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Hybrid Whale Optimization Algorithm with Differential Evolution for Color Image Segmentation

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***Abstract*—**The whale optimization algorithm (WOA)

Multilevel thresholding is a very active research field in image segmentation, and has been used in various applications effectively. However, the computational time will increase exponentially as the number of threshold increases, and the quality of segmented images becomes poor as well, color image are even worse. In this paper, a modified dragonfly algorithm based on opposition-based learning(OBLDA) for color image segmentation is proposed to enhance the efficiency and effectiveness of threshold determination process. The optimal threshold values are determined by the maximization of Between-class variance and Kapur's entropy. Opposition-based learning can be valid for applying to initialization stage and updated stage. In order to verity the superiority of the OBLDA, the performance of proposed method is evaluated using ten standard images, and compared with seven meta-heuristic algorithms namely dragonfly algorithm(DA), particle swam optimization (PSO), sine cosine algorithm(SCA), bat algorithm(BA), harmony search algorithm(HSO), ant lion optimization(ALO) and salp swarm algorithm(SSA). And then four indicators, namely PSNR, FSIM, SSIM and the optimal fitness values, are used as quality metrics. The outstanding results reveal that proposed method has the advantages of high accuracy, fast convergence and good stability. A statistical analysis is also performed to proves that the OBLDA outperforms all the other algorithms. Hence, the OBLDA algorithm is a feasible and effective method for multilevel color image segmentation.

***Index Terms*—**Image segmentation, dragonfly algorithm, , Opposition-based learning, Kapur's entropy and Otsu method.

I. Introduction

Image segmentation is a vital processing stage of object recognition and robotic vision. In other words, it can be considered as a technique which partitions the components of an image into several distinct and disjoint regions with respect to some features such as color or texture, and then extracts the interested objects or meaningful contours. In general, the quality of the segmentation results has a major impact on the subsequent processes such as image classification and autonomous target recognition. Each of the pixels in the same region is homogeneous whereas the adjacent regions vary greatly based on the measurement of certain characteristics[1]. The fundamental goal of image segmentation is to simplify or change the representation of the given image, making it easier for human visual observation and analysis. Nowadays, image segmentation technique has already become a widespread application in various fields and more intensive researches are carried out continually[2].

In the last few years, a great variety of methods has been proposed for image segmentation , which can be summarized as four types, including region-based method , clustering-based method, graph-based method and thresholding-based method[3]. The criterion of the region-based method is that the entire image is divided into lots of subregions continuously ,and then the subregions with similar characteristics are merged to obtain objectives[4]; the clustering-based method divides the image pixels into several sub-collections based on the similarity such as K-means and hierarchical clustering algorithm[5]; in the graph-based method, the global segmentation and local information processing can be combined together based on the good correspondence between image and graph theory features[6]; thresholding-based method, employing the image histogram, classifies the image pixels into corresponding regions by comparing with threshold values[7]. Thereinto thresholding is the most popular compared with the existing methods because of its simple implementation and high accuracy, which composes of bi-level and multilevel segmentation depending on the number of thresholds[8]. Bi-level segmentation means a given image should be segmented into two classes with a single threshold value, namely, object and background. Nevertheless, it is difficult to select a preeminent threshold when the histogram of image is multi-modal. Hence, in order to improve the universality and practicability of thresholding-based method, some scholars and researchers extend bi-level into multi-level thresholding which subdivides a given image into several non-overlapping classes with multiple threshold values.

Numerous techniques based on respective criteria has been developed for getting appropriate thresholds during the last couple of decades. They can be divided into two different categories: global and local. Otsu's method and Kapur's entropy which belongs to the former are the most widely used ones[9]. Otsu [10]proposed a available method which selects the optimum values for thresholds by maximizing between class variance of each segmented class in 1979. Kapur's method was presented by Kapur in 1985[11], which is used to classify image into multiple classes by comparing the entropy of histogram, a higher entropy value indicates the more homogeneous the classes are. However, the foremost restriction among the available techniques is the computational time will increase when the number of thresholds increases[12]. Hence, further researches are proceeding in multilevel thresholding image segmentation to enhance the performance of methods.

The purpose of optimization is to find the optimal solutions which are more realistic and feasible for a specific problem under certain constraints. The process of finding optimal thresholds for image segmentation can be regarded as a single-objective optimization problem. Over the years lots of swarm intelligence algorithm inspired by nature have been applied to the calculation of object function in the optimization model. Many of them have wide application of multilevel thresholding image segmentation to reduce the time complexity and increase accuracy effectively, such as Lifang He and Songwei Huang proposed a modified firefly algorithm (MFA) based on the processing of mutual attraction and movement in the swarm for color image segmentation, using between-class variance, Kapur's entropy and minimum cross entropy techniques[13]. Abdul Kayon Md Khairuzzaman and Saurabh Chsudhury applied the grey wolf optimizer(GWO) to image segmentation, using the Otsu's method and Kaour's method[14]. In addition, particle swarm optimization(PSO)[15], bacterial foraging optimization(BFO)[16], bat algorithm(BA)[17], whale optimization algorithm(WOA)[18], artificial bee colony(ABC)[19] and cuckoo search algorithm(CSA)[20] are also used extensively in multilevel thresholding segmentation.

The Dragonfly Algorithm (DA) is a swarm-based algorithm which was proposed in 2015 by Mirjalili[21]. The main inspiration of the DA algorithm is two different behaviors of dragonflies, static and dynamic. In static swarm, the dragonflies form several small groups which are characterized as local movements and abrupt changes in flying path, and afterwards they fly in all directions over a small area to search for food sources. Meanwhile in dynamic swarm, a large number of the dragonflies fly along one direction with the purpose of migrating. Static and dynamic swarming behaviors are similar to the exploration and exploitation phases of meta-heuristic optimization. The position of each dragonfly in the search space denotes a solution in optimization process. Many real applications of the DA have been found in various areas such as medical image analysis[22] and optimization of PID controller[23], meanwhile the simulation results proved strong robustness and high accuracy of the DA algorithm.

It is evident that color images contain more information compared with gray images, highlighting the difficulty of color image segmentation. And there are some drawbacks of the standard DA algorithm mentioned as follow: premature convergence because of its fast convergence speed, escaping from local optimal solution with difficulty[24]. In order to enhance the performance of the traditional DA algorithm as well as provide an efficient method to solve the problems in multilevel color image segmentation, a modified dragonfly algorithm based opposition-based learning(OBLDA) is presented in this paper. The advantages of proposed method include ability to fast convergence to the global optimal solution, powerful optimizing ability, higher optimizing precision and good stability. Between-class variance and Kapur's entropy are used as objective functions which will be maximized to find the optimal thresholds. We choose DA, PSO, SCA, BA, HSO, ALO, and SSA as comparison algorithms. Furthermore, four indicators, the peak signal-to noise ratio(PSNR), the feature similarity index(FSIM), the structure similarity index (SSIM) and the optimal fitness values are used as quality metrics to compare the segmentation performance of proposed algorithm with other algorithms. A statistical analysis is also performed to see the merits of OBLDA is superior to all the other algorithms.

The reminder of this paper is organized as follows: Section II introduces between-class variance and Kapur's entropy techniques for multilevel thresholding briefly. Section III gives an overview of the standard dragonfly algorithm. Section IV describes the proposed method based on opposition-based learning, and it can be effectively applied to initialization stage and updated stage. Section V presents a description of experiment in detail. Subsequently, the experimental results of proposed algorithm compared to other algorithms and its analysis in terms of four indicators are discussed in Section VI. Finally, the conclusion is illustrated in Section VII.

II. Multilevel thresholding

In this section, we introduce two most widely used image thresholding techniques, including Otsu's method which is based on between class variance and Kapur's method which is based on the criterion of entropy. There are two categories in image segmentation: bi-level and multilevel. We will provide a brief formulation in the following subsections.

A. Otsu Method

Otsu method selects the optimum values of thresholds by maximizing between class variance of each segmented class[25]. It can be defined as follows: assume that L denotes the number of gray levels in a given image so that the range of intensity values is $[0,\ L\text{-}1]$. N is the total number of pixels, and then n_i represents the number of pixels in which gray level is i

$$N = \sum_{i=0}^{L-1} n_i \tag{1}$$

The probability of each gray level i is calculated as follows:

$$p_i = \frac{n_i}{N}\ \ (p_i \geq 0) \tag{2}$$

The optimum threshold t partitions the given image into two classes, namely, foreground and background, which can be described as follows:

$$\begin{cases} D_1 = \{g(x,y) \mid 0 \leq g(x,y) \leq t\} \\ D_2 = \{g(x,y) \mid t+1 \leq g(x,y) \leq L-1\} \end{cases} \tag{3}$$

The between class variance of two classes can be described using the following equation:

$$\sigma_B{}^2(t) = P_0 \times (m_0 - m_G)^2 + P_1 \times (m_1 - m_G)^2 \tag{4}$$

where

$$P_0 = \sum_{i=0}^{t} p_i \qquad P_1 = \sum_{i=t+1}^{L-1} p_i$$

$$m_0 = \frac{1}{P_0}\sum_{i=0}^{t} ip_i \qquad m_1 = \frac{1}{P_1}\sum_{i=t+1}^{L-1} ip_i$$

$$m_G = \sum_{i=0}^{L-1} ip_i$$

P_0 and P_1 denote the cumulative probabilities of foreground and background respectively. m_0 and m_1 represent the mean level of two classes respectively. m_G is the mean level of given image.

Eq.(4) is maximized to obtain the optimal threshold t^* for image segmentation which is describe by:

$$t^* = \underset{0 \leq t \leq L-1}{\arg} \max\left(\sigma_B^t(t)\right) \tag{5}$$

Further, Otsu's method can be effectively extended for multilevel thresholding problems. Assume that the given image is subdivided into n classes so that there are n - 1 optimal thresholds for maximizing the objective function. The classes are described by:

$$\begin{cases} D_0 = \{g(x,y) \mid 0 \leq g(x,y) \leq t_1 - 1\} \\ D_1 = \{g(x,y) \mid t_1 \leq g(x,y) \leq t_2 - 1\}, \cdots \\ D_i = \{g(x,y) \mid t_{i-1} \leq g(x,y) \leq t_i - 1\}, \cdots \\ D_{n-1} = \{g(x,y) \mid t_{n-2} \leq g(x,y) \leq t_{n-1} - 1\} \end{cases} \tag{6}$$

The cumulative probabilities of each class is calculated by :

$$P_k = \sum_{i=T_k}^{T_{k+1}-1} p_i \ \ (k = 0, 1, \cdots, n-1) \tag{7}$$

The mean level of each class is defined as follows:

$$\mu_k = \frac{1}{P_k}\sum_{i=T_k}^{T_{k+1}-1} ip_i \ \ (k = 0, 1, \cdots, n-1) \tag{8}$$

The mean level of whole image is defined as follows:

$$\mu = \sum_{i=0}^{L\text{-}1} ip_i \tag{9}$$

The objective function based between-class variance is calculated by:

$$\sigma_B^2(t) = \sum_{k=0}^{n-1} P_k (\mu_k - \mu)^2 \tag{10}$$

The optimum thresholds $t^*\left(t_1,t_{2,}\cdots t_n\right)$ are obtained by maximizing the between-class variance objective function. A higher value of objective function refers to a better quality of the segmented images.

B. Kapur's Entropy

The Kapur's method was proposed by Kapur, which is used to determine the optimal thresholding values based on the maximization of Kapur's entropy. It has attracted the interest of a lot of researchers because of its superior performance and been widely applied to solve image segmentation problems. The entropy of a given image represents the compactness of each distinctive and separateness among classes[26].

Let N be the number of pixels and L be the number of levels in a given image. We can describe the probability p_i of each gray level i as follows:

$$p_i=\frac{h_i}{\sum_{i=0}^{L-1}h\left(i\right)} \tag{11}$$

where h_i denotes the number o pixels with gray level i

For bi-level thresholding, The Kapur's entropy objective function is defined using the following equation:

$$f\left(t\right)=H_0+H_1 \tag{12}$$

where

$$H_0=-\sum_{t=0}^{t-1}\frac{p_i}{\omega_0}\ln\frac{p_i}{\omega_0},\ \omega_0=\sum_{i=0}^{t-1}p_i$$

$$H_1=-\sum_{i=t}^{L-1}\frac{p_i}{\omega_1}\ln\frac{p_i}{\omega_1},\ \omega_1=\sum_{i=t}^{L-1}p_i$$

The Kapur's method finds the optimal threshold t^* by maximizing the objective function, that is

$$t^*=\underset{0\le t\le L-1}{\arg}\ \max\left(f\left(t\right)\right) \tag{13}$$

The Kapur's method can be also extended to multi-level thresholding, which can find the n optimal thresholds $\left(t_1,t_{2,}\cdots t_n\right)$ based on the Kapur's entropy maximization.

$$f\left(t_1,t_2,\ldots\ldots,t_n\right)=H_0+H_1\ldots H_n \tag{14}$$

where

$$H_0=-\sum_{t=0}^{t_1-1}\frac{p_i}{\omega_0}\ln\frac{p_i}{\omega_0},\ \omega_0=\sum_{i=0}^{t_1-1}p_i$$

$$H_1=-\sum_{i=t_1}^{t_2-1}\frac{p_i}{\omega_1}\ln\frac{p_i}{\omega_1},\ \omega_1=\sum_{i=t_1}^{t_2-1}p_i$$

$$H_2=-\sum_{i=t_2}^{t_3-1}\frac{p_i}{\omega_2}\ln\frac{p_i}{\omega_2},\ \omega_2=\sum_{i=t_2}^{t_3-1}p_i,\cdots$$

$$H_n=-\sum_{i=t_n}^{L-1}\frac{p_i}{\omega_n}\ln\frac{p_i}{\omega_n},\ \omega_n=\sum_{i=t_n}^{L-1}p_i$$

The optimal thresholds are found by maximizing the objective function, that is:

$$t^*=\underset{0\le t\le L-1}{\arg}\ \max\left(f\left(t_1,t_2,\ldots\ldots t_n\right)\right) \tag{15}$$

However, the foremost restriction between Otsu's and Kapur's methods is that the computational time is increasing exponentially as the number of thresholds increases. Hence, it is time-consuming practically for multilevel image segmentation applications. In order to overcome the above shortcomings, this paper presents a new method based on the modified Dragonfly Algorithm to find the optimal thresholds. The purpose of proposed method is to find the optimal thresholds accurately by maximizing the objective function using Otsu's and Kapur's techniques in less processing time.

III. Dragonfly algorithm

The Dragonfly Algorithm (DA) is a swarm-based algorithm which was proposed in 2015 by Mirjalili[21]. The main inspiration of the DA algorithm is two different swarming behaviors of dragonflies, static and dynamic. In static swarm, the dragonflies form several small groups which are characterized as local movements and abrupt changes in flying path, and afterwards they fly in all directions over a small area to search for food sources. Meanwhile in dynamic swarm, a large number of the dragonflies fly along one direction with the purpose of migrating. Static and dynamic swarming behaviors are similar to the exploration and exploitation phases of meta-heuristic optimization. The position of each dragonfly in the search space denotes a solution in optimization process.

Reynolds proposed that the behavior of swarms consists of three primitive principles, which are set as follows:

Separation: This mechanism avoids the static collision among individuals in the same neighborhood.

Alignment: This process denotes how an individual matches its velocity with the other neighboring individuals.

Cohesion: This procedure refers to the tendency of the individuals towards the neighboring center of the mass.

The principles can be also adapted to the DA algorithm, besides, in order to model the swarming behavior of dragonflies in detail, two behaviors, the individuals of the swarm should be attracted towards food sources and diverted away from enemies, are also taken into account. Hence, the position of each dragonfly is updated by five different type of actions, which are mathematically modeled as Eq. (16)-(20). The two dragonflies are in the same neighborhood, in which the distance between them is less than the radii of neighborhood, on the contrary, they will be not in the same neighborhood. Meanwhile the radii of neighborhoods increases linearly with the number of iterations to improve the algorithm convergence until all the dragonflies become one group at the final phase of optimization. It is calculated by Eq. (21).

1) Separation: $$S_i = \sum_{j=1}^{W} \left(X - X_j\right) \tag{16}$$

where X denotes the position of the current dragonfly. X_j denotes the j-th position neighboring dragonfly, and W is the number of neighboring dragonflies.

2) Alignment: $$A_i = \frac{\sum_{j=1}^{W} V_j}{W} \tag{17}$$

where V_j is the velocity of the j-th neighboring dragonfly.

3) Cohesion: $$C_i = \frac{\sum_{j=1}^{W} X_j}{W} - X \tag{18}$$

where X represents the position of the current dragonfly. X_j represents the j-th position neighboring dragonfly, and W is the number of neighboring dragonflies.

4) Attraction towards a food source:

$$F_i = X^+ - X \tag{19}$$

where X shows the position of the current dragonfly, and X^+ shows the position of the food source ,and it is chosen from the best dragonfly that the swarm has found up to now.

5) Distraction outwards an enemy:

$$E_i = X^- + X \tag{20}$$

where X denotes the position of the current dragonfly, X^- denotes the position of the enemy , and it is chosen from the worst dragonfly that the swarm has found up to now.

$$r = \Delta b/4 + \left(\Delta b * \left(t/max\_iteration\right) * 2\right) \tag{21}$$

where $\Delta b = ub - lb$, ub and lb are the upper and lower bound of search space. $max\_iteration$ represents the max iteration, and t is the current iteration counter.

The velocity vector which can denote the direction of the movement of the dragonflies is calculated as follows:

$$\Delta X_{t+1} = \left(sS_i + aA_i + cC_i + fF_i + eE_i\right) + \omega \Delta X_t \tag{22}$$

where s, a, c, f , and e denote weight factor for separation , alignment, cohesion, attraction towards a food source, and distraction outwards an enemy, respectively, ω shows the inertia weight. The above swarming parameters will adjust adaptively in DA algorithm for the purpose of balancing exploration and exploitation. t is the current iteration counter.

The position of dragonfly is updated by

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{23}$$

When there is no neighboring individuals, the behavior of dragonflies are assumed to be a random walk (Le′vy flight) around the search place to enhance randomness, stochastic behavior and exploration. The position of dragonfly is updated as follows

$$X_{t+1} = X_t + \text{Levy}(d) \times X_t \tag{24}$$

Where t is the current iteration, and d represents the dimension of position vectors.

The Le′vy flight is mathematically modeled using the following equation.

$$\text{Levy}(d) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{1/\beta}} \tag{25}$$

Where r_1 and r_2 are the random numbers in between 0 and 1. β is a constant which equal to 1.5[], and σ is mathematically modeled as follows：

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\beta\pi}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{1/\beta} \tag{26}$$

Initialize the position of dragonflies population $X_i\,(i=1,2,\ldots,\ n)$ based on opposition-based learning.
Initialize step vectors $\Delta X_i\,(i=1,2,\ldots,n)$.
WHILE the end condition is not satisfied
FOR $i=1:n$
Calculate the objective value of each dragonfly by using the Eq. (10) for Between-class variance or Eq. (14) for Kapur's entropy.
Update the position of the food source X_f and enemy X_e
Update $w, s, a, c, f,$ and e
Calculate $S, A, C, F,$ and E using Eqs. (16) to (20)
Update neighbouring radius
IF a dragonfly has at least one neighboring dragonfly
Update velocity vector using Eq. (22)
Update position vector using Eq. (23)
ELSE
Update position vector using Eq. (24)
END IF
Select half of dragonflies from the current population randomly, and the opposition-based learning is embedded in them.
Check and correct the new positions based on the boundaries of variables
END FOR
END WHILE
Return X_f, which represents the optimal values for multilevel thresholding segmentation.

IV. The proposed method (OBLDA)

A. The Opposition-based Learning

The Opposition-based Learning (OBL), which considers the current solution and opposite solution simultaneously to accelerate the convergence of meta-heuristic methods[27]. On the basis of probability theory, there is a fifty-fifty chance that distance between the current solution and optimal solution is farther than its corresponding opposite. Hence, we can utilize the concept of OBL to obtain a higher chance for approaching the promising regions. In general, the initial solutions are created randomly which are absence of priori knowledge about the solution. In addition, the convergence of the meta-heuristic methods will be time-consuming when they are far away from the optimal solution. The application of OBL can solve the problem in initialization effectively, meanwhile the OBL also provides a strategy to search for the closer solution in the current population.

Let $x\in[\mu,l]$ be a real number, and its corresponding opposite, x', is calculated as follow[]:

$$x'=\mu+l-x \tag{27}$$

The above mathematical model can be also extended to the higher dimension, which has been given in the following definition.

Let $x_{ij}\left(x_{i1},x_{2j},\cdots,x_{iD}\right)$ be a point in D-dimensional space, and the opposite of x_{ij} is calculated by $x_{ij}^*\left(x_{i1}^*,x_{i2}^*,\cdots,x_{iD}^*\right)$ as follow[-]:

$$x_{ij}^*=k\left(a_j+b_j\right)-x_{ij} \tag{28}$$

Where a_j and b_j are predefined as the lower and the upper bound of the search place respectively. k represents the type of OBL.

B. Opposition-based optimization in the OBLDA

The standard dragonfly algorithm is a simple yet practical method in optimization, but there are some drawbacks mentioned as follow: premature convergence because of its fast convergence speed, trapping into local optimal solution, and having trouble in accurately converging to global optimal solution. In order to enhance the performance of the traditional DA algorithm as well as provide an efficient method to solve the problem in multilevel color image thresholding segmentation, a modified dragonfly algorithm based the opposition-based learning is proposed in this paper.

According to the IBLDA, the opposition-based learning can be employed in two stages of the standard DA effectively. Firstly, the OBL is embedded to the initialization of population to improve the diversity of dragonflies, and then the OBLDA algorithm can obtain fitter initial solutions which can help converge to global optimal solution accurately. Secondly, in the updating phase of the DA algorithm, the OBL is used in half of the current population randomly to check if the current solution is fitter than its corresponding opposite, increasing the randomness of algorithm while saving more optimizing time.

a. Initialization stage

The proposed method takes a random population X of size N as its initial solutions. The OBL is used to computed the opposite solution for each member. The steps of initialization are shown as follows:

1) Initialize the population X with a size of N randomly.

2) Calculate the opposite population x_{ij}^* as:

$$x_{ij}^* = k\left(a_j + b_j\right) - x_{ij} \quad \left(i = 1,2,\cdots,N;\ j = 1,2,\cdots,D\right) \qquad (29)$$

3) Select a fitter one between x_{ij} and x_{ij}^* based on fitness function values to construct a new initial population.

b. Updated stage

In this stage, we select half of dragonflies from current population randomly which will be embedded in the OBL, and then compute their fitness functions respectively based on the DA to choose the best solutions from $x_{ij} \cup x_{ij}^*$. a new population will be generated using the OBLDA algorithm in each iteration. All the steps will carry out constantly until the end conditions are reached. The proposed method is illustrated in Fig1.

Besides, the flowchart of WOA-DE for finding the optimal threshold values is shown in Fig. 2.

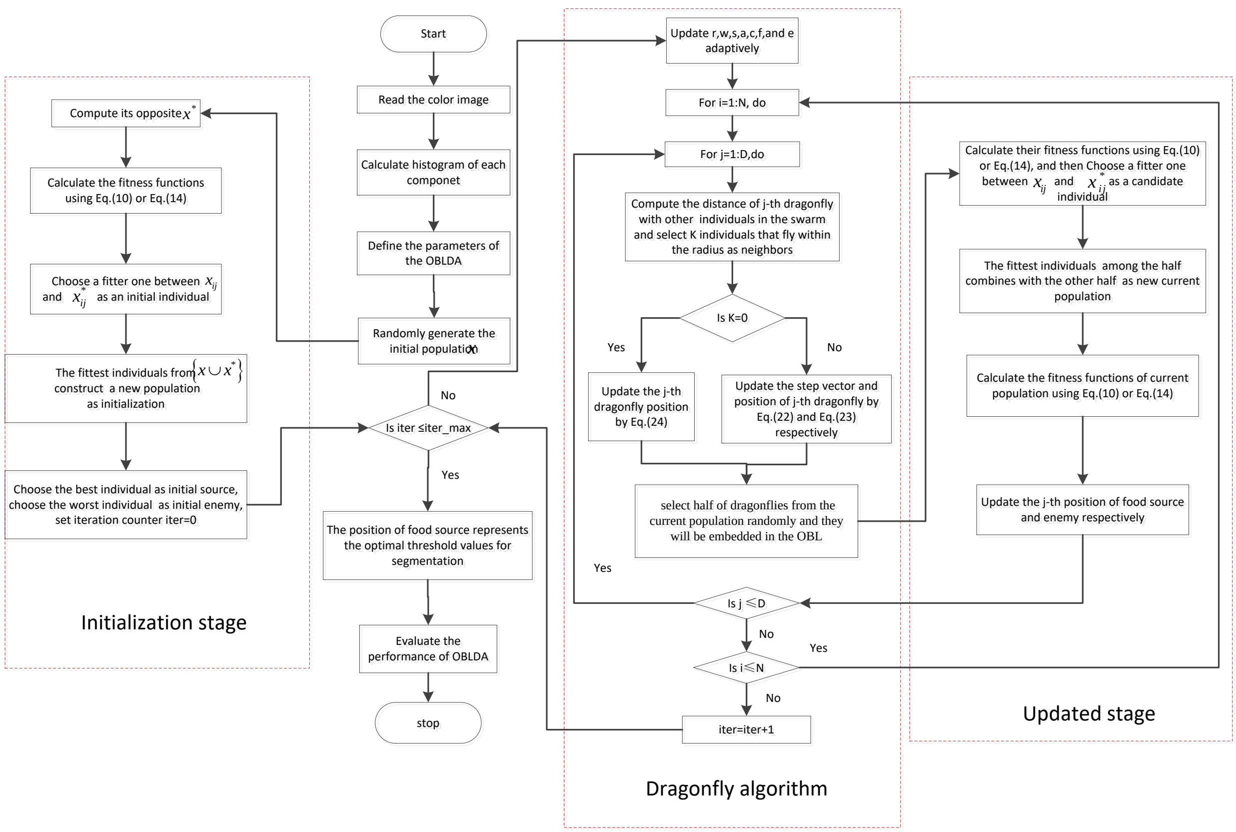


Fig. 2. **Framework of the OBLDA based method**

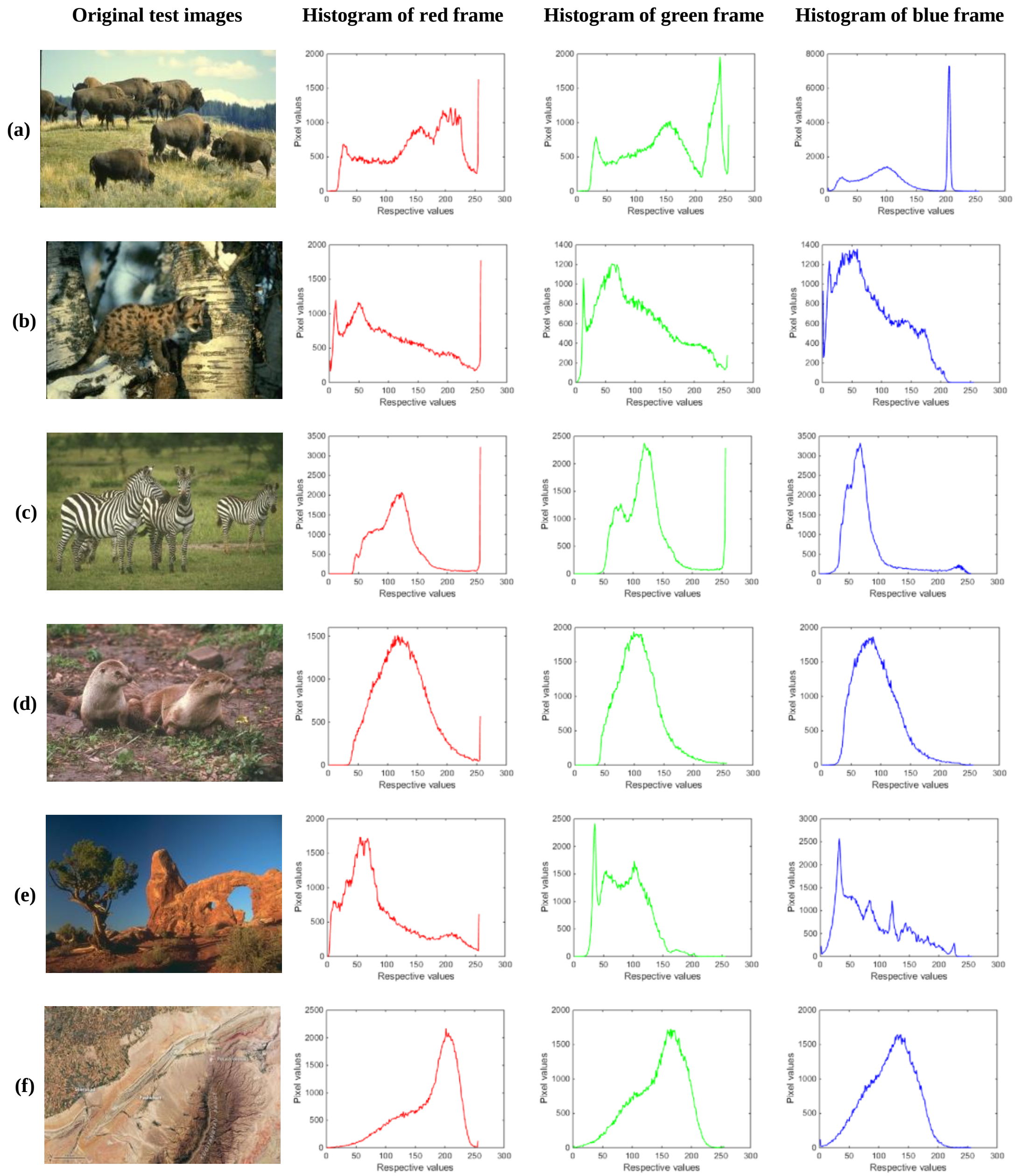
Fig. 4. **Schematic diagram of the change in random variable A**

V. Experiments

In this section, firstly, we present a brief description of the experimental setup associated with multilevel thresholding. Then we show the parameter values which are used in all algorithms. Finally, in order to compare the segmentation performance of the proposed algorithm with other algorithms ,four indicators, PSNR, FSIM, SSIM, the optimal fitness function values, are used as quality metrics.

A. Experimental Setup

In this paper, the proposed algorithm is tested on ten standard color images, namely Image1, Image2, Image3, Image4, Image5, Image6, Image7, Image8, Image9, and Image10, respectively. Images 1-5 are taken from the database of Berkeley University (Martin, Fowlkes, Tal, & Malik, https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/BSDS300/html/dataset/images.html,which are of size 481×321,and satellite images 6-10 are taken from https://landsat.visibleearth.nasa.gov/index.php?&p=1. which are also of size 481×321. Besides, all the test images and their corresponding histogram images are presented in Fig. 5. Performance of the proposed algorithm associated with Kapur's entropy and Otsu's method is compared with seven widely used optimization algorithms, namely, DA,PSO,SCA,BA, HSO, ALO, and SSA. All experiments are performed on the images with the following number of thresholds:4, 6, 8, 10, and 12.



