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Breast Cancer Detection Technique using MRI Segmentation Approach

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Abstract: A Novel method for the segmentation of breast MRI images and to provide a better breast cancer detection technique by solving the drawbacks of current existing methods. Thus, we intended to propose a new breast cancer detection technique to detect the breast cancer from the breast MRI images, using region based active contours. The proposed technique includes four major steps, namely pre-processing, segmentation, feature extraction, and classification. The segmentation process was achieved by implementing the technique of localizing region-based active contours in which typical region-based active contour energies are localized in order to handle images with no homogeneous foregrounds and backgrounds.

Keywords: Image Segmentation, Breast Cancer Detection.

I. Introduction

Cancer is a type of diseases that causes the cells of the body to change its characteristics and cause abnormal growth of cells. Most types of cancer cells eventually become a mass called tumor. Breast cancer is the most common non skin malignancy in women and the second leading cause of female cancer mortality [6]. Recently studies show that one in 10 women will contract breast cancer in their lifetime. Although breast cancer has very high incidence and death rate, the cause of breast cancer is still unknown [1]. Risk factors of Breast cancer are Gender, Age risk and Genetic risk. Simply being a woman is the main risk factor for developing breast cancer. Men can develop breast cancer, but this disease is about 100 times more common among women than men. This is probably because men have less of the female hormones estrogen and progesterone, which can promote breast cancer cell growth [3]. About 1 out of 8 invasive breast cancers are found in women younger than 45, while about 2 of 3 invasive breast cancers are found in women age 55 or older. Genetic risk factors about 5% to 10% of breast cancer cases are thought to be hereditary, meaning that they result directly from gene defects (called mutations) inherited from a parent [13]. No effective way to prevent the occurrence of breast cancer exists. Therefore, early detection is the first crucial step and it plays a key role in breast cancer diagnosis and treatment [5].

Breast cancer can be diagnosed by classifying tumors. There are two different types of tumors such as malignant and benign tumors[12]. A typical benign mass has a round, smooth and well circumscribed boundary; on the other hand, a malignant tumor usually has a speculated, rough, and blurry boundary [8]. Physicians need a reliable

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diagnosis procedure to distinguish between these tumors [16]. But generally it is very difficult to distinguish tumors even by the experts [10]. Hence automation of diagnostic system is needed for diagnosing tumors [10]. Breast cancer screening is vital to detecting breast cancer. Mammography is the standard method for breast cancer screening at the present [19] [4]. Mammography is a low dose X-Ray procedure that allows the visualization of internal structure of the breast [11] and it is one of the imaging modality in early breast cancer detection typically through detection of characteristic masses and micro calcifications. Micro calcification is considered to be an important sign of breast cancer [2]. Visualization and detection of cancer cells in mammography play a crucial role in reducing the rate of mortality from breast cancer [15].

II. LITERATURE SURVEY

Sylvia Glaber et al. [21] have presented a visual analytics approach for breast tumors in DCE-MRI data that comprises a voxel-wise glyph-based overview and a region-based analysis. The regions were extracted via region merging and each region contains voxels with similar perfusion characteristics. As a result, they avoided the inter-observer variability and reduce distortion due to averaging over differently perfused tissue.

Ni He et al. [22] have presented that Malignant axillary lymph nodes are an important predictor for breast cancer recurrence, but invasive dissection or biopsy was required for the diagnosis. They determined whether and how malignant nodes could be diagnosed preoperatively with magnetic resonance (MR) imaging. They obtained MR images of all women evaluated for breast cancer at the Sun Yat-Sen University Cancer Center in 2010 and correlated the image characteristics of ach axillary node with the pathologic diagnosis of the same node.

Chien-Shun Lo et al. [23] have proposed a method to detect the breast tissues within multi-spectral MR images. In the image classification, they applied a support vector machine (SVM) to breast multi-spectral magnetic resonance images to classify the tissues of the breast. In order to verify the feasibility and efficiency of this method, evaluations using classification rate and likelihood ratios were adopted based on manifold assessment and a series of experiments were conducted and compared with the commonly used C-means (CM) for performance evaluation. The results have shown that the SVM method is a promising and effective spectral technique for MR image classification.

