Current Signal Transduction Therapy, **2016**, *11*, 000-000

RESEARCH ARTICLE

Performance Identification Using Morphological Approach on Digital Mammographic Images

Karthick Subramanian[a,*] and Sathiyasekar Kumarasamy[b]

[a]*Department of Electrical and Electronics Engineering, The Kavery Engineering College, Mecheri, Salem District-636453, Tamilnadu, India;* [b]*Department of Electrical and Electronics Engineering, S A Engineering college, Poonamallee - Avadi Road, Veeraraghavapuram, Thiruverkadu, Chennai, Tamil Nadu 600077, India*

ARTICLE HISTORY

Received: February 10, 2016
Revised: May 04, 2016
Accepted: May 13, 2016

DOI: 10.2174/157436241166616061710231 5

Abstract: ***Background***: Digital Mammography is the most vital and successful imaging modality used by radio diagnosis method to find out breast cancer. Breast cancer is the most significant and common cause of cancer death in women. The main problem is to find the accurate and efficient method for breast cancer segmentation.

Method: The morphological method is the most important approach in image segmentation method. There are various new methods available for breast cancer image segmentation but those methods are not upto the mark. They fall behind the image segmentation.

Results: On comparing both the algorithms for segmenting the mammographic images, applying the Neural Networks algorithm will be a better option rather than applying Region Growing Algorithm. The accuracy of the segmentation is higher in the morphological image segmentation approach.

Conclusion: The results show that, the performance of morphological approach is more efficient than other methods.

Karthick Subramanian

Keywords: Breast Cancer, Region Growing Algorithm, Mammography, Image Segmentation, back propagation, feed forward network, neural network.

INTRODUCTION

Breast cancer is the most important cause of women death in many countries [1]. If it is diagnosed at early stages, there is a good opportunity to reduce the mortality. For early disgnosis of breast cancer for women, mammography is the good and efficient approach. Finding an effective and accurate method to detect breast cancer remains an uphill task in digital mammography [1]. In this approach the gradient function plays an important role in finding the abnormalities. This gradient function is also used to find out other cancer types, such as skin cancer. In medical image processing, image segmentation is an important research area to obtain desired results.

Image segmentation is the process in which the original natural image is partitioned into meaningful region. It helps the radiologists to identify the affected area of the human body to analyze the shape and size of the cancer. This paper is organized as follows. In section I, literature survey is discussed. Section II, contains methodology of the image segmentation approaches and in Section III, Experimental results on breast cancer and the future work are discussed.

LITERATURE SURVEY

Zhao Yu-qian *et al.*, proposed a new process to identify lungs CT medical image edge with salt and pepper noise. In this study, they proposed algorithm for medical image denoising and edge recognition, and common morphological image processing such as morphological gradient process and dilation edge detector [2].

Jawad Nagi, Sameem Kareem and Farrukh Nagi discussed Breast cancer fragmentation approaches [3]. It is a computerized technique for mammogram identification. In their method, they eliminated digitization noises, that contained radiopaque artefacts and take away the pectoral muscle to accentuate the breast cancer region in CAD approaches. Region growing performs fragmentation of an image with respect to seed points. Removal of the breast cancer region and the pectoral muscle is an important pre-processing step in the procedure of algorithms. It mainly allows the search for abnormality present in the image of the breast tissue without unnecessary influence from the surroundings of the mammogram. This approach has been tested using mammogram images of different densities from

*Address correspondence to this author at the Department of Electrical and Electronics Engineering, The Kavery Engineering College, Mecheri, Salem District-636453, Tamilnadu, India; Tel: +91 9842557879, +91 9486937253; E-mail: researchkarthick@gmail.com

1574-3624/16 $58.00+.00

numerous databases and has shown good results with better precision.

