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A Research on Breast Cancer Detection using Mammography

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Abstract*: *The digital mammogram has developed as the standard screening approach for breast cancer detection and further defects in human breast tissue problem. Early detection is an efficient manner to decrease mortality in worldwide. In the past decades, several researchers implemented many methods to consistently identify the breast cancer by mammogram images. Those methods were employed to produce systems to support radiologists and physicians attain more accurate diagnosis. Accurate segmentation and classification of various tumors in the mammography plays a complex role in the early diagnosis of breast cancer. This paper defines the research on Breast Cancer Detection (BCD) methods which includes two major steps such as segmentation and classification. This research presented the different types of BCD methods with their main contributions. Additionally, it assists the researchers in the area of breast cancer detection by providing the basic knowledge and common understanding of the newest BCD methods.

Index Terms*: *Breast cancer, Classification, Mammogram, Segmentation, and Radiologists.

I. INTRODUCTION

Breast cancer is the second most general and the prominent reason of cancer demise amongst womanhood [1-3]. The existing mammogram based procedures were utilized to produce computer systems to achieve precise analysis [4]. The mammography examination is a significant tool to help early detection of breast cancer [5], which helps in lessening breast cancer mortality and morbidity [6]. Different types of the techniques applied in the early diagnosis and the screening of the breast cancer, such as ultrasound [7], Computed Tomography (CT) [8], Magnetic Resonance Imaging (MRI) [9], mammography [10]. The mammography is a type of X-rays imaging on the breast that produces high-resolution pictures by means of high bit-depth and delivers the probability of determining irregularities covered by neighboring and overlapping breast tissue [11]. The conventional mammogram enhancement approaches use the transform domain filtering that provides some artifacts in the breast image [12].

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In the digital Mammograms, automatic categorization of the breast masses for the breast cancer diagnosed by utilizing the Neural Network (NN). The approach classifies the segmented region of interest in a normal or abnormal region of interest. The learning time of NN is high, which is the major drawback of the NN technique [13]. The existing methodologies performances are highly affected by the number of samples in the training set in order to enhance breast cancer segmentation and classification techniques. This paper analyzed the BCD approaches, including segmentation and classification. This research paper explained different types of BCD approaches with major contributions of existing methods. Finally, the performance of different BCD approaches is compared based on accuracy and the complexity of the techniques. This paper will help the researchers to make further improvement in the performance of mammogram based BCD by segmentation and classifier techniques.

II. BREAST CANCER DIAGNOSTIC TECHNIQUES

The analysis and capture of a breast image plays a main part in breast cancer identification. Different software and various types of machines involve in the breast cancer cell detection process. The mammogram is the fundamental trial to recognize breast cancer diseases. The Iron Radiation (IR) drives into the breast that displays the suspicious regions of the physique during the mammogram test. It represents tissues of veins and breast. Once the mammogram trial finished, the output is shown in the X-ray film sheet. The mammogram cannot continuously deliver a decisive diagnosis of the existence/nonexistence of the cancer cell. This mammogram image permits physicians to realize an irregularity in the breast region. Some of the mammography based diagnostics techniques used for breast cancer detections are Computer Aided Design (CAD), digital mammography, and breast tomosynthesis.

A.Computer Aided Design based BCD

The CAD technique produces digitally acquired mammogram, and it plays a significant role in the mammogram BCD method to detect abnormal regions of the density and mass calcifications. The CAD is much more helpful to a radiologist to find the cancer cell in the breast regions. The CAD systems improve radiologists' performance in discriminating and detecting between the normal/abnormal tissues. Fig. 1 illustrates the block diagram of the CAD for breast cancer detection.

Generally, the CAD systems have five stages, those are preprocessing stage, segmentation stage, feature extraction & selection stage and classification stage.

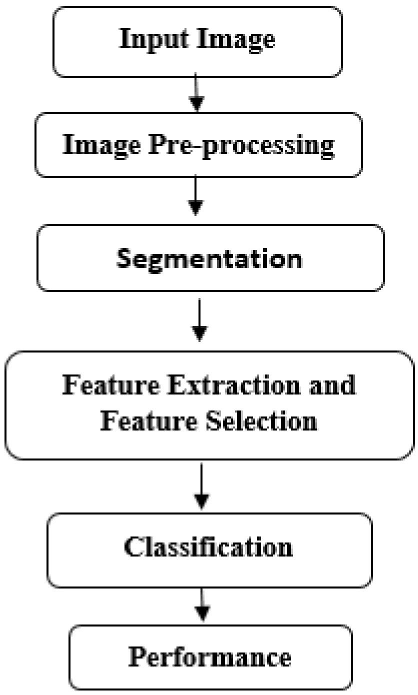

Figure 1. Overview of the CAD for breast cancer detection

In the image processing stage, the pre-processing is the primary step for some modality like ultrasonic for improving image quality and reducing the noise with low distortion of the image features. The image segmentation is a significant stage towards the wider development of the CAD techniques. The main purpose of the segmentation is separation of RoI with desired properties. In feature extraction and selection, various features extracted from the image and these features used to distinguish malignant or benign. The set of the feature is generally very large and the selection of effective features is much critical for the next step.

