



Cumulative Techniques for Early Detection of Breast Cancer: A Review

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Abstract: Mammography is one of the frequently known terms associated with early detection of breast cancer. The precise identification of breast cancer followed by diagnosis is one of the critical and sophisticated phenomena which require higher dimensionality of preciseness and accuracy. Reviewing the majority of the commonly adopted process in the existing system, it was explored that the stages of breast cancer detection in viewpoint of image processing is classified as preprocessing, segmentation, and decomposition. This paper discusses about the frequently adopted techniques explored from the prior to most recent research work that contributes to the early identification of breast cancer. The study elaborates and encapsulates briefly about the contribution of image processing towards detection of breast cancer.

Keywords: Component; Breast Cancer; Mammogram; Preprocessing; Segmentation; Decomposition;

I. Introduction

Cancer begins in cells, the building blocks that make up tissues. Tissues make up the breasts and other parts of the body. Normal cells grow and divide to form new cells as the body needs them. When normal cells grow old or get damaged, they die, and new cells take their place. Sometimes, this process goes wrong. New cells form when the body doesn't need them, and old or damaged cells don't die as they should. The buildup of extra cells often forms a mass of tissue called a lump, growth, or tumor. Cancer that forms in the tissues of breast [1], usually in the ducts (tubes that carry milk to the nipple) and in the lobules (glands that make milk) is the breast cancer. It occurs in both men and women, although male breast cancer is rare. Early detection of cancer through screening has been determined to reduce mortality from cancers of the colon and rectum, breast, uterine cervix, and lung. Screening refers to testing in individuals who are asymptomatic for a particular disease (i.e., they have no symptoms that may indicate the presence of disease). In addition to detecting cancer early, screening for various types of cancers can identify and result in the removal of abnormalities that may become precancerous and prevent potential progression to cancer. In the US, overweight and obesity contribute to 14%-20% of all cancer-related deaths [2]. Breast cancer risk appears to increase with increasing intake of alcohol, and studies suggest a modest increased risk at even a few drinks per week. Breast cancer screening has been shown to reduce breast cancer mortality. In the US, death rates from breast cancer in women have been declining since 1990, due in part to early detection by mammography screening and improvements in treatment. Currently, 60% of breast cancers are diagnosed at a localized stage, for which the five-year survival rate is 98% [3]. Further reductions in breast cancer death rates are possible by improving regular use of mammography screening and providing timely access to high-quality follow up and treatment. Scientific knowledge of how to identify women at increased risk of breast cancer is enabling the development of tools for risk assessment for clinical practice.

For most women at high risk, screening with MRI and mammograms should begin at age 30 years and continue for as long as a woman is in good health. But because the evidence is limited about the best age at which to start screening, this decision should be based on shared decision making between patients and their health care providers, taking into account personal circumstances and preferences. Several risk assessment tools, with names like the Gail model, the Claus model, and the Tyrer-Cuzick model [4], are available to help health professionals estimate a woman's breast cancer risk. These tools give approximate, rather than precise, estimates of breast cancer risk based on different combinations of risk factors and different data sets

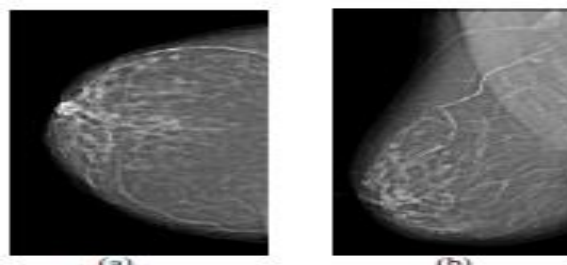
There is no evidence right now that MRI is an effective screening tool for women at average risk. MRI is more sensitive than mammograms, but it also has a higher false-positive rate (it is more likely to find something that turns out not to be cancer). This would lead to unneeded biopsies and other tests in many of these women, which can lead to a lot of worry and anxiety. A mammogram cannot prove that an abnormal area is cancer. To confirm cancer is present, a small amount of tissue must be removed and looked at under a microscope. This procedure, called a biopsy, therefore, early detection of the cancer is extremely critical from research viewpoint. This paper, however, will discuss about the various standard techniques that were adopted in the past for the purpose of detecting cancer from image processing viewpoint.

