Automated Knowledge Extraction of Liver Cysts From CT Images Using Modified Whale Optimization and Fuzzy C Means Clustering Algorithm

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ABSTRACT

In this study, the integrated modified whale optimization and modified fuzzy c-means clustering algorithm using morphological operations are developed and implemented for appropriate knowledge extraction of a cyst from computer tomography (CT) images of the liver to facilitate modern intelligent healthcare systems. The proposed approach plays an efficient role in diagnosing the liver cyst. To evaluate the efficiency, the outcomes of the proposed approach have been compared with the minimum cross entropy based modified whale optimization algorithm (MCE and MWOA), teaching-learning optimization algorithm based upon minimum cross entropy (MCE and TLBO), particle swarm intelligence algorithm (PSO), genetic algorithm (GA), differential evolution (DE) algorithm, and k-means clustering algorithm. For this, various parameters such as uniformity (U), mean structured similarity index (MSSIM), structured similarity index (SSIM), random index (RI), and peak signal-to-noise ratio (PSNR) have been considered. The experimental results show that the proposed approach is more efficient and accurate than others.

KEYWORDS

Fuzzy C-Means Clustering, Healthcare, Knowledge Extraction, Liver Cyst, Segmentation, Thresholding, Whale Optimization

1. INTRODUCTION

The requirement for intelligent health care systems is increasing day by day as human health diseases, such as brain tumors, liver cysts, breast tumors, kidneys, covid-19, etc. These ailments are diagnosed by various imaging techniques such as X-ray, ultrasound CT scan, and MRI scan. Doctors use these scanned images for diagnosis purposes (Gupta et al., 2020). One such important organ of the human body is the liver and it’s important to diagnose every disorder related to the liver. The liver cyst is a rare disease. A cyst is a fluid or a solid mass. It is present either inside or outside the human body (Nathan & Mulholland, 2019)(Matsuura et al., 2017). Only 5% of the population has this condition. Patients usually do not have any symptoms. The presence of a cyst can be detected by
using imaging techniques only. If these are not taken care of, cysts can sometimes be the reason for cancer. Cysts grow in size day by day (Oda et al., 2020). The captured computed tomography (CT)/magnetic resonance imaging (MRI) images typically have limited spatial resolution, low contrast, noise and non-uniform variability in intensity due to environmental effects. Therefore, the objects’ distinctions are blurred and distorted and the meanings of the objects are not quite precise (Kaur et al., 2020). Image processing field is very helpful to enhance the quality of images so that each disorder can be diagnosed clearly. Image segmentation plays an important role in diagnosing such conditions. With the help of image segmentation, identification of any disease such as brain tumor, cyst, breast tumor, kidney, COVID-19, etc., from a medical image is very simple. Image segmentation process is useful for feature extraction and pattern recognition (Qureshi & Ahamad, 2018). The segmented chromosome images are used for feature selection in classifying chromosomes (Arora & Dhir, 2020). Many applications have been developed for image segmentation in recent years, but this is a challenging task (Anter et al., 2020). So, in this paper the segmentation process is used to detect internal cysts in a liver. To improve the visual quality, median filter is applied to the dataset (Joao et al., 2020). A median filter is a type of non-linear filter (Zhu & Huang, 2012) (Arasi & Suganthi, 2019). It is widely used in image processing field as compared to other filters. The main advantage of the median filter is that it keeps the edges while removing noise from images. These filters use a m×n neighborhood mask and salt-and-pepper noise to filter the image (Liu et al., 2020). To improve the efficiency of results, soft computing based approaches are used to support health care diagnosis. There are numerous types of soft computing approaches like Evolutionary algorithms (Abdel-Khalek et al., 2017), an artificial neural network (ANN) (Hamad et al., 2019), Fuzzy logic based algorithms (Kyi et al., 2019), particle swarm optimization algorithms (PSO) (Xiaoqiong & Zhang, 2020), nature-inspired algorithms and metaheuristic optimization algorithms. Some of the metaheuristic optimization algorithms are Harmony search (HS) (Srikanth & Bikshalu, 2020), Ant lion optimization (ALO) (Anter et al., 2020), Ant colony Optimization (Tao & Jin, 2007), bat algorithm (G. Zhou et al., 2015), Grey wolf optimization (GWO) (Kapoor et al., 2017), Whale optimization algorithm (WOA) (Abdel-basset et al., 2020), Firefly algorithm (Rodrigues et al., 2017), moth flame optimization (MFO), Teaching learning optimization algorithm (TLBO) (Rao et al., 2011) and many more. The segmentation process is done using different methods like clustering, region growing, region splitting & merging and multilevel thresholding based upon the image intensity values. In thresholding, the grouping of pixels is according to the threshold value (T) (S. Singh et al., 2020) (Upadhyay & Chhabra, 2019). Threshold level or value is selected for the segmentation purpose in many cases. Levels are of many types like binary level, tri-level, four levels and n levels. In the case of binary level, one selected value is used as a threshold that converts the whole image into a binary image. Here binary image means the intensity of each pixel is either 0 or 1. More than one level is called multilevel thresholding. Increasing the number of threshold levels means grouping pixels in more than two groups. As the level of thresholds increases, computation time also increases. Many algorithms have been developed till date to overcome this drawback. The major problem is a selection of optimal number of thresholds (Aziz et al., 2017).

