



A non-entropy-based optimal multilevel threshold selection technique for COVID-19 X-ray images using chance-based birds' intelligence

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Abstract

Recently, image thresholding methods based on various entropy functions have been found popularity. Nonetheless, entropic-based methods depend on the spatial distribution of the grey level values in an image. Hence, the accuracy of these methods is limited due to the non-uniform distribution of the grey values. Further, the analysis of the COVID-19 X-ray images is evolved as an important area of research. Therefore, it is needed to develop an efficient method for the segmentation of the COVID-19 X-ray images. To address these issues, an efficient non-entropy-based thresholding method is suggested. A novel fitness function in terms of the segmentation score (SS) is introduced, which is used to reduce the segmentation error. A soft computing approach is suggested. An efficient optimizer using the chance-based birds' intelligence is introduced to maximize the fitness values. The new optimizer is validated utilizing the benchmark test functions. The statistical parameters reveal that the suggested optimizer is efficient. It shows a quite significant improvement over its counterparts—optimization based on seagull/cuckoo birds. Precisely, the paper includes three novel contributions—(i) fitness function, (ii) chance-based birds' intelligence for optimization, (iii) multiclass segmentation. The COVID-19 X-ray images are taken from the Kaggle Radiography database, to the experiment. Its results are compared with three different state-of-the-art entropy-based techniques—Tsallis, Kapur's, and Masi. For providing a statistical analysis, Friedman's mean rank test is conducted and our method Ranked one. Its superiority is claimed in terms of Peak Signal to Noise Ratio (PSNR), Feature Similarity Index (FSIM) and Structure Similarity Index (SSIM). On the whole, an improvement of about 11% in PSNR values is achieved using the proposed method. This method would be helpful for medical image analysis.

Keywords Soft computing · Machine learning · Chance-based birds' intelligence · Multilevel thresholding · COVID-19 X-ray image analysis

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1 Introduction

In medical image analysis, the segmentation is an essential phase. It is needed to partition the image into several regions. The accuracy of a segmentation methodology is crucial. Hence, researchers try to investigate efficient methods in this connection. The threshold selection-based image segmentation method is the easiest one. Through this technique, foreground objects are separated from the background easily. Good enough research papers are found in the literature (Freixenet et al. 2002; Sezgin and Sankur 2004; Zaitoun and Aqel 2015). Some of the important thresholding-based segmentation methods are found in (Freixenet et al. 2002). Many other interesting threshold selection schemes are available in (Sezgin and Sankur 2004; Zaitoun and Aqel 2015). These methods, more or less, are classified into two categories—(i) bi-level, (ii) multilevel. We need to choose one threshold value in the case of bi-level segmentation, in which one can find only two classes, i.e., background and foreground. Therefore, it is inadequate to analyze the medical image in a better way. When there are more regions in an image, it is not suitable. This has led the researchers to develop multilevel segmentation schemes to facilitate a better analysis of the medical images. In general, multilevel segmentation schemes use $K (> 1)$ thresholds in order to partition the digital image into $K + 1$ classes (segments or regions)

(Yue and Zhang 2020). The abbreviations with their descriptions are itemized below in Table 1 for an easy readability.

In the earlier technologies, bi-level thresholding was used to segment the X-ray image into two distinct regions. The bi-level segmented output image was used for the analysis. However, a limited number of features are seen in a bi-level threshold X-ray image. Therefore, it is suggested to extend the idea of bi-level thresholding into a multiclass thresholding, yielding a multiclass segmented image. Remarkably, more useful features are observed in a multilevel thresholded (output) image of a COVID-19 X-ray image, which is important for the analysis. Note that the output attained is the multiclass segmented output. A generalized block diagram of the thresholding-based multiclass segmentation methodology is displayed in Fig. 1.

As shown in Fig. 1, a chest X-ray image is the input. Then, it is the user who has to decide the number of threshold levels K . Then, pixel counts in different classes are optimized using an efficient optimizer. As a result, the error in segmentation gets minimized, which is the underlying principle. Thus, K numbers of the optimum threshold values are computed using different objective functions.

Mostly, entropy-based methods are used for multilevel segmentation. These entropy-based schemes already proposed for the threshold selection greatly rely on the image histogram (Zaitoun and Aqel 2015). The scholars utilize the image histogram for computing various entropy information. Then by maximizing the information, they used to compute the multiple threshold values for multilevel thresholding. Some of the popular entropic methods are—Otsu (Otsu 1979), Tsallis entropy (Sharma et al. 2020), Kapur's entropy (Kapur et al. 1985), and Masi entropy (Masi 2005). The histogram-based techniques require the computation of order $O(L^K)$, where L is the number of grey level values and K is the number of thresholds. Therefore,

Table 1 Abbreviations with descriptions

Abbreviations	Description
SS	segmentation Score
SGCS	Seagull Cuckoo Search
GWO	Grey Wolf Optimizer
KHO	Krill Herd Optimization
MFO	Moth-Flame Optimization
WOA	Whale Optimization Algorithm
LSMA	Leader Slime Mould Algorithm
OEO	Opposition Equilibrium Algorithm
SOA	Seagull Optimization Algorithm
Ave	Average
Std	Standard deviation
CT	Computerized Tomography
PET	Positron Emission Tomography
PSNR	Peak Signal to Noise Ratio
SSIM	Structure Similarity Index
FSIM	Feature Similarity Index
Th	Threshold
PC	Phase Congruency
GM	Gradient Magnitude

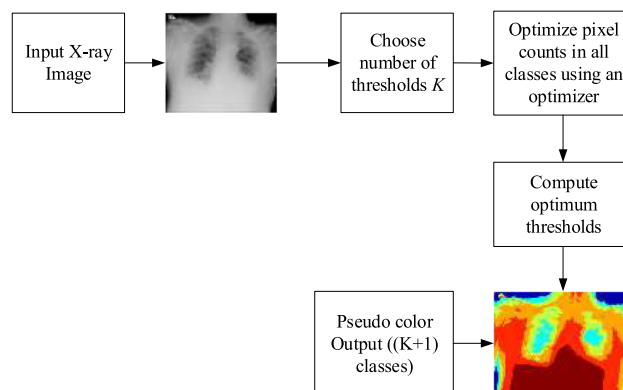


Fig. 1 Block diagram for the thresholding-based multiclass segmentation

the problem is an exhaustive search one. When K increases, the number of computations increases fast. There is also a drawback in the entropy-based approaches. When the grey level spatial distribution is not uniform, the result is less accurate. In some real world images, spatial distribution of these grey level pixels is not uniform. Therefore, these methods are not suited for the multiclass segmentation of the medical images. Especially, for the multiclass segmentation of the COVID-19 X-ray images, there is a strong need to develop new methods.

This has motivated the authors to investigate a novel non-entropy-based multiclass threshold selection scheme, which is free from the spatial distribution of the grey level pixels. In this work, it is proposed. A firsthand fitness function is introduced to compute the optimal multiple threshold values. This contribution may enrich the image processing literature. First, we suggest a segmentation score (SS) as the fitness function for the bi-level thresholding. Then, it extends to the multilevel threshold selection. The method is not dependent on any calculation of the entropy, rather it maximizes the SS to minimize the segmentation error. As opposed to the entropy methods, the proposed technique is unique in the sense that it never depend on the spatial grey level distribution. The novel idea contributed in this paper may be a breakthrough technique for the future multiclass segmentation application. More importantly, the proposal may benefit researchers in achieving significantly better results. Nevertheless, COVID-19 X-ray images have inherent characteristics that limits the uniform distribution of grey level values throughout the entire picture. Hence, entropic-based methods are less useful for the multiclass segmentation of these images. In contrary, the contribution would be more useful for such applications. This is the main contribution of the paper. The proposed method may deal with other biomedical images, because of the low contrast and non-uniform distribution of grey levels.

It may be noted that the conventional mathematical tools are not useful to solve the exhaustive search problems due to their complexity issue as discussed above. Instead, it is wise to utilize the nature-inspired optimization algorithms. These optimizers help us to maximize/minimize the fitness values. Hence, for the optimal threshold selection, it is essential to deploy the nature-inspired optimization algorithms. Some of the recently used optimizers are—Cuckoo Search (CS) (Agrawal et al. 2013), Crow Search Algorithm (CSA) (Shahabi et al. 2020), Krill Herd Optimization (KHO) (Baby Resma and Nair 2018), Moth-Flame Optimization (MFO) (Aziz et al. 2017), newly proposed Whale Optimizer (WOA) (Aziz et al. 2017), Leader Slime Mould Algorithm (LSMA) (Naik et al. 2022), Opposition Equilibrium Algorithm (OEO) (Naik et al. 2021), A Covariance-based Moth-flame Optimization Algorithm

(Zhao et al. 2022), horizontal and vertical multiverse optimization (Su et al. 2022), Entropy-Controlled Firefly Optimization (Khan et al. 2021), Chaotic marine predators' algorithm (Kumar et al. 2023), Marine predator inspired naked mole-rat algorithm (Salgotra et al. 2022), Multi-trial vector-based monkey king evolution algorithm (Nadimi-Shahraki et al. 2023). More or less, these optimizers have shown their potential use in the meticulous segmentation. The primary versions of these algorithms are found not useful for solving different optimization problems. This has led the scholars to enhance the scope by updating the position vectors through hybridization. There is a merit in devolving hybrid models for maximizing/minimizing the fitness values to obtain the optimal thresholds for multilevel thresholding. These enhanced versions could ensure the improvements in the optimization applications. Further, it is noticed that the birds' intelligence plays more important role in the metaheuristics. These birds are God's creatures. They possess both exploring and exploiting the solution space. More chances of exploring the search space (solution space) are the present focus of the study.

This is the motivation behind the proposed optimizer. The contribution in this direction is quite significant in the sense that the study on the chance-based bird intelligence is carried out here. The findings are quite encouraging. A new idea of incorporating the chance factor in enhancing the solution space is contributed in this paper. Here, the inherent feature of the cuckoo bird, i.e., the Levy flight along with a chance factor is embedded within the Seagull bird (Panagant et al. 2020). It ensures a better solution. This could improvise the exploration and the exploitation mechanism. It is interesting to understand that the present research is a countless breakthrough. Its innovator in its implications. Someone may claim the superiority for certain merits. These new discoveries, offered in this paper, are in fact the outcomes of the innovative idea. One must realize this and then, and only then, one can begin to explore its applications to solve real world optimization problems. According to the "No Free Lunch Theorem" (Wolpert and Macready 1997), only one or a particular optimizer cannot solve all types of problems. In this sense, the suggested optimizer may be useful for optimal multilevel threshold selection.