II. Current Approach

Detection and diagnosis of breast cancer in its early stage increases the chances for successful treatment and complete recovery of the patient. Screening mammography is currently the best available radiological technique

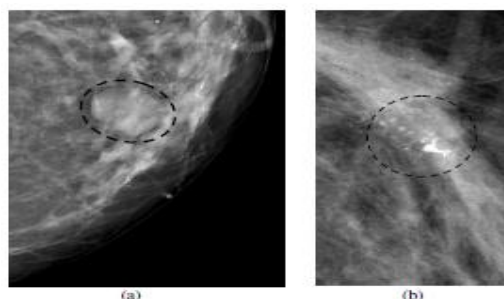
for early detection of breast cancer [5]. It is an x-ray examination of the breasts in a woman who is asymptomatic. The diagnostic mammography examination is performed for symptomatic women who have an abnormality found during screening mammography. Nowadays, in most hospitals the screen film mammography is being replaced with digital mammography. With digital mammography the breast image is captured using a special electronic x-ray detector which converts the image into a digital mammogram for viewing on a computer monitor or storing. Each breast is imaged separately in craniocaudal (CC) view and mediolateral-oblique (MLO) view shown in Figure 1(a) and Figure 1(b), respectively. The American College of Radiology (ACR) [6] Breast Imaging Reporting and Data System (BI-RADS) suggests a standardized method for breast imaging reporting [7]. Terms have been developed to describe breast density, lesion features and lesion classification. Screening mammography enables detection of early signs of breast cancer such as masses, calcifications, architectural distortion and bilateral asymmetry.

Figure 1 Two basic views of mammographic image: (a) craniocaudal (CC) view, (b) mediolateraloblique (MLO) view



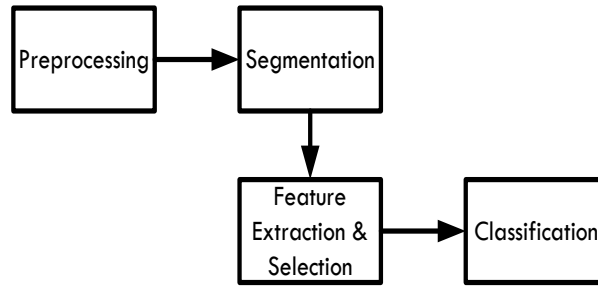
A mass is defined as a space occupying lesion seen in at least two different projections. If a potential mass is seen in only a single projection it should be called 'Asymmetry' or 'Asymmetric Density' until its three-dimensionality is confirmed. Masses have different density (fat containing masses, low density, isodense, high density), different margins (circumscribed, microlobular, obscured, indistinct, spiculated) and different shape (round, oval, lobular, irregular). Round and oval shaped masses with smooth and circumscribed margins usually indicate benign changes. On the other hand, a malignant mass usually has a spiculated, rough and blurry boundary. However, there exist atypical cases of macrolobulated or speculated benign masses, as well as microlobulated or well-circumscribed malignant masses [8]. A round mass with circumscribed margins is shown in Fig. 2(a). Calcifications are deposits of calcium in breast tissue. Calcifications detected on a mammogram are an important indicator for malignant breast disease but are also present in many benign changes. Benign calcifications are usually larger and coarser with round and smooth contours [9]. Malignant calcifications tend to be numerous, clustered, small, varying in size and shape, angular, irregularly shaped and branching in orientation. Calcifications are generally very small and they may be missed in the dense breast tissue. Another issue is that they sometimes have low contrast to the background and can be misinterpreted as noise in the inhomogeneous background. Fine pleomorphic clustered calcifications with high probability of malignancy are shown in Fig. 2(b).

