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A Genetic Algorithm Approach to Segment Household Objects from an Image

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Abstract:
In the field of computer image, Segmentation of colour image is being considered as one of the challenging problems. In order to effectively carry out tasks assigned by human operators, robots operating in domestic environments should be able to detect and distinguish the things utilized in the home. Segmentation enables robots to understand the context of the environment by identifying and categorizing objects. An Image Segmentation using Genetic algorithm is presented in this work. It is a natural evolutionary approach for optimization problems. In most of the colour image segmentation techniques the clustering is used at beginning to segregate colour images and then Genetic Algorithm (GA) is applied just as an optimization tool. Here K-means Clustering technique along with genetic algorithm has been used to find optimal thresholds between the multiple objects and the complex background. For optimization a Genetic algorithm is applied on the clustering output in which segmentation is improved through different steps of GA. The experimental results shown that the combination of K-means and GA gave promising results with an accuracy of 90% on home object dataset. Also, a comparison is made between the suggested algorithm and the most widely used watershed segmentation algorithm and it is proved that our algorithm has given equivalent results on both standard and real time datasets.

Keywords: Segmentation, Genetic Algorithm, K-means Clustering, Watershed algorithm, House-hold Objects

1.Introduction

The process of segregating an image into regions which are of non-overlapping, connected, homogenous in nature is termed as Image Segmentation. These regions are partitioned in such a way that merging of any two dimensionally adjacent regions will not be homogenous. There will be either one or more-pixel attributes defined with homogeneity constraints such as texture, colour, intensity etc. There are mainly two conditions for a region to be homogenous, first is when all pixels of a region meet homogeneity constraints and next is the existence of a path connecting two pixels within the region. An important pace of image perception is improvement of quality of the images. This is achieved by amplifying the image contrast and eliminating noise signals.

Segmentation is one of the most complicate but pivotal computer innovation and picture perusal tasks that has been broadly researched. Inaccessible of a universal segregating algorithm with performance parallel to human innovation especially for colour image segregating still keeps this field famous for study. Image segregating is appraised as the first step of perusal and conception. In the extreme10 years, multi-dimensional image segregating has awarded a great deal of awareness for remote sensing and industrial applications because it greatly improves the differentiation and the recognition capabilities compared with grey-levels image segregating methods.

Generally, the segmentation methods are categorised based on the approaches used such as Histogram, Edge, Region, Cluster and Hybrid. Numerous techniques for segmenting an image are accessible based on wrapper approach, prior knowledge, colour basis, object matching and etc. The progress in automatic segmentation technique is vital region in field of research. Segmentation can be treated as an optimal research problem; an evolutionary algorithm can be used to solve this problem known as Genetic Algorithm (GA). The primary goal is to extract high-quality segmented objects from color images and enhance performance to extract the optimal segmented image with few number of iterations.

1.1Genetic Algorithm

GA operates on the population search space. Every component of the population is referred to as a chromosome. GA starts by selecting a set of workable solutions at random from the population. Every chromosome is a standalone solution. The fitness of every chromosome is assessed, and this fitness determines the solution's quality. GA employs an adaptive heuristic search strategy to identify the population's optimal set of solutions. The chromosomes are used by operators like selection, crossover, and mutation to create new offspring and evolve them. Majority fit chromosomes will be taken to next generation. Less fit candidates have a lower chance of getting into the following generation. This is so because GA is predicated on the idea that "survival is the best," which is a tenet of Darwin's theory of evolution. Until the chromosomes find the best suitable solution to the given challenge, this procedure is repeated. In summary, more optimal solutions are found by repeating the procedure multiple times, as the population's average fitness rises with each iteration. GA has been extensively researched and tested in a variety of engineering domains. GA offers substitute techniques for issues that are challenging to resolve using conventional techniques.

The two main reasons to use GA in Image segmentation techniques are, **Parameter selection,** where the parameters required in image segregation techniques are selected with optimised values using genetic algorithms to enhance its output. **Segmentation at the pixel level,** where region labelling is accomplished by genetic algorithms. The details of how it has been used in segmenting object from image are given in ensuing section.

