Original Article

MODIFIED WHALE OPTIMIZATION ALGORITHM AND MINIMUM CROSS ENTROPY BASED SEGMENTATION OF CT LIVER IMAGE

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Abstract

In the modern healthcare system, the segmentation process is really helpful to aid in the diagnosis process. In this paper, the efficient metaheuristic approach - Modified Whale Optimization Algorithm and Minimum Cross Entropy (MWOA & MCE) based multilevel thresholding is proposed for segmentation of the computer tomography (CT) liver image. Segmentation of liver cyst image is the main objective of this paper, which will assist doctors to diagnose liver cysts. The results of segmentation of CT liver images are compared with other algorithms, Teaching-Learning-based optimization algorithm, Jaya algorithm and Genetic algorithm, to evaluate the efficiency of the MCE & MWOA approach. Different performance calculating methods like Uniformity, Structure Similarity Index (SSIM), Root Mean Square Error (RMS Error), Rand Index (RI), Execution time, Variation of Information (VoI) and Peak Signal-to-Noise Ratio (PSNR) are assessed from an original and resultant image. In comparison to other algorithms, the proposed method's findings demonstrate that the MCE & MWOA algorithm achieve accurate and efficient segmentation results.

Keywords Whale optimization Algorithm, Entropy, Threshold, Liver, Cyst, Image Segmentation.

INTRODUCTION

The second-most significant organ in the human body is the liver. A major problem of the liver is cyst. It grows slowly and is not detected till maturity. The cyst is basically a nonstandard sac that is filled with fluid [1]. The identification of liver issues is greatly aided by the diagnosis of cystic lesions. The liver contains a variety of cyst forms. There are several benign or malignant cysts. Numerous diagnoses of abdominal imaging modality are used for detection of these types of diseases like Magnetic Resonance Imaging (MRI), Computer Tomography (CT), X-rays, Ultrasound (US), etc. Surrounding tissues are similar to tumors, so it is difficult to diagnose[2]. Detection arises two main challenges: one is to differentiate if the lesion is either benign or malignant. Second one is, if diagnosing the same is cost efficient, accurate and safe [3]. The technique of image segmentation is a significant component of image processing. After preprocessing, an image is segmented. Image segmentation divides the complete image into several segments to clearly identify every part of an image. There are several image segmentation algorithms in the image processing field like thresholding, region growing, split and merge, k means clustering and many more hybrid methods. Thresholding is one of the highly recommended methods which give better results. Thresholding is basically dividing the whole image according to its intensity value. Thresholding is of many types in which the number of thresholds are selected: in bi-level one threshold is selected, in three-level two thresholds are selected, in four-level three thresholds are selected and by increasing the number of thresholds the level also increases. Optimization technique refers to the best possible solutions in case of maximization or minimization. Soft computing is an emerging field in the era of science. Artificial neural networks [4], Evolutionary computing[5], Fuzzy logic[6][7] and Particle swarm intelligence are the main fields of soft computing.

The development of metaheuristic algorithms increases day by day. Each algorithm gives better performance. Many optimization algorithms developed in past years are based on animal, bird, and human behavior. Human behavior algorithms are those which mimic the behavior of humans and their examples are Genetic algorithms, Tabu search, Harmony Search (HS) and many more. A Teaching-Learning-Based Optimization (TLBO) method is based on the teacher-student learning process [8]. The TLBO algorithm was proposed by Rao [9]. Animal and Bird's behavior are those which are based on natural phenomena of the searching food process of animals, birds and other species. Numerous algorithms and their improved or enhanced methods are proposed to find out optimal results. Ant Colony Optimization(ACO), Biogeographical based optimization, Particle Swarm Optimization (PSO), Artificial Bee Colony Optimization(ABCO), Ant Lion Optimization(ALO), BAT optimization, Island BAT optimization, Grey wolf optimization, Whale optimization algorithm, Monkey Search, Cuckoo search algorithms, etc. are a few examples of metaheuristic algorithms.

Karaboga proposed the Artificial Bee Colony (ABC) metaheuristic algorithm[10]. This reduces the bee colony's behavior. It uses three types of bees, worker, spectator and bee groups; they find new sources of food by working together in groups. The food source is a solution in the optimization model. Yang[11] described Firefly Algorithm (FF) : Firefly community utilizes firefly brightness as a strategy to be a focus on low brightness; this means that fewer bright fireflies will fly to the brightest. The hybrid method proposed for image segmentation is considered, at the initial step consistently generating a population from random clustering solutions and then for better results use an evolutionary algorithm. The Fuzzy C-Means (FCM) procedure was applied to get final segmentation results in every iteration. FCM and better Biogeography Based Optimization (BBO) versions were combined for image splitting[12].

Thulasidass[13] proposed a method to segment the liver tumors using median filter and watershed segmentation. Anter et. al deployed a hybrid approach which combines the fuzzy method and Particle swarm intelligence applied for accurate segmentation of liver tumor [14]. The Feature difference method was implemented to enhance the accuracy by 98.6% while classifying the liver lesions [15]. For accurate segmentation of liver and their tumors, a deep learning approach was applied on CT liver images [15]. For diagnosis of liver cancer, the Convolution neural network based method was implemented by Wu [16]. Improved DA (IDA) is used for the color image. Optimal threshold values were calculated using Minimum cross entropy and Ostu's method [17]. Multilevel thresholding identifies appropriate threshold values for optimizing entropy criterion or between-class variance. Optimizations similar to these used nature -inspired metaheuristic algorithms. The Crow search algorithm was proposed for finding optimal values of multilevel thresholds using Kapur's entropy [18]. Fireworks algorithm was developed for solving multilevel image thresholding problems. This is a significant problem because it is often used in image processing for image segmentation purposes, right from the era when the count of sufficient threshold combinations increases rapidly with respect to the number of required thresholds [19]. Non-extensive Tsallis entropy, along with an image-inspired firefly algorithm was employed for segmentation by multi-thresholding [20] . In Modified grasshopper optimization, multilevel Tsallis cross-entropy reduces the complexity[21]. In Image segmentation, the most important segment is multilevel thresholding. Still, the complexity of computation of multilevel thresholding grows rapidly as the number of thresholds increases. Khairuzzaman et al.[22], proposed a new approach GWO (Grey Wolf Optimizer) to address the weakness of multilevel thresholding. This method is based upon the social behavior of gray wolves and their methodology of hunting. Multilevel image thresholding is an extensible approach used for the segmentation process [10][23] . Detection of brain tumor with the help of Whale Harris hawk optimization algorithm was proposed by Rammurthy et al. [24].

An enhanced method of WOA in a combination of multilayer perceptron networks proposed for selecting optimal features and classification by removing background [25]. With the help of WOA, the multi-objective function problem is solved by considering the problem as multilevel thresholding [26]. Edges are formed by the pixels where intensity values change significantly. The whale optimization algorithm was also used for edge detection in the field of image processing [27]. The hybrid model is proposed using WOA and multilevel thresholding, divided into two parts: one is preprocessing and the second is the segmentation of the vessel, for extracting vasculature in retinal fundus images [28]. The comparison was done between antlion optimization and whale optimization for image segmentation process using multilevel thresholding [29]. Abdalla et. al [30] proposed a WOA for image segmentation using clustering and morphological operations to get better results of liver detection. Low pass filters designed using Whale optimization algorithm[31][32]. Rohit et al. [33] discussed various improved versions of WOA. Yan et al. proposed an enhanced approach of whale optimization for global optimization[34]. In a paper [35], Sayed et. al proposed an analysis of breast cancer facts by using a combination of clustering and bio-inspired methods i.e. Moth Flame Optimization (MFO) and Whale Optimization Algorithm (WOA). Evaluation is based on two criteria: clustering and statistics respectively. Nature-inspired two algorithms MFO and WOA are implemented with the help of histogram in segmentation of image to find out optimal value of thresholding at multilevel[36]. Despite the fact that many research papers on image segmentation have been published, this is still a complex process[37]. A modified version of the whale optimization approach is used to achieve accurate segmentation. The CT scan image of the whole abdominal is segmented using the proposed method (the Minimum Cross Entropy based Modified Whale Optimization (MCE & MWOA) algorithm). The proposed approach is compared against the teaching-learning-based algorithm, jaya algorithm, and genetic algorithm, which are all well-known optimization algorithms. TLBO is inspired by the teacher student learning process. In this process students learn things in two phases, one is the teacher and the other is the student phase. In the teacher phase, students learn under the guidance of the teacher. In the second phase, a student learns by itself or with the help of the other students. The optimal result is found out with the help of both phases. TLBO technique is used for getting good results for segmentation [38]. Jaya algorithm [39] is based upon the criteria to find the global best solution. In addition to the global solution in Jaya algorithm, it also neglects the worst solution. In the Genetic algorithm, the optimal value is evaluated by applying the methodology of biological evolution [40][41]. Various approaches based upon genetic algorithms have been used for multilevel medical image segmentation [42]. Comparison of the MCE & MWOA approach with the other three algorithms is conducted to check the efficiency of the MCE & MWOA approach in case of segmentation of image. In this paper, the whole CT scan image of the abdomen of a human is used. Although many algorithms have been developed till now for various medical images, there is still a need for better optimization algorithm for liver cyst detection. The purpose of the proposed approach is to segment the liver image i.e. left side of the abdominal image. To get some useful information from the CT Liver image, the proposed approach segments the CT Liver image. The next section illustrates the minimum cross entropy technique. Cross entropy is minimized to produce reliable results. Thereafter the various steps of the proposed approach (MCE & MWOA) and performance metrics are explored in detail. In the last section, the description of the experimental setup and the outcomes from all approaches, including the resulting segmentation images and their fitness evaluation, the performance measure values in tabular form, and their graphical depiction.

