solution D^{s+1} to a given problem from the current solution D^s at iteration or schedule *s*. Mathematically speaking, a random walk can be written as

$$R_{s+1} = R_s + p_s \tag{23}$$

 R_s =existing solution; s=steps and p_s =perturbation

$$\overline{D_i^{s+1}} = \overline{D_i^{s+\mu}}_{0e^{-Yr^2}ij} (\overline{D_j^{s-D}}_i^s) + \alpha \epsilon_i^s$$
(24)

The next generation can be updated by using the optimality function given below: Maximize the performance of

$$\xi = DTO\left(\Phi, \mathbf{p}, \boldsymbol{\varepsilon}\right) \tag{25}$$

4. The IDTO Algorithm

To summarize the observations from ducks' foraging behavior, the following tasks are presented.

Task 1: A duck population comprises of several groups. Each group containing a number of ducks that optimizes the food search activity using their stack of intelligence.

Task 2: Based on the height of the neck+head, the duck uses that information to select the hunting region.

Task 3: They travel as a flock and follow their local guide which has fed in most food in the last location.

Task 4: After a number of tasks, ducks return to the surface to share with its local affiliates, via communication of exploitation, the locations and abundance of food sources.

Task 5: If the food support is less for the ducks of a given group to live, in part of the group migrates to another place via communication for exploration.

Task 6: Based on the satisfaction of end criteria, output the optimal solution. Otherwise, go to Task 2.

4.a. Pseudo code of Duck Traveler Optimization (IDTO)

Step 1: Initialization

Step 2: Evaluation

Step 3: Updating

Step 4: Next Generation

Initialize Duck Flock
While iter <max iteration<="" td=""></max>
Generate and classify ducks
Initialize the position of ducks and
Classifying the ducks
Form Duck groups (D _i)
Reach Ducks in a Row1
Next
Evaluate fitness of duck team
For n=1 to number of ducks
Find greedy ducks
Perform the travelling process 2
For d=1 to number of dimension of ducks
Form chick groups (C _i)
Update Duck groups3
Next d
Next n
Update the maximum fitness value
Next Generation 4
A L C I C I D L AL (CD A) C T

4. b.Self-seeking Duck Algorithm (SDA) for IDTO

```
Step 1: Population Initialization
Step 2: Growth and Reproduction
Step 3: Competitive exclusion
Step 4: Robustness calculation
Step 5: Obtaining optimal solution
If i_{max} > i_{final}
Set D_g = D_1 = D_2 = \Phi;
Initialize DP_{ij}=1/n_i;
arbitrary();
robustness();
greatest();
recompense();
reprimand();
Set D<sub>g</sub>= Pick_greatest();
Do {
D<sub>1</sub>= Pick_ arbitrary();
D<sub>2</sub>= Pick_ arbitrary();
If robustness (D_1) \ge robustness (D_2)
{
recompense(D_1);
reprimand(D<sub>2</sub>);
D_g = D_1;
}
Else
{
recompense(D<sub>2</sub>);
reprimand(D<sub>1</sub>);
D_{g} = D_{2};
}
}while end condition is satisfied;
Return D<sub>g</sub>;
```

ALGORITHM 1

In algorithm 1 D_g means the greatest duck; D_1 and D_2 are two temporary ducks in duck flock.i.e $D=(D_1, D_2, ..., D_n)$. DP_{ij} i.e $P_i=(P_1, P_2, ..., P_n)$ means the probability of food foraging speed (f_{ij}) i.e $(j=1,2,...,n_i)$. robustness() is a function to calculate the fitness value of the ducks. recompense() and reprimand() are two functions used to realize the competitive mechanism. Where n & $n_i =$ number of ducks in the duck flock; $P_i=$ the survival rate of the ith duck.

The block diagram of IDTO based image segmentation is shown in Fig.3.

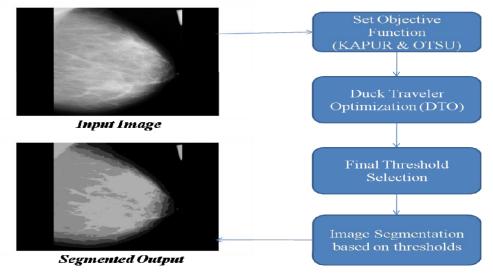


Figure 3:Block diagram of IDTO based mammogram image segmentation.