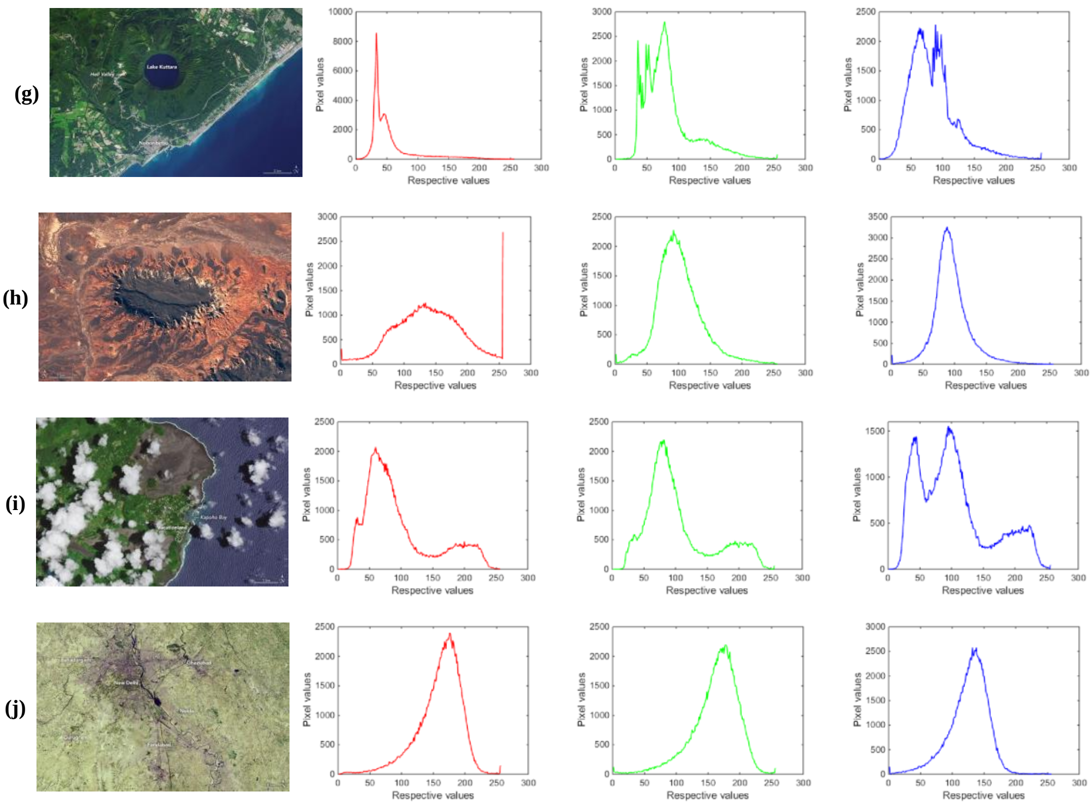


Fig. 5. Original test images named 'Image1', 'Image2', 'Image3', 'Image4', 'Image5', 'Image6', 'Image7', 'Image8', 'Image9', and 'Image10' respectively and the corresponding histograms for each of color channels (Red, Green, and Blue).

B. Parameter setting

As we know, the value of parameters is of significance in determining the performance of each algorithm. In this paper, all algorithms have the same stopping conditions for a fair comparison. The max iteration is 500 with a total of 30 runs each algorithm, and the population size is set to be 30. The parameters of all algorithms are presented in Table 1.

All the algorithms are developed by using " Matlab 2014b" and implemented on "Windows 10-64bit" environment on a computer having Pentium(R) Dual core T4500 @ 2.30 GHz and 2 GB of memory.

C. Segmented image quality metrics

a. The Peak Signal-to-Noise Ratio (PSNR)

The parameter of PSNR based on the produced mean square error (MSE) is used to verify the difference of the original image and segmented image[28] , and the value refers to the quality of the segmented image. The PSNR is evaluated by Eq. (30).

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{30}$$

Where

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j) - K(i,j)\right]^2$$

Where $I(i,j)$ and $K(i,j)$ are the original and segmented images which are of size $M \times N$

b. The Feature Similarity Index (FSIM)

A comparison of the features contained in the segmented image is performed using the FSIM and it is calculated as Eq. (31). A higher FSIM value indicates a higher segmentation accuracy of the original image[29].

$$FSIM = \frac{\sum_{x\in\Omega} S_L(x) \times PC_m(x)}{\sum_{x\in\Omega} PC_m(x)} \tag{31}$$

where, Ω represents the entire domain of the image.

$PC_m(x)$ is defined as Eq. (18).

$$PC_m(x) = max(PC_1(x), PC_2(x)) \quad (32)$$

where, $PC_1(x)$ and $PC_2(x)$ represent the phase congruence of the original and segmented images, respectively.

The value of $S_L(x)$ is defined as follows:

$$S_L(x) = [S_{PC}(x)]^{\alpha} \cdot [S_G(x)]^{\beta} \quad (33)$$

where

$$S_{PC}(x) = \frac{2PC_1(x) \times PC_2(x) + T_1}{PC_1^2(x) \times PC_2^2(x) + T_1}$$

$$S_G(x) = \frac{2G_1(x) \times G_2(x) + T_2}{G_1^2(x) \times G_2^2(x) + T_2}$$

$S_{PC}(x)$ is the similarity of phase consistency between two images, $S_G(x)$ is the similarity of gradient magnitude between two images, $G_1(x)$ and $G_2(x)$ are the gradient magnitude of the original and segmented images, respectively. α, β, T_1 and T_2 are all constants

c. The Structure Similarity Index (SSIM)

The SSIM index, helps to access the structural similarity between the original and segmented image[30]. The SSIM is defined as:

$$SSIM(x,y) = [l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma} \quad (34)$$

Where, $l(x,y)$, $c(x,y)$,and $s(x,y)$ represent brightness comparison, contrast comparison and structural information comparison function respectively. α, β , and γ are three parameters which is decided by the weight of the three parts. The functions are evaluated by

$$\begin{cases} l(x,y) = \dfrac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \\ c(x,y) = \dfrac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \\ s(x,y) = \dfrac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \end{cases} \quad (35)$$

where μ_x and μ_y represent the average intensity of the original and segmented images respectively. σ_x^2 and σ_y^2 represent the variance of the original and segmented images respectively. σ_{xy} is the covariance between the original and segmented images. C_1, C_2 ,and C_3 are set as follows: 6.5025, 58.5525, and 29.2613 respectively considering experiments of [31]

d. The Optimal Fitness Function Values by Eq.(10) or Eq.(14)

VI. The results and discussions

In this section, we present the experimental results of the proposed algorithm compared to other algorithms based Kapur's method and Otsu's method, and its analysis in terms of PSNR, FSIM,SSIM, and the optimal fitness function values. A statistical analysis is also performed to see the advantage of the proposed algorithm outperforms all the other algorithms. All these are discussed in the following section.

A. Segmentation Accuracy

The optimal threshold values for each of the color component as obtained by all algorithms are shown in Figs. 5 and 6. In order to evaluate the quality of the segmented images quantitatively, four indicators, PSNR, FSIM, SSIM, and fitness value, are used in this paper. And the convergence curves for fitness function using Otsu method compared with other seven algorithms at 12 levels thresholding are shown in Fig.

First of all, the PSNR index based on the grayscale information is used to estimate the degree of image distortion. The PSNR index values of the segmented images obtained by OBLDA, DA, PSO, SCA, BA, HSO, ALO and SSA algorithm based on between-class variance and Kapur's entropy are given in Tables 1-2 and Figs 5-6. PSNR index gives a higher value when the degree of image distortion is small, A comparative analysis of the results indicates that all the algorithms performed nearly close when K=4, however, the proposed algorithm still shows certain superiority over the other algorithms (such as Images 3 and 9). For instance, the PSNR values are 17.7278, 17.4278, 17.2685, 17.2833, 17.4849, 17.2554, 17.7270 and 17.7068 for OBLDA, DA, PSO, SCA, BA, HSO, ALO and PSO, respectively, when the segmentation operation of Image3 using Otsu's method. As the number of thresholds increases, the PSNR values also increases for all algorithms, and the advantage of proposed algorithm is becoming more and more remarkable. It is evident that the proposed algorithm based on between-class variance or Kapur's entropy for different threshold values is superior in performance to the other algorithms compared.

Then, the FSIM index based on phase consistency and spatial gradient feature is used to compare the quality of the segmented images and the range is [0,1]. The FSIM values achieved using Kapur and Otsu method based OBLDA, DA, PSO, SCA, BA, HSO, ALO ,and SSA are shown in Tables

1-2 and Figs 5-6.From the experiment results it is clearly observed that the proposed algorithm outperforms all the other algorithms for each benchmark image since the FSIM index in all cases obtain the highest values. Hence, the OBLDA algorithm using Kapur's entropy and Otsu's method has better quality for multilevel color image thresholding segmentation compared to other algorithms. For example, the FSIM index values in case of Image 10 with ten thresholds based Kapur's method are 0.9737, 0.9725, 0.9726, 0.9707, 0.9651, 0.9705, 0.9726, and 0.9731 for OBLDA, DA, PSO, SCA, BA, HSO, ALO, and PSO, respectively. Through experimental results comparison and Figs.7 and 8. It is no doubt that the FSIM value of the OBLDA associated with Kapur's and Otsu's method is largest and has the smallest gap with 1. The experiments also indicates that the proposed algorithm has high optimization accuracy and improves the segmentation quality.

After that, the SSIM index based on brightness, contrast and structural information is used to assess the visual similarity of the original image and the segmented image. The SSIM index values of the segmented images using Kapur and Otsu method obtained by all algorithms are given in Tables 1-2 and Figs 5-6.A higher value of SSIM index indicates that the segmented image is more similarity to the original image. It can be seen from Tables 1-2 and Figs 5-6 that, for the same image segmentation, the proposed algorithm achieves the best results which are more competitive in the SSIM values. At the same time, as the number of thresholds increases, the value of SSIM is keep increasing, as well as all algorithms can obtain more original image information Hence, we can extract the interested objects more accurately, and the segmented images is more similar to the original images visually. For example, the SSIM values of Image 2 using Otsu's methods (OBLDA) are 0.6805, 0.7857, 0.8364, 0.8798 and 0.9031 for the number of thresholds is 4, 6, 8, 10, 12, respectively, as a contrast, the SSIM values of Image 2 using Otsu's methods (DA) are 0.6775, 0.7754, 0.8354, 0.8788 and 0.9004 for the number of thresholds is 4, 6, 8, 10, 12, respectively.

Last but not the least, Between-class variance method and Kapur's entropy is used as the objective function that is maximized based on OBLDA, DA, PSO, SCA, BA, HSO, ALO and SSA. Tables 1-2 and Figs 5-6 present the optimal fitness function values based multilevel thresholding after application of all algorithms, the higher value of optimal fitness function lead to better solution. These values indicate that performance of the proposed algorithm is the most outstanding, for almost all the cases when compared to DA, PSO, SCA, BA, HSO, ALO and SSA, it can improve segmentation accuracy while ensuring algorithm stability. For instance, the optimal fitness function values are 33.6991, 33.3882, 33.3775, 32.1851, 31.6970, 33.4260, 33.5922 and 33.4392 for OBLDA, DA, PSO, SCA, BA, HSO, ALO and SSA, respectively, when Kapur's method is applied on Image 7, the optimal fitness function value of OBLDA algorithm is the highest and the ALO algorithm comes at the second rank followed by SSA. The experiment results also show that the proposed algorithm not only has advantage of multidimensional function for extremum problems, but also shows strong engineering practicability in color image segmentation.

Through the above analysis, the proposed algorithm using Kapur's method and Otsu's method provide a great balance between exploitation and exploration in ten benchmark images at low and high threshold numbers. The performance of the OBLDA based multilevel thresholding for color image segmentation is satisfactory, for the reason that the segmented images has high quality and accuracy. It is evident the proposed algorithm can be effectively for solving color image segmentation problems.

B. Statistical analysis

A non-parametric statistical based on Wilcoxon rand sum[32] is performed with a 5% significance level. The null hypothesis is defined as: there is no significant difference between the OBLDA algorithm and seven other algorithms. And the alternative hypothesis considers a significant difference among them. The p-values are applicable to judge " whether or not to reject the null hypothesis". If p-value is greater than 0.05 and h=0 simultaneously, the null hypothesis will be rejected, indicating there is no significant difference among all algorithms. On the contrary, the alternative hypothesis will be accepted at 5% significance level in which p is less than 0.05 or h=1. In order to prove the superiority of OBLDA algorithm from statistics analysis, firstly, the fitness function values of proposed method using between-calss variance are compared with DA,PSO, SCA, BA, HSO, ALO, and SSA algorithms, and the p and h values are shown in Fig. Secondly, the SSIM values of proposed method using Kapur's entropy is selected as control group, which will be compared with seven other algorithms, and the p and h values are shown in Fig. Each algorithm runs thirty times in tests for statistics analysis. To sum up, the results indicate that the OBLDA algorithm based on multilevel thresholding segmentation outperforms the seven other algorithms in most cases.

VII. Conclusion

The paper presents a novel multilevel thresholding technique based on the OBLDA algorithm for mitigating color image segmentation problems, the merits of it are high accuracy and strong robustness. The between-class variance and Kapur's entropy are used as objective function, which will be maximized to find the optimum threshold values. All experiments are performed on the ten standard images with the following number of thresholds:64,6,8,10, and 12. In addition, PSNR, FSIM, SSIM, and the optimal fitness function values are applied to compare the performance of proposed algorithm with seven other algorithms. The obtained results indicate that the OBLDA using Otsu method and Kapur's entropy can accomplish real-world and complex task of color image segmentation, as well as provides a more precise technique for multilevel segmentation. In the future, we aim to find a much simpler and more effective method based on improved dragonfly algorithm for color image segmentation. We will also take up the deep study of how to make the proposed method adaptive to more practical engineering problems with superior performance.

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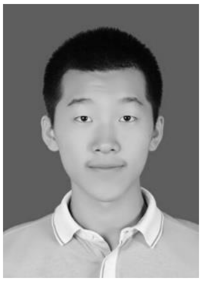

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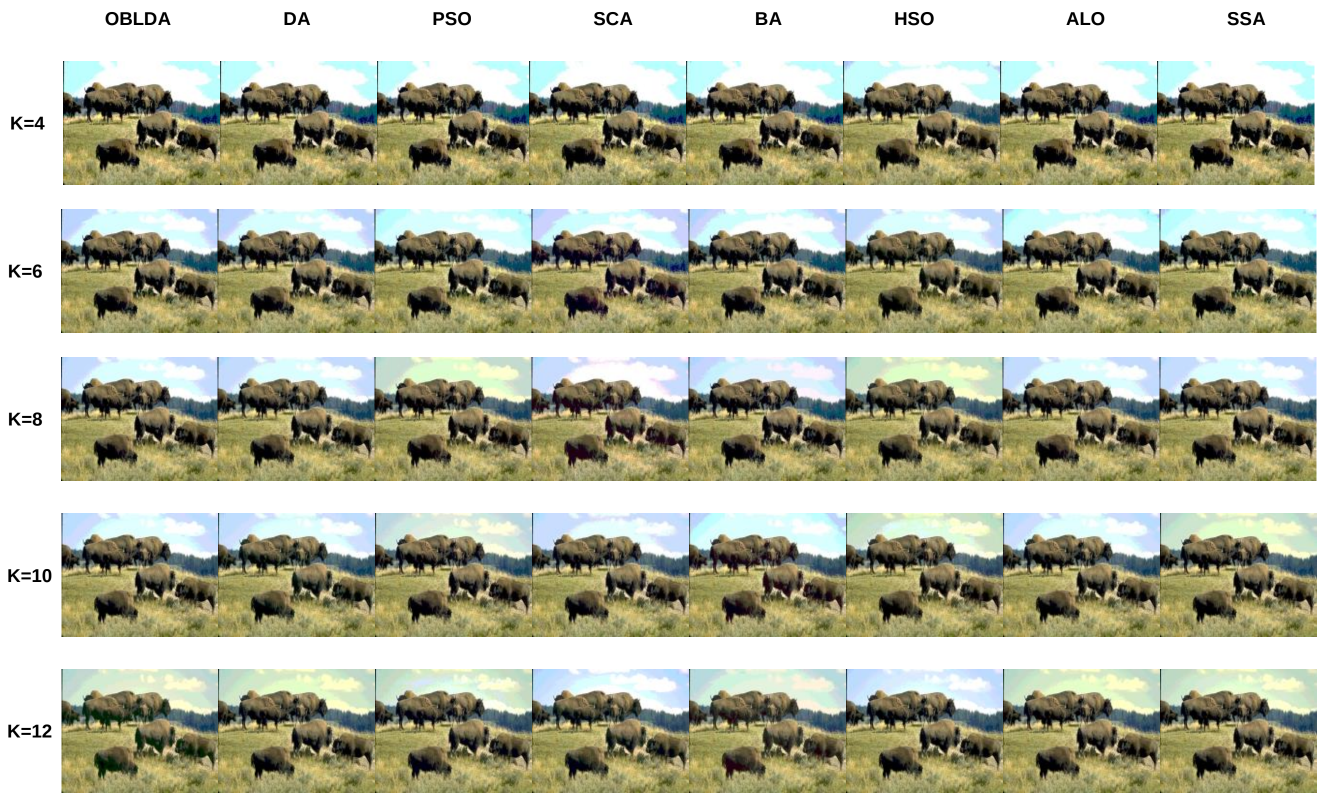

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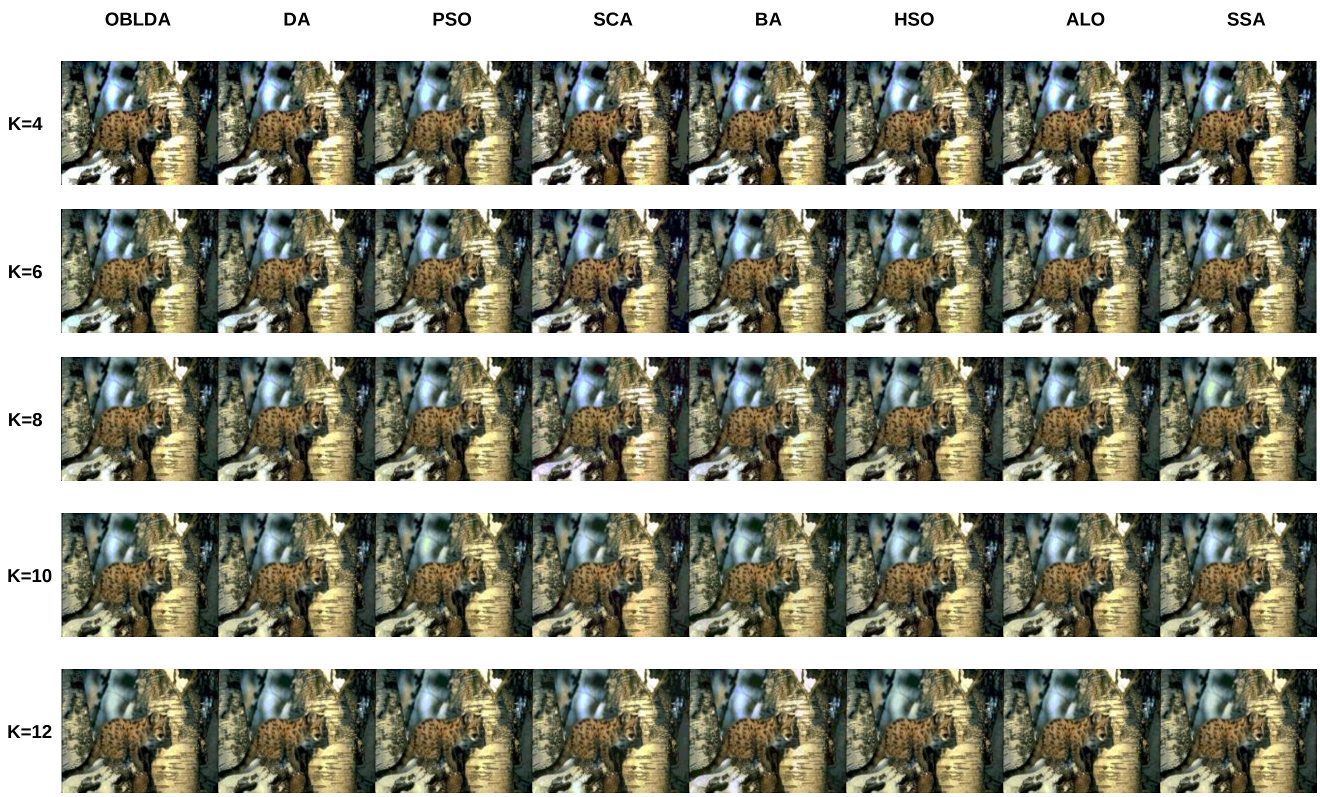

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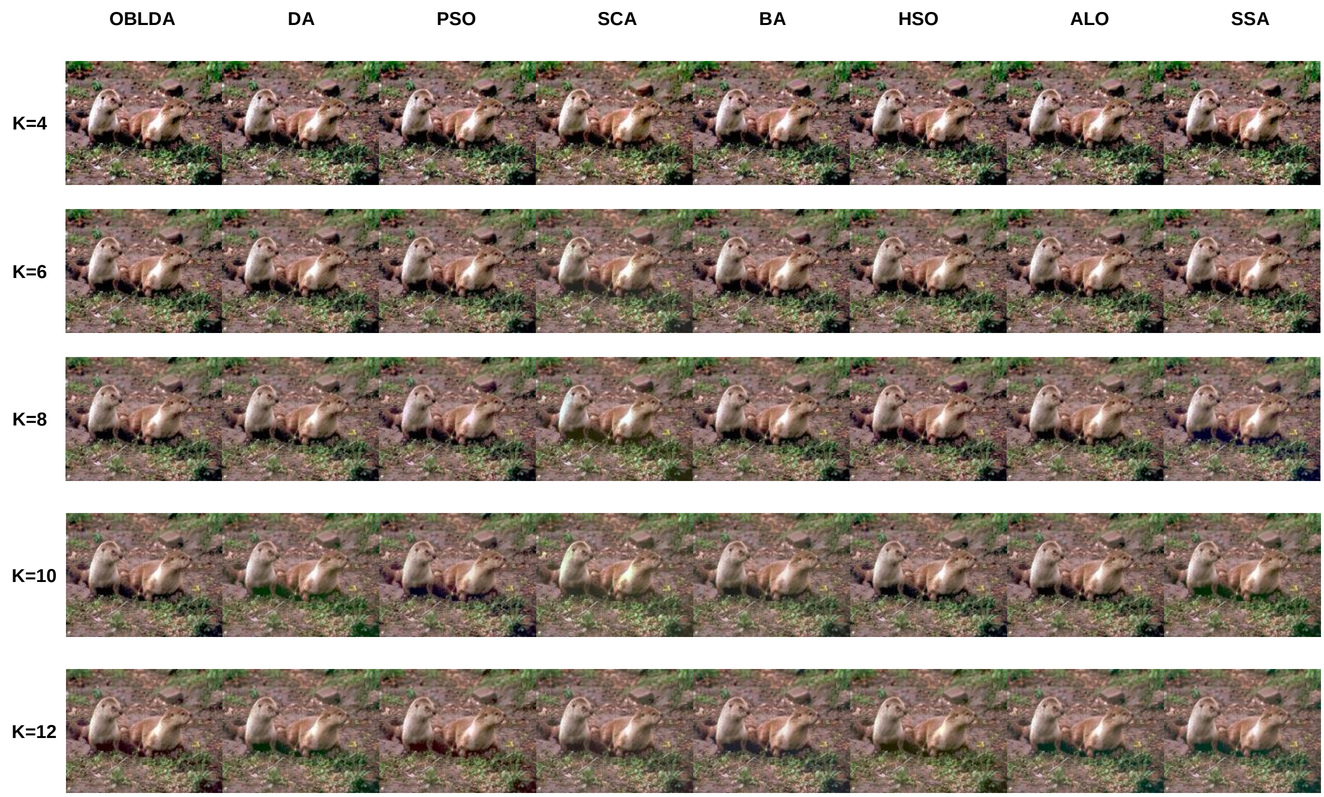

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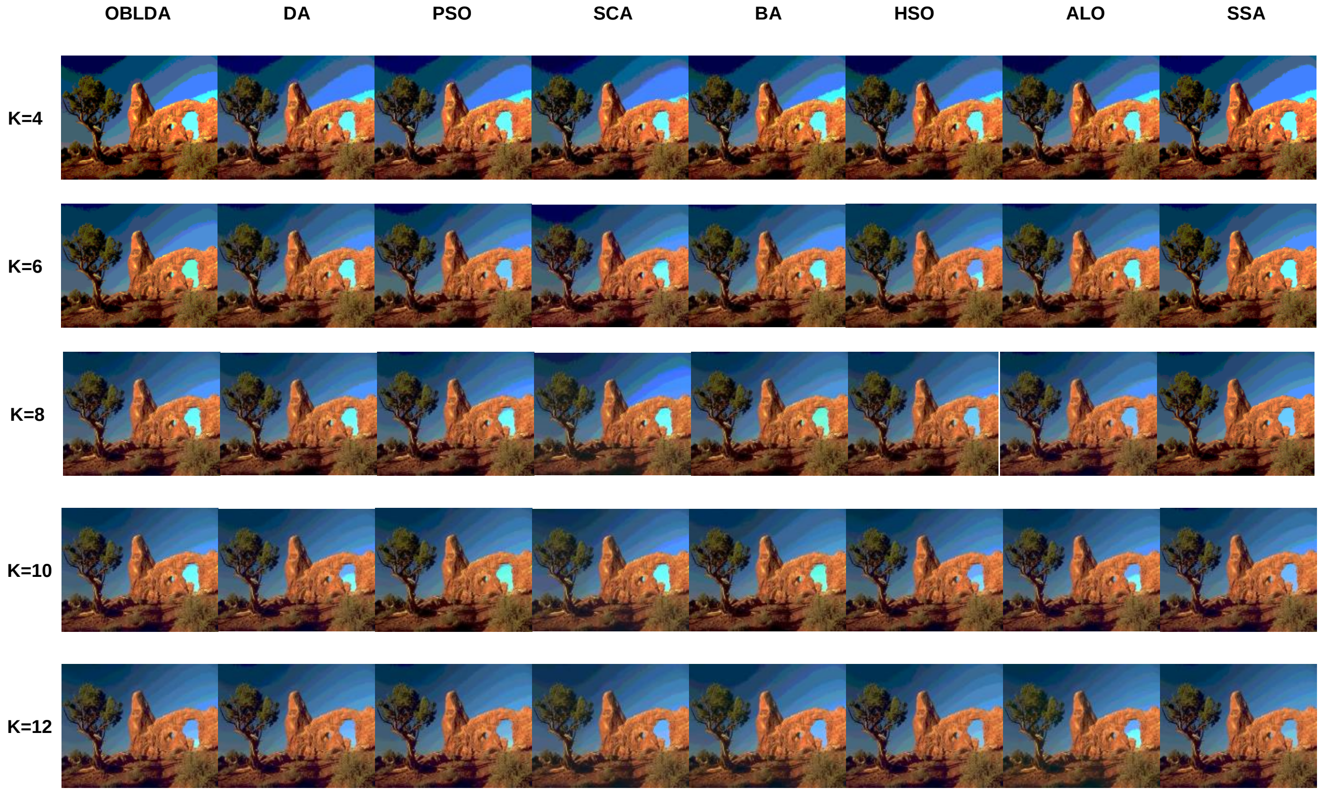

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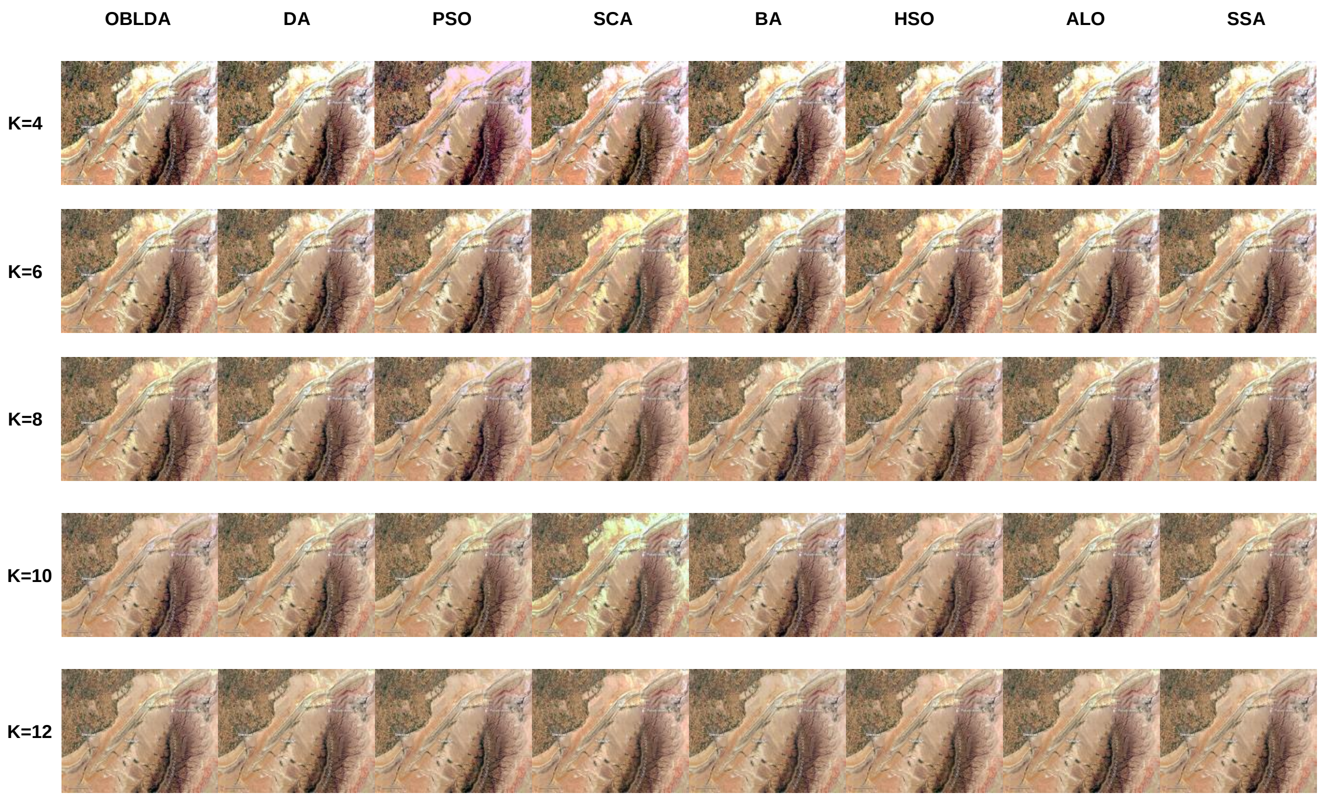

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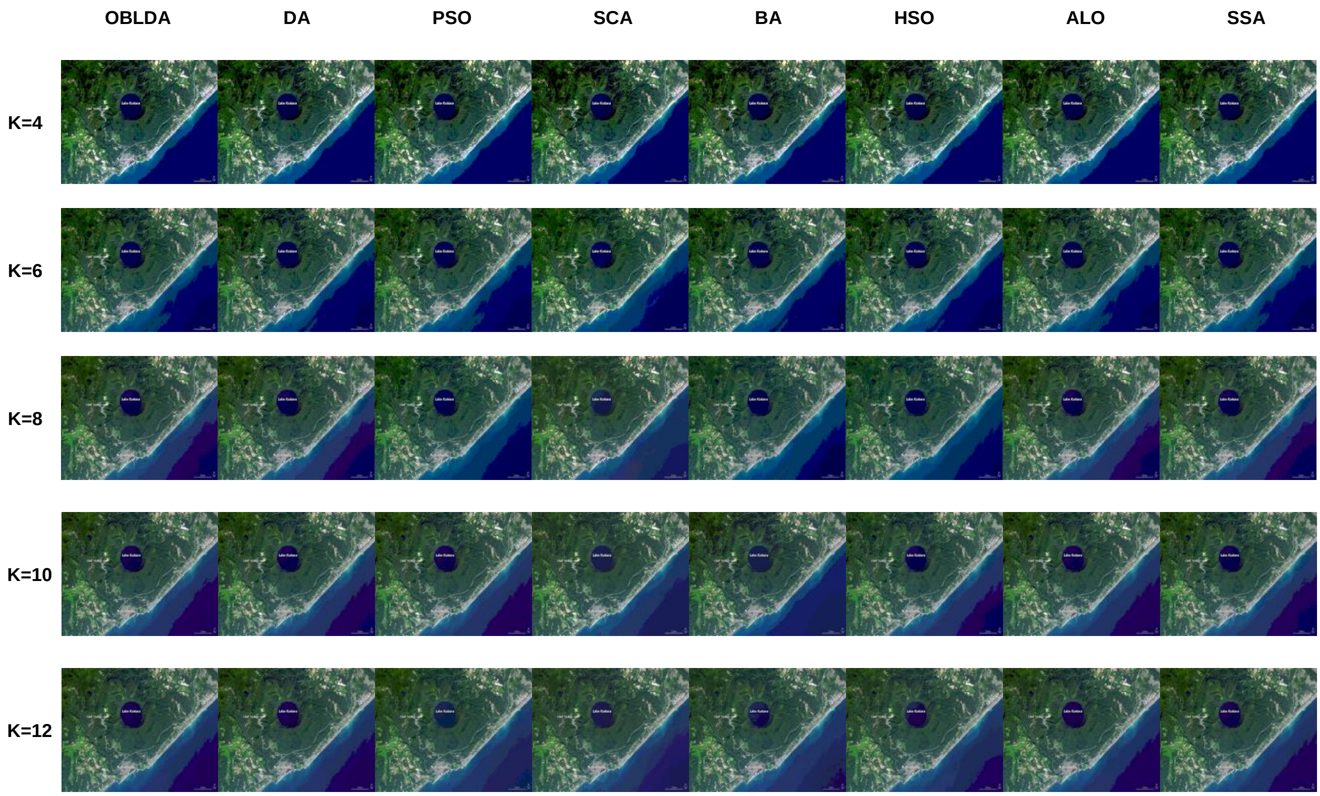

