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Surveyon Different Techniques UsedFor Detection of Malignancy in Mammograms of Breast Cancer

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Abstract—Breast cancer detection is still complex and challenging problem. Diagnosis of cancer tissues in mammograms is a time consuming task even for highly skilled radiologists as it contains low signal to noise ratio and a complicated structured background. Therefore, in digital mammogram there is still a need to enhance imaging, where enhancement in medical imaging is the use of computers to make image clearer. Studies show that relying on pure naked-eye observation of experts to detect such diseases can be prohibitively slow and inaccurate in some cases. Providing automatic, fast, and accurate image-processing-and artificial Intelligence-based solutions for that task can be of great realistic significance. This paper discusses about different techniques used to scans the whole mammogram and performs filtering, segmentation, features extraction.

***Keywords*—Mammography, Image enhancement, Segmentation, ROI(region of interest), Micro-calcification, Masses, Architectural distortion.**

I. INTRODUCTION

Breast cancer is a malignant tumor that grows in or around the breast tissue, mainly in the milk ducts and glands. A tumor usually starts as a lump or calcium deposit that develops as a result of abnormal cell growth. Most breast lumps are benign but can be premalignant (may become cancer). Breast cancer is classified as either primary or metastatic. The initial malignant tumor that develops within the breast tissue is known as primary breast cancer. Sometimes, primary breast cancer can also be found when it is spread to lymph nodes that are close by in the arm pit. Metastatic breast cancer, orAdvanced cancer, is formed when cancer cells located in the breast break away and travel to another organor part of the body [10].Breast cancer is one of the leading causes of death in women. Studies have indicated that cure rates dramatically increase if the breast lesion can be detected at a size less than 1 centimetre, which is too small for the lesion to be palpable [9].

II. BREAST CANCER DIAGNOSTIC METHODS

Breast image capture and analysis techniques play major role in detecting breast cancer.In order to determine if a breast lump is malignant or benign, one or more of the following imaging testsmay be performed. Some of the medical diagnostic methods for breast cancer are given below:

A. *Mammogram*

Mammogram is the basic test to detect breast cancer. During the mammogram test, the Iron Radiation that goes into the breast shows internal parts of the body and also the suspicious region. It shows tissues of breast and veins. After completing the mammogram test, the result will be shown in X-ray film sheet. Nowadays there are 3advanced techniques included in mammography.

a. Digital mammography.
b. CAD.
c. Breast tomosynthesis.

a. Digital mammography. Digital Mammography is fully upgraded by full fielddigital mammography (FFDM). Here x-ray film isreplaced by solid state detector .The solid state detectorsdo the X-ray film image converted into electrical signals.Signals are used to capture the breast inner part to produces special digital image. In mammogram test, onlyone picture can be taken at a time and also only one sideof the breast will be captured. Compression of breastcauses overlapping of tissues and hides certain details. Somammogram sometimes doesn't show the cancer tumor.Main disadvantage is compression of breast is notcomfortable for all women. It may be a painful procedure].

b. Computer Aided Design (CAD). CAD produces digitally acquired mammogram.Computer software plays major role in this mammogram. Itdetects abnormal areas of density and mass calcification thatmay be the presence of cancer. CAD is very helpful toradiologist to detect the cancer.

c. Breast Tomosynthesis. It is a 3 dimensional picture representation of breast using X-rays. It is not considered as standard testing of breast cancer. Main drawback in this testing is that the device is not available in many hospitals. Breasttomosynthesis overcome the above said disadvantage ofmammogram. Breast tomosynthesis takes multiple imagesof breast at many different angles. Breast tomosynthesishave x-ray tube arc. During the test, x-ray tube arc aroundthe breast and takes 11 highly clear 3 dimensional images.

B. *Ultrasound*

Ultrasound is one of the techniques used to detectbreast cancer. Ultrasound is otherwise called as sonography or ultrasound screening. Ultrasound device consists ofcomputer, electronic transducer, ultrasound gel and videodisplay. Transducer is used to scan the body. Transducer isa hand-held device and it has attached microphone.Ultrasound test is non-invasive test and painless. Ultrasound gel exposes the body to high frequency sound waves. During the ultrasound testing, it does not emit any iron radiation as in mammogram. The ultrasound gel is applied in suspicious breast region. Transducer helps display of the internal structure of breast and movements of internal organ, showing the flow of blood vessels. Ultrasound is less expensive.