1.1 Related Work

The standard test images are segmented using multilevel thresholding Grey wolf optimization algorithm (Khairuzzaman & Chaudhury, 2017). The convolution neural network was used for the classification purpose of human metaspread images (Arora, 2020). The super pixel fuzzy clustering method is used as an evaluation function to segment the tumor from a brain MRI image (Khosravanian et al., 2021). The new fuzzy c-means based method is effective and robust for noisy data (Xu et al., 2017). The fuzzy c-means clustering is an algorithm that is popularly used in segmentation of classification algorithms. By the combination of metaheuristic algorithms Firefly algorithm (FA), Biogeography based optimization (BBO) and Genetic algorithm (GA), a new cooperative approach is proposed for segmentation purpose (Abdellahoum et al., 2021). For better accuracy and noise reduction, fuzzy c-means and dictionary learning method is applied (Miao et al., 2020). The multiobjective ant lion
and fuzzy clustering shows higher performance in case of segmentation of MRI images of brain tumor (M. Singh et al., 2020). To increase the performance, the fuzzy c-means clustering algorithm method is improved and it provides accurate segmentation (Dubey et al., 2016). An automatic medical segmentation method is developed using level set formulation and fuzzy clustering (Yang et al., 2020). Fuzzy c-means clustering is a simpler and effective approach for segmentation (Dhanachandra & Chanu, 2020). A noise reduction hybrid method was implemented to overcome the problem related to sensitivity of noise using fuzzy c-means approach (Dhanachandra & Chanu, 2020). Fuzzy set and fuzzy logic are best for resolving blurriness and ambiguity.

Lung tumor detection is done by a whale optimization algorithm (WOA) and support vector machine (Vijh et al., 2020). A modified flower pollination algorithm is deployed for segmentation based on multilevel thresholding (Shen et al., 2018). The problem of sensitivity to noise is recovered using the fuzzy c-means clustering and particle swarm intelligence (Pham et al., 2018). Fuzzy clustering techniques have been commonly used to segment images over the past decade (Kaur et al., 2020). Due to this reason, fuzzy c-means clustering is used in the proposed approach. The major drawback of traditional fuzzy c-means clustering is sensitivity to noise. To overcome the noise sensitivity, median filter is used.

The combination of median filter, modified fuzzy c-means clustering, modified whale optimization algorithm (MFCMC & MWOA) and morphological operations are applied to detect liver cyst from CT scan image of a complete abdominal image. The proposed approach is interested in the left part of the CT scan abdominal image i.e. liver. Different algorithms are compared with the proposed method, like minimum cross entropy based modified whale optimization algorithm (MCE & MWOA), minimum cross entropy based Teacher learning optimization algorithm (MCE & TLBO), Particle Swarm Intelligence algorithm (PSO), Genetic algorithm (GA) (Khan et al., 2019) (Abdellahoum et al., 2021), differential evolution algorithm (DE) (Tarkhaneh & Shen, 2019) (Bhandari, 2020) and K-means clustering algorithm (Mousavirad & Ebrahimpour-Komleh, 2020). The MCE & MWOA algorithm segments the image by minimizing the cross entropy (Mirjalili & Lewis, 2016). The TLBO is based upon the teacher learning-based approach (Rao et al., 2011) (Khehra & Pharwaha, 2015). Two types of learning processes are there: the first is the teacher phase and the second is the learner’s phase. The students gain knowledge in both stages, teacher as well as from their friends. The Teaching-Learning process was implemented to segment the image with minimizing cross entropy (Singh Gill et al., 2019). The field of image processing involves preprocessing, which includes image acquisition and image enhancement. Various types of filters do image enhancement.

In this paper, knowledge extraction of a cyst from medical images using the integrated modified whale optimization and modified fuzzy c-means clustering algorithm using morphological operations is done. The median filter is used in this proposed approach to enhance the visual quality of the medical image for better knowledge extraction. Section 2, describes the process of the depreciation of fitness value using modified fuzzy c-means clustering. The concept of the whale optimization algorithm is represented in section 3. While section 4 depicts morphological operations. In section 5, the complete description of the proposed approach with the help of steps and a flowchart is described systematically. Section 6 deployed the performance measures. A full description of the experimental setup and results are discussed in section 7. The detailed discussion about results is described in section 8.

2. FITNESS EVALUATION FUNCTION: MODIFIED FUZZY C-MEANS CLUSTERING (MFCMC)

Fuzzy c-means clustering is a part of the soft computing approach which deals with uncertainty. It is a soft clustering method that is different from hard c means clustering because it shows the relationship of each data point with one or more clusters. The proposed approach used this technique for finding out the minimum fitness value. Process of Modified fuzzy c-means clustering (MFCMC) is as follows:
1. Select \( k \) points from an image to make \( k+1 \) clusters, where \( k=1, 2, 3, \ldots, n \).
2. Selected points need to satisfy the criteria, i.e., if \( n \) threshold values are given, then it must meet the given condition \( k_1<k_2<k_3<\ldots<k_n \).
3. Assign \( k+1 \) point as a cluster center and make clusters of an initial population according to the cluster center value.

Find out the membership value \( \mu \) of the initial population using the following formula:

\[
\mu_{ij} = \frac{1}{\sum_{i=1}^{t} \left( \frac{|x_i - C_j|}{|x_i - C_k|} \right)^{\frac{m}{m+1}}} \tag{1}
\]

where:

\[
C_j = \frac{\sum_{i=1}^{n} C_i}{n}
\]

Here, \( j = \) cluster center, \( n = \) number of elements in a cluster \( j \), \( t = \) number of clusters, \( m = \) hyper-parameter or fuzziness parameter i.e. selected without any problem constraint. According to Bezdek, \( m=2 \) is a optimal selection (BEZDEK, 1993)(K. Le Zhou et al., 2014).