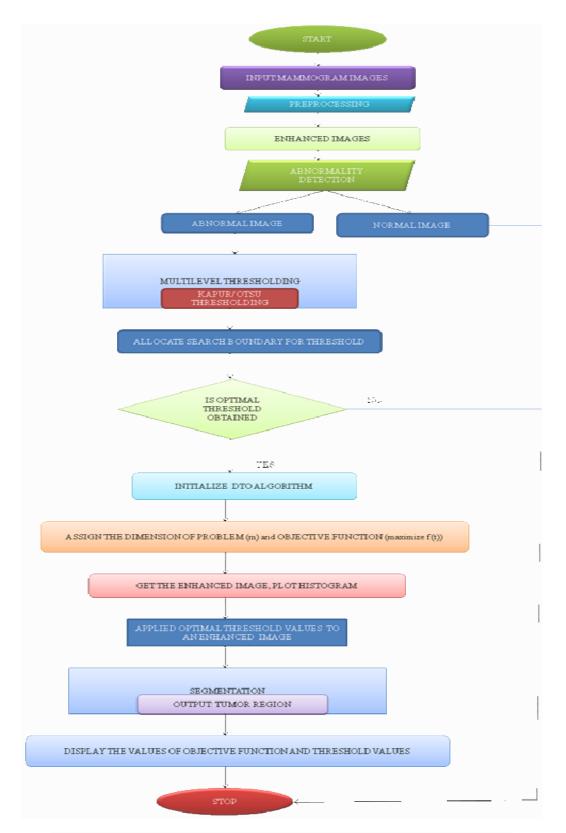


Figure 4: Framework of IDTO algorithm for Mammogram Image Segmentation.

5. Experimental Results

Fragmenting a picture to remove concealed data is a significant undertaking. Tables 1, 2, and 3 represent the various parameters chosen for the implementation of IDTO, PSO, and GA algorithms, respectively. Mammogram images, namely, mdb003, mdb036, and mdb042, taken as the test images and are gathered with their histograms in Figure 7.

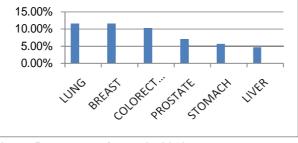


Figure 5: Number of cases in 2019, both sexes, all ages.

Fig.5 is clearly highlights the importance of breast cancer's prediction.

Table 1. Parameter values for IDTO.						
Parameter	Value					
Number of iterations M _{max}	200					
Narrow search (Ns)	20					
Dimension (d)	0.020					
Population (D)	25					

Number of iterations M _{max}	200
Narrow search (Ns)	20
Dimension (d)	0.020
Population (D)	25

Parameter	Value
Number of iterations I max	200
W _{max} , W _{min}	0.8, 0.3
C_1, C_2	2
Number of Particles (P _{size})	25

Table 2. Parameter values for PSO.

Table 3. Parameter values for GA.

Parameter	Value
Number of iterations R_{max}	200
Crossover _{probability} , Mutation _{probability}	0.9, 0.5
C_1, C_2	2
Population size (O)	25

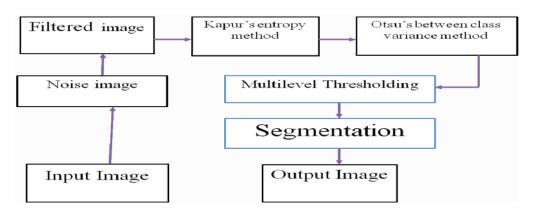


Figure 6: System Architecture of IDTO algorithm for Mammogram Image Segmentation.

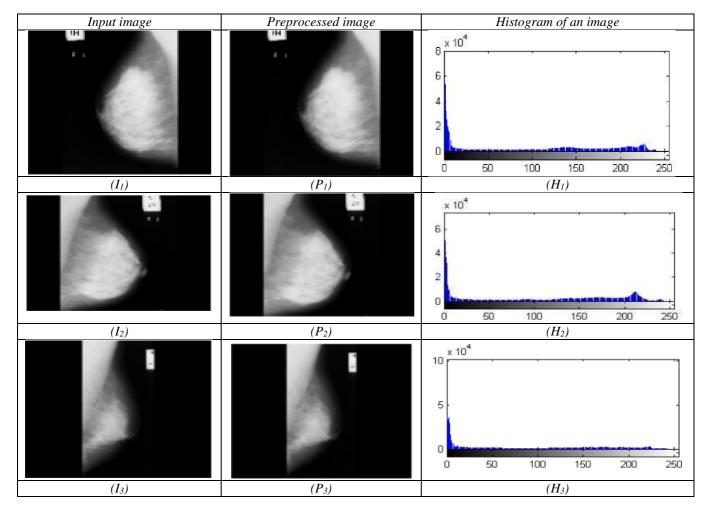
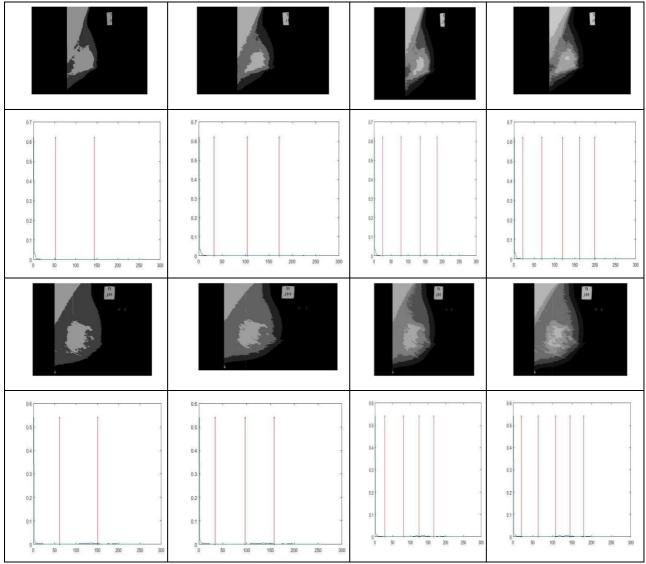