OBJECTIVE FUNCTION

Let FN(x, y) is a digital image function with size m*n where $FN(x, y) \in \{0,1,2,3\ldots\ldots.,u,\ldots..Imax\}$ is a value of the pixel having gray level value with coordinate position (x, y) and $x\{1,2,3\ldots\ldots m\}$ and $y \in \{1,2,3,\ldots..,n\}$, Imax+1 be the gray levels of an image having a range from 0 to Imax. Let the frequency of occurrence of u gray level value in a digital image denoted by h_u and $p_u=h_u/(m*n)$ is the possibility of occurrence of gray level u in the image [43].

Cross entropy is defined as a measure of closeness between two sampling distributions. Assume that $W=\{w_1, w_2, w_3,\ldots\ldots\ldots,w_n\}$ and $Z=\{z_1,z_2,z_3,\ldots\ldots\ldots,z_n\}$ are two probability distributions that are defined for the equal set of values. The Cross Entropy between these two is defined as [43][44].

$$ET_c(W,Z)=\sum_{i=1}^{n} w_i \log\frac{w_i}{z_i} \quad (1)$$

To calculate cross entropy, firstly select the level of image segmentation which depends upon the number of threshold values. The threshold value $T1 \in [0, Imax]$, (Imax=maximum value of gray level), is selected in case of bi-level image segmentation which segments the image into two regions. These are: Background (BG) and Target (TG). Let segmented image gT1 (x, y), FN(x, y) is an original image, L is a segmented region, following is the description of each pixel that either pixel (x, y) belongs to BG or belongs to TG regions

$$gT1(x, y)=\left[L\left(0, T1\right) \qquad FN(x, y) =< T1\right]$$
$$gT1(x, y)=\left[L\left(T1+1, Imax\right) \qquad FN(x, y)>T1\right] \quad (2)$$

where $L(A,B)=\frac{\sum_{u=A}^{B} up_u}{\sum_{u=A}^{B} p_u}$

A=minimum gray level value;

B=maximum gray level value;

For Background region up_u, where u = 0, 1, 2, 3,.., T1, is a probability distribution that belongs to the background region of the input image. L (0, T1) p_u, where u= 0, 1, 2, 3…, T1, is the distribution of probability of gray level values of background region (BG). Cross entropy of BG region of an input image is described as

$$ET_{c,BG}(T1)=\sum_{u=0}^{T1} up_u \log\frac{up_u}{L(0,T1)p_u} \quad (3)$$

For target region up_u, where u = T1 + 1, T1 + 2,… Imax , is a probability distribution belonging to the target region of the input image region . L (T1 + 1, Imax) p_u, where u = T1 + 1, T1 + 2,...., Imax is a probability distribution of the gray level values of the TG region. Cross entropy of TG region of an input image is described as

$$ET_{c,TG}(T1)=\sum_{u=T1+1}^{u=Imax} up_u \log\frac{up_u}{L(T1+1,Imax)p_u}$$

(4)

Total Cross Entropy by combining the equations (3) and (4)

$$ET_c(T1)= ET_{c,BG}(T1)+ ET_{c,TG}(T1) \quad (5)$$

$$ET_c(T1)=\sum_{u=0}^{T1} up_u \log\frac{up_u}{L(0,T1)p_u}+\sum_{u=T1+1}^{Imax} up_u \log\frac{up_u}{L(T1+1,Imax)p_u} \quad (6)$$

$$ET_c(T1)=\sum_{u=0}^{T1} up_u \log\frac{u}{L(0,T1)}+\sum_{u=T1+1}^{Imax} up_u \log\frac{u}{L(T1+1,Imax)} \quad (7)$$

$$ET_c(T1)=\sum_{u=0}^{T1} up_u \log u-\sum_{u=0}^{T1} up_u \log\left[L(0,T1)\right]+\sum_{u=T1+1}^{Imax} up_u \log u-\sum_{u=T1+1}^{Imax} up_u \log\left[L(T1+1,Imax)\right]$$

(8)

$$ET_c(T1)=\sum_{u=0}^{Imax} up_u \log u-\sum_{u=0}^{T1} up_u \log\left[L(0,T1)\right]-\sum_{u=T1+1}^{Imax} up_u \log\left[L(T1+1,Imax)\right] \quad (9)$$

The main aim of segmentation is to find minimum variance among original image and segmented image. Select the optimal number of thresholds which minimizes the total cross entropy.

$$T1=\arg\min_{T1}^{Imax}[ET_c(T1)] \tag{10}$$

Where $\sum_{u=0}^{Imax} up_u \log u$ is a constant term in an equation (9).

After the knowledge of constant term Objective function is

$$Obj(T1)=-\sum_{u=0}^{T1} up_u \log[L(0,T1)]-\sum_{u=T1+1}^{Imax} up_u \log[L(T1+1,Imax)] \tag{11}$$

$$Obj(T1)=-\sum_{u=0}^{T1} up_u \log\left[\frac{\sum_{u=0}^{T1} up_u}{\sum_{u=0}^{T1} p_u}\right]-\sum_{u=T1+1}^{Imax} up_u \log\left[\frac{\sum_{u=T1+1}^{Imax} up_u}{\sum_{u=T1+1}^{Imax} p_u}\right] \tag{12}$$

$$K^0(A,B)=\sum_{u=A}^{B} p_u \text{ and } K^1(A,B)=\sum_{u=A}^{B} up_u \tag{13}$$

By putting these values equation (9) become

$$Obj(T1)=-K^1(0,T1)\log[\frac{(K^1(0,T1))}{(K^0(0,T1)}]-K^1(T1+1,Imax)\log[\frac{(K^1(T1+1,Imax))}{(K^0(T1+1,Imax))}]$$

(14)

Equation (14) uses the above mentioned function for bi-level image segmentation[44].

For n-level image segmentation

$$Obj(T1,T2,\ldots.T(n-1))=-\sum_{j=1}^{n} K^1(T(j-1),T(j))\log\left[\frac{K^1(T(j-1),T(j))}{K^0(T(j-1),T(j))}\right] \tag{15}$$

PROPOSED APPROACH MCE & MWOA

The proposed approach is based upon the WOA algorithm. The proposed strategy was influenced by a metaheuristic whale optimization method. Basically Whale optimization algorithm is based upon whale hunting method. Exploration and exploitation process is applied in respective methods; two methods are applied - one is encircling prey and the second is spiral updating position. Both methods have 0.5% probabilities each. In this, a complete process of WOA algorithm [45] is used except the last step where any whale search agent goes beyond the boundary then amends that whale search agent in whale population. The starting step of the proposed approach is to select the size of the population in which a random population is generated. A number of decision variables (d) are also decided before the calculation of the fitness value of each agent or whale. Choose a maximum number of iterations for the whale optimization algorithm. After that apply the minimum cross entropy objective function as discussed in section 2 for computing the best fitness value and also the best location for the whale. Then update the values of different parameters used in the WOA algorithm so that a new location of a whale is generated. Then find out the fitness of the updated whale search agent and the process will continue till it gives good results. Using the best fitness value, two threshold values are selected. Constraints of the proposed approach are given below

- $0 \leq T1, T2 \leq Imax$. {T1,T2 are the two threshold values, Imax=255}
- $0 \leq T1 \leq T2 \leq Imax$.