Evaluate the main objective function i.e. to minimize the below function:

\[
obj = \sum_{j=1}^{c} \sum_{i=1}^{n} \mu_{ij}^{m} x_i - C_j^{2} \tag{2}
\]

where:

\( \mu = \) membership value \\
\( c = \) cluster number \\
\( C = \) cluster center \\
\( x_i = \) element \\
\( n = \) number of elements (Kaur et al., 2020)

3. CONCEPT OF WHALE OPTIMIZATION ALGORITHM (WOA)

The proposed approach uses the concept of the humpback whales hunting method. The Whale optimization algorithm, a metaheuristic approach, is deployed in this proposed approach. Two methods, each having 0.5% probability, first encircling prey is for exploration purpose and another spiral updating position is for exploitation process. Each step of an algorithm with the complete mathematical formulation is detailed below:

3.1 Procedure

3.1.1 Process of Encircling Prey

The behavior of humpback whales is considered in the WOA algorithm. The whales can find the best location and circle around that location. In the initial state, the best location is not known, so
the current best location is chosen as best. The best location is found, then accordingly, others will update their locations with respect to the best location. All equations used during updating location are mentioned below:

\[ \text{Dist} = \left| CV \times X'_{\text{new}}(t) - X'(t) \right| \]  

(3)

\[ X'(t+1) = X'_{\text{new}}(t) - At \times \text{Dist} \times X'(t+1) \]  

(4)

Calculation of \( At \) and \( CV \) vectors:

\[ At = 2 \times a^* \times \vec{r} - \vec{a}^* \]  

(5)

\[ CV = 2 \times \vec{a}^* \]  

(6)

where \( || \) is an absolute value, * is multiplication, \( t \) is current iteration, \( At \) and \( CV \) coefficient vectors, \( X'_{\text{new}} \) is best solution location vector and \( X' \) is the location vector. \( a^* \) is linearly decreased from 2 to 0 in both phases, random vector \( \vec{r} \) having a value between (0,1) (Mirjalili & Lewis, 2016).

3.1.2 Exploitation Phase: Method of Bubble Net Attacking

1. **Shrinking encircle mechanism:** Vector \( At \) is also linearly decreased according to \( a^* \).
2. **Spiral updating:** Spiral equation is generated in two processes; one is the position of the whale and target prey. From this equation, a helix-shaped path is created to find the target prey:

\[ X'(t+1) = \text{Dist'} \times e^{bi'} \times \cos(2\pi l) + X'_{\text{new}}(t) \]  

(7)

\( b^i = 1, l \)

is rand no. between [-1, 1].

\[ \text{Dist'} = X'_{\text{new}}(t) - X'(t) \]  

(8)

There 50% probability to select shrinking mechanism and 50% for spiral updating:

\[ X'(t+1) = X'_{\text{new}}(t) - At \times \text{Dist} \text{ if } p < 0.5 \]  

(9)

\[ X'(t+1) = \text{Dist'} \times e^{bi'} \times \cos(2\pi l') + X'_{\text{new}}(t) \text{ if } p \geq 0.5 \]  

(10)
3.1.3 Exploration Phase: Search for Prey

This mechanism is for $|At| > 1$:

$$\text{Dist}^n = |CV \times X^{\text{rand}}(t) - X^t(t)|$$

$$X^{\text{rand}}(t + 1) = X^{\text{rand}}(t) - At \times \text{Dist}^n$$  \hspace{1cm} (12)

where:

$X^{\text{rand}} = \text{random position of the whale}$

4. MORPHOLOGICAL OPERATIONS

Morphological operations are applied after the segmentation process is complete. Dilation and erosion methods are used to extract the cyst part from segmented liver images. Dilation is an image that adds pixels to the boundary of the objects shown. The purpose of erosion is to remove the pixels from a boundary of an object in the image. The structuring element plays a crucial role in the case of morphological operations. The process of adding and removing pixels depends upon the size and shape of the structuring element. The proposed approach applies all the steps of morphological operations very carefully so that the detection process of cyst gives accurate results. The description of the dilation and erosion process is below:

- **Dilation:**

$$Q \odot R = \bigcup_{r \in R} Q_{r1}$$  \hspace{1cm} (13)

where $Q$ is a binary image, $R$ is structuring element, $Q_{r1}$ is a translation of $Q$ by $r1$.

- **Erosion:**

$$Q \Theta R = \bigcup_{r \in Q} Q_{-r1}$$  \hspace{1cm} (14)

where $Q$ is a binary image, $R$ is structuring element, $Q_{-r1}$ denotes translation of $Q$ by $-r1$ (Lei et al., 2017).

5. PROPOSED APPROACH: MODIFIED FUZZY C-MEANS CLUSTERING AND MODIFIED WHALE OPTIMIZATION ALGORITHM (MFCMC AND MWOA)

A whale optimization algorithm inspires the proposed approach. In a modified whale optimization algorithm, the initial population is created. Decision variables and maximum iteration are also decided before calculating fitness value and best whale position. Once all variables are declared, start evaluating fitness value using fuzzy c mean objective function as discussed in section 2 to select a minimum value. By using the best whale position, minimum fitness is computed. After that, different parameter values are updated in the WOA algorithm. Now position needs to be updated again to calculate the
fitness value. Find out the fitness until the best result is found. In the MWOA algorithm, the last part of the WOA algorithm is omitted where if any search agent crosses the boundary, that agent gets added to the whale population. Three multilevel threshold values are selected based on the best fitness value. These multilevel threshold values segment the whole image into three clusters. After that threshold image is converted into binary image. To extract the cyst part, apply morphological operations erosion and dilation on a resultant binary image. In previous sections, each algorithm is described in detail. This section describes the sequence of the complete proposed algorithm Modified fuzzy c-means clustering and modified whale optimization algorithm in Table 1. In addition, the whole process is described with the help of a flowchart which is shown in Figure 1.

6. PERFORMANCE EVALUATORS

Different parameters are used to measure the efficiency of the proposed approach. These parameters are well-known for checking the efficiency of an algorithm.