Figure 7: Mammogram images: (I_1) Mdb003, (I_2) Mdb036, (I_3) Mdb042, Preprocessed images of (I_1) , (I_2) and (I_3) are (P_1) , (P_2) and (P_3) . Histograms of these images are (H_1) , (H_2) , and (H_3) .

THRESOLD=2	THRESHOLD=3	THRESHOLD=4	THRESHOLD=5
	0.5 0.4 0.4 0.30 0.25 0.25 0.2 0.15 0.1 0.05 0.50 100 150 200 250 300	25 -	

Table 4. Otsu'S threshold values at different level using the DTO method.



The above Table 4 furnishes the segmented images based on Otsu's objective best objective function values after applied different level thresholds such as (THRESHOLD=(2,3,4,5)).

Table 5. Comparison of Standard deviation and PSNR values between Otsu's and Kapur's methods.

		Otsu method			Kapur method		
Image	L	Threshold	STD	PSNR	Threshold	STD	PSNR
	2	67,168	6.19	18.27	24,120	15.20	16.34
Mdb003	3	37,107,176	6.29	21.39	23,107,175	20.06	20.97
	4	33,98,153,195	6.33	23.40	16,67,119,180	24.65	22.71
	5	24,72,119,162,201	6.35	25.47	16,66,116,156,196	28.83	25.10
	2	52,144	3.94	20.60	32,134	14.84	19.76
Mdb036	3	33,104,172	4.02	23.03	23,96,165	19.71	22.59
	4	25,79,136,185	4.06	25.20	16,70,128,181	24.25	24.66
	5	22,69,120,162,199	4.07	56.71	16,60,104,146,190	28.44	26.59
	2	61,151	4.30	18.14	31,109	14.37	18.45
Mdb042	3	34,97,158	4.41	21.76	30,100,161	19.34	21.77
	4	28,81,125,166	4.45	23.97	18,63,109,163	23.68	23.51
	5	21,64,108,145,180	4.47	25.36	18,63,108,156,212	28.04	23.90

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Otsu and Kapur multilevel thresholding-based mammogram image segmentation methods are compared in Table 5. From this table, it can be observed that the Otsu thresholding method generates segmented images with high accuracy and higher values of PSNR and STD compared with Kapur method.

		Best Thres	hold values		Robustness values			
Image	L	(IDTO)	(PSO)	(GA)	IDTO	PSO	GA	
	2	67,168	67,167	65,159	2675.7	2670.4	2432.3	
Mdb003	3 37,107,176 34,104,169		32,101,164	2774.5	2764.4	2544.7		
	4	33,98,153,195	31,97,149,192	32,94,147,190	3234.9	3233.5	3111.6	
	5	24,72,119,162,201	22,72,115,161,200	23,71,115,161,188	3654.6	3652.8	3473.9	
	2	52,144 51,142 33,104,172 33,102,169		49,139	2756.4	2756.4	2611.6	
Mdb036	3			33,104,164	3177.3	3176.2	3173.5	
	4 25,79,136,185 25,78,136,183		24,77,136,182	3186.2	3185.1	3180.4		
	5	22,69,120,162,199	23,67,120,161,190	22,66,119,161,190	3199.1	3182.3	3182.3	
	2	61,151	60,150	59,148	3546.3	3546.2	3543.5	
Mdb042	Mdb042 3 34,97,158		37,94,157	36,93,155	3630	3629.2	3628.7	
	4	28,81,125,166	28,83,120,161	29,81,119,159	3732.8	3729.7	3727.9	
	5	21,64,108,145,180	22,63,106,146,181	22,62,107,142,179	3909.5	3909.5	3904.7	

Table 6. Otsu's based optimal threshold limits with their corresponding objective function values for all algorithms.

From table 6, it can be observed that the DTO thresholding method using Otsu's generates segmented images with high objective function values compared with other bio inspired algorithms.