C. *Doppler Ultrasound*

It tests the blood flow through blood vessels and alsoshows body's major arteries, veins, abdomen, arms and neck. During the breast ultrasound test, the sonographerknows the blood flow in breast. So they use Doppler ultrasound test and also find lack of flow in breast mass. The transducer produce some sounds like frequency soundwaves and sends into the body to test. The waves touch the internal organs and return the echoes from the body. At the same time internal organs are displayed in the computer screen.

D. *Magnetic Resonance Imaging:*

It is full of magnetic field and radio frequency pulses. MRI produces strong magnetic rays into the body. It is little expensive. Computer MRI tests the internal organs, soft tissues, bones and internal structure. Images are shown in computer screen and transmitted into electronic signals then the details are printed or copied in CD in image format. MRI does not produce any iron radiation. MRI test helps to find how large cancer is and suspected muscles are underlying. MRI is capable of capturing the images of both the breasts simultaneously. Any abnormality tumor or lymph nodes in armpit, it can easily detect. MRI finds current stage of cancer and also abnormalities. MRI easily detects dense breast tissue in younger women.

E. *Positron Emission Tomography (PET):*

PET helps to detect cancer area and body's cells first. PET scan starts with an injection of radiopharmaceutical called Fludeoxyglucose(FDG).During the PET scan gamma rays are emitted by FDG.FDG are recorded by the PET scanner and images are reconstructed and reviewed. This helps to identify the suspected malignancy. If physician can find suspicious area, it will accumulate the signals stronger to suspected tissues.

In this paper we discuss different developed computer-aided diagnostic techniques for automatic detection and basic feature extractions from mammogram of breast cancer [24].

III. FEATURES OF BREAST ABNORMALITIES IN MAMMOGRAMS

Usually breast abnormalities are characterized into following classes:

A. *Micro calcifications:*

Calcifications are tiny deposit of calcium which appears as small bright spots on the mammogram. They are described by their type and distribution properties. Radiologists give special attention to calcifications with dimensions of 0.2 to 0.3 mm, with a higher suspicious degree to aligned or clustered micro calcifications.[2, 7]

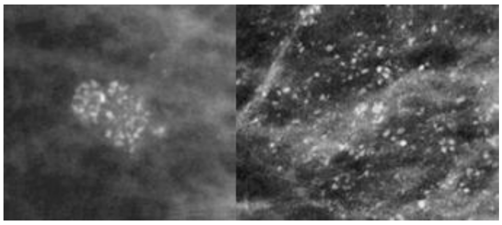


Fig. 1.Figure of Micro calcifications

B. *Masses:*

A mass is defined as a space which occupy lesion. These are seen at least two dissimilar projection. Massesare identified by their shape and margin property. Masses are the most common asymmetric signs of cancer and appear brighter than the surrounding tissue. Most benign masses possess well-defined sharp orders, while malignant tumours often have ill-defined, micro-lobulated, or speculated borders. [2, 7]

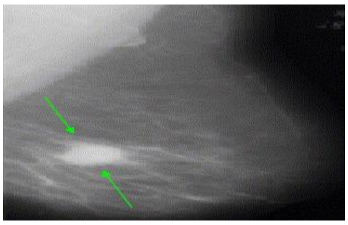


Fig. 2. Figure of Mass

C. *Bilateral Asymmetry and Architectural Distortion:*

Bilateral Asymmetry: Bilateral asymmetry is an asymmetry of the breast parenchyma between left and right breast, may indicate breast cancer in its early stage.