Table 1. Algorithm for Modified fuzzy c-means clustering and modified whale optimization algorithm

| STEP 1 | Initialize the population size popsize, decision variables d, m=2. |
|--------|---------------------------------------------------------------|
| STEP 2 | Select a random population popi, where i=1, 2, 3, 4, ……, n. |
| STEP 3 | Call MFCMC algorithm to evaluate the fitness of the initial population using an objective function. |
|        | \[
|        | \text{obj}_j = \sum_{j=1}^{c} \sum_{i=1}^{n} \mu_{ij}^m x_i - C_j^2 |
|        | \text{Where } c \text{ is a number of clusters, } n \text{ is a number of elements and } x_i \text{ is an element.} |
| STEP 4 | //MWOA algorithm to evaluate the best position of whale. |
|        | Select the best whale location. |
|        | Start while condition (iteration< maximum iteration) |
|        | For each whale |
|        | Update the value of At, CV, l, p (parameters used) |
|        | If condition1 (p < 0.5) |
|        | If condition2 (abs (At) <1) |
|        | Updating by using equation (3) the current whale location |
|        | Else if condition2 (abs (At) > = 1) |
|        | Choose random whale location. |
|        | Updating by using equation (10) the current whale location |
|        | End of if condition2 |
|        | Else if condition1 (p > = 0.5) |
|        | Updating by using equation (11), the current whale location |
|        | End of if condition1 |
|        | End for condition |
|        | Find out the fitness of each whale |
|        | If better results are found, then updated whale |
|        | Increment the iteration by 1 |
|        | End of while condition |
| STEP 5 | Repeat steps 3 and 4 till the best results are not obtained for three thresholds. |
| STEP 6 | Best threshold values used to segment the image, T_i, where i=1, 2, 3. |
| STEP 7 | Convert the segmented image into a binary image. |
| STEP 8 | To extract the cyst part, apply morphological operations erosion and dilation on a resultant binary image. |
| STEP 9 | Exit. |
1. **Uniformity (U):** Uniformity is a well-known quality measure of an image. The higher the uniformity value, the higher the segmented image quality. The value is evaluated between 0 and 1. The formula for calculating the value of uniformity is given below:

\[
U = 1 - 2 \cdot c \cdot \frac{\sum_{j=0}^{c} \sum_{i \in R_j} (f_i - \mu_i)^2}{N \cdot (f_{\text{max}}^2 - f_{\text{min}}^2)}
\]

(15)

where:
- \(c\) = number of thresholds
- \(N\) = total number of pixels
- \(R_j\) = segmented region of \(j\)
- \(f_i\) = level of pixel \(i\)
- \(\mu_i\) = mean of all gray level values of pixels belongs to the segmented region
- \(f_{\text{min}}\) and \(f_{\text{max}}\) = minimum and maximum gray levels in an image respectively (Tang et al., 2011)

2. **Structure similarity index (SSIM):** The similarity between the source image and the segmented image. The whole image is divided into \(M\) number of blocks. A higher value of SSIM provides more efficiency:

\[
SSIM = \left( \frac{2 \mu_i \mu_j + C1}{\sigma_i^2 + \sigma_j^2 + C2} \right) \left( \frac{2 \sigma_{ij} + C1}{\sigma_i^2 + \sigma_j^2 + C2} \right)
\]

(16)

where:
\( \mu_I \) = mean value of source image
\( \mu_{I'} \) = mean value of the segmented image
\( \sigma_I \) and \( \sigma_{I'} \) = the standard deviation of the source image and segmented image, respectively
\( \sigma_{II} \) = cross correlation
C1, C2 = constants (Naidu et al., 2018)

3. **Mean Structured Similarity Index (MSSIM):** It provides the mean value of the structured similarity index. The quality of the image is indicated with a higher value of MSSIM:

\[
MSSIM = \frac{1}{M} \sum_{j=1}^{M} SSIM \left( I_j, I_{j'} \right) \tag{17}
\]

where:

\( M \) = number of blocks
\( I_j \) = source image
\( I_{j'} \) = segmented image

4. **Random Index (RI):** Let I and G are two images. I is a test, and G is ground truth segmentation. The formula to calculate the Rand Index (RI) between these two segmentations is defined as:

\[
RI = \frac{a + b}{a + b + c + d} = \left[ \left( \frac{n}{2} \right) \cdot 0.5 \left\{ \sum_i \left( \sum_j n_{ij} \right)^2 + \sum_j \left( \sum_i n_{ij} \right) \right\}^2 - \sum \sum n_{ij}^2 \right] \left( \frac{n}{2} \right) \tag{18}
\]

The number of objects defined by \( n \) belongs to the \( i, j \) clusters in the U and V set, respectively. Binomial coefficient = \( n/2 \) (Xess & Agnes, 2014).

The higher the value of the random index, the higher the efficiency.

| Variable(number of pairs of elements in I) | Belong to the Same set in | Belong to a Different set |
|------------------------------------------|---------------------------|---------------------------|
| a                                       | U, V                      | -                         |
| b                                       | -                         | U, V                      |
| c                                       | U                         | V                         |
| d                                       | V                         | U                         |
Global Consistency Error (GCE): Minimum value of GCE indicates that there is no error between the segmented images. It means one of segmentations is refinement of the other. \( s_1 \) and \( s_2 \) are two segmented images. It evaluates the value between 0 and 1:

\[
GCE = \frac{1}{n} \min \left\{ \sum_i E(s_1, s_2, pi), \sum_i E(s_2, s_1, pi) \right\}
\]

(19)

\( pi = \) pixel belongs to the segmented image

Peak Signal to noise ratio (PSNR): It provides the homogeneity of final partitioning. It is computed in DB decibels. Higher the value of PSNR, the quality of an image is better:

\[
PSNR = 10 \log \left( \frac{255^2}{MSE} \right) (dB)
\]

(20)

where MSE is the Mean Square error of segmented image computed using the following equation:

\[
MSE = \frac{1}{m*n} \sum_i \sum_j \left( w(i, j) - \overline{w(i, j)} \right)^2
\]

(21)

where:

\( w(i, j) = \) segmented image

\( \overline{w(i, j)} = \) original image

\( m*n = \) number of pixels in an original image

7. EXPERIMENTAL SETUP AND RESULTS

The proposed approach is implemented with the help of MATLAB R2013a on the Windows 7 operating system and Intel (R) corei3 processor having RAM 3 GB. The initial population size selected is 10, and 3 of the decision variable are used in the proposed approach. The maximum iterations used are 100 for the selection of threshold values. For this purpose, the six CT scan medical images of the whole abdominal are tested using the proposed approach. In this approach, the left part of the CT scan image is considered because the problem definition belongs to liver disease. From the entire image, the proposed approach is implemented to extract the cyst present in the liver part. The CT scan image datasets of liver cysts are collected from different scan centers and internet resources for the segmentation process. In this paper, six original CT scan images of abdominal named LImage1 to LImage6 are used, shown in Table 3 (a) to 7(a). LImage1 and LImage2, collected from internet sources, and the other four (LImage3 to LImage6) are the real datasets collected from different CT scan centers from various cities in Punjab. The visual results are shown in sequence, starting from the Table (a) to (p), e.g., refer to Table 3. Table 3 (a) describes the original CT scan image. Table 3 (b), 2(d), 2(h), 2(j), 2(l) illustrates the fitness evaluation by the proposed approach, MCE & MWOA, MCE & TLBO algorithm, PSO, GA, DE, respectively. Table 3 (c),(e),(g),(i),(k),(m) shows the threshold image by the proposed approach, MCE & MWOA, MCE & TLBO algorithm, PSO, GA, DE, K-means clustering algorithm, respectively. Table 3(o) shows a binary image of the proposed
approach. Table 3 illustrates cyst detection by using the proposed approach. Table 3 to Table 8 illustrates the segmented results of the earlier approaches. Also, Table 3 to Table 8 shows the detection of a liver cyst, which is the main objective of the proposed approach.

Along with the qualitative image results, quantitative results are also evaluated. All algorithms which are previously mentioned are compared with various parameters. Parameters are like Uniformity (U), Mean structured similarity index (MSSIM), structured similarity index (SSIM), Random Index (RI), Peak Signal to noise ratio (PSNR), and Global Consistency Error (GCE). Table 9 deployed the fitness evaluation of all seven methods. Three threshold values are shown in Table 10, which are obtained by seven different methods for accurate segmentation of the medical images. The uniformity values (U) and SSIM values are shown in Table 11 and Table 12. MSSIM values obtained by various methods are shown in Table 13. Table 14 depicts the Random Index values obtained by seven different methods, and Table 15 represents the Global consistency Error values. The well-known measure Peak signal to noise ratio values of all methods are shown in Table 16.

To visualize the above experimental results, bar graphs are used. All values are plotted in bar graphs shown in Figures 2-7.

8. RESULT DISCUSSION

Each image is enhanced with preprocessing step. A median filter is used at the initial stage to overcome the drawback of Fuzzy c-means clustering noise sensitivity. This paper compares two types of results: one is qualitative (visual) and the other quantitative (parameter-based). For checking the accuracy and efficiency of the proposed approach, it has to be compared with minimum cross entropy based Modified whale optimization algorithm (MCE & MWOA), Minimum cross entropy based Teacher learning optimization algorithm (MCE & TLBO) and other well-known soft computing algorithms like PSO, GA, DE algorithm. In addition to these algorithms, the proposed approach is also compared with the K-means clustering algorithm. The visual quality of the proposed approach is better than the other six algorithms shown in Table 3 to Table 8. The resultant image is helpful in the diagnosis of cyst in the liver image. The proposed method extracted the accurate cyst part from the threshold image using morphological operations. In the case of quantitative results, various parameters are evaluated. It is observed that values of Uniformity (Table 11) and MSSIM parameters (Table 13) obtained by the proposed approach are significantly higher than the other six algorithms. The SSIM and RI values are shown in Table 12 and Table 14, respectively, indicating better results from the proposed approach. GCE values suggest that the proposed approach has higher performance (minimum value) than the other six algorithms (Table 15). The most commonly used parameter in a quality measure is the PSNR value. The higher values of PSNR (in dB) shown in Table 16 depict that the proposed approach gives more accurate and superior values in each medical image than other algorithms. These values are visualized with the help of bar graphs. Figure 2 to Figure 7 shows higher values of Uniformity, MSSIM and PSNR, respectively, obtained by the proposed approach, indicating that the proposed approach is better than other algorithms. In Figure 6, the proposed approach provides minimum values in maximum cases compared to the six different algorithms. The proposed approach also gains maximum values in the case of SSIM and RI values compared to other methods, which depict in Figure 3 and Figure 6, respectively. In maximum cases (86%), the proposed approach achieved better results as compared to other algorithms. Thus, it is concluded that the proposed approach presented in this paper provides highly reliable, precise and accurate results compared to the other six algorithms.

9. CONCLUSION AND FUTURE SCOPE

Knowledge extraction using segmentation has a big role in the modern healthcare diagnosis process. It assists the doctors in identifying the area of interest in a particular image. The soft computing
Table 3. Results of LImage1

| (a) | (b) |
| (c) | (d) |
| (e) | (f) |
| (g) | (h) |

Continued on following page
Table 3. Continued

| (i) | (j) |
|-----|-----|
| (k) | (l) |
| (m) | (n) |
| (o) | (p) |

Figure 2. 1) Image: a) Original image (Type 1-Hydatic Cyst, 2021). b) Fitness Evaluation of Proposed approach. c) Threshold image by the proposed approach. d) Fitness Evaluation of MCE & MWOA algorithm. e) Threshold image by MCE & MWOA algorithm. f) Fitness Evaluation of MCE & TLBO algorithm. g) Threshold image by MCE & TLBO algorithm. h) Fitness Evaluation of PSO algorithm. i) Threshold image by PSO algorithm. j) Fitness Evaluation of GA algorithm. k) Threshold image by GA algorithm. l) Fitness Evaluation of DE algorithm. m) Threshold image by DE algorithm. n) Threshold image by K-means clustering algorithm. o) Binary image of the proposed approach. p) Detection of the cyst by using the proposed approach.
Table 4. Results of LImage2