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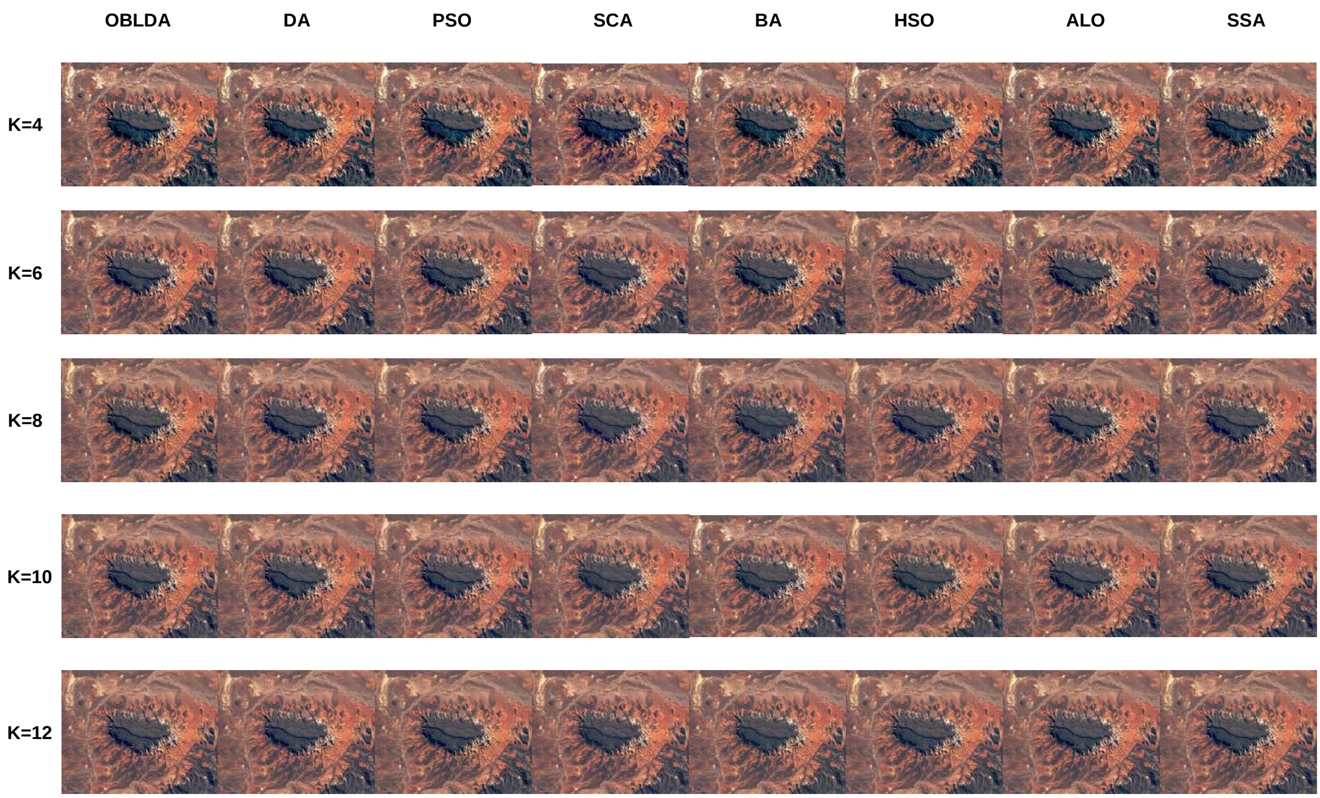

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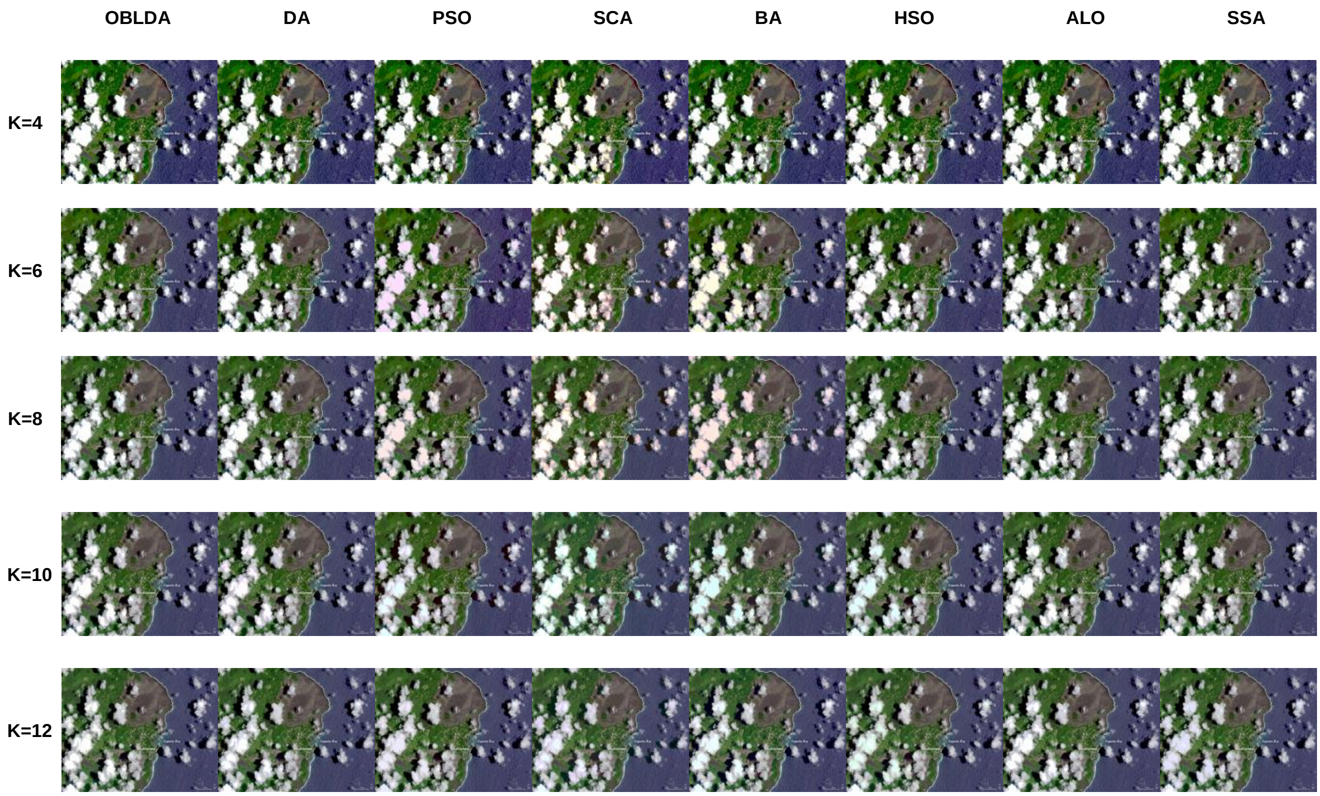

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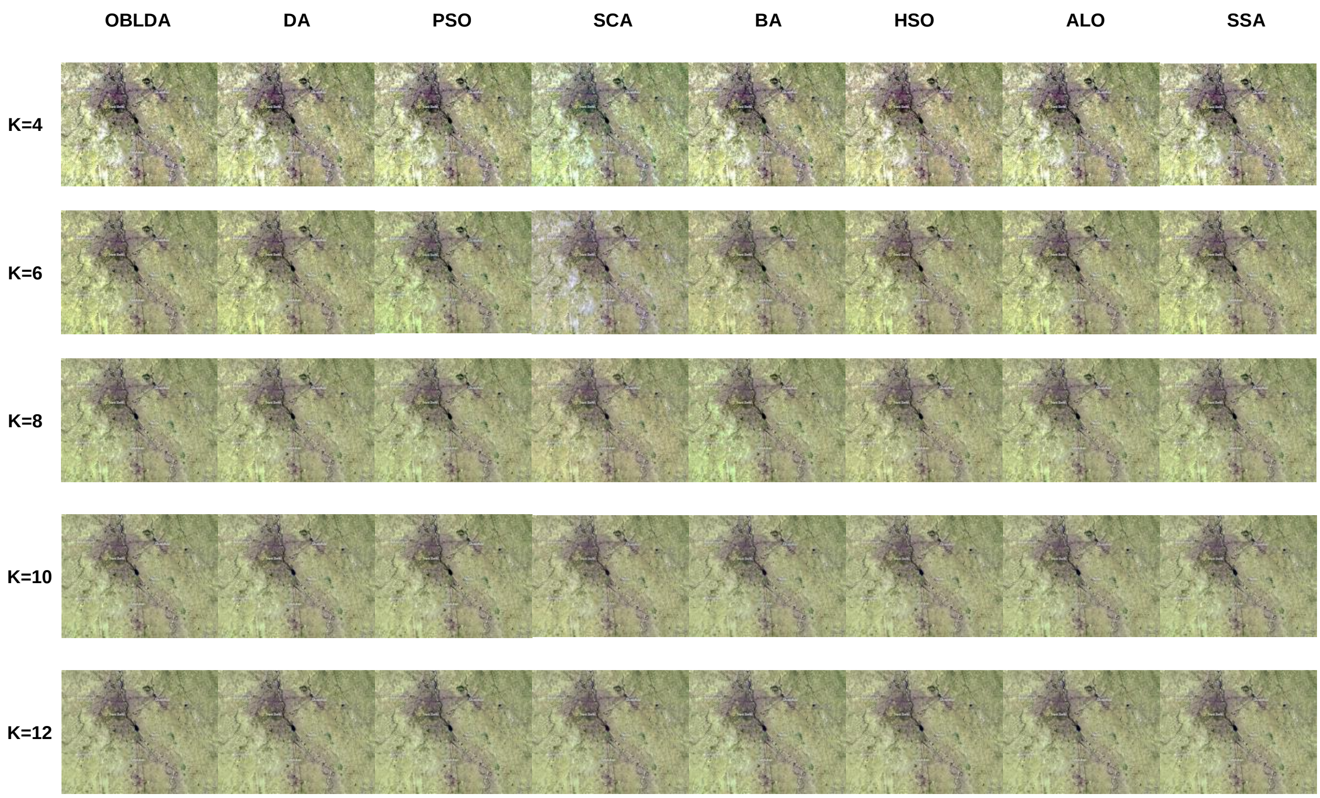
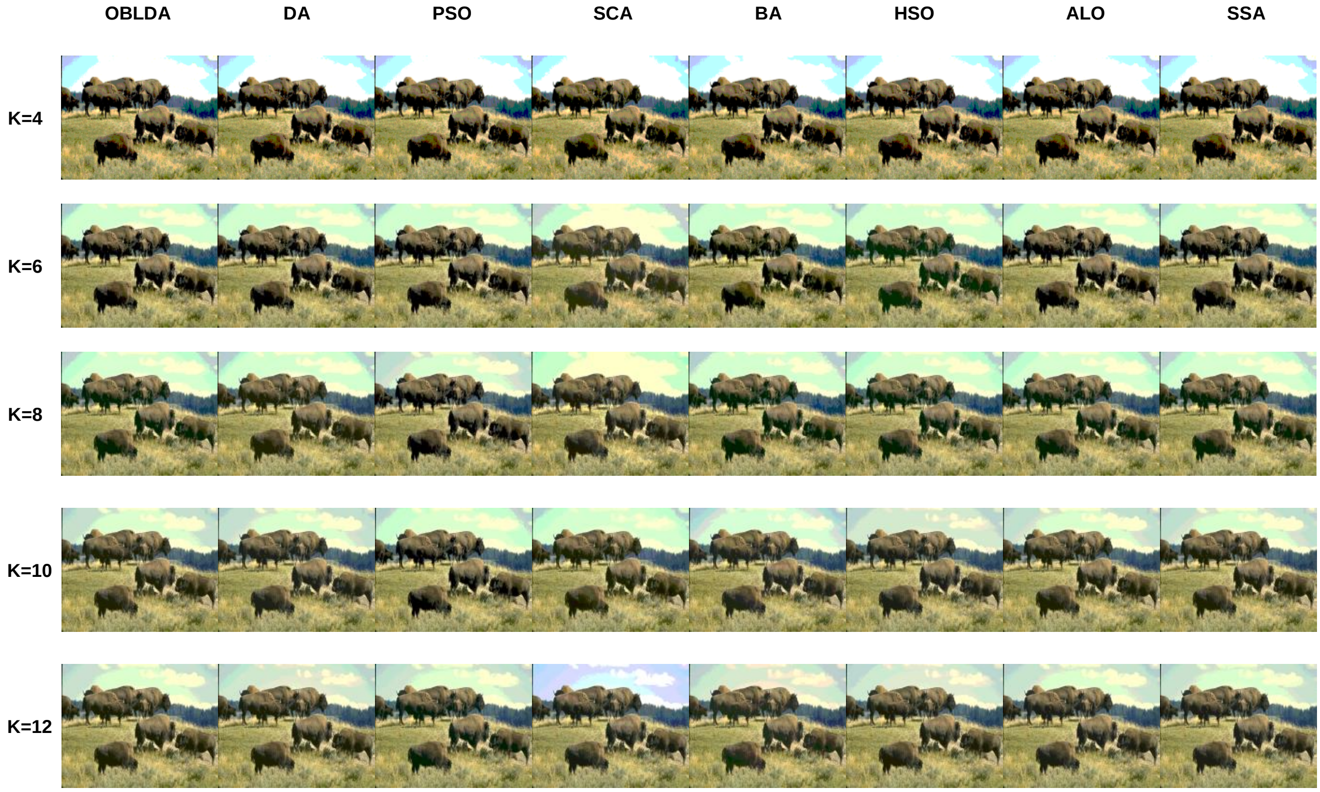


(j) Image10

Fig. 6. The segmented images using Otsu's method by the OBLDA, DA,PSO,SCA,BA,HSO,ALO, and SSA.at K=4,6,8,10, and 12.



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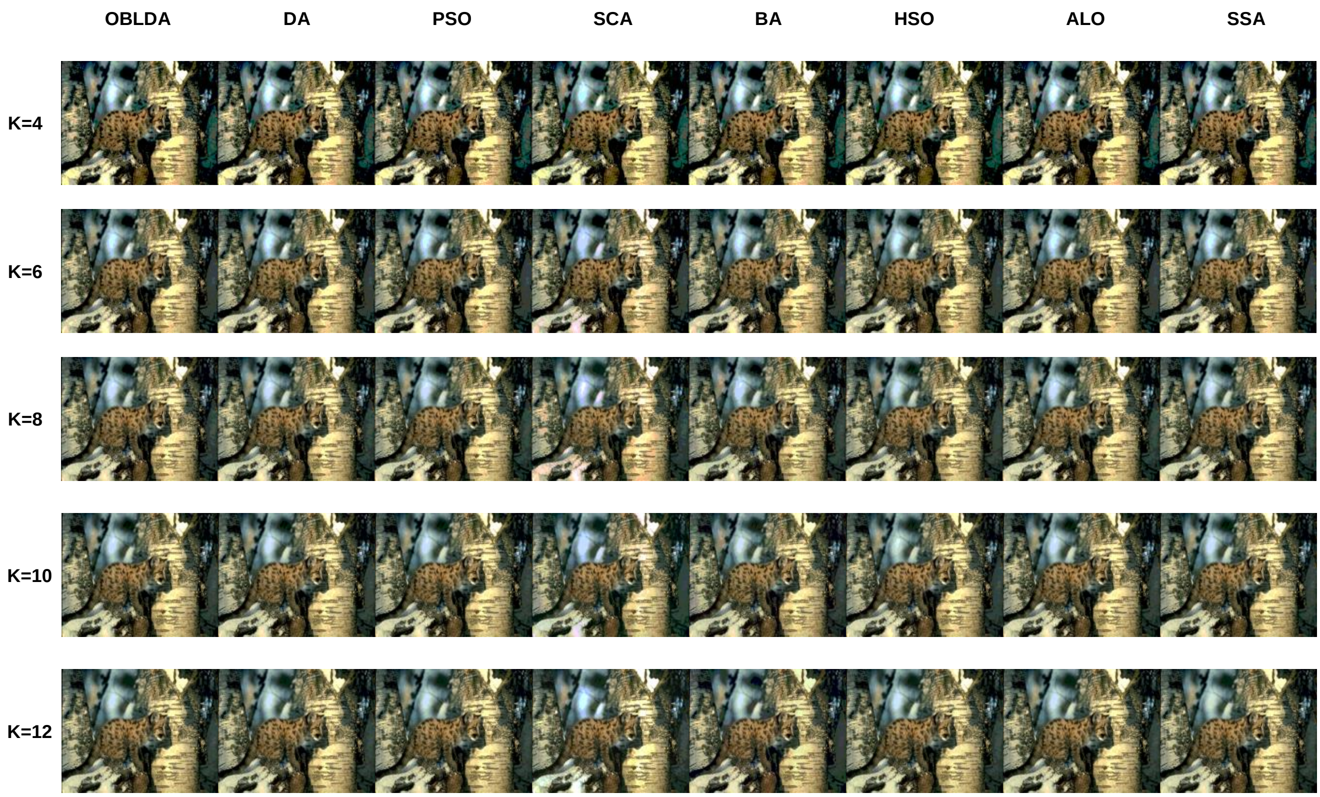

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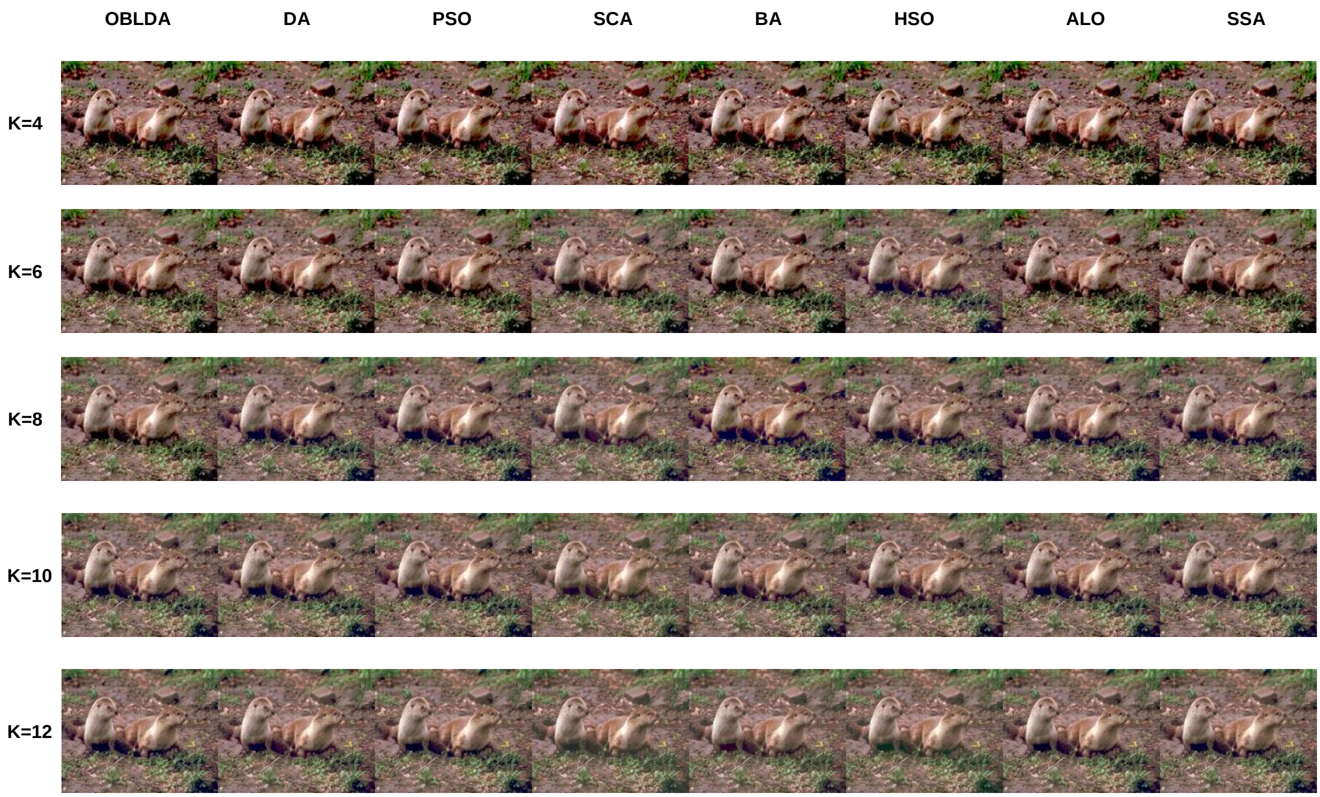
(c) Image3



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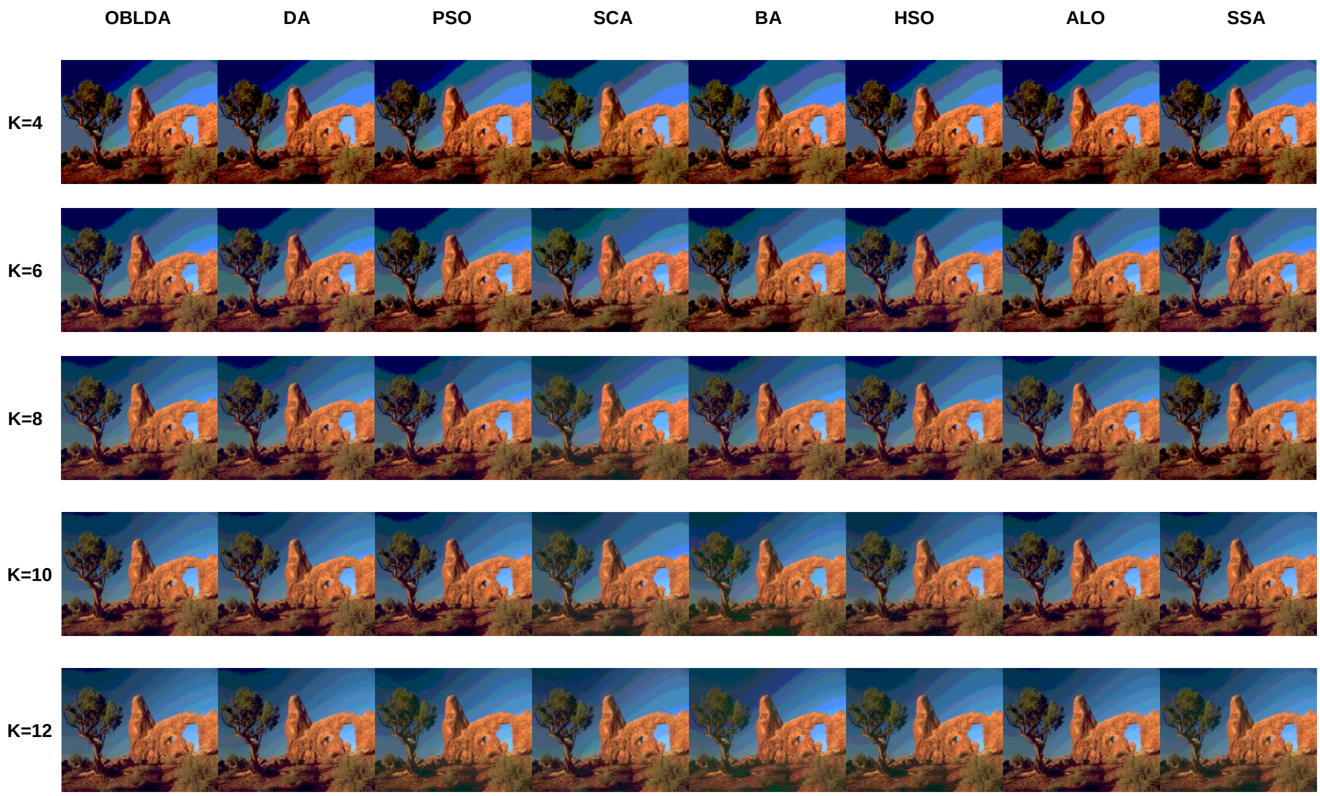

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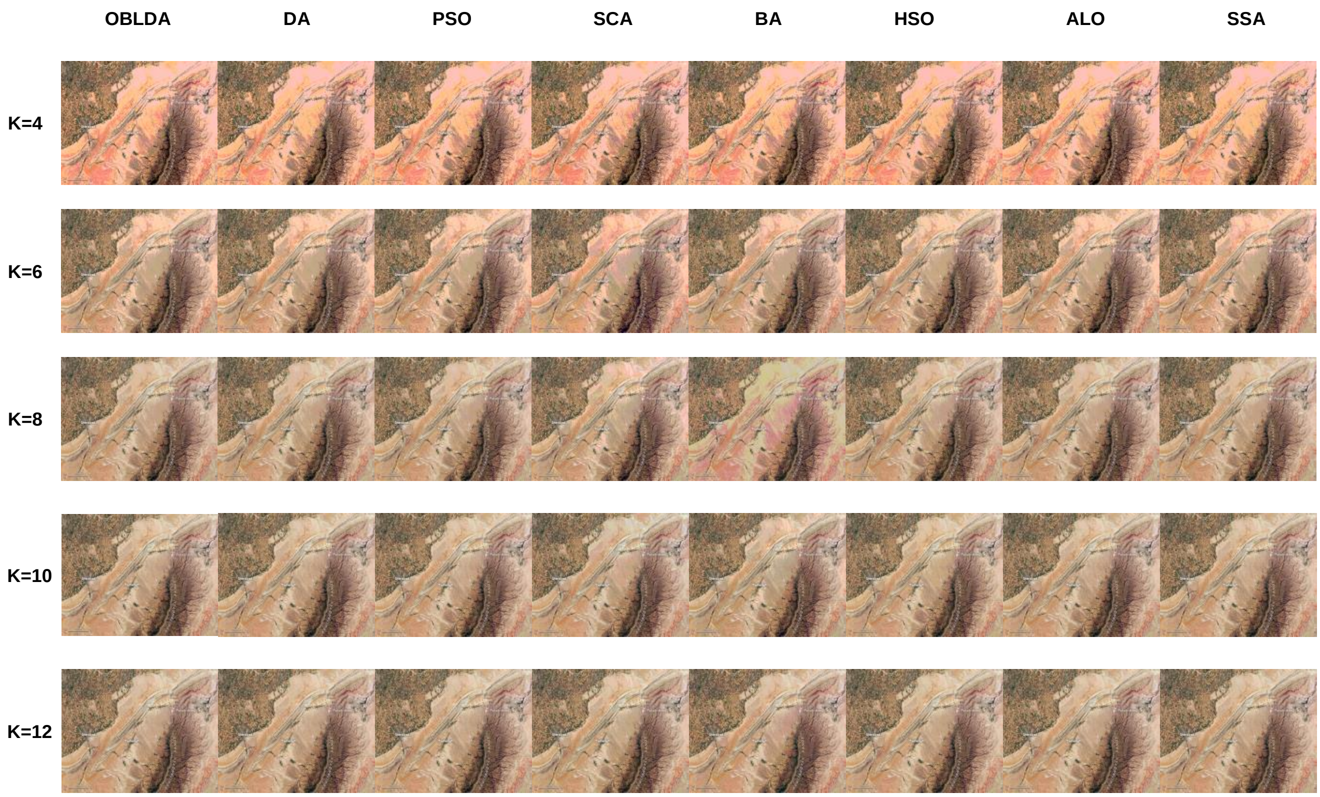

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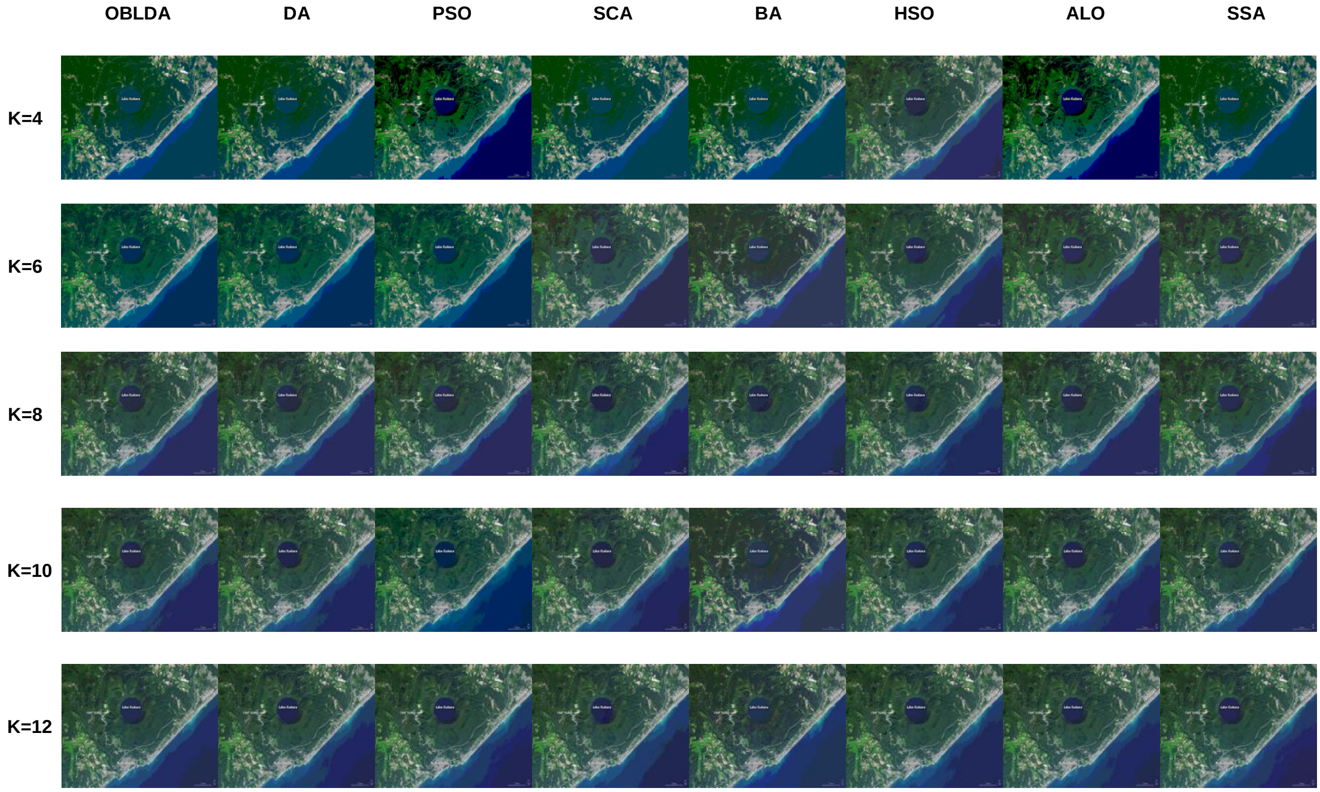