The search strategy of a Cuckoo bird (Agrawal et al. 2013) using a Levy step has shown the encouraging results in the benchmark test functions. It has shown superiority in the multimodal functions with fixed dimensions. However, there is no improvement over the unimodal/multimodal (variable dimensions) benchmark functions. Recently, the Seagull birds' intelligence has shown good performances over its counterparts. The disadvantage of Seagull bird is its requirement of creating more number of generations. Hence, its convergence is sluggish. In this paper, the

solution update rule adapted the Levy flight feature of the Cuckoo bird along with a chance factor. This step guides the bird's intelligence to global optimal solutions with a faster convergence. This is the reason why the suggested optimizer is worth for optimizing fitness functions. It is basically a chance-based birds' intelligence. The contribution is the development of a chance-based birds' intelligence for optimization. In this work, the performances of the suggested algorithm have shown better convergences, when tested using 23 standard benchmark functions. It provides the quality optimal solutions. These merits of the optimizer enforce the authors to deploy it for maximizing the pixel counts (SS score). As a result, the segmentation error is automatically reduced. Further, an efficient scheme for the optimal multilevel threshold selection called SS-SGCS is presented for the segmentation of the X-ray images (Chowdhury et al. 2020). To experiment, the COVID-19 X-ray images are taken from the COVID-19 Radiography Database | Kaggle (Kaggle dataset 2021). The performances of the SS-SGCS scheme also compares with the recently published work using Tsallis, Kapur's and Masi entropy-based multiclass segmentation. The statistical analysis in terms of PSNR (Naik et al. 2021), SSIM (Zhou et al. 2004), FSIM (Lin Zhang et al. 2011) also provides for a comparison.

In summary, the present work established a new non-entropic objective function, for the first time. New technology in terms of the segmentation score is developed firsthand. The investigated technology is used for X-ray image segmentation for analysis. This method is compared with state-of-the-art technologies. The thrust is to enrich the literature to encourage researchers to explore more in this track. The following are the main contributions:

- i. A novel multilevel fitness function is suggested by maximizing the segmentation score (SS), which is independent of the spatial distribution of the grey level pixels in an image.
- ii. An efficient chance-based birds' intelligence algorithm is introduced which is found better than the Seagull and the Cuckoo birds' intelligence. The best optimal solutions are achieved.
- iii. A novel SS-SGCS technique is proposed for multiclass segmentation of the COVID-19 X-ray images.

The rest of the paper is ordered as follows. The suggested SS-based multilevel thresholding objective function is derived in Section 2. A novel chance-based SOA-CS algorithm is proposed in Section 3. The SS-SGCS method for the optimal multilevel threshold selection is presented in Section 4. The results and discussions are presented in Section 5. The concluding remark is presented in Section 6.

2 The proposed non-entropy objective function

In this section, a novel idea for the computation of the optimal threshold values for multiclass segmentation is presented. The contribution in the development of this article is quite significant. Original theoretical investigations are made. New equations for the calculation of the optimal threshold values are explicitly derived. This proposal is different from the entropy-based techniques reported for the multilevel threshold selection. Here, the idea is to reduce the segmentation error significantly, which is practically very close to zero. The problem is empirically formulated below. The method is clearly illustrated empirically. Interesting numerical examples are cited for a clear understanding of the problem on hand.

Let $I \in \mathbb{R}^M$ be an image. Let M be the total number of pixels. Note that the pixel intensities range from 0 to 255. First, the image I is partitioned into two classes using a threshold T . Initially, the value of T is chosen arbitrarily. Thus, the image is separated into two segments called C_0 and C_1 . The 0 -th segment C_0 contains pixel values ranging from 0 to T . Similarly, the 1 -th segment has pixel values ranging from $T + 1$ to 255.

Let C_i agrees whether the i -th pixel fits to the class (segment) zero or one. It is clear that the sum of the squared error of the segmented image I_s is expressed as in Eq. (1):

$$E = \sum_{C_i=0} (I_i - \eta_0)^2 + \sum_{C_i=1} (I_i - \eta_1)^2 \quad (1)$$

where I_i represents the intensity value of the i th pixel in the class (segment) zero or one, $\eta_0 = \sum_{C_i=0} \frac{I_i}{m_c}$, $\eta_1 = \sum_{C_i=1} \frac{I_i}{(M-m_c)}$ are the means of the class zero (C_0) and one (C_1), respectively. It is assumed that the 0 -th segment (class) contains m_c number of pixels. Hence, primarily m_c is a count. It may be noted that the number of pixels in the 1 -th segment of the bi-level segmented image is $(M - m_c)$. Thus, the segmentation error in this methodology is written as in Eq. (2):

$$E_{\text{seg}} = \|I\|_2^2 - \frac{1}{m_c} \left(\sum_{C_i=0} I_i \right)^2 - \frac{1}{M - m_c} \left(\sum_{C_i=1} I_i \right)^2 \quad (2)$$

where the 1 -st term $\|I\|_2$ is the norm of the original image considered for the segmentation. Note that the mean terms disappear in the 2-nd and the 3-rd terms of Eq. (2). For simplification in the calculations, an approximate error formula is presented here.

For further simplification of Eq. (2), it is assumed that the 2-nd and the 3-rd term are identical. With this assumption, Eq. (2) is further simplified to be as Eq. (3):

$$E_{\text{seg}} = \|I\|_2^2 - \frac{M}{m_C(M - m_C)} \left(\sum_{C_i=0} I_i \right)^2 \quad (3)$$

Eq. (3) plays an important role in this theoretical development. This is treated as an approximate rule for computing the segmentation error. The primary objective is to reduce the segmentation error to achieve a better segmentation accuracy. Such an assumption is needed to make the development simple. Interestingly, the maximization of the 2-nd term leads to the minimization of the segmentation error, which is explicitly clear from Eq. (3). From these ideas, a segmentation score (SS) is newly defined as in Eq. (4):

$$SS_{I,T} = \max_{C \in \{0,1\}^M} \frac{M}{m_C(M - m_C)} \left(\sum I_i \right) \quad (4)$$

Need to mention here that, Eq. (4) is the objective function of the work. Most importantly, the SS gets maximized when T is the optimal value. Alternatively, there is a close connection between the SS and the threshold T . The objective is to optimize the count m_C , because the count m_C depends on the value of T . In other words, the corresponding T is the optimum value of the threshold point. It is important to note that, initially the thresholds are taken randomly. Then the segmentation score is computed using Eq. (4). The optimizer then uses Eq. (4) to obtain a maximum value of the segmentation score (corresponding to the maximum number of pixel counts in segments). The corresponding value of T is the optimum value of the threshold and is fixed in the work.

For a clear understanding of the problem, it is demonstrated empirically. Especially, it helps readers to understand that the proposed scheme is based on non-entropy values. Instead, the method depends on the SS. To be more specific, Eq. (4) plays the important role in this work. To explain the problem on hand, plots for 2 digital standard test images ((a) Cameraman and (b) Lena of size 512×512 and 151×152 , respectively) available in MATLAB are shown in Fig. 2. In this figure, the results on a bi-level segmentation are highlighted. The empirical values are shown in Table 2. It is clearly observed that the count m_C and their corresponding thresholding T values are optimal when the SS gets maximized. Note that the maximum SS and its corresponding m_C and T values are noticeable in boldface letters. For instance, the optimal values of m_C and T are 173,422 and 158 for a maximum SS of 379.16 (for Cameraman sample test image). Hence, the optimal threshold (T_{opt}) for the bi-level segmentation is 158, to separate it into 2 distinct classes. It is to be noted that the total number of pixels in the Cameraman image is

$512 \times 512 = 262,144$. Similarly, for the Lena image, the maximum SS is 324.40 for a corresponding threshold T value of 160, which is the optimal threshold value (T_{opt}). Note that for Lena test image, the total number of pixels is $151 \times 152 = 22,952$.

The main contribution of the work is primarily to investigate a non-entropy methodology for multiclass threshold selection. The above bi-level threshold selection method is extended below for the multilevel medical image thresholding.

Multiple thresholds are utilized to partition I into K segments $S_1, S_2, \dots, S_K$ through the use of the thresholds $T_1, T_2, \dots, T_{K-1}$. It is assumed that T_0 is equal to 0 and T_K takes a value of $L-1$. Note that Eq. (4) plays the central role. The optimal counts m_C are calculated using Eq. (4). Their corresponding T values are chosen as the optimum threshold values. The firsthand fitness functions are derived below. The key to the success is to optimize the multiple $f(\cdot)$ for obtaining the optimum threshold values. To be more precise, the thrust is to obtain the best count m_C so as to get an optimum T out of the range [2, 254]. Therefore, the complexity of the problem depends on the number of thresholds T_K . The threshold selection process described here is quite interesting. The suggested fitness functions are maximized to achieve the optimal thresholds. The new fitness function is defined below in Eq. (5):

$$[T_{1 \text{ opt}}, T_{2 \text{ opt}}, \dots, T_{(K-1) \text{ opt}}] \\ = \arg \max \{f(m_{C1}, m_{C2}, \dots, m_{C(K-1)})\} \quad (5)$$

with the constraints as in Eq. (6):

$$0 < T_{1 \text{ opt}} < T_{2 \text{ opt}} < \dots < T_{(K-1) \text{ opt}} < L - 1 \quad (6)$$

There are profound differences between our method and the earlier techniques. It is important to note that the thresholds are optimal, when the SS (summation over the count m_C) is maximized. The 0 -th segment pixel count m_C is optimized using the proposed algorithm; the chance-based birds' intelligence is deployed. In a multilevel threshold selection problem, the dimension of the search space increases with an increase in the threshold values. The T value is initialized randomly at the beginning. Subsequently, the pixel counts, i.e., m_C are randomly chosen. Finally, the solutions with the best fitness values are chosen as the best optimal values here. The multiple optimal thresholds are calculated by utilizing the following derivations in Eqs. (7) to (9):

$$T_{1 \text{ opt}} = \arg \max \left(\left(\frac{M}{m_C(M - m_C)} \right) \sum_{u=0}^{m_{C1}} \sum_{v=m_{C1}+1}^{m_{C2}} (I_{u,v}) \right) \quad (7)$$