(a) 

(b) 

(c) 

(d) 

(e) 

(f) 

(g) 

(h) 

continued on following page
Table 4. Continued

|   |   |
|---|---|
|   |   |
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|   |   |
|   |   |
|   |   |

Figure 3. LImage2: a) Original image (Simple Hepatic Cyst | Radiology Reference Article | Radiopaedia.Org, 2020). b) Fitness Evaluation of Proposed approach. c) Threshold image by the proposed approach. d) Fitness Evaluation of MCE & MWOA algorithm. e) Threshold image by MCE & MWOA algorithm. f) Fitness Evaluation of MCE & TLBO algorithm. g) Threshold image by MCE & TLBO algorithm. h) Fitness Evaluation of PSO algorithm. i) Threshold image by PSO algorithm. j) Fitness Evaluation of GA algorithm. k) Threshold image by GA algorithm. l) Fitness Evaluation of DE algorithm. m) Threshold image by DE algorithm. n) Threshold image by K-means clustering algorithm. o) Binary image of the proposed approach. p) Detection of the cyst by using the proposed approach.
Table 5. Results of LImage3

| (a) | (b) |
|-----|-----|
| ![Image](image1.png) | ![Convergence Plot](plot1.png) |
| (c) | (d) |
| ![Image](image2.png) | ![Convergence Plot](plot2.png) |
| (e) | (f) |
| ![Image](image3.png) | ![Convergence Plot](plot3.png) |
| (g) | (h) |
| ![Image](image4.png) | ![Convergence Plot](plot4.png) |

continued on following page
Figure 4. Image3: a) Original image patient age 82 years (Jyot Singh, 2018). b) Fitness Evaluation of Proposed approach. c) Threshold image by the proposed approach. d) Fitness Evaluation of MCE & MWOA algorithm. e) Threshold image by MCE & MWOA algorithm. f) Fitness Evaluation of MCE & TLBO algorithm. g) Threshold image by MCE & TLBO algorithm. h) Fitness Evaluation of PSO algorithm. i) Threshold image by PSO algorithm. j) Fitness Evaluation of GA algorithm. k) Threshold image by GA algorithm. l) Fitness Evaluation of DE algorithm. m) Threshold image by DE algorithm. n) Threshold image by K-means clustering algorithm. o) Binary image of the proposed approach. p) Detection of the cyst by using the proposed approach.
Table 6. Results of LImage4

| Image | Convergence Plot |
|-------|------------------|
| ![Image A](<image-url>) | ![Convergence Plot A](<image-url>) |
| ![Image B](<image-url>) | ![Convergence Plot B](<image-url>) |
| ![Image C](<image-url>) | ![Convergence Plot C](<image-url>) |
| ![Image D](<image-url>) | ![Convergence Plot D](<image-url>) |
| ![Image E](<image-url>) | ![Convergence Plot E](<image-url>) |
| ![Image F](<image-url>) | ![Convergence Plot F](<image-url>) |
| ![Image G](<image-url>) | ![Convergence Plot G](<image-url>) |

continued on following page
Table 6. Continued

Figure 5. Image4: a) Original image patient age 66 years (Dhillon, 2021) b) Fitness Evaluation of Proposed approach. c) Threshold image by the proposed approach. d) Fitness Evaluation of MCE & MWOA algorithm. e) Threshold image by MCE & MWOA algorithm. f) Fitness Evaluation of MCE & TLBO algorithm. g) Threshold image by MCE & TLBO algorithm. h) Fitness Evaluation of PSO algorithm. i) Threshold image by PSO algorithm. j) Fitness Evaluation of GA algorithm. k) Threshold image by GA algorithm. l) Fitness Evaluation of DE algorithm. m) Threshold image by DE algorithm. n) Threshold image by K-means clustering algorithm. o) Binary image of the proposed approach. p) Detection of the cyst by using the proposed approach.
Table 7. Results of LImage5

|   |   |
|---|---|
| (a) | (b) |
| (c) | (d) |
| (e) | (f) |
| (g) | (h) |

continued on following page
Table 7. Continued

| (i)  | (j)  |
|------|------|
| ![Image](image1.png) | ![Chart](chart1.png) |
| (k)  | (l)  |
| ![Image](image2.png) | ![Chart](chart2.png) |
| (m)  | (n)  |
| ![Image](image3.png) | ![Image](image4.png) |
| (o)  | (p)  |
| ![Image](image5.png) | ![Image](image6.png) |

Figure 6. LImage5:  
(a) Original image patient age 30 years (Garg, 2021)  
(b) Fitness Evaluation of Proposed approach  
(c) Threshold image by the proposed approach  
(d) Fitness Evaluation of MCE & MWOA algorithm  
(e) Threshold image by MCE & MWOA algorithm  
(f) Fitness Evaluation of MCE & TLBO algorithm  
(g) Threshold image by MCE & TLBO algorithm  
(h) Fitness Evaluation of PSO algorithm  
(i) Threshold image by PSO algorithm  
(j) Fitness Evaluation of GA algorithm  
(k) Threshold image by GA algorithm  
(l) Fitness Evaluation of DE algorithm  
(m) Threshold image by DE algorithm  
(n) Threshold image by K-mean clustering algorithm  
(o) Binary image of the proposed approach  
(p) Detection of the cyst by using the proposed approach
Table 8. Results of LIimage6