S. Meenalosini *et al.*, [4] proposed a new approach of, segmented mammograms with the help of region growing algorithms. In this proposed technique, pre-processing was done by means of median filter, morphological operations and thresholding techniques. Segmentation of mammogram was completed in the following steps: 1. Dissimilarity improvement was done using histogram: 2. Pixel production was completed and also histogram and cumulative histogram were calculated and the spot of peaks in the histogram was noted: 3. Then the pixel was calculated and from the chosen candidates the seed pixel was generated based on a particular situation. This pixel was used in the next step in region growing algorithm. The first pixels acted as the early seed point for region growing algorithm. This process was calculated for the entire pixel; and, 4. Gabor filter was added in the last step to eliminate noise on the image. This method was designed to find out the masses without any personal dealings.

Many techniques have proposed thresholding [5, 6], gradients [7] mammogram with a polynomial [8], or active contours method [9]. One of the initial methods of segmentation of the breast cancer using contour was proposed by Semmlow *et al.* [10], who used a Sobel edge detection spatial filter for, locating the breast cancer area mammograms. The noticeable methods were thresholding, since there will be an overlapping between breast cancer area and background. Abo *et al.* approached a new methods to identify the distrustful areas on digital mammograms [11]. Bethapudi *et al.* proposed new technique to detect and identify mass in digital mammogram images [12]. It detects the malignant tissues in following three steps: In the first step,:- the unwanted background information was eliminated with the help of thresholding. Second step is used for noise removal with the help of median filter.

In step three, the binary image contours are pulled out. Authors planned to identify the shape of mass. Basheer *et al.* approached a new breast mass segmentation technique based on texture analysis and adaptive median filtering methods. In this approach, adaptive median filtering is used for contouring the image. Dalmiya *et al.* proposed a new segmentation method for mammograms with the help of wavelet and k-means clustering algorithm [13]. Authors distinct their approach in the subsequent steps. In the first step, high level details are eliminated from MRI images with the help of discrete wavelet transform. In the next step, input image get sharpened. Finally the tumor location is deducted with the help of k-means clustering algorithm.

METHODOLOGIES

Seeded Region Growing Algorithm

Region growing algorithmic technique is an important method to deduct breast cancer image segmentation. For doing better image segmentation, seed pixel selection is most important.

Selection of seed point is based on various user criteria. The early region begins as the precise position of these seeds pixel. Then the regions are growing from the seed pixel to neighboring pixel and go on to complete the entire image [14]. The process flow diagram of image segmentation is given below in Fig. (**1**). The seed selection criteria may be intensity level, gray / color level texture.

In region based image segmentation, the seeded region growing algorithm is the most important approach for the deduction of breast cancer. In this approach, main problem is to select the seed point because it performs the major role in the diagnosis of breast cancer [15]. The algorithm has six functional steps.

Gradient functions are used to get the data from the cancer images. From the original input image, the gradient images are created. The input image's intensity values are verified by all the pixels present in the gradient images in a specified direction. To compute value of gradient images, the vertical and horizontal directions are used. The two variables of the gradient functions G(x, y) are mentioned in equation number (1) as follows:

$$\nabla G = \frac{\partial G}{\partial x} i + \frac{\partial G}{\partial y} j \qquad (1)$$

Where

$$\frac{\partial G}{\partial x} = gradiant\ values\ is\ x\ directions$$

$$\frac{\partial G}{\partial y} = gradiant\ values\ is\ y\ directions$$

Edge detection is the most commonly used techniques in image segmentation methods. After the calculations of the

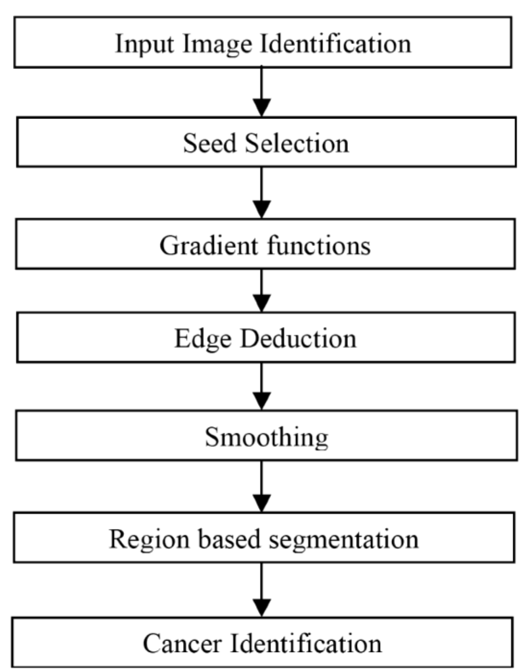


Fig. (1). Process Flow Diagram of an Image using region growing approach. It contains input image, seed selection process, Gradient functions, Edge detection operations, smoothing process, region based segmented approach and finally cancer identification.