Fig. 2 Plots of the segmentation scores. **a** Cameraman image, **b** Lena image

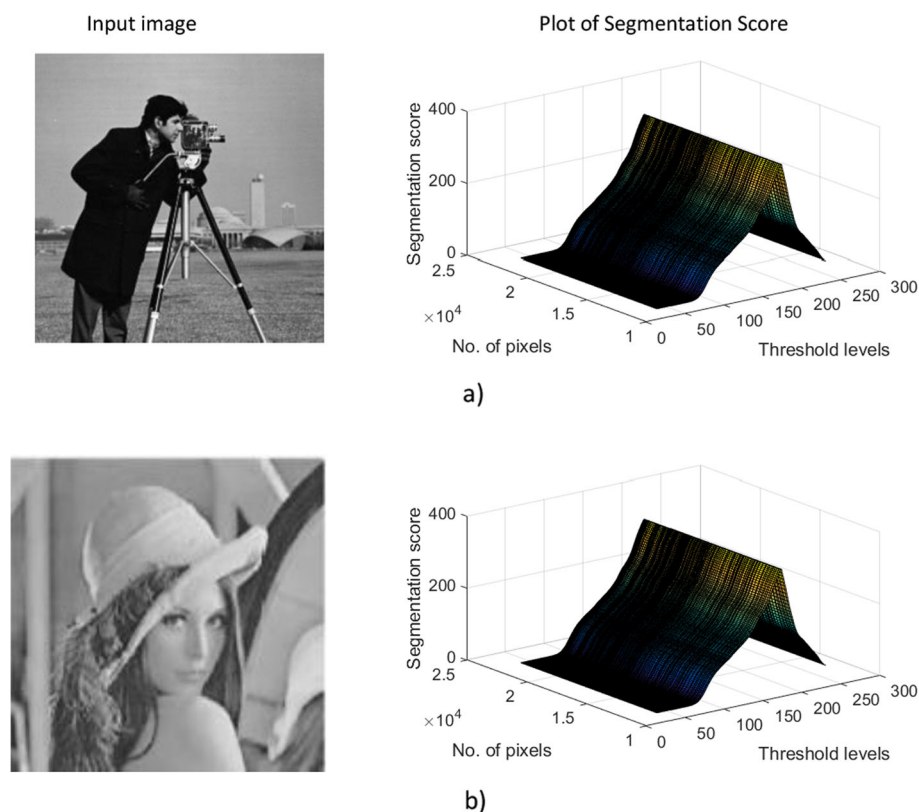


Table 2 Numerical values for the two different images (Cameraman image and Lena image)

Input image	Threshold (T)	No. of Pixels (m_C)	Segmentation Score	Optimal threshold
Cameraman	155	165,119	364.14	158
	156	168,080	369.52	
	157	170,804	374.45	
	158	173,422	379.16	
	159	176,027	365.13	
	160	178,587	350.37	
	161	181,095	336.27	
Lena	157	13,516	315.59	160
	158	13,744	319.70	
	159	13,975	323.81	
	160	14,214	324.40	
	161	14,459	313.33	
	162	14,660	304.36	
	163	14,873	294.97	

Bold values indicate the the best results

$$T_{2 \text{ opt}} = \arg \max \left(\left(\frac{M}{m_C(M - m_C)} \right) \sum_{u=m_{C1}+1}^{m_{C2}} \sum_{v=m_{C2}+1}^{m_{C3}} (I_{u,v}) \right) \quad (8)$$

$$T_{(K-1) \text{ opt}} = \arg \max \left(\left(\frac{M}{m_C(M - m_C)} \right) \sum_{u=m_{C(K-2)}+1}^{m_{C(K-1)}} \sum_{v=m_{C(K-1)}+1}^{M-m_{C(K-1)}} (I_{u,v}) \right) \quad (9)$$

In the above Eqs. (7), (8), (9), $m_{C1}, m_{C2}, \dots, m_{C(K-1)}$ represent the pixel counts of different segments (classes) corresponding to their optimal threshold values. It is important to mention here that m_C (appearing) in Eqs. (7), (8), and (9) is the highest count among the classes. For example, m_C assumes the highest count value out of three counts m_{C1}, m_{C2} , and m_{C3} while dealing with the Eq. (8). It is reiterated that the number of classes is three when the

number of thresholds are two. Thus, three counts are found for three different classes. The optimal thresholds required for multiclass segmentation are obtained using the suggested algorithm. It is reiterated that the threshold values obtained here are optimal, while the SS is maximized. The suggested process is displayed in Fig. 3.

As opposed to the earlier methodologies, the proposed idea is based on the optimization of the pixel counts only. As the pixel counts are simple numbers only, these are completely free from the spatial grey level distributions throughout the image I . The above counts $m_{C_1}, m_{C_2}, \dots, m_{C_{(K-1)}}$ are numbers only. Further, the process of maximization of the SS reduces the error of the multiclass segmentation significantly. Even more interesting idea is to get their corresponding threshold values T_K 's, which are eventually the optimal values. The beauty of the proposal is that it is good enough to maximize the functional $f(\cdot)$. To solve this exhaustive search problem, we use the newly suggested optimization algorithm.

3 The proposed chance-based birds' intelligence algorithm

To maximize the segmentation score, an efficient optimizer is needed. The corresponding optimal thresholds would provide us a better segmented image. It is reiterated that the suggested objective function Eq. (9) is utilized here in a computationally efficient manner. This headed to the investigation of a new algorithm by awakening the intelligence of the sea birds (Zhao et al. 2022), the cuckoo birds (Agrawal et al. 2013) through the use of chance factor. As a result, the convergences and the performances of the algorithm are improved.

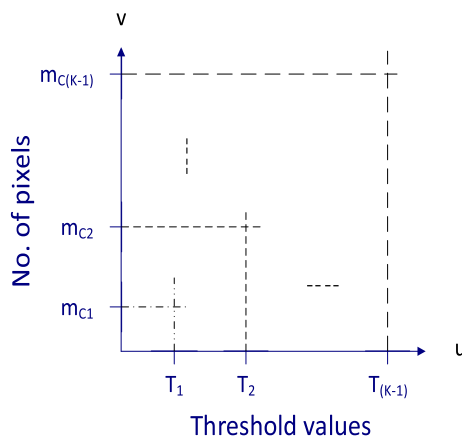


Fig. 3 Primary concept of the methodology

3.1 Background

3.1.1 Algorithm based on the cuckoo bird's intelligence

Search strategies (CS) based on the intelligence of cuckoo birds are a general community-based nature-driven algorithm. Cuckoo birds incubate their eggs astutely, puts her eggs inside others nest. Usually, they prefer that of crows. In this sense, the Indian species of cuckoo birds are very intelligent. The inherent intelligence of cuckoo birds is an inherent gift for them by God. When the crow goes outside the nest, a Cuckoo bird puts her eggs very intelligently. The crow may identify the eggs with a probability $p_a \in [0, 1]$. In case it identifies, then probably it leaves the nest or destroys the eggs.

Numerically it is portrayed like the equations presented here. Let us assume that N is the no. of cuckoos available here and a cuckoo addresses a nest. Interestingly, a nest implies a solution to the given task. Assume that the dimension of the problem is n . Note that the dimension decides the complexity. The vector representation of the i -th bird at period t is $K_i(t) = (k_i^1, \dots, k_i^d, \dots, k_i^n)$. For the instance, when the period is $t + 1$, the corresponding vector for the i -th bird is shown in Eq. (10):

$$K_i(t+1) = K_i(t) + \alpha \otimes \text{Levy}(\gamma) \quad (10)$$

Note that $\alpha > 0$. Normally α is equal to one. The step size $\text{Levy}(\gamma)$ is computed using the well-known Lévy flight principle. Here, $\otimes$ is an entry-wise multiplication. Its walking strategy adopted is quite genuine. In more iterations, this idea provides good enough exploration space. That is the reason why the Lévy step idea is implemented while developing the cuckoo search strategy. This is basically resulting from the Lévy spread, got from the Mantegna algorithm. Thus, it is expressed as in Eq. (11):

$$\text{Levy}(\gamma) = u/|v|^{\frac{1}{\gamma-1}} \quad (11)$$

In Eq. (11) both u and v denote the Gauss kind of dispersion, γ varies within the range $1 < \gamma < 3$. Further, the both deviations are expressed by Eq. (12):

$$\begin{aligned} \sigma_v(\gamma) &= 1 \\ \sigma_u(\gamma) &= \left[\frac{\Gamma(1+\gamma) \sin(\frac{\pi\gamma}{2})}{\Gamma(\frac{1+\gamma}{2}) \gamma 2^{\frac{\gamma-1}{2}}} \right]^{\frac{1}{\gamma}} \end{aligned} \quad (12)$$

Note that $\Gamma(\cdot)$ is called Gamma function. An infinite variance is depicted below in Eq. (13):

$$\text{Levy} \sim u = t^{-\gamma} \quad (13)$$

Hence, the CS uses a search strategy which is interesting enough. Its step sizes are small for a shorter length while these are long for the lengthier distances. However, it is not

just sufficient to explore the all possible solutions. There is always more scope to further include and verify other possible solutions. The accuracy in achieving the optimal solution may be further improved. This is the reason behind the present study. Later on it is explained how to explore other possible solutions which are not successfully explored so far. The inclusion of these chances is the key contribution in this study, which is presented in Section 3.2.

3.1.2 Algorithm based on the seagull bird's intelligence

Sea birds also possess a certain amount of intelligence, which is God gifted. Seagull's migration and attacking behavior are modeled as an algorithm and is named as SOA (Panagant et al. 2020). Their attacking behaviors for food is very interesting. They do it intelligently. Upon change of season, they move to another place for food and shelter. They create a spiral system of effort to assault their prey. This kind of a mathematical model is depicted as underneath.

The parameter M is used to simulate avoiding collision issues among adjacent seagulls as in Eq. (14).

$$\vec{F}_c = M \times \vec{F}_{\text{current}}(x) \quad (14)$$

$\vec{F}_{\text{current}}(x)$ denotes the current location. Here, M represents the parameter for drive of the agent as in Eq. (15):

$$M = f_c - (x \times (f_c / \text{Max}_{\text{iteration}})). \quad (15)$$

Here, the minimum value of x is zero and the max value is $\text{Max}_{\text{iteration}}$. The number of iterations decide the speed of the convergence. The seagull birds' intelligence is used here to minimize the number of iterations in getting the optimal solution.

Note that f_c is the boundary condition of the parameter M , it is decremented in each iteration linearly. The value should change smoothly over iterations. Here, the value of $f_c = 2$. The decision is taken from the knowledge acquired through the extensive simulation results. The phenomena are very carefully studied with different values of f_c . Finally, to achieve the best results, it is decided to fix the value of f_c as 2.

Next, the swarm of seagull birds move near the location of the best bird. This location is treated as the best solution. This position is defined as Eq. (16):

$$\vec{G}_s = N \times (\vec{F}_{\text{best}}(x) - \vec{F}_{\text{current}}(x)) \quad (16)$$

In this model, $\vec{G}_s$ denotes the most efficient locations near the best-fit contender $\vec{F}_{\text{best}}(x)$. N assumes a random value. This parameter is used to monitor the good balance between the exploration and the exploitation. The value of N is shown in Eq. (17):

$$N = 2 \times M^2 \times \text{rand} \quad (17)$$

where rand is a random number within the range $[0, 1]$.

Then, the next updated location is as in Eq. (18):

$$\vec{D}_s = \left| \vec{F}_c + \vec{G}_s \right| \quad (18)$$

This is basically the parting between the search agent and the best bird.