Figure 2 Examples of abnormalities: (a) round mass with circumscribed margins, (b) fine pleomorphic clustered calcifications



Architectural distortion is defined as distortion of the normal architecture with no definite mass visible, including spiculations radiating from a point and focal retraction or distortion at the edge of the parenchyma [10]. Architectural distortion of breast tissue can indicate malignant changes especially when integrated with visible lesions such as mass, asymmetry or calcifications. Architectural distortion can be classified as benign when there is a scar and soft-tissue damage due to trauma. Asymmetry of breast parenchyma between the two sides is useful sign for detecting primary breast cancer. Bilateral asymmetries of concern are those that are changing or enlarging or new, those that are palpable and those that are associated with other findings, such as microcalcifications or architectural distortion [11]. If a palpable thickening or mass corresponds to an asymmetric density, the density is regarded with a greater degree of suspicion for malignancy. Most image processing algorithms consist of a few typical steps depicted in Fig. 3.

Figure 3 Typical steps in image processing algorithms



The screen film mammographic images need to be digitized prior the image processing. This is one of the advances of digital mammography where the image can be directly processed. The first step in image processing is the preprocessing step. It has to be done on digitized images to reduce the noise and improve the quality of the image. Most digital mammographic images are high quality images. Another part of the preprocessing step is removing the background area and removing the pectoral muscle from the breast area if the image is a MLO view. The segmentation step aims to find suspicious regions of interest (ROIs) containing abnormalities. In the feature extraction step the features are calculated from the characteristics of the region of interest. Critical issue in algorithm design is the feature selection step where the best set of features are selected for eliminating false positives and for classifying lesion types. Feature selection is defined as selecting a smaller feature subset that leads to the largest value of some classifier performance function [12]. Finally, on the basis of selected features the false positive reduction and lesion classification are performed in the classification step. In the case of mammographic image analysis, the results produced using a certain method can be presented in a few ways. The interpretation being mostly used is the confusion matrix (1) or just the number of true positives (TPs) and false positives (FPs). The confusion matrix consists of true negative (TN), false positive (FP), false negative (FN) and true positive (TP).

$$C = \begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} \quad (1)$$

We have tested the performance of these classifiers by calculating and analysis of accuracy, sensitivity and specificity for malignancy detection. These are defined as follows:

Accuracy: number of classified mass / number of total mass

$(TP+TN)/(TP+TN+FP+FN)$

Sensitivity: number of correct classified malignant mass / number of total malignant mass

$(TP)/(TP+FN)$

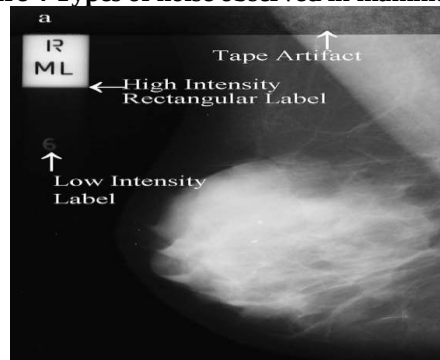
Specificity: number of correct classified benign mass / number of total benign mass

$(TN)/(TN+FP)$

III. Preprocessing

Digital mammograms are medical images that are difficult to be interpreted, thus a preparation phase is needed in order to improve the image quality and make the segmentation results more accurate. The main objective of this process is to improve the quality of the image to make it ready to further processing by removing the unrelated and surplus parts in the back ground of the mammogram. Breast border extraction and pectoral muscle suppression is also a part of preprocessing. The types of noise observed in mammogram are high intensity rectangular label, low intensity label, tape artifacts etc [13]. The types of noises present in mammogram are represented in Fig.4.

Figure 4 Types of noise observed in mammogram



Various frequently practiced preprocessing operations observed in the existing system are as follows:

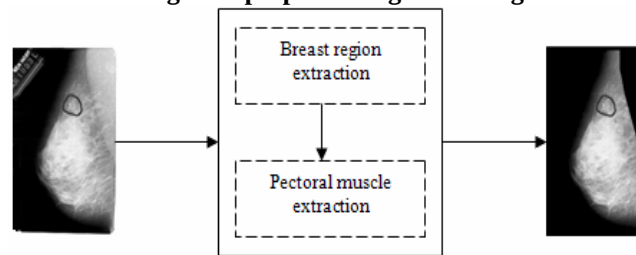
- **Adaptive Median Filter:** Adaptive median filter works on a rectangular region S_{xy} . Each output pixel contains the median value in the 3-by-3 neighborhood around the corresponding pixel in the input images. Adaptive Median filtering has been found to smooth the non repulsive noise from two-dimensional signals without blurring edges and preserve image details
- **Denoising Using filters:** One of the most important problems in image processing is denoising. Usually the procedure used for denoising, is dependent on the features of the image, aim of processing and also post-processing algorithms [14]. Denoising by low-pass filtering not only reduces the noise but also blurs the edges. Spatial and frequency domain filters are widely used as tools for image enhancement. Low pass filters smooth the image by blocking detail information.
- **Mean Filter:** The mean filter replaces each pixel by the average value of the intensities in its neighborhood. It can locally reduce the variance and is easy to implement [15]. It has the effect of smoothing and blurring the image, and is optimal for additive Gaussian noise in the sense of mean square error.
- **Adaptive Mean Filter:** In order to alleviate the blurring effect, the adaptive mean filters [15] have been proposed to achieve a balance between straightforward averaging (in homogeneous regions) and all-pass filtering (where edges exist). They adapt to the properties of the image locally and selectively remove speckles from different parts of the image. They use local image statistics such as mean, variance and spatial correlation to effectively detect and preserve edges and features.
- **Histogram Equalization:** This technique corresponds to redistribution of gray levels in order to obtain uniform histogram. In this case every pixel is replaced by integral of the histogram of the image in that pixel [16]. Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to get better contrast.
- **Contrast Limited Adaptive Histogram Equalization (CLAHE) technique:** The contrast enhancement phase is done using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, which is a special case of the histogram equalization technique that functions adaptively on the image to be enhanced [17]. The original image & its enhanced image is given in Fig. 5(a)-(b). The CLAHE method seeks to reduce the noise and edge shadowing effect produced in homogeneous areas and was originally developed for medical imaging.

Figure 5 a) Original image b) Enhanced CLAHE image



- **Image Orientation:** The orientation of the mammogram is determined. The image is rotated and reflected, so that the chest wall location, i.e., the side of the image containing the pectoral muscle, is on the left side of the image and the pectoral muscle is at the upper-left corner of the image. In order to determine the chest wall location, the decreasing pixel intensity of the breast tissue near the skin-air interface (breast boundary) is used. This tissue is located by employing the minimum cross-entropy thresholding technique, proposed by authors in [18], twice in the original image. By estimating the first derivatives in these pixel transition areas, using the appropriate convolution masks, we can determine the chest wall location. The image is rotated, in order for the chest wall location to be placed on the left side of the image. Next, the top of the image is determined: At first, the vertical centroid of the image is extracted, as the row dividing the skin tissue mask into two equal parts. Then, the asymmetric regions with respect to the vertical centroid are estimated. We assert that the asymmetric region closest to the right side of the vertical centroid is the tip of the breast. The image is flipped vertically, if needed, to place this asymmetric region below the vertical centroid, resulting in an image the right way up.
- **Breast Region and Pectoral Muscle Extraction:** The Preprocessing step based on segmentation has to be done to remove the background area (High intensity rectangular label, Tape, artifact and noise) and to remove the pectoral muscle from the breast region if the image is a MLO view. Generally, pre-processing step is composed of two stages: breast region and pectoral muscle extraction. Figure 6 shows that the Breast region extraction approach is used to separate the breast from the background (first stage), and a pectoral muscle extraction approach (second stage) is used to eliminate the pectoral muscle from breast region.

Figure 6 preprocessing block diagram



Two preprocessing algorithms, one for the breast contour extraction and the other for pectoral muscle segmentation are proposed in [19] in which breast region extraction consist of following steps. They are Histogram equalization, Convolver with mask, Thresholding and labeling, Modifying ends of breast border, Non-Linear Diffusion.

- **Morphological Operation:** Morphology is an operation of image processing based on shapes. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors [20]. The morphological operations are applied on the grayscale mammography images to segment the abnormal regions. Erosion and dilation are the two elementary operations in Mathematical Morphology.