gradient image, the edge pixel values are calculated from the largest pixel value from the gradient images. The gradient directions are perpendicular to edge pixel direction. Canny edge detectors are used in edge detection algorithms approach. This canny edge detection algorithmic approach is classified as follows:

- The noises are removed by applying Gaussian filter to smooth the surface of the input cancer images.
- The image intensity gradients values are calculated.
- To clear the spurious response to edge detection, the non-maximum suppression is applied.
- The possible edges are calculated by applying dual threshold values.
- Hysteresis are tracked by the edge values. Weaker edges are suppressed.

The high spatial frequency noises from the breast cancer image are eliminated with the help of low pass filtering. It is also named as smoothing. The regions are selected to be as consistent as possible. We were aware that segmentation region has high color similarity, and therefore we had few problems while doing segmentation, such as selection of first seed-points and prolonged time problems.

The selection of first seed-points problem means, the different set of first seed points causes dissimilar segmentation outcomes [16]. Due to this, stability of the segmentation is reduced for that image. Moreover, a large number of seeds are tested before selecting the first seed point, because different breast cancer images have to be tested individually. The other one is, prolonged time problem, because Seeded Region Growing requires more number of calculation times.

Morphological Image Processing

Morphological image processing is used to extract the image from the component regions. This algorithm is mainly used for grey level images such as medical images. This morphological process deals with the profile quality in an image. In morphological approaches, the following frameworks are used to find the abnormalities: 1. Pre- Processing: 2. Enhancing object structure: 3. Segmentation: and 4. Quantitative description. Morphological operations are normally useful to remove the imperfect parts during the image segmentation [17]. Therefore, this method is adoptable for grey level image segmentation. Morphological image processing consists of two basic operations named as Erosion and dilation.Opening and closing are two significant operators from mathematical morphology. Both opening and closing are calculated from the fundamental operations of erosion and dilation [18, 19]. The fundamental result of an opening is to some extent like erosion in that it tends to eliminate some of the foreground (bright) pixels from the boundaries of regions of foreground pixels. Conversely, it is less critical than erosion in general.

As with other morphological operators, the correct operation is determined by a structuring component [20, 21]. The outcome of the operator is to protect foreground regions that have a similar outline to this structuring component, or that can totally surround the structuring component, while eliminating all the other regions of foreground pixels [22]. Closing is to extent similar to dilation in that it tends to increase the borders of foreground (bright) regions in an image (and reduce in size of background color holes in such regions), but it is less critical of the original border shape [20, 22]. The result of the operator is to protect background regions that have a similar shape to this structuring component, or that can totally contain the structuring component, while eliminating all the other regions of background pixels.

Erosion

Erosion of picture *f* by structuring component *s* is given by $f \ominus s$. The structuring component s is situated with its source at *(x, y)* and the new pixel rate is calculated with the help of below equation (2)

$$g(x,y) = \begin{cases} ! \ 1 \text{ if } s \text{ fits } f \\ 0 \ \text{ Otherwise} \end{cases} \quad (2)$$

During the erosion operation, the images are taken as inputs. At that time, first cancer image is taken as input and then it is eroded. Then another normally undersized image is taken. The first one is named as structuring component. It is also named as kernel. This structuring component is the verdict of the accurate result of erosion.

The grey - scale image of erosion process is as follows:

- For the input grey scale image, X is the set of Euclidian coordinates and corresponding structuring coordinates for that set is K.
- K is the translation of *Kx*, for that origin point of x.
- Then the K of X is erosion to set all the points of x , such that Kx is a subset of X

The structuring component of an input image is used to calculate the erosion. While processing the algorithm, the pixel of the input image should beat the centre. Then overlay the structuring component on top of the input image.