Interestingly, their attacking behavior is just like a spiral path that changes speed continuously. This kind of movement in the x, y and z plane is as follows in Eqs. (19) to (22).

$$x' = r \times \cos(k) \quad (19)$$

$$y' = r \times \sin(k) \quad (20)$$

$$z' = r \times k \quad (21)$$

$$r = u \times e^{kv} \quad (22)$$

Note that r represents the radial turn of spiral defined in Eq. (22), k range is $[0 \leq k \leq 2\pi]$. Here, u, v assume constant values. These values decide the shape (kind of spiral twist). The new location is computed using Eqs. (18) to (22) and is displayed in Eq. (23).

$$\vec{F}_{\text{current}}(x) = (\vec{D}_s \times x' \times y' \times z') + \vec{F}_{\text{best}}(x) \quad (23)$$

Here, $\vec{F}_{\text{current}}(x)$ saves the best sites. The locations of other agents are also updated.

It is noteworthy to mention here that the foraging strategy adapted by the seagull birds is based on their intelligence. Nonetheless, the exploration capacity of the seagull bird is better than the cuckoo bird. However, still the exploration capacity is limited by the seagull birds' intelligence. An effort is made here to enhance the exploration capacity by using a chance factor. Further, the exploitation capability is also improved by using the cuckoo birds' intelligence. These novel ideas are explained in the following section.

3.2 The proposed algorithm using chance-based birds' intelligence

In this section, the main idea behind this proposed method is highlighted. The strategic development of the work is explained. The search strategy, adapted by the Cuckoo birds, employs the random walk via a Lévy flight. This makes it supplementary active in exploring the required search space. This provides an appropriate step size. It is primarily the idea behind this proposal. It is also needed to further include some more solutions, which are not covered during the search process. It is wise to explore more possible solutions from the entire search space to improvise the results. This contribution has considered the chances of

the inclusions of more solutions. Investigations are made in this direction. Finally, it is proposed to incorporate a chance factor to address the problem. The newest contribution is the chance-based birds' intelligence, which is discussed in this section.

In this contribution, the chance factor is used to improve both the exploration and the exploitation issues. To strengthen the algorithm, the Lévy flight along with a chance factor is used. Considering the Lévy flight with a chance factor, Eq. (18) is modified below as in Eq. (24):

$$\vec{D}_s = \left| \vec{F}_c + \vec{G}_s \times \text{Levy}(\gamma) \right| \quad \text{for } r_1 < z, \quad (24)$$

$$= \left| \vec{F}_c + \vec{G}_s \right| \quad \text{otherwise.}$$

As a result, the exploration stage as well as the exploitation phase becomes dominant. Note that z is a positive number decided by the user. It is important to note that a random value for the chance factor r_1 is chosen. It

This is the novelty of the approach, which is efficient in finding out the best solution candidate. The best candidate is prepared now to wisely follow an exploitation phase. Its solution space is shown in Fig. 4. The projection parts $x'y'$ (as expressed in Eq. (19) and Eq. (20)) are consistently lessening. It similarly takes care of the elevation by deploying the proper assaulting strategy. It is noteworthy to mention here that the radius r is responsible to ensure a better exploitation stage. This concept of the shape that looks like spiral in nature is its confronting behavior. This kind of attack (the prey attitude) is blended here to develop a new chance-based optimizer. Finally, Eq. (23) is expressed as Eq. (25) below:

$$\vec{F}_{\text{current}}(x) = \left(\vec{D}_s \times x' \times y' \times z' \right) + \vec{F}_{\text{best}}(x) \quad (25)$$

Here, Eq. (25) is considered as the key expression used to implement the proposed optimizer. The pseudocode is presented below:

The Pseudocode:

Begin:

Input: $N, pa, f_c, MaxIteration$

Initialization: Initialize population, define LB and UB.

While $t \leq MaxIteration$

 Define movement characteristic M using Eq. (15).

 Update the new solution, keep the best one.

 Calculate Lévy steps by Eq. (11) and Eq. (12), choose a random value for the chance factor r_1 .

For (each solution X_i)

 Position update using Eq. (16).

 Apply Lévy coefficients using Eq. (24) with the chance factor r_1 .

 Spiral movement in $x y z$ plane using Eq. (25).

 Calculate the current best

 Update the position.

End For

$t = t + 1$

End While

Output: Global best solution.

enables us to consider additional search areas, which is targeted for, chances of trapping in the local minima are avoided. The choice of this factor r_1 is crucial. This improves the optimization methods under various uncertainties. Through this, it is ensured that the optimization problem can explore more solutions beyond some level. Here, the confidence of getting better solutions is quite high compared to the existing algorithms. The chance-based birds' intelligence is especially important to improve the optimal solutions. Wherever, there is a chance of exclusion of some possible solutions for the solution space, the chance factor enforces it to explore further solutions that are not covered so far.

3.3 Performance evaluation of the proposed chance-based optimizer

In this section, the performance analysis of the method is carried out. The purpose of this section is to validate the algorithm using standard test functions. A good optimization algorithm should have a good trade-off between the exploitation and exploration capability to obtain the optimal solutions. The exploitation capability better describes how fast the optimization algorithm converges to optimal solutions. The exploitation capability describes how the optimization algorithm avoided local minima. For the validation of the proposed algorithm called SOA-CS, 23

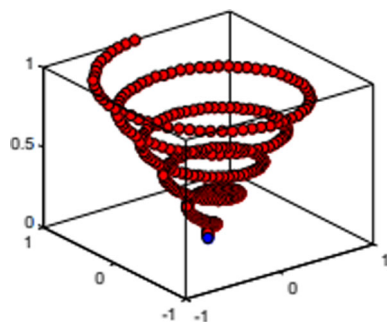


Fig. 4 Confronting behavior of Seagull

test functions are considered, which are reported in (Naik et al. 2021). Here, all 23 test functions constitute a combination of three groups such as unimodal ($f_1 - f_7$), multimodal with variable dimensions ($f_8 - f_{13}$) and multimodal with fixed dimensions ($f_{14} - f_{23}$). The unimodal test functions are used to test the exploitation

capability. Note that the multimodal test functions are utilized for the exploration.

To maintain the consistency among the performance of the compared algorithm SOA-CS, SOA and CS, the same parameters are chosen. The experiments are carried out for population count N as 25, $f_c = 2$ and maximum generation t_{MAX} as 500 and abandoned probability p_a as 0.25. It is reiterated that a random value for the chance factor r_1 is chosen. The algorithms are runs 31 times to obtain the average fitness value ‘Ave.’ and standard deviation ‘Std.’ for performance comparison. The lower ‘Ave.’ and ‘Std.’ reported the best results among the optimization algorithms.

Its performance on 23 test functions is reported in Table 3. The SOA-CS shows superior performance on the test functions $f_1 - f_{13}$ than SOA and CS except for the test function f_8 . However, SOA-CS shows similar performances like SOA and CS on test functions $f_{14} - f_{23}$. A statistical comparison based on Freedman’s mean rank is conducted. The SOA-CS ranked one as compared to the

Table 3 Performance comparison of SOA-CS with SOA and CS

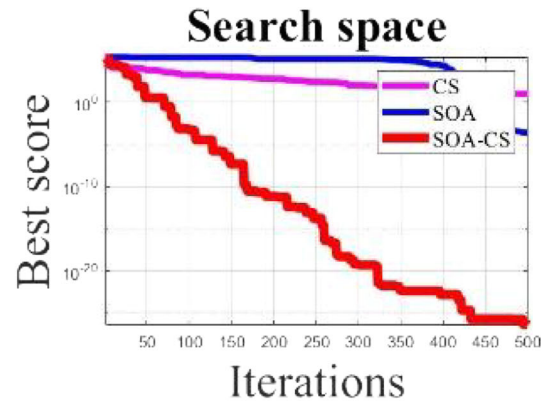
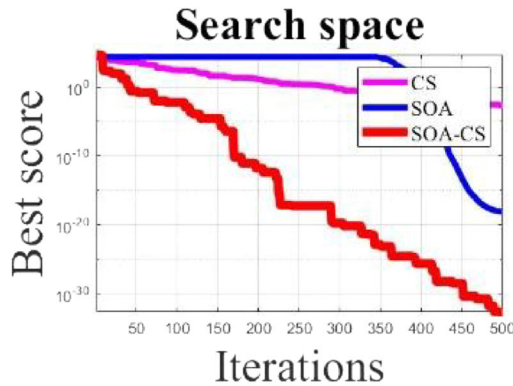
Function type	Test function	SOA-CS		SOA		CS	
		Ave	Std	Ave	Std	Ave	Std
Unimodal	f_1	1.21e-30	4.32e-30	6.56e-19	1.14e-18	0.0040	0.0029
	f_2	1.77e-16	8.97e-16	3.28e-08	3.57e-08	0.0916	0.0345
	f_3	7.53e-22	3.65e-21	4.32e-04	0.0012	14.3940	5.0768
	f_4	3.45e-14	1.31e-13	0.0254	0.0847	1.3424	0.6374
	f_5	26.6754	0.4252	28.3940	0.5040	17.6889	6.5084
	f_6	0	0	3.4397	0.5619	0	0
	f_7	0.0040	0.0028	0.0040	0.0026	0.0193	0.0080
Multimodal (variable dimensions)	f_8	− 8.45e + 03	1.36e + 03	− 5.02e + 03	567.0950	− 4.57e + 03	168.3655
	f_9	0	0	2.9063	10.0971	31.9087	5.4852
	f_{10}	3.25e-15	4.78e-15	19.9613	0.0014	2.1064	0.7928
	f_{11}	0	0	0.0172	0.0276	0.1735	0.0355
	f_{12}	5.31e-04	3.07e-04	0.3294	0.1581	0.4805	0.3986
	f_{13}	0.0666	0.0682	2.1234	0.2093	0.0253	0.0218
Multimodal (fixed dimensions)	f_{14}	0.9980	1.35e-16	3.1904	3.3545	0.9980	1.35e-16
	f_{15}	0.0013	0.0036	0.0011	2.99e-04	4.40e-04	1.33e-04
	f_{16}	− 1.0316	2.34e-16	− 1.0316	2.34e-16	− 1.0316	2.34e-16
	f_{17}	0.3979	0	0.5529	0.8475	0.3979	0
	f_{18}	3	0	3.0001	1.53e-04	3	0
	f_{19}	− 3.8628	0	− 3.8550	0.0012	− 3.8628	0
	f_{20}	− 3.2792	0.0572	− 2.8532	0.4872	− 3.3220	1.36e-15
	f_{21}	− 10.1532	0	− 2.5544	3.5899	− 10.1532	0
	f_{22}	− 10.4029	0	− 5.3456	4.5773	− 10.4029	0
	f_{23}	− 10.5364	0	− 7.4852	4.0973	− 10.5364	0
	Friedman’s mean rank	1.46	2.50				
	Rank	1	3				