IV. Segmentation

Segmentation is one of the frequently practiced techniques in majority of the medical image processing where the inputs are images and outputs are the attributes extracted from those images. Segmentation divides image into its constituent regions or objects. The level to which segmentation is carried out depends upon the problem being solved. For the segmentation of intensity images like digital mammograms, the common approaches found are as follows:

- Threshold techniques:** These techniques are based on the postulate that all pixels whose value (gray level, color value, or other) lies within a certain range belong to one class. Such methods neglect all of the spatial information of the image and do not cope well with noise or blurring at boundaries. For mammograms, thresholding usually involves selecting a single gray level value from an analysis of the grey-level histogram, to segment the histogram into background and breast tissues. All the pixels with grey level value less than the threshold are marked as background and the rest as breast. Thresholding uses only grey level value and no spatial information is considered. Therefore, the major shortcoming of the threshold is that there is often an overlap between grey levels of the objects in the breast and the background.
- Boundary based methods:** The above methods use the postulate that the pixel values change rapidly at the boundary between two regions. The complement of the boundary-based approach is to work with the regions [21].
- Hybrid Technique:** These techniques combine boundary and region criteria. This class includes morphological watershed segmentation and variable-order surface fitting. The watershed method is generally applied to the gradient of the image.
- Watershed transform:** It can be classified as region based segmentation approach. Watersheds are one of the classics in the field of topography and have long been admitted as a useful tool in image segmentation [22]. It is based on the morphological concepts and the idea of watershed is straight forward. The idea underlying this method comes from geography: it is that of a topographic relief which is flooded by water, watersheds being the divide lines of the domains of rain falling over the region specified. Basins (also called 'catchment basins') will fill up with water starting at these local minima, and, at points where water coming from different basins would meet, dams are built [23]. When the water level has reached the highest point, the landscape is partitioned into or basins separated by dams, called watershed lines or watersheds.
- Edge detection:** An edge is defined as the boundary between two regions with relationally distinct gray level properties. Since the tumor is circular in shape, one alternative to detect tumors is to extract image edges and then look for ring like structures [24]. Different operators were used for edge detection such as Roberts, Prewitt, Sobel, Laplacian of Gaussian, Zero-cross, Canny etc. From the observations, it is concluded that Sobel operator gives more sharp and clear edges as compared to other operators.
- Region based methods:** Region based method rely on the postulate that neighbouring pixels within the one region have similar value. This leads to the class of algorithms known as region growing of which the "split and merge" technique is probably the best known. The general procedure is to compare one

pixel to its neighbour(s). If a criterion of homogeneity is satisfied, the pixel is said to belong to the same class as one or more of its neighbours.

- vii. Split and Merge Technique: The split and merge technique is the other classical region-based segmentation method. As the name indicates, the process consists of recursively splitting the image until all regions satisfy a homogeneity criterion. In an accompanying step, all adjacent regions satisfying a second homogeneity criterion are merged
- viii. Seeded Region Growing: Seeded region growing (SRG), which is closer to that of the watershed with some necessary change is proposed in [21], which is based on the conventional region-growing postulate of similarity of pixels within the regions. For seeded region growing (SRG), seed or a set of seeds can be fairly robust, quick, and parameter free except for its dependency on the order of pixel processing.
- ix. Level Set Segmentation: Level set methods offer a powerful approach for the medical image segmentation since it can handle any of the cavities, concavities, convolution, splitting or merging. The level set method has been used to capture rather than track interfaces. Because the method is stable, the equations are not unnecessarily stiff, geometric quantities such as curvature become easy to compute, and three dimensional problems present no difficulties, this technique has been used in a wide collection of problems involving moving interfaces, including the generation of minimal surfaces, singularities and geodesics in moving curves and surfaces, flame propagation, etching etc .