Dilation

Dilation of picture *f* by structuring component *s* is given by $f \ominus s$. The structuring component s is situated with its source at *(x, y)* and the new pixel rule is calculated with the help of below equation (3)

$$\text{g(x, y)} = \begin{cases} 1 \text{ if } s \text{ hits } f \\ 0 \text{ Otherwise} \end{cases} \quad (3)$$

During the dilation operation, the images are taken as inputs. At that time, first cancer image is taken as input and then it is dilated. Then another normally undersized image is taken. The first one is named as structuring component. It is also named as kernel [23]. This structuring component is verdict of the accurate result of dilation.

The grey - scale image of dilation process is as follows:

- For the input binary image, X is the set of Euclidian coordinates and equivalent structuring coordinates for that set is K.
- K is the translation of *Kx,* for that origin point of x.
- Then the K of X is erosion to set all the points of x, such that Kx is a subset of X, - where X is non-empty for all the intersection points.

The structuring component of an input image is used to calculate the dilation [24-26]. While processing the algorithm, the pixel of the input image should beat the centre. Then overlay the structuring component on top of the input image.

Artificial Neural Network

It is the best method modelled on the learning approach of the brain. Its mechanism is processing the information like biological neurons in the brain and having miniature working units known as neurons. This is used to do more complex calculations and also more real time problems in the present situations. The most popular network is back propagation network and oldest neural network is feed forward network [27-29]. The back propagation network is mainly used for error calculating in the output layers. Due to this process, this method is used for solving wide range of applications. [30-32]. The input and output vectors are trained the supervised learning algorithms. The output layer's errors are measured, and then error output is propagated to intermediate layers [33-34]. Then these weight values are compared with the input weight values to update. This back propagation network process consists of two different passes named as forward pass and backward pass.

1. Forward pass process.
   - Firstly the input vector is given to the network, and then it propagates into layer by layer.
   - Then the output is produced according to the input applied to the network.
   - The weight of the synaptic is fixed.
2. Backward pass process:
   - According to the error correction rule, the synaptic weight values are modified.
   - The error signal is calculated by subtracting actual weight values to desired weight values and
   - Then this error signal is sent back to the network, against synaptic network flow way.
   - The weights of the synaptic are modified to get desired weight values and
   - This process is repeated until the desired output is achieved.

EXPERIMENT RESULTS

Region Growing Approaches

By using the region growing algorithm breast cancer can be diagnosed. Figs. **2-5** show the process of region growing approaches during the operation and it takes more time to segment the malignant from the mammographic images.

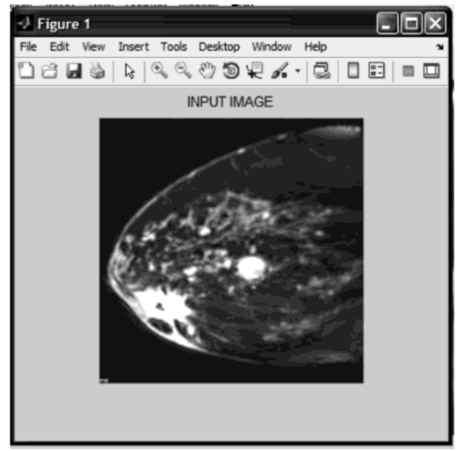


Fig. (2). Displays the gray scale image, specifying the display range for black and white. The value LOW (and any valueless than LOW) displays as black, the value HIGH (and any value greater than HIGH) displays as white.

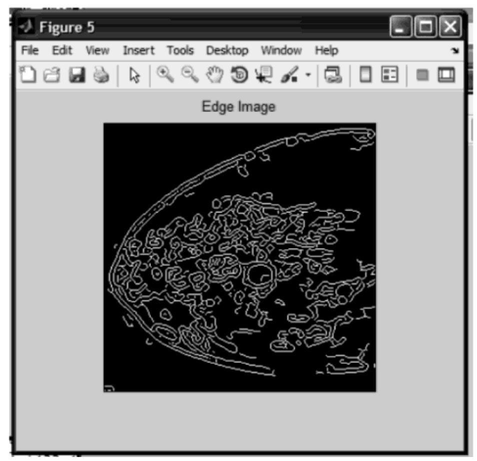


Fig. (3). Edge Image shows the function finds edges in I and 0's elsewhere in the image.