Architectural distortion: An architectural distortion occurs when normal architecture is distorted with no definite mass visible. An architectural distortion on a mammogram is basically a disruption of the normal 'random'pattern of curvilinear and fine linear radiopaque structures. There is no visible mass, but the distortion often appears as a'stellate' shape or with radiating speculation. [2, 7]

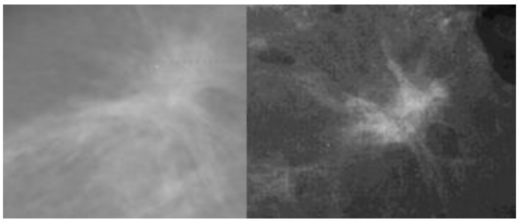


Fig. 3. Figure of Architectural distortion

IV. TECHNIQUE FOR FEATURES EXTRACTION FROM MAMMOGRAMS

A. Image enhancement: Image enhancement can be defined as changing of the image quality to a better and more comprehensible level. It is primarily improving the understandably or perception of information in images for human viewers and facilitating `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task.

Some image enhancement techniques are as follow:

Adaptive Median Filter:

The main idea of the median filter [26] is to run through the image pixel by pixel, replacing each pixel with the median of neighbouring pixels. The pattern of neighbours is called the "window". This window slides pixel by pixel, over the image. The median filter is a nonlinear filter which, under certain conditions, can preserve edges, and it is often used to remove noise as a pre-processing step to improve the results of later processing (for our example, cancer segmentation).

Histogram Equalization:

This technique [27] when applied on an image, adjust the contrast of the image using the image's histogram. This method is used for increasing the global contrast of images. It is generally used when the data of the image is represented by close contrast values. So that the lower local contrast areas gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark and this is particularly true for the mammograms.

Histogram Modified Local contrast Enhancement:

HE uniformly distributes the output histogram by using cumulated histogram as its mapping function. However it produces over enhancement in the output image which leads to loss of more local information in the original mammogram. One more problem with HE is its large backward difference values of mapping functions and the contrast enhancement potential should be enriched without losing the fine details in the mammogram image. Input histogram can be changed so that the modified histogram is closer to a uniformly distributed histogram which lessens the amount of enhancement that would be obtained by HE. HM-LCE method incorporates a two stage processing both histogram modification and local contrast enhancement technique. The main objective of this method is to find a modified histogram that is closer to uniform histogram and to make the difference between modified and input histogram small, which in turn increases the potentiality of image contrast enhancement and resultant image would be the more relevant to the input image. Although the global approach for image contrast enhancement is suitable for some cases, there are situations in which it is necessary to enhance local details in the mammogram image. The number of pixels in that area may have minor influence on the estimation of the global transformation. The solution is to device transformation function based on gray level distribution or other properties in the neighbourhood of every pixel in the image. This method of approach is called local contrast enhancement.

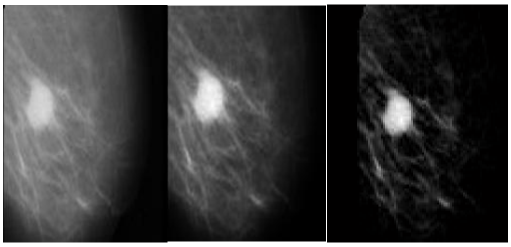
Top-hat Morphological Processing:

Top-hat morphological processing uses gray scale opening to extract regional maxima or objects which differ in brightness from the surrounding background in images with uneven background intensity [28] [29]. The high intensity regions, i.e., the features that cannot accommodate the SE are removed by performing a structural opening. The features removed by opening are emphasized by subtraction of opened image (OI) from the original image (I), which yields a top-hat transformed image.

Top-hat morphological processing returns an image of objects from the input image which is brighter than their surroundings and smaller than the SE.

Fuzzy Contrast Enhancement:

Fuzzy image enhancement is based on gray level mapping into a fuzzy plane, using a membership transformation function. The aim is to generate an image of higher contrast than the original image by giving a larger weight to the gray levels that are closer to the mean gray level of the image than to those that are farther from the mean. We tried to implement an interesting work which uses the same concept for enhancing the contrast of mammograms [30], but unfortunately due to limited time, we were not able to fully implement this algorithm and include its final result in this report. In fact the algorithm presented in the original work, to the best of our knowledge, is lacking some details and the enhanced image resulting from our implementation is clearly wrong for a set of pixels (as can be seen on one set of result in Fig). Therefore for the rest of this report, we skip further explanation of the algorithm and elaborate more on the blind deconvolution and the final experimental results.[25]