V. Feature Extraction & Selection

In the feature extraction and selection step the features that characterize specific region are calculated and the ones that are important are selected for the classification of the mass as benign or malignant. The feature space is very large and complex due to the wide diversity of the normal tissues and the variety of the abnormalities. Some of the features are not significant when observed alone, but in combination with other features can be significant for classification. [25][26]

VI. Feature Classification

In feature classification step masses are classified as benign or malignant using the selected features. Various methods have been used for mass classifications [27] in past. Some of the most popular techniques are artificial neural networks and linear discriminant analysis.

VII. Decomposition

Discrete wavelet transform (DWT) is commonly used in image processing. The dyadic wavelet transform decomposes the original image into sub-images using the desired wavelet function called "mother wavelet" that is scaled to get so called "daughter wavelets" and translated through the image. other techniques of decomposition are as follows,

- Gabor Wavelets: Procedure for the analysis of left–right (bilateral) asymmetry in mammograms was proposed in [28]. The procedure is based upon the detection of linear directional components by using a multiresolution representation based upon Gabor wavelets. A particular wavelet scheme with two-dimensional Gabor filters as elementary functions with varying tuning frequency and orientation, specifically designed in order to reduce the redundancy in the wavelet-based representation, is applied to the given image. The filter responses for different scales and orientation are analyzed by using the Karhunen–Loeve (KL) transform and Otsu’s method of thresholding [29]. The KL transform is applied to select the principal components of the filter responses, preserving only the most relevant directional elements appearing at all scales. The selected principal components, threshold by using Otsu’s method, are used to obtain the magnitude and phase of the directional components of the image.
- 3D Wavelet: A separable 3D wavelet, taking full advantage of the 3D structures correlation, decomposes the original volume into sub volumes which can be separately quantized by a uniform scalar quantizer or by a 3D lattice vector quantizer [29]. Concentric hyper-pyramids lying on the cubic lattice are used for searching code words. A distortion minimization algorithm both selects the best number of decomposition and the best set of quantizers in order to minimize the overall mean square error. The whole algorithm is applied on a 3D image data base issued from the Morphometer (a new true 3D X-Ray scanner). The results presented include traditional signal-to-noise ratio performances and a subjective evaluation made by radiologists.
- Curvelet: Curvelet was developed by Candes and Donoho, for providing efficient representation of smooth objects with discontinuities along curves. Detecting and enhancing the boundaries between different structures is very important in image processing, especially in medical imaging. In many important applications, images exhibit edge discontinuities across curves [30].
- Some studies have been done with curvelet in image processing where majority of the authors presented a comparative study between wavelet, ridgelet and curvelet transform on some computed tomography (CT) scans. The comparative study indicated that curvelet yields better results than wavelet or ridgelet.

- Discrete Wavelet Transform: The discrete wavelet transform (DWT) translates the image into an approximation sub-band consisting of the scale coefficients and a set of detail sub-bands at different orientations and resolution scales composed of the wavelet coefficients. DWT provides an appropriate basis for separating the noise from an image. As the wavelet transform is good at energy compaction, the small coefficients more likely represent noise, and large coefficients represent important image features. The coefficients representing features tend to persist across the scales and form spatially connected clusters within each sub-band. These properties make DWT attractive for denoising. A number of wavelet-based despeckling techniques have been developed. The general procedure is: (1) calculate the discrete wavelet transform; (2) remove noise by changing the wavelet coefficients and (3) apply the inverse wavelet transform (IDWT) to construct the despeckled image. The techniques are grouped as: (1) wavelet shrinkage; (2) wavelet despeckling under Bayesian framework; and (3) wavelet filtering and diffusion

VIII.Related Work

The preliminary work on Early Detection of Breast cancer has been done by Qi et al. [31] where the authors have used thermal infrared imaging (TIR). The study has presented a method for analyzing a thermal system based on an analogy to electrical circuit theory called as thermal-electric analog.

Xie et al. [32] have presented two improved Multi-static Adaptive Microwave Imaging (MAMI) methods: MAMI-2 and MAMI-C, for early breast cancer detection.

MAMI [33] is one of the microwave imaging modalities based the significant contrast between the dielectric properties of normal and malignant breast tissues and employs multiple antennas that take turns to transmit ultra wideband (UWB) pulses while all antennas are used to receive the reflected signals.