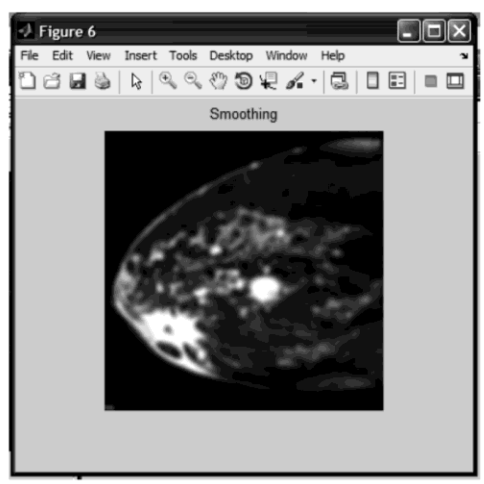


Fig. (4). Smoothing process has been done using a low pass filter.

Fig. (5). Time Chart containing total time required for tumor identification

Back Propagation Network

The back propagation is the most popular algorithm for the medical image segmentation. By using this algorithm, we can get more accurate results. Figs. **6-12** figures show the breast cancer segmentation approaches.

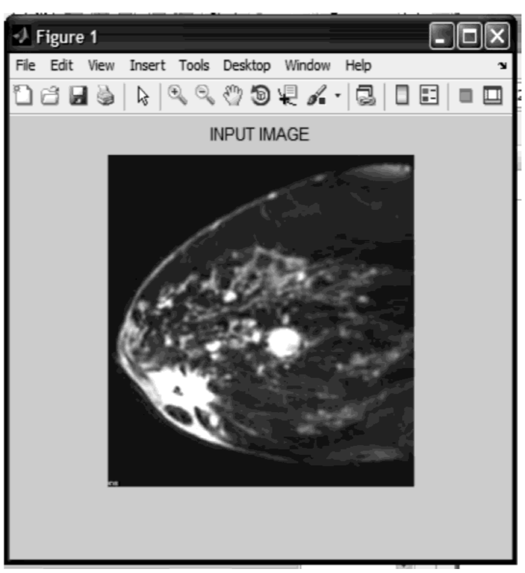


Fig. (6). Displays the gray scale image, specifying the display range for black and white. The value LOW (and any value less than LOW) displays as black, the value HIGH (and any value greater than HIGH) displays as white.

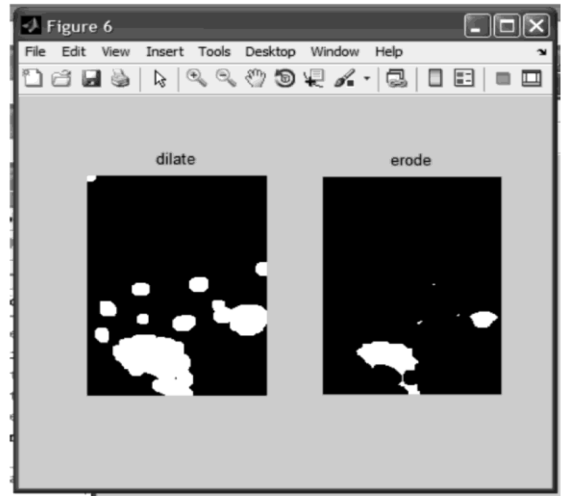


Fig. (7). Shows the Dilation and Erosion process. This process is used to reduce the noise and to detect the intensity bumps in the input image.

