Research Journal of Recent Sciences ISSN 2277-2502
Vol. **2(10),** 88-98, October **(2013)** *Res.J.Recent Sci.*

Review Paper

Survey Paper on Diagnosis of Breast Cancer Using Image Processing Techniques

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Available online at: www.isca.in, www.isca.me
Received 22nd October 2012, revised 27th November 2012, accepted 2nd June 2013

Abstract

Breast cancer is the oldest known type of cancer in humans. The oldest identification and definition of cancer was recorded in Egypt in around 1600 BC. Since then this disease has been researched and studied to avoid outcomes caused by it but still this disease is considered as one of the most deadliest diseases of all times, as deaths caused by breast cancer only in US in 2012 reached 40,000. In the modern medical science there are plenty of newly devised methodologies and techniques for the timely detection of breast cancer. Most of these techniques make use of highly advanced technologies such as medical image processing. This research study is an attempt to highlight the available breast cancer detection techniques based on image processing and provides an overview about the affordability, reliability and outcomes of each technique.

Keywords: Computer aided diagnosis (CAD), mammograms, masses, micro calcifications, thermograph, thresholding, multi wavelet, RGB.

Introduction

"Breast Cancer affects one in eight women in their lifetime", a general saying about a malignant tumor that begins in cells of the breast and gets into the surrounding tissues as well. This disease is usually evident in women but men can also get affected from it. United States cancer statistics showed that only in United States the number of deaths caused by breast cancer crossed forty thousand in one year. The stats showed that this disease is very common in women and there is plenty of work being done and to be done in this field to get control over such a deadliest disease. Medical research targeting breast cancer is not new and its roots go back into 16th century. Due to the lack of communication and advancement in medical field this disease kept on taking edge on humans and still considered one of the most deadly diseases of all the times. Recent advancement in medical field and more precisely the involvement of information technology in the medical field introduces a new diagnosis mechanism called Medical Image Processing. Medical Image Processing is not only limited to cancer disease, instead it has helped greatly in the diagnosis of different kinds of diseases and it is evident through statistics. With the help of image processing techniques it has become easier to detect tumor from an infected breast and diagnose breast cancer. Early detection can help in proper diagnosis and treatment resulting in minimizing the risk of most unwanted outcome of this disease (death).

Medical images are different in nature and need special processing before diagnosis is made. Also there are many different sources (machines) which produce the images of human body parts. A special technique to deal with special kind of images is required thus leading to different categories and mechanisms for diagnosis process. In this research study we have attempted to provide an insight of the available different breast cancer detection techniques and their numerous impacting factors. We have also tried to provide the performance, accuracy and affordability matrix of the discussed techniques. Each discussed technique is unique in its nature and targets a special kind of scenario. The details and pros and cons of each methodology are discussed in the following lines.

Mammography: Like in other medical diagnosis systems, X-rays are used as diagnostic tool in mammography for the examination of human breast. These examinations are recorded as specialized images which are then observed by radiologists for any possible abnormality[1]. In the following lines few techniques are discussed that use mammography for early detection of breast cancer.

Abnormal Mass Identification in Digital Mammography Images: Mammography cannot detect every kind of breast cancer but still it is world widely used for breast cancer detection due to its inexpensiveness and low complexity. Mammography detects around 80% to 90% of breast cancers[2]. Masses or abnormalities detection at early stage is quite possible with the usage of mammography. Mammography is used as a primary tool for detecting breast cancer[3]. The breast area is extracted as an image and processed before printing on the film for better visualization of size, location and angle of the mass. These optimized images are then observed by radiologist for detection of possible abnormalities. These observations are specific to patients and vary among them[4]. This analysis is based on many existing methods[5]. The proposed technique identifies abnormal masses in mammography image. The algorithm will only identify abnormal masses to ease further investigation. The mammogram images used are taken from mini MIAS database [6]. These images are in the map format of 8-bit having 256 grey levels. All types of breast tissues are considered. This research has also focused on calcification, circumscribed, speculated and other ill-defined masses. The proposed identification technique consists of two stages which are preprocessing and post processing stages.