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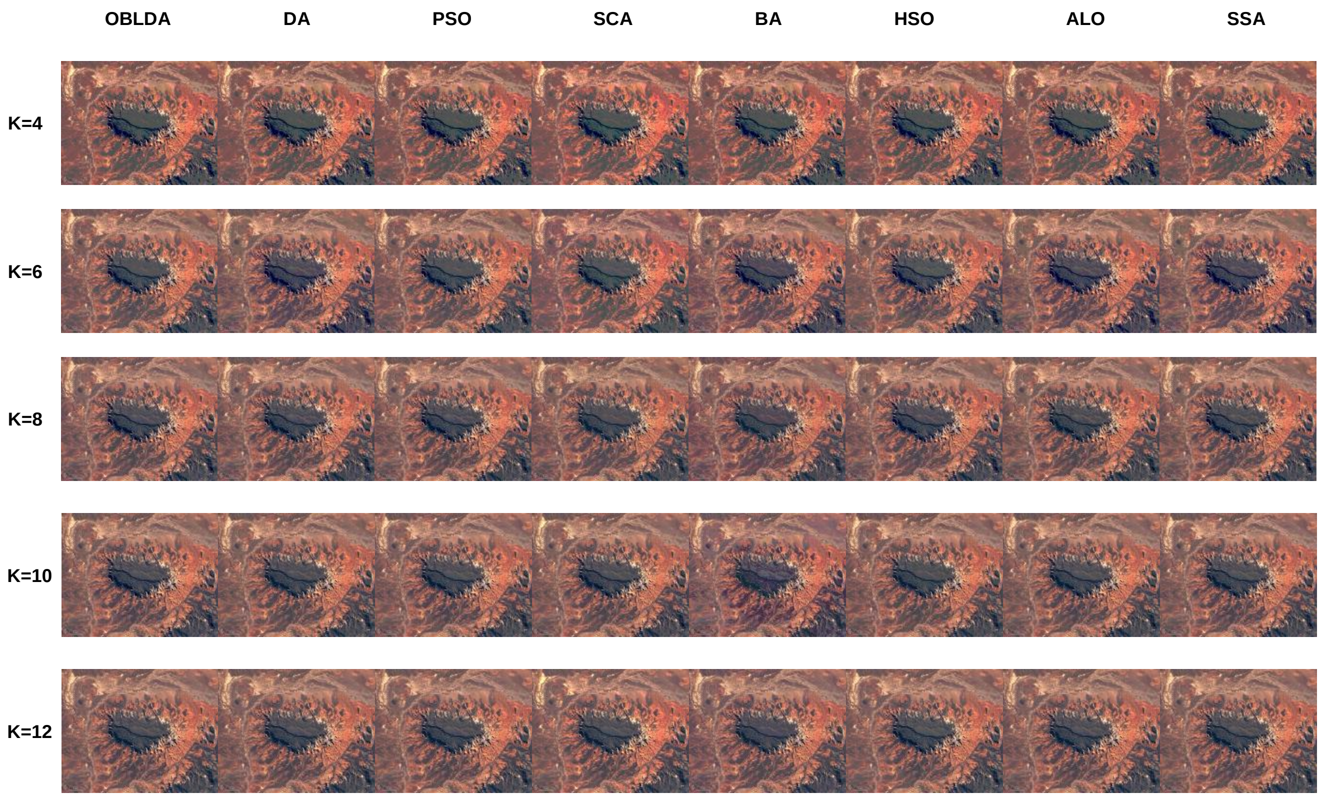

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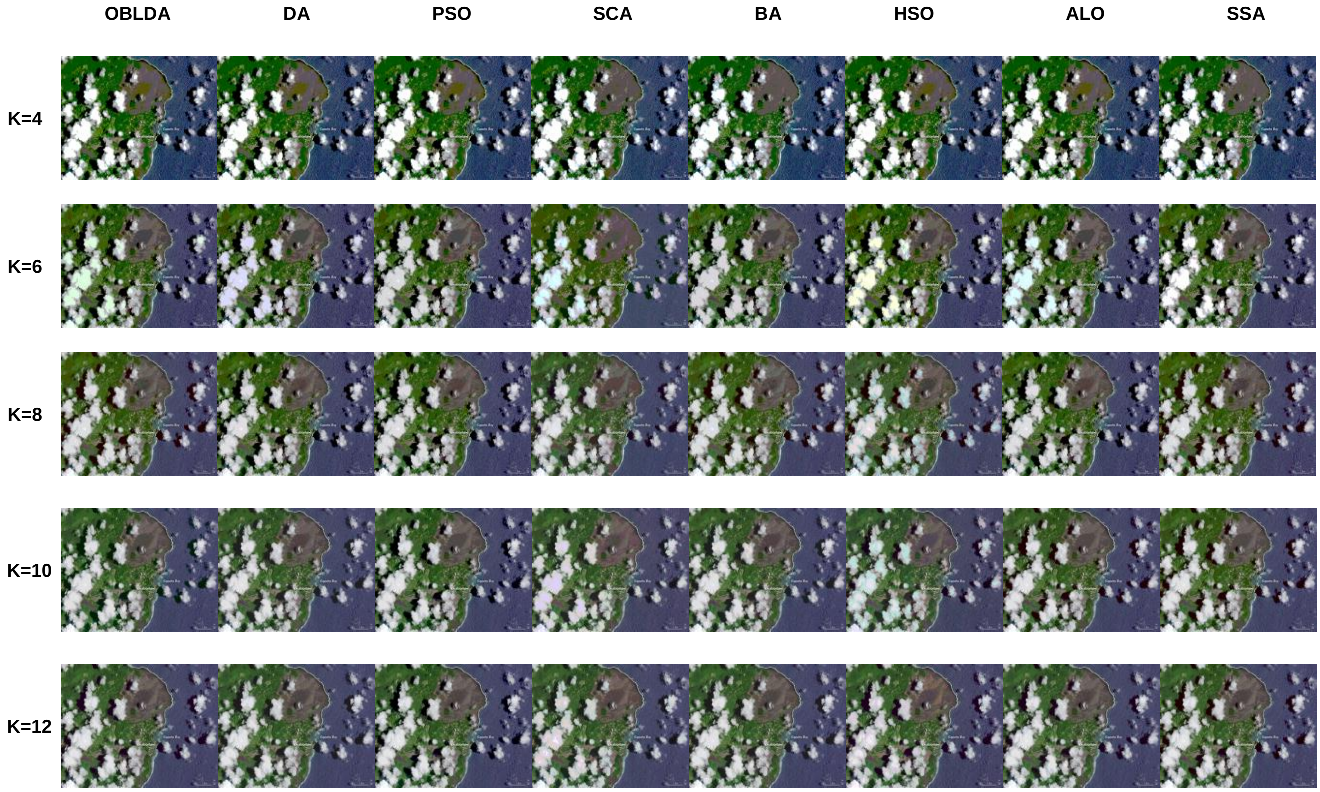

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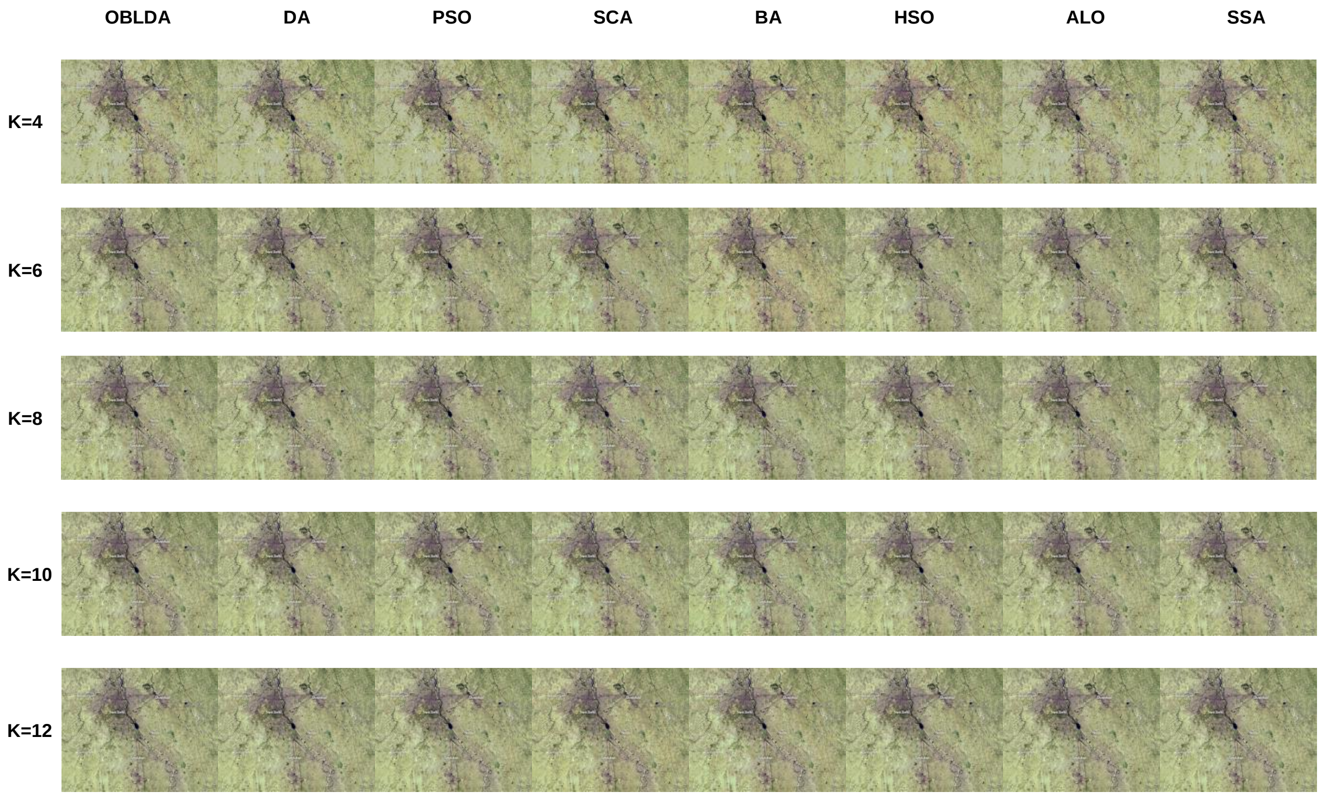


(j) Image10

Fig. 7. The segmented images using Kapur's entropy by the OBLDA, DA,PSO,SCA,BA,HSO,ALO, and SSA.at K=4,6,8,10, and 12.

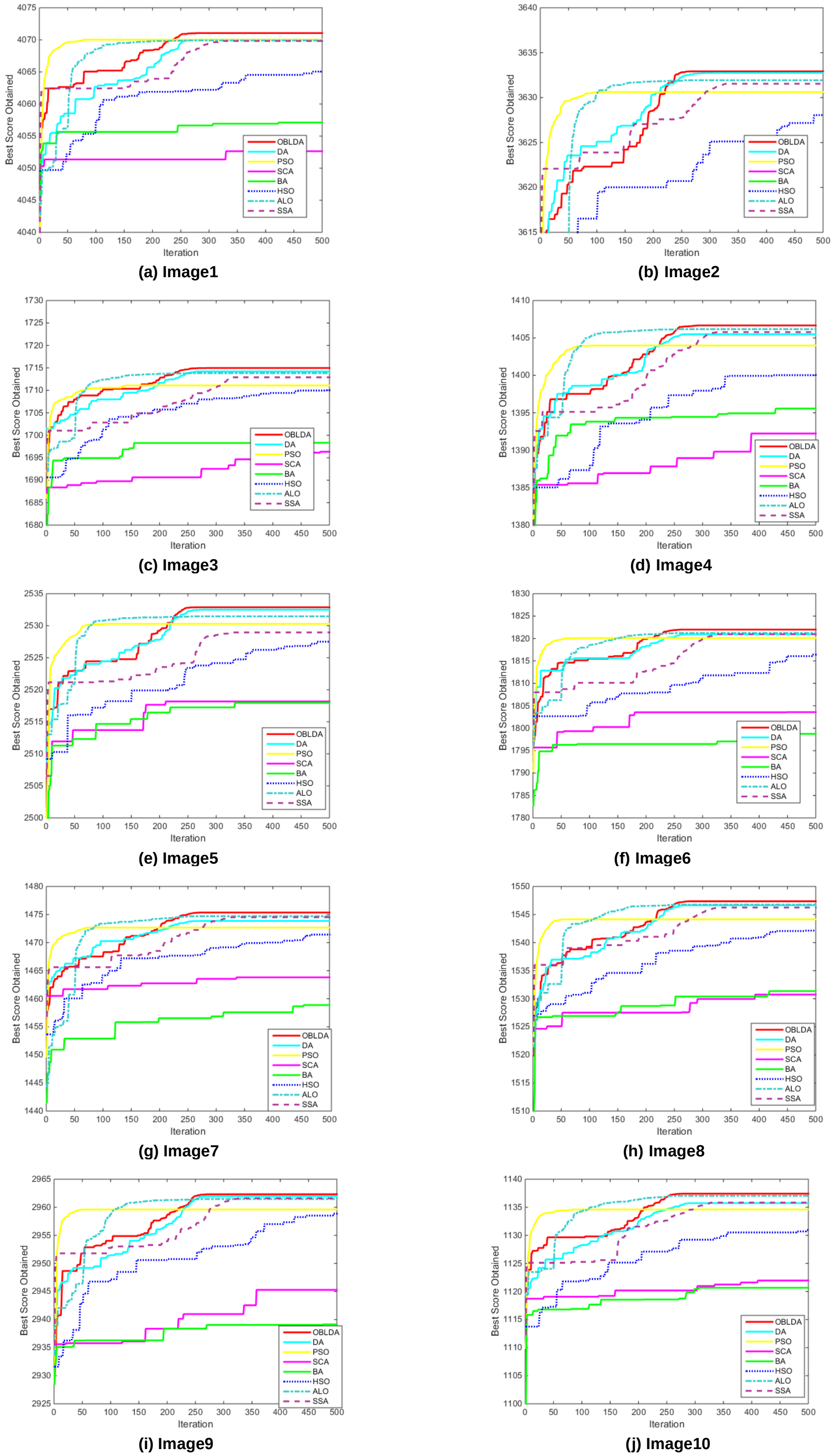
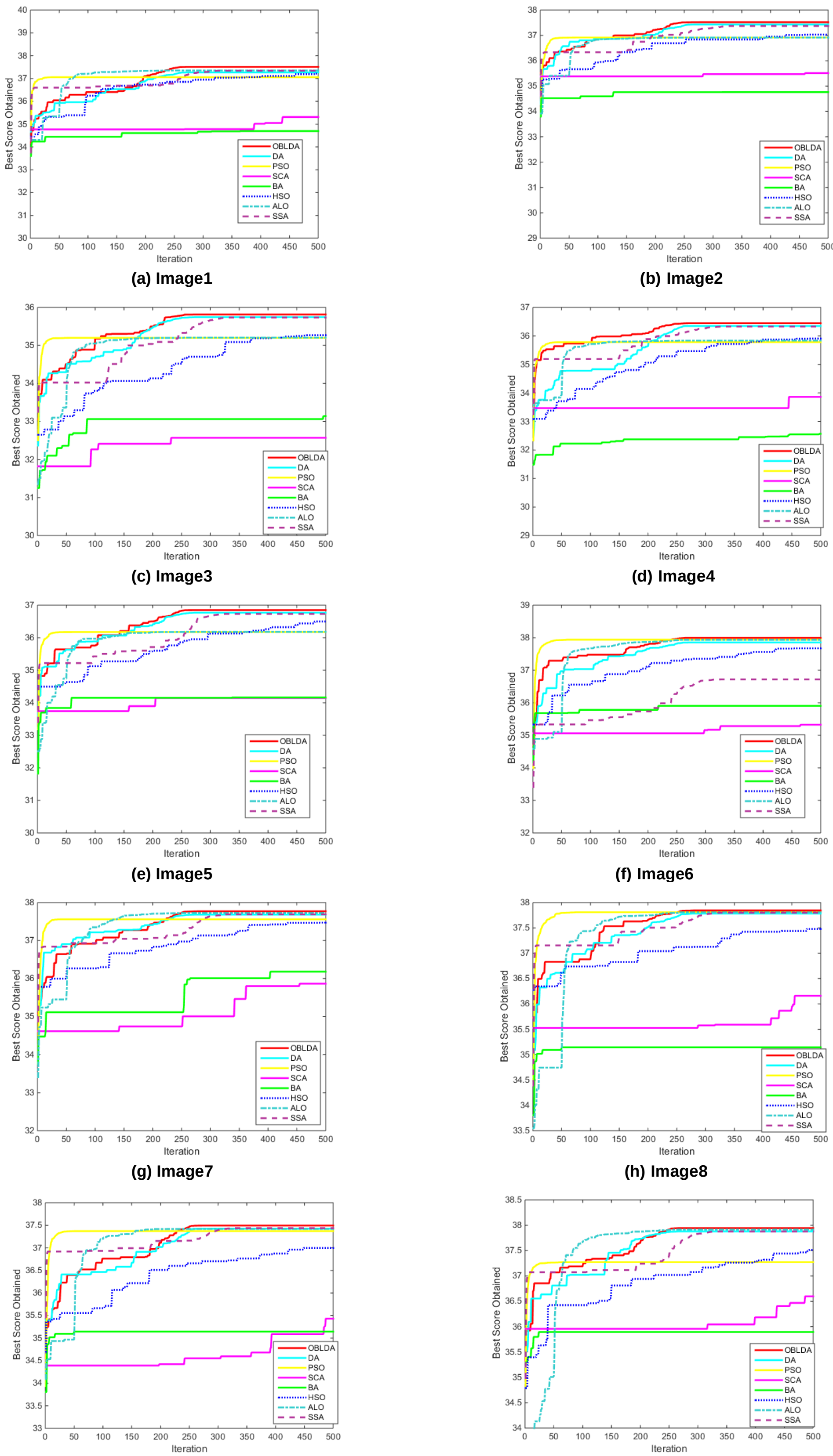


Fig. 10. **The convergence curves for fitness function using Otsu method compared with other seven algorithms at 12 levels thresholding.**



(a) Image1
(b) Image2
(c) Image3
(d) Image4
(e) Image5
(f) Image6
(g) Image7
(h) Image8
(i) Image9
(j) Image10

Fig. 11. The convergence curves for fitness function using Kapur's entropy method compared with other seven algorithms at 12 levels thresholding.

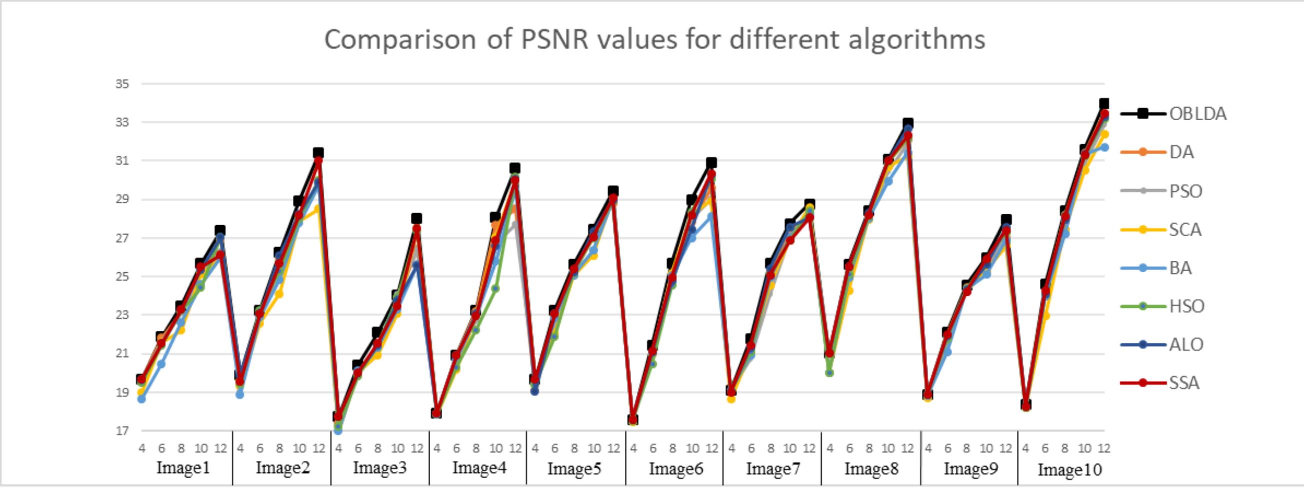


Fig. 12. **Comparison of PSNR values for different algorithms using Otsu's method at 4,6,8, 10, and 12 levels.**

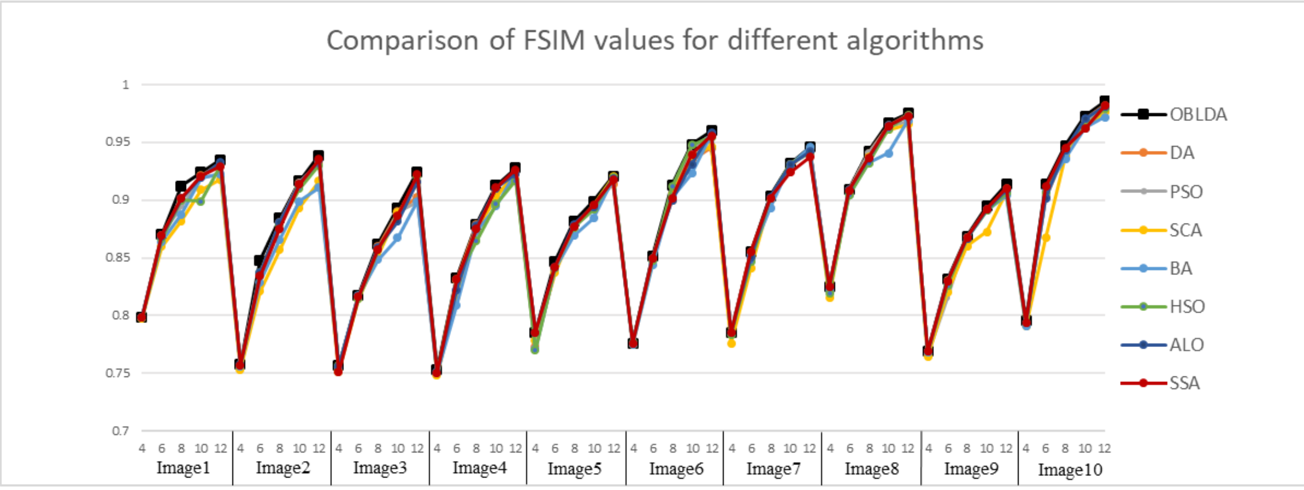


Fig. 13. **Comparison of FSIM values for different algorithms using Otsu's method at 4,6,8, 10, and 12 levels.**

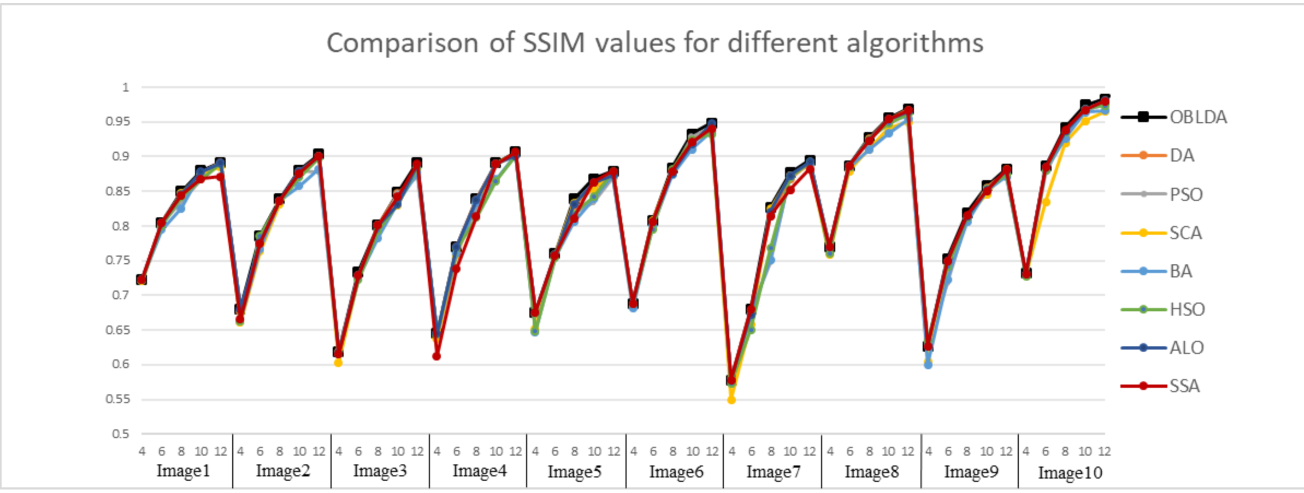


Fig. 14. **Comparison of SSIM values for different algorithms using Otsu's method at 4,6,8, 10, and 12 levels.**

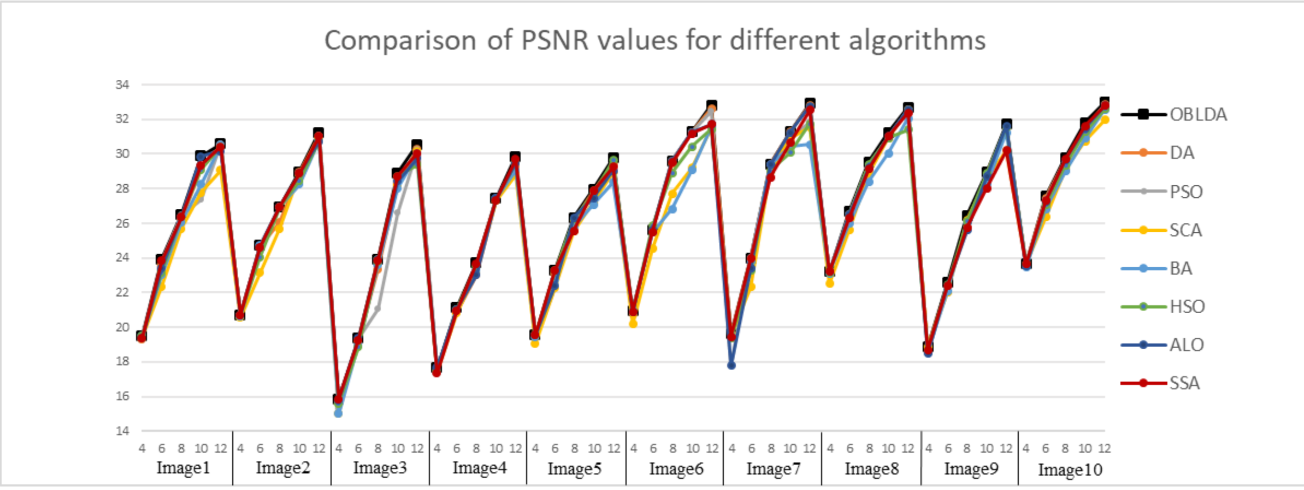


Fig. 15. Comparison of PSNR values for different algorithms using Kapur's entropy method at 4,6,8, 10, and 12 levels.

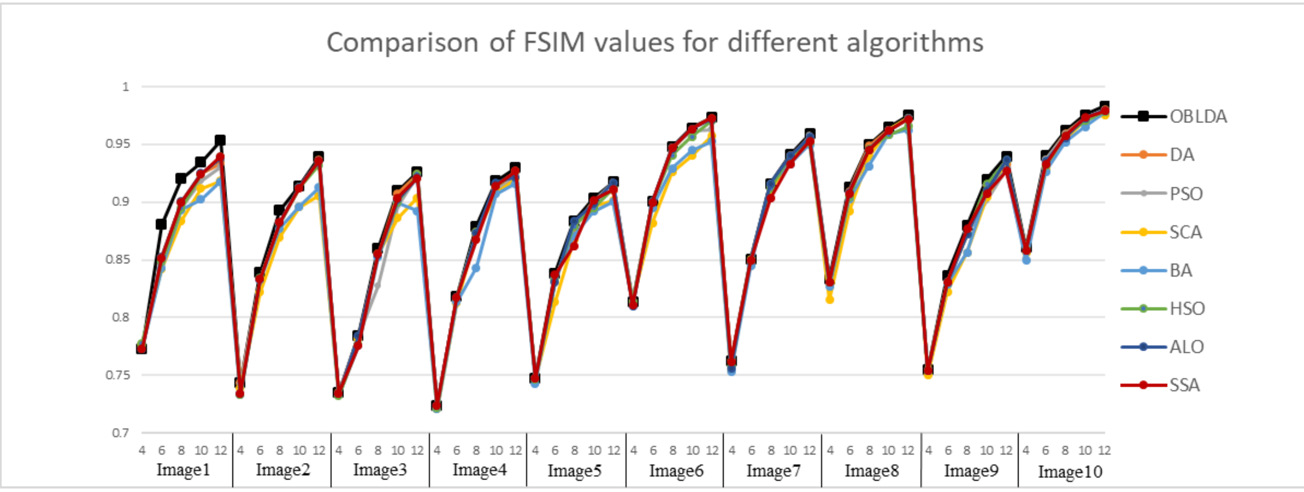


Fig. 16. Comparison of FSIM values for different algorithms using Kapur's entropy method at 4,6,8, 10, and 12 levels.

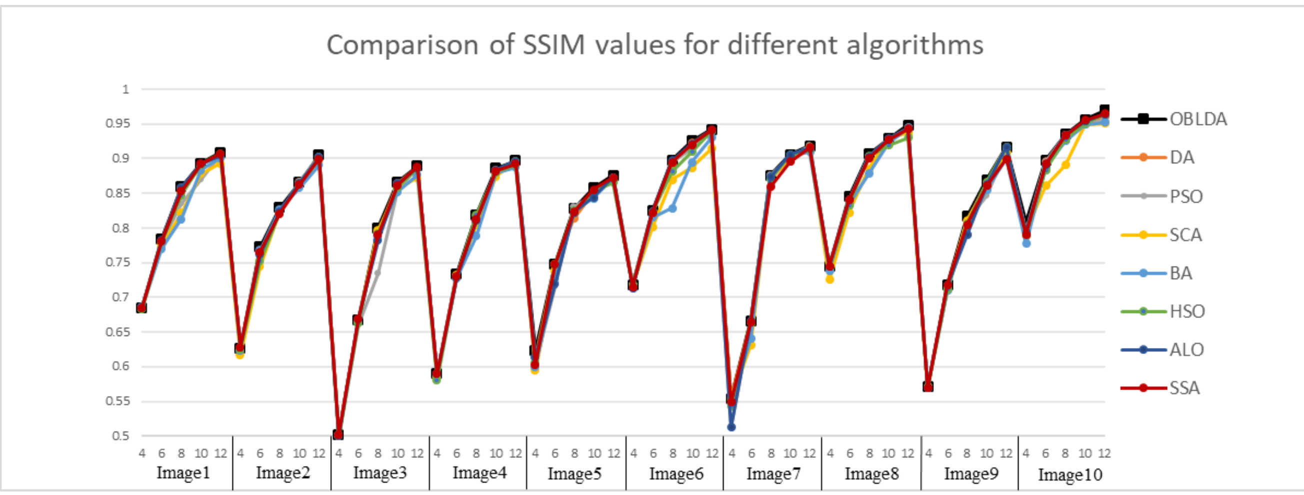


Fig. 17. Comparison of SSIM values for different algorithms using Kapur's entropy method at 4,6,8, 10, and 12 levels.