These two threshold values segment the CT liver image into different parts. This is followed by post processing to find the final binary image. The whole process is given below:

Table 1: Algorithm for MCE & MWOA

1	Generate a random whale population (pop) and select the whale population's initial size (popsize) Decision variable (d), and iterations (it). Where i=1,2,3,...,n, pop(i)
2	Employing the minimum cross entropy approach as the objective function. (each whale's fitness value) $Obj(T1,T2,\ldots T(n-1)) = -\sum_{j=1}^{n} K^1(T(j-1),T(j)) \log\left[\frac{K^1(T(j-1),T(j))}{K^0(T(j-1),T(j))}\right]$
3	Choose the whale's best location start clock While condition (it< maximum iteration) For each whale Update the parameter values $\vec{At}$, $\vec{CV}$, l, and p using the following equations. $\vec{At} = 2*a'*r-a'$ $\vec{CV} = 2*a'$ $a'=2$ to 0 r=rand[0,1], l=rand[-1,1], p(probability) Ifcondition1 (p < 0.5) If condition2 (abs ($\vec{At}$) < 1) updating the location of the current whale using equations (16 & 17) $\vec{X'}(t+1)=\vec{X'new}(t)-\vec{At}*\vec{Dist}$ (16) $\vec{Dist}=\lvert\vec{CV}*\vec{X'new}(t)-\vec{X'}(t)\rvert$ (17) else ifcondition2 (abs ($\vec{At}$) >=1) Choose a random whale's location. Updating the location of the current whale using equations (18 & 19)

	$X'rand(t+1)=X'rand(t)-At*Dist''$ (18) Where $Dist''=\|CV*X'rand(t)-X'(t)\|$ (19) end of ifcondition2 else ifcondition1 (p>=0.5) Updating by using equation (20 & 21) the current whale location $X'(t+1)=Dist'*e^{b'l}*\cos(2\pi l)+X'new(t)$ (20) $Dist'=X'new(t)-X'(t)$ (21) end of ifcondition1 end for condition By using the minimum cross entropy approach as the objective function, determine each whale's fitness. If better results found then update whale Increment the iteration by 1 end of while condition end clock
4	Choose two threshold values using the best cost.
5	Using the selected threshold values, segment the image.
6	To achieve better results, post processing is used to the segmented image.
7	Convert resultant image into Binary image.
8	Exit

PERFORMANCE MEASURES

In this paper, various performance measures are used to test the efficiency of the proposed method. The details of each performance measure are given below.

1. Uniformity

A value between 0 and 1 represents uniformity. It determines an image’s quality. Good image quality can be inferred from a high value for uniformity. Below is the formula for the uniformity measure.

$$U=1-2*c*\frac{\sum_{j=0}^{c}\sum_{i\in R_j}\left(f_i-u_i\right)^2}{N*\left(f_{max}-f_{min}\right)^2} \quad (22)$$

where N and c represents number of pixels and thresholds, respectively, R_j indicates the segmented region for j pixels, f_i shows each pixel level in that segment, i represents mean of all the gray level values of those pixels, f_{min} and f_{max} least and highest grey levels in image, respectively[46].

2. Structure similarity index (SSIM)

The similarity between the source image and the segmented image is determined by the structured similarity index. Each block in the image is partitioned into an even m number of blocks. More efficiency is achieved by a higher SSIM value.

$$SSIM=(2\mu_I\mu_{\bar{I}}+C1)(2\sigma_{I\bar{I}}+C2)/(\mu_I^2+\mu_{\bar{I}}^2-C1)(\sigma_I^2+\sigma_{\bar{I}}^2-C2) \quad (23)$$

Table 2: Variable description of equation (23)

	Source image	Segmented image
Mean value	μ_I	$\mu_{\bar{I}}$
Standard deviation	σ_I	$\sigma_{\bar{I}}$
Cross correlation	$\sigma_{I\bar{I}}$	
Constants	C1,C2 [47]	

3. Peak Signal-to-Noise Ratio (PSNR)

Using PSNR as a measure, one can also evaluate an image's quality. As the PSNR value rises, image quality improves.

$$PSNR=10*\log\left(\frac{255^2}{MSE}\right)(dB) \quad (24)$$

Using the following equation, Mean Square Error (MSE), is calculated.

$$MSE=\frac{1}{P*Q}\sum_i^P\sum_j^Q\{w(i,j)-\bar{w}(i,j)\}^2 \quad (25)$$

Where $w(i,j)$ and $\bar{w}(i,j)$ represents segmented image and the source image, respectively. Number of pixel in a source image are represented by P*Q [47].

Root mean square error (RMSE): RMSE value is evaluated from the MSE value. The square root of MSE provides the RMSE value [36].

$$RMSE=\sqrt{\sum_i^P\sum_j^Q\left\{w(i,j)-\left(\bar{w}(i,j)\right)\right\}^2/P*Q} \quad (26)$$

4. Rand Index

Assume that the S_1 and G are two segmentations, S_1 is a test and G is ground truth segmentation [48]. For evaluation of the Rand Index (RI) between these two segmentations equation (27) is used.

$$RI=\frac{a+b}{a+b+c+d}=\frac{\left[\left(\frac{n}{2}\right)\left[0.5\left\{\Sigma_i\left(\Sigma_i n_{ij}\right)^2+\Sigma_j\left(\Sigma_i n_{ij}\right)\right\}^2-\Sigma\Sigma n_{ij}^2\right]\right]}{\left(\frac{n}{2}\right)} \quad (27)$$

Table 3: Equation (27) Variables description

Number of pairs of elements in S_1	a	b	c	d
Belong to Same set in S_1	U,V	-	U	V
Belongs to Different set in S_1	-	U,V	V	U

Number of objects defined by n which belongs to i and j cluster in U and V set respectively. Binomial coefficient is defined by n/2 [49] .

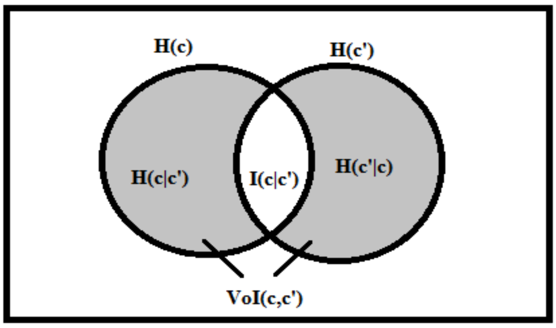
5. Execution time

The execution time is also used as the performance metric to assess the efficiency of the proposed methodology. It is a time complexity that measures the time it takes for a program to run in seconds. Efficient algorithm is one which takes less time to compute anything.

6. Variation of Information

Lowering the value of variation of information increases the performance of the image. Another performance parameter used in this paper is Variation of Information (VoI). It measures the amount of randomness in segmentation. Figure 1 depicts the graphical representation of VoI and its related quantities.

Figure 1: The variation of information and related quantities



$$VoI(c,c')=H(c)+H(c')-2I(c,c') \quad (28)$$

Where $H(c)$, $H(c')$ and $I(c,c')$ are the cluster c entropies and mutual information I [49].

EXPERIMENTAL SETUP AND RESULTS ANALYSIS

The specifications of experimental setup used for the implementation of the proposed approach are mentioned below

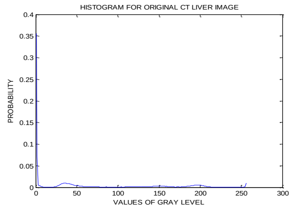
- Operating System: Windows 7, 64 bit.
- Software for implementation : MATLAB R2013a
- Processor : Intel Core (TM) i3 CPU
- RAM : 3.00 GB
- Images for testing: Thirty computer tomography scanned (CT) images of the whole abdominal.
- Format of images: Joint photographic experts group (jpeg) and portable network graphics (png).
- Number of Images = 15.
- Population size=10 and maximum number of iterations=100.
- Decision variables = 2, used to select two threshold values to segment the whole image.

The details of the experimental findings are covered in this section. The obtained results of the proposed method are compared with the well-known optimization methods Teaching-learning-algorithm, Jaya algorithm and Genetic algorithm. This comparison is being done to analyze the efficiency and visual quality of the proposed method. The key objective of this paper is to segment the image of the entire abdomen, which will assist doctors to diagnose liver cysts. Red color arrow indicates the liver cyst (refer to figure 2 (a)-(c)[50][51]) in each image. Figure 3(a)-5(a) shows the original CT images of the liver and their histograms are represented in Figure 3(b)-5(b). The segmentation results obtained by the proposed method using multilevel thresholding are shown in Figure 3(c)-5(c) and also their fitness evaluation are depicted in figure 3(d)-5(d). The segmented results obtained by TLBO based method and their fitness evaluations are shown in figure 3(e)-5(e) and figure 3(f)-5(f) respectively. Figure 3(g)-5(g) show the segmentation result obtained by Jaya Algorithm and figure 3(h)-5(h) depicts their fitness evaluation. The segmentation results and fitness evaluation of the Genetic algorithm are shown in Figure 3(i)-5(i) and Figure 3(j)-5(j) respectively. In all segmented images, the proposed approach gives better and accurate visual quality compared to other three methods. The cyst portion indicated by red arrows in Figure 2(a)-(c) is clearly highlighted in each segmented image obtained by the MCE & WOA algorithm.

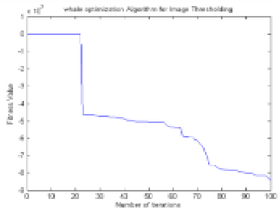
Figure 2(a)-(c): Original liver CT scan images. The hepatic cyst is indicated by the red arrow.