Preprocessing: Mammogram images are difficult to interpret. Therefore these images are processed in a way so that they can be further used for segmentation. Preprocessing includes removal of unwanted or irrelevant areas and to make prominent the area of interest by increasing the contrast. This is done by setting a certain threshold value.

Post processing: In this stage the preprocessed mammogram image is divided into pixels of small blocks of 2x2 after which all pixels values of the block are scanned and the value having maximum occurrence within the block is assigned to all pixels of that block i.e., this value is propagated to remaining pixels of that block. It means that now the whole block pixels consist of the same value.

These 2x2 homogenous blocks combine to form a 4x4 pixel block containing four 2x2 pixel blocks. After this again these 4x4 block pixels are scanned and the maximum occurrence pixel value is assigned to all pixels of the block. Similarly an 8x8 pixel block is further constructed. Up till now the abnormal mass area is highlighted[7]. After highlighting the area, segmentation of breast is performed through color quantization technique[8]. Through this technique the 8x8 homogenous mammogram image can be segmented to different color regions with each region representing specific part and properties.

The algorithms were tested on the mammogram images and the results are analyzed by constructing the histograms in MATLAB in which a comparison is made between a normal and a diseased breast and then calculating ratio for finding area of the region or the set of pixels were the abnormality lies[9].

Crisp K-Nearest Neighbor and Fuzzy C-Means: The intensity discriminations are utilized as a tool for detecting micro calcifications that further develop into a breast tumor[10,11]. Addition of standard deviation and window means to the visual figure has improved the segmentation results produced by the k-nn means [12]. The technique mentioned in this paper used two methods and they are supervised (crisp k-nn) and unsupervised (fuzzy c-Means) [13]. Both these methods use the physical labeling and clustering of input image by the operator or human[14]. The unsupervised method segments the breast tissues appearing in digital image in disconnected regions. In K-nn means, breast area is segmented by finding out the Euclidean norm and standard deviation. The unsupervised pixel is set to zero or 255 depending upon the result of K-nn i.e., the result show the pixel is a tumor tissue or not a tumor tissue.

Vector Quantization

The method of clustering and texture analysis is also known as vector quantization. This is the method used for segmentation of mammographic images that implemented the generation of codebook or training vector by dividing the whole image into small boxes of equal size. There is use of LindeBuzo and Grey Algorithm (LBG) for vector quantization classifying the complete image into training vectors[15]. After that a centroid is computed and the Euclidean distance is computed between training vectors on the basis of which 8 clusters and a codebook of size 128 are formed. But image constructed using first code vector displayed the result correctly. There were certain other algorithms like Grey level co-occurrence Matrix algorithm (GLCM) [16] and watershed segmentation algorithm that segment the mammograms with 90% accuracy[17].

Image processing techniques and optimization techniques: A lot of research has been done for the early diagnosis of breast micro calcifications from the digitalized mammograms by the application of digital image processing techniques and different preprocessing algorithms proposed in different papers[18-33]. All these papers follow almost the same steps with some difference in techniques. The common steps are preprocessing, segmentation of breast image, feature extraction, tumor segmentation and extracted feature classification[34]. The tracking algorithm is applied to remove the noise that is in the form of X-ray marks from the digital mammographic image[35,36]. This filtered image is then forwarded to median filter in order to further remove the noise and high frequency components without disturbing the edges[26]. The infected region or a region with micro calcifications is segmented by Markov random field (MRF) hybrid with HPACO algorithm[28,32]. Threshold or MAP value is computed through MRF[19,20]. The segmented features are extracted for classification through Dependency Matrix (SRDM) and Grey Level Difference Matrix (GLDM)[10]. Receiver operating characteristics (ROC) is evaluated for classification performances[24]. The results have shown that the detection rate of this algorithm is 94.8%.