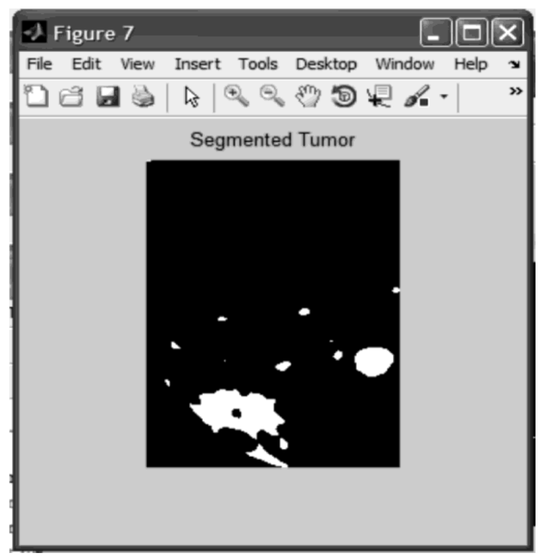


Fig. (8). Tumour Image is segmented from the input image

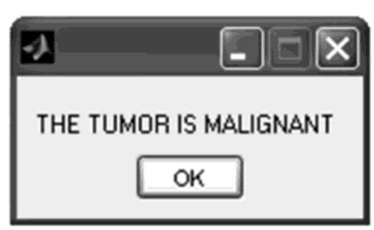


Fig. (9). Tumor is Malignant.

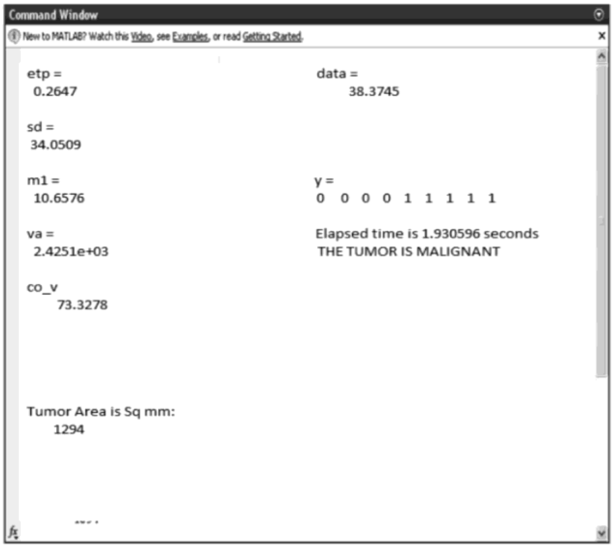


Fig. (10). Command Window shows the elapsed time, standard deviation.

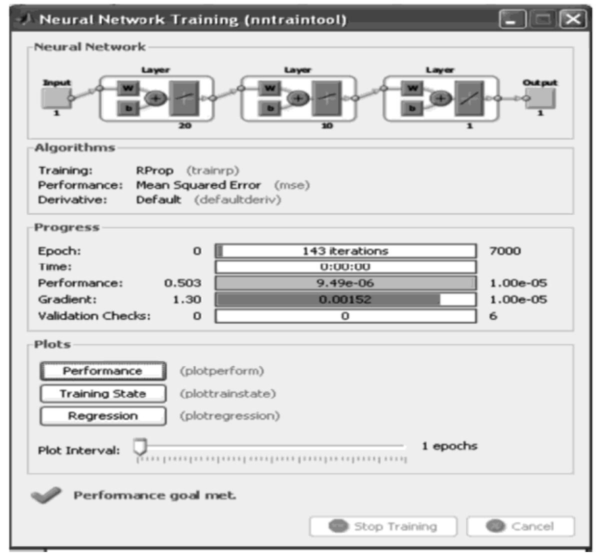


Fig. (11). Neural Network is used to find the number of iterations and time.

