EDGE DETECTION IN MRI BRAIN TUMOR IMAGES USING MODIFIED ACO ALGORITHM BASED ON WEIGHTED HEURISTICS

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ABSTRACT

Images play a crucial role in the medical field across various aspects, from diagnosis to treatment planning. The Magnetic Resonance Imaging (MRI) brain tumor images are always associated with noise. Therefore, to diagnose diseases, image edge detection plays a challenging role in the medical field. It identifies edges, boundaries, disruptions, irregularities, and other valuable features. Ant colony optimization (ACO) is a well-known metaheuristic algorithm inspired by the way ants lay down a chemical pheromone while searching for food. It generates a pheromone matrix, which provides edge information accessible at every pixel of the image, developed by ants navigating across the image. The movements of ants depend on the local variance of the image intensity value. Conventional statistical range-based approaches are limited in accurately identifying weak edges. The proposed approach enhances edge detection using ACO, integrating weighted statistical range-based heuristics information and Gaussian gradients to generate a binary image that enables to detect the strong edges. Thus by assigning weights to the neighborhood range of pixels helps to determine the direction in which ants are able to move. The Gauss gradient produces the edges effectively. The proposed method was tested with standard MRI brain tumor images. Experimental results exhibit the comparable performance of the proposed method with conventional edge detectors in terms of performance parameters like Figure of Merit, Sensitivity, Accuracy, and output images.

Keywords: *Ant Colony Optimization, Statistical Range, Edge Detection, Brain Tumor, Weighted Heuristics.*

1. INTRODUCTION

In the field of medicine, an MRI medical image is extremely significant. To diagnose diseases and provide appropriate treatment for patients, the quality of MRI images must be clear. Since the MRI images are always impacted by various noises and errors, it directly or indirectly affects the diagnosis of the diseases. To get the various features from MRI images the edges, boundaries, disruptions, and irregularities of the image should be accurately detected. Therefore, it is prime importance to develop a technique to identify the edges of an MRI medical image accurately. Edge detection plays a crucial role in MRI medical image processing, serving as a fundamental technique for identifying boundaries. Therefore, research in the development of the edge detection field needs of an hour.

A number of techniques of image edge detection are found in literature, like the Laplacian operator, Prewitt [1], Sobel [2], Canny [3], Log [4], Robert [5], Neuro-fuzzy (NF) [6]. However, most of these are affected by noise or blurring of the image edge [7, 8]. To overcome this problem, edge detection is assumed as an optimization problem.

Ant Colony Optimization (ACO) is a nature-inspired computational technique that models the food-searching behavior of real ants. In nature, ants initially explore their surroundings randomly in search of food. Upon locating a food source, they return to the colony while depositing pheromones along the path taken. These chemical trails serve as signals for other ants, increasing the likelihood that they follow the same path. As more ants use this route, the pheromone trail becomes stronger, reinforcing the optimal path. Conversely, paths not frequently used gradually lose their pheromone concentration due to natural evaporation. This dynamic process enables the ant colony to collectively discover and reinforce the shortest route to the food source. The foundational algorithm developed using this principle was called the Ant System [9], which was later refined

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into more advanced models such as the Max-Min Ant System and the Ant Colony System (ACS). ACO techniques have found applications across various domains, includingimage analysis. For example, a recent study [10] employed ACS for detecting edges in digital images, where artificial ants randomly explore pixel positions and move based on probabilistic rules within an eight-neighbor grid, leaving behind pheromone trails. Another approach proposed in [11] built upon this method by introducing an adaptive thresholding strategy to enhance the precision of edge detection.

Various techniques are reviewed [12, 13] and innovative approaches are available for edge detection. A robust edge detection algorithm was proposed [14] in which focus was on edge connectivity and edge thinning. An improved method of edge identification from images in which a Gaussian filter is used for edge enhancement and statistical range is used for edge detection [15]. A real-time capable, adaptive, and resilient edge segment detection method was introduced in [16], which utilizes two-dimensional image entropy to identify edges. The parallel and improved teaching-learning optimization algorithm for noisy data was proposed [17]. The optimized edge detection methods are based on the genetic algorithm proposed in [18]. The local k-mean algorithm from machine learning was applied for edge detection for focused images proposed [19]. Edge Detection using Gauss Gradient Algorithm in Retinal Optical Coherence Tomography Images is proposed [20]. The enhanced histogram integrated morphological image quality enhancement model using dermoscopy images with edge-based segmentation was presented [21].

Recently, an ant colony optimization algorithm modified to improve edge detection and to detect diseases. ACO based hybrid algorithm is proposed for edge detection by using new heuristics and knowledge data to update the result [22, 23]. In [24] proposed edge detection based on ACO, which apply a new heuristic function, adopting a user-mentioned threshold. F ratio techniques are used to determine the optimum threshold value from the updated pheromone matrix, which is further used for edge detection using ACO [25]. In [26] proposed a hybridized ACO algorithm, by initializing the pheromone trail matrix based on canny enhance the edge detection. Edges are enhanced using guided image filtering further enhanced ACO method is applied for edge detection [27]. Max-Min ant colony optimization to detect edges of images group bas using group-based heuristic information function was proposed [28]. A fuzzy ant colony optimization algorithm for edge detection was proposed [29].

Traditional gradient-based and statistical range-based methods of edge detection are often inadequate due to sensitivity to noise for detecting edges with high accuracy for medical images. To overcome these challenges, this study introduces a hybrid edge detection approach that integrates ACO with heuristic information. The proposed method influences the strengths of both strategies. Thereby, it prioritizes based on the edginess of the range of pixels, enabling the identification of strong edges, and using the Gauss gradient operator, the proposed method becomes efficient.

This paper is arranged as follows: Section 2 provides brief ant colony optimization; Section 3 provides details of proposed edge detection. The result and discussion are given in section 4. The section 5 concludes the paper.

1.1 Problem Statement

Gradient-based algorithms often suffer from sensitivity to noise and struggle to detect subtle intensity variations in images, which can lead to inaccurate edge detection. This limitation highlights the need for adaptive edge detection techniques that prioritize pixel regions based on their edge strength. Such methods should be capable of capturing even small intensity changes to reliably identify both strong and weak edges

2. ANT COLONY OPTIMIZATION

ACO is a biological-inspired optimization algorithm, related to the concept of stigmergy [30], that differentiates the natural adaption of ACO from other systems. It is a distant producing and reacting communication via stimuli. The ants deposit a pheromone on the ground while foraging for food. Other ants made the searching process by behaving in a particular way. The general steps of ACO are presented [31].

2.1 Ant Colony System

The decision rule and pheromone update distinguish ACS from AS [24]. Ant Colony System (ACS) has its own probabilistic decision and pheromone update rules. In ACS, starting from the source node, the ant of the colony builds a solution sequentially. At each node, ant read the local information stored on node and to decide next movement they follow stochastic. Ant k located on vertex i moves towards vertex j which is computed by particular probability as the next node, as per pseudo-random proportional rule (Eq. 1):

$$(i,j) = \begin{cases} argmax_{(l,m)\in\aleph_{(i_0\ j_0)}} \left\{\tau_{lm}[n_{l,m}]^{\beta}\right\} & if\ q \leq q_0 \\ \frac{\left\{\tau_{ij}[n_{ij}]^{\beta}\right\}}{\sum_{(i,j)\in\aleph_{(i_0\ j_0)}}\left\{\tau_{lm}[n_{l,m}]^{\beta}\right\}} & otherwise \end{cases} \quad (1)$$

where q is a random variable, and q_0 algorithm parameters, with$(0 \leq q_0 \leq 1)$. β is used to adjust the relative importance of heuristic information. The local pheromone update is as follows (Eq. 2):

$$\tau_{ij\leftarrow}(1-\varphi)\tau_{ij} + \varphi\tau_0 \quad (2)$$

where $\varphi(0 \leq \varphi \leq 1)$ and τ_0 are algorithm parameters.

In the Ant Colony System (ACS), the global pheromone update is exclusively carried out by the best-performing ant, denoted as bs. After each iteration, this ant updates the pheromone levels along its tour T^{bs} globally, as described in Equation (3).

$$\tau_{ij\leftarrow}(1-\rho)\tau_{ij} + \rho\Delta\tau_{ij}^{bs} \quad \forall(i,j) \in T^{bs} \quad (3)$$

where $\Delta\tau_{ij}^{bs} = \frac{1}{C^{bs}}$ value represents the tour length traversed by the best ant, and ρ is the pheromone evaporation rate $(0 \leq \tau \leq 1)$. bs stands for best ant. It is assumed that the pheromone evaporation and deposit simultaneously.

3. PROPOSED METHOD

This section proposes modifications to the existing ant colony optimization for edge detection method in MRI brain images. We have assigned weights to the statistical range [32] of pixels by multiplying a constant value to calculate the heuristic value. Due to large local range distance, it provides strong edges in edge detection. Searching for edges through an input image intensity matrix $I(0 \leq I(i,j) \leq 225, i = 1, \ldots, m; j = 1, \ldots, n)$ of $m \times n$ size and finally get a binary image as output. The steps of implementation of the algorithm as follows:

3.1 Initial Stage

To initialize the algorithm, both the weighted heuristic matrix and the pheromone matrix of size $m \times n$ are created. The pheromone matrix is set with a small positive value of $1/(m \times n)$, encouraging ants to explore a wider range of pixels that could potentially be part of an edge. In [33] $n_{i,j}$is determined using structures of 3x3 ideal images based on [34, 35]. In the proposed method, weights are assigned based on the pixel intensity range to compute the transition probabilities. This approach enables the ants to perceive intensity variations over a broader area, allowing them to make more informed decisions about their movement direction. As a result, the accuracy and effectiveness of edge detection are significantly improved. It is calculated as

$$n_{i,j} = 2(p_j - p_i) \quad (4)$$

where p_j is the maximum intensity of pixel j and p_i is minimum intensity of pixel i. The norm of the gradient is given by

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (5)$$

where G_x and G_y are Gaussian smoothed versions of the image in x and y directions [20, 36] when ants follow the transition rule. From every 3x3 matrix partition statistical range from inputted images is considered here. Every pixel is replaced by a range of neighboring grey values. The neighborhood's range will be greater at an object's edge than it is inside [15, 37]. Here statistical range is considered heuristic information because it acts as an edge detector.

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3.2 Construction Stage

In each iteration, ants proceed among pixels searching for edges. In each movement, the ant applies the rule of the ant colony system to determine the pixel to visit following the equation (Eq.6)

$$(i,j) = \begin{cases} argmax_{(l,m)\in \aleph_{(i_0\ j_0)}} \left\{\tau_{lm}\left[n_{l,m}\right]^{\beta}\right\} & if\ q \le q_0 \\ \dfrac{\left\{\tau_{ij}\left[n_{ij}\right]^{\beta}\right\}}{\sum_{(i,j)\in \aleph_{(i_0\ j_0)}}\left\{\tau_{lm}\left[n_{l,m}\right]^{\beta}\right\}} & otherwise \end{cases} \quad (6)$$

where $\aleph_{(i_0 j_0)}$ is a restricted neighborhood.

3.3 Update Stage

Proceeding to the new pixel, each ant locally updates pheromone levels by (Eq.7)

$$\tau_{ij} \leftarrow (1-\varphi)\tau_{ij} + \varphi\tau_0 \quad (7)$$

During the L-movement phase, once all ants have completed their tours, the global pheromone update is performed before initiating the next iteration, as defined in Equation (8)

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij}^{bs}\ \forall(i,j) \quad (8)$$

In order to avoid stagnation, it updates pheromone levels across the entire image.

3.4 Decision stage

Here per run of the program, all ants cooperate to build one solution. Therefore, when the program is stopped, the final pheromone matrix is obtained. The improved final pheromone matrix leads to edge detection.

In this phase, a binary classification is performed at each pixel by applying a threshold T to the final pheromone matrix τ_{ij}, determining whether the pixel represents an edge, as described in [10]. The final pheromone and corresponding range matrices are examined locally using a 3×3 window to refine the edge detection results. For a given pixel at position (i, j), if its pheromone value exceeds the predefined threshold (T) while its range value falls below a global threshold (GT), the pheromone value is reset to 0, indicating that the pixel is not part of an edge. Conversely, if these conditions are not met, the pheromone value is set to 255, signifying that the pixel is classified as an edge.

The condition to develop binary matrix E based on all final pheromone values τ_{ij} and algorithm threshold T as follows

$$E(i,j) = \begin{cases} 1 & \tau_{ij} \ge T \\ 0 & otherwise \end{cases} \quad (9)$$

During first iteration

$$T = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\tau_{ij}}{M \times N} \quad (10)$$

Next, a new threshold T is calculated as the average of two mean values: one representing the average pheromone values less than a lower threshold TL, and the other representing values greater than an upper threshold TU, where TU is initially determined as the mean of TL and TU. This iterative process continues until the threshold (T) stabilizes and no longer changes between iterations, indicating that the algorithm has converged and no additional edges are being detected. Regarding other alternatives to obtain the T, [38] and [39] have used Otsu's method to compute the threshold.

4. RESULTS AND DISCUSSION

The suggested approach has been compared with the classical edge detectors like Sobel, Prewitt, Canny, and Log operator. All experimentation is performed using the following system specification as shown in Table 1:

Table 1 System specification

Sr. No.	Particulars
1	Desktop PC, Windows 7
2	64-bit processor, i5 at 2.5 GHz
3	8 GB RAM with HDD - 500 GB

All images used in the study are 8-bit grayscale PNGs with a fixed resolution of 128 × 128 pixels. The parameters and values during experimentation are as follows:

Number of ants K=$\sqrt{m \times n}$

Initial pheromone matrix value $\tau_0 = 1/(m \times n)$
Weigh heuristic information β= 0.1
Pheromone decay coefficient φ =0.05
The global threshold used GT=70
Weight of pheromone information $\alpha = 4$
Pheromone evaporation rate $\rho = 0.1$
Tolerance value considered in stopping condition $\epsilon = 0.01$
Number of moves per ant L_m= 40

To evaluate the quality of the proposed edge detection method, the dataset of standard medical images, including MRI brain images, is used from https://medpix.nlm.nih.gov/topiclist.

The experimentations are performed using 100 images. Figure 1 shows six different sample medical input MRI brain images characterized by different locations of tumor and different types.

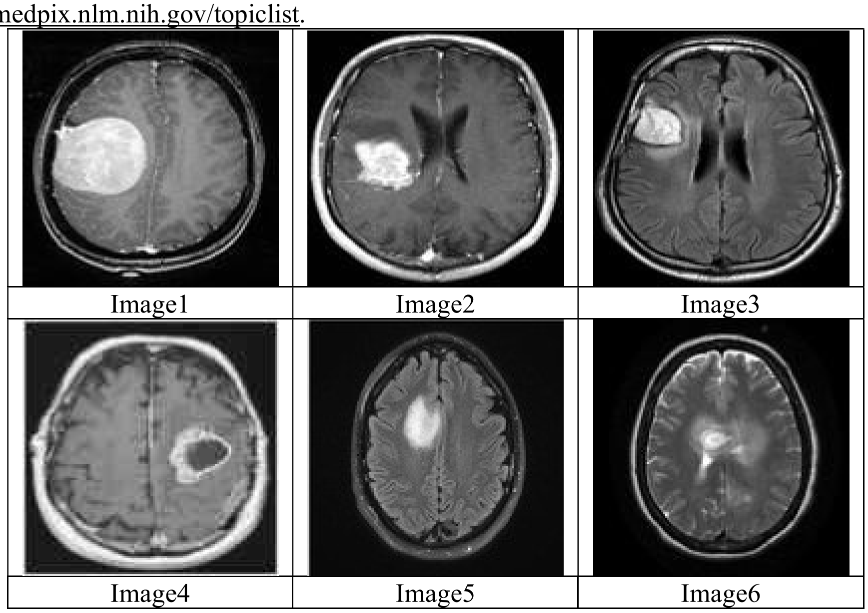
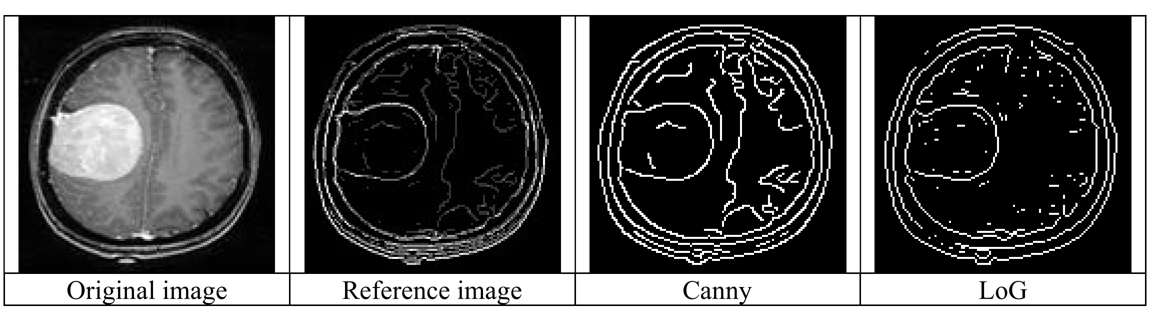


Figure 1: Test medical MRI brain images

In this paper, the majority image is considered a reference image that was created by five established standard edge detection algorithms, namely Canny, Sobel, Prewitt, Robert, and Log edge detectors. The outcome of the proposed method is compared pixel by pixel with the majority image. A majority image is obtained from n number of methods as M (method 1, method 2... method n). If the majority of the detector detects an edge pixel in its neighborhood with at least one centered on it, then the pixel in the majority image represents an edge pixel [40].



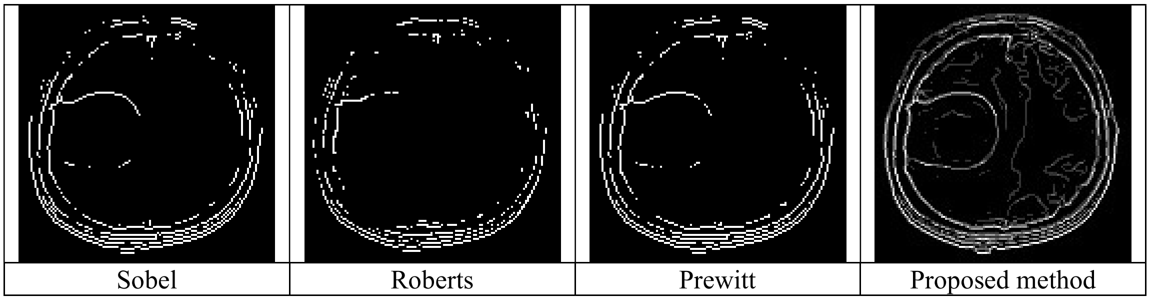


Figure 2: Comparison of the original image, reference image, and outcomes of Canny, LoG, Sobel, Robert, Prewitt operator, and proposed method for image 1 (Figure 1)

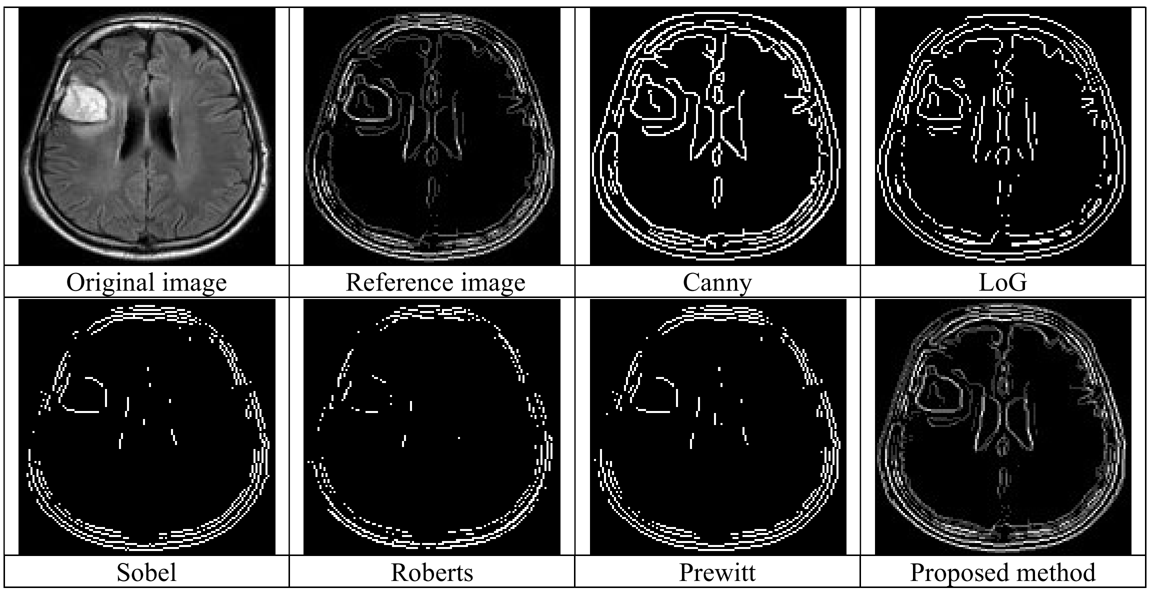
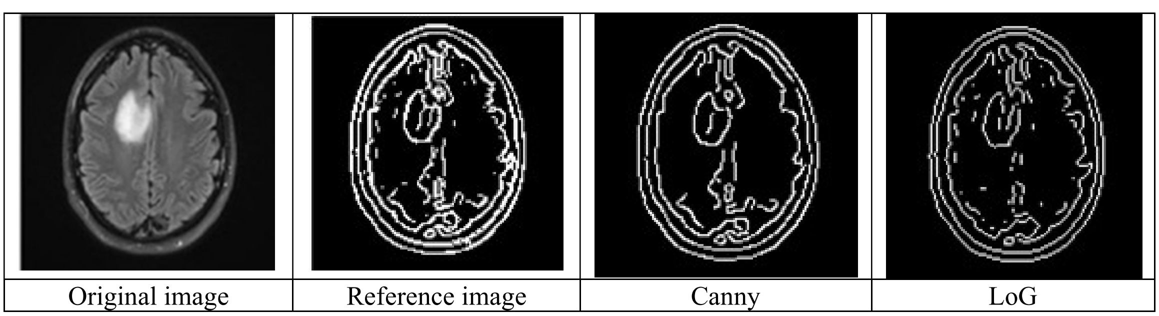
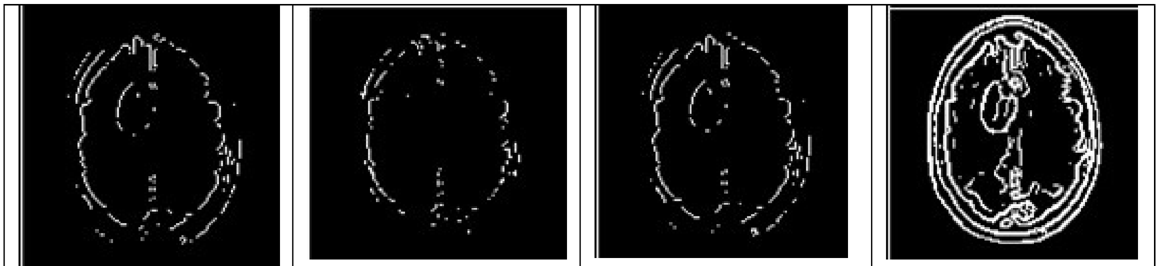


Figure 3: Comparison of the original image, reference image, and outcomes of Canny, LoG, Sobel, Robert, Prewitt operator, and proposed method for image 3 ((Figure 1)





Sobel	Roberts	Prewitt	Proposed method

Figure 4: Comparison of the original image, reference image, and outcomes of Canny, LoG, Sobel, Robert, Prewitt operator, and proposed method for image 5 ((Figure 1)

To evaluate the correctness and performance of the proposed edge detection method, the parameters used are as follows: % of correctly detected pixels ((P_{CD}) and not detected (P_{ND}) while false alarm (P_{FA}), the figure of merit (FOM), sensitivity, and accuracy depend on the value of TP, TN, FP, FN and I_I, [18,41] as

The % of correctly detected pixels is defined as:

$$P_{CD} = \frac{TP}{I_I} \tag{11}$$

The % of correctly not detected pixels is defined as:

$$P_{ND} = \frac{FN}{I_I} \tag{12}$$

The % of false alarm is defined as:

$$P_{FA} = \frac{FP}{I_I} \tag{13}$$

The Pratt's Figure of Merit (FOM): It represents the deviation from an ideal image to a known image [42]. It is defined as:

$$FOM = \frac{1}{max(I_I,I_A)} \sum_{i=1}^{I_A} \frac{1}{1+\alpha_f . d_i^2} \tag{14}$$

The sensitivity can be calculated as:

$$Sensitivity = \frac{TP}{TP \quad FN}$$
(15)

The accuracy is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+F}$$
(16)

The outcomes of three images are shown in Figures 2 to 4 for demonstration. The performance of the proposed approach and that of the conventional detectors like Sobel, Canny, LoG, Robert, and Prewitt is visually compared with the edge map. It appears that the edges developed by the proposed method are clearer and stronger than those with Canny, Sobel Log, Robert, and Prewitt. Overall, the visual performance of the proposed method is comparable with the reference image.

Table 2: Performance parameters for Sobel, Canny, LoG, Robert, and Prewitt and the proposed method

Test image	Method	P_{CD}	P_{ND}	P_{FA}	FOM	Sensitivity	Accuracy
1	Proposed	0.4991	0.5009	0.1302	0.9449	0.9555	0.9978
	Sobel	0.4321	0.5679	0.9779	0.5087	0.5432	0.9542
	Canny	0.4663	0.5337	0.3001	0.5867	0.5532	0.9446
	LoG	0.3876	0.6124	1.0311	0.3112	0.4032	0.9012
	Roberts	0.3112	0.6888	0.3995	0.4123	0.4998	0.9342
	Prewitt	0.3322	0.6678	0.7999	0.4256	0.4832	0.9445

2	Proposed	0.5134	0.4866	0.1032	0.8999	0.9301	0.9812
	Sobel	0.4423	0.5577	0.8331	0.5443	0.5223	0.9545
	Canny	0.4662	0.5338	0.2999	0.5743	0.5342	0.9423
	LoG	0.3956	0.6044	1.4292	0.5323	0.5541	0.9045
	Roberts	0.3101	0.6899	0.5889	0.5112	0.4889	0.9351
	Prewitt	0.3421	0.6579	0.8265	0.4991	0.4711	0.9532
3	Proposed	0.5110	0.5889	0.1399	0.9311	0.9545	0.9977
	Sobel	0.4561	0.5656	0.9179	0.5567	0.5652	0.9842
	Canny	0.4656	0.5817	0.3621	0.5247	0.5542	0.9696
	LoG	0.3988	0.6124	1.4292	0.5323	0.5211	0.9022
	Roberts	0.3910	0.6999	0.5119	0.5182	0.4899	0.9671
	Prewitt	0.3652	0.6978	0.7909	0.4256	0.4832	0.9445

Table 2 shows the comparison of performance parameters for Canny, Sobel, Log, Robert, and Prewitt with the proposed method for brain tumor images. The proposed method exhibits a lower false detection rate, indicating that fewer pixels were incorrectly identified as edges in brain tumor images. It is seen that the performance parameters of the proposed method are comparable with the corresponding reference images.

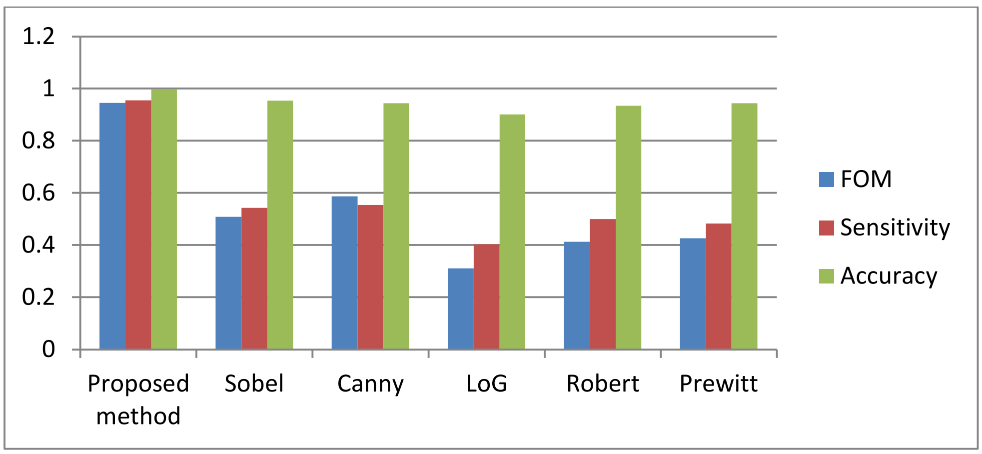


Figure 5: Comparison of the edge map of the proposed method and conventional edge detectors

The average value of FOM, sensitivity, and accuracy parameters are compared in figure 5 for the presented method and conventional edge detectors. The outcome of the presented method achieved an average accuracy of 99.01%, an average Pratts FOM value of 95.91%, and an average sensitivity of 90.99%.

5. CONCLUSION

This paper presents a method for edge detection in MRI brain tumor images using a modified ant colony algorithm. In the proposed method, heuristic information is calculated by assigning weights to the statistical range of pixels. Thereby, it prioritizes based on the edginess of the range of pixels, enabling the identification of strong edges. The incorporation of the Gauss gradient improves the effectiveness of edge detection. Visual comparisons demonstrate that the proposed method accurately identifies meaningful edges, while quantitative analysis confirms its superior accuracy in detecting edges in MRI brain tumor images. It has been found that the ACO-based method is very efficient with an average detection accuracy of nearly 99 %. A high value of the FOM parameter represents a more accurate match with the majority image. The average sensitivity of the proposed method is 90% compared with averages of conventional edge detectors, indicating that 90% of the proposed edge map pixels were correctly detected as pixels of the reference image. Overall, the performance of the proposed edge detection algorithm is better compared to conventional edge detectors. This method helps doctors during the diagnosis of diseases.

AUTHOR CONTRIBUTIONS

All the authors have equally contributed.

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