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ORIGINAL ARTICLE

Improving the estimation of distribution algorithm with a differential mutation for multilevel thresholding image segmentation

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Abstract
Image segmentation consists of separating an image into regions that are entirely different from each other, and multilevel thresholding is a method used to perform this task. This article proposes an Estimation of Distribution Algorithms (EDA) combined with a Differential Evolution (DE) operator as a metaheuristic to solve the multilevel thresholding problem. The proposal is called the Differential Mutation Estimation of Distribution Algorithm (DMEDA), where the inclusion of the Differential Mutation increases the standard EDA's exploration capacity. The performance of the DMEDA for image segmentation is tested using Otsu's between-class variance and Kapur's entropy as objective functions applied separately over the Berkeley Segmentation Data Set 300 (BSDS300). Besides, a comparative study includes eight well-known algorithms in the literature. In this sense, statistical and non-parametric tests are performed to verify the efficiency of the DMEDA in solving the image segmentation problem from an optimization perspective. In terms of segmentation, different metrics are employed to verify the capabilities of the DMEDA to segment digital images properly. Regarding the two objective functions, the proposed DMEDA obtains better results in 97% of the experiments for Otsu's between-class variance and 85% for Kapur's entropy.

Keywords Image segmentation · Multilevel thresholding · Estimation of Distribution algorithm · Differential mutation

1 Introduction

Digital Image Processing (DIP) is a set of operations that can be applied to an image to obtain useful information or generate an image with better features [1, 2]. Based on the characteristics found in the analysis of an image, decisions can be made, and developments can be carried out that allow the industry to improve its processes [3]. Image processing segmentation is a method for extracting desired information from an image [4]. Multilevel segmentation separates an image into more than two mutually exclusive regions. Some techniques can be mentioned to segment an image [5]: thresholding [6–8], edge-based methods [9, 10], region-based methods [11], clustering [12], and artificial neural networks, [13–15]. In image segmentation by thresholding, the primary objective is to divide an image into classes that share characteristics or are very different from the other classes. The simplicity and efficiency of segmentation by multilevel thresholding generate interest from the scientific community, which generates further exploration and progress in this branch of digital image processing [16]. In multilevel image thresholding, n regions of a digital image are obtained using $n-1$ thresholds located in the histogram corresponding to the image. The operations in multilevel thresholding are based on the gray-scale histogram to obtain different classes based on some criteria.

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There are different criteria for separating an image into regions using segmentation by multilevel thresholding. One of these criteria is Otsu; this criterion maximizes the between-class variance so that the regions obtained have the greatest possible difference [17, 18]. Otsu is a useful algorithm that is applied in threshold-based image segmentation algorithms [19]. Otsu algorithm is based on two-dimensional histograms, which consider gray-scale neighbor pixel information. Thus, it has much higher segmentation precision and robustness to low-contrast images [20]. Other methods are based on the entropy in each class or specific regions from the scene. Kapur [21] proposes his method for separating gray-scale images into different classes. Kapur's entropy tries to separate images into subdivisions by maximizing the entropy of the histogram of gray-scale intensities [22]. Another entropy used is minimum cross entropy; this type of entropy is minimized [23], while the other type of entropy is maximized. The minimum cross entropy is another alternative used as a separation criterion in the images. In addition to the ones already mentioned, other criteria are based on the histogram information used to divide images into regions. This article will use Otsu to maximize the variance between classes. The Otsu and Kapur methods are simple and have a stable affection. They are used because they are widely applied in image segmentation in practice [24], and it has precision and robustness to low-contrast images.

Metaheuristic algorithms have been used among academic researchers in various fields, such as science and engineering, in solving optimization problems [25–27]. The computational inefficiency of exhaustive search makes using metaheuristics attractive for solving problems with a vast search space [28–31]. Segmentation by multilevel thresholding can be performed using metaheuristics to optimize the objective function that maximizes the observed difference between classes in the histogram. Metaheuristic finds a combination of thresholds that maximizes the variance between classes (Otsu fitness) for separating the image into multiple regions. Some widely used metaheuristics for multilevel thresholding are Genetic Algorithms (GA) [32], Particle Swarm Optimization (PSO) [33], Artificial Bee Colonies (ABC) [34], Cuckoo Search (CS) [35], Gravitational Search Algorithm (GSA) [36], Runge Kutta Algorithm (RUN) [37], Differential Evolution (DE) [38], Battle Royal Optimizer (BRO) [39], African Vultures Optimization Algorithm (AVOA) [40], among others.

Evolutionary algorithms have been applied in multilevel thresholding using different algorithms in this field of artificial intelligence. Hammouche et al. in 2008 used GA with a wavelet transform to reduce the length of the original histogram. Based on this lower-resolution histogram version, the classification problem is solved using a GA that uses a new string representation of the chromosome [32]. Wang et al. used an Estimation of Distribution Algorithm (EDA) to solve the segmentation problem, but they only programmed it for two thresholds. This EDA has the characteristic of converging rapidly [41]. Oliva et al. proposed a Bayesian Network-based EDA for multilevel image (BNMTH). The presented algorithm allows us to find the best combination that is obtained when using different thresholding techniques, exploring the inter-dependencies between the thresholds and the thresholding techniques [42]. EDAs are a variation of genetic algorithms. The EDA replaces the mutation and crossovers operators by the sampling operation to generate new individuals [43]. Instead, DE uses the mutation and recombination operators to obtain new individuals [44]. Several mutation operators can be applied to the DE algorithm. Each of them generates different results. As with other evolutionary approaches, EDA then fails into a sub-optimal solution[45].

Differential Evolution (DE) is an essential method widely used for solving complex optimization problems [44, 46]. Some authors use DE operators to improve their algorithms. Muangkote et al. in 2017 used to improve the search success rate in a DE an adaptation of the scale factor sF, repair of the crossover rate, and changed the direction of a randomly selected individual to a leader based on the classification. It successfully diversifies its population with the proposed operator [47]. In 2021, Liu et al. proposed a Modified Differential Evolution (MDE) Algorithm with a Slime Mould Foraging behavior. They proved that MDE has high convergence accuracy and exploration ability [48]. A variant of differential evolution named Transformed Differential Evolution (TDE) was presented by Ramadas & Abraham in 2020; they propose an improved mutation strategy optimized to fewer function evaluations. The thresholding outcomes were improved for the TDE approach in judgment with traditional DE [49]. Soleimanian works with a binary multi-objective dynamic algorithm Harris Hawks Optimization (HHO) enhanced with mutation operator (MODHHO). They applied this algorithm in Botnet Detection in IoT, achieving good results to solve this problem [50]. Also, Shen et al. propose a variant of the Whale Optimization Algorithm (WOA) based on multi-population evolution (MEWOA) to make the original algorithm converge fast and not fall into local optima quickly. The algorithm was tested on CEC 2019 and engineering problems, testing its competitiveness [51]. Sun et al. use a DE/EDA; they use an EDA to avoid falling into local optima and reach global optima. They compare their improvement with the EDA using some minimization problems using up to 10 dimensions. The proposed algorithm obtains better results than EDA and DE in most cases. They hybridize the EDA using a DE mutation strategy at the start of the EDA; the mutated individuals become the probability model that will be used for sampling, and replacement is generated by elitism [52].

This paper joins concepts of two evolutionary algorithms, EDA and DE, to improve and obtain global optima, and it is called DMEDA. This proposal is made because there is no dominant algorithm in all areas of knowledge as established by the No Free Lunch Theorem [53]. The classic EDA is simple and does not use parameters to calibrate, but it is trapped in the local optimum at the time of optimization. An improvement in the EDA after sampling is proposed by adding the mutation operator to diversify the results and thus not fall into the local optimum. In sampling, the EDA works with individuals chosen by the tournament; the tournament winners are those with a better objective function. Therefore, the EDA has good exploitation by the sampling operation. While the mutation strategy helps the EDA with exploration, leaving the local optima and increasing the number of points visited from the sample space. Thus, it has an algorithm that can explore and exploit the sample space that does not have many parameters to configure. Several experimental studies indicate that estimating a distribution has positive effects on the exploration of the search space [54]. It has also been shown that the potential of EDA to discover the dependencies of the problem variables can make the search more effective, as in this case, in which the thresholds are dependent [55]. In recent years, this algorithm has achieved great success in combinatorial and continuous problems [56–58], generating attraction to use it to optimize complex objective functions. The research aims to solve the image segmentation problem optimizing the Otsu or Kapur objective functions using an EDA improved with a Differential Mutation Operator (DM) with the ability to obtain global optima in the search space of the Otsu and Kapur, independently. The main contributions of this paper are:

- The improvement that is generated in the EDA using the Differential Mutation Operator for the mutation after sampling to explore the search space better.
- The ability to get out of local optima when using the Differential Mutation operator in the EDA.
- It has been proved the proposed DMEDA solves the multilevel thresholding problem using two objective functions, Otsu and Kapur.
- A hybridization approach to EDA and not focusing on improving the probabilistic model used in the sampling phase.

The current article is divided into the following parts: Sect. 2 describes the problem and the concepts of the EDA and the DM. Section 3 shows the proposal to improve the EDA and the image thresholding problem. Section 4 describes the experimentation, its metrics, the images used to compare the algorithms, and experimental results and comparisons, including statistical and non-parametric tests, to generate confidence in the research results. Finally, Sect. 5 discusses some conclusions and future works.

2 Background

Machine vision is a scientific discipline that consists of image acquisition, image preprocessing, image segmentation, feature extraction, and analysis [59]. Segmentation is used to obtain the interest regions of an image. Then, the interest regions of the image are obtained and analyzed with algorithms to extract features [28].

2.1 Problem definition

The segmentation problem consists of classifying the pixels of an image into a set of classes [60]. There are several techniques to segment an image; one of them is multilevel thresholding. Multilevel thresholding segmentation will find more than one region in an image [61]. Each threshold is a histogram value that separates the image in different regions. These regions may contain pixels that correspond to an object of interest, and using image segmentation with some other digital image processing operations, those regions can be extracted for analysis. Multilevel thresholding can be performed in one dimension, as in the case of gray-scale segmentation, or more than one dimension, as in the case of segmenting images on a color scale, such as RGB color space. To solve the gray-scale problem, it is possible to use Eq. 1 that defines the set of classes into which an image will be separated, taking into account the thresholds obtained from the histogram that represents the image.

$$\begin{aligned} C_0 &= \{I_{ij} \in I(x,y) | 0 \leq I_{ij} \leq th_1 - 1\} \\ C_1 &= \{I_{ij} \in I(x,y) | th_1 \leq I_{ij} \leq th_2 - 1\} \\ &\vdots \\ C_k &= \{I_{ij} \in I(x,y) | th_k \leq I_{ij} \leq th_{L-1}\} \end{aligned} \tag{1}$$

From Eq. 1, th_i is the ith threshold, $I(x, y)$ is the original image, th_k is the kth threshold, C_k is the kth class or region of the segmented image, and L is the maximum level in the gray-scale. The number of classes depends on the number of interested regions to detect in the image. It could be variable for each study case.

2.2 Otsu's between-class variance

The Otsu method is used as a fitness function. The discriminant criterion selects an optimal threshold to maximize the separability of the resultant classes in gray levels using the inter-class variance computed with the frequency histogram [17]. In the Otsu method, the bins displayed in a histogram show the number of pixels that are at an intensity level ith on the gray-scale for the case of image segmentation on this scale. A histogram is a visual tool that helps choose the thresholds and calculate the variances needed to maximize the Otsu objective function. The probability distribution is computed in Eq. 2.

$$p_i = \frac{n_i}{N} \tag{2}$$

where:

$$p_i \geq 0$$
$$\sum_{i=1}^{L} p_i = 1$$

where n_i is the number of pixels inside of each class from 0 to 255, p_i is the probability of obtaining each intensity level in the frequency histogram, the number of the class is k, and it is necessary to obtain the thresholds. Each class denotes pixels into each threshold. Then, the probabilities of class occurrence and the class mean levels, respectively, are given by Eq. 3.

$$\begin{aligned} \omega_0 &= P(C_0) = \textstyle\sum_{i=1}^{th_1-1} p_i \\ \omega_1 &= P(C_1) = \textstyle\sum_{i=th_1}^{th_2-1} p_i \\ &\vdots \\ \omega_k &= P(C_k) = \textstyle\sum_{i=th_k}^{L-1} p_i \end{aligned} \tag{3}$$

The probability to obtain a pixel in the kth class is ω_k. The mean of each class is denoted by Eq. 4.

$$\begin{aligned} \mu_0 &= \textstyle\sum_{i=0}^{th_1-1} iP(i|C_0) = \frac{1}{\omega_0} \sum_{i=1}^{th_1-1} ip_i \\ \mu_1 &= \textstyle\sum_{i=th_1}^{th_2-1} iP(i|C_1) = \frac{1}{\omega_1} \sum_{i=th_1}^{th_2-1} ip_i \\ &\vdots \\ \mu_k &= \textstyle\sum_{i=th_k}^{L-1} iP(i|C_k) = \frac{1}{\omega_k} \sum_{i=th_k}^{L-1} ip_i \end{aligned} \tag{4}$$

The class variances are given by Eq. 5.

$$\begin{aligned} \sigma_0^2 &= \textstyle\sum_{i=0}^{th_1-1} (i-\mu_0)^2 P(i|C_0) = \frac{1}{\omega_0} \sum_{i=1}^{th_1-1} (i-\mu_0)^2 p_i \\ \sigma_1^2 &= \textstyle\sum_{i=th_1}^{th_2-1} (i-\mu_0)^2 P(i|C_1) = \frac{1}{\omega_1} \sum_{i=th_1}^{th_2-1} (i-\mu_1)^2 p_i \\ &\vdots \\ \sigma_k^2 &= \textstyle\sum_{i=th_k}^{L-1} (i-\mu_0)^2 P(i|C_k) = \frac{1}{\omega_k} \sum_{i=th_k}^{L-1} (i-\mu_k)^2 p_i \end{aligned} \tag{5}$$

Therefore, with the equations shown previously, it is possible to calculate the between-class variance with Eq. 6

$$F_{Otsu} = \sum_{i=C_0}^{C_k} \sigma_i \tag{6}$$

Here σ_i is the variance corresponding to the ith class. Then, the problem is reduced to an optimization problem to search for a threshold k that maximizes the objective function Otsu given by the Eq. 7.

$$th_1^*, th_2^*, \ldots, th_k^* = \max_{th_1^*, th_2^*, \ldots, th_k^*} F_{Otsu}(th_1^*, th_2^*, \cdots, th_k^*) \tag{7}$$

Where $th_1^*, th_2^*, \ldots, th_k^*$ is the vector of thresholds that maximize Otsu fitness shown in Eq. 6.

2.3 Kapur's entropy

The Kapur's entropy is another popular criterion for obtaining thresholds [21]. The method finds the thresholds (th) that maximize the entropy, as shown in Eq. 8.

$$th_1^*, th_2^*, \ldots, th_k^* = \max_{th_1^*, th_2^*, \ldots, th_k^*} F_{Kapur}(th_1^*, th_2^*, \ldots, th_k^*) \tag{8}$$

$th_1^*, th_2^*, \ldots, th_k^*$ is the vector of thresholds that maximize Kapur fitness, and the objective function is constituted by the Eq. 9, which is the sum of a set of entropies.

$$F_{Kapur} = \sum_{i=C_0}^{C_k} H_i \tag{9}$$

From Eq. 9 each entropy is obtained with its respective threshold, for which Eq. 10, which allows it to be calculated.

$$\begin{aligned} H_0 &= \textstyle\sum_{i=0}^{th_1-1} \frac{p_i}{\omega_0} \ln\left(\frac{p_i}{\omega_0}\right) \\ H_1 &= \textstyle\sum_{i=th_1}^{th_2-1} \frac{p_i}{\omega_1} \ln\left(\frac{p_i}{\omega_1}\right) \\ &\vdots \\ H_k &= \textstyle\sum_{i=th_k}^{L-1} \frac{p_i}{\omega_k} \ln\left(\frac{p_i}{\omega_k}\right) \end{aligned} \tag{10}$$

Here the probability occurrence ω_i of the ith class are obtained with Eq. 3 and the probability distribution using Eq. 2.

2.4 Estimation of distribution algorithm

Estimation of Distribution Algorithm (EDA) was introduced by [62] in the area of evolutionary computation. EDA takes into account interacting variables to generate new populations. That approach is different from GA, which uses two operators: crossover and mutation. The EDA begins with a selection process on the initial population, just like the GA. The vectors that are selected from the initial population are analyzed to obtain a probability model that will be used to sample and generate new offspring [63, 64]. The EDA in each iteration improves its results by the sampling process, learning from the distributions that are generated and getting the optimal new individual. This case is used to solve a Multilevel Thresholding Problem. The operations carried out by the EDA are described in the following subsections (initial population generation, selection, sampling, and replacement) to optimize the objective function.

2.4.1 Generate initial population

The first step begins with the generation of the first population. The first population is generated randomly [41]. Each individual has a sorted discrete combination vector (**th**) defined as $\mathbf{th} \in \mathbb{R}^{tn} | 0 \leq th_i \leq 255, i = 1, 2, \ldots, tn$. The value of tn depends on the quantity of classes that want to be identified. Equation 11 is used to obtain each threshold to generate the initial population.

$$th_{ij} = L_j + rand_j \times (U_j - L_j) \tag{11}$$

Where L_j and U_j represent the lower and upper boundary of th_i in the jth dimension, respectively. The $rand_j \in [0, 1]$ is random number [65]. A set of P_i conforms to the initial population. The initial population is described in the Eq. 12:

$$\vec{P}_i^{[0]} = \{th_{i1}, th_{i2}, \ldots, th_{iL-1}\} \tag{12}$$

where $\vec{P}_i^{[0]}$ is the sorted discrete solution vector that corresponds to ith inhabitant, and a superscript is placed to denote that it is the initial population. After generating the initial population, it is necessary to evaluate the fitness function to pass at the next operator.

2.4.2 Select operator

The select operator chooses the vectors with the conditions to be parents. A selection by the tournament is used in which two vectors compete, and the one with a higher value of the objective function (Otsu or Kapur) goes to the mating pool. Using a selection operator has less chance of convergence, making it the best choice for working in a large workspace [66].

2.4.3 Sampling

All selected parents must be sampled in this phase to generate new children. th_{ij} represents a random variable. Here, we use discrete variables th_{ij}, and the mass probability for the variable is $p_k(th_{ij})$ [63]. For the probabilistic model, we use a Gaussian model in Eq. 13 to generate new children.

$$p_k(th_{ij}) = \prod_{i=1}^{k} N(th_{ij} | \mu_j^k, \sigma_j^k) \tag{13}$$

From Eq. 13, $N(th_{ij} | \mu_j^k, \sigma_j^k)$ is defined by the Eq. 14.

$$N(th_{ij} | \mu_j^k, \sigma_j^k) = \frac{1}{\sqrt{2\pi\sigma_j}} e^{\frac{(th_{ij}-\mu_j)^2}{2\sigma_j^2}} \tag{14}$$

Where th_{ij} is the jth threshold in the position ith, μ_j^k is the average of the thresholds in the jth level in the kth iteration, and σ_j^k is the standard deviation of the thresholds in the jth level in the kth iteration.

The parameters used in the normal distribution are calculated using the corresponding statistics for each thresholding level. To calculate μ_j^k the Eq. 15 is used.

$$\mu_j^k = \frac{1}{P} \sum_{i=1}^{P} th_{ij} \tag{15}$$

Where σ_j^k is computed using Eq. 16.

$$\sigma_j^k = \frac{1}{P-1} \sum_{i=1}^{P} (th_{ij} - \mu_j^k)^2 \tag{16}$$

From Eq. 16, P is the population size of the selected children. This sampling method ensures that new individuals converge when a local optimum is found. 99.7% of each threshold generated will be at $\mu_j^k \pm 3\sigma_j^k$. As the number of iterations increases, the mean stabilizes, and the standard deviation is smaller because the populations tend to be similar. Therefore, the EDA is weak in finding global optima because it can get stuck in a local optimum.

2.4.4 Replacement

The replacement is generated by comparing the generation $k-1$th with the generation that was generated in the current iteration k. Only children that improve parental fitness can be placed in generation k. With this replacement strategy, the quality of the populations is maintained because the optimums found by the EDA are exploited. The pseudocode used in the EDA is shown in the Algorithm 1.

Algorithm 1 Estimation of Distribution Algorithm (*EDA*)

Require: Gray-scale Image, Number of Thresholds, Population
Ensure: Thresholds, Segmented Image

```
for i = 1 : n do
    Generate Population
    Evaluate Population with Otsu
    Selection by tournament
    Sampling
end for
return thresholds and segmented image
```

2.5 Differential mutation operator

The Differential Mutation (DM) strategy is used after the sampling process in the EDA. The DM operator used in this article is taken from the Differential Evolution, and it is known as mutation DE/current-to-best/1 [67]. In DE, the mutation generates a mutant vector for each solution of the current population and it is called that because it is based on the differences of individuals in the population or a set of vectors; this allows information to be transmitted between them [68]. The main benefit of using DM is that diversity in the population is maintained on a certain level [67]. The EDA is based on the mean of the set of individuals used, and there is a high probability of generating individuals close to the mean. Furthermore, the difference between the best and each individual converges to the global optimum. The DM used in the proposed approach is defined in Eq. 17.

$$\vec{m}_i = \vec{th}_i + sF \times (\vec{th}_{best} - \vec{th}_i + \vec{th}_{r1} - \vec{th}_{r2}) \tag{17}$$

Here $\vec{m}_i$ is the mutation as a candidate solution, sF is the scaling factor and is the parameter of this mutation strategy that controls the magnitude in which the population will evolve, $\mathbf{th}_i$ is the vector of thresholds located at the ith position, $\mathbf{th}_{best}$ is the threshold vector with the best fitness, $\mathbf{th}_{r_1}$ and $\mathbf{th}_{r_2}$ are two random thresholds vectors. With the use of this operator, the diversity is maintained, which is good because it allows exploration at the beginning of the process and exploitation at the end of the process. Here $\vec{m}_i$ is the mutation as a candidate solution, sF is the scaling factor and is the parameter of this mutation strategy that controls the magnitude in which the population will evolve, $\mathbf{th}_i$ is the vector of thresholds located at the ith position, $\mathbf{th}_{best}$ is the threshold vector with the best fitness, $\mathbf{th}_{r_1}$ and $\mathbf{th}_{r_2}$ are two random thresholds vectors.

3 Differential mutation estimation of distribution algorithm

This section describes how the EDA works with the Differential Mutation (DM) operator. This algorithm is named Differential Mutation Estimation of Distribution Algorithm (DMEDA). Figure 1 shows the improvement proposal to the EDA. Using the mutation strategy increases the capacity of the EDA to get out of the local optimum and increase the exploration capacity.

The pseudocode is collocated in the Algorithm 2. It can be seen that Eq. 17 is located after the sampling operation and before the replacement operation.

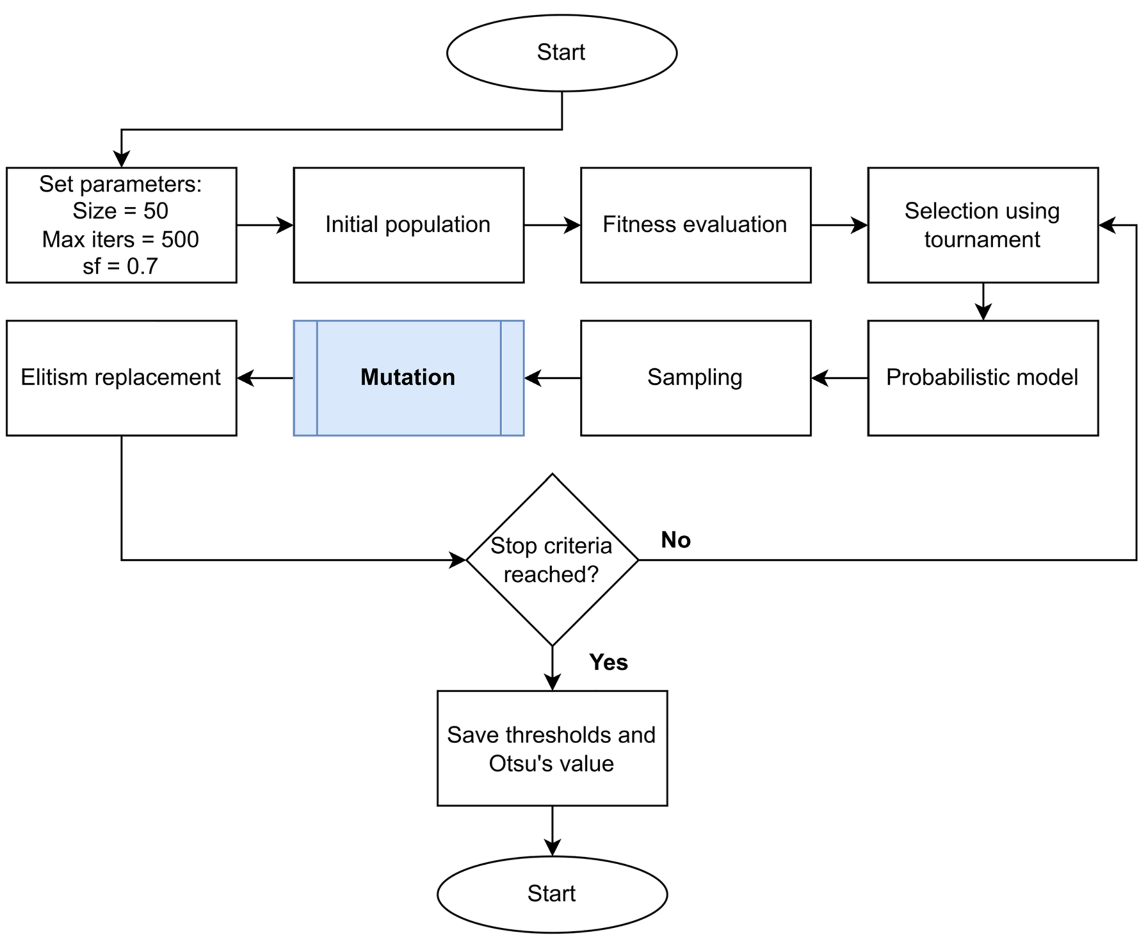


Fig. 1 Flowchart of the proposed DMEDA

Algorithm 2 Differential Mutation Estimation of Distribution Algorithm (*DMEDA*)

```
Require: Gray-scale Image, Number of Thresholds, Population, sf
Ensure: Thresholds, Segmented Image
for i = 1 : n do
    Generate Population
    Evaluate Population with Otsu
    Selection by tournament
    Sampling Eq. 13
    Differential Mutation (Improvement Eq. 17)
    replacement for elitism
end for
return thresholds and segmented image
```

3.1 Implementation of the DMEDA for image thresholding

To make the implementation of DMEDA easier to understand, Fig 2. Shows a flow chart of how the algorithm solves the maximization problem to obtain the thresholds that segment the image. It begins by reading the gray-scale image, and then the histogram of the read image is calculated. A population of vectors ($\mathbf{X} = [\mathbf{Th}_1, \mathbf{Th}_2, \dots, \mathbf{Th}_N]$) containing the thresholds ($\mathbf{Th}_i = [th_1, th_2, \dots, th_k]^T$) that meet the constraints; thresholds are subject to $th_1 < th_2 < \cdots < th_k < L$ where $L = 255$, is generated. The objective functions are maximized; in this article, there are two: Otsu and Kapur. Finally, the set of thresholds that will output the segmented image is obtained.

The number of thresholds or regions into which the image is divided is placed manually; the greater the number of regions, the details in the segmented images are perceptible with greater precision.

4 Experiments and results

This section presents the experiments and results obtained using the proposed DMEDA in the multilevel thresholding problem. The experimental conditions, the metrics used to evaluate the algorithm's performance from another perspective, and the results obtained with the algorithm in comparison with other metaheuristics are presented.

4.1 Experimental setup

The experiments were carried out using the Matlab programming language. A computer with a 64-bit Windows 11 operating system, Intel Core i7-1165G7 processor, and 12 GB of RAM was used. All algorithms were implemented using the Berkeley Segmentation Data Set 300 (BSDS300) [69]. The algorithms used to compare the DMEDA are: Cuckoo Search Algorithm (CS) [35], Gravitational Search Algorithm (GSA) [36], Jellyfish Search Optimizer (JF) [70], Artificial Hummingbird Algorithm (AHA) [71], Osprey Optimization Algorithm (OOA) [72], Salp Swarm Algorithm (SSA) [73], Sine Cosine Algorithm (SCA) [74], and Estimation of Distributions (EDA) [43]. Table 1 describes the configuration of each algorithm's internal parameters. Notice that the values of such parameters were originally taken from the article. In the case of the EDA and DMEDA, the parameters were set based on the values commonly used in the related literature [45, 75].

All the algorithms use a maximum number of iterations set to 500 as a stop criterion. According to the related literature, the experiments were conducted using 2, 3, 4, and

Table 1 Algorithms parameter settings

Algorithm	Parameters
DMEDA	N=100, iters = 500, scaling_factor = 0.2
EDA	N = 100, iters = 500
CS	N = 100, iters = 500, ap = 0.25, n_nest = 25
GSA	N = 100, iters = 500, boundary_points = [-pi,pi]
JF	N = 100, iters = 500
SCA	N = 100, iters = 500, a = 2
AHA	N = 100, iters = 500
OOA	N = 100, iters = 500
SSA	N = 100, iters = 500, st = 0.8

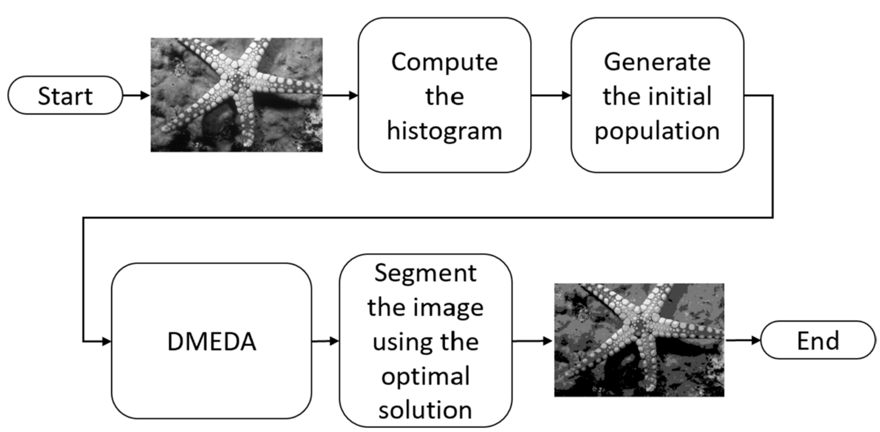


Fig. 2 Flowchart of the implementation of DMEDA for image thresholding

5 thresholds [5, 76–79]. Finally, for statistical purposes, 30 independent experiments were performed by the algorithm over each image using a specific number of thresholds. The experiments are divided into three groups; in the first group, the DMEDA is tested and compared using Otsu's between-class variance as an objective function; in the second group, Kapur's is used as a criterion for image segmentation. Notice that the ten most representative images were chosen from the BSD300 for the first and second groups based on a classification within the same dataset described as the most complex to segment [69]. This is because such images help to graphically show the performance of the algorithms. The selected images with their histograms are presented in Fig. 3. In this sense, in the third group of experiments, the DMEDA is compared with the other optimization methodologies using all the images in the BSD300 dataset with both thresholding criteria, Otsu and Kapur. It is important to mention that different metrics are used to compare the performance of the optimization algorithms in terms of image segmentation (see Subsection 4.2). Also, statistical analysis and non-parametric tests complement the experimental study.

The evaluation of the metaheuristics is carried out using the mean and the standard deviation because all of them have stochastic behavior. Therefore, the results obtained in each replicate have variations, and it is necessary to measure how dispersed (stability) the results are and where they are located (accuracy) using these two statistics. When a metaheuristic is stable, the standard deviation tends to be zero because the results acquired from a set of individuals over the iterations tend to be the same. The precision of the metaheuristics can be observed by measuring the mean of the set of results obtained by the populations at the step of the iterations.

4.2 Metrics used for image segmentation

Image segmentation quality can be measured in seven ways [80–82]: Peak Signal to Noise Ratio (PSNR), Structure Similarity Index Measure (SSIM), Featured Similarity Index Measured (FSIM), Quality Index based on Local Variance (QILV), Haar wavelet-based Perceptual Similarity Index (HPSI), and Universal Image Quality Index (UIQI). The PSNR can be obtained with Eq. 18.

$$PSNR = 20\log\left(\frac{255}{\text{RMSE}}\right) \tag{18}$$

Where RMSE is the Root Mean Square Error calculated by Eq. 19

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - S(i,j))^2} \tag{19}$$

M, N are the size of image, $I(i,j)$ is the unsegmented image and $S(i,j)$ is the segmented image with a given thresholding level. When the PSNR is higher, the segmentation quality is lower because there is less difference between the original and processed images. The SSIM is calculated by Eq. 20:

$$SSIM = \frac{(2\mu_I\mu_S + c_1)(2\sigma_{IS} + c_2)}{(\mu_I^2 + \mu_S^2 + c_1)(\sigma_I^2 + \sigma_S^2 + c_2)} \tag{20}$$

where I and S designate the original and segmented images, respectively. μ_I and μ_S are the mean values of original and segmented images, respectively. σ_I^2 and σ_S^2 are the variances, σ_{IS} the covariance. The constants $c_1 = (0.01 \times 255)^2$ and $c_2 = (0.03 \times 255)^2$ are employed in order to stabilize the division with weak denominator [83]. A SSIM near one indicates better results in segmentation.

Another metric is the Featured Similarity Index (FSIM). FSIM evaluates the importance of the local structure between the non-segmented image and segmented image [84]. The maximum FSIM value that can be attended is 1. Equation 21 introduces the FSIM.

$$FSIM = \frac{\sum_{I\in\Omega} S_L(I)PC_m(I)}{\sum_{I\in\Omega} PC_m(I)} \tag{21}$$

where Ω represents the entire domain of the image, $S_L(I)$ is the product of the similarity measure of the Gradient Magnitude map and Phase Congruency map and is calculated with Eq. 22.

$$S_L(I) = S_{PC(I)}S_{G(I)} \tag{22}$$

In this Eq. $S_{PC(I)}$ and $S_{G(I)}$ are calculated with the next Eqs.

$$S_{PC(I)} = \frac{2PC_{1(I)}2PC_{2(I)} + T_1}{PC_{1(I)}^2 PC_{2(I)}^2 + T_1} \tag{23}$$

To calculate PC is necessary the Eq. 24.

$$PC(I) = \frac{E(I)}{\varepsilon + \sum_n A_n(I)} \tag{24}$$

where $A_n(I)$ is the local amplitude on scale n, and $E(I)$ is the magnitude of the response vector in I over n, ε is a small positive number. To continue with the description of Eq. 22, we define $S_{G(I)}$ as:

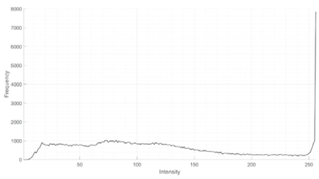
$$S_{G(I)} = \frac{2G_{1(I)}G_{2(I)} + T_2}{G_{1(I)}^2 G_{2(I)}^2 + T_2} \tag{25}$$

Here T_1 and T_2 are constants with values 0.85 and 160, respectively. G is the magnitude of the gradient of a digital image and is calculated by Eq. 26.

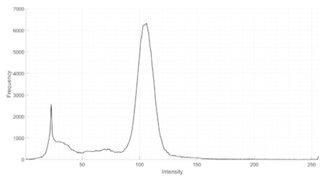
(a) 12003.

(b) 37073.

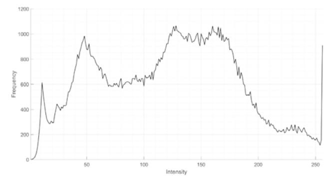
(c) 56028.



(d) 12003 histogram.



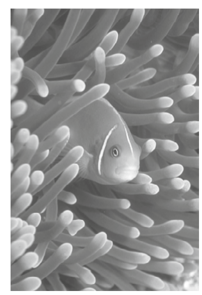
(e) 37073 histogram.



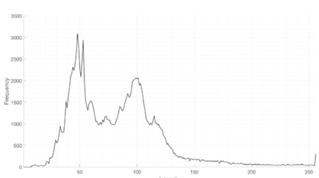
(f) 56028 histogram.

(g) 66075.

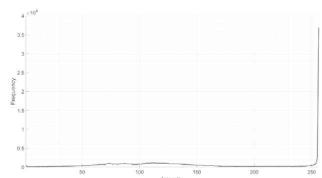
(h) 101087.



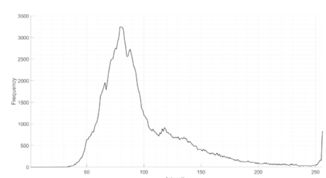
(i) 210088.



(j) 66075 histogram.



(k) 101087 histogram.

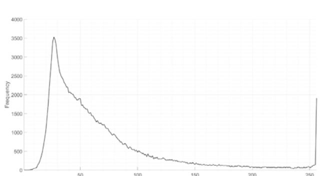


(l) 210088 histogram.

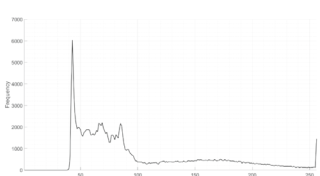
(m) 108070.

(n) 160068.

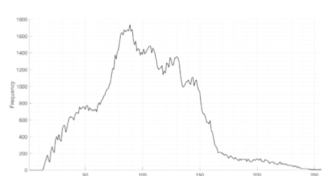
(o) 296059.



(p) 108070 histogram.



(q) 160068 histogram.



(r) 296059 histogram.

Fig. 3 Selected images from the BSD300 and their histograms

$$G = \sqrt{G_x^2 + G_y^2} \tag{26}$$

G_x is the gradient in the x direction and $G\,y$ is the gradient in the y direction. To complete the description of Eq. 21 $PC_m(I)$ is the maximum of the Phase Congruency map between segmented and non-segmented images.

$$PC_m(I) = \max\left(PC_1(I), PC_2(I)\right) \tag{27}$$

Metric QILV focuses on the image structure to appraise the changes in the non-stationarity behavior of images [85] and is computed by the Eq. 28.

$$QILV = \frac{2\mu_{V_I}\mu_{V_S}}{\mu_{V_I}^2 + \mu_{V_S}^2} \cdot \frac{2\sigma_{V_I}\sigma_{V_S}}{\sigma_{V_I}^2 + \sigma_{V_S}^2} \cdot \frac{\sigma_{V_I V_S}}{\sigma_{V_I}\sigma_{V_S}} \tag{28}$$

This Equation is constituted by the local variance of the image; the local variance is obtained with the Eq. 29.

$$\mathrm{Var}(I(i,j)) = \frac{\sum_{p\in\eta_{i,j}} \omega_p (I_p - \bar{I}(i,j))^2}{\sum_{p\in\eta_{i,j}} \omega_p} \tag{29}$$

Here $\eta_{i,j}$ is a neighborhood with defined size, ω_p are the weights with a Gaussian distribution given to the pixels under analysis p, and $\bar{I}(i,j)$ is the mean of the local variance computed by Eq. 30.

$$\bar{I}(i,j) = \frac{\sum_{p\in\eta_{i,j}} \omega_p I_p}{\sum_{p\in\eta_{i,j}} \omega_p} \tag{30}$$

The remaining variables (variables) of Eq. 28 can be estimated with Eqs. 31, 32, 33, respectively.

$$\mu_{V_I} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} \mathrm{Var}(I(i,j)) \tag{31}$$

$$\sigma_{V_I} = \left(\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\mathrm{Var}(I(i,j)) - \mu_{V_I}\right)^2\right)^{1/2} \tag{32}$$

And

$$\sigma_{V_I V_S} = \frac{1}{MN-1}\sum_{i=1}^{M}\sum_{j=1}^{N}(\mathrm{Var}(I(i,j)) - \mu_{V_I})(\mathrm{Var}(S(i,j)) - \mu_{V_S}) \tag{33}$$

this can be extrapolated for the segmented image, and QILV can be calculated.

HPSI evaluates the perceptual similarity between a reference image and a segmented image [86].

$$HPSI = l_\alpha^{-1}\left(\frac{\sum_x \sum_{k=1}^{2} HS_{I,S}^{(k)}[x] \cdot W_{I,S}^{(k)}[x]}{\sum_x \sum_{k=1}^{2} W_{I,S}^{(k)}[x]}\right) \tag{34}$$

The function $l_\alpha^{-1}(\cdot)$ maps the weighted average from the interval $[1/2, l_\alpha(1)]$. The local similarity measure HS is based on the discrete Haar wavelet transform Eq. 35.

$$HS_{I,S}^{(k)}[x] = l_\alpha \tag{35}$$

Here l_α is given by

$$l_\alpha = \frac{1}{1 + e^{-\alpha x}} \tag{36}$$

the parameter $\alpha > 0$, and $W_{I,S}^{(k)}[x]$ is obtained with

$$W_{I,S}^{(k)}[x] = \max(W_I^{(k)}[x], W_S^{(k)}[x]) \tag{37}$$

where $W_I^{(k)}[x]$ and $W_S^{(k)}[x]$ are a single low-frequency Haar wavelet filter for the original and the segmented images, respectively.

And UIQI measures image distortion as a combination of correlation loss, luminance distortion, and contrast distortion [87] is calculated using Eq. 38.

$$UIQI = \frac{4\sigma_{x,y}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)(\bar{x}^2 + \bar{y}^2)} \tag{38}$$

Where

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{39}$$

are the means, and

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2 \qquad \sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2 \tag{40}$$

are the standard deviations, and

$$\sigma_{x,y} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y}) \tag{41}$$

is the covariance of the original and the segmented image signals, respectively. This metric is in the range $[-1, 1]$.

4.3 Otsu test with benchmark images discussion

For research, the most important thing is to obtain an improvement concerning the objective function. This aims to verify that the DMEDA is proposed to obtain better results in the Otsu objective function than the EDA. Table 2 shows the mean and standard deviation (std) fitness obtained by each algorithm in the ten images and in each threshold (running the algorithm thirty times in each case). Only in one case does the DMEDA not obtain the best average compared to the other eight algorithms (97.5%).