1.2 An Overview of the work

Here, the input for K-means clustering has been a color image with dimensions of mxn, where each pixel comprises of components Red, Green, and Blue, by which we get segmented RGB colour components. For optimization a Genetic algorithm is applied on the clustering output in which segmentation is improved through different steps of GA. The difference between k-means output and randomly generated output is used as a fitness whose minimum value is the best fitness. Images with multiple objects and complex background are also considered in this work. The innovative aspect of the suggested method is that the chromosomal length varies according to the estimated value of k, or the number of clusters. This provides us with the optimal cluster centres for accurate segmentation.

1.3 Literature Survey

Few of contemporary mechanisms for segmentation of colour images found in related literature is presented in this section.

[1] In this study, they conduct a thorough review of the progress made in image segmentation techniques. Three key phases of image segmentation—classic segmentation, collaborative segmentation, and semantic segmentation based on deep learning—are mostly examined in accordance with the segmentation principles and features of the picture data. They go into detail about the primary algorithms and critical approaches in each step, evaluate and condense the benefits and drawbacks of several segmentation models.

A comprehensive analysis of the literature covering a wide range of works for semantic and instance-level segmentation, including fully convolution pixel-labeling networks, encoder-decoder architectures, multi-scale and pyramid based approaches, recurrent networks, visual attention models, and generative models in adversarial settings, is provided in the surveys [3], [4], [5], [6], [7], and [8]. Also, some modern DNN-based approaches, such as completely convolutional network, upsample techniques, FCN in conjunction with CRF methodologies, dilated convolution techniques, advancements in backbone networks, pyramid techniques, supervised, poorly supervised, unsupervised, multi-level features, and multi-stage approaches are discussed in these articles. They also look at the most popular datasets such PASCAL VOC, MS COCO, Cityscapes, and ADE20k, to report performances, and discuss promising future directions for this field of study. Each method showed performance according to its design, and they conducted both qualitative and quantitative comparisons of the key elements and performances of the different ways. Ultimately, all these determined the main obstacles that different object segmentation techniques now face and suggested a number of interesting future paths.

In paper [2] they mainly focuses on updating the multi-target recognition and image segmentation algorithm using the support vector machine algorithm in machine learning (ML). Experiments were conducted to compare the effectiveness of the image segmentation and multiclass object recognition algorithms suggested in this study against the traditional approaches. The findings demonstrated that the multiclass object identification and ML-based picture segmentation methods suggested in this work had improved by an average of 29.1% across the board.

[9] In this work, they produced a segmentation mask for a target object of instructions for domestic duties, with a particular focus on the OSMI (Object Segmentation from Manipulation Instructions) task. They suggested the two-stage multimodal diffusion segmentation model (MDSM). Using CLIP and Swin Transformer, they presented a crossmodal parallel feature extraction mechanism. On the SHIMRIE dataset, the MDSM performed better than the baseline technique.

[10] Research presents a novel sustainable architecture for object recognition in intricate depth environments. Important results were obtained in this work, including the robust extraction of depth kernel descriptors and kernel sliding perceptron for object differentiation and the sustainable segmentation of interior scene depth items. The recognition accuracies over RGB-D scenes, RGB-D object samples, and NYUDv1 datasets are 92.2%, 88.5%, and 90.5%, respectively.

[11] This paper presents the architecture and implementation of a system that estimates a point-cloud-based scene representation, enhanced with articulated object information, from a single RGB-D image. It analyzes various neural network topologies to recognize handles, the fronts of drawers and cabinets, and estimate rotational joints. Ultimately, the data is combined to create a three-dimensional representation of the environment's articulated objects.

In literature some of Genetic algorithm based segmentation techniques also been existed applied in different fields like medical image segmentation [12] and [17], Objet segmentation in a scene [13], [14], [15], [16] [18], [19] and [20]. In order to diagnose melanoma cancer, [12] research suggests an Ensemble-based Genetic Algorithm Explainer (EGAE), which identifies and shows the user the informative portions of the image automatically. Three phases make up EGAE. First, a heuristic approach is used to determine the sparsity of chromosomes in GAs. Next, several GAs are carried out one after the other. Finally, majority and consensus votes are used to combine the GA results. Based on melanoma dataset experiments, EGAE automatically identifies lesions that provide information and enhances explanation accuracy.

The [15] study highlights that the conventional two-dimensional Otsu technique solely took into account the lack of the greatest variance between classes. Instead, it suggests the threshold discriminant function, which may represent both variance within classes and variance between classes.