| (a) | (b) |
|-----|-----|
| ![Image](image1.png) | ![Graph](graph1.png) |

| (c) | (d) |
|-----|-----|
| ![Image](image2.png) | ![Graph](graph2.png) |

| (e) | (f) |
|-----|-----|
| ![Image](image3.png) | ![Graph](graph3.png) |

| (g) | (h) |
|-----|-----|
| ![Image](image4.png) | ![Graph](graph4.png) |

continued on following page
Table 8. Continued

| (i) | (j) |
| --- | --- |
| ![Image](image1.png) | ![Image](image2.png) |

| (k) | (l) |
| --- | --- |
| ![Image](image3.png) | ![Image](image4.png) |

| (m) | (n) |
| --- | --- |
| ![Image](image5.png) | ![Image](image6.png) |

| (o) | (p) |
| --- | --- |
| ![Image](image7.png) | ![Image](image8.png) |

Figure 7. LImage6: a) Original image patient age 60 years (Singla, 2021) b) Fitness Evaluation of Proposed approach. c) Threshold image by the proposed approach. d) Fitness Evaluation of MCE & MWOA algorithm. e) Threshold image by MCE & MWOA algorithm. f) Fitness Evaluation of MCE & TLBO algorithm. g) Threshold image by MCE & TLBO algorithm. h) Fitness Evaluation of PSO algorithm. i) Threshold image by PSO algorithm. j) Fitness Evaluation of GA algorithm. k) Threshold image by GA algorithm. l) Fitness Evaluation of DE algorithm. m) Threshold image by DE algorithm. n) Threshold image by K-means clustering algorithm. o) Binary image of the proposed approach. p) Detection of the cyst by using the proposed approach.
Table 9. Fitness evaluation values of different methods

| Image no. | FCMC based MWOA | MCE based MWOA | MCE based TLBO | FCMC based PSO | FCMC based GA | FCMC based DE |
|-----------|------------------|----------------|----------------|----------------|----------------|----------------|
| LImage1   | -3.06x10^{-5}    | -4.3x10^{7}   | -1.5788x10^{7} | 1              | 0.02           | 0.12x10^{-3}  |
| LImage2   | -9.6x10^{7}      | -5.44x10^{7}  | -5.8145x10^{7} | 2              | 0.045          | 0.231x10^{-3} |
| LImage3   | 3.9x10^{-7}      | -4.49x10^{7}  | -3.297x10^{7}  | 7              | 0.2x10^{-3}    | 0.01x10^{3}   |
| LImage4   | 3.6x10^{-6}      | -2.296x10^{8} | -1.75x10^{8}   | 2483           | 0.21x10^{-3}   | 0.001          |
| LImage5   | 3.9x10^{-4}      | -2.48x10^{7}  | -2.5x10^{7}    | 261            | 0.012          | 0.001          |
| LImage6   | 7.46x10^{-7}     | -6.96x10^{8}  | -5.08x10^{8}   | 0.1            | 0.023          | 0.37x10^{-3}  |

Table 10. Threshold values of different methods

| Image No. | Proposed Approach | MCE & MWOA | MCE & TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|------------|------------|-----|----|----|---------|
| LImage1   | 44,169,89         | 1,197,103  | 246,32,96  | 23,42,94 | 21,234,76 | 9,98,249 | 122,182,97 |
| LImage2   | 20,138,170        | 126,71,155 | 224,49,155 | 107,149,225 | 34,123,221 | 92,142,190 | 74,42,157 |
| LImage3   | 89,127,147        | 175,34,136 | 184,64,140 | 2,76,133 | 38,90,123 | 19,150,255 | 21,218,144 |
| LImage4   | 73,94,159         | 110,78,151 | 252,57,169 | 84,88,137 | 82,75,160 | 54,131,255 | 68,75,124 |
| LImage5   | 66,92,121         | 75,126,97  | 235,27,76  | 23,42,94 | 19,230,88 | 66,111,120 | 177,29,101 |
| LImage6   | 137,95,162        | 167,70,136 | 252,57,169 | 104,135,216 | 111,30,234 | 84,149,228 | 228,28,151 |

Table 11. Uniformity (U) values of different methods

| Image No. | Proposed Approach | MCE & MWOA | MCE & TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|------------|------------|-----|----|----|---------|
| LImage1   | 0.9119            | 0.8005     | 0.6129     | 0.9054 | 0.9117 | 0.9049 | 0.7857 |
| LImage2   | 0.9381            | 0.8918     | 0.5448     | 0.9281 | 0.9221 | 0.9211 | 0.9234 |
| LImage3   | 0.9419            | 0.6150     | 0.6190     | 0.9407 | 0.9391 | 0.9233 | 0.8784 |
| LImage4   | 0.9585            | 0.9115     | 0.3865     | 0.9425 | 0.9432 | 0.9505 | 0.9451 |
| LImage5   | 0.9535            | 0.9294     | 0.5771     | 0.9345 | 0.9489 | 0.9499 | 0.6608 |
| LImage6   | 0.9346            | 0.7837     | 0.5348     | 0.9307 | 0.9329 | 0.9102 | 0.5374 |

Table 12. Structured Similarity Index values (SSIM) of different methods

| Image No. | Proposed Approach | MCE & MWOA | MCE & TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|------------|------------|-----|----|----|---------|
| LImage1   | 0.9789            | 0.9698     | 0.9788     | 0.9788 | 0.9687 | 0.9768 | 0.9232 |
| LImage2   | 0.9894            | 0.9859     | 0.9845     | 0.9863 | 0.9853 | 0.9855 | 0.9844 |
| LImage3   | 0.9815            | 0.9768     | 0.9840     | 0.9831 | 0.9812 | 0.9751 | 0.9818 |
| LImage4   | 0.9770            | 0.9749     | 0.9769     | 0.9737 | 0.9721 | 0.9712 | 0.9743 |
| LImage5   | 0.9720            | 0.9396     | 0.9663     | 0.9718 | 0.9703 | 0.9719 | 0.9720 |
| LImage6   | 0.9764            | 0.9685     | 0.9794     | 0.9690 | 0.9632 | 0.9716 | 0.9427 |
### Table 13. Mean Structured Similarity Index (MSSIM) values of different methods