Table 3 shows the best results obtained for each thresholding level in each image with each algorithm. A certain similarity is observed between the algorithms that obtain the best results in maximizing the objective function. Table 4 shows the mean and standard deviation (std) of the PSNR obtained by the nine algorithms presented in this research, including the proposed DMEDA. For the PSNR the EDA obtains first place. The EDA obtains the best PSNR average in 55% of the cases, the OOA in 25% of the cases, the SCA in 15% of the cases, and the JF in only 5% of the cases. These algorithms do not obtain the best results by optimizing the objective function, but the structure of the region obtained is similar to the original image.

On the other hand, Table 5 presents the mean and standard deviation for the SSIM. To this indicator, the EDA generates better results in 82.5% of the cases (behaves better at high threshold levels), the OOA and the SSA are better in two cases, the AHA, the JF and the SCA only in one case are better. It is desired that the standard deviation of the algorithms be much smaller because this metric indicates the ability of an algorithm to be consistent with its results each time it is run. The DMEDA is better when comparing its standard deviation in these two metrics.

Table 6, the results for the FSIM metric are obtained. In this table, the OOA is better in most cases because it has a higher value. Although it has a low standard deviation, it is no better than the standard deviation of the DMEDA. This corroborates that the proposed mutation operator into the EDA balances the exploration and exploitation of the algorithm, making it find a global optimum in a smaller number of iterations. According to the information shown, it is concluded that the DMEDA has better results optimizing the Otsu fitness function. In metrics such as PSNR, SSIM, and FSIM, leadership is not obtained due to the nature of the problem being solved. Although the segmented regions obtained with the DMEDA maximize the variance between the pixel classes of the ten images, they generate a more significant difference between the original image and the region chosen to generate the aforementioned metrics.

In Table 7 JF is the algorithm with the best results, compared to the others in most cases, SCA and OOA are algorithms that also win but to a lesser extent. For Table 8 that represents the HPSI metric, JF remains the algorithm with the most won cases, while OOA takes second place. In Table 9 of the metric UIQI, it is observed that no algorithm is conclusive, but the DMEDA does not obtain the best results in most of the metrics. Although it remains close to the best and optimizes the objective function better than the other algorithms, it fails to outperform in these aspects.

Figure 4 show the convergence curves of the objective function (Otsu's between-class variance) of the algorithms used to solve the multilevel thresholding problem. There is a clear difference between the proposed algorithm and the EDA in the four cases observed; this does not vary when the thresholding level is changed. Also, it is observed how the algorithm converges to the highest point compared to the other algorithms; in some cases, such as SCA, this algorithm does not converge. Although the SCA does not converge, it can be seen in some metrics how it wins in some cases. In another case, as in the AHA, it can be seen that there is a result that is much lower in the curves shown.

Figures 5, 6, 7, and 8 show the thresholds at which the DMEDA maximizes the objective function. Three images are shown in Fig. 5, namely, 12,003, 37,073, and 56,028, with the four thresholding levels, the respective frequency histograms, and the processed images. The images are thresholded using the Otsu criterion, and groups of pixels are generated in regions with maximum inter-class variance. Each region that is obtained by the algorithm takes on a different shade of gray. Thresholded images take on a shade of gray according to the regions or thresholds that you define. If there are three thresholds, the thresholded image will take four shades of gray to represent the pixel classes. Figure 6 shows three other images (108,070, 160,068, and 296,059) segmented using four thresholding levels. All three segmented images contain animals. Image 108,070 shows a tiger covered by the shadows of some object, and the pixels corresponding to the tiger have two different intensities; the thresholding results using DMEDA are better by increasing the thresholds. The thresholded images with a larger number of thresholds show the pixel regions; it is possible to locate the tiger's body in these regions. A similar problem occurs in image 160,068 because the cat shown in that image has similar colors to the trunk on which it rests. It is possible to distinguish the regions more clearly by increasing the thresholds. The third image shows two elephants, one of which obstructs the correct identification of the other. Still, the regions shown in the segmented image successfully identify the pixels corresponding to the animals. In the Figs. 5 and 6 some images have a rectangular shape in which the width (i) is greater than the length (j).

Figures 7, and 8 have thresholded images with a different shape than the first two already described. Figure 7 shows

Table 2 Comparisons of the objective function using Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu	Mean Otsu	sd Otsu
101,087	2	**5.07E+03**	9.25E-13	5.07E+03	2.95E+00	5.07E+03	1.71E+00	5.05E+03	1.98E+01	5.02E+03	5.63E+01	5.05E+03	1.58E+01	5.04E+03	2.78E+01	5.07E+03	1.83E-02	5.06E+03	2.37E+01
	3	**5.23E+03**	2.78E-12	5.22E+03	6.78E+00	5.23E+03	4.40E+00	5.20E+03	2.08E+01	5.19E+03	2.82E+01	5.22E+03	1.20E+01	5.20E+03	3.03E+01	5.23E+03	5.09E-01	5.23E+03	5.88E+00
	4	**5.31E+03**	3.00E-02	5.30E+03	4.71E+00	5.30E+03	1.09E+01	5.27E+03	2.13E+01	5.26E+03	1.99E+01	5.29E+03	8.42E+00	5.27E+03	2.38E+01	5.31E+03	1.17E+00	5.30E+03	1.10E+01
	5	**5.35E+03**	3.95E-02	5.34E+03	4.70E+00	5.33E+03	5.84E+00	5.31E+03	1.54E+01	5.32E+03	8.53E+00	5.33E+03	1.20E+01	5.32E+03	1.71E+01	5.35E+03	5.24E-01	5.34E+03	6.18E+00
108,070	2	**1.59E+03**	1.16E-12	1.59E+03	1.11E+00	1.59E+03	1.31E+00	1.56E+03	2.18E+01	1.57E+03	1.60E+01	1.58E+03	3.71E+00	1.57E+03	9.19E+00	**1.59E+03**	1.16E-12	1.59E+03	2.50E+00
	3	**1.71E+03**	2.68E-02	1.71E+03	2.43E+00	1.71E+03	4.02E+00	1.68E+03	3.07E+01	1.68E+03	2.38E+01	1.71E+03	3.08E+00	1.69E+03	1.66E+01	1.71E+03	4.58E-01	1.71E+03	6.52E+00
	4	**1.77E+03**	1.45E-01	1.77E+03	2.65E+00	1.76E+03	5.49E+00	1.73E+03	2.65E+01	1.74E+03	1.53E+01	1.77E+03	3.78E+00	1.74E+03	1.44E+01	1.77E+03	2.26E+00	1.77E+03	7.23E+00
	5	**1.81E+03**	7.95E-02	1.80E+03	2.84E+00	1.79E+03	6.18E+00	1.77E+03	1.20E+01	1.78E+03	5.75E+00	1.80E+03	7.09E+00	1.78E+03	1.26E+01	1.81E+03	1.81E+00	1.80E+03	6.86E+00
12,003	2	**2.55E+03**	4.63E-13	2.55E+03	2.70E+00	2.55E+03	3.37E+00	2.52E+03	3.69E+01	2.53E+03	1.83E+01	2.55E+03	4.01E+00	2.53E+03	1.57E+01	**2.55E+03**	4.63E-13	2.55E+03	6.11E+00
	3	**2.78E+03**	2.04E-02	2.78E+03	5.36E+00	2.77E+03	9.90E+00	2.72E+03	3.54E+01	2.74E+03	3.31E+01	2.77E+03	1.15E+01	2.74E+03	2.73E+01	2.78E+03	9.15E-01	2.78E+03	6.39E+00
	4	**2.87E+03**	9.97E-02	2.86E+03	5.89E+00	2.85E+03	1.04E+01	2.81E+03	3.00E+01	2.82E+03	2.39E+01	2.86E+03	6.47E+00	2.83E+03	1.86E+01	2.87E+03	1.34E+00	2.86E+03	8.43E+00
	5	**2.92E+03**	1.89E-01	2.91E+03	4.87E+00	2.89E+03	9.17E+00	2.86E+03	2.37E+01	2.87E+03	9.17E+00	2.91E+03	5.72E+00	2.87E+03	2.34E+01	2.92E+03	4.74E-01	2.90E+03	9.74E+00
160,068	2	**1.99E+03**	3.93E-02	1.98E+03	3.74E+00	1.98E+03	2.15E+00	1.98E+03	6.62E+00	1.97E+03	1.20E+01	1.98E+03	2.82E+00	1.98E+03	6.77E+00	1.99E+03	5.13E-02	1.99E+03	1.10E+00
	3	**2.13E+03**	1.85E-12	2.13E+03	2.89E+00	2.12E+03	7.85E+00	2.08E+03	3.36E+01	2.09E+03	2.51E+01	2.13E+03	4.71E+00	2.10E+03	1.71E+01	2.13E+03	7.76E-01	2.13E+03	5.36E+00
	4	**2.19E+03**	4.68E-02	2.18E+03	4.29E+00	2.17E+03	6.79E+00	2.13E+03	2.91E+01	2.15E+03	1.48E+01	2.18E+03	4.83E+00	2.16E+03	1.98E+01	2.19E+03	4.40E-01	2.18E+03	7.75E+00
	5	**2.22E+03**	3.19E-02	2.22E+03	2.60E+00	2.20E+03	6.86E+00	2.17E+03	1.64E+01	2.19E+03	4.85E+00	2.21E+03	4.17E+00	2.18E+03	1.40E+01	2.22E+03	1.77E+00	2.21E+03	7.57E+00
210,088	2	**1.46E+03**	0.00E+00	1.46E+03	8.14E-01	1.46E+03	2.29E+00	1.44E+03	3.11E+01	1.44E+03	1.78E+01	1.46E+03	1.75E+00	1.45E+03	1.56E+01	**1.46E+03**	0.00E+00	1.46E+03	2.52E+00
	3	**1.56E+03**	4.42E-02	1.56E+03	3.96E+00	1.55E+03	6.21E+00	1.52E+03	2.86E+01	1.52E+03	2.47E+01	1.56E+03	5.27E+00	1.53E+03	1.79E+01	1.56E+03	4.18E-01	1.56E+03	4.16E+00
	4	**1.61E+03**	2.49E-01	1.60E+03	5.62E+00	1.59E+03	6.61E+00	1.57E+03	1.92E+01	1.57E+03	1.15E+01	1.60E+03	5.34E+00	1.57E+03	1.56E+01	1.61E+03	8.30E-01	1.60E+03	1.04E+01
	5	**1.63E+03**	1.25E-01	1.62E+03	5.28E+00	1.62E+03	8.92E+00	1.59E+03	2.29E+01	1.61E+03	4.00E+00	1.63E+03	3.53E+00	1.60E+03	1.42E+01	1.63E+03	1.56E+00	1.63E+03	6.86E+00
296,059	2	**1.53E+03**	2.31E-13	1.53E+03	3.69E-01	1.53E+03	3.45E+00	1.50E+03	3.06E+01	1.51E+03	2.32E+01	1.53E+03	2.30E+00	1.53E+03	1.22E+01	**1.53E+03**	2.31E-13	1.53E+03	4.81E+00
	3	**1.63E+03**	3.70E-02	1.62E+03	4.58E+00	1.61E+03	8.54E+00	1.58E+03	2.80E+01	1.59E+03	2.10E+01	1.62E+03	5.75E+00	1.60E+03	1.73E+01	1.63E+03	9.02E-02	1.62E+03	7.09E+00
	4	**1.68E+03**	1.32E-02	1.67E+03	4.10E+00	1.66E+03	1.38E+01	1.62E+03	2.80E+01	1.64E+03	1.34E+01	1.67E+03	3.01E+00	1.64E+03	1.97E+01	1.68E+03	1.91E-01	1.66E+03	1.02E+01
	5	1.70E+03	4.52E-01	1.69E+03	2.48E+00	1.68E+03	6.16E+00	1.65E+03	2.17E+01	1.68E+03	1.54E+00	1.69E+03	3.16E+00	1.66E+03	1.35E+01	**1.70E+03**	1.92E-01	1.69E+03	5.62E+00
302,008	2	**3.83E+03**	9.25E-13	3.83E+03	7.35E-01	3.82E+03	4.12E+00	3.80E+03	3.27E+01	3.81E+03	1.54E+01	3.82E+03	2.63E+00	3.82E+03	1.13E+01	3.83E+03	1.57E-02	3.83E+03	3.02E+00
	3	**3.94E+03**	4.57E-04	3.94E+03	1.45E+00	3.93E+03	5.43E+00	3.90E+03	2.32E+01	3.92E+03	1.53E+01	3.94E+03	3.95E+00	3.92E+03	1.40E+01	3.94E+03	1.07E+00	3.94E+03	4.33E+00
	4	**3.99E+03**	1.64E-02	3.99E+03	1.84E+00	3.98E+03	5.07E+00	3.96E+03	2.27E+01	3.97E+03	9.74E+00	3.99E+03	2.92E+00	3.97E+03	1.17E+01	3.99E+03	7.94E-01	3.99E+03	3.71E+00
	5	**4.03E+03**	3.99E-02	4.02E+03	1.91E+00	4.01E+03	5.82E+00	3.99E+03	1.48E+01	4.00E+03	7.31E+00	4.02E+03	4.05E+00	4.00E+03	8.82E+00	4.02E+03	1.72E+00	4.02E+03	8.36E+00
37,073	2	**7.21E+02**	0.00E+00	7.20E+02	4.34E+00	7.20E+02	1.26E+00	7.14E+02	6.21E+00	7.13E+02	6.76E+00	7.20E+02	1.86E+00	7.14E+02	6.54E+00	7.21E+02	5.16E-02	7.20E+02	1.49E+00
	3	**7.72E+02**	4.63E-13	7.71E+02	4.90E-01	7.68E+02	3.57E+00	7.55E+02	1.14E+01	7.54E+02	1.12E+01	7.70E+02	2.31E+00	7.61E+02	6.05E+00	7.72E+02	1.52E-01	7.70E+02	2.37E+00
	4	**7.96E+02**	2.24E-02	7.93E+02	2.50E+00	7.89E+02	3.96E+00	7.76E+02	1.03E+01	7.80E+02	6.49E+00	7.93E+02	2.88E+00	7.81E+02	6.82E+00	7.96E+02	3.49E-01	7.91E+02	4.29E+00
	5	**8.10E+02**	8.79E-01	8.10E+02	9.65E-01	8.03E+02	3.84E+00	7.91E+02	7.82E+00	7.97E+02	1.93E+00	8.07E+02	1.48E+00	7.94E+02	4.95E+00	8.10E+02	1.72E+00	8.06E+02	3.45E+00
56,028	2	**2.35E+03**	9.25E-13	2.35E+03	2.37E+00	2.35E+03	2.95E+00	2.31E+03	3.24E+01	2.32E+03	3.71E+01	2.34E+03	5.17E+00	2.33E+03	1.93E+01	2.35E+03	2.01E-01	2.35E+03	4.20E+00
	3	**2.54E+03**	4.63E-13	2.54E+03	3.26E+00	2.54E+03	8.04E+00	2.49E+03	3.36E+01	2.49E+03	3.32E+01	2.54E+03	5.66E+00	2.51E+03	1.80E+01	2.54E+03	3.36E-01	2.54E+03	4.17E+00
	4	**2.64E+03**	1.12E-02	2.63E+03	6.35E+00	2.62E+03	1.53E+01	2.58E+03	3.35E+01	2.59E+03	2.27E+01	2.63E+03	6.28E+00	2.59E+03	2.86E+01	2.64E+03	2.40E-01	2.63E+03	1.52E+01
	5	**2.69E+03**	2.38E-01	2.68E+03	3.21E+00	2.67E+03	7.24E+00	2.64E+03	2.24E+01	2.65E+03	1.07E+01	2.68E+03	6.20E+00	2.65E+03	2.20E+01	2.69E+03	7.34E-01	2.68E+03	1.06E+01
66,075	2	**1.07E+03**	0.00E+00	1.07E+03	7.61E-01	1.07E+03	1.86E+00	1.04E+03	3.57E+01	1.05E+03	2.55E+01	1.07E+03	2.04E+00	1.06E+03	1.52E+01	**1.07E+03**	0.00E+00	1.07E+03	4.34E+00
	3	**1.14E+03**	3.01E-02	1.14E+03	2.36E+00	1.13E+03	5.05E+00	1.11E+03	1.91E+01	1.12E+03	1.56E+01	1.14E+03	2.86E+00	1.12E+03	1.07E+01	1.14E+03	1.24E-01	1.14E+03	3.89E+00
	4	**1.18E+03**	1.66E-01	1.17E+03	3.16E+00	1.17E+03	6.42E+00	1.15E+03	1.44E+01	1.16E+03	1.08E+01	1.17E+03	3.28E+00	1.15E+03	1.20E+01	1.18E+03	8.69E-01	1.17E+03	4.23E+00
	5	**1.20E+03**	9.11E-02	1.20E+03	2.46E+00	1.19E+03	6.77E+00	1.17E+03	1.50E+01	1.18E+03	5.01E+00	1.20E+03	3.81E+00	1.18E+03	1.08E+01	1.20E+03	1.11E+00	1.20E+03	5.83E+00

Bold means the best value provided by each algorithm

two images using from 3 to 6 regions. Image 66,075 is an animal that is not obstructed by any object, and its segmentation should be simple; from a low level of thresholding, the region belonging to the bird in the image is not lost. In image 101,087, a person is drawn on a raft, and by thresholding it into three regions, it is possible to identify the sky of the other regions. Increasing the number of regions presents a greater amount of detail with similar intensities. In this way, it is possible to distinguish the pixels corresponding to the sky and those corresponding to other regions of interest.

Figure 8 also contains two images. These images are more complex because you have an animal whose vision is obstructed by a plant and a person dressed in clothing with similar tones as the image's background. In these two images, the good work of the multilevel thresholding method can also be observed, finding regions corresponding to the person's clothing and the background. Post-processing tasks are facilitated by having a greater number of regions and ensuring that these regions contain the object of interest. Furthermore, by increasing the number of regions, it is possible to detect a greater amount of detail in the man's face and clothing.

4.4 Kapur test with benchmark images discussion

As already mentioned, the goal is to obtain an algorithm for optimizing the objective function (in this case, Kapur's entropy) with better results. This subsection presents the results obtained with DMEDA using Kapur's entropy. As with Otsu, DMEDA obtains good results in maximizing the Kapur objective function, as shown in Table 10. In 85% of the total cases, DMEDA is superior to the other algorithms. For the remaining 15%, the OOA is the winner. In this objective function, it wins a smaller number of times with the ten images used to construct the results of this Section.

The thresholds shown in Table 11 differ from those obtained with Otsu. For this reason, the result in the metrics is different. However, DMEDA performs better when Kapur's criterion is used to segment the images. By changing the positions of the thresholds, the perception of the images changes, and the results shown in Figs. 10, 11, 12, and 13.

Table 12 shows the mean and standard deviation of the PSNR in which DMEDA is better for high thresholding levels in most cases. The other algorithm with good results is SSA, but as will be seen later in the convergence curves, this algorithm does not converge. Therefore, consistent results on the objective function and the metric are not expected. In 35% of the cases, the DMEDA is the one that expires; another 35% is distributed in the SSA, and the remaining 30% is divided into the OOA, AHA, CS, GSA, and JF. This shows how there is no conclusive algorithm for this metric.

For the SSIM at almost 50% of the thresholding levels for each image, the DMEDA is the best. And secondly, the SSA is maintained with 40% of the victories. CS and SCA algorithms won twice each. OOA and GSA won only once each. Table 13 shows how DMEDA continues to win in the high dimensions for this metric. Unlike the SSIM results obtained in Otsu, DMEDA performs better for Kapur.

In 52.5% of the cases of the FSIM shown in Table 14, the DMEDA obtains better results than the other algorithms, in six cases (15%), the OOA is victorious, and in five of them the SSA. In less than three cases, the algorithms with good results were JF, CS, GSA, and AHA, tying JF and AHA with three moments and CS with GSA in one case.

QILV metric presented in Table 15 shows that the DMEDA wins eleven times (27.5%). In this metric, OOA beats DMEDA on one occasion, accumulating 12 wins. GSA obtain five victories, while JF and GSA get 4 each. And CS win in one case. In nineteen of the forty cases reported in Table 16, corresponding to the HPSI metric, the DMEDA wins, while the OOA and the AHA win five times, and the SSA and JF wins four times. In Table 17, DMEDA only expires in 25% of the cases. The majority of victories are obtained by the SSA in this metric. Until now, there is no dominant algorithm for all the proposed metrics. The DMEDA is an algorithm that won in the majority of the evaluations corresponding to the two objective functions (Otsu and Kapur). Still, the dominance of the metrics is divided into the proposed algorithms. It is important to mention that the DMEDA has better metrics with Kapur than with Otsu.

Based on the convergence curves shown in Fig. 9 show that the proposed algorithm performs better on the Kapur objective function compared to the others. The algorithm, as in Otsu, converges and is superior to EDA. The impact that the mutation operator has on the EDA results is significant for the two objective functions of the multilevel thresholding problem. Being a minor modification, improvements are obtained in the results of the original EDA. In both metrics, the algorithm shows fast convergence and to a better optimum than EDA. Therefore, we have an algorithm with better characteristics than EDA only by applying the current to best Differential Mutation operator.

Figs. 10, 11, 12, and 13 contain the segmented images at the different thresholding levels. For this case, the images were thresholded using Kapur's entropy criterion. As with Otsu, increasing the number of thresholds brings out the details in the images. Images 12,003, 37,073, and 56,028 are shown in Fig. 10. In image 12,003, it is observed that the background details are not perceptible for two thresholds, but for five thresholds, these details can be found. In images 37,073 and 56,028, when using two thresholds, the details of the concrete and the wall are not perceived. In image 37,073,

Table 3 Thresholds obtained using Otsu's between-class variance

Image	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
101,087	178 234	112 221	94 137	178 238	178 188	179 216	174 177	178 256	178 232
	108 196 228	40 121 203	73 111 166	94 200 205	108 196 242	118 196 223	116 187 239	108 196 249	101 198 210
	89 135 206 229	70 102 150 201	65 90 132 157	116 162 211 222	45 99 120 227	98 148 188 204	94 112 202 211	89 135 206 237	74 126 184 186
	68 106 145 210 223	30 88 114 159 214	43 83 108 134 159	13 85 138 210 239	80 103 121 146 205	73 107 139 202 232	43 81 139 221 234	68 106 145 209 231	66 109 139 201 246
108,070	111 157	76 161	67 109	110 182	78 142	107 159	110 142	111 159	103 231
	74 147 222	52 93 155	51 93 129	69 149 202	58 103 190	76 150 187	76 152 215	74 147 175	69 153 227
	62 104 172 199	62 110 134 163	63 89 113 137	77 126 157 225	46 82 148 182	67 106 167 215	59 115 156 157	62 104 172 192	88 94 137 219
	55 84 126 189 220	54 85 135 168 218	45 61 81 93 139	52 62 97 194 236	46 86 111 149 223	54 82 121 174 208	59 74 132 153 212	55 84 126 189 231	29 60 87 146 158
12,003	116 149	75 152	82 126	115 173	68 152	117 175	117 214	116 231	112 215
	85 157 241	61 103 165	52 88 135	62 145 153	91 137 187	97 172 211	83 171 195	85 157 212	81 154 182
	69 120 178 223	66 90 116 163	59 92 126 148	64 122 216 236	76 101 138 168	72 121 186 221	64 139 172 183	69 120 178 243	69 116 182 205
	60 100 138 187 213	62 94 135 161 187	61 93 118 138 190	78 123 150 175 219	60 101 138 187 208	68 107 139 180 212	66 76 122 189 232	61 100 136 186 231	57 98 139 190 196
160,068	111 205	95 159	61 107	105 186	76 132	112 124	101 140	111 117	52 98
	94 157 187	56 105 169	58 87 129	104 152 241	80 115 177	94 166 170	83 132 169	94 157 244	92 153 164
	64 107 164 208	54 111 140 195	59 96 125 148	71 96 155 211	63 79 130 192	69 112 160 215	57 99 173 233	64 107 164 205	71 107 149 177
	62 98 139 182 201	52 64 103 154 180	48 73 92 132 171	58 87 147 182 244	61 101 135 184 195	61 95 138 173 200	63 104 129 196 227	62 97 138 181 240	60 101 137 177 194
210,088	131 156	97 155	79 126	127 232	110 171	130 170	130 172	131 161	133 177
	92 146 189	78 113 155	85 111 144	80 133 248	103 123 178	90 138 184	79 130 167	92 146 178	92 145 178
	85 123 172 224	90 115 155 177	70 97 112 144	64 114 151 218	85 123 172 207	85 132 178 191	80 129 159 236	85 123 172 193	83 107 131 224
	81 108 144 187 224	77 104 129 184 201	78 89 118 140 168	81 100 152 174 214	73 103 130 155 172	74 99 124 162 213	83 108 138 225 235	81 109 146 186 207	68 69 111 118 200
296,059	108 145	65 122	69 107	108 123	75 127	109 115	107 130	108 140	107 245
	70 120 179	67 107 150	48 93 114	97 152 239	51 99 140	72 119 207	73 122 190	70 120 166	70 118 219
	66 106 146 166	50 76 102 154	50 81 122 150	63 90 134 167	66 106 146 177	68 100 132 196	60 120 180 252	66 106 146 164	74 115 161 192
	58 86 117 151 206	63 85 117 155 175	48 56 85 114 138	58 88 114 158 204	58 86 117 151 202	60 90 118 152 187	64 98 151 177 218	58 86 117 151 194	61 97 122 157 170
302,008	81 243	56 126	35 95	76 95	60 144	81 190	79 240	81 109	112 196
	57 137 191	45 116 172	44 96 141	63 146 226	52 96 155	66 142 178	52 140 235	57 137 220	146 171 228
	44 103 159 199	32 77 138 161	38 73 122 163	36 99 165 245	38 80 97 154	42 99 158 232	27 86 152 203	44 103 159 187	44 111 160 169
	34 80 126 171 217	18 55 104 146 197	35 52 96 117 159	40 74 122 163 186	33 66 104 114 160	38 83 128 165 177	43 99 156 169 240	34 79 124 170 205	31 79 127 176 213
37,073	73 82	72 129	55 89	76 91	72 143	74 131	74 203	73 78	73 86
	72 142 208	56 80 141	50 84 104	60 102 245	53 78 144	73 145 190	78 150 222	72 142 179	65 131 165
	54 89 144 189	56 84 112 179	38 57 79 103	75 122 158 192	35 76 99 158	56 93 150 167	30 36 42 188	54 89 144 207	52 87 141 176
	51 83 105 151 228	44 77 98 125 224	47 70 94 107 114	47 92 107 176 199	42 67 92 124 186	44 78 99 138 178	61 97 151 168 197	51 83 105 149 197	6 49 62 121 142
56,028	107 231	96 143	74 123	102 141	89 157	109 194	108 127	107 141	165 239
	91 158 183	75 131 187	74 117 140	107 164 181	75 124 206	88 155 195	77 139 155	91 158 251	88 156 205
	71 122 177 192	58 103 150 189	55 87 125 161	65 119 168 187	53 98 164 202	73 120 175 223	18 173 183 244	71 122 177 222	85 135 193 254
	56 99 139 186 212	60 74 108 155 196	44 86 131 154 182	92 111 148 192 254	56 99 139 186 200	65 107 148 191 225	62 97 153 192 228	56 99 139 186 204	61 107 137 190 204
66,075	83 197	79 133	76 114	84 135	93 148	73 133	86 97	83 144	83 216
	75 135 238	69 99 140	69 92 123	82 133 217	75 116 139	79 142 242	76 142 241	75 135 206	75 136 137
	69 101 149 183	47 84 133 174	42 63 87 118	60 108 161 251	71 92 130 151	67 98 140 171	80 119 181 243	70 102 150 177	64 103 139 203
	65 92 125 176 184	24 55 89 114 173	50 68 91 123 155	60 72 102 138 254	66 93 126 176 217	70 95 132 183 244	65 91 108 128 203	66 93 126 176 221	49 62 79 124 176

Bold means the best value provided by each algorithm

Table 4 PSNR comparisons using the Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR
101,087	2	1.25E+01	3.61E-15	1.26E+01	1.97E-01	8.57E+00	3.24E-02	1.29E+01	6.12E-01	1.32E+01	1.15E+00	1.31E+01	6.91E-01	1.34E+01	1.37E+00	**1.36E+01**	3.03E-01	1.28E+01	1.26E+00
	3	1.50E+01	5.42E-15	1.56E+01	4.11E-01	1.07E+01	1.98E-01	1.52E+01	1.09E+00	**1.62E+01**	1.34E+00	1.58E+01	8.70E-01	1.55E+01	1.96E+00	1.62E+01	3.94E-01	1.51E+01	1.42E+00
	4	1.77E+01	3.99E-01	1.75E+01	6.25E-01	1.20E+01	4.76E-01	1.64E+01	1.27E+00	1.78E+01	1.39E+00	1.89E+01	1.04E+00	1.74E+01	1.89E+00	**1.97E+01**	5.91E-01	1.73E+01	3.06E+00
	5	1.89E+01	5.21E-02	1.88E+01	5.26E-01	1.31E+01	7.86E-01	1.85E+01	1.44E+00	2.02E+01	9.71E-01	2.01E+01	1.10E+00	1.93E+01	1.89E+00	**2.09E+01**	8.46E-01	1.93E+01	1.63E+00
108,070	2	1.47E+01	1.81E-15	1.48E+01	1.75E-01	1.32E+01	7.86E-02	1.44E+01	6.40E-01	1.50E+01	6.40E-01	**1.50E+01**	4.00E-01	1.49E+01	8.30E-01	1.50E+01	9.33E-02	1.50E+01	1.30E+00
	3	1.66E+01	3.75E-02	**1.70E+01**	2.24E-01	1.53E+01	2.69E-01	1.59E+01	1.06E+00	1.67E+01	1.11E+00	1.68E+01	4.45E-01	1.70E+01	1.32E+00	1.69E+01	5.25E-02	1.65E+01	1.57E+00
	4	1.83E+01	1.12E-01	**1.92E+01**	3.85E-01	1.68E+01	5.46E-01	1.84E+01	1.34E+00	1.80E+01	1.45E+00	1.84E+01	7.44E-01	1.86E+01	1.31E+00	1.83E+01	1.11E-01	1.79E+01	1.89E+00
	5	2.00E+01	1.07E-01	**2.08E+01**	4.03E-01	1.84E+01	8.36E-01	1.89E+01	1.68E+00	1.91E+01	1.03E+00	1.98E+01	1.23E+00	1.90E+01	1.53E+00	1.99E+01	1.44E-01	1.91E+01	2.05E+00
12,003	2	1.48E+01	8.51E-02	1.50E+01	2.52E-01	1.20E+01	5.34E-02	1.46E+01	4.70E-01	1.52E+01	7.09E-01	1.52E+01	4.08E-01	1.48E+01	1.37E+00	**1.53E+01**	2.00E-01	1.47E+01	1.85E+00
	3	1.73E+01	6.70E-04	1.75E+01	1.71E-01	1.49E+01	1.65E-01	1.67E+01	5.74E-01	1.72E+01	6.12E-01	**1.78E+01**	3.13E-01	1.67E+01	1.55E+00	1.77E+01	1.34E-01	1.65E+01	1.91E+00
	4	1.92E+01	3.49E-02	**1.96E+01**	1.91E-01	1.67E+01	4.15E-01	1.82E+01	6.40E-01	1.87E+01	7.63E-01	1.94E+01	3.88E-01	1.87E+01	8.37E-01	1.95E+01	1.31E-01	1.86E+01	1.58E+00
	5	2.07E+01	1.04E-01	**2.11E+01**	2.13E-01	1.81E+01	5.39E-01	1.91E+01	6.55E-01	1.98E+01	4.06E-01	2.08E+01	4.45E-01	1.96E+01	1.04E+00	2.11E+01	1.11E-01	1.95E+01	1.86E+00
160,068	2	1.32E+01	5.99E-03	**1.43E+01**	7.90E-01	1.21E+01	2.32E-02	1.35E+01	7.10E-01	1.41E+01	9.88E-01	1.34E+01	3.73E-01	1.38E+01	9.73E-01	1.33E+01	4.24E-02	1.34E+01	1.06E+00
	3	1.69E+01	5.10E-02	**1.71E+01**	2.13E-01	1.51E+01	4.38E-01	1.58E+01	1.31E+00	1.68E+01	1.39E+00	1.70E+01	5.49E-01	1.65E+01	1.35E+00	1.71E+01	8.45E-02	1.62E+01	1.59E+00
	4	1.79E+01	9.47E-02	**1.89E+01**	4.61E-01	1.69E+01	4.30E-01	1.68E+01	1.54E+00	1.72E+01	1.03E+00	1.80E+01	6.46E-01	1.74E+01	1.01E+00	1.79E+01	5.06E-02	1.73E+01	1.78E+00
	5	2.00E+01	3.52E-02	**2.06E+01**	2.39E-01	1.82E+01	9.33E-01	1.83E+01	1.54E+00	1.83E+01	9.09E-01	1.96E+01	1.07E+00	1.81E+01	2.88E+00	2.02E+01	2.72E-01	1.88E+01	2.18E+00
210,088	2	1.32E+01	3.61E-15	**1.35E+01**	2.92E-01	1.17E+01	3.49E-01	1.30E+01	1.41E+00	1.25E+01	1.51E+00	1.34E+01	5.99E-01	1.27E+01	1.72E+00	1.34E+01	1.07E-01	1.31E+01	1.80E+00
	3	1.50E+01	7.04E-02	**1.57E+01**	3.47E-01	1.41E+01	5.98E-01	1.46E+01	2.26E+00	1.46E+01	2.30E+00	1.52E+01	8.72E-01	1.49E+01	1.93E+00	1.51E+01	4.39E-02	1.45E+01	2.97E+00
	4	1.64E+01	1.68E-01	**1.84E+01**	8.50E-01	1.53E+01	9.48E-01	1.69E+01	2.10E+00	1.63E+01	1.70E+00	1.67E+01	9.68E-01	1.60E+01	2.37E+00	1.62E+01	5.63E-02	1.59E+01	3.02E+00
	5	1.86E+01	8.33E-02	**2.09E+01**	8.14E-01	1.69E+01	1.33E+00	1.77E+01	2.21E+00	1.67E+01	1.34E+00	1.81E+01	1.30E+00	1.84E+01	2.43E+00	1.80E+01	3.47E-01	1.79E+01	2.04E+00

Table 4 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR
296,059	2	1.69E+01	1.84E-01	1.73E+01	3.90E-01	1.31E+01	8.24E-02	1.61E+01	1.34E+00	1.69E+01	1.27E+00	1.72E+01	6.15E-01	1.67E+01	1.00E+00	**1.73E+01**	3.60E-01	1.56E+01	2.22E+00
	3	1.86E+01	1.20E-01	**1.92E+01**	3.04E-01	1.63E+01	6.45E-01	1.77E+01	1.37E+00	1.81E+01	1.28E+00	1.86E+01	6.80E-01	1.80E+01	1.66E+00	1.86E+01	8.55E-02	1.80E+01	2.11E+00
	4	2.04E+01	3.07E-03	**2.09E+01**	2.47E-01	1.83E+01	6.04E-01	1.93E+01	1.13E+00	1.93E+01	9.89E-01	2.05E+01	3.70E-01	1.92E+01	1.79E+00	2.05E+01	9.92E-02	1.93E+01	2.21E+00
	5	2.15E+01	1.44E-01	**2.25E+01**	4.11E-01	1.98E+01	8.73E-01	1.98E+01	1.44E+00	2.06E+01	5.20E-01	2.13E+01	5.39E-01	2.06E+01	1.52E+00	2.15E+01	1.01E-01	1.99E+01	2.20E+00
302,008	2	1.84E+01	4.93E-02	1.86E+01	2.49E-01	1.35E+01	2.60E-01	1.80E+01	4.31E-01	1.88E+01	6.71E-01	**1.93E+01**	4.49E-01	1.88E+01	9.19E-01	1.90E+01	4.45E-01	1.90E+01	7.49E-01
	3	2.07E+01	3.03E-04	2.09E+01	2.75E-01	1.70E+01	5.88E-01	1.98E+01	6.97E-01	2.08E+01	7.45E-01	**2.13E+01**	4.47E-01	2.06E+01	8.13E-01	2.13E+01	2.75E-01	2.06E+01	1.40E+00
	4	2.25E+01	1.22E-01	2.27E+01	2.67E-01	1.98E+01	6.78E-01	2.13E+01	6.29E-01	2.18E+01	7.55E-01	2.29E+01	4.31E-01	2.13E+01	2.19E+00	**2.30E+01**	2.21E-01	2.22E+01	1.16E+00
	5	2.36E+01	6.79E-02	2.37E+01	1.76E-01	2.14E+01	6.06E-01	2.25E+01	6.48E-01	2.30E+01	4.08E-01	2.37E+01	2.99E-01	2.26E+01	1.52E+00	**2.38E+01**	1.30E-01	2.27E+01	1.47E+00
37,073	2	1.73E+01	7.23E-15	1.75E+01	8.67E-01	1.69E+01	2.28E-01	1.75E+01	8.80E-01	**1.76E+01**	1.32E+00	1.74E+01	2.37E-01	1.68E+01	2.07E+00	1.73E+01	1.79E-02	1.59E+01	2.93E+00
	3	2.12E+01	1.45E-14	2.10E+01	2.35E-01	2.02E+01	4.81E-01	2.02E+01	1.08E+00	1.99E+01	1.19E+00	2.13E+01	4.74E-01	2.03E+01	2.31E+00	**2.13E+01**	7.19E-02	1.90E+01	3.80E+00
	4	2.24E+01	6.97E-02	**2.32E+01**	5.22E-01	2.15E+01	7.65E-01	2.15E+01	1.35E+00	2.20E+01	1.27E+00	2.25E+01	6.27E-01	2.17E+01	2.07E+00	2.25E+01	1.07E-01	2.01E+01	3.67E+00
	5	2.47E+01	6.37E-01	**2.51E+01**	3.97E-01	2.30E+01	7.23E-01	2.24E+01	1.15E+00	2.29E+01	7.62E-01	2.45E+01	1.01E+00	2.31E+01	1.45E+00	2.46E+01	7.24E-01	2.31E+01	2.07E+00
56,028	2	1.46E+01	5.42E-15	1.48E+01	1.19E-01	1.23E+01	1.26E-01	1.46E+01	5.73E-01	1.49E+01	7.47E-01	**1.51E+01**	3.97E-01	1.43E+01	1.82E+00	1.50E+01	8.05E-02	1.46E+01	1.57E+00
	3	1.72E+01	3.00E-02	1.75E+01	1.23E-01	1.53E+01	2.16E-01	1.65E+01	7.84E-01	1.69E+01	8.97E-01	**1.77E+01**	3.61E-01	1.70E+01	7.86E-01	1.75E+01	1.16E-01	1.65E+01	1.92E+00
	4	1.95E+01	9.49E-03	1.97E+01	2.03E-01	1.73E+01	3.86E-01	1.81E+01	8.83E-01	1.84E+01	7.01E-01	1.97E+01	3.54E-01	1.87E+01	1.02E+00	**1.98E+01**	9.17E-02	1.88E+01	1.63E+00
	5	2.10E+01	8.02E-02	**2.15E+01**	1.87E-01	1.89E+01	3.89E-01	1.96E+01	8.09E-01	2.02E+01	5.33E-01	2.10E+01	4.64E-01	1.99E+01	1.27E+00	2.13E+01	8.80E-02	2.01E+01	2.17E+00
66,075	2	1.56E+01	0.00E+00	1.57E+01	8.98E-02	1.45E+01	2.53E-02	1.54E+01	5.54E-01	1.56E+01	6.13E-01	1.58E+01	1.64E-01	1.57E+01	4.44E-01	**1.58E+01**	6.98E-02	1.50E+01	1.66E+00
	3	1.67E+01	7.56E-02	**1.70E+01**	2.02E-01	1.59E+01	2.41E-01	1.63E+01	9.44E-01	1.66E+01	9.37E-01	1.68E+01	2.90E-01	1.68E+01	7.30E-01	1.68E+01	3.44E-02	1.62E+01	2.03E+00
	4	1.74E+01	9.04E-02	**1.90E+01**	8.94E-01	1.69E+01	5.39E-01	1.78E+01	1.88E+00	1.74E+01	9.39E-01	1.76E+01	6.40E-01	1.84E+01	2.02E+00	1.74E+01	4.86E-02	1.79E+01	1.78E+00
	5	1.95E+01	2.05E-01	**2.11E+01**	5.91E-01	1.83E+01	1.28E+00	1.91E+01	2.07E+00	1.78E+01	1.19E+00	1.92E+01	8.99E-01	1.83E+01	2.26E+00	1.89E+01	2.34E-01	1.98E+01	1.90E+00