A unique approach [17] called GA-UNet employs genetic algorithms to automatically generate a U-shape convolution neural network with good performance while lowering the complexity of its architecture-based parameters. This eliminates the aforementioned challenges. The proposed GA-UNet is evaluated on three datasets: lung image segmentation, liver image segmentation, and cell nuclei segmentation in microscope images (DSB 2018). Surprisingly, it achieves an accuracy of 98.78% for lung image segmentation, 95.96% for cell nuclei segmentation in microscope images (DSB 2018), and 98.58% for liver image segmentation using only 0.24%, 0.48%, and 0.67% of the number of parameters in the original U-Net architecture.

[13] This study develops a genetic method to determine the accurate segmentation in a given dataset of images from many subjects. Every member of the population represents a potential remedy for the issue of inadequate segmentation. The individual also consists of various variables, such as segmentation, colour space, colour channel, morphological, and pre-processing techniques. To make each generation better, the genetic algorithm assesses each person, chooses the best, and then crosses and mutates each individual.

In [21], [22], [23], [24] and [25] traditional as well improved watershed segmentation algorithm is employed to segment an object. Two variants of watershed transform with morphological gradients and wavelet coefficients are proposed in all these articles.

Some of the issues and challenges in task of segmentation are identified during survey. Those are as follows

- Segmenting the particular object from complex background and multiple objects is a major issue.

- Segmentation of trivial and non-uniform illumination images is also one of the difficult tasks.
- Overlapping objects are also difficult to segment as they are hidden by other objects.
- Segmentation is difficult mainly because of picture noise, fragile object boundaries, heterogenous object area, fragilecontrast, soothe boundaries, and texture boundary great calculation time etc….
- Others problems shall produce undesirable results like the segregated section may be smaller or larger than actual, disconnected edges, arising false edges, intersection segregation.
- Deciding the number of iterations in any algorithm for every input image

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2. Proposed Methodology

In this section the detail System implementation shown in Fig. 1 is discussed with every step, formulas and results. It mainly consists of stages like acquiring images of household objects, image preprocessing, initial segmentation using k-mean clustering, optimization using Genetic Algorithm and then extraction of objects from an original image.

2.1 Input Image

In this work, a standard dataset namely Caltech Home object dataset [26] shown in Fig.2 along with some real time images from house hold objects shown in Fig.3 are used. In Caltech object dataset, there are 101 indoor object categories considered. The input to this system is colour image, where each pixel is comprises of Red, Green and Blue components.

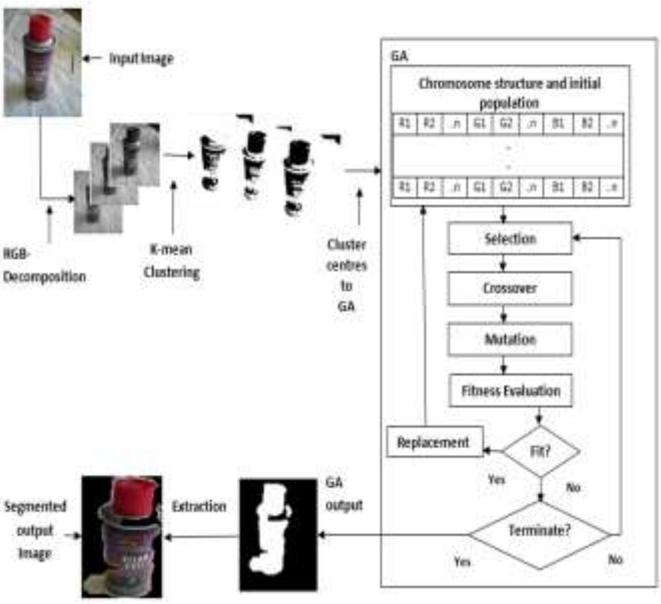

Fig. 1. *Block diagram of proposed methodology*

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Fig. 2. *Samples from Home Object Dataset*

2.2 Image Preprocessing

The important aspect in Image segmentation is to separate foreground and background of an image which can be accomplished by identifying active and inactive pixels in an image. To achieve this, given color image is first decomposed into R, G and B component and Guassian Filter is applied for eah of these components. The result is shown in Fig. 4.