Figure 3(a): Original CT Image of Liver. (b) Histogram plot of original image. (c) Fitness evaluation using proposed algorithm. (d) Segmented resultant image using proposed algorithm. (e) Fitness evaluation using multilevel thresholding based on TLBO algorithm. (f) Segmented resultant image using multilevel thresholding based on TLBO algorithm. (g) Fitness evaluation using Jaya algorithm. (h) Segmented resultant image using Jaya algorithm. (i) Fitness evaluation using Genetic algorithm. (j) Segmented resultant image using Genetic algorithm.

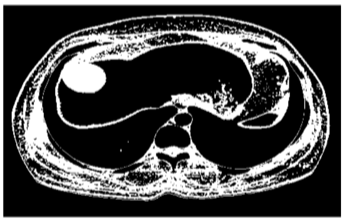
(a) [52]



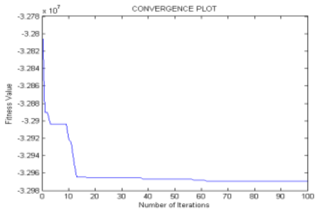
(b)



(c)

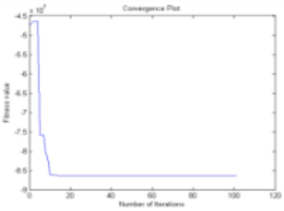


(d)



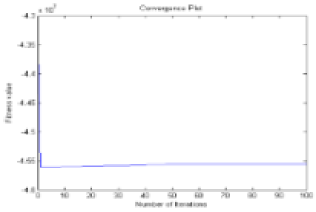
(e)

(f)

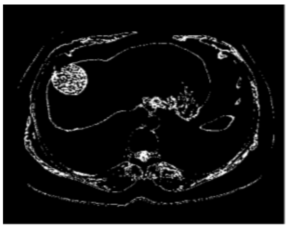


(g)

(h)



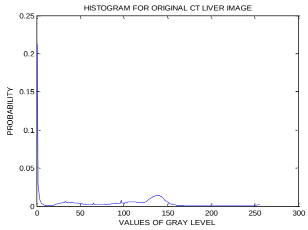
(i)



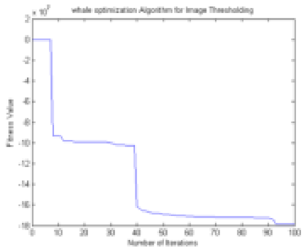
(j)

Figure 4 (a): Original CT Image of Liver. (b) Histogram plot of original image. (c) Fitness evaluation using proposed algorithm. (d) Segmented resultant image using proposed algorithm. (e) Fitness evaluation using multilevel thresholding based on TLBO algorithm. (f) Segmented resultant image using multilevel thresholding based on TLBO algorithm. (g) Fitness evaluation using Jaya algorithm. (h) Segmented resultant image using Jaya algorithm. (i) Fitness evaluation using Genetic algorithm. (j) Segmented resultant image using Genetic algorithm.

(a) [53]

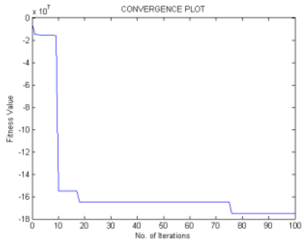


(b)

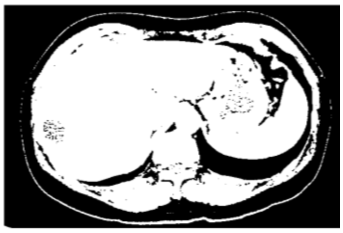


(c)

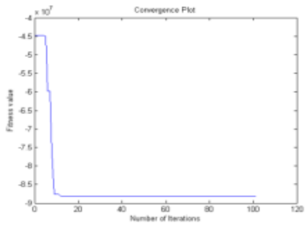
(d)



(e)

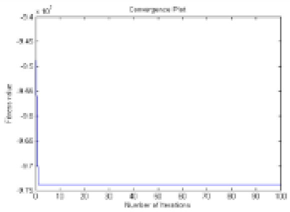


(f)



(g)

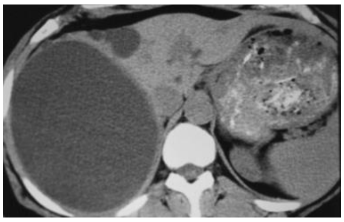
(h)



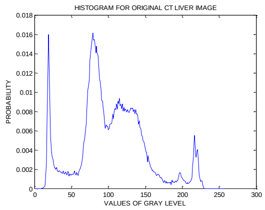
(i)

(j)

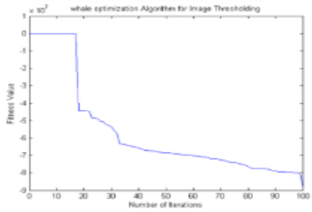
Figure 5 (a): Original CT Image of Liver. (b) Histogram plot of original image. (c) Fitness evaluation using proposed algorithm. (d) Segmented resultant image using proposed algorithm. (e)) Fitness evaluation using multilevel thresholding based on TLBO algorithm. (f) Segmented resultant image using multilevel thresholding based on TLBO algorithm. (g) Fitness evaluation using Jaya algorithm. (h) Segmented resultant image using Jaya algorithm. (i) Fitness evaluation using Genetic algorithm. (j) Segmented resultant image using Genetic algorithm.



(a)[54]

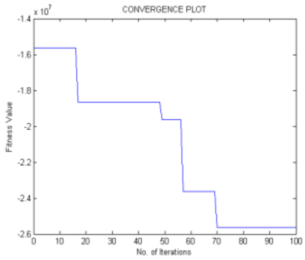


(b)



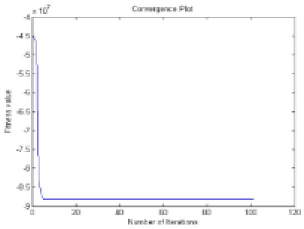
(c)

(d)



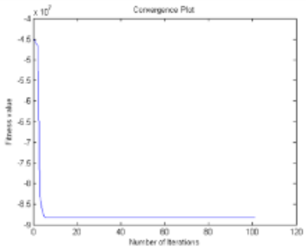
(e)

(f)



(g)

(h)



(i)

(j)

In addition to visual quality results, a comparison is also made with the help of different performance measures like Uniformity (U), Root mean Square error (RMSE), Structured Similarity Index (SSIM), Peak signal to noise ratio (PSNR), Execution time, Rand Index (RI) and Variation of Information (VoI). Table 4 shows the threshold values computed by the proposed method and other three algorithms. The bold values in Table 5-11 indicate that the proposed technique gives better results than other algorithms. Table 5 describes the values of uniformity measure (by all methods) between an original image and a resultant image. Higher the value of uniformity, higher is the performance of a particular segmentation method. In maximum cases, the proposed approach provides higher values of uniformity than the other algorithms. The number of cases is given in Table 6 which contains the minimum value of RMSE by the proposed method. A minimum value of RMSE describes the efficiency of a particular algorithm. Table 7 shows that the SSIM value of the proposed approach is better in most cases than other methods. The high value of PSNR shown in Table 8 indicates that the proposed approach performs well. Execution time is observed less to compute the threshold values by the proposed method, and is shown in Table 9. This shows that the proposed method is much more efficient than the other methods. Table 10 depicts that the Rand Index (RI) [49] values obtained by the proposed approach is higher in all cases which indicates the superior performance of the current approach. For better performance of segmentation results, VoI value should be minimum and the outperformance in terms of minimum value by the proposed method can be seen from Table 11. Illustration of the values of each performance measure is shown in Figure 6-12. From the above result analysis, it is concluded that the proposed method is observed to be more accurate and efficient for image segmentation than the TLBO method, Jaya Algorithm and Genetic Algorithm.

Table 4: Values of Threshold obtained from different methods.

Image no.	**Proposed method**	**TLBO based method**	**Jaya Algorithm**	**GA Algorithm**
1	28,104	26,159	26,155	110,242
2	44,151	14,92	23,255	93,163
3	44,151	10,93	17,255	118,140
4	62,114	10,79	19,243	107,210
5	39,119	49,114	16,255	36,91
6	62,114	10,79	29,236	76,79
7	40,137	28,140	20,223	132,166
8	44,110	18,107	20,212	190,243
9	40,74	18,103	30,255	140,222
10	39,119	10,112	26,255	165,205
11	86,167	15,105	15,104	95,186
12	62,114	7,65	18,255	66,134
13	98,131	53,119	29,234	46,195
14	83,137	61,149	16,240	141,184
15	71,178	32,127	8,255	96,106

Table 5: Values of Uniformity obtained from different methods.