Bold means the best value provided by each algorithm

Table 5 SSIM comparisons using the Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM
101,087	2	6.11E-01	1.13E-16	6.18E-01	1.25E-02	5.26E-01	7.98E-03	6.18E-01	3.32E-02	6.00E-01	7.08E-02	6.02E-01	3.76E-02	**6.34E-01**	5.98E-02	6.19E-01	2.39E-03	6.09E-01	6.86E-02
	3	7.19E-01	1.13E-16	**7.73E-01**	2.12E-02	6.65E-01	2.45E-02	7.22E-01	6.05E-02	7.48E-01	6.16E-02	7.19E-01	3.89E-02	7.27E-01	6.26E-02	7.21E-01	4.30E-03	7.20E-01	5.88E-02
	4	8.46E-01	1.55E-03	**8.61E-01**	4.53E-03	7.76E-01	3.92E-02	7.81E-01	5.83E-02	7.94E-01	5.00E-02	8.36E-01	2.99E-02	8.01E-01	5.70E-02	8.48E-01	5.01E-03	8.23E-01	6.42E-02
	5	8.79E-01	5.52E-04	**9.00E-01**	4.01E-03	8.28E-01	2.11E-02	8.45E-01	3.85E-02	8.57E-01	2.34E-02	8.70E-01	2.35E-02	8.54E-01	4.10E-02	8.80E-01	4.02E-03	8.63E-01	4.05E-02
108,070	2	4.25E-01	2.82E-16	4.35E-01	1.37E-02	3.41E-01	1.18E-02	4.01E-01	5.83E-02	4.38E-01	5.12E-02	4.39E-01	3.24E-02	4.31E-01	6.81E-02	4.37E-01	3.73E-03	**4.54E-01**	9.84E-02
	3	5.62E-01	1.87E-03	**5.89E-01**	1.52E-02	5.06E-01	2.64E-02	5.06E-01	8.36E-02	5.63E-01	8.00E-02	5.61E-01	3.14E-02	5.83E-01	8.58E-02	5.68E-01	1.59E-03	5.48E-01	1.23E-01
	4	6.59E-01	6.82E-03	**7.12E-01**	2.19E-02	6.01E-01	4.68E-02	6.82E-01	9.72E-02	6.35E-01	9.17E-02	6.55E-01	4.36E-02	6.70E-01	8.34E-02	6.54E-01	6.05E-03	6.29E-01	1.32E-01
	5	7.41E-01	4.90E-03	**7.79E-01**	1.96E-02	6.88E-01	6.06E-02	6.84E-01	1.01E-01	6.92E-01	5.41E-02	7.21E-01	6.28E-02	6.90E-01	8.48E-02	7.30E-01	6.12E-03	6.93E-01	1.31E-01
12,003	2	5.41E-01	2.11E-03	5.48E-01	1.19E-02	4.28E-01	5.44E-03	5.35E-01	3.63E-02	5.46E-01	4.19E-02	5.42E-01	2.14E-02	5.35E-01	7.85E-02	**5.51E-01**	7.59E-03	5.35E-01	9.82E-02
	3	6.60E-01	3.88E-05	**6.72E-01**	6.13E-03	5.84E-01	1.59E-02	6.40E-01	4.42E-02	6.45E-01	3.65E-02	6.61E-01	1.76E-02	6.34E-01	5.17E-02	6.62E-01	3.45E-03	6.36E-01	7.41E-02
	4	7.25E-01	2.05E-03	**7.50E-01**	7.35E-03	6.68E-01	1.72E-02	7.00E-01	4.30E-02	7.10E-01	4.03E-02	7.23E-01	1.78E-02	7.13E-01	4.21E-02	7.22E-01	3.41E-03	7.08E-01	6.66E-02
	5	7.81E-01	1.66E-03	**8.01E-01**	5.23E-03	7.25E-01	2.60E-02	7.31E-01	3.24E-02	7.37E-01	2.36E-02	7.72E-01	1.81E-02	7.44E-01	4.25E-02	7.77E-01	2.25E-03	7.37E-01	6.34E-02
160,068	2	3.42E-01	2.27E-04	**4.18E-01**	5.45E-02	2.70E-01	1.02E-03	3.67E-01	5.35E-02	4.02E-01	6.88E-02	3.56E-01	2.50E-02	3.98E-01	9.39E-02	3.50E-01	3.89E-03	3.68E-01	5.96E-02
	3	6.02E-01	1.72E-03	**6.17E-01**	1.60E-02	5.15E-01	4.65E-02	5.29E-01	1.03E-01	6.03E-01	1.13E-01	6.02E-01	3.87E-02	5.92E-01	9.44E-02	6.08E-01	5.82E-03	5.77E-01	8.10E-02
	4	6.52E-01	5.94E-03	**7.03E-01**	2.44E-02	6.15E-01	3.54E-02	5.89E-01	1.12E-01	6.09E-01	6.57E-02	6.56E-01	4.11E-02	6.31E-01	7.79E-02	6.51E-01	2.54E-03	6.25E-01	1.28E-01
	5	7.52E-01	5.49E-04	**7.78E-01**	1.14E-02	6.83E-01	6.55E-02	6.75E-01	9.50E-02	6.65E-01	4.75E-02	7.29E-01	5.23E-02	6.59E-01	1.49E-01	7.51E-01	1.25E-02	7.02E-01	1.24E-01

Table 5 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM
210,088	2	4.44E-01	1.69E-16	**4.62E-01**	2.24E-02	3.84E-01	4.58E-02	4.29E-01	1.15E-01	3.83E-01	1.13E-01	4.49E-01	4.49E-02	4.00E-01	1.26E-01	4.52E-01	4.83E-03	4.43E-01	1.24E-01
	3	5.67E-01	4.80E-03	**6.12E-01**	2.18E-02	5.40E-01	5.27E-02	5.36E-01	1.55E-01	5.30E-01	1.54E-01	5.75E-01	5.62E-02	5.55E-01	1.29E-01	5.71E-01	2.58E-03	5.31E-01	1.90E-01
	4	6.46E-01	8.32E-03	**7.34E-01**	3.41E-02	5.95E-01	6.77E-02	6.67E-01	1.13E-01	6.28E-01	8.87E-02	6.55E-01	4.89E-02	6.17E-01	1.48E-01	6.36E-01	3.08E-03	6.27E-01	1.49E-01
	5	7.46E-01	3.67E-03	**8.23E-01**	2.49E-02	6.78E-01	7.24E-02	7.04E-01	1.11E-01	6.57E-01	6.07E-02	7.20E-01	5.35E-02	7.34E-01	1.07E-01	7.15E-01	1.45E-02	7.22E-01	9.24E-02
296,059	2	6.36E-01	1.81E-03	**6.40E-01**	1.33E-02	5.37E-01	2.68E-02	6.12E-01	9.79E-02	6.37E-01	8.56E-02	6.25E-01	3.58E-02	6.19E-01	6.70E-02	6.38E-01	4.43E-03	6.05E-01	1.32E-01
	3	6.92E-01	4.18E-03	**7.21E-01**	1.40E-02	6.66E-01	4.44E-02	6.66E-01	8.80E-02	6.82E-01	8.13E-02	6.84E-01	3.69E-02	6.99E-01	6.72E-02	6.88E-01	7.51E-04	6.72E-01	1.18E-01
	4	7.65E-01	1.48E-04	**7.81E-01**	9.51E-03	7.40E-01	2.84E-02	7.38E-01	6.58E-02	7.21E-01	4.54E-02	7.61E-01	1.68E-02	7.26E-01	7.49E-02	7.64E-01	2.26E-03	7.26E-01	1.03E-01
	5	7.97E-01	6.60E-03	**8.29E-01**	1.52E-02	7.75E-01	4.68E-02	7.48E-01	7.63E-02	7.70E-01	2.14E-02	7.82E-01	1.91E-02	7.77E-01	6.39E-02	7.90E-01	1.84E-03	7.59E-01	8.79E-02
302,008	2	7.14E-01	3.67E-04	7.16E-01	2.48E-03	6.21E-01	7.63E-03	7.09E-01	5.38E-03	7.16E-01	9.45E-03	7.21E-01	5.49E-03	7.14E-01	2.30E-02	7.19E-01	3.84E-03	**7.23E-01**	2.26E-02
	3	7.49E-01	8.22E-06	**7.52E-01**	1.75E-03	7.14E-01	5.13E-03	7.40E-01	1.54E-02	7.48E-01	1.11E-02	7.50E-01	5.94E-03	7.48E-01	1.14E-02	7.52E-01	1.89E-03	7.44E-01	4.75E-02
	4	7.77E-01	6.38E-04	**7.83E-01**	2.75E-03	7.54E-01	4.51E-03	7.68E-01	2.41E-02	7.70E-01	1.20E-02	7.75E-01	6.98E-03	7.57E-01	5.87E-02	7.79E-01	1.17E-03	7.77E-01	2.64E-02
	5	7.95E-01	7.48E-04	**8.03E-01**	2.98E-03	7.80E-01	8.37E-03	7.87E-01	2.40E-02	7.85E-01	9.98E-03	7.91E-01	5.00E-03	7.88E-01	2.57E-02	7.93E-01	1.73E-03	7.93E-01	3.40E-02
37,073	2	7.27E-01	3.39E-16	**7.32E-01**	1.76E-02	7.12E-01	2.27E-03	7.26E-01	1.28E-02	7.31E-01	1.99E-02	7.29E-01	1.57E-03	6.81E-01	1.46E-01	7.29E-01	5.44E-04	6.33E-01	1.92E-01
	3	8.09E-01	3.39E-16	**8.13E-01**	2.29E-03	7.91E-01	1.82E-02	7.81E-01	4.27E-02	7.89E-01	4.24E-02	8.08E-01	7.39E-03	7.65E-01	1.32E-01	8.11E-01	7.70E-04	7.10E-01	2.08E-01
	4	8.01E-01	9.70E-04	8.16E-01	2.73E-02	7.93E-01	2.96E-02	8.04E-01	4.47E-02	**8.18E-01**	2.92E-02	8.06E-01	1.77E-02	8.13E-01	5.21E-02	8.01E-01	3.83E-03	7.38E-01	1.52E-01
	5	8.65E-01	2.06E-02	**8.73E-01**	7.63E-03	8.32E-01	3.05E-02	8.32E-01	3.99E-02	8.15E-01	2.49E-02	8.57E-01	2.70E-02	8.31E-01	4.30E-02	8.60E-01	2.09E-02	8.35E-01	4.23E-02

Table 5 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM
56,028	2	5.70E-01	2.26E-16	5.75E-01	4.36E-03	4.97E-01	3.29E-03	5.73E-01	3.17E-02	5.83E-01	3.63E-02	**5.88E-01**	1.60E-02	5.55E-01	1.12E-01	5.81E-01	3.66E-03	5.70E-01	7.95E-02
	3	6.91E-01	3.67E-04	**7.13E-01**	9.07E-03	6.35E-01	1.50E-02	6.68E-01	4.87E-02	6.85E-01	4.82E-02	7.03E-01	1.85E-02	6.89E-01	3.86E-02	6.94E-01	3.76E-03	6.64E-01	7.76E-02
	4	7.81E-01	5.04E-04	**7.95E-01**	6.45E-03	7.33E-01	1.74E-02	7.34E-01	4.53E-02	7.49E-01	3.71E-02	7.80E-01	1.47E-02	7.57E-01	4.34E-02	7.84E-01	1.86E-03	7.49E-01	7.74E-02
	5	8.30E-01	1.42E-03	**8.49E-01**	3.65E-03	7.83E-01	1.69E-02	7.89E-01	3.74E-02	8.02E-01	2.30E-02	8.21E-01	1.59E-02	7.91E-01	5.10E-02	8.29E-01	1.64E-03	7.95E-01	8.67E-02
66,075	2	5.32E-01	0.00E+00	5.34E-01	5.29E-03	4.97E-01	8.75E-03	5.22E-01	5.49E-02	5.23E-01	5.20E-02	5.36E-01	1.40E-02	5.35E-01	4.17E-02	**5.38E-01**	2.84E-03	4.98E-01	1.14E-01
	3	5.71E-01	2.52E-03	**5.91E-01**	1.23E-02	5.52E-01	2.13E-02	5.64E-01	6.32E-02	5.75E-01	5.48E-02	5.79E-01	1.67E-02	5.81E-01	4.31E-02	5.73E-01	1.64E-03	5.58E-01	1.50E-01
	4	6.08E-01	5.41E-03	**6.91E-01**	4.63E-02	6.04E-01	4.32E-02	6.50E-01	1.28E-01	6.09E-01	5.49E-02	6.16E-01	3.55E-02	6.82E-01	1.33E-01	6.04E-01	2.96E-03	6.42E-01	9.29E-02
	5	7.13E-01	1.06E-02	**7.88E-01**	2.70E-02	6.69E-01	7.98E-02	7.07E-01	1.16E-01	6.30E-01	6.33E-02	6.95E-01	4.43E-02	6.56E-01	1.39E-01	6.86E-01	1.11E-02	7.42E-01	1.09E-01

Bold means the best value provided by each algorithm

Table 6 FSIM comparisons using the Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM
101,087	2	6.96E-01	1.13E-16	6.98E-01	3.15E-03	6.59E-01	1.81E-03	6.98E-01	5.43E-03	6.94E-01	1.27E-02	6.98E-01	7.04E-03	**6.99E-01**	1.78E-02	6.99E-01	4.24E-03	6.93E-01	2.36E-02
	3	7.24E-01	5.65E-16	**7.44E-01**	9.75E-03	7.00E-01	4.83E-03	7.33E-01	1.85E-02	7.43E-01	2.38E-02	7.33E-01	1.27E-02	7.37E-01	2.24E-02	7.29E-01	2.97E-03	7.33E-01	2.19E-02
	4	8.01E-01	1.27E-03	**8.14E-01**	3.68E-03	7.65E-01	1.98E-02	7.66E-01	2.71E-02	7.69E-01	2.61E-02	7.98E-01	1.82E-02	7.77E-01	3.11E-02	8.03E-01	2.66E-03	7.93E-01	2.99E-02
	5	8.39E-01	3.83E-04	**8.50E-01**	1.96E-03	8.03E-01	1.46E-02	8.04E-01	2.60E-02	8.13E-01	1.63E-02	8.32E-01	1.68E-02	8.14E-01	2.56E-02	8.40E-01	4.96E-03	8.25E-01	2.76E-02
108,070	2	7.28E-01	4.52E-16	7.33E-01	5.45E-03	5.93E-01	1.65E-03	7.11E-01	2.40E-02	7.43E-01	1.89E-02	**7.53E-01**	1.49E-02	7.38E-01	3.39E-02	7.53E-01	9.65E-03	7.15E-01	1.08E-01
	3	8.01E-01	1.47E-03	8.05E-01	4.97E-03	6.97E-01	1.31E-02	7.71E-01	2.76E-02	7.97E-01	2.38E-02	8.14E-01	7.53E-03	7.94E-01	5.71E-02	**8.17E-01**	4.65E-03	7.80E-01	6.41E-02
	4	8.41E-01	8.24E-04	8.45E-01	4.54E-03	7.62E-01	2.04E-02	8.21E-01	2.04E-02	8.30E-01	1.85E-02	8.50E-01	9.41E-03	8.35E-01	1.91E-02	**8.50E-01**	4.57E-03	8.19E-01	7.13E-02
	5	8.66E-01	1.05E-03	8.71E-01	4.13E-03	8.08E-01	2.29E-02	8.39E-01	2.29E-02	8.57E-01	1.33E-02	8.70E-01	1.43E-02	8.45E-01	2.99E-02	**8.72E-01**	3.54E-03	8.44E-01	3.80E-02
12,003	2	6.22E-01	3.89E-03	6.27E-01	9.29E-03	5.06E-01	1.52E-03	6.18E-01	8.99E-03	6.39E-01	1.93E-02	6.40E-01	1.40E-02	6.25E-01	4.07E-02	**6.40E-01**	1.15E-02	6.28E-01	4.40E-02
	3	7.06E-01	1.96E-04	7.12E-01	4.76E-03	6.24E-01	3.78E-03	6.85E-01	1.82E-02	7.01E-01	1.74E-02	**7.22E-01**	1.24E-02	6.84E-01	4.39E-02	7.16E-01	6.50E-03	6.79E-01	5.29E-02
	4	7.68E-01	5.78E-04	7.74E-01	5.50E-03	6.96E-01	1.30E-02	7.27E-01	2.04E-02	7.44E-01	2.34E-02	7.73E-01	1.06E-02	7.46E-01	2.65E-02	**7.74E-01**	4.21E-03	7.44E-01	4.25E-02
	5	8.15E-01	1.86E-03	8.16E-01	3.85E-03	7.46E-01	1.49E-02	7.64E-01	1.84E-02	7.81E-01	1.26E-02	8.14E-01	1.24E-02	7.71E-01	2.97E-02	**8.21E-01**	3.94E-03	7.76E-01	4.86E-02
160,068	2	7.84E-01	5.08E-04	7.54E-01	1.98E-02	6.97E-01	5.22E-03	7.68E-01	2.48E-02	7.81E-01	2.48E-02	**8.10E-01**	9.80E-03	7.75E-01	3.93E-02	8.06E-01	1.03E-02	7.82E-01	5.32E-02
	3	7.80E-01	4.36E-03	7.82E-01	8.22E-03	6.85E-01	1.02E-02	7.72E-01	1.59E-02	7.83E-01	1.60E-02	**8.04E-01**	9.93E-03	7.77E-01	4.25E-02	8.01E-01	9.53E-03	7.77E-01	4.88E-02
	4	8.24E-01	1.78E-03	8.16E-01	8.33E-03	7.50E-01	1.74E-02	7.92E-01	1.87E-02	8.08E-01	1.27E-02	8.32E-01	6.95E-03	8.08E-01	1.88E-02	**8.36E-01**	4.16E-03	8.16E-01	2.88E-02
	5	8.43E-01	1.48E-03	8.50E-01	5.87E-03	7.84E-01	1.93E-02	8.13E-01	1.51E-02	8.35E-01	6.18E-03	8.50E-01	8.67E-03	8.12E-01	5.72E-02	**8.54E-01**	2.85E-03	8.38E-01	1.65E-02

Table 6 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM
210,088	2	6.78E-01	0.00E+00	6.86E-01	8.00E-03	6.21E-01	6.13E-04	6.76E-01	6.96E-03	6.92E-01	1.38E-02	**7.02E-01**	9.87E-03	6.94E-01	1.49E-02	6.96E-01	1.06E-02	6.94E-01	2.59E-02
	3	7.20E-01	3.04E-04	7.25E-01	7.68E-03	6.74E-01	6.51E-03	7.09E-01	1.11E-02	7.20E-01	1.69E-02	7.37E-01	8.21E-03	7.20E-01	1.55E-02	**7.37E-01**	7.09E-03	7.22E-01	2.95E-02
	4	7.52E-01	1.91E-03	7.60E-01	1.14E-02	7.09E-01	7.07E-03	7.39E-01	1.55E-02	7.49E-01	1.29E-02	**7.64E-01**	7.29E-03	7.38E-01	1.90E-02	7.63E-01	3.37E-03	7.42E-01	4.29E-02
	5	7.85E-01	9.22E-04	**7.97E-01**	7.76E-03	7.39E-01	1.29E-02	7.57E-01	1.68E-02	7.68E-01	8.88E-03	7.89E-01	1.26E-02	7.68E-01	2.26E-02	7.86E-01	4.21E-03	7.77E-01	1.84E-02
296,059	2	7.22E-01	3.56E-03	7.29E-01	8.90E-03	6.31E-01	6.44E-03	7.13E-01	2.36E-02	7.28E-01	2.37E-02	7.28E-01	1.29E-02	7.21E-01	1.98E-02	**7.30E-01**	6.72E-03	7.01E-01	3.95E-02
	3	7.67E-01	3.34E-03	**7.86E-01**	7.37E-03	7.26E-01	1.48E-02	7.47E-01	2.77E-02	7.56E-01	2.83E-02	7.69E-01	1.68E-02	7.53E-01	3.29E-02	7.68E-01	2.17E-03	7.59E-01	3.92E-02
	4	8.19E-01	2.14E-04	**8.26E-01**	2.72E-03	7.79E-01	1.26E-02	7.80E-01	2.46E-02	7.85E-01	2.07E-02	8.20E-01	7.21E-03	7.78E-01	3.97E-02	8.22E-01	1.86E-03	7.90E-01	4.74E-02
	5	8.44E-01	2.81E-03	**8.53E-01**	2.64E-03	8.07E-01	1.55E-02	7.92E-01	2.72E-02	8.24E-01	5.48E-03	8.40E-01	1.01E-02	8.06E-01	3.07E-02	8.43E-01	2.25E-03	8.01E-01	5.21E-02
302,008	2	7.95E-01	3.23E-04	7.97E-01	2.78E-03	7.31E-01	3.90E-03	7.90E-01	4.83E-03	8.02E-01	9.78E-03	**8.08E-01**	6.81E-03	8.00E-01	1.33E-02	8.03E-01	7.04E-03	8.02E-01	1.15E-02
	3	8.22E-01	3.12E-05	8.24E-01	2.91E-03	7.88E-01	4.61E-03	8.14E-01	7.03E-03	8.24E-01	8.01E-03	**8.31E-01**	6.72E-03	8.24E-01	1.18E-02	8.30E-01	5.39E-03	8.20E-01	2.18E-02
	4	8.46E-01	1.96E-03	8.49E-01	4.28E-03	8.20E-01	3.71E-03	8.32E-01	1.14E-02	8.42E-01	9.53E-03	8.53E-01	6.41E-03	8.31E-01	3.37E-02	**8.54E-01**	4.41E-03	8.42E-01	1.79E-02
	5	8.68E-01	7.08E-04	8.67E-01	3.94E-03	8.38E-01	5.95E-03	8.47E-01	1.28E-02	8.55E-01	6.68E-03	8.68E-01	5.04E-03	8.51E-01	1.78E-02	**8.70E-01**	2.24E-03	8.51E-01	1.93E-02
37,073	2	7.54E-01	1.13E-16	7.56E-01	6.70E-03	7.33E-01	7.03E-04	7.53E-01	5.59E-03	**7.60E-01**	1.27E-02	7.58E-01	3.06E-03	7.38E-01	5.46E-02	7.58E-01	1.12E-03	7.15E-01	7.84E-02
	3	8.02E-01	3.39E-16	8.04E-01	2.60E-03	7.76E-01	6.04E-03	7.84E-01	1.55E-02	7.87E-01	1.60E-02	8.05E-01	5.07E-03	7.83E-01	4.69E-02	**8.07E-01**	1.20E-03	7.55E-01	8.46E-02
	4	8.33E-01	1.64E-03	8.31E-01	4.71E-03	8.05E-01	1.09E-02	8.05E-01	1.96E-02	8.17E-01	1.50E-02	8.35E-01	9.25E-03	8.13E-01	2.70E-02	**8.38E-01**	2.67E-03	7.84E-01	7.24E-02
	5	8.67E-01	8.38E-03	**8.71E-01**	4.86E-03	8.32E-01	9.91E-03	8.24E-01	1.45E-02	8.41E-01	6.65E-03	8.64E-01	1.31E-02	8.31E-01	2.60E-02	8.67E-01	9.07E-03	8.45E-01	3.11E-02

Table 6 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM
56,028	2	6.59E-01	1.13E-16	6.63E-01	3.50E-03	5.66E-01	1.23E-03	6.53E-01	1.33E-02	6.79E-01	2.36E-02	**6.93E-01**	1.36E-02	6.57E-01	6.35E-02	6.87E-01	7.15E-03	6.67E-01	5.07E-02
	3	7.41E-01	8.47E-04	7.48E-01	4.17E-03	6.67E-01	5.68E-03	7.20E-01	2.13E-02	7.40E-01	2.65E-02	**7.68E-01**	9.70E-03	7.36E-01	2.49E-02	7.60E-01	8.46E-03	7.29E-01	6.18E-02
	4	8.01E-01	2.63E-04	8.02E-01	8.11E-03	7.27E-01	1.19E-02	7.65E-01	2.12E-02	7.80E-01	1.35E-02	**8.19E-01**	8.44E-03	7.84E-01	2.73E-02	8.19E-01	6.69E-03	7.92E-01	4.13E-02
	5	8.36E-01	3.38E-03	8.44E-01	5.61E-03	7.75E-01	1.41E-02	8.01E-01	1.83E-02	8.28E-01	1.27E-02	8.49E-01	9.61E-03	8.14E-01	3.10E-02	**8.54E-01**	5.88E-03	8.19E-01	6.17E-02
66,075	2	8.09E-01	3.39E-16	8.12E-01	4.19E-03	7.70E-01	1.65E-03	7.95E-01	1.29E-02	8.08E-01	1.41E-02	8.19E-01	5.67E-03	8.06E-01	1.10E-02	**8.20E-01**	4.68E-03	7.99E-01	2.44E-02
	3	8.12E-01	5.44E-03	8.08E-01	5.54E-03	7.79E-01	8.86E-03	8.06E-01	1.27E-02	8.13E-01	1.50E-02	**8.20E-01**	5.03E-03	8.10E-01	1.07E-02	8.19E-01	3.19E-03	8.04E-01	2.28E-02
	4	8.19E-01	7.60E-04	8.10E-01	5.72E-03	7.94E-01	1.23E-02	8.17E-01	1.37E-02	8.16E-01	1.15E-02	8.24E-01	6.33E-03	8.14E-01	1.77E-02	**8.25E-01**	2.73E-03	8.19E-01	7.99E-03
	5	8.13E-01	8.40E-04	8.11E-01	3.63E-03	8.03E-01	1.40E-02	8.16E-01	1.55E-02	**8.26E-01**	6.60E-03	8.23E-01	7.42E-03	8.19E-01	1.60E-02	8.26E-01	4.29E-03	8.24E-01	1.39E-02

Bold means the best value provided by each algorithm

Table 7 QILV comparisons using the Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV
101,087	2	8.61E-01	6.03E-02	8.76E-01	7.09E-02	1.33E-01	9.90E-03	8.97E-01	6.03E-02	**9.06E-01**	3.26E-02	8.82E-01	5.00E-02	8.71E-01	1.11E-01	9.01E-01	4.30E-02	8.01E-01	2.37E-01
	3	9.26E-01	4.15E-02	9.21E-01	5.70E-02	3.14E-01	4.06E-02	9.40E-01	3.59E-02	**9.48E-01**	1.59E-02	9.18E-01	4.19E-02	9.24E-01	1.09E-01	9.48E-01	2.65E-02	8.63E-01	1.32E-01
	4	9.47E-01	3.15E-02	9.42E-01	5.03E-02	3.90E-01	6.25E-02	9.47E-01	3.65E-02	**9.64E-01**	1.56E-02	9.31E-01	4.94E-02	9.21E-01	9.54E-02	9.44E-01	2.94E-02	8.48E-01	2.10E-01
	5	9.63E-01	2.18E-02	9.52E-01	4.74E-02	4.82E-01	8.16E-02	9.51E-01	4.25E-02	**9.69E-01**	1.55E-02	9.46E-01	3.56E-02	9.40E-01	5.20E-02	9.56E-01	2.31E-02	8.65E-01	1.26E-01
108,070	2	5.92E-01	5.26E-02	5.98E-01	6.14E-02	1.24E-01	5.19E-03	5.82E-01	6.03E-02	**6.18E-01**	2.89E-02	6.13E-01	3.93E-02	5.91E-01	5.90E-02	6.06E-01	3.29E-02	5.90E-01	7.75E-02
	3	7.53E-01	3.04E-02	7.35E-01	4.02E-02	3.48E-01	3.27E-02	7.30E-01	3.87E-02	**7.64E-01**	1.07E-02	7.52E-01	2.63E-02	6.75E-01	1.41E-01	7.47E-01	2.28E-02	7.02E-01	7.39E-02
	4	8.32E-01	1.95E-02	8.10E-01	2.90E-02	5.32E-01	5.82E-02	8.01E-01	3.59E-02	**8.41E-01**	8.05E-03	8.35E-01	1.79E-02	7.84E-01	1.51E-01	8.38E-01	1.35E-02	7.95E-01	5.16E-02
	5	8.86E-01	1.21E-02	8.46E-01	2.91E-02	6.46E-01	7.05E-02	8.35E-01	3.42E-02	**8.94E-01**	5.74E-03	8.78E-01	1.96E-02	8.10E-01	8.24E-02	8.89E-01	8.41E-03	8.26E-01	8.96E-02
12,003	2	7.89E-01	4.20E-02	7.55E-01	5.85E-02	1.91E-01	1.88E-02	7.52E-01	6.97E-02	8.02E-01	3.29E-02	**8.10E-01**	2.34E-02	7.28E-01	1.29E-01	7.75E-01	4.87E-02	7.28E-01	1.20E-01
	3	8.75E-01	2.27E-02	8.52E-01	3.80E-02	4.81E-01	4.57E-02	8.40E-01	4.48E-02	8.79E-01	1.79E-02	**8.81E-01**	1.88E-02	8.47E-01	4.90E-02	8.79E-01	2.00E-02	8.40E-01	1.20E-01
	4	9.24E-01	1.36E-02	8.93E-01	3.09E-02	6.43E-01	5.70E-02	8.92E-01	2.19E-02	9.25E-01	1.15E-02	9.23E-01	1.47E-02	8.85E-01	9.30E-02	**9.25E-01**	1.33E-02	8.67E-01	1.22E-01
	5	9.44E-01	1.01E-02	9.14E-01	2.32E-02	7.38E-01	8.43E-02	9.12E-01	2.54E-02	9.47E-01	6.34E-03	**9.48E-01**	7.07E-03	9.06E-01	6.20E-02	9.47E-01	1.10E-02	9.10E-01	1.05E-01
160,068	2	7.04E-01	2.37E-02	7.03E-01	3.73E-02	2.70E-01	1.87E-02	7.05E-01	3.82E-02	7.13E-01	1.79E-02	7.12E-01	3.37E-02	6.84E-01	1.08E-01	**7.16E-01**	1.88E-02	6.75E-01	6.81E-02
	3	8.52E-01	1.36E-02	8.25E-01	3.41E-02	4.86E-01	6.44E-02	8.09E-01	4.00E-02	8.54E-01	1.12E-02	**8.59E-01**	1.62E-02	7.92E-01	1.43E-01	8.53E-01	1.59E-02	8.18E-01	4.86E-02
	4	9.02E-01	6.21E-03	8.80E-01	2.38E-02	7.18E-01	7.33E-02	8.74E-01	3.39E-02	**9.06E-01**	4.52E-03	9.06E-01	8.97E-03	8.76E-01	2.58E-02	9.06E-01	6.43E-03	8.46E-01	1.02E-01
	5	9.30E-01	4.89E-03	8.95E-01	2.44E-02	7.99E-01	5.66E-02	9.00E-01	2.60E-02	9.29E-01	5.14E-03	9.30E-01	9.01E-03	8.72E-01	1.23E-01	**9.33E-01**	5.96E-03	9.10E-01	2.80E-02

Table 7 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV
210,088	2	7.68E-01	4.05E-02	7.45E-01	5.77E-02	2.65E-01	2.06E-02	7.15E-01	7.74E-02	7.86E-01	3.31E-02	**7.95E-01**	3.05E-02	7.28E-01	7.50E-02	7.85E-01	3.37E-02	7.22E-01	1.16E-01
	3	8.69E-01	1.02E-02	8.39E-01	2.82E-02	5.64E-01	4.46E-02	8.26E-01	3.81E-02	**8.71E-01**	8.95E-03	8.61E-01	2.36E-02	7.97E-01	1.16E-01	8.68E-01	1.12E-02	8.13E-01	1.12E-01
	4	9.03E-01	6.12E-03	8.85E-01	2.29E-02	7.39E-01	7.51E-02	8.73E-01	2.83E-02	9.06E-01	3.35E-03	**9.07E-01**	1.36E-02	8.05E-01	1.98E-01	9.05E-01	5.21E-03	8.19E-01	1.42E-01
	5	9.37E-01	2.86E-03	9.17E-01	1.65E-02	8.15E-01	5.95E-02	8.94E-01	2.82E-02	9.38E-01	2.48E-03	9.34E-01	8.15E-03	8.99E-01	3.52E-02	**9.38E-01**	3.14E-03	8.45E-01	1.65E-01
296,059	2	7.77E-01	6.60E-02	7.65E-01	6.12E-02	1.70E-01	2.94E-02	7.54E-01	7.68E-02	8.17E-01	5.76E-02	**8.19E-01**	5.86E-02	6.83E-01	2.06E-01	8.05E-01	6.92E-02	7.37E-01	1.67E-01
	3	8.87E-01	1.15E-02	8.65E-01	4.41E-02	5.58E-01	8.78E-02	8.47E-01	5.97E-02	**8.93E-01**	1.09E-02	8.92E-01	1.56E-02	8.29E-01	8.40E-02	8.91E-01	1.52E-02	7.77E-01	2.26E-01
	4	9.22E-01	8.33E-03	9.05E-01	2.36E-02	7.49E-01	7.56E-02	8.91E-01	3.17E-02	9.22E-01	5.86E-03	9.30E-01	1.31E-02	8.43E-01	1.68E-01	**9.32E-01**	9.34E-03	8.95E-01	6.98E-02
	5	9.51E-01	6.07E-03	9.24E-01	1.97E-02	7.79E-01	1.06E-01	9.10E-01	2.85E-02	9.50E-01	4.16E-03	9.52E-01	7.95E-03	8.68E-01	1.81E-01	**9.55E-01**	5.70E-03	8.75E-01	1.92E-01
302,008	2	7.46E-01	5.30E-02	7.09E-01	6.57E-02	5.50E-02	1.42E-02	6.94E-01	8.02E-02	7.50E-01	4.88E-02	**7.70E-01**	4.56E-02	6.81E-01	8.48E-02	7.61E-01	5.90E-02	7.11E-01	1.58E-01
	3	8.54E-01	2.23E-02	8.24E-01	3.71E-02	4.11E-01	8.15E-02	8.34E-01	3.57E-02	8.40E-01	2.77E-02	**8.65E-01**	2.24E-02	8.08E-01	6.10E-02	8.58E-01	2.40E-02	8.35E-01	6.94E-02
	4	8.99E-01	1.59E-02	8.79E-01	2.74E-02	6.86E-01	6.86E-02	8.62E-01	3.10E-02	8.98E-01	1.30E-02	9.04E-01	1.53E-02	8.17E-01	2.08E-01	**9.04E-01**	1.49E-02	8.77E-01	4.04E-02
	5	9.20E-01	6.20E-03	9.01E-01	2.06E-02	7.99E-01	5.91E-02	8.95E-01	2.53E-02	9.16E-01	5.12E-03	**9.28E-01**	9.85E-03	8.87E-01	6.92E-02	9.23E-01	5.91E-03	8.93E-01	7.26E-02
37,073	2	6.17E-01	6.56E-03	5.93E-01	5.21E-02	5.02E-01	3.07E-02	6.08E-01	8.86E-02	6.15E-01	7.74E-03	6.34E-01	3.27E-02	**6.47E-01**	9.48E-02	6.18E-01	5.50E-03	6.12E-01	1.22E-01
	3	8.73E-01	4.26E-03	8.34E-01	6.57E-02	7.47E-01	4.31E-02	8.20E-01	8.45E-02	**8.74E-01**	3.42E-03	8.69E-01	2.90E-02	7.71E-01	1.77E-01	8.72E-01	5.09E-03	7.69E-01	2.21E-01
	4	9.32E-01	3.71E-03	8.91E-01	5.39E-02	8.16E-01	3.85E-02	8.63E-01	6.32E-02	**9.34E-01**	6.61E-04	9.27E-01	1.60E-02	8.77E-01	6.33E-02	9.31E-01	4.50E-03	8.77E-01	1.49E-01
	5	9.49E-01	3.99E-03	9.20E-01	3.33E-02	8.80E-01	3.54E-02	9.06E-01	5.16E-02	**9.50E-01**	2.09E-03	9.48E-01	8.87E-03	8.67E-01	1.69E-01	9.45E-01	6.46E-03	8.95E-01	1.09E-01

Table 7 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV
56,028	2	7.63E-01	2.77E-02	7.44E-01	4.43E-02	2.74E-01	2.20E-02	7.44E-01	5.80E-02	7.77E-01	3.00E-02	**7.92E-01**	2.40E-02	7.32E-01	4.12E-02	7.67E-01	2.71E-02	7.14E-01	1.40E-01
	3	8.72E-01	1.27E-02	8.52E-01	2.59E-02	5.83E-01	6.31E-02	8.31E-01	4.73E-02	**8.76E-01**	8.15E-03	8.72E-01	1.45E-02	8.18E-01	1.30E-01	8.67E-01	1.19E-02	8.47E-01	8.09E-02
	4	9.14E-01	1.16E-02	8.95E-01	2.24E-02	7.19E-01	5.19E-02	8.87E-01	3.02E-02	**9.20E-01**	6.07E-03	9.19E-01	1.38E-02	8.81E-01	4.32E-02	9.20E-01	9.58E-03	8.95E-01	3.71E-02
	5	9.46E-01	6.12E-03	9.30E-01	1.20E-02	8.19E-01	4.11E-02	9.10E-01	2.98E-02	9.46E-01	5.37E-03	9.42E-01	9.56E-03	9.04E-01	8.42E-02	**9.49E-01**	4.27E-03	9.03E-01	1.28E-01
66,075	2	7.37E-01	3.02E-02	7.12E-01	4.94E-02	2.55E-01	1.89E-02	6.86E-01	5.59E-02	7.29E-01	3.92E-02	**7.49E-01**	1.50E-02	6.84E-01	7.21E-02	7.29E-01	3.75E-02	6.78E-01	1.01E-01
	3	8.33E-01	2.21E-02	8.13E-01	3.42E-02	5.09E-01	3.96E-02	7.83E-01	4.77E-02	**8.46E-01**	1.26E-02	8.36E-01	1.93E-02	7.75E-01	5.32E-02	8.44E-01	1.36E-02	7.70E-01	1.26E-01
	4	8.78E-01	1.22E-02	8.52E-01	2.85E-02	6.82E-01	4.79E-02	8.48E-01	3.83E-02	8.82E-01	1.01E-02	**8.84E-01**	1.03E-02	8.11E-01	1.21E-01	8.84E-01	9.25E-03	7.99E-01	1.23E-01
	5	9.14E-01	9.79E-03	8.70E-01	2.78E-02	7.43E-01	4.19E-02	8.70E-01	3.04E-02	9.14E-01	8.13E-03	**9.20E-01**	6.64E-03	8.72E-01	5.04E-02	9.18E-01	7.96E-03	8.32E-01	1.69E-01

Bold means the best value provided by each algorithm

Table 8 HPSI comparisons using the Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI
101,087	2	3.04E-01	3.23E-03	3.05E-01	3.25E-02	2.53E-01	6.44E-03	3.05E-01	3.51E-02	3.07E-01	2.56E-03	3.10E-01	2.76E-02	3.07E-01	5.06E-02	3.06E-01	3.29E-03	**3.16E-01**	5.21E-02
	3	4.29E-01	3.36E-03	4.28E-01	4.64E-02	3.71E-01	1.07E-02	4.26E-01	5.63E-02	4.32E-01	1.95E-03	**4.35E-01**	3.41E-02	4.22E-01	5.73E-02	4.29E-01	4.45E-03	4.13E-01	3.86E-02
	4	5.87E-01	9.39E-03	5.34E-01	6.55E-02	4.80E-01	2.88E-02	5.22E-01	4.81E-02	**5.91E-01**	4.14E-03	5.51E-01	4.64E-02	5.31E-01	5.95E-02	5.84E-01	1.32E-02	4.97E-01	1.14E-01
	5	6.59E-01	1.06E-02	5.99E-01	4.16E-02	5.40E-01	3.08E-02	5.66E-01	5.45E-02	**6.64E-01**	4.68E-03	6.37E-01	3.96E-02	5.90E-01	6.82E-02	6.60E-01	5.41E-03	5.87E-01	8.39E-02
108,070	2	4.39E-01	8.78E-03	4.39E-01	3.27E-02	2.75E-01	3.81E-03	4.23E-01	4.50E-02	**4.43E-01**	4.37E-03	4.43E-01	1.79E-02	4.43E-01	3.82E-02	4.41E-01	4.81E-03	4.33E-01	6.19E-02
	3	5.36E-01	4.51E-03	5.32E-01	2.98E-02	4.00E-01	2.02E-02	5.27E-01	4.07E-02	**5.38E-01**	1.62E-03	5.32E-01	2.23E-02	4.75E-01	1.03E-01	5.35E-01	4.80E-03	5.26E-01	5.64E-02
	4	6.00E-01	3.06E-03	5.87E-01	4.37E-02	4.93E-01	3.08E-02	5.65E-01	6.35E-02	**6.01E-01**	2.00E-03	5.91E-01	3.19E-02	5.69E-01	1.13E-01	5.98E-01	4.54E-03	5.72E-01	7.59E-02
	5	6.61E-01	7.05E-03	6.18E-01	5.94E-02	5.46E-01	3.98E-02	6.12E-01	6.87E-02	**6.62E-01**	6.42E-03	6.36E-01	3.69E-02	5.77E-01	9.78E-02	6.55E-01	5.36E-03	6.16E-01	9.92E-02
12,003	2	3.74E-01	9.50E-03	3.67E-01	2.00E-02	1.69E-01	7.70E-03	3.61E-01	2.32E-02	3.77E-01	8.03E-03	**3.84E-01**	1.68E-02	3.54E-01	5.32E-02	3.71E-01	1.08E-02	3.42E-01	6.66E-02
	3	4.95E-01	8.03E-03	4.71E-01	2.59E-02	3.16E-01	2.13E-02	4.63E-01	4.19E-02	4.95E-01	7.40E-03	4.96E-01	1.62E-02	4.64E-01	4.82E-02	**4.96E-01**	8.00E-03	4.52E-01	8.53E-02
	4	6.05E-01	7.56E-03	5.46E-01	3.05E-02	4.21E-01	3.50E-02	5.33E-01	4.71E-02	**6.05E-01**	7.63E-03	5.91E-01	3.04E-02	5.45E-01	6.07E-02	6.05E-01	8.91E-03	5.43E-01	9.26E-02
	5	6.85E-01	9.27E-03	6.10E-01	2.73E-02	5.00E-01	5.76E-02	5.88E-01	3.82E-02	**6.86E-01**	6.87E-03	6.70E-01	2.38E-02	5.67E-01	6.64E-02	6.85E-01	9.77E-03	6.14E-01	1.00E-01
160,068	2	4.41E-01	8.89E-03	4.32E-01	1.64E-02	2.71E-01	7.75E-03	4.25E-01	1.69E-02	4.46E-01	6.90E-03	4.41E-01	1.36E-02	4.21E-01	5.16E-02	**4.46E-01**	6.74E-03	4.17E-01	4.10E-02
	3	4.85E-01	5.37E-03	4.76E-01	1.57E-02	3.05E-01	3.01E-02	4.66E-01	2.24E-02	4.87E-01	4.21E-03	**4.92E-01**	1.14E-02	4.62E-01	7.20E-02	4.86E-01	6.25E-03	4.80E-01	3.70E-02
	4	5.28E-01	2.62E-03	5.14E-01	2.31E-02	4.14E-01	4.49E-02	5.15E-01	3.32E-02	5.30E-01	2.03E-03	5.29E-01	1.28E-02	5.17E-01	2.88E-02	**5.30E-01**	2.70E-03	5.01E-01	5.71E-02
	5	**5.71E-01**	2.45E-03	5.43E-01	3.80E-02	4.70E-01	3.83E-02	5.49E-01	3.77E-02	5.71E-01	2.82E-03	5.64E-01	2.22E-02	5.24E-01	7.31E-02	5.71E-01	7.08E-03	5.60E-01	4.94E-02