Fig. 3. *Some real time household objects*

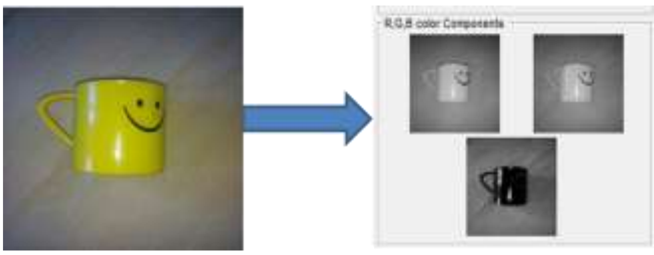

Fig. 4. Gaussian filtered R, G and B components

2.3 K-mean Clustering

After getting Gaussian filtered R, G and B components, the K-mean clustering with k=5 is applied on these components to get initial segmentation as shown in Fig.5.

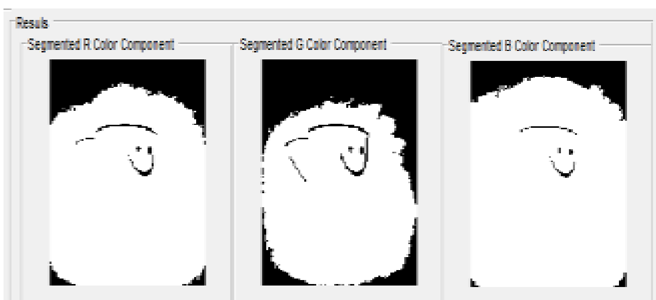

Figure 5: K-mean Clusters

2.4 Genetic Algorithm Implementation

Genetic Algorithms (GAs) can be used as an optimization tool for color image segmentation, where the goal is to partition an input color image into meaningful regions. The process involves representing potential segmentation solutions as chromosomes, applying genetic operators (crossover and mutation), and evolving a population of solutions over multiple generations.

2.4.1 Chromosome structure and initial population

A solution is represented by each chromosome, which is defined as a series of collection centres of k clusters as shown in Figure 6. Every gene represents a real number that corresponds to the intensity of the Red, Green, and Blue components of k clusters. In every round, the population is randomly initialized by taking into account the values that fall within the range of the number of groups. For example each chromosome consists of 6 thresold intensities values in k=2 clusters belongs to Red Green and Blue respectively.

R1	R2	..k	G1	G2	..k	B1	B2	..k
				.				
				.				
R1	R2	..n	G1	G2	..n	B1	B2	..n

Fig. 6.*Chromosome structures*

2.4.2 Fitness Evaluation

The computation of fitness is done in two stages. Stage 1: In this stage the pixels o image are clusterd based on centres encoded in chromosomes such that each value of intensity Xi(r,g,b) of a color image combined with three components, i.e., red, green, and blue (24 bit), i = 1, 2,..., m x n, is assigned to cluster with center Zj(r,g,b), j = 1, 2,..., K. If p = 1,2,...,K, and p ≠ j, then || Xi(r,g,b)-Zj(r,g,b)|| < || Xi(r,g,b)-Zp(r,g,b)||.

Stage 2: In this stage, mean points of the corresponding clusters are used to replace the values of the cluster centers encoded in the chromosome. Eqn. (1) provides the cluster Ci's new center Zi(r,g,b).

$$Z_i(r,g,b) = \frac{1}{n_i}\sum_{x_j \in C_i} X_j(r,g,b) \qquad (1)$$

The fitness metric is now determined by adding up the intra-cluster spread, which is the sum of the Euclidean distances between each pixel and its corresponding cluster, given by Eqn. (2)

$$M = \sum_{i=1}^{k} M_i$$

$$M_i = \sum_{x_j \in c_i} \left|\left(x_j(r,g,b) - z_i(r,g,b)\right)\right| \qquad (2)$$

2.4.3 Selection module

This step of GA involves selecting two parent chromosomes from the population based on their fitness. Stochastic Universal Sampling selection method has been used for choosing the singles with the greatest fitness value and those are moved to next generation.

The steps involved in this module of selection using stochastic universal sampling are as follows.