Tumor Identification through Image Segmentation and 3d Structure Analysis: There are many sources like mammography and electromagnetic imaging by which we can capture the image for cancer diagnosis[37]. A high resolution mammography is the technique that uses high contrast X-ray system for breast examination. This imaging technique gives a bit inaccurate results in detection and determining the actual stage of tumor resulting in a need to add accuracy if this type of imaging technique is used[38]. The other technique used for early stage tumor detection is electromagnetic imaging which uses microwave technology and the concept of back scattering from the water content present in the tissues. This technique is further divided into three categories and they are microwave hybrid approach, microwave tomography and ultra wide band radar technique. So far the paper only highlighted the imaging techniques being used for early stage breast and lungs tumors detection. The previous CAD system that identifies the early stage breast and lungs tumor with the help of image processing and artificial intelligence gives 85%-93.1% accurate results. The enhanced CAD system identifies the early stage tumor with 100% accuracy for both breast and lungs cancer. This proposed system provides the exact size of tumor with the help of image processing and 3D structure analysis.

The detection technique needs to be dynamic because of different nature of image problems at the time of detection[39]. For this all types of edge operators are applied and the one which gives the ideal result for the particular nature of image is adopted. Next step feature extraction is applied to get the area of tumor and then to calculate this area 3D image reconstruction is used by taking multiple images of the same infected patient from different angles so that a complete tumor image can be reconstructed with the help of MATLAB 3D graph utility. Exact size of the tumor is calculated by the summation of 2D segmented pixels and the pixels of tumor thickness[40]. Area calculation of tumor then proceeds towards the stage classification by the proposed CAD system[41].

Use of Hard Threshold and Multi Wavelet for De-Noising and Enhancement of Image: Another technique known as multi wavelet with hard threshold is proposed which aims at making better contrast of the digital mammographic images and to remove the noise from these images as much as possible so that physician can do better interpretation on the digital mammograms[42]. In the preprocessing stage noise equalization process has been used. Previous researches used the technique of discrete wavelet transform (DWT) but it disturbs the image origin. So the multi wavelet approach was used which is flexible but it does not adjust any parameters for image de-noising. Recently the work has been done on this de-noising problem in multi wavelet based approach. Contrast enhancement takes place in preprocessing stage[41]. Fluctuations are contained in all radiological images which make it difficult to detect small structures and abnormalities. Thus contrast of images can be increased by the equation provided in the paper that takes a form of high pass spatial filter. Different methods are proposed for calculating the threshold in image de-noising band in wavelet transform[43]. All those data values are set to zero which are less than the threshold value whereas threshold value is assigned to data values that are greater than it. Area of multi wavelet transform having high frequency undergoes de-noising. At last original image is retrieved by inverse multi wavelet transform[44]. Error is calculated between the original and transformed image for the evaluation of technique. So by experiments it has been proved that the proposed multi wavelet technique produced better results for physicians for diagnosis of breast tumor at the start. And the proposed method has also produced best peak signal to noise ratio (PSNR) value.

Segmentation of Breast Cancer Mass in Mammograms: Detection of breast cancer at the earliest stage increases the percentage of life to 5years for the infected patient. This cancer has four stages. In the first stage the size of mass varies between 0-2cm and diagnosis at this stage improves the life quality and 5 year survival rate of 96%[45]. At the last or fourth stage, there may be a need of partial or total removal of breast. At this stage 5 year survival rate drops to 20%[46]. For diagnosis, a computer aided (CAD) system is developed for breast and tumor segmentation. Frequency and spatial domain filters are used for image enhancement. Because of the reason that MRI is much more expensive and having lower resolution as compared to mammography, it is not used for cancer diagnosis at starting stage[47].