Bold values indicate the the best results

Unimodal Test Functions

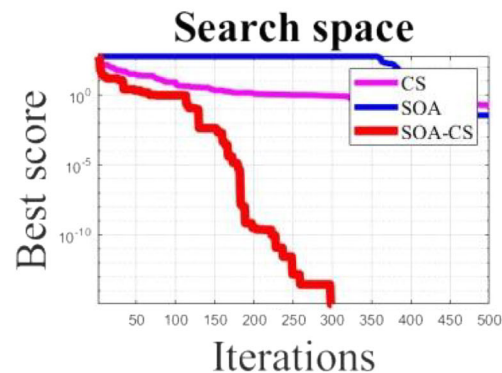
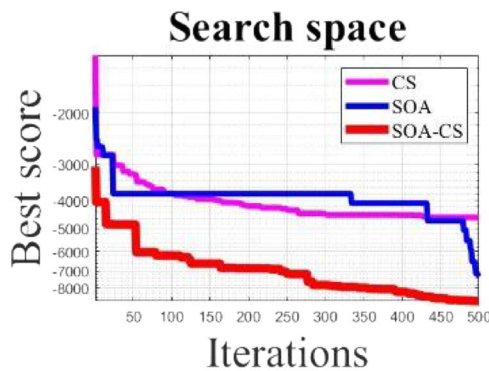
$$f_1(x) = \sum_{i=1}^n x_i^2$$

$$f_3(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2$$

**Multimodal Test Functions with variable dimensions**

$$f_8(x) = \sum_{i=1}^n -x_i \sin(\sqrt{|x_i|})$$

$$f_{11}(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

**Multimodal Test Functions with fixed dimensions**

$$f_{20}(x) = -\sum_{i=1}^4 c_i \exp\left(-\sum_{j=1}^6 a_{ij} (x_j - p_{ij})^2\right)$$

$$f_{22}(x) = -\sum_{i=1}^7 \left[(X - a_i)(X - a_i)^T + c_i \right]^{-1}$$

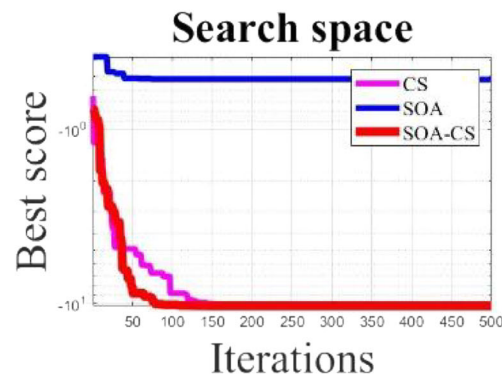
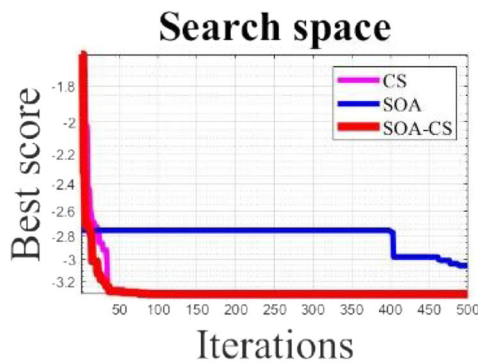


Fig. 5 Convergence curves of SOA-CS vs. others for 6 test functions

others. Moreover, it is also observed that the standard deviation values obtained in the case are consistent, variation is minimum, which is desirable for an efficient algorithm. This property is depicted in Table 3. In this simulation experiment, the number of maximum iterations

considered are 500. A comparative performance, convergence curves for six different test functions, is presented in Fig. 5.

From Fig. 5, it is noted that SOA-CS has shown significant improvements in the convergence as compared to

the SOA. The algorithm quickly converges to the minimum value. Now, it is claimed that the suggested SOA-CS has a better ability to solve various engineering problems, where an optimizer is needed. The improved performances of the proposed chance-based birds' intelligence could yield better results. The convergence is also faster, which is needed to quickly get the optimum solutions. These statistical and convergences-based result analysis evoke us many more ideas regarding the use of the proposed optimizer for solving constrained optimization problems in engineering application areas. In summary, the Lévy flight along with a chance factor could improve the results significantly.

4 The suggested SS-SGCS for optimal multilevel thresholding

In this section, the proposed method called SS-SGCS is described. The suggested SOA-CS optimizer is used to maximize the thresholding objective functions discussed in Sect. 2. The corresponding optimal threshold values

$(T_1^*, T_2^*, \dots, T_K^*)$ are obtained from the knowledge of the maximum counts. The flow diagram is displayed in Fig. 6. The computed optimal threshold values are used for the multiclass segmentation of the images.

5 Results and discussion

The purpose of this section is to highlight the results. An in-depth discussion is also carried out. The proposal, of the SS-SGCS for optimal multilevel threshold selection, is validated using randomly selected 6 chest X-ray images out of a total of 3616 images from (Kaggle database 2021; Chakraborty et al. 2021). To conserve space only, six sample images are chosen. Fig. 7 shows the six grey scale images of chest X-rays with an identification number and their histograms. For a performance comparison, the suggested SGCS methodology is also employed for Tsallis entropy named Tsallis-SGCS, Kapur's entropy named as Kapur-SGCS, and Masi entropy named as Masi-SGCS to find the optimal threshold values. All these methods are implemented in MATLAB. The implementation steps are