- Calculate the average fitness, denoted as `F_avg`, of the population.
- Choose a random starting point between 0 and `F_avg`.
- Select individuals by iteratively adding `F_avg` to the starting point until the population is sampled.
- This method ensures that individuals with higher fitness have a higher chance of being selected multiple times, while still providing a chance for lower fitness individuals to be selected.

2.4.4 Crossover module

The goal of crossover is to create new individuals (offspring) by exchanging genetic information between two parent individuals. This system uses uniform linear crossover, with a randomly selected crossover point and crossover probability 0.9. The following are the steps in uniform crossover.

- For each gene (pixel) in the chromosome, a random number is generated
- If the random number falls below a predefined probability threshold, exchange the corresponding genes between the parents.
- If the random number is above the threshold, keep the genes from the parents unchanged.
- The exchanged genes create two offspring, each with a combination of genetic information from both parents

2.4.5 Mutation

The mutation operation introduces random changes to the chromosomes, allowing the algorithm to explore new regions of the solution space. In the context of image segmentation using genetic algorithms, mutation is applied to individual chromosomes (representing potential segmentation solutions) to explore new possibilities and prevent the algorithm from getting stuck in local optima. The mutation involve flipping the state of a pixel (changing it from foreground to background or vice versa) or modifying its value with the default probability between 0 to 1.

2.4.6 Replacement

- Evaluate the fitness of the newly created offspring based on how well they perform in terms of image segmentation.
- Replace less fit individuals in the current population with the newly created offspring.

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2.4.7 Termination Criterion

Here the GA steps such as selection, crossover, mutation and replacement are repeated for several generations until a termination criterion is met. Here maximum number of generations 10 is taken as termination criteria. At each iteration the fitness is modified as shown in Figure 7. The best-segmented solution found in the final population is considered the output of the genetic algorithm for image segmentation and the final k-means GA output is given in Figure 8.

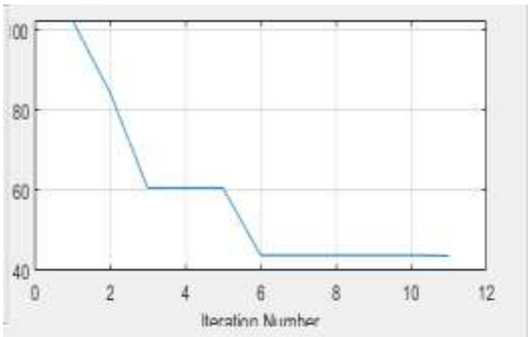
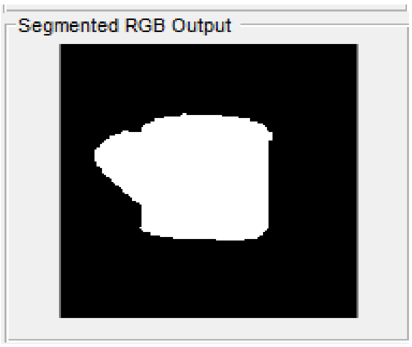


Fig. 7. Varying fitness



F Fig. 8. K-mean GA output

2.4 Object Extraction

Using the processed masks obtained from GA the individual objects are extracted from the original images as shown in Figure 9. This can be done by multiplying the original image with the binary mask for each object.

Fig. 9. Final output

3.Results and Discussions

Ideally, a model should be evaluated across multiple dimensions, including quantitative accuracy, inference speed, and memory efficiency. However, most existing research primarily emphasizes metrics like IoU (Intersection over Union), Pixel Accuracy, Mean Pixel Accuracy, Dice Coefficient (F1 Score), Precision, Recall, Mean IoU (mIoU), Boundary IoU (bIoU), Pixel-wise Precision and Recall and many more for evaluation. Below, we outline the most commonly used metrics for measuring the accuracy of segmentation algorithms. The proposed algorithm has been compared with the most popular watershed segmentation algorithm using these metrics and the results are shown in the Table 1. Also the visual segmentation differences between proposed algorithm and watershed algorithm are shown in Table 2. First seven images in Table 2 are from Caltech home object dataset and last 4 images are real captured images.

Pixel accuracy (PA) measures the ratio of correctly classified pixels to the total number of pixels. For K+1 classes, including K foreground classes and a background class, it is defined as shown in Eq.(3).

$$PA = \frac{\sum_{i=0}^{k} P_{ii}}{\sum_{i=0}^{k}\sum_{j=0}^{k} P_{ij}} \quad (3)$$

Here, P_{ij} represents the numbers of pixels from class i that are predicted to belong to class j.