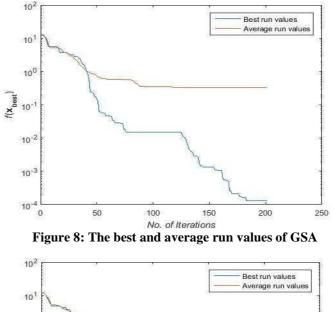
PSNR values								
Image	L	(IDTO)	(PSO)	(GA)				
	2	16.34	16.32	15.57				
Mdb003	3	20.97	20.99	19.96				
	4	22.71	22.69	20.23				
	5	25.10	24.49	23.92				
	2	19.76	19.34	18.92				
Mdb036	3	22.59	22.48	21.89				
	4	24.66	23.59	23.52				
	5	26.59	24.49	24.48				
	2	18.45	17.47	18.43				
Mdb042	3	21.77	21.56	20.73				
	4	23.51	23.49	22.89				
	5	23.90	23.88	23.69				

From table 7, The peak signal-to-noise ratio (PSNR) value has been used to measure the segmentation quality and similarity between the original image and the segmented image. The PSNR measure proved the efficiency of the algorithm compared with the other algorithms. From the experimental results of the proposed algorithm, compared with the original PSO and GA algorithms, the developed algorithm has good performance regarding to the fitness function and PSNR in all images.

Table 8. Average time in second's value comparison of IDTO and GSA method

Gravitational Search Algorithm						Duck Traveler Optimization Algorithm				
Input	2 level	3 level	4 level	5 level	Average	2 level	3 level	4 level	5 level	Average
images	run	run	run	run	time in	run	run	run	run	time in
	time	time	time	time	seconds	time	time	time	time	seconds
Mdb001	8.346	9.687	10.88	12.31	10.305	8.345	9.586	10.11	12.30	10.085
Mdb005	8.221	9.703	10.96	12.27	10.288	8.202	9.701	10.85	12.21	10.240
Mdb008	8.479	9.473	11.01	12.35	10.328	8.475	9.471	11.00	12.30	10.311
Mdb015	8.284	9.750	11.02	13.47	10.631	8.280	9.749	11.87	12.30	10.549
Mdb021	8.268	9.751	10.90	12.32	10.309	8.266	9.751	10.87	12.31	10.299
Mdb320	8.393	9.828	11.02	12.34	10.395	8.389	9.829	11.05	12.32	10.397

From table 8, The average computation time value has been used to measure the segmentation quality and similarity between the original image and the segmented image. The computation time measure proved the efficiency of the algorithm compared with the other algorithms.



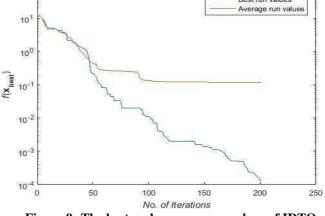


Figure 9: The best and average run values of IDTO

Extraordinary Features of Proposed Algorithm

- The core intention for multilevel thresholding is to find out multiple thresholds that divide pixels into many groups.
- To calculate the objective function values for obtained thresholds are maximized by using objective function of both Kapur's and Otsu technique to improving the clarity of image segmentation.
- To identify the optimum threshold for efficient segmentation, Improved Duck Traveler optimization (IDTO) is a versatile, robust, population based mostly meta-heuristic search/optimization algorithm with inherent parallelism.
- User intervention (e.g., initialization, validating results, and correcting errors) provides further source of knowledge for image segmentation, so probably produces correct segmentation results.
- The unwavering quality of the proposed calculation has been demonstrated utilizing diverse mammogram pictures.
- Less computation time leads fast completion of all the steps rather than GSA algorithm.

6. Concluding Remarks and Future Works

This study displays a novel Improved Duck Traveler Optimization (IDTO) based calculation for multilevel thresholding, which can be successfully utilized for tackling picture segmentation issues. In this study, three mammogram test images are used to check the effectiveness of the optimization algorithm. These images are taken from mini-MIAS database which is of size 1024 ×1024 pixels in Portable Greymap (PGM) format. The proposed IDTO calculation recreates

the duck search to choose the best limits for multilevel thresholding. So as to assess the presentation of the proposed IDTO calculation, two target capacities, one dependent on Kapur's technique and the other dependent on Otsu's, were considered. The proposed IDTO figured the PSNR and STD measure esteems to decide the best possible thresholding, and the results are additionally contrasted and other bio-inspired multilevel thresholding strategies. Whenever the number of threshold values expands, the PSNR esteem likewise is expanded for all calculations. IDTO based multilevel thresholding saw to have the most noteworthy PSNR values than the current bio-roused methods for picture division. The division consequences of IDTO calculation for more than two thresholding are promising, and henceforth the proposed strategy can be successfully utilized for multilevel image segmentation issue. As a future work, the chance of utilizing the proposed calculation for a higher number of thresholds to improve the exhibition of the proposed technique will be explored.

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