The imaging technique used is screening mammography [48]. CAD and screening mammography are combined in order to obtain accurate and efficient results. Image enhancement is accomplished by applying spatial and frequency domain filters and low pass filter is used to smooth the edges of the image where as high pass filters are used to make the details sharp and enhanced[49]. These high pass and sharpening filters involve laplacian and gradient filters. For frequency domain filtering, firstly the computation of image Fourier transforms is done. Then transformed image gets multiplied with filter mask. The resulted image shows the prominent abnormal area. After high pass filtering fractal analysis is performed to remove the tissues in which cancer cells are not present; this is done to make segmentation step efficient as smaller area is left. All this work is done on the basis of roughness that varies in case of cancer tissues and normal tissues.

The segmentation is performed by using morphological algorithm that extracts the boundaries. This algorithm consists of two steps and they are: i. Preprocessing, ii. Segmentation.

Preprocessing step consists of converting an image to binary image by using the method of thresholding. The tumor tissues having greater intensity may be represented by 1. After this process two morphological operations are applied and they are dilation and erosion for highlighting tumor pixels or white pixels. Now the boundary extraction of binary image is performed to extract the tumor area by morphology boundary extraction. Through this way tumor is extracted from the mammogram images. Table 1 gives a comparison of different techniques for cancer diagnosis on mammographic images.

Thermal Infrared Images

All previous papers used mammography imaging technique for the breast tumor detection keeping in view the fact that X-rays used are harmful for the body especially for women of age above 40 years and the excessive exposure of body parts to radioactive rays may have dangerous results. The papers provide a new way of detecting breast cancer in which the body is not exposed to radiations and cancer is diagnosed through thermal indicators at infrared images[50-53]. On these images, image processing techniques along with computer artificial tools are applied[54]. The phenomenon behind using thermal indicators or infrared images is that high metabolic activity takes place in cancerous cells instead of normal cells[55]. As a function of their temperature, the entire universe objects emit infrared radiations[56]. This thermal imaging technique is known as thermography[57].Thermography uses thermal infrared camera[58]. The camera takes a picture of a region which is to be considered i.e., the picture of the breast.

Breast Cancer Diagnosis Based On Thermal Features in Infrared Images: The papers proved the proposed technique by analyzing the results of experiments involving two stages[50-53]. The first stage uses Asymmetry method.

Asymmetry: This method is known as asymmetry because the left and right breasts are asymmetric to each other. Firstly the initial or RGB image is converted to grey image by using the function rgb2grey in MATLAB. After that the next task is to segment the breast area for which the parabolic Hough transforms is applied. To accomplish this task the grey image is converted to edge detected image by applying the edge operator.

Thermal Image Development: The pixels in thermogram image represent thermal radiation of temperature by the human body. Different tissues and organs of a body produce different amounts of radiation on the basis of which we can identify where the abnormality actually lies. For this the pick pixel intensity of thermal image technique is applied which uses the logic of fuzzy procedures of K-means and C-means.

Automated Image Segmentation: In this approach the top body edges are manually removed. After that a canny edge detectors series is applied. The main step was the lower breast boundaries detection [59]. This task got accomplished by applying the canny edge operator and repeatedly checking the effects by changing the threshold so that only bottom breast boundary is left. Threshold is selected by using the automatic threshold selected filters algorithm. After edge detection the left and right edges are separated and Hough transform is computed so that lower breast boundary can be detected or extracted[60].

Analysis through Artificial Neural Network: Previously, because of the lack of image processing tools and image acquisition equipment, results happened to be varying and inconsistent [61]. But now we have automated tools for breast analysis.

Like every algorithm the methodology proposed consists of certain steps which are as follows[62]: i. Image acquisition, ii. Image preprocessing, iii. Image analysis with ANN(Artificial neural networks).

Thermal images are acquired and preprocessed by first identifying outside boundaries of the breast. Edges are detected by applying the canny edge operator and are further trimmed. The breast is found by applying the morphological operators to the edge detected image by considering the breast shape of two convex or a smallest ellipse. The segmented breast is further divided in to four quadrants according to proposed division [63]. Table 2 gives a brief overview of different diagnosis techniques applied on infrared images.