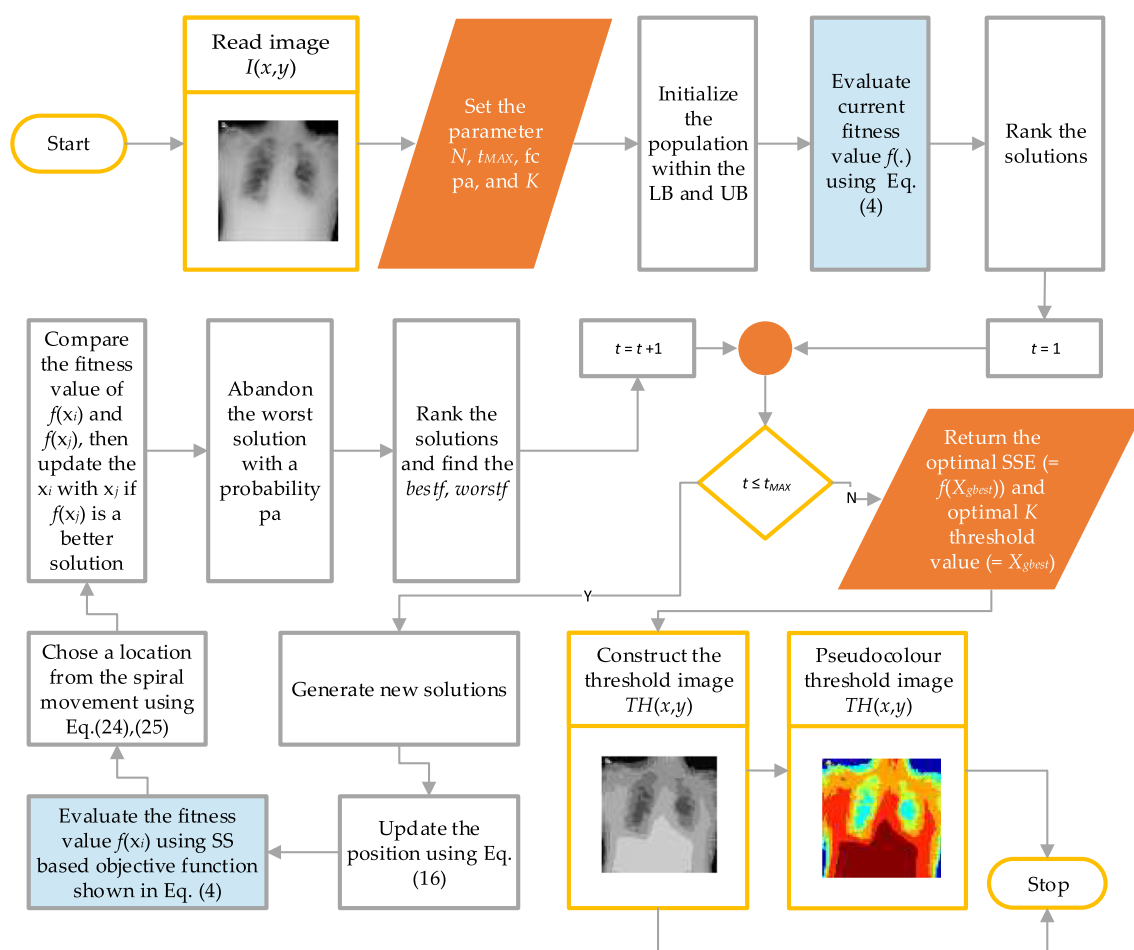


Fig. 6 Flowchart of SS-SGCS-based optimal multilevel thresholding

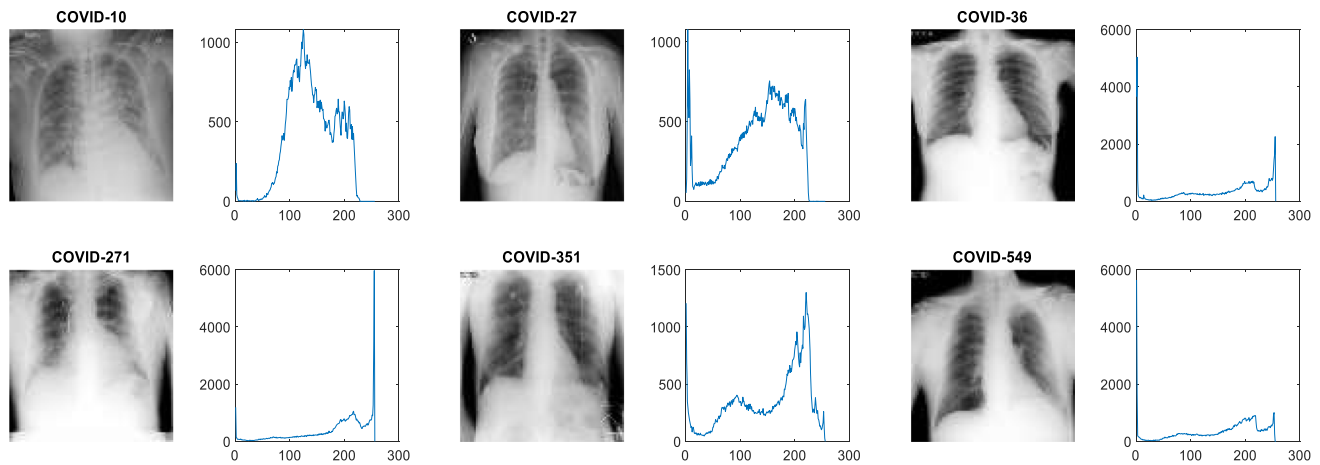


Fig. 7 Original six COVID-19 X-ray chest images along with the histograms

Table 4 Optimal threshold values

Test Image	K	SS-SGCS	Tsallis-SGCS	Kapur-SGCS	Masi-SGCS
COVID-10	2	81, 158	73, 148	108, 157	119, 220
	4	58, 129, 175, 197	55, 107, 165, 189	91, 133, 173, 193	79, 103, 155, 213
	6	46, 96, 134, 155, 185, 201	35, 73, 113, 143, 181, 198	27, 67, 103, 143, 174, 188	58, 75, 114, 144, 176, 214
COVID-27	2	64, 154	84, 164	114, 175	115, 173
	4	52, 122, 176, 195	66, 124, 184, 201	83, 134, 186, 213	89, 134, 184, 203
	6	35, 82, 122, 157, 196, 216	43, 82, 123, 163, 197, 209	13, 52, 98, 148, 193, 219	38, 55, 102, 142, 182, 234
COVID-36	2	74, 124	62, 123	68, 128	96, 187
	4	63, 102, 142, 159	48, 97, 144, 167	56, 103, 143, 159	68, 126, 186, 199
	6	37, 67, 95, 125, 145, 168	32, 62, 96, 124, 155, 185	36, 67, 97, 125, 155, 183	32, 55, 103, 148, 189, 223
COVID-271	2	76, 176	85, 174	114, 187	112, 182
	4	43, 52, 133, 203	46, 63, 125, 194	39, 85, 142, 197	61, 88, 144, 194
	6	35, 95, 144, 185, 201, 224	43, 84, 125, 173, 203, 214	56, 97, 144, 184, 197, 217	65, 105, 146, 186, 192, 224
COVID-351	2	145, 207	96, 175	55, 145	53, 143
	4	85, 118, 172, 223	58, 124, 188, 201	55, 118, 178, 205	56, 119, 180, 209
	6	96, 135, 168, 199, 209, 234	54, 94, 133, 175, 207, 212	57, 98, 126, 164, 186, 195	22, 55, 96, 147, 187, 211
COVID-549	2	126, 187	88, 169	78, 166	77, 165
	4	58, 87, 144, 195	45, 73, 133, 192	49, 73, 135, 185	33, 67, 135, 186
	6	66, 107, 143, 173, 209, 224	53, 95, 136, 176, 216, 231	66, 97, 137, 175, 204, 229	65, 99, 137, 177, 207, 221

illustrated in terms of a flowchart shown in Fig. 6. To evaluate the optimal multiclass thresholding methodologies, the PSNR, FSIM, and SSIM metrics are used. All parameters chosen to implement the SS-SGCS are considered the same as discussed in Section 3.3. These parameters are selected based on the results achieved through extensive simulations.

Each method runs 11 times to get the optimal thresholds. The optimal thresholds for $K = 2, 4, 6$ are presented in Table 4 and used to generate the thresholded images. Note that K is the number of threshold levels. Optimal threshold values for other values of K are not shown to conserve the space only. Then the efficiency of the method is assessed

by the performance metrics PSNR, FSIM and SSIM. Note that these metrics are evaluated using the output (thresholded images). The higher PSNR, FSIM and SSIM values suggest better thresholding methods. The performance of the proposed method SS-SGCS vs. others are presented in Tables 5, 6 and 7. The boldface represents the better one.

For the clinical use, it is needed to obtain the multilevel thresholded X-ray images. Multiclass segmented X-ray image is commonly in use for measuring and visualizing dissimilar chest assemblies, for outlining the defected area, for extracting lungs features, for image-guided instructions and treatment planning. Nevertheless, it is undeniable that automated computerized multiclass segmentation

Table 5 Optimal PSNR values

Test Image	Th	SS-SGCS	Tsallis-SGCS	Kapur-SGCS	Masi-SGCS
COVID-10	2	24.1998	21.7798	22.3730	22.3179
	4	27.6732	24.9059	26.3667	25.3641
	6	30.5850	27.5265	29.3114	28.5146
COVID-27	2	21.5150	20.5498	20.4413	20.4134
	4	26.4169	24.4584	25.2260	23.9794
	6	29.3024	27.2071	28.6479	27.5392
COVID-36	2	19.8122	14.7762	18.6207	18.5871
	4	25.3635	17.6144	22.3043	22.3593
	6	28.5762	18.5796	26.9090	26.4929
COVID-271	2	20.7808	19.4156	19.3851	19.3959
	4	25.4405	21.2717	24.1392	23.9916
	6	28.9200	23.5132	26.5652	26.2041
COVID-351	2	20.9447	19.4950	19.8463	19.8663
	4	25.6174	23.5130	24.1366	24.1513
	6	28.5247	25.5639	27.4418	27.1387
COVID-549	2	20.0056	16.2735	19.2439	19.2720
	4	25.2249	17.0582	22.3701	22.2937
	6	26.6466	18.9007	24.7988	25.5701

Bold values indicate the the best results

Table 6 Optimal FSIM values

Test Image	Th	SS-SGCS	Tsallis-SGCS	Kapur-SGCS	Masi-SGCS
OVID-10	2	0.7637	0.7368	0.7180	0.7090
	4	0.7938	0.7526	0.7484	0.7229
	6	0.8376	0.7970	0.7934	0.7490
COVID-27	2	0.6897	0.6727	0.6760	0.6530
	4	0.7471	0.7156	0.7162	0.6766
	6	0.8054	0.7680	0.7569	0.7264
COVID-36	2	0.7079	0.6391	0.6868	0.6685
	4	0.7520	0.7016	0.7224	0.7126
	6	0.8203	0.7309	0.7841	0.7876
COVID-271	2	0.7301	0.7426	0.7382	0.7269
	4	0.7628	0.7898	0.7491	0.7464
	6	0.8185	0.8068	0.7884	0.7954
COVID-351	2	0.7267	0.7069	0.7057	0.6852
	4	0.7505	0.7331	0.7299	0.7238
	6	0.8091	0.7579	0.7559	0.7564
COVID-549	2	0.7266	0.6617	0.7068	0.6944
	4	0.7550	0.6950	0.7277	0.7212
	6	0.8127	0.7316	0.7750	0.7751

Bold values indicate the the best results

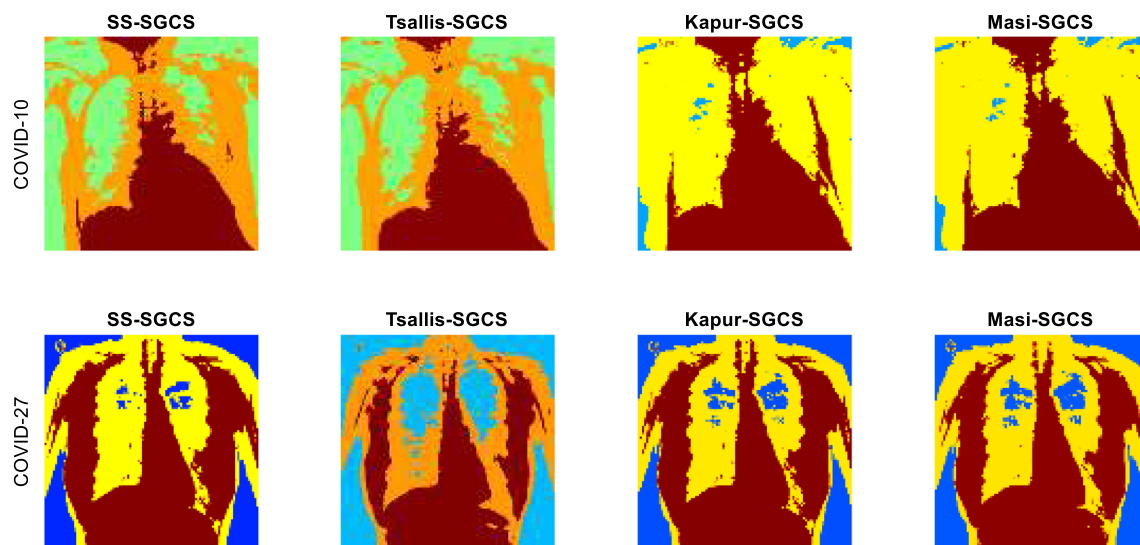
technologies have revealed their abilities for use in the doctor assisted diagnosis/therapy planning. In this context, the results embodied in Table 4 is very crucial. These optimal threshold values decides the accuracy, efficacy of a method over the existing techniques. The input image is segmented to produce an output image with different distinct regions. The implementation equations to construct the output images are given in Appendix A. In this paper,

the chest X-ray image is in grey scale form (Fig. 7). Output images (the segmented X-ray) are displayed (Figs. 8, 9 and 10) using pseudocoloring, to provide a superior visual representation. For instance, when $K=6$, $K+1$, i.e., 7 segments (seven distinct colors) are seen. For a detailed statistical analysis, standard metrics are used for a comparison of our method with other state-of-the-art methods. The optimal PSNR values are presented in Table 5.

Table 7 Optimal SSIM values

Test Image	Th	SS-SGCS	Tsallis-SGCS	Kapur-SGCS	Masi-SGCS
COVID-10	2	0.7517	0.7361	0.7278	0.7066
	4	0.7997	0.7628	0.7564	0.7200
	6	0.8379	0.8033	0.8049	0.7547
COVID-27	2	0.6489	0.6225	0.6378	0.6112
	4	0.7327	0.6880	0.7041	0.6496
	6	0.7979	0.7475	0.7603	0.7204
COVID-36	2	0.6549	0.5208	0.6104	0.6011
	4	0.7249	0.6127	0.6493	0.6468
	6	0.7944	0.6467	0.7865	0.7338
COVID-271	2	0.7220	0.7510	0.7473	0.7361
	4	0.7836	0.7901	0.7725	0.7695
	6	0.8397	0.8166	0.8055	0.80927
COVID-351	2	0.7001	0.6825	0.6779	0.6646
	4	0.7481	0.7196	0.7246	0.7214
	6	0.8102	0.7448	0.7509	0.7527
COVID-549	2	0.6703	0.5576	0.6460	0.6364
	4	0.7236	0.6201	0.6709	0.6656
	6	0.7977	0.6704	0.7184	0.7216

Bold values indicate the the best results

**Fig. 8** 2-level pseudo color threshold outputs

It is noteworthy to mention here that the PSNR mainly quantifies the quality of a reconstructed or thresholded (output) image in relation to the ground truth. In this work, Table 5 shows the PSNR values computed for four different technologies. Interestingly, the method yields higher PSNR values than the other state-of-the-art techniques. For instance, the suggested method yields 11.1%, 8.1%, 8.4% higher values (for COVID-10 image with a threshold level of $K = 2$) than the Tsallis-SGCS, Kapur-SGCS, Masi-SGCS, respectively. It is also observed that the proposed method exhibits 11.2%, 4.3%, 7.2% higher values (for COVID-10 image with a threshold level of $K = 6$) than the