Intersection over Union (IoU), also referred to as the Jaccard Index, is a widely adopted metric for semantic segmentation1. It is defined as the ratio of the overlap area between the predicted segmentation map and the ground truth to the total area covered by their union as shown in Eq. (4).

$$IoU = J(A,B) = \frac{|A \cap B|}{|A \cup B|} \quad (4)$$

Here, A represents the ground truth, and B represents the predicted segmentation map. The value of IoU ranges from 0 to 1.

Precision (P), Recall (R), and F1 Score are widely used metrics for evaluating the accuracy of classical image segmentation models. These metrics can be calculated for individual classes or at an aggregate level. They are defined as shown in Eq. (5), (6) and (7) respectively. The F1 score is defined as the harmonic mean of precision and recall

$$Precision\ (P) = \frac{TP}{TP+FP} \quad (5)$$

$$Recall\ (R) = \frac{TP}{TP+FN} \quad (6)$$

$$F_1 score\ (F1) = \frac{2 \times Precision \times Recall}{Precision \times Recall} \quad (7)$$

Here, TP represents the true positive fraction, FP denotes the false positive fraction, and FN refers to the false negative fraction.

The proposed algorithm has been compared with the most popular watershed segmentation algorithm using these metrics and the results are shown in the Table 1. Also the visual segmentation differences between proposed algorithm and watershed algorithm are shown in Table 2. First seven images in Table 2 are from Caltech home object dataset and last 4 images are real captured images. These parameters are calculated for 10 different household object images

Table 1: Performance Comparision

Testing Image	**Watershed Algorithm**					**Proposed Algorithm**				
	PA	**IoU**	**P**	**R**	**F1**	**PA**	**IoU**	**P**	**R**	**F1**
Klear kote	0.4	0.38	0.43	0.35	0.47	0.8	0.75	0.83	0.75	0.87
Hershy Syrup	0.5	0.47	0.56	0.46	0.58	0.9	0.85	0.93	0.85	0.97
Tele phone	0.41	0.39	0.44	0.36	0.48	0.75	0.7	0.78	0.7	0.82

Fish Toy	0.79	0.77	0.85	0.75	0.86	0.9	0.85	0.93	0.86	0.97
Land phone	0.4	0.33	0.43	0.35	0.47	0.92	0.87	0.95	0.87	0.99
Green bottle	0.15	0.12	0.21	0.11	0.22	0.82	0.77	0.85	0.77	0.89
Spray	0.49	0.46	0.55	0.45	0.57	0.68	0.63	0.71	0.62	0.76
Oil	0.8	0.77	0.86	0.77	0.87	0.93	0.88	0.96	0.89	0.98
Cup	0.6	0.57	0.66	0.56	0.67	0.95	0.9	0.97	0.91	0.99
bottle	0.89	0.86	0.94	0.84	0.94	0.94	0.9	0.97	0.9	0.99
Avg.	**0.54**	**0.51**	**0.59**	**0.5**	**0.61**	**0.86**	**0.81**	**0.89**	**0.81**	**0.92**

Table 2: Segmentation Results

Input Image	Output of Watershed	Output of Proposed
1.Klear kote 		
2.Hersheys Syrup 		
3.Telephone 		
4.Fish Toy 		

5.Landphone 		
6.Green Bottle 		
7. Spray 		
8.Parachute 		
9.Smiley Cup 		
10. Bottle 		
11.Bowl 		

Conclusion

A novel methodology for Image Segregation utilizing Genetic Algorithm has been proposed. GA has been used because of its computational powers and searching capabilities. Moreover, the features are modified using hereditary methods to enhance image segregation. In order to provide better results, such as a better segmented image, the number of generations is also changing. The innovative aspect of the suggested method is that the chromosomal length varies according to the estimated value of k, or the number of clusters. Based on the house object dataset, the experimental findings demonstrated that combining K-means with GA produced promising results with an accuracy of 90%. Furthermore, a comparison is presented between the proposed

algorithm and the most popular watershed segmentation algorithm, demonstrating that our algorithm produces results that are comparable on conventional and real-time datasets.

Conflicts of interest: The authors have no conflicts of interest to declare.

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