Table 8 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI
210,088	2	3.28E-01	1.52E-02	3.28E-01	2.04E-02	2.05E-01	7.60E-03	3.28E-01	2.36E-02	3.36E-01	1.26E-02	**3.42E-01**	1.35E-02	3.26E-01	2.80E-02	3.35E-01	1.30E-02	3.25E-01	2.92E-02
	3	3.89E-01	6.96E-03	3.80E-01	2.65E-02	2.96E-01	1.24E-02	3.78E-01	3.32E-02	**3.91E-01**	6.26E-03	3.87E-01	2.36E-02	3.66E-01	4.55E-02	3.88E-01	7.47E-03	3.74E-01	4.75E-02
	4	4.39E-01	4.03E-03	4.31E-01	4.53E-02	3.54E-01	2.33E-02	4.18E-01	4.97E-02	**4.42E-01**	2.09E-03	4.41E-01	2.75E-02	3.91E-01	8.16E-02	4.41E-01	4.60E-03	4.06E-01	6.60E-02
	5	**5.09E-01**	7.11E-03	4.84E-01	5.55E-02	4.14E-01	3.54E-02	4.77E-01	6.00E-02	5.04E-01	9.12E-03	4.89E-01	3.58E-02	4.65E-01	5.60E-02	5.02E-01	7.41E-03	4.55E-01	9.28E-02
296,059	2	4.72E-01	6.49E-03	4.60E-01	3.22E-02	3.07E-01	2.45E-03	4.59E-01	4.02E-02	**4.76E-01**	5.48E-03	4.66E-01	2.48E-02	4.29E-01	8.36E-02	4.74E-01	6.65E-03	4.48E-01	7.41E-02
	3	5.32E-01	6.23E-03	5.19E-01	3.90E-02	4.58E-01	2.90E-02	5.22E-01	4.58E-02	**5.36E-01**	4.65E-03	5.34E-01	2.67E-02	5.03E-01	7.30E-02	5.34E-01	6.49E-03	4.92E-01	1.03E-01
	4	6.14E-01	6.29E-03	5.71E-01	3.78E-02	5.37E-01	2.62E-02	5.44E-01	4.63E-02	6.17E-01	7.18E-03	6.11E-01	2.14E-02	5.33E-01	9.58E-02	**6.22E-01**	6.59E-03	5.61E-01	9.08E-02
	5	6.47E-01	7.64E-03	6.03E-01	3.84E-02	5.67E-01	3.27E-02	5.86E-01	4.16E-02	6.48E-01	6.74E-03	6.44E-01	1.90E-02	5.64E-01	1.10E-01	**6.56E-01**	7.02E-03	5.78E-01	1.15E-01
302,008	2	4.62E-01	9.63E-03	4.49E-01	2.18E-02	2.20E-01	2.03E-02	4.41E-01	3.75E-02	4.63E-01	8.93E-03	4.64E-01	1.86E-02	4.37E-01	5.89E-02	**4.65E-01**	1.16E-02	4.32E-01	6.46E-02
	3	5.45E-01	6.92E-03	5.24E-01	2.44E-02	4.11E-01	3.28E-02	5.25E-01	3.32E-02	5.42E-01	7.76E-03	**5.56E-01**	1.95E-02	5.14E-01	6.87E-02	5.52E-01	9.72E-03	5.24E-01	3.98E-02
	4	6.15E-01	6.25E-03	5.90E-01	3.11E-02	5.33E-01	1.87E-02	5.74E-01	4.02E-02	6.15E-01	5.17E-03	6.16E-01	1.74E-02	5.51E-01	1.11E-01	**6.22E-01**	1.01E-02	5.87E-01	5.73E-02
	5	6.85E-01	2.51E-03	6.37E-01	3.08E-02	5.99E-01	2.37E-02	6.18E-01	3.68E-02	6.84E-01	2.49E-03	6.81E-01	1.58E-02	6.11E-01	6.29E-02	**6.89E-01**	4.70E-03	6.38E-01	8.42E-02
37,073	2	5.08E-01	1.24E-03	5.08E-01	1.03E-02	4.34E-01	1.94E-03	5.08E-01	2.04E-02	5.07E-01	1.48E-03	5.08E-01	4.12E-03	5.03E-01	1.24E-02	**5.08E-01**	1.13E-03	4.81E-01	8.87E-02
	3	6.09E-01	1.37E-03	5.88E-01	2.51E-02	5.28E-01	1.13E-02	5.86E-01	2.85E-02	**6.10E-01**	1.04E-03	6.08E-01	6.09E-03	5.61E-01	9.53E-02	6.09E-01	1.68E-03	5.37E-01	1.18E-01
	4	6.99E-01	1.24E-03	6.54E-01	3.04E-02	6.08E-01	2.66E-02	6.29E-01	4.16E-02	**7.00E-01**	2.99E-04	6.86E-01	2.13E-02	6.18E-01	8.55E-02	6.99E-01	1.66E-03	6.43E-01	1.03E-01
	5	7.49E-01	2.52E-02	6.87E-01	4.00E-02	6.71E-01	2.31E-02	6.71E-01	3.74E-02	**7.66E-01**	2.26E-03	7.42E-01	2.76E-02	6.43E-01	1.12E-01	7.58E-01	1.54E-02	6.84E-01	9.55E-02

Table 8 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI
56,028	2	4.32E-01	8.66E-03	4.21E-01	2.09E-02	2.67E-01	3.97E-03	4.12E-01	3.68E-02	4.37E-01	8.26E-03	**4.42E-01**	1.33E-02	4.18E-01	2.73E-02	4.33E-01	7.55E-03	4.11E-01	5.80E-02
	3	5.44E-01	5.76E-03	5.19E-01	2.73E-02	3.88E-01	2.26E-02	5.24E-01	4.05E-02	**5.47E-01**	3.42E-03	5.43E-01	1.68E-02	4.96E-01	8.52E-02	5.42E-01	5.06E-03	5.19E-01	6.27E-02
	4	6.45E-01	7.35E-03	6.06E-01	2.82E-02	4.88E-01	3.29E-02	5.90E-01	3.86E-02	6.49E-01	3.98E-03	6.41E-01	2.15E-02	5.89E-01	6.81E-02	**6.49E-01**	6.42E-03	6.10E-01	6.08E-02
	5	7.20E-01	5.75E-03	6.70E-01	2.70E-02	5.79E-01	3.33E-02	6.35E-01	3.68E-02	**7.22E-01**	3.92E-03	7.10E-01	2.30E-02	6.21E-01	7.00E-02	7.21E-01	5.54E-03	6.45E-01	1.10E-01
66,075	2	**3.56E-01**	1.24E-02	3.39E-01	2.71E-02	1.90E-01	3.13E-03	3.36E-01	2.30E-02	3.55E-01	1.34E-02	3.56E-01	1.15E-02	3.37E-01	3.08E-02	3.53E-01	1.42E-02	3.24E-01	4.62E-02
	3	3.88E-01	1.10E-02	3.80E-01	2.15E-02	2.68E-01	2.17E-02	3.69E-01	2.25E-02	**3.95E-01**	6.15E-03	3.91E-01	1.12E-02	3.70E-01	3.07E-02	3.94E-01	7.23E-03	3.77E-01	4.01E-02
	4	4.34E-01	4.93E-03	4.14E-01	2.16E-02	3.36E-01	2.30E-02	4.15E-01	3.18E-02	**4.36E-01**	4.04E-03	4.29E-01	1.43E-02	4.04E-01	4.58E-02	4.35E-01	5.04E-03	3.82E-01	7.01E-02
	5	4.57E-01	8.06E-03	4.43E-01	4.63E-02	3.68E-01	2.04E-02	4.45E-01	4.70E-02	4.54E-01	4.16E-03	4.58E-01	9.62E-03	4.47E-01	7.40E-02	**4.62E-01**	7.84E-03	4.15E-01	8.55E-02

Bold means the best value provided by each algorithm

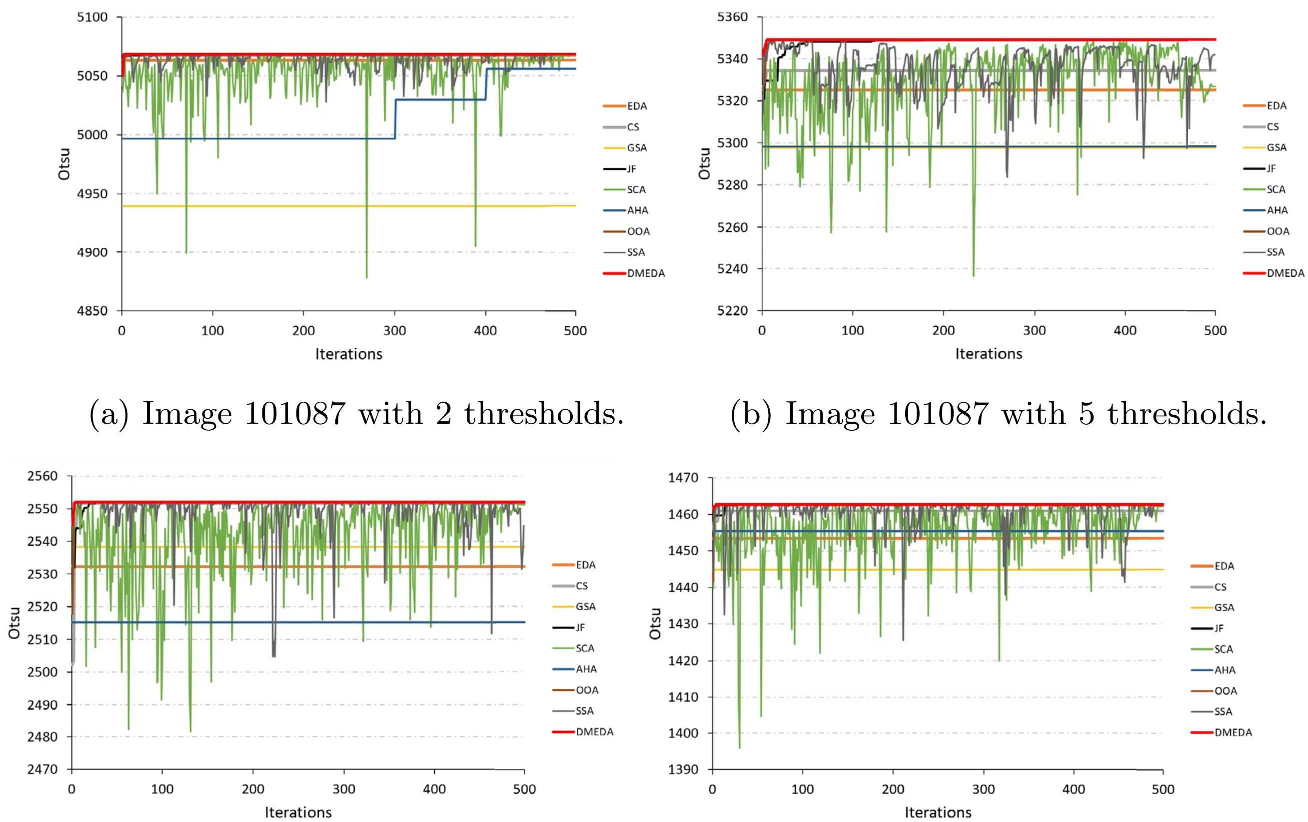
Table 9 UIQI comparisons using the Otsu's between-class variance

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI
101,087	2	8.73E-01	4.24E-02	8.80E-01	1.15E-01	6.27E-01	4.28E-03	9.00E-01	9.16E-02	9.04E-01	3.30E-02	8.86E-01	5.85E-02	**9.72E-01**	3.33E-01	9.04E-01	4.24E-02	9.58E-01	4.10E-01
	3	9.50E-01	1.98E-02	9.50E-01	2.91E-02	8.12E-01	8.88E-03	**9.66E-01**	2.83E-02	9.60E-01	1.11E-02	9.48E-01	1.81E-02	9.64E-01	3.32E-02	9.62E-01	1.84E-02	9.36E-01	4.18E-02
	4	9.76E-01	8.86E-03	9.73E-01	2.01E-02	8.93E-01	8.26E-03	9.72E-01	1.37E-02	**9.79E-01**	5.20E-03	9.71E-01	1.13E-02	9.71E-01	2.23E-02	9.74E-01	8.19E-03	9.45E-01	7.79E-02
	5	9.83E-01	5.45E-03	9.82E-01	1.20E-02	9.23E-01	6.98E-03	9.80E-01	1.31E-02	**9.84E-01**	3.87E-03	9.80E-01	8.02E-03	9.79E-01	1.30E-02	9.81E-01	5.50E-03	9.66E-01	2.50E-02
108,070	2	8.44E-01	1.05E-02	8.45E-01	5.30E-02	-5.95E-01	6.20E+00	8.16E-01	6.81E-02	8.39E-01	4.21E-03	8.39E-01	2.80E-02	**9.72E-01**	6.85E-01	8.40E-01	5.14E-03	7.63E-01	2.37E-01
	3	9.16E-01	7.66E-03	**9.20E-01**	1.30E-01	8.40E-01	3.21E-01	9.09E-01	1.86E-01	9.13E-01	2.89E-03	9.11E-01	3.25E-02	8.87E-01	9.32E-02	9.15E-01	5.83E-03	8.96E-01	7.00E-02
	4	9.38E-01	8.39E-03	**1.19E+00**	1.23E+00	8.32E-01	6.35E-01	9.00E-01	4.41E-02	9.35E-01	3.77E-03	7.89E-01	7.82E-01	9.47E-01	1.98E-01	9.31E-01	7.57E-03	9.38E-01	7.86E-02
	5	1.08E+00	1.72E+00	**1.96E+00**	5.45E+00	1.07E+00	4.24E-01	9.17E-01	7.65E-02	8.92E-01	1.76E+00	8.90E-01	1.61E-01	8.93E-01	1.44E-01	6.71E-01	9.65E-01	8.70E-01	1.92E-01
12,003	2	8.34E-01	7.65E-03	8.26E-01	2.40E-02	6.93E-01	1.96E-03	8.16E-01	3.85E-02	8.36E-01	7.44E-03	**8.40E-01**	2.14E-02	8.08E-01	7.61E-02	8.31E-01	1.05E-02	8.09E-01	7.56E-02
	3	9.11E-01	4.39E-03	9.08E-01	1.12E-02	8.71E-01	2.76E-03	9.06E-01	1.67E-02	9.11E-01	3.96E-03	**9.13E-01**	6.24E-03	9.07E-01	2.32E-02	9.12E-01	4.29E-03	8.77E-01	1.51E-01
	4	9.48E-01	2.37E-03	9.39E-01	8.26E-03	9.27E-01	4.68E-03	9.40E-01	1.24E-02	9.48E-01	2.19E-03	9.47E-01	7.07E-03	9.42E-01	1.20E-02	**9.49E-01**	2.32E-03	9.45E-01	1.93E-02
	5	9.67E-01	1.51E-03	9.61E-01	5.65E-03	9.51E-01	5.94E-03	9.59E-01	6.83E-03	9.67E-01	1.08E-03	9.66E-01	4.25E-03	9.57E-01	2.04E-02	**9.67E-01**	1.80E-03	9.64E-01	1.20E-02
160,068	2	9.05E-01	2.41E-02	1.00E+00	2.23E-01	–1.85E+00	2.27E+00	9.27E-01	9.66E-02	8.98E-01	1.78E-02	9.12E-01	4.38E-02	**1.10E+00**	7.39E-01	8.95E-01	2.00E-02	8.86E-01	7.19E-02
	3	7.56E-01	1.27E-02	9.16E-01	3.11E-01	7.34E-01	8.91E-02	8.43E-01	3.41E-01	7.49E-01	1.09E-02	**1.05E+00**	8.52E-01	9.49E-01	7.16E-01	7.52E-01	1.55E-02	9.10E-01	3.46E-01
	4	8.54E-01	3.89E-03	9.22E-01	1.41E-01	8.37E-01	7.22E-02	8.63E-01	1.46E-01	8.54E-01	3.66E-03	**1.17E+00**	1.39E+00	9.35E-01	1.67E-01	8.56E-01	4.92E-03	1.01E+00	4.34E-01
	5	9.65E-01	1.48E-03	9.52E-01	1.36E-01	9.14E-01	5.25E-02	**1.77E+00**	4.71E+00	9.64E-01	1.46E-03	9.64E-01	1.55E-02	9.19E-01	6.62E-02	9.65E-01	6.29E-03	9.37E-01	4.65E-02
210,088	2	7.87E-01	1.90E-02	6.90E-01	1.66E-01	5.97E-01	6.49E-02	5.82E-01	3.34E-01	**7.95E-01**	1.70E-02	7.87E-01	6.46E-02	6.58E-01	2.54E-01	7.95E-01	1.71E-02	7.39E-01	1.81E-01
	3	**9.03E-01**	4.78E-03	8.85E-01	3.79E-02	8.25E-01	4.01E-02	8.37E-01	2.07E-01	9.03E-01	4.17E-03	8.87E-01	3.96E-02	7.59E-01	2.98E-01	9.02E-01	5.01E-03	5.33E-01	1.23E+00
	4	9.39E-01	2.38E-03	9.29E-01	3.47E-02	8.94E-01	3.07E-02	9.20E-01	4.36E-02	**9.39E-01**	1.60E-03	9.39E-01	1.40E-02	8.38E-01	3.51E-01	9.39E-01	2.10E-03	–2.14E-01	4.78E+00
	5	**9.72E-01**	1.27E-03	9.60E-01	1.53E-02	9.43E-01	2.47E-02	9.49E-01	1.96E-02	9.71E-01	1.84E-03	9.64E-01	8.98E-03	9.53E-01	1.76E-02	9.71E-01	1.31E-03	–1.97E-01	3.85E+00

Table 9 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI
296,059	2	8.92E-01	1.82E-02	8.77E-01	3.60E-02	6.79E-01	1.03E-02	8.72E-01	4.85E-02	9.02E-01	1.77E-02	8.94E-01	2.21E-02	8.31E-01	1.37E-01	8.99E-01	1.90E-02	**9.30E-01**	3.47E-01
	3	9.29E-01	3.92E-03	9.30E-01	1.51E-02	8.60E-01	1.51E-02	9.27E-01	1.81E-02	9.31E-01	3.76E-03	**9.32E-01**	8.68E-03	9.14E-01	3.90E-02	9.31E-01	4.44E-03	8.92E-01	1.45E-01
	4	9.59E-01	1.94E-03	9.53E-01	9.34E-03	9.26E-01	1.03E-02	9.48E-01	1.33E-02	9.59E-01	7.34E-04	9.61E-01	3.65E-03	9.25E-01	8.78E-02	**9.61E-01**	2.13E-03	8.65E-01	3.86E-01
	5	9.73E-01	1.16E-03	9.64E-01	9.31E-03	9.46E-01	1.26E-02	9.61E-01	1.10E-02	9.73E-01	6.22E-04	9.72E-01	4.93E-03	7.01E-01	1.37E+00	**9.74E-01**	8.74E-04	8.31E-01	6.76E-01
302,008	2	8.61E-01	1.45E-02	8.49E-01	2.12E-02	4.07E-01	3.75E-02	8.40E-01	3.66E-02	8.61E-01	1.38E-02	**8.68E-01**	1.65E-02	8.31E-01	5.99E-02	8.66E-01	1.65E-02	8.35E-01	9.51E-02
	3	9.18E-01	5.41E-03	9.07E-01	1.14E-02	7.64E-01	4.37E-02	9.08E-01	1.30E-02	9.14E-01	6.24E-03	**9.22E-01**	6.93E-03	8.94E-01	5.50E-02	9.20E-01	5.89E-03	9.08E-01	3.04E-02
	4	9.44E-01	3.45E-03	9.34E-01	1.04E-02	8.83E-01	1.86E-02	9.28E-01	1.16E-02	9.43E-01	2.81E-03	9.43E-01	5.31E-03	8.94E-01	1.42E-01	**9.45E-01**	3.57E-03	9.31E-01	2.90E-02
	5	9.55E-01	1.09E-03	9.47E-01	6.73E-03	9.22E-01	1.47E-02	9.43E-01	8.64E-03	9.55E-01	9.16E-04	**9.57E-01**	3.17E-03	9.39E-01	2.38E-02	9.56E-01	1.15E-03	9.40E-01	4.81E-02
37,073	2	8.24E-01	3.18E-04	8.15E-01	2.29E-02	8.23E-01	1.21E-02	8.26E-01	4.43E-02	8.24E-01	3.86E-04	8.29E-01	1.28E-02	**8.39E-01**	4.18E-02	8.24E-01	2.86E-04	8.17E-01	1.31E-01
	3	9.50E-01	1.09E-04	9.39E-01	2.32E-02	9.43E-01	1.33E-02	9.35E-01	3.00E-02	**9.50E-01**	7.95E-05	9.49E-01	1.06E-02	8.97E-01	1.73E-01	9.50E-01	1.41E-03	8.69E-01	2.36E-01
	4	9.70E-01	7.17E-05	9.62E-01	1.87E-02	9.60E-01	1.91E-02	9.53E-01	2.54E-02	9.70E-01	2.90E-05	9.70E-01	8.15E-03	9.59E-01	1.63E-02	**9.70E-01**	4.17E-04	9.40E-01	1.45E-01
	5	9.81E-01	3.73E-03	9.73E-01	1.09E-02	9.74E-01	9.31E-03	9.71E-01	1.68E-02	**9.83E-01**	6.51E-04	9.81E-01	5.76E-03	9.37E-01	1.64E-01	9.82E-01	2.65E-03	9.64E-01	4.97E-02
56,028	2	8.30E-01	6.06E-03	8.23E-01	3.29E-02	6.89E-01	5.76E-03	8.31E-01	4.87E-02	8.32E-01	6.83E-03	**8.42E-01**	1.80E-02	8.22E-01	4.09E-02	8.30E-01	6.67E-03	8.23E-01	5.20E-02
	3	9.22E-01	2.39E-03	9.16E-01	8.07E-03	8.86E-01	3.49E-03	9.17E-01	2.10E-02	9.22E-01	1.76E-03	9.23E-01	5.38E-03	**1.43E+00**	2.89E+00	9.21E-01	2.17E-03	9.00E-01	1.06E-01
	4	9.56E-01	1.60E-03	9.50E-01	6.66E-03	9.39E-01	4.31E-03	9.47E-01	1.12E-02	9.57E-01	1.03E-03	9.56E-01	4.26E-03	9.53E-01	1.76E-02	9.57E-01	1.46E-03	**9.58E-01**	2.76E-02
	5	9.71E-01	8.31E-04	9.68E-01	3.99E-03	9.60E-01	4.29E-03	9.65E-01	6.80E-03	9.71E-01	7.72E-04	9.70E-01	3.05E-03	9.59E-01	3.27E-02	**9.72E-01**	5.41E-04	9.64E-01	2.11E-02
66,075	2	6.67E-01	4.20E-03	6.63E-01	2.61E-02	6.46E-01	2.70E-03	6.68E-01	2.35E-02	6.66E-01	3.13E-03	6.67E-01	7.07E-03	**6.74E-01**	1.96E-02	6.68E-01	4.14E-03	6.13E-01	5.77E-01
	3	7.99E-01	1.66E-03	7.85E-01	6.39E-02	7.69E-01	4.70E-02	7.70E-01	7.81E-02	7.99E-01	1.26E-03	7.91E-01	3.71E-02	7.78E-01	8.50E-02	**7.99E-01**	1.86E-03	6.44E-01	8.09E-01
	4	8.66E-01	2.45E-03	8.62E-01	4.97E-02	8.46E-01	3.51E-02	8.62E-01	6.41E-02	**8.67E-01**	1.91E-03	8.66E-01	2.06E-02	8.55E-01	1.31E-01	8.66E-01	3.81E-03	7.86E-01	5.98E-01
	5	9.40E-01	4.26E-03	9.10E-01	4.92E-02	9.11E-01	3.31E-02	9.18E-01	4.24E-02	9.42E-01	3.51E-03	9.43E-01	1.32E-02	9.25E-01	1.97E-01	9.39E-01	3.29E-03	**1.03E+00**	6.29E-01

Bold means the best value provided by each algorithm



(a) Image 101087 with 2 thresholds. (b) Image 101087 with 5 thresholds.

(c) Image 12003 with 2 thresholds. (d) Image 12003 with 5 thresholds.

Fig. 4 Convergence curves using Otsu's between-class variance as an objective function

the man who walks does not appear when segmented with two thresholds.

Figure 11 shows three images of animals (108,070, 160,068, 296,059). In image 108,070 you can see a tiger camouflaged with the shadow of some trees, with thresholding by Kapur using two thresholds. The tiger is imperceptible, but it can be detected more easily with five. Image 160,068 is another spotted feline on a trunk. The details of the spots and the trunk can be observed from three thresholds. Finally, the superimposed elephants presented in image 296,059 can be seen in greater detail from four thresholds. The environment can be better appreciated when you have a threshold level greater than three.

In Figs. 12 and 13, four images are shown with different sizes than the previous ones. The images presented are 66,075, 101,087, 210,088, and 302008. The first of them is an ostrich that does not have great complexity for its segmentation. With two thresholds, it is possible to perceive the bird's position. In image 101,087, which shows a boatman, the details of the environment can be better appreciated by increasing the number of thresholds. The fish shown in image 210,088 with five thresholds can be easily detected; having smaller thresholds decreases the amount of detail. Finally, the person wearing dark clothing loses detail when thresholded in three regions; with a level of five thresholds, the details of the shirt and face can be perceived. In some real cases, it is necessary to extract small regions from the images that are segmented to be analyzed; therefore, a higher level of detail is necessary and, using segmentation by thresholding, it is possible to define the number of necessary regions, this gives flexibility in image processing.

4.5 Analysis on the entire BSDS300 dataset using Otsu and Kapur as objective functions

This section shows a general analysis of the behavior of the algorithms over the 300 images of the BSDS300 dataset using Otsu and Kapur as objective functions. First, the results using Otsu's between-class variance will be discussed, and an analysis will be carried out by thresholding level in which it is observed how the DMEDA has better results over the objective function at all thresholding levels. Table 18 shows the general results for two thresholds. In this case, it can be seen that DMEDA is better for

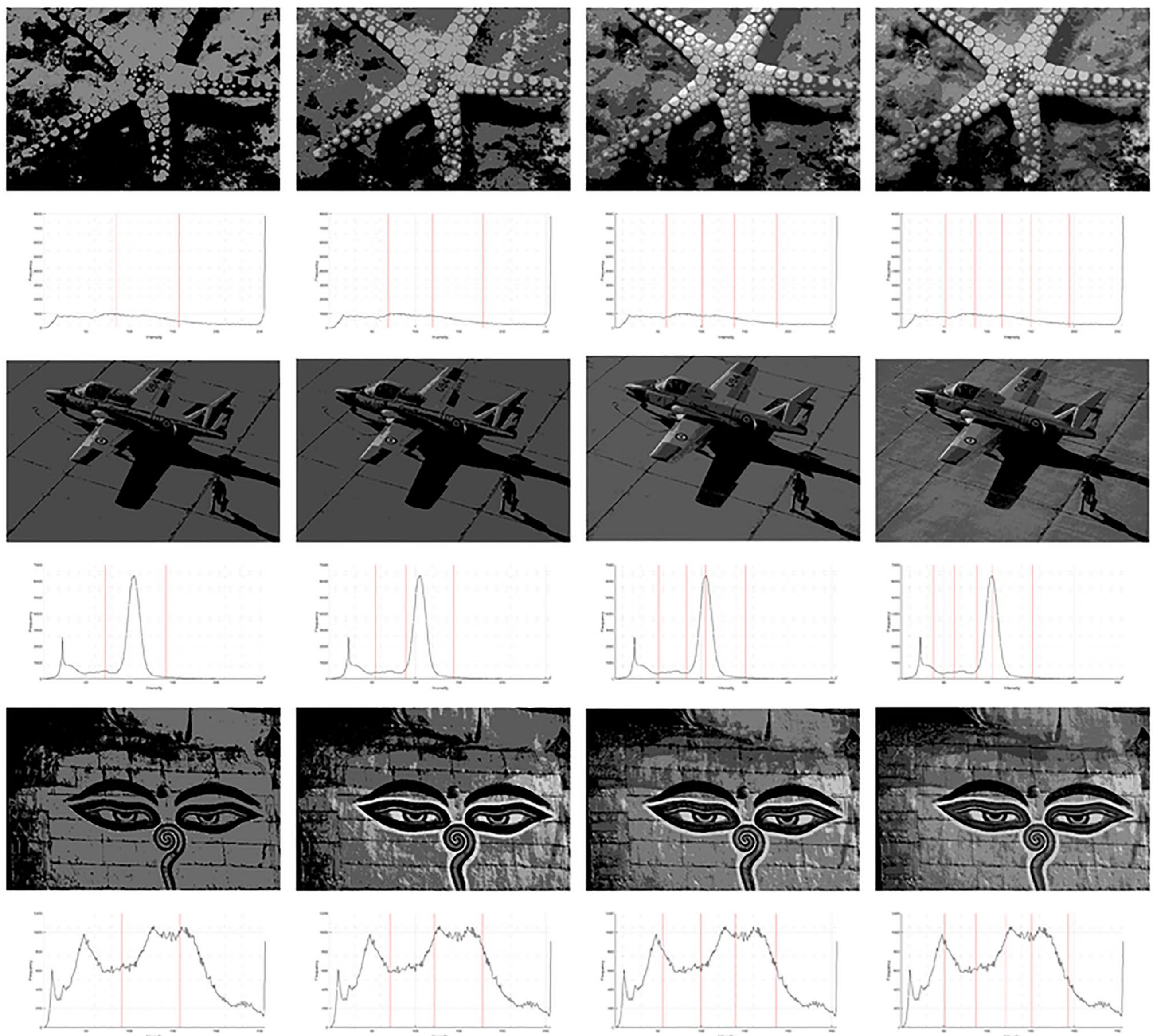


Fig. 5 Images and the different thresholds obtained using the Otsu's between-class variance

Otsu, but the JF and SCA algorithms perform better in the metrics.

Tables 19, 20, and 21 show that the DMEDA is better in the objective function and the SSIM metric as the number of thresholds increases. For the three and five thresholds, the OOA generates better general results in the metrics; in the four thresholds, the JF is the winner. The performance of the JF for two and four thresholds, in terms of the objective function, is similar to the performance of the DMEDA. The distance of DMEDA on the metrics concerning the algorithms with the best results is small. Notably, when comparing DMEDA with EDA, a considerable difference is observed between the two algorithms when the number of thresholds increases. Therefore, it can be said that the mutation operator positively impacts increasing dimensionality.

To review the behavior of the data on the different indicators that have already been discussed, the use of the boxplot graph is proposed in Fig. 14. As an example, the boxplots are generated with the result obtained using 2 thresholds. With this type of graph, it is possible to compare a set of algorithms visually, and together with the tables, you can reach a better conclusion about what is observed. In the different metrics, the values must be high, indicating that the algorithm obtained good results. As mentioned, the algorithms that obtain good results in the previous Tables appear to be at the same level graphically

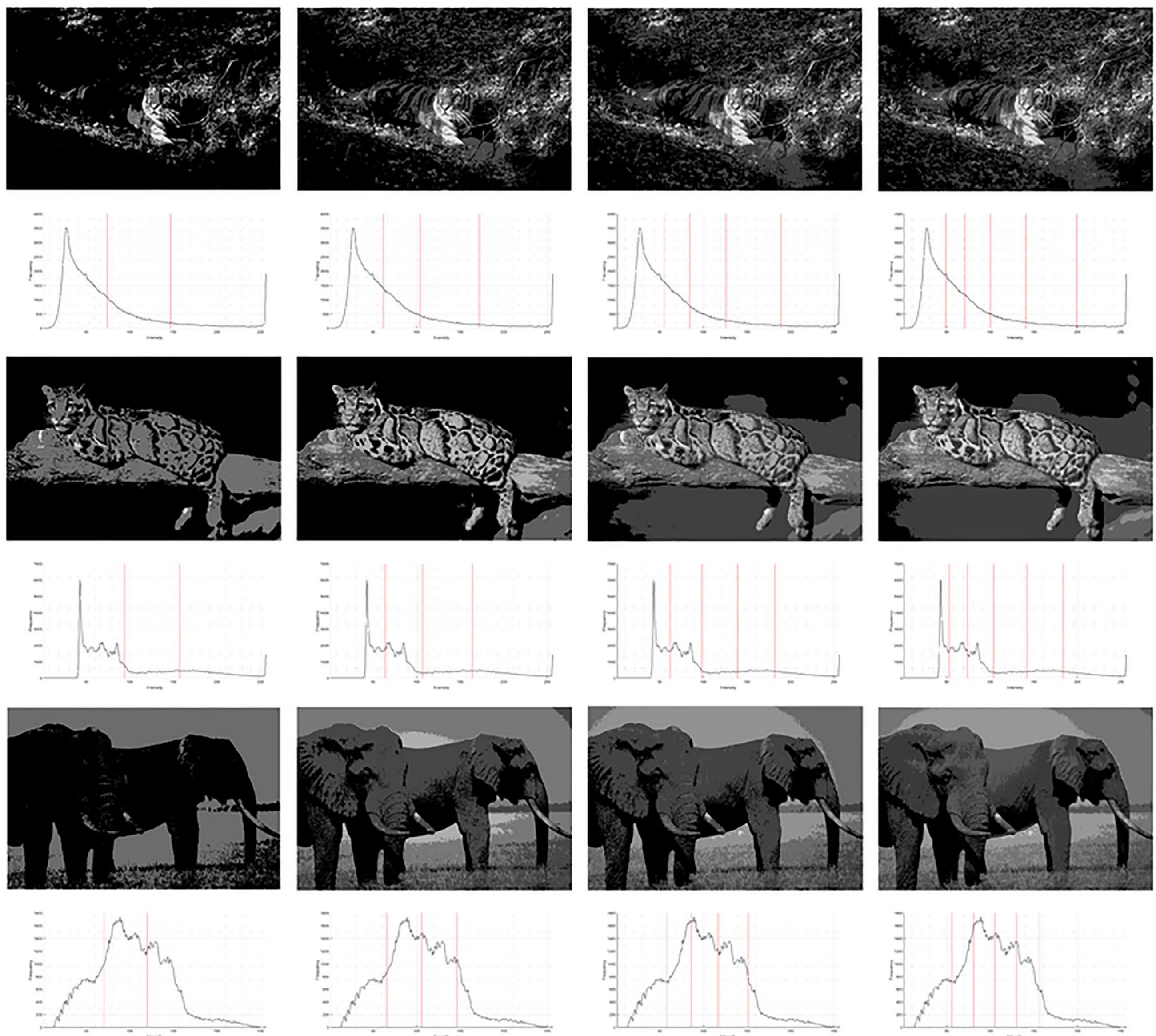


Fig. 6 Images and the different thresholds obtained using the Otsu's between-class variance

on the objective function and the seven metrics described in Subsection 4.2. In some algorithms, such as CS, the difference with the others is evident due to their low performance.

On the other hand, an analysis similar to the previous one is done, but now with the Kapur objective function. In this case, DMEDA improves its results by increasing the number of thresholds, but unlike Otsu, it is done globally. The Table 22 shows that DMEDA is outperformed by OOA over two thresholds on a set of meaningful metrics. However, the Tables show how DMEDA is significantly superior to the other algorithms, optimizing with better results in Kapur and obtaining better metrics than with Otsu. Therefore, the optimization with Kapur and DMEDA provides better solutions on the metrics than using Otsu and DMEDA, although the objective function in both cases was optimized with better results with the algorithm in question (Tables 23, 24, 25).

A graphical analysis was also carried out on the results obtained with Kapur. In this case, a slight visual difference can be noticed between DMEDA and the other algorithms. The worst algorithm is now the SCA. Using the previous tables and this boxplot, you can see the superiority of DMEDA compared to the other algorithms. As with Otsu, an example of the boxplots is placed using two thresholds (Fig. 15).

DMEDA optimizes the two objective functions with better results than the other algorithms, and by increasing the number of thresholds, it increases its superiority in both

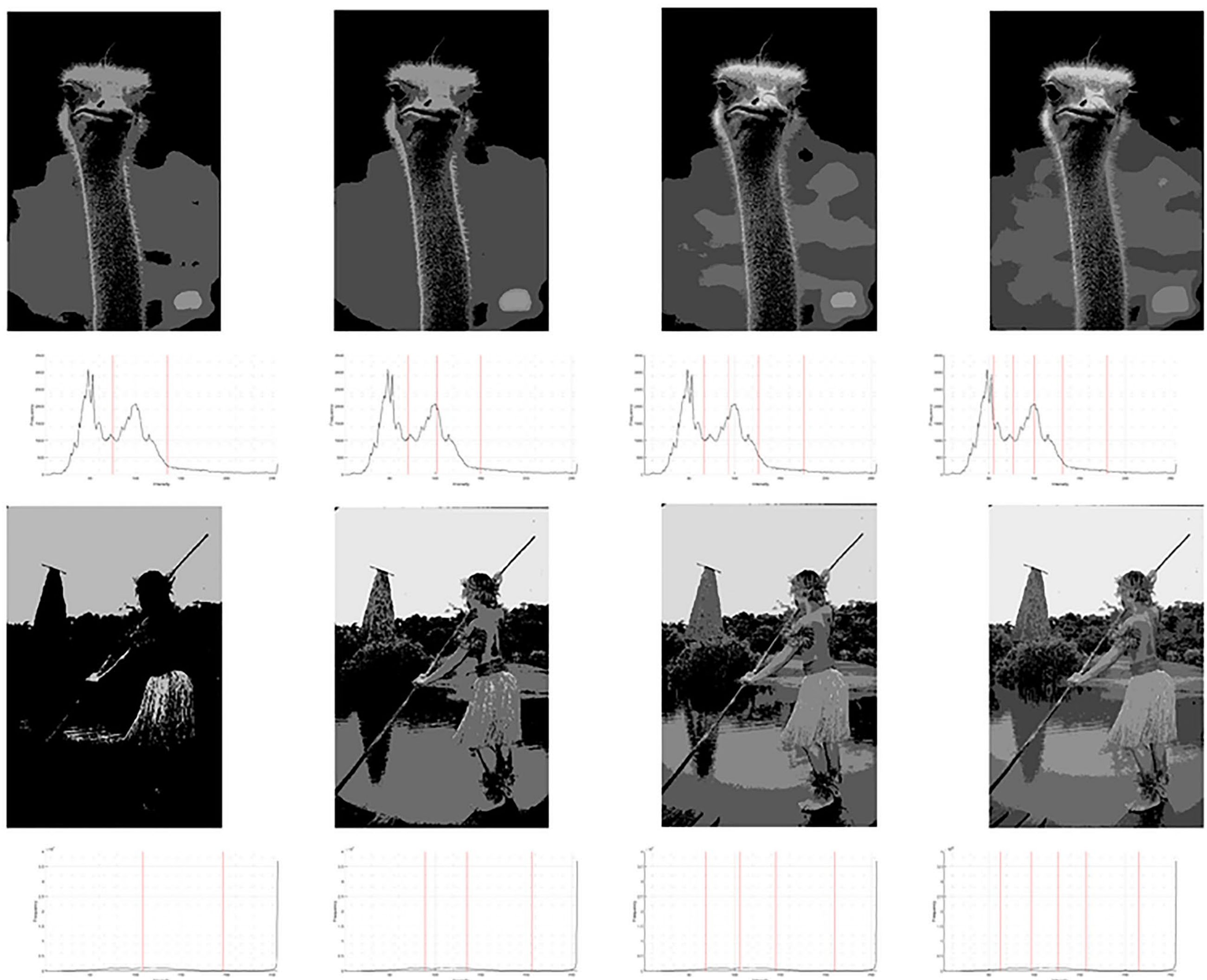


Fig. 7 Images and the different thresholds obtained using the Otsu's between-class variance

cases. Using Kapur achieves better overall performance than using Otsu. Therefore, this algorithm performs better using Kapur.

4.6 Statistical analysis using paired Wilcoxon test

To use a parametric test, it is necessary to comply with normality, homogeneity, and independence assumptions. When any of these assumptions are not met, it is necessary to use a non-parametric test such as Wilcoxon to pair data [88]. In this case, the Wilcoxon test is used because some of the residuals or populations do not meet the normality assumption when using some parametric tests. A comparison of each algorithm was performed on each image and each thresholding level. The test was performed by comparing the data obtained in thirty replicates of each algorithm for each threshold.