Microscopic Slide Images: Histological slide images are captured by placing CCD camera with the microscope to capture the microscopic picture of a slide so that CAD can be performed on it.

Table-1
Comparison between different diagnosis techniques on mammographic images

Technique/ Algorithm	Advantages / Characteristics	Limitations
Digital Mammography[3]	Calcification, circumscribed, speculated and other ill-defined masses can be diagnosed	Frequent intensity changes may not give 100% diagnostic results
K-nn and fuzzy means algorithm[10]	Change of intensity is used as a discriminating feature	-
Vector quantization[15]	Absence of over and under segmentation	Lot of segmentation areas and information
MRF and HPACO algorithm[34]	Success rate of this algorithm is 94.8%	-
Image segmentation with 3D structure analysis[37]	Exact size and thickness of tumor can be calculated	CAD system has to be combined with the segmentation algorithm to get highest success rate
Multi-wavelet and hard threshold[42]	Gives good results in case of dense mammograms by noise cancellation	-
Screening Mammography [48]	Diagnosis is based on the roughness (between normal and tumor tissues)	-

Watershed Segmentation of Breast Cancer Cells: The steps contained in the treatment proposed for breast cancer cells diagnosis are as follows[64]: i. Segmentation through watershed method that goes by performing mathematical morphology. It actually divides the image on the basis of discontinuities. ii. Feature extraction is performed using Fourier descriptors. The attributes for extraction are shape and color. iii. Classification and marking of tumor cells.

Segmentation through Neural Network and Morphology: The researchers aimed to ease the pathologists by proposing an automated system for the diagnosis of cancer cells from stained slides of breast tissues. The idea behind this observation is to display progesterone and estrogen receptors existence in the cells infected by tumor. This demonstration process is carried out by applying the concepts of neural networks[65]. The steps followed in the paper to achieve the goal are: i. Preprocessing, ii. Image segmentation, iii. Segmentation of cancer cells, iv. Object classification and, v. Feature extraction.

The cells after applying to the neural network are classified into two classes on the basis of color and size i.e., blue (N) and brown (P). Brown color means positive, that is, cancer cells are present and blue color represents a negative result. Pixel values for background, P, or N regions respectively are -1, 0 and 1 from the neural network. Segmentation presented in the paper is based on the local adaptive threshholding and morphological operators for the breast tumor cells[66]. Lastly the removal of spike noise is accomplished through morphological erosion and opening by considering a structuring element of disk shape.

Marker-Controlled Watershed Segmentation of Nuclei in H&E Stained Breast Cancer Biopsy Images: The researcher has proposed a technique for the segmentation of breast biopsy stained images[67]. The technique includes color de convolution and morphological operations to remove image unnecessary or extra areas during preprocessing phase. Markers are obtained for the marker controlled watershed segmentation. Watershed segmentation is the method suited for nuclei segmentation. These markers are actually nuclei positions obtained from the fast radial transform. Nuclei are removed in the post processing stage. Nuclei can also be segmented by template matching done[68]. The watershed segmentation for the segmentation of nuclei is proposed[69]. Closing and opening is performed in the preprocessing step by considering a structuring element of disk shape. Preprocessing is performed for the removal of unwanted areas from the image while preserving the boundaries of nuclei. Color de convolution is the first task to be done in the preprocessing stage[70]. The success rate of this algorithm is almost 81.2%. Table 3 gives a comparison between different techniques for cancer diagnosis on microscopic slide images.

Ultrasound Images: Ultrasound is the second most common method that is used to detect breast cancer in an early stage.

Segmentation of Breast Lesions: The ultrasound image is taken as an input in the technique explained in paper which is then filtered using anisotropic diffusion algorithm for the removal of speckle noise[71]. Edges were enhanced by using un-sharp masking technique. Image segmentation was performed by using normalized cut (N-cut) technique. This technique is applied to detect the lesion region. The image was cut into multiple sets. After detection of lesions in each set the grey image was converted into binary one and morphological closing operation was applied to close the boundary of lesion. The closed lesion region was then extracted. The successful results have shown that this approach of segmentation is effective to diagnose breast lesions or tumors.