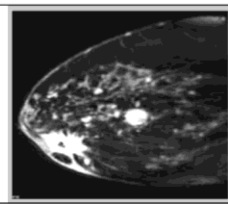
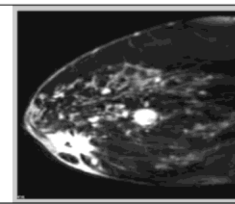
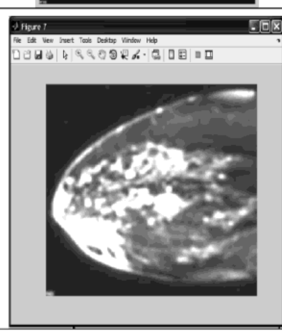
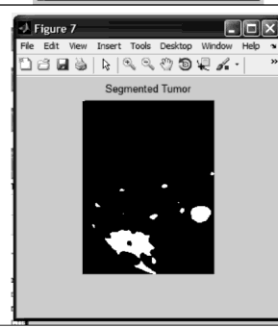
Parameters	Region Growing Algorithm	Morphology Algorithm
Input Image		
Segmented Tumor		
Standard Deviation	36.976	34.0509
Elapsed Time	21.8906 Seconds	1.9305 Seconds

Fig. (12). Comparative statement of region growing algorithm with morphological algorithm.

Conclusion and Future Scope

Finding an automatic process for breast cancer segmentation is a quite difficult task. In this paper, a novel morphological image segmentation method and region growing approaches are proposed. In these approaches, many parameters are adopted to solve these problems. On comparing both the algorithms for segmenting the mammographic images, applying the Neural Networks algorithm will be a better option rather than applying Region Growing Algorithm. Future work will demand to improve the accuracy and to reduce the processing time.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