The Table 26 shows a summary of all the possible combinations of the algorithms and the p-values and the h-values. The p-value shows the area under the curve of the statistic used in the Wilcoxon test, and it is known that if the p-value is less than 0.05, the null hypothesis of the test is not accepted. The null hypothesis that is posed is that the distributions of the two algorithms that are compared at the time are equal. Therefore, if the p-value is less than 0.05, it is said that the data distributions obtained by the two compared algorithms are significantly different. The h-value is a

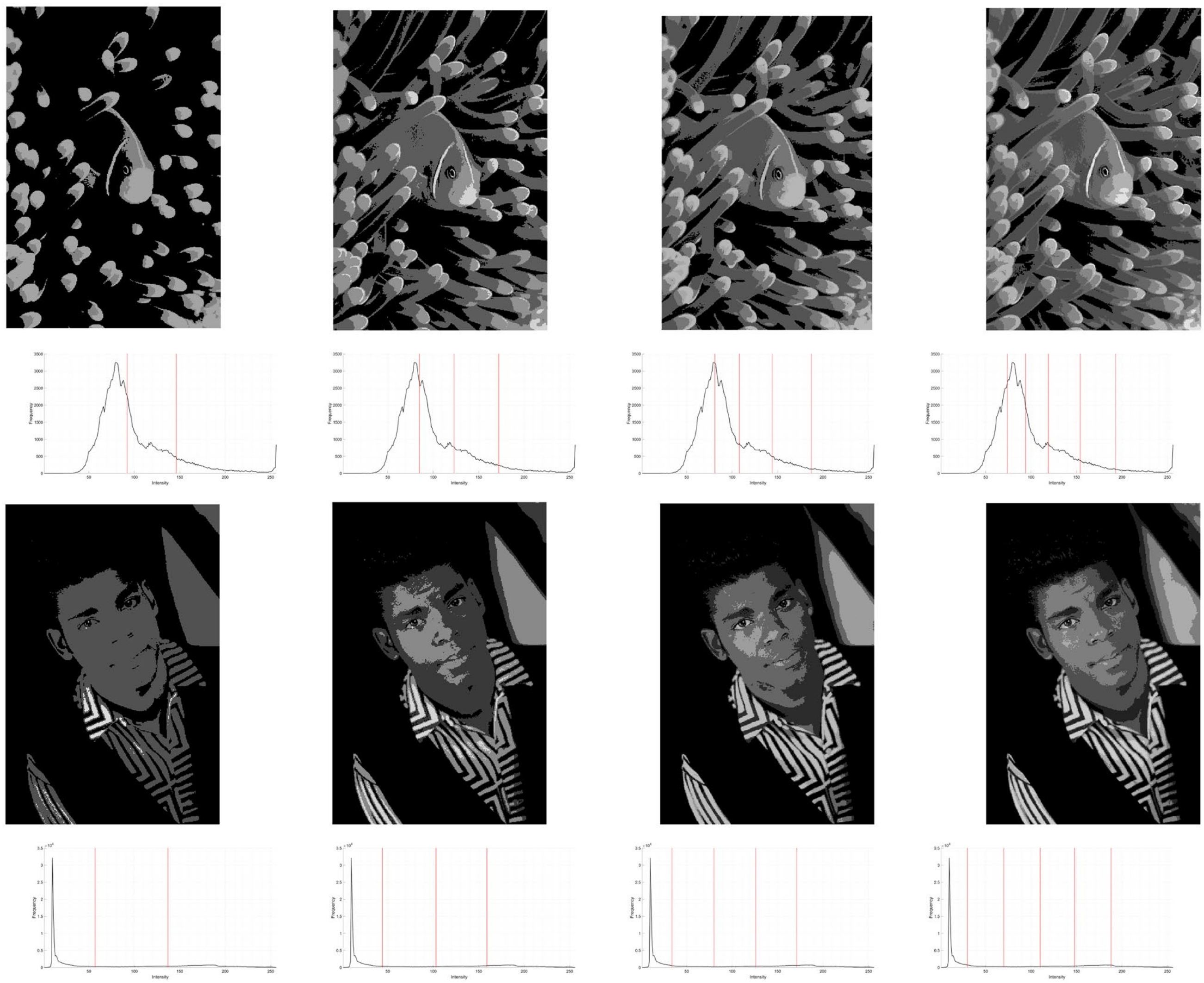


Fig. 8 Images and the different thresholds obtained using the Otsu's between-class variance

dummy variable that returns T if there is a significant difference between the algorithms and F if there is not.

The comparison of the DMEDA in Otsu with most of the algorithms shows significant differences, except with two. The first of these is CS, with which there is no significant difference in three cases, which coincide at a threshold level of 5. The second is the OOA, with which there are no significant differences in 72.5% of the cases. Using the information obtained by the Wilcoxon test and the information in Table 2, it can be said that the DMEDA has better overall results on fitness function.

To complement what was observed in the Otsu objective function, the same analysis is done on Kapur (Table 27). For Kapur, all the results obtained with the different algorithms have a significant difference. Taking Table 10 that shows the algorithm's results on the objective function and this statistical analysis, we also conclude that DMEDA is superior to the other algorithms in the majority of this set of ten images of this dataset.

Table 10 Comparisons of the objective function using Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur
101,087	2	1.29E+01	5.27E-04	1.28E+01	5.00E-02	1.28E+01	4.50E-02	1.28E+01	8.17E-02	1.28E+01	8.26E-02	5.66E+00	4.63E+00	1.28E+01	7.92E-02	**1.29E+01**	7.73E-05	1.27E+01	8.72E-02
	3	**1.80E+01**	1.10E-03	1.78E+01	8.32E-02	1.79E+01	7.38E-02	1.78E+01	1.37E-01	1.78E+01	1.32E-01	8.32E+00	5.73E+00	1.78E+01	1.03E-01	1.80E+01	4.13E-02	1.77E+01	1.55E-01
	4	**2.28E+01**	4.13E-03	2.25E+01	1.36E-01	2.26E+01	1.10E-01	2.23E+01	2.45E-01	2.23E+01	2.65E-01	1.27E+01	5.65E+00	2.23E+01	2.42E-01	2.28E+01	1.84E-02	2.21E+01	2.93E-01
	5	**2.73E+01**	6.03E-03	2.66E+01	2.79E-01	2.69E+01	2.02E-01	2.64E+01	2.82E-01	2.63E+01	3.86E-01	1.27E+01	8.62E+00	2.65E+01	2.78E-01	2.72E+01	2.77E-02	2.62E+01	4.98E-01
108,070	2	**1.33E+01**	7.36E-04	1.32E+01	8.81E-02	1.33E+01	1.55E-03	1.31E+01	1.03E-01	1.31E+01	1.14E-01	6.70E+00	3.07E+00	1.31E+01	1.11E-01	1.33E+01	1.12E-02	1.30E+01	1.97E-01
	3	**1.84E+01**	3.66E-03	1.82E+01	1.45E-01	1.84E+01	5.70E-02	1.81E+01	1.60E-01	1.80E+01	2.87E-01	7.57E+00	4.41E+00	1.81E+01	1.95E-01	1.84E+01	2.12E-02	1.79E+01	3.19E-01
	4	**2.30E+01**	6.44E-03	2.26E+01	2.18E-01	2.29E+01	1.00E-01	2.23E+01	3.48E-01	2.23E+01	3.39E-01	9.87E+00	5.90E+00	2.24E+01	2.89E-01	2.30E+01	2.48E-02	2.23E+01	4.11E-01
	5	**2.72E+01**	1.10E-02	2.66E+01	2.29E-01	2.70E+01	1.16E-01	2.62E+01	4.20E-01	2.61E+01	3.71E-01	1.40E+01	7.09E+00	2.64E+01	3.02E-01	2.72E+01	2.03E-02	2.59E+01	6.47E-01
12,003	2	**1.35E+01**	9.41E-15	1.35E+01	5.78E-02	1.35E+01	1.71E-03	1.34E+01	7.92E-02	1.34E+01	9.51E-02	6.10E+00	3.91E+00	1.34E+01	1.07E-01	1.35E+01	3.93E-03	1.34E+01	2.15E-01
	3	**1.87E+01**	2.97E-14	1.85E+01	9.67E-02	1.87E+01	3.40E-02	1.83E+01	2.34E-01	1.84E+01	2.31E-01	6.18E+00	5.80E+00	1.84E+01	1.72E-01	1.87E+01	9.71E-03	1.83E+01	2.91E-01
	4	**2.33E+01**	4.17E-14	2.29E+01	2.18E-01	2.31E+01	1.41E-01	2.27E+01	3.06E-01	2.27E+01	3.30E-01	1.07E+01	6.31E+00	2.28E+01	3.03E-01	2.33E+01	1.65E-02	2.25E+01	3.86E-01
	5	**2.75E+01**	1.15E-02	2.70E+01	2.92E-01	2.73E+01	1.48E-01	2.66E+01	4.62E-01	2.66E+01	3.92E-01	1.39E+01	7.58E+00	2.67E+01	2.69E-01	2.75E+01	1.01E-02	2.66E+01	4.16E-01
160,068	2	**1.29E+01**	2.17E-14	1.29E+01	1.93E-02	1.29E+01	4.33E-04	1.29E+01	9.13E-02	1.29E+01	6.12E-02	4.66E+00	3.56E+00	1.29E+01	4.64E-02	1.29E+01	8.83E-04	1.29E+01	6.26E-02
	3	**1.82E+01**	6.86E-14	1.80E+01	1.20E-01	1.82E+01	2.95E-02	1.78E+01	2.33E-01	1.79E+01	1.74E-01	9.31E+00	4.69E+00	1.79E+01	1.83E-01	1.82E+01	1.81E-02	1.77E+01	1.98E-01
	4	**2.31E+01**	1.88E-01	2.24E+01	2.31E-01	2.28E+01	1.57E-01	2.23E+01	3.36E-01	2.23E+01	3.28E-01	1.01E+01	6.08E+00	2.23E+01	3.14E-01	2.28E+01	1.28E-01	2.21E+01	4.39E-01
	5	**2.78E+01**	1.61E-01	2.67E+01	4.79E-01	2.71E+01	3.00E-01	2.63E+01	4.35E-01	2.63E+01	5.46E-01	1.25E+01	7.22E+00	2.64E+01	4.03E-01	2.74E+01	2.89E-01	2.63E+01	5.33E-01
210,088	2	**1.29E+01**	1.34E-04	1.28E+01	5.47E-02	1.29E+01	5.38E-03	1.28E+01	1.33E-01	1.28E+01	8.37E-02	4.98E+00	3.74E+00	1.28E+01	6.61E-02	1.29E+01	1.71E-03	1.27E+01	1.66E-01
	3	**1.79E+01**	7.44E-02	1.77E+01	1.31E-01	1.79E+01	7.23E-02	1.75E+01	2.48E-01	1.75E+01	2.38E-01	6.69E+00	4.97E+00	1.76E+01	1.60E-01	1.79E+01	5.21E-02	1.75E+01	3.11E-01
	4	**2.30E+01**	1.35E-01	2.22E+01	3.38E-01	2.25E+01	2.27E-01	2.20E+01	3.82E-01	2.18E+01	3.08E-01	1.04E+01	6.10E+00	2.19E+01	3.61E-01	2.27E+01	2.83E-01	2.17E+01	5.38E-01
	5	**2.73E+01**	9.89E-02	2.62E+01	4.14E-01	2.67E+01	2.44E-01	2.60E+01	5.40E-01	2.58E+01	5.20E-01	1.32E+01	7.27E+00	2.59E+01	5.40E-01	2.70E+01	3.81E-01	2.58E+01	6.55E-01

Table 10 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur	Mean Kapur	sd Kapur
296,059	2	**1.26E+01**	3.61E-15	1.26E+01	9.07E-03	1.26E+01	1.33E-03	1.26E+01	4.60E-02	1.26E+01	2.61E-02	5.85E+00	3.93E+00	1.26E+01	3.82E-02	1.26E+01	2.18E-03	1.25E+01	1.20E-01
	3	1.73E+01	6.58E-02	1.71E+01	7.79E-02	1.72E+01	5.97E-02	1.71E+01	1.10E-01	1.70E+01	1.25E-01	5.56E+00	4.81E+00	1.71E+01	8.31E-02	**1.73E+01**	1.15E-02	1.70E+01	1.26E-01
	4	**2.17E+01**	4.58E-04	2.13E+01	1.30E-01	2.16E+01	7.93E-02	2.12E+01	2.09E-01	2.13E+01	2.02E-01	9.64E+00	6.58E+00	2.13E+01	1.75E-01	2.17E+01	1.47E-02	2.11E+01	1.96E-01
	5	**2.59E+01**	1.02E-01	2.52E+01	1.99E-01	2.55E+01	1.40E-01	2.51E+01	3.02E-01	2.50E+01	3.35E-01	1.04E+01	7.34E+00	2.50E+01	2.57E-01	2.58E+01	8.77E-02	2.49E+01	3.35E-01
302,008	2	**1.15E+01**	0.00E+00	1.15E+01	1.96E-02	1.15E+01	1.69E-03	1.14E+01	4.07E-02	1.14E+01	7.11E-02	5.14E+00	3.63E+00	1.15E+01	4.99E-02	1.15E+01	4.66E-04	1.14E+01	9.75E-02
	3	1.64E+01	1.86E-03	1.64E+01	3.79E-02	1.64E+01	5.36E-03	1.63E+01	1.04E-01	1.63E+01	9.00E-02	7.09E+00	4.95E+00	1.63E+01	8.91E-02	**1.64E+01**	7.51E-04	1.63E+01	1.53E-01
	4	**2.13E+01**	4.87E-14	2.10E+01	1.19E-01	2.12E+01	7.01E-02	2.09E+01	2.01E-01	2.09E+01	1.69E-01	1.04E+01	6.09E+00	2.10E+01	1.56E-01	2.12E+01	3.34E-02	2.09E+01	2.63E-01
	5	**2.57E+01**	1.97E-05	2.52E+01	2.50E-01	2.55E+01	1.03E-01	2.50E+01	3.88E-01	2.50E+01	3.49E-01	1.22E+01	7.29E+00	2.51E+01	2.56E-01	2.57E+01	7.49E-02	2.48E+01	4.11E-01
37,073	2	**1.24E+01**	2.96E-13	1.23E+01	1.21E-01	1.24E+01	1.60E-02	1.21E+01	3.21E-01	1.21E+01	2.38E-01	5.98E+00	3.52E+00	1.22E+01	1.48E-01	1.24E+01	1.26E-02	1.21E+01	2.42E-01
	3	**1.74E+01**	3.75E-13	1.71E+01	1.34E-01	1.73E+01	5.25E-02	1.69E+01	2.66E-01	1.69E+01	2.83E-01	8.45E+00	4.55E+00	1.70E+01	1.65E-01	1.73E+01	3.49E-02	1.69E+01	2.30E-01
	4	**2.22E+01**	9.94E-04	2.16E+01	3.21E-01	2.20E+01	2.43E-01	2.13E+01	3.76E-01	2.14E+01	3.98E-01	1.08E+01	6.29E+00	2.15E+01	3.80E-01	2.22E+01	5.84E-02	2.11E+01	5.17E-01
	5	2.64E+01	3.31E-02	2.56E+01	3.57E-01	2.59E+01	2.16E-01	2.52E+01	4.66E-01	2.53E+01	4.65E-01	1.25E+01	5.46E+00	2.53E+01	4.49E-01	**2.64E+01**	3.32E-02	2.50E+01	6.55E-01
56,028	2	1.35E+01	4.11E-02	1.34E+01	5.87E-02	1.35E+01	1.03E-02	1.33E+01	8.85E-02	1.33E+01	8.28E-02	5.21E+00	3.88E+00	1.33E+01	8.84E-02	**1.35E+01**	1.74E-14	1.33E+01	9.11E-02
	3	**1.89E+01**	5.56E-14	1.87E+01	1.24E-01	1.88E+01	5.50E-02	1.84E+01	2.31E-01	1.84E+01	2.59E-01	8.30E+00	5.75E+00	1.86E+01	1.84E-01	1.89E+01	3.18E-02	1.82E+01	3.74E-01
	4	**2.35E+01**	6.90E-14	2.31E+01	2.48E-01	2.34E+01	8.71E-02	2.28E+01	3.92E-01	2.28E+01	2.78E-01	1.02E+01	7.12E+00	2.29E+01	2.28E-01	2.34E+01	8.06E-02	2.27E+01	4.92E-01
	5	**2.77E+01**	1.52E-02	2.72E+01	2.02E-01	2.75E+01	1.47E-01	2.69E+01	4.61E-01	2.69E+01	3.75E-01	1.31E+01	7.83E+00	2.70E+01	2.81E-01	2.77E+01	3.73E-02	2.69E+01	3.97E-01
66,075	2	**1.31E+01**	2.08E-14	1.30E+01	4.75E-02	1.31E+01	7.23E-03	1.30E+01	1.33E-01	1.29E+01	1.38E-01	6.20E+00	4.09E+00	1.30E+01	8.23E-02	1.31E+01	8.22E-03	1.28E+01	2.72E-01
	3	1.82E+01	6.20E-02	1.78E+01	1.99E-01	1.81E+01	8.49E-02	1.76E+01	2.56E-01	1.76E+01	3.19E-01	8.92E+00	4.85E+00	1.77E+01	2.37E-01	**1.82E+01**	1.25E-02	1.76E+01	2.71E-01
	4	**2.26E+01**	2.88E-13	2.21E+01	1.81E-01	2.24E+01	1.02E-01	2.19E+01	2.51E-01	2.20E+01	3.14E-01	9.47E+00	7.02E+00	2.20E+01	2.72E-01	2.25E+01	5.65E-02	2.19E+01	3.30E-01
	5	**2.68E+01**	8.61E-03	2.61E+01	2.30E-01	2.64E+01	1.92E-01	2.58E+01	3.41E-01	2.59E+01	3.36E-01	9.98E+00	7.55E+00	2.60E+01	2.90E-01	2.67E+01	2.95E-02	2.57E+01	4.22E-01

Bold means the best value provided by each algorithm

Table 11 Thresholds obtained using Kapur's entropy

Image	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
101,087	149 252	153 254	105 168	99 248	118 251	82 130	129 250	149 252	22 70
	69 154 252	83 181 248	42 107 167	107 178 248	44 151 250	40 125 194	86 91 194	69 158 252	5 12 38
	55 126 190 247	79 127 175 245	51 117 156 198	51 91 154 245	80 113 183 242	72 79 105 130	32 108 196 248	58 125 186 248	46 47 129 239
	46 99 149 196 246	42 75 151 195 238	33 65 113 150 212	53 127 158 192 220	31 76 143 184 237	85 85 148 158 200	48 92 120 192 242	47 103 151 196 246	107 134 155 200 227
108,070	132 256	130 240	113 178	150 250	105 253	14 112	146 158	132 256	47 210
	103 172 256	96 152 233	72 126 190	105 172 245	119 191 235	44 143 174	86 143 236	103 172 256	72 87 245
	87 138 198 256	112 142 179 238	90 128 190 222	78 119 141 219	78 120 151 224	53 56 146 221	88 144 176 251	94 144 201 256	61 116 246 253
	74 115 160 205 256	17 84 132 182 234	86 119 152 185 209	64 102 132 186 240	44 67 132 192 252	62 90 227 243 245	17 95 163 187 246	73 115 160 205 256	78 118 220 239 239
12,003	155 256	167 250	103 176	144 236	153 229	31 56	111 248	155 255	158 178
	91 170 256	68 160 250	71 134 199	64 162 242	76 160 245	58 130 144	81 140 249	91 170 254	117 154 251
	75 130 183 256	54 118 213 251	59 105 152 196	47 106 177 231	47 94 186 240	126 233 242 255	115 148 201 247	75 135 189 251	27 28 53 58
	68 116 164 206 252	75 107 161 205 242	68 106 139 170 203	41 92 156 211 250	72 127 145 191 249	12 25 33 73 111	63 119 145 188 243	69 116 162 203 252	12 60 60 104 131
160,068	120 256	122 251	95 168	163 245	110 251	28 36	128 239	120 256	98 117
	93 176 255	112 205 248	29 99 149	99 183 248	29 108 234	51 130 237	72 176 250	99 185 252	114 213 229
	32 93 176 256	93 127 188 238	79 118 149 207	71 111 205 247	67 96 169 251	38 49 163 194	32 125 207 254	91 146 198 254	24 78 107 241
	90 131 171 210 254	97 134 152 189 248	26 99 145 173 197	30 132 156 177 251	104 148 175 206 227	10 15 71 74 109	88 126 143 185 232	32 97 134 179 242	31 39 52 54 79
210,088	130 255	121 252	34 121	141 255	120 249	73 205	122 249	130 256	83 147
	118 190 255	130 185 248	32 130 176	118 158 244	120 187 225	6 21 43	124 172 244	35 134 252	6 137 210
	35 118 190 256	33 134 212 255	33 133 189 210	34 90 196 237	92 130 174 235	47 67 96 117	29 95 141 241	35 124 191 254	2 45 200 255
	35 112 158 205 255	27 119 177 199 224	24 92 119 163 207	34 128 197 211 255	109 162 186 219 232	16 44 49 172 228	28 107 128 165 242	83 121 166 212 256	12 19 29 183 239
296,059	106 256	100 244	110 180	105 228	109 255	16 100	107 216	106 223	174 219
	103 182 256	103 181 243	67 136 181	93 151 253	84 148 232	60 86 103	89 166 181	103 182 236	185 216 243
	83 133 182 255	110 147 188 219	60 114 154 194	99 133 206 245	107 145 186 238	40 63 113 143	59 127 183 238	88 136 182 226	138 138 156 159
	64 101 141 182 255	20 102 145 212 231	20 84 114 138 179	55 107 131 191 238	67 99 155 183 242	74 83 94 115 131	56 99 174 209 251	64 100 140 182 227	21 21 40 47 143
302,008	132 256	125 241	77 155	148 241	138 244	35 50	141 252	132 256	58 104
	67 151 256	65 164 240	50 125 185	49 129 223	114 175 253	30 38 41	94 164 239	101 183 256	14 200 252
	43 112 183 256	33 94 152 239	59 105 144 193	68 110 183 234	59 99 200 246	11 20 40 62	44 111 181 223	57 118 183 242	8 113 183 219
	32 83 134 185 255	67 110 182 220 248	33 69 121 180 219	33 83 106 160 203	32 55 126 155 240	36 82 106 118 222	19 52 116 196 238	44 91 142 184 240	43 66 109 129 149
37,073	142 256	134 243	78 153	139 243	137 234	55 172	126 242	142 255	87 243
	86 142 255	132 194 243	84 156 195	73 155 249	86 130 228	29 50 105	92 158 245	88 155 252	157 211 212
	86 131 181 251	87 121 171 249	59 90 129 187	63 119 158 253	37 91 128 250	92 133 152 201	88 125 147 254	86 131 181 251	22 35 209 230
	85 124 160 205 250	43 89 175 214 246	50 79 137 167 201	53 93 137 186 226	73 136 167 176 252	40 59 101 131 211	43 84 146 177 244	78 131 169 208 249	80 92 137 174 186
56,028	174 256	188 254	97 172	99 237	173 245	18 111	177 244	174 256	190 203
	95 180 256	118 189 250	49 110 176	106 180 246	95 185 240	42 65 95	61 181 252	95 180 255	24 39 136
	63 120 183 254	84 128 162 224	55 114 159 199	73 109 155 247	64 109 177 230	66 71 105 240	34 75 168 246	93 164 210 254	38 141 203 236
	58 107 156 200 255	88 134 173 202 240	42 97 130 163 194	53 104 161 197 245	28 114 159 186 252	15 57 84 129 173	63 147 168 199 235	62 113 167 208 256	27 37 91 102 135
66,075	126 256	156 251	115 177	138 233	136 250	151 159	168 251	127 249	152 173
	120 180 256	115 151 233	65 135 201	107 179 249	125 188 227	24 89 105	115 199 246	120 180 255	11 158 198
	76 125 184 256	41 120 198 246	29 70 134 161	114 179 218 248	73 128 179 246	20 38 66 183	75 126 153 233	76 125 184 250	66 153 181 204
	74 120 161 202 255	29 96 148 190 255	29 75 138 166 193	90 132 195 221 250	25 117 163 209 255	29 83 122 156 172	70 118 176 211 246	81 120 164 206 248	54 86 119 148 183

Bold means the best value provided by each algorithm

Table 12 PSNR comparisons using the Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR	Mean PSNR	sd PSNR
101,087	2	1.00E+01	2.47E-02	1.09E+01	1.52E+00	8.44E+00	1.59E-01	1.13E+01	1.85E+00	**1.16E+01**	1.51E+00	4.61E+00	1.66E+00	1.14E+01	1.61E+00	1.00E+01	1.04E-02	1.03E+01	1.76E+00
	3	**1.60E+01**	1.79E-01	1.51E+01	1.31E+00	1.16E+01	3.97E-01	1.52E+01	1.18E+00	1.51E+01	1.09E+00	5.64E+00	2.72E+00	1.49E+01	1.62E+00	1.59E+01	4.47E-01	1.18E+01	3.48E+00
	4	1.80E+01	2.08E-01	1.76E+01	1.18E+00	1.42E+01	9.18E-01	1.73E+01	1.79E+00	1.71E+01	1.24E+00	6.35E+00	2.59E+00	1.70E+01	2.34E+00	**1.80E+01**	3.08E-01	1.30E+01	3.80E+00
	5	2.02E+01	5.97E-02	1.91E+01	1.39E+00	1.60E+01	9.03E-01	1.87E+01	1.37E+00	1.90E+01	1.59E+00	6.42E+00	3.59E+00	1.81E+01	2.52E+00	**2.02E+01**	1.70E-01	1.44E+01	2.50E+00
108,070	2	1.16E+01	1.60E-02	1.17E+01	2.94E-01	1.16E+01	3.69E-02	1.18E+01	3.47E-01	1.17E+01	4.76E-01	1.14E+01	1.98E+00	1.21E+01	8.93E-01	1.16E+01	6.43E-02	**1.25E+01**	1.94E+00
	3	1.29E+01	8.19E-02	1.31E+01	7.12E-01	1.28E+01	3.70E-01	1.33E+01	1.02E+00	1.32E+01	1.00E+00	1.19E+01	2.46E+00	1.33E+01	8.80E-01	1.28E+01	1.27E-01	**1.43E+01**	1.79E+00
	4	1.42E+01	1.40E-01	1.46E+01	1.51E+00	1.42E+01	7.57E-01	1.42E+01	1.41E+00	1.53E+01	1.74E+00	1.23E+01	2.71E+00	1.48E+01	1.73E+00	1.38E+01	1.93E-01	**1.59E+01**	2.02E+00
	5	1.56E+01	2.26E-01	1.57E+01	1.44E+00	1.59E+01	1.44E+00	1.58E+01	2.08E+00	1.59E+01	2.16E+00	1.35E+01	3.31E+00	1.53E+01	1.65E+00	1.48E+01	3.60E-01	**1.65E+01**	2.51E+00
12,003	2	9.07E+00	1.81E-15	9.51E+00	9.20E-01	8.98E+00	1.12E-01	9.80E+00	1.08E+00	9.59E+00	1.09E+00	7.98E+00	1.99E+00	9.80E+00	1.33E+00	9.06E+00	9.03E-02	**1.11E+01**	2.26E+00
	3	**1.43E+01**	5.42E-15	1.40E+01	8.47E-01	1.41E+01	6.11E-01	1.38E+01	1.21E+00	1.38E+01	1.13E+00	8.32E+00	2.80E+00	1.35E+01	1.46E+00	1.42E+01	2.56E-01	1.28E+01	2.58E+00
	4	**1.70E+01**	3.61E-15	1.59E+01	1.19E+00	1.62E+01	8.30E-01	1.63E+01	1.05E+00	1.59E+01	1.40E+00	9.67E+00	3.31E+00	1.63E+01	1.03E+00	1.68E+01	2.39E-01	1.32E+01	2.68E+00
	5	**1.84E+01**	1.74E-01	1.77E+01	1.08E+00	1.79E+01	8.13E-01	1.73E+01	1.54E+00	1.74E+01	1.33E+00	1.12E+01	3.56E+00	1.70E+01	1.55E+00	1.82E+01	9.76E-02	1.58E+01	2.63E+00
160,068	2	1.19E+01	5.42E-15	1.16E+01	4.54E-01	1.19E+01	1.09E-01	1.15E+01	7.53E-01	1.16E+01	6.61E-01	9.48E+00	1.55E+00	1.17E+01	5.02E-01	1.17E+01	2.14E-01	**1.23E+01**	1.69E+00
	3	1.30E+01	5.42E-15	1.30E+01	7.44E-01	1.30E+01	1.23E-01	1.28E+01	6.93E-01	**1.36E+01**	1.15E+00	1.14E+01	3.03E+00	1.31E+01	9.77E-01	1.29E+01	8.39E-02	1.34E+01	2.48E+00
	4	1.59E+01	1.53E+00	1.55E+01	1.66E+00	**1.61E+01**	1.27E+00	1.54E+01	1.71E+00	1.53E+01	1.25E+00	1.07E+01	2.68E+00	1.47E+01	1.87E+00	1.45E+01	1.53E+00	1.48E+01	2.34E+00
	5	**1.81E+01**	8.00E-01	1.69E+01	1.95E+00	1.74E+01	1.43E+00	1.72E+01	1.33E+00	1.65E+01	2.38E+00	1.17E+01	3.57E+00	1.67E+01	1.92E+00	1.75E+01	1.74E+00	1.66E+01	2.22E+00
210,088	2	9.83E+00	3.56E-05	9.83E+00	2.90E-01	9.84E+00	5.20E-02	9.71E+00	5.20E-01	9.73E+00	3.60E-01	8.63E+00	2.44E+00	9.92E+00	5.46E-01	9.82E+00	1.52E-02	**1.19E+01**	2.33E+00
	3	1.19E+01	1.51E+00	1.15E+01	1.39E+00	1.18E+01	1.46E+00	1.17E+01	1.54E+00	1.14E+01	1.49E+00	8.55E+00	1.81E+00	1.09E+01	1.21E+00	1.12E+01	1.30E+00	**1.30E+01**	2.67E+00
	4	1.42E+01	6.39E-01	1.41E+01	2.03E+00	1.42E+01	1.24E+00	1.36E+01	2.08E+00	1.41E+01	2.27E+00	1.02E+01	3.10E+00	**1.48E+01**	2.63E+00	1.35E+01	1.65E+00	1.35E+01	3.14E+00
	5	1.59E+01	1.39E+00	1.57E+01	2.16E+00	1.62E+01	2.00E+00	**1.63E+01**	2.14E+00	1.61E+01	2.40E+00	1.19E+01	3.73E+00	1.57E+01	2.40E+00	1.61E+01	2.36E+00	1.54E+01	2.90E+00
296,059	2	1.22E+01	7.23E-15	1.22E+01	1.09E-01	1.22E+01	4.15E-02	**1.23E+01**	2.70E-01	1.22E+01	2.41E-01	9.55E+00	2.65E+00	1.16E+01	1.33E+00	1.22E+01	8.90E-03	1.15E+01	2.34E+00
	3	1.26E+01	5.50E-01	1.30E+01	8.78E-01	1.24E+01	4.58E-01	1.37E+01	1.52E+00	1.38E+01	1.57E+00	9.28E+00	2.34E+00	**1.38E+01**	2.33E+00	1.24E+01	5.96E-02	1.31E+01	2.92E+00
	4	1.52E+01	4.46E-03	1.53E+01	1.60E+00	1.56E+01	1.38E+00	1.55E+01	1.75E+00	**1.59E+01**	1.62E+00	1.12E+01	3.59E+00	1.58E+01	1.63E+00	1.51E+01	2.46E-01	1.50E+01	2.59E+00
	5	**1.85E+01**	6.31E-01	1.66E+01	1.84E+00	1.73E+01	1.57E+00	1.70E+01	1.97E+00	1.72E+01	1.77E+00	1.14E+01	4.04E+00	1.71E+01	2.14E+00	1.80E+01	1.23E+00	1.58E+01	2.24E+00
302,008	2	1.45E+01	0.00E+00	1.44E+01	6.47E-01	1.45E+01	1.42E-01	1.42E+01	8.47E-01	1.45E+01	9.62E-01	1.14E+01	2.39E+00	1.42E+01	8.44E-01	1.45E+01	2.04E-02	**1.52E+01**	1.68E+00
	3	**1.82E+01**	4.38E-01	1.77E+01	7.84E-01	1.80E+01	6.90E-01	1.76E+01	6.53E-01	1.77E+01	1.07E+00	1.12E+01	1.92E+00	1.77E+01	1.02E+00	1.70E+01	7.07E-03	1.60E+01	2.84E+00
	4	1.96E+01	3.61E-15	1.96E+01	7.18E-01	1.96E+01	5.41E-01	1.96E+01	9.05E-01	1.94E+01	9.29E-01	1.29E+01	3.82E+00	1.93E+01	1.76E+00	**1.99E+01**	2.09E-01	1.76E+01	2.87E+00
	5	2.20E+01	3.96E-03	2.13E+01	7.42E-01	2.16E+01	4.16E-01	2.09E+01	1.12E+00	2.09E+01	1.01E+00	1.37E+01	4.01E+00	2.08E+01	9.12E-01	**2.20E+01**	1.00E-01	1.87E+01	2.82E+00
37,073	2	8.77E+00	3.61E-15	8.78E+00	3.52E-02	8.77E+00	1.19E-02	9.10E+00	1.70E+00	8.77E+00	5.95E-02	1.14E+01	3.03E+00	8.78E+00	4.99E-02	8.77E+00	5.15E-03	**1.24E+01**	4.06E+00
	3	**1.82E+01**	3.61E-15	1.56E+01	3.91E+00	1.69E+01	2.76E+00	1.42E+01	4.01E+00	1.40E+01	4.21E+00	1.20E+01	3.35E+00	1.47E+01	4.51E+00	1.41E+01	4.69E+00	1.32E+01	5.06E+00
	4	**1.83E+01**	5.62E-03	1.72E+01	2.16E+00	1.78E+01	9.81E-01	1.70E+01	2.92E+00	1.69E+01	3.09E+00	1.38E+01	4.78E+00	1.70E+01	1.93E+00	1.83E+01	1.28E-01	1.61E+01	4.37E+00
	5	**2.07E+01**	1.52E+00	1.93E+01	2.29E+00	1.90E+01	2.18E+00	1.93E+01	2.05E+00	1.82E+01	2.19E+00	1.40E+01	5.12E+00	1.87E+01	2.19E+00	1.84E+01	6.07E-01	1.66E+01	4.65E+00
56,028	2	7.88E+00	8.84E-01	9.01E+00	2.02E+00	7.67E+00	1.32E-01	1.04E+01	2.27E+00	9.78E+00	2.34E+00	7.41E+00	1.91E+00	9.70E+00	2.34E+00	7.66E+00	5.42E-15	**1.04E+01**	2.71E+00
	3	**1.40E+01**	3.61E-15	1.36E+01	5.87E-01	1.39E+01	1.93E-01	1.33E+01	1.21E+00	1.33E+01	1.26E+00	9.16E+00	3.50E+00	1.34E+01	1.45E+00	1.39E+01	2.30E-01	1.33E+01	2.34E+00
	4	**1.74E+01**	7.23E-15	1.64E+01	9.00E-01	1.67E+01	5.70E-01	1.58E+01	1.37E+00	1.58E+01	1.33E+00	9.64E+00	3.70E+00	1.61E+01	8.78E-01	1.69E+01	6.09E-01	1.43E+01	2.48E+00
	5	**1.86E+01**	3.21E-01	1.80E+01	1.01E+00	1.79E+01	7.94E-01	1.75E+01	1.55E+00	1.79E+01	1.22E+00	1.01E+01	3.97E+00	1.72E+01	1.76E+00	1.81E+01	2.24E-01	1.56E+01	2.29E+00
66,075	2	1.05E+01	0.00E+00	1.04E+01	1.50E-01	1.05E+01	5.43E-02	1.04E+01	2.35E-01	1.03E+01	2.65E-01	1.13E+01	2.22E+00	1.06E+01	1.05E+00	1.05E+01	4.67E-02	**1.30E+01**	2.64E+00
	3	1.08E+01	4.80E-02	1.16E+01	1.83E+00	1.08E+01	2.53E-01	1.18E+01	1.72E+00	1.21E+01	2.03E+00	1.20E+01	2.59E+00	1.17E+01	1.78E+00	1.08E+01	1.97E-02	**1.33E+01**	2.52E+00
	4	1.59E+01	7.23E-15	1.45E+01	2.09E+00	1.56E+01	9.66E-01	1.50E+01	1.97E+00	1.47E+01	2.10E+00	1.29E+01	3.78E+00	1.42E+01	2.14E+00	1.55E+01	1.26E+00	**1.60E+01**	2.48E+00
	5	**1.79E+01**	2.13E+00	1.70E+01	2.38E+00	1.72E+01	1.84E+00	1.68E+01	1.93E+00	1.66E+01	2.65E+00	1.39E+01	4.37E+00	1.64E+01	2.07E+00	1.62E+01	7.75E-01	1.69E+01	2.41E+00

Bold means the best value provided by each algorithm

Table 13 SSIM comparisons using the Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM
101,087	2	3.81E-01	3.72E-04	4.37E-01	9.76E-02	4.05E-01	6.22E-02	4.69E-01	1.24E-01	4.82E-01	1.05E-01	1.96E-01	2.16E-01	4.79E-01	1.13E-01	3.81E-01	5.74E-04	**5.73E-01**	1.15E-01
	3	**7.56E-01**	1.70E-03	7.11E-01	5.78E-02	7.07E-01	4.06E-02	7.14E-01	7.04E-02	7.33E-01	4.39E-02	2.98E-01	2.61E-01	7.25E-01	5.90E-02	7.39E-01	3.33E-02	6.39E-01	1.92E-01
	4	**8.14E-01**	4.11E-03	8.05E-01	3.19E-02	7.86E-01	2.98E-02	7.95E-01	6.72E-02	7.95E-01	4.62E-02	4.17E-01	2.64E-01	7.94E-01	5.87E-02	8.12E-01	7.70E-03	6.71E-01	2.13E-01
	5	8.63E-01	1.03E-03	8.49E-01	3.29E-02	8.45E-01	1.43E-02	8.36E-01	3.77E-02	8.38E-01	3.47E-02	3.63E-01	2.84E-01	8.26E-01	7.90E-02	**8.64E-01**	3.33E-03	7.45E-01	1.12E-01
108,070	2	1.67E-01	1.33E-03	1.74E-01	2.32E-02	1.68E-01	3.11E-03	1.77E-01	2.76E-02	1.73E-01	3.68E-02	2.85E-01	1.87E-01	2.16E-01	9.33E-02	1.64E-01	5.12E-03	**2.87E-01**	1.94E-01
	3	2.63E-01	7.28E-03	2.84E-01	6.02E-02	2.56E-01	3.23E-02	2.97E-01	8.71E-02	2.94E-01	8.79E-02	3.24E-01	2.21E-01	2.96E-01	7.45E-02	2.56E-01	1.08E-02	**4.35E-01**	1.65E-01
	4	3.70E-01	1.18E-02	3.98E-01	1.20E-01	3.71E-01	6.32E-02	3.71E-01	1.19E-01	4.52E-01	1.36E-01	3.43E-01	2.38E-01	4.13E-01	1.35E-01	3.40E-01	1.65E-02	**5.59E-01**	1.71E-01
	5	4.72E-01	1.69E-02	4.85E-01	1.08E-01	5.04E-01	1.17E-01	4.85E-01	1.58E-01	4.94E-01	1.53E-01	4.36E-01	2.71E-01	4.63E-01	1.43E-01	4.14E-01	2.78E-02	**5.55E-01**	1.90E-01
12,003	2	1.98E-01	8.47E-17	2.23E-01	5.44E-02	1.93E-01	6.04E-03	2.40E-01	6.78E-02	2.27E-01	6.63E-02	2.46E-01	1.66E-01	2.48E-01	9.40E-02	1.98E-01	4.97E-03	**3.72E-01**	1.57E-01
	3	**5.14E-01**	4.52E-16	5.03E-01	6.33E-02	5.03E-01	4.40E-02	4.99E-01	8.72E-02	4.90E-01	7.74E-02	2.50E-01	2.17E-01	4.72E-01	9.61E-02	5.03E-01	1.65E-02	4.73E-01	1.67E-01
	4	**6.31E-01**	0.00E+00	5.89E-01	6.99E-02	5.98E-01	4.78E-02	6.19E-01	5.54E-02	5.99E-01	8.24E-02	3.54E-01	2.35E-01	6.14E-01	6.38E-02	6.19E-01	1.46E-02	5.27E-01	1.27E-01
	5	**6.87E-01**	8.35E-03	6.63E-01	6.05E-02	6.76E-01	4.24E-02	6.63E-01	7.55E-02	6.65E-01	5.74E-02	4.65E-01	2.33E-01	6.50E-01	7.67E-02	6.76E-01	5.84E-03	6.47E-01	1.38E-01
160,068	2	2.51E-01	1.13E-16	2.38E-01	2.59E-02	2.50E-01	6.57E-03	2.35E-01	4.24E-02	2.35E-01	3.68E-02	2.72E-01	1.96E-01	2.42E-01	2.95E-02	2.42E-01	1.24E-02	**3.96E-01**	1.83E-01
	3	3.31E-01	1.13E-16	3.44E-01	1.07E-01	3.28E-01	8.20E-03	3.36E-01	9.68E-02	4.44E-01	1.86E-01	4.17E-01	2.20E-01	3.61E-01	1.25E-01	3.26E-01	5.97E-03	**4.50E-01**	2.13E-01
	4	6.63E-01	1.97E-01	6.21E-01	1.88E-01	**7.02E-01**	1.55E-01	6.06E-01	1.80E-01	5.85E-01	1.56E-01	3.76E-01	2.37E-01	5.30E-01	2.12E-01	4.89E-01	1.97E-01	5.75E-01	1.86E-01
	5	**8.10E-01**	8.01E-02	7.00E-01	1.69E-01	7.52E-01	1.35E-01	7.20E-01	1.24E-01	6.32E-01	2.07E-01	4.43E-01	2.53E-01	6.68E-01	1.57E-01	7.51E-01	1.67E-01	6.86E-01	1.22E-01

