Cancerous Masses Segmentation by Using Heuristic Ant Colony Algorithms in Medical Images

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***Abstract*—The implementation of operators known as edge detection in medical images at times lead to elicitation of unimportant or inaccurate information as to the target spot in the image. In the compressed images and the ones with noise, edge detection accuracy reduces. In this paper, the technique of edge detection of medical images based on ant colony algorithm is introduced. By dispatching ants to the image pixels and relying on edge specifications, the pheromones matrix is formed which contains information related to the damaged tissue. Receiving 220 medical images composed of 90 retina images taken from diabetic patients, 80 MRI images as well as 50 microscopic images taken from various medical databases and applying system to them in contrast to such known operators as Canny and Sobel, an acceptable level of accuracy 94.90%, sensitivity 94.16% and specificity 94% was separated in the target area from the rest of image. The 88.79% Kappa coefficient indicates the high reliability factor of system in terms of performance. The application of this system to tissue imaging systems not only increases the accuracy of detection, but also steps up the process speed to a large extent. Reduced expenses, cost savings in long term and non-destructive quality of this system are the main distinguishing features of this system.**

***Index Terms*—edge detection, image processing, ant colony, medical images, cancerous masses**

I. Introduction

Medical images are a proper instrument to detect tissue damage and suspicious cancerous masses mass. However, they are usually characterized by such problems as complex formal structures, blurry demonstration of details, non-homogeneity of the brightness as well as poor contrast. There are a variety of methods for segmentation of image features, each conducting the act of segmenting in a particular way. Medical images are a proper instrument to detect tissue damage and suspicious cancerous masses mass. However, they are usually characterized by such problems as complex formal structures, blurry demonstration of details, non-homogeneity of the brightness as well as poor contrast. There are a variety of methods for segmentation of image features, each conducting the act of segmenting in a particular way. Researchers in computational intelligence have drawn on the advantages of insect social life in order to solve optimization problems. Ant colony algorithm is one of the active algorithms in which different ant species attempt to find the shortest path to the food [1]. That is, they are able to distinguish the shortest path from their nest to the food from different available routes [2]. The ant colony optimization (ACO) algorithm was first used by M. Dorigo *et al.* [3] in order to find answer in complex optimize problems. A chemical substance produced by ants, pheromone is absorbed by other ants helping them to find the optimized path already crossed by other ants. In other words, the high secretion of pheromone in a path is indicative of its optimization.

Laplacian or Gaussian filters [4] as well as canny filter [5] are other examples of edge detector filters with high efficiency and accuracy. In the conventional edge detection methods, the movement of mask on the image might produce unwanted noise in the image [6]. In medical images with high light intensity (such as CT or MRI), continuous border tissue (like Mammography) or noise, the common image processing methods will not be helpful. The first integrated method for segmentation of similar tissues in medical images was proposed by Gudmundsson *et al.* [7] which consisted of edge detection and evolutionary genetic technique. Fluid edge was an innovative technique introduced by Yin and Manjunath [8] in 2000 in which, on the basis of a predictive coder mode, a vector was designed to detect edges in medical images. This algorithm is used for different images in image processing. As to edge detection using heuristic ant algorithm, various methods have been proposed by Rezaee, [9] Tian et al. [10], Nezamabadi-pour et al. [11] and Zhuang [12]. Drawing on conditional optimization, Geman at al. [13] separated the boundaries of various images in 2007. Veronica and Oppus in 2010 [14] managed to detect edges based on ant colony algorithm and image processing benchmark images. The ranking separation of active contours from edge technique in medical images was also proposed by Holtzman and Goldshe [15]. Ant colony algorithm preceded by anisotropic diffusion is used for optic disc detection in color fundus images [16]. Ant colony algorithm preceded by anisotropic diffusion is used for optic disc detection in color fundus images [17].