Image no.	**Proposed method**	**TLBO based method**	**Jaya Algorithm**	**GA Algorithm**
1	0.9505	**0.9710**	0.9708	0.9377
2	**0.9763**	0.9728	0.9414	0.9737

3	**0.9674**	0.9666	0.8340	0.9474
4	**0.9703**	0.9656	0.9197	0.9449
5	0.9582	**0.9593**	0.8381	0.9450
6	**0.9675**	0.9552	0.8486	0.9376
7	**0.9722**	0.9693	0.9204	0.8739
8	**0.9571**	0.9529	0.8970	0.7925
9	0.9255	**0.9467**	0.8424	0.8999
10	**0.9422**	0.9407	0.6970	0.9129
11	**0.9815**	0.9684	0.9682	0.9762
12	**0.9720**	09586	0.8966	0.9703
13	**0.9758**	0.9503	0.8961	0.9504
14	**0.9701**	0.9431	0.9283	0.8969
15	0.9530	**0.9755**	0.9262	0.9299

Table 6: Values of RMSE obtained from different methods.

Image no.	**Proposed method**	**TLBO based method**	**Jaya Algorithm**	**GA Algorithm**
1	**95.15**	**95.15**	95.16	95.48
2	95.48	**95.22**	95.43	95.40
3	**97.25**	97.93	97.81	98.29
4	**99.20**	99.30	99.21	99.80
5	111.58	111.66	**111.12**	111.78
6	**82.12**	83.26	82.78	82.86
7	**105**	105.75	105.36	105.84
8	**119.12**	119.80	119.13	119.23
9	**112.03**	112.90	112.31	112.74
10	**143**	143.25	143.58	143.07
11	**111.56**	111.57	111.57	111.85
12	**78.02**	**78.02**	77.96	78.30
13	124.72	124.71	**124.70**	124.71
14	**114.19**	114.21	114.24	114.20

15	**99.45**	99.47	99.56	99.78

Table 7: Values of SSIM obtained from different methods.

Image no.	Proposed method	TLBO based method	Jaya Algorithm	GA Algorithm
1	**0.9786**	0.9751	0.9751	0.9223
2	0.9836	**0.9918**	0.9866	0.9887
3	0.9787	**0.9951**	0.9719	0.9819
4	0.9773	**0.9837**	0.9661	0.9275
5	0.9577	0.9593	0.9513	**0.9608**
6	**0.9802**	0.9667	0.9643	0.9891
7	**0.9805**	0.9798	0.9839	0.9241
8	**0.9682**	0.9651	0.9736	0.9450
9	**0.9672**	0.9540	0.9648	0.9289
10	**0.9321**	0.9278	0.9600	0.9325
11	0.9784	**0.9946**	**0.9946**	0.9825
12	0.9871	**0.9917**	0.9790	0.9868
13	0.9686	**0.9886**	0.9558	0.9280
14	0.9396	**0.9844**	0.9610	0.9493
15	0.9380	**0.9608**	0.9420	0.9315

Table 8: Values of PSNR obtained from different methods.

Image no.	Proposed method	TLBO based method	Jaya Algorithm	GA Algorithm
1	**8.5626**	**8.5626**	8.5617	8.5325
2	8.5325	**8.5562**	8.5371	8.5398
3	**8.3730**	8.3125	8.3231	8.2806
4	**8.2005**	8.1918	8.1996	8.1481
5	**7.1790**	7.1728	7.2149	7.1635
6	**9.8418**	9.7220	9.7720	9.7639
7	**7.7070**	7.6451	7.6772	7.6378
8	**6.6111**	6.5616	6.6103	6.6030
9	**7.1441**	7.0769	7.1224	7.0892

10	**5.0240**	5.0087	4.9889	5.0198
11	**7.1806**	7.1798	7.1798	7.1580
12	10.2866	10.2866	**10.2933**	10.2555
13	6.2120	6.2127	**6.2134**	6.2127
14	**6.9782**	6.9767	6.9744	6.9774
15	**8.1787**	8.1769	8.1691	8.1499

Table 9: Values of Execution time obtained from different methods

Image no.	Proposed method	TLBO based method	Jaya Algorithm	GA Algorithm
1	**0.0128**	1.0063	1.7835	0.0197
2	**0.0299**	4.7283	2.8434	0.0385
3	**0.0264**	3.3607	4.4609	0.0270
4	**0.0314**	1.8742	1.7189	0.0320
5	**0.0269**	1.7153	1.1953	0.0743
6	**0.0768**	7.4831	8.1901	0.0769
7	**0.0188**	0.3939	0.8288	0.0221
8	**0.0121**	1.3131	1.0256	0.0195
9	**0.0247**	1.7641	3.4689	0.0288
10	**0.0330**	7.0065	1.5749	0.0389
11	**0.0311**	4.4523	6.4348	0.0316
12	**0.0507**	8.7567	2.7227	0.0659
13	**0.0167**	6.9895	1.0963	0.0453
14	**0.0178**	1.9689	2.6088	0.0181
15	**0.0188**	1.8443	6.0740	0.0313

Table 10: Values of RI obtained from different methods.

Image no.	Proposed method	TLBO based method	Jaya based Algorithm	GA Algorithm
1	**0.6544**	0.5000	0.5000	0.5807
2	**0.6022**	0.5336	0.5062	0.5857
3	**0.6692**	0.5909	0.5028	0.9002
4	**0.7005**	0.5013	0.5816	0.5143

5	**0.5082**	0.5001	0.5061	0.5022
6	**0.6195**	0.5424	0.5229	0.5424
7	0.5949	0.5736	0.5014	**0.6184**
8	**0.6531**	0.6258	0.6336	0.6442
9	**0.7521**	0.5422	0.6394	0.6039
10	0.5096	0.5043	0.5014	**0.5572**
11	**0.6940**	0.5262	0.5257	0.6218
12	**0.7934**	0.5944	0.5092	0.7200
13	**0.8997**	0.5077	0.5523	0.5138
14	0.5056	0.5027	0.5012	**0.6076**
15	**0.5189**	0.5009	0.5029	0.5178

Table 11: Values of Variation of Information (VoI) obtained from different methods

Image no.	Proposed method	TLBO based method	Jaya Algorithm	GA Algorithm
1	**0.8778**	1.1308	1.1308	1.0049
2	**0.8814**	0.9865	1.0270	0.9072
3	0.7954	0.9236	1.0578	**0.3345**
4	**0.7014**	1.0133	0.7020	0.9945
5	**0.9882**	0.9999	0.0845	**0.9882**
6	**0.8453**	0.9642	0.9931	0.9642
7	**0.9220**	0.9555	1.0651	0.9847
8	**0.8542**	0.9002	0.8871	0.8636
9	**0.6284**	0.9742	0.8224	0.8793
10	**0.9907**	0.9984	0.9999	0.9993
11	**0.7473**	1.0166	1.0173	0.8680
12	**0.5486**	0.8920	1.0208	0.6841
13	**0.2988**	0.9888	0.9282	0.9799
14	**0.8369**	0.9867	0.8503	0.8435
15	**1.0219**	1.0485	1.0714	1.0287

Figure 6: Illustration of Uniformity values obtained from different methods

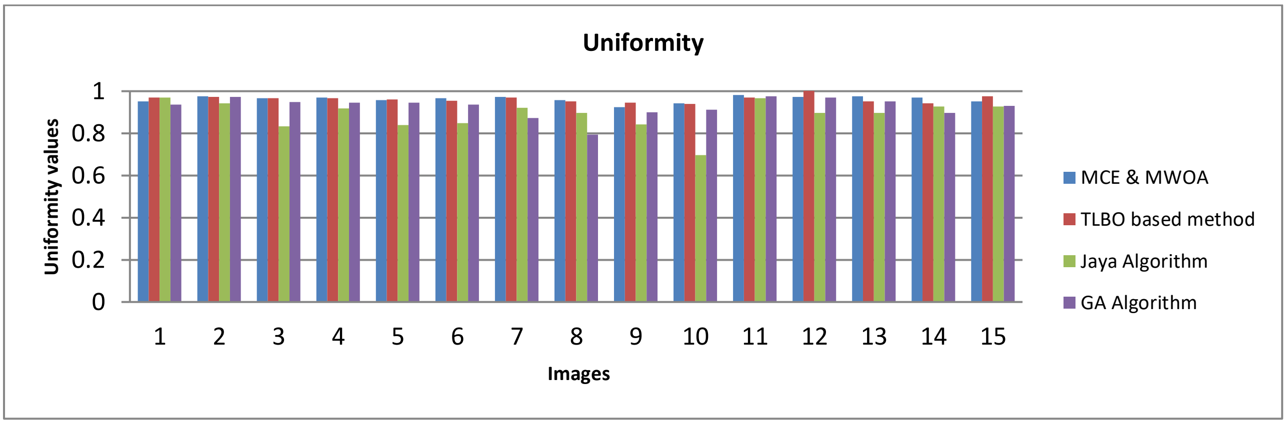


Figure 7: Illustration of Root mean square error values obtained from different methods