Table 13 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM
210,088	2	1.93E-01	1.81E-05	1.94E-01	2.49E-02	1.94E-01	4.85E-03	1.85E-01	3.83E-02	1.86E-01	2.99E-02	2.29E-01	2.39E-01	2.02E-01	5.20E-02	1.92E-01	1.46E-03	**4.39E-01**	2.11E-01
	3	4.39E-01	2.12E-01	3.84E-01	1.93E-01	4.29E-01	2.07E-01	3.91E-01	1.73E-01	3.50E-01	1.72E-01	2.65E-01	2.25E-01	3.18E-01	1.69E-01	3.38E-01	1.86E-01	**5.19E-01**	2.33E-01
	4	**6.57E-01**	7.42E-02	6.13E-01	1.20E-01	6.52E-01	5.21E-02	5.51E-01	1.73E-01	5.56E-01	1.74E-01	4.02E-01	2.67E-01	6.07E-01	1.86E-01	5.64E-01	1.84E-01	5.83E-01	2.09E-01
	5	**7.16E-01**	3.99E-02	6.73E-01	9.80E-02	7.09E-01	8.07E-02	6.89E-01	1.14E-01	6.55E-01	1.51E-01	5.20E-01	2.61E-01	6.58E-01	1.41E-01	6.85E-01	1.42E-01	6.57E-01	1.87E-01
296,059	2	3.65E-01	5.65E-17	3.67E-01	9.93E-03	3.66E-01	4.16E-03	**3.74E-01**	2.62E-02	3.63E-01	2.04E-02	2.59E-01	2.25E-01	3.24E-01	9.51E-02	3.65E-01	1.05E-03	3.67E-01	1.92E-01
	3	3.80E-01	2.47E-02	4.02E-01	4.79E-02	3.70E-01	3.12E-02	4.40E-01	9.20E-02	4.51E-01	9.77E-02	2.76E-01	2.36E-01	4.55E-01	1.52E-01	3.69E-01	5.32E-03	**4.88E-01**	2.17E-01
	4	5.08E-01	5.84E-04	5.50E-01	1.11E-01	5.50E-01	9.32E-02	5.55E-01	1.11E-01	5.79E-01	1.09E-01	4.23E-01	2.60E-01	5.70E-01	1.06E-01	5.00E-01	1.45E-02	**6.06E-01**	1.68E-01
	5	**7.11E-01**	1.72E-02	6.32E-01	1.20E-01	6.67E-01	8.82E-02	6.36E-01	1.09E-01	6.60E-01	1.04E-01	4.01E-01	2.71E-01	6.63E-01	1.28E-01	6.85E-01	5.47E-02	6.63E-01	1.35E-01
302,008	2	5.72E-01	2.26E-16	5.69E-01	2.44E-02	5.73E-01	5.51E-03	5.64E-01	3.30E-02	5.76E-01	3.96E-02	5.47E-01	9.99E-02	5.66E-01	3.63E-02	5.72E-01	7.77E-04	**6.40E-01**	7.13E-02
	3	**7.00E-01**	1.77E-02	6.90E-01	2.20E-02	6.90E-01	2.58E-02	6.82E-01	2.69E-02	6.87E-01	3.10E-02	5.55E-01	9.15E-02	6.91E-01	3.45E-02	6.51E-01	4.38E-04	6.66E-01	9.61E-02
	4	**7.37E-01**	1.13E-16	7.35E-01	1.42E-02	7.37E-01	8.28E-03	7.36E-01	1.60E-02	7.31E-01	2.16E-02	6.11E-01	1.11E-01	7.35E-01	3.17E-02	7.36E-01	2.32E-03	7.06E-01	8.08E-02
	5	**7.75E-01**	6.47E-05	7.62E-01	1.45E-02	7.67E-01	1.04E-02	7.62E-01	1.64E-02	7.58E-01	2.04E-02	6.47E-01	1.27E-01	7.64E-01	2.32E-02	7.70E-01	5.08E-03	7.36E-01	8.47E-02
37,073	2	5.90E-02	3.53E-17	6.06E-02	4.09E-03	5.93E-02	1.33E-03	8.37E-02	1.19E-01	6.01E-02	7.06E-03	**3.56E-01**	2.36E-01	6.15E-02	6.08E-03	5.87E-02	5.02E-04	3.47E-01	2.83E-01
	3	**7.09E-01**	3.39E-16	5.48E-01	2.72E-01	6.41E-01	1.96E-01	4.86E-01	3.03E-01	4.61E-01	3.05E-01	4.06E-01	2.56E-01	4.95E-01	3.08E-01	4.32E-01	3.22E-01	3.80E-01	3.31E-01
	4	7.13E-01	9.91E-04	6.64E-01	1.36E-01	**7.15E-01**	3.29E-02	6.98E-01	1.35E-01	6.59E-01	2.07E-01	5.07E-01	2.81E-01	7.03E-01	6.42E-02	7.08E-01	1.85E-02	6.14E-01	2.35E-01
	5	**7.86E-01**	4.40E-02	7.60E-01	5.99E-02	7.46E-01	5.03E-02	7.51E-01	6.75E-02	7.23E-01	1.06E-01	5.10E-01	2.75E-01	7.39E-01	8.30E-02	7.26E-01	1.76E-02	6.25E-01	2.50E-01

Table 13 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM	Mean SSIM	sd SSIM
56,028	2	1.49E-01	5.83E-02	2.23E-01	1.36E-01	1.35E-01	8.62E-03	3.20E-01	1.57E-01	2.74E-01	1.57E-01	1.62E-01	1.55E-01	2.69E-01	1.56E-01	1.35E-01	0.00E+00	**3.50E-01**	1.93E-01
	3	**5.56E-01**	1.13E-16	5.39E-01	4.77E-02	5.53E-01	1.89E-02	5.21E-01	8.39E-02	5.19E-01	8.27E-02	2.89E-01	2.38E-01	5.36E-01	8.80E-02	5.43E-01	2.15E-02	5.45E-01	1.42E-01
	4	**7.07E-01**	1.13E-16	6.71E-01	3.80E-02	6.78E-01	3.48E-02	6.43E-01	6.95E-02	6.34E-01	7.24E-02	3.26E-01	2.62E-01	6.67E-01	4.19E-02	6.75E-01	3.26E-02	5.90E-01	1.29E-01
	5	**7.50E-01**	1.24E-02	7.31E-01	4.83E-02	7.31E-01	3.16E-02	7.16E-01	7.68E-02	7.32E-01	5.94E-02	3.61E-01	2.66E-01	7.09E-01	8.71E-02	7.25E-01	1.24E-02	6.56E-01	1.04E-01
66,075	2	1.15E-01	4.23E-17	1.06E-01	1.03E-02	1.12E-01	4.12E-03	1.08E-01	1.57E-02	9.96E-02	1.70E-02	3.37E-01	2.41E-01	1.32E-01	1.29E-01	1.13E-01	3.59E-03	**3.90E-01**	2.53E-01
	3	1.33E-01	3.69E-03	2.05E-01	1.51E-01	1.34E-01	1.95E-02	2.26E-01	1.62E-01	2.51E-01	1.81E-01	**4.37E-01**	2.56E-01	2.20E-01	1.49E-01	1.33E-01	1.46E-03	4.06E-01	2.24E-01
	4	5.39E-01	2.26E-16	4.37E-01	1.78E-01	5.40E-01	8.59E-02	5.32E-01	1.84E-01	4.74E-01	1.86E-01	4.37E-01	2.77E-01	4.37E-01	1.95E-01	5.08E-01	9.94E-02	**6.36E-01**	1.81E-01
	5	**6.78E-01**	1.56E-01	6.41E-01	1.76E-01	6.71E-01	1.42E-01	6.40E-01	1.45E-01	6.23E-01	2.00E-01	5.05E-01	3.12E-01	6.12E-01	1.51E-01	5.52E-01	6.10E-02	6.64E-01	1.86E-01

Bold means the best value provided by each algorithm

Table 14 FSIM comparisons using the Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM
101,087	2	6.35E-01	3.65E-04	6.40E-01	2.44E-02	6.49E-01	1.67E-02	6.51E-01	3.08E-02	6.50E-01	2.86E-02	5.56E-01	7.20E-02	6.50E-01	3.20E-02	6.35E-01	3.03E-04	**6.74E-01**	3.52E-02
	3	**7.25E-01**	3.25E-04	7.14E-01	1.79E-02	7.18E-01	1.34E-02	7.18E-01	2.52E-02	7.21E-01	2.30E-02	5.90E-01	8.31E-02	7.17E-01	2.47E-02	7.18E-01	9.09E-03	6.99E-01	6.17E-02
	4	**7.69E-01**	1.21E-03	7.67E-01	1.98E-02	7.54E-01	1.71E-02	7.68E-01	2.68E-02	7.64E-01	2.19E-02	6.34E-01	7.48E-02	7.64E-01	2.79E-02	7.68E-01	4.48E-03	7.19E-01	7.23E-02
	5	8.14E-01	1.07E-03	8.03E-01	2.08E-02	8.00E-01	1.24E-02	7.93E-01	2.35E-02	7.95E-01	2.27E-02	6.13E-01	9.33E-02	7.90E-01	3.96E-02	**8.16E-01**	3.40E-03	7.53E-01	4.30E-02
108,070	2	4.97E-01	1.20E-03	5.06E-01	2.91E-02	4.98E-01	2.87E-03	5.07E-01	3.62E-02	5.00E-01	5.11E-02	3.19E-01	1.49E-01	**5.25E-01**	5.83E-02	4.94E-01	6.38E-03	4.99E-01	1.28E-01
	3	6.25E-01	9.68E-03	6.39E-01	6.53E-02	6.12E-01	3.97E-02	6.43E-01	7.42E-02	6.35E-01	6.81E-02	3.70E-01	1.84E-01	**6.47E-01**	7.19E-02	6.15E-01	1.46E-02	6.05E-01	1.26E-01
	4	7.30E-01	7.48E-03	7.17E-01	7.14E-02	7.20E-01	4.81E-02	6.87E-01	7.75E-02	**7.32E-01**	8.66E-02	4.00E-01	1.97E-01	7.17E-01	8.32E-02	7.10E-01	1.27E-02	6.79E-01	9.57E-02
	5	**7.92E-01**	7.59E-03	7.72E-01	5.48E-02	7.74E-01	4.90E-02	7.63E-01	7.26E-02	7.59E-01	7.43E-02	4.65E-01	2.18E-01	7.30E-01	7.68E-02	7.63E-01	1.55E-02	7.28E-01	1.09E-01
12,003	2	5.00E-01	5.65E-17	5.04E-01	8.61E-03	4.98E-01	1.16E-03	5.06E-01	8.99E-03	5.04E-01	9.24E-03	4.04E-01	6.95E-02	5.06E-01	1.08E-02	4.99E-01	6.02E-04	**5.35E-01**	5.06E-02
	3	**6.12E-01**	1.13E-16	6.03E-01	1.52E-02	6.09E-01	7.37E-03	5.99E-01	2.29E-02	5.98E-01	2.33E-02	4.12E-01	9.69E-02	5.94E-01	2.84E-02	6.11E-01	2.45E-03	5.69E-01	5.96E-02
	4	**6.93E-01**	1.13E-16	6.62E-01	2.85E-02	6.76E-01	1.91E-02	6.72E-01	2.85E-02	6.65E-01	3.02E-02	4.64E-01	1.15E-01	6.75E-01	2.58E-02	6.87E-01	5.97E-03	5.88E-01	7.26E-02
	5	**7.45E-01**	4.92E-03	7.22E-01	2.87E-02	7.26E-01	2.16E-02	7.06E-01	3.62E-02	7.04E-01	3.56E-02	5.15E-01	1.22E-01	7.02E-01	4.20E-02	7.40E-01	3.62E-03	6.56E-01	6.67E-02
160,068	2	**7.12E-01**	1.13E-16	7.07E-01	8.15E-03	7.11E-01	1.06E-03	7.07E-01	2.09E-02	7.07E-01	1.43E-02	4.71E-01	8.47E-02	7.08E-01	1.17E-02	7.10E-01	2.43E-03	6.69E-01	7.43E-02
	3	7.79E-01	0.00E+00	7.66E-01	1.91E-02	**7.82E-01**	9.27E-03	7.66E-01	2.57E-02	7.58E-01	2.77E-02	5.34E-01	1.18E-01	7.60E-01	2.70E-02	7.80E-01	3.16E-03	7.02E-01	7.72E-02
	4	8.05E-01	6.47E-03	7.82E-01	3.07E-02	7.97E-01	1.63E-02	7.83E-01	3.39E-02	7.77E-01	2.26E-02	5.17E-01	1.21E-01	7.84E-01	2.95E-02	**8.09E-01**	1.09E-02	7.19E-01	6.45E-02
	5	**8.44E-01**	2.94E-03	8.14E-01	2.34E-02	8.21E-01	1.86E-02	8.09E-01	2.84E-02	8.10E-01	2.74E-02	5.43E-01	1.23E-01	7.99E-01	2.78E-02	8.32E-01	1.86E-02	7.42E-01	6.52E-02

Table 14 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM
210,088	2	**6.60E-01**	2.98E-05	6.58E-01	3.61E-03	6.60E-01	7.31E-04	6.59E-01	1.06E-02	6.58E-01	5.53E-03	5.17E-01	5.95E-02	6.59E-01	5.87E-03	6.60E-01	6.75E-05	6.46E-01	3.90E-02
	3	6.81E-01	6.77E-03	6.80E-01	7.92E-03	6.80E-01	7.38E-03	6.80E-01	1.50E-02	6.78E-01	1.37E-02	5.07E-01	4.58E-02	6.81E-01	1.41E-02	**6.84E-01**	6.42E-03	6.73E-01	2.80E-02
	4	**7.09E-01**	4.95E-04	7.02E-01	1.32E-02	7.01E-01	6.12E-03	7.03E-01	9.62E-03	7.06E-01	1.30E-02	5.61E-01	8.65E-02	7.08E-01	1.53E-02	7.07E-01	5.61E-03	6.77E-01	4.82E-02
	5	7.40E-01	7.42E-03	7.27E-01	1.69E-02	7.31E-01	1.22E-02	7.36E-01	1.19E-02	7.35E-01	1.40E-02	6.01E-01	9.49E-02	7.30E-01	1.67E-02	**7.41E-01**	1.15E-02	7.10E-01	3.83E-02
296,059	2	6.65E-01	2.26E-16	6.63E-01	3.70E-03	6.65E-01	1.00E-03	6.58E-01	8.64E-03	6.59E-01	7.67E-03	5.31E-01	8.73E-02	6.43E-01	3.69E-02	**6.66E-01**	2.03E-04	6.24E-01	5.33E-02
	3	6.63E-01	2.41E-03	6.59E-01	1.25E-02	6.57E-01	8.00E-03	6.69E-01	2.02E-02	6.69E-01	2.49E-02	5.17E-01	7.92E-02	**6.74E-01**	4.39E-02	6.63E-01	1.32E-03	6.44E-01	5.80E-02
	4	6.95E-01	3.62E-04	6.99E-01	2.60E-02	7.03E-01	2.13E-02	7.02E-01	3.21E-02	**7.08E-01**	2.85E-02	5.76E-01	1.05E-01	7.03E-01	2.75E-02	6.94E-01	2.44E-03	6.81E-01	5.47E-02
	5	**7.60E-01**	2.73E-02	7.24E-01	3.78E-02	7.36E-01	3.20E-02	7.37E-01	3.67E-02	7.39E-01	3.20E-02	5.79E-01	1.21E-01	7.36E-01	4.05E-02	7.54E-01	3.29E-02	7.00E-01	4.83E-02
302,008	2	7.18E-01	2.26E-16	7.16E-01	1.19E-02	7.19E-01	2.29E-03	7.13E-01	1.54E-02	7.18E-01	1.72E-02	6.37E-01	9.50E-02	7.14E-01	1.79E-02	7.18E-01	3.62E-04	**7.40E-01**	3.26E-02
	3	**7.88E-01**	7.74E-03	7.81E-01	1.07E-02	7.83E-01	1.14E-02	7.78E-01	1.24E-02	7.80E-01	1.44E-02	6.38E-01	8.40E-02	7.80E-01	1.35E-02	7.66E-01	1.51E-04	7.57E-01	5.05E-02
	4	**8.22E-01**	3.39E-16	8.15E-01	7.21E-03	8.18E-01	3.14E-03	8.13E-01	8.53E-03	8.11E-01	1.05E-02	6.82E-01	9.47E-02	8.08E-01	2.24E-02	8.21E-01	1.05E-03	7.79E-01	4.36E-02
	5	**8.48E-01**	1.51E-04	8.36E-01	9.13E-03	8.41E-01	5.94E-03	8.31E-01	1.19E-02	8.33E-01	1.02E-02	7.00E-01	9.34E-02	8.30E-01	1.15E-02	8.48E-01	3.12E-03	7.93E-01	5.66E-02
37,073	2	5.66E-01	1.13E-16	5.74E-01	1.76E-02	5.68E-01	6.34E-03	5.84E-01	3.73E-02	5.72E-01	2.12E-02	5.80E-01	9.49E-02	5.78E-01	2.48E-02	5.66E-01	5.21E-04	**6.29E-01**	7.90E-02
	3	**7.34E-01**	3.39E-16	6.99E-01	6.14E-02	7.22E-01	4.17E-02	6.91E-01	7.20E-02	6.84E-01	6.93E-02	5.93E-01	1.08E-01	6.94E-01	7.20E-02	6.81E-01	6.21E-02	6.47E-01	1.00E-01
	4	7.43E-01	1.01E-03	7.28E-01	5.03E-02	7.49E-01	2.22E-02	**7.53E-01**	3.90E-02	7.38E-01	5.71E-02	6.44E-01	1.16E-01	7.47E-01	3.40E-02	7.40E-01	1.29E-02	6.98E-01	9.43E-02
	5	**7.95E-01**	2.83E-02	7.76E-01	3.09E-02	7.71E-01	2.78E-02	7.71E-01	3.49E-02	7.53E-01	5.39E-02	6.45E-01	1.21E-01	7.65E-01	4.45E-02	7.57E-01	1.15E-02	7.22E-01	8.78E-02

Table 14 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM	Mean FSIM	sd FSIM
56,028	2	4.49E-01	2.11E-02	4.77E-01	4.82E-02	4.44E-01	3.38E-03	5.15E-01	5.86E-02	4.99E-01	5.89E-02	3.37E-01	8.88E-02	4.97E-01	6.02E-02	4.43E-01	2.26E-16	**5.16E-01**	8.97E-02
	3	**6.42E-01**	4.52E-16	6.36E-01	2.02E-02	6.41E-01	7.54E-03	6.30E-01	3.55E-02	6.28E-01	4.05E-02	4.17E-01	1.53E-01	6.30E-01	4.00E-02	6.37E-01	8.59E-03	6.06E-01	7.64E-02
	4	**7.45E-01**	3.39E-16	7.25E-01	2.28E-02	7.28E-01	1.44E-02	7.04E-01	4.32E-02	7.05E-01	3.87E-02	4.37E-01	1.68E-01	7.16E-01	2.14E-02	7.34E-01	1.29E-02	6.49E-01	7.77E-02
	5	**7.91E-01**	4.38E-03	7.70E-01	2.32E-02	7.71E-01	2.03E-02	7.55E-01	4.01E-02	7.65E-01	3.11E-02	4.60E-01	1.70E-01	7.51E-01	4.44E-02	7.83E-01	5.10E-03	6.93E-01	6.26E-02
66,075	2	7.50E-01	3.39E-16	7.48E-01	3.76E-03	7.50E-01	1.45E-03	7.47E-01	4.98E-03	7.45E-01	6.03E-03	6.91E-01	7.35E-02	7.47E-01	9.37E-03	**7.51E-01**	4.74E-04	7.49E-01	2.42E-02
	3	7.60E-01	4.55E-04	7.69E-01	1.44E-02	7.60E-01	3.26E-03	7.66E-01	1.31E-02	**7.71E-01**	1.75E-02	7.14E-01	6.64E-02	7.65E-01	1.98E-02	7.60E-01	5.06E-04	7.69E-01	2.59E-02
	4	**8.21E-01**	2.26E-16	7.97E-01	2.00E-02	8.12E-01	1.14E-02	7.98E-01	1.72E-02	7.98E-01	1.86E-02	7.13E-01	8.34E-02	7.97E-01	2.30E-02	8.17E-01	1.31E-02	7.92E-01	2.11E-02
	5	**8.39E-01**	6.18E-03	8.13E-01	1.65E-02	8.25E-01	1.40E-02	8.07E-01	1.97E-02	8.07E-01	1.87E-02	7.22E-01	8.39E-02	8.12E-01	1.98E-02	8.32E-01	4.42E-03	7.95E-01	2.19E-02

Bold means the best value provided by each algorithm

Table 15 QILV comparisons using the Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV
101,087	2	9.18E-01	1.15E-04	9.18E-01	1.94E-02	3.02E-01	9.36E-02	**9.18E-01**	2.04E-02	9.15E-01	2.56E-02	1.13E-02	4.86E-02	9.11E-01	2.83E-02	9.18E-01	2.33E-04	4.96E-01	3.05E-01
	3	9.56E-01	1.90E-03	9.45E-01	1.93E-02	4.76E-01	8.73E-02	9.38E-01	2.82E-02	9.24E-01	4.03E-02	6.90E-02	1.85E-01	9.05E-01	1.18E-01	**9.57E-01**	2.58E-03	5.89E-01	3.18E-01
	4	**9.70E-01**	1.77E-03	9.60E-01	1.10E-02	6.84E-01	1.04E-01	9.49E-01	2.77E-02	9.45E-01	3.91E-02	5.48E-02	1.32E-01	8.89E-01	1.72E-01	9.70E-01	2.27E-03	6.76E-01	3.14E-01
	5	**9.79E-01**	9.00E-04	9.60E-01	2.51E-02	7.73E-01	7.01E-02	9.59E-01	2.60E-02	9.59E-01	3.05E-02	1.08E-01	2.66E-01	9.25E-01	1.06E-01	9.78E-01	1.62E-03	7.68E-01	2.31E-01
108,070	2	1.51E-01	3.48E-04	2.31E-01	5.67E-02	1.51E-01	6.04E-04	**2.54E-01**	5.35E-02	2.43E-01	5.58E-02	3.78E-02	9.67E-02	2.40E-01	6.34E-02	1.50E-01	1.32E-03	2.23E-01	1.36E-01
	3	4.04E-01	6.12E-03	4.78E-01	7.77E-02	3.92E-01	2.77E-02	4.90E-01	8.47E-02	4.80E-01	6.97E-02	6.83E-02	1.53E-01	**4.92E-01**	7.96E-02	3.99E-01	8.33E-03	3.94E-01	1.81E-01
	4	5.93E-01	7.49E-03	6.24E-01	8.62E-02	5.87E-01	4.67E-02	5.90E-01	9.35E-02	**6.50E-01**	1.11E-01	1.18E-01	2.09E-01	6.24E-01	1.04E-01	5.76E-01	1.21E-02	5.18E-01	1.72E-01
	5	7.30E-01	8.71E-03	**7.32E-01**	7.10E-02	7.00E-01	6.37E-02	7.20E-01	9.23E-02	7.22E-01	9.66E-02	1.72E-01	2.21E-01	6.68E-01	1.20E-01	6.95E-01	1.88E-02	6.42E-01	1.69E-01
12,003	2	3.34E-01	1.69E-16	3.52E-01	4.34E-02	3.26E-01	9.60E-03	3.67E-01	5.78E-02	3.58E-01	5.53E-02	2.25E-02	6.74E-02	3.42E-01	5.62E-02	3.32E-01	7.90E-03	**4.03E-01**	2.06E-01
	3	6.88E-01	2.26E-16	6.73E-01	6.02E-02	6.83E-01	2.66E-02	6.55E-01	8.16E-02	6.70E-01	7.49E-02	5.77E-02	1.49E-01	6.69E-01	9.59E-02	**6.94E-01**	6.80E-03	5.35E-01	1.62E-01
	4	8.36E-01	4.52E-16	8.07E-01	3.75E-02	8.28E-01	2.33E-02	7.99E-01	5.64E-02	7.88E-01	5.93E-02	1.67E-01	2.60E-01	7.98E-01	5.58E-02	**8.42E-01**	6.02E-03	5.19E-01	2.97E-01
	5	9.04E-01	2.49E-03	8.79E-01	3.03E-02	8.86E-01	2.67E-02	8.53E-01	5.61E-02	8.58E-01	4.46E-02	2.06E-01	2.68E-01	8.32E-01	7.02E-02	**9.07E-01**	2.37E-03	6.74E-01	2.35E-01
160,068	2	**3.97E-01**	0.00E+00	3.77E-01	3.90E-02	3.96E-01	3.83E-03	3.67E-01	7.77E-02	3.71E-01	5.84E-02	2.82E-02	8.83E-02	3.74E-01	5.97E-02	3.96E-01	3.53E-03	3.26E-01	1.92E-01
	3	5.92E-01	3.39E-16	5.84E-01	5.60E-02	**5.99E-01**	3.52E-02	5.88E-01	9.37E-02	5.65E-01	8.83E-02	1.41E-01	2.45E-01	5.83E-01	9.68E-02	5.87E-01	1.30E-02	4.62E-01	2.34E-01
	4	6.89E-01	4.18E-02	6.94E-01	7.95E-02	6.84E-01	4.83E-02	6.89E-01	1.01E-01	6.86E-01	7.24E-02	1.11E-01	1.90E-01	6.87E-01	7.85E-02	**7.18E-01**	4.82E-02	5.38E-01	2.23E-01
	5	**8.13E-01**	2.49E-03	7.83E-01	4.24E-02	7.89E-01	3.54E-02	7.94E-01	6.11E-02	7.91E-01	5.12E-02	1.48E-01	2.57E-01	7.88E-01	7.37E-02	8.07E-01	2.89E-02	6.45E-01	2.53E-01

Table 15 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV
210,088	2	3.68E-01	4.55E-05	3.71E-01	2.05E-02	3.67E-01	5.64E-03	3.73E-01	6.74E-02	3.75E-01	2.44E-02	4.50E-02	1.47E-01	3.79E-01	2.23E-02	3.69E-01	1.81E-03	**4.03E-01**	2.13E-01
	3	5.10E-01	4.96E-02	5.22E-01	6.44E-02	5.02E-01	5.74E-02	**5.45E-01**	1.22E-01	5.41E-01	9.42E-02	5.36E-03	1.70E-02	5.19E-01	1.05E-01	5.37E-01	3.06E-02	4.67E-01	2.41E-01
	4	6.57E-01	3.74E-03	6.49E-01	9.32E-02	6.36E-01	6.43E-02	6.64E-01	8.23E-02	**6.99E-01**	9.79E-02	1.11E-01	2.35E-01	6.89E-01	1.00E-01	6.65E-01	4.16E-02	5.02E-01	2.57E-01
	5	7.87E-01	2.68E-02	7.69E-01	8.77E-02	7.67E-01	5.88E-02	7.91E-01	7.62E-02	**8.10E-01**	6.76E-02	2.24E-01	3.04E-01	7.80E-01	7.03E-02	8.02E-01	4.74E-02	6.35E-01	2.38E-01
296,059	2	4.77E-01	2.82E-16	4.74E-01	2.56E-02	4.73E-01	1.08E-02	4.62E-01	6.06E-02	**4.85E-01**	4.77E-02	1.10E-01	2.34E-01	4.54E-01	1.45E-01	4.78E-01	3.01E-03	3.61E-01	2.99E-01
	3	5.58E-01	8.17E-02	5.83E-01	1.14E-01	5.54E-01	7.67E-02	**6.67E-01**	1.05E-01	6.43E-01	1.30E-01	3.23E-02	1.15E-01	6.09E-01	1.75E-01	5.32E-01	1.17E-02	4.48E-01	2.80E-01
	4	**8.21E-01**	4.34E-04	7.44E-01	9.69E-02	7.75E-01	5.86E-02	7.51E-01	9.71E-02	7.71E-01	6.67E-02	1.89E-01	3.14E-01	7.69E-01	7.85E-02	8.19E-01	2.66E-03	5.68E-01	2.56E-01
	5	**8.66E-01**	3.28E-02	7.94E-01	7.45E-02	8.33E-01	5.96E-02	8.22E-01	7.98E-02	8.21E-01	7.25E-02	2.21E-01	3.40E-01	7.81E-01	1.35E-01	8.63E-01	3.44E-02	6.10E-01	2.14E-01
302,008	2	4.80E-01	1.69E-16	4.66E-01	1.76E-02	4.78E-01	5.17E-03	4.60E-01	3.66E-02	4.45E-01	6.82E-02	5.63E-02	1.44E-01	4.65E-01	4.46E-02	**4.80E-01**	4.98E-04	4.05E-01	1.97E-01
	3	**6.64E-01**	5.01E-03	6.28E-01	7.37E-02	6.61E-01	1.94E-02	6.55E-01	7.44E-02	6.27E-01	1.19E-01	3.02E-02	1.20E-01	6.37E-01	1.05E-01	6.46E-01	1.06E-03	4.86E-01	2.54E-01
	4	7.43E-01	3.39E-16	7.60E-01	4.49E-02	7.45E-01	3.90E-02	7.48E-01	6.68E-02	7.45E-01	7.41E-02	1.76E-01	3.11E-01	7.19E-01	1.58E-01	**7.70E-01**	1.88E-02	6.29E-01	2.36E-01
	5	8.54E-01	9.07E-05	8.45E-01	3.63E-02	8.54E-01	2.43E-02	8.19E-01	6.37E-02	8.25E-01	7.15E-02	2.11E-01	2.89E-01	8.02E-01	5.93E-02	**8.62E-01**	9.70E-03	6.74E-01	2.25E-01
37,073	2	6.35E-03	0.00E+00	8.28E-03	2.99E-03	6.44E-03	8.21E-04	3.37E-02	1.35E-01	7.96E-03	4.74E-03	1.07E-01	2.39E-01	8.66E-03	3.80E-03	6.18E-03	3.43E-04	**2.62E-01**	3.12E-01
	3	**7.81E-01**	0.00E+00	5.65E-01	3.36E-01	6.53E-01	2.31E-01	4.08E-01	3.22E-01	4.06E-01	3.52E-01	1.34E-01	2.42E-01	4.53E-01	3.55E-01	4.49E-01	3.84E-01	3.15E-01	3.69E-01
	4	**8.19E-01**	1.08E-03	6.90E-01	2.10E-01	7.10E-01	1.35E-01	5.50E-01	2.54E-01	6.04E-01	2.46E-01	2.45E-01	3.38E-01	5.86E-01	2.20E-01	8.17E-01	1.94E-02	4.73E-01	3.61E-01
	5	**8.74E-01**	3.26E-02	7.56E-01	1.86E-01	7.66E-01	1.73E-01	7.71E-01	1.61E-01	7.12E-01	1.77E-01	2.50E-01	3.54E-01	7.23E-01	1.85E-01	8.08E-01	3.36E-02	5.16E-01	3.49E-01

Table 15 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV	Mean QILV	sd QILV
56,028	2	1.80E-01	5.36E-02	2.53E-01	1.12E-01	1.64E-01	1.61E-02	**3.35E-01**	1.48E-01	3.10E-01	1.55E-01	2.66E-02	1.01E-01	3.07E-01	1.53E-01	1.63E-01	2.82E-17	3.16E-01	2.52E-01
	3	6.49E-01	1.13E-16	6.30E-01	8.38E-02	6.36E-01	5.30E-02	6.27E-01	1.10E-01	6.20E-01	1.22E-01	1.33E-01	2.67E-01	5.94E-01	1.42E-01	**6.68E-01**	2.25E-02	5.22E-01	2.06E-01
	4	8.17E-01	2.26E-16	7.94E-01	8.72E-02	8.11E-01	3.31E-02	7.63E-01	8.49E-02	7.96E-01	6.95E-02	1.42E-01	2.51E-01	7.78E-01	8.59E-02	**8.29E-01**	1.60E-02	6.27E-01	1.94E-01
	5	8.84E-01	5.59E-03	8.63E-01	3.45E-02	8.61E-01	3.01E-02	8.48E-01	4.67E-02	8.45E-01	5.89E-02	1.64E-01	2.74E-01	8.31E-01	5.66E-02	**8.85E-01**	6.69E-03	6.93E-01	1.74E-01
66,075	2	1.76E-01	2.82E-17	1.74E-01	1.59E-02	1.75E-01	2.52E-03	1.82E-01	3.95E-02	1.70E-01	3.86E-02	7.09E-02	1.48E-01	1.66E-01	2.64E-02	1.75E-01	1.85E-03	**2.89E-01**	1.91E-01
	3	3.17E-01	8.70E-03	3.87E-01	1.39E-01	3.19E-01	4.10E-02	4.00E-01	1.49E-01	**4.23E-01**	1.69E-01	7.11E-02	1.56E-01	3.97E-01	1.65E-01	3.17E-01	2.84E-03	4.13E-01	2.24E-01
	4	**7.66E-01**	3.39E-16	6.49E-01	1.36E-01	7.12E-01	9.95E-02	6.22E-01	1.57E-01	6.23E-01	1.49E-01	1.91E-01	2.92E-01	6.03E-01	1.97E-01	7.43E-01	9.44E-02	5.43E-01	1.73E-01
	5	8.09E-01	7.95E-04	7.50E-01	1.18E-01	7.66E-01	7.73E-02	7.32E-01	1.10E-01	7.24E-01	1.44E-01	2.11E-01	2.88E-01	7.27E-01	1.32E-01	**8.13E-01**	9.23E-03	6.76E-01	1.33E-01

Bold means the best value provided by each algorithm

Table 16 HPSI comparisons using the Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI
101,087	2	1.96E-01	1.01E-03	2.12E-01	3.23E-02	2.12E-01	2.28E-02	2.32E-01	4.82E-02	2.26E-01	4.01E-02	9.17E-02	7.31E-02	2.27E-01	4.61E-02	1.96E-01	1.23E-04	**2.70E-01**	6.52E-02
	3	3.63E-01	3.86E-03	3.57E-01	4.88E-02	3.63E-01	2.75E-02	3.63E-01	6.20E-02	**3.64E-01**	5.71E-02	1.28E-01	1.11E-01	3.58E-01	6.16E-02	3.58E-01	7.26E-03	3.15E-01	1.16E-01
	4	4.82E-01	2.88E-03	4.65E-01	5.35E-02	4.63E-01	3.00E-02	4.64E-01	7.31E-02	4.58E-01	5.40E-02	1.59E-01	1.18E-01	4.69E-01	6.58E-02	**4.86E-01**	9.08E-03	3.67E-01	1.35E-01
	5	5.94E-01	3.84E-03	5.48E-01	5.72E-02	5.61E-01	3.16E-02	5.23E-01	6.13E-02	5.29E-01	7.23E-02	1.53E-01	1.36E-01	5.14E-01	9.63E-02	**6.00E-01**	8.37E-03	4.20E-01	1.03E-01
108,070	2	1.96E-01	1.37E-03	2.06E-01	2.63E-02	1.96E-01	3.32E-03	2.09E-01	3.05E-02	2.05E-01	4.15E-02	8.40E-02	9.88E-02	**2.27E-01**	5.19E-02	1.92E-01	6.17E-03	2.07E-01	1.03E-01
	3	3.02E-01	7.50E-03	3.19E-01	5.69E-02	2.92E-01	3.28E-02	3.27E-01	7.16E-02	3.22E-01	6.83E-02	1.12E-01	1.28E-01	**3.28E-01**	6.57E-02	2.94E-01	1.20E-02	3.06E-01	1.32E-01
	4	3.97E-01	8.77E-03	4.09E-01	8.72E-02	3.95E-01	5.09E-02	3.75E-01	8.03E-02	**4.38E-01**	1.02E-01	1.39E-01	1.54E-01	4.12E-01	9.70E-02	3.75E-01	1.35E-02	3.87E-01	1.27E-01
	5	**4.78E-01**	1.22E-02	4.70E-01	7.55E-02	4.72E-01	7.33E-02	4.71E-01	1.04E-01	4.69E-01	1.04E-01	1.92E-01	1.79E-01	4.23E-01	9.04E-02	4.35E-01	2.09E-02	4.54E-01	1.45E-01
12,003	2	1.68E-01	0.00E+00	1.78E-01	2.28E-02	1.65E-01	3.39E-03	1.84E-01	2.34E-02	1.79E-01	2.60E-02	5.51E-02	4.58E-02	1.77E-01	3.14E-02	1.67E-01	3.07E-03	**2.00E-01**	8.37E-02
	3	**3.37E-01**	5.65E-17	3.18E-01	2.71E-02	3.29E-01	1.44E-02	3.08E-01	3.72E-02	3.09E-01	4.11E-02	7.27E-02	8.42E-02	3.05E-01	4.93E-02	3.34E-01	5.55E-03	2.59E-01	9.31E-02
	4	**4.58E-01**	5.65E-17	4.05E-01	4.70E-02	4.25E-01	3.32E-02	4.18E-01	5.21E-02	4.04E-01	5.46E-02	1.19E-01	1.18E-01	4.22E-01	4.29E-02	4.48E-01	1.09E-02	2.62E-01	1.29E-01
	5	**5.45E-01**	9.92E-03	4.99E-01	5.29E-02	5.12E-01	4.31E-02	4.70E-01	6.99E-02	4.70E-01	6.88E-02	1.54E-01	1.33E-01	4.54E-01	7.06E-02	5.32E-01	6.42E-03	3.63E-01	1.26E-01
160,068	2	**2.87E-01**	2.26E-16	2.79E-01	1.27E-02	2.86E-01	2.09E-03	2.79E-01	3.19E-02	2.79E-01	2.21E-02	6.67E-02	6.08E-02	2.82E-01	1.81E-02	2.84E-01	4.60E-03	2.44E-01	1.02E-01
	3	**4.06E-01**	2.82E-16	3.77E-01	2.65E-02	4.04E-01	1.56E-02	3.72E-01	4.28E-02	3.76E-01	3.58E-02	1.29E-01	1.32E-01	3.73E-01	3.94E-02	4.01E-01	8.19E-03	3.11E-01	1.14E-01
	4	**4.86E-01**	2.43E-02	4.51E-01	5.03E-02	4.82E-01	3.55E-02	4.49E-01	5.90E-02	4.41E-01	2.90E-02	1.12E-01	1.06E-01	4.28E-01	5.71E-02	4.59E-01	2.12E-02	3.46E-01	1.20E-01
	5	**5.75E-01**	2.05E-02	5.15E-01	3.93E-02	5.36E-01	4.09E-02	5.16E-01	4.78E-02	5.03E-01	6.28E-02	1.32E-01	1.44E-01	4.95E-01	5.63E-02	5.49E-01	4.82E-02	4.00E-01	1.33E-01

Table 16 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI
210,088	2	2.43E-01	5.27E-05	2.42E-01	1.13E-02	2.43E-01	9.99E-04	2.40E-01	2.59E-02	2.39E-01	1.53E-02	7.85E-02	6.28E-02	**2.44E-01**	1.20E-02	2.43E-01	4.98E-04	2.28E-01	7.34E-02
	3	2.91E-01	1.27E-02	2.91E-01	1.50E-02	2.89E-01	1.32E-02	2.88E-01	3.60E-02	2.88E-01	3.03E-02	6.52E-02	1.86E-02	2.86E-01	3.54E-02	**2.94E-01**	1.38E-02	2.60E-01	7.93E-02
	4	3.54E-01	3.20E-03	3.37E-01	3.82E-02	3.39E-01	2.48E-02	3.39E-01	2.88E-02	3.47E-01	3.19E-02	1.15E-01	1.03E-01	**3.55E-01**	4.00E-02	3.49E-01	1.46E-02	2.67E-01	9.84E-02
	5	**4.25E-01**	1.96E-02	3.95E-01	4.48E-02	4.05E-01	3.33E-02	4.13E-01	3.65E-02	4.09E-01	3.77E-02	1.65E-01	1.32E-01	3.94E-01	4.10E-02	4.25E-01	3.66E-02	3.34E-01	9.88E-02
296,059	2	3.12E-01	1.69E-16	3.11E-01	3.69E-03	**3.12E-01**	1.29E-03	3.09E-01	7.17E-03	3.04E-01	1.71E-02	1.45E-01	1.06E-01	2.75E-01	6.62E-02	3.12E-01	3.33E-04	2.38E-01	1.00E-01
	3	3.29E-01	1.16E-02	3.32E-01	2.20E-02	3.16E-01	1.70E-02	3.49E-01	4.84E-02	3.52E-01	5.16E-02	1.19E-01	8.86E-02	**3.54E-01**	8.39E-02	3.24E-01	2.31E-03	2.87E-01	1.17E-01
	4	4.05E-01	9.75E-04	4.05E-01	5.39E-02	4.22E-01	4.98E-02	4.14E-01	6.08E-02	**4.25E-01**	5.40E-02	1.91E-01	1.37E-01	4.20E-01	5.42E-02	4.02E-01	6.34E-03	3.59E-01	1.05E-01
	5	**5.15E-01**	4.85E-02	4.48E-01	6.86E-02	4.69E-01	6.53E-02	4.69E-01	7.27E-02	4.71E-01	6.45E-02	2.08E-01	1.64E-01	4.64E-01	8.10E-02	5.03E-01	6.19E-02	3.93E-01	9.10E-02
302,008	2	2.42E-01	8.47E-17	2.41E-01	2.80E-02	2.44E-01	6.22E-03	2.35E-01	3.69E-02	2.49E-01	4.30E-02	1.11E-01	1.18E-01	2.35E-01	3.74E-02	2.42E-01	7.09E-04	**2.94E-01**	8.41E-02
	3	**4.12E-01**	2.49E-02	3.90E-01	3.61E-02	3.98E-01	3.71E-02	3.78E-01	3.71E-02	3.96E-01	5.47E-02	9.11E-02	9.06E-02	3.89E-01	4.98E-02	3.44E-01	1.00E-03	3.21E-01	1.27E-01
	4	4.88E-01	5.65E-17	4.78E-01	3.26E-02	4.82E-01	2.60E-02	4.80E-01	4.44E-02	4.71E-01	5.01E-02	1.68E-01	1.73E-01	4.60E-01	8.62E-02	**5.00E-01**	7.66E-03	3.80E-01	1.24E-01
	5	6.00E-01	4.42E-04	5.56E-01	4.27E-02	5.71E-01	2.60E-02	5.35E-01	5.42E-02	5.34E-01	4.49E-02	2.10E-01	1.95E-01	5.33E-01	5.05E-02	**6.02E-01**	8.35E-03	4.40E-01	1.32E-01
37,073	2	1.13E-01	5.65E-17	1.16E-01	8.36E-03	1.13E-01	2.72E-03	1.30E-01	6.39E-02	1.15E-01	1.40E-02	1.77E-01	1.24E-01	1.17E-01	1.25E-02	1.12E-01	1.15E-03	**2.48E-01**	1.54E-01
	3	**4.56E-01**	3.39E-16	3.77E-01	1.45E-01	4.31E-01	1.06E-01	3.55E-01	1.69E-01	3.37E-01	1.65E-01	2.10E-01	1.48E-01	3.57E-01	1.69E-01	3.17E-01	1.62E-01	2.92E-01	1.92E-01
	4	4.68E-01	2.19E-03	4.54E-01	9.77E-02	4.88E-01	4.35E-02	**4.96E-01**	9.84E-02	4.66E-01	1.25E-01	2.75E-01	1.91E-01	4.89E-01	6.25E-02	4.64E-01	2.27E-02	3.85E-01	1.71E-01
	5	**5.81E-01**	6.38E-02	5.49E-01	6.86E-02	5.36E-01	6.42E-02	5.42E-01	7.56E-02	5.03E-01	9.01E-02	2.75E-01	2.08E-01	5.35E-01	8.32E-02	4.99E-01	2.72E-02	4.41E-01	1.72E-01