Table-2
Comparison between different diagnosis techniques on infrared images

Algorithm/ Technique	Advantages/ Characteristics	Limitations
Thermal infrared images[50]	Tumor is diagnosed depending upon the radiation emitted by different body parts	May give false results in case of flat lower part of the breast
Automated image segmentation[59]	Only lower breast part is taken into account and upper body parts are filtered out	——
Artificial Neural Network[62]	BP neural network has been provided with fairly good results of classification and statistical parameters	Careful temperature inspection

Table-3
Comparison between different diagnosis techniques on microscopic slide images

Algorithm/ Technique	Advantages/ Characteristics	Limitations
Watershed[64]	Division of image on the basis of discontinuities	More accuracy and validation is needed in case of larger histological slides
Neural Network and morphology[65]	Complete removal of spike noise through morphology	-------
Marker controlled Watershed[67]	Success rate is 81.2%	Low success rates as compared to other algorithms

Use of Non-Extensive Entropy for Breast Cancer Images Automated Diagnosis: To detect cancer tissues of breast from the ultrasound images the task needed to be done is the classification and extraction of lesion from the noisy background so that it can be investigated whether the lesion is malignant or benign. Different algorithms were proposed to perform this task and one of them was entropy that can be used to calculate the threshold so that lesion boundary can be extracted. All these algorithms for calculating or investigating the correct segmentation are explained[72-75]. Another approach known as non-entropy approach that is followed in paper can be used as well to achieve the desired threshold[76]. So the proposed algorithm using this approach is known as Non-Extensive Segmentation Recursive Algorithm (NESRA). The input image to this algorithm should be in grey scale having certain number of grey levels. Probability distributions are calculated for the foreground and background pixels, normalization takes place and the resulted pixels are separated on the basis of luminance. It is recursive method for the segmentation of ultrasound image that generates region of 2r+1 such that r represents the recursions number. After segmentation morphological erosion operation was applied to extract tumor boundary from the background. Experiments and results have shown that this algorithm is 97.92% accurate. The major advantage of NESRA is that it is also effective or sensitive to regions like lesion's boundary and transitions between the boundary elements.

Segmentation through Wavelet Transform: Segmentation of solid nodule lesion of breast can also be done by acquiring the texture information and to accomplish this task 2D wavelet transform (DWT) is computed on the ultrasound image of breast[77]. The phenomenon behind DWT is the decomposition of original image into sub bands i.e., in the higher and lower bands. Each pixel of the original image is searched for 4 features and they are: i. Texture extraction characteristics through 1-D and 2-D DWT algorithm, ii. Threshold value determination through the above texture information, iii. Texture classification, iv. Smoothening of classified region and segmentation in the end.

Results have shown that segmentation results were correct most of the times but the proposed algorithm proved to be more successful in case of malignant tissues.

Segmentation of Breast Cancer Masses in Ultrasound Using Signal Derived Parameters of RF and Estimates of Strain: Ultrasound images consist of speckle and attenuation noise. These images also have varying texture and shape. Due to invasion tumor area in these images lacks a proper boundary. To incorporate all these problems an algorithm for detection of breast cancer and its successful segmentation is proposed in paper that uses the concept of RF signal parameter with strain estimation in case of moving picture [78]. This paper used the prior residue rp of AR model for power estimation without speckle and attenuation noise in the graph plotted images for the breast masses[79]. The ultrasound moving image is acquired and recorded at some radio frequency and a sampling frequency is adjusted. To minimize shadowing effects from the ultrasound images a filter is applied so that horizontal features can be made prominent.