(a) (b) (c)

Fig. 4.(a)original image, (b) Contrast Enhanced Image, (c) Morphological top hat filtered image

B. *Segmentation and detection of mass and micro-calcification*:

The process of partitioning a digital image into multiple segments is known as Image segmentation. The aim of segmentation is to streamline and/or modify the representation of an image into something that is more expressive and easier to analyse. Image segmentation is typically used to locate objects and boundaries in images. The result of image segmentation is a set of segments that mutually cover the entire image, or a set of contours take out from the image (see edge detection. Some characteristic i.e. property such as color, intensity, or texture are similar for each of the region of pixels.

Mostly used segmentation techniques are as follow:

Region-Growing Segmentation:

Segmentation tends to partition an image into regions. Region-based segmentation directly determines the regions after pre-processing as compared with thresholding method. Since thresholding method collects the boundaries between regions based on discontinuities. The formulation of Region-Based Segmentation is:

$P(R_i)$ is a logical predicate that defined the points in setR_i and ø is the null set.

(1) Every pixel must be in a region, it represents that thesegmentation is completed.

(2) i represent the points in a region and must be connected in some predefined sense.

(3) Intersection indicates that the regions must be disjoint.

(4) Carriers the characteristicthat are to be fulfilled by the pixels
in a segmented region.

(5) The sense of predicate P indicates that the regions R_i and R_j are different.

Region-growing segmentation profit rewards that itsseparates the region correctly and defines the when it has the sameproperties. Region-growing segmentation provides theclear edges of the images. Region growing segmentationneeds the minimum seed points to represent the property togrow the region. The seed points can determine themultiple criteria at the same time respect to the noise[31].

Segmentation Using Clustering Method

The K-means algorithm is use to divide an image into K clusters. It is an iterative technique. The basic algorithm is: (1). Pick K cluster centres, either randomly or based on some heuristic; (2). The cluster is assigned all the pixels of the image, so that the distance between the pixel and the cluster centre can be minimized; (3). Averaging all of the pixels in the cluster is done to again compute the clusters centres; (4) Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters).

Here, Pixel color, intensity level, texture, and location are the factor that determines the difference. K can be selected manually, randomly, or by a heuristic[32].

Local Binary Pattern (LBP):

LBP operator combines the characteristics of statistical and structural texture analysis. The LBP operator is used to perform gray scale invariant two-dimensional texture analysis. The LPB operator labels the pixel of an image by Thresholding the neighbourhood (i.e. 3x3) of each pixel with the centre value and considering the result of this Thresholding as a binary number. When all the pixels have been labelled with the corresponding LBP codes, histogram of the labels are computed and used as a texture descriptor. Given a pixel in the image LBP code can be computed by comparing it with its neighbours:

$$LBP_{p,r} = \sum_{p=0}^{p=1} S(g_p - g_0)2^p \, S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (1)$$

Where, g0 = gray level value of the central pixel, $g_p$is the value of its neighbours. P is the number of involvedneighbours [32].

Gray Level Co-occurrence Matrix (GLCM):

GLCM is a statistical texture measure. GLCM collect information about pixel pairs, hence it is of second order statistics. GLCM is a tabulation of frequencies or how the pixel brightness values in an image occur. The matrix is constructed at a distance of d = 1 and for direction of given as 0° (horizontal), 45°(diagonal),90°(vertical), and135° (anti-diagonal). Several statistics are derived from theco-occurrence matrix. These statistics provide information about the texture of an image. In the classical paper,Haralick et al. have introduced fourteen textural features from the GLCM and the reference stated that only four of the textural features are considered to be the most relevant. Those textural features are Contrast, Correlation, Energy, and Homogeneity[32].

foveal segmentation:

In [6] Marius George Linguraru, Michael Brady and Margaret Yamhavedetected micro-calcifications byfoveal segmentation based on the algorithm of Heucke et al.[15]theyprimarily removed the glare, shot-noise[16] and CLSs[14]. After that theycalculated set of mean values by using means of masks for the inner area, itsneighbourhood and background; having theSMF (shot-noise free) & no CLS image. Now the meanof the object (•O) is provided by histogram of the inner surface, while themean of thebackgroundis obtained by histogram of the entire image gives the (•B). The weighted summation ofintensities that depends on the range of the mask is called mean in a neighbourhood (•N). The perceivable contrast C is:

$$C = \frac{|\mu_0 - \mu_N|}{\mu_N} \qquad (2)$$

Based on[15]we compute Cmin, where •A=0.923· •N + 0.077· •B [15]. Thesegmentation parameters are set-up automatically based on the value of k, which isimage-adapted. They found that $c_w = \sqrt{k} / 200$ gave stable results. SMF regions whose contrast C>Cmin an adaptable threshold are marked as micro calcifications:

$$C_{min} = \begin{cases} \frac{C_w}{\mu_N}(0.0808 + \sqrt{\mu_A})^2, \ \mu_A \geq \mu_N \\ \frac{C_w}{\mu_N}\left(0.808 + \sqrt{\frac{{\mu_N}^2}{\mu_A}}\right)^2, \ \mu_N \geq \mu_A \end{cases} \qquad (3)$$

In [1] Segmentation of masses is done by using region growing technique. Canny edge detection is used in extraction of the border. This border is processed with grayscale erosion followed by gray scale dilation

In [7] SpandanaParamkusham,Kunda.M.M.Rao, B.V.V.S.N.Prabhakar Rao are done segmentation of mass using region growingtechnique[20], where Harris corner technique is used to get theseed value. Micro-calcifications aredetected using wavelets[18] where an image is decomposedinto sub-bands, from which low frequency sub-band iseliminated and image is reconstructed from remaining bands. Pyramid segmentation and decision tree classification were used to detect the masses[19].

In [8]Nalini Singh, Ambarish G Mohapatra, Biranchi Narayan Rath, and Guru KalyanKanungo have presented a novel approach to identify the presence of breast cancer mass and calcification in mammograms using image processing functions, K-means and Fuzzy C-Means clustering for clear identification of clusters. The K-means and fuzzy C-meansclustering algorithm is applied as segmentation strategy. Here itfunctions as aimproved classifier and aims to group data in separate groups according to their property. Theclustering method for both K-means algorithm and fuzzy C-meansalgorithm is same, but in K-means algorithm when itclusters, it takes the mean of the weighted clusters so as easyto identify masses or the origin point of cancer/ tumor.Similarly in FCM, it considers that each point has weighted value associated with cluster. This is directly implies that, the cluster that have a small value, that will also take in to calculation. Doing this we were able to find out how much the cancer has spread out.

C. Techniques for Detection of Bilateral Asymmetry and Architectural Distortion:

In [7] Bilateral asymmetry was detected using B-spline interpolation [21]. Bilateral breast volume asymmetry in screening mammograms is calculated as a potential marker of breast cancer analysis[22]. Breast shape is assumed as conical shape for volume calculations.

In [1], bilateral asymmetry by calculating fluctuating asymmetry with the volumes of CCleft and CC right breast. Fluctuating asymmetry (FA)is used as a measure of phenotype-based deformation and it isuseful predictor. Low FA can successfully predict lowermorbidity. This is a primaryexamination of thisconcept with respect to breast cancer. These measures included the height, width, andvolume and they were calculated separately for each breastand for each CC view in labview. The breast volume wascalculated assuming a conical shape[23]. The height h is themaximum depth perpendicular to the chest wall at theproximal edge of the film. The breast width w represents themaximum breast outline at the proximal edge of the film.Accordingly the breast volume for the CC views iscalculated as

Volume V=Π × $w^2 \times h/12$

Fluctuating Asymmetry= $V^L + V^R/2 \ |V^L - V^R|$

V^L =Volume of the left breast

V^R =Volume of the right breast

Vdiff = Volume Difference.

IV. CONCLUSION

In this review paper different techniques are being used to detect the breast tumor from scanned images of breast are studied. A comparative study of various techniques is done and after the evaluation of all techniques it is clearly shown the various methods can detect the tumor efficiently and provide accurate results.

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