Table 16 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI	Mean HPSI	sd HPSI
56,028	2	1.61E-01	2.28E-02	1.89E-01	5.21E-02	1.54E-01	7.39E-03	**2.27E-01**	6.03E-02	2.11E-01	6.36E-02	5.55E-02	6.75E-02	2.11E-01	6.50E-02	1.54E-01	2.82E-17	2.13E-01	1.04E-01
	3	**3.75E-01**	0.00E+00	3.63E-01	2.61E-02	3.73E-01	1.20E-02	3.51E-01	4.81E-02	3.52E-01	5.51E-02	1.21E-01	1.46E-01	3.52E-01	6.01E-02	3.70E-01	1.08E-02	3.20E-01	9.23E-02
	4	**5.21E-01**	2.26E-16	4.81E-01	4.56E-02	4.97E-01	2.39E-02	4.53E-01	6.11E-02	4.56E-01	5.29E-02	1.36E-01	1.50E-01	4.70E-01	4.03E-02	5.07E-01	2.06E-02	3.76E-01	1.09E-01
	5	**5.97E-01**	1.84E-02	5.54E-01	4.74E-02	5.57E-01	4.05E-02	5.30E-01	6.74E-02	5.44E-01	5.90E-02	1.55E-01	1.70E-01	5.20E-01	7.38E-02	5.74E-01	8.52E-03	4.24E-01	1.06E-01
66,075	2	**2.06E-01**	2.82E-17	1.96E-01	1.65E-02	2.04E-01	4.85E-03	1.98E-01	2.17E-02	1.85E-01	2.66E-02	1.13E-01	5.98E-02	1.90E-01	2.15E-02	2.04E-01	3.97E-03	2.01E-01	6.61E-02
	3	2.40E-01	3.83E-03	2.44E-01	3.06E-02	2.37E-01	3.79E-03	2.37E-01	2.96E-02	**2.53E-01**	3.61E-02	1.19E-01	6.07E-02	2.37E-01	4.14E-02	2.40E-01	4.71E-04	2.45E-01	6.78E-02
	4	**3.73E-01**	2.82E-16	3.14E-01	6.02E-02	3.57E-01	2.97E-02	3.27E-01	4.77E-02	3.24E-01	5.58E-02	1.57E-01	1.13E-01	3.08E-01	6.50E-02	3.58E-01	3.21E-02	3.04E-01	6.93E-02
	5	**4.41E-01**	6.22E-02	3.86E-01	5.23E-02	4.04E-01	5.71E-02	3.76E-01	5.32E-02	3.66E-01	6.27E-02	1.80E-01	1.32E-01	3.73E-01	5.15E-02	3.85E-01	3.11E-02	3.46E-01	6.48E-02

Bold means the best value provided by each algorithm

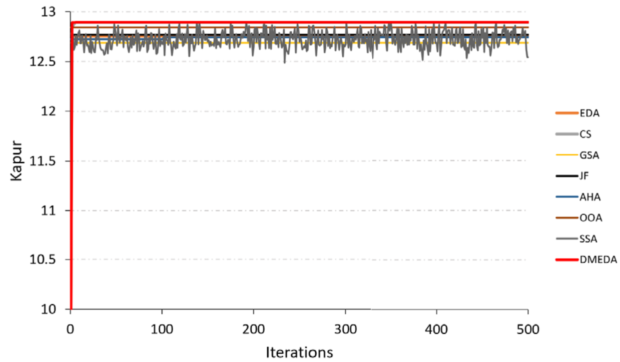
Table 17 UIQI comparisons using the Kapur's entropy

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI
101,087	2	6.97E-01	2.85E-03	7.04E-01	7.40E-01	3.65E-01	1.95E-01	**2.21E+00**	7.93E+00	1.06E+00	1.24E+00	1.28E-01	2.25E-01	5.09E-01	1.94E+00	6.97E-01	5.32E-04	7.96E-01	4.68E-01
	3	9.79E-01	6.81E-04	**1.22E+00**	1.35E+00	7.99E-01	1.86E-02	9.80E-01	5.88E-02	9.59E-01	2.45E-02	1.85E-01	4.17E-01	1.01E+00	2.86E-01	9.80E-01	2.94E-03	7.40E-01	2.75E-01
	4	**9.78E-01**	1.89E-03	9.73E-01	1.12E-02	8.99E-01	1.80E-02	9.71E-01	2.15E-02	9.67E-01	1.75E-02	3.64E-01	3.22E-01	9.56E-01	4.67E-02	9.78E-01	2.32E-03	7.89E-01	2.84E-01
	5	**9.83E-01**	7.11E-04	9.75E-01	1.03E-02	9.38E-01	1.00E-02	9.76E-01	1.14E-02	9.77E-01	1.48E-02	3.19E-01	3.45E-01	9.58E-01	6.39E-02	9.82E-01	1.12E-03	9.28E-01	8.01E-02
108,070	2	6.27E-01	4.33E-03	5.58E-01	6.14E-02	6.29E-01	1.04E-02	5.41E-01	8.87E-02	5.34E-01	9.58E-02	2.88E-01	4.24E-01	**6.33E-01**	1.89E-01	6.16E-01	1.86E-02	5.84E-01	3.27E-01
	3	6.54E-01	1.14E-02	6.58E-01	8.65E-02	6.41E-01	5.34E-02	6.70E-01	1.23E-01	6.66E-01	1.26E-01	-9.99E-02	2.92E+00	6.69E-01	1.04E-01	6.43E-01	1.91E-02	**7.98E-01**	3.92E-01
	4	7.58E-01	1.32E-02	7.67E-01	1.31E-01	7.56E-01	7.58E-02	7.18E-01	1.23E-01	8.16E-01	1.47E-01	4.65E-01	3.99E-01	6.42E-01	6.89E-01	7.24E-01	2.04E-02	**9.06E-01**	2.77E-01
	5	8.35E-01	1.39E-02	8.35E-01	9.82E-02	**8.87E-01**	1.53E-01	7.47E-01	3.09E-01	8.21E-01	1.36E-01	5.98E-01	4.22E-01	8.03E-01	1.28E-01	7.84E-01	2.61E-02	8.40E-01	2.98E-01
12,003	2	1.43E+00	2.26E-16	1.43E+00	9.60E-01	1.46E+00	3.48E-02	1.69E+00	2.55E+00	1.34E+00	5.94E-01	1.98E-01	2.63E-01	**1.74E+00**	2.06E+00	1.44E+00	5.49E-02	7.16E-01	5.48E-01
	3	7.65E-01	1.13E-16	8.18E-01	4.43E-01	6.84E-01	2.51E-01	6.63E-01	6.12E-01	7.53E-01	1.59E-01	2.31E-01	3.26E-01	1.97E+00	7.21E+00	7.49E-01	3.06E-02	**7.44E+00**	3.59E+01
	4	8.94E-01	3.39E-16	8.63E-01	4.04E-02	8.75E-01	2.86E-02	8.84E-01	3.52E-02	8.60E-01	7.91E-02	4.25E-01	4.53E-01	8.88E-01	4.62E-02	8.89E-01	5.01E-03	**2.02E+00**	7.00E+00
	5	9.26E-01	2.73E-03	9.29E-01	2.65E-02	9.23E-01	1.53E-02	9.15E-01	5.55E-02	9.23E-01	3.70E-02	5.82E-01	4.14E-01	9.14E-01	5.59E-02	9.25E-01	1.71E-03	**9.91E-01**	4.65E-01
160,068	2	1.12E+00	2.26E-16	1.12E+00	9.70E-01	1.12E+00	8.33E-02	**3.60E+00**	1.39E+01	1.47E+00	5.29E+00	2.76E-01	5.04E-01	–5.70E-01	9.45E+00	1.02E+00	1.24E-01	7.39E-01	7.14E-01
	3	**1.05E+00**	4.52E-16	1.01E+00	2.23E-01	1.02E+00	6.97E-02	9.34E-01	1.97E-01	9.59E-01	2.64E-01	4.74E-01	3.90E-01	9.59E-01	5.55E-01	1.03E+00	4.26E-02	7.39E-01	7.05E-01
	4	8.53E-01	2.50E-02	8.59E-01	8.55E-02	8.21E-01	5.17E-02	8.05E-01	2.90E-01	8.56E-01	4.83E-01	3.88E-01	4.25E-01	8.02E-01	2.01E-01	**8.76E-01**	2.76E-02	7.66E-01	2.78E-01
	5	8.73E-01	4.34E-03	**1.06E+00**	1.07E+00	8.45E-01	1.55E-01	8.37E-01	1.06E-01	8.20E-01	2.02E-01	4.86E-01	3.84E-01	8.50E-01	2.51E-01	8.80E-01	2.20E-02	8.70E-01	1.11E-01
210,088	2	1.79E-02	2.79E-05	1.16E-02	9.38E-02	2.11E-02	2.01E-02	–2.07E-02	1.06E-01	–1.88E-02	1.00E-01	1.80E-01	3.00E-01	2.48E-02	1.54E-01	1.37E-02	6.17E-03	**3.98E-01**	4.78E-01
	3	2.74E-01	4.05E-01	1.59E-01	4.53E-01	2.45E-01	4.21E-01	2.27E-01	5.00E-01	1.42E-01	4.52E-01	1.78E-01	2.53E-01	–2.64E-02	4.67E-01	7.02E-02	3.64E-01	**4.73E-01**	5.70E-01
	4	7.01E-01	2.12E-01	6.94E-01	1.58E-01	**7.27E-01**	9.03E-02	4.14E-01	8.37E-01	5.57E-01	6.28E-01	3.56E-01	3.41E-01	6.64E-01	4.01E-01	4.48E-01	5.14E-01	5.03E-01	7.14E-01
	5	8.33E-01	5.18E-02	8.19E-01	1.12E-01	8.35E-01	9.41E-02	8.23E-01	2.51E-01	7.60E-01	3.89E-01	5.12E-01	3.49E-01	7.75E-01	3.12E-01	7.70E-01	2.94E-01	**9.13E-01**	5.76E-01

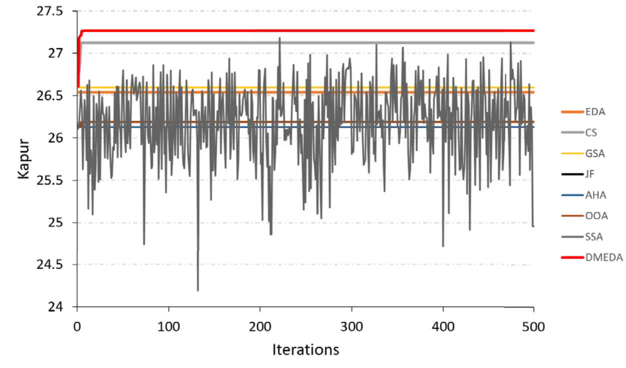
Table 17 (continued)

Image	Th	DMEDA		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
		Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI	Mean UIQI	sd UIQI
296,059	2	3.65E-01	1.69E-16	3.70E-01	3.67E-02	3.69E-01	1.45E-02	**3.90E-01**	8.68E-02	3.43E-01	1.10E-01	3.11E-01	6.86E-01	3.00E-01	2.79E-01	3.64E-01	3.75E-03	1.75E-02	1.70E+00
	3	4.28E-01	1.08E-01	4.95E-01	1.67E-01	3.67E-01	1.41E-01	4.78E-01	6.56E-01	5.60E-01	3.08E-01	2.00E-01	2.81E-01	5.57E-01	3.03E-01	3.78E-01	2.27E-02	**1.26E+00**	3.56E+00
	4	**8.27E-01**	5.09E-04	7.52E-01	1.99E-01	8.03E-01	1.17E-01	7.84E-01	1.21E-01	8.10E-01	1.37E-01	4.11E-01	3.71E-01	7.97E-01	1.73E-01	8.18E-01	1.49E-02	7.74E-01	2.19E-01
	5	**9.23E-01**	1.61E-02	8.57E-01	8.11E-02	8.87E-01	5.73E-02	8.91E-01	6.13E-02	8.87E-01	7.33E-02	3.92E-01	3.90E-01	8.91E-01	9.14E-02	9.10E-01	3.70E-02	8.07E-01	1.63E-01
302,008	2	5.86E-01	3.39E-16	5.74E-01	5.73E-02	5.89E-01	1.15E-02	5.58E-01	7.65E-02	5.80E-01	9.49E-02	1.69E-01	2.53E-01	5.60E-01	8.05E-02	5.86E-01	1.70E-03	**6.19E-01**	1.35E-01
	3	**8.26E-01**	1.95E-02	7.99E-01	4.09E-02	8.15E-01	3.05E-02	7.99E-01	3.33E-02	7.97E-01	5.53E-02	1.35E-01	1.94E-01	7.99E-01	5.33E-02	7.71E-01	2.86E-04	6.53E-01	2.40E-01
	4	8.76E-01	0.00E+00	8.76E-01	2.25E-02	8.74E-01	1.58E-02	8.73E-01	2.89E-02	8.67E-01	3.37E-02	2.86E-01	3.54E-01	8.49E-01	1.16E-01	**8.85E-01**	5.82E-03	7.54E-01	1.97E-01
	5	9.30E-01	6.04E-05	9.19E-01	1.62E-02	9.25E-01	7.46E-03	9.07E-01	3.05E-02	9.08E-01	2.64E-02	3.66E-01	3.72E-01	9.06E-01	2.23E-02	**9.32E-01**	1.60E-03	8.08E-01	1.81E-01
37,073	2	9.96E-04	8.82E-19	1.26E-03	6.48E-04	1.04E-03	2.08E-04	3.13E-02	1.63E-01	1.29E-03	1.32E-03	2.78E-01	3.18E-01	1.44E-03	1.03E-03	9.55E-04	7.49E-05	**3.98E-01**	4.19E-01
	3	**9.06E-01**	6.78E-16	6.75E-01	3.84E-01	7.95E-01	2.71E-01	5.48E-01	4.01E-01	5.23E-01	4.16E-01	3.56E-01	3.38E-01	5.65E-01	4.18E-01	5.14E-01	4.55E-01	3.99E-01	4.45E-01
	4	**9.09E-01**	7.44E-04	8.40E-01	1.83E-01	8.65E-01	6.56E-02	7.61E-01	1.98E-01	7.65E-01	2.68E-01	4.64E-01	3.80E-01	8.03E-01	1.17E-01	9.09E-01	1.31E-02	6.75E-01	3.40E-01
	5	**9.41E-01**	2.21E-02	8.90E-01	9.82E-02	8.89E-01	9.11E-02	8.99E-01	8.87E-02	8.75E-01	8.78E-02	4.63E-01	3.84E-01	8.80E-01	9.13E-02	8.99E-01	1.83E-02	6.83E-01	3.44E-01
56,028	2	−2.22E-01	2.72E-01	−4.14E-01	1.09E+00	−1.95E-01	6.50E-02	2.58E-03	1.10E+00	−3.28E-01	1.74E+00	1.18E-01	2.19E-01	6.35E-02	1.00E+00	−1.83E-01	8.47E-17	**4.78E-01**	4.22E-01
	3	7.57E-01	5.65E-16	7.54E-01	2.37E-02	7.55E-01	1.13E-02	7.30E-01	1.84E-01	7.12E-01	2.28E-01	3.09E-01	3.60E-01	7.55E-01	7.90E-02	**7.60E-01**	3.38E-03	6.46E-01	6.19E-01
	4	**9.14E-01**	5.65E-16	9.01E-01	2.20E-02	9.03E-01	1.41E-02	8.90E-01	6.39E-02	9.06E-01	6.29E-02	3.67E-01	3.76E-01	8.92E-01	3.17E-02	9.04E-01	1.94E-02	8.43E-01	1.71E-01
	5	9.38E-01	5.32E-03	9.35E-01	1.50E-02	9.30E-01	1.19E-02	9.56E-01	1.09E-01	9.35E-01	2.34E-02	4.08E-01	3.83E-01	**9.68E-01**	2.25E-01	9.32E-01	2.73E-03	9.15E-01	1.30E-01
66,075	2	−6.33E-02	0.00E+00	−6.11E-02	1.19E-02	−6.24E-02	1.97E-03	−7.16E-02	4.65E-02	−5.99E-02	3.03E-02	2.43E-01	3.08E-01	−2.57E-02	1.66E-01	−6.27E-02	1.44E-03	**2.84E-01**	4.98E-01
	3	−2.56E-01	1.69E-02	−2.57E-01	6.62E-01	−3.19E-01	3.80E-01	−4.03E-01	1.14E+00	8.93E-02	8.52E-01	**3.54E-01**	3.29E-01	−2.22E-01	4.89E-01	−2.55E-01	8.36E-03	−1.12E+01	5.44E+01
	4	6.76E-01	3.39E-16	5.36E-01	5.72E+00	5.89E-01	4.57E-01	5.94E-01	6.38E-01	4.61E-01	9.14E-01	4.00E-01	3.94E-01	6.49E-01	1.64E+00	5.76E-01	3.69E-01	**6.92E-01**	2.89E-01
	5	7.79E-01	1.13E-01	7.99E-01	3.60E-01	7.57E-01	1.64E-01	**8.66E-01**	5.46E-01	6.93E-01	4.05E-01	4.81E-01	4.24E-01	7.16E-01	3.24E-01	6.94E-01	4.04E-02	8.56E-01	2.85E-01

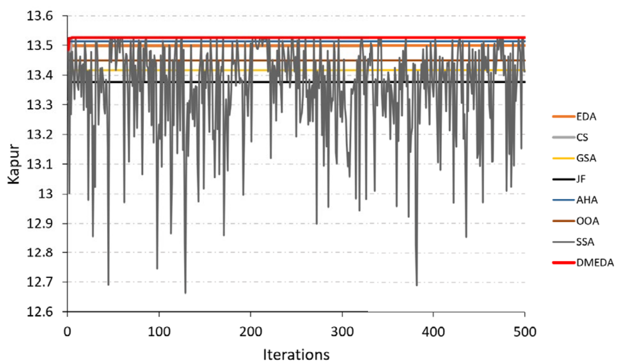
Bold means the best value provided by each algorithm



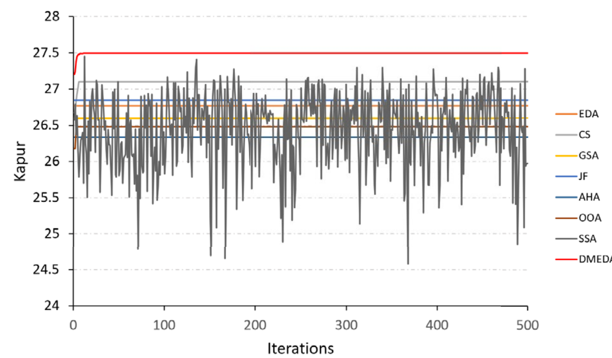
(a) Image 101087 with 2 thresholds.



(b) Image 101087 with 5 thresholds.



(c) Image 12003 with 2 thresholds.



(d) Image 12003 with 5 thresholds.

Fig. 9 Convergence curves using Kapur's entropy as an objective function

5 Conclusions and future works

In this paper, a hybrid EDA algorithm is proposed that improves its exploratory capacity by adding a simple Differential Mutation operator. It tested how the algorithm can give better results than EDA and a set of metaheuristic algorithms on the Otsu and Kapur objective functions. A different approach is shown in the proposal of probabilistic models for the sampling process through hybridization of the algorithm, providing significant improvements in the results. With the DMEDA, better results are obtained on the objective function. The EDA is improved in exploring the search space using the Differential Mutation operator, and its results are consistent at each iteration. After the sampling phase, the DM operator is proposed so that the new population of individuals to be sampled can better explore the search space and leave possible local optimums. Therefore, the DMEDA optimizes the objective function with better results, balancing the exploration and exploitation of its individuals in the search for local optima in the Otsu objective function maximization problem and Kapur objective function maximization problem for image segmentation by multilevel thresholding. Also, the DMEDA has greater exploitation capacity than the EDA because the results have less variation at each iteration.

In this research, images of an established dataset were studied. Metrics such as processing PSNR, SSIM, FSIM, QILV, HPSI, and UIQI were analyzed to evaluate the algorithms concerning the original image. It is observed that other algorithms generate results that favor the structures that result from the segmentation process. Still, the DMEDA is always consistent with its results and achieves better results in the standard deviation of all metrics and in some cases with Kapur, it is better. The PSNR, SSIM, FSIM, QILV, HPSI, and UIQI metrics are smaller when

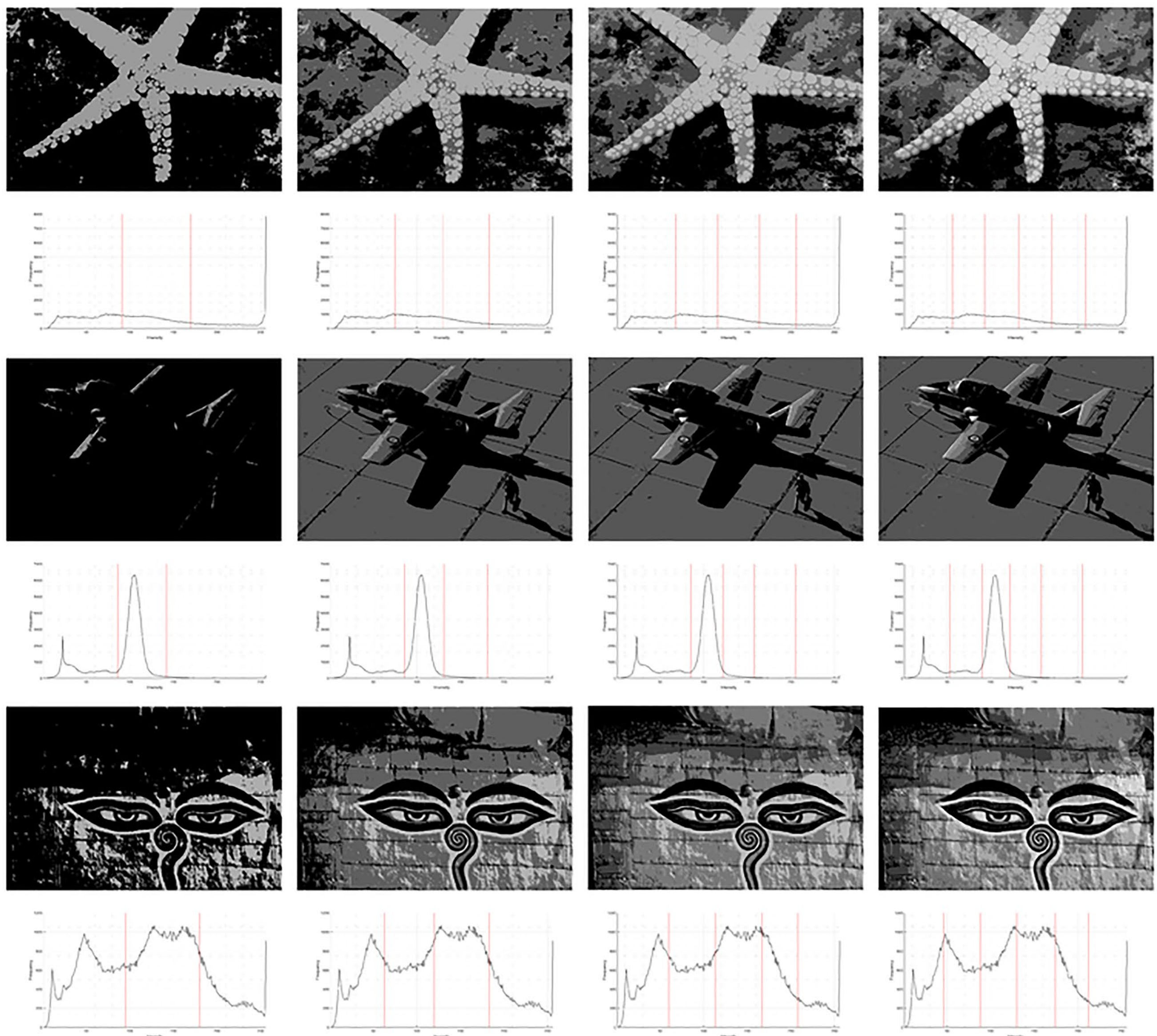


Fig. 10 Images and the different thresholds obtained using Kapur's entropy

the number of thresholds increases; this is generated because the regions are smaller and the similarity of the region of interest with the original image is lower, and these three metrics provide a measure of similarity based on different criteria.

The EDA has the advantage of using few hyper-parameters for its operation; only the size of the population must be configured. This helps because you don't have to solve the problem of optimizing the hyper-parameters based on the algorithm's results. It is known that increasing the size of the population will have better results because it is based on the construction of a probabilistic model that works based on the observed probability distribution. The disadvantage of EDA is that it gets stuck in local optima, and the stability is not what it is. Therefore, an operation that improves the stability of the results without affecting the advantage that the EDA is used adds only one hyperparameter to the metaheuristics and sacrifices a bit of simplicity. In addition, precision is obtained in the results with higher means of the fitness function.

The proposed algorithm for segmentation obtains better metrics using Kapur than with Otsu, but both objective functions are attacked well by DMEDA. Although, there are some limitations of the proposed algorithm, which are listed below:

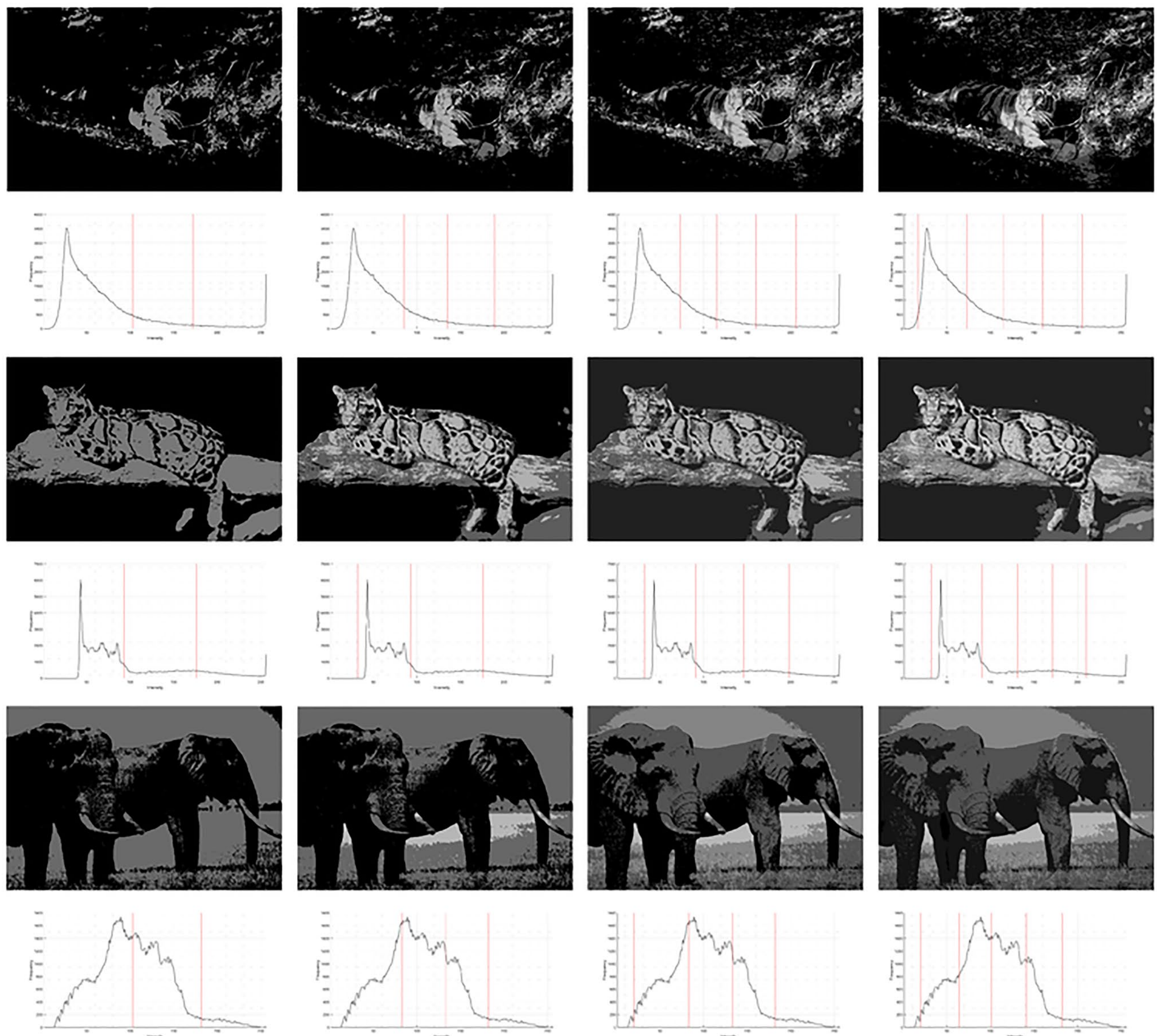


Fig. 11 Images and the different thresholds obtained using Kapur's entropy

- In low dimensions (fewer number of thresholds), the algorithm is unstable and imprecise.
- It cannot be used in real-time applications, and the number of thresholds must be set manually.
- The method was exclusively designed for image segmentation by multilevel thresholding.

As future work, the proposed DMEDA can be implemented in multilevel thresholding color image segmentation problems using different objective functions as criteria. In the multilevel thresholding color image segmentation, the objective function is optimized in the three color channels in which the image is located to obtain the different regions of the image. The DMEDA should be compared with state-of-the-art algorithms already applied in image color segmentation. Besides, another branch of future work is the use of the DMEDA as a preprocessing step for a machine learning classifier using medical images.

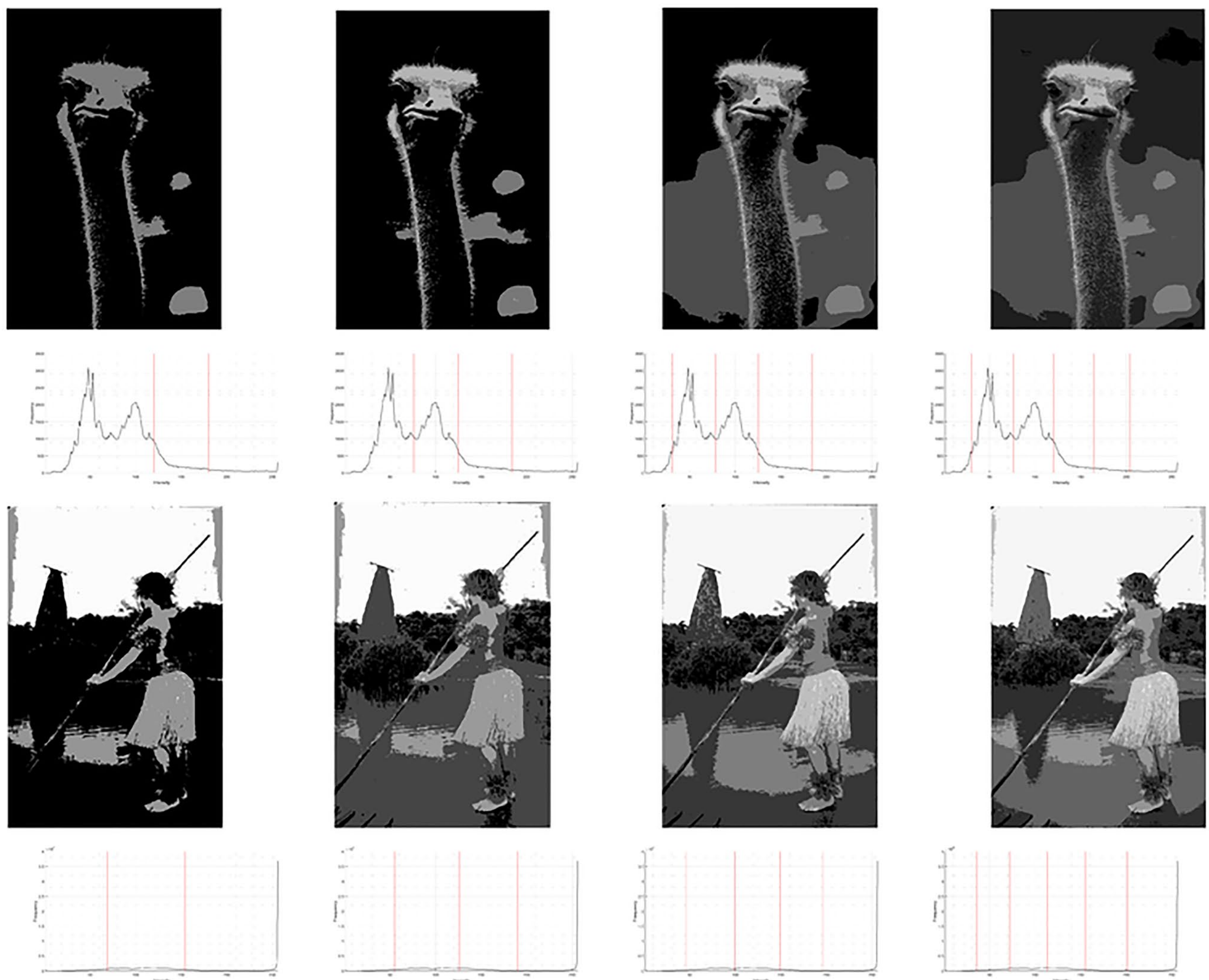


Fig. 12 Images and the different thresholds obtained using Kapur's entropy

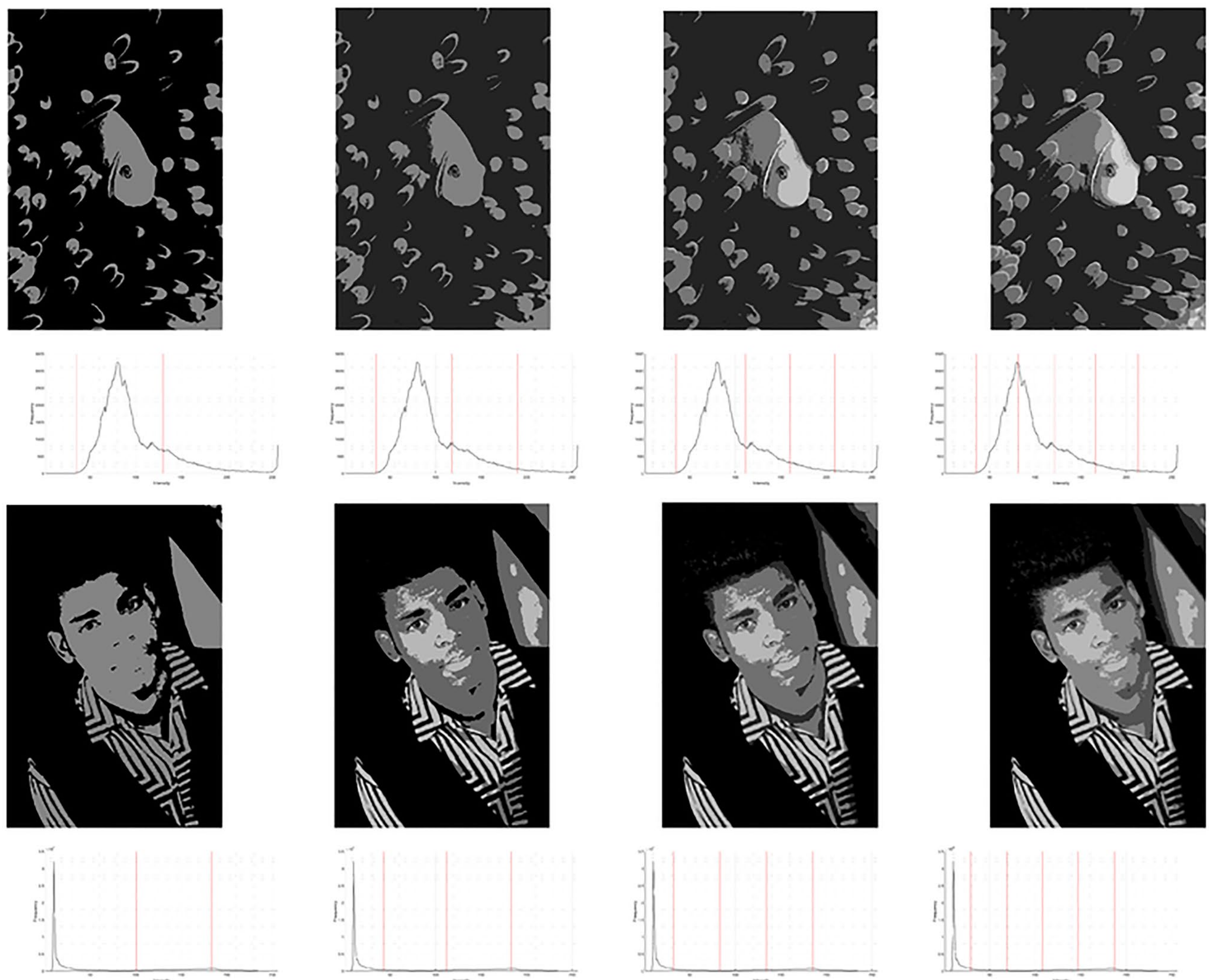


Fig. 13 Images and the different thresholds obtained using Kapur's entropy

Table 18 Comparison of using Otsu's between-class variance over the BSD300 for two thresholds

Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Otsu	**2.04E+03**	2.04E+03	2.04E+03	2.02E+03	**2.04E+03**	2.04E+03	2.03E+03	2.04E+03	2.04E+03
PSNR	1.54E+01	1.53E+01	1.20E+01	1.52E+01	**1.55E+01**	1.54E+01	1.51E+01	1.55E+01	1.50E+01
SSIM	5.98E-01	5.92E-01	4.80E-01	5.87E-01	**5.99E-01**	5.97E-01	5.83E-01	5.97E-01	5.78E-01
FSIM	7.15E-01	7.09E-01	5.93E-01	7.04E-01	7.19E-01	**7.19E-01**	7.00E-01	7.17E-01	7.00E-01
QILV	7.98E-01	7.80E-01	1.98E-01	7.67E-01	8.10E-01	**8.10E-01**	7.48E-01	8.01E-01	7.34E-01
HPSI	4.21E-01	4.11E-01	2.45E-01	4.05E-01	4.23E-01	**4.23E-01**	3.99E-01	4.22E-01	3.93E-01
UIQI	8.92E-01	8.85E-01	6.68E-01	8.77E-01	**8.98E-01**	8.95E-01	8.68E-01	8.95E-01	8.49E-01

Bold means the best value provided by each algorithm

Table 19 Comparison of using Otsu's between-class variance over the BSD300 for three thresholds

Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Otsu	**2.20E+03**	2.18E+03	2.19E+03	2.16E+03	2.20E+03	2.19E+03	2.17E+03	2.20E+03	2.19E+03
PSNR	1.80E+01	1.75E+01	1.49E+01	1.73E+01	1.80E+01	1.79E+01	1.71E+01	**1.80E+01**	1.70E+01
SSIM	7.06E-01	6.93E-01	6.40E-01	6.87E-01	7.05E-01	7.04E-01	6.80E-01	**7.06E-01**	6.76E-01
FSIM	7.73E-01	7.61E-01	6.87E-01	7.54E-01	7.74E-01	7.74E-01	7.48E-01	**7.75E-01**	7.49E-01
QILV	8.81E-01	8.58E-01	5.05E-01	8.47E-01	8.85E-01	**8.86E-01**	8.30E-01	8.85E-01	8.22E-01
HPSI	5.21E-01	5.00E-01	3.74E-01	4.91E-01	5.23E-01	**5.23E-01**	4.79E-01	5.23E-01	4.80E-01
UIQI	9.42E-01	9.34E-01	8.70E-01	9.29E-01	9.44E-01	9.43E-01	9.18E-01	**9.44E-01**	9.05E-01

Bold means the best value provided by each algorithm

Table 20 Comparison of using Otsu's between-class variance over the BSD300 for four thresholds

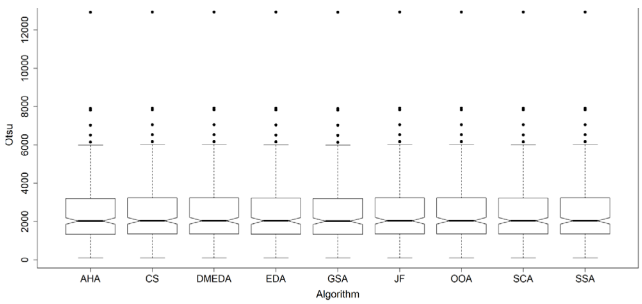
Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Otsu	**2.26E+03**	2.24E+03	2.25E+03	2.23E+03	2.26E+03	2.25E+03	2.23E+03	2.26E+03	2.26E+03
PSNR	1.96E+01	1.90E+01	1.70E+01	1.87E+01	**1.97E+01**	1.96E+01	1.85E+01	1.97E+01	1.85E+01
SSIM	**7.81E-01**	7.56E-01	7.26E-01	7.48E-01	7.81E-01	7.72E-01	7.38E-01	7.79E-01	7.38E-01
FSIM	8.13E-01	7.94E-01	7.48E-01	7.87E-01	8.16E-01	8.12E-01	7.82E-01	**8.17E-01**	7.84E-01
QILV	9.23E-01	9.00E-01	6.96E-01	8.91E-01	**9.27E-01**	9.25E-01	8.75E-01	9.26E-01	8.62E-01
HPSI	6.03E-01	5.62E-01	4.68E-01	5.50E-01	**6.05E-01**	5.95E-01	5.37E-01	6.03E-01	5.40E-01
UIQI	9.65E-01	9.56E-01	9.32E-01	9.50E-01	**9.65E-01**	9.63E-01	9.44E-01	9.65E-01	9.33E-01

Bold means the best value provided by each algorithm

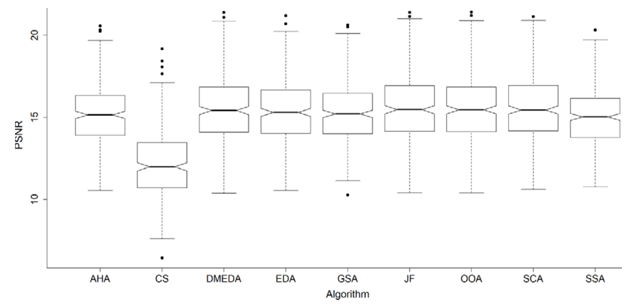
Table 21 Comparison of using Otsu's between-class variance over the BSD300 for five thresholds

Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Otsu	**2.30E+03**	2.27E+03	2.28E+03	2.26E+03	**2.30E+03**	2.29E+03	2.27E+03	2.29E+03	2.28E+03
PSNR	2.13E+01	2.04E+01	1.86E+01	1.99E+01	**2.13E+01**	2.11E+01	1.98E+01	2.13E+01	1.98E+01
SSIM	**8.28E-01**	8.00E-01	7.80E-01	7.90E-01	8.27E-01	8.16E-01	7.81E-01	8.23E-01	7.80E-01
FSIM	8.44E-01	8.20E-01	7.86E-01	8.11E-01	8.45E-01	8.40E-01	8.06E-01	**8.45E-01**	8.10E-01
QILV	9.45E-01	9.24E-01	7.94E-01	9.16E-01	9.48E-01	9.46E-01	9.02E-01	**9.48E-01**	8.92E-01
HPSI	6.61E-01	6.09E-01	5.36E-01	5.96E-01	6.63E-01	6.52E-01	5.87E-01	**6.64E-01**	5.88E-01
UIQI	9.76E-01	9.69E-01	9.56E-01	9.64E-01	9.76E-01	9.75E-01	9.59E-01	**9.77E-01**	9.51E-01

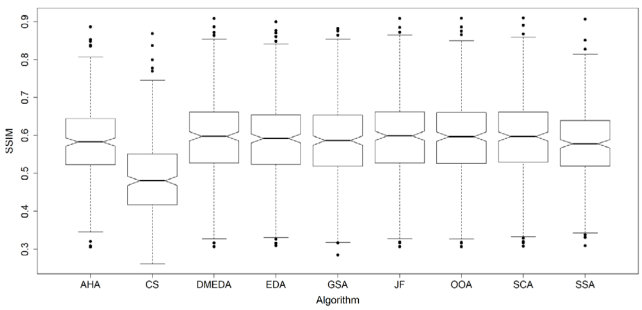
Bold means the best value provided by each algorithm



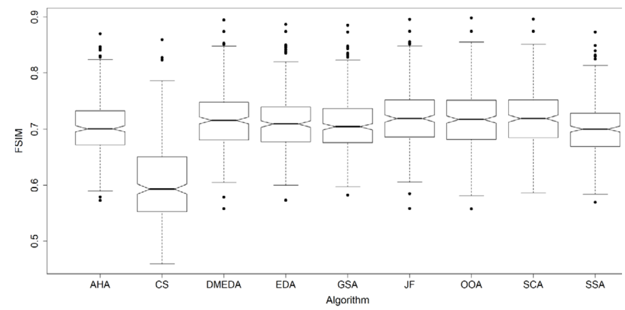
(a) Otsu's between-class variance.