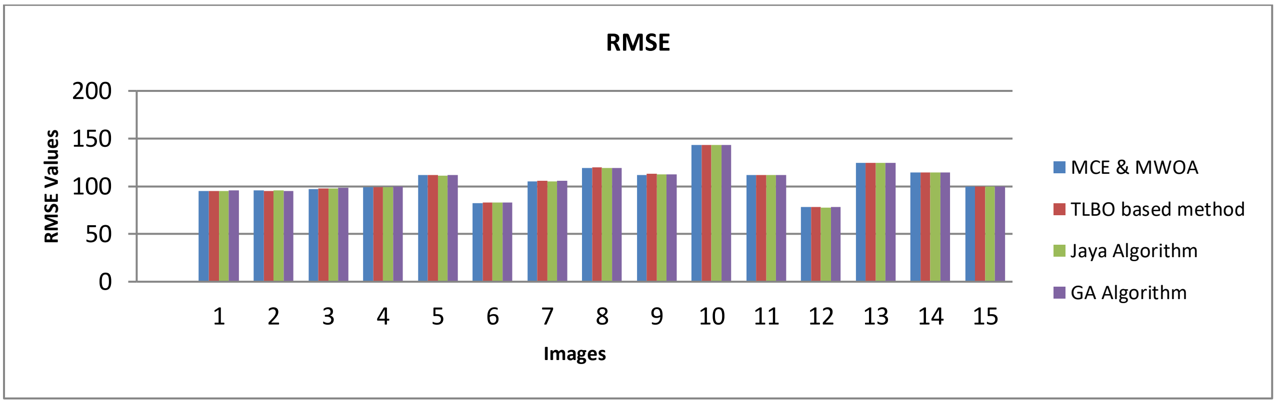


Figure 8: Illustration of Structured Similarity Index (SSIM) values obtained from different methods

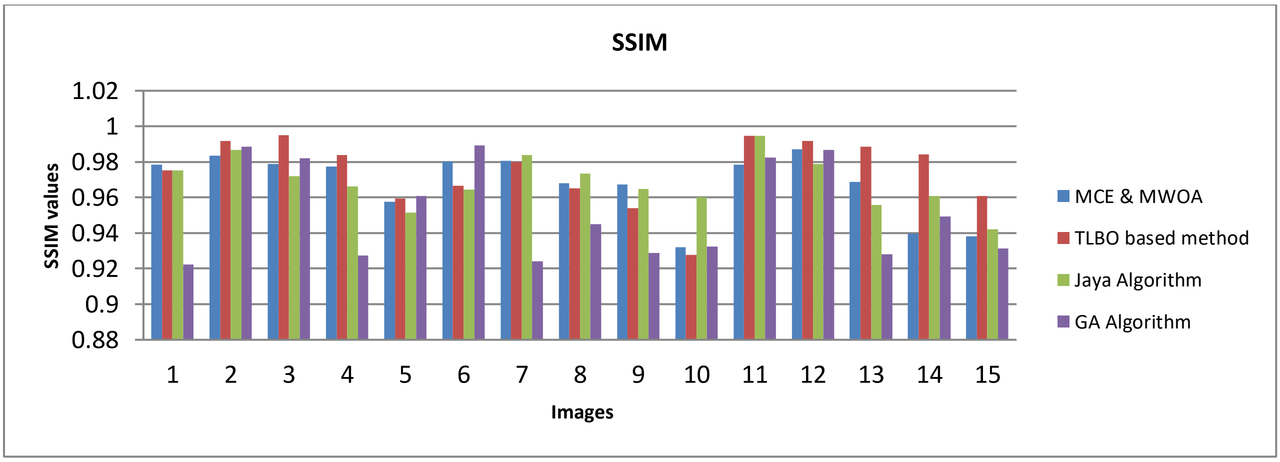


Figure 9: Illustration of PSNR values obtained from different methods

Figure 10: Illustration of execution time values obtained from different methods

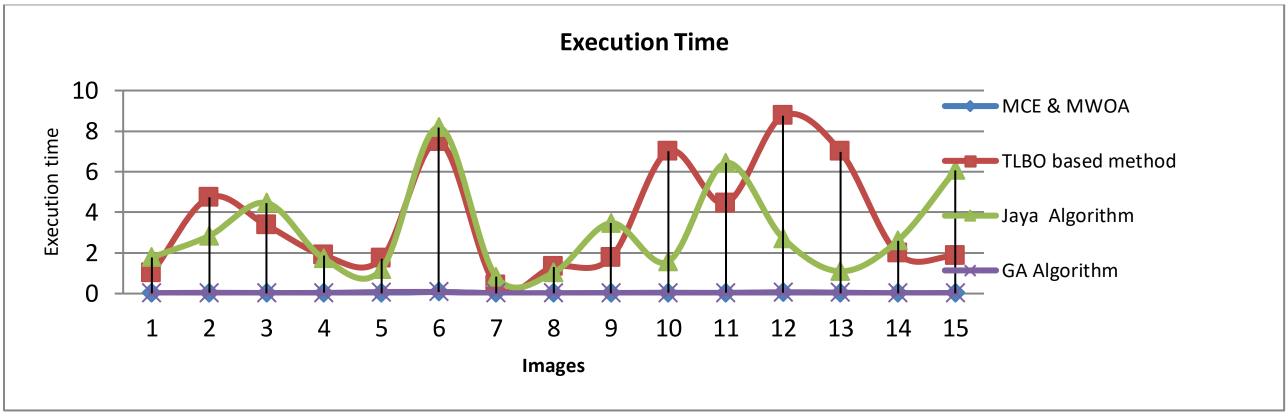


Figure 11: Illustration of Rand Index (RI) values obtained from different methods.

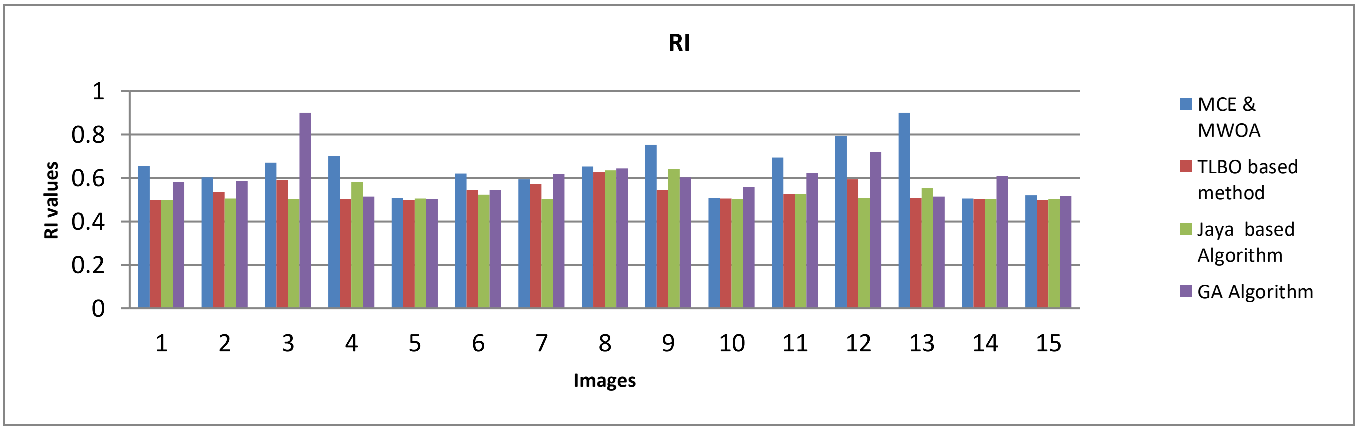
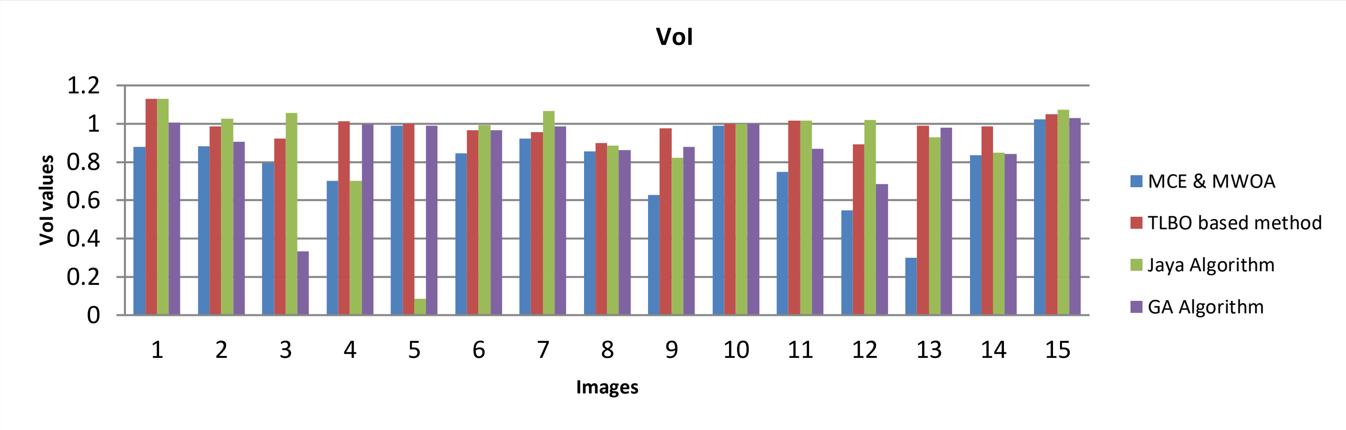


Figure 12: Illustration of Variation of information (VoI) values obtained from different methods.