TABLE I
PARAMETERS OF THE ALGORITHMS

Algorithm	Parameters	Values
WOA-DE	Number of search agents	30
	No. of iterations	500
	Mutation scaling factor SF	0.5
	Crossover probability CR	0.9
WOA [21]	controlling parameter a	[0,2]
	Number of search agents	30
	No. of iterations	500
SSA [37]	controlling parameter c_1	[0,2]
	Number of salps	30
	No. of iterations	500
SCA [38]	controlling parameter r_1	[0,2]
	Population size	30
	No. of iterations	500
ALO [39]	Number of antlions	30
	No. of iterations	500
HSO [40]	Pitch Adjustment Rate	0.3
	Harmony Memory Considering Rate	0.95
	Tuning bandwidth BW	25.5
	Harmony memory size	30
	No. of iterations	500
BA [41]	Loudness	0.25
	Pulse emission rate	0.5
	Maximum frequency	2
	Minimum frequency	0
	Factor updating loudness α	0.95
	Factor updating pulse emission rate γ	0.05
	Scaling factor	4
	Number of bats	30
	No. of iterations	500
PSO [42]	Maximum particle velocity	25.5
	Inertia weight	[0.4,0.9]
	Learning factors c_1 and c_2	2
	Number of particles	30
	No. of iterations	500

TABLE II
COMPARISON OF OPTIMAL THRESHOLDS FOR DIFFERENT ALGORITHMS USING OTSU'S METHOD AT 4, 6, 8, 10, AND 12 LEVELS

Images	K	OBLDA			DA			PSO			SCA			BA			HSO			ALO			SSA		
		R	G	B	R	G	B	R	G	B	R	R	G	B	R	G	B	R	G	R	G	R	G	B	R
Image1	4	69 121 168 208	68 116 158 205	49 84 115 168	69 121 168 208	68 116 158 205	49 84 115 168	69 121 168 208	68 116 158 205	49 84 115 168	68 109 161 206	67 107 151 199	47 80 112 167	68 120 169 209	68 116 157 205	49 84 116 169	71 123 166 205	69 116 158 205	49 84 116 167	69 121 168 208	68 116 158 205	49 84 115 168	44 87 136 192	51 91 136 188	38 72 110 151
	6	59 100 138 170 200 227	58 96 130 162 197 228	38 64 87 108 132 175	58 99 136 169 199 227	58 96 130 162 197 228	37 63 86 107 131 175	59 100 137 169 199 227	55 89 120 148 176 212	38 64 87 107 131 175	43 87 119 160 194 227	60 98 123 145 179 207	2 46 64 93 120 175	60 99 130 157 190 218	58 95 130 160 194 226	36 62 83 105 132 175	52 86 117 147 181 215	55 88 122 150 175 213	40 67 85 107 128 172	55 93 129 161 190 219	55 89 121 149 176 212	38 64 87 108 132 175	35 68 102 138 177 218	40 69 99 131 167 206	27 50 74 101 130 161
	8	47 76 106 134 158 181 205 230	51 79 105 128 152 175 205 231	32 52 71 88 104 121 142 180	48 77 107 135 159 183 206 231	49 77 104 129 152 175 205 232	32 53 72 89 104 121 142 180	46 75 105 134 158 182 206 231	52 83 112 136 158 180 207 232	37 63 86 107 131 175 238 256	1 55 73 103 130 159 184 212	47 60 98 138 153 182 205 235	1 5 38 67 89 102 118 184	55 82 100 133 161 184 211 230	58 100 126 141 166 199 226 256	34 56 75 91 111 134 166 180	43 70 98 127 154 178 203 230	41 66 94 125 148 173 202 230	36 58 78 94 110 126 156 188	46 74 104 132 156 181 206 231	50 78 105 130 153 176 205 231	32 52 71 88 104 121 143 179	28 52 77 104 132 161 191 225	34 58 81 105 131 158 188 219	25 46 67 90 115 140 167 228
	10	41 64 88 112 135 156 176 196 214 235	44 66 88 109 129 148 166 185 208 232	27 43 60 75 89 102 115 130 150 183	42 66 92 117 131 159 179 198 215 235	32 53 72 89 104 121 142 179 204 214	39 52 65 78 92 110 130 150 174 210	44 68 92 116 138 157 176 195 213 234	49 78 100 121 143 162 181 205 226 240	29 47 65 82 97 111 128 150 190 256	1 44 46 74 115 131 161 182 204 243	16 55 71 110 121 146 154 178 212 237	1 25 46 69 70 89 113 135 178 200	26 55 71 79 102 124 154 178 200 233	44 72 85 113 126 140 161 179 201 219	1 36 55 69 80 97 108 121 146 177	35 57 77 99 123 146 173 193 210 233	41 66 87 111 134 151 171 196 213 234	31 46 65 87 97 111 121 146 180 205	43 67 91 114 136 156 176 195 213 234	44 67 90 111 130 148 166 185 209 232	28 45 61 76 89 102 115 130 151 185	24 45 65 87 109 131 154 178 203 231	31 52 72 92 113 134 156 179 202 227	19 35 50 66 82 100 119 139 159 180
	12	41 63 85 108 129 147 163 180 196 210 225 241	42 64 85 105 125 144 160 176 192 210 227 239	25 39 54 69 82 94 105 116 129 143 162 189	39 58 78 98 117 135 152 169 186 202 217 236	40 60 79 99 118 136 152 168 185 206 225 238	24 38 53 67 81 94 106 119 134 155 185 211	40 60 80 101 122 141 159 177 195 213 235 256	46 71 94 115 134 150 166 185 208 223 254 256	23 37 51 66 80 92 104 118 134 155 187 211	35 50 58 86 95 121 138 166 194 203 210 223	33 55 71 96 129 137 153 155 179 212 228 235	1 3 31 34 54 60 76 90 105 130 145 190	1 8 17 52 70 108 134 168 197 217 237 238	30 61 74 99 113 135 151 172 206 228 254 256	1 7 21 37 47 74 90 108 119 144 185 256	42 55 72 92 113 136 148 168 188 202 218 237	23 47 70 87 101 119 142 165 183 202 227 242	30 46 62 74 92 103 122 135 142 163 189 227	38 58 80 101 121 139 155 172 188 203 218 236	42 62 81 100 118 135 151 167 184 206 225 238	27 43 59 74 88 101 114 129 149 183 213 229	22 41 58 75 92 110 129 149 169 190 212 236	27 46 63 80 99 118 137 157 179 197 216 235	20 37 54 70 86 103 121 140 158 174 192 233
Image2	4	44 87 136 192	51 91 136 188	37 71 109 150	44 87 136 192	51 91 136 188	38 72 110 151	44 87 137 193	51 91 136 188	37 71 109 150	39 83 137 187	53 100 148 186	40 72 107 146	44 87 135 193	52 92 135 187	38 74 111 149	42 86 135 190	50 91 136 189	37 73 113 153	44 87 136 192	51 91 136 188	38 72 110 151	82 113 145 202	89 118 147 203	58 82 123 186
	6	35 68 102 138 176 217	40 69 99 131 167 206	27 50 74 101 130 161	35 68 102 138 176 217	40 69 99 131 167 207	27 50 74 101 130 161	35 68 102 138 176 218	40 69 98 130 166 206	27 50 74 101 130 161	38 68 101 125 168 212	50 75 102 137 184 210	1 31 62 90 130 164	33 68 109 160 193 217	42 73 100 129 164 203	29 53 77 106 136 161	33 67 100 139 178 219	36 64 92 124 157 201	27 50 75 100 129 160	35 68 102 138 176 217	40 69 98 130 166 206	26 49 73 100 129 161	72 96 118 141 173 220	79 102 122 144 175 221	52 68 86 114 154 202
	8	28 52 76 103 131 160 191 225	33 67 80 105 131 158 188 219	24 43 63 81 102 125 148 172	27 51 75 102 130 159 191 225	35 60 85 110 134 160 189 219	23 42 61 81 103 126 150 174	28 52 76 103 131 158 189 224	33 56 80 105 130 157 187 218	25 46 65 85 107 130 152 175	1 11 50 74 106 141 174 210	36 57 79 88 122 166 204 219	2 26 38 67 88 118 145 159	1 35 68 95 139 192 223 256	35 60 80 110 133 160 184 217	17 36 57 76 95 118 140 163	23 41 69 96 134 162 196 231	35 56 79 104 131 157 190 221	24 36 50 74 101 125 143 171	27 51 75 102 130 159 190 225	33 57 80 104 129 156 186 218	23 43 61 81 103 126 149 173	67 87 105 121 138 160 192 231	73 91 108 122 137 156 186 227	48 61 74 90 114 144 179 214
	10	24 44 64 85 107 130 153 178 203 231	28 48 66 84 105 126 148 172 197 224	21 39 56 71 88 106 126 146 163 183	23 43 62 82 104 127 151 176 202 230	30 49 68 86 107 129 152 176 202 227	19 34 50 66 102 122 123 141 161 182	24 44 63 83 105 128 152 177 203 230	29 48 65 83 103 124 146 170 197 224	21 38 54 71 88 107 127 149 173 228	1 5 27 41 72 100 134 148 188 211	27 48 66 86 104 134 172 182 213 242	1 26 33 41 54 78 91 122 153 184	22 40 63 93 124 130 170 194 220 256	1 29 54 70 99 147 165 185 216 256	25 53 82 105 126 166 210 216 254 256	23 48 67 92 119 141 163 187 210 227	36 46 67 87 111 129 148 169 199 227	17 47 56 70 93 117 138 151 169 186	24 44 64 86 108 130 153 177 202 230	29 49 68 87 107 128 150 173 198 224	19 35 50 65 99 118 119 138 158 180	61 77 93 108 121 134 151 173 202 235	70 85 100 114 126 139 155 176 204 235	45 57 68 79 94 115 142 169 199 224
	12	24 43 62 80 98 115 132 150 169 189 210 235	26 43 58 73 90 109 130 151 172 196 215 236	17 31 45 58 73 89 105 123 142 161 182 235	25 44 61 79 98 117 137 158 180 200 220 241	26 42 57 71 87 104 122 141 162 183 206 230	17 31 44 57 70 84 98 114 131 148 165 184	23 43 61 80 100 121 142 165 188 213 236 256	28 46 63 81 100 119 139 159 179 200 217 237	17 30 44 56 69 82 98 114 130 147 165 185	6 22 43 71 98 103 123 137 173 191 206 237	9 30 40 47 79 103 117 133 161 187 205 222	5 9 17 31 39 59 76 96 109 122 154 175	1 28 51 58 91 119 135 259 186 204 226 251	16 55 68 72 93 110 135 153 184 213 224 256	22 40 53 72 80 93 102 110 132 145 147 169	18 35 53 72 92 107 129 143 161 186 214 236	28 36 54 78 99 111 127 142 156 195 214 234	19 33 48 54 71 90 108 127 143 154 175 208	21 38 55 72 90 108 127 147 167 188 210 235	26 43 59 74 90 107 125 143 163 184 206 229	17 31 44 56 69 83 98 114 130 146 163 183	59 74 88 101 113 125 137 152 171 196 223 243	29 69 84 98 111 122 133 146 163 186 213 240	43 54 64 73 84 97 115 137 162 188 213 232
Image3	4	82 113 145 202	89 118 147 203	58 82 123 186	82 113 145 202	89 118 147 203	58 82 123 186	83 113 145 202	89 118 147 203	58 83 123 186	85 114 142 193	90 121 152 192	60 84 128 190	82 113 146 203	90 119 148 204	58 83 123 187	82 111 143 202	90 119 149 204	58 81 120 180	82 113 145 202	89 118 147 203	58 82 123 186	84 117 149 190	77 104 132 173	65 91 119 159
	6	72 96 118 141 173 221	79 102 122 144 176 222	52 68 85 113 153 201	71 95 117 140 172 220	79 102 122 144 175 221	52 68 86 115 156 205	72 96 117 140 172 220	78 101 122 143 174 220	52 86 86 114 154 202	74 86 111 130 153 202	1 84 107 127 153 201	1 56 77 103 151 196	67 94 123 146 186 241	81 103 124 145 171 216	50 69 86 119 164 204	71 96 118 139 167 219	81 106 125 146 177 225	53 70 88 119 156 200	72 96 118 141 173 221	79 102 122 144 175 221	52 68 86 114 154 202	73 98 121 144 171 207	70 91 110 130 156 194	57 77 96 117 142 178
	8	65 84 101 117 133 154 184 226	73 91 108 124 139 160 189 229	48 61 73 88 110 140 176 215	65 84 102 118 134 154 186 227	73 91 108 123 138 157 187 228	48 61 73 88 110 141 176 213	64 83 101 117 132 151 183 225	74 94 113 129 149 180 224 256	48 61 73 88 110 139 174 212	1 60 76 95 114 133 172 221	1 72 95 114 138 170 212 256	1 2 51 63 76 98 140 183	66 89 111 122 139 179 215 243	74 89 106 120 142 163 185 232	49 62 74 92 107 125 157 202	66 85 98 118 137 159 185 229	71 87 107 121 138 165 198 234	49 63 74 85 112 151 188 218	65 84 101 117 133 153 183 226	73 91 108 123 138 158 188 229	48 61 73 88 110 140 175 213	66 87 105 124 142 161 185 217	64 81 97 112 127 145 170 204	27 55 73 90 107 126 150 185
	10	62 78 93 107 120 133 149 171 200 235	68 85 101 115 128 143 162 181 207 234	45 57 68 79 93 112 137 166 197 223	61 77 92 106 119 132 148 170 199 234	67 82 98 112 124 136 152 173 201 235	44 55 66 77 90 107 131 158 188 219	59 74 90 106 120 135 152 195 202 235	67 81 95 108 120 132 146 166 196 234	45 56 67 77 89 106 130 157 188 219	1 56 74 99 116 125 144 163 168 216	1 6 71 91 117 129 154 191 243 256	6 40 53 58 64 78 94 127 162 200	70 80 104 122 130 149 187 217 254 256	66 89 109 128 151 170 186 196 247 256	1 6 54 74 90 111 133 160 207 256	66 67 78 98 117 129 146 168 208 243	61 77 88 101 119 128 148 166 196 230	47 57 67 77 89 113 142 168 204 227	61 77 92 106 119 132 148 170 200 235	69 84 98 111 123 136 151 172 200 234	44 55 65 75 87 104 127 154 183 216	62 80 97 112 127 142 158 176 198 226	16 63 79 94 108 123 140 160 186 216	50 64 77 89 102 116 130 148 170 200
	12	15 20 61 77 92 106 119 133 149 172 199 233	66 79 92 104 115 125 135 147 161 181 209 237	43 54 65 76 88 106 127 145 168 187 206 228	58 72 86 99 112 124 137 152 171 195 220 242	70 84 98 110 121 132 144 160 175 195 217 241	43 54 64 73 83 95 111 133 156 182 209 232	55 68 82 95 107 118 130 142 158 178 205 236	67 81 94 104 114 125 137 153 174 197 233 256	48 61 73 86 104 125 157 190 207 222 235 256	49 69 78 92 95 105 116 143 157 192 223 242	1 4 43 74 90 106 115 122 132 152 192 236	1 4 16 25 48 58 73 86 104 140 186 211	60 75 94 103 117 124 134 169 191 234 255 256	70 82 99 109 112 130 143 161 186 207 241 246	1 54 63 70 81 90 121 163 214 219 245 256	4 57 73 88 98 108 120 137 157 177 201 225	66 72 83 97 109 120 129 154 173 204 225 240	33 46 60 73 86 104 128 158 179 202 220 242	57 71 84 96 108 119 130 143 158 178 205 237	66 78 91 103 114 124 134 146 160 179 205 236	41 51 61 70 79 89 103 122 144 168 195 223	58 74 89 104 118 131 145 161 177 196 219 244	34 61 76 90 103 115 127 142 160 182 209 240	19 47 59 70 81 93 106 119 133 151 173 203
Image4	4	84 117 149 190	77 104 132 173	65 91 119 159	84 171 149 190	77 104 132 173	65 91 119 159	84 117 149 190	77 104 132 174	65 91 119 159	82 112 139 186	77 102 128 168	69 94 123 117	84 117 151 191	77 105 139 180	64 91 119 161	85 119 151 191	78 106 135 175	64 93 121 161	84 117 149 190	77 104 132 173	65 91 119 159	82 113 145 202	89 118 147 203	58 82 123 186
	6	73 98 121 144 171 207	69 90 109 129 155 193	57 77 96 117 142 178	73 98 121 144 171 207	69 90 109 129 155 193	57 77 96 117 142 178	73 99 122 145 172 208	70 91 110 130 156 194	57 77 96 117 142 178	69 86 113 129 156 202	14 68 94 122 145 175	49 62 84 104 120 161	76 98 119 142 170 207	70 88 110 137 164 212	57 75 95 116 143 181	74 101 127 152 175 212	68 89 107 128 156 197	58 78 98 120 148 186	73 98 121 144 171 207	69 90 109 129 155 193	57 775 96 117 142 178	72 96 118 141 173 220	79 102 122 144 175 221	52 68 86 114 154 202
	8	66 87 106 125 145 166 189 220	64 81 96 111 126 144 169 204	51 67 82 98 114 132 155 188	66 88 107 126 145 165 188 219	63 80 95 110 126 145 170 206	52 67 82 97 114 133 158 193	67 89 108 126 146 167 190 221	67 86 103 120 140 166 201 255	52 67 82 97 114 132 155 188	1 72 89 115 137 159 197 241	18 42 61 93 118 140 154 177	53 62 80 101 118 141 163 172	67 88 105 122 139 158 180 213	63 80 98 113 131 146 170 205	53 66 83 99 119 134 157 189	68 88 108 123 141 164 185 215	70 84 99 118 136 156 184 219	53 67 83 99 123 147 171 201	65 86 104 122 140 160 184 216	64 81 96 111 127 145 169 204	52 68 82 97 113 131 154 187	67 87 105 121 138 160 192 231	73 91 108 122 137 156 186 227	48 61 74 90 114 144 179 214
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	12	7 59 76 91 105 118 132 147 162 180 202 230	60 73 85 97 108 118 129 141 156 175 195 222	47 59 70 80 90 101 112 135 139 157 180 211	58 73 87 101 114 127 142 156 172 191 213 237	12 59 72 86 98 111 123 136 153 174 201 225	46 58 69 80 91 103 116 130 147 168 192 213	27 58 73 87 101 115 128 143 158 175 196 224	59 74 88 100 111 124 139 155 175 200 224 256	50 63 77 89 100 111 122 134 147 163 184 208	1 39 57 80 103 117 140 163 172 198 202 229	1 24 59 67 87 104 126 144 156 169 189 232	1 6 13 45 50 69 91 103 115 137 166 209	1 58 75 95 116 145 148 165 177 199 239 256	10 23 66 91 105 122 133 150 168 188 217 238	45 51 62 73 84 98 110 125 143 158 175 210	2 54 72 81 96 110 125 145 164 184 208 233	55 70 81 93 106 119 136 149 169 195 231 248	15 50 62 75 89 108 118 134 153 167 194 229	58 73 87 100 113 125 138 152 168 186 206 232	22 59 73 85 97 108 120 133 148 167 190 218	12 47 60 72 83 95 107 120 134 151 174 202	58 74 89 104 118 131 145 161 177 196 219 244	34 61 76 90 103 115 127 142 160 182 209 240	19 47 59 70 81 93 106 119 133 151 173 203
Image5	4	45 84 130 186	54 83 111 145	52 90 130 172	45 84 130 186	54 83 111 145	44 74 113 162	45 84 130 186	54 83 111 145	44 74 113 162	50 85 127 182	54 82 115 150	47 83 123 163	45 83 128 185	55 83 110 142	52 90 129 172	45 86 133 187	55 85 115 147	52 90 128 170	54 83 111 145	54 83 111 145	44 74 113 162	45 84 130 186	54 83 111 145	44 74 113 162
	6	35 61 89 124 165 207	46 66 86 106 126 157	42 70 101 135 173 256	35 61 89 124 165 207	46 66 87 107 127 158	42 69 99 131 161 192	35 62 90 125 166 208	49 72 95 119 153 256	42 69 99 131 161 192	28 53 74 104 151 201	54 65 89 111 127 167	34 63 96 128 163 192	35 62 90 121 167 208	46 66 88 107 125 163	43 69 101 129 152 183	37 64 91 127 171 207	43 70 95 117 145 185	43 69 101 130 160 194	46 66 87 107 127 158	46 66 87 107 127 158	42 69 100 131 161 192	35 61 89 124 165 207	46 66 87 107 127 158	42 69 99 131 161 192
	8	26 47 66 89 117 148 183 218	43 59 74 90 106 120 137 163	30 47 67 87 108 134 161 192	26 47 66 89 117 149 185 221	43 59 74 89 104 119 136 163	33 50 70 90 111 135 162 193	29 51 72 95 123 154 187 220	44 61 78 97 117 129 143 167	32 49 69 90 111 134 160 190	1 27 59 76 101 132 164 225	1 4 49 72 85 105 130 160	1 3 40 68 87 103 135 168	21 41 63 93 104 139 184 220	43 57 75 92 104 120 135 162	39 69 87 107 139 176 193 242	24 48 68 92 124 155 186 219	43 62 84 102 119 131 153 256	35 52 72 102 130 151 175 199	43 59 74 90 115 120 137 163	43 59 74 90 115 120 137 163	29 46 67 87 109 134 162 193	27 48 67 90 118 149 183 218	44 62 79 96 113 132 161 245	36 55 76 101 128 150 172 198
	10	24 42 59 76 94 117 142 170 199 227	41 54 66 77 89 100 112 125 140 165	26 39 54 71 89 109 130 151 174 199	24 42 59 75 93 116 141 168 196 225	41 55 68 81 94 107 121 136 156 179	26 41 56 72 90 110 132 154 178 202	25 45 64 84 108 135 165 195 224 256	40 53 65 77 89 100 112 126 142 166	35 53 71 90 110 134 160 187 208 256	1 6 21 42 62 92 121 161 180 230	2 39 53 61 81 102 115 125 141 164	1 3 14 46 75 99 113 146 172 191	18 46 67 79 109 131 166 198 217 227	41 56 68 80 90 112 122 132 141 165	33 44 71 106 133 166 197 213 238 256	27 40 61 81 97 118 142 171 196 222	41 50 64 79 96 111 133 154 182 252	30 48 63 82 108 127 152 172 194 204	42 56 69 83 97 109 122 137 157 181	42 56 69 83 97 109 122 137 157 181	25 40 55 72 90 109 131 152 173 199	24 43 60 78 98 121 147 174 202 229	43 59 75 90 105 120 137 163 206 225	25 40 56 73 91 110 131 152 173 199
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		132 156	111 124	111 130	128 150	112 124	109 130	121 143	127 142	124 141	146 179	111 118	141 170	111 136	155 207	113 131	129 152	124 142	113 132	117 138	99 111	112 130	130 152	122 137	130 148
		182 201	138 157	146 162	175 198	138 157	149 167	166 189	168 186	158 177	190 219	136 159	191 206	157 177	234 245	141 170	174 190	162 182	161 177	160 184	123 137	148 166	174 196	157 179	166 186
		219238	180 195	181 202	221 228	179 212	188 209	209 230	197 256	200 239	238	203		200 218	256	198 205	207 236	209 251	200 248	207 230	157 179	185 207	217 237	212 230	208 232
Image6	4	93 136	79 117	65 99	93 136	79 117	65 99	93 136	92 136	65 99	91 132	74 119	68 97	90 134	79 117	63 98	94 139	79 116	68 101	93 136	79 117	65 88	93 136	79 117	65 99
		174 205	150 180	129 158	174 205	150 180	129 158	174 205	174 246	129 158	172 201	153 184	130 154	172 203	150 181	129 159	177 206	151 182	130 159	174 205	150 180	129 158	174 205	150 180	129 158
	6	77 112	64 95	52 81	77 113	64 95	52 80	67 111	65 96	52 80	68 92	23 77	31 77	79 111	65 96	56 84	76 108	65 97	52 78	76 111	64 95	53 81	76 111	64 95	52 80
		142 170	122 147	106 128	144 171	122 147	104 126	141 169	123 147	103 125	120 153	106 134	106 131	141 173	121 147	104 125	131 156	121 146	105 130	141 169	122 146	105 127	131 169	122 147	104 126
		193 213	168 190	149 172	194 214	169 191	147 170	193 213	168 190	146 169	186 206	158 187	145 181	195 214	169 190	145 169	184 207	170 190	148 173	193 213	168 190	148 171	193 213	169 191	147 170
	8	63 94	54 82	46 71	66 96	54 82	44 68	66 98	64 95	41 67	1 61 74	3 50 89	44 69	57 101	50 79	9 51 88	62 93	62 91	41 69	64 95	54 82	44 68	64 97	54 82	44 68
		120 143	105 126	92 113	121 144	105 126	88 107	124 148	122 147	89 109	117 146	109 148	76 100	127 155	101 116	102 122	116 140	115 133	96 115	120 143	105 126	88 107	123 146	105 126	89 108
		165 185	146 163	133 151	166 186	146 163	124 142	170 188	169 191	127 162	170 192	159 184	116 144	180 185	141 161	142 168	162 182	150 166	135 152	165 185	146 163	124 141	168 187	146 163	125 142
		202 218	180 198	172 192	203 219	180 198	159 180	203 219	245 256	182 233	215	212	165 196	202 220	180 197	256	201 218	184 198	170 219	202 218	180 198	159 180	203 219	180 198	160 181
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		148 167	138 154	106 122	150 168	129 146	111 125	155 174	131 147	122 137	139 167	111 136	104 125	155 173	115 136	113 129	136 157	128 144	108 128	148 166	128 144	111 125	139 158	131 147	114 129
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		211 224	197 222	169 190	212 225	187 203	168 188	220 249	188 204	190 256	256	187	174	213 225	185 204	167 179	206 220	194 211	167 196	209 223	196 202	168 187	206 221	188 204	172 193
	12	53 78	44 67	33 53	44 67	39 63	34 54	67 87	41 64	41 64	1 3 39	1 40 47	31 40	30 65	1 54 86	23 44	30 49	29 63	39 46	53 79	43 65	33 53	45 73	45 68	39 61
		98 115	85 101	71 87	91 112	82 99	71 86	105 121	82 98	82 98	69 99	64 97	52 53	88 106	108 128	52 85	67 96	85 98	66 81	99 117	82 98	70 85	95 114	88 104	79 95
		131 148	117 133	101 115	132 149	116 132	101 115	137 151	114 129	114 129	129 148	111 137	78 97	139 155	150 165	103 121	108 127	106 121	88 106	134 151	113 127	100 113	131 148	120 136	111 125
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		191 202	170 181	154 168	191 203	168 180	153 166	190 201	170 183	170 183	177 195	177 194	150 161	200 212	216 226	169 176	183 192	168 188	155 170	192 203	167 180	151 165	192 203	176 189	165 182
		214 226	193 209	185 222	214 236	193 208	181 206	212 225	198 217	198 217	204 218	208	176 196	221 236	256	222 256	206 222	201 210	173 202	213 226	193 208	182 215	214 256	203 234	212 239
Image7	4	43 72	59 85	56 82	43 72	59 85	56 82	43 72	59 85	56 82	45 75	64 86	58 79	42 72	60 86	56 82	43 75	60 83	56 83	43 72	59 85	56 82	43 72	59 85	56 82
		115 167	119 168	114 160	115 167	119 167	114 160	115 167	119 167	114 160	118 171	124 170	112 164	114 163	121 167	115 163	122 176	115 163	115 161	115 167	119 167	114 160	115 167	119 167	114 160
	6	39 56	51 70	50 70	39 56	53 72	49 68	39 58	51 70	50 70	42 66	48 63	53 73	40 55	53 71	49 65	39 57	54 75	54 75	39 55	49 68	49 68	39 56	51 70	50 69
		79 111	89 116	89 112	79 111	92 120	87 111	80 112	89 116	89 113	79 121	87 108	95 122	76 103	93 119	85 110	80 116	96 123	98 123	78 110	87 111	87 111	80 112	89 116	88 112
		146 187	149 188	144 186	147 188	152 192	143 185	141 189	149 188	146 191	165 181	132 173	153 196	143 191	151 186	147 189	148 185	156 190	159 200	147 188	143 184	143 184	148 188	149 188	144 186
	8	29 40	46 61	45 62	30 41	46 62	45 62	38 52	45 60	43 60	4 34 49	7 37 61	1 57 66	37 57	44 70	1 45 57	38 52	43 59	33 53	29 40	45 60	45 61	30 41	46 62	45 62
		54 73	76 91	78 94	55 74	77 93	78 94	71 96	74 90	77 93	63 82	74 97	81 104	69 102	89 120	89 113	64 89	80 100	67 84	54 73	75 90	77 93	56 76	77 93	78 94
		99 128	112 136	112 135	101 131	116 144	112 136	126 159	112 139	111 134	116 143	126 161	128 154	128 167	152 178	141 184	113 154	122 150	106 134	98 127	111 137	111 135	102 132	116 142	112 135
		160 197	164 200	162 199	162 199	172 212	163 200	196 256	171 206	162 199	176	194	187	223 256	200 250	26	186 217	180 213	173 212	160 197	166 201	163 201	165 201	170 205	162 199
	10	27 39	45 58	40 55	28 39	44 58	41 56	27 39	44 58	40 54	15 33	1 2 10	21 49	1 3 37	1 59 76	40 56	29 39	42 58	32 45	27 38	44 58	41 55	29 40	45 59	41 56
		50 65	71 84	68 82	51 66	71 83	68 81	50 66	71 83	67 81	37 48	46 65	68 74	51 66	78 92	67 81	53 70	68 78	61 78	49 61	70 81	68 81	52 67	73 87	69 82
		83 104	99 119	95 111	86 110	96 114	95 111	88 111	96 115	95 111	62 76	89 100	79 94	99 119	121 147	92 108	93 116	94 120	92 112	78 99	93 110	95 110	88 113	105 126	96 112
		127 152	141 165	132 153	134 159	135 156	130 151	133 156	133 152	129 151	113 131	126 150	108 133	143 179	173 205	121 149	142 170	139 162	137 171	124 151	130 151	127 148	140 166	148 172	131 153
		180 211	194 224	179 214	184 213	180 212	177 211	181 211	174 203	179 211	164 201	191	164 220	205	256	172 214	191 221	191 233	190 218	178 210	175 210	176 210	196 228	199 233	180 212
	12	26 35	44 57	39 53	25 33	44 57	39 63	28 38	12 22	41 56	1 21 31	1 3 4 46	1 6 9 44	26 33	34 44	5 35 47	23 35	37 49	31 44	25 34	44 56	36 48	27 38	43 55	41 56
		43 54	68 78	65 77	40 49	68 77	65 77	48 59	45 59	69 83	41 45	49 66	65 74	42 50	61 76	61 68	40 47	62 72	56 72	42 51	67 77	58 70	49 62	66 77	69 82
		67 85	99 103	89 100	59 73	87 99	89 100	75 96	72 84	97 114	58 79	83 107	87 108	65 97	93 123	76 88	59 75	89 102	83 100	63 79	87 100	82 94	80 102	88 103	95 110
		106 129	121 138	115 133	91 111	115 133	114 130	110 135	99 121	135 158	103 106	140 166	131 167	117 124	152 154	94 115	101 127	120 137	117 133	98 120	118 137	107 122	124 148	123 144	128 146
		154 183	153 173	150 172	133 157	153 175	147 167	160 181	146 173	187 221	139 168	180 218	191 228	156 193	172 191	142 162	150 179	153 172	148 169	142 165	158 179	142 167	172 195	166 192	167 190
		207 229	195 222	199 234	182 212	204 225	190 219	200 224	207 231	251 256	216			224 255	233 256	232	197 221	201 222	198 232	188 216	202 233	198 230	215 234	220 249	216 246
Image8	4	71 115	61 92	64 89	82 113	89 118	58 82	72 116	61 92	63 89	73 115	67 94	63 87	70 114	69 91	65 90	75 118	63 94	66 92	71 115	61 92	64 89	71 115	61 92	64 89
		156 202	122 166	113 151	145 202	147 203	123 186	156 202	122 166	113 151	153 198	119 164	113 155	156 203	121 167	111 146	158 203	123 168	116 154	156 202	122 166	113 151	156 202	122 166	113 151
	6	52 91	52 79	52 75	71 95	79 102	52 68	51 90	51 78	52 76	43 96	42 82	1 42	55 94	52 78	53 76	53 89	42 77	54 79	51 90	51 78	53 76	52 91	51 78	53 76
		121 150	99 120	91 108	117 140	122 144	86 115	120 149	98 119	92 109	117 143	100 112	76 93	129 154	97 116	92 109	121 151	101 125	96 115	121 150	97 118	92 109	121 150	97 118	92 109
		180 217	148 188	131 166	172 220	175 221	156 205	179 217	145 182	132 167	169 215	133 182	119 163	177 215	139 182	132 169	181 224	150 187	139 176	180 217	144 183	132 176	180 217	144 183	132 167
	8	44 77	44 69	53 73	65 84	73 91	48 61	44 76	45 70	46 69	10 45	38 64	2 4 47	15 17	36 76	42 69	39 73	45 70	34 62	44 77	45 69	43 66	44 78	46 70	42 66
		101 124	86 102	88 100	102 118	108 123	73 88	101 124	87 103	83 96	85 112	87 109	66 90	87 116	96 115	83 97	96 124	87 101	85 100	102 125	85 100	81 93	103 126	86 101	81 94
		147 170	118 138	115 133	134 154	138 157	110 141	146 169	120 141	111 130	135 162	117 138	111 132	150 171	133 170	109 123	146 175	123 146	118 142	147 170	116 135	106 123	148 171	117 136	108 125
		195 226	164 199	159 197	186 227	187 228	176 213	194 225	170 207	153 185	197 230	172 205	162	208 239	200 256	152 182	198 228	186 222	168 202	194 226	160 195	146 180	196 227	161 196	148 181
	10	36 66	39 61	38 61	61 77	67 82	44 55	37 65	42 65	27 48	1 12	1 39	2 36	29 48	25 57	11 49	25 58	25 45	48 64	37 67	39 61	36 59	38 68	41 64	39 61
		87 107	76 89	75 86	92 106	98 112	66 77	86 105	80 94	70 81	50 55	66 78	60 74	70 107	76 90	73 87	79 100	67 84	78 90	89 108	76 89	73 84	90 110	79 92	76 87
		126 145	101 116	96 108	119 132	124 136	90 107	124 142	109 126	91 101	89 110	93 105	82 103	133 150	105 119	95 108	117 141	101 118	101 116	126 145	101 115	94 105	128 146	105 120	98 111
		164 183	133 152	121 137	148 170	152 173	131 158	161 181	146 172	113 130	132 158	120 135	119 135	168 187	130 133	115 122	164 187	136 154	141 151	163 182	131 150	117 133	164 183	136 165	127 146
		205 232	178 209	158 189	199 234	201 235	188 219	203 231	207 256	152 184	189 231	163 205	162 192	225 236	154 184	139 160	207 226	187 239	177 199	204 232	175 207	155 188	205 232	183 218	170 201
	12	31 58	40 58	33 55	58 72	70 84	43 54	39 69	36 58	44 66	1 3 45	2 3 7 50	3 13 40	1 29 72	11 34	35 39	25 45	24 54	30 51	31 58	32 54	29 51	35 64	32 53	32 54
		78 96	72 83	69 79	86 99	98 110	64 73	90 109	73 86	79 90	74 82	76 87	54 73	86 111	49 64	62 76	74 95	70 83	70 82	79 97	69 80	66 77	83 101	68 80	69 79
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		146 162	118 132	106 118	137 152	144 160	111 133	165 184	124 139	126 141	125 145	127 154	109 135	171 190	111 124	105 118	145 165	123 137	121 141	145 161	114 127	103 114	149 164	113 126	108 120
		178 195	148 170	132 150	171 195	175 195	156 182	204 222	156 180	161 189	164 196	175 217	166 196	224 239	147 170	147 172	184 192	156 166	156 173	177 194	143 161	127 143	180 197	141 159	136 155
		215 238	193 222	170 198	220 242	217 241	209 232	242 256	212 256	210 256	219		246	241	193 210	180 214	211 243	189 211	208 215	214 238	184 212	164 194	216 238	183 214	179 209
Image9	4	59 90	61 92	62 99	59 90	61 92	62 99	59 90	61 92	62 99	57 90	63 88	61 96	59 89	61 92	62 99	57 88	60 90	62 100	59 90	61 92	62 99	59 90	61 92	62 99
		135 187	135 186	142 192	135 187	135 186	142 192	135 187	135 186	142 192	132 178	131 182	148 198	136 189	134 185	143 193	132 185	135 188	142 193	135 187	135 186	142 192	135 187	135 186	142 192
	6	47 69	51 74	50 76	48 70	51 75	50 77	47 69	61 92	52 79	1 51 77	2 59 87	49 82	47 71	51 75	54 81	49 71	54 77	49 72	47 69	51 74	50 76	47 69	51 74	50 76
		92 122	95 124	100 126	93 124	96 124	101 127	92 125	135 186	103 129	106 146	123 171	113 134	95 130	96 130	108 145	92 121	102 133	93 116	92 122	95 123	100 126	92 122	95 123	100 126
		160 198	162 199	162 201	162 199	162 199	163 201	165 201	245 256	164 202	179	194	173 201	171 206	171 308	191 256	158 198	169 203	152 200	161 199	161 199	162 201	160 198	161 199	162 201
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		124 157	122 152	121 148	120 151	122 151	121 149	121 151	147 178	140 174	120 136	128 173	135 150	124 157	176 208	166 189	127 165	123 155	127 156	121 151	120 149	121 149	126 155	126 155	122 150
		187 213	182 208	180 208	181 208	181 208	180 209	181 207	206 256	206 256	164 192	207	181 218	193	256	256	190 215	185 214	188 215	181 207	179 207	180 209	184 209	184 209	181 209
	10	40 56	42 60	38 54	40 55	40 56	39 56	42 58	43 62	37 54	1 4 54	1 4 5 43	1 31 65	30 53	7 43	1 32	37 51	43 60	36 51	40 55	42 59	38 55	40 55	42 61	39 56
		70 83	75 88	71 88	69 83	75 91	75 91	74 91	77 91	72 89	74 87	63 89	89 98	74 84	59 72	60 74	66 80	70 84	69 89	68 82	73 86	73 90	68 82	76 90	75 92
		98 117	103 122	103 120	100 121	106 123	106 123	111 137	108 130	105 122	108 127	116 126	116 129	115 144	91 110	101 129	100 130	100 125	111 129	98 117	100 117	105 121	97 117	105 124	108 126
		141 166	146 171	142 168	146 171	145 170	145 170	166 192	158 185	144 170	159 201	161 197	155 180	168 188	140 159	141 164	164 190	143 174	151 175	141 167	139 165	143 169	142 168	148 173	150 175
		190 212	194 214	193 215	193 214	194 216	194 216	214 256	209 253	194 217	215		209	197 240	179 208	185 213	211 238	200 215	199 216	191 213	190 212	193 215	191 213	194 215	198 218
	12	39 54	40 56	34 45	39 54	40 57	36 50	37 51	44 61	37 52	33 49	1 3 21	8 29 40	43 54	46 60	8 36 46	35 49	38 54	31 47	37 50	40 56	35 49	40 55	42 59	35 49
		67 80	69 80	61 78	67 80	70 82	66 82	63 75	76 88	68 84	54 71	47 61	52 73	72 76	77 91	65 91	60 73	63 78	63 77	61 72	69 80	63 78	68 82	73 85	64 79
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		122 141	118 137	122 142	132 156	126 147	121 139	113 132	141 165	126 144	144 158	108 159	110 130	115 140	132 16	153 166	126 152	120 145	130 149	115 136	122 143	118 134	136 159	131 154	120 138
		161 180	159 180	165 188	176 191	169 188	161 182	154 176	188 208	165 182	177 182	195 225	156 182	163 183	168 181	193 216	170 181	166 189	176 192	158 179	165 183	154 176	179 198	176 196	160 181
		198 217	198 217	206 222	206 221	205 221	202 220	196 216	223 256	201 218	209 256	245	214	210 256	201 217	217	198 230	203 217	208 226	198 217	201 218	197 217	215 236	213 235	200 219
Image10	4	88 131	87 132	70 105	88 131	88 132	70 105	88 131	86 131	70 105	89 135	66 119	60 98	89 131	86 131	70 104	80 126	87 133	71 104	88 131	87 132	70 105	88 131	87 132	70 105
		160 185	163 190	130 154	160 185	162 190	130 154	160 185	162 189	130 154	162 189	153 186	126 153	159 185	162 190	130 154	156 183	164 192	130 153	160 185	163 190	130 154	160 185	163 189	130 154
	6	69 108	67 108	59 92	69 108	67 108	59 92	77 118	66 107	59 92	21 93	62 123	1 45 67	66 108	9 80	63 95	61 107	63 107	64 97	69 108	67 108	59 92	69 108	67 108	59 92
		135 157	137 169	115 134	135 157	137 159	115 134	146 169	137 160	115 134	122 147	146 169	107 128	135 157	112 151	117 133	134 156	140 165	117 138	135 157	137 159	115 134	135 157	137 159	115 134
		176 195	179 200	152 184	176 195	179 200	153 187	191 256	179 200	152 183	169 198	186 215	155	176 197	181 208	151 177	176 197	183 202	154 183	176 195	179 200	152 184	176 195	179 200	152 183
	8	59 96	52 91	46 75	53 90	48 88	49 78	62 100	55 95	54 85	1 31 87	1 24 93	1 45 65	48 81	48 82	58 84	48 86	39 84	48 82	54 91	48 88	49 79	57 94	50 89	50 80
		120 140	118 139	98 116	116 137	116 138	99 116	127 149	121 143	107 124	118 146	123 155	95 113	112 135	115 139	106 119	112 134	111 133	102 120	117 138	116 138	100 117	120 140	117 139	101 118
		167 172	157 173	131 145	155 170	156 172	130 144	167 183	161 177	140 157	167 185	171 188	130 153	152 169	159 176	141 160	155 171	155 172	136 149	155 170	156 172	131 145	157 172	157 173	132 146
		187 205	189 207	161 195	185 202	188 207	160 194	202 256	193 210	189 256	253	212	197	187 206	184 203	202 256	184 200	190 211	165 198	185 203	188 207	161 195	187 205	189 207	162 196
	10	52 85	45 82	43 70	46 78	41 79	40 68	53 88	45 80	53 82	1 5 61	1 21 69	2 43 58	1 32 92	35 70	7 17	46 79	41 63	34 75	50 84	43 79	38 65	52 87	45 82	42 70
		109 129	108 128	89 105	101 121	105 126	88 104	114 134	106 126	101 117	99 129	102 132	76 103	115 138	102 125	54 81	109 124	98 123	92 111	108 127	106 127	86 102	112 132	109 130	91 107
		145 159	145 159	118 130	139 154	143 158	117 129	151 166	143 157	129 140	153 169	157 177	114 133	158 177	146 162	98 121	145 154	140 161	122 136	143 157	144 158	116 128	148 161	147 161	120 132
		172 184	172 184	141 153	167 180	171 184	140 152	181 197	170 183	149 160	177 197	196 222	146 166	190 211	178 194	134 148	166 178	177 189	144 153	170 182	171 184	140 152	173 185	173 185	143 156
		197 217	198 215	168 202	194 213	198 215	167 202	223 256	198 218	174 206	250	256	225	256	219 232	167 199	192 216	202 233	172 224	194 213	198 215	167 203	198 218	199 216	173 215
	12	47 77	43 75	39 66	43 75	43 77	38 62	55 84	32 63	42 70	1 39 78	1 19 41	1 14 31	19 81	23 31	9 33 62	40 59	10 44	39 61	41 73	38 72	31 58	46 78	36 71	38 65
		99 117	98 117	85 100	98 116	100 118	82 99	108 125	85 103	88 103	107 129	83 107	37 67	115 126	38 76	90 110	75 97	75 99	73 93	96 115	96 116	77 93	101 119	96 116	84 101
		132 146	134 146	112 123	132 146	134 148	113 126	140 154	120 135	115 126	145 153	126 142	92 109	140 146	110 121	119 134	116 138	118 137	116 129	131 144	133 147	106 117	135 148	132 146	114 126
		158 169	161 172	134 144	158 169	160 171	139 150	167 178	151 165	135 146	164 182	167 174	113 136	155 165	140 153	139 145	152 164	151 164	135 142	156 168	159 170	128 138	160 171	159 170	137 148
		180 191	183 195	155 169	180 191	181 192	160 173	190 204	178 192	157 169	202 215	184 203	156 172	177 193	169 179	153 160	178 188	181 196	158 178	179 180	181 193	148 159	181 192	181 192	160 179
		203 224	208 232	187 222	203 224	205 223	192 227	227 256	212 256	189 228	256	225	212	218 240	195 214	201	201 244	210 237	204 243	203 225	206 224	174 220	205 228	205 223	219 255