B. Digital Mammography Based BCD

The digital mammography progressed by full-field digital Mammography [14]. At this point, X-ray substituted by solid-state detector. This solid-state detector transforms the X-ray image into electrical signals. These signals are employed to detect the interior region of the breast that provides Special Digital Image (SDI). Only one image can be taken into an account at a time and likewise a single side of the breast can be detected in the mammogram test.

C. Breast Tomosynthesis based BCD

The breast tomosynthesis is a three-dimensional image presentation of the breast utilizing X-rays [15], it is not deliberated as regular analysis of breast cancer. The breast tomosynthesis consumes several images of the breast at various angles. The breast tomosynthesis has X-ray tube arc for breast cancer detection. For the duration of experiment, the arc nearby breast consumes 11 proper 3-D images. Aforementioned three mammogram BCD methods are implemented by different types of methods. Among these process, segmentation and classification plays a significant part in the cancer detection.

D. Segmentation Methods for BCD

The major objective of segmentation is to isolate the Region of the Interest (ROI) based on its problem and features in image analysis. Presently, extracting the features from the image is a stimulating task in medical image processing. The images are analyzed for the improvisation of decision making in several areas such as the medical field, cryptography, image processing and so on, but still it is very complex to create any precise decision from the obtained image. In medical imaging aspect, the selection of segmentation methods is significantly depending on the particular application and imaging modality. Generally, the segmentation methods are classified into two groups, those are semi-automatic and fully automatic. This automatic algorithm finds and locates abnormality is highly desirable in the medical field. The low rate of the False Positive (FP) and False Negative (FN) detection is much important in medical application. The segmentation method helps to enhance the diagnosis accuracy; it can confirm the impact of the diseases. Some of the segmentation methods used in medical images, which is represented in Fig. 2.

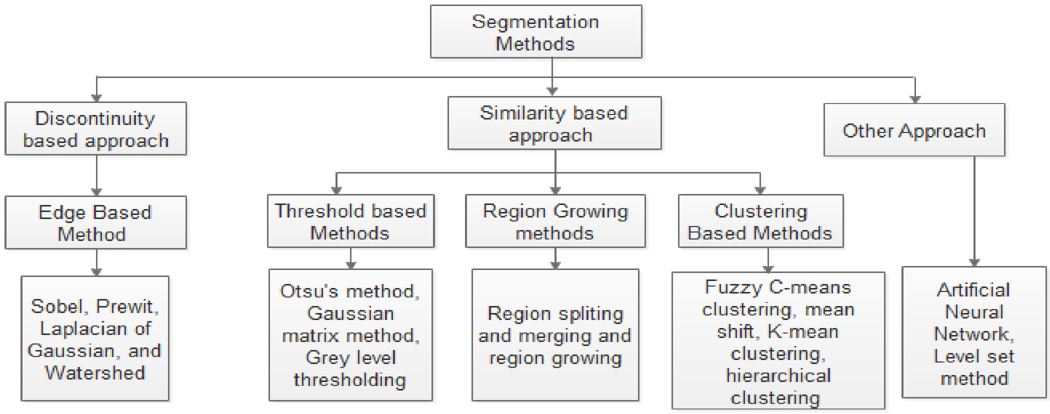

Figure 2. Segmentation methods for breast cancer detection

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Edge-based segmentation methods are a structural approach to find edges among the various region, it has abrupt intensity change. The edge-based segmentation algorithm performs in high contrast without noise images. Presently, there are many methods used for edge-based segmentation: Prewitt, Sobel, Laplacian of Gaussian, canny, and watershed. The edge-based segmentation method is much more sensitive to noise. The threshold-based segmentation method has been significantly used to implement a CAD system in order to extract important regions for additional analysis. There are several methods used for threshold-based segmentation: Otsu's, Gaussian matrix and grey level. This type of segmentation method does not perform well in the images with a close color spectrum. Grouping pixels in the homogeneous areas are based on seed points in the region-based method. It requires more computation time and expensive memory. The clustering based segmentation methods classify objects into the specific groups based on their similarity.

E. Classification for Breast Cancer Detection

The classification methods play a substantial part in the diagnosis and educational purpose in the medical field. These classification methods are classified into two types such as unsupervised and supervised. The unsupervised classification method includes Kernel-mean Clustering (KMC) and Self-Organize Map (SOM). The supervised classification method includes Support Vector Machine (SVM). Nave Base (NB), Neural Network (NN) and Linear Discriminant Analysis (LDA). The supervised classification method examines a huge number of unknown data and assigns them into related classes based on their features. The unsupervised method does not require a pre-determined class, which is the major difference between supervised and unsupervised methods. During the training phase, all classes must be defined and the spectral properties of these classes have to be extracted in supervised classification methods. Selection of a reliable classifier is complex to succeed in distinctive benign breast tumors from malignant. Different types of classification method have been implemented for BCD in various modalities. Although artificial intelligence methods and SVM have been mostly investigated to develop a classification framework in the diagnosis of breast cancer.