Automated Segmentation of Ultrasonic Breast Lesions through High and Low Level Empirical Facts: The processing on ultrasound can detect images up to 100% accuracy and also eliminates the need for needle biopsy[80]. CAD is used for the effectiveness of breast screening after acquiring the image[81]. The technique proposed for breast cancer screening is fully automated that does not require human intervention[82]. The lesion boundary and contours are extracted along with the texture, intensity and shape[83]. Shadowing effects and false positive results in case of fat granular tissue are dealt [84]. The proposed system proved to be robust as it can incorporate changes in the system parameters, training sequence and can also figure out seed point in the lesion[85]. Low level model includes image enhancement by first removing the speckle noise and then enhancing the contrast or sharpening of edges of the lesions[85,86]. The second major step is lesion intensity and texture classification[87]. The third concern is the seed point determination followed by lesion feature extraction or region growing by estimating the threshold. Segmentation through region growing may separate all the pixels containing tumor[88]. Boundary points are then found on the edges by calculating the directional gradient and drawing the radial lines. The boundary points sometimes consist of maxima that are removed and are known as outliers[89]. Similarly segmentation is computed on high level areas and the results are proved to be highly accurate i.e., near to 99.089%. Table 4 compares the techniques applied on microscopic slide images.

Magnetic Resonance Images (MRI): Mammography is the safest and cheap approach but suffers from the drawback of its low dose and high resolution as a result of which some 3D mass tissues get overlapped[90]. So for this special case, the most suitable and appropriate techniques to diagnose the tumor masses and its classification are: i. Magnetic resonance (MR)[91], ii. Computed Tomography (CT).

3D Hidden-Markov Model for Breast Tissue Segmentation and Density Estimation from MR Images: For breast tissue detection and tumor segmentation 3D hidden Markov model (HMM) is taken in account[92]. Previously in case of mammograms it is explained that 2D hidden Markov random field is applied to estimate density and other features from the mammographic images[93,94]. According to the algorithm proposed first the background segmentation is performed through automatic edge detection[95,96]. Due to this edge detection there remains some gaps on the edges for which 20 voxel average filters is applied to the edge detected image for making the edges thick [97, 98]. Histograms are then drawn and threshold is estimated [99]. HMM is then applied for tumor segmentation. Images are reconstructed by backscattered filtering. The results proved that HMM is highly robust with low training sequence. HMM segmentation proved to be reliable and accurate for breast tumor segmentation.

Table-4
Comparison between different techniques on microscopic slide images

Algorithm/ Technique	Advantages/ Characteristics	Limitations
NESRA Algorithm [71]	Effective technique for the detection of breast lesions having removal of speckle noise and edge enhancement properties	——
Non-Extensive Entropy [76]	The algorithm is 97.92% accurate. It is also effective or sensitive to regions like lesion's boundary and transition areas	——
Wavelet Transform [77]	Efficient diagnosis technique in case of malignant tissues	Unsuccessful in case of benign
RF Signal parameters and Strain Estimates [78]	Successful approach in case of small tumor size in the ultrasound moving images	Low success rate in case of large tumor size or tumor at later stage
High and low empirical facts model [85]	Gives highly approximate correct diagnosis of tumor lesions	——

Table-5
Performance Comparison of all imaging techniques based on the image processing results

Image Acquisition Technique	Affordable	Performance/ Accuracy	Reliable
Mammography	Yes	97%-98%	Yes but regular mammography has side effects
Thermal Infrared Imaging	Very less	85%-90%	Yes and no side effects
Microscopic Slide Images	Yes	99%	Yes
Ultrasound	Less	97.92%	Yes but has side affects
MRI and CT Scan	Less	97%-99%	Yes

Conclusion

This survey paper overviewed the techniques and algorithms proposed for the detection of breast tumor and for interpreting its stage in some cases so that proper treatment can be given to the cancer patient for improving his life quality. Digital mammography technique is widely used for early stage breast cancer diagnosis but due to its negative effects on human body other safe techniques like infrared imaging, MRI, Biopsy are also proposed. The most accurate imaging techniques proved include Mammography and Biopsy. Table 5 gives a performance comparison of imaging techniques based on the image processing results.

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