TABLE III
COMPARISON OF OPTIMAL THRESHOLDS FOR DIFFERENT ALGORITHMS USING KAPUR'S ENTROPY METHOD AT 4, 6, 8, 10, AND 12 LEVELS

Images	K	OBLDA			DA			PSO			SCA			BA			HSO			ALO			SSA		
		R	G	B	R	G	B	R	G	B	R	G	B	R	G	B	R	G	B	R	G	B	R	G	B
Image1	4	66 114 159 205	71 121 171 217	58 107 152 188	66 114 159 205	72 123 171 217	62 115 157 198	66 114 159 206	71 121 171 217	62 116 157 198	61 102 145 198	64 116 167 215	63 108 151 195	66 114 161 206	71 125 175 217	61 112 157 198	63 110 157 204	71 121 171 217	59 105 152 198	66 114 159 205	71 121 171 217	62 115 157 198	66 114 159 205	71 121 171 217	62 115 147 198
	6	53 88 123 157 191 226	53 88 123 157 191 226	47 85 124 160 198 214	53 89 123 157 191 226	54 87 121 154 185 218	46 83 125 160 198 214	52 87 122 156 191 226	54 87 120 152 185 218	46 84 124 160 198 214	16 67 107 147 180 213	19 73 103 145 190 222	27 60 103 149 192 220	53 92 126 153 186 224	48 80 109 151 184 216	57 92 135 162 195 215	56 82 121 160 191 231	19 68 109 145 182 219	44 88 128 157 198 214	53 88 123 157 191 226	54 87 120 153 185 218	47 85 124 160 198 214	53 88 123 157 191 226	53 86 119 152 185 218	46 84 124 160 198 214
	8	44 70 97 123 150 176 202 228	18 49 77 105 133 162 190 219	38 67 97 123 148 171 198 214	16 47 77 106 135 165 195 227	18 50 79 107 134 162 190 220	37 65 93 121 148 171 198 214	44 70 97 123 149 175 201 228	47 75 102 130 158 185 212 232	35 63 90 118 145 171 198 214	18 42 69 90 109 149 186 210	11 39 63 79 113 153 178 204	25 41 84 106 141 187 211 229	50 80 101 120 140 168 192 230	16 42 79 113 134 161 190 221	39 69 97 129 149 167 191 222	46 72 93 120 143 170 201 228	19 43 76 105 136 171 193 218	33 68 92 127 166 196 213 230	43 70 97 123 150 176 202 228	18 48 76 104 132 161 190 219	34 61 89 117 143 170 198 214	44 71 98 126 152 178 203 228	19 52 83 112 139 167 193 220	38 67 95 123 148 171 198 214
	10	16 44 69 93 117 140 164 188 209 230	18 46 71 96 121 146 169 191 214 232	30 54 77 104 129 150 172 198 213 229	16 42 65 89 112 135 159 184 206 229	18 46 70 95 118 141 165 190 214 233	13 37 59 83 114 142 170 198 213 229	38 59 80 102 123 144 165 187 209 230	40 60 80 100 120 139 159 178 198 220	32 56 80 104 127 150 172 198 213 229	14 39 62 100 122 156 186 199 225 244	11 26 47 64 104 123 146 165 194 217	39 53 82 100 112 150 162 196 217 236	16 42 55 61 87 109 130 150 195 232	19 56 78 87 100 135 161 183 217 228	8 28 77 88 95 117 145 175 192 233	15 36 63 94 112 127 156 189 211 234	18 45 62 82 107 134 161 184 210 231	21 41 65 90 106 125 145 168 199 215	16 41 65 88 111 135 159 182 205 228	18 46 70 94 118 142 166 190 214 233	30 52 75 99 126 150 171 198 213 230	16 40 61 83 105 129 153 177 203 228	18 46 70 95 119 143 167 190 214 233	29 51 75 101 127 150 172 198 213 229
	12	16 39 59 80 101 120 138 157 173 190 210 230	18 41 61 81 102 121 140 159 178 196 216 233	33 54 74 95 113 131 147 162 178 197 213 229	16 39 57 76 94 113 134 156 177 198 220 236	18 43 66 88 109 131 148 166 184 201 220 243	29 51 73 91 106 124 142 160 176 198 213 229	36 54 72 91 109 127 145 163 181 198 215 233	18 40 58 77 96 116 136 156 176 196 216 234	24 43 61 79 98 117 135 153 172 198 213 229	10 35 49 64 71 88 125 161 186 201 227 243	7 17 36 65 78 123 136 170 178 191 200 237	8 21 30 44 64 72 90 128 153 168 186 193	20 42 63 97 123 136 160 176 184 196 207 224	20 72 78 101 117 130 135 140 162 191 222 244	17 42 72 79 102 121 130 149 160 178 192 218	15 36 52 73 97 119 136 160 176 194 227 240	19 39 52 69 93 111 139 158 180 202 222 224	13 32 51 73 91 111 133 155 177 198 214 230	16 38 60 79 98 117 135 153 171 190 209 230	18 41 60 80 99 118 137 157 176 196 217 235	14 34 56 77 98 118 138 157 176 197 213 229	16 43 67 91 112 132 152 172 190 208 226 240	18 40 59 78 97 117 137 157 176 196 216 234	13 34 54 74 94 115 135 156 176 198 213 229
Image2	4	54 104 154 202	57 108 158 207	45 90 135 180	53 102 152 201	57 107 157 207	45 90 135 180	53 102 152 201	57 108 158 207	45 90 135 180	55 107 154 207	57 111 161 207	49 95 138 182	54 103 153 202	57 108 158 207	47 89 134 180	54 104 153 203	54 107 157 208	48 91 136 180	53 102 152 201	57 108 158 207	45 90 135 207	53 102 152 201	57 108 158 207	45 90 135 180
	6	35 70 106 142 178 214	42 79 115 151 186 222	32 63 93 123 153 183	37 72 108 143 178 214	42 78 114 150 185 221	32 64 94 123 153 183	37 72 107 142 178 214	42 79 115 151 186 222	32 62 92 123 153 183	39 70 109 143 182 212	47 81 121 151 193 233	35 65 95 113 144 174	39 77 113 143 175 212	40 77 111 153 191 225	28 60 88 122 158 184	34 71 108 144 180 216	40 78 116 152 186 221	31 64 99 134 159 187	37 72 107 142 178 214	42 78 114 150 185 221	32 63 93 123 153 183	37 72 107 142 178 214	42 78 114 150 185 221	32 63 93 123 153 183
	8	30 58 86 113 140 167 194 221	38 68 97 125 152 178 205 232	24 47 70 94 117 141 164 187	30 58 86 113 140 167 195 222	36 65 93 120 148 175 203 231	25 48 71 94 118 140 163 187	30 58 86 113 140 167 194 221	35 63 91 119 147 175 203 231	25 48 71 94 117 140 163 187	27 61 78 111 137 167 188 204	27 38 70 104 127 159 209 229	17 34 55 85 97 120 151 175	22 51 74 95 140 163 206 234	34 57 81 111 157 179 196 232	21 45 70 100 113 139 169 185	27 51 75 101 134 167 193 223	32 59 84 114 143 169 202 229	30 58 74 104 125 150 169 190	30 58 86 113 140 167 195 221	35 63 91 119 147 175 203 232	25 48 71 94 117 141 164 187	30 58 86 113 140 167 194 221	35 64 92 120 149 177 204 232	26 49 73 97 121 145 168 190
	10	25 49 72 94 116 138 161 184 207 229	31 54 76 99 122 145 166 189 211 233	24 45 65 85 105 124 142 160 177 192	23 45 67 90 113 136 159 182 204 227	31 56 80 103 126 150 172 194 214 235	21 40 59 77 96 115 135 154 173 191	25 47 69 92 115 138 161 183 206 228	30 52 74 97 120 143 165 188 211 233	20 39 59 78 97 116 135 154 173 191	31 63 73 89 115 142 166 179 218 232	12 31 47 88 111 130 163 185 200 241	8 18 31 50 64 94 110 121 162 174	13 45 72 100 123 145 173 194 219 235	29 48 71 97 107 158 172 179 214 237	10 27 49 63 87 103 116 157 181 199	22 39 68 88 110 133 156 183 209 231	30 59 82 103 121 150 172 193 220 238	20 37 61 81 103 126 144 165 180 196	25 47 69 91 114 137 160 183 206 228	30 53 76 98 120 142 165 188 211 233	21 40 60 79 98 116 134 153 173 191	26 49 72 95 118 140 163 186 208 229	30 53 77 101 125 148 170 192 213 235	21 41 61 80 99 118 136 154 173 191
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	12	55 72 89 105 121 138 154 169 187 205 223 240	49 69 88 107 126 145 163 179 197 214 230 246	32 56 80 101 120 138 156 173 189 206 222 238	23 60 79 99 117 135 151 169 187 205 223 240	49 66 83 101 119 138 155 172 188 205 223 241	32 51 69 87 104 122 139 157 175 193 214 232	55 70 88 105 121 138 155 172 189 206 224 241	49 67 85 103 120 138 155 172 188 205 223 241	50 68 84 109 125 139 165 179 189 200 220 254	1 61 72 79 93 112 134 154 158 177 207 232	2 51 63 88 124 138 166 179 190 235 245 252	11 25 47 71 99 131 154 170 184 191 220 242	1 61 71 86 97 108 118 142 162 211 228 254	66 79 98 110 124 152 168 189 198216 230 246	11 28 71 90 98 136 173 179 190 207 219 254	50 61 77 88 108 122 139 160 181 197 217 242	43 52 71 85 100 126 67 188 210 231 235 247	22 36 52 66 91 112 128 161 183 200 215 245	55 72 89 105 121 137 154 171 189 206 223 241	49 67 84 104 122 140 158 175 193 212 229 246	20 33 55 75 93 111 130 150 169 189 208 227	4 57 77 97 116 135 152 169 187 205 223 240	49 70 89 108 127 144 164 180 197 213 230 246	32 53 73 91 109 130 149 168 186 204 222 238
Image4	4	79 122 165 206	84 133 174 215	74 117 157 198	79 122 165 206	84 133 174 215	74 117 157 198	79 122 165 206	84 133 174 215	74 117 157 198	68 111 160 206	85 133 171 214	75 119 153 193	79 119 163 206	84 128 166 214	73 115 166 198	81 127 170 209	82 128 173 215	75 128 173 215	79 122 165 206	84 133 174 215	74 117 157 198	79 122 165 206	84 133 174 215	74 117 157 198
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	12	58 78 98 117 134 150 166 181 196 211 225 238	60 79 98 117 132 148 164 179 195 211 226 241	28 52 72 92 110 129 145 162 179 197 215 233	48 64 82 97 116 136 155 174 192 207 223 237	58 75 92 109 125 141 156 172 189 206 221 239	23 35 54 73 94 114 135 155 175 196 214 233	53 70 86 103 120 136 151 167 183 199 216 233	56 72 88 104 121 138 155 172 189 206 222 239	28 47 64 81 98 117 135 152 169 191 212 233	11 39 45 76 88 110 123 138 149 177 202 232	38 49 77 106 117 123 155 179 193 195 218 230	20 26 33 59 92 107 115 131 165 173 210 223	34 49 58 79 94 141 153 179 212 216 224 242	49 61 79 102 119 127 148 169 200 210 224 242	20 35 46 57 81 114 130 142 190 194 219 237	47 64 81 99 117 143 158 170 190 206 230 243	38 52 66 82 104 124 144 163 184 203 226 240	21 45 62 92 109 132 150 172 188 204 221 234	50 66 81 97 115 132 148 165 182 199 216 233	56 73 89 106 121 136 152 167 184 202 220 238	28 47 66 86 105 125 143 160 179 198 216 233	52 68 85 101 118 134 151 167 183 200 216 233	56 72 89 106 123 139 156 173 189 206 222 239	28 52 73 94 113 132 151 168 185 202 218 233
Image5	4	45 95 148 200	70 114 155 208	55 97 144 185	46 95 148 200	70 114 155 208	55 97 144 185	46 95 148 200	70 114 150 208	55 97 144 185	43 96 149 203	54 101 154 207	55 91 142 183	46 92 145 198	62 115 154 208	54 94 137 193	45 93 148 201	69 112 154 206	56 97 145 186	46 95 148 200	70 114 155 208	55 97 144 185	46 95 148 200	69 112 155 208	55 97 144 185
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	12	23 44 62 81 102 122	45 62 79 93 105 120	16 36 54 72 90 108	23 42 61 80 99 120	46 64 83 101 115 129	18 36 52 69 87 105	24 43 63 83 102 121	28 50 71 92 113 134	19 39 58 77 95 114	12 27 39 44 91 108	34 40 63 72 86 101	1 14 20 44 65 81 103	13 21 45 66 85 117	25 33 88 101 107 123	14 22 37 64 104 122	23 36 62 83 102 117	27 45 59 80 98 121	14 35 58 74 95 115	23 43 62 82 101 121	43 60 76 110 124 139	20 39 58 75 91 108	25 46 66 85 105 125	28 48 66 85 103 121	19 39 58 76 94 111

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Image5	4	42 87 136 184	55 109 162 228	50 102 154 216	42 90 137 184	51 102 156 228	60 102 154 216	42 87 136 184	55 107 159 228	50 102 154 216	40 91 141 187	53 100 158 224	45 109 159 209	42 90 140 185	51 105 160 228	51 103 158 216	42 93 138 185	44 101 156 224	50 102 153 214	42 87 136 184	44 98 153 228	50 102 154 216	49 93 139 185	44 98 152 228	50 102 154 216
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	12	20 39 58 77 96 114 134 154 193 211 229 245	19 37 55 74 94 113 134 154 176 196 216 235	23 40 59 78 99 122 144 166 184 202 221 240	20 39 57 75 94 113 133 152 171 190 209 228	20 41 60 78 97 116 134 153 173 194 215 235	25 45 65 85 104 121 142 162 181 202 221 240	20 38 57 75 95 114 133 152 170 189 208 226	20 41 60 81 103 124 145 163 180 199 218 236	25 43 63 81 100 118 136 155 176 195 215 240	14 22 30 50 62 888 105 131 142 160 176 202	16 27 44 58 73 97 117 126 142 152 170 197	10 45 62 84 108 120 149 169 196 205 218 232	9 49 60 97 118 122 143 150 161 184 214 231	20 25 47 53 90 112 123 148 186 218 238 256	1 10 42 63 84 114 145 152 183 199 229 256	17 31 49 69 88 110 133 153 176 190 209 223	24 44 57 72 102 123 147 163 186 201 216 236	21 36 59 76 101 121 142 160 180 200 217 240	29 39 58 76 95 114 133 151 169 188 208 227	20 40 59 77 96 115 134 153 173 194 213 233	28 45 65 85 105 23 142 162 180 197 215 240	22 44 62 81 101 120 139 157 175 193 211 228	20 41 60 81 102 122 141 159 177 195 215 235	27 49 70 93 114 133 152 170 187 205 224 240
Image9	4	68 113 157 199	59 111 154 197	72 132 162 202	68 113 157 199	59 111 154 197	72 122 163 203	68 113 157 199	59 111 154 197	72 122 163 203	66 113 158 196	55 105 151 193	63 106 152 194	70 114 160 202	58 111 156 197	62 104 142 193	68 113 155 198	58 109 155 198	71 122 164 203	68 113 157 199	59 111 154 197	72 122 163 203	68 113 157 199	59 111 154 197	63 105 143 192
	6	49 88 123 161 198 236	51 82 112 143 176 209	55 91 128 165 201 228	49 88 124 163 199 236	53 91 125 164 200 236	51 82 113 143 177 210	49 86 121 160 197 236	53 91 125 163 199 236	54 90 128 165 201 238	43 76 112 147 187 234	17 49 107 133 175 216	59 88 120 157 189 213	49 85 118 154 195 239	48 82 114 151 187 236	48 89 130 167 199 237	49 85 113 147 180 212	50 84 113 143 174 208	62 95 133 169 198 236	49 88 124 162 198 236	50 82 112 143 176 210	51 83 115 143 177 210	46 79 111 141 173 207	50 82 112 143 176 210	51 82 113 143 177 210
	8	16 48 82 113 142 174 204 236	43 67 94 121 149 177 206 236	48 67 94 121 149 177 206 238	44 73 102 131 159 184 210 236	45 70 97 123 150 178 207 236	49 77 105 132 158 183 210 238	44 71 98 124 152 179 207 236	47 73 101 126 153 180 207 236	49 77 104 130 156 182 209 238	15 31 73 109 120 171 211 237	28 48 88 120 150 194 217 238	11 47 79 102 135 166 213 233	17 46 77 114 142 172 201 237	35 67 93 123 161 186 206 236	45 67 88 116 147 178 205 234	16 45 83105 125 211 220 249	34 47 74 105 136 167 201 235	38 86 112 136 164 176 199 235	44 71 98124 152 179 207 236	47 73 99 125 151 178 206 236	49 77 104 130 156 182 209 238	16 47 80 111 141 172 203 236	47 74 102 128 155 181 209 236	50 80 109 136 162 187 212 238
	10	41 63 84 104 125 147 170 192 214 238	17 41 62 87 110 134 158 184 210 236	35 55 76 97 122 145 170 194 216 239	16 44 69 92 117 141 165 189 214 238	17 48 76 105 125 145 168 190 213 236	19 45 68 90 115 138 163 189 214 239	42 65 89 111 133 154 175 196 217 238	41 62 85 107 128 149 170 192 213 236	37 59 81 104 126 147 169 192 214 238	20 25 47 62 81 134 150 177 198 242	17 24 47 63 88 101 125 150 176 240	11 20 27 46 68 112 138 181 212 225	17 43 66 90 109 134 158 182 207 237	12 38 64 87 108 134 155 183 212 235	14 45 72 97 126 147 171 191 217 236	15 31 54 69 83 109 127 144 224 245	31 59 84 96 108 126 156 191 203 245	19 27 33 62 114 133 160 187 209 233	16 44 68 91 115 140 164 188 212 237	41 62 85 107 128 150 171 192 213 236	37 58 80 101 122 143 168 190 213 238	16 43 67 91 114 138 163 187 211 237	41 63 86 108 128 150 172 193 214 236	42 65 87 110 132 153 174 195 216 239
	12	14 40 60 80 100 119 139 159 179 200 219 238	37 56 74 93 111 128 145 163 181 199 217 236	19 42 63 83 104 124 143 163 183 202 221 239	17 41 61 80 99 118 137 157 178 199 218 238	17 38 56 76 96 115 135 156 175 195 215 236	19 40 60 80 99 119 139 161 180 199 218 239	39 57 75 93 111 127 145 162 179 197 217 238	39 58 76 94 111 128 146 164 182 200 218 236	33 52 71 90 109 127 144 163 181 200 219 239	2 12 39 48 65 77 105 151 179 210 219 242	8 21 27 45 54 82 106 121 138 161 183 233	11 32 42 53 85 99 121 140 146 173 181 230	18 42 63 100 126 139 158 173 188 212 236 254	12 45 62 76 92 109 127 152 175 192 214 237	18 39 55 79 87 113 138 161 175 202 223 239	2 18 38 63 75 104 161 183 204 212 226 234	41 63 76 88 100 108 127 133 161 180 223 240	1 19 41 58 93 105 118 140 160 185 206 232	16 40 58 76 97 117 138 157 177 198 217 238	35 53 71 89 107 143 161 179 197 216 236 245	14 37 57 76 96 17 137 157 177 197 217 239	16 42 66 90 111 131 151 170 188 204 221 238	12 41 62 82 102 121 139 158 177 196 215 236	14 38 59 80 101 121 141 161 180 199 218 249
Image10	4	53 102 151 220	56 108 158 225	46 90 136 193	53 102 151 220	48 100 153 225	46 92 138 193	53 102 151 220	56 108 158 225	46 92 138 193	61 105 151 215	51 104 159 223	52 100 144 197	59 103 148 220	55 103 156 225	51 98 156 193	48 98 146 220	57 110 160 225	52 98 148 193	53 102 151 220	56 108 158 225	46 88 133 193	53 102 151 220	56 108 158 225	46 92 138 193
	6	39 74 112 148 186 220	46 85 120 154 191 226	39 73 108 146 181 212	39 78 114 150 186 220	46 85 120 154 191 226	39 74 109 146 181 212	39 74 110 145 183 220	46 82 119 154 191 226	39 74 109 146 181 212	45 71 110 145 197 223	31 81 113 142 191 227	40 68 100 144 178 203	36 70 104 135 164 222	50 89 121 153 182 225	46 78 114 151 178 204	40 72 109 144 185 220	34 71 112 151 192 226	34 66 101 141 179 216	39 74 111 147 186 220	46 79 114 151 191 226	39 73 108 146 181 212	39 74 110 145 183 220	46 82 118 153 191 226	42 78 113 152 187 218
	8	33 61 89 115 142 169 197 223	36 65 93 120 147 174 202 229	33 62 92 121 151 179 201 228	33 61 89 117 145 172 199 223	33 60 87 113 140 168 197 226	33 62 92 121 151 179 201 227	33 61 88 114 141 168 196 223	32 57 85 113 140 168 197 226	32 59 86 113 141 168 193 221	17 33 44 87 125 152 195 224	21 46 74 102 147 161 186 218	12 38 61 89 110 159 190 216	19 53 87 110 148 181 205 226	41 77 103 131 154 166 201 227	13 33 91 113 134 165 198 230	27 53 80 106 133 165 194 221	28 51 80 108 145 174 198 227	29 53 84 112 141 173 201 225	33 60 86 112 139 166 194 221	32 57 85 113 141 170 199 226	30 57 85 112 140 168 193 221	33 61 89 117 144 171 199 223	33 60 87 114 143 172 201 229	33 62 90 118 147174 200 227
	10	27 52 74 96 118 139 161 183 205 224	26 48 73 94 116 139 162 185 208 230	28 51 73 96 118 141 163 182 203 228	24 47 70 92 116 140 162 184 205 225	26 48 74 99 122 144 167 191 213 233	26 46 66 87 109 134 159 181 203 231	24 45 68 90 112 134 157 181 204 224	25 48 71 93 115 138 162 186 208 230	26 46 67 90 113 136 159 181 203 228	18 39 71 92 109 120 161 202 221 228	10 27 35 59 83 119 147 174 206 234	8 24 38 55 90 110 145 170 195 227	17 23 52 67 131 151 196 234 240 248	15 48 72 107 121 141 147 156 186 232	27 34 75 97 111 120 158 186 213 245	26 46 69 89 119 137 161 180 207 227	24 44 72 97 123 147 166 188 212 233	20 36 65 88 110 137 164 187 204 230	24 45 68 91 114 136 159 182 204 224	26 48 73 97 120 143 167 191 214 233	26 45 67 91 113 136 160 181 203 229	24 47 71 93 116 138 160 183 205 224	26 48 74 98 122 145 168 191 214 233	28 53 76 99 121 144 167 186 204 228
	12	24 47 69 88 107 127 146 167 186 204 220 235	19 38 57 76 95 115 135 155 175 195 215 233	26 43 62 82 102 123 143 162 181 200 218 236	21 40 60 79 98 117 136 156 177 197 213 229	19 39 63 87 109 129 149 168 188 203 219 235	26 46 65 85 103 123 145 164 181 200 218 236	21 39 57 75 93 112 132 151 171 191 210 227	21 41 60 80 100 120 140 160 180 199 217 233	26 44 63 82 101 120 141 162 181 200 218 236	5 13 33 56 67 88 97 109 137 151 179 215	7 27 46 70 84 101 130 168 182 190 218 232	9 26 30 48 60 102 143 164 178 206 223 238	26 39 53 72 92 110 127 134 146 174 209 220	14 23 40 60 87 98 123 150 184 194 205 245	8 28 41 67 73 117 128 138 148 184 206 223	17 39 58 78 100 120 135 156 177 195 214 231	15 33 48 74 98 124 155 169 188 203 223 235	17 38 58 73 88 109 126 146 169 185 213 242	20 39 59 77 96 115 134 153 172 191 211 228	20 38 57 76 96 116 135 154 174 194 214 233	26 46 65 85 104 121 140 159 176 193 212 234	21 40 61 82 102 122 143 163 184 203 220 235	25 46 65 85 104 123 141 159 178 197 215 233	26 46 65 85 104 123 143 163 181 200 218 236