| Image no. | Proposed Approach | MCE & MWOA | MCE & TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|------------|------------|-----|----|----|---------|
| LImage1   | 0.9477            | 0.9105     | 0.9418     | 0.9437 | 0.9470 | 0.9347 | 0.8298  |
| LImage2   | 0.9725            | 0.9643     | 0.9616     | 0.9645 | 0.9610 | 0.9619 | 0.9615  |
| LImage3   | 0.9568            | 0.9417     | 0.9540     | 0.9551 | 0.9366 | 0.9377 | 0.9364  |
| LImage4   | 0.9478            | 0.9424     | 0.9476     | 0.9404 | 0.9444 | 0.9352 | 0.9381  |
| LImage5   | 0.9398            | 0.8580     | 0.9158     | 0.9343 | 0.9366 | 0.9363 | 0.9232  |
| LImage6   | 0.9405            | 0.9281     | 0.9403     | 0.9312 | 0.9400 | 0.9324 | 0.8760  |

### Table 14. Random Index (RI) values of different methods

| Image No. | Proposed Approach | MCE & MWOA | MCE & TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|------------|------------|-----|----|----|---------|
| LImage1   | 0.7258            | 0.5456     | 0.6817     | 0.6990 | 0.6598 | 0.6394 | 0.5534  |
| LImage2   | 0.7031            | 0.6065     | 0.5872     | 0.6879 | 0.6834 | 0.7019 | 0.5724  |
| LImage3   | 0.7982            | 0.6024     | 0.6635     | **0.7289** | 0.6513 | 0.5239 | 0.5914  |
| LImage4   | 0.6643            | **0.6836** | 0.5620     | 0.6630 | 0.6751 | 0.7309 | 0.5445  |
| LImage5   | 0.9309            | 0.5087     | 0.7400     | 0.7802 | 0.8031 | 0.8131 | 0.7456  |
| LImage6   | 0.6856            | **0.8139** | 0.5456     | 0.6190 | 0.6718 | 0.6811 | 0.5000  |

### Table 15. Global Consistency Error (GCE) values of different methods

| Image No. | Proposed Approach | MCE & MWOA | MCE & TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|------------|------------|-----|----|----|---------|
| LImage1   | **0.0194**        | 0.0546     | 0.0550     | 0.0550 | 0.0549 | 0.0549 | 0.0525  |
| LImage2   | **0.0051**        | 0.0109     | 0.0101     | 0.0101 | 0.0101 | 0.0101 | 0.0101  |
| LImage3   | **0.0142**        | 0.0231     | 0.0231     | 0.0232 | 0.0231 | 0.0230 | 0.0230  |
| LImage4   | **0.0324**        | 0.0350     | 0.0348     | 0.0350 | 0.0351 | 0.0350 | 0.0350  |
| LImage5   | 0                 | 0.0000965  | 0.0009     | 0.0009 | 0.0009 | 0.0009 | 0.0009  |
| LImage6   | 0.00002           | 0          | 0          | 0     | 0   | 0   | 0       |

### Table 16. Peak Signal to Noise Ratio (PSNR) (in dB) values of different methods

| Image No. | Proposed Approach | MCE&MWOA | MCE&TLBO | PSO | GA | DE | K-means |
|-----------|-------------------|----------|----------|-----|----|----|---------|
| LImage1   | **9.0874**        | 8.5293   | 8.5269   | 8.5262 | 8.5270 | 8.5279 | 8.5281  |
| LImage2   | **8.5619**        | 8.5342   | 8.5355   | 8.5258 | 8.5339 | 8.5223 | 8.5375  |
| LImage3   | **8.4882**        | 8.4501   | 8.4489   | 8.4436 | 8.4510 | 8.4612 | 8.4562  |
| LImage4   | **6.8293**        | 6.8123   | 6.8235   | 6.8065 | 6.8221 | 6.8073 | 6.8046  |
| LImage5   | **7.0815**        | 6.9793   | 6.9733   | 6.9738 | 6.9738 | 6.9765 | 6.9753  |
| LImage6   | **6.2323**        | 6.2059   | 6.2255   | 6.2034 | 6.2234 | 6.2085 | 6.2179  |
Figure 2. Graphical representation of uniformity values of different methods

Figure 3. Graphical representation of structured similarity index values of different methods

Figure 4. Graphical representation of mean structured similarity index values of different methods
Figure 5. Graphical representation of random index values of different methods

Figure 6. Graphical representation of Global consistency error values of different methods

Figure 7. Graphical representation of Peak Signal to Noise Ratio values of different methods
approach gives more precise and accurate results in the automatic extraction process. This research paper’s main objective is to extract a cyst from CT scan images using the integrated modified whale optimization and modified fuzzy c-means clustering algorithm using morphological operations. The CT scan images of the liver cyst are collected from different scan centers and internet resources for the segmentation process. The proposed approach is compared with the other six algorithms: MCE & MWOA algorithm, MCE & TLBO algorithm, PSO algorithm, GA algorithm, DE algorithm, and K-means clustering algorithm. From the experimental findings, it has been observed that U, MSSIM and PSNR, the renowned quality measures of images, found higher performance using the proposed approach. While the remaining three performance measures also show superior values than the other approaches. Herein, it is concluded that the overall performance of the proposed approach is very effective and accurate compared to the MCE & MWOA algorithm, MCE & TLBO algorithm, PSO algorithm, GA algorithm, DE algorithm, K-means clustering algorithm. The proposed approach accurately segments the cyst part that facilitates the doctor’s diagnostic procedure. From qualitative (visual) and quantitative (parameters) measures, it is concluded that this approach can be applied to the detection of other diseases like brain tumor, kidney disease, breast tumor, etc. The major limitation is the selection of number of thresholds used for segmentation purpose. The forthcoming paper will present selection of optimal number of thresholds from different combinations of threshold values obtained by the proposed approach. The optimal number of thresholds used for segmentation purpose.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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