CONCLUSIONS AND FUTURE SCOPE

In this study, the accurate segmentation of CT scan liver pictures is accomplished using a modified whale optimization and minimum cross entropy. For this, 15 liver CT scan images are segmented using the proposed method. Three optimized algorithms—TLBO, Jaya, and Genetic Algorithm (GA)—used for diverse disease diagnosis purposes are compared to the outcomes of the proposed approach. The proposed approach segments the CT scan liver image quite accurately when compared to the other three optimization algorithms, as shown by all of the segmented images that were produced in terms of visual quality. The resultant images will be highly useful for doctors to diagnose liver cyst disease. In the maximum cases, the proposed method yielded higher values of the structure Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Rand Index (RI), and uniformity measures than the TLBO algorithm, Jaya algorithm and Genetic algorithm. It is also noticed that the proposed approach provides minimum values of Root Mean Square Error (RMS Error), Variation of Information (VoI) measurement and takes less computational time, which shows that the proposed method outperforms than the other three algorithms. The aforementioned experimental findings show that the proposed methodology is quite accurate and effective for segmentation purposes. It can be tested in future with other algorithms like an artificial neural network and other metaheuristic algorithms for the segmentation process.

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REFERENCES

[1] "Liver Cysts - Symptoms, Causes, and Treatment." https://liverfoundation.org/for-patients/about-the-liver/diseases-of-the-liver/liver-cysts/#information-for-the-newly-diagnosed (accessed Jul. 08, 2020).

[2] R. V. Manjunath and K. Kwadiki, "Automatic liver and tumour segmentation from CT images using Deep learning algorithm," *Results Control Optim.*, vol. 6, no. December 2021, p. 100087, 2022, doi: 10.1016/j.rico.2021.100087.

[3] M. G. Mavilia, T. Pakala, M. Molina, and G. Y. Wu, "Differentiating Cystic Liver Lesions: A Review of Imaging Modalities, Diagnosis and Management," *J. Clin. Transl. Hepatol.*, vol. 6, no. 2, pp. 1–9, 2018, doi: 10.14218/jcth.2017.00069.

[4] H. Das, B. Naik, and H. S. Behera, "Medical disease analysis using Neuro-Fuzzy with Feature Extraction Model for classification," *Informatics Med. Unlocked*, vol. 18, p. 100288, 2020, doi: 10.1016/j.imu.2019.100288.

[5] H. Abdellahoum, N. Mokhtari, A. Brahimi, and A. Boukra, "CSFCM: An improved fuzzy C-Means image segmentation algorithm using a cooperative approach," *Expert Syst. Appl.*, vol. 166, p. 114063, 2021, doi: 10.1016/j.eswa.2020.114063.

[6] S. K. Choy, T. C. Ng, and C. Yu, “Unsupervised fuzzy model-based image segmentation,” *Signal Processing*, vol. 171, p. 107483, 2020, doi: 10.1016/j.sigpro.2020.107483.

[7] K. Huang, Y. Zhang, H. D. Cheng, and P. Xing, “MSF-GAN: Multi-Scale Fuzzy Generative Adversarial Network for Breast Ultrasound Image Segmentation,” *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Int. Conf.*, vol. 2021, pp. 3193–3196, Nov. 2021, doi: 10.1109/EMBC46164.2021.9630108.

[8] B. S. Khehra and A. S. Pharwaha, “Image Segmentation Using Teaching-Learning-Based Optimization Algorithm and Fuzzy Entropy,” in *Proceedings - 15th International Conference on Computational Science and Its Applications, ICCSA 2015*, Jul. 2015, pp. 67–71. doi: 10.1109/ICCSA.2015.10.

[9] R. V. Rao, V. J. Savsani, and D. P. Vakharia, “Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems,” *CAD Comput. Aided Des.*, vol. 43, no. 3, pp. 303–315, Mar. 2011, doi: 10.1016/j.cad.2010.12.015.

[10] X. S. Yang, “An idea based on honey bee swarm for numerical optimization.,” *Stud. Comput. Intell.*, vol. 585, pp. v–vi, 2014, doi: 10.1007/978-3-319-02141-6.

[11] X.-S. Yang, “Engineering Optimization: An Introduction with Metaheuristic Applications - Xin-She Yang - Google Books,” *John Wiley & Sons, Inc*, 2010.

[12] M. Zhang, W. Jiang, X. Zhou, Y. Xue, and S. Chen, “A hybrid biogeography-based optimization and fuzzy C-means algorithm for image segmentation,” *Soft Comput.*, vol. 23, no. 6, pp. 2033–2046, 2019, doi: 10.1007/s00500-017-2916-9.

[13] S. Thulasidass, D. V. Soundari, S. Chinnapparaj, and R. Naveen, “Liver tumor diagnosis by using hybrid watershed segmentation method,” *Mater. Today Proc.*, vol. 37, no. 2, pp. 2848–2857, 2020, doi: 10.1016/j.matpr.2020.08.660.

[14] A. M. Anter and A. E. Hassenian, “Computational intelligence optimization approach based on particle swarm optimizer and neutrosophic set for abdominal CT liver tumor segmentation,” *J. Comput. Sci.*, vol. 25, pp. 376–387, 2018, doi: 10.1016/j.jocs.2018.01.003.

[15] R. M. Devi and V. Seenivasagam, “Automatic segmentation and classification of liver tumor from CT image using feature difference and SVM based classifier-soft computing technique,” *Soft Comput.*, vol. 1, 2020, doi: 10.1007/s00500-020-05094-1.

[16] J. Wu *et al.*, “Segmentation of liver tumors in multiphase computed tomography images using hybrid method,” *Comput. Electr. Eng.*, vol. 97, no. June 2021, p. 107626, 2022, doi: 10.1016/j.compeleceng.2021.107626.

[17] L. Xu, H. Jia, C. Lang, X. Peng, and K. Sun, “A Novel Method for Multilevel Color Image Segmentation Based on Dragonfly Algorithm and Differential Evolution,” *IEEE Access*, vol. 7, pp. 19502–19538, 2019, doi: 10.1109/ACCESS.2019.2896673.

[18] P. Upadhyay and J. K. Chhabra, “Kapur’s entropy based optimal multilevel image segmentation using Crow Search Algorithm,” *Appl. Soft Comput. J.*, vol. 97, p. 105522, 2019, doi: 10.1016/j.asoc.2019.105522.

[19] M. Tuba, N. Bacanin, and A. Alihodzic, “Multilevel image thresholding by fireworks algorithm,” *Proc. 25th Int. Conf. Radioelektronika, RADIOELEKTRONIKA 2015*, vol. 255, pp. 326–330, 2015, doi: 10.1109/RADIOELEK.2015.7129057.

[20] P. S. Rodrigues, G. A. Wachs-Lopes, H. R. Erdmann, M. P. Ribeiro, and G. A. Giraldi, “Improving a firefly meta-heuristic for multilevel image segmentation using Tsallis entropy,” *Pattern Anal. Appl.*, vol. 20, no. 1, 2017, doi: 10.1007/s10044-015-0450-x.

[21] H. Liang, H. Jia, Z. Xing, J. Ma, and X. Peng, “Modified grasshopper algorithm-based multilevel thresholding for color image segmentation,” *IEEE Access*, vol. 7, pp. 11258–11295, 2019, doi: 10.1109/ACCESS.2019.2891673.

[22] A. K. M. Khairuzzaman and S. Chaudhury, “Multilevel thresholding using grey wolf optimizer for image segmentation,” *Expert Syst. Appl.*, vol. 86, pp. 64–76, 2017, doi: 10.1016/j.eswa.2017.04.029.

[23] S. Liu, Z. Xiao, X. You, and R. Su, “Multistrategy boosted multicolony whale virtual parallel optimization approaches,” *Knowledge-Based Syst.*, vol. 242, p. 108341, Apr. 2022, doi: 10.1016/J.KNOSYS.2022.108341.