TABLE VI
THE STD VALUES OF FITNESS FUNCTIONS USING OTSU'S METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	WOA-DE	WOA	SSA	SCA	ALO	HSO	BA	PSO
Image1	4	**0.00E+00**	**0.00E+00**	6.42E-03	6.05E+00	9.05E-04	1.65E-01	1.84E-01	7.27E-03
	6	**1.12E+00**	2.32E+00	1.95E+00	6.28E+00	1.76E+00	1.32E+00	3.10E+00	4.77E+00
	8	**1.89E-01**	1.57E+00	1.28E+00	3.19E+00	1.57E+00	7.74E-01	4.95E+00	7.33E-01
	10	**4.01E-01**	1.29E+00	2.14E+00	5.73E+00	6.77E+01	1.63E+00	1.05E+01	2.01E+00
	12	**4.29E-01**	1.07E+00	5.24E-01	2.32E+00	1.70E+00	1.12E+00	2.85E+00	1.71E+00
Image2	4	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.50E+00	3.92E-03	2.83E-01	3.06E-01	1.11E-02
	6	4.20E-03	1.23E-02	2.00E-01	**2.66E-03**	1.40E-02	7.43E-01	5.70E+00	4.58E-02
	8	**2.67E-02**	1.64E-01	9.30E-01	3.11E+00	3.03E-02	8.62E-01	5.31E+00	2.13E-01
	10	**5.36E-02**	5.54E-01	1.12E+00	3.47E+00	8.20E-02	7.32E-01	2.80E+00	3.31E-01
	12	**2.92E-01**	4.97E-01	2.12E+00	3.47E+00	3.92E-01	1.46E+00	4.82E+00	1.03E+00
Image3	4	**0.00E+00**	1.57E-02	4.43E-04	1.44E+00	3.74E-03	2.29E-01	4.62E-01	7.58E-03
	6	**6.11E-03**	7.02E-02	1.42E+00	6.96E+00	6.28E-03	3.56E-01	1.14E+01	3.04E-02
	8	**1.38E-02**	3.15E-02	3.39E-01	3.80E+00	6.21E-01	3.90E-01	6.54E+00	1.33E-01
	10	**1.68E-01**	2.31E-01	4.07E-01	2.00E+00	1.83E-01	9.01E-01	6.07E+00	1.09E+00
	12	**1.14E-01**	3.93E-01	1.09E+00	1.71E+00	2.78E-01	5.77E-01	3.37E+00	1.36E+00
Image4	4	**0.00E+00**	7.73E-03	**0.00E+00**	1.51E+00	6.96E-03	2.92E-01	1.06E+01	1.95E-02
	6	**5.65E-03**	1.01E-02	1.01E-01	1.37E+01	4.66E+00	1.75E+00	1.48E+01	4.60E+00
	8	**1.56E-01**	1.10E+00	7.33E-01	3.39E+00	3.88E+00	9.82E-01	3.12E+00	1.13E+00
	10	**7.23E-01**	1.06E+00	1.81E+00	4.47E+00	2.28E+00	8.98E-01	8.12E+00	1.48E+00
	12	**5.38E-01**	1.10E+00	8.72E-01	2.52E+00	1.67E+00	1.25E+00	1.86E+00	1.18E+00
Image5	4	**0.00E+00**	5.42E+00	**0.00E+00**	5.40E+00	7.46E-03	4.56E-01	6.26E-02	5.39E+00
	6	**2.33E-01**	2.56E+00	2.33E+00	3.93E+00	2.24E+00	2.28E+00	6.81E+00	4.76E+00
	8	**1.09E-01**	1.58E+00	3.01E+00	2.95E+00	3.42E+00	3.24E+00	3.78E+00	2.06E+00
	10	**4.76E-01**	1.51E+00	1.53E+00	2.16E+00	1.95E+00	1.69E+00	8.68E+00	3.05E+00
	12	**3.81E-01**	1.08E+00	1.33E+00	3.89E+00	9.99E-01	7.95E-01	5.31E+00	1.73E+00
Image6	4	**0.00E+00**	**0.00E+00**	**0.00E+00**	8.00E-01	**0.00E+00**	3.63E-01	9.84E-02	7.75E-03
	6	**1.13E-02**	2.52E-01	1.47E-02	6.88E+00	2.91E-02	1.02E+00	7.34E+00	2.69E+00
	8	**2.73E-01**	1.74E+00	8.53E-01	3.90E+00	5.23E-01	1.19E+00	6.32E+00	2.34E+00
	10	**2.81E-01**	5.38E-01	3.77E-01	1.52E+00	4.98E-01	1.93E+00	5.20E+00	1.68E+00
	12	**4.05E-01**	1.47E+00	8.97E-01	4.10E+00	5.40E-01	1.24E+00	6.78E+00	1.11E+00
Image7	4	**0.00E+00**	**0.00E+00**	2.81E-03	1.42E+00	**0.00E+00**	4.52E-01	1.55E-01	1.17E-02
	6	2.03E-01	**3.19E-03**	3.36E-02	8.21E+00	1.24E-02	1.01E+00	4.89E+00	3.01E+00
	8	**1.69E-02**	3.65E-01	5.65E-02	6.11E+00	1.26E+00	1.30E+00	5.92E+00	2.37E+00
	10	**8.97E-02**	1.16E+00	4.61E-01	4.04E+00	5.72E-01	8.96E-01	6.74E+00	1.38E+00
	12	**3.31E-01**	1.18E+00	8.77E-01	2.56E+00	3.88E-01	6.27E-01	3.87E+00	1.30E+00
Image8	4	**0.00E+00**	0.00E+00	2.32E-03	1.00E+00	0.00E+00	3.51E-01	1.42E+01	1.24E-02
	6	**1.14E-03**	1.64E-02	2.27E-01	7.04E+00	8.82E-03	5.63E-01	5.06E+00	4.41E+00
	8	**5.07E-03**	3.59E-02	2.69E-01	4.18E+00	1.59E+00	1.60E+00	7.97E+00	1.59E+00
	10	**1.36E-01**	9.16E-01	1.21E+00	1.83E+00	2.71E+00	2.03E+00	4.90E+00	8.47E-01
	12	**0.00E+00**	1.80E+00	1.71E+00	3.36E+00	8.11E-01	9.35E-01	4.74E+00	5.56E-01
Image9	4	**0.00E+00**	1.06E-02	8.86E-03	9.78E-01	1.98E-03	2.22E-01	9.04E-02	1.02E+01
	6	**1.02E-02**	6.16E-02	1.47E-01	6.30E+00	2.85E+00	1.20E+00	5.99E+00	3.62E+00
	8	**4.16E-01**	4.36E-01	9.25E-01	5.59E+00	1.83E+00	1.50E+00	5.78E+00	1.62E+00
	10	**2.93E-01**	1.03E+00	7.44E-01	3.45E+00	1.80E+00	8.54E-01	5.90E+00	1.37E+00
	12	**4.18E-01**	4.21E-01	1.49E+00	1.78E+00	8.50E-01	7.43E-01	1.69E+00	6.50E-01
Image10	4	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.85E+00	2.47E+00	1.58E-01	4.44E+00	6.05E+00
	6	**1.77E-02**	1.10E+00	1.55E+00	2.64E+00	8.41E-01	1.59E+00	7.06E+00	3.44E+00
	8	**1.13E-01**	9.96E-01	5.65E-01	2.25E+00	1.30E+00	9.98E-01	3.09E+00	2.70E+00
	10	**4.03E-01**	5.97E-01	8.68E-01	1.16E+00	7.76E-01	7.27E-01	2.55E+00	1.47E+00
	12	**5.06E-01**	6.81E-01	5.12E-01	1.42E+00	6.66E-01	6.65E-01	4.26E+00	1.26E+00

TABLE VII
THE STD VALUES OF FITNESS FUNCTIONS USING KAPUR'S ENTROPY METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	WOA-DE	WOA	SSA	SCA	ALO	HSO	BA	PSO
Image1	4	**0.00E+00**	2.66E-05	2.66E-05	4.39E-03	5.83E-05	3.19E-03	2.17E-03	2.68E-05
	6	**3.25E-05**	1.61E-04	9.58E-04	7.45E-02	2.95E-04	1.97E-02	5.39E-02	4.33E-04
	8	**4.32E-04**	2.74E-02	8.89E-03	1.33E-01	3.24E-02	3.38E-02	1.82E-01	7.30E-03
	10	**3.38E-03**	5.36E-03	3.90E-02	2.67E-01	4.91E-02	3.24E-02	1.51E-01	3.34E-02
	12	6.12E-02	3.25E-02	7.48E-02	2.30E-01	**1.83E-02**	5.02E-02	6.41E-01	7.35E-02
Image2	4	**8.54E-05**	2.07E-04	1.62E-04	9.64E-03	9.08E-05	6.59E-03	4.58E-03	2.78E-04
	6	1.16E-02	8.98E-03	1.32E-03	8.35E-02	**1.20E-03**	9.51E-03	4.80E-02	8.95E-03
	8	**6.72E-04**	2.96E-03	2.25E-03	1.26E-01	3.61E-02	3.18E-02	2.56E-01	6.78E-04
	10	**3.47E-03**	6.29E-03	4.43E-02	2.04E-01	9.37E-03	2.06E-02	8.19E-01	1.78E-02
	12	**1.75E-02**	4.53E-02	6.48E-02	2.49E-01	6.03E-02	5.29E-02	4.95E-01	2.42E-02
Image3	4	**0.00E+00**	8.06E-03	1.85E-03	1.31E-02	7.93E-03	2.86E-03	3.86E-03	5.71E-05
	6	**2.15E-03**	2.99E-03	3.74E-03	7.16E-02	3.31E-03	5.25E-03	3.87E-02	3.08E-03
	8	**4.02E-03**	5.48E-03	1.10E-02	8.30E-02	5.62E-03	7.05E-03	3.18E-01	1.00E-02
	10	1.47E-02	1.85E-02	1.18E-02	3.41E-01	**6.93E-03**	3.88E-02	5.30E-01	8.38E-03
	12	**1.60E-02**	2.97E-02	4.72E-02	4.45E-01	2.21E-02	6.83E-02	8.76E-01	3.76E-02
Image4	4	**4.06E-03**	5.91E-03	5.90E-03	7.22E-03	7.23E-03	1.93E-02	6.91E-03	7.20E-03
	6	**3.35E-04**	3.54E-03	1.48E-03	8.15E-02	6.23E-04	1.94E-02	1.14E-02	8.43E-04
	8	**3.23E-03**	2.71E-02	6.74E-03	1.38E-01	2.37E-02	7.51E-02	3.64E-01	5.84E-03
	10	**6.28E-02**	2.73E-01	2.88E-01	6.56E-01	2.65E-01	1.92E-01	6.44E-01	2.82E-01
	12	**0.00E+00**	2.02E-01	4.72E-01	3.57E-01	4.99E-01	1.90E-01	4.93E-01	2.42E-01
Image5	4	**3.06E-03**	1.96E-02	1.96E-02	1.69E-02	1.95E-02	1.18E-01	4.97E-03	1.59E-02
	6	8.64E-03	7.49E-03	4.79E-03	2.75E-02	4.00E-03	3.58E-02	1.05E-02	**3.30E-03**
	8	**1.49E-02**	5.27E-02	3.11E-02	3.06E-01	1.11E-01	7.25E-02	2.77E-01	1.87E-02
	10	**2.27E-02**	7.89E-02	5.90E-02	3.41E-01	3.11E-02	1.44E-01	8.65E-01	6.96E-02
	12	**3.80E-02**	7.09E-02	1.58E-01	4.77E-01	9.69E-02	1.21E-01	6.81E-01	1.52E-01
Image6	4	**3.91E-03**	7.91E-03	4.81E-03	1.24E-02	8.29E-01	5.49E-03	4.60E-03	3.93E-03
	6	1.68E-02	**3.81E-03**	1.94E-02	6.82E-02	4.20E-03	3.58E-02	2.96E-02	5.03E-03
	8	**1.57E-02**	2.64E-02	1.64E-02	1.60E-01	2.48E-02	4.37E-02	3.94E-01	6.14E-02
	10	**2.15E-02**	4.26E-02	3.64E-02	1.40E-01	5.49E-02	2.50E-02	4.03E-01	3.55E-02
	12	3.02E-02	**1.53E-02**	9.90E-02	2.85E-01	2.52E-02	6.41E-02	3.37E-01	3.43E-02
Image7	4	**0.00E+00**	2.13E-05	2.17E-04	1.09E-02	4.94E-05	3.14E-03	1.17E-03	4.82E-05
	6	**7.14E-06**	3.92E-03	7.01E-04	4.78E-02	9.32E-05	9.79E-03	3.82E-01	4.49E-04
	8	3.48E-02	**1.03E-03**	4.78E-03	1.54E-01	1.18E-03	2.91E-02	2.04E-01	2.70E-03
	10	**1.20E-02**	1.97E-02	3.17E-02	2.84E-01	1.68E-02	4.83E-02	3.35E-01	2.26E-02
	12	**2.77E-02**	3.54E-02	9.50E-02	5.27E-01	2.64E-01	7.73E-02	5.95E-01	3.88E-02
Image8	4	**5.90E-03**	2.46E-02	7.34E-03	4.83E-02	5.85E-02	2.10E-02	5.03E-01	1.97E-02
	6	**2.78E-02**	8.57E-02	3.06E-02	1.13E-01	4.02E-02	6.68E-02	3.97E-01	3.44E-01
	8	**5.02E-02**	8.48E-02	3.09E-01	2.95E-01	4.39E-01	2.67E-01	5.05E-01	1.04E-01
	10	**2.61E-01**	2.63E-01	5.06E-01	2.86E-01	6.82E-01	5.71E-01	5.52E-01	5.96E-01
	12	7.86E-01	8.51E-01	**3.28E-01**	8.86E-01	3.73E-01	6.04E-01	1.86E+00	4.25E-01
Image9	4	**1.45E-05**	4.58E-05	1.19E-03	1.27E-02	2.52E-02	2.62E-03	2.33E-02	4.58E-05
	6	**1.02E-04**	1.26E-04	1.16E-04	7.03E-02	3.11E-04	1.78E-02	4.02E-02	1.36E-04
	8	**1.06E-03**	1.30E-02	8.44E-03	2.36E-01	2.56E-02	4.40E-02	1.33E-01	1.47E-02
	10	**3.12E-02**	5.74E-02	5.53E-02	2.04E-01	8.96E-02	4.70E-02	5.86E-01	3.18E-02
	12	**5.73E-02**	7.55E-02	9.80E-02	3.02E-01	3.67E-01	1.23E-01	6.49E-01	8.41E-02
Image10	4	**2.98E-03**	1.30E-02	4.83E-03	7.86E-03	4.09E-03	3.39E-03	4.17E-03	4.23E-03
	6	4.84E-03	3.45E-03	4.01E-03	5.70E-02	2.66E-03	9.82E-03	3.22E-02	**1.89E-03**
	8	**1.07E-03**	5.04E-03	8.39E-03	2.18E-01	7.55E-03	2.04E-02	3.20E-01	4.92E-03
	10	**5.63E-03**	1.54E-02	3.77E-02	1.54E-01	9.08E-03	7.61E-02	9.00E-01	1.11E-02
	12	**1.20E-02**	7.00E-02	5.56E-02	1.26E-01	6.88E-02	8.69E-02	7.11E-01	6.01E-02

TABLE VIII
THE PSNR VALUES OF OTSU'S METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
	4	**19.7033**	19.7013	19.600	19.6186	19.6601	19.5234	**19.7033**	**19.7033**
	6	**21.8649**	21.8189	21.655	21.6041	21.4816	21.4611	21.5362	21.5369
Image1	8	**23.4972**	23.1839	23.1208	23.2054	22.6285	23.2486	23.3038	23.3073
	10	**25.6864**	25.2335	25.1624	25.148	24.5879	25.4305	25.3776	25.4946
	12	**27.3897**	26.9431	26.9885	25.9617	27.0112	27.0671	27.0406	26.143
	4	**19.9135**	19.6017	19.5352	19.3290	19.2107	19.4322	**19.9135**	19.5517
	6	**23.2804**	23.0052	22.9732	22.5877	22.885	**23.2804**	23.0664	23.0738
Image2	8	**26.2533**	25.9845	24.9794	24.1305	24.8595	25.9982	26.0905	25.6888
	10	**28.9395**	28.4902	28.2119	27.879	27.7862	28.0375	28.2625	28.1941
	12	**31.3912**	29.7802	29.8094	28.5135	29.7677	31.0032	29.9079	31.0095
	4	**17.7278**	17.4278	17.2685	17.2833	17.4849	17.2554	17.7270	17.7268
	6	**20.1331**	20.0389	20.1276	20.1286	20.1239	19.8524	20.0422	20.0423
Image3	8	**21.9897**	21.3036	20.9691	20.946	21.3404	21.5033	21.4431	21.5688
	10	**24.0625**	23.9133	24.054	23.9914	23.7254	23.9112	23.7495	23.4686
	12	**27.9966**	26.4174	26.4214	27.493	25.6114	27.4125	25.5777	27.5016
	4	**17.9481**	17.9079	17.8881	17.8483	17.8859	17.9023	**17.9481**	17.9478
	6	**20.9517**	20.9412	20.8772	20.2104	20.6978	20.3277	20.9007	20.9109
Image4	8	**23.2585**	23.1969	22.690	23.0061	22.9611	22.2352	23.0629	22.9587
	10	**28.045**	27.7032	26.6908	27.6716	25.7947	24.3622	26.584	26.857
	12	**30.6278**	28.4995	27.7143	30.0034	29.5504	30.1566	30.029	30.0012
	4	**19.6629**	19.0959	**19.6629**	19.4531	19.4549	19.413	19.0429	**19.6629**
	6	**23.2763**	23.0646	22.5352	23.0648	22.8631	22.9148	23.0768	23.0763
Image5	8	**25.6073**	25.1607	25.0672	25.0543	25.0796	25.1999	25.255	25.3789
	10	**27.3709**	27.0939	26.3669	27.1081	26.3639	27.0202	27.0111	27.0624
	12	**29.3325**	28.8226	29.0715	29.0485	28.9539	28.930	29.0663	29.0679
	4	**17.5938**	**17.5938**	17.4302	17.4934	17.5439	17.5319	**17.5938**	**17.5938**
	6	**21.4539**	21.1178	21.0694	20.9656	21.042	20.9784	21.1761	21.1806
Image6	8	**25.698**	24.8418	25.1531	25.1862	25.0441	24.551	24.7773	24.9808
	10	**28.9968**	27.8246	28.0103	28.2305	27.003	28.3563	27.4537	28.1933
	12	**30.9243**	29.5892	29.3285	28.9393	30.1188	30.0701	30.3753	30.3459
	4	**19.1099**	19.0931	19.0931	18.6358	19.0946	19.0638	19.0331	19.0231
	6	21.7178	21.0705	20.7217	21.0922	20.9022	21.0713	21.3445	**21.7223**
Image7	8	**25.5061**	25.3034	24.0494	25.1621	24.9356	25.4958	25.4275	25.2951
	10	**27.7526**	27.1161	27.0466	26.9274	27.0499	27.0001	27.5672	26.8535
	12	**28.7689**	28.4672	28.3964	28.600	28.3072	28.3893	28.0723	28.0633
	4	**21.0402**	21.0002	21.0400	20.0306	20.0304	20.0109	21.0302	**21.0402**
	6	**25.6341**	25.5060	25.5196	24.5882	25.2380	25.1438	25.5021	25.5314
Image8	8	**28.3869**	28.0797	27.9839	27.9604	28.0032	28.1241	28.2974	28.1922
	10	**31.0668**	30.9264	30.8508	30.7022	30.9291	30.9623	31.0095	31.0051
	12	**32.9738**	32.1190	31.9224	31.7351	32.2205	32.1691	32.6930	32.3057
	4	**18.8874**	**18.8874**	18.8874	18.7372	18.8024	18.8784	**18.8874**	**18.8874**
	6	**22.1063**	21.9519	21.4675	21.9566	21.9881	21.7803	21.9279	21.9953
Image9	8	**24.5687**	24.4303	24.3599	24.2723	24.3586	24.3810	24.3258	24.3198
	10	**25.9981**	25.8817	25.5570	25.3325	25.1005	25.8147	25.9219	25.9211
	12	**27.4864**	27.4158	27.0575	27.3899	27.0975	27.3056	27.3506	27.4006
	4	**18.2657**	18.2062	18.2051	18.2332	18.2614	18.2038	**18.2657**	**18.2657**
	6	**24.3971**	24.2836	24.1443	22.9569	24.0071	24.1080	24.1143	**24.2971**
Image10	8	**28.4264**	27.8217	28.1905	27.4765	27.2180	28.1973	27.9721	28.1360
	10	**31.5970**	31.3952	30.8956	30.5105	31.3302	31.2475	31.3435	31.3022
	12	**33.9870**	33.4820	32.8541	32.3615	31.7282	33.1746	33.2766	33.8361

TABLE IX
THE PSNR VALUES OF KAPUR'S ENTROPY METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
	4	**19.4750**	19.3356	19.3706	19.3806	19.4689	19.4744	19.3706	19.3706
	6	**23.8210**	23.8085	23.8193	23.3457	23.3029	23.4661	23.8195	23.8205
Image1	8	**26.4949**	26.3995	26.4632	25.6860	26.0663	26.3664	26.3772	26.3399
	10	**29.8752**	29.5593	27.3546	27.7523	28.2441	29.2968	29.8428	29.8475
	12	**30.5762**	30.5130	30.5617	29.0523	30.4961	30.4026	30.1777	30.4134
	4	**20.7093**	20.7057	20.7039	20.5676	20.6287	20.7049	20.7039	20.7039
	6	**24.7169**	24.6151	24.6293	23.4359	24.7080	**24.0609**	24.6209	24.6209
Image2	8	**26.9450**	26.0753	26.9355	25.6847	26.9416	26.9123	26.9382	26.9350
	10	**28.9597**	28.9432	28.2014	28.8242	28.2416	28.4495	28.8604	28.8834
	12	**31.2273**	31.0342	31.0524	31.0769	30.7237	30.7580	30.7323	31.2044
	4	**15.8514**	15.8500	15.8046	15.2550	15.0207	15.6000	15.8046	15.8496
	6	**19.3513**	19.3237	19.3511	19.2672	19.0172	18.8515	19.3511	19.2556
Image3	8	**23.9135**	23.3676	21.0652	23.9021	23.6011	23.7920	23.9036	23.8593
	10	**28.9140**	28.2481	26.5681	28.1633	28.0198	28.7127	28.4303	28.7283
	12	**30.3360**	30.2954	30.2453	30.1170	29.9916	29.3663	29.7551	30.0429
	4	**17.5402**	17.5432	17.5430	17.4082	17.4320	17.5064	**17.5402**	**17.5402**
	6	**21.0287**	20.8622	20.9463	21.0111	21.0027	21.0224	21.0190	20.9463
Image4	8	**23.6951**	23.0057	23.5741	23.2311	23.2877	23.5594	22.9985	23.6688
	10	**27.4367**	27.3158	27.3663	27.2996	27.4253	27.3368	27.4272	27.3232
	12	**29.8606**	29.2868	29.3172	29.8050	29.1546	29.5117	29.4611	29.7782
	4	**19.5459**	19.5456	**19.5459**	19.5360	19.9356	19.5399	**19.5459**	19.5405
	6	**23.2976**	23.2897	22.3092	23.2746	22.6859	23.2530	22.3994	23.2941
Image5	8	**26.3319**	26.1589	25.8872	26.3282	25.7686	26.2365	26.3241	25.5760
	10	**27.9426**	27.8632	27.6461	27.8923	27.8778	27.7056	27.4648	27.8665
	12	**29.6375**	29.6018	29.6139	28.9346	28.3683	29.6299	29.0308	29.4359
	4	**20.9339**	**20.7613**	20.9238	20.1705	20.9285	20.8635	20.8660	20.9130
	6	**25.6136**	25.5797	25.4875	24.5233	25.4788	25.8449	25.5849	25.5031
Image6	8	**29.5949**	29.4437	29.5942	27.7031	26.8124	28.9011	29.5669	29.5023
	10	**31.2752**	31.2391	31.2632	29.1699	29.0723	30.4147	31.2416	31.1817
	12	**32.7062**	32.7057	32.6528	31.4706	31.5570	31.4130	31.7004	31.7054
	4	**19.6073**	19.6070	17.7962	19.5500	19.4862	19.3513	17.7962	19.4469
	6	**23.9781**	23.9160	23.9769	26.3119	23.8114	23.2545	23.3820	23.9610
Image7	8	**29.4077**	29.4029	29.3525	29.0220	29.3681	29.0404	29.3606	28.6433
	10	**31.2740**	31.2685	30.9379	30.8732	30.4239	30.0603	31.2221	30.6465
	12	**32.8087**	32.8051	31.8051	31.5437	30.5348	31.7261	32.7316	32.5315
	4	23.1908	23.1880	23.1896	22.5049	23.1099	23.1332	**23.1911**	**23.1911**
	6	**26.5493**	26.4671	26.5431	25.5831	25.9652	26.4371	26.4842	26.3018
Image8	8	**29.4421**	29.4371	29.3587	28.8669	28.3915	29.4009	29.1930	29.1201
	10	**31.0298**	30.9124	31.0130	30.9193	30.0281	30.9286	31.0160	31.0242
	12	**32.5960**	32.5613	32.5810	32.5112	32.2456	31.3975	32.5697	32.3718
	4	**18.8490**	**18.8490**	18.4584	18.8398	18.5748	18.7000	18.4584	18.6894
	6	**22.4570**	22.3798	22.3829	23.4000	22.0565	22.4511	22.3999	22.3822
Image9	8	**26.1876**	25.7069	25.5774	26.1860	26.0718	26.0935	25.5890	25.7421
	10	**28.9195**	28.9091	28.9037	28.5837	28.2289	28.8733	28.6700	28.0352
	12	**31.6151**	31.5256	31.4884	30.2003	31.2357	31.5339	31.6147	30.1877
	4	**23.6410**	23.6410	23.6362	23.6200	23.4499	23.6394	23.5247	23.6362
	6	**27.4453**	27.4391	27.4181	26.3370	26.8253	27.0323	27.2658	27.3044
Image10	8	**29.6973**	29.6682	29.6356	29.5843	28.9887	29.3319	29.6642	29.6924
	10	**31.6905**	31.4941	31.4582	30.7384	30.8928	31.2535	31.4782	31.6231
	12	**32.8536**	32.8503	32.8479	31.9603	32.5720	32.5949	32.7922	32.7666

TABLE X
THE FSIM VALUES OF OTSU'S METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
Image1	4	**0.7988**	**0.7988**	0.7983	0.7977	0.7987	0.7984	**0.7988**	0.7983
	6	**0.8699**	0.8697	0.8695	0.8598	0.8638	0.8665	0.8687	0.8696
	8	**0.9021**	0.9015	0.8940	0.8821	0.8878	0.8997	0.9015	0.9017
	10	**0.9221**	0.9213	0.9186	0.9089	0.9191	0.8988	0.9199	0.9209
	12	**0.9331**	0.9321	0.9224	0.9179	0.9224	0.9306	**0.9331**	0.9291
Image2	4	**0.7577**	0.7570	0.7576	0.7535	0.7562	0.7567	**0.7577**	0.7574
	6	**0.8369**	0.8367	0.8341	0.8212	0.8289	**0.8369**	0.8369	0.8340
	8	**0.8815**	0.8809	0.8804	0.8568	0.8661	0.8792	0.8810	0.8753
	10	**0.9156**	0.9151	0.9148	0.8933	0.8989	0.9100	0.9140	0.9134
	12	**0.9357**	0.9331	0.9324	0.9163	0.9108	0.9300	0.9344	0.9354
Image3	4	**0.7567**	**0.7567**	0.7563	0.7514	0.7564	0.7566	0.7563	0.7512
	6	**0.8176**	0.8164	0.8171	0.8143	0.8170	0.8143	0.8163	0.8163
	8	**0.8600**	0.8599	0.8560	0.8516	0.8484	0.8571	0.8594	0.8574
	10	**0.8901**	0.8899	0.8897	0.8888	0.8671	0.8850	0.8813	0.8868
	12	**0.9227**	0.9028	0.8986	0.9156	0.8990	0.9203	0.9158	0.9220
Image4	4	**0.7512**	0.7502	**0.7512**	0.7484	0.7503	0.7510	**0.7512**	0.7504
	6	**0.8326**	0.8310	0.8316	0.8166	0.8291	0.8320	0.8226	0.8316
	8	**0.8793**	0.8785	0.8711	0.8743	0.8749	0.8646	0.8776	0.8750
	10	**0.9116**	0.9061	0.9104	0.9021	0.8945	0.8968	0.9105	0.9109
	12	**0.9268**	0.9177	0.9253	0.9247	0.9246	0.9171	0.9227	0.9264
Image5	4	**0.7855**	0.7730	**0.7855**	0.7783	0.7708	0.7701	**0.7855**	**0.7855**
	6	**0.8472**	0.8401	0.8411	0.8372	0.8410	0.8412	0.8422	0.8422
	8	**0.8817**	0.8778	0.8761	0.8760	0.8694	0.8765	0.8792	0.8773
	10	**0.8988**	0.8954	0.8915	0.8953	0.8844	0.8921	0.8941	0.8957
	12	**0.9206**	0.9140	0.9149	0.9200	0.9178	0.9193	0.9183	0.9174
Image6	4	**0.7759**	**0.7759**	0.7747	0.7753	0.7750	0.7771	**0.7759**	**0.7759**
	6	**0.8513**	0.8496	0.8464	0.8493	0.8435	0.8473	0.8500	0.8495
	8	**0.9131**	0.9001	0.9060	0.9054	0.9021	0.9118	0.8997	0.9020
	10	**0.9482**	0.9344	0.9462	0.9384	0.9232	0.9476	0.9309	0.9398
	12	**0.9597**	0.9453	0.9510	0.9464	0.9571	0.9547	0.9587	0.9555
Image7	4	**0.7853**	0.7850	0.7850	0.7762	0.7845	0.7838	0.7850	0.7850
	6	**0.8552**	0.8548	0.8524	0.8409	0.8524	0.8465	0.8504	**0.8552**
	8	**0.9037**	0.9014	0.8982	0.9002	0.8934	0.9017	0.9029	0.9017
	10	**0.9314**	0.9284	0.9313	0.9310	0.9301	0.9310	0.9305	0.9239
	12	**0.9459**	0.9447	0.9417	0.9423	0.9457	0.9409	0.9420	0.9372
Image8	4	**0.8253**	**0.8253**	0.8250	0.8160	0.8219	0.8196	0.8250	**0.8253**
	6	**0.9093**	0.9091	0.9084	0.9078	0.9047	0.9040	0.9087	0.9085
	8	**0.9413**	0.9404	0.9407	0.9370	0.9326	0.9322	0.9359	0.9366
	10	**0.9648**	0.9645	0.9638	0.9607	0.9406	0.9611	**0.9648**	0.9643
	12	**0.9742**	0.9734	0.9682	0.9655	0.9690	0.9736	0.9725	0.9725
Image9	4	**0.7689**	**0.7689**	**0.7689**	0.7675	0.7682	0.7689	**0.7689**	**0.7689**
	6	**0.8306**	0.8302	0.8150	0.8290	0.8267	0.8258	0.8303	0.8303
	8	**0.8689**	0.8677	0.8680	0.8604	0.8670	0.8672	0.8668	0.8678
	10	**0.8927**	0.8917	0.8918	0.8723	0.8911	0.8907	0.8921	0.8924
	12	**0.9104**	0.9101	0.9083	0.9067	0.9040	0.9059	0.9091	0.9101
Image10	4	**0.7939**	0.7934	0.7929	0.7909	0.7913	0.7934	**0.7939**	**0.7939**
	6	**0.9115**	0.9023	0.9020	0.8673	0.9082	0.9064	0.9017	**0.9115**
	8	**0.9453**	0.9415	0.9420	0.9384	0.9359	0.9442	0.9432	0.9451
	10	**0.9706**	0.9700	0.9680	0.9639	0.9702	0.9631	0.9704	0.9618
	12	**0.9825**	0.9823	0.9780	0.9758	0.9695	0.9792	0.9813	0.9817