Manuscript received July 1, 2014; revised December 21, 2014.

doi: 10.12720/joig.2.2.128-134

II. Ant Colony Algorithm for Edge Detection

To associate ant colony algorithm with constructive pixels of image edge, we first need to recognize the edge constructive pixels [12]. Edge pixels, in contrast to their neighboring pixels, are significantly intense in terms of brightness. Red box in Fig. 1 shows the edge pixels in a unit of bacterial community. Here, there is an instantaneous leap in the brightness intensity of the edge which is indicative of a border line of bacteria edge with a vertical curve. The movement from one pixel to the adjacent pixels embraces eight different routes which are connected to one another to reach constructive pixels in the edge or the corners. The local search of ants is carried out by moving from one pixel to another adjacent one. By definition, ants can only move to the adjacent pixels [18]. Therefore, ants have eight choices to move from one pixel to the adjacent ones. Ants are scattered in each image, moving from one pixel to another. Their movement is commensurate with the change pheromone. The purpose of ants' move is to build a pheromone matrix that can extract information about the edges. Each element in pheromone matrix is corresponding to an pixel in the image, which determines whether that pixel is an edge or not.

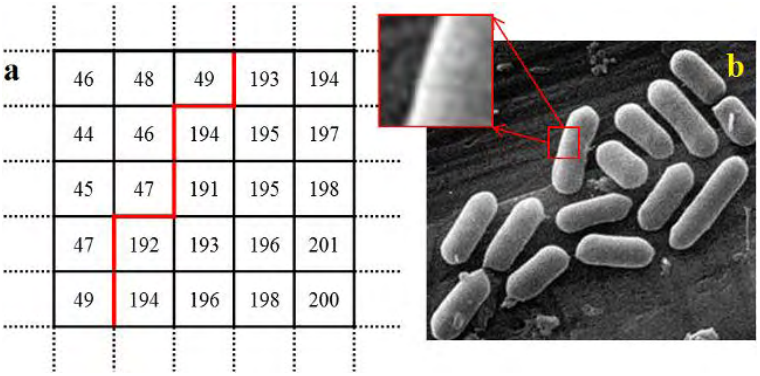

Figure 1. (a) the red box shows the edge bacteria pixels and (b) Brightness intensity in a unit of bacterial community

III. The Proposed Algorithm

The algorithm has three basic steps. First, ant population generation; second, the upgrading and repetitive construction process which is aimed at making the pheromone matrix, and finally, the decision process which is conducted based on the amount of pheromone.

A. Population Generation

In the course of population generation process, K numbers of ants are placed in a random location in $m_1 \times m_2$ images. The initial value of each pheromone matrix is generated according to η_{start} constant, which is negligible. When only one pixel value is independent of the image, the search information during population generation is constant. Fig. 2 shows the local search of ants and the way they move. Thus, the search information with regard to (i, j) pixels are introduced in (1) using the following function:

$$\eta_{ij} = \frac{V_m(P_{i,j})}{V_{\max}} \quad (1)$$

where $P_{i,j}$ is the brightness intensity of (i, j) pixel. In other words, it can be concluded that P is a function applied to the local accumulation of pixels. According to (2), V_{max} is the maximum fluctuation of image brightness between image pixels which is calculated in eight directions for the pixel in which ants are present.

$$V_m(P_{i,j}) = \left|P_{i-1,j} - P_{i+1,j+1}\right| + \left|P_{i-1,j} - P_{i+1,j}\right| + \left|P_{i-1,j+1} - P_{i+1,j-1}\right| + \left|P_{i,j-1} - P_{i,j+1}\right| \quad (2)$$

$V_m(P_{i,j})$ is the sum of difference for the reciprocal pixel (as shown in Fig. 2).

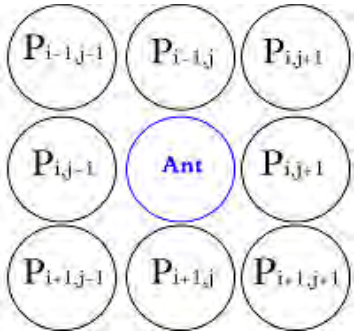

Figure 2. Local search of ant

B. Repetition Framework and Update Process

Inspired by the social life of ants, the optimization method is based on random search and population generation. In biological systems, ants are connected with each other and each ant provides its response to problem. After leaving the nest in search of food, ants follow different, yet shortest, routes to reach the food [19]. The pheromones secreted by ants increased the probability of choosing a particular path. Therefore, the trails to food are marked. The shortest route has the highest amount of pheromones and thus there is a high probability to see large number of ants in that route. One the other hand, due to the evaporation, the amount of pheromones cannot exceed unlimitedly. In each repetition, each ant moves across the image from one pixel to another and it continues until a basic step including a particular movement between two

pixels is established. An ant moves from (i_0,j_0) pixel to the neighborhood pixel (i, j) in accordance with the properties and the relative rules of random moves. The possibility of transfer for the purpose of exploration has been shown in (3) [20]:

$$p^{(n)}_{(i_0,j_0),(i,j)} = \frac{[\tau^{(n-1)}_{i,j}(t)]^{\alpha} \cdot [\eta_{i,j}]^{\beta}}{\sum_{i,j \in \varphi(i_0,j_0)} [\tau^{(n-1)}_{i,j}(t)]^{\alpha} \cdot [\eta_{i,j}]^{\beta}} \quad (3)$$

where $\tau^{(n-1)}_{i,j}(t)$ is the Pheromone value for pixel (i, j) at time t, $\varphi(i_0, j_0)$ are the neighborhood pixels of (i_0,j_0) and η_{ij} is the exploration information related to (i, j) pixels. The value of α and β controls the effect of pheromone and exploration data respectively. By changing these values in the algorithm analysis, the desired results would be achieved. Fig. 3 shows all the steps of the algorithm. When an ant moves from the current pixel to another one, the local update is performed instantaneous. The amount of pheromone $\tau^{(n)}_{i,j}$ at pixel (i,j) in the n iteration is calculated by (4).

$$\tau^{(n)}_{(i,j)} = (1-\theta).\tau^{(n-1)}_{(i,j)} + \theta.\tau_{start} \quad (4)$$

where $\theta \in (0,1]$ is the vanishing coefficient of the equation. τ_{start} is the initial pheromone value. The local pheromone is updated, reinforced or eliminated in accordance with construction process of the problem. The value of pheromone changes proportional to repetition of program loops. An ant can move to any of its neighboring pixels. Nevertheless, each ant can visit a node only once due to situational restrictions. To keep track of the visited nodes, each ant, by definition of the ant colony algorithm optimization, has a memory. With all ants going through the target process, it is time for the global pheromone update to be applied to the pixels already explored by the ants. The updating process is shown in (5) as:

$$\tau^{(n)}_{(i,j)} = (1-\rho).\tau^{(n-1)}_{(i,j)} + \rho.\sum_{k=1}^{k} \Delta\tau^{k}_{ij} \quad (5)$$

where $\Delta\tau^{k}_{ij}$ is the value of pheromone stored for k ant at pixel (i,j). It is equal to the average shared exploration data with pixels that belong to k ant route corresponding to the travelled route; otherwise (i.e. if pixels do not belong) its value would be zero. The global pheromone can be updated by some of the proposed methods which might not be in line with the operation and primary goal of solving various problems. The primary goal of every ant is to generate only one route for the minor edges in the image. The total work done by the ants constitute a pheromone matrix which is able to conduct edge detection completely.

Decision Making Process

The final pheromone matrix is used for classification and segmentation of each pixel for each section of the edge. Table I presents the controlling parameters of algorithm performance which affects the identification of $\tau^{(N)}$ pixel by applying a threshold on pheromone matrix which increases the accuracy of edge detection for q_0 image and edge N. These parameters cannot be permanently on rise because the algorithm loses its convergence with their increase. Overall, the increase in these two parameters will enhance the accuracy of edge detection. In Fig. 4, the proposed algorithm is implemented by changing parameters.

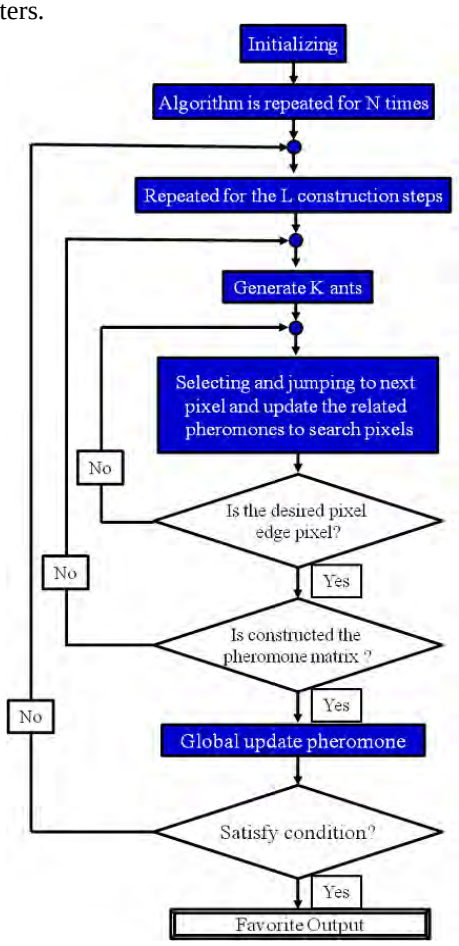

Figure 3. Schematic implementation of algorithm

TABLE I. . INFLUENTIAL PARAMETERS IN EDGE DETECTION OF IMAGES

PARAMETERS	DESCRIPTION	INITIALIZING
N	The number of repetitions of the ant algorithm	5, 10, 20
L	The number of construction stages	40
K	The number of ants distributed	300
α	Control parameter of the pheromone pathway	0.1
β	Exploration control parameter	1
ξ	Pheromone decay coefficient in the local update	0.05
ρ	Evaporation coefficient of pheromone global update	0.1
q_0	Flexibility of control parameters in Revelation	0.1, 0.3, 0.5, 0.7, 1
τ_{start}	The initial pheromone	0.1

IV. Results and Discussion

The proposed algorithm has been implemented on a series of medical images. Among these images, 90 retina images taken from diabetic patients (40 healthy and 50 diabetic), 80 MR images of brain tumors (30 healthy and 50 with tumors) and 50 microscopic (blood cancer cells, mammographic images and histopathology images; overall, there were illness symptoms only in 20 images) were used.

MR images were received from McConnell Imaging Center and Montreal Nerve Institute (MNI) in McGill University [21] [22]. All three categories of images were resized to 256? 56 pixels so that the algorithm will generate its output in the specified time period. Except for 7 images, the algorithm was successful in recognition of the mass and desired section in 220 medical images. Of 100 disease images; it did not function properly in diagnosis of the disease in 7 images. Three factors, i.e. accuracy (AC), specificity (SP) and sensitivity (SE), which were introduced for assessing the accuracy of the system in performance detection, are calculated according to the (6) to (8). Where TP is the positive diagnosis, TN is the negative diagnosis, FP is the positive error and FN is the negative error.

$$Senestivity = \frac{N_{TP}}{N_{TP} + N_{FN}} \tag{6}$$

$$Specificity = \left(\frac{N_{TN}}{N_{TN} + N_{FP}} \right) \tag{7}$$

$$Accuracy = \frac{N_{TP} + N_{TN}}{N_{TP} + N_{FN} + N_{TN} + N_{FP}} \tag{8}$$

After calculating of these parameters, 94.16% sensitivity, 94% specificity and 94.90% accuracy were achieved. Kappa coefficient shows the reliability of the system performance which is introduced in (9).

$$K = \frac{2(N_{TP}N_{TN} + N_{FN}N_{FP})}{(N_{TP} + N_{FN})(N_{TN} + N_{FN}) + (N_{TN} + N_{FP})(N_{TP} + N_{FP})} \tag{9}$$

The results indicates Kappa=88.79% which is suitable for system performance. The coefficients of three factors have been calculated for each image in TABLE II. We use overlap procedure to evaluate the performance of the system and the output of it that based on the edges of images compared with the edges of Ground Truth images; Thus the pixels of edges in each image is obtained by counting and the similarity of edges is identified based on (10):

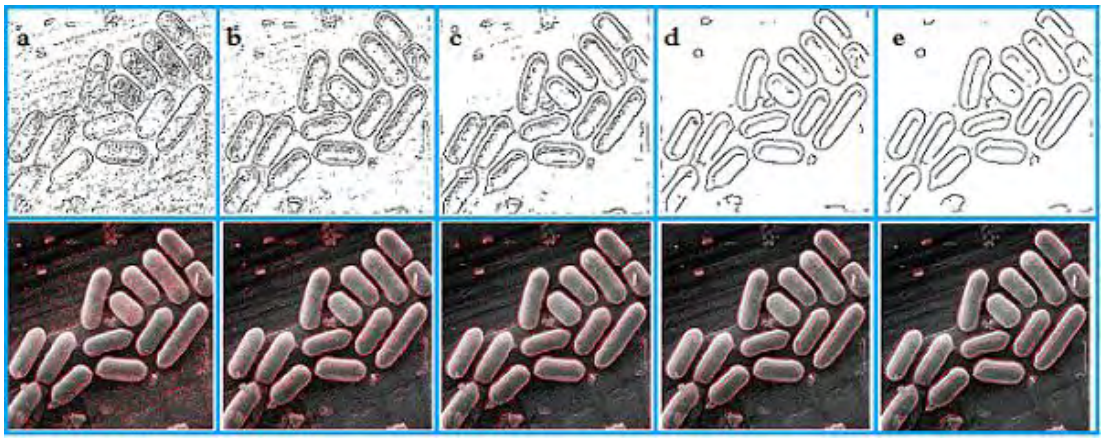

Figure 4. Implementation of the proposed algorithms on image of bacterial community by changing (a) N = 5 and q_0 = 0.1, (b) N = 5 and q_0 = 0.3, (c) N = 10 and q_0 = 0.5, (d) N = 10 and q_0 = 0.7 and (e) N = 20 and q_0 = 1

$$OvL = \frac{2|A \cap B|}{(|A| + |B|)} \tag{10}$$

In this equation the *OvL* is similarity factor, *A* is the number of edge pixels of Ground Truth, *B* is the number of edge pixels of our image and $|*|$ is size of the target sets. We can decide that the obtained edge is classified in true positive class without any sign of mass and in true negative case with sign of mass by choosing an appropriate threshold in similarity factor equal 0.8 in output of this equation. If the image hasn't any sign of mass or illness and SM<0.8, then output is classified in false positive and otherwise has sign of illness and SM>0.8, then the output is classified in false negative case.

TABLE II. The Calculation of 3 Factors for Each Medical Image

Images	Classification	N_{FN}	N_{TN}	N_{TN}	N_{FP}
Retinas of diabetic patients	40 normal images	-	37	-	3
	50 abnormal images	2	-	48	-
Brain MRI	30 images without tumor	-	29	-	1
	50 images with tumor	3	-	47	-
Microscopic images	30 images without illness	-	28	-	2
	20 images with illness	2	-	18	-
Total	**220 images**	**7**	**113**	**94**	**7**
Accuracy	94.90%				
Sensitivity	94.16%				
Specificity	94.00%				
Kappa	88.79%				

The proposed system, in comparison to other robust systems in edge detection, exhibits the proper accuracy and

time consumption. In comparison to methods such as Canny and Sobel filters, our algorithm obtains a high accuracy, in the cost of more time to implement. Patients had already been diagnosed with cancer by radiologist and specialists and thus the presence of malignant tissues in images was obvious. In Fig. 5 the proposed algorithm is applied on the image of the chest which the percentage of noise is added at each level so that the noise level is multiplied four, but the proposed algorithm detected the edge of pixels correctly.

We use MATLAB software programming and 2GHz Intel Core Due CPU operating system with 2GB RAM to implement the algorithm to detect edges in medical image using ant colony. The proper convergence was achieved in 50 loops. These repetitions were to achieve the ideal output, but in 20 loops the convergence was achieved. In each of the output images the harmonic mean of precision and sensitivity or F-measure was higher than 75% which represents the output of the system is efficient. One of the important factors that could affect the accuracy of the real edge is q_0. With increasing q_0, the resulting edge images are more realistic edge.

However, this amount cannot be increased to any value; because it would result in the loss of some key features of edge image and hence there is a trade-off in the selection of this factor. We can use of a fuzzy inference system to select the optimal value of q_0 so that appropriate amounts to be provided for each image because selecting the appropriate values of q_0 is dependent the on the nature of image. In implementation level the value of q_0 was used for images in the interval values [0-1.2]. In some methods are not discussed on the choice of the constants such as q_0 or other parameters.

The major drawback of this factor in the choice of a fixed amount is improper extraction of edges with noise or detachable structure in images. An important factor that is used to evaluate of system and output of algorithm is time which in evolutionary algorithm is known as full benchmark. In our proposed algorithm the time was spent less time in comparing with many similar technical methods.

In MF/Ant [23] the time to achieve output of algorithm was about 35 seconds yet in proposed method the time was 13 second. Also in GMF [24] or Kirsch [25] the accuracy weren't basic factor to output but algorithm operated in in less time.

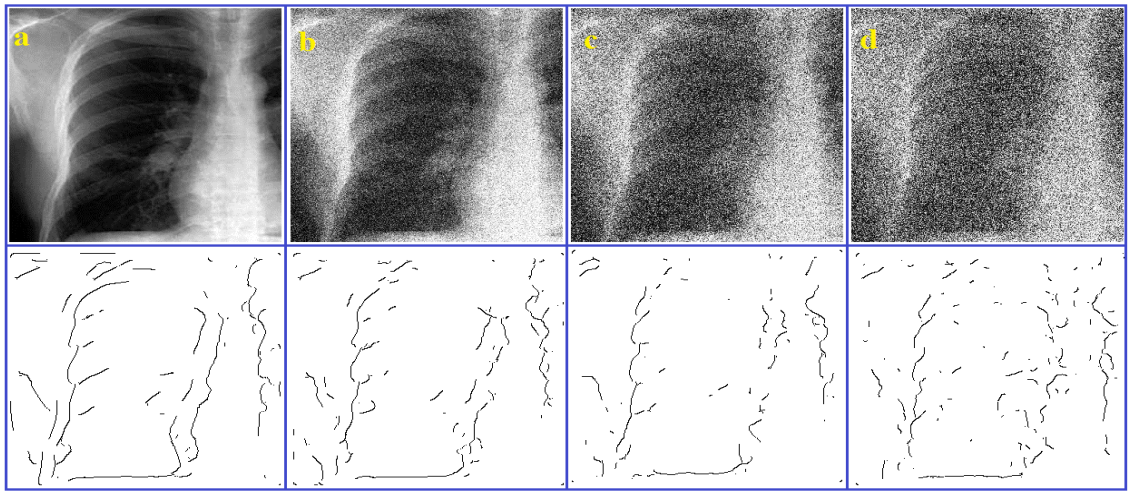

Figure 5. (a) The algorithm is applied on the original image, (b) by adding 4%noise to the original image and the proposed detect image edge with little change, (c) increasing 15% noise in original image and edge is seen at the bottom of the column and (d) Noise increases to 60%, but still the edges of the image by the proposed algorithm has been detected.

TABLE I. COMPARISON ALGORITHM WITH SOME VALID METHODS

The Technique	Accuracy ratio	Kappa	Time(sec)
MF/Ant [23]	92.93%	93.20%	~35
GMF [24]	88.50%	75.70%	~12
Kirsch [25]	89.39%	86.87%	~6
Sobel Operator	89.36%	75.71%	~0.26
Canny Operator	89.51%	74.78%	~0.28
Zana and K [26]	94.39%	91.74%	Indeterminate
Proposed Method	**94.90%**	**88.79%**	**~13**

High accuracy and low false positive rate in segmentation [27] distinguishes this method from other techniques used for detection of cancer in various images. Fig. 6 indicates the statistical comparison of proposed algorithm with two valid methods. In Table III a comparison with some valid methods is represented.

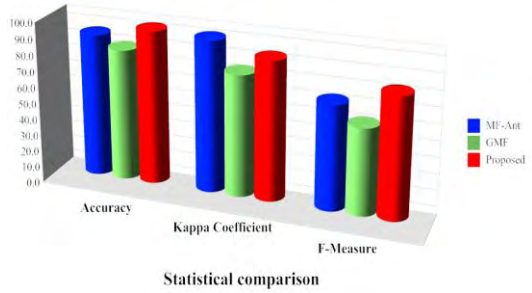

Figure 6. Indicates the statistical comparison of proposed algorithm with MF-Ant and GMF Techniques of the Accuracy, Kappa coefficient and F-measure factors.

In Fig. 7, the proposed system has been compared with two methods of Canny and Sobel edge detection method [9], [10] which are commonly used in scientific literatures. The

low PPV and high NPV of the system (reliability coefficient for clinical specialists and the patient) is a guarantee of the system reliability and both clinical specialist and patients can trust its software and output.

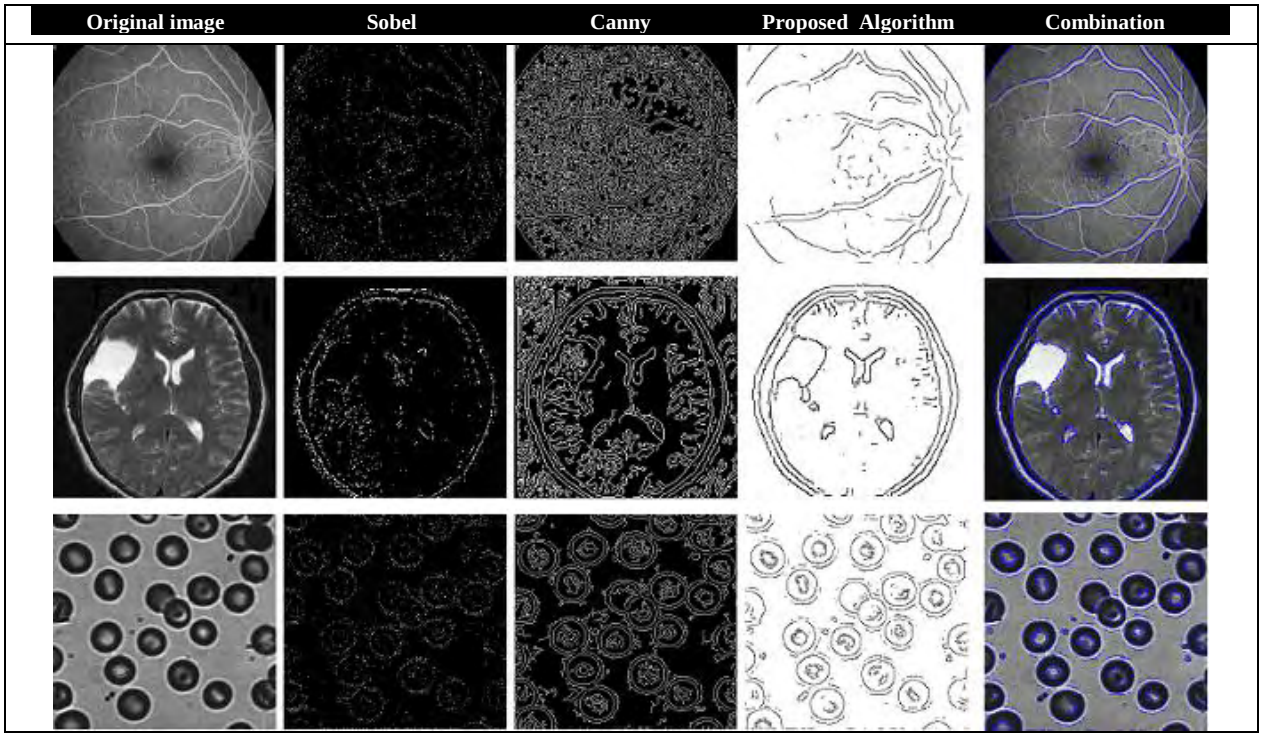

Figure 7. The comparison of two edge detection methods with the proposed algorithm. From left to right, the main image, Sobel edge detection and Canny edge detection, implementation of the proposed algorithm and its combination with the main image have been displayed respectively

V. Conclusion

In image processing, the extraction of information through edge detection is useful in identifying targets in the images. The wide changes in brightness intensity, the lack of discrete boundaries, the presence of noise and compression of medical images are among the reasons which sometimes make difficult the diagnosis of the disease and suspicious masses in the tissues for clinical specialists. In this paper, based on ant optimization algorithm, the edge of medical images and the target sections were identified with 94.90% accuracy, 94.16% sensitivity and 94.00% specificity. The images, taken from three medical data databases, included retina images of diabetes, brain MRI images and microscopic images. By constructing a pheromone matrix and changing search parameters in the ant colony algorithm, more desirable results were obtained compared to common edge detection and section isolation of the image. The low PPV and high NPV of the system (the reliability coefficients for clinical specialist and the patient respectively) is a warranty of the system and both clinical specialist and patients can trust its software and output.

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