Guardiola et al. [24] have proposed a 3-D quasi real-time algorithm, inspired in a computationally efficient modified-Born method, for early-stage breast cancer detection using 3-D anthropomorphic breast phantoms. The algorithm uses multi frequency information over a portion of the UWB range to produce robust images with a fair tradeoff between resolution and penetration.

Delwar Hossain et al. [25] have proposed beam space-DORT and beam space-TR-MUSIC for microwave imaging to detect breast cancer. The proposed imaging methods employ beam space transformation in the receiving mode of time reversal process prior to back propagation of recorded received signals. They investigated the effectiveness of the proposed imaging methods using anatomically realistic MRI-derived dense numerical breast phantoms. It is found that the proposed methods, especially the beam space-TR-MUSIC, achieve improved focusing ability even

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in the presence of dense fibro glandular tissue clutter.

A computer-aided diagnosis (CAD) system was developed by Reza Rasti et al. [26] in breast dynamic contrast enhanced magnetic resonance imaging (DCE-MRI), based on a mixture ensemble of convolutional neural networks (ME-CNN) to discriminate between benign and malignant breast tumors. ME-CNN is a modular and image-based ensemble, which can stochastically partition the high-dimensional image space through simultaneous and competitive learning of its modules. ME-CNN achieves competitive classification performances, and has the advantages of fast execution time in both training and testing. However, for further improvement, ME-CNN can be combined with recent advances in fully convolutional networks for semantic segmentation.

III. Research Methodology

- The main aim of this research is to provide a better breast cancer detection technique by solving the drawbacks that currently exist in the literary works. Thus, we intended to propose a new breast cancer detection technique to detect the breast cancer from the breast MRI images, using deep learning.
- The proposed technique includes four major steps, namely pre-processing, segmentation, feature extraction, and classification. Initially, the input breast images will be subjected to pre-processing, where the noise in the images will be removed by the DWT based thresholding technique.
- Then, the cancer region in the images will be segmented by the proposed clustering approach, named Taylor Fuzzy c Means clustering (TFCM), which will be designed by integrating Taylor series in the FCM clustering technique.
- Thus, the segmented part from the proposed TFCM, will be given to the feature extraction process, through which statistical and PCA features will be extracted, to detect the cancer area.
- Finally, the extracted features will be given to the Deep Convolutional Neural Network (Deep CNN) to classify the normal and abnormal regions of the breast images. To train Deep CNN, an optimization algorithm, named Oppositional Particle-Salp Swarm Algorithm (OPSSA), will be proposed by combining Oppositional Particle Swarm Optimization Algorithm (OPSO) and Salp Swarm Algorithm (SSA) such that the weights in the Deep CNN will be selected optimally.
- Thus, the proposed technique, depicted in figure 1, will classify the images into either normal or abnormal class. The implementation of the proposed technique will be in MATLAB and the experimentation will be carried out using the dataset, RIDER Breast MRI .
- The performance of the proposed technique will be evaluated in terms of accuracy, sensitivity, and specificity. Finally, the performance attained by the proposed technique will be compared with the existing works.

Fig 1
(Please see Fig 1 on Page 123)

IV. Results and Discussions

The performance of our proposed technique is tested by using more number of breast images and one image implementation is as shown below.

Fig 2 (Please see page 123)

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MRI taken from https://wiki.cancerimagingarchive.net/display/Public/RIDER+Breast+MRI#29e1254a511549deaad8af406c88fab9", accessed on July 2018

Fig 3 **(Please see page 124)**

V. CONCLUSION

This method shows the segmentation of the MRI Breast images using the proposed methodology. We applied a unique algorithm to detect cancer from breast image. But edges of the image are not sharp in early stage of breast cancer. So we apply image segmentation on image to detect edges of the images. In this method we applied image segmentation to detect cancer