Tsallis-SGCS, Kapur-SGCS, Masi-SGCS, respectively. A similar trend is also seen in the other COVID-19 X-ray images. For example—with the COVID-549 image for a threshold level of $K = 2$, it is seen that 22.9%, 3.9%, 3.8% higher values than the other three methods, respectively, are obtained. And for $K = 6$, the improvements seen are 40.7%, 7.4%, 4.2% higher values than others, respectively. The reason of improvements could be due to the minimization of the segmentation error. Further, the pixel counts are optimized to get the maximum segmentation score. Note that the pixel count is independent of the image histogram. Therefore, the proposal is more suitable for

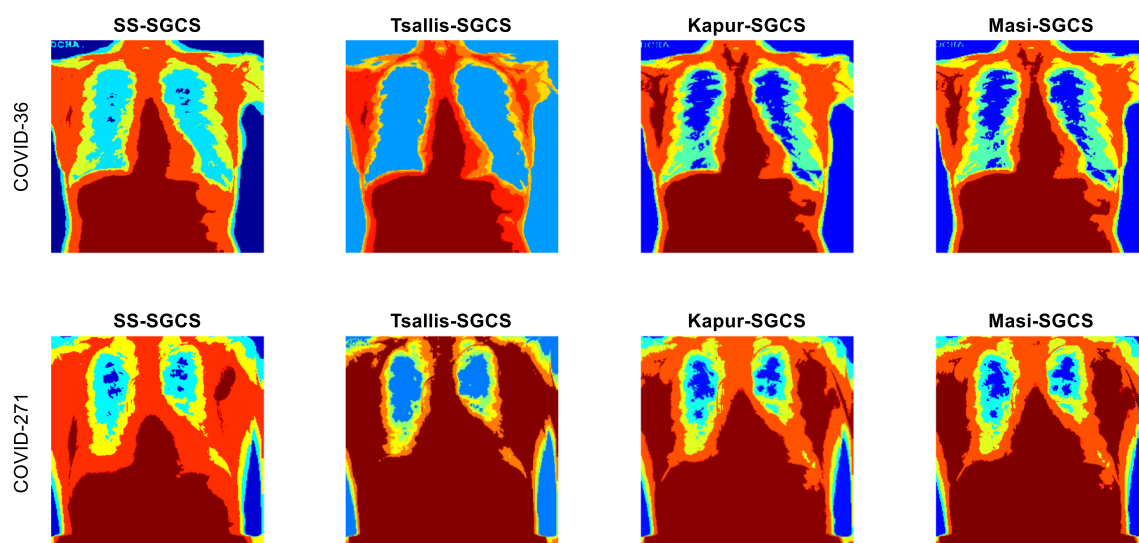


Fig. 9 4-level pseudo color threshold outputs

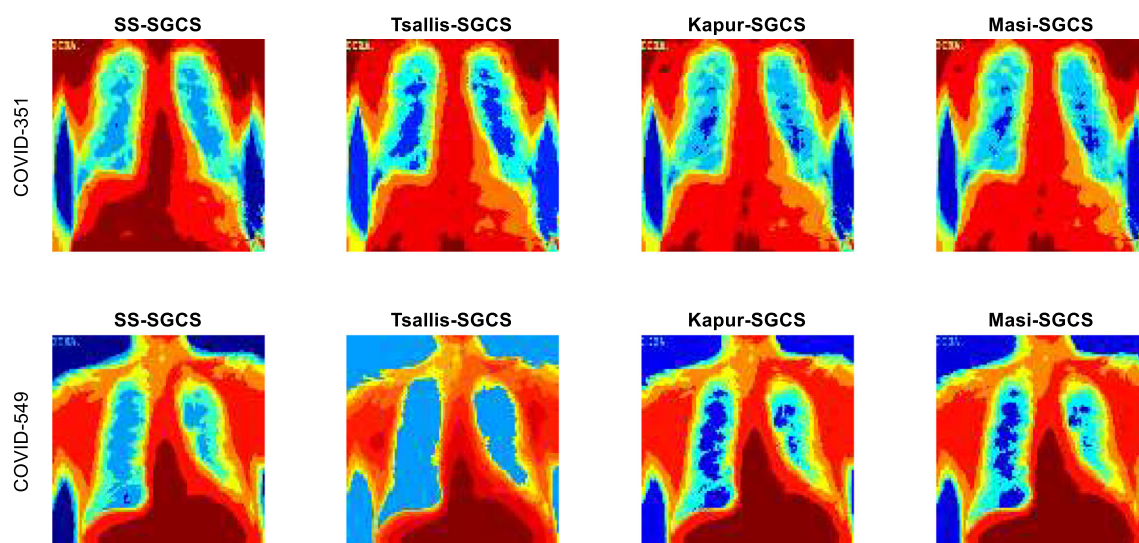


Fig. 10 6-level pseudo color threshold outputs

multiclass segmentation, as opposed to the existing techniques.

On the other hand, the SSIM (Structural Similarity) index and the FSIM (Feature Similarity) index are more authoritative image structure measurement metrics found in the segmentation literature (Zhou et al. 2004; Lin Zhang et al. 2011). These metrics are generally used for the measurements in the image processing field. The ideal value for the SSIM and FSIM of a reconstructed image to ground-truth is always one, and a value close to one indicates that the image is of good quality. The SSIM computes the visual similarity between the original image I and the thresholded image $\tilde{I}$, at a specific threshold level K . In the segmentation literature (Zhou et al. 2004; Lin Zhang et al. 2011), it is treated as a comprehensive reference index.

This implies that the image quality assessment or measurement is based on an original distortion-free image considered as a reference image. The quality assessment using SSIM and FSIM is treated as an improvement over the classical approaches using metrics such as PSNR and RMSE. The formula for computation of the SSIM and the FSIM are given in Appendix B.

Usually, the SSIM is a perception-based metric that takes image deterioration into account when structural information changes. It includes crucial perceptual phenomena, such as brightness masking requirements and contrast factors. It should be emphasized that structural information indicates a high degree of interaction between the spatially closer pixels. These dependencies communicate critical information about the image's object structure

Table 8 Friedman's mean rank

Methods	SS-SGCS	Tsallis-SGCS	Kapur-SGCS	Masi-SGCS
Friedman's mean rank	3.2998	2.8152	2.6123	1.3112
Rank	1	2	3	4

Bold values indicate the the best results

(Zhou et al. 2004). Table 7 explicitly reveals that SSIM is higher for the suggested scheme. Interestingly, the suggested method achieves results that are visually better than the entropic value-based method. The FSIM is also deployed here to measure the similarity. The FSIM index is used to assess the performance using the low-level features. It makes use of two key components: the phase congruency (PC) and the gradient magnitude (GM). These are the first and second attributes, respectively. The PC denotes the importance of local structures (Lin Zhang et al. 2011). The detailed definitions of the performance indexes are given in the respective references. The optimal FSIM values are shown in Table 6. In this work, the FSIM values are also higher for the suggested method, which is seen from Table 6.

From Table 6, it is evident that the FSIM values are higher for the suggested method, which is implicit. For instance, the methodology yields 3.6%, 6.3%, 7.7% higher FSIM values (for COVID-10 image with a threshold level of $K = 2$) than the Tsallis-SGCS, Kapur-SGCS, Masi-SGCS, respectively. For threshold level $K = 6$, the values are 5.1%, 5.5%, 11.8% higher than the other three methods, respectively. Similarly, for COVID-549 sample image, with $K = 2$ the values are 9.8%, 2.8%, 4.6% higher, and with $K = 6$ the values are 11.1%, 4.8%, 4.7% higher than the other three methods, respectively. This speaks good about the performance of the suggested methodology. Results are better achieved, because the method is independent of grey level distributions. Here, in this paper, the segmentation score is maximized over the summation by optimizing the pixel counts. It is reiterated that the pixel counts are free from the non-uniform grey intensity

distributions. Although the method is also based on the pixel intensities, it is different from the entropy-based methods in the sense that it is histogram independent. Therefore, free from the non-uniform distribution of the grey intensity values throughout the image. The optimal SSIM values are shown in Table 7.

Table 7 explicitly reveals that the SSIM is higher for the methodology. Interestingly, the suggested method achieves results that are visually better than the entropic value-based methods. The SSIM is also used here to measure the structural similarity. The SSIM index is used here for the assessment of the segmentation performance using low-contrast features. From Table 7, it is obvious that the SSIM values are higher for the method. For instance, the proposal yields 2.1%, 3.3%, 6.4% higher SSIM values (for COVID-10 image with a threshold level of $K = 2$) than the Tsallis-SGCS, Kapur-SGCS, Masi-SGCS, respectively. When $K = 6$, the values are 4.3%, 4.1%, 11.0% higher than the other three methods, respectively. Similarly, for COVID-549 sample image, with $K = 2$ the values are 20.2%, 3.7%, 5.3% higher, and with $K = 6$ the values are 18.9%, 11.0%, 10.5% higher than the other three methods, respectively. This shows the improvement of the suggested methodology. Better results are achieved, because it is independent of the grey intensity distributions. In this work, the segmentation score is maximized over the summation by considering the best pixel counts. It yields better values, because the pixel counts are free from the non-uniform grey intensity distributions.

Based on the comparison of the optimal PSNR results presented in Table 5, it is claimed that the SS-SGCS completely dominated other methods. It is implicit (from

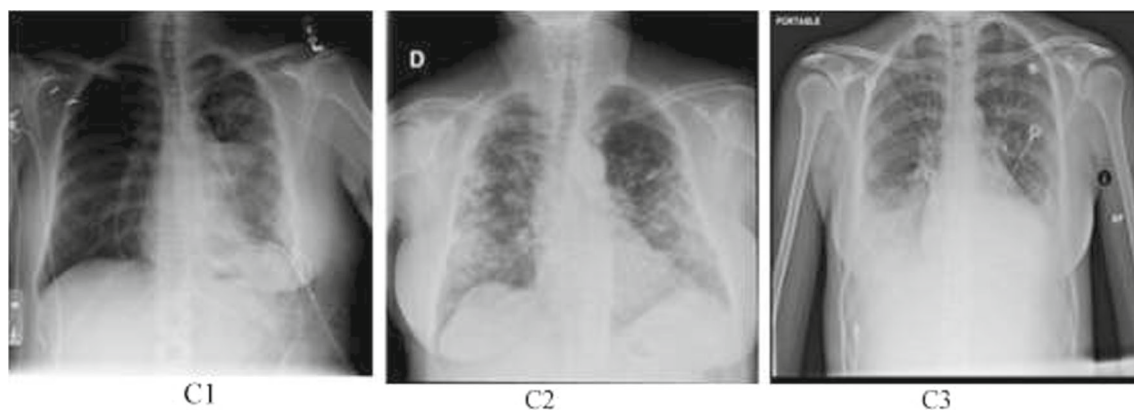


Fig. 11 COVID-19 chest X-ray images in (Chakraborty et al. 2021) used for the experiment

Table 9 Comparison of results with (Chakraborty et al. 2021)

Images	Th	PSNR		SSIM	
		mWOAPR (Chakraborty et al. 2021)	Proposed	mWOAPR Proposed (Chakraborty et al. 2021)	Proposed
C1	3	14.9556	16.6121	0.4004	0.4502
	4	17.7907	19.8623	0.5080	0.5654
	5	18.7213	20.8669	0.5189	0.5861
	6	20.4227	22.9132	0.5700	0.6397
C2	3	16.6228	18.5147	0.6226	0.6956
	4	19.4197	21.6687	0.6671	0.7537
	5	19.4291	21.8018	0.6672	0.7514
	6	19.0259	21.2862	0.7189	0.8003
C3	3	15.0644	16.8625	0.5109	0.5726
	4	18.4500	20.5293	0.6078	0.6839
	5	20.3347	22.6020	0.6597	0.7349
	6	20.5418	23.1714	0.6639	0.7494

Table 5) that the proposed method yields more PSNR values than the other techniques. The optimal FSIM results of Table 6 is concerned; the Tsallis-SGCS has shown some improvements over SS-SGCS while considering two images COVID-10 and COVID-271. However, if we consider the optimal SSIM results in Table 7, the SS-SGCS shows much better results than other methods in many cases. In summary, the proposal achieves better results than other methods. For providing a more detailed result analysis, statistical tests are also steered on the output data.