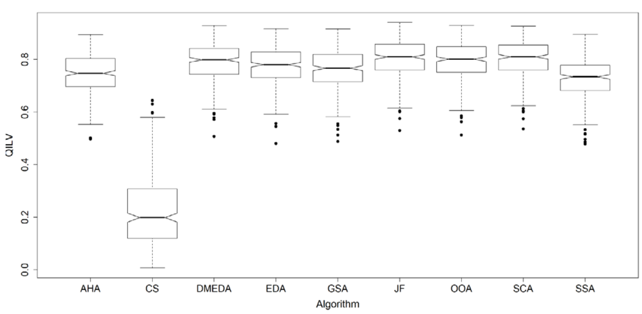
(b) PSNR.



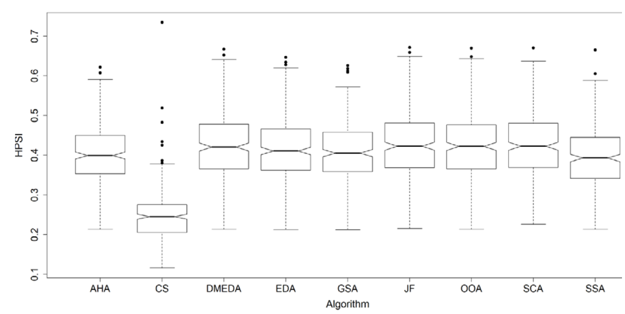
(c) SSIM



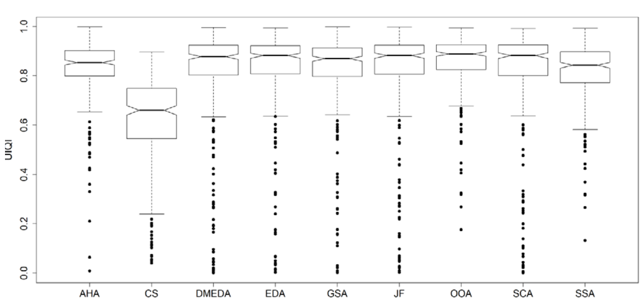
(d) FSIM.



(e) QILV.



(f) HPSI.



(g) UIQI.

Fig. 14 Boxplot representation for two thresholds general results with Otsu's between-class variance

Table 22 Comparison of using Kapur's entropy over the BSD300 for two thresholds

Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Kapur	1.29E+01	1.28E+01	1.29E+01	1.28E+01	1.27E+01	5.54E+00	1.28E+01	**1.29E+01**	1.27E+01
PSNR	1.07E+01	1.08E+01	1.03E+01	1.10E+01	1.10E+01	8.53E+00	1.10E+01	1.06E+01	**1.16E+01**
SSIM	3.14E-01	3.18E-01	3.02E-01	3.31E-01	3.35E-01	2.65E-01	3.35E-01	2.99E-01	**4.37E-01**
FSIM	5.79E-01	5.83E-01	5.75E-01	5.86E-01	**5.87E-01**	4.62E-01	5.71E-01	5.62E-01	5.73E-01
QILV	3.49E-01	3.69E-01	2.80E-01	**3.92E-01**	3.92E-01	5.76E-02	3.81E-01	3.45E-01	3.55E-01
HPSI	2.18E-01	2.22E-01	2.09E-01	2.28E-01	2.30E-01	1.02E-01	2.27E-01	2.13E-01	**2.34E-01**
UIQI	2.49E-01	–1.88E-01	**7.56E-01**	2.61E-01	–1.23E-01	2.16E-01	2.21E-01	8.39E-02	2.42E-01

Bold means the best value provided by each algorithm

Table 23 Comparison of using Kapur's entropy over the BSD300 for three thresholds

Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Kapur	**1.80E+01**	1.77E+01	1.79E+01	1.76E+01	1.76E+01	8.08E+00	1.76E+01	1.79E+01	1.75E+01
PSNR	**1.40E+01**	1.38E+01	1.35E+01	1.39E+01	1.39E+01	9.38E+00	1.38E+01	1.36E+01	1.33E+01
SSIM	5.23E-01	5.14E-01	5.09E-01	5.20E-01	5.19E-01	3.36E-01	5.18E-01	4.91E-01	**5.37E-01**
FSIM	**6.67E-01**	6.65E-01	6.60E-01	6.67E-01	6.66E-01	4.94E-01	6.61E-01	6.59E-01	6.39E-01
QILV	6.29E-01	6.27E-01	5.71E-01	**6.32E-01**	6.29E-01	9.66E-02	6.15E-01	6.28E-01	4.96E-01
HPSI	**3.48E-01**	3.44E-01	3.35E-01	3.45E-01	3.43E-01	1.30E-01	3.39E-01	3.37E-01	3.01E-01
UIQI	7.24E-01	6.29E-01	–8.53E-02	5.65E-01	8.26E-01	3.20E-01	**9.11E-01**	6.88E-01	6.60E-01

Bold means the best value provided by each algorithm

Table 24 Comparison of using Kapur's entropy over the BSD300 for four thresholds

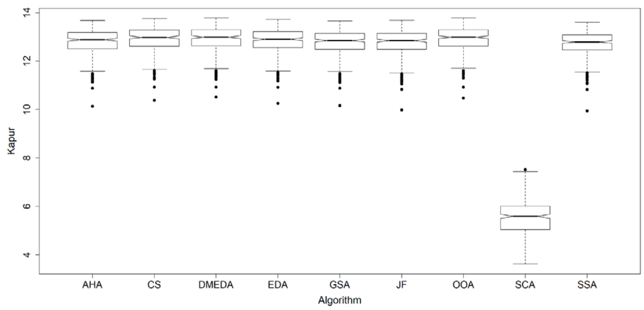
Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Kapur	**2.26E+01**	2.21E+01	2.24E+01	2.19E+01	2.19E+01	1.04E+01	2.20E+01	2.25E+01	2.18E+01
PSNR	**1.67E+01**	1.61E+01	1.59E+01	1.59E+01	1.60E+01	1.00E+01	1.59E+01	1.61E+01	1.48E+01
SSIM	**6.58E-01**	6.36E-01	6.37E-01	6.30E-01	6.31E-01	3.83E-01	6.29E-01	6.17E-01	6.13E-01
FSIM	**7.33E-01**	7.21E-01	7.20E-01	7.18E-01	7.19E-01	5.14E-01	7.15E-01	7.25E-01	6.78E-01
QILV	**7.83E-01**	7.58E-01	7.28E-01	7.50E-01	7.52E-01	1.30E-01	7.37E-01	7.82E-01	5.96E-01
HPSI	**4.55E-01**	4.33E-01	4.30E-01	4.26E-01	4.27E-01	1.51E-01	4.22E-01	4.38E-01	3.58E-01
UIQI	8.60E-01	8.81E-01	**1.02E+00**	8.61E-01	8.47E-01	3.97E-01	8.54E-01	8.36E-01	8.07E-01

Bold means the best value provided by each algorithm

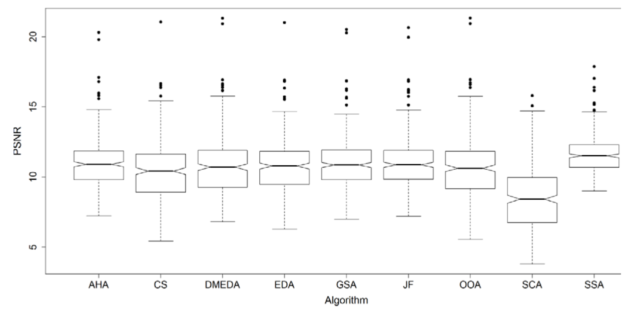
Table 25 Comparison of using Kapur's entropy over the BSD300 for five thresholds

Metric	Algorithm								
	DMEDA	EDA	CS	GSA	JF	SCA	AHA	OOA	SSA
Kapur	**2.69E+01**	2.61E+01	2.65E+01	2.58E+01	2.58E+01	1.23E+01	2.60E+01	2.68E+01	2.57E+01
PSNR	**1.87E+01**	1.77E+01	1.77E+01	1.75E+01	1.75E+01	1.05E+01	1.75E+01	1.80E+01	1.59E+01
SSIM	**7.41E-01**	7.08E-01	7.14E-01	7.00E-01	7.01E-01	4.16E-01	7.01E-01	7.01E-01	6.60E-01
FSIM	**7.83E-01**	7.61E-01	7.63E-01	7.55E-01	7.55E-01	5.31E-01	7.53E-01	7.73E-01	7.04E-01
QILV	**8.61E-01**	8.29E-01	8.14E-01	8.19E-01	8.20E-01	1.59E-01	8.09E-01	8.60E-01	6.64E-01
HPSI	**5.40E-01**	5.00E-01	5.04E-01	4.89E-01	4.89E-01	1.70E-01	4.85E-01	5.19E-01	3.99E-01
UIQI	9.07E-01	9.44E-01	9.03E-01	8.84E-01	9.42E-01	6.02E-02	**1.21E+00**	1.20E+00	8.31E-01

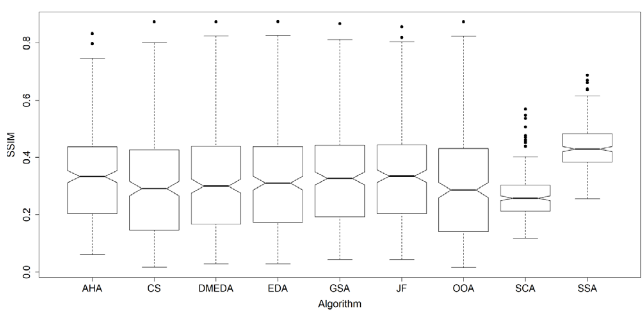
Bold means the best value provided by each algorithm



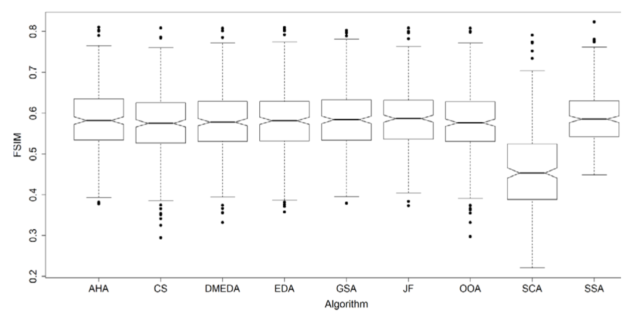
(a) Kapur's entropy.



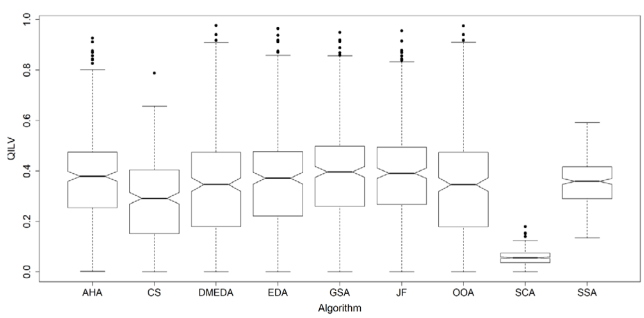
(b) PSNR.



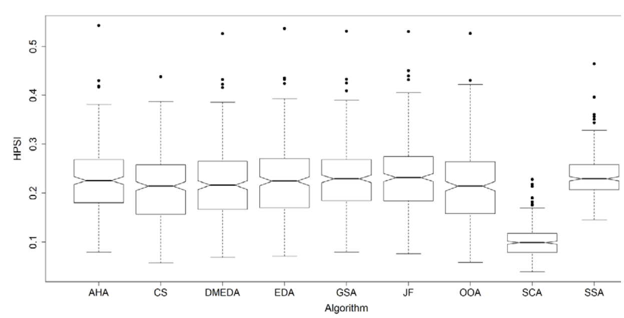
(c) SSIM.



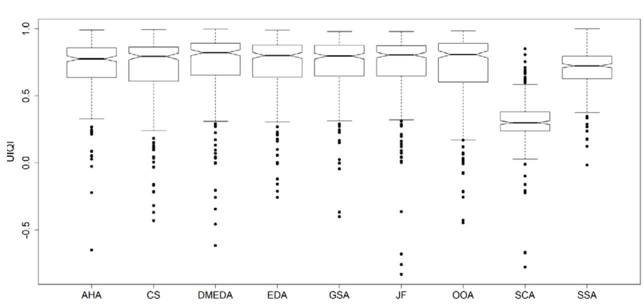
(d) FSIM.



(e) QILV.



(f) HPSI.



(g) UIQI.

Fig. 15 Boxplot representation for two thresholds general results with Kapur's entropy

Table 26 Wilcoxon test over the Otsu's between-class variance results

DMEDA VS		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
Image	Th	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value
101,087	2	3.38225E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	5.24248E-16	T	1	F	2.41154E-14	T
	3	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	1.69112E-17	T	7.61006E-16	T	1.69112E-17	T	0.375041917	F	1.29478E-09	T
	4	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.18379E-16	T	1.69112E-17	T	0.019481044	T	1.53723E-14	T
	5	1.69112E-17	T	0.000565106	T	1.69112E-17	T	1.69112E-17	T	3.21313E-16	T	1.69112E-17	T	0.743761796	F	1.23875E-13	T
108,070	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	0.112399643	F	7.84275E-13	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	0.108435382	F	3.04233E-14	T
	4	6.76449E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	9.71043E-14	T	3.38225E-17	T	0.008852741	T	1.05795E-11	T
	5	1.69112E-17	T	0.00023663	T	1.69112E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	0.000345682	T	2.41442E-13	T
12,003	2	6.76449E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.18379E-16	T	1.69112E-17	T	0.491525424	F	2.51125E-09	T
	3	1.18379E-16	T	1.69112E-17	T	3.38225E-17	T	3.38225E-17	T	1.5051E-15	T	6.76449E-17	T	0.321911331	F	2.3997E-14	T
	4	1.69112E-17	T	3.52126E-13	T	1.69112E-17	T	1.69112E-17	T	5.93584E-15	T	1.69112E-17	T	0.357693471	F	4.59326E-13	T
	5	1.69112E-17	T	0.001960421	T	1.69112E-17	T	1.69112E-17	T	5.92908E-14	T	1.69112E-17	T	0.886013273	F	4.58971E-14	T
160,068	2	1.07927E-13	T	1.69112E-17	T	1.18379E-16	T	1.69112E-17	T	4.17707E-15	T	1.69112E-17	T	0.362176628	F	7.73702E-09	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	1.69112E-17	T	0.000520581	T	1.18379E-16	T
	4	5.07337E-16	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	2.44051E-12	T	3.38225E-17	T	0.535444629	F	1.41933E-10	T
	5	1.69112E-17	T	0.126316063	F	1.69112E-17	T	1.69112E-17	T	9.25858E-11	T	3.38225E-17	T	0.433045943	F	3.07579E-10	T

Table 26 (continued)

DMEDA VS		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
Image	Th	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value
210,088	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	5.24248E-16	T	1.69112E-17	T	1	F	3.29396E-11	T
	3	3.38225E-17	T	1.69112E-17	T	3.38225E-17	T	1.69112E-17	T	5.40821E-14	T	1.69112E-17	T	0.481720276	F	1.77862E-12	T
	4	3.21313E-16	T	4.24129E-07	T	1.69112E-17	T	1.69112E-17	T	1.15626E-09	T	1.69112E-17	T	0.05512962	F	3.4892E-06	T
	5	1.69112E-17	T	0.840030329	F	1.69112E-17	T	1.69112E-17	T	1.06832E-11	T	3.38225E-17	T	0.085273257	F	1.10706E-12	T
296,059	2	5.07337E-17	T	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	7.62697E-15	T	3.38225E-17	T	1	F	1.26658E-12	T
	3	6.10496E-15	T	4.62691E-14	T	6.76449E-17	T	1.69112E-17	T	1.01533E-11	T	3.21313E-16	T	1	F	6.24329E-09	T
	4	1.69112E-17	T	0.007016085	T	1.69112E-17	T	1.69112E-17	T	1.11614E-15	T	1.69112E-17	T	0.028383448	T	5.07337E-16	T
	5	1.69112E-17	T	0.003359807	T	1.69112E-17	T	1.69112E-17	T	5.7987E-11	T	1.69112E-17	T	1.97639E-09	T	4.57555E-09	T
302,008	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1	F	7.84275E-13	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	2.29993E-15	T	3.38225E-17	T	0.002888566	T	7.32415E-12	T
	4	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.12121E-14	T	1.69112E-17	T	0.01350897	T	4.07502E-12	T
	5	1.69112E-17	T	2.00891E-05	T	1.69112E-17	T	1.69112E-17	T	1.15673E-14	T	1.69112E-17	T	0.006371497	T	1.52784E-11	T
37,073	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.03159E-15	T	5.24248E-16	T	1.69112E-17	T	0.137580083	F	5.07337E-17	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	0.517770828	F	2.04626E-15	T
	4	1.18379E-16	T	2.89289E-11	T	6.76449E-17	T	3.38225E-17	T	2.98111E-13	T	1.18379E-16	T	0.357266794	F	2.38753E-13	T
	5	1.69112E-17	T	0.006261978	T	1.69112E-17	T	1.69112E-17	T	1.4853E-05	T	3.38225E-17	T	0.009485006	T	3.18974E-05	T

Table 26 (continued)

DMEDA VS		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
Image	Th	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value
56,028	2	3.3097E-13	T	1.69112E-17	T	2.02935E-16	T	2.02935E-16	T	6.24194E-14	T	2.02935E-16	T	0.112399643	F	4.08339E-09	T
	3	3.38225E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	4.287E-14	T	1.69112E-17	T	0.432197699	F	2.02641E-12	T
	4	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.99891E-14	T	1.69112E-17	T	0.436892785	F	1.95719E-12	T
	5	1.69112E-17	T	1.37268E-05	T	1.69112E-17	T	1.69112E-17	T	2.89784E-12	T	1.69112E-17	T	0.318539835	F	6.18951E-15	T
66,075	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	5.24248E-16	T	1.69112E-17	T	1	F	5.48993E-12	T
	3	3.38225E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	2.02935E-16	T	1.69112E-17	T	0.803947837	F	1.8604E-13	T
	4	1.69112E-17	T	3.42114E-14	T	3.21313E-16	T	1.18379E-16	T	4.5247E-09	T	1.13305E-15	T	0.016941218	T	2.87321E-06	T
	5	1.69112E-17	T	0.379696272	F	1.69112E-17	T	1.69112E-17	T	1.15673E-14	T	1.69112E-17	T	0.182078697	F	2.49238E-13	T

Table 27 Wilcoxon test over the Kapur's entropy results

DMEDA VS		EDA		CS		GSA		JF		SCA		AHA		OOA		SSA	
Image	Th	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value	p-value	h-value
101,087	2	3.38225E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	5.24248E-16	T	1	F	2.41154E-14	T
	3	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	1.69112E-17	T	7.61006E-16	T	1.69112E-17	T	0.375041917	F	1.29478E-09	T
	4	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.18379E-16	T	1.69112E-17	T	0.019481044	T	1.53723E-14	T
	5	1.69112E-17	T	0.000565106	T	1.69112E-17	T	1.69112E-17	T	3.21313E-16	T	1.69112E-17	T	0.743761796	F	1.23875E-13	T
108,070	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	0.112399643	F	7.84275E-13	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	0.108435382	F	3.04233E-14	T
	4	6.76449E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	9.71043E-14	T	3.38225E-17	T	0.008852741	T	1.05795E-11	T
	5	1.69112E-17	T	0.00023663	T	1.69112E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	0.000345682	T	2.41442E-13	T
12,003	2	6.76449E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.18379E-16	T	1.69112E-17	T	0.491525424	F	2.51125E-09	T
	3	1.18379E-16	T	1.69112E-17	T	3.38225E-17	T	3.38225E-17	T	1.5051E-15	T	6.76449E-17	T	0.321911331	F	2.3997E-14	T
	4	1.69112E-17	T	3.52126E-13	T	1.69112E-17	T	1.69112E-17	T	5.93584E-15	T	1.69112E-17	T	0.357693471	F	4.59326E-13	T
	5	1.69112E-17	T	0.001960421	T	1.69112E-17	T	1.69112E-17	T	5.92908E-14	T	1.69112E-17	T	0.886013273	F	4.58971E-14	T
160,068	2	1.07927E-13	T	1.69112E-17	T	1.18379E-16	T	1.69112E-17	T	4.17707E-15	T	1.69112E-17	T	0.362176628	F	7.73702E-09	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	1.69112E-17	T	0.000520581	T	1.18379E-16	T
	4	5.07337E-16	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	2.44051E-12	T	3.38225E-17	T	0.535444629	F	1.41933E-10	T
	5	1.69112E-17	T	0.126316063	F	1.69112E-17	T	1.69112E-17	T	9.25858E-11	T	3.38225E-17	T	0.433045943	F	3.07579E-10	T
210,088	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	5.24248E-16	T	1.69112E-17	T	1	F	3.29396E-11	T
	3	3.38225E-17	T	1.69112E-17	T	3.38225E-17	T	1.69112E-17	T	5.40821E-14	T	1.69112E-17	T	0.481720276	F	1.77862E-12	T
	4	3.21313E-16	T	4.24129E-07	T	1.69112E-17	T	1.69112E-17	T	1.15626E-09	T	1.69112E-17	T	0.05512962	F	3.4892E-06	T
	5	1.69112E-17	T	0.840030329	F	1.69112E-17	T	1.69112E-17	T	1.06832E-11	T	3.38225E-17	T	0.085273257	F	1.10706E-12	T
296,059	2	5.07337E-17	T	1.69112E-17	T	1.69112E-17	T	3.38225E-17	T	7.62697E-15	T	3.38225E-17	T	1	F	1.26658E-12	T
	3	6.10496E-15	T	4.62691E-14	T	6.76449E-17	T	1.69112E-17	T	1.01533E-11	T	3.21313E-16	T	1	F	6.24329E-09	T
	4	1.69112E-17	T	0.007016085	T	1.69112E-17	T	1.69112E-17	T	1.11614E-15	T	1.69112E-17	T	0.028383448	T	5.07337E-16	T
	5	1.69112E-17	T	0.003359807	T	1.69112E-17	T	1.69112E-17	T	5.7987E-11	T	1.69112E-17	T	1.97639E-09	T	4.57555E-09	T
302,008	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1	F	7.84275E-13	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	2.29993E-15	T	3.38225E-17	T	0.002888566	T	7.32415E-12	T
	4	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.12121E-14	T	1.69112E-17	T	0.01350897	T	4.07502E-12	T
	5	1.69112E-17	T	2.00891E-05	T	1.69112E-17	T	1.69112E-17	T	1.15673E-14	T	1.69112E-17	T	0.006371497	T	1.52784E-11	T
37,073	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.03159E-15	T	5.24248E-16	T	1.69112E-17	T	0.137580083	F	5.07337E-17	T
	3	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	0.517770828	F	2.04626E-15	T
	4	1.18379E-16	T	2.89289E-11	T	6.76449E-17	T	3.38225E-17	T	2.98111E-13	T	1.18379E-16	T	0.357266794	F	2.38753E-13	T
	5	1.69112E-17	T	0.006261978	T	1.69112E-17	T	1.69112E-17	T	1.4853E-05	T	3.38225E-17	T	0.009485006	T	3.18974E-05	T
56,028	2	3.3097E-13	T	1.69112E-17	T	2.02935E-16	T	2.02935E-16	T	6.24194E-14	T	2.02935E-16	T	0.112399643	F	4.08339E-09	T
	3	3.38225E-17	T	1.69112E-17	T	6.76449E-17	T	1.69112E-17	T	4.287E-14	T	1.69112E-17	T	0.432197699	F	2.02641E-12	T
	4	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.99891E-14	T	1.69112E-17	T	0.436892785	F	1.95719E-12	T
	5	1.69112E-17	T	1.37268E-05	T	1.69112E-17	T	1.69112E-17	T	2.89784E-12	T	1.69112E-17	T	0.318539835	F	6.18951E-15	T
66,075	2	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	5.24248E-16	T	1.69112E-17	T	1	F	5.48993E-12	T
	3	3.38225E-17	T	1.69112E-17	T	1.69112E-17	T	1.69112E-17	T	2.02935E-16	T	1.69112E-17	T	0.803947837	F	1.8604E-13	T
	4	1.69112E-17	T	3.42114E-14	T	3.21313E-16	T	1.18379E-16	T	4.5247E-09	T	1.13305E-15	T	0.016941218	T	2.87321E-06	T
	5	1.69112E-17	T	0.379696272	F	1.69112E-17	T	1.69112E-17	T	1.15673E-14	T	1.69112E-17	T	0.182078697	F	2.49238E-13	T

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Data Availability The data used to support the findings are cited within the article. Also, the datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

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References

1. Abd Elaziz M, Ewees AA, Oliva D (2020) Hyper-heuristic method for multilevel thresholding image segmentation. Expert Syst Appl 146:113201
2. Teoh TT, Rong Z (2022) Python for data analysis. In: Artificial Intelligence with Python, pp 107–122. Springer
3. Özbay E, Özbay FA, Gharehchopogh FS (2023) Peripheral blood smear images classification for acute lymphoblastic leukemia diagnosis with an improved convolutional neural network. J Bionic Eng 1–17
4. Chauhan R, Joshi R (2021) Comparative evaluation of image segmentation techniques with application to mri segmentation. In: Proceedings of International Conference on Machine Intelligence and Data Science Applications, pp 521–537, Springer
5. Oliva D, Abd Elaziz M, Hinojosa S (2019) Metaheuristic algorithms for image segmentation: theory and applications. Springer, New York
6. Abd El Aziz M, Ewees AA, Hassanien AE (2017) Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation. Expert Syst Appl 83:242–256 (2017)
7. Houssein EH, Helmy BE-D, Oliva D, Elngar AA, Shaban H (2021) A novel black widow optimization algorithm for multilevel thresholding image segmentation. Exp Syst Appl 167:114159
8. Jiang Z, Zou F, Chen D, Kang J (2021) An improved teaching-learning-based optimization for multilevel thresholding image segmentation. Arab J Sci Eng 46(9):8371–8396
9. Liu C, Liu W, Xing W (2019) A weighted edge-based level set method based on multi-local statistical information for noisy image segmentation. J Vis Commun Image Represent 59:89–107
10. Prathusha, P., Jyothi, S.: A novel edge detection algorithm for fast and efficient image segmentation. In: Data Engineering and Intelligent Computing, pp. 283–291 (2018). Springer
11. Bakkay MC, Chambon S, Rashwan HA, Lubat C, Barsotti S (2018) Automatic detection of individual and touching moths from trap images by combining contour-based and region-based segmentation. IET Comput Vision 12(2):138–145
12. Huang H, Meng F, Zhou S, Jiang F, Manogaran G (2019) Brain image segmentation based on fcm clustering algorithm and rough set. IEEE Access 7:12386–12396
13. Hao S, Zhou Y, Guo Y (2020) A brief survey on semantic segmentation with deep learning. Neurocomputing 406:302–321
14. Asgari Taghanaki S, Abhishek K, Cohen JP, Cohen-Adad J, Hamarneh G (2021) Deep semantic segmentation of natural and medical images: a review. Artif Intell Rev 54(1):137–178
15. Milioto, A., Vizzo, I., Behley, J., Stachniss, C.: Rangenet++: Fast and accurate lidar semantic segmentation. In: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 4213–4220 (2019). IEEE
16. Upadhyay P, Chhabra JK (2021) Multilevel thresholding based image segmentation using new multistage hybrid optimization algorithm. J Ambient Intell Humaniz Comput 12:1081–1098
17. Otsu N (1979) A threshold selection method from gray-level histograms. IEEE Trans Syst Man Cybern 9(1):62–66
18. Merzban MH, Elbayoumi M (2019) Efficient solution of otsu multilevel image thresholding: A comparative study. Expert Syst Appl 116:299–309
19. Zhang, Z., Zhou, N.: A novel image segmentation method combined otsu and improved pso. In: 2012 IEEE Fifth International Conference on Advanced Computational Intelligence (ICACI), pp. 583–586 (2012). IEEE
20. Fengjie, S., He, W., Jieqing, F.: 2d otsu segmentation algorithm based on simulated annealing genetic algorithm for iced-cable images. In: 2009 International Forum on Information Technology and Applications, vol. 2, pp. 600–602 (2009). IEEE
21. Kapur JN, Sahoo PK, Wong AK (1985) A new method for gray-level picture thresholding using the entropy of the histogram. Computer vision, graphics, and image processing 29(3):273–285
22. Manic KS, Priya RK, Rajinikanth V (2016) Image multithresholding based on kapur/tsallis entropy and firefly algorithm. Indian J Sci Technol 9(12):89949
23. Li CH, Lee C (1993) Minimum cross entropy thresholding. Pattern Recogn 26(4):617–625
24. Huang, M., Yu, W., Zhu, D.: An improved image segmentation algorithm based on the otsu method. In: 2012 13th ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing, pp. 135–139 (2012). IEEE
25. Gharehchopogh FS, Ucan A, Ibrikci T, Arasteh B, Isik G (2023) Slime mould algorithm: A comprehensive survey of its variants and applications. Archives of Computational Methods in Engineering 30(4):2683–2723
26. Piri J, Mohapatra P, Acharya B, Gharehchopogh FS, Gerogiannis VC, Kanavos A, Manika S (2022) Feature selection using artificial gorilla troop optimization for biomedical data: A case analysis with covid-19 data. Mathematics 10(15):2742
27. Gharehchopogh FS, Khargoush AA (2023) A chaotic-based interactive autodidactic school algorithm for data clustering problems and its application on covid-19 disease detection. Symmetry 15(4):894
28. Abd Elaziz M, Lu S, He S (2021) A multi-leader whale optimization algorithm for global optimization and image segmentation. Expert Syst Appl 175:114841
29. Brajevic, I., Tuba, M.: Cuckoo search and firefly algorithm applied to multilevel image thresholding. Cuckoo Search and Firefly Algorithm: Theory and Applications, 115–139 (2014)
30. Wong, W., Ming, C.I.: A review on metaheuristic algorithms: recent trends, benchmarking and applications. In: 2019 7th International Conference on Smart Computing & Communications (ICSCC), pp. 1–5 (2019). IEEE
31. Ólafsson S (2006) Metaheuristics. Handbooks Oper Res Management Sci 13:633–654

32. Hammouche K, Diaf M, Siarry P (2008) A multilevel automatic thresholding method based on a genetic algorithm for a fast image segmentation. Comput Vis Image Underst 109(2):163–175
33. Kennedy, J., Eberhart, R.: Particle swarm optimization. In: Proceedings of ICNN'95-international Conference on Neural Networks, vol. 4, pp. 1942–1948 (1995). IEEE
34. Karaboga D (2010) Artificial bee colony algorithm. scholarpedia 5(3):6915
35. Yang, X.-S., Deb, S.: Cuckoo search via lévy flights. In: 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), pp. 210–214 (2009). Ieee
36. Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) Gsa: a gravitational search algorithm. Inf Sci 179(13):2232–2248
37. Ahmadianfar I, Heidari AA, Gandomi AH, Chu X, Chen H (2021) Run beyond the metaphor: An efficient optimization algorithm based on runge kutta method. Expert Syst Appl 181:115079
38. Sarkar, S., Patra, G.R., Das, S.: A differential evolution based approach for multilevel image segmentation using minimum cross entropy thresholding. In: Swarm, Evolutionary, and Memetic Computing: Second International Conference, SEMCCO 2011, Visakhapatnam, Andhra Pradesh, India, December 19-21, 2011, Proceedings, Part I 2, pp. 51–58 (2011). Springer
39. Rahkar Farshi T (2021) Battle royale optimization algorithm. Neural Comput Appl 33(4):1139–1157
40. Gharehchopogh, F.S., Ibrikci, T.: An improved african vultures optimization algorithm using different fitness functions for multilevel thresholding image segmentation. Multimedia Tools and Applications, 1–47 (2023)
41. Wang, W., Duan, L., Wang, Y.: Fast image segmentation using two-dimensional otsu based on estimation of distribution algorithm. Journal of Electrical and Computer Engineering **2017** (2017)
42. Oliva D, Martins MS, Osuna-Enciso V, Morais EF (2020) Combining information from thresholding techniques through an evolutionary bayesian network algorithm. Appl Soft Comput 90:106147
43. Larrañaga, P., Lozano, J.A.: Estimation of Distribution Algorithms: A New Tool for Evolutionary Computation vol. 2, (2001). Springer Science & Business Media
44. Storn R, Price K (1997) Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces. J Global Optim 11(4):341
45. Ceberio, J., Mendiburu, A., Lozano, J.A.: A roadmap for solving optimization problems with estimation of distribution algorithms. Natural Computing, 1–15 (2022)
46. Das S, Suganthan PN (2010) Differential evolution: A survey of the state-of-the-art. IEEE Trans Evol Comput 15(1):4–31
47. Muangkote N, Sunat K, Chiewchanwattana S (2017) Rr-crijade: An efficient differential evolution algorithm for multilevel image thresholding. Expert Syst Appl 90:272–289
48. Liu L, Zhao D, Yu F, Heidari AA, Ru J, Chen H, Mafarja M, Turabieh H, Pan Z (2021) Performance optimization of differential evolution with slime mould algorithm for multilevel breast cancer image segmentation. Comput Biol Med 138:104910
49. Ramadas M, Abraham A (2020) Detecting tumours by segmenting mri images using transformed differential evolution algorithm with kapur's thresholding. Neural Comput Appl 32:6139–6149
50. Gharehchopogh FS, Abdollahzadeh B, Barshandeh S, Arasteh B (2023) A multi-objective mutation-based dynamic harris hawks optimization for botnet detection in iot. Internet of Things 24:100952
51. Shen Y, Zhang C, Gharehchopogh FS, Mirjalili S (2023) An improved whale optimization algorithm based on multi-population evolution for global optimization and engineering design problems. Expert Syst Appl 215:119269
52. Sun J, Zhang Q, Tsang EP (2005) De/eda: A new evolutionary algorithm for global optimization. Inf Sci 169(3–4):249–262
53. Wolpert DH, Macready WG (1997) No free lunch theorems for optimization. IEEE Trans Evol Comput 1(1):67–82
54. Chen, T., Lehre, P.K., Tang, K., Yao, X.: When is an estimation of distribution algorithm better than an evolutionary algorithm? In: 2009 IEEE Congress on Evolutionary Computation, pp. 1470–1477 (2009). IEEE
55. Pelikan M, Sastry K, Goldberg DE (2002) Scalability of the bayesian optimization algorithm. Int J Approximate Reasoning 31(3):221–258
56. Li Y, Han T, Tang S, Huang C, Zhou H, Wang Y (2023) An improved differential evolution by hybridizing with estimation-of-distribution algorithm. Inf Sci 619:439–456
57. Zhou A, Sun J, Zhang Q (2015) An estimation of distribution algorithm with cheap and expensive local search methods. IEEE Trans Evol Comput 19(6):807–822
58. Pang S, Li W, He H, Shan Z, Wang X (2019) An eda-ga hybrid algorithm for multi-objective task scheduling in cloud computing. IEEE Access 7:146379–146389
59. Ren Z, Fang F, Yan N, Wu Y (2022) State of the art in defect detection based on machine vision. International Journal of Precision Engineering and Manufacturing-Green Technology 9(2):661–691
60. Rahaman J, Sing M (2021) An efficient multilevel thresholding based satellite image segmentation approach using a new adaptive cuckoo search algorithm. Expert Syst Appl 174:114633
61. Suresh S, Lal S (2016) An efficient cuckoo search algorithm based multilevel thresholding for segmentation of satellite images using different objective functions. Expert Syst Appl 58:184–209
62. Mühlenbein, H., Paass, G.: From recombination of genes to the estimation of distributions i. binary parameters. In: Parallel Problem Solving from Nature-PPSN IV: International Conference on Evolutionary Computation-The 4th International Conference on Parallel Problem Solving from Nature Berlin, Germany, September 22–26, 1996 Proceedings 4, pp. 178–187 (1996). Springer
63. Larranaga, P.: A review on estimation of distribution algorithms. Estimation of distribution algorithms, 57–100 (2002)
64. Pérez-Rodríguez R (2021) A hybrid estimation of distribution algorithm for the quay crane scheduling problem. Mathematical and Computational Applications 26(3):64
65. Abd Elaziz M, Bhattacharyya S, Lu S (2019) Swarm selection method for multilevel thresholding image segmentation. Expert Syst Appl 138:112818
66. Sharma K, Singh S, Doriya R (2021) Optimized cuckoo search algorithm using tournament selection function for robot path planning. Int J Adv Rob Syst 18(3):1729881421996136
67. Gao S, Wang K, Tao S, Jin T, Dai H, Cheng J (2021) A state-of-the-art differential evolution algorithm for parameter estimation of solar photovoltaic models. Energy Convers Manage 230:113784
68. Kumar A, Biswas PP, Suganthan PN (2022) Differential evolution with orthogonal array-based initialization and a novel selection strategy. Swarm Evol Comput 68:101010
69. Martin, D., Fowlkes, C., Tal, D., Malik, J.: A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In: Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001, vol. 2, pp. 416–423 (2001). IEEE
70. Chou J-S, Truong D-N (2021) A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean. Appl Math Comput 389:125535
71. Zhao W, Wang L, Mirjalili S (2022) Artificial hummingbird algorithm: A new bio-inspired optimizer with its engineering applications. Comput Methods Appl Mech Eng 388:114194

72. Dehghani M, Trojovskỳ P (2023) Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems. Frontiers in Mechanical Engineering 8:1126450
73. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp swarm algorithm: A bio-inspired optimizer for engineering design problems. Adv Eng Softw 114:163–191
74. Mirjalili S (2016) Sca: a sine cosine algorithm for solving optimization problems. Knowl-Based Syst 96:120–133
75. Ahmad MF, Isa NAM, Lim WH, Ang KM (2022) Differential evolution: A recent review based on state-of-the-art works. Alex Eng J 61(5):3831–3872
76. Jena, B., Naik, M.K., Wunnava, A., Panda, R.: A comparative study on multilevel thresholding using meta-heuristic algorithm. In: 2019 International Conference on Applied Machine Learning (ICAML), pp. 57–62 (2019). IEEE
77. Hussein WA, Sahran S, Abdullah SNHS (2016) A fast scheme for multilevel thresholding based on a modified bees algorithm. Knowl-Based Syst 101:114–134
78. Al-Rahlawee ATH, Rahebi J (2021) Multilevel thresholding of images with improved otsu thresholding by black widow optimization algorithm. Multimedia Tools and Applications 80(18):28217–28243
79. Alsahafi YS, Elshora DS, Mohamed ER, Hosny KM (2023) Multilevel threshold segmentation of skin lesions in color images using coronavirus optimization algorithm. Diagnostics 13(18):2958
80. Agrawal S, Panda R, Bhuyan S, Panigrahi BK (2013) Tsallis entropy based optimal multilevel thresholding using cuckoo search algorithm. Swarm Evol Comput 11:16–30
81. Hilali-Jaghdam I, Ishak AB, Abdel-Khalek S, Jamal A (2020) Quantum and classical genetic algorithms for multilevel segmentation of medical images: A comparative study. Comput Commun 162:83–93
82. Aranguren I, Valdivia A, Morales-Castañeda B, Oliva D, Abd Elaziz M, Perez-Cisneros M (2021) Improving the segmentation of magnetic resonance brain images using the lshade optimization algorithm. Biomed Signal Process Control 64:102259
83. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP (2004) Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Process 13(4):600–612
84. Zhang L, Zhang L, Mou X, Zhang D (2011) Fsim: A feature similarity index for image quality assessment. IEEE Trans Image Process 20(8):2378–2386
85. Aja-Fernandez, S., Estepar, R.S.J., Alberola-Lopez, C., Westin, C.-F.: Image quality assessment based on local variance. In: 2006 International Conference of the Ieee Engineering in Medicine and Biology Society, pp. 4815–4818 (2006). IEEE
86. Reisenhofer R, Bosse S, Kutyniok G, Wiegand T (2018) A haar wavelet-based perceptual similarity index for image quality assessment. Signal Processing: Image Communication 61:33–43
87. Wang Z, Bovik AC (2002) A universal image quality index. IEEE Signal Process Lett 9(3):81–84
88. Zimmerman DW (1996) An efficient alternative to the wilcoxon signed-ranks test for paired nonnormal data. J Gen Psychol 123(1):29–40