TABLE XI
THE FSIM VALUES OF KAPUR'S ENTROPY METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
Image1	4	**0.7729**	**0.7729**	0.7726	0.7771	0.7731	**0.7779**	0.7726	0.7726
	6	**0.8906**	0.8528	0.8517	0.8424	0.8429	0.8486	0.8525	0.8519
	8	**0.9274**	0.9003	0.8958	0.8837	0.8931	0.8948	0.9005	0.9000
	10	**0.9452**	0.9243	0.9181	0.9115	0.9024	0.9242	0.9250	0.9240
	12	**0.9732**	0.9334	0.9300	0.9185	0.9177	0.9392	0.9381	0.9397
Image2	4	**0.7437**	**0.7437**	0.7423	0.7392	0.7330	0.7329	0.7343	0.7343
	6	**0.8341**	0.8331	0.8331	0.8221	0.8324	**0.8341**	0.8334	0.8334
	8	**0.8926**	0.8820	0.8819	0.8695	0.8774	0.8816	0.8819	0.8824
	10	**0.9130**	0.9129	0.9123	0.8958	0.8963	0.9128	0.9129	0.9121
	12	**0.9371**	0.9363	0.9365	0.9238	0.9226	0.9320	0.9358	0.9357
Image3	4	**0.7349**	**0.7349**	0.7339	0.7332	0.7330	0.7319	0.7339	0.7346
	6	**0.7848**	0.7825	0.7839	0.7818	0.7756	0.7770	0.7840	0.7757
	8	**0.8561**	0.8539	0.8277	0.8549	0.8522	0.8550	0.8546	0.8550
	10	**0.9079**	0.9076	0.8968	0.8862	0.8994	0.8998	0.9022	0.9036
	12	**0.9259**	0.9239	0.9230	0.9037	0.8924	0.9240	0.9211	0.9206
Image4	4	**0.7243**	0.7241	0.7240	0.7210	0.7208	0.7217	**0.7243**	**0.7243**
	6	**0.8183**	0.8166	0.8178	0.8127	0.8133	0.8175	0.8173	0.8178
	8	**0.8740**	0.8737	0.8732	0.8724	0.8431	0.8738	0.8736	0.8675
	10	**0.9182**	0.9109	0.9178	0.9099	0.9068	0.9137	0.9169	0.9139
	12	**0.9277**	0.9273	0.9213	0.9264	0.9161	0.9264	0.9215	0.9266
Image5	4	**0.7476**	0.7474	**0.7476**	0.7473	0.7431	0.7468	**0.7476**	0.7471
	6	**0.8383**	0.8377	0.8302	0.8135	0.8340	0.8322	0.8310	0.8380
	8	**0.8835**	0.8773	0.8773	0.8673	0.8718	0.8791	**0.8835**	0.8619
	10	**0.9030**	0.9029	0.9000	0.8961	0.8920	0.8947	0.8983	0.9019
	12	**0.9174**	0.9164	0.9171	0.9002	0.9036	0.9117	0.9168	0.9108
Image6	4	**0.8141**	0.8117	0.8139	0.8140	0.8120	0.8136	0.8095	0.8106
	6	**0.9006**	0.9002	0.8995	0.8820	0.8953	0.9003	0.9003	0.8999
	8	**0.9474**	0.9455	**0.9474**	0.9258	0.9291	0.9405	0.9462	0.9466
	10	**0.9642**	0.9641	0.9632	0.9403	0.9446	0.9566	0.9630	0.9634
	12	**0.9732**	0.9730	0.9728	0.9571	0.9523	0.9702	0.9715	0.9726
Image7	4	0.7625	**0.7626**	0.7564	0.7568	0.7592	0.7581	0.7564	**0.7626**
	6	**0.8507**	0.8483	0.8503	0.8502	0.8447	0.8500	0.8496	0.8492
	8	**0.9160**	0.9159	0.9138	0.9102	0.9155	0.9115	0.9159	0.9034
	10	**0.9408**	0.9402	0.9358	0.9354	0.9329	0.9397	0.9403	0.9331
	12	**0.9591**	0.9560	0.9581	0.9537	0.9500	0.9514	0.9563	0.9528
Image8	4	**0.8307**	0.8304	0.8306	0.8153	0.8266	0.8304	**0.8307**	**0.8307**
	6	**0.9095**	0.9094	0.9077	0.8919	0.9023	0.9040	0.9083	0.9073
	8	**0.9487**	0.9484	0.9480	0.9391	0.9311	0.9460	0.9455	0.9449
	10	**0.9625**	0.9624	0.9623	0.9621	0.9587	0.9578	0.9617	0.9620
	12	**0.9730**	0.9724	0.9727	0.9726	0.9625	0.9654	0.9721	0.9719
Image9	4	**0.7548**	**0.7548**	0.7540	0.7538	0.7539	0.7545	0.7541	0.7539
	6	**0.8315**	0.8311	0.8310	0.8225	0.8290	0.8311	0.8306	0.8309
	8	**0.8785**	0.8719	0.8722	0.8563	0.8564	0.8720	0.8722	0.8768
	10	**0.9169**	0.9145	0.9011	0.9043	0.9083	0.9155	0.9096	0.9073
	12	**0.9366**	0.9326	0.9287	0.9352	0.9278	0.9362	0.9363	0.9270
Image10	4	**0.8599**	**0.8599**	0.8512	0.8566	0.8495	0.8589	0.8580	0.8592
	6	**0.9372**	0.9365	0.9369	0.9279	0.9264	0.9315	0.9353	0.9347
	8	**0.9600**	0.9594	0.9589	0.9538	0.9521	0.9574	0.9577	0.9596
	10	**0.9737**	0.9725	0.9726	0.9707	0.9651	0.9705	0.9726	0.9731
	12	**0.9799**	0.9798	0.9795	0.9756	0.9778	0.9785	0.9795	0.9799

TABLE XII
THE SSIM VALUES OF OTSU'S METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
	4	**0.7231**	**0.7231**	0.7230	0.7203	0.7231	0.7223	**0.7231**	**0.7231**
	6	**0.8052**	0.8049	0.8044	0.8004	0.7948	0.7997	0.8044	0.8048
Image1	8	**0.8494**	0.8463	0.8349	0.8474	0.8255	0.8416	0.8456	0.8445
	10	**0.8795**	0.8758	0.8664	0.8753	0.8769	0.8667	0.8778	0.8681
	12	**0.8916**	0.8912	0.8904	0.8854	0.8896	0.8898	0.8904	0.8708
	4	**0.6805**	0.6775	0.6667	0.6606	0.6629	0.6627	**0.6805**	0.6655
	6	**0.7857**	0.7754	0.7753	0.7628	0.7673	**0.7857**	0.7768	0.7752
Image2	8	**0.8364**	0.8354	0.8350	0.8319	0.8360	0.8354	0.8361	0.8360
	10	**0.8798**	0.8788	0.8785	0.8717	0.8578	0.8699	0.8785	0.8760
	12	**0.9031**	0.9004	0.8775	0.9005	0.8817	0.8979	0.9005	0.9006
	4	**0.6178**	**0.6178**	0.6166	0.6034	0.6160	0.6162	0.6175	0.6150
	6	**0.7302**	0.7288	0.7301	0.7299	0.7296	0.7225	0.7286	0.7287
Image3	8	**0.8011**	0.8005	0.7959	0.8006	0.7829	0.7927	0.8010	0.8007
	10	**0.8481**	0.8469	0.8459	0.8400	0.8332	0.8326	0.8306	0.8415
	12	**0.8914**	0.8756	0.8718	0.8838	0.8768	0.8835	0.8882	0.8895
	4	**0.6450**	0.6448	**0.6450**	0.6370	0.6441	0.6441	**0.6450**	0.6128
	6	**0.7702**	0.7700	0.7678	0.7577	0.7606	0.7680	0.7700	0.7384
Image4	8	**0.8384**	0.8382	0.8246	0.8339	0.8321	0.8117	0.8373	0.8134
	10	**0.8910**	0.8901	0.8880	0.8901	0.8673	0.8644	0.8895	0.8908
	12	**0.9066**	0.9023	0.9016	0.9037	0.9024	0.9014	0.9006	0.9064
	4	**0.6757**	0.6732	**0.6757**	0.6517	0.6473	0.6479	**0.6757**	**0.6757**
	6	**0.7599**	0.7573	0.7510	0.7591	0.7549	0.7539	0.7580	0.7579
Image5	8	**0.8385**	0.8300	0.8177	0.8335	0.8055	0.8174	0.8310	0.8112
	10	**0.8656**	0.8536	0.8334	0.8536	0.8386	0.8419	0.8624	0.8631
	12	**0.8792**	0.8701	0.8705	0.8755	0.8725	0.8777	0.8736	0.8787
	4	**0.6881**	**0.6881**	0.6852	0.6842	0.6815	0.6878	**0.6881**	**0.6881**
	6	**0.8071**	0.8069	0.8026	0.8070	0.7995	0.7955	0.8055	0.8058
Image6	8	**0.8836**	0.8771	0.8759	0.8797	0.8736	0.8811	0.8757	0.8789
	10	**0.9323**	0.9226	0.9303	0.9316	0.9107	0.9238	0.9176	0.9205
	12	**0.9480**	0.9345	0.9466	0.9408	0.9365	0.9321	0.9472	0.9403
	4	**0.5780**	0.5777	0.5777	0.5494	0.5776	0.5733	0.5777	0.5777
	6	**0.6793**	0.6743	0.6790	0.6580	0.6705	0.6503	0.6721	**0.6793**
Image7	8	**0.8269**	0.8147	0.7477	0.8243	0.7511	0.7678	0.8208	0.8144
	10	**0.8741**	0.8678	0.8732	0.8717	0.8716	0.8705	0.8728	0.8524
	12	**0.8923**	0.8902	0.8900	0.8893	0.8912	0.8921	0.8920	0.8821
	4	**0.7703**	**0.7703**	0.7700	0.7585	0.7675	0.7597	0.7701	**0.7703**
	6	**0.8869**	0.8861	0.8865	0.8788	0.8846	0.8852	**0.8869**	0.8867
Image8	8	**0.9268**	0.9255	0.9212	0.9100	0.9095	0.9242	0.9226	0.9223
	10	**0.9552**	0.9540	0.9524	0.9402	0.9333	0.9471	0.9538	0.9540
	12	**0.9668**	0.9667	0.9578	0.9501	0.9540	0.9618	0.9647	0.9661
	4	**0.6270**	**0.6270**	**0.6270**	0.6250	0.6263	0.6338	**0.6270**	**0.6270**
	6	**0.7519**	0.7489	0.7174	0.7499	0.7426	0.7407	0.7500	0.7500
Image9	8	**0.8181**	0.8105	0.8027	0.8134	0.8157	0.8121	0.8136	0.8156
	10	**0.8562**	0.8554	0.8538	0.8561	0.8546	0.8529	0.8545	0.8545
	12	**0.8819**	0.8780	0.8748	0.8810	0.8706	0.8742	0.8806	0.8810
	4	**0.7306**	0.7301	0.7290	0.7302	0.7301	0.7278	**0.7306**	**0.7306**
	6	**0.8842**	0.8840	0.8763	0.8348	0.8802	0.8804	0.8840	**0.8842**
Image10	8	**0.9398**	0.9347	0.9330	0.9198	0.9262	0.9356	0.9367	0.9390
	10	**0.9690**	0.9678	0.9654	0.9514	0.9642	0.9684	0.9679	0.9669
	12	**0.9809**	0.9804	0.9757	0.9646	0.9665	0.9731	0.9805	0.9800

TABLE XIII
THE SSIM VALUES OF KAPUR'S ENTROPY METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
Image1	4	**0.6850**	0.6847	0.6847	0.6840	0.6858	0.6836	0.6847	0.6847
	6	**0.7821**	0.7812	0.7802	0.7745	0.7705	0.7801	0.7816	0.7813
	8	**0.8590**	0.8573	0.8349	**0.8590**	0.8427	0.8474	0.8582	0.8525
	10	**0.8931**	0.8914	0.8702	0.8783	0.8834	0.8913	0.8923	0.8929
	12	**0.9077**	0.9059	0.9066	0.8932	0.9008	0.9075	0.9051	0.9070
Image2	4	**0.6268**	**0.6268**	0.6266	0.6162	0.6233	0.6250	0.6284	0.6283
	6	**0.7722**	0.7654	0.7656	0.7440	0.7680	0.7721	0.7657	0.7657
	8	**0.8293**	0.8212	0.8226	0.8241	0.8269	0.8289	0.8226	0.8204
	10	**0.8654**	0.8652	0.8661	0.8641	0.8645	0.8645	0.8650	0.8627
	12	**0.9046**	0.9013	0.9026	0.8978	0.8906	0.8998	0.9015	0.8996
Image3	4	**0.5026**	**0.5026**	0.5013	0.5008	0.5015	0.4963	0.5003	0.5020
	6	**0.6699**	0.6668	0.6607	0.6659	0.6643	0.6630	0.6696	0.6688
	8	**0.8001**	0.8000	0.7347	0.7972	0.7891	0.7917	0.7823	0.7897
	10	**0.8650**	0.8646	0.8560	0.8551	0.8522	0.8584	0.8635	0.8616
	12	**0.8882**	0.8868	0.8875	0.8725	0.8861	0.8858	0.8866	0.8880
Image4	4	**0.5896**	0.5894	0.5894	0.5852	0.5880	0.5806	**0.5896**	**0.5896**
	6	**0.7336**	0.7303	0.7330	0.7316	0.7279	0.7289	0.7284	0.7330
	8	**0.8191**	0.8107	0.8102	0.8142	0.7879	0.8189	0.8104	0.8118
	10	**0.8838**	0.8828	0.8827	0.8744	0.8798	0.8806	0.8836	0.8822
	12	**0.8968**	0.8905	0.8965	0.8963	0.8874	0.8906	0.8960	0.8926
Image5	4	**0.6234**	0.6032	**0.6234**	0.6042	0.6203	0.6062	**0.6234**	0.6031
	6	**0.7480**	0.7479	0.7159	0.7390	0.7271	0.7473	0.7188	0.7471
	8	**0.8254**	0.8135	0.8088	0.8240	0.8247	0.8247	0.8222	0.8233
	10	**0.8575**	0.8515	0.8485	0.8512	0.8428	0.8529	0.8443	0.8553
	12	**0.8734**	0.8698	0.8729	0.8708	0.8719	0.8710	0.8724	0.8728
Image6	4	0.7179	**0.7181**	0.7178	0.7174	0.7153	0.7173	0.7136	0.7151
	6	**0.8248**	0.8232	0.8226	0.8010	0.8154	0.8230	0.8238	0.8223
	8	**0.8961**	0.8922	0.8954	0.8692	0.8283	0.8814	0.8971	0.8943
	10	**0.9233**	0.9208	0.9139	0.8871	0.8946	0.9094	0.9213	0.9200
	12	**0.9417**	0.9405	0.9412	0.9141	0.9299	0.9393	0.9410	0.9412
Image7	4	**0.5540**	**0.5540**	0.5126	0.5528	0.5473	0.5436	0.5226	0.5489
	6	**0.6658**	0.6641	0.6657	0.6646	0.6603	0.6646	0.6657	0.6642
	8	**0.8754**	0.8743	0.8744	0.8702	0.8700	0.8709	0.8751	0.8595
	10	**0.9059**	0.9020	0.9012	0.9053	0.9057	0.9048	0.9054	0.8951
	12	**0.9160**	0.9153	0.9142	0.9159	0.9095	0.9132	0.9152	0.9157
Image8	4	**0.7450**	0.7445	0.7446	0.7251	0.7388	0.7441	**0.7450**	**0.7450**
	6	**0.8407**	0.8404	0.8406	0.8225	0.8330	0.8335	0.8401	0.8406
	8	**0.9031**	0.9024	0.9023	0.8854	0.8783	0.9029	0.9027	0.9004
	10	**0.9286**	0.9259	0.9278	0.9276	0.9217	0.9188	0.9283	0.9266
	12	**0.9448**	0.9442	0.9440	0.9374	0.9444	0.9302	0.9432	0.9429
Image9	4	**0.5710**	**0.5710**	0.5701	0.5697	0.5704	0.5709	0.5701	0.5692
	6	**0.7185**	0.7175	0.7145	0.7161	0.7093	0.7112	0.7175	0.7184
	8	**0.8150**	0.8098	0.8092	0.8108	0.8052	0.8057	0.7901	0.8045
	10	**0.8663**	0.8653	0.8465	0.8634	0.8652	0.8660	0.8620	0.8609
	12	**0.9169**	0.9165	0.9122	0.9083	0.9002	0.9167	0.9164	0.8996
Image10	4	**0.8091**	0.7891	0.7965	0.7959	0.7770	0.7902	0.7934	0.7905
	6	0.8977	0.8972	0.8950	0.8608	0.8873	0.8837	**0.8979**	0.8920
	8	**0.9349**	0.9323	0.9347	0.8904	0.9256	0.9276	0.9336	0.9329
	10	**0.9557**	0.9533	0.9531	0.9520	0.9500	0.9504	0.9533	0.9550
	12	**0.9657**	0.9655	0.9651	0.9603	0.9624	0.9638	0.9651	0.9650

TABLE IV
THE AVERAGE FITNESS VALUES USING OTSU'S METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
	4	**3953.7954**	**3953.7954**	3953.7950	3948.8042	3953.6831	3953.3067	**3953.7954**	**3953.7954**
	6	**4019.8423**	4019.5048	4018.7985	4006.9266	4017.3416	4017.2234	4018.8162	4018.8103
Image1	8	**4048.9152**	4048.8504	4043.3223	4024.1493	4037.8143	4045.3231	4048.8877	4048.9101
	10	**4063.1978**	4063.1284	4061.1137	4039.0225	4050.5883	4059.3896	4062.5624	4061.703
	12	**4070.6228**	4070.1573	4070.6001	4054.429	4046.507	4066.2912	4069.932	4068.7841
	4	**3485.1247**	3485.1199	3485.1147	3479.1374	3484.6777	3484.7292	**3485.1247**	**3485.1247**
	6	**3569.7989**	3569.7975	3569.7922	3553.9263	3562.3733	**3569.7989**	3569.7902	3569.7900
Image2	8	**3604.7775**	3604.7703	3604.6050	3576.8452	3583.8077	3600.4796	3604.7761	3601.4317
	10	**3622.8818**	3622.4558	3620.6747	3597.7083	3583.8832	3618.0966	3622.6152	3622.5331
	12	**3631.3102**	3630.5562	3630.7006	3614.941	3612.3747	3626.1269	3630.062	3630.8461
	4	**1632.9348**	**1632.9348**	1632.9325	1629.3742	1632.8832	1632.5101	1632.9329	**1632.9348**
	6	**1679.6273**	1679.6224	1679.6217	1663.4943	1675.7384	1678.9156	1678.6165	1679.0983
Image3	8	**1699.6539**	1699.6112	1696.9162	1677.6783	1694.3511	1697.2418	1699.6475	1699.3764
	10	**1709.7547**	1709.2274	1709.5613	1691.5336	1689.6933	1704.8673	1709.7315	1709.4691
	12	**1715.2551**	1714.8516	1712.1207	1700.6739	1700.4449	1709.738	1715.0877	1714.0964
	4	**1319.9491**	1319.9489	**1319.9491**	1315.3303	1318.9811	1319.5916	**1319.9491**	1319.9488
	6	**1369.0221**	1369.0213	1368.9969	1357.1484	1366.7841	1367.9945	1369.0211	1369.0126
Image4	8	**1390.0326**	1390.0305	1387.4005	1374.3224	1389.2622	1387.4095	1389.1814	1388.5589
	10	**1399.6458**	1399.4009	1393.7362	1384.4908	1384.9509	1396.9234	1399.0229	1187.096
	12	**1405.8609**	1405.6402	1404.5624	1384.8868	1393.2781	1401.2297	1403.591	1404.5764
	4	**2424.6317**	2424.5708	2424.5708	2421.2203	2424.5139	2424.2945	2424.5708	2424.5708
	6	**2487.0084**	2480.7669	2482.092	2478.4116	2485.5045	2483.8617	2487.0064	**2487.0084**
Image5	8	**2512.4189**	2512.3053	2510.9344	2483.7068	2501.1752	2507.5583	2512.0236	2509.5901
	10	**2525.6094**	2523.4752	2519.899	2501.6225	2509.8173	2520.1389	2525.2327	2523.6277
	12	**2530.8468**	2528.9949	2529.6907	2516.2091	2520.8127	2527.7053	2529.6778	2530.163
	4	**1729.2257**	**1729.2257**	1710.9382	1726.02	1728.9882	1728.7219	**1729.2257**	**1729.2257**
	6	**1779.9929**	1779.9572	1779.9568	1763.9461	1779.0967	1777.7373	1779.9756	1779.9854
Image6	8	**1803.9526**	1802.8008	1795.0211	1784.771	1790.259	1799.7721	1802.807	1802.7834
	10	**1815.0429**	1814.9534	1811.5293	1790.7357	1801.2403	1810.245	1814.0664	1814.4409
	12	**1821.8206**	1820.4563	1820.6098	1808.1162	1811.6587	1815.7141	1820.9947	1820.3147
	4	1400.5487	1400.5411	**1401.5411**	1398.0046	1400.263	1399.7372	1400.5411	1400.5411
	6	**1441.0137**	1440.9204	1440.957	1434.6068	1439.9286	1438.5452	1441.0115	1441.0045
Image7	8	**1459.6243**	1459.4003	1457.3171	1444.2693	1437.1488	1454.8626	1459.6151	1459.5502
	10	**1469.8421**	1469.7252	1469.5444	1454.5045	1456.5918	1466.0482	1469.7097	1468.6476
	12	**1475.6342**	1475.1504	1470.2697	1458.6954	1464.184	1472.219	1475.04	1472.8635
	4	**1435.7222**	**1435.7222**	1435.6897	1433.7968	1435.3505	1435.276	1435.7102	**1435.7222**
	6	**1500.0958**	1500.0244	1500.0858	1484.1328	1498.127	1497.5381	1500.0134	1500.0237
Image8	8	**1525.3523**	1524.7003	1525.3076	1510.2877	1501.9411	1521.2577	1525.1779	1525.17
	10	**1539.6603**	1539.1758	1537.4876	1523.3336	1526.3035	1533.9908	1539.5515	1539.3363
	12	**1547.4005**	1547.3542	1542.4244	1530.2169	1535.4957	1542.9102	1547.3996	1547.319
	4	**2853.1743**	**2853.1743**	**2853.1743**	2849.576	2853.0584	2852.8073	**2853.1743**	**2853.1743**
	6	**2915.6723**	2915.6408	2894.6826	2890.4899	**2905.9451**	2914.0036	2915.6679	2915.6702
Image9	8	**2941.2851**	2941.1941	2933.3113	2918.6224	2910.8135	2939.6153	2941.0111	2941.237
	10	**2954.834**	2954.2199	2951.2338	2927.0843	2937.4698	2950.6298	2954.8092	2954.7299
	12	**2962.1541**	2961.8913	2960.7891	2959.7651	2952.4187	2958.9889	2962.037	2961.0798
	4	**1052.6908**	1052.6841	1052.6714	1048.6873	1052.5839	1052.0294	**1052.6908**	**1052.6908**
	6	**1098.1595**	1098.1333	1092.3076	1074.308	1088.9246	1096.6478	1098.1543	**1098.1595**
Image10	8	**1119.4996**	1119.4816	1113.553	1095.8843	1113.587	1118.2696	1119.4058	1119.4948
	10	**1130.8408**	1130.7943	1127.75	1112.7634	1119.2282	1126.4325	1130.8091	1130.5106
	12	**1137.1022**	1136.8308	1133.8866	1121.5446	1126.9476	1131.71	1137.0952	1136.4462

TABLE V
THE AVERAGE FITNESS VALUES USING KAPUR'S ENTROPY METHOD COMPARED WITH OTHER ALGORITHMS

Images	K	OBLDA	DA	PSO	SCA	BA	HSO	ALO	SSA
Image1	4	18.5002	18.5000	18.4897	18.4613	18.4166	18.4963	**18.5004**	18.5000
	6	**24.0001**	23.9799	23.9811	23.6436	23.8908	23.8975	23.9811	23.9812
	8	**28.8948**	28.8129	28.7723	27.9375	28.5409	28.7200	28.8752	28.8702
	10	**33.4351**	33.3523	33.1358	32.1934	31.8645	33.1194	33.3902	**33.3934**
	12	**37.4560**	37.4284	37.3461	34.7885	35.2101	37.2779	37.4413	37.4221
Image2	4	**19.1186**	**19.1186**	19.1185	19.1085	19.1174	19.1166	19.1180	**19.1186**
	6	**24.5049**	24.5036	24.5045	24.3797	24.4700	24.4768	24.5040	24.5040
	8	**29.2700**	29.2643	29.2628	28.6983	28.8901	29.1724	29.2609	29.2626
	10	**33.6123**	33.5556	33.5548	32.2689	32.6558	33.4410	33.5631	33.5566
	12	**37.5249**	37.5245	37.5247	34.4781	35.1123	37.1587	37.4867	37.4748
Image3	4	**17.9080**	17.9078	**17.9080**	17.8708	17.9068	17.8966	**17.9080**	17.9078
	6	**23.0198**	23.0113	23.0190	22.8565	22.9702	22.9593	23.0187	23.0159
	8	**27.6599**	27.6578	27.5934	26.8723	27.5156	27.5298	27.6759	27.6531
	10	**31.9288**	31.9280	31.8964	30.1086	30.4496	31.6635	31.9204	31.9034
	12	**35.7785**	35.2063	35.7770	32.6783	32.7375	35.2639	35.7784	35.1769
Image4	4	**18.4918**	18.4916	18.4912	18.4622	18.4872	18.4819	**18.4918**	**18.4918**
	6	**23.6922**	23.6914	23.6905	23.4468	23.6669	23.6125	23.6912	23.6905
	8	**28.3095**	28.3024	28.3067	27.9281	27.9847	28.2587	28.3063	28.3095
	10	**32.5892**	32.5865	32.5866	31.5723	31.3348	32.2579	32.5867	32.5830
	12	**36.3739**	36.3688	36.3520	35.5627	34.4852	35.9779	36.3635	36.3490
Image5	4	**18.7381**	18.7380	18.7372	18.6731	18.7217	18.7326	18.7368	**18.7381**
	6	**24.0292**	24.0291	24.0237	23.6952	23.9584	24.0064	24.0234	24.0273
	8	**28.7437**	28.7079	28.7114	27.7347	28.2776	28.5286	28.7435	28.5687
	10	**32.9891**	32.9847	32.9252	30.6967	31.0099	32.6646	32.9300	32.9754
	12	**36.8054**	36.8009	36.0273	34.6304	34.6947	36.4877	36.8046	36.7984
Image6	4	**18.7778**	18.7777	**18.7778**	18.7436	18.7745	18.7679	18.7769	18.7771
	6	**24.3551**	24.3548	24.3540	24.1236	24.3076	24.3070	24.3542	24.3547
	8	**29.3048**	29.2998	29.3031	28.8361	28.7555	29.1911	29.3036	29.3047
	10	**33.8351**	33.8267	33.8347	31.9216	32.8086	33.6537	33.8307	33.8329
	12	**37.9567**	37.9542	37.9549	35.9544	35.8609	37.7342	37.9491	37.9458
Image7	4	**18.8176**	**18.8176**	18.7891	18.7644	18.8076	18.8011	18.7891	**18.8176**
	6	**24.2838**	24.2726	24.2829	24.1141	24.0625	24.2560	24.2830	24.2811
	8	**29.2380**	29.2294	29.2352	28.9236	28.6026	29.1200	29.2287	29.1742
	10	**33.6991**	33.3882	33.5775	32.1851	31.6970	33.4260	33.5922	33.5392
	12	**37.7112**	37.7027	37.7076	36.0898	35.1335	37.5058	37.7066	37.7104
Image8	4	**18.9585**	18.9577	**18.9585**	18.9197	18.9482	18.9551	18.9583	**18.9585**
	6	**24.4135**	24.4116	24.4134	24.2572	24.3735	24.3847	24.4119	24.4102
	8	**29.3185**	29.3176	29.3148	28.8671	28.7157	29.2512	29.3110	29.3181
	10	**33.7653**	33.7651	33.7626	32.6958	31.8454	33.4981	33.7650	33.7640
	12	**37.8293**	37.8240	37.8254	36.2574	35.9844	37.6199	37.8005	37.8229
Image9	4	18.7385	18.7381	18.7384	18.7146	18.7368	18.7333	18.7380	**18.7399**
	6	**24.0631**	24.0627	24.0627	23.7434	24.0047	23.9918	24.0582	24.0356
	8	**28.9499**	28.9433	28.9440	28.1130	27.8489	28.7974	28.9490	28.9297
	10	**33.3109**	33.3062	33.3021	31.6533	31.6872	33.3069	33.3070	33.2021
	12	**37.5425**	37.5421	37.3316	34.9365	34.8915	37.3107	37.5144	37.4505
Image10	4	**18.8252**	**18.8252**	18.8250	18.7850	18.8041	18.8167	18.8246	18.8246
	6	**24.4177**	24.4173	24.4172	24.2592	24.3146	24.3716	24.4170	24.4144
	8	**29.3734**	29.3678	29.3727	28.5648	28.7556	29.2970	29.3724	29.3639
	10	**33.8442**	33.8427	33.8357	32.6137	32.3177	33.7053	33.8423	33.8435
	12	**37.9201**	37.9055	37.9185	37.9017	37.0123	37.5918	37.9171	37.9133

TABLE XIV
STATISTICAL ANALYSIS (WILCOXON RANK SUM TEST) FOR THE RESULTS OF EXPERIMENTS ON OTSU METHOD

Images	K	OBLDA VS DA		OBLDA VS PSO		OBLDA VS SCA		OBLDA VS BA		OBLDA VS HSO		OBLDA VS ALO		OBLDA VS SSA	
		p-Value	h	p-Value	h	p-Value	h	p-Value	h	p-Value	h	p-Value	h	p-Value	h
Image1	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image2	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image3	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	0.2345	0	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image4	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	0.1209	1	<0.05	1	<0.05	1	<0.05	1	0.7568	0
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image5	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	0.3167	0	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image6	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image7	4	<0.05	1	0.5643	0	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image8	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image9	4	0.3471	0	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image10	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1

TABLE XV
STATISTICAL ANALYSIS (WILCOXON RANK SUM TEST) FOR THE RESULTS OF EXPERIMENTS ON KAPUR'S ENTROPY METHOD

Images	K	OBLDA VS DA		OBLDA VS PSO		OBLDA VS SCA		OBLDA VS BA		OBLDA VS HSO		OBLDA VS ALO		OBLDA VS SSA	
		p-Value	h	p-Value	h	p-Value	h	p-Value	h	p-Value	h	p-Value	h	p-Value	h
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image1	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image2	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image3	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	0.4111	0	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image4	8	<0.05	1	<0.05	1	0.0445	0	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	0.3490	0	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image5	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image6	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	0.095	0	<0.05	1	0.4387	0	<0.05	1	<0.05	1	<0.05	1
Image7	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image8	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image9	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	4	0.2567	0	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	6	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
Image10	8	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	10	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1
	12	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1	<0.05	1