Xiao et al. [34] have proposed a method of extracting calibration waveform during detection in which the tumor is arranged randomly located in the breast tissue.

Xiao et al. [35] in their studies, the tumor detection in a two dimensional breast model with dispersive characteristic properties of the breast organisms is carried out numerically by the finite difference time domain method (FDTD).

Xiao et al. [36], in this study, the tumor detection in a two dimensional breast model with hemi-elliptical configuration is carried out numerically. The influences from the skin, breast gland and the chest wall are involved in the study. The dispersion characteristics of the breast organisms are taken into account to approach the actual properties of the human breast. Results show that the tumor could be clearly recognized from the reconstructed images created by the confocal algorithm after the appropriate signal processing.

Rejani and Selvi [37] have presented a early tumor detection algorithm from mammogram. The proposed system focuses on the solution of two problems. One is how to detect tumors as suspicious regions with a very weak contrast to their background and another is how to extract features which categorize tumors. The tumor detection method follows the scheme of (a) mammogram enhancement. (b) The segmentation of the tumor area. (c) The extraction of features from the segmented tumor area. (d) The use of SVM classifier.

Abbosh [38] has presented a theoretical model to investigate the possibility of using a hybrid imaging method for early breast cancer detection. The model exploits the high contrast in elasticity between healthy and malignant tissues. It uses an acoustic excitation using Doppler frequency to cause vibrations in the different tissues of the breast depending on their elasticity.

Halloran et al. [39] have outlined two modifications to the MIST system for the early detection of breast cancer, resulting in a quasi-multistatic MIST beam former (multi-MIST). Multistatic MIST beamforming involves illuminating the breast with an ultra wide band (UWB) signal from one antenna while collecting the reflections at an array of antennas, as opposed to traditional monostatic MIST beamforming where only the transmitting antenna records the reflections from the breast.

Patel and Sinha [40] present a method for medical image enhancement based on the well established concept of fractal derivatives and selecting image processing techniques like segmentation of an image with self similar properties for early detection of breast cancer.

Mencattini et al. [41] present an automated procedure for bilateral asymmetry detection composed of the following steps: (1) mammography density analysis and fibro-glandular disc detection through adaptive clustering techniques, (2) analysis and implementation of bilateral asymmetries detection algorithms based on Gabor filters analysis, (3) use of a linear Bayes classifier with the leave-one-out method to asses the asymmetry degree of the two breasts, (4) metrological evaluation of the whole system through random and systematic measurement uncertainty contributions modeling.

Chiu et al. [42] has investigated the feasibility of visualization of micro calcification using opto-acoustic (photo-acoustic) imaging (PAI) technique.

Guardiola et al. [43] have proposed a work on early breast cancer detection using microwave imaging and the worked on algorithm was termed as 3-D quasi real time algorithm that was basically inspired from the computational ability of efficient modified –Born method for assessing the early stage of the cancer.

Spandana et al. [44] implemented algorithm for 1) Image enhancement using wavelets and adaptive histogram equalization technique 2) Segmentation of masses is done using region growing technique 3) Extraction of border of the mass using canny edge detection and morphological operations. Bilateral asymmetry was detected using fluctuating asymmetry. The work presents case studies of four patients, though fourteen patient breast images are processed having different mammographic features.

Hence, it is quite evident from the investigation being performed in this paper that majority of the work being previously conduct deals with the detection of breast cancer while very few work has been explored that addresses the issues of 'early' stage detection of breast cancer.

IX. Conclusion

The paper discusses specifically about the standard techniques applied in medical image processing in relation to detection of breast cancer. The prime techniques illustrated are preprocessing, segmentation, feature extraction and Selection, and feature classification. Prior research works are also elaborated. Basically, it can be seen that there are abundant work being done for the cause of detection of breast cancer where majority of the clinical condition of the cancer stage are reported. But, it becomes a challenging task to implementation the same existing techniques to identify breast cancer in its early stage without any prior medical report of clinical condition of the patient. Hence, working towards this issue of early identification of breast cancer with higher precision will be focus of our future work direction.

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