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Fig 1

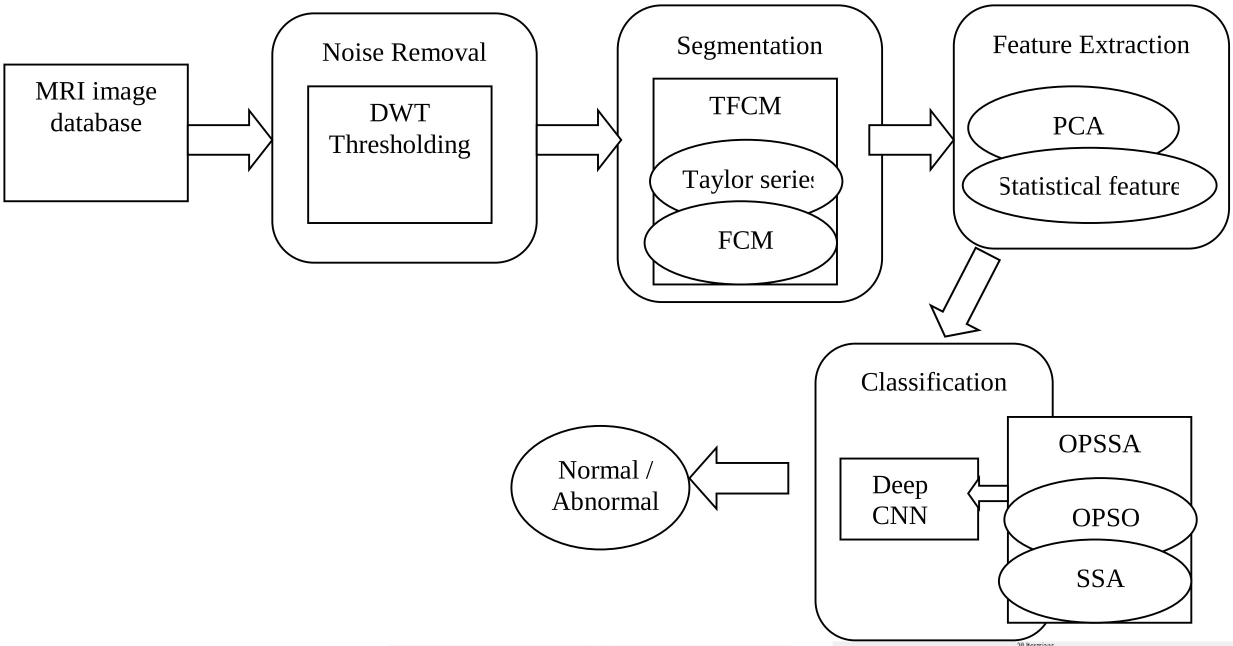
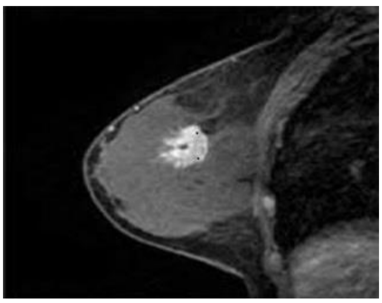


Fig 2



Original image of Breast

Contour at end of 10th iteration

Contour at end of 30th iteration

Contour at end of 40th iteration

Contour at end of 50th iteration

Contour at end of 60th iteration

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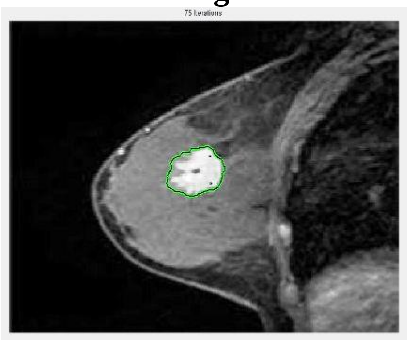
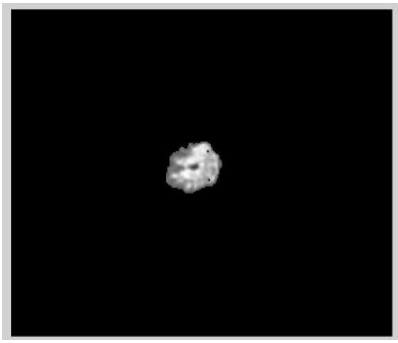
Fig 3





Contour at end of 70th iteration **Contour at end of 75th iteration** **Segmented image**