For providing a more detailed result analysis, statistical tests are also steered on the output data. Friedman's mean rank test is conducted and results are displayed in Table 8.

A Friedman's mean ranks statistical test using four techniques is conducted by combining the PSNR, SSIM and FSIM values. Based on this test, SS-SGCS-based optimal multilevel thresholding ranked one by getting the highest score among all methods. The reason behind such an improvement could be due to the inclusion of all chances of exploring possible best solutions from an enhanced search space. The chance factor incorporated here may help us to exploit some of the missed best solution candidates exploring better solution candidates. To be precise, the proposal could enhance both the exploration and the exploitation capabilities.

The optimal threshold values displayed in Table 4 are used to construct the output (segmented) images. It is reiterated that the number of classes (C) is one higher than that of the number of threshold levels ($C = K + 1$). For illustration, thresholded images (outputs) are presented in Figs. 8, 9 and 10.

The thresholded images are presented for $K = 2$ in Fig. 8, $K = 4$ in Fig. 9 and $K = 6$ in Fig. 10. The visual

illustrations of Figs. 8, 9 and 10 exhibit that SS-SGCS-based optimal multilevel thresholding results in a quality thresholded image. It is notable to point out here that the spatial domain grey intensity distribution of the X-ray images is not uniform, which may be seen from Fig. 7. It is implied that the entropy-based methods are not efficient in such situations. This is also observed from the results shown in Figs. 8, 9 and 10. For instance, the segmented output of the COVID-19 X-ray image (sample image COVID-549) at threshold level $K = 6$ shows the superiority of the proposal over other methods, where blue patches are the precisely segmented outputs. The improvements in quality may be due to a better sense of intensity variation in the case of the SS-based approach.

Here, an in-depth analysis is delivered to clarify why the suggested method could perform better than the comparable (existing) methods. Nevertheless, the entropic-based approaches suffer from their dependencies on spatial distribution of grey values. In reality, the grey level distribution is not uniform in some of the images. The entropic-based procedures use 1D, 2D and 3D image histograms for multilevel threshold selection. A large variation in the image histograms outcomes in a low segmentation accuracy. However, the proposed method is a non-entropic procedure which is independent of the spatial distribution of the grey levels. Moreover, it never uses image histograms. These inherent properties of the suggested technique could improve the results compared to the other entropic-based threshold selection techniques.

For a comparison, a case study is presented here. The paper published recently (Chakraborty et al. 2021) is considered here, for a further justification. Three X-ray test images are taken into the experiment. These are shown in

Fig. 11. Results are compared in Table 9. Two metrics PSNR and SSIM as reported in the previous work (Chakraborty et al. 2021) are considered for a comparison. Note that the Kapur's entropy-based method using the modified whale optimization algorithm with population reduction (mWOAPR) is used in (Chakraborty et al. 2021).

To further strengthen the claim, an in-depth analysis of the results is carried out here. From Table 9, it is explicitly clear that the suggested method yields better results as compared to (Chakraborty et al. 2021). For all three covid-19 affected chest images **C1**, **C2** and **C3** shown in Fig. 11, the proposed method works well. An overall improvement of approximately 12% is observed. For instance, the proposed technique shows 11.5% higher values for PSNR in the case of **C1** image, 11.7% higher in the case of **C2** image and 11.8% higher in the case of **C3** images. Similar is the situation in the case of SSIM. Further, from this study, it is seen that the suggested method is well suited for both the low and high-resolution COVID-19 X-ray images taken from different datasets.

6 Conclusion

The paper presented an efficient methodology for the analysis of the COVID-19 X-ray images. The paper demonstrated many merits for a variety of reasons, although the proposed fitness function plays a primary role. It is important to realize that the suggested idea is a great breakthrough, it is really revolutionary in its implications. This method never relied on the spatial distribution of the grey values of an image histogram. Instead, it emphasizes on the optimal pixel counts. While maximizing the segmentation score, the optimal threshold values are achieved, which is an interesting idea. This enforces the segmentation error to be reduced to a minimum value. The results presented are very encouraging. The method is compared with the state-of-the-art approaches and it is observed that the proposal outperforms the other techniques. More significantly, the proposed method yields about 11% improvement in the PSNR values. Similarly, significant improvements are achieved for six random samples. Exemplary outcomes achieved discloses the detail that the proposed technology is efficient for COVID-19 X-ray image segmentation. The limitation of this study may be the over segmentation issue, which may occur for higher K values, say $K = 10$ or higher. It needs to be explored in future. The limitation may be due to the inherent characteristics of the X-ray images or due to the limitation of this method.

The proposed new SOA-CS algorithm may be very useful for optimizing functions, because it provides better statistical results for the standard benchmark test functions.

Further, the chance factor embedded within the optimizer enables it to explore more search space to find better solutions, if available. The suggested SS-SGCS method may be useful for multiclass segmentation of the COVID-19 X-ray images. The reason is that it has certain merits over other techniques to capture the low-contrast features. The success of the method is primarily due to the minimization of the segmentation error. The work would be useful for the segmentation of biomedical images such as the brain MR images (MRI), CT scans and other modalities, where one can find the intensity variations. The idea may be extended to the multiclass segmentation of the color images.

Appendix A

Here, the image reconstruction rules are illustrated for easy implementation by the researchers. Note that the image I with size $(M \times N)$ is transformed into a segregated image $\hat{I}$ with $K+1$ classes $(C_1, C_2, \dots, C_{K+1})$ using the K number of thresholds, which are given as:

$$\begin{aligned} C_1 &\leftarrow l_{m,n} & \text{if } l_{\min} \leq l_{m,n} < t_{1opt} \\ C_2 &\leftarrow l_{m,n} & \text{if } t_{1opt} \leq l_{m,n} < t_{2opt} \\ &\vdots & \vdots \\ C_{K+1} &\leftarrow l_{m,n} & \text{if } t_{Kopt} \leq l_{m,n} < l_{\max} \\ &\in (1, 2, \dots, M) \text{ and } n \in (1, 2, \dots, N) \end{aligned}, m \quad (26)$$

Note that here the optimum thresholds $(t_{1opt}, t_{2opt}, \dots, t_{Kopt})$ need to satisfy the condition $l_{\min} < t_{1opt} < t_{2opt} < \dots < t_{Kopt} < l_{\max}$. Here, $l_{\min}$ and $l_{\max}$ represent the minimum and maximum intensity levels. Further, $l_{m,n}$ denotes the intensity level at the spatial coordinates (m, n) . Most importantly, the following condition is also met:

$$\forall t \in [l_{\min} + 1, l_{\max} - 1] \quad (27)$$

These discussions make it explicitly clear how to implement the proposed method.

Appendix B

Formula used for calculations of PSNR, SSIM and FSIM are given here for a completeness. In this work, the simple and popular performance metric PSNR is used to provide a comparison with the recently published important works, and is evaluated using the following formula:

$$\text{PSNR(dB)} = 10 \log 10 \left(\frac{255^2}{\text{MSE}(I, \hat{I})} \right) \quad (28)$$

where MSE (Mean Square Error) between the target image I and the multiclass segmented image $\hat{I}$ is given by:

$$\text{MSE} = \frac{1}{M \times N} \sum_{m=1}^M \sum_{n=1}^N (I_{m,n} - \hat{I}_{m,n})^2$$

The SSIM between the two images I and $\hat{I}$ is calculated as (Zhou et al. 2004):

$$\text{SSIM}(I, \hat{I}) = \frac{(2\mu_I \mu_{\hat{I}} + c_1)(2\sigma_{I\hat{I}} + c_2)}{(\mu_I^2 + \mu_{\hat{I}}^2 + c_1)(\sigma_I^2 + \sigma_{\hat{I}}^2 + c_2)} \quad (29)$$

where μ_I denotes the mean value of I , $\mu_{\hat{I}}$ signifies the average value $\hat{I}$. Note that σ denotes the variance of both the images. Here, $\sigma_{I\hat{I}}$ represents the covariance of I and $\hat{I}$. Note that c_1 and c_2 are two variables which depend on the dynamic range of the pixel values. The SSIM is used as a metric for assessment.

The FSIM index is used to evaluate the performance of the segmentation methodology using the low-level features. The formula for the calculation of the FSIM is given below (Lin Zhang et al. 2011):

$$\text{FSIM}(x, y) = \frac{\sum_{x \in \Omega} S_L(x) \cdot PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \quad (30)$$

where the symbol Ω implies the total image area, $S_L(x)$ is the similarity between the input and the multiclass segmented output images. Nonetheless, a higher FSIM value specifies higher similarity between the two images.

These formulas are useful for computing SSIM and FSIM values for a comparison with the state-of-the-art methodologies. Hence, these formula are provided here for a completeness.

Author contributions GD contributed to methodology, software, writing—original draft. MS contributed to validation, interpretation, editing draft. RP contributed to methodology, writing—review and editing, conceptualization, interpretation, supervision. MKN contributed to software, validation, visualization, writing—review and editing, conceptualization. SA contributed to visualization, conceptualization.

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Data availability The datasets generated and/or analysed during the current study are available in the COVID-19 Radiography Database | Kaggle. <https://www.kaggle.com/tawsifurrahman/covid19-radiography-database>.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

Ethical approval The authors mentioned in the manuscript have agreed for authorship, read and approved the manuscript, and given consent for submission and subsequent publication of the manuscript.

Consent to participate Informed consent was obtained from all individual participants included in the study.

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