[24] D. Rammurthy and P. K. Mahesh, “Whale Harris hawks optimization based deep learning classifier for brain tumor detection using MRI images,” *J. King Saud Univ. - Comput. Inf. Sci.*, no. xxxx, 2020, doi: 10.1016/j.jksuci.2020.08.006.

[25] B. Yin, C. Wang, and F. Abza, “New brain tumor classification method based on an improved version of whale optimization algorithm,” *Biomed. Signal Process. Control*, vol. 56, p. 101728, 2020, doi: 10.1016/j.bspc.2019.101728.

[26] M. A. El Aziz, A. A. Ewees, A. E. Hassanien, M. Mudhsh, and S. Xiong, “Multi-objective whale optimization algorithm for multilevel thresholding segmentation,” *Stud. Comput. Intell.*, vol. 730, pp. 23–39, 2018, doi: 10.1007/978-3-319-63754-9_2.

[27] A. Gautam and M. Biswas, “Whale Optimization Algorithm Based Edge Detection for Noisy Image,” *Proc. 2nd Int. Conf. Intell. Comput. Control Syst. ICICCS 2018*, no. Iciccs, pp. 1878–1883, 2019, doi: 10.1109/ICCONS.2018.8663022.

[28] G. Hassan and A. E. Hassanien, “Retinal fundus vasculature multilevel segmentation using whale optimization algorithm,” *Signal, Image Video Process.*, vol. 12, no. 2, pp. 263–270, 2018, doi: 10.1007/s11760-017-1154-z.

[29] S. Iyer, A. P. Nadkarni, and T. N. Padmini, “Antlion optimization and Whale optimization Algorithm for multilevel thresholding segmentation,” *2019 Innov. Power Adv. Comput. Technol. i-PACT 2019*, no. 1, pp. 1–8, 2019, doi: 10.1109/i-PACT44901.2019.8960178.

[30] A. Mostafa, A. E. Hassanien, M. Houseni, and H. Hefny, “Liver segmentation in MRI images based on whale optimization algorithm,” *Multimed. Tools Appl.*, vol. 76, no. 23, pp. 24931–24954, 2017, doi: 10.1007/s11042-017-4638-5.

[31] A. Mukherjee, N. Chakraborty, and B. K. Das, “Whale optimization algorithm: An implementation to design low-pass FIR filter,” *2017 Innov. Power Adv. Comput. Technol. i-PACT 2017*, vol. 2017-Janua, no. 2, pp. 1–5, 2017, doi: 10.1109/IPACT.2017.8244929.

[32] S. Chakraborty, A. K. Saha, R. Chakraborty, and M. Saha, “An enhanced whale optimization algorithm for large scale optimization problems,” *Knowledge-Based Syst.*, vol. 233, p. 107543, Dec. 2021, doi: 10.1016/J.KNOSYS.2021.107543.

[33] R. Salgotra, U. Singh, and S. Saha, *On Some Improved Versions of Whale Optimization Algorithm*, vol. 44, no. 11. Springer Berlin Heidelberg, 2019. doi: 10.1007/s13369-019-04016-0.

[34] Z. Yan, J. Zhang, J. Zeng, and J. Tang, “Nature-inspired approach: An enhanced whale optimization algorithm for global optimization,” *Math. Comput. Simul.*, vol. 185, pp. 17–46, 2021, doi: 10.1016/j.matcom.2020.12.008.

[35] G. I. Sayed, A. Darwish, and A. E. Hassanien, “Binary Whale Optimization Algorithm and Binary Moth Flame Optimization with Clustering Algorithms for Clinical Breast Cancer Diagnoses,” *J. Classif.*, 2019, doi: 10.1007/s00357-018-9297-3.

[36] M. A. El Aziz, A. A. Ewees, and A. E. Hassanien, “Whale Optimization Algorithm and Moth-Flame Optimization for multilevel thresholding image segmentation,” *Expert Syst. Appl.*, vol. 83, pp. 242–256, 2017, doi: 10.1016/j.eswa.2017.04.023.

[37] A. Khosravanian, M. Rahmanimanesh, P. Keshavarzi, and S. Mozaffari, “Fast level set method for glioma brain tumor segmentation based on Superpixel fuzzy clustering and lattice Boltzmann method,” *Comput. Methods Programs Biomed.*, vol. 198, p. 105809, 2021, doi: 10.1016/j.cmpb.2020.105809.

[38] S. Singh, N. Mittal, and H. Singh, “A multilevel thresholding algorithm using LebTLBO for image segmentation,” *Neural Comput. Appl.*, vol. 32, no. 21, pp. 16681–16706, 2020, doi: 10.1007/s00521-020-04989-2.

[39] R. A. Zitar, M. A. Al-Betar, M. A. Awadallah, I. A. Doush, and K. Assaleh, “An Intensive and Comprehensive Overview of JAYA Algorithm, its Versions and Applications,” *Arch. Comput. Methods Eng.*, vol. 29, no. 2, pp. 763–792, 2022, doi: 10.1007/s11831-021-09585-8.

[40] G. Nagarajan, R. I. Minu, B. Muthukumar, V. Vedanarayanan, and S. D. Sundarsingh, “Hybrid Genetic Algorithm for Medical Image Feature Extraction and Selection,” *Procedia Comput. Sci.*, vol. 85, no. Cms, pp. 455–462, 2016, doi: 10.1016/j.procs.2016.05.192.

[41] N. B. Bahadure, A. K. Ray, and H. P. Thethi, “Comparative Approach of MRI-Based Brain Tumor Segmentation and Classification Using Genetic Algorithm,” *J. Digit. Imaging*, vol. 31, no. 4, pp. 477–489, 2018, doi: 10.1007/s10278-018-0050-6.

[42] I. Hilali-Jaghdam, A. Ben Ishak, S. Abdel-Khalek, and A. Jamal, “Quantum and classical genetic algorithms for multilevel segmentation of medical images: A comparative study,” *Comput. Commun.*, vol. 162, pp. 83–93, Oct. 2020, doi: 10.1016/J.COMCOM.2020.08.010.

[43] Solomom kullback, “Information theory and statistics,” *Dover Publication Inc.*, 1968. http://index-of.co.uk/Information-Theory/Information theory and statistics - Solomon Kullback.pdf (accessed Jul. 20, 2020).

[44] H. Singh Gill, B. Singh Khehra, A. Singh, and L. Kaur, “Teaching-learning-based optimization algorithm to minimize cross entropy for Selecting multilevel threshold values,” *Egypt. Informatics J.*, vol. 20, no. 1, pp. 11–25, 2019, doi: 10.1016/j.eij.2018.03.006.

[45] S. Mirjalili and A. Lewis, “The Whale Optimization Algorithm,” *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[46] K. Tang, X. Yuan, T. Sun, J. Yang, and S. Gao, “An improved scheme for minimum cross entropy threshold selection based on genetic algorithm,” *Knowledge-Based Syst.*, vol. 24, no. 8, pp. 1131–1138, 2011, doi: 10.1016/j.knosys.2011.02.013.

[47] M. S. R. Naidu, P. Rajesh Kumar, and K. Chiranjeevi, “Shannon and Fuzzy entropy based evolutionary image thresholding for image segmentation,” *Alexandria Eng. J.*, vol. 57, no. 3, pp. 1643–1655, 2018, doi: 10.1016/j.aej.2017.05.024.

[48] P. Arbeláez, M. Maire, C. Fowlkes, and J. Malik, “Contour detection and hierarchical image segmentation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 5, pp. 898–916, 2011, doi: 10.1109/TPAMI.2010.161.

[49] M. Xess and S. Agnes, “Analysis of Image Segmentation Methods Based on Performance Evaluation Parameters,” *Int. J. Comput. Eng. Res.*, vol. 4, no. 3, pp. 68–75, 2014, [Online]. Available: http://files.figshare.com/1447850/I04302068075.pdf

[50] “Polycystic Liver Disease on CT - Stock Image - M130/0999 - Science Photo Library.” https://www.sciencephoto.com/media/253093/view (accessed Sep. 15, 2020).

[51] “Biliary cystadenoma | Radiology Reference Article | Radiopaedia.org in 2020 | Radiology, Reference, Cysts.” https://www.pinterest.com/pin/584342120387350496/ (accessed Sep. 14, 2020).

[52] “Simple hepatic cyst | Radiology Reference Article | Radiopaedia.org.” https://radiopaedia.org/articles/simple-hepatic-cyst (accessed Jul. 22, 2020).

[53] “Preoperative abdominal CT of the donor revealed a liver cyst of 20 × 26... | Download Scientific Diagram.” https://www.researchgate.net/figure/Preoperative-abdominal-CT-of-the-donor-revealed-a-liver-cyst-of-20-26-mm-in-diameter-at_fig1_263131956 (accessed Sep. 14, 2020).

[54] “Computed tomography (CT) scan appearance of large hepatic cyst.” https://emedicine.medscape.com/article/190818-questions-and-answers (accessed Sep. 14, 2020).