III. PREVIOUS RESEARCH WORKS ON BCD

Researchers suggested several segmentation and classification methods for early breast cancer detection. In this section, a brief evaluation of some important contributions of the traditional segmentation and classification method used for BCD and their advantages and disadvantages have been discussed in Table 1.

Table 1. Mammographic breast segmentation methods for breast cancer detection

Author	Methodology	Advantage	Limitation	Performance Measure/Database
Maitra et al. [16] (2012)	Contrast limited adaptive histogram equalization. The rectangle to isolate the pectoral muscle form RoI. Region growing segmentation method.	It reduced the Edge Shadowing Effect (SES), noise, and conquer the pectoral muscle successfully without loss of information from the rest of the mammogram images.	Region-based segmentation was required more execution time.	Accuracy of segmentation -95.7% (MIAS database)
Kumar et al.[17] (2016)	HAAR wavelet for de-noising. OTSU algorithm for threshold analysis. Digital segmentation Neural Network Classification	The mammogram images were trained by backpropagation NN in different categories and the samples was tested. The unknown images of 13-feature neurons were employed for NN training and testing as well.	Require high processing time for the large neural network.	The accuracy of classifier - 89 %. (MIAS database)
Xie et al [18]	Level set segmentation method. Combination of SVM and Extreme Learning Machine (ELM) based feature selection. ELM classification	The simple principle for ELM, excellent generalization performance, and low computational cost. Combination of SVM and ELM to choose the most efficient features and to classify masses.	Best feature selection was required more execution time because the feature selection performed by a combination of SVM and ELM.	Classifier Accuracy-95.73% Classifier Accuracy-96.02% (MIAS , DDSM database)
Abdel-Nasser et al.[19]	The pre-processing, integration scale, feature normalization, pixel resolution based on the presentation of some texture approaches for the mass classification. This performance of grouping was evaluated respecting linear and non-leaner SVM classifier.	The proposed approaches easily recognized to obtain the finest selective control of every texture approach.	Exhaustive Search (ExS) algorithm achieved a better result. But, computational complexity was very high.	The area under the curve of the Receiving Operating Characteristics (ROC) is 0.78 (MIAS database)

Khan et al. [20]	The comparison of the various Gabor feature extraction techniques for mass classification in the mammography.	The classification model provided better computational efficiency and generalization.	The presentation of the technique is quiet reduced in terms of Area under the curve of ROC and average sensitivity.	The area under the curve of the ROC is 0.95 (DDSM database)
Jiao et al. [21]	Proposed Parasitic Metric Learning Net (PMLN) used breast mass classification based on mammography.	The structure CNN performed good by giving likewise in feature extraction net and reference point of the classification for breast mass.	The proposed method performance was poor in a large number of the feature set.	Classification of accuracy of 96.7%. (MIAS database)
Chokri et al. [22]	Proposed a CAD system to differentiate between breast image reporting and data system classes in the digitized mammograms.	The execution time of the proposed method was very less.	Once the classification was executed by means of several classes, the precision of the classifiers reduces.	Classification accuracy 88.02%. (DDSM database)
Mouelhi et al. [23]	Adaptive local thresholding and improved morphological algorithm used for the segmentation process. The unsupervised ordering of the cancer nuclei was attained by a grouping of four regular color separation methods.	The proposed method reduced processing time in the cancer detection process.	The proposed method affected from over segmentation because of histochemical noise.	Classifier accuracy ratio is 98.8%. Computation time is 72.3 seconds/ image.
Al-antari et al. [24]	Full resolution neural network for the segmentation process. CNN technique for classification.	The suggested CAD scheme was applied to support radiologist in all levels of segmentation, detection and classification.	The false positive rates were affected by specificity through with and without segmentation of the CAD system.	The accuracy of 95.64%, Area under ROC curve of 94.78%, Matthews correlation coefficient of 89.91%, F1 score of 96.84%. (IN breast database)
Shi et al. [11] (2018)	Pixel-wise clustering based segmentation process	Proposed method along with post-processing is used to divide the boundaries of breast exactly.	The breast tissues were divided as pixel clusters in different intensities and it requires more time.	97.08% of segmentation accuracy. (MIAS database)

IV. Conclusion

Breast cancer is the second leading disease for women in the world. In recent years, different types of methods developed to segment the mammogram images and it helped the radiologist to make an accurate decision about breast cancer cells. This research analyzed different stages of CAD and diagnosis methods for breast cancer using mammography. The mammogram image processed through various stages to detect whether a person is suffering from benign or malignant breast cancer. This paper analyzed segmentation and classification methods for breast cancer detection, which are much helpful for other researchers to enhance the traditional techniques in order to get better and accurate results. Also, this research paper is much useful for software developers to develop algorithms to improve the existing methods of fulfilling future requirements. The unsupervised classification of the cancer nuclei obtained 98.8% of accuracy by a combination of four CCS techniques in comparative analysis. In future work, the performance of the BCD can be enhanced by efficient classification and segmentation with optimization algorithms such as Ant colony algorithm, cuckoo search algorithm, particle swarm optimization and so on.

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