Declared none

REFERENCES

[1] Sharma J, Sharma S, Mammogram Image Segmentation Using Watershed. Int J Inform Technol Knowl Manage 2011; 4(2): 423-25.
[2] Qian Z, Hua G, Cheng C, Tian T, Yun L. Medical Images Edge Detection Based on Mathematical Morphology. Eng Med Biol 27th Annul Conf: 2005: proce IEEE. Sep 1-4
[3] Jawad N, Sameem AK, Farrukh N. Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms: 2010: IEEE EMBS Conf on Biomed Eng & Sci.
[4] Meenalosini S. Segmentation of Cancer Cells in Mammogram using Region Growing Method and Gabor Features. Int J Eng Res Appl 2012; 2(2): 1055-62.
[5] Bick U, Giger ML, Schmidt RA, Nishikawa RM, Wolverton DE, Doi K. Automated Segmentation of Digitized Mammograms. Acade Radiol 1995; 2(2): 1-9.
[6] Yin FF, Giger ML, Doi K, Metz CE, Vyborny CJ, Schmidt RJ. Computerized Detection of Masses in Digital Mammograms: Analys Bilate Subtrac Imag. Med Phys 1991; 18(5): 955-63.
[7] Mendez AJ, Tahoces PJ, Lado MJ, Souto M, Correa JL, Vidal JJ. Automatic Detection of Breast Border and Nipple in Digital Mammograms. Comput Methods Programs Biomed 1996; 49: 253-62.
[8] Chandrasekhar R, Attikiouzel Y. Automatic Breast Border Segmentation by Background Modeling and Subtraction: 2000: Proce 5th Int Worksh Digit Mammogra (IWDM), Med Phys Publis; 2000 560-65; Toronto, Canada.
[9] Wirth MA, Stapinski A. Segmentation of the breast region in mammograms using active contours. Visu Comm Imag Process: 1995 -2006.
[10] Semmlow JL, Shadagopappan A, Ackerman LV, Hand W, Alcorn FS. A Fully Automated System for Screening Xeromammograms. Comput Biomed Res 1980; 13: 350-62.
[11] Abo-Eleneen ZA, Gamil A-A. A Novel Statistical Approach for Detection of Suspicious Regions in Digital Mammogram. J Egypt Mathem Soc 2013; 21(2): 162-8.
[12] Prakash B, Sreenivasa RE, Srinivas Y. Detection and Identification of Mass Structure in Digital Mammogram. Int J Comput Appl 2013; 78(14): 17-20.
[13] Shruti D, Avijit D, Soumya KD. Application of Wavelet Based k-means Algorithm in Mammogram Segmentation. Int J Comput Appl 2012; 52(15): 15-9.
[14] Sahakyan Y, Sarukhanyan H. Automatic Segmentation of the Breast Region in Digital Mammograms. Proc Comput Sci Inform Technol; 2011: 386-9.
[15] Konrad B, Mariusz N. Mathematical Morphology (MM) Features for Classification of Cancerous Masses in Mammograms. Inform Technol Biomed Adva Soft Comput 2008; 47: 129-38.
[16] Tetsushi K, Takashi M, Yohmei H, Hans JM. Digital Gray-Scale/Color Image-Segmentation Architecture for Cell-Network-Based Real-Time Applications: 2002: ASIC. Proce IEEE Asia- Pacif Conf; 2002: 237-40.
[17] Kosko B. Neural Network and Fuzzy Systems. 1st ed. Prent Hall Ind 1994.
[18] Nastaran SK, Vidya T. Biotechnological Approach Towards Breast Cancer. Int J Pharm Bio Sci 2016; 7(2): 101-6.
[19] Zsuzsanna S. Causal Therapy of Breast Cancer Irrelevant of Age Tumor Stage and ER-Status: Stimulation of Estrogen Signaling Coupled With Breast Conserving Surgery. Recent Pat Anticancer Drug Discov 2016 [Epub ahead of print].
[20] Ritu S, Rajesh S. Image Segmentation Using Morphological Operation for Automatic Region Growing. Int J Innov Res Comput Comm Eng 2014; 2(9).
[21] Sabah MA, Mohammed J, Fiaidhi AW, Lei Y. Comp-Aided Intelli Recogn Techniq Applica. Ch.15: The Roadmap for Recogn Region Interest Medical Image 2005.
[22] Schirripa S, Renzo SG. Virtual restoration: detection and removal of craquelure in digitized image of old paintings: 2011: Proce SPIE 8084 Optic Arts, Archite Archaeol III; 2011 June 06.
[23] Hamreeza, Nawi N, Ghazali NM. The effect of Adaptive Gain and adaptive Momentum in improving Training Time of Gradient Descent Back Propagation Algorithm on Classification problems 2011: 2nd Int Conf Scien Engg Technol; 2011: 178-84.
[24] Krasnopolsky, Chevallier VM, Some F. Neural Network application in environmental sciences. Advan Computatio Efficien environmen numeric model Neural Netwo 2003; 16(3-4): 335-48.
[25] Coppin B. In: Jones Bartlet Illuminated Series Chapter 11. Artifi Intellig Illumina USA 2004; 291-324.
[26] Basheer IA, Hajmeer M. Artificial neural networks fundamentals computing design and application. J Microbiol Methods 2000; 43(1): 3-31.
[27] Zheng H, Meng W, Gong B. Neural Network and its Application on Machine fault Diagnosis 1992: ICSYSE 1992 Sep 17-19; 576-9.
[28] Rumelhart DE, Hinton GE, Williams RJ. Learning Internal Representations by error Propagation. In: Parallel distributed processing: explorations in the microstructure of cognition, vol: 1, pp. 318-62.
[29] Lee K, Booth D, Alam PA. Comparison of Supervised and Unsupervised Neural Networks in Predicting Bankruptcy of Korean Firms. J Expe Syst Appl 2005; 29: 1-16.
[30] Saleha M, Muhammad S, Afifa M, Mussarat Y, Mudassar R. A Survey on Medical Image Segmentation. Curr Med Imaging Rev 2015; 11: 3-14.
[31] Francesca PF, Gloria M. Performance Evaluation in Medical Image Segmentation. Curr Med Imaging Rev 2013; 9: 7-17.
[32] Amel HA, Aryan, Kareem A, Mohammed YK. Breast cancer image segmentation using morphological operations. Int J Electron Comm Eng techno 2015; 6(4): 08-14.
[33] Magda IA, Essam EIS, Mona GS, Mona MA. Expression of enhancer of zeste homolog 2 and cytokeratin 5/6 in triple negative versus non-triple negative breast cancer: An immunohistochemical study. Int J Adv Res 2016; 4(4): 389-400.
[34] Raihan F, Mohammed SA, Nasir Uddin KM, Mohammed KH, Mohammed KI, Mohammed S. Medical Image Enhancement Using Morphological Transformation. J Data Analy Inform Proc 2016; 4: 1-12.