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Research Article

APPLICATION OF FIREFLY ALGORITHM IN BREAST CANCER DETECTION IN MAMMOGRAPHIC IMAGES

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ABSTRACT. Breast cancer is one of the most common cancers in women. In many cases, there are no obvious symptoms in patients with it. Accurate diagnosis of this type of cancer in the early stages is essential to reduce mortality. Mammography is a standard method used to diagnose breast diseases. To prevent mental analysis of mammographic images by radiologists and increase the accuracy of breast cancer detection, artificial intelligence systems have received much attention in recent years. In this paper, a method based on combining firefly algorithm and applying appropriate pre-processing on the image to detect breast cancer in mammographic images is presented. To do this, mammographic images in the mammography screening (DDSM) digital data set are used. Three performance criteria of accuracy, sensitivity and precision (93.4%, 91%, 95%) indicate the proper performance of the proposed method compared to existing studies. This work shows better performance when compared to existing work in literature.

Keywords: *breast cancer, digital mammography images, dilation, firefly algorithm, morphology*

INTRODUCTION

Breast cancer is one of the most common cancers [1]. Typically, one in eight women has breast cancer. If this disease is diagnosed in time, it can be easily treated [2, 3].

Cancer is the third leading cause of death in Iran and between 101 and 105 people die of cancer every day. Abnormalities such as the presence of glands in the breast, changes in the size and dimensions of the breast, differences in the color of the breast skin, chest pain, etc. are among the physical symptoms of breast cancer [4, 5]. Currently, about 75% of people with breast cancer in the second stage and only 18% of people in the early stages of the disease seek treatment [6, 7]. The methods used to diagnose breast cancer are usually based on image processing. In this method, cancer is diagnosed using mammography or thermography images [8]. Compared to other diagnostic methods such as ultrasound or magnetic resonance imaging (MRI), mammography is the most accurate method for early detection of breast cancer [9]. During mammography, some X-rays are absorbed in proportion to the tissue and other rays pass through it, which is proportional to the amount of energy absorbed in proportion to the nature of the tissue. The amount of signal emitted from the tumor tissue is different from normal tissue, and based on the amount of changes, it can be determined whether the tissue has a tumor or not.

Mammographic imaging processing helps the physician and radiologist in the easy diagnosis of the disease and thus protects the patient from irreversible risks [10].

In mammographic images, changes in gray areas in different parts of the image are minimal. This makes it difficult to segment areas containing the tumor through light levels alone. Mammographic images also include high-frequency components and different levels of noise that make it difficult to detect the tumor [11, 12].

In several studies, many methods have referred to the characteristics of optimization based on collective intelligence [13, 14]. Among the methods based on collective intelligence, we can mention artificial bee colony [15], ant colony optimization [16] and bee particle optimization method [17, 18]. The best methods based on collective intelligence currently available are the firefly algorithm, cuckoo search and bat algorithm [19, 20].

The ability of electrical impedance spectroscopy to roughly localize and clearly distinguish cancers from normal tissues and benign lesions is presented in [21], which localization of these lesions is confirmed by simultaneous, in register digital breast tomosynthesis mammography or 3-D mammograms. A computer aided detection system to help reduce reading time and prevent errors is developed in [22], which in the multi-stage system segmentations of the breast, the nipple and the chestwall are performed, providing landmarks for the detection algorithm.

In this paper, a combination of incandescent algorithm and morphology is used to find the tumor area. The tumor has a high light intensity in mammographic images, so using the light worm algorithm, one can find the area where the tumor is most likely to be present. The firewall algorithm at its lowest level focuses on generating solutions within a search space and selects the best solution for survival. Random search avoids getting caught in the local optimal trap. In general, this algorithm has the following three main advantages, and according to the problem of this research, which is of multi-quality type, this algorithm will be used:

- Automatic segmentation of the entire population into subgroups
- Ability to deal with multi-quality optimization
- Variety in solutions

For this method to be successful, proper pre-processing must be performed on the images. Then, using the morphology algorithm, the desired area can be expanded and the entire tumor area can be extracted. Using the morphology algorithm, it is possible to compare the uniformity of brightness and structure of each point with respect to the extracted tumor region, and if it is close, that point is added to the tumor region. In the second part of the article, the study of firefly algorithm and morphology is presented. Details of the proposed method are given in the third section. In the fourth section, the results are presented and finally the conclusion and discussion are expressed in the fifth section of the paper.

ALGORITHMS USED IN RESEARCH

Firefly algorithm

Fireflies live in nature in groups and their main characteristic is their blinking light [23, 24]. These lights have two basic functions: attracting the opposite sex and alerting the enemy. The dimmer cream always moves towards the brighter cream [25, 26]. The blinking behavior of fireflies is based on the criteria of attractiveness, brightness and distance [27, 28].

Morphology

Morphology is a wide range of nonlinear image processing operations that process images based on shape. In a morphology operation, the value of each pixel in the output image is set based on the value of other pixels in its neighborhood. In fact, morphological operations use neighborhood pixel values. Morphological operators include expansion, erosion, opening and closing [29].

SUGGESTED METHOD

This section describes the steps of the proposed method. First, the images are collected. An appropriate pre-processing is then applied to the collected images, after which the main processing will be performed. Fig. 1 shows the algorithm of the proposed method.

Data collection	From the DDSM database
Preprocessing	1. Reduce the size of images and remove empty edges from the movie 2. Remove background and noise from images (a) Thresholding algorithm (b) Area growth algorithm
Processing	1. Find the probable point of the tumor site using the firefly algorithm 2. Expand the starting point found using morphology operators 3. Determining the boundaries of the tumor area in mammographic images

Fig. 1. *Proposed method algorithm*

Collect pictures

This study uses mammographic images from a digital database for mammography screening (DDSM) prepared at the University of South Florida. The DDSM database consists of 2620 items, each of which is a collection of mammographic images and information corresponding to a patient's chest examination. In this database, the range of each suspicious area is specified. There is also background information on the location of the tumor determined by at least two experienced radiologists [30, 31]. Each item contains two images of each breast with tail (CC) and oblique (MLO) (two angles). In addition, more information such as examination time, breast tissue density, patient age, type of pathology (pathology), number of abnormal cases, file name, file type, scan date, etc. are also available [32].

Pre-processing

Images in the DDSM database contain noise and common elements in mammograms that may interfere with the results of the proposed method used. These adverse elements include patient profile, type of test performed, pre-image pixels, and noise generated due to defects in image production or scanning processes. The purpose of the pre-processing step is to remove unwanted elements. Fig. 2 shows an example of images in the DDSM database that contain various information [33].

Resize images and remove blank edges from the movie

The first step in the pre-processing process is to reduce the size of the original images and create images with a height of 1024 pixels. A similar reduction operation is also applied to the width of the images. The purpose of this step is to reduce the processing time, because if you work with the original size of the images (average height of 6000 pixels) the processing time will be very long. It should be noted that this reduction does not lead to data loss [34, 35]. Then all points are removed at a distance of 30 pixels from the vertical border and 60 pixels from the horizontal border. These omissions are intended to remove the area between the edges of the film and the empty spaces without the film.

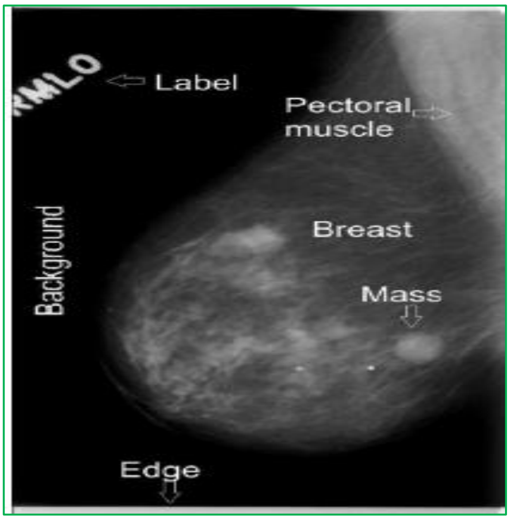


Fig. 2. *An example of the information contained in DDSM database images*

REMOVE BACKGROUND PIXELS

To remove background pixels, the threshold and area growth algorithm is used.

Resize images and remove blank edges from the movie

The background has near-black gray surfaces that are removed using the threshold algorithm. First, the image is divided into two halves and the sum of the gray surface values of each half of the image is calculated [36, 37].

The gray surfaces in the background are close to the black surfaces and have values close to zero, so the part with the lowest total contains the background part.

A medium filter is used to remove noise. This filter uses the mean (μ) and standard deviation (σ) of gray surfaces and calculates the L threshold based on it. The image is considered as a n×n matrix in the following form:

$$\begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{bmatrix} \tag{1}$$

The mean (μ) and standard deviation (σ) are calculated from Equations (2) and (3), where m is the number of pixels in the image:

$$\mu = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}}{m} \tag{2}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} (x_{ij} - \mu)^2}{m}} \tag{3}$$

The value of L is calculated as follows:

$$L = \mu + \sigma \tag{4}$$

If the value of L is less than 50, it is used as a threshold. Otherwise μ (calculated mean value) is used. This threshold is to separate the background area, thus preserving the contour of the chest.

By thresholding, higher-intensity pixels, such as chest pixels and its detection marks, are placed in one cluster (white) and lower-intensity pixels, such as background and noise pixels, are placed in another (black) cluster. Therefore, background pixels are removed from the image.

Area growth algorithm

The area growth algorithm uses uniformity in the area. In this algorithm, each pixel is compared to its adjacent pixels and the degree of similarity between the pixels is evaluated. If the absolute value of the difference between their gray values is less than the threshold value, they are called two similar pixels.

By selecting a pixel as the starting point, the regional growth algorithm examines and controls the pixels adjacent to the starting pixel. If a pixel is large enough to resemble the pixel in the target area, the pixels in that area are added. This operation continues until it covers all the pixels in the image, or in other words, another pixel does not have the conditions to be added to the area.

In the image from the threshold operation, there are still components outside the chest, such as test identification labels and some noise. These components are removed from the image by the area growth algorithm, which separates areas not related to the image. Only the area with the largest area, which is the breast tissue, is selected.

PROCESSING

The main processing is performed on the final image obtained from the pre-processing stage. In this step, first the firefly algorithm is applied on the image and then using morphological operations, the location of the tumor in the images is detected.

Firefly algorithm

As mentioned, the tumor has a high brightness in mammography images, so using the firefly algorithm, we can find the point where the tumor is more likely to be present. Details of the firefly algorithm used are shown in Fig. 4.

In this process, 25 fireflies have been used. 25 fireflies are randomly placed on the 2D view of the image (Fig. 5). Then the firefly algorithm is applied to the image 100 times. Finally, by applying the firefly algorithm, the fireflies are located at the site of the tumor and are absorbed (Fig. 6). Fireflies are attracted to each other based on the intensity of light and attractiveness. (Creams that are less bright and attractive are attracted to creams that are more attractive and bright.)

Morphological operations

In morphological operations, the desired point obtained from the implementation of the firefly algorithm is expanded and the entire tumor area is extracted. In morphological operations, the degree of luminosity and structure uniformity of each point relative to the extracted tumor area is compared.

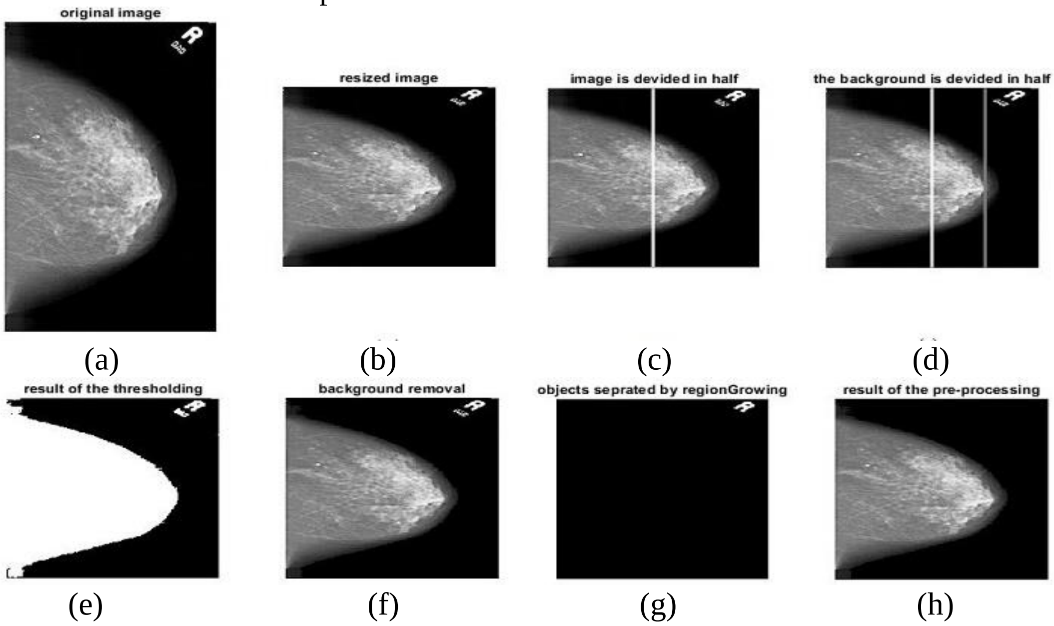


Fig. 3. *Eliminate background and noise (a) Original images, (b) Diminished image, (c) White line halving image, (d) Gray line dividing the background content of the image, (e) Thresholding results, (f) Delete background, (g) delete objects unrelated to area growth algorithm and (h) Pre-processing results*

Objective function f(x), $X=(x_1,\ldots,x_d)^T$
Initialize population of fireflies x_i (i=1,2,…,n)
Define light absorption coefficient γ
While (t<MaxGeneration)
For i=1:n all n fireflies
For j=1:I all n fireflies
Light intensity I_i at x_i is determined by $f(x_i)$
If ($I_j > I_i$)
Move firefly I towards j in all d dimensions
End If
Attractiveness varies with distance r via exp[$-\gamma r$]
Evaluate new solutions and update light intensity
End for j
End for i
Rank the fireflies and find the current best
End while
Postprocess results and visualization

Fig. 4. *Firefly Algorithm*

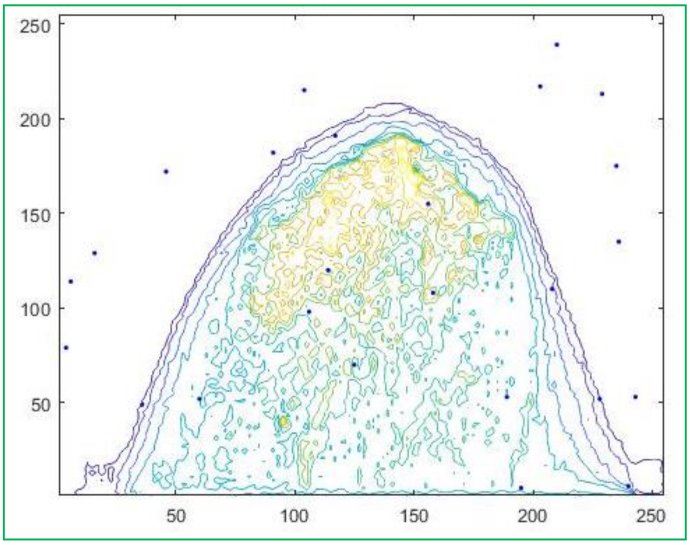


Fig. 5. *Initial locations of 25 fireflies*

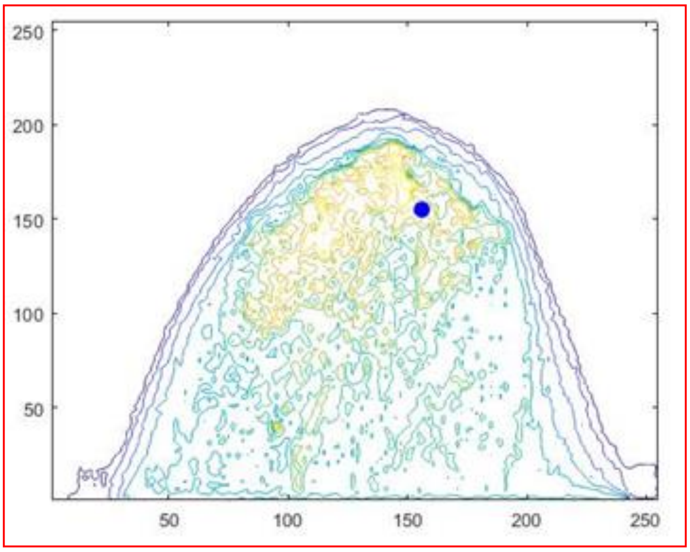
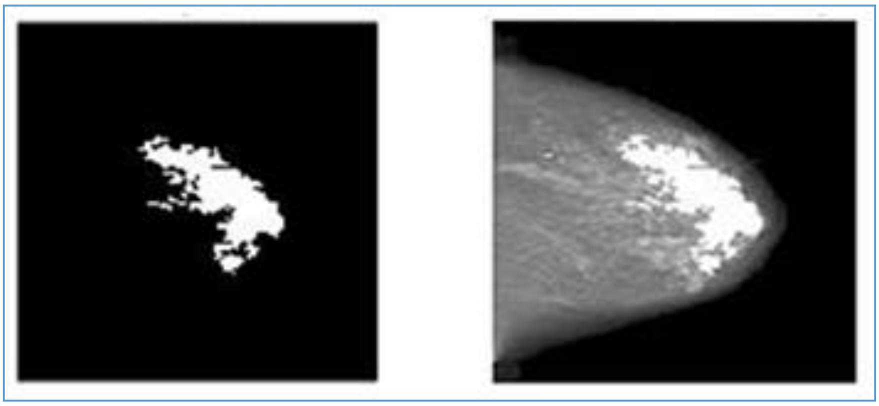


Fig. 6. *Final locations after 100 iterations*



(a) Gained *(b) Extracted*

Fig. 7. *Tumor area obtained and extracted from breast mammography image*

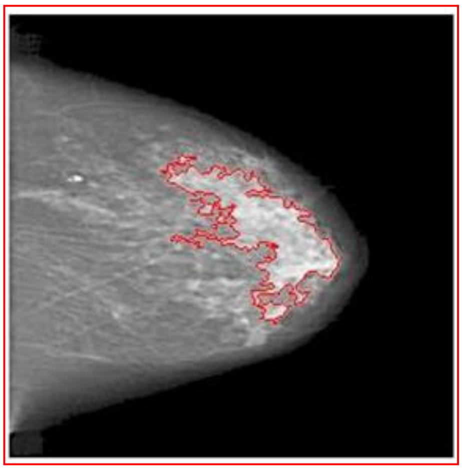


Fig. 8. *Determining the boundaries of the tumor area in mammography*

If similar, that point is added to the tumor area. As mentioned, morphological operators such as opening and closing, erosion and expansion are used to extract the entire tumor area, and the entire tumor area is obtained according to Fig. 7. In Fig. 8, the borders of the extracted tumor area are shown in red.

RESULTS AND DISCUSSION

Mammographic images are considered in two groups of healthy and tumor. The applied algorithm is evaluated based on whether it can correctly detect the tumor in the images or not. Four parameters to evaluate the performance of the algorithm are defined as follows:

If the applied algorithm can correctly identify the images that contain the tumor, they will be considered as real positives. Images that do not have a tumor and are not correctly detected by the system are also considered negative. The system can also be classified and evaluated according to the following classification:

True Positive (TP): Equals the number of tumor images that the applied algorithm has correctly identified as tumor.

True Negative (TN): Equals the number of healthy images that the applied algorithm has correctly identified as tumorous.

False Positive (PF): Equivalent to the number of tumor images that the applied algorithm has erroneously identified as healthy.

False Negative (FN): Equals the number of healthy images that the applied algorithm has incorrectly identified as tumorous.

With the help of defined parameters (TP, TN, FP, FN), the performance of the proposed algorithm can be evaluated using sensitivity, specificity and accuracy. The results of the algorithm evaluation are presented in Table (1).

$$\text{sensitivity} = \frac{TP}{TP + FN} \times 100 \tag{5}$$

$$\text{specificity} = \frac{TN}{TN + FP} \times 100 \tag{6}$$

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{7}$$

Table 1. *The function of the proposed algorithm.*

Algorithm performance	Evaluation percentage
allergy	93.4%
being special	91%
Accuracy	95%

CONCLUSION

In this paper, using the firefly algorithm, the texture of the image was extracted based on the uniformity of light intensity and structure of each pixel compared to neighbouring pixels. The tumor has a higher brightness in mammographic images. Due to the nature of the firefly algorithm, fireflies are attracted to the area with greater light intensity. Of course, light intensity alone is not the only consideration, and the tumor area should have uniform characteristics in the whole area and be significantly different from the adjacent tissue, which is examined by the morphology algorithm in this article. In studies, the sensitivity and accuracy of tumor diagnosis in breast tissue is about 80 to 90%. The sensitivity and accuracy of the proposed method in tumor diagnosis were evaluated as 93.4% and 95%, respectively, which indicates the high efficiency of the proposed algorithm. According to the evaluation criteria obtained from the proposed algorithm, it can be said that the use of luminosity cream algorithm and morphology can increase the accuracy